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THE EFFECTIVENESS OF GENETIC ALGORITHMS FOR EVALUATING E-BUSINESS STRATEGIES

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Mshvidobadze T. I., Osadze L. T., Sosanidze M. O. The Effectiveness of Genetic Algorithms for Evaluating E-Business Strategies

Nowadays, timely transformation of information is important for the viability of an organization. Big data solutions directly affect how an organization should work with the help of artificial intelligence components. The article shows an algorithmic approach to strategic planning and performance assessment of e-business. Various artificial intelligence methodologies and their use in various applications of large organizations are shown. The conception of genetic algorithms is presented, which is related to e-business strategy in various applications. Genetic algorithms can be used to solve e-business problems, especially for strategic planning and performance evaluation, leading to improved overall performance of large organizations. A new scheme for e-business strategy planning and performance evaluation, based on adaptive algorithmic modeling techniques, is used to improve the performance of genetic algorithms. The proposed algorithmic approach can be effectively used to solve a wide class of e-business and strategic management problems. In the context of "Genetic Algorithm Optimization, Genetic Algorithm Optimization of Business Strategies", we can delve into the future trends of genetic algorithms optimization for business strategies: 1) The development and improvement of genetic algorithms is expected to lead to improved performance in business strategy optimization. This can be achieved through more efficient selection mechanisms, crossover techniques, and mutation operators; 2) The integration of genetic algorithms with machine learning techniques holds great potential for business strategy optimization. By combining the power of genetic algorithms with the ability to learn from data, businesses can uncover hidden patterns and make more informed decisions; 3) Genetic algorithms are well suited to solving multi-objective optimization problems, where multiple conflicting objectives must be considered simultaneously. Future trends may focus on developing advanced techniques to effectively handle such complex scenarios; 4) As technology advances, genetic algorithms can be used in real-time scenarios, allowing businesses to optimize their strategies on the fly. This can be especially useful in dynamic environments where rapid adaptation is crucial; 5) Genetic algorithms can be combined with other optimization techniques, such as simulated annealing or particle swarm optimization, to create hybrid approaches. These hybrid methods can leverage the strengths of different algorithms and provide more robust optimization solutions.

Keywords: *e-business, strategic planning, artificial intelligence, genetic algorithm, performance evaluation.*
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Мшвідобадзе Т. Я., Осадзе Л. Т., Сосанідзе М. О. Ефективність генетичних алгоритмів для оцінки стратегій електронного бізнесу

Сьогодні своєчасна трансформація інформації є важливою для життєздатності організації. Рішення на основі великих даних безпосередньо впливають на те, як організація повинна працювати за допомогою компонентів штучного інтелекту. У статті показано алгоритмічний підхід до стратегічного планування та оцінки ефективності електронного бізнесу. Показано різні методології штучного інтелекту та їх використання в різних застосуваннях великих організацій. Представлено концепцію генетичних алгоритмів, яка пов'язана зі стратегією електронного бізнесу в різних застосуваннях. Генетичні алгоритми можуть бути використані для вирішення проблем електронного бізнесу, особливо для стратегічного планування та оцінки ефективності, що приводить до покращення загальної ефективності великих організацій. Нова схема планування стратегії електронного бізнесу та оцінки ефективності, заснована на адаптивних методах алгоритмічного моделювання, використовується для покращення продуктивності генетичних алгоритмів. Запропонований алгоритмічний підхід може бути ефективно використаний для вирішення широкого класу проблем електронного бізнесу та стратегічного управління. У контексті «Оптимізація генетичних алгоритмів, оптимізація генетичних алгоритмів бізнес-стратегій» ми можемо заглибитися в майбутні тенденції оптимізації генетичних алгоритмів для бізнес-стратегій: 1) очікується, що розробка та вдосконалення генетичних алгоритмів приведе до покращення ефективності оптимізації бізнес-стратегій. Цього можна досягти за допомогою ефективніших механізмів відбору, методів кросовера та операторів мутації; 2) інтеграція генетичних алгоритмів з методами машинного навчання має великий потенціал для оптимізації бізнес-стратегії. Поєднуючи потужність генетичних алгоритмів зі здатністю навчатися на основі даних, підприємства можуть виявляти приховані закономірності та приймати більш обґрунтовані рішення; 3) генетичні алгоритми добре підходять для вирішення задач багатоцільової оптимізації, де необхідно одночасно розглядати кілька суперечливих

цілей. Майбутні тенденції можуть зосередитися на розробці передових методів для ефективної обробки таких складних сценаріїв; 4) з розвитком технологій генетичні алгоритми можна використовувати в сценаріях реального часу, що дозволяє підприємствам оптимізувати свої стратегії «на льоту». Це може бути особливо корисним у динамічних середовищах, де швидка адаптація має вирішальне значення; 5) генетичні алгоритми можна поєднувати з іншими методами оптимізації, такими як імітація відпалу або оптимізація рою частинок, для створення гібридних підходів. Ці гібридні методи можуть використовувати сильні сторони різних алгоритмів та забезпечувати більш надійні рішення для оптимізації.
Ключові слова: *електронний бізнес, стратегічне планування, штучний інтелект, генетичний алгоритм, оцінка ефективності.*
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Every day businesses are faced with large volumes of data that are beyond the scope of Master Data Management (MDM) such as Big Data, which moves at the speed of the Internet. Daily operations in any organization or enterprise are expanding the Internet of Things (IoT) to interact with this data, in a structured or unstructured form.

Big Data depends on the size of the organization. Companies are trying to better understand their customers so that they can provide them with more targeted products and services. To do this, they are increasingly using artificial intelligence (AI) analytical techniques such as machine learning (ML) and deep learning to analyze larger data sets.

Big data typically has three characteristics:

1. *Volume:* Organizations collect data from a variety of sources, including business transactions and social media.

2. *Velocity:* Data is coming in at an unprecedented rate and needs to be processed in a timely manner. Tags, sensors, and smart metering are driving the need to deal with data structures in real time.

3. *Diversity:* Data comes in all types of formats – structured databases and unstructured text documents, such as e-mails, stock ticker data, and financial transactions.

Data is growing at a compound annual growth rate of almost 60% per year. According to studies, 70% of this huge data is unstructured such as social media related data, etc. As such, Big Data is a hot topic for businesses all over the world [1].

Artificial Intelligence software delivers relevant decisions to organizations by accelerating online simulation processes. Artificial Intelligence in business decision-making refers to the use of algorithms and computational models to support or automate decision processes. This encompasses machine learning techniques, deep learning, rule-based systems, and other approaches that analyze vast datasets, identify patterns, and recommend optimal actions. A key concept is AI-driven decision support systems, which integrate internal and external data to present managers with valuable analyses and forecasts. These systems range from predictive models for demand forecasting to optimization algorithms for resource allocation.

AI could manage both structured and unstructured decisions. However, advances in AI challenge this paradigm by demonstrating that certain models can emulate or even match aspects of human reasoning in strategic contexts. For instance, large language models have generated and evaluated business strategies at a level comparable to human entrepreneurs and investors in controlled settings, indicating that AI can contribute meaningfully to strategic formulation by offering speed and diverse perspective.

Recently, the field of artificial intelligence has had a significant impact on the financial services sector and global financial markets. Algorithmic trading systems are known to process approximately 75% of global trading volume, with industry forecasts showing continued growth.

LITERATURE REVIEW

The role of artificial intelligence in the business world is growing phenomenally. It has penetrated various sectors, including manufacturing, healthcare, finance and retail, transforming business models and processes.

In the field of marketing, artificial intelligence helps businesses understand consumer behavior, predict market trends and personalize advertising to different groups of users.

AI is also revolutionizing supply chain management and efficient inventory management. Predictive analytics allow businesses to forecast demand and reduce inventory costs accordingly.

Small and medium-sized businesses (SMEs) can benefit significantly from the use of artificial intelligence. AI can improve business efficiency in various ways. For example, it can automate administrative tasks, and with the help of machine learning, SMEs have the ability to make data-driven decisions, improve their products or services and identify new opportunities.

We will discuss various models and applications of artificial intelligence.

Machine learning. One subset of artificial intelligence is machine learning (ML). It is a technique that allows computers to understand data and provide intelligent applications [2].

Machine learning models are exposed to new data, they can adapt independently. They learn from previous calculations to produce reliable, repeatable solutions and results. Machine learning can also be defined as the process of solving a practical problem: collecting data and building a statistical model algorithm based on this data.

Machine learning is an integral part of commercial applications such as medical, banking, e-commerce and research projects, but this field is not exclusive to large companies. The Python programming language, as a software engineer in the field of artificial intelligence, provides practical ways to create your own ML solutions.

Within the domain of Segmentation, ML is employed to improve business-to-customer (B2C) and business-to-business (B2B) relationships. Techniques like K-means clustering and Gaussian mixture models facilitate the customization of high-value-added products and services tailored to specific customer needs, thereby enhancing customer satisfaction and loyalty. Additionally, ML algorithms support the provision of supplementary services that elevate the overall customer experience.

Another significant application is the use of ML for personalized advertising on social media platforms and Google Ads. By leveraging customer profiling through algorithms such as logistic regression, decision trees, and random forests, businesses can deliver more personalized and effective marketing strategies.

The banking industry prominently utilizes clustering algorithms for customer segmentation and service targeting, distinguishing its ML applications from other sectors that focus on areas like risk assessment, asset management, and stock market analysis .

Within C4, ML clustering techniques also complement analytic hierarchical process (AHP), multicriteria decision-making (MCDM), and decision support systems (DSS) in strategic management. ML algorithms enhance the segmentation, targeting, and positioning (STP) process in marketing by providing data-driven insights that inform more effective segmentation and targeting strategies [3].

The use of ML in innovation is also discussed in the context of user experience (UX) design tools [4], where algorithms such as reinforcement learning and recommendation systems could potentially enhance user engagement and product development processes. While the exact applications of ML in entrepreneurship remain somewhat ambiguous, ongoing research suggests that ML could play a pivotal role in understanding and forecasting innovation trends and entrepreneurial success.

Moreover, the contemporary surge in ML applications, exemplified by the exponential growth of the user base witnessed by ChatGPT since its launch [5], has sparked inquiries encompassing ethical considerations, usability concerns, and the anticipated impact of ML and AI across various industries. Notably, one significant enquiry revolves around the transformation of existing business models and process optimization within the domain of business and management.

Deep Learning. Deep learning (DL) is a subset of machine learning that allows computers to solve more complex problems. Deep learning has also been defined as the study of multiple levels of representation and abstraction.

Simply put, deep learning is the use of neural networks with more neurons, layers, and their interconnections.

In short, artificial intelligence has taken over the center of business intelligence. Major companies such as IDC Technology predict that by 2025, it will reach 40% in terms of digital transformation [6].

Digital transformation (DX) is reaching macroeconomic scale. Intelligent applications based on artificial intelligence (AI), machine learning (ML), and deep learning (DL) are the next wave of technological transformation.

Companies such as Google and Apple are using the TensorFlow programming interface, written in the Python programming language, for AI.

Super-AI (SAI), powered by artificial neural networks (ANNs) and their cognitive, natural language capabilities, is the matrix of the future [7]. An artificial neural network (ANN) is a computational model based on the structure and function of biological neural networks, and is one of the main tools used in machine learning.

ARTIFICIAL INTELLIGENCE AS A DRIVER OF ECONOMIC GROWTH

Artificial intelligence has significant potential to contribute to the development of global economic activity. But it is necessary to expand the connections between different countries and their companies to maximize the benefits. Super Artificial Intelligence (SAI) acts as a capital-labor hybrid. Artificial intelligence offers the ability to enhance the current capabilities of capital and labor to increase economic growth.

According to an international study (Accenture) on the impact of artificial intelligence on the economy, AI could double the annual economic growth rate by 2035. It is predicted that the impact of AI technologies on business will increase labor productivity by 40%.

Global economic activity will be about $ 13 trillion by 2030, or about 16% of gross domestic product (GDP) higher than today. That amounts to an additional 1.2% of GDP growth per year [8]. In short, AI offers the potential to boost economic growth by acting as a hybrid of capital and labor.

GENETIC ALGORITHMS IN BUSINESS

A genetic algorithm is a stochastic search algorithm based on the evolutionary process of natural systems. It has been applied to many optimization problems. For example traveling salesman problems, bin packing, scheduling, sequencing, facility layout problems, and facility location problems.

Different from local search strategies, genetic algorithms can accept temporary solutions with a worse objective function value, in comparison to the preceding solution to overcome local optima and to find the global one.

Since genetic algorithms are stochastic search algorithms working with probabilities, in general they can come up with different solutions, even if they are started with the same initial solution and the same parameter settings.

Genetic algorithms are used in many different areas of computing, including optimization, machine learning, and artificial intelligence. They are particularly useful for problems where the search space is large, complex, and poorly understood.

Function optimization is one of the most common use cases for genetic algorithms. This involves finding the maximum or minimum of a function, which can be a complex and computationally intensive task. Genetic algorithms are particularly useful for this task because they can search a large and complex space efficiently and effectively. Genetic algorithms have been used to optimize a wide range of functions, including mathematical functions, engineering functions, and economic functions. They have also been used to optimize functions in machine learning and artificial intelligence, such as neural network weights and decision tree structures.

Genetic algorithms, which originated from the principles of Darwinian evolution, are a heuristic modeling technique that is inspired by natural evolution and can be effectively applied. This computational technique can lead to optimized solutions to certain complex problems [9].

A simple genetic algorithm can be represented as follows: Algorithm GA1 (GPC, FCP, ISO, RNP, BSGA). The GA1 algorithm describes the basic steps of a genetic algorithm, where each iteration or repeated process is called a generation.

A genetic algorithm is a computational method for solving constrained and unconstrained optimization problems based on natural selection, the process that drives biological evolution.

Genetic algorithms use two basic rules at each step to generate future generations from current populations, namely selection rules (parental selection) and crossover rules (mating) [10].

The wide range of applications of genetic algorithms includes the following topics: *Optimization* (numerical optimization and combinatorial optimization – scheme layout and job scheduling), *Automatic programming* (automata, network sorting), *Machine learning* (protein structure, neural networks, sensors for robots), *Economics* (modeling, bidding strategies, economic markets), *Immune systems* (modeling of the natural immune system), *Ecology* (modeling of biological processes, symbiosis), *Population genetics* (gene viability), *Social systems* (evolutionary behavior of social systems, evolution of communication in multi-agent systems), *Effective e-business model*, *so-called Lipitakis-Phillips* (LP) model, for strategic planning and performance evaluation [11].

The e-business models and corresponding hypotheses proposed by Lipitakis were statistically tested using explanatory and confirmatory factor analysis, correlation between independent and dependent variables, and regression analysis. Using this analysis, it was found that the independent variables of the principal components can be used to predict the dependent variables of financial and non-financial activities [12].

RESULTS AND DISCUSSION

Recently, a class of adaptive algorithms has also been presented for solving e-business problems.

HYBRID GENETIC ALGORITHM SCHEME FOR E-BUSINESS STRATEGIC PLANNING AND EXECUTION

The Modified Adaptive Algorithmic Modeling (MADAM) scheme using a hybrid genetic algorithm and a set of dependent and independent variables, which are given in eleven computational modules, can be described as follows:

Algorithm MADAM-1 (GA1, FNFP, FPST, ε_ST STR, ε_LE LEA, ε_PC PCU, ε_CO, COH, ε_KN KNO, ε_AL ALL, ε_AD, ADM, ε_UN, ADAMS).

Purpose: Describes a modified adaptive algorithmic modeling scheme for computing the best performance measures and solving a wide class of e-business strategic management problems. Under uncertainty.

The genetic algorithm GA1 is used for the corresponding solutions.

Input: Genetic Algorithm – GA1, Formation – FORM, Participation – PART, Sophistication – SOPH, Accuracy – THOR, Financial Performance – FINP, Non-Financial Performance – NFIP, Structure – STR, Leadership – LEA, People & Culture – PCU, Coherence – COH, Knowledge – KNO, Alliance – ALL.

Agility & Decision Making – and ADM, SP-parameters ε_{FO}, ε_{PA}, ε_{PC}, ε_{TH}, ε_{FP}, ε_{NF}, ε_{ST}, ε_{LE}, ε_{PC}, ε_{CO}, ε_{KN}, ε_{AL}, ε_{AD}, uncertainty factor parameter.

Output: (Optimized) Modified Adaptive Algorithmic Model Solution (MADAMS) (*Fig. 1*).

Computational procedure:
Step 1: Use CA1 to find a feasible solution
Step 2: If no feasible solution exists, go to Module 1, otherwise go to Step 11.1
Module 1: Estimate independent variables FPST (FORM, PART, SOPH, THOR)
Module 2: Estimate dependent strategic planning variables FNFP (FINP, NFIP)
Module 3: Determine input SP-parameters
Module 4: Use CA1 and design structure STR (MRE, POR, SAR, DBF)
Module 5: Use CA1 and improve leadership LEA (TCH, LAD, LAC, LEIS)
Module 6: Focus on people and culture in PCU (REW, RCR, LRE, RTR, ICO)
Module 7: Emphasis on Coh Consistency (MPE, III, SIN, DDS, CCS)
Module 8: Knowledge KNO Commentary (KDA, KFO, KEM, KAC, KSH)
Module 9: Use CA1 and Define Alliances All (ART, APE, CRI)
Module 10: Use CA1 and Focus on Agility and Decision Making ADM (IRE, MSR, TRTO, MSA, ADE)
Module 11: Build an E-Business Solution
Step 11.1: Determine the uncertainty parameter ε_{UN}
Step 11.2: Formulate a solution (ε_{UN} MADAMS)

Fig. 1. Program code

The parameter values that affect the optimized corresponding input variables in the algorithm – MADAM-1 can be determined experimentally or approximately by an appropriate mathematical model. In the special case, when the sp-parameters take the values:

$$\varepsilon_{FO}, \varepsilon_{PA}, \varepsilon_{PC}, \varepsilon_{TH}, \varepsilon_{FP}, \varepsilon_{NF} = 1 \text{ and}$$
$$\varepsilon_{ST}, \varepsilon_{LE}, \varepsilon_{PC}, \varepsilon_{CO}, \varepsilon_{KN}, \varepsilon_{AL}, \varepsilon_{AD} = 1.$$

A simplified form of the algorithm can be adopted, and the selection of appropriate parameters in terms of optimized solutions depends on the nature of the problem under consideration and often requires extensive experimentation [13].

The main advantage of the proposed algorithmic approach is twofold. First, adaptive algorithms can be effectively used to solve a wide class of e-business and strategic management problems [14], and second, the dynamic choice of SP-parameter values, which can be related to both the quantitative and qualitative nature of the input parameters for a given problem, can lead to an optimal solution [15].

Genetic programming implementation can be achieved with several programming languages, such as: MATLAB [GPLAB, GPTIPS], Python, pySTEP, Java, PMDGP, ECF, C# (Heuristic Lab), GPdotNET, Prolog, Ruby Perl [PerlGP], .NET [GPE], and others.

BEST PRACTICES FOR USING GENETIC ALGORITHMS IN BUSINESS STRATEGIES

Problem Formulation and Representation:

Before applying GAs, it's crucial to define the problem clearly. For example, if optimizing marketing budgets, consider binary strings where each bit represents an advertising channel (e. g., 1 for online ads, 0 for print).

Population Size and Diversity:

The population size affects exploration and exploitation trade-offs. Too small, and you risk premature convergence; too large, and computation becomes expensive. Start with a moderate-sized population and experiment.

Crossover and Mutation Rates:

Crossover combines genetic material from parents, while mutation introduces small random changes. The rates impact exploration and exploitation. Tune these rates based on problem characteristics. High crossover encourages convergence, while moderate mutation prevents stagnation.

Fitness Function Design:

The fitness function evaluates how well a solution performs. It's domain-specific and should reflect business goals.

Define a fitness function that captures both quantitative metrics (e. g., profit, cost, revenue) and qualitative aspects (e.g., customer satisfaction, brand reputation).

Domain-Specific Constraints:

Real-world problems often have constraints (e. g., budget limits, capacity constraints, legal requirements). Incorporate constraints into the GA. Penalize infeasible solutions or use repair mechanisms.

The success of using GAs lies not only in their implementation but also in understanding the problem context deeply. By combining theoretical knowledge with practical insights, businesses can optimize their strategies effectively

CHALLENGES AND LIMITATIONS OF GENETIC ALGORITHM OPTIMIZATION IN BUSINESS

When discussing the challenges and limitations of genetic algorithms optimization in the context of business strategies, the following should be considered.

Lack of Domain Knowledge: One of the challenges of using genetic algorithms in business optimization is the requirement of domain knowledge. Genetic algorithms rely on the understanding of the problem domain to define appropriate fitness functions and genetic operators. Without a deep understanding of the business context, it can be difficult to design an effective genetic algorithm.

Complex problem spaces: Genetic algorithms face challenges when working with complex problem spaces that involve a large number of variables and constraints. In such cases, finding an optimal solution becomes more difficult and time-consuming.

Premature convergence: Genetic algorithms can experience premature convergence, where the algorithm settles on a suboptimal solution before exploring the entire search space. This can limit the efficiency of the optimization process and hinder the discovery of better solutions.

Computational resources: Genetic algorithms can be computationally intensive, especially when working with large-scale optimization problems. The time and resources required to estimate fitness functions and generate new populations can be limiting in real-time business scenarios.

Sensitivity to parameters: The performance of genetic algorithms is very sensitive to the choice of parameters such as population size, mutation rate, and crossover rate. Selecting optimal parameter values can be difficult and may require extensive experimentation.

In summary, genetic algorithms offer a powerful approach to business optimization, but they come with challenges and limitations. Understanding the problem domain, addressing computational complexity, mitigating premature convergence, handling scalability, and fine-tuning parameter settings are crucial for maximizing the effectiveness of genetic algorithms in optimizing business strategies.

FUTURE TRENDS AND INNOVATIONS IN GENETIC ALGORITHM OPTIMIZATION FOR BUSINESSES

Enhanced Performance: Genetic algorithms are expected to evolve further, leading to improved performance in optimizing complex business strategies. With advancements in computing power and algorithmic techniques, businesses can expect more efficient and effective solutions.

Integration with Machine learning: The integration of genetic algorithms with machine learning techniques holds great potential. By combining the power of genetic algorithms' evolutionary search with the adaptability of machine learning models, businesses can achieve more accurate and dynamic optimization results. [16].

Multi-Objective optimization: Genetic algorithms are increasingly being applied to solve multi-objective optimization problems. This allows businesses to optimize multiple conflicting objectives simultaneously, such as maximizing profit while minimizing costs or balancing customer satisfaction with resource allocation.

Real-Time optimization: As technology advances, genetic algorithms are being adapted to perform real-time optimization. This enables businesses to dynamically adjust their strategies based on changing market conditions, customer preferences, and other relevant factors.

Hybrid Approaches: Hybrid approaches that combine genetic algorithms with other optimization techniques, such as swarm intelligence or simulated annealing, are gaining popularity. These approaches leverage the strengths of multiple algorithms to tackle complex optimization problems more effectively.

Domain-Specific Applications: Genetic algorithms are being applied to various domains, including supply chain management, financial portfolio optimization, scheduling, and resource allocation. As businesses continue to explore new applications, domain-specific innovations in genetic algorithm optimization are expected to emerge.

CONCLUSION

With all the possibilities of deep learning, genetic algorithms, and their combination, it's tempting to see these technologies as a default solution for every problem. However, it's crucial to remember that each tool has unique pros and cons for specific technical challenges and domain requirements.

AI's evolving capabilities also unlock new possibilities when combined with other technologies like blockchain, the Internet of Things (IoT), and Big Data analytics.

The article describes one of the latest forms of artificial intelligence used to solve business problems – genetic algorithms (GAs). GAs are useful when a problem has many possible solutions, some of which are better than others. Unlike deterministic, linear, and nonlinear optimization models, GAs test different solutions and, through an evolutionary process, try to find the best solution through processes that parallel metaphors such as survival of the fittest, mutation, and natural selection.

The concepts of genetic and general algorithms are discussed in several important aspects and related applications in a wide range of topics are presented. A modified genetic e-business model has been presented and implemented.

Various implementations of genetic programming with relevant software products are given, and several artificial intelligence software packages, genetic algorithm methodology and applications are also presented.

Observations from the existing literature are presented and future research directions are suggested. ■

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