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Optimisation-in-the-loop simulation of multi products single vendor-multi buyers supply chain systems with reactive lateral transhipment

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A B S T R A C T

Considering that batik is one of the most popular products in Indonesia, it is important to analyse the supply chain system for batik products. In reality, the supply chain system for batik products enables orders between buyers to receive products more rapidly, allowing them to anticipate stock outs and obtain lower ordering costs than when ordering from vendors. It is referred to as reactive lateral transshipment. This paper discusses the development of a simulation-based stochastic optimisation model for a batik product supply chain system with multiproducts and single vendor-multi buyers. The utilised solution searching algorithm is a modified Genetic Algorithms (GA) executed in-loop with the developed simulation-based stochastic model. The results demonstrate that the proposed modified GA is able to provide a global optimum solution, allowing the proposed simulation-based stochastic model to reduce the joint total cost (JTC) of the investigated supply chain system by up to 19% when compared to the local optimisation model in each supply chain party.

1. INTRODUCTION

In a supply chain system, customer demand for a product will occur randomly and in random quantities. On the buyer side, which is the chain that deals directly with customers, when product inventory reaches a certain threshold (stock on hand), the buyer will place an order with the vendor (stock on order) [1], and it is known as continuous review inventory policy [2], [3]. Therefore, if there are multiple buyers, the demand received by the vendor will be random and arrive at different times. The vendor will produce the products daily, anticipating the buyer's uncertain demand. In order to fulfil urgent requests, it is sometimes necessary for the buyer to purchase products from one another; this is known in the logistics industry as reactive lateral transhipment [4]. It occurred in the supply chain system for batik products, one of Indonesia's most popular products.

Considering that batik is one of the most popular products in Indonesia, it is important to analyse the supply chain system for batik products. Uncertain demand at the batik buyers makes them often experience overstock and understock, which results in losses and costs. In addition, the unpredictable order timing and quantity from buyers causes the batik vendor to anticipate the demand with large production quantity, which often results in extremely high production and holding costs.

When demand is uncertain, the buyer will typically employ a minimum inventory policy, considering the lead time for orders from suppliers and other buyers. Thus, the minimum inventory level and the order quantity to vendors and other buyers are the decision variables for the buyers. In the meantime, the vendor must determine the economic production quantity (EPQ), as the EPQ is one of the most crucial aspects of production planning when considering the optimum utilisation of production resources [5], [6]. In this situation, the problem will become complex due to numerous variables and even more complicated when multiple products must be managed.

The buyers and vendors must coordinate the decision-making processes to achieve a global optimum. The decision variable consists of the order quantity of each buyer, considering the demand from customers and the demand between buyers, as well as the production lot size at the vendor. These decision variables are commonly known as the joint lot size (JLS) [7]–[9]. The following sub-sections will detail the various study topics prior researchers used to explore JLS in general cases.

Goyal [10] initiated JLS research by introducing the joint total cost in a supply chain system with a single vendor and buyer. He postulated a lot-for-lot shipment policy and an infinite production rate between the vendor and buyer. The shipping policy is known as lot-for-lot when the vendor dispatches all the products produced in a production run. This study was expanded by Banerjee [11], who relaxed the assumption of an infinite production rate. Ben-Daya and Nassar have investigated the application of JLS in a three-layer supply chain with deterministic demand and costs [12]. Abdelsalam and Elassal [13] expanded that study by relaxing the assumption of deterministic demand, fixed ordering and holding cost for all of the buyers

In reality, price incentives from buyers to purchase more at a reduced price and fluctuating product prices will influence customer demand. In the JLS study, this condition is referred to as price-sensitive demand [14], [15]. Another study that combines pricing strategy has been carried out by Hanh *et al*. [16] while considering perishable materials has been investigated by Liu *et al*. [17]. A similar study by applying a common policy from the vendor who gave a time-based temporary price discount has also been investigated by Sari *et al*. [18]. In order to have long-term benefits, strategic decisions in a supply chain have also been investigated by Marchi *et al*. [19], who investigated financial collaboration and uncertain investment and Tolooie *et al*. [20], who investigated supply chain network design under uncertain disaster and demand.

When there are multiple buyers, they can order products from one another to meet unpredictable demand. In addition, faster ordering timeframes and lower ordering costs due to distance are other reasons buyers place orders with one another. Meneses *et al*. [21] and Emadi and Pasek [22] discussed the blood supply chain, and due to uncertain supply and demand, high service level requirements, and perishable products, the blood supply chain has lateral transhipment. A similar study has been conducted by Dehghani *et al*. [23], intending to balance wastage and shortage of a blood supply chain. Samuel *et al*. [24] have modelled a supply chain with transhipment to support a closed-loop sustainable supply chain. Dijkstra *et al*. [25] modelled a closed-loop supply chain like that study. Achamrah *et al*. [26] modelled a supply chain system with lateral shipment for substitution products.

Lateral transhipment allows buyers and vendors to share inventory to alleviate a shortage. Firouz *et al*. [27] considered multiple warehouses that proactively applied lateral transhipment to become reliable suppliers for a firm. Dhahri *et al*. [28] studied a model to depict integrated production-transhipment between two unreliable manufacturing system locations to minimise total holding, backlog, and transhipment costs. A policy of unidirectional lateral transhipment has positively impacted the determination of the minimum inventory stock required to support system reliability. Patriarca *et al*. [4] developed a mathematical model to implement such a policy for an airline with fleets at three locations.

According to the above literature review, all optimisation models proposed by previous researchers are complex. This study, which investigates a single vendor-multiple buyer supply chain system with reactive lateral transhipment, will result in a complex optimisation model. Soft-computing models, such as genetic algorithm (GA) and simulated annealing, can be used to solve problems with a high level of complexity [29]. Gholizadeh and Fazlollahtabar [30] have used a modified GA to solve a closed-loop supply chain system. In that study, the GA was simplified to accelerate the computation process and combined with a local search algorithm to enhance the current solution. Fathi *et al*. [31] used GA to determine optimum distribution centre locations and inventory management policy. The GA has been combined with an Artificial Neural Network (ANN) to optimise supply chain networks with internal and external risks in more complex situations [32].

As previously discussed, most research on supply chains with the transhipment system focuses on inventory balancing within the same echelon, known as the proactive lateral transhipment system. In addition, most researchers have previously modelled uncertain demand with a continuous model or taken the demand's average value. To our knowledge, deriving the objective function equation or employing an intelligent algorithm to solve the static objective function equation is the standard optimisation method used by previous researchers. Thus, a significant contribution of this study is implementing the reactive lateral transhipment model as the response for the buyer-to-buyer order in the batik supply chain system. Another significant contribution from this study is modelling demand uncertainty using a simulation model and integrating GA into the simulation system to minimise the total cost of the entire supply chain. This method is known as optimisation-in-the-loop simulation.

2. RESEARCH METHODS

2.1. Supply chain system description

This study investigates a supply chain system for batik products in Yogyakarta, Indonesia. There is a prominent vendor that sells five batik products to five buyers. Customers demanded probabilistically from each of the buyers. In order to anticipate unpredictable demand, the buyer may place an order with a different buyer for faster ordering timeframes and relatively low ordering costs. The supply chain diagram under consideration is depicted in Fig. 1.

Based on the historical data, Buyer 2 and Buyer 3 occasionally place orders with Buyer 1. Buyer 1 and Buyer 3 occasionally place orders with Buyer 5, whereas Buyer 4 occasionally places orders with Buyer 2. In general, the on-hand inventory of the buyers can be used by other buyers; this practice is known as lateral transhipment. It is referred to as reactive transhipment when buyers place orders with other buyers in anticipation of stockouts due to unforeseen demand [33].

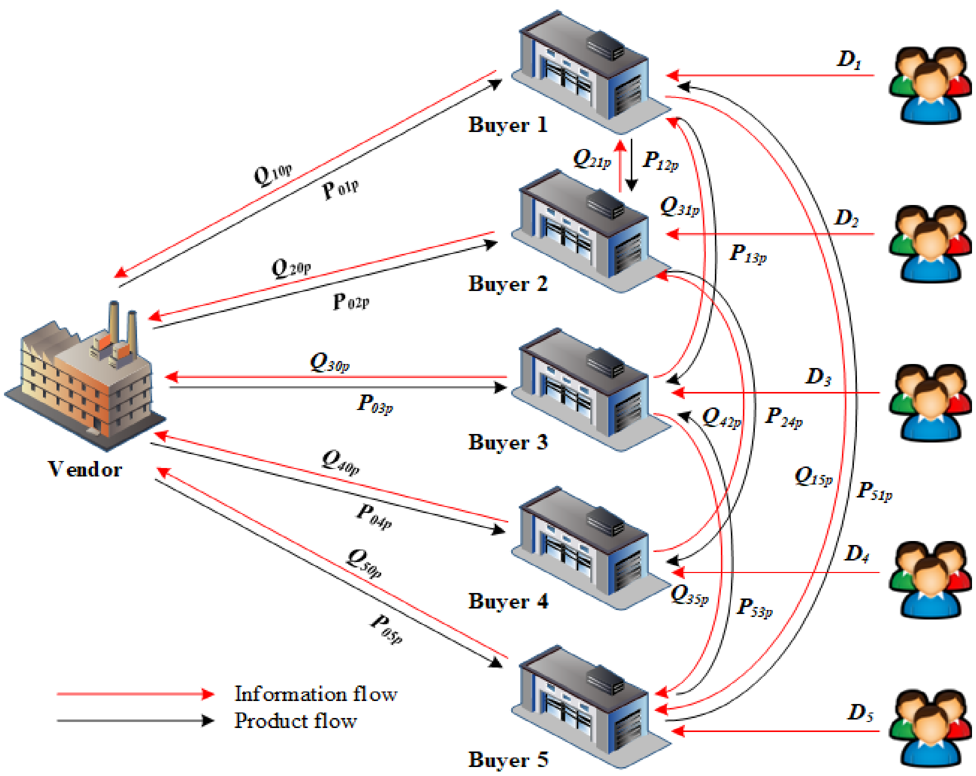

Fig. 1. Supply system diagram under consideration

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2.2. System variables and parameters

This case study is considered simulation-based stochastic optimisation, meaning the customers' stochastic demand will be modelled probabilistically during simulation. In order to model the supply chain system, the following variables and parameters are used.

General indexes:

- *p* : product index
- *a, b* : buyer index
- *c* : customer index
- *t* : simulation period index

General variable:

- *JTC* : joint total cost of the supply chain system
- *T* : number of simulation periods
- *P* : number of products
- *B* : number of buyers

Vendor side:

Parameters:

- *S* : set-up cost per production run (IDR)
- LS_p : lost-sales cost per unit of product-*p* (IDR/unit)
- H_p : carrying cost per unit of product-*p* per month (IDR/unit/month)
- D_p : demand from buyers of product-*p*

Variables:

- PD_p : optimum production lot-size of product-*p* (units)
- RP_p : optimum reproduction point of product-*p* (units)
- PR_p : number of production runs of product-*p* (times)
- LQ_p : number of lost-sales occurred of product-p
- I_p : number of ending inventories of product-*p*
- *VSC* : vendor's total setup cost (IDR)
- *VLC* : vendor's total lost sales cost (IDR)
- *VHC* : vendor's total holding cost (IDR)
- *VTC* : vendor's total cost (IDR)

Buyers side:

Parameters:

- A_0 : ordering cost per order with the vendor (IDR/order)
- A_{ab} : ordering cost per order of buyer-*a* with the buyer-*b* (IDR/order)
- ls_p : lost-sales cost per unit of product-*p* (IDR/unit)
- h_p : carrying cost per unit of product-*p* per month (IDR/unit/month)
- d_{pt} : demand from customers of product-*p* at simulation period-*t* (units)

Variables:

- Q_{pa0} : optimum order quantity of product-*p* of buyer-*a* with the vendor (units)
- Q_{pab} : optimum order quantity of product-*p* of buyer-*a* with the buyer-*b* (units)
- r_{pa} : optimum reorder point of product-*p* (units) at buyer *a*
- no_{pa0} : number of orders of product-*p* of buyer-*a* with the vendor
- no_{pab} : number of orders of product-*p* of buyer-*a* with the buyer-*b*
- lo_p : number of lost-sales occurred of product-*p*
- i_p : number of ending inventories of product-*p*
- *BOC* : buyers' total ordering cost (IDR)
- *BLC* : buyers' total lost sales cost (IDR)
- *BHC* : buyers' total holding cost (IDR)
- *BTC* : buyers' total cost (IDR)

GA

- *i-pop_size* : initial population size
- *pc* : crossover rate/probability
- *pm* : mutation rate/probability
- *gen* : number of generations

2.3. Optimisation models

The general objective of the optimisation model is to minimise *JTC*, which consists of *VTC* and BTC. The following sub-sections explain the process of the model development.

2.3.1. *TC model*

The first cost component of the *VTC* is *VSC*, formulated as the number of production run of all of the products multiplied by set-up cost per production run. The formula for *VSC* is shown in the following formula.

$$VSC = \sum_{p=1}^{P}\sum_{t=1}^{T} S_{pt} \times PR_{pt} \qquad (1)$$
$$PR_{pt} = \begin{cases} 1, if\ PD_p > 0 \\ 0, otherwise \end{cases}$$

The second cost component of the *VTC* is *VLC* that formulated as the number of lost-sales occurred of all of the products multiplied by lost-sales cost per unit of all of the products. The *VLC* formula is shown in following equation.

$$VLC = \sum_{p=1}^{P}\sum_{t=1}^{T} LS_{pt} \times LO_{pt} \qquad (2)$$

$$LO_{pt} = max\left(0;\ D_{pt} - \left(PD_{pt} + P_{pt-1}\right)\right)$$
$$D_{pt} = \sum_{b=1}^{B} Q_{ptb}\ ; \forall p; \forall t$$

The following cost component of *VTC* is *VHC*, formulated as the number ending inventories of all products multiplied by carrying cost. The following equation shows the formula of VHC.

$$VHC = \sum_{p=1}^{P}\sum_{t=1}^{T} H_{pt} \times I_{pt}$$
$$I_{pt} = max\left(0;\ \left(PD_{pt} + P_{pt-1}\right) - D_{pt}\right) \quad (3)$$
$$D_{pt} = \sum_{b=1}^{B} Q_{ptb}\ ; \forall p; \forall t$$

Therefore, the *VTC* can be formulated as shown by the following formula.

$$VTC = VSC + VLC + VHC \quad (4)$$

2.3.2. *BTC model*

The BTC consists of BOC, BLC and BHC. The following formula shows that the BOC is formulated as order frequency during simulation multiplied by ordering cost to the vendor or another buyer.

$$BOC = \sum_{a=1}^{B}\sum_{b=1}^{B}\sum_{p=1}^{P}\sum_{t=1}^{T}\left(\left(A_{0t} \times no_{pa0t}\right) + \left(A_{abt} \times no_{pabt}\right)\right); a \neq b \quad (5)$$
$$no_{pa0t} = \begin{cases} 1, if\ Q_{pa0} > 0 \\ 0, otherwise \end{cases}$$
$$no_{pabt} = \begin{cases} 1, if\ Q_{pab} > 0 \\ 0, otherwise \end{cases}$$

The *BLC* is calculated by multiplying the cost of lost sales for all products across all buyers by the number of lost sales across all buyers, as shown by the following equation.

$$BLC = \sum_{b=1}^{B}\sum_{p=1}^{P}\sum_{t=1}^{T} ls_{bpt} \times lo_{bpt}$$
$$lo_{bpt} = max\left(0;\ d_{bpt} - \left(Q_{pa0} + Q_{pab} + i_{pt-1}\right)\right) \quad (6)$$

As the total holding cost across all buyers for all products, the BHC is calculated by multiplying the carrying cost for all products across all buyers by the number of ending inventories for all products across all buyers, as shown by the following equation.

$$BHC = \sum_{b=1}^{B}\sum_{p=1}^{P}\sum_{t=1}^{T} h_{bpt} \times i_{bpt}$$
$$i_{bpt} = max\left(0;\ \left(Q_{pa0} + Q_{pab} + i_{pt-1}\right) - d_{bpt}\right) \quad (7)$$

The following equation demonstrates that the BTC can be determined by adding the BOC, BLC, and BHC.

$$BTC = BOC + BLC + BHC \quad (8)$$

2.3.3. *TC model*

The *JTC*, as the total cost across the supply chain system, is calculated by summing the *VTC* and *BTC*, as shown in the following formula.

$$JTC = VTC + BTC \quad (9)$$

2.4. GA modelling

2.4.1. *Chromosome design*

As an evolutionary optimisation algorithm, GA will discover the optimal value of a model's decision variables by encoding the variables as chromosomes. Table 1 displays the supply chain optimisation model's decision variables and their encoding in the proposed GA. The maximum value for all decision variables is set to 10000 due to the maximum production capacity of the vendor and the maximum total customer demand for all products, which never exceeds 10000 units.

Table 1. The decision variables and their encoding

Decision Variable	Encoding	Max.	Min.
PD_p	Binary	10000	0
RP_p	Binary	10000	0
Q_{pa0}	Binary	10000	0
Q_{pab}	Binary	10000	0
r_p	Binary	10000	0

This study considers multiple batik products; therefore, a chromosome contains a total of *P x* 25 genes. The proposed GA will also be used in-the-loop with the supply chain simulation, which will significantly lengthen the computation process. In

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order to accelerate the computation time, population size is made dynamic. The initial population size is set to a constant, and in the subsequent generation, the same chromosomes will be reduced to only two copies, reducing the population size. It will also prevent the GA from becoming trapped in local optimum conditions due to the dominance of super chromosomes.

2.4.2. *Crossover operation*

A standard one-cut point crossover is used in this study. However, the crossover operation is implemented for every gene in a chromosome. Fig. 2 shows the mechanism of the one-cut point crossover for every gene.

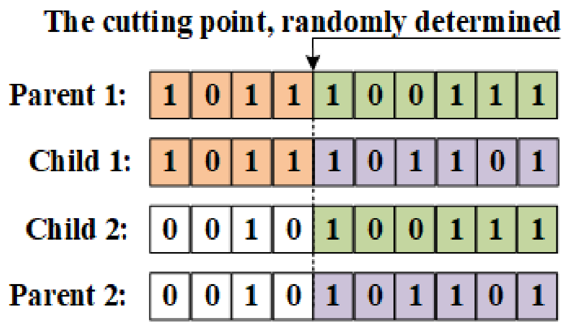

Fig. 2. Mechanism of the used one-cut point crossover operation

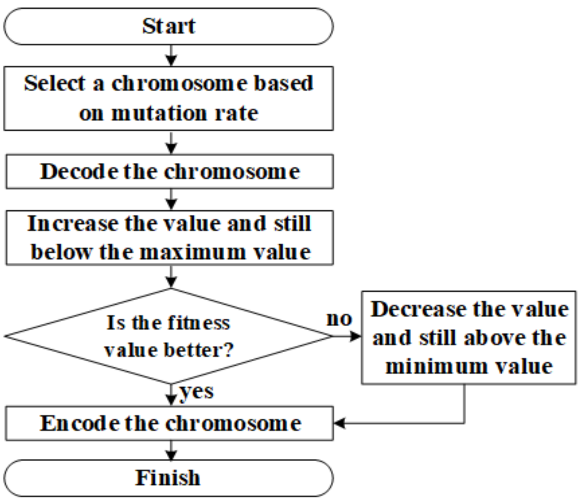

Fig. 3. Mechanism of the used semi-guided non-uniform mutation

2.4.3. *Mutation operation*

A semi-guided uniform mutation operation that enables GA to explore values between the current and limit values of a variable is used. This mutation operation is the modification of the standard non-uniform mutation proposed by Michalewicz [34]. The modification is intended to make the GA's exploration more effective while maintaining its stochastic process nature. The procedure instructs the GA to increase or decrease the mutated gene in accordance with its fitness value. Nonetheless, the value change remains arbitrary. Fig. 3 depicts the semi-guided non-uniform mutation procedure.

3. RESULTS AND DISCUSSION

After modelling the supply chain system and the GA as the optimisation algorithm, the next step is solving the supply chain system model using the GA. This study was conducted on a batik supply chain system in Yogyakarta, Indonesia. Five products (P = 5) and five buyers (B = 5) sell the products to the customers. Table 2 lists the parameter values for the vendor and all buyers, while Table 3 displays the demand distribution from buyers to vendors. Table 4 depicts the demand distribution from buyer 1 to buyer 5, whereas Table 5 depicts the demand distribution from buyer 2 to buyer 1. Table 6 illustrates the demand distribution from Buyer 3 to Buyer 1 and 5, while Table 7 depicts the demand distribution from Buyer 4 to Buyer 2.

The simulation was performed for 5 years (*T* = 60) to get steady-state conditions. The GA will be executed with *i-pop_size* = 30, *pc* = 0.3, and *pm* = 0.5. The stopping condition of the GA is the number of generations (*gen*) set to 500. Table 8 shows the optimum value for the decision variables after optimisation. The *VTC* and *BTC* of that solution are IDR 672.045.100 and IDR 482.783.500, respectively, and the resulting *JTC* is IDR 1.154.828.600.

In order to demonstrate the efficacy of the proposed global optimisation through the *JTC* model, the outcome of the optimisation will be contrasted to the outcome of the local optimisation through individual optimisation of the entire supply chain. Using a similar model to compute the total cost of buyers and vendors, however, with separate optimisation, the total cost of the supply chain system is IDR 1.374.246.034. It indicates that the proposed optimisation model can reduce the costs of the global supply chain system by

$$\frac{1.374.246.034 - 1.154.828.600}{1.154.828.600} \times 100\%$$

= 19%.

This improvement is confirmed with a theory stated that a supply chain performance can be improved by combining all of the supply chain parties into a single function [35].

Table 2. The parameter value for the costs

Chain	Parameter	Value	Chain	Parameter	Value	Chain	Parameter	Value
Vendor	S	5700	Buyer 2	A_0	8000	Buyer 4	A_0	8000
	H_1	3500		A_{21}	8000		A_{42}	8000
	LS_1	5500		h_1	2000		h_1	2000
	H_2	3500		ls_1	25000		ls_1	35000
	LS_2	6500		h_2	2000		h_2	2000
	H_3	3500		ls_2	25000		ls_2	25000
	LS_3	4000		h_3	2000		h_3	2000
	H_4	3500		ls_3	25000		ls_3	25000
	LS_4	7000		h_4	2000		h_4	2000
	H_5	3500		ls_4	25000		ls_4	25000
	LS_5	4000		h_5	2000		h_5	2000
				ls_5	25000		ls_5	25000
Buyer 1	A_0	13000	Buyer 3	A_0	10000	Buyer 5	A_0	13000
	A_{15}	13000		A_{31}	8000		h_1	2000
	h_1	2000		A_{35}	8000		ls_1	25000
	ls_1	20000		h_1	2000		h_2	2000
	h_2	2000		ls_1	25000		ls_2	25000
	ls_2	25000		h_2	2000		h_3	2000
	h_3	2000		ls_2	30000		ls_3	25000
	ls_3	20000		h_3	2000		h_4	2000
	h_4	2000		ls_3	25000		ls_4	35000
	ls_4	20000		h_4	2000		h_5	2000
	h_5	2000		ls_4	30000		ls_5	30000
	ls_5	25000		h_5	2000			
				ls_5	25000			

Table 3. The demand distribution from buyers to vendor

Product	From Buyer				
	1	2	3	4	5
1	Normal(300, 35)	Normal(150, 20)	Uniform(30, 70)	Uniform(120, 155)	Normal(60, 25)
2	Normal(10, 7)	Normal(50, 13)	Normal(40, 10)	Uniform(30, 65)	Uniform(20, 35)
3	Uniform(22, 47)	Uniform(100, 130)	Uniform(44, 83)	Uniform(20, 75)	Uniform(80, 110)
4	Uniform(2, 17)	Uniform(10, 30)	Uniform(24, 93)	Uniform(10, 35)	Normal(50, 20)
5	Normal(87, 7)	Normal(80, 20)	Uniform(14, 33)	Uniform(10, 30)	Normal(90, 15)

Table 4. The demand distribution from buyer 1 to buyer 5

To Buyer	Product				
	1	2	3	4	5
5	Uniform(2, 5)	Uniform(2, 5)	Uniform(3, 4)	Uniform(4, 5)	Uniform(5, 8)

Table 5. The demand distribution from buyer 2 to buyer 1

To Buyer	Product				
	1	2	3	4	5
1	Uniform(2, 10)	Uniform(5, 8)	Uniform(5, 15)	Uniform(4, 7)	Uniform(2, 10)

Table 6. The demand distribution from Buyer 3 to buyer 1 and buyer 5

To Buyer	Product				
	1	2	3	4	5
1	Uniform(2, 15)	Uniform(5, 7)	Uniform(7, 9)	Uniform(3, 11)	Uniform(2, 7)
5	-	-	-	-	Uniform(3,6)

Table 7. The demand distribution from buyer 4 to buyer 2

To Buyer	Product				
	1	2	3	4	5
2	Uniform(7, 13)	Uniform(2, 5)	Uniform(4, 11)	Uniform(3, 9)	Uniform(1, 3)

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Table 8. The decision variables' values

Decision Variable	Value	Decision Variable	Value
Q_{110}	609	r_{11}	1605
Q_{120}	306	r_{12}	2536
Q_{130}	96	r_{13}	533
Q_{140}	282	r_{14}	112
Q_{150}	112	r_{15}	387
PD_1	1406	RP_1	28
Q_{210}	40	r_{21}	13
Q_{220}	116	r_{22}	42
Q_{230}	84	r_{23}	40
Q_{240}	104	r_{24}	35
Q_{250}	64	r_{25}	21
PD_2	421	RP_2	32
Q_{310}	88	r_{31}	306
Q_{320}	235	r_{32}	907
Q_{330}	126	r_{33}	1783
Q_{340}	116	r_{34}	31
Q_{350}	188	r_{35}	806
PD_3	753	RP_3	0
Q_{410}	31	r_{41}	9
Q_{420}	44	r_{42}	36
Q_{430}	130	r_{43}	82
Q_{440}	48	r_{44}	22
Q_{450}	141	r_{45}	42
PD_4	395	RP_4	1
Q_{510}	181	r_{51}	788
Q_{520}	154	r_{52}	798
Q_{530}	44	r_{53}	737
Q_{540}	38	r_{54}	148
Q_{550}	187	r_{55}	307
PD_5	467	RP_5	0

The performance of the proposed GA can be evaluated through its searching process graph. Fig. 4 depicts the searching performance of the proposed GA based on average *JTC* value during simulation. According to the graph, the average fitness value never matches the best fitness value, indicating that the proposed GA is able to preserve the diversity of the chromosomes in each generation to prevent monotonous solution exploration. Therefore, it can be said fairly that the proposed GA has the capability to explore the solution domain effectively and is not confined to a local optimum solution.

In the introduction section, it was stated that the optimisation model for supply chain systems with reactive lateral transhipment based on simulation models has never been examined by previous researchers and represents a substantial contribution to this study. A valid optimisation model must have an optimum solution, and Fig. 4 demonstrates that the proposed model is also a convex model with an optimum solution. It can be seen from the GA graph, which converges to the optimum solution. Therefore, the proposed optimisation model is a valid model that can be used to solve the presented case study.

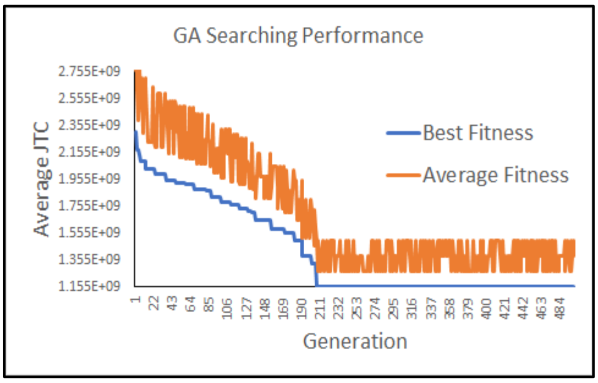

Fig. 4. Searching performance of the proposed GA

4. CONCLUSION

The supply chain system for the batik products under consideration, which is characterised by probabilistic customer demand, can be modelled using a simulation-based stochastic model. Ordering to vendor systems and reactive lateral transhipment must be modelled to obtain a *JTC*-integrated total cost model for the entire supply chain. GA is one of the optimisation algorithms that can be used in the loop with the proposed simulation-based stochastic model. However, modifying the standard GA to explore the solutions domain and provide global optimum solutions effectively is necessary.

The simulation was conducted for a lengthy period (5 years) to acquire a steady-state solution. Therefore, from a managerial standpoint, optimisation results can be readily adopted and applied to the supply chain system under consideration. The proposed optimisation-in-the-loop simulation model also applies to other supply chain systems with comparable characteristics.

The production lot size of the vendor is nearly identical to the sum of orders from all the buyers. Thus, from a managerial standpoint, it also proposed that the strategy of the supply chain system under consideration can be transformed into Make-to-Order (MTO), which produces batik based on orders from buyers. Consequently, production activities can be started after orders are received, resulting in lengthy buyer waiting times. In addition to knowing the production lot size, the vendors must reduce production lead times.

Further research is also recommended to consider the reprocessing of defective batik products. It often happens in the real world because, like in the garment industry, the quality of batik products is determined by several factors such as the fabric's quality, the cutting process's accuracy and the colouring. Thus, the resulting model will better represent a realistic batik supply chain system.

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