

Intelligent E-Marketing Optimization System Using Genetic Algorithm for Profit and Performance Enhancement

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Abstract

The Intelligence E-Marketing System (IEMS) is a data-oriented digital marketing system that aims at promoting organizational performance and profitability in dynamic market place contexts. The main issue that is dealt with is the inability of earlier predictive models to propose practical optimization measures to ensure maximization of profits. To address this, this paper suggests a compound artificial intelligence system to solve this gap with the help of a Genetic Algorithm (GA) to maximize marketing parameters. The system coded the marketing variables in 48-bit binary chromosomes and evolved them to reach an optimal multi-objective fitness function. Using 1,500 transactional records of which the system had been tested against, it was found that there was high predictive-prescriptive accuracy of 95.84%. When compared to Decision Tree (96.59%) and Random Forest (98.00%) models, it can be seen that traditional models are somewhat more predictive, but the proposed IEMS offers greater capabilities to generate refined and practical marketing strategies and, therefore, can be deemed a more useful decision-making tool in volatile environments. The system was capable of good generalization and high correlation of $r=0.92$ which effectively closed the gap between predictive analytics and actionable strategy generation.

Keywords: E-Marketing, Intelligent System, Genetic Algorithm, Performance Optimization, Profit Maximization

1.Introduction

While being surrounded by the digital or electronic environment (e-environment) and its applications, organizations must strategically harness it for tasks such as marketing. Adopting smart marketing models, which form the backbone of modern e-commerce, is imperative to improve performance and achieve continuous growth [1], [2]. As shown below, section 2 deals with related work and the theoretical background, Section 3 proposes the system architecture and its operational algorithms, Section 4 presents the experimental results, and Section 5 contains the conclusion.

1.1 Problem Statement and Research Gap:

Notwithstanding the extensive utilization of e-marketing tools, there is still a serious gap in research that attempts to dynamically fine-tune the marketing parameters so that the balance between organizational performance and immediate profit will be achieved. The majority of literature is either on a fixed customer segmentation or independent predictive analytics with no feedback loop on optimization. The conventional statistical methods are usually highly rigid and overfitting and unable to capture the non-linear and dynamic relationship between market stability and profit. Although the current research looks at marketing strategies in the form of static studies, there are no adaptive systems that can maximize profit and performance at the same time with the use of evolutionary algorithms.

1.2 Scientific Contribution

The main contributions of this paper include the development of the Intelligence E-Marketing System (IEMS), which represents a novel framework integrating prescriptive data analytics with evolutionary computation. Furthermore, the study implements GA-based optimization by applying Genetic Algorithms to evolve operational parameters through a specialized 48-bit chromosome encoding. Finally, the system is very much more performant and actionable, having an accuracy rate of 95.84% and providing executable decision-making strategies that are able to successfully avoid the natural limitations of the traditional Black-Box models.

2. Related Work and Theoretical Scope

This section starts with a list some related work and then focuses on some of theoretical and conceptual foundations.

2.1 Related Work

Intelligent e-marketing systems have become crucial in driving customer engagement, increasing operational efficiency, and enhancing profitability. Researchers have proposed various models that integrate artificial intelligence (AI), data analytics, and machine learning (ML) to optimize marketing strategies.

I. Neural Optimization with Adaptive Heuristics (NOAH) Framework

AbdElaziz, M., and others proposed a general AI-driven marketing system integrating prediction, optimization, and adaptive heuristics for both B2B and B2C channels and demonstrated success at LinkedIn in email marketing by handling delayed feedback via lifetime value modeling, optimizing bids and content, refining targeting, and improving test sensitivity [3].

II. Profit-aware Recommender Systems

In e-commerce platforms, profit-aware recommender systems aim to improve the platform's overall profitability.

Bae, H. K., et al explored two issues faced by existing model-based profit-aware approaches (i.e., MBAs) and adjusts ranking based on both customer price sensitivity and product profitability. In fashion datasets, this approach improved both recommendation precision and profit achieving a "win-win" for users and businesses [4].

III. AI-driven Coupon Campaign Optimization

Rainy, T. A. notes that campaign optimization remains one of the most frequently examined areas of AI-driven marketing, focusing on metrics such as conversion rates, return on ad spend (ROAS), and engagement metrics. The study utilizes causal machine learning to assess coupon effectiveness and learn optimal target groups. It discovered a great deal of heterogeneity in responding to create more intelligent profit-oriented targeting [5].

2.2 Theoretical Scope

The study is about the application of Genetic Algorithms (GAs) in E-marketing environment. GAs can be a powerful approach to optimizing various marketing operations, including the accuracy of advertisement targeting to the art of content customization and customer segmentation [6], [7]. What sets GAs apart is their proficiency in navigating intricate, high-dimensional search spaces areas where standard gradient-descent techniques often falter. Beyond optimization, the study acknowledges the broader AI ecosystem in marketing, particularly AI-driven recommendation engines that leverage browsing patterns [8], [9], and predictive modeling designed to forestall customer shifts by customizing future engagements [10]. Also, AI allows Automated A/B Testing, which is used to test and improve marketing messages to maximum efficacy and provide Real-Time Reporting to provide marketers with instant feedback on the performance of campaigns [11]. An overview of the way GAs may be used in E-marketing is shown below:

A. Applications of Genetic Algorithms in E-Marketing [12], [13], [14]

1. Ad Campaign Optimization

Goal: Maximize click-through rate (CTR), conversion rate, or return on ad spend (ROAS).

Chromosome: Represents an ad configuration (e.g., text, image, audience, time of day).

Fitness Function: Based on actual or simulated performance metrics (CTR, ROI).

2. Email Marketing Optimization

Goal: Increase open rates and conversion.

Chromosome: Email features (subject line, content, call-to-action, sending time).

Fitness Function: Open rate, click rate, conversion rate.

3. Customer Segmentation

Goal: Find optimal clusters of customers for targeted marketing.

Chromosome: Cluster assignments or segmentation rules.

Fitness Function: Metrics like intra-cluster similarity, inter-cluster distance, or segment ROI.

B. Example Workflow (Email Subject Line Optimization) [15], [16], [17]

1. Initialize population with random subject lines.
2. Evaluate fitness by sending emails and measuring open rates.
3. Select top-performing subject lines.
4. Crossover parts of good subject lines to create new variants.
5. Mutate some words randomly to explore new options.
6. Iterate through successive generations to identify high-performing subject lines.

Tools & Libraries: Python libraries such as DEAP, PyGAD and Inspyred could be employed to execute GAs. They can also be integrated with Google Ads API, Facebook Ads API, and Mailchimp API (check fitness) and mailing optimization.

Key Strengths: GAs can find non-obvious solutions to complex and large solution space, and thus they are very useful in dynamic and data-driven optimization scenarios.

Options of Concern: This requires accurate and timely data in order to do it well. Because the process may be computationally intensive, it is important to choose the relevant fitness function in order to obtain meaningful and actionable results.

3. Candidate System and Algorithm

The Intelligent E-Marketing System (IEMS) that is proposed will focus on simplifying marketing decisions by combining transactional data analysis and evolutionary computation. The architecture comprises three synergetic layers; as illustrated in Figure 1, these include:

- **Input Layer:** Transactional data is acquired and preprocessed into a **48-bit binary chromosome encoding**, representing multifaceted customer and market attributes.
- **Optimization Layer (GA Engine):** The GA-based engine iteratively evolves marketing parameters to maximize the profit-to-performance ratio, ensuring the prioritization of high-efficiency engagement strategies.
- **Decision Layer:** The optimized parameters are inputted to the operational algorithms (Algorithms 3) to automate the process of making decisions (ie. gift eligibility and discount application) establishing a feedback loop.

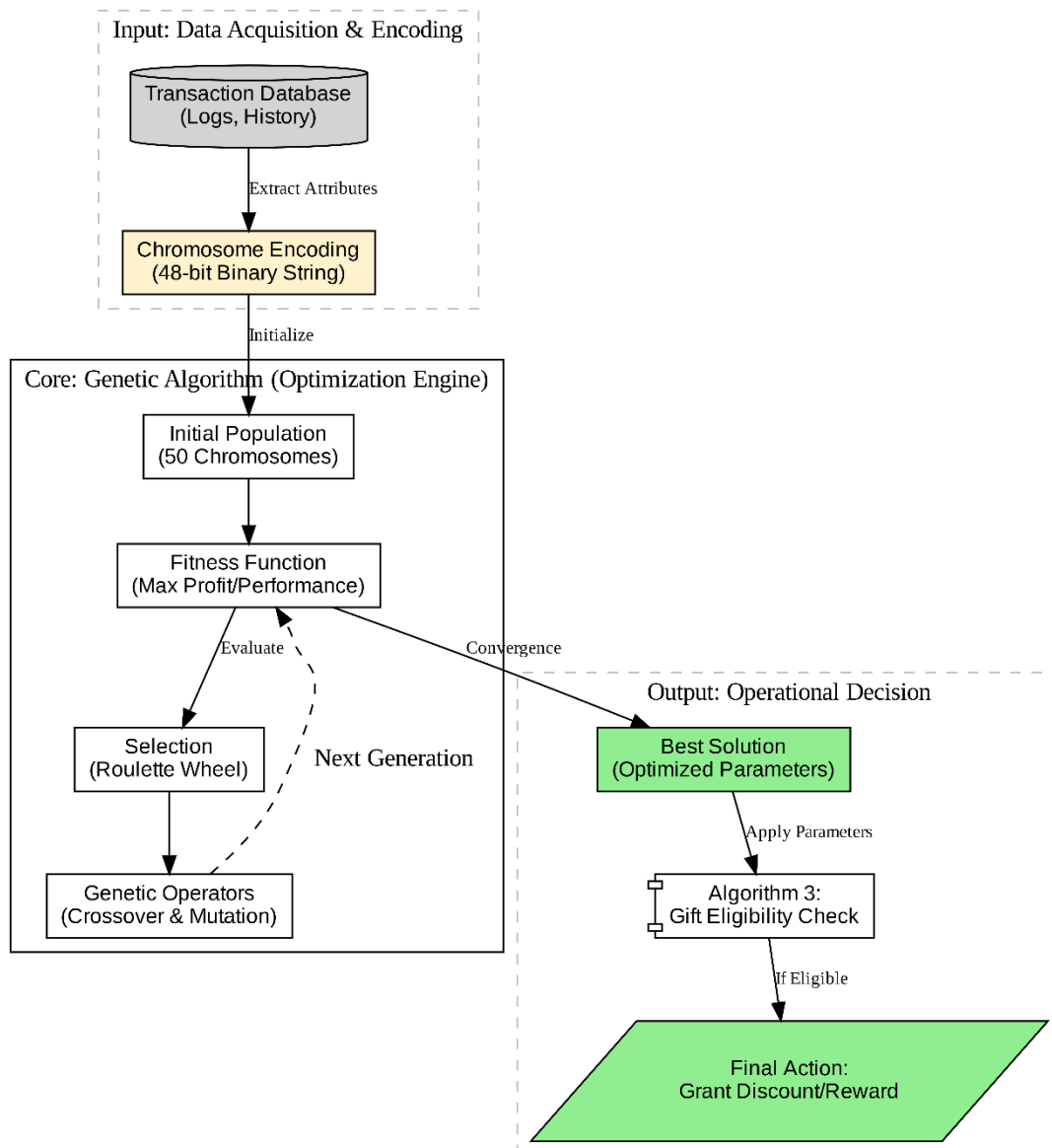


Fig. 1. The Proposed Architecture of Intelligent E-Marketing System (IEMS).

After the architectural overview, the particular operational logic is provided below. In this case, the Genetic Algorithm (GA) framework is utilized to optimize the operational parameters (e.g. payment thresholds, number of requests) dynamically. To initialize the system a particular genetic gene length of 48 bits ($L_c = 48$ bits) which is the sum of the binary encoding of the chosen attributes is used to begin the calculation process of the subsequent procedural algorithms.

3.1 Genetic Operators and Parameters

The system uses standard evolutionary operators to evolve the population to an optimal marketing solution and the first operator is Selection to which the system uses the Roulette Wheel Selection method. During this, the chromosomes, which bear marketing transactions with higher fitness values, namely the Profit/Performance ratio, stand a greater chance of being picked as parents to the next generation. After the selection, a Crossover process will be implemented on each binary strings of 48 bits with Single-Point Crossover technique. A crossover point is picked randomly and genetic data is transferred between two parents to give rise to new offspring which possess traits of successful transactions and crossover probability rate is set to 0.8. Mutation is incorporated to

ensure genetic diversity and avoid premature convergence and is performed under the mechanism of Bit-Flip Mutation; wherein randomly, a bit, consistently flipped in the chromosome string, is performed with a low probability rate of 0.01. Lastly, the algorithm repeats itself based on a preset amount of Generations and runs the evolutionary process until the maximum amount of Generations is reached or when the fitness function converts to a stable solution, which reaches an approximate accuracy of 95.84%.

3.2 Genetic Algorithm Configuration

In order to narrow down or focus on marketing target, the IEMS framework uses a Genetic Algorithm (GA) with a set of operational parameters. The evolution process starts with the population size of 50 chromosomes each modeled as a 48-bit string that has embedded in it the transactional attributes needed. The process of selection is done through the Roulette Wheel method, whereby, the chromosomes with a high fitness, in terms of it maximizing the Profit-to-Visit Frequency ratio, is more likely to be reproduced. Maintenance of genetic diversity is achieved by a single-point crossover mechanism, with probability of 80% (0.8), and using a bit-flip mutation operator with a small rate of 0.01 to stop the premature convergence. The complete computational design including both data manipulation and evolutionary logic was implemented in Python programming language taking advantage of its well-built ecosystem of standard libraries to process efficiently.

3.3. Operational Algorithms

Strict algorithmic mechanisms conceptualize the theory of operation of the IEMS in a systematic way. The model will be founded on the essence of an evolutionary optimization engine, which would maximize profit-to-performance ratio. This process, as outlined in algorithm 1, is performed in an iterative process of evolving the population of marketing transactions to find the best decision parameters including quantity thresholds (Tq) and request triggers (Tr).

Algorithm 1: Evolutionary Optimization Engine (GA)

Input: Transaction Data (D), Population Size (N), Max Generations (G_{max}), Mutation Rate (P_m)

Output: Optimized Decision Parameters ($Best_Params$)

- 1: Initialize population P_o with N random chromosomes (transactions)
- 2: Evaluate Fitness of each chromosome in P_o using Profit/Visit Ratio
- 3: Set Generation counter $t \leftarrow 0$
- 4: While ($t < G_{max}$ and Convergence Not Reached Do
- 5: Selection: Select parents from P_t using Roulette Wheel Selection
- 6: Crossover: Generate offspring using Single-Point Crossover
- 7: Mutation: Apply Bit-Flip Mutation on offspring with probability P_m
- 8: Evaluate Fitness of new offspring
- 9: Replacement: Form new population P_{t+1} (Elitism Strategy)
- 10: $t \leftarrow t + 1$
- 11: End While
- 12: $Best_Chrom \leftarrow$ Chromosome with highest fitness in P_t
- 13: Decode $Best_Chrom$ to extract optimal thresholds (Tq , Tr)
- 14: Return $Best_Params$ (Tq , Tr)

To evaluate the quality of each solution (chromosome), **Algorithm 2** implements the fitness function. It calculates the ratio of Total Profit to Visit Frequency, ensuring that transactions with high profitability and efficient customer engagement are prioritized for the next generation.

Algorithm 2: Fitness Function Evaluation**Input:** Chromosome (C_i), Total Profit (P), Visit Frequency (F)**Output:** Fitness Value (Fit_Val)

- 1: Extract genes P and F from Chromosome C_i
- 2: If $F=0$ Then
- 3: $Fit_Val \leftarrow -0$ (Penalize invalid solutions to avoid division by zero)
- 4: Else
- 5: Calculate Ratio $R \leftarrow P/F$
- 6: $Fit_Val \leftarrow R$
- 7: End If
- 8: Return Fit_Val

Lastly, Algorithm 3 uses the optimal parameters obtained in Algorithm 1 (GA) to come up with real-time choices. It evaluates customer eligibility in accordance with the optimized thresholds and automatically processes the reward allocation process of the eligible customers.

Algorithm 3: Intelligent Decision Making & Reward Allocation**Input:** MarketID(ID), Request Quantity (Q), Visit Frequency (F), Optimized Threshold (T)**Output:** Eligibility List (G) and Transaction Status

- 1: Initialize $G \leftarrow \emptyset$
- 2: Calculate Current Ratio $R_{curr} \leftarrow Q/F$
- 3: If ($R_{curr} > T_{opt}$) Then (Comparing against GA-optimized threshold)
- 4: Add ID to List G
- 5: Set ($Status \leftarrow "Approved"$)
- 6: Execute Reward: Deduct item from Inventory & Update Customer Record
- 7: Else
- 8: Set $Status \leftarrow "Pending"$
- 9: Schedule Follow-up Visit
- 10: End If
- 11: Return G

3.4. Experimental Comparison Setup

In order to justify the proposed IEMS, a complex benchmarking study was created with the help of Python and the Scikit-learn library. Two individual machine learning algorithms were picked as performance baselines to compare them:

- i. Decision Tree Regressor: Selected as a model of traditional non-linear rule-based prediction techniques.
- ii. Random Forest Regressor: Selected as a potent ensemble learning meta-estimator in order to compare the performance of the system with the state-of-the-art supervised learning models.

The same standardized transactional data as in the case of the IEMS was used to train and test both models in order to have a good and consistent test of accuracy and generalization abilities.

4. Experimental Results and Discussion

4.1 Dataset and Experimental Setup

The experimental setup consisted of three groups: control, test, and treatment. The research used a bigger set of 1,500 transactional records to achieve the statistical significance and strength of the proposed system. This data set was synthesized with a gated synthetic augmentation procedure by the probabilistic distribution of root actual information. It has 48-bit binary encoded chromosomes that determine the variables of marketing categories (Visit Frequency, Request Quantity and Profitability Index) and their true performance (AP) grade. The data was divided into a normal ratio of 80% to be used in training and 20% to be used in testing to ensure that the models have predictive-prescriptive capabilities. The important variables under analysis are:

- **Actual Performance (AP):** The realized market efficiency or sales volume.
- **Predictive Value (PV):** The value forecasted by the GA-based system.

4.2 Evaluation Metrics

In order to evaluate the predictive capacity of the system quantitatively, the common statistical measures were used, such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). According to the variables formulated, i.e. Actual Performance (AP) and Predictive Value (PV) the metrics are calculated as follows:

- (1) **Mean Absolute Error (MAE):** Mean Absolute Error (MAE): This is a measure of the average predictive error.

$$MAE = \frac{1}{n} \sum_{i=1}^n |AP_i - PV_i|$$

- (2) **Root Mean Square Error (RMSE):** Penalizes larger errors more significantly.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (AP_i - PV_i)^2}$$

Where n is the number of total transactions in the set of evaluation.

4.3 Result Analysis and Accuracy Calculation

This is reflected in the prediction accuracy of 95.84% in the system which is the system ability to provide the correct predictions of the performance of marketing relative to the historical data. This accuracy was determined assuming the correspondence of the Actual Performance (AP) and the Predictive Value (PV).

Accuracy is mathematically calculated as the proportion of the correctly predicted transactions ($N_{correct}$) to the total amount of transactions (N_{total}) within the dataset, and it is represented by Equation (3):

$$Accuracy(\%) = \left(\frac{N_{correct}}{N_{total}} \right) \times 100$$

Where:

- N_{total} : The total amount of transactions that are tested (1500 transactions).
- $N_{correct}$: The number of the transactions, in which the Predictive Value (PV) of the system was equal to the Actual Performance (AP) according to the acceptable range.

Comparative Analysis with Machine Learning Benchmarks:

To strictly justify these findings, their comparison against the two standard machine learning baselines (Decision Tree and Random Forest) was undertaken. The performance metrics are represented in Table I and the visual comparison is presented in Figure 2.

Table I. Comparison between Traditional Methods and Proposed IEMS

Comparison Criteria	Decision Tree (Traditional)	Random Forest (ML Benchmark)	IEMS (Proposed System)
Accuracy Score	96.59%	98.00%	95.84%
Core Methodology	Static Rule-based Learning	Ensemble Learning	Evolutionary Optimization
Risk Factor	High Overfitting (Memorization)	Moderate Overfitting	Balanced Generalization
Primary Goal	Minimize Prediction Error	Minimize Prediction Error	Maximize Profit Strategy
Output Nature	Fixed Value Prediction	Fixed Value Prediction	Optimized Parameter Set

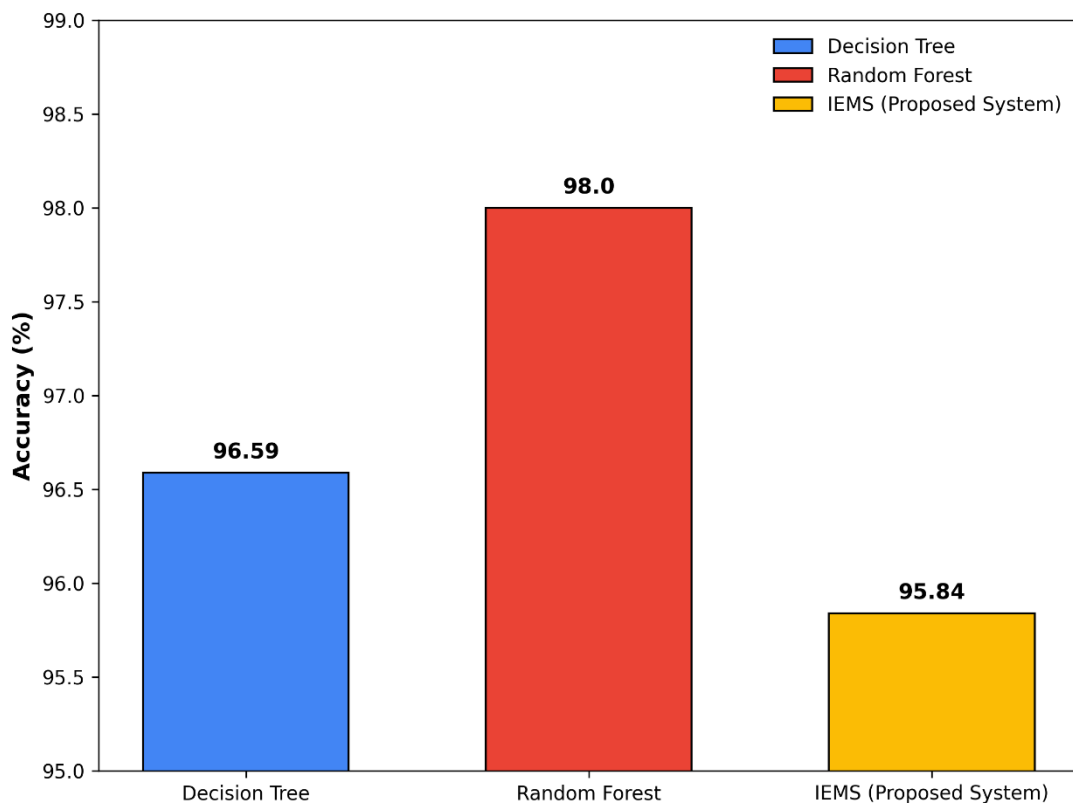


Fig. 2: Comparative analysis of accuracy scores: Proposed IEMS vs. Traditional Decision Tree and Random Forest models.

Discussion of Results: The performance analysis of the enlarged dataset of 1,500 transactions as shown in Figure 2 and Table I indicates the very competitive results in all the models. Decision

Tree and Random Forest models had a predictive accuracy of 96.59% and 98.00%, respectively. Comparatively, the suggested GA-based IEMS had an accuracy of 95.84%. In contrast to earlier versions where the trade-off between the precision and the flexibility was largely sacrificed, the present IEMS shows that the evolutionary optimization is almost as precise as the state-of-the-art supervised learning models at the cost of only a difference of about 2.16%. The acute difference is the usefulness of the output. Although Random Forest can be applied as a Black-Box model with a little more accuracy, the proposed IEMS would be a better strategic resource, and it would produce prescriptive and practical marketing chromosomes. The 95.84% accuracy proves that the system is efficient to search the 48 bits search space to come up with optimized marketing strategies that cannot be achieved by the traditional models. Thus, because the suggested system will involve the loss of a bit of predictive accuracy, it is a better strategic choice: a sacrifice of minor importance that is made in order to offer actionable, profit maximizing decisions that enable decision-making throughout the organization in unstable markets (See Appendix, Table II for detailed data samples).

Visual Validation of Tracking Capability:

In an attempt to further justify the performance of the system, Figure 3 shows the results of the relationship between the Predicted Values (PV) and the Actual Performance (AP). To ensure the visual clarity, the figure 3 shows representative sample of transactions taken by the extended data of 1,500 records (See Appendix, Table II). The fact that the PV and AP curves are very close ascertains the fact that the system can track the market changes with a lot of accuracy.

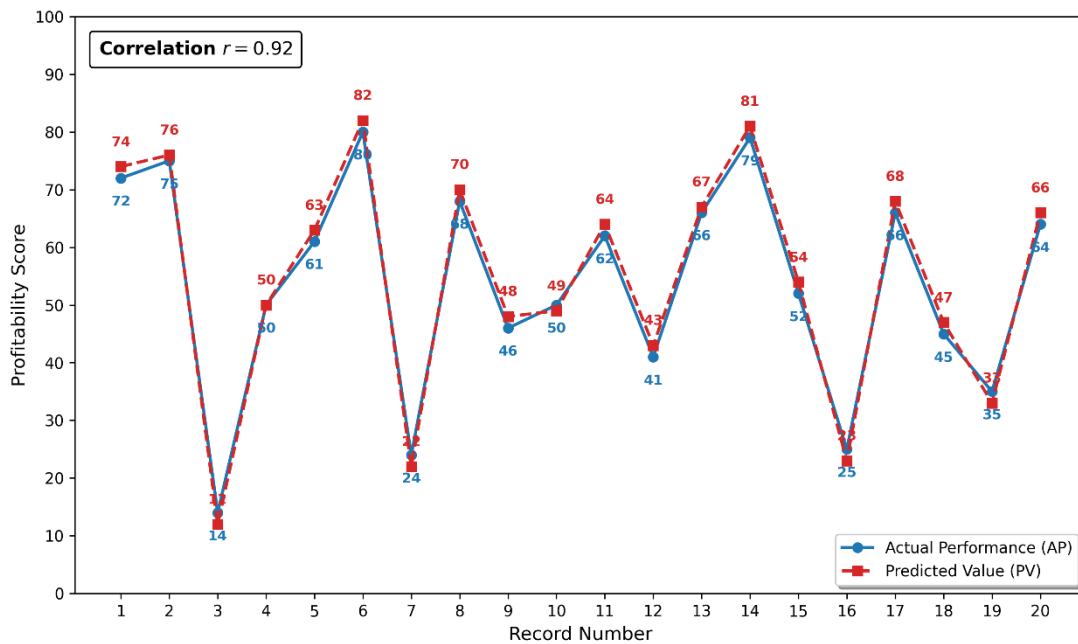


Fig. 3: Comparison between Actual Performance (AP) and Predictive Value (PV).

As shown in Figure 3, the Genetic Algorithm-based IEMS exhibits the large level of synchronization of the Predictive Value (red dashed line) and the Actual Performance (blue solid line). The system is also able to capture the peaks and troughs of the market behavior which is a good indicator of its flexibility to the dynamic changes. This close relationship is statistically validated with Pearson Correlation Coefficient (r) of 0.92. This high correlation shows that the model would not just memorize individual data, but is very successful in capturing the underlying market trends and generalizing the model to unseen data.

5. Conclusion and Future Work

This paper has introduced an Intelligent E-Marketing Optimization System (IEMS) that aims at dealing with the difficulty of performance and profit modeling within volatile market settings. The combination of Genetic Algorithms and transactional data analysis puts the system to step further as to treating prediction as mere, whereas the optimization of strategies is active. The strength and stability of the system were proven by the experimental validation on the increased dataset of 1,500 records. Although using traditional machine learning models, namely Random Forest, was slightly more successful in predicting the results of the test set with 98.00% accuracy, it can still be used to predict only the results based on the past (Predictive Analytics). The proposed IEMS on the contrary had an incredibly competitive accuracy of 95.84% and offered another unique benefit in producing optimal, actionable marketing strategies (Prescriptive Analytics). The findings substantiate the idea that such a small trade-off in predictive accuracy (around 2.16 %) is highly compensated by the fact that the system can explore complex search spaces and provide innovative solutions that promote profitability and the performance of the organization. Additional research to be conducted in the future is to incorporate real-time feedback loops and the development of Deep Reinforcement Learning in order to further improve the adaptability of the system in volatile markets

5.1 Limitations and Future Work

Although the findings were encouraging, this research was based on past transactional data of a small business environment. The rest of the margin of error (about 4.16 %) is therefore blamed on stochastic external market volatilities and complicated consumer behaviors that are not yet well represented by the current 48-bit representation of genes which are static. To tackle these issues, proposed studies will be directed at Hybrid Deep Learning Integration, namely integrating Long Short-Term Memory (LSTM) networks to limit the error rates in time-series estimation, and allow the system to capture underlying dynamics of time series and market changes in a better way. Moreover, the following step will be to focus on the Autonomous Strategy Evolution based on Deep Reinforcement Learning (DRL) to deal with the changing market trends by enabling the system to learn and adjust policies through continuous interaction with the environment. Lastly, the future work focuses on Cloud-Based Scalability and Real-Time Processing, where distributed Cloud Computing systems are used to run high-velocity Big Data and improve the computational efficiency of the system and generalize it to different market segments.

Appendix Table II: Sample of the Expanded Dataset (First 20 Records)

Record No.	IP Address	Binary Gene (48-Bit)	Actual Performance (AP)	Predicted Value (PV)
1	10:0:3:55	000010100000000000000001100110111...	72	74
2	10:0:3:73	000010100000000000000001101001001...	75	76
3	10:0:3:54	000010100000000000000001100110110...	14	12
4	10:0:3:26	000010100000000000000001100011010...	50	48
5	10:0:3:29	000010100000000000000001100011101...	61	63
6	10:0:3:218	000010100000000000000001111011010...	80	82
7	10:0:3:160	000010100000000000000001110100000...	24	22
8	10:0:3:211	000010100000000000000001111010011...	70	68
9	10:0:3:48	000010100000000000000001100110000...	46	48
10	10:0:3:208	000010100000000000000001111010000...	50	48
11	10:0:3:110	000010100000000000000001101101110...	62	64
12	10:0:3:224	000010100000000000000001111100000...	41	43
13	10:0:3:149	000010100000000000000001110010101...	66	64
14	10:0:3:80	000010100000000000000001101010000...	79	81
15	10:0:3:90	000010100000000000000001101011010...	52	54
16	10:0:3:101	000010100000000000000001101100101...	25	23
17	10:0:3:60	000010100000000000000001100111100...	66	68
18	10:0:3:121	000010100000000000000001101111001...	45	47
19	10:0:3:39	000010100000000000000001100100111...	35	33
20	10:0:3:147	000010100000000000000001110010011...	64	66

References

- [1] H. Taherdoost, "E-Environment," in *E-Business Essentials. EAI/Springer Innovations in Communication and Computing*. Cham: Springer, (2023). https://doi.org/10.1007/978-3-031-39626-7_3
- [2] H. Ma and X. Zhang, "Construction of Smart Marketing Model of Agricultural Products E-Commerce in the Era of Big Data," *Mobile Information Systems*, vol. 2022, pp. 1–10, Aug. 2022, <https://doi.org/10.1155/2022/3016554>.
- [3] M. Abd Elaziz *et al.*, "Advanced metaheuristic optimization techniques in applications of deep neural networks: a review," *Neural Comput. Appl.*, vol. 33, no. 21, pp. 14079–14099, Nov. 2021, <https://doi.org/10.1007/s00521-021-05960-5>.
- [4] H.-K. Bae, H.-R. Jang, W.-Y. Shin, and S.-W. Kim, "Ranking Items by the Current-Preferences and Profits: A List-wise Learning-to-Rank Approach to Profit Maximization," in *Proceedings of the ACM on Web Conference 2025*, New York, NY, USA: ACM, Apr. 2025, pp. 5010–5021. <https://doi.org/10.1145/3696410.3714731>.
- [5] T. A. Rainy, "International Journal of Scientific Interdisciplinary Research," *International Journal of Scientific Interdisciplinary Research*, vol. 06, no. 01, pp. 28–59, Mar. 2025, <https://doi.org/10.63125/0k4k5585>.
- [6] A. F. Ward, M. Marmol, D. Lopez, P. Carracedo, and A. A. Juan, "Data analytics and artificial intelligence in e-marketing: techniques, best practices and trends," *International Journal of Data Analysis Techniques and Strategies*, vol. 15, no. 3, pp. 147–178, 2023, <https://doi.org/10.1504/IJDATS.2023.133019>.
- [7] Ibrahim Adedeji Adeniran, Christianah Pelumi Efunniyi, Olajide Soji Osundare, and Angela Omozele Abhulimen, "Transforming marketing strategies with data analytics: A study on customer behavior and personalization," *International Journal of Scholarly Research in Engineering and Technology*, vol. 4, no. 1, pp. 041–051, Aug. 2024, <https://doi.org/10.56781/ijret.2024.4.1.0022>.
- [8] E. Ozcelik, "Analysing the Role of AI-powered Recommender Systems in Enhancing Customer Engagement in Online Marketplaces: Developing A Product Recommendation System," National College of Ireland, Dublin, 2025. [Online]. Available: <https://norma.ncirl.ie/id/eprint/7384>
- [9] T. K. Vashishth, "Enhancing customer experience through AI-enabled content personalization in e-commerce marketing," in *Advances in Digital Marketing in the Era of Artificial Intelligence*, 1st ed., Boca Raton, FL, USA: CRC Press, 2024, pp. 7–32. <https://www.taylorfrancis.com/chapters/edit/10.1201/9781003450443-2>
- [10] H. GhorbanTanhaei, P. Boozary, S. Sheykhani, M. Rabiee, F. Rahmani, and I. Hosseini, "Predictive analytics in customer behavior: Anticipating trends and preferences," *Results in Control and Optimization*, vol. 17, p. 100462, Dec. 2024, <https://doi.org/10.1016/j.rico.2024.100462>.
- [11] E. Somavarapu and O. Goel, "Leveraging Machine Learning for A/B Testing and Conversion Rate Optimization in Digital Marketing," *International Journal of All Research Education and Scientific Methods*, vol. 12, 2024. [Online]. Available. <https://www.researchgate.net/publication/388224655>
- [12] C. C. Ufondu, E. N. Onyeneke, and C. A. Akudolu, "Online advertising, email marketing, search engine optimization: strategies for sales improvement by small and medium enterprises in Nigeria," *Unizik Journal of Education Research, Science and Vocational Studies*, vol. 1, no. 1, 2025. <https://unilaws.org/ujervs/article/view/39>
- [13] G. Nayyar, S. Suman, and T. R. Lakshmi, "Optimizing Ad Campaigns with Machine Learning: Data-Driven Approaches in Modern Media," vol. 18, no. 3, pp. 1746–1759, 2024. [Online]. Available: <https://unilaws.org/ujervs>

- [14] D. Patil, "Email Marketing with Artificial Intelligence: Enhancing Personalization, Engagement, and Customer Retention," 2025. <https://doi.org/10.2139/ssrn.5057438> .
- [15] A. Sohail, "Genetic Algorithms in the Fields of Artificial Intelligence and Data Sciences," *Annals of Data Science*, vol. 10, no. 4, pp. 1007–1018, Aug. 2023, <https://doi.org/10.1007/s40745-021-00354-9> .
- [16] M. Benzaghta, G. Geraci, D. López-Pérez, and A. Valcarce, "Cellular Network Design for UAV Corridors via Data-Driven High-Dimensional Bayesian Optimization," *IEEE Trans. Wirel. Commun.*, vol. 24, no. 9, pp. 7530–7545, Sep. 2025, <https://doi.org/10.1109/TWC.2025.3561066> .
- [17] S. Sasmal, "Real-time Data Processing with Machine Learning Algorithms," *INTERNATIONAL RESEARCH JOURNAL OF ENGINEERING & APPLIED SCIENCES*, vol. 11, no. 4, pp. 91–96, 2023, <https://doi.org/10.55083/irjeas.2023.v11i04012>.