

Genetic Algorithm Optimization for Strategic Marketing Decision-Making in Indonesian MSMEs

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ABSTRACT

Indonesian Micro, Small, and Medium Enterprises (MSMEs) face challenges in developing effective marketing strategies amid rapid digital transformation and changing consumer behavior. This study applies a Genetic Algorithm (GA) to optimize key marketing variables, including price, promotion, product quality, and social media utilization. Using survey data from MSME owners, the GA identifies marketing strategy combinations with high predicted performance. The results show that balanced pricing, strong digital promotion, and improved product quality contribute to better marketing performance. The study demonstrates the potential of GA as a decision-support approach for developing data-driven marketing strategies for Indonesian MSMEs. Future research may incorporate real-time consumer data and hybrid AI methods.



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I. INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) constitute one of the central pillars of Indonesia's economic structure, contributing significantly to national GDP, driving employment, and promoting equitable distribution of economic opportunities [1][2]. Despite their vital role, many MSMEs continue to struggle in formulating marketing strategies that are responsive to rapid technological shifts and evolving consumer behavior. As digital ecosystems advance, the competitive landscape grows increasingly complex, making traditional intuition-driven decision-making insufficient for maintaining business resilience and sustainable growth [3][4].

The pressure to adapt highlights the urgent need for MSMEs to adopt data-driven and technology-supported methods in marketing decision-making. However, most MSME actors still face limitations in analytical capability, digital literacy, and access to intelligent decision-support tools. This results in marketing decisions that are often reactive, fragmented, and misaligned with market dynamics. These structural gaps underscore the urgency of developing systematic, efficient, and accessible approaches that can guide MSMEs toward evidence-based strategic planning.

Artificial Intelligence (AI) is increasingly being used to support decision-making in small businesses. One of the methods that can be applied is the Genetic Algorithm (GA), which helps find better combinations of marketing variables. In this study, GA is used to examine factors such as price, promotion, product quality, and social media use based on data collected from MSME respondents.

Previous studies related to optimization, data analytics, artificial intelligence, and decision support systems have provided a strong methodological foundation for developing the Genetic Algorithm (GA) model in this study. Findings on system and web application performance evaluation [5][6], combined with UX and website performance analysis [7] as well as the identification of system activity patterns such as peak hours [8], highlight the importance of objective performance measurement approaches to support data-driven decision-making. Research on AHP optimization using GA [9] and the development of decision support systems in agricultural sectors and vendor selection [10][11], further strengthens the evidence of GA's effectiveness in addressing multicriteria decision problems. In addition, studies on IT governance based on COBIT [12][13][14] provide a relevant organizational structure foundation when GA is applied within business environments or organizational systems.

Theoretical discussions on nature-inspired optimization mechanisms [15] emphasize that GA possesses adaptive capabilities in solving complex nonlinear optimization problems. Research on improving GA computational efficiency through variations in mutation probability [16] further enhances the understanding of how algorithmic parameters influence solution quality and speed. Meanwhile, artificial intelligence literature that outlines comprehensive theories and applications of AI [17], along with GA-based modelling for grouping students in software project collaborations [18], demonstrate the flexibility of GA across diverse application domains. Furthermore, innovative integrations of GA with the Taguchi method and neural networks for hyperparameter optimization in disease risk prediction [19] illustrate that GA is not only effective but also capable of achieving high precision in large-scale and sensitive computational scenarios. Overall, the integration of these theoretical and empirical foundations reinforces the position of the Genetic Algorithm as an adaptive, precise, computationally efficient optimization technique capable of comprehensively handling MSME marketing variables in a data-driven manner. Recent studies show that digital technology adoption positively impacts MSME growth and competitiveness in Indonesia [20][21]. E-commerce utilization and digital marketing strategies can expand market reach and improve efficiency, although gaps in digital literacy and analytical capability persist [21][22][23]. These findings support the integration of AI-driven optimization techniques, such as Genetic Algorithms, to enable data-driven and effective marketing strategy formulation for MSMEs. Previous studies have demonstrated that Genetic Algorithm (GA) and artificial intelligence techniques are effective for MSME segmentation, business optimization, logistics, and predictive modeling, including K-Means centroid optimization for MSME clustering [24], retail resource allocation [25], operational and routing optimization [26], [27], financial and trading optimization [28], customer segmentation [29], and AI-based frameworks for prediction, analytics, and optimization tasks [30], [31], [32]. GA has also been applied to classification problems, income optimization, service scheduling, and hybrid predictive models [33],[34],[35],[36],[37]. Furthermore, digital marketing studies have confirmed its significant impact on MSME performance and strategic decision-making [38], [39], [40], [41]. However, limited studies have integrated multiple marketing variables into a quantitative optimization framework for Indonesian MSMEs. This study addresses this gap by applying a Genetic Algorithm (GA) to identify and evaluate optimal marketing strategy combinations from empirical MSME data.

The main contribution of this study is the use of a Genetic Algorithm to help determine suitable marketing strategy combinations for Indonesian MSMEs. Unlike previous studies that mainly discuss digital marketing

adoption or AI applications, this study uses data collected directly from MSMEs and processes it into measurable strategy recommendations. The model also considers the practical conditions faced by MSMEs when developing the recommendations.

II. METHODS

This study employs a quantitative approach with a computational experiment method to optimize the marketing strategies of Micro, Small, and Medium Enterprises (MSMEs) by applying Artificial Intelligence (AI) through the Genetic Algorithm (GA). The research process begins with problem identification and a literature review, followed by data collection through MSME questionnaires and secondary sources, which are then normalized and analysed. The next stage involves designing the GA model, including population representation and initialization, fitness function

determination, selection and crossover, mutation, as well as termination and evaluation to obtain the optimal marketing strategy combination.

The designed model is implemented using Python programming to simulate the optimization process and generate recommendations for optimal marketing strategies. The optimization results are then analysed and compared with the actual strategies employed by MSME actors to assess improvements in marketing decision-making effectiveness. Through this approach, it is expected that an AI-based marketing strategy model will be developed that is adaptive, efficient, and data-driven, supporting the competitiveness of MSMEs in the digital era.

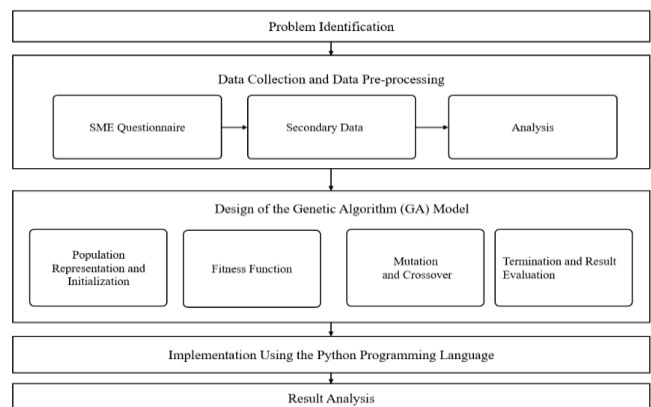


Figure 1. Method for Genetic Algorithm Flow

III. RESULTS AND DISCUSSION

A. Data Collection

Data were collected through questionnaires and interviews with MSME owners. The instruments measured key marketing strategy variables, including price, promotion, product quality, social media utilization, customer service, distribution, brand awareness, customer loyalty, digital engagement, and innovation.

B. Marketing Performance Measurement

Marketing performance was assessed based on the overall implementation of the marketing strategies used by MSMEs. The scores from the selected marketing variables were combined to obtain an overall performance score. This score was then used to evaluate the solutions generated by the Genetic Algorithm, with higher scores indicating better marketing performance.

C. Genetic Algorithm

Genetic Algorithm (GA) is an optimization method based on principles of natural selection and evolutionary genetics. GA represents potential solutions as chromosomes composed of genes, which correspond to decision variables. Optimization is performed through selection, crossover, and mutation operators to generate successive generations with improved fitness levels. In this study, chromosomes were represented using ten key marketing variables:

TABEL I
CHROMOSOME REPRESENTATION OF MARKETING STRATEGY VARIABLES FOR SMES

Gene	Variable	Symbol	Description
g_1	Price Factor	x_1	Multiplier of product base price (competitive pricing strategy)
g_2	Promotion Intensity	x_2	Level of promotional efforts
g_3	Product Quality Level	x_3	Product quality and consistency
g_4	Social Media Budget	x_4	Proportion of budget allocated for social media campaigns
g_5	Customer Service Quality	x_5	Quality and responsiveness of customer service
g_6	Distribution Efficiency	x_6	Efficiency of product distribution and delivery
g_7	Brand Awareness	x_7	Consumer recognition and familiarity with the brand
g_8	Customer Loyalty Program	x_8	Existence of loyalty or retention programs
g_9	Digital Engagement	x_9	Customer interactions on digital platforms (e.g., Instagram, TikTok, marketplace)
g_{10}	Innovation Level	x_{10}	Degree of product or service innovation

Python was employed as the primary programming tool to implement and simulate GA due to its robust AI and data science libraries such as NumPy, Pandas, and DEAP. Using Python, fitness calculation, selection, crossover, and mutation are automated efficiently, producing actionable recommendations for MSME marketing strategies.

D. Chromosome Representation

The first step in constructing the Genetic Algorithm (GA) was to define an appropriate chromosome representation

(encoding). A well-defined chromosome is critical because it directly influences all subsequent GA processes. In this study, each chromosome consists of ten genes (g_1 – g_{10}), with each gene representing a key variable in the MSME marketing strategy.

This approach enables the GA-based optimization model to capture the dynamics and interrelationships among marketing factors more comprehensively. The chromosome structure based on the ten variables is as follows.
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

Each gene is represented by a continuous value between 0 and 5, based on the measurement scale used in the questionnaire. The value reflects how strongly a particular marketing strategy is implemented by an MSME. A value close to 0 indicates that the strategy is rarely or not implemented, while a value closer to 5 indicates a higher level of implementation. In this way, each gene represents the current level of a specific marketing activity and can be adjusted by the Genetic Algorithm during the optimization process.

TABEL 2
CHROMOSOME REPRESENTATION FOR EACH GENE

Value	Assessment Category	Interpretation
0	Not applied	The strategy is not implemented or is not part of marketing activities.
1	Very low	The strategy is considered but not yet consistently implemented.
2	Low	The strategy has been applied but has limited impact.
3	Moderate	The strategy is applied consistently, though effectiveness can be improved.
4	High	The strategy is well-implemented and shows positive results.
5	Very high / Optimal	The strategy is fully implemented, measurable, and delivers maximum results.

This value range corresponds to a five-point Likert scale questionnaire, ensuring that the data representation is consistent and easily transformable for computational purposes in GA. An example of a chromosome representation is illustrated below:

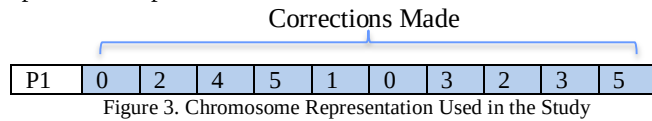
Position	1	2	3	4	5	6	7	8	9	10
Gen	0	2	4	5	1	0	3	2	3	5

Figure 2. Chromosome Representation

Based on the above, where g_i is the gene position and $C(g_i)$ is the contribution of the gene at position i . the number of selected genes in a chromosome can be constrained using the following equation:

$$\sum C(g_i) \leq 110 \quad (1)$$

This figure illustrates the values assigned to each gene, reflecting the marketing strategy variables applied in the optimization process.



The fitness value measures how well a solution (chromosome) solves the optimization problem. In this study, the fitness value reflects the effectiveness of MSME marketing strategies based on the combination of variables generated by GA. The primary goal of GA is to maximize fitness, producing the individual with the highest strategic effectiveness. For instance, for chromosome P1:

$$fitness = x \quad (2)$$

Where x represents the total value of the combination of genes reflecting the level of marketing strategy implementation. The higher the value of x , the greater the effectiveness of the strategy, and thus the chromosome is considered more optimal. For example, to calculate the fitness value of P1, it can be represented as follows for clarity:

P1	0	2	4	5	1	0	3	2	3	5
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Figure 4. Representation Chromosome of Chromosome P1 in the Study

$$fitness = 0 + 2 + 4 + 5 + 1 + 0 + 3 + 2 + 3 + 5 = 25$$

In this case, one of the MSMEs achieves an optimal process domain while considering budget limitations. In this study, the population size (pop size) was set to 10 individuals to represent the initial candidate solutions to be evaluated using the Genetic Algorithm. Since this research aims to maximize the effectiveness of MSME marketing strategies, the fitness value is calculated by summing the values of each gene in the chromosome without inversion. This approach is chosen because the higher the total gene value, the higher the effectiveness of the resulting marketing strategy.

Individual s	g ₁	g ₂	g ₃	g ₄	g ₅	g ₆	g ₇	g ₈	g ₉	g ₁₀	Fitness (Σ gen)
P1	0	2	4	5	1	0	3	2	3	5	25
P2	1	3	2	4	2	1	3	4	2	5	27
P3	2	1	3	5	0	2	4	3	1	4	25
P4	3	4	5	2	1	3	2	4	2	3	29
P5	0	1	2	3	2	0	1	3	2	4	18
P6	2	3	4	4	3	2	4	1	3	2	28
P7	1	4	3	2	5	4	2	3	1	5	30
P8	0	2	3	1	3	2	4	5	3	2	25
P9	4	5	3	4	2	1	3	4	2	4	32
P10	2	3	1	2	4	3	2	1	3	5	26

Figure 5. Chromosome Initialization

During the reproduction phase, crossover was performed using the one-cut point method, and mutation was implemented using the swap method. The crossover rate was set at 0.1, and the mutation rate at 0.1, resulting in one offspring generated from each crossover and mutation event. An example of the one-cut point crossover process is illustrated below. A cut point was randomly selected at position 3, and the parents chosen were P4 and P5:

P4	3	4	5	2	1	3	2	4	2	3
P5	0	1	2	3	2	0	1	3	2	4

Figure 6. One-cut point crossover

The resulting offspring was:

C1	3	4	5	2	1	0	1	2	3	2
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Figure 7. Offspring from One-Cut Crossover

In this study, mutation was applied using the swapping method, which randomly selects two genes within a chromosome and swaps their positions. For instance, P8 was randomly selected for mutation:

P8	0	2	3	1	3	2	4	5	3	2
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P8	0	2	3	1	3	2	4	5	3	2
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Figure 8. Swapping mutation

The resulting offspring after mutation was:

C2	0	2	2	1	3	2	4	5	3	3
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Figure 9. Offspring from swapping mutation

Subsequently, the selection process was conducted using the elitism method, which ranks individuals from highest to lowest fitness values. Individuals with the highest fitness were selected to maintain the original population size. This iterative process continued until the tenth generation, resulting in the selection of the individual with the highest fitness value, as illustrated below:

position	1	2	3	4	5	6	7	8	9	10	Fitness
P9	4	5	3	4	2	1	3	4	2	4	32

Figure 10. Selected individual

E. Experimental Evaluation

The experimental evaluation was conducted to determine the optimal parameter configuration for the Genetic Algorithm (GA) applied to the optimization of MSME marketing strategies. The primary objective of this testing phase was to identify the combination of parameters capable of producing the highest fitness value, which represents the most effective marketing strategy configuration. Three key parameters were examined: population size (n), crossover rate (cr), and mutation rate (mr). These parameters affect how the GA works and how the solutions improve during the

optimization process. Population size influences the diversity of initial solutions; the crossover rate governs the exchange of genetic material between chromosomes to explore new solution spaces; and the mutation rate introduces random variations to prevent premature convergence. In this study, the number of generations was fixed at 100, and every parameter combination was executed ten times to obtain a stable mean of the maximum fitness value.

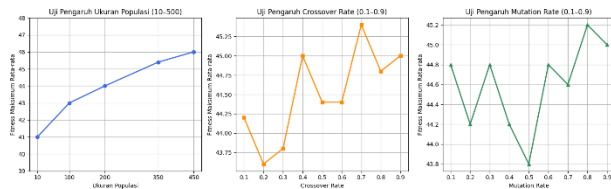


Figure 11. GA Parameter Testing

The experimental results indicate that population size, crossover rate, and mutation rate significantly affect the performance of the GA in identifying an optimal marketing strategy configuration. The first graph shows that increasing the population size consistently elevates the average maximum fitness value. A small population of 10 individuals yields a fitness value of approximately 41, whereas medium-sized populations (100–200 individuals) achieve improved fitness levels of 43–44, reflecting enhanced genetic diversity and solution quality. The most substantial improvement occurs at a population size of 450, where the highest average fitness value of 46 is recorded demonstrating that larger populations enable more effective selection, crossover, and mutation processes. The maximum fitness value of approximately 46 represents the average best fitness obtained during the parameter tuning experiments. This value was used to identify the most suitable GA configuration, rather than as the fitness value of a single evolutionary run.

Testing the crossover rate (0.1–0.9) reveals a fluctuating pattern, with the optimal performance observed at $cr = 0.7$ (fitness ≈ 45.7), indicating a balanced level of exploration and exploitation. Meanwhile, mutation rate testing (0.1–0.9) yields relatively stable fitness values between 43.8 and 45.2, with the best performance at $mr = 0.8$. This suggests that moderate-to-high mutation rates help prevent premature convergence while maintaining the structural integrity of promising chromosomes. Overall, the combination of a population size of 450 individuals, a crossover rate of 0.7, and a mutation rate of 0.8 provides the highest fitness value, fastest convergence, and most stable results. Thus, this configuration is identified as the optimal parameter setting for the GA-based marketing strategy optimization model.

F. Implementation in Python

The implementation of the Genetic Algorithm using Python aims to optimize solutions through a population-based evolutionary process. Everyone in the population is represented by a chromosome consisting of ten genes, each containing continuous values ranging from 0–5. These gene

values represent the level of implementation of each marketing strategy variable. The initial population is generated randomly so that the GA starts with a variety of possible solutions. Evaluation is then performed by calculating the fitness of everyone as the sum of all gene values (Σ gene). As reflected in the initial results, fitness values range from 24 to 35 across the first-generation population, indicating relatively low initial adaptation to the objective function.

Individu	g1	g2	g3	g4	g5	g6	g7	g8	g9	g10	Fitness (Σ gen)
P1	1	4	3	0	0	1	4	2	5	5	25
P2	0	4	5	1	1	5	4	5	5	5	35
P3	3	4	1	0	0	5	5	5	4	1	28
P4	5	2	5	2	2	1	2	3	0	4	26
P5	4	1	0	4	0	4	2	1	4	4	24
P6	2	3	5	1	2	4	3	0	2	5	27
P7	1	4	3	0	0	1	5	4	2	5	25
P8	2	3	5	5	2	4	3	4	3	5	36
P9	5	1	5	3	3	3	2	2	4	3	31
P10	3	4	5	4	0	4	5	2	2	3	32

Figure 12. The initial population

The subsequent evolutionary process incorporates three primary GA operators: selection, crossover, and mutation. The selection operator identifies individuals with the highest fitness scores to serve as parents for the next generation. The crossover operator recombines genetic material from selected parents to produce new offspring, while the mutation operator introduces random alterations to maintain genetic diversity. Through iterative generational updates, the population's fitness improves steadily. The evaluation shows that the maximum fitness value in the first generation is 38, increasing progressively and reaching 40 by the tenth generation. This upward trend demonstrates the effectiveness of the combined crossover–mutation mechanism in enhancing solution quality over successive iterations.

📌 Perkembangan Nilai Fitness Maksimum per Generasi:

Generasi 01: Fitness Maksimum = 38
 Generasi 02: Fitness Maksimum = 38
 Generasi 03: Fitness Maksimum = 38
 Generasi 04: Fitness Maksimum = 39
 Generasi 05: Fitness Maksimum = 39
 Generasi 06: Fitness Maksimum = 39
 Generasi 07: Fitness Maksimum = 39
 Generasi 08: Fitness Maksimum = 39
 Generasi 09: Fitness Maksimum = 39
 Generasi 10: Fitness Maksimum = 40

• Python • Markdown

Figure 13. Fitness

Overall, the Python-based implementation successfully demonstrates the capability of GA to identify optimal solutions through artificial evolutionary processes. The increase in maximum fitness over the generations shows that the GA was able to find better solutions during the optimization process. Through selection and crossover, the algorithm gradually improved the quality of the chromosomes and moved toward better marketing strategy combinations. Python's flexibility facilitates computation,

iteration management, and result visualization, ensuring a transparent and measurable optimization process. These findings confirm that GA is a robust and adaptive method for handling complex optimization problems, particularly in identifying data-driven optimal marketing strategies for MSMEs.

G. Feasibility Constraints

To ensure that the generated marketing strategy remains interpretable and feasible, each marketing variable is constrained to the range of 0 to 5 according to the questionnaire measurement scale. Therefore, the GA cannot generate values outside the predefined implementation range. The resulting strategy should be interpreted as a recommended level of marketing strategy implementation rather than a direct financial decision. Practical considerations such as production costs, promotional budgets, profit margins, production capacity, and market conditions should be considered before implementing the recommended strategy in an actual MSME environment.

IV. DISCUSSION

The optimization results show that the GA was able to improve the fitness of the solutions over several generations. This indicates that the GA gradually selected better combinations of marketing variables rather than producing random solutions. The results also show that changes in population size, crossover rate, and mutation rate affected the quality of the solutions.

However, the results should not be considered as proof that a specific marketing strategy directly causes better business performance. The data used in this study came from survey responses and only describe the marketing practices reported by MSMEs. Therefore, the GA results are better viewed as recommended combinations of marketing strategies based on the available data, rather than predictions of future sales or revenue.

V. CONCLUSION

This study demonstrates that the GA is an effective and adaptive method for addressing complex optimization problems involving multiple parameters. The algorithm consistently showed stable convergence and strong performance through balanced exploration and exploitation mechanisms. The evaluation also highlights how appropriate tuning of GA parameters such as population size, crossover rate, and mutation rate—plays a crucial role in improving solution quality and preventing premature convergence.

Overall, this study provides both academic and practical benefits. The results add to previous research by showing how GA can be used to support marketing decisions based on real MSME data. The findings also show that different GA parameter settings can affect the quality of the results. In

practice, the proposed approach can help MSMEs identify suitable combinations of marketing strategies based on the available data. Future research can further improve this approach by combining GA with other methods and testing it with a larger and more diverse MSME dataset.

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