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The Evolutionary Optimization of a Company's Return on Equity Factor: Towards the Agent-Based Bio-Inspired System Supporting Corporate Finance Decisions

RAFAŁ DREŻEWSKI[1], SYLWIA KRUK[2], AND MACIEJ MAKÓWKA[1]
[1]AGH University of Science and Technology, Department of Computer Science, 30-059 Cracow, Poland
[2]Cracow University of Economics, Department of Economics and Organization of Enterprises, 31-510 Cracow, Poland

Corresponding author: Rafał Dreżewski (drezew@agh.edu.pl)

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ABSTRACT Return on Equity (ROE) is an important factor from the perspective of formulating and implementing a company's financial strategies. It is also one of its evaluation criteria. It presents to investors the effectiveness of using their capital. Increasing profitability may be treated as a symptom of shareholder wealth, while its reduction may be a signal indicating a deterioration of the financial situation of the company. An investment in a company will be attractive to investors if the results obtained by it will enable the benefit from the dividend to be paid and if the share prices will show an upward trend. Therefore, profit and profitability are categories dependent on the company and affect the wealth of its owners. The ROE ratio is synthetic and is linked to, among others with the size of sales, asset use activity, and the size of the company's debt. However, the decisions regarding the capital structure of a company should be made not only by purely economic and financial analyses but also should take into account the social and environmental effects of economic activities. To take into account not only short-term financial goals but also long-term sustainable development goals during the decision-making process, we need intelligent and creative multi-criteria decision support tools. Bio-inspired artificial intelligence techniques—such as evolutionary algorithms, deep neural networks, or swarm algorithms, to give only a few examples—are gaining more and more popularity in the recent years. Evolutionary algorithms are optimization techniques that are modeled on the processes of evolution that are taking place in natural populations. They can find approximate solutions to the NP-hard global, multi-modal, and multi-objective optimization problems. In this paper, we propose an innovative approach—an agent-based bio-inspired system supporting decisions in the area of corporate finance, which takes into account not only financial goals but also the sustainable development goals. The system will allow for multi-objective optimization with the use of bio-inspired algorithms. In this paper, we will concentrate on one module of the proposed system—the evolutionary algorithm optimizing the ROE factor. During the experiments, we will verify the ability of the proposed algorithm to provide decision makers with reasonable, useful, and, at the same time, also innovative and non-obvious solutions concerning the desired capital structure of a given company, which usually operates in a rapidly changing environment. The proposed system will allow for taking into account more than one criteria and perform multi-objective optimization with the use of an evolutionary algorithm or an agent-based co-evolutionary algorithm, so it will be possible to include also the long-term goals of sustainable development in the future.

INDEX TERMS Agent-based bio-inspired algorithms, bio-inspired artificial intelligence algorithms, corporate finance, decision support systems, DuPont analysis, evolutionary algorithms, Return on Equity, sustainable development.

I. INTRODUCTION AND MOTIVATION

The concept of sustainable development means such a development process that aims to meet the needs of the present generation without reducing the development opportunities of future generations [1, p. 974]. In this context, maintaining the financial stability of the company is of crucial importance. Financial stability management requires a system of self-regulation based on alerting mechanisms that would allow detecting any deviations from the accepted standards.

From a company perspective, sustainable development involves the balancing of three areas: economic, environmental and social. Such concept is generally in line with the primary objective of corporate finance management, which assumes that profit can be considered as a superior goal, but on condition that the goal is to maximize it in the long run. In this sense, it becomes a condition for the development of a company translating into an increase in its value. Economic analysis includes two departments: financial analysis and technical and economic analysis. Very often the emphasis is put on the economic analysis, that is on the analysis of the financial condition and financial results of a company. It is, therefore, necessary, as a part of the strengthening of corporate sustainability strategies, to pay more attention to social and environmental issues. If the purpose of the financial analysis is to identify the reasons for changes in the state of assets, capital position and profitability of a company, it should be noted that among this reasons the social and environmental effects have to be included. For the success of a company, such factors as quality management systems, environmental management system, the management system of health and safety at work, cleaner production, ecolabelling and responsible care also translate into success [2, p. 668]. K. Lindow, A. Kaluza, and R. Stark note that growing customer interest in sustainable products and services can provide companies with a competitive advantage and therefore aid securing the success of the company in the long term [3, p. 346]. The implementation of sustainable development goals in the economic, environmental and social aspect is not possible without the support of economic analysis. Planning should, therefore, take into account these aspects, and the control should make it possible to compare the desired state with the actual state. As a consequence, it will be possible to remove the distortions that occurred in the past and to adopt future-oriented actions in line with the plan. A. Takala notes that sustainable development should be considered as a continuous process rather than as a goal [4, p. 502]. I. P. Sudana emphasizes that it is justified to prepare a new concept of financial statements in which economic, social and environmental aspects will be included. New concepts of reports should be prepared in the spirit of sustainable development [5, pp. 157 and 161].

The derivative of the primary purpose of the company's operation is the increase in its market value, which leads to the maximization of the owners' benefits. These benefits may be expressed in the form of dividends and long-term increase in the value of shares/stocks, with the increase being higher than the inflation increase. It should be noted that this goal cannot be realized if there is no postulate of survival and development [6, p. 170]. The neoclassical concept was further discussed and in the eighties M. Friedman presented an approach that the only responsibility of the responsible company should be the concern for the interest and wealth of its owners [7, p. 88]. The neoclassical theory is reflected in this approach, as profit as a source of paid dividends is related to the benefits of shareholders. The primary objective thus formulated has been a criterion since the beginning of the nineties, which increasingly affects changes of the company's development strategy. Each potential investor, having multiple investment options, will choose a variant of investing, which, given a certain level of risk, will provide him with the highest possible rate of return. Failure to obtain the expected rate of return may result in the withdrawal of funds, which from the perspective of the company means the loss of part of the capital for running a business. Therefore, in the course of managing the company, it is necessary to adopt the criterion of investor expecting measurable financial benefits, including risk and opportunity costs.

The strategy, as well as the entire system of organization and management, is built around such goal of the company—it is the so-called value management. However, it raises some controversies, at the source of which is the approach to interest groups, environmental factors, which implies the assumption that the company should not function only to increase its value and benefits for the owners. In response to the concept of M. Friedman, R. Freeman and W. Evan presented their approach to the primary objective of a company that is based on the concept of stakeholders and remains in the spirit of corporate social responsibility [8, p. 319].

The idea of stakeholders draws attention to the fact that the company is an inseparable part of society, therefore, in the course of its activity, the needs and aspirations of the other interest groups should be taken into account. At the basis of such an approach lies A. Smith's statement that the entrepreneur who is trying to satisfy his own needs contributes to the well-being of the society to a greater extent than if he was guided by social goals [9, p. 11]. Thus, accepting the owners' interest as the supreme goal of a company creates also opportunities for the whole society. Accepting the main objective formulated in this way does not contradict the concept of the social company model. Building stable, long-term relationships with individual stakeholder groups is the basis for realizing values for owners. However, the implementation of the postulate of maximization of the benefits of owners does not have to be synonymous with ignoring the needs of other stakeholders. Shareholders use the generated value as the last interest group, after creditors, contractors, employees, central and local authorities. Furthermore, in well-run companies, the value is created not only for owners.

However, the business practice provides evidence of differences between the approach presented above and the behavior of companies. Above all, it should be noted that there is a lack of compatibility between the financial system that would support sustainable development by supporting pro-environmental attitudes in economic activities [10]–[12]. This mismatch is primarily because the primary goal of the financial system and financial institutions is to generate profits. Such an approach translates into the approach of many companies and is incompatible with the concept of sustainable development, which requires the perception of the company in the long-term perspective [11], [12]. As shown by the experience related to the economic crisis in 2008, focusing on short-term goals has a detrimental effect on companies and the financial system.

Some authors indicate that the impact of the financial system on sustainable development in some countries is minimal or non-existent [10, pp. 40–47]. Sometimes this is justified by the fact that the socially responsible stock exchange shows a lower efficiency compared to the traditional stock exchange, which is mainly the case in developing countries [13, pp. 94–106]. Some authors suggest that despite the inclusion of environmental, social and management criteria (ESG), the concept of sustainable development is still not included in economic practice [14, pp. 303–329]. They argue that the cause of this deadlock is the fact that financial institutions do not consider sustainable development in their long-term goals and the lack of reliability of environmental, social and governance (ESG) measurements [14, pp. 303–329]. In the literature on the subject, it is pointed out that the general objectives of financial institutions are opposed to those resulting from the concept of sustainable development [10, pp. 40–47], [11], [12]. Such incompatibility results from the fact that the financial system is oriented towards achieving quick profits while sustainable development requires a long-term policy. Such an approach, represented by financial institutions, is transferred more or less consciously to companies.

It should be noted that the postulate of maximizing the value of a company cannot be met if the demand for maximizing profits, in the long run, is not met. This fact means that profit, which is reflected in profitability, becomes an essential factor in the course of the company's operation and development. The very survival on the market under the conditions of competition and the changing environment will lead to stagnation and gradual death [6, p. 170]. Therefore, profitability is related to the fundamental purpose of the company's operations.

Profitability is considered a synthetic measure of the economic effectiveness of a company, which is a consequence of the method of calculating the financial result, which is determined as the difference between the cash revenues obtained from the sale of the generated effects and the costs incurred for their production. A positive result means profit, which indicates the economic efficiency of the company's operation. A negative result will indicate economic inefficiency, which is the result of obtaining worse effects at given assumed costs, or specific effects at too high costs.

Three aspects of profitability are distinguished: profitability of sales, assets, and equity involved. The last one is of interest primarily to investors, as it indicates the rate of profit that an investment in a company's shares brings. In this study, the Return on Equity (ROE) becomes the point of interest. Therefore, its higher level implies a better situation for the company and its shareholders. A higher rate of Return on Equity capital creates opportunities for higher dividends in the future and an increase in the value of shares. Taking into account the above, it becomes justified to examine which factors favor the increase in Return on Equity.

The above considerations lead to the conclusion that there is a need for computer systems, algorithms, and techniques that could support managers' decisions regarding the capital structure of a company, taking into account not only financial aspects but also corporate social responsibility goals. It seems that especially interesting in this context are bio-inspired artificial intelligence techniques because of their potential ability to propose new and creative solutions to hard global, multi-modal and multi-objective optimization problems.

The popularity of biologically inspired artificial intelligence algorithms has been continuously growing in the recent years. The bio-inspired algorithms include, among others, evolutionary algorithms, artificial neural networks, deep neural networks and deep learning, artificial immune systems, ant colony optimization algorithms and swarm algorithms [15]–[17]. Such techniques are sometimes combined with the agent-based approach, and there are several possibilities in this regard. They can be used as computational techniques for the multi-agent systems [18]. Another possibility can be the integration of several bio-inspired techniques or algorithms on the basis of the agent-based approach, which will allow for using them simultaneously and for utilizing the effect of synergy [19], [20]. Finally, the agent-based versions of evolutionary [21] and co-evolutionary [22] algorithms can be developed.

The term "evolutionary algorithms" defines a group of techniques modeled on the mechanisms of biological evolution. The evolutionary algorithms can find approximate (sub-optimal) solutions for NP-hard global, multi-modal and multi-objective optimization problems, where traditional methods and algorithms usually cannot find a valid solution at all or the time they seek a solution is unacceptable from our point of view [23].

During the years of research on the evolutionary algorithms, many different versions have been proposed, such as evolution strategies, evolutionary programming, and genetic algorithms, to name a few. One of the most interesting is the agent-based evolutionary algorithm (or the so-called evolutionary multi-agent system—-EMAS) [21].

The economic and financial applications of the evolutionary algorithms were mainly focused on finding optimal investment strategies—the amount of research papers, in which the evolutionary algorithms were applied to the optimization of a company's capital structure is somewhat marginal. This paper tries to expand the scope of research on economic and financial applications of the evolutionary algorithms by exploring the possibilities of using them as a decision support tool for managers of a company. Thus, the idea of an agent-based bio-inspired decision support system that provides managers possible variants regarding the optimal capital structure of a given company is proposed. The proposed system will take into account not only short-term financial goals but also long-term goals of sustainable development. In this paper, we develop and experimentally verify one module of the system—the evolutionary algorithm, which is used to optimize the ROE factor. During the experiments, we will examine whether the evolutionary algorithm can provide managers or decision-makers with useful, realistic but at the same time innovative and non-obvious information about the desired capital structure of a company and possible changes in it.

The paper is organized as follows. First, we introduce the ROE factor, and the review of research on its importance in the process of assessment of the company's economic and financial condition is presented. Next, the evolutionary algorithms and their selected applications in economic and financial domains are discussed. In the following section, the idea of an agent-based bio-inspired system supporting corporate finance decisions using financial and sustainable development objectives is presented. Next, the evolutionary algorithm used for the ROE factor optimization is presented. In the following part of the paper, we will show the results of experiments aimed at verifying the ability of the evolutionary algorithm to generate realistic and innovative solutions that can be potentially used by decision-makers to improve the economic and financial condition of a company. In the experiments, real data from the construction sector was used as the constraints for the optimization problem.

II. RETURN ON EQUITY FACTOR

Behavioral theories are oriented towards taking actions aimed at satisfying all expectations of stakeholders. Adoption of this approach contributes to taking actions that will translate into a positive perception of a company in the environment, which will improve its competitive position and translate into financial success. There is, however, a controversial issue regarding the possibility of simultaneously meeting the expectations of all stakeholders. Satisfying the needs of one group can sometimes take place at the expense of another group, which sometimes means pursuing opposing goals. In this way, the goals of one group cease to be treated as superior. As already noted, it is assumed that this goal is to maximize the benefits of the owners.

This behavioral concept of the company's objective, referring to stakeholder groups, directly refers to the concept of corporate social responsibility. Corporate social responsibility is related to the responsibility of a company for the impact of its decisions and actions on the society and the environment. Corporate social responsibility postulates to take into account the needs of all stakeholders, thanks to which it contributes to sustainable development.

Considerations regarding sustainable development can be conducted at the macroeconomic and microeconomic level. If they are transferred from the macroeconomic to the microeconomic level, then we can talk about the sustainable development of the company understood as a sustainable and stable development within which the needs of the present generation are met, while opportunities for the future generations are not diminished. In the context of sustainable company development, it is essential to maintain stability, especially that companies operate in a turbulent, rapidly changing environment. It is possible to formulate the conclusion that the sustainable development of a company requires its activity to be based on stable financial foundations. Then it will have the possibility to implement actions which enable proper functioning in a continually changing environment. Financial stability is most often identified with the stability of the financial system, but it can also be considered from the perspective of the company. A financially stable company will achieve its objectives despite the occurrence of disruptions. The financial stability can be assessed using various parameters in the area of financial liquidity, solvency, and profitability. Therefore, factors that should be of interest include, among others, capital structure and ROE factor. Identification of irregularities allows for taking appropriate corrective actions or eliminating irregularities. Maintaining financial stability is possible only if the company has an efficient system of self-regulation that will enable elimination of deviations from the adopted standards. It can be described as a warning system for which the starting point is the index analysis.

The subject literature gives many diverging opinions considering the possible impact of CSR on shareholder value. Some of the authors believe that the impact of CSR on shareholder value is positive, for example, Luo and Bhattacharya [24, p. 15], Kempf and Osthoff [25, pp. 908–922], Sharfman and Fernando [26, p. 590], Guenster *et al.* [27, p. 702], Deng *et al.* [28, pp. 87 and 108], Eccles *et al.* [29, p. 2836], and Crifo *et al.* [30, pp. 170–171]. The others, however, point to the adverse effects of CSR on shareholder value, for example, Hamilton *et al.* [31, p. 66], Bauer *et al.* [32, p. 1766], Benabou and Tirole [33, pp. 1–19], Borghesi *et al.* [34, p. 164], Masulis and Reza [35, p. 631], and Adhikari [36, pp. 201 and 215].

If it is assumed that the primary goal of business management is to maximize the benefits of the owners, it should be noted that this is only possible if the company is not managed only from the perspective of short-term profit. In the context of shaping the long-term value of companies, the strategic dimension is intimately connected with the dimension of social responsibility. Gregory *et al.* [37] draw attention to the positive impact of socially responsible activities in the long run. It is necessary at the stage of strategy building to take into account social interests, relations between different groups of stakeholders and the aspect of environmental protection. To this end, it is necessary to ensure better cooperation and coordination between individual parts of the company. The work focuses on the aspect of the return on equity ratio, and thus on maximizing profit with simultaneous care for shaping an appropriate capital structure, its optimal level will provide the company with the financial stability necessary to achieve the set goals. According to the authors, the concern to maximize profits should cover an extended period, and this will only be possible if the needs of different stakeholder groups, including social interests, and caring for the natural environment are met. The social responsibility is connected with investing in human resources and protecting the environment, so a company's relations with the environment and informing about company's activities are of crucial importance. Such activities translate into an increase in the competitiveness of the company. In the context of company-employee relations, a more subjective approach to employees is essential, which will enable the attainment of individual goals, professional development, will encourage the reconciliation of professional and personal life and promote a healthy lifestyle. Such an approach will translate into timely payments of salary, employment stability, constant professional development and different opportunities for women and men. Care for this area will improve the efficiency of employees' work, which will translate into improved financial performance in various areas of the company's activity, and consequently the profit generated in various areas of activity. Profit increase at a given level of equity will translate into an increase in the ROE factor.

In the social area, the implementation of the CSR concept will be associated with an increase in social involvement, manifesting itself, for example, in engaging in work for the benefit of local communities. Within the framework of social benefits, it is necessary to mention the implementation of social goals and reducing the negative impact of the company's activities on the environment. These actions will enable the company to reach new customer groups and strengthen the trust and attachment to the company, which will be conducive to the increase in the sales of products and services offered by the company and positively translates into the financial results and ROE factor.

The most recognizable area of CSR is a concern for the environment. It may be manifested in the implementation of environmental management standards, which will translate into the rational management of natural resources and waste as well as the increase of pro-ecological awareness both among employees and within the environment in which a given company operates. It should be noted that the application of the principles of social responsibility is connected with incurring additional costs. Thus, in the short-term, the implementation of CSR will translate into a reduction in profits, because they are related to investment outlays and incurring operational expenses, which is why they increase production costs. However, in the long-term, the natural environment protection policies will improve efficiency and reduce the production costs, which will support the growth of profits and, consequently, the increase in the value of the company and the benefits of its owners.

Assessing the efficiency and ability of the management to manage the company in a way that ensures profit generation can be made, among others through the use of profitability ratios. The issue of assessing the effectiveness of the company's operations is complex. Return on Equity is an important measure and criterion for evaluating the equity involved. The Return on Equity ratio shows how much of net profit is generated by 1 PLN of investment. It is a cumulative one, which means that the higher its value will be obtained by the company, the better it will have to be assessed. It is estimated as the ratio of net profit to the book value of shareholders' equity [38, p. 73]. Botika [39, p. 1180] notes that irregularities in the area of net profit are usually the result of price volatility, product market position, brand fluctuation, and market inflation.

Performance indicators, in principle, do not have boundary norms. The threshold value in their case is zero. The interpretation of the Return on Equity ratio may pose some difficulties when negative values of the numerator or denominator appear. If a company shows a negative level of net profit with a positive capital value, it is said about a deficit in which the use of equity causes a loss, which translates into a loss of equity. The analysis of the economic and financial situation of a company that generates losses should be carried out carefully. If both net profit and equity have negative values, the financial loss creates or increases depreciation of equity. If, however, only the own capital shows a negative value, then the interpretation is difficult.

Both the level of profitability of equity and its dynamics are significant. The increase in this ratio shows in a synthetic form the increase in the effectiveness of the equity involved and the increase in the current value of the company, and thus the increase in the value of shares. Therefore, it promotes the payment of higher dividends and increases the company's development opportunities. Also, it contributes to the improvement of the company's position in the capital market, because it has a positive impact on credit credibility, and thus, as already noted, increases the possibility of raising external capital. The level of profitability of equity translates, to a certain extent, into the value of shares and the value of the company, if its valuation is based on the amount of profit.

In order to obtain information on whether the rate of return on invested capital is satisfactory, it should be compared with the profitability of other potential investments. If the return on capital is higher than them, the investment should be considered as a good one. It is assumed that the limit of the rate of return that is the one that provides the absolute minimum is the profitability of government bonds.

The level of ROE should also be related to the level of inflation. If Return on Equity is lower than the level of inflation, it means lowering the purchasing power of invested capital.

In order to deepen the understanding of the company's efficiency aspect, DuPont's analysis can be used. The formula for Return on Equity (ROE) is presented in (1) as the product of Return on Assets (ROA) and Capital Multiplier (CM).

$$\begin{aligned} ROE &= ROA \times CM \\ &= \frac{\text{Net Profit}}{\text{Avg. Total Assets}} \times \frac{\text{Avg. Total Assets}}{\text{Avg. Shareholders' Equity}} \end{aligned} \tag{1}$$

By developing (1), ROE can be broken down into three factors: operating efficiency, asset use efficiency, and financial leverage [40, p. 83]. Therefore, Return on Equity can be represented by (2), where ROS is Return on Sales.

$$ROE = ROS \times TAT \times CM \tag{2}$$

Such presentation of the ROE indicator enables the verification, based on the use of data from financial statements, of which elements and how they affect the effectiveness of the equity involved. Thus, the Return on Equity can be considered in three areas: Net Profit Margin, Total Asset Turnover (TAT) and Financial Leverage Multiplier [41, p. 150].

Profitability of sales (Return on Sales—ROS), defined by (3), shows how much net profit is generated by every 1 PLN of net revenues from the sale of products, goods, and materials.

$$ROS = \frac{\text{Net Profit}}{\text{Revenues from Sales}} \tag{3}$$

Total Asset Turnover ratio (TAT), defined by (4), shows the effectiveness of using assets (management efficiency), that is, how many times the sale is higher than the value of the company's assets.

$$TAT = \frac{\text{Revenues from Sales}}{\text{Avg. Total Assets}} \tag{4}$$

Capital Multiplier (Equity Multiplier), defined by (5), illustrates the degree of equity involvement in company's assets. This indicator informs whether the company is financed with external capital. If it is 1, it means that the company is financed only with the equity. The value higher than one indicates that external capital is used to finance the operation.

$$CM = \frac{\text{Avg. Total Assets}}{\text{Avg. Total Equity}} \tag{5}$$

The impact of individual factors on the level of ROE may be offset against each other, for example, a corresponding increase in asset turnover may cover the reduction in sales profitability.

III. EVOLUTIONARY ALGORITHMS AND THEIR APPLICATIONS IN ECONOMICS AND FINANCE

A. EVOLUTIONARY ALGORITHMS

The term "evolutionary algorithms" defines a group of techniques modeled on the mechanisms of biological evolution [23], [42]–[48].

These techniques make it possible to find approximate solutions for NP-hard global, multi-modal and multi-objective optimization problems, in the case of which it is not possible to find a valid solution with the use of traditional methods and algorithms or a time needed for finding such a solution is not acceptable from our point of view. Evolutionary algorithms can be successfully used in cases where finding a solution to a global optimization problem is generally not possible within a reasonable timeframe, but any improvement of an already found one is a great success (sub-optimal solutions) [23].

The concepts used in the evolutionary algorithms derive from the theory of evolution, which is the theoretical basis of modern biology and integrates the most of its divisions [49]. This theory provides explanations for two groups of issues: the formation of various properties of living organisms and the formation of multiple types of individuals (species). According to the theory of evolution created by Charles Darwin, the primary process that shapes the properties of living organisms is natural selection [50]. The second fundamental element of the theory of evolution is the thesis about the common origin of all modern organisms and the emergence of new life forms mainly in the result of natural selection. The existence of natural selection is an empirical fact and a consequence of the occurrence of specific essential features of all living organisms, such as mortality, reproduction, and genetic variability of features affecting the way they function. The existence of natural selection is also related to the limited resources of the environment that are necessary for survival and reproduction of organisms. Contemporary, synthetic theory of evolution, which is a synthesis of Darwinism and the achievements of population genetics, was developed in the 1920s and 1930s.

The evolutionary algorithm processes population of individuals, each of which is a point in the space of potential solutions to a problem for which the objective function is defined $f : D \rightarrow \mathbb{R}$ [47]. The objective function can be given in the form of a real-world system of any complexity, a computer simulation of a certain model or in an analytical form. Each individual $a_i \in I$ (where I is the space of individuals) has a genotype containing the set of information needed to create the phenotype $\vec{x}^{a_i} \in D$. The genotype of an individual consists of chromosomes, of which at least one contains information encoding the phenotype. Other chromosomes may contain some parameters relevant to the operation of the evolutionary algorithm itself. The chromosome consists of genes that are the elementary units of the individual's genotype.

In an environment, in which the evolutionary algorithm operates, the so-called "fitness function" $\varphi : I \rightarrow \mathbb{R}$ is defined. This function is a measure of the quality of the individual as a solution to the given problem. The fitness function, in the general case, does not have to be identical to the objective function f; however, the objective function is always a part of it. The fitness function (φ) in the general form is a composition of the objective function (f) and a function decoding an individual's phenotype ($fen : I \rightarrow D$; $fen' : D \rightarrow I$ is a function that encodes the phenotype of an individual): $\varphi = f \circ fen$.

The initial population is randomly generated (or we can take into account our knowledge of the problem) and gradually evolves towards the "better" (from the point of view of the problem being solved) areas of a search space thanks to the probabilistic (or deterministic) mechanism of selection and recombination and mutation operators.

The process of selection is defined in the literature as the combination of the process of reproduction, in which randomly selected individuals are replicated and the replacement strategy, which is a process of choosing individuals forming the base population of the next generation [47]. The selection process favors individuals with better fitness, thanks to which they have a better chance of reproducing and transferring their genetic material to the next generation than those, which are less well adapted.

The recombination mechanism allows the exchange of information, encoded in genotypes, between different individuals of the population by ''mixing'' appropriate chromosomes from different parents during the transfer of genetic material to offspring.

The mutation mechanism is responsible for introducing innovations. It works by randomly disturbing the offspring genotype—most often small disturbances are more likely than large ones.

Algorithm 1 The Basic Scheme of the Evolutionary Algorithm

$t = 0$;
generate the population $A(t)$;
evaluate the individuals from $A(t)$;
while *stop condition is not fulfilled* **do**
    $A^1(t) =$ apply the reproduction operator to $A(t)$;
    $A^2(t) =$ apply the recombination operator to $A^1(t)$;
    $A^3(t) =$ apply the mutation operator to $A^2(t)$;
    evaluate the individuals from $A^3(t)$;
    $A(t+1) =$ apply the replacement strategy to $A^3(t) \cup A^4(t)$, where $A^4(t) \subseteq A(t)$;
    $t = t + 1$;
end

The general scheme of operation of the evolutionary algorithm has been presented with an Algorithm 1. $A(t) = \{a_1(t), \ldots, a_\mu(t)\}$ is the base population of the generation t composed of μ individuals, each of which is a solution to a given problem. The population $A^1(t)$ contains copies of individuals from the base population that were selected taking into account the value of the fitness function—these individuals form the population of parents. Then, the individuals of the population $A^1(t)$ are subjected to genetic operations (recombination and mutation) resulting in an offspring population $A^3(t)$, which is composed of $\lambda \geqslant \mu$ individuals. The assessment of individuals consists in calculating the value of the fitness function $\varphi(a_k)$ for all individuals $a_k \in A^3(t)$. The $A^4(t)$ is the set of individuals from the old base population that must be taken into account when applying the replacement strategy—it can be the empty set, or it can contain some of the best individuals from the old base population to ensure their survival.

The main loop of the algorithm is repeated to reach the maximum number of generations, to find a sufficiently good solution or to meet some other condition for completing the calculations.

During many years of research on evolutionary algorithms, quite a number of their varieties have been developed. However, the most developed and the best known are three of them: evolution strategies proposed by Rudolph [51], evolutionary programming proposed by Whitley [44] and genetic algorithms proposed by Goldberg [48].

B. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

Deb and Kalyanmoy [52] primarily distinguishes elitist and non-elitist multi-objective evolutionary algorithms (MOEAs). However, his classification also includes constrained MOEAs, which support constraints handling [52].

In the case of elitist MOEAs, a technique which allows for preserving the elite individuals is used. Such elite includes all non-dominated individuals (according to Pareto dominance relation [52]), which should be directly transferred to the next generation population. The technique of preserving the elite should also constantly update the set of non-dominated solutions and get rid of individuals that are dominated by newly generated non-dominated ones. The examples of elitist MOEAs are Rudolph's algorithm [53], strength Pareto evolutionary algorithm (SPEA) [54], strength Pareto evolutionary algorithm 2 (SPEA2) [55] and multi-objective micro GA [56].

The MOEAs which do not use the elitism mechanism include vector-optimized evolution strategy [57], niched-pareto GA [58], non-dominated sorting GA (NSGA) [59] (in the second version of this algorithm, NSGA-II, the elitism was added).

Some authors also tried to use co-evolution and sexual selection in their MOEAs. The predator-prey co-evolution was the basis of the algorithm proposed in [60]. The proposed approach was further improved in [52] by allowing the predators to eliminate preys based on the weighted sum of all criteria. In [61] the algorithm was modified in such a way that also preys could migrate within the graph in which individuals were located.

The examples of using sexual selection in multi-objective evolutionary algorithms include [62] in which Allenson proposed the algorithm in which the number of sexes corresponded with the number of criteria, the sex of a child was determined randomly, and the selection of a partner for reproduction was based on preferences encoded within the genotype.

Also, in [63] each sex was connected with one criterion. The authors introduced multi-parent crossover operator, and the sex of a child was established based on a number of genes provided by each parent. The algorithm maintained the set of non-dominated solutions.

C. AGENT-BASED EVOLUTIONARY AND CO-EVOLUTIONARY ALGORITHMS

The agent-based evolutionary algorithms are a result of introducing evolutionary processes into a multi-agent system. In evolutionary multi-agent systems (EMAS) [21] the process of evolution is decentralized, allowing agents to make decisions concerning all of their activities in the system.

The size of the population is controlled with the use of resources [64], which are needed for performing actions like reproduction and migration. An agent can get resources from the environment or other agents. The rule is such that better-fitted agents get more resources than less fitted ones. The agents lose resources when they perform actions. An agent can die when it is out of resources. The total amount of resource in the whole system is constant so it limits the maximal number of agents that can live within the system.

The reproduction takes place when an agent that has enough resources can find a partner that is also ready for reproduction. During the reproduction, parents transfer a certain amount of resource to their children.

The agents can migrate within the environment in order to find partners for reproduction or resources. During the migration, an agent loses some of its resources.

The basic EMAS model has been extended to include the possibility of interactions between multiple species and sexes that can exist within the population. The so-called co-evolutionary multi-agent system (CoEMAS) was proposed in [22]. The approach based on the CoEMAS model was applied, among others, to multi-modal optimization [65], multi-objective optimization [66], [67], multi-objective portfolio optimization [68] and to the problem of generating investment strategies [69]. The sexual selection mechanism for co-evolutionary multi-agent systems was proposed in [70]. In [71] the techniques of maintaining population diversity for agent-based multi-objective evolutionary algorithms were proposed.

The CoEMAS model was further developed, and eventually, a general model of bio-inspired multi-agent systems (BSMAS) was proposed [72], [73]. The BSMAS model enables the creation of computational and simulation multi-agent systems that can use any bio-inspired artificial intelligence algorithms.

D. SELECTED ECONOMICS AND FINANCE APPLICATIONS OF THE EVOLUTIONARY ALGORITHMS

The bio-inspired artificial intelligence techniques are becoming more and more popular, also in economic and financial applications (for example compare [74], [75]). In this section, the review of selected applications of evolutionary algorithms in economics and financial domains is presented.

The genetic algorithm was used for finding optimal values of parameters of trade models in [76]. Three versions of the algorithm were compared: the genetic algorithm, the genetic algorithm with the fitness sharing technique proposed by Yin and Germay [77] and the genetic algorithm with the fitness sharing technique introduced by the authors of [76]. The latter one was able to find the most general solutions.

Kassicieh *et al.* [78] proposed a system that chose a company worth investing in. The genetic algorithm was used to select logical operators, used during decision making, based on current market conditions.

Allen and Karjalainen [79] used the genetic algorithm to select structures and parameters for rules organized as a tree and composed, among others, of logical functions, constants, and functions operating on historical data. The rules were then used for the Standard & Poor's 500 (S&P 500) Index trading.

In [80] the quantum-inspired evolutionary algorithm was used for Option Pricing model calibration. The authors argued that the results obtained by the quantum-inspired evolutionary algorithm were robust and comparable to the results obtained by other algorithms.

In [81] the evolutionary algorithm has been applied in the area of business intelligence. The evolutionary algorithm was used to design and optimize fuzzy rules, which were then used to predict the customer behavior.

Hochreiter [82] used the genetic algorithm to solve the stochastic single stage scenario-based risk-return portfolio optimization problem. The proposed approach was based on the loss distribution of a scenario set, and the author argued that it could be applied to a general set of risk measures to compare them within the one coherent framework.

In [83] the evolutionary algorithm was used for the optimization of architecture and fine-tuning of a neural network, which was then applied to financial instruments trading.

In [84] the agent-based co-evolutionary algorithm with predator-prey interactions was applied to multi-objective portfolio optimization. The results of experiments showed that the algorithm was able to find more robust solutions than other techniques used in the experiments.

In [85] the agent-based co-evolutionary genetic programming was used to generate the investment strategies. The genotype of an individual was a tree with functions located in the nodes. The output of the root node was the decision whether to buy or sell the assets. The set of possible functions included mathematical and logical ones and functions calculating selected technical analysis indicators. The results of experiments showed that the proposed agent-based co-evolutionary approach generated the most general rules, which performed well in all possible market conditions.

The genetic programming was used to construct a function based on historical data, which was then used for assessing the financial condition of a company [86]. The goal was to detect financial problems, potentially leading to the bankruptcy. The generated functions obtained the classification efficiency of 75%.

Lipinski *et al.* [87] performed experiments aimed at comparing the results obtained by the evolutionary algorithm with the results obtained by some simple investing strategies. The authors argued that in some cases the evolutionary algorithm was able to achieve better results than the buy-and-hold strategy and the index investing strategy.

In [88] the evolutionary algorithm was used together with the time window. The proposed algorithm was adapted continuously to the current market conditions in such a way that it was trained on historical data from a short period and then used for predicting the nearest future trend. The time window was moved synchronously with the subsequent listings, and the algorithm was retrained each time the window was moved. The authors argued that their algorithm obtained better results than the buy-and-hold strategy.

The agent-based cooperative co-evolutionary algorithm was applied to the multi-objective portfolio optimization problem in [89]. The results of experiments showed that the agent-based co-evolutionary algorithm obtained better results than the SPEA2 and NSGA-II algorithms in the case of multi-objective test problems and also in the case of some of the portfolio optimization problems.

A thorough review of the applications of evolutionary algorithms to the problem of investment strategies generation can be found in [90]. The author provided some recommendations regarding the use of evolutionary algorithms in generating the investment strategies. For example, the author argued that the evolutionary algorithms used should not be too complicated because otherwise the algorithms are overly specialized and too well suited for a given period. The author also noted that the best strategies were found after 25–75 generations and the use of more generations may also lead to over specialization.

The multi-objective evolutionary algorithm was applied to the portfolio optimization problem in [91]. The authors used two objectives, the risk and the rate of return, based on the Markovitz model.

Ibrahim *et al.* [92] used three higher moment models and three median models for asset allocation on the emerging economy stock market. The models were formulated as multi-objective problems, which were then solved with the use of NSGA-II multi-objective evolutionary algorithm. The results of experiments showed that the median models outperformed the higher moment models.

In [93] the agent-based co-evolutionary algorithm with sexual selection was applied to the multi-objective portfolio optimization problem. The primary role of the sexual selection mechanism was to maintain a high level of the population diversity. The results of experiments showed that the proposed algorithm was able to find sustainable investment strategies, which used both risky and safe decisions.

As it can be seen, the research on economic and financial applications of the evolutionary algorithms was mainly focused on generating or optimizing the investment strategies. The number of works on optimization of the financial structure of a company or optimization of financial and economic indicators of a company (or a sector of the economy) and taking into account sustainable development objectives is somewhat marginal. The research presented in this paper tries to fill this gap. As a first stage of the development of the proposed multi-criteria decision support system (see Section IV), which will include short-term financial goals as well as long-term sustainable development goals, we have selected the evolutionary optimization of the Return on Equity factor. Thus, we can use the evolutionary algorithm to find possible optimal capital structures of a company and as a consequence, to support the managers' decisions concerning the changes in company's capital structure and its financing sources. The next step will be the conversion of the evolutionary algorithm into a multi-objective evolutionary algorithm or an agent-based multi-objective evolutionary algorithm, and the introduction of sustainable development objectives.

IV. THE IDEA OF BIO-INSPIRED AGENT-BASED SYSTEM SUPPORTING CORPORATE FINANCE DECISIONS

The general architecture of the proposed bio-inspired agent-based decision support system, which will allow for taking into account multiple objectives when proposing the possible corporate finance decisions is presented in Fig. 1. The modules in the implementation phase are marked gray.

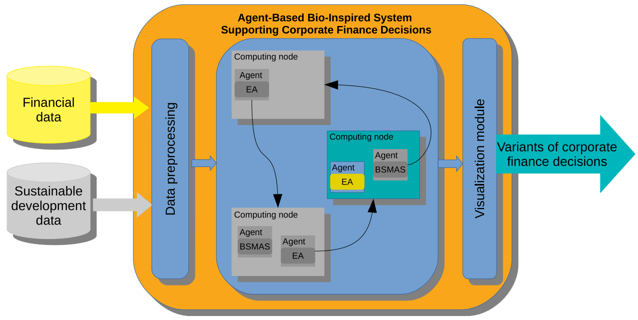

FIGURE 1. The general architecture of the bio-inspired agent-based system supporting corporate finance decisions using financial and sustainable development objectives. The modules in the implementation phase are marked gray. EA means evolutionary algorithm and BSMAS means agent-based bio-inspired algorithm.

The system is composed of modules, which can be relatively easy exchanged. The essential components of the system are the data processing module, the computing module, and the visualization module (see Fig. 1).

The data processing module takes external data (financial, social, environmental) and on that basis generates financial and sustainable development objectives, which presumably will be contradictory. Such contradictory criteria are then used by an evolutionary algorithm or a multi-objective evolutionary algorithm, which will find the set of Pareto optimal solutions [52]. Some of the solutions from the Pareto set will be better according to financial objectives while the others will be better according to sustainable development objectives. Such a set of solutions will be then presented to decision makers, who will pick one of them and implement it in their company.

The computing module will use hybrid agent-based architecture for managing computations, as proposed in [89]. Such architecture uses the agent-based approach to manage computing tasks and resources and agent-based bio-inspired algorithms to realize computations.

Each computing agent will contain an evolutionary algorithm (denoted as EA in Fig. 1) or an agent-based evolutionary algorithm (denoted as BSMAS in Fig. 1). The goal of computing agents will be to search for available computing resources and to run computing tasks. Each computing agent will be able to migrate between the computing nodes and search for available resources.

In the proposed system there will be a possibility of using many bio-inspired optimization algorithms together. It will be possible to use an evolutionary algorithm (proposed in this paper), one of the multi-objective evolutionary algorithms presented in Section III-B or an agent-based bio-inspired algorithm constructed following the bio-inspired multi-agent system (BSMAS) model (see Section III-C). The agent-based bio-inspired algorithms that can be used will include agent-based multi-objective evolutionary algorithms proposed in our previous works—the agent-based co-evolutionary algorithm using host-parasite interactions [66], the agent-based co-evolutionary algorithm with sexual selection mechanism [94], the agent-based co-evolutionary algorithm with predator-prey interactions [67] or the agent-based co-operative co-evolutionary algorithm [95].

In this paper, we have focused on the evolutionary algorithm. During the experiments, the ability of the evolutionary algorithm to generate valid and non-obvious solutions concerning a company's capital structure in a situation when only one objective (the Return on Equity factor) is taken into account was verified.

V. THE EVOLUTIONARY ALGORITHM FOR RETURN ON EQUITY FACTOR OPTIMIZATION

In this section, the evolutionary algorithm for ROE factor optimization is presented. This algorithm is a part of the proposed intelligent multi-criteria system supporting corporate finance decisions, which is introduced in Section IV. The evolutionary algorithm for ROE factor optimization can be used as a tool supporting decisions concerning the capital structure and financing sources of a company. The algorithm was designed and implemented with the use of *Jenetics* library [96], which is the Java library for evolutionary computations.

A. PSEUDO-CODE OF THE ALGORITHM

The pseudo-code of the genetic algorithm (GA), which is the basis of the *Jenetics* library [96], is presented in Algorithm 2, where i is the number of generation and P_i is the population of individuals in generation i.

Algorithm 2 The Genetic Algorithm From *Jenetics* Library [96]

1 $i \leftarrow 1$;
2 initialize population P_i;
3 compute fitness of individuals from P_i;
4 **while** *stop condition is not fulfilled* **do**
5 $\quad survivor_i \leftarrow$ select survivor from P_{i-1};
6 $\quad offspring_i \leftarrow$ select offspring from P_{i-1};
7 $\quad offspring_i \leftarrow$ apply genetic operators to $offspring_i$;
8 $\quad$ compute fitness of individuals from $offspring_i$;
9 $\quad P_i \leftarrow$ best individuals from $survivor_i \cup offspring_i$;
10 $\quad i \leftarrow i + 1$;
11 **end**

In the first step of the algorithm, the population is initialized. The initialization means, among others, that the fitness function value for every individual has to be calculated. Next, several steps of the algorithm are repeated until the predefined termination criterion is not fulfilled. The steps inside the loop include selecting survivors (the individuals that will survive and find themselves in the next generation population), selecting parents and generating offspring, applying genetic operators (for example mutation and recombination), that are changing ("altering") the offspring genotypes. The replacement strategy consists in combining the survivor population and the offspring population and thus forming the next generation population (see line 9 of Algorithm 2). The replacement strategy includes the removal of individuals, which have not found their place in the next generation population. The value of i parameter indicates the current generation number.

Algorithm 3 The Algorithm for Updating the Set of Best Solutions

Input: list of the best solutions found so far: *bestList*
Input: the best individual from current population
Output: updated *bestList*
if *bestList* == *null* OR fitness of the best individual from current population > fitness of the best individual from *bestList* **then**
$\quad$ add the best individual from current population to *bestList*;
end

The function, which updates the set of best solutions found so far, is presented in Algorithm 3. In the *Jenetics* library this function updates the set of best solutions in such a way that the current best solution from the set is compared to the best individual from the current generation. If the best individual from the current base population is better than the best solution from the set, then the best individual from the base population is added to the set of best solutions found so far.

The optimization of Return on Equity factor requires that all of the mentioned in this paper DuPont indicators have to be calculated in each generation. In the *Jenetics* library, the processing of population in each generation relies on the so-called "evolution stream", which is used for executing all steps of the evolutionary algorithm. The steps of the evolutionary algorithm are parallelized whenever it is possible, for example, the evaluation of the fitness of individuals is done in parallel. The statistics that are collected during each run of the evolution stream can be used to analyze the performance of evolutionary operators and the impact of parameters' values on the course of evolutionary processes.

B. THE REPRESENTATION OF A SOLUTION

The representation decides how the solution to a given problem, and possibly also other parameters that are important for the functioning of the genetic algorithm, are encoded in the genotype. The encoding used in our algorithm has been prepared using the `Codec` interface from the *Jenetics* library.

It included, among others, the constraints for all essential economic indicators that were used during optimization.

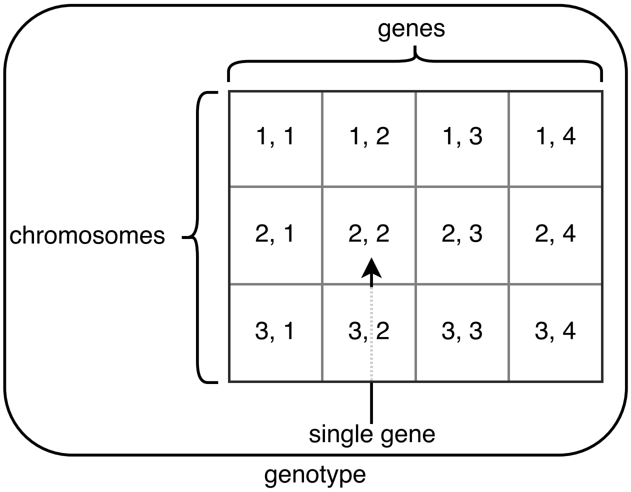

FIGURE 2. The structure of genotype in the *Jenetics* library. The indicators within a gene denote, respectively, the chromosome number and the gene number.

The diagram from Figure 2 depicts the genotype from the *Jenetics* library. In our algorithm, the genotype of an individual has one chromosome composed of four genes, which values correspond to the Net Profit, Assets Total Equity, Revenues, and Average Total Assets parameters' values. A single gene value is of type `DoubleGene` which corresponds to Java `Double` type.

C. THE FITNESS FUNCTION

In the fitness function (see Algorithm 4) the *ROS*, *TAT* and *CM* indicators have to be calculated on the basis of *NETPROFIT*, *ATE*, *REVENUES* and *ATA* parameters, which are encoded in individuals' genotypes. The correctness test (line 8 of Algorithm 4), which validates genotypes in accordance to the constraints, has to be performed due to the need to reject solutions that are not valid. If a solution is valid the result of the function is a value of $ROE = ROS \times TAT \times CM$. The problem being solved is the maximization problem.

Algorithm 4 The Fitness Function

Input: genotype of an individual
Output: ROE value
1 $NETPROFIT \leftarrow genotype.getChromosome(0).val$;
2 $ATE \leftarrow genotype.getChromosome(1).val$;
3 $REVENUES \leftarrow genotype.getChromosome(2).val$;
4 $ATA \leftarrow genotype.getChromosome(3).val$;
5 $ROS \leftarrow \frac{NETPROFIT}{REVENUES}$;
6 $TAT \leftarrow \frac{REVENUES}{ATA}$;
7 $CM \leftarrow \frac{ATA}{ATE}$;
8 **if** *ROS, TAT and CM meet the constraints* **then**
9   **return** $ROS * TAT * CM$;
10 **else**
11   **return** -100;
12 **end**

D. GENETIC OPERATORS

The genetic operators (so-called "alterers" in the *Jenetics* library) are responsible for genetic diversity and generation of potentially useful solutions. The selection operator (so-called "selector" in the *Jenetics* library) is responsible for selecting individuals from the population according to some criteria [96].

The selectors can be used to divide the population into survivors and offspring. In the *Jenetics* library the selection is performed on the phenotypes of individuals. The following equation defines the number of selected survivors [96]:

$$\| survivor_i \| = \| P_i \| - \| offspring_i \| \tag{6}$$

The following equation determines the number of offspring in generation i [96]:

$$\| offspring_i \| = nearbyint(\| P_i \| \cdot f_O) \tag{7}$$

$$f_O \in [0, 1] \tag{8}$$

The $nearbyint(arg)$ function rounds an argument to the nearest integer and f_O is the parameter called *offspringFraction*—it decides how many offspring are created in each generation [96].

The tournament selection mechanism is used in the evolutionary algorithm for ROE optimization. In each tournament, s randomly chosen individuals take part. An individual wins the tournament if its fitness value is higher than the fitness values of all other competitors.

The genetic operators ("alterers") can be divided into two groups: mutation and recombination [96]. The recombination is responsible for mixing genes coming from parents, and the mutation operator is responsible for introducing new elements into offspring's genotypes. The proposed evolutionary algorithm uses Gaussian mutation (`GaussianMutator`) and mean recombination (`MeanAlterer`) [96].

`GaussianMutator` is the operator, which is responsible for performing mutations of genotypes. The value of the random variable with the normal distribution is added to the current value of a gene. The following equation defines the variance of a new value of gene [96]:

$$\hat{\sigma}^2 = \left(\frac{g_{max} - g_{min}}{4} \right)^2 \tag{9}$$

g_{max} and g_{min} are constraints of the gene values.

`MeanAlterer` is the recombination operator, in which the primary step is to calculate the arithmetic mean of two genes. The resulting values are used for constructing the offspring genotypes [96].

VI. THE EXPERIMENTS

In this section, the results of experiments are presented. The primary goal of the experiments was to verify whether the evolutionary algorithm can provide correct and valuable but also innovative and non-obvious information regarding the desired capital structure of a company. During the experiments, real data from the construction sector was used. The details about configuration of the computing environment and the values of parameters of the evolutionary algorithm are provided below.

A. THE METHODOLOGY AND VALUES OF PARAMETERS

During the experiments, data from all companies from the WIG-construction sector were used. The sector includes 45 companies listed on The Warsaw Stock Exchange: ABMSOLID, ATREM, AWBUD, BUDIMEX, NOWAGALA, CNT, DECORA, DEKPOL, ELBUDOWA, ELEKTROTI, ENERGOINS, ENAP, ERBUD, ESSYSTEM, FERRO, HERKULES, INSTALKRK, KBDOM, LIBET, LENTEX, MERCOR, MDIENERGIA, MFO, MIRBUD, MOSTALPLC, MOSTALWAR, MOSTALZAB, PANOVA, PEKABEX, PROJPRZEM, POZBUD, PROCHEM, POLIMEXMS, RESBUD, RAFAKO, REMAK, ROPCZYC, SELENAFM, SNIEZKA, TORPOL, TRAKCJA, TESGAS, ULMA, UNIBEP and ZUE.

The indicated sector was chosen for research because of the crucial role it plays in the national economy. On the one hand, it is a challenging market. Construction output in Poland is characterized by, among others, a considerable seasonality, a long production cycle, high investment costs and the production of large amounts of waste. It should be noted that there have always been network connections between companies operating in the construction industry, and therefore they were still, stronger or weaker, interrelated. Companies from any other WIG index are not as closely related as entities in the construction industry. For example, entities producing reinforced elements used in construction and dealing with electrical installations will provide products/services to industrial construction companies. These compounds facilitate a flexible reaction to changes in the environment, and as a result, even in a downturn, the indicated entities can show high dynamics of profit. On the other hand, unfortunately, this sector is currently experiencing frequent defaults on payment. This situation sometimes translates into other entities, and it may give rise to significant tensions in maintaining financial liquidity and thus difficulties in timely settlement of their obligations.

It was decided to narrow the levels of individual parameters in order to obtain valid and rational research results. For this, the maximum and minimum levels of values of particular economic indicators within the surveyed sector in 2017 were checked. The data came from 2017-11-21 and was taken from the Business Radar website [97], to which Quant Research Limited company provides financial data. The following restrictions were adopted for the research:

- −14 221 PLN < Net Profit < 142 429 PLN;
- 8 003 PLN < Assets < 5 579 882 PLN;
- 49 PLN < Net revenues from sales of goods, products and materials <<1 831 587 PLN;
- 7 752 PLN < Shareholders' equity < 836 843 PLN.

Some extreme values were excluded, such as the negative equity value for ABMSOLID company (−163 922 PLN).

Additional constraints used during the experiments were as follows:

- 0.0 < ROS < 1.0;
- 0 < TAT < 10;
- CM > 1;
- ATE >= 0.33 * (Revenues + ATA).

During the experiments, the following values of parameters of the evolutionary algorithm were used:

- Population size: 2500;
- Gaussian mutation probability: 0.2;
- Mean recombination probability: 0.2;
- Stop the evolutionary algorithm after $n = 18$ generations, when there is no progress;
- Maximal number of generations: 150;
- Maximal age of an individual: 15.

During the experiments, the following computing environment was used:

- CPU: Intel® Core™ i7-4700HQ;
- Memory: 8 GB DDR3-12800 (PC3-1600) RAM;
- Disk drive type: SSD;
- OS: Microsoft Windows [Version 10.0.16299.248];
- JDK: 1.8;
- IDE: Intellij IDEA 2017.2.5;
- Build automation system: Gradle 2.9;
- Evolutionary algorithm library: Jenetics 3.9.0.

B. THE RESULTS OF EXPERIMENTS

The results that are presented in Fig. 3–9 were generated by the proposed evolutionary algorithm and were selected according to the Algorithm 3. Thus, the proposed algorithm generates not a single solution but a whole set of best solutions found during a single run. In such a way, decision makers can choose a single solution according to their preferences.

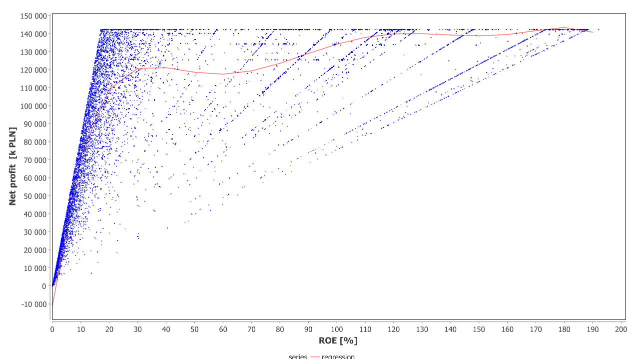

FIGURE 3. **The impact of Net Profit (NP) on the Return on Equity (ROE). The regression function (red line) is defined as follows:** $\boldsymbol{f(x) = -2.72332 \times 10^{-7}x^6 + 1.80236 \times 10^{-4}x^5 - 0.04660x^4 + 5.91686x^3 - 379.97422x^2 + 11579.49852x - 10876.74217.}$

Regression function $f(x)$, which can be seen in Fig. 3–9 (it is depicted as a red line), is a result of regression analysis,

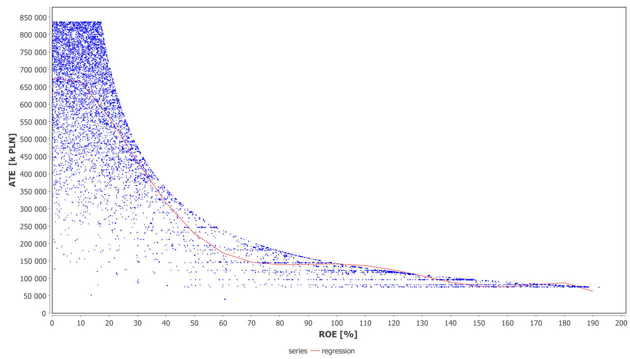

FIGURE 4. **The impact of Assets Total Equity (ATE) on the Return on Equity (ROE). The regression function (red line) is defined as follows: $f(x) = -1.23184 \times 10^{-6}x^6 + 7.67199 \times 10^{-4}x^5 - 0.18168x^4 + 19.96324x^3 - 943.07424x^2 + 6619.27584x + 674489.012686$.**

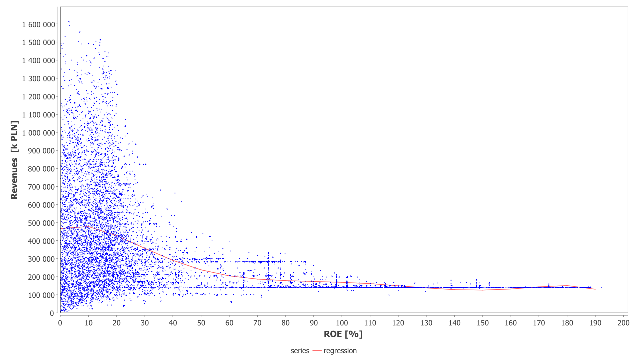

FIGURE 7. **The impact of Revenues on the Return on Equity (ROE). The regression function used: $f(x) = -8.32675 \times 10^{-7}x^6 + 5.06736 \times 10^{-4}x^5 - 0.11758x^4 + 12.79526x^3 - 618.51396x^2 + 6160.93727x + 467089.47424$.**

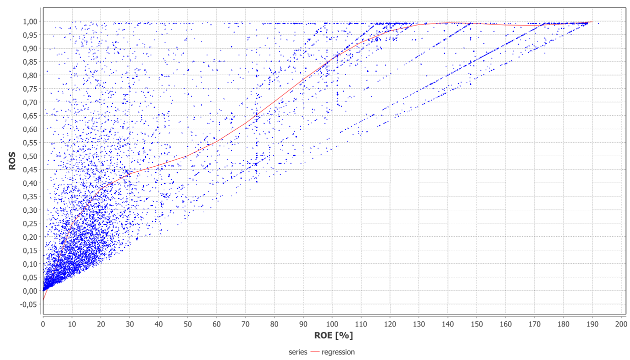

FIGURE 5. **The impact of Return on Sales (ROS) on the Return on Equity (ROE). The regression function (red line) is defined as follows: $f(x) = -1.01029 \times 10^{-12}x^6 + 6.91884 \times 10^{-10}x^5 - 1.80782 \times 10^{-7}x^4 + 2.22900 \times 10^{-5}x^3 - 0.00132x^2 + 0.039436x - 0.035836$.**

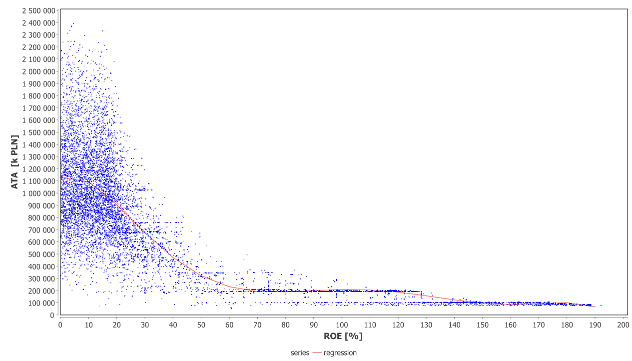

FIGURE 8. **The impact of Average Total Assets (ATA) on the Return on Equity (ROE). The regression function (red line) is defined as follows: $f(x) = -2.10788 \times 10^{-6}x^6 + 0.00132x^5 - 0.31391x^4 + 34.38787x^3 - 1594.43022x^2 + 9228.14245x + 1128873.45020$.**

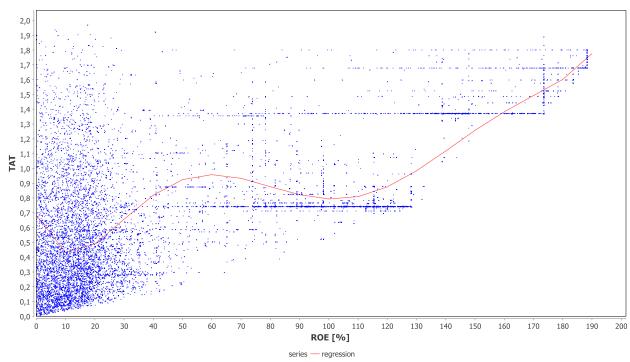

FIGURE 6. **The impact of Rotation of Assets (TAT) on the Return on Equity (ROE). The regression function (red line) is defined as follows: $f(x) = 3.53892 \times 10^{-12}x^6 - 2.23604 \times 10^{-9}x^5 + 5.35312 \times 10^{-7}x^4 - 5.93664 \times 10^{-5}x^3 + 0.00297x^2 - 0.04928x + 0.68239$.**

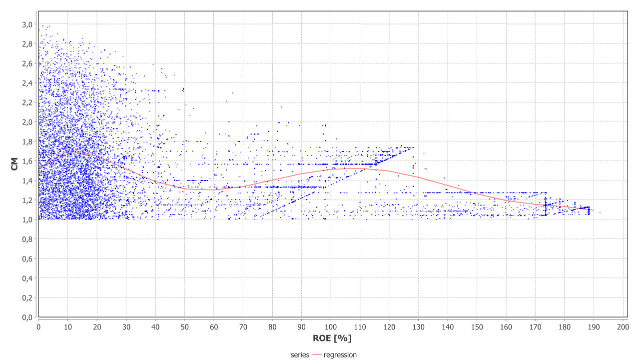

FIGURE 9. **The impact of Capital Multiplier (CM) on the Return on Equity (ROE). The regression function (red line) is defined as follows: $f(x) = -2.74947 \times 10^{-12}x^6 + 1.75952 \times 10^{-9}x^5 - 4.24580 \times 10^{-7}x^4 + 4.71928 \times 10^{-5}x^3 - 0.00233x^2 + 0.03758x + 1.51669$.**

which aim was to estimate the relationship among resulting values. Regression function generation aimed to help in ROE and other indicators analysis. For each figure, the function was built using the Apache Commons Math™ library with the following parameters:

- curve fitter: polynomial;
- degree of the polynomial: 6;
- type of points: weighted observed points, all with the same weight 1;
- library version: 3.6.1.

As already noted, the Return on Equity ratio is calculated as Net Profit (NP) to average equity [98, pp. 288–289]. The increase in net profit and/or the fall in equity will have a positive effect on ROE (Fig. 3 and 4).

The conducted research confirmed that the increase in net profit would be accompanied by a gradual increase in the profitability ratio. An interesting fact is that with a Net Profit of 20 000 k PLN, ROE achieved a maximum level of 16%. Only in one case, the profit reached 18 500 k PLN, and Return on Equity was higher (22.63%).

TABLE 1. Best, typical and worst ROE values ([%]) obtained for Net Profit (NP) ([k PLN]).

	Best		Typical		Worst	
No.	ROE	Net Profit	ROE	Net Profit	ROE	Net Profit
1.	192.046	142 429.00	58.006	141 747.72	4.919	40 427.61
2.	188.267	142 429.00	57.292	84 360.89	2.278	8 661.18
3.	187.670	142 429.00	55.578	84 063.74	1.554	12 866.67
4.	186.766	141 293.65	55.499	137 005.56	0.631	4 608.99
5.	181.340	137 187.86	54.904	140 222.17	0.051	243.99

For the whole ROE survey carried out, the most frequent result was at a level close to 50%. Table 1, presenting the best, worst and typical results for NP and ROE, shows that in three cases out of five, with the Net Profit of about 140 000 k PLN per annum the Return on Equity will be on average at the level of about 56%. Noteworthy is the fact that the Net Profit level close to 142 500 k PLN is accompanied by the highest ROE—on average about 187%. On the other hand, the lowest levels of the Return on Equity have been demonstrated with a Net Profit not exceeding 13 000 k PLN.

TABLE 2. Best, typical and worst ROE values ([%]) obtained for ATE ([k PLN]).

	Best		Typical		Worst	
No.	ROE	ATE	ROE	ATE	ROE	ATE
1.	192.046	74 164.00	58.006	244 367.41	6.991	706 421.37
2.	188.267	75 652.58	57.292	147 247.28	4.919	821 702.42
3.	187.670	75 895.06	55.578	151 254.72	2.278	380 291.21
4.	186.766	75 652.58	55.499	246 856.91	1.554	827 795.40
5.	181.340	75 652.58	54.904	255 395.31	0.631	730 928.56

Interesting results are provided by the observation of the most common ROE levels with reference to equity (Table 2). The highest levels of the Return on Equity have been obtained with the amount of equity of about 75 700 k PLN. In relation to the average ROE level, the interpretation is no longer so unambiguous, as in three cases out of five the equity totaled close to 250 000 k PLN, however, there are also cases when similar ROE level was obtained for the average level of equity of about 150 000 k PLN.

While the increase in Net Profit is always positively interpreted [99, p. 340], the decline in equity can be explained differently. Profit increase means that the company is profitable, which translates into benefits of shareholders, which may manifest themselves directly in the form of paid dividends, or indirectly because the retained profit in the company favors the implementation of new profitable investments, which will translate into an increase in the value of shares. Besides, the increase in profit has a motivating function.

On the other hand, the involvement of external capital in the financing of operations improves the efficiency of using equity, manifested in the growth of ROE [100, pp. 232–233]. We then deal with the so-called positive leverage effect. The existence of a positive leverage effect, which translates into an increase in Return on Equity and Earnings Per Share (EPS) [100, pp. 754–755], allows us to expect higher dividends in the future. However, its occurrence is possible only when the profitability of assets measured by operating profit is higher than the average nominal interest rate on debt. Otherwise, there will be no positive leverage effect, and a significant charge of financial costs resulting from a significant level of interest may translate into a deficit in equity, as operating profit will not be able to cover interest. Thus, an excessive burden on the company with external capital will translate into a negative leverage effect.

Also, it should be noted that the degree of risk encumbered by own and external capital is different, hence the cost of obtaining them is also different. Acquiring own capital is characterized by a higher cost than obtaining external capital. It is because the owners investing their capital expect a higher rate of return on this account than that which could be achieved, for example, through investments with a risk-free rate of return. Besides, interest on external capital employed reduces the tax base, and therefore a lower tax is paid. In this way, the state somehow participates in the costs incurred by the company for the use of external capital, and the actual cost of this capital is lower than its nominal interest rate.

It does not mean that the company can freely increase the share of debt in the capital structure. The lenders react to the increase in the share of debt by raising the interest rate for the capital provided.

The DuPont's model shows that the sales profitability is determined by such factors as the margin generated on sales (expressed as Earnings Before Interest and Taxes (EBIT) to Sales Revenues ratio), costs of servicing external financing (expressed as Gross Result to EBIT ratio), and financial burden (expressed as Net Profit to Gross Profit ratio). The analysis of the regression curve shows that along with the increase of the Net Profit Margin, the Return on Equity increases (Fig. 5).

The results generated by the evolutionary algorithm rightly show that the increase in ROE will be supported by the improvement of operational efficiency (ROS). It can be achieved both as a result of increased revenues and reduced costs, for example by introducing new production technologies, sales techniques or innovativeness. Currently, the literature on the subject emphasizes that innovation processes can be implemented, for example, through cooperation with external partners, thanks to which the company will gain access to necessary resources and reduce costs [101, p. 3].

TABLE 3. Best, typical and worst ROE values ([%]) obtained for ROS.

No.	Best ROE	Best ROS	Typical ROE	Typical ROS	Worst ROE	Worst ROS
1.	192.046	0.992	58.006	0.987	4.919	0.032
2.	188.267	0.992	57.292	0.832	2.278	0.079
3.	187.670	0.992	55.578	0.846	1.554	0.010
4.	186.766	0.984	55.499	0.751	0.631	0.018
5.	181.340	0.956	54.904	0.463	0.051	0.0004

The analysis of the relationship between the Net Profit Margin and ROE shows that achieving the ROS index on the average of 98.32% promotes ROE maximization (Table 3). It means that within the industry in question one should strive for a situation in which every 1 PLN of sales revenues involved will generate nearly 1 PLN of Net Profit [102, pp. 5–6]. Keeping ROS lower than 7.9% will lead to minimizing the Return on Equity. For the most frequently occurring ROE, the ROS index was reported on average at 77.58%.

The Rotation of Assets, and thus the speed of asset turnover, shows the level of use of resources at the disposal of the company. The analysis of dependencies allows concluding that the highest ROE was reported for asset turnovers at 1.802. This level will inform that every 1 PLN of assets translates into 1.802 PLN of sales (Table 4) [102, pp. 5–6]. In other words—the sales of the company should be higher by 1.802 than the value of its assets.

TABLE 4. Best, typical and worst ROE values ([%]) obtained for TAT.

No.	Best ROE	Best TAT	Typical ROE	Typical TAT	Worst ROE	Worst TAT
1.	192.046	1.802	58.006	0.475	4.919	1.399
2.	188.267	1.802	57.292	0.572	2.278	0.255
3.	187.670	1.679	55.578	0.297	1.554	1.178
4.	186.766	1.802	55.499	0.528	0.631	0.189
5.	181.340	1.802	54.904	0.876	0.051	0.869

The better use of assets favors increasing Return on Equity (Fig. 6). As a part of the improvement of Total Asset Turnover ratio, it should be considered which assets are inefficient and worth getting rid of, thus improving the Rotation of Assets. It is worth mentioning that the level of the indicator will depend on the specificity of the industry in which the company operates.

If the asset rotation aspect is taken into consideration, it should also be noted that the evolutionary algorithm proposed that for the highest ROE levels a company should generate revenues of 143 550.83 k PLN (Table 5) and average assets equal to about 80 000 k PLN (Table 6).

TABLE 5. Best, typical and worst ROE values ([%]) obtained for Revenues ([k PLN]).

No.	Best ROE	Best Revenues	Typical ROE	Typical Revenues	Worst ROE	Worst Revenues
1.	192.046	143 550.83	58.006	143 550.83	6.991	229 079.76
2.	188.267	143 550.83	57.292	101 384.11	4.919	1 260 169.39
3.	187.670	143 550.83	55.578	99 342.48	2.278	109 420.68
4.	186.766	143 550.83	55.499	182 472.94	1.554	1 286 968.90
5.	181.340	143 550.83	54.904	302 712.87	0.631	259 553.02

TABLE 6. Best, typical and worst ROE values ([%]) obtained for ATA ([k PLN]).

No.	Best ROE	Best ATA	Typical ROE	Typical ATA	Worst ROE	Worst ATA
1.	192.046	79 672.78	58.006	302 352.79	6.991	1 803 478.11
2.	188.267	79 672.78	57.292	177 375.42	4.919	900 389.13
3.	187.670	85 479.27	55.578	334 785.32	2.278	428 667.98
4.	186.766	79 672.78	55.499	345 742.60	1.554	1 092 784.80
5.	181.340	79 672.78	54.904	345 742.60	0.631	1 374 360.97

The algorithm did not suggest such unambiguous values in the revenues and ATA area for typical and lowest ROE levels. The results of the conducted research show that the increase in ROE will be supported by the decrease in revenues (Fig. 7) and the average asset value (Fig. 8).

One of the elements determining ROE is Capital Multiplier showing the level of external financing and measuring financial leverage [103, p. 148]. This ratio, greater than one, indicates that external capital is used to finance the company's operations, and therefore less capital is obtained from the owners of the company. However, it should be noted that if these external capitals are interest-bearing, net profit will decrease, which will lower the rate of Return on Equity. Based on the conducted analyses, it can be seen that for situations in which ROE showed the highest levels, Capital Multiplier ranged from 1.053–1.126 (Table 7), which allows concluding that the share of debt in the business financing structure should not be too high. The evolutionary algorithm proposed, therefore, the involvement of external capital in the financing

TABLE 7. Best, typical and worst ROE values ([%]) obtained for CM.

No.	Best ROE	Best CM	Typical ROE	Typical CM	Worst ROE	Worst CM
1.	192.046	1.074	58.006	1.237	4.919	2.547
2.	188.267	1.053	57.292	1.205	2.278	1.127
3.	187.670	1.126	55.578	2.213	1.554	1.320
4.	186.766	1.053	55.499	1.401	0.631	1.880
5.	181.340	1.053	54.904	1.354	0.051	1.358

of operations, which, thanks to the use of financial leverage, will support the increase in Return on Equity.

However, this commitment is not significant, and its level fluctuates slightly (Fig. 9) so that the company will not be overburdened with interest charges. Such a capital structure will be conducive to the company's financial stability in the long-term and to maintaining financial liquidity, understood as the ability to pay current liabilities on time.

The results of experiments prove that the evolutionary algorithm can propose solutions regarding the capital structure optimization that are valid, sensible and sometimes also innovative and non-obvious. Thus, the evolutionary algorithms can serve as a basis for decision support tools for managers that have to undertake decisions on financing structure of a company that operates in a rapidly changing environment. Additionally, the proposed algorithm can be extended to deal with multi-objective problems. In such a case it would also be possible to take into account environmental and social goals, which would lead to improving the corporate social responsibility of a company.

VII. SUMMARY AND CONCLUSIONS

The research presented in this paper aimed at the use of evolutionary algorithms in the area of ROE optimization. The work draws attention to interconnections between financial and sustainable development aspects, because, according to the authors, there is no way to care for sustainable development in a company without having stable financial foundations. At the same time, it has been shown that considering the sustainability aspects of a company's activities may significantly contribute to maximizing profits in the long run, thereby maximizing ROE and optimizing the capital structure.

As noted, the level of Return on Equity depends on three factors: sales profitability, asset turnover, and equity multiplier. It should be remembered that the ratios presented in the DuPont model, the level of which translates into the rate of Return on Equity, will compensate each other and, for example, a decrease in one factor may be compensated by the growth of another. Thus, with a given financing structure, the expected level of ROE may be obtained, for example, due to the implementation of low sales profitability, but high turnover. But also thanks to showing low turnover but high sales profitability. Looking at it from a different angle, the increase of the Capital Multiplier ratio will result in a decrease in profit, and therefore the profitability of net sales will decrease. Increasing external financing can also achieve an increase in the Return on Equity. However, the use of capital with which the need to pay interest is associated will translate into lower net profit. From this perspective, it will, therefore, be beneficial to use interest-free debt, for example from trade credit. However, this may negatively affect the use of the positive leverage effect. Consequently, it is necessary to be able to carry out a proper economic calculation. It is, therefore, essential to consider the company as a whole, taking into account the specific conditions of its operation within a given industry, the market in which it operates, socio-economic conditions and environmental and social effects of its economic activities.

The use of an evolutionary algorithm to solve a given problem has shown that an increase in the Return on Equity will be favored by:

- increase in net profit and decrease in equity (Fig. 3 and 4);
- increase in sales revenues and increase in sales profitability (Fig. 5 and 7);
- non-excessive indebtedness of the company (Fig. 9).

The obtained results which are the outcome of the conducted research testify to the legitimacy of using evolutionary algorithms in the area of corporate finance, because these methods demonstrate a great ability to adapt to changing conditions, to learn and to innovate. It is a significant incentive to conduct deepened research in the indicated area.

As the experimental results indicate, the highest level of Return on Equity will be obtained at:

- net profit of 142 500 k PLN;
- average equity equal to 75 700 k PLN;
- sales profitability at the level of 98.32%;
- development of revenues at 143 550.83 k PLN;
- Capital Multiplier maintained in the range of 1.053–1.126.

The above results may seem not very common in business practice. The proposed evolutionary algorithm generates a whole set of possible solutions, among which are more typical (usually used in business practice), as well as less obvious, more experimental and innovative, which the decision maker may or may not take into consideration. An evolutionary algorithm is a tool that can propose innovative solutions that have not been applied in practice so far and this is the strength of this tool. It is true that some of the results obtained are not widely used in business practice, but they are correct and rational and prove that the evolutionary algorithm can propose innovative and non-obvious solutions. It is a good prognosis for the future because we plan to add additional criteria related to sustainable development and we are just looking for innovative and non-obvious solutions from our system.

The conducted research showed that the highest ROE results were obtained at the level of ROS index at the average of 98.32% and the level of CM index falling within the range of 1.053–1.126. Taking actions that shape the level of net profit in relation to revenues from sales has the impact on the changes of ROS indicator. In the CM context, however, it is reasonable to maintain an appropriate ratio of assets to equity. When the CSR is taken into account, this requires the implementation of a long-term company management strategy taking into account relations with employees as well as the social and environmental area. Proper care for employees (paying employees on time, equal treatment, respect for their private life) will improve the quality of working environment, which will help them to identify with the company, and will consequently reduce wastage of resources and improve the efficiency of resource use. It will translate into an increase in employees' involvement and will improve the efficiency of the company's operation, and thus increase sales while, at the same time, encouraging a reduction of wastage of funds, which will translate into the financial result. In order to maximize ROS, it is important to minimize costs, and this will not be possible if CSR policy is incidental. The reduction of costs will also be favored by the rational management of the assets and the implementation of the pro-environmental policy, the introduction of which at the first stage generates costs, but at a later time allows the company to reduce them. Besides, functioning in the spirit of sustainable development will result in companies being better perceived by financial institutions, which will increase their possibilities regarding acquiring cheaper external financing sources, remembering that interest costs translate into the level of net profit. Therefore, social and environmental engagement will support the maintenance of the required capital structure. Current and potential shareholders will also be more inclined to engage their capital in a company that is considered to be stable and enjoys a large social commitment.

Because companies operating in the spirit of sustainable development implement specific activities, and if these activities are to meet the needs of stakeholders, then they must be based on solid financial foundations. It is conditioned by the possibility of uninterrupted, lasting action. In other words, the implementation of stable development postulates without having firm financial foundations is very difficult to achieve.

The experiments carried out have shown that the use of evolutionary algorithms can provide realistic, valuable, and sometimes also innovative and not so evident results in the area of corporate finance. It indicates the legitimacy of using them as techniques supporting the decisions of managers regarding the capital structure and financing sources of a company, which operates in a rapidly changing environment. Future research on the use of a multi-objective optimization technique will lead to very interesting results because many, often contradictory, goals can be taken into account. It will allow to include sustainable development objectives in the process of making decisions concerning corporate finance.

The application of multi-objective evolutionary algorithms, or agent-based multi-objective co-evolutionary algorithms [66], [67], [94], [95] in the proposed intelligent system supporting capital structure decisions taking into account multiple contradictory criteria, including financial and sustainable development ones, would allow us to fully incorporate the goals of sustainable development into the process of searching for an optimal financial structure of a company. In such a situation, social and environmental objectives and constraints can be entirely taken into account, and the result would be a set of Pareto optimal solutions. The decision maker would then be able to choose a preferred financing structure of a company, which takes into account not only the increasing profitability and shareholders' wealth but also the goals of sustainable development. Additionally, the ability of evolutionary algorithms to generate and propose innovative and non-obvious solutions would allow presenting new (not applied previously) solutions to the managers, which is very important in a situation of rapidly changing economic, environmental and social conditions in which a company operates.

The application of our agent-based multi-objective co-evolutionary algorithms in the intelligent system supporting corporate finance decisions and using financial as well as sustainable development criteria will also have implications for the research on agent-based bio-inspired artificial intelligence techniques. The agent-based co-evolutionary algorithms will be tested in a very demanding, dynamically changing environment, in a situation where multiple and contradictory criteria have to be taken into account. Such conditions will allow for thorough verification of the ability of agent-based co-evolutionary algorithms to generate diverse and robust solutions and to propose innovative and non-obvious variants of decisions.

In this paper, an attempt was made to combine financial and non-financial factors because we have a deep conviction that practical and effective actions in the area of CSR will not be possible without the financial stability of the company. Unfortunately, in Polish conditions, the aspects of CSR and sustainable development are insufficiently addressed. Some theoretical literature is available; however, it is very difficult to carry out valuable empirical studies. It is because the obligation of non-financial reporting was introduced in 2017 and applies only to entities that employ on average more than 500 people and at the same time the total balance sheet assets exceed EUR 20 million or net revenues from sales of goods and products exceed EUR 40 million. It should be noted that the Warsaw Stock Exchange has the RESPECT index that groups companies managed responsibly and sustainably, however, in this index only 28 companies from various sectors are grouped. There is no single set of reporting, so the data is not comparable. Besides, the data presented in those reports are mainly of a qualitative, not quantitative nature. In order to obtain reliable quantitative data for Polish companies, it is necessary to conduct in-depth research.

In conclusion, the conducted research has shown that to maximize ROE it is reasonable to maximize the ROS index and maintain the CM index at the desired level. The objectives of sustainable development that have been taken into account in the context of current research are as follows (taking into account the objectives of the World Bank):

1) financial stability—the improvement of financial results by reduction of wastage of assets, greater concern for the financial area, will translate into a reduction of costs and improve the financial situation of the company and will create conditions for easier access to sources of financing,
2) jobs and development—caring about employees manifested, for example, in paying employees on time, respect for their private lives, equal treatment, cause that they begin to identify with the company, which in the financial context translates into an improvement in their efficiency and a reduction of wastage of resources,

3) environment—care for the environment is related to the rationalization of resource use, which translates into a reduction in costs. It also affects better perception by the environment, which promotes sales growth and easier access to sources of financing,
4) health - caring for employees and the environment translates into the health of people.

To fully integrate the above objectives into our research and to use them in the developed system, the reliable quantitative data for Polish companies are needed. As it was mentioned, in-depth research to obtain such data is needed, which the authors intend to carry out as part of a separate research project.

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RAFAŁ DREŻEWSKI received the M.S. and Ph.D. degrees in computer science from the AGH University of Science and Technology, Cracow, Poland, in 1998 and 2005, respectively.

Since 2006, he has been an Assistant Professor with the Department of Computer Science, AGH University of Science and Technology. He has authored over 60 papers. His research interests include bio-inspired artificial intelligence algorithms and agent-based modeling and simulation of complex and emergent phenomena.

SYLWIA KRUK received the M.S. and Ph.D. degrees in management science from the Cracow University of Economics, Poland, in 2005 and 2011, respectively.

Since 2012, she has been an Assistant Professor with the Department of Economics and Organization of Enterprises, Cracow University of Economics, Poland. She has authored about 30 papers. Her current research interests focus on corporate finance.

MACIEJ MAKÓWKA received the B.S. degree in computer science from the AGH University of Science and Technology, Cracow, Poland, in 2017, where he is currently pursuing the master's degree with the Department of Computer Science.

His research interests include bio-inspired artificial intelligence algorithms and big data sets replication in distributed databases and cloud environment.