Opsi

Vol. 18, No. 1, June 2025

p-ISSN 1693-2102

e-ISSN 2686-2352

Intelligent products pricing in dynamic competition based-on Stackelberg game theory

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Article history:

Received: 27 December 2024

Revised: 2 June 2025

Accepted: 15 June 2025

Published: 30 June 2025

Keywords:

Strategic product pricing

Dynamic competition

Stackelberg game theory

Intelligent optimisation

Genetic algorithm

ABSTRACT

Optimising product price is essential in dynamic competitive markets to maximise the total profit of all players and secure their survival in the market. This study addresses the intelligent optimisation of product prices in a competitive environment using Stackelberg game theory (SGT), where both a leader and follower player are considered. The objective is to determine the optimum selling prices for five main products to maximise the profits of all the players. Novel aspects of this study are the integration of optimisation models of all of the players and incorporation demand prediction accuracy into the optimisation process, ensuring that the predicted demand resulting from optimised prices aligns with historical demand data—a factor that has been disregarded by prior studies. Genetic Algorithm (GA) is employed for the optimisation algorithm due to the complexity of the model that involves numerous parameters and decision variables. The results demonstrate that the proposed products selling prices not only enhances the total profits of all of the players but also ensures that the predicted demand pattern closely fits the historical demand data pattern, validating the effectiveness of the approach.

DOI:

https://doi.org/10.31315/opsi.v18i1.14284

1. INTRODUCTION

In competitive market environment, strategic pricing plays a critical role in determining the success of businesses. The strategy for determining product selling prices, often known as product pricing, should consider the external factors such as customers dynamics and concentration [1]–[4], competitors [5]–[8] and both customers and competitors [9]. The dynamic interactions between companies will make product pricing strategies complicated because they will change from time to time according to circumstances and it necessitates sophisticated, particularly in markets characterised by the presence of both leader and follower players [10]. One such robust method that can be used in this situation is Stackelberg Game Theory (SGT) [11-13], which models the leader (or, major) and follower (or, minor) player dynamics prevalent in many industries [14]–[16]. The hierarchical structure which adopted in SGT is particularly relevant in markets where one player has a significant market power advantage in situations where consumers easily move to-and-from one player to another.

Products pricing by utilising SGT can be categorised as strategic pricing, which enables both leader and follower players to dynamically set the selling price of their products in shared market [17], [18] and it will cause a corresponding adjustment in the market [19]. Other player can then use this market response as a parameter to adjust the selling price of the products. Therefore, all players will have the opportunity to increase their sales by maximising the market response to their products when other player make modifications to their techniques for determining product selling price.

Studies about SGT for product pricing have been investigated by previous researhcers, and several adjustments have been incorporated to the SGT in order to solve the cases. Chua et al [20] have applied SGT for not only product pricing, but also determining production and ordering quantity of a supply chain. The dynamics factors namely prices and lead time markets were also considered when optimising the total profit of all of the chains. Sometime, companies in the competitive market doesn't know the strategy applied by the competitors. In that situation, a company will determine the pricing strategy based on bounded rationality, however, after that, the company can start to predict the strategy implemented by the competitor. Study about the implementation of SGT in that condition has been carried out by Khanlarzade and Farughi [21]. Object of that study in a supply chain for deteriorating products. After proposing a Bayesian conjugate pair to solve the Stackelberg game with bounded rationality, they also provided an algorithm for comparison under the assumption that the follower can completely observe the leader's strategy.

Implementation of SGT in a supply chain optimisation has conducted by Narang et al [22] that managing retired electric vehicle (EV) batteries by developing a closed-loop supply chain with four mixed-channel recycling models under a carbon cap-trade and reward-penalty mechanism. The proposed SGT optimised the model by considering the influence of carbon trading prices, reward-penalty intensity, and competition coefficients on supply chain decisions. The results highlight that the recycling models do not alter the forward supply chain decisions, therefore it has positive impact to the manufacturer on reducing the recycling load and increasing the profitability. Another similar study about application of SGT on sustainable supply chain has been conducted by Paksersesht et al [23]. This study focuses on Green Product Families (GPFs) and their associated green supply chains (GSCs), addressing the critical need for sustainable optimisation in response to customer demands, governmental regulations, and competitive pressures. The model in that study simultaneously considers economic, environmental, and social criteria to optimise GPF design and GSC configuration. The leader problem seeks to maximise profit and product greenness by selecting optimal components, modules, and product variants, while the follower problem minimises GSC costs with environmental considerations like carbon emissions. The problem is modeled as a bi-level multi-objective linear programming problem (B-MOLP) and solved with a novel bi-level multi-objective particle swarm optimisation algorithm (B-MOPSO). Early version of that model also can be found from previous study [24], and several applications of SGT for supply chain optimisation can be found in [25]–[27].

Usually, SGT model is developed as an optimisation model, hence, it requires optimisation algorithm to solve. SGT model always simulates leader-follower interactions, therefore, it necessitates a large number of parameters and decision variables. Consequently, the evolution-based optimisation algorithm was widely implemented by previous reserahcers [28]. A study about joint decision-making in dyadic supply chains involving a manufacturer and an independent retailer, under the constraints of carbon emission taxes and subsidies imposed by local governments has been carried out by previous researcher [29]. The key decisions considered in that study are manufacturer's technology selection, production quantities, wholesale price, and retailer's retail price. The authors develop a bilevel 0–1 mixed nonlinear programming model to represent the problem, which becomes a complicated model. The resulted model then been solved using a nested genetic algorithm (NGA). Similar study that also used NSG for SGT-based optimisation of a supply chain has been carried out by Zhang et al [30].

Study by Kwong et al [31] shows that NGA is crucial because of hierarchical structure of the problem and the multitude of parameters and decision variables involved, such as product attribute settings, pricing, and market shares. The study considers four contract types which are wholesale price (WP), revenue sharing (RS), quantity discount (QD), and retail price maintenance (RPM) to capture diverse coordination mechanisms. Generally, the reasons of using NGA for SGT optimisation are the the solution generated by GA that optimising the leader company considers the quality solution generated by another GA that optimising the follower company, sometime, it called as bi-level optimisation.

The use of bi-level optimisation model will cause non-convex, non-dfifferentiable and discontinuous solution spaces, making the problem computationally demanding [32]. Occasionally, the high level of model complexity will make it impracticable. Novelty of this study lies in overcoming this disadvantages by combining the optimisation model of the leader and follower companies and will be optimised together using GA. GA was selected as the optimisation algorithm due to its capacity to resolve complex problems, including combinatorial optimisation [33] and real number optimisation [34]. In addition, to the best of our knowledge, there has been no previous studies that has tried to validate the results of the proposed selling price of products resulting from SGT optimisation. This validation will be a trade-off between extreme optimum results and feasible solutions. The balance between optimisation and realism is largely absent in the previous literature.

2. METHODS

2.1. Problem Descriptions

The study was carried out at two batik retailers in Indonesia that offer identic batik clothing items. One of the retailer is a leader batik retailer, while the remaining retailer is follower retailer located in the vicinity of the leader retailer. The selection of batik products was based on their status as one of Indonesia's original commodities and their significant sales performance. Therefore, enhancements to the batik supply chain system, encompassing the retailers as well, will yield a substantial economic effects to all of the involved supply chain players.

The focus of this study is on the 5 key batik clothes in the investigated leader an follower retailers. The leader retailer has the autonomy to establish the predetermined selling price for all of the products. Nevertheless, calculating the selling price of the products still considers the selling price of the follower retailer and its market shares. The batik cloth market dynamics arise when the leader retailer establishes an excessively high selling price, prompting numerous customers to shift their purchases to the follower retailer. Consequently, the leader retailer's profits will decline. During periods of high demand, the follower retailer are inclined to increase prices, prompting the leader retailer to adjust their prices in order to attract back the customers. Under such circumstances, the profitability of the follower retailer will diminish. The primary objective of this study is to ascertain the optimum selling price for both the leader and follower retailers in order to maximise their profitability. This will be achieved by analysing the revenue and cost functions of both retailers. Bellow are the decision variables, parameters and indices used to model the system.

Indices:

p : product index
t : time index
c : chromosome index

Parameters:

SIL_{pt} : seasonal index of product-p at time-t of the leader player
SIF_{pt} : seasonal index of product-p at time-t of the follower player
$SPLc_p$: current selling price of product-p of the leader player
$SPFc_p$: current selling price of product-p of the follower player
DL_{pt} : historical demand of product-p at time-t of the leader player
DF_{pt} : historical demand of product-p at time-t of the follower player
HSL_{pt} : historical selling price of product-p at time-t of the leader player
HSF_{pt} : historical selling price of product-p at time-t of the follower player
PCL_{pt} : total replenishment cost of product-p at time-t of the leader player
PCF_{pt} : total replenishment cost of product-p at time-t of the follower player
P : number of product considered
T : number of periods considered to develop the model
G : number of generation of the GA
p_size : population size of the GA
pc : crossover probability of the GA

pm : mutation probability of the GA
wp : weight of the total profit
wf : weight of the MSE

Variables:
DFL_{pt} : demand forecast of product-p at time-t of the leader player
DFF_{pt} : demand forecast of product-p at time-t of the follower player
$MSEL_p$: Mean Squared Error of product-p forecast of the leader player
$MSEF_p$: Mean Squared Error of product-p forecast of the follower player
fit_c : fitness of chromosome-c
TPL : total profit leader player
TPF : total profit follower player
TP : total profit
$TPLc$: current total profit leader player
$TPFc$: current total profit follower player
TPc : current total profit

Decision variables:
SPL_p : selling price of the leader player for product-p
SPF_p : selling price of the minor player for product-p
αL_p : forecasting base value of product-p of the leader player
αF_p : forecasting base value of product-p of the follower player
βL_p : effect of the SPL_{pt} to the forecasting of product-p of the leader player
βF_p : effect of the SPL_{pt} to the forecasting of product-p of the follower player
γL_p : effect of the SPF_{pt} to the forecasting of product-p of the leader player
γF_p : effect of the SPF_{pt} to the forecasting of product-p of the follower player
δL_p : effect of the SIL_{pt} to the forecasting of product-p of the leader player
δF_p : effect of the SIF_{pt} to the forecasting of product-p of the follower player
φL_p : variable replenishment cost of product-p of the leader player
φF_p : variable replenishment cost of product-p of the follower player
ωL_p : fixed replenishment cost of product-p of the leader player
ωF_p : fixed replenishment cost of product-p of the follower player

2.2. Optimisation Model

The selling price has a direct impact on the demand for the product, making it comparable to the demand forecasting technique. Traditional applications of SGT primarily focus on maximising the profit of all players within a hierarchical supply chain structure, with the assumption that players behave as rational leaders or followers. In such models, the interaction is frequently simplified by assuming that each player's decision primarily impacts their own profit, with an overly linear or limited consideration of interdependencies among players. Nevertheless, this assumption becomes problematic in realistic competitive environments, particularly in decentralised retail systems where multiple participants offer substitutable products. Traditional SGT models frequently generate unrealistic or exaggerated pricing strategies when the influence of one player's price on the demand of others is disregarded or oversimplified. Although these strategies may theoretically maximise total system profit, they may result in impractical, such as the leaders setting substantially high price and the followers being priced out of competition. Therefore, in order to maximise the total profit, it is necessary to concurrently maximise the accuracy of the demand forecasting by minimising the error in demand forecasting with refere to the historical equilibrium conditions. An effective metric for this objective is the Mean Squared Error (MSE) [35], [36]. Hence, an additional objective to accomplish is to minimise the MSE of the demand forecasting. Eq. (1) below shows the first objective while Eq. (2) and Eq. (3) below show the second objective.

$$Max\ TP = \sum_{p=1}^{P}(SPL_{pt+1} \times DFL_{pt+1}) - PCL_{pt+1} + \sum_{p=1}^{P}(SPF_{pt+1} \times DFF_{pt+1}) - PCF_{pt+1} \quad (1)$$

$$Min\ MSEL_p = \frac{\sum_{t=1}^{T}(DL_{pt} - DFL_{pt})^2}{T}; \forall p, p = 1, 2, \dots, P \quad (2)$$

$$Min\ MSEF_p = \frac{\sum_{t=1}^{T}(DF_{pt} - DFF_{pt})^2}{T}; \forall p, p = 1, 2, \dots, P \quad (3)$$

The products examined in this study are generic products, specifically batik garments, where consumers are very easy to switch from one retailer to another based on price competitiveness. Therefore, the product's demand is highly responsive to changes in the selling price. Nevertheless, there exist consumers who already exhibit a proclivity to purchase batik garments exclusively from a particular player due to the effects of the promotional efforts. Another determinant of product demand is the SIL_{pt} and SIF_{pt}. This is particularly relevant for the two players being studied, as they are situated in a popular tourist area in Indonesia that experiences a surge in visitors during the holiday season. Eq. (4) and Eq. (5) below show the estimator formula to predict the demand of every product in every player.

$$DFL_{pt} = \left(\alpha L_p - (\beta L_p \times HSL_{pt}) + (\gamma L_p \times HSF_{pt})\right) \times (\delta L_p \times SIL_{pt}) \quad (4)$$

$$DFF_{pt} = \left(\alpha L_p + (\beta F_p \times HSF_{pt}) - (\gamma F_p \times HSL_{pt})\right) \times (\delta F_p \times SIF_{pt}) \quad (5)$$

The sales manager of each player provided information that the replenishment cost is comprised of the cost of placing orders with the batik manufacturer and the cost associated with managing the product from the time it is received until it is sold. The retailers have meticulously documented the cost of replenishing each product. Therefore, the entire replenishment cost can be approximated using an equation that links the quantity of demand with the overall replenishment cost at a specific point in time. Eq. (6) and Eq. (7) show the predictor formula of the total replenishment cost in every player.

$$PCL_{pt} = (\varphi L_p \times DFL_{pt}) + \omega L_p \quad (6)$$

$$PCF_{pt} = (\varphi F_p \times DFF_{pt}) + \omega F_p \quad (7)$$

Based on the models explained, there are a total of 14 decision variables types. These variables will be utilised to represent 5 different products within the context of a competition involving 2 players. Therefore, there are a total of 14 x 5 x 2 = 140 decision variables in the optimisation, indicating that this is a complex optimisation problem. The optimisation model will be further compounded due to the non-linear nature of the demand and replenishment cost prediction models. Hence, GA that proposed in this study is a suitable optimisation approach for solving the faced large-scale optimisation problems under non-linear models.

2.3. GA Modelling

Since GA works with encoded solutions, the first critical thing in GA modeling is chromosome encoding. In its searching process, GA manipulates the chromosomes in each generation to get a better solution than the previous generation. Thus, chromosome encoding will be carried out based on the solution to be sought for the problem at hand. Figure 1 shows the proposed chromosome design for this study.

$$|SPL_1||\alpha L_1||\beta L_1||\gamma L_1||\delta L_1||\varphi L_1||\omega L_1||SPF_1||\alpha F_1||\beta F_1||\gamma F_1||\delta F_1||\varphi F_1||\omega F_1| \cdots |\gamma F_5||\delta F_5||\varphi F_5||\omega F_5|$$

Figure 1. The chromosome design

The next critical thing of GA is the identification of fitness function for every chromosome. The fitness function generates a value that indicates the effectiveness of each chromosome in solving the optimisation problem at hand. GA operates without knowledge of the problem being solved and lacks perception. Instead, GA relies on the fitness of chromosomes to steer it towards the optimal solution. Essentially, GA will preserve and enhance chromosomes with high fitness values, which is analogous to the maximisation function.

Technically, this study has two objectives: maximising the profit for both the leader and follower players by determining the selling price of the products, and minimising the error in demands prediction resulting from the determined selling price. The first objective function aligns with the fundamental principle of GA, which is resembling a maximisation function. However, the second objective function contradicts the core concept of GA, hence requires a modification. Besides, normalisation is necessary to ensure that the first and second objective function values, which have distinct scales, are brought to a normal scale of 0 to 1. By considering the factors explained above, Eq. (8) bellow is proposed as the fitness function of the chromosomes.

$$fit_c = wp \times \left(\frac{(TP)_c}{max((TP)_c; \forall c)}\right) - wf \times \left(\left(\frac{\left(MSEL_p\right)_c}{max\left(\left(MSEL_p\right)_c; \forall c\right)}\right) + \left(\frac{\left(MSEF_p\right)_c}{max\left(\left(MSEF_p\right)_c; \forall c\right)}\right)\right) \quad (8)$$

In GA, the enhancement of chromosomes performance is carried out through two evolutionary operations that are crossover and mutation. Crossover recombines two parent chromosomes to generate two offspring chromosomes, while mutation modifies a parent chromosome to produce a single offspring chromosome. Mechanism of the both operations must be determined carefully to avoid invalid offspring chromosomes that generate infeasible solutions for the optimisation problem. In this study, the crossover operation implements a two-cut points crossover, as depicted in Figure 2, while the mutation operation implements a delta mutation, as illustrated in Figure 3.

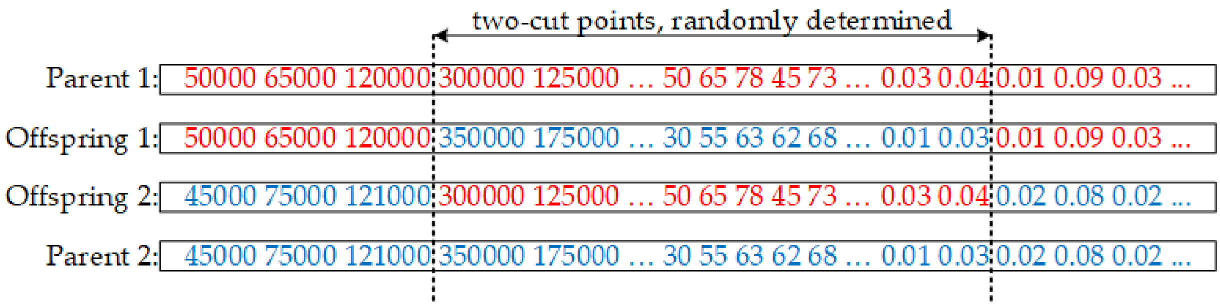


Figure 2. Two-cut points crossover proposed in this study

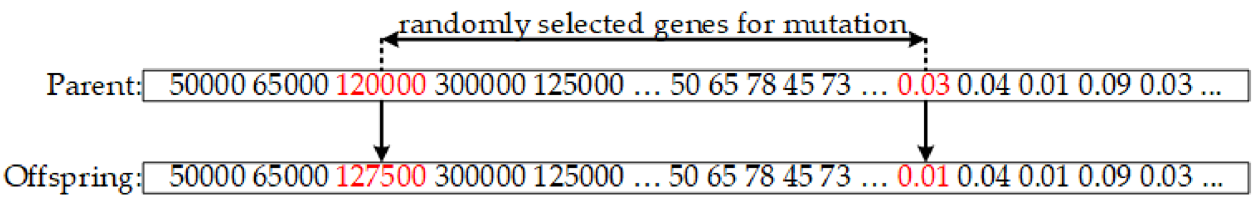


Figure 3. Delta mutation proposed in this study

2.4. Result analysis

Analysis on the reault is carried out to assess the effectiveness of the proposed method. The analysis is conducted based on historical data on the demand and the selling prices of each product, for both the leader and follower player. The effectiveness of the suggested model is evaluated based on enhancement of the total profit obtained by all players when implementing the recommended selling price compared with the total profit obtained when implementing the current selling prices.

3. RESULTS

This study commences by gathering historical data on *DL, DF, HSL, HSF, PCL and PCF*. Data was gathered over a span of 36 months ($t \in T, T = 1, 2, \ldots 36$) for 5 primary products sold by both the leader and follower player ($p \in P, P = 1, 2, \ldots, 5$). GA employs stochastic intergenerational transfer and random search techniques. Therefore, GA must be ran with a variety of parameter values in order to achieve satisfactory results. The outcomes that necessitate evaluation are the best chromosome fitness value that represents the quality of the solution and the standard deviation of the chromosomes in the last generation that represents the ability of GA to maintain chromosome diversity. Table 1 illustrates the results of five GA runs conducted in this study.

Table 1. Result of five GA runs with different parameter values

p_size	*pc*	*pm*	*best fit*	*st.dev*
10	0.5	0.2	7.98	1.92
25	0.5	0.3	8.12	2.02
50	0.4	0.1	8.23	1.20
75	0.6	0.2	8.23	1.20
100	0.5	0.3	8.23	1.97

Table 1 indicates that the optimal fitness value is 8.23, which can be attained by setting *p_size* greaters than or equals to 50. The high *pm* value is the cause of the high chromosome diversity, and the quality of the solution is not influenced by the variation of the *pc* value between 0.3 and 0.5. Thus, the GA was executed with the following parameter settings: *p_size* = 50, *pc* = 50%, *pm* = 30%, and *G* = 1000. It is important to recognise that GA is an offline optimisation algorithm that necessitates a relatively long computation time. Consequently, it cannot be used in real time to accommodate the uncertainty occurred in other cases. Therefore, the parameter settings are only good for solving this case study.

An important factor to be aware of while utilising GA for optimisation is the local optimum trap, which prevents GA's to explore the solution space. The phenomenon of GA becoming trapped in a local optimum is indicated by the occurrence of premature convergence, which can be identified by analysing the GA searching graph. If the mean fitness value of chromosomes in a generation aligns with the best fitness value of the chromosomes in the early generations, then the GA is indicated unable to preserve the diversity of chromosomes and has been trapped in premature convergence. Figure 4 depicts the GA searching graph in this work.

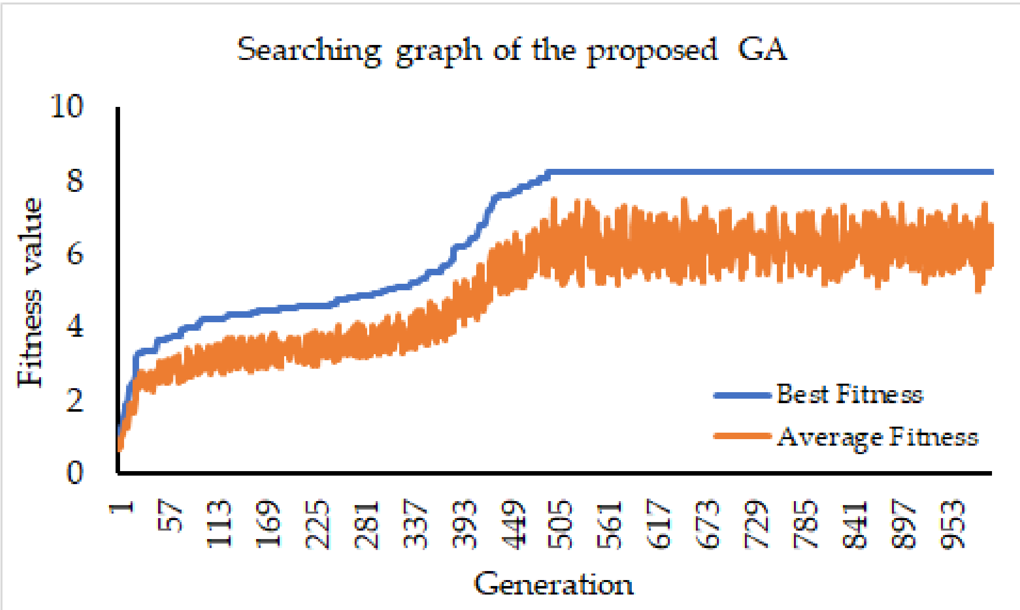


Figure 4. Searching graph shows the proposed GA

Figure 4 demonstrates that the GA has the capability to enhance chromosome performance over time while also preserving chromosome variety. Therefore, when the proposed GA converged to a solution, it can be considered an optimum solution. The optimum value for all of the devision variables regarding the selling price and the replenishment cost are shown in Table 2, while Table 3 shows the optimum value for the deision variables regarding the demand forecasting variables and Table 4 shows the profits earned by both the leader and follower players for the sale of all the products.

Table 2. Value of the optimised decision variables regarding selling price and replenishment cost

p	SPL	SPF	φL	φF	ωL	ωF
1	455206	262136	80000	80000	30000	20000
2	387847	289396	80000	70000	30000	20000
3	304471	162639	70000	65000	28000	18000
4	298351	137166	40000	25000	35000	28000
5	985799	915298	400000	370000	35000	28000

Table 3. Value of the optimised decision variables regarding the demand forecasting variables

p	SPL	SPF	φL	φF	ωL	ωF
1	455206	262136	80000	80000	30000	20000
2	387847	289396	80000	70000	30000	20000
3	304471	162639	70000	65000	28000	18000
4	298351	137166	40000	25000	35000	28000
5	985799	915298	400000	370000	35000	28000

Table 4. Potential profits earned by the players for the sale of all the products

p	DFL_{t+1}	DFF_{t+1}	TPL	TPF	TP
1	567	333	191888642.46	56724210.20	248612852.67
2	354	346	104008790	65341168	169349958
3	174	176	36107066	8962576	45069642
4	299	301	60934654.77	10506200.72	71440855.50
5	346	54	308527102	40620740	349147842
Total			701466255.23	182154895.9	883621150.2

The proposed model has also been solved using the Generalised Reduced Gradient (GRG Nonlinear) algorithm implemented in the Microsoft Excel solver for the purpose of comparison study. The results of optimisation achieved with this algorithm are illustrated in Table 5.

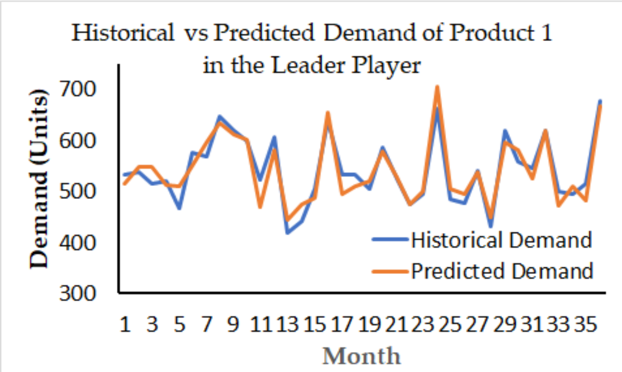
Table 5. Solutions provided by GRG Nonlinear algorithm

p	DFL_{t+1}	DFF_{t+1}	SPL	SPF	TP
1	556	344	399338	295857	227308897.39
2	359	341	382349	293606	169292921
3	205	145	251113	191116	42588265
4	299	301	298351	137166	71440855.50
5	530	27	987000	915298	341501296
Total			2318151	1833043	852132235

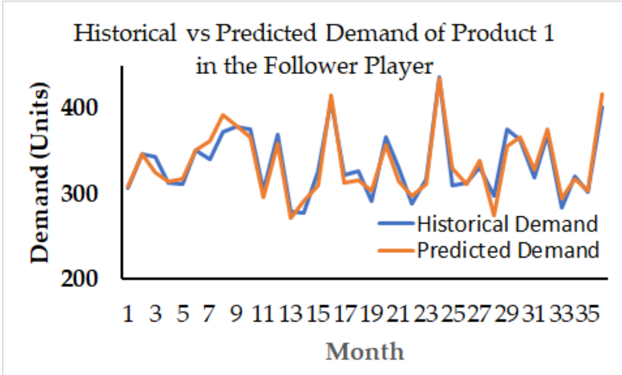
Table 5 above shows that the optimisation results of GRG Nonlinear are identical to those of GA for product 4. However, for other products, the solution generated by GA is superior to that of GRG Nonlinear.

4. DISCUSSION

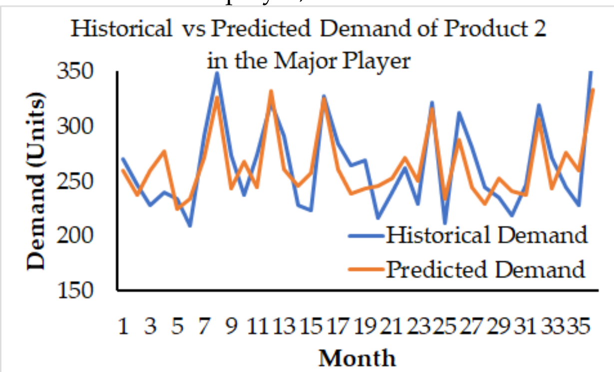
Prior studies concerning the determination of selling price have indicated that the determined selling price influences consumer demand response [37]–[39]. Nevertheless, those studies have not accounted for the validation of the demand forecasting resulting from the determined selling price; thus, the predicted demand may deviate from the historical demand patterns. This work incorporates the validation of demand forecasting into the objective functions of the developed optimisation model. Consequently, the selling price determined to optimise profit will yield an accurate demand forecast, which constitutes the novel aspect of this study. The outcomes of the demand forecasting based on historical demand for each product across all players are illustrated in Figure 5 below.



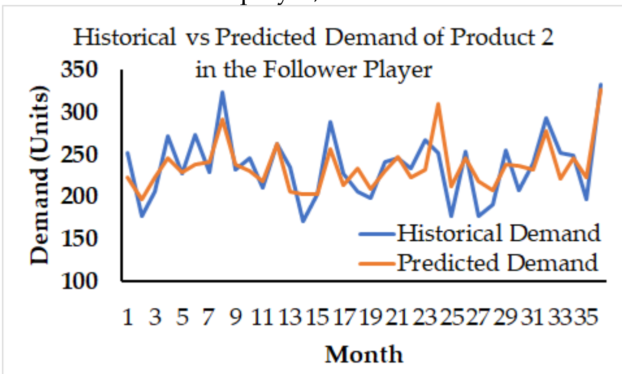
(a) Historical vs predicted demand of $p = 1$ in the leader player, MSE = 559.08



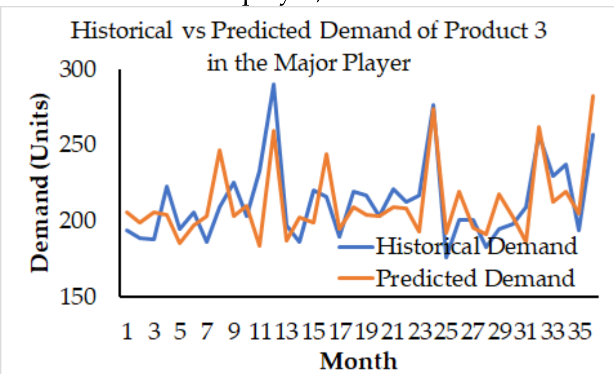
(b) Historical vs predicted demand of $p = 1$ in thye follower player, MSE = 130.22



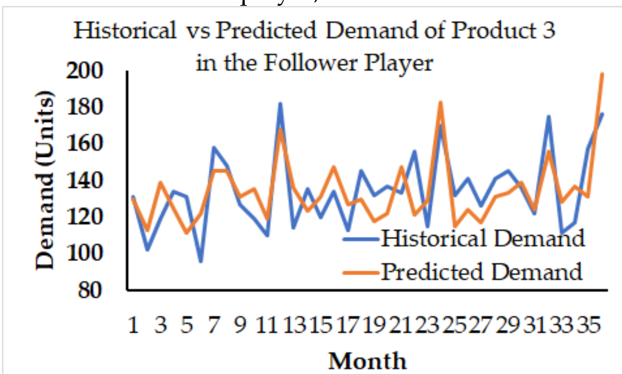
(c) Historical vs predicted demand of $p = 2$ in the leader player, MSE = 581



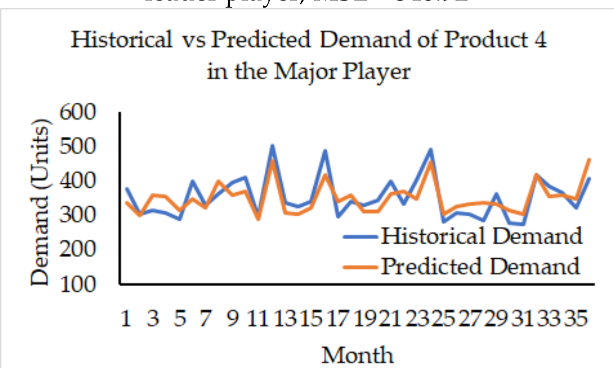
(d) Historical vs predicted demand of $p = 2$ in the follower player, MSE = 551.19



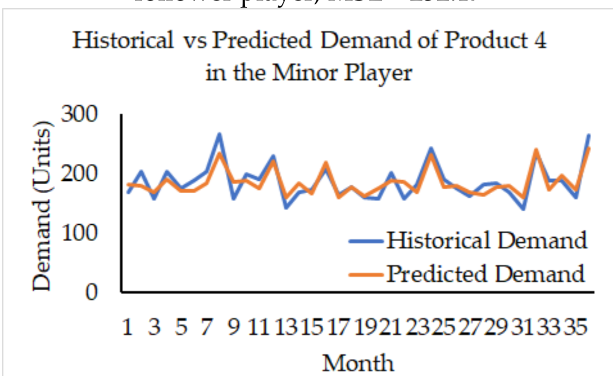
(e) Historical vs predicted demand of $p = 3$ in the leader player, MSE = 346.92



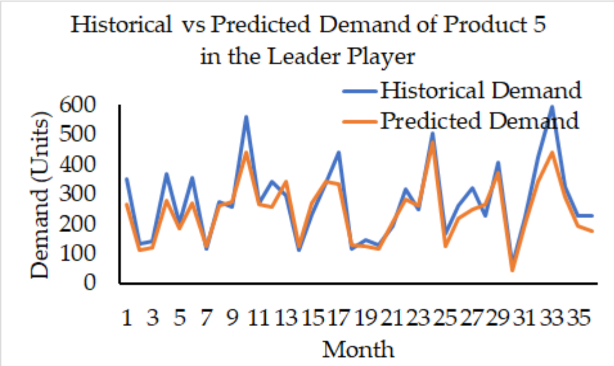
(f) Historical vs predicted demand of $p = 3$ in the follower player, MSE = 252.17



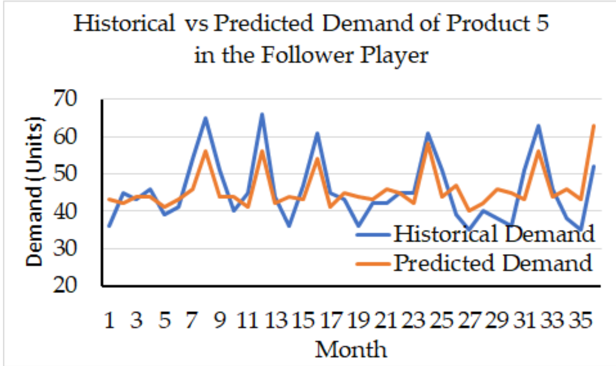
(g) Historical vs predicted demand of $p = 4$ in the leader player, MSE = 1277.33



(h) Historical vs predicted demand of $p = 4$ in the follower player, MSE = 228.61



(i) Historical vs predicted demand of $p = 5$ in the leader player, MSE = 3080.86

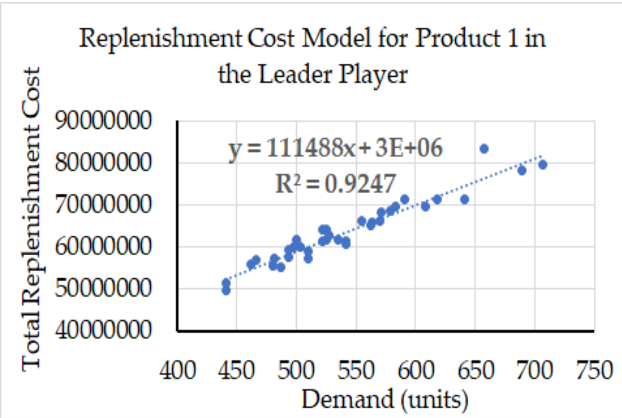


(j) Historical vs predicted demand of $p = 5$ in the follower player, MSE = 36.17

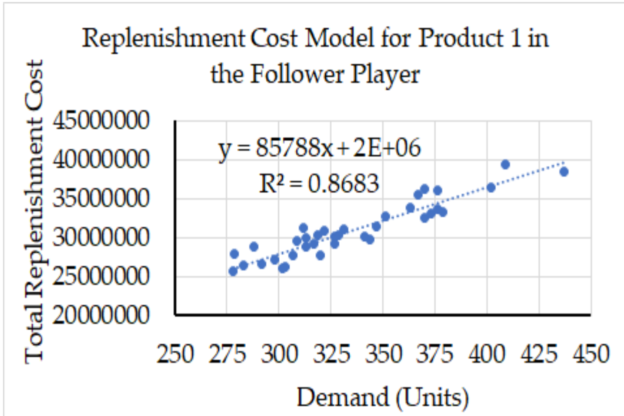
Figure 5. Historical versus predicted demand for all of the products in the leader and follower player

Figure 5 (a-j) illustrates that the pattern of demand prediction results aligns with the historical demand data pattern. Consequently, it can be asserted that the demand prediction derived from product price optimisation results aligns with the established demand data patterns.

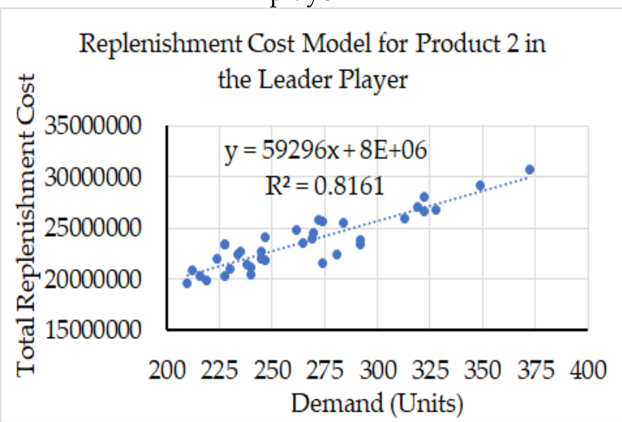
As the PCL_p and PCF_p are aggregated, it is necessary to validate the replenishment cost models as well. Figure 6 illustrates the replenishment cost models and their validation by comparison with the historical PCL_p and PCF_p.



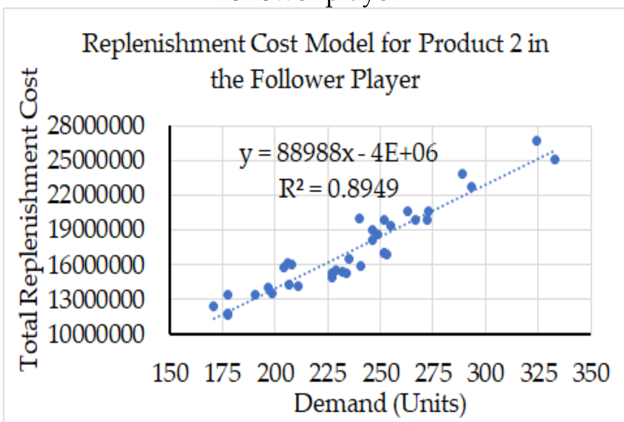
(a) Replenishment cost model for $p = 1$ in the leader player



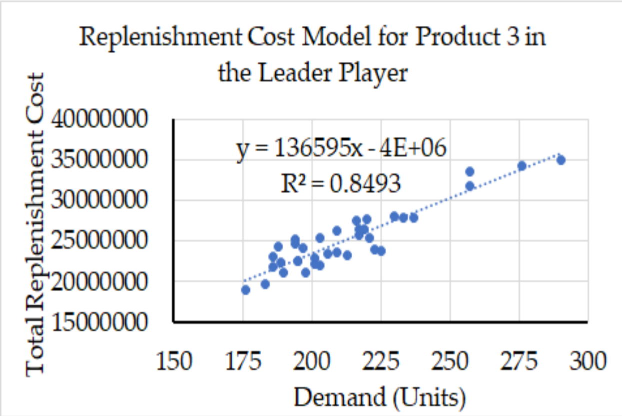
(b) Replenishment cost model for $p = 1$ in the follower player



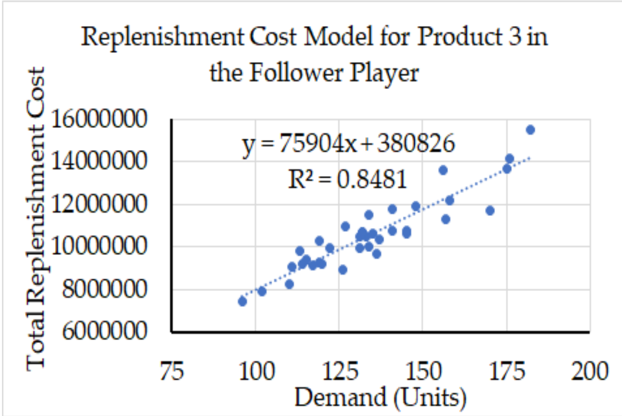
(c) Replenishment cost model for $p = 2$ in the leader player



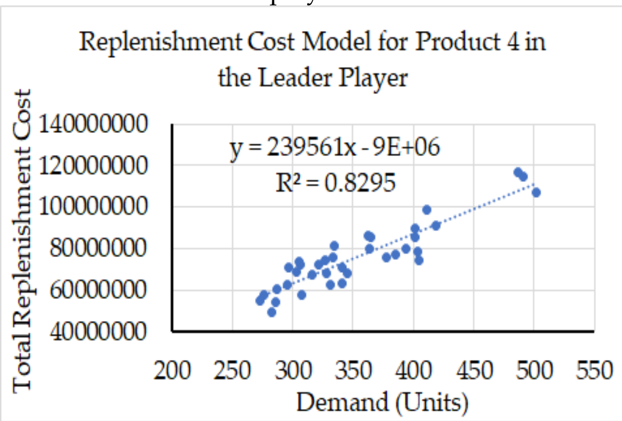
(d) Replenishment cost model for $p = 2$ in the follower player



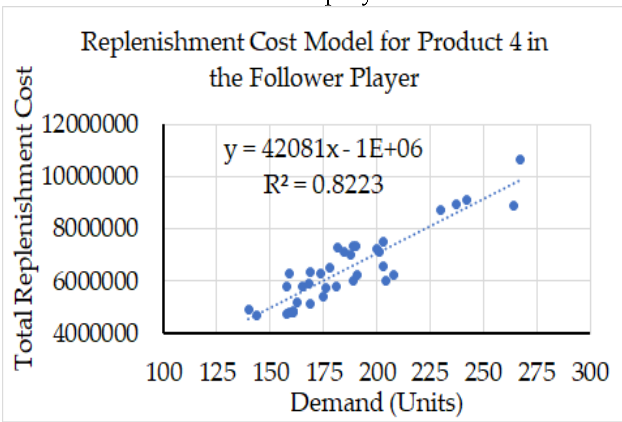
(e) Replenishment cost model for p = 3 in the leader player



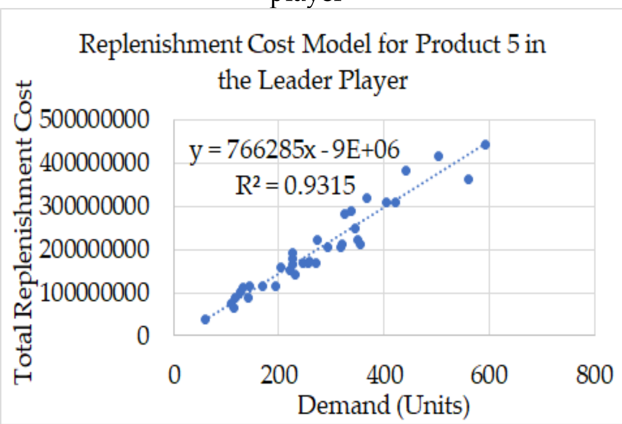
(f) Replenishment cost model for p = 3 in the follower player



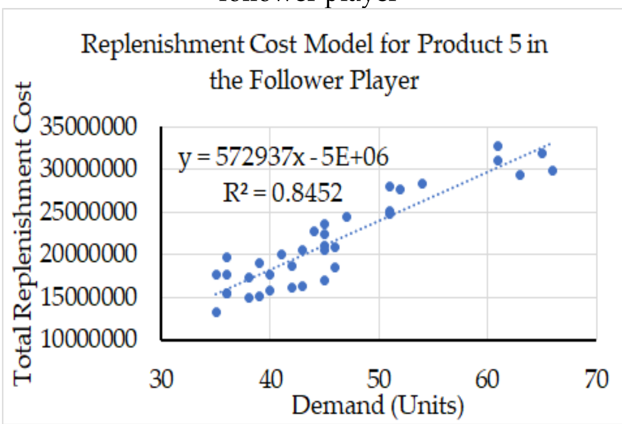
(g) Replenishment cost model for p = 4 in the leader player



(h) Replenishment cost model for p = 4 in the follower player



(i) Replenishment cost model for p = 5 in the leader player



(j) Replenishment cost model for p = 5 in the follower player

Figure 6. The total replenishment cost models for all of the products in leader and follower player

Figure 6 (a-j) demonstrates that the predictive equations for PCL_p and PCF_p closely align with historical data, as evidenced by a relatively high R^2value. Therefore, the equations employed for predicting PCL_p and PCF_p are deemed valid. The validation of the predicted demand and the replenishment cost results for each product across all players has confirmed the validity of the new contributions discussed in this study.

Alongside the valid results, the superiority of the resultant solution is compared to the potential profit achievable by the leader and follower players when applying the existing selling price. Table 6 presents the existing selling price of each product, together with the prospective demand and profit potential for each player.

Table 6. Potential profits earned by the players based on existing selling price

p	$SPLc$	$SPFc$	DFL_{t+1}	DFF_{t+1}	$TPLc$	$TPFc$	TPc
1	465000	270000	489	288	169867368	51053056	220920424
2	395000	285000	328	332	98642464	61075984	159718448
3	315000	165000	161	166	35029868	8617992	43647860
4	315000	145000	269	271	59198972	11179252	70378224
5	1000000	920000	279	55	252551852	41705660	294257512
Total					615290524	173631944	788922468

From Table 3 and Table 4 above, it can be calculated that improvement on *TPL*, *TPF* and *TP* based on the optimised SGT model are $\frac{(701466255.23-615290524)}{615290524} \times 100\% = 14\%$, $\frac{(182154894.92-173631944)}{173631944} \times 100\% = 4.91\%$, and $\frac{(883621150.17-788922468)}{788922468} \times 100\% = 12\%$ respectively.

In this case, the leader and follower have the same market share, but the leader has a stronger brand image than the follower. Therefore, the proposed model can be developed by duplicating the model built for the follower if there is a new player in the same market and its position as a follower.

5. CONCLUSION

This research presents an optimised SGT model utilising GA to ascertain the selling price of five batik clothes. The significant different of the proposed SGT model relative to prior studies is its simultaneous modelling of the impact of selling price on demand for both leader and follower players, thereby obviating the need for bi-level optimisation and NGA as the optimisation algorithm. The model's simplification enhances its practicality for managers in both leader and follower player to adopt and implement it. Furthermore, another significant aspect of the suggested approach is the incorporation of a demand forecasting validation to the SGT optimisation model. Validating model outcomes against historical data ensures that optimised prices are not only mathematically feasible but also market-acceptable. This prevents all players from making extreme pricing decisions that could potentially undermine their businesses. The suggested optimised SGT model enhances the total profits of the leader, follower, and all players by 14%, 5%, and 12%, respectively. For further study, the analysis can be continued by extending the scope to a multi-echelon supply chain system in order to optimise inventory at all retailers and production quantity at supplier.

ACKNOWLEDGMENT

The author would like to express appreciation to the Department of Industrial Engineering, Universitas Islam Indonesia for funding the publication of this paper.

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