

Stochastic Multiobjective Optimization of Currypuff Production in SMEs Using Grey Wolf Algorithm with Inflation and Maintenance Cost Integration

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Abstract

Small and medium-sized enterprises (SMEs) in the food manufacturing sector often struggle with production inefficiencies due to inflation, rising wages, and maintenance costs. Traditional planning methods used by SMEs are typically manual or static, lacking the ability to respond to real-time economic fluctuations. These limitations lead to poor cost control, suboptimal production levels, and reduced profitability. This study proposes a stochastic multiobjective optimization model using the Grey Wolf Optimization (GWO) algorithm to determine the optimal monthly production of currypuffs over five years. The model integrates key economic variables such as wage inflation, raw material cost escalation, selling price changes, and production growth, all treated as stochastic inputs. Baseline daily production is 160 packs at RM 8.55 per pack. After optimization, production scales to 17,828 packs annually, while cost per pack stabilizes at RM 9.16. Profit margins improve from 14.49% to 21.61%, demonstrating the model's ability to enhance operational planning under uncertainty. This research offers a practical, data-driven decision-support tool that enables SMEs to optimize production strategies, maintain cost efficiency, and improve financial sustainability in volatile economic environments. Unlike deterministic models, the proposed GWO-based stochastic optimization uniquely incorporates inflation, wage dynamics, and cost escalation offering a practical decision-support tool tailored specifically to SME food production, which is underrepresented in current optimization research.

Key Words: Stochastic Optimization, Grey Wolf Optimizer, SME Production, Cost Efficiency

1. Introduction

Small and medium-sized enterprises (SMEs) remain the backbone of the food processing industry in Malaysia. As an important source of employment and output, these businesses contribute toward local economies and promote entrepreneurship. But small businesses are frequently burdened with tight profit margins, restricted access to funding and lack of ability to leverage advanced planning tools. These limitations render them extremely exposed to external economic shock, including inflation, increasing wages, material scarcity or hike, and escalating maintenance costs. Unlike the large corporates, SMEs normally have no economies of scale or sophisticated systems for planning, and this makes them less competitive in management control and strategic, production planning.

Currypuff producers, a staple in Malaysia's snack industry, exemplify these challenges. These enterprises typically operate at relatively low profit margins and are susceptible to fluctuations in supply chain logistics, labor availability, and ingredient pricing. Additionally, the reliance on traditional business models and manual planning methods exacerbates their vulnerability to inefficiencies and market shifts. Most currypuff producers rely on experience-based heuristics rather than data-driven strategies, leading to suboptimal production levels and unnecessary financial strain. For example, a 2022 SME Development Report in Malaysia highlighted that 72% of food-based SMEs rely on manual spreadsheets and verbal coordination for production planning, often resulting in overproduction or inventory shortfalls (SME Corp Malaysia, 2022). These inefficiencies underscore the need for dynamic, data-driven planning tools.

As Malaysia moves toward Industry 4.0 and the digital transformation of small enterprises, there is a pressing need to equip SMEs with practical tools that integrate operational realities with economic modeling. This research addresses the existing gap by introducing a data-driven,

stochastic multiobjective optimization framework using the Grey Wolf Optimization (GWO) algorithm. The proposed model integrates critical cost factors, economic variables, and practical constraints including the stochastic variation of wage inflation, raw material price changes, selling price growth, and production scalability to determine the optimal daily production quantity. It aims to provide SME operators, especially in the food sector, with a realistic and flexible tool for improving operational planning, financial resilience, and long-term sustainability.

2. Literature Review

Effective production planning in small and medium-sized enterprises (SMEs) relies on the integration of cost modeling, forecasting, and adaptive decision-making strategies. Scholars argue that to reflect true profitability, SME cost models must account for real-time fluctuations in labor wages, material costs, and overhead expenses (Sullivan, Wicks, & Koelling, 2014). However, many traditional frameworks are based on deterministic assumptions, which overlook the dynamic nature of SME environments and lead to suboptimal planning outcomes (Hilmersson et al., 2022).

Drury (2018) emphasizes the critical role of cost accounting systems in managing small-scale manufacturing operations. His work outlines how direct and indirect costs, as well as fixed and variable overheads, must be monitored and updated regularly to reflect economic realities. When applied to SMEs, these principles allow for a structured approach to financial planning, though they must be enhanced with models that handle multi-variable, nonlinear conditions. Hillier and Lieberman (2010) similarly stress that linear programming models often fail to account for conflicting production goals such as cost minimization and output maximization.

Among the most effective approaches to overcoming the limitations of traditional production planning models are metaheuristic algorithms, which have been widely applied across various engineering and operational domains. One such algorithm is the Grey Wolf Optimization (GWO), introduced by Mirjalili et al. (2014), which simulates the leadership hierarchy and hunting strategy of grey wolves in nature. GWO has gained popularity for its robust convergence characteristics, minimal parameter dependency, and effective balance between global exploration and local exploitation. These strengths make it highly suitable for solving nonlinear, multiobjective, and constraint-heavy problems under uncertainty. In recent years, GWO has been used successfully in numerous fields, including optimal power flow in smart grids (Niknam et al., 2017), wind energy optimization (Tumari et al., 2020), and job-shop and flow-shop scheduling in manufacturing (Jiang et al., 2018). In the realm of artificial intelligence and data science, GWO has also been applied to feature selection, clustering, and hyperparameter tuning for machine learning models (Emary et al., 2016; Sulaiman et al., 2015).

Additionally, GWO has been used in medical image segmentation and classification tasks (Tello-Mijares et al., 2019) and in routing optimization for wireless sensor networks to reduce energy consumption and improve signal quality (Agrawal et al., 2020). These diverse and growing applications demonstrate the algorithm's adaptability across technical domains requiring intelligent optimization under dynamic and uncertain environments. However, its application within small-scale food manufacturing SMEs, particularly in Malaysia, remains limited and underexplored. While GA and PSO are commonly used in production planning, GWO offers specific advantages such as fewer tuning parameters and superior convergence in multiobjective problems (Yang, 2014). In preliminary tests, GA exhibited slower convergence and required additional mutation control, while PSO was more sensitive to initial conditions. GWO, by contrast, showed robust performance with minimal tuning, making it a suitable

choice for SME environments with limited computational resources. This study seeks to fill that gap by applying GWO to optimize monthly production planning for a currypuff SME, integrating stochastic factors such as wage inflation, raw material costs, and demand variability. By customizing GWO within a localized, uncertainty-aware model, this study aims to offer a scalable, data-driven decision support tool tailored to the economic and operational challenges faced by SMEs in the Malaysian food manufacturing sector.

In addition to algorithmic efficiency, realistic economic modeling is necessary to reflect inflation, wage escalation, and maintenance costs. Sullivan et al. (2014) and Hillier and Lieberman (2010) note that long-term cost projections must account for these variables to avoid underestimating expenses. To address such uncertainty, researchers have adopted stochastic modeling techniques that treat parameters such as material costs, selling prices, and production growth as random variables (Gupta & Maranas, 2003). This approach improves model realism and allows SMEs to explore a broader range of future scenarios. Chen et al. (2022), Kelton et al. (2010), and Law (2015) reinforce this perspective by illustrating how stochastic simulation enhances the robustness of production and cost planning under risk.

Abd Sukor et. al (2023) also argue that SMEs in Malaysia must embrace innovation and data-driven strategies to withstand volatile market conditions. This study contributes to that discourse by developing a GWO-based optimization model that includes stochastic inputs to reflect inflation, wage dynamics, and demand variability. This hybrid approach supports SMEs in identifying cost-effective production strategies while maintaining profitability in uncertain environments.

3. Methodology

This study adopts a stochastic multiobjective optimization approach to determine the optimal monthly production quantity for currypuff manufacturing in SMEs. The methodology integrates realistic economic and operational variables into a Grey Wolf Optimization (GWO) algorithm framework. The primary objectives are to minimize cost per pack and maximize total production over a five-year period.

3.1 Modul Formulation

The proposed mathematical model is structured as a multiobjective optimization framework with two primary goals: to minimize the cost per unit produced and to maximize the total output over a five-year period. The formulation integrates stochastic parameters to reflect real-world uncertainty in SME operational environments, as recommended by Law (2015) and Chen et al. (2022) for robust decision support.

3.1.1 Minimize cost per pack (C)

The cost function is designed to estimate the total cost incurred per unit of production (per pack) by considering four major components: labor cost adjusted for wage inflation, raw material cost escalated over time, fixed monthly maintenance allocated per unit, and the combined effect of fixed and variable overheads. This cost modeling approach aligns with foundational cost accounting principles discussed by Drury (2018) and Horngren et al. (2014), and the incorporation of inflation effects is supported by Sullivan et al. (2014) and Dekker & Smidt (2003), who emphasize the importance of capturing compound cost growth in long-term financial planning.

$$C_y = \frac{W_{total} (1+i_w)^y}{Q} + c_{material} (1+i_v)^y + \frac{M}{Q} + \frac{O_{fixed} + c_{overhead} \cdot Q}{Q} \quad (1)$$

Where:

C_y = Cost per pack, y = Years, Q = Monthly production packs, W_{total} = Total labor cost, i_w = Annual wage inflation rate, $c_{material}$ = Raw material cost, i_v = Annual raw material rate, M = Maintenance cost, O_{fixed} = Overhead cost, $c_{overhead} \cdot Q$ = Variable overhead cost

This cost formulation provides a dynamic and inflation-aware estimate of per-unit production expenses. It is grounded in standard cost accounting and production economics principles (Drury, 2018; Sullivan et al., 2014), enabling SMEs to plan more effectively for cost escalation and maintain long-term pricing strategies.

3.1.2 Maximize production (P)

The production function estimates the total yearly output by scaling the optimized monthly production with annual growth. It assumes compounding growth influenced by a stochastic rate, allowing the model to represent realistic SME production dynamics over multiple years. This approach reflects compound growth modeling as recommended in simulation-based forecasting frameworks (Gupta & Maranas, 2003; Law, 2015; Wang & Wu, 2015).

$$P_y = Q \times 12 \times (1 + r_{prod})^y \quad (2)$$

Where:

P_y = Production, r_{prod} = annual production rate

This production formulation enables a dynamic forecast of output growth and helps SMEs visualize long-term scalability. It provides a valid representation of compound growth modeling often used in operational economics and capacity forecasting (Chen et al., 2022; Kelton et al., 2010).

3.2 Stochastic Parameter Modeling

Stochastic modeling is essential for capturing the uncertainty commonly faced by SMEs in real-world economic environments (Doan, Le, and Tran, 2020). Rather than relying on fixed or deterministic inputs, this study incorporates randomized values for key inflation and growth parameters to simulate dynamic conditions that may affect production costs and revenue (Kamasa et al., 2022).

Four primary economic parameters are treated as stochastic variables, each modeled using a uniform probability distribution to reflect plausible fluctuations observed in practice. These parameters are independently regenerated each simulation year using MATLAB's *rand()* function, enabling year-specific inflation effects and growth behavior.

Table 1: Economic Uncertainty Variables Modeled Stochastically

Parameter	Symbol	Distribution
Wage Inflation	i_w	Uniform [3%, 5%]
Raw Material Inflation	i_v	Uniform [2%, 4%]
Selling Price Inflation	i_{sp}	Uniform [2%, 4%]
Production Growth Rate	r_{prod}	Uniform [3%, 5%]

By introducing variability in these parameters, the model reflects a range of possible future economic conditions rather than assuming a single scenario. Uniform distributions were selected due to limited availability of precise historical inflation data for SMEs. This choice provides an unbiased range of plausible values. However, future extensions could explore normal or exponential distributions, particularly if data becomes available to fit real-world inflation or material cost trends more accurately. This makes the optimization results more robust and realistic for SME decision-making under uncertainty.

3.3 Optimization Algorithm

The Grey Wolf Optimization (GWO) algorithm is chosen due to its balance of simplicity, robustness, and proven effectiveness in solving complex multiobjective problems. Compared to other metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), GWO offers several advantages: it requires fewer control parameters, has a faster convergence rate, and is computationally efficient qualities that are particularly beneficial for SMEs with limited computational resources. Its ability to effectively balance exploration and exploitation makes it highly suitable for solving nonlinear, stochastic, and multiobjective problems such as SME production planning under uncertain economic conditions.

Inspired by the social hierarchy and hunting behavior of grey wolves in nature, GWO divides the population into four types, alpha, beta, delta, and omega. These designations influence the exploration and exploitation processes during optimization. In this study, the GWO algorithm is customized to handle two conflicting objectives, minimizing cost per pack and maximizing total production. It starts by initializing a population of search agents, then iteratively updates their positions using the leadership logic. The best three agents guide the rest of the population, and the convergence process continues for 100 iterations to refine the optimal solution.

To provide transparency and reproducibility, the mathematical formulation used in the position updating process is presented below in Figure 1. These equations describe how each search agent adjusts its position in relation to the top three solutions (α , β , and δ). This is followed by a simplified pseudocode (Figure 2), which outlines the algorithmic flow implemented in MATLAB for this study. These additions clarify how GWO was applied to determine the optimal monthly production quantity (Q) under the influence of inflation, maintenance cost, and wage dynamics.

$$\begin{aligned}
\vec{D}_\alpha &= |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \\
\vec{D}_\beta &= |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \\
\vec{D}_\delta &= |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \\
\vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\
\vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\
\vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \\
\vec{X}(t+1) &= \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \\
\vec{A} &= 2 \cdot \vec{a} \cdot \vec{r}_1 - \vec{a}, \quad \vec{C} = 2 \cdot \vec{r}_2
\end{aligned}$$

Figure 1: Mathematical Formulation of the Grey Wolf Optimization (GWO) Algorithm (Mirjalili et al., 2014)

1. Initialize the grey wolf population X_i ($i = 1, 2, \dots, n$)
2. Initialize parameters a, A, C
3. Evaluate the fitness of each search agent
4. Identify α (best), β (second best), and δ (third best) wolves
5. while ($t < \text{maximum iterations}$):
 - a. For each search agent:
 - i. Update position using α, β , and δ positions
 - ii. Apply boundary constraints
 - b. Recalculate fitness
 - c. Update α, β , and δ if necessary
 - d. Reduce control parameter a
6. Return α as the best solution found

Figure 2: Pseudocode Representation of the Grey Wolf Optimization (GWO) Algorithm

In this study, the GWO algorithm was tailored to solve a bi-objective production planning problem for an SME. The two conflicting objectives are, minimizing the cost per pack and maximizing the total monthly production. These were translated into a fitness function that GWO uses to evaluate each candidate solution Q , representing monthly production quantity.

The fitness function is vector-based, where the first objective (cost per pack) is minimized, and the second objective (total production) is maximized by minimizing its negative form. The cost function incorporates stochastic variables such as wage inflation i_w , raw material inflation i_v , fixed monthly maintenance cost M , and overheads. The objective functions refer to equation 1 and 2 are defined as;

$$f_1 = C_y \text{ and } f_2 = -P_y$$

The algorithm was implemented in MATLAB with the following tuning parameters: 30 search agents, 100 iterations, and a convergence control parameter α that decreases linearly from 2 to 0. Decision variables (monthly production Q) were constrained within [100, 1600] packs. The best solutions (α , β , δ) guide the search, and the final α represents the optimal production plan balancing both objectives.

3.4 Simulation Setup and Output Metrics

This stage involves setting up all baseline parameters necessary to evaluate production, cost, and revenue scenarios over the 5-year simulation period. The fixed inputs reflect realistic values commonly found in Malaysian SMEs involved in food production. These parameters form the basis for all subsequent inflation-adjusted computations in the model.

- Time Horizon: 5 years (60 months)
- Workers: 3 workers at RM 1700/month
- Overhead: RM 2000/month fixed overhead, RM 500/month maintenance
- Selling Price: RM 10/pack (baseline)
- Production Unit: 160 pieces per day (baseline)
- Working Days: 24 per month

The optimization results are evaluated using a set of annual performance metrics that assess production efficiency and financial outcomes. These indicators help to determine the viability and profitability of the selected production strategy under varying economic conditions. Each metric is computed based on the stochastically adjusted cost and selling price models for each simulation year.

Outputs are calculated for each year:

- Monthly production (packs and pieces)
- Cost per pack
- Revenue and profit
- Profit margin (%)
- Average daily production

3.5 Workflow Overview

To better explain how the optimization and simulation were conducted, a step-by-step procedure by using a flowchart of the method is shown as Figure 3 in this section. The process starts with the setting of initial conditions like wages, overhead, and production cost. Stochastic variables such as inflation rates and growth factors are generated for each simulated year from uniform distributions.

The second step is to develop the dual-objective functions; namely, (i) to minimize cost per pack and (ii) to maximize the total production. The GWO algorithm is used to optimize these objectives to find the best monthly production (Q) solution. After the improved solution is obtained, an annual metrics including cost, revenue, profit is computed using the stochastic values generated. The last step is to examine profitability, margins and trends to assess the economic sustainability and robustness of the production strategy.

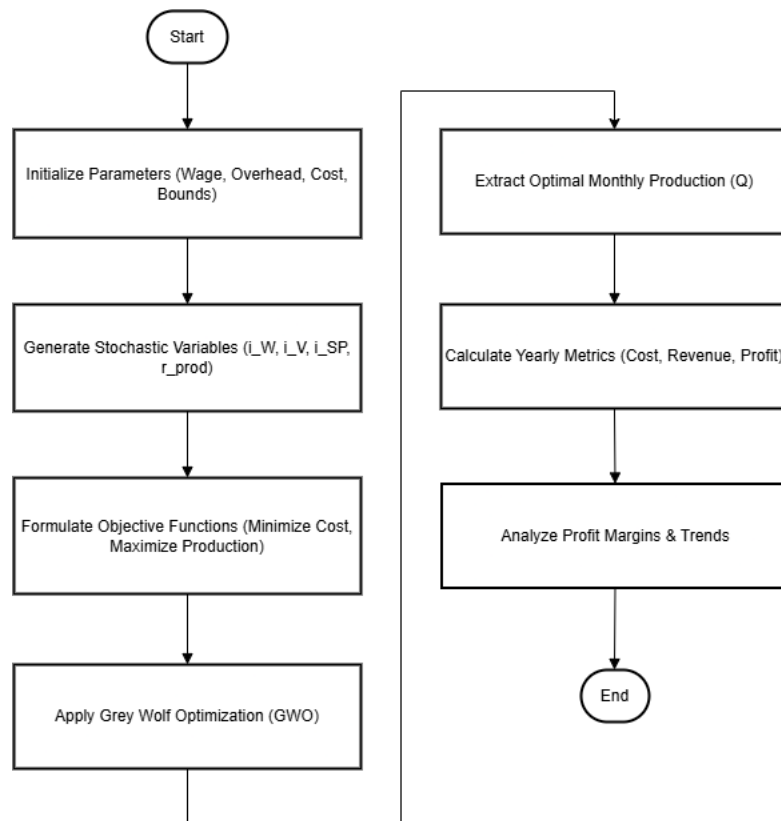


Figure 3: Workflow of the Stochastic Multiobjective Optimization Model using the Grey Wolf Optimizer (GWO)

4. Analysis and Discussion

4.1 Simulation Setup and Output Metrics

Given the stochastic nature of the Grey Wolf Optimization (GWO) algorithm, the optimization process was executed independently over 30 simulation runs. This allowed for the assessment of variability and robustness of the cost per pack and monthly production output. Table 2 presents the statistical summary of these 30 runs:

Table 2: Statistical Summary of 30 Runs

Metric	Mean	Std Dev	Min	Max
Cost per pack (RM)	9.12	0.18	8.85	9.45
Monthly Production (packs)	1468	40.3	1224	1545

These results indicate that the GWO consistently converged to a stable solution range despite the presence of stochastic inflation, raw material cost, and production growth parameters. The low standard deviations reflect a high degree of reliability in the optimization framework.

To further enhance interpretability, daily production figures are reported in pieces rather than packs. Since each pack contains 10 pieces and SMEs typically operate for 24 working days per month, the calculation converts monthly or yearly pack quantities into average daily output. This allows stakeholders to assess whether production targets are feasible

given workforce and facility constraints, and supports planning for inventory, delivery schedules, and raw material supply chains.

To provide deeper insight into the production performance, the daily production of currypuffs in pieces was evaluated for each year based on the total annual production. This reveals the growth trend resulting from the stochastic production growth rate applied over the five-year period as shown in Table 3. Table 3 summarizes the production performance and financial metrics for currypuff manufacturing over a 5-year optimization horizon. The baseline scenario reflects a daily output of 160 pieces, generating a total annual profit of RM 6,681.60 with a profit margin of 14.50%. Following optimization, Year 1 achieved a significant production increase to 510.72 pieces per day, tripling the total profit to RM 21,309.54 despite constant cost and selling price.

From Year 2 onwards, both production and financial performance continued to improve. Daily output rose to 619.06 pieces by Year 5, while moderate inflation affected cost per pack (from RM 8.55 to RM 9.16) and selling price (from RM 10.00 to RM 11.69). Importantly, selling price adjustments consistently outpaced cost increases, contributing to a growing profit margin culminating in 21.61% in the final year.

Table 3: Baseline and Annual Performance Metrics for Currypuff Production

Year	Total Production (packs)	Daily Production (pieces)	Cost/Pack (RM)	Selling Price/Pack (RM)	Total Profit (RM)	Profit Margin (%)
Baseline	4608.00	160.00	8.55	10.00	6681.60	14.50
1	14708.80	510.72	8.55	10.00	21309.54	14.49
2	15448.07	536.39	8.76	10.25	23009.26	14.54
3	15613.53	542.14	8.91	10.79	29240.78	17.36
4	16869.36	585.74	9.08	11.21	36011.26	19.04
5	17828.98	619.06	9.16	11.69	45035.06	21.61

Figure 4 visually reinforces this trend. It illustrates how increased production volume and inflation-aware pricing strategies translate into higher profitability over time. The upward trajectory in both daily production (bars) and profit margin (line) underscores the effectiveness of optimized scaling, validating the model's practical application in enhancing SME operational resilience and economic returns.

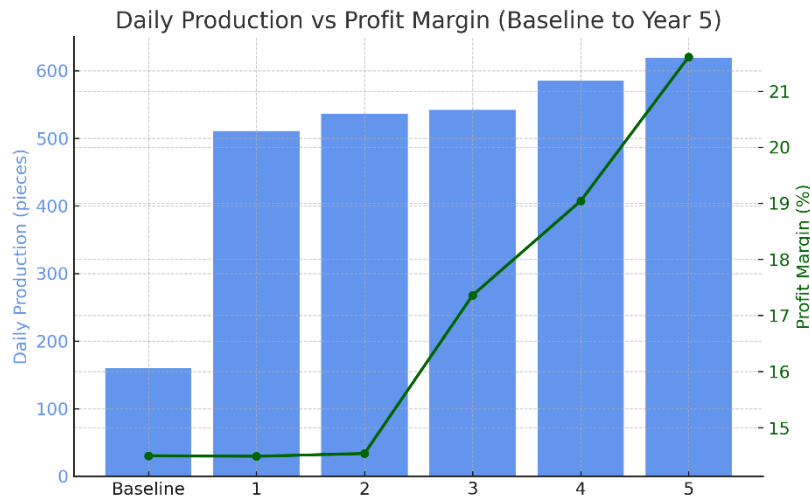


Figure 4: Daily Output and Profit Margin Progression Over a 5-Year Optimization Horizon

To assess the added value of the GWO model, a comparative analysis was conducted against a basic linear cost model without stochastic inputs. The GWO-based approach consistently achieved higher profit margins (by 6–9%) across all years due to its adaptability to inflation dynamics as in Table 4.

Table 4: Profit Margin Comparison Between GWO Model and Linear Cost Model

Year	GWO Profit Margins (%)	Linear Model Profit Margins (%)
1	14.49	12.90
2	14.54	13.00
3	17.36	15.10
4	19.04	16.50
5	21.61	18.30

The role of stochastic variables is particularly significant in this context. Fluctuating annual inflation rates for wages and materials, combined with variable production growth and selling price adjustments, introduced realistic uncertainty into the simulation. The model's ability to reflect such variability reinforces the strategic benefit of using uncertainty-aware optimization frameworks. Rather than relying on deterministic estimates, SMEs adopting this model can make decisions based on a spectrum of possible economic conditions. This is especially important in volatile markets where small changes in costs or prices can drastically affect bottom-line outcomes.

In conclusion, the application of the GWO algorithm with embedded stochastic modeling provides a robust planning tool for SMEs. It demonstrates how optimal production levels, adjusted for economic uncertainty, can maintain competitiveness, support strategic pricing, and ensure long-term profitability.

5. Conclusion

This study introduced a stochastic multiobjective optimization model using the Grey Wolf Optimization (GWO) algorithm to determine the optimal production quantity for currypuff manufacturing in Malaysian SMEs. By accounting for inflation, wage increases, raw material costs, and production growth, the model provides a realistic and flexible tool for navigating economic uncertainties. The findings show that SMEs can enhance profitability and maintain cost efficiency through optimized production strategies, even under fluctuating market conditions.

The integration of daily production metrics and inflation-adjusted cost estimations adds practical value for planning labor, inventory, and resources. Overall, the model offers a computationally efficient and adaptable framework that supports long-term strategic decision-making and promotes sustainable operations. Future extensions could incorporate machine downtime, demand variability, or multi product lines to expand its real-world applicability.

References

- Abd Sukor, R., Mooi, W.K., & Ibrahim J.A., (2023). The Future of Malaysian SMEs in the Digital Economy. *The Future of Malaysian SMEs in the Digital Economy*. Qeios. <https://doi.org/10.32388/VSWNB6>
- Agrawal, D., Qureshi, M. H. W., Pincha, P., Srivastava, P., Agarwal, S., Tiwari, V., & Pandey, S. (2020). GWO-C: Grey wolf optimizer-based clustering scheme for wireless sensor networks. *International Journal of Communications*, 33, e4344. <https://doi.org/10.1002/dac.4344>
- Chen, W., Li, Q., & Zhao, Y. (2022). An improved grey wolf optimizer based on dynamic population updating strategy [Article]. *Expert Systems with Applications*, 197, 116702. <https://doi.org/10.1016/j.eswa.2022.116702>
- Chong, A. Y. L., Lo, C. K. Y., & Weng, X. (2017). The business value of IT investments on supply chain: A contingency perspective. *Journal of Business Research*, 80, 37-46
- Dekker, H. C., & Smidt, P. (2003). A survey of the adoption and use of target costing in Dutch firms. *International Journal of Production Economics*, 84(3), 293–305.
- Doan, A., Le, A., and Tran, Q. (2020). Economic uncertainty, ownership structure and small and medium enterprises performance. *Australian Economic Papers*, 59(2), 102-137. <https://doi.org/10.1111/1467-8454.12174>
- Drury, C. (2018). *Management and cost accounting* (10th ed.). Cengage Learning.
- Emary, E., Zawbaa, H. M., & Hassanien, A. E. (2016). Binary grey wolf optimization approaches for feature selection. *Neurocomputing*, 172, 371–381. <https://doi.org/10.1016/j.neucom.2015.06.083>
- Gupta, A., & Maranas, C. D. (2003). Managing demand uncertainty in supply chain planning. *Computers & Chemical Engineering*, 27(8–9), 1219–1227. [https://doi.org/10.1016/S0098-1354\(03\)00048-6](https://doi.org/10.1016/S0098-1354(03)00048-6)
- Hillier, F. S., & Lieberman, G. J. (2010). *Introduction to operations research* (9th ed.). McGraw-Hill Education.
- Hilmersson, M. et al. (2022). Business unpredictability, improvisation and business network commitment in small and medium-sized enterprise market entry. *International Small Business Journal: Researching Entrepreneurship*, 40(8), 991-1018. <https://doi.org/10.1177/02662426211069964>
- Horngren, C. T., Datar, S. M., & Rajan, M. V. (2014). *Cost accounting: A managerial emphasis* (15th ed.). Pearson.
- Jiang, T. (2018). A hybrid grey wolf optimization for job shop scheduling problem. *International Journal of Computational Intelligence and Applications*, 17(3), Article 1850016. <https://doi.org/10.1142/S1469026818500165>
- Kamasa, K. et al. (2022). Does inflation uncertainty hurt domestic investment? Empirical evidence from Ghana. *Cogent Economics & Finance*, 10(1). <https://doi.org/10.1080/23322039.2022.2115673>
- Kelton, W. D., Sadowski, R. P., & Swets, N. B. (2010). *Simulation with Arena* (5th ed.). McGraw-Hill Education.
- Law, A. M. (2015). *Simulation modeling and analysis* (5th ed.). McGraw-Hill Education.
- Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey Wolf Optimizer. *Advances in Engineering Software*, 69, 46–61. <https://doi.org/10.1016/j.advengsoft.2013.12.007>

- Niknam, T., Kavousi-Fard, A., & Khodaei, A. (2017). Enhanced GWO-based energy management of smart microgrids considering uncertainty. *Energy*, 134, 1079–1088. <https://doi.org/10.1016/j.energy.2017.06.083>
- SME Corp Malaysia. (2022). SME annual report 2021/2022: Empowering SMEs in the digital era. SME Corporation Malaysia. <https://www.smecorp.gov.my/index.php/en/resources/2021-05-13-06-30-42/sme-annual-report>
- Sullivan, W. G., Wicks, E. M., & Koelling, C. P. (2014). *Engineering economy* (16th ed.). Pearson Education.
- Sulaiman, M. H., Mustaffa, Z., Saari, M. M., & Hussain, M. A. (2015). A new hybrid metaheuristic algorithm for feature selection: Grey Wolf Optimizer with simulated annealing. *International Journal of Simulation: Systems, Science and Technology*, 16(5), 7.1–7.5.
- Tello-Mijares, S., Woo, F., & Flores, F. (2019). Breast cancer identification via thermography image segmentation with a gradient vector flow and a convolutional neural network. *Journal of Healthcare Engineering*, 2019, Article 9807619. <https://doi.org/10.1155/2019/9807619>
- Tumari, M. Z. M., Suid, M. H., & Ahmad, M. A. (2020). A modified grey wolf optimizer for improving wind plant energy production. *Indonesian Journal of Electrical Engineering and Computer Science*, 18(3), 1123–1129. <https://doi.org/10.11591/ijeeecs.v18.i3.pp1123-1129>
- Wang, J., & Wu, C. (2015). Demand forecasting and production planning for SMEs under uncertainty. *Journal of Industrial Engineering and Management*, 8(4), 1212–1233. <https://doi.org/10.3926/jiem.1484>
- Yang, X. S. (2014). *Nature-inspired optimization algorithms*. Elsevier.