An Optimal Production Plan for Cashew Nuts Community Enterprise Using Metaheuristic Algorithms

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ABSTRACT

The proper production plan plays an important role in the cashew nuts market enterprise in order to reduce cost. This study aims to find the optimal production plan for cashew nuts using ant lion optimization (ALO), symbiotic organisms search (SOS), particle swarm optimization (PSO), and artificial bee colony algorithm (ABC). The novel objective function is introduced in this study. Three input data sets, including production cost, holding cost, and inventory quantity are investigated. The experiment cases consist of the frequency of production cycle time in January, February, and March, respectively. As a result, four algorithms are available to estimate not only the proper production plan of cashew nuts but also an ability in reducing the inventory and the holding costs. In summary, the ALO algorithm provides better predictive skill than others for the cashew nuts production plan with the lowest RMSE value of 0.0913.

KEYWORDS

Ant Lion Optimization, Artificial Bee Colony, Cashew Nuts, Particle Swarm Optimization, Production Plan, Symbiotic Organisms Search

INTRODUCTION

In recent years, the optimal production plan problem became one of the most important factors in the manufacturing process. The good plan can help the manufacturers in reducing the cost and the waste of the product. Thailand is a country full of the agricultural products. In order to increase the value, the products are always fed into various kinds of manufacturing system, for example, transformation, extending life cycle and packaging. Cashew nuts are a well-known product of Thailand exported to world-wide market. Thailand ranks as the third most important cashew nuts producing in Asia. In 2016, Thailand has only 14,704.64 hectare with major area in Uttaradit, Chonburi and Ubonratchathani, respectively (Department of Agricultural Extention, 2017). However, cashew nuts product trends to greatly decrease due to poor fruit set, cut down and substitute with other trees and low maintenance. Therefore, the proper production plan for cashew nuts during the manufacturing process is needed.

Optimization algorithms play an important role in various fields of study such as economic (Abdi et al., 2018), business (Wang et al., 2019), environment (Longo et al., 2019), biology (Remeseiro & Canedo, 2019), engineering (Houssein et al., 2020), computer science (Devikanniga et al., 2019),

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electronic (Janprom et al., 2020) and especially in industry. The main concept of optimization is designed to find the optimal solutions in the aspect of maximum or minimum value. It can be classified into deterministic and heuristic approaches (Lin et al., 2012). For industrial application, optimization is widely contributed to solve the optimal production plan or lot sizing problem. Based on related studies, a deterministic model is the most efficient method to solve production scheduling problem in various industrial sectors. However, as the problem becomes larger and more complex, the time taking to solve the problem will also increase. Silver meal algorithm (SM) (Silver & Miltenburg, 1984) is specifically designed to determine simply and effectively a replenishment strategy for the case of a time-varying, but deterministic demand pattern. The solution is to minimize average cost in each period. In addition, Rezaei and Davoodi (2008) use the deterministic model to solve the problem of supply chain with multiple suppliers and multiple products. Based on classical optimization methods, social and cultural data could not be analyzed in the model. The genetic algorithm (GA) is therefore applied to solve the problem. Khakdaman et al. (2015) develop a new optimization model through the development of linear programming to incofse production planning efficiency for hybrid make-to-stock–make-to-order business. The results show that the presented model can be applied in real life problem. However, complex mathematical processing requires high resources, so the integration of artificial intelligence can increase processing efficiency. However, deterministic model is unable to consider any uncertainties. The heuristic algorithm is developed to solve large-scale production scheduling. For example, Ho et al. (2007) propose production planning methods based on the effects of inventory deterioration. Three heuristic methods are improved as follows; net least period cost (nLPC), part-period algorithm (PPA), least total cost (LTC). It is the improvement of nLPC is the best performance under 100 conditions. Beck et al. (2015) propose a dynamic lot-sizing approach to inventory management using leinz–bossert–habenicht (LBH) method. Groff's rule (GR) and least unit cost (LUC) are applied in LBH and called LBH-LUC and LBH-GR, respectively. The results show that LBH-LUC can be to reduce the cost variability of LUC compared to the WW method.

However, when the problem is more complicated and need to determine the value of parameters, the heuristic method cannot solve the problem effectively. The metaheuristic algorithms become preferable to create mathematical models for complex production management problems solution with the objective of production time and cost reduction. It has powerful performance especially in optimization problem and also accepted by many researches until now. Metaheuristic algorithms are computational intelligence designed for solving optimization problems classified on metaphor based and non-metaphor based (Mohamed et al., 2018). In metaphor based, there are many algorithms applied in production plan and lot sizing problem. Production plan and lot sizing problems intend to the same target of reducing cost and time. For production plan problem, some researches are contributed as follows. Sortrakul et al. (2005) use genetic algorithm (GA) for maintenance planning and production scheduling for a single machine. They found that GA can be established to solve integrated problems efficiently. Francesco et al. (2014) use harmony search (HS) for machine maintenance planning. They found that has ability to plan the machine maintenance efficiently and quickly. Delgoshaei and Ali (2020) combine ant colony optimization (ACO) with simulated annealing (SA) to find the best schedule for cellular manufacturing system under the condition of uncertainty product demand. The proposed algorithm can generate the best schedule in terms of time, cost and load variance in a reasonable time. For lot sizing problem, Pitakaso et al. (2007) apply ant system for multi-level lot-sizing algorithm (ASMLLS) to determine the optimum production volume. The results show that ASMLLS is one of the best algorithms in order to solve only small problem. Wei et al. (2019) introduce two-stage ant colony algorithm with lot sizing (TSACAWLS) in order to schedule production for circuit board assembly. The results show that two-stage ant colony algorithm can find the optimal solution closer than other methods in terms of stability, calculation time and production volume. For other applications, Cheng and Prayogo (2014) present symbiotic organisms search (SOS) tested with 26 benchmark functions and solved four practical structural design problems. By comparing performance with GA, particle swarm optimization (PSO), differential evolution (DE), bees algorithm (BA), particle bee algorithm

(PBA), SOS is more effective at finding answers than other mentioned algorithms. Seyedali (2015) proposes a metaheuristic method called ant lion optimization (ALO) to determine the optimum shape for boar propeller by comparing with 7 algorithms, including GA, PSO, BA, states of matter search (SMS), flower pollination algorithm (FPA), cuckoo search (CS) and firefly algorithm (FA). The results found that ALO can design boar propeller shapes better than other methods. However, there are no theoretical to define what the best algorithm should be. It depends on various factors, especially problem characteristics. Among those algorithms, ALO, SOS, PSO and artificial bee colony algorithm (ABC) are collected to apply in this study. Over the last decade, a comparison of metaheuristic algorithm performance is investigated to identify the most suitable algorithms applied to their problem. Gunasekaran and Sonialpriya (2013) test 20 benchmark functions in cloud computing with cuckoo-search (CK), PSO, DE, and ABC. As a result, the CK and DE algorithms deliver more robust than PSO and ABC. Lai et al. (2017) compare the performance of three algorithms: GA, PSO and HS on the learning process of neural networks. All three give similar and comparable performance. Arici and Kaya (2019) compare six algorithms, involving artificial algae algorithm (AAA), gravitational search algorithm (GSA), ABC, DE, GA and PSO to evaluate the performance tested on benchmark functions. They found that AAA provides the most reliable results than others. Meanwhile, Sharma and Saha (2019) introduce a novel butterfly optimization algorithm called modified mutual butterfly optimization algorithm (m-MBOA) to minimize the cost of gear ratio of the gear train compared to Butterfly optimization algorithm (BOA), SOS, DE, PSO and JAYA algorithm. The m-MBOA provide the best solutions than other algorithms. Hu et al. (2019) improve ant lion optimization to minimize the parameter in neural network for predicting the Chinese influenza. The performance of an improved ant lion optimization (IALO) is compared to five algorithms tested on 23 benchmark functions. The comparative results showed that the proposed IALO is better than others. According to above mentioned metaheuristic algorithms, four of them are selected based on the same inspiration type of swarm-base. There are ALO, SOS, PSO and ABC algorithms. The common advantages are simplicity, flexibility, few control parameters and fast convergence, which is great characteristics in solving real-world application problems.

For this study, the novel objective function is introduced to solve the optimal production plan for cashew nuts in Uttaradit, Thailand. Four metaheuristic algorithms, including ALO, SOS, PSO and ABC are investigated for performance comparison. The parameter values of all algorithms will be found the optimal case. The brief description of related theories is explained in section 2. The experimental design and the proposed model are determined in section 3. The results of the optimal production plan are found and discussed in section 4. Finally, the summary of the whole paper is concluded in section 5.

THEORY

Inventory Management

Inventory management is an essential part in financial activities performance for all industries. It has the most valuable physical assets on the balance sheet (Muchaendepi et al., 2019). Inventory management composes of policies about control and monitor inventory levels. It commonly applied to determine what maintained level should be, what large orders are and when replenish stock need to. There are many available mathematical models for calculating the order based on the philosophy of minimizing the total inventory cost. Various costs associated with inventory control are often classified into four types. Firstly, ordering cost, it is an essential cost incurred every time when the order is placed. Secondly, holding cost, it is the cost involved with storing inventory before it is sold. Thirdly, shortage cost, it occurs when business becomes out of stock for whatever reason. Finally, purchase cost, it is the unit cost of an item obtained either from and external source or from the unit replenishment cost of internal production (Onanaye & Oyebode, 2019).

Symbiotic Organisms Search

The symbiotic organisms search (SOS) algorithm is first introduced in 2014 as a new metaheuristic optimization algorithm by Cheng and Prayogo (2014). It is inspired by the symbiotic relationship between two or more biological species. Moreover, the concept of SOS is based on finding the optimum solution by searching suitable subjects to solution a given objective function. There are three fundamental symbiotic relationship types found in nature, including mutualism, commensalism and parasitism. The SOS algorithm has two control parameters, an ecosize (ECS) and maximum function evaluation (MaxFE). The ECS represents the number of organisms in the ecosystem. The MaxFE represents the maximum number of iterations (Ezugwu & Prayogo, 2019).

Mutualism Phase: Main idea of mutualism phase is to find the optimum from the ecosystem. For each organism X_i, an organism X_j is randomly selected from the ecosystem to interact with X_i (where $X_i \neq X_j$) on the basic of establishing a relationship in finding a global optimum solution. The new solutions X_{inew} and X_{jnew} using the expression given in equations (1) and (2). The F_{obj} is an objective function for a minimum value. The MV in the equation (3) indicates the mutual vector represented the relationship characteristic between organism X_i and X_j. BF_1 and BF_2 are the beneficial factors determined randomly as either 1 or 2 using the expression given in equations (4) and (5) (Cheng & Parayogo, 2014).

$$X_{inew} = X_i + rand(0,1) \times (X_{best} - MV \times BF_1), \quad if\ F_{obj}(X_{inew}) < F_{obj}(X_i) \tag{1}$$

$$X_{jnew} = X_j + rand(0,1) \times (X_{best} - MV \times BF_2), \quad if\ F_{obj}(X_{jnew}) < F_{obj}(X_j) \tag{2}$$

$$MV = \frac{X_i + X_j}{2} \tag{3}$$

$$BF_1 = Round\left[rand(0,1)\right] + 1 \tag{4}$$

$$BF_2 = Round\left[rand(0,1)\right] + 1 \tag{5}$$

Commensalism Phase: The basic concept of commensalism phase is one organism participant benefit and other organism participants do not lose benefits. In the commensalism phase, an organism X_j is selected randomly from the ecosystem to interact with the second organism X_i. The new solutions X_{inew} using the expression given in the equation (6) (Cheng & Parayogo, 2014).

$$X_{inew} = X_i + rand(-1,1) \times (X_{best} - X_j), \quad if\ F_{obj}(X_{inew}) < F_{obj}(X_i) \tag{6}$$

Parasitism Phase: The parasitism phase involves an association between two organisms, for which one of the organisms derives all the benefit by harming the partner organism. An example of parasitism is parasites that live in the body, people and animals. Organism X_i creation of an artificial parasite called ‘‘Parasite_Vector’’. Parasite_Vector is created in the search space by duplicating organism X_i, then modifying the randomly selected dimensions using a random number. The organism X_j is selected randomly from the ecosystem and serves as a host to the parasite vector. The new solutions X_{jnew} using the expression given in the equation (7) (Cheng & Parayogo, 2014).

$$X_{jnew} = \begin{cases} X_j, & if\ F_{obj}(Parasite\_Vector) > F_{obj}(X_{jnew}) \\ Parasite\_Vector, & if\ F_{obj}(Parasite\_Vector) \le F_{obj}(X_{jnew}) \end{cases} \tag{7}$$

Ant Lion Optimization

The ant lion optimization (ALO) algorithm is inspired by the idea of the hunting behavior of ant lion in nature which the interaction between predator (ant lion) and prey (ant) by Seyedali (2015). Ants use a stochastic movement to find food locations. This behavior is expressed mathematically by the following equations (Seyedali, 2015).

$$X(t) = [0,\ cumsum(2r(t_1) - 1),\ cumsum(2r(t_2) - 1),\ ...,\ cumsum(2r(t_n) - 1)] \tag{8}$$

Where $X(t)$ is the random walk of ants, $cumsum$ is the cumulative sum, t is the step random walk of ants, n is the maximum iteration (Maxiter), $r(t)$ is a stochastic function the expression given in the equation (9).

$$r(t) = \begin{cases} 1, & if\ rand(0,1) > 0.5 \\ 0, & if\ rand(0,1) \le 0.5 \end{cases} \tag{9}$$

The position of ants is saved and utilized during optimization in the following equation.

$$M_{Ant}^{Position} = \begin{bmatrix} A_{1,1} & A_{1,2} & \cdots & A_{1,d} \\ A_{2,1} & A_{2,1} & \cdots & A_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ A_{n,1} & A_{n,2} & \cdots & A_{n,d} \end{bmatrix} \tag{10}$$

Where $M_{Ant}^{Position}$ is the matrix for saving the position of each ant, $A_{i,j}$ shows the value of the $j-th$ variable (dimension) of $i-th$ ant, n is the number of ants, and d is the number of variables. For evaluating each ant, a fitness function is utilized during optimization and the following matrix stores the fitness value of all ants, the following equation (11)

$$M_{Ant}^{fitness} = \begin{bmatrix} f([A_{1,1}, A_{1,2}, \cdots, A_{1,d}]) \\ f([A_{2,1}, A_{2,2}, \cdots, A_{2,d}]) \\ \vdots \\ f([A_{n,1}, A_{n,2}, \cdots, A_{n,d}]) \end{bmatrix} \tag{11}$$

Where $M_{Ant}^{fitness}$ is the matrix for saving the fitness value of each ant, $A_{i,j}$ shows the value of $j-th$ dimension of $i-th$ ant, and f is then objective function.

The position and fitness of ant lion are represented by the matrices $M_{Antlion}^{Position}$ and $M_{Antlion}^{fitness}$ as follows.

$$M_{Antlion}^{Position} = \begin{bmatrix} AL_{1,1} & AL_{1,2} & \cdots & AL_{1,d} \\ AL_{2,1} & AL_{2,1} & \cdots & AL_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ AL_{n,1} & AL_{n,2} & \cdots & AL_{n,d} \end{bmatrix} \tag{12}$$

Where $M_{Antlion}^{Position}$ is the matrix for the saving the position of each ant lion, $AL_{i,j}$ shows the $j-th$ dimension's value of $i-th$ ant lion, n is the number of ant lion, and d is the number of variables.

$$M_{Antlion}^{fitness} = \begin{bmatrix} f([AL_{1,1}, AL_{1,2}, \cdots, AL_{1,d}]) \\ f([AL_{2,1}, AL_{2,2}, \cdots, AL_{2,d}]) \\ \vdots \\ f([AL_{n,1}, AL_{n,2}, \cdots, AL_{n,d}]) \end{bmatrix} \tag{13}$$

Where $M_{Antlion}^{fitness}$ is the matrix for saving the fitness of each ant lion, $AL_{i,j}$ shows the $j-th$ dimension's value of $i-th$ ant lion, n is the number of ant lion, d is the number of variables, and f is then objective function.

There are six main steps of hunting prey of the ALO algorithm presented in this section (Seyedali, 2015).

Random walk of ants. The position of ant from the equation (8), ants update their positions with random walk at every step of optimization. To restrict the random works inside the search space, which is based on min-max normalization. Position of ants can be updated by the equation (14).

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t \tag{14}$$

Where a_i and b_i are minimum and maximum of a random walk of $i-th$ variable, c_i^t and d_i^t are minimum and maximum of $i-th$ variable at $t-th$ iteration.

Step 2: Building traps. The ALO algorithm requires a roulette wheel operator for selecting ant lion based on their fitness during optimization.

Entrapment of ants in traps. The trap of ant lion will affect the random walk of ants. The mathematical model of this assumption can be written as in equations (15) and (16).

$$c_i^t = Antlion_j^t + c^t \tag{15}$$

$$d_i^t = Antlion_j^t + d^t \tag{16}$$

Where c_i^t and d_i^t are minimum and maximum variable of $i{-}th$ ant at $t{-}th$ iteration, $Antlion_j^t$ is selected the position of $j{-}th$ ant lion at $t{-}th$ iteration, c^t and d^t are minimum and maximum variable of $t{-}th$ iteration.

Sliding ants towards ant lion. The ant lion shoots sands outwards the center of the pit once they realize that an ant is in the trap. This behavior slides down the trapped ant that is trying to escape. The mechanism mathematical model can be expressed as follows.

$$c^t = \frac{c^t}{I} \tag{17}$$

$$d^t = \frac{d^t}{I} \tag{18}$$

$$I = \begin{cases} 1 & if\ t \le 0.1T \\ 1 + 10^w \dfrac{t}{T} & \text{otherwise} \end{cases} \tag{19}$$

$$w = \begin{cases} 2 & if\ t > 0.1T \\ 3 & if\ t > 0.5T \\ 4 & if\ t > 0.75T \\ 5 & if\ t > 0.9T \\ 6 & if\ t > 0.95T \end{cases} \tag{20}$$

Where I is the ratio, t is the current iteration, and T is the maximum number of iterations.

Catching preys and rebuilding traps. After the ant lion has captured the ant, an ant lion is then required to update its position to the latest position of the hunted ant to enhance its chance of catching new prey. This behavior is expressed mathematically by the equation (21).

$$Antlion_j^t = Ant_i^t \quad if\ f(Ant_i^t) > f(Antlion_j^t) \tag{21}$$

Where $Antlion_j^t$ is selected the position of $j{-}th$ ant lion at $t{-}th$ iteration, and Ant_i^t is the position of $i{-}th$ ant at $t{-}th$ iteration.

Elitism. Elitism is an important characteristic of evolutionary algorithms to maintain the best solution to the optimization process next round. The mathematical model of this assumption is shown in the equation (22).

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{22}$$

Where R_A^t is a random walk around the ant lion chosen by the roulette wheel at $t-th$ iteration, R_E^t is a random walk around the elitism at $t-th$ iteration, and Ant_i^t is a position of $i-th$ ant at $t-th$ iteration.

Particle Swarm Optimization

Particle swarm optimization (PSO), is invented for solving the non-linear optimization proposed by Kennedy and Eberhart (1995). The idea of PSO is based on the foraging of bird flock behavior to find the optimized solution area. Each of the birds in the flock is represented with the particle. In each particle, the fitness value implies the distance between the particle and food source as having the best fitness value in each interval the fitness value of the particle which be found by the equation (23)

$$f(x_1, x_2, x_3, \ldots x_n) = f(x) \tag{23}$$

In defining the particle, x_i is the defined fitness function. Accordingly, PSO begins with randomizing a set of particle positions, then optimizing by adjusting the parameters in each decision cycle. Each particle keeps their best position value, $P_{best,i}$ during that interval, including the whole particle best position data, in every process interval t, and the movement speed would be adjusted by using $P_{best,i}$ and G_{best}, which can be demonstrated by the equation (24) at the next time step, $t+1$, where $t \in [0, \ldots, N]$ and can be calculated by equation (25) at time step t, respectively (Talukder, 2011).

$$P_{best,i}^{t+1} = \begin{cases} P_{best,i}^{t+1} & if \;\; f(x_t^{t+1}) > P_{best,i}^t \\ x_i^{t+1} & if \;\; f(x_t^{t+1}) \le P_{best,i}^t \end{cases} \tag{24}$$

$$G_{best} = \min\left\{P_{best,i}^{t+1}\right\}, \; where \; i \in \left[1, \ldots, n\right] \; and \;\; n > 1 \tag{25}$$

Where $P_{best,i}$ is the best position that the individual particle, i has visited since the first time step, G_{best} is the best position discovered by any particles in the entire swarm. In this method, each individual particle, $i \in \left[1, \ldots, n\right]$, where $n > 1$, has been calculated in the search space x_i. The new velocity is calculated as in the equation (26).

$$v_{ij}^{t+1} = \omega v_{ij}^t + c_1 r_{1j}^t [P_{best,i}^t - x_{ij}^t] + c_2 r_{2j}^t [G_{best} - x_{ij}^t] \tag{26}$$

Where v_{ij}^t is the velocity of the particle i in the dimension j of time t, ω is an inertia weight, x_{ij}^t is a position, $P_{best,i}^t$ is the best position of a particle of time t, G_{best} is the best position of the whole particle system, c_1 and c_2 are the constant accelerations in searching, and r_{1j}^t and r_{2j}^t are the random numbers between 0 and 1 at time t.

Artificial Bee Colony

The artificial bee colony algorithm (ABC), proposed by Karaboga (2005), is a swarm-based optimization technique mimicking the behavior of honey bees when seeking food sources near their hives. In ABC, the position of a food source represents a solution to the considered problem while the nectar amount corresponds to its fitness. According to different responsibilities, bees in the colony are classified into three kinds of employed bees, onlookers and scouts. The algorithm is designed based on above three types of bees with different activities and the main steps are depicted below (Karaboga, 2005; Meng et al., 2018).

Step 1: Initialize parameters, the number of food sources (PS) and the number of trials that a food source will be abandoned if no improvement are observed (limit).

Step 2: Generate PS food sources randomly and allocate each of them to a different employed bee. This implies that, we also have PS employed bees in the algorithm.

Step 3: Behavior of employed bees. Every employed bee needs to find a new food source in the vicinity of the current one, followed by a greedy selection where the new candidate will substitute the incumbent if it is preferable.

Behavior of onlookers. The ABC algorithm supposes there are also PS onlooker bees in the swarm. Each onlooker evaluates the quality of food sources current and selects one source depending on its probability P_i calculated as equation below, where fit_i denotes its fitness value.

$$P_i = \frac{fit_i}{\sum_{i=1}^{PS} fit_i} \tag{27}$$

Thereafter, the onlooker will explore near the chosen food source acting like an employed bee described in step 3.

Step 5: Behavior of scouts: If a food source cannot be improved after a pre-defined trial limit, it is abandoned and its corresponding employed bee becomes a scout bee and searches a new source randomly to replace it.

Step 6: Repeat step 3 to step 5 until the stopping condition is met.

Performance Evaluation

In order to verify the accuracy of metaheuristic algorithms, two measurements are performed: root mean square error (RMSE) and mean absolute percentage error (MAPE). They are commonly used to describe how accurate the algorithm is. The RMSE and MAPE are defined as follows (Botchkarev, 2019).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2} \tag{28}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|A_i - P_i\right|}{\left|A_i\right|} \tag{29}$$

Where A_i is the actual value, P_i is the prediction value, and N is the total number of input data.

DATA AND METHOD

The Cashew Nuts Production Process

In order to transform raw cashew nuts into finished products, there are six stages, including drying, pre-treatment, de-shelling, peeling, grading and packaging. The normally six stages in cashew nuts processing in Uttaradit are as follows (Weidinger, 2019).

Stage 1: Dry the raw cashew nuts on the field.
Stage 2: Pre-treat of raw cashew nuts in which the process of warehousing, calibration and heat treatment.
Stage 3: De-shell humidification of kernels in the oven drying.
Stage 4: Peel the outer seed coat from the cashew kernel.
Stage 5: Grade the kernels into different quality grades.
Stage 6: Package the kernels for storage and shipment.

Data

Data used in this study are from the community enterprise in Tha Pla district, Uttaradit, Thailand. Tha pla district is located in the north of Thailand. The way to access the data is rather difficult. Moreover, the enterprise records the data manually over decade caused missing data. It consists of demand, production quantity, production cost and holding cost. When data are accessed, it is necessary to record again on computer by authors and uses long time to finish them. Therefore, experimental data are collected of three months from January to March in 2019. Data description is illustrated in Table 1.

Table 1. *The production quantity and the demand of cashew nuts in Uttaradit from January to March in 2019*

Time	JAN		FEB		MAR	
	Production quantity (Kg)	Demand (Kg)	Production quantity (Kg)	Demand (Kg)	Production quantity (Kg)	Demand (Kg)
1	276	249	282	83	282	426
2	276	98	276	192	276	81
3	282	110	276	165	276	46
4	276	51	276	224	282	84
5	276	256	282	26	276	216
6	276	128	276	68	276	68
7	282	111	276	369	282	345
8	276	295	276	24	276	444
9	276	38	282	98	276	194
10	282	195	276	96	276	274

Table 1 continued on next page

Table 1 continued

Time	JAN		FEB		MAR	
	Production quantity (Kg)	Demand (Kg)	Production quantity (Kg)	Demand (Kg)	Production quantity (Kg)	Demand (Kg)
11	276	30	276	149	282	77
12	276	328	282	61	-	-
13	282	70	-	-	-	-
14	276	12	-	-	-	-
15	276	48	-	-	-	-
Total	3,888	2,019	3,336	1,555	3,060	2,255

From Table 1, the total frequency of the production process is 15, 12 and 11 times in January, February and March, respectively. It can be seen that the relationship between the production quantity and the demand is not balanced. This reason may cause excess inventory influenced the expensive cost. Thus, this study aims to plan the production for cashew nuts and to find the most suitable method.

Experimental Setup

In Uttaradit, two main inventory costs for the cashew nuts production plan are the production cost and the holding cost. The production cost and the holding cost per period of time are 14,420 baht and 0.17 baht per kg, respectively. In order to find the optimal solutions, the ALO, SOS, PSO and ABC algorithms are applied. Five different cases of ECS for SOS, number of search agents (NSA) for ALO, population size (nPop) for PSO and the number of employed bees (BN) for ABC varied from 10 to 50 are determined. The number of MaxFE for SOS and Maxiter for ALO, PSO and ABC are set as the same value (Dinakara et al., 2018; Majhi & Biswal, 2018). The parameters setting is shown in Table 2. Figure 1 shows the diagram of ALO, SOS, PSO and ABC for cashew nuts production plans.

Table 2. *Parameters setting of the ALO, SOS, PSO and ABC algorithms*

ALO	SOS	PSO	ABC
NSA = 10, 20, 30, 40,50	ECS = 10, 20, 30, 40,50	nPop = 10, 20, 30, 40,50	BN = 10, 20, 30, 40,50
Maxiter = 500, 1000, 1500	MaxFE = 500, 1000, 1500	Maxiter = 500, 1000, 1500	Maxiter = 500, 1000, 1500

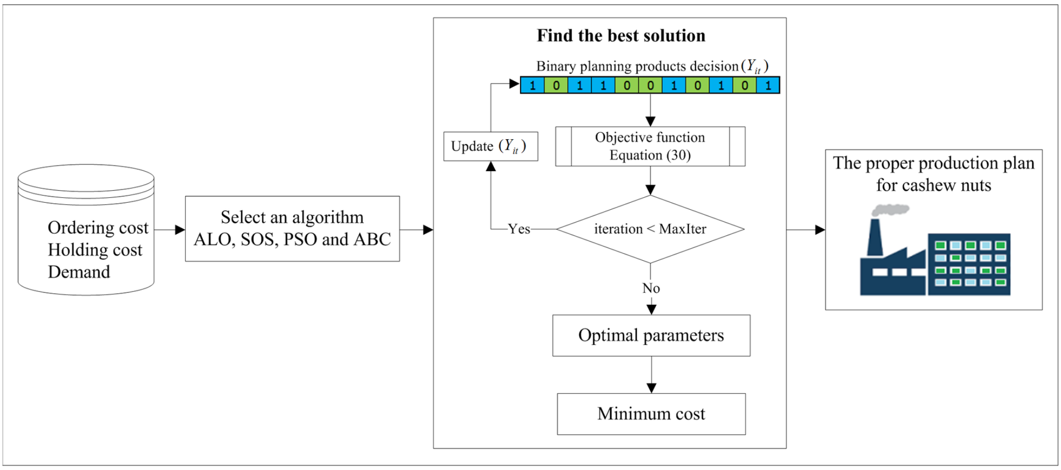
Mathematical Model for Cashew Nuts Production Plan

The novel objective function based on the total production setup costs and holding costs has been introduced as in equation (30).

Objective function

$$MinCost = \sum_{i=1}^{m} \sum_{t=1}^{n} (S_{it} Y_{it} + h_{it} I_{it}) \tag{30}$$

Figure 1. *The diagram of the cashew nuts production plan using ALO and SOS algorithms*



Constraints

$$I_{it} = I_{it-1} + X_{it} - D_{it} \qquad \forall t > 1 \tag{31}$$

$$X_{it} - MY_{it} \leq 0 \qquad \forall t > 1 \tag{32}$$

$$I_{it} \geq 0 \qquad \forall t > 1 \tag{33}$$

$$X_{it} \geq 0 \qquad \forall t > 1 \tag{34}$$

From the equation (30), the summation of total production setup costs, $S_{it}Y_{it}$, and holding costs, $h_{it}I_{it}$, of all periods in the whole planning horizon are minimized, where m represents the number of months, n represents the number of periods, t is the index of period, i is the index of month, h_{it} represents the unit holding cost at month i and period t, I_{it} represents the inventory level at the end of month i and period t, X_{it} represents the number of production quantity of month i and period t, S_{it} represents the setup cost occurred in month i and period t, and Y_{it} is binary decision variables indicating a production is setup in month i and period t.

Table 3. The optimal parameters of ALO algorithm

Maxiter	NSA	Minimum cost of JAN (THB.)	Minimum cost of FEB (THB.)	Minimum cost of MAR (THB.)
500	10	72,375.06	72,427.25	86,725.87
	20	86,656.85	57,940.44	86,738.28
	30	86,656.85	57,940.44	86,725.87
	40	86,656.85	57,940.44	86,738.28
	50	86,675.72	57,940.44	86,738.28
1000	10	86,741.00	72,286.83	86,771.77
	20	86,688.64	72,286.83	86,725.87
	30	72,375.06	57,940.44	86,725.87
	40	86,685.58	57,940.44	86,725.87
	50	72,375.06	72,288.87	86,738.28
1500	10	86,729.61	72,318.96	86,725.87
	20	86,656.85	57,940.44	86,725.87
	30	72,349.73	57,942.48	86,771.77
	40	86,656.85	57,942.48	86,725.87
	50	72,349.73	72,318.45	86,725.87

RESULTS AND DISCUSSION

The Optimal Parameter

For ALO, SOS, PSO and ABC algorithms, there are no theoretical in determining effected parameters. According to Table 2, parameter values for each algorithm are applied. The minimum cost of all algorithms can be computed as in Table 3, Table 4, Table 5 and Table 6, respectively.

Table 4. The optimal parameters of SOS algorithm

MaxFE	ECS	Minimum cost of JAN (THB.)	Minimum cost of FEB (THB.)	Minimum cost of MAR (THB.)
500	10	86,729.61	57,942.48	86,725.87
	20	86,656.85	57,940.44	86,725.87
	30	86,675.72	57,940.44	86,725.87
	40	72,349.73	72,306.21	86,725.87
	50	72,349.73	57,940.44	86,738.28
1000	10	86,688.64	57,942.48	86,725.87
	20	72,375.06	57,940.44	86,725.87
	30	86,688.47	57,940.44	86,725.87
	40	72,349.73	57,942.48	86,725.87
	50	72,349.73	72,286.83	86,738.28

Table 4 continued on next page

Table 4 continued

MaxFE	ECS	Minimum cost of JAN (THB.)	Minimum cost of FEB (THB.)	Minimum cost of MAR (THB.)
1500	10	72,349.73	57,940.44	86,738.28
	20	86,656.85	57,940.44	86,725.87
	30	72,349.73	57,940.44	86,725.87
	40	72,349.73	57,940.44	86,725.87
	50	72,349.73	57,940.44	86,725.87

Table 5. The optimal parameters of PSO algorithm

Maxiter	nPop	Minimum cost of JAN (THB.)	Minimum cost of FEB (THB.)	Minimum cost of MAR (THB.)
500	10	101,085.18	72,288.87	86,738.28
	20	72,349.73	57,942.48	86,725.87
	30	86,686.43	57,940.44	86,725.87
	40	86,656.85	57,940.44	86,725.87
	50	86,656.85	57,940.44	86,725.87
1000	10	101,056.45	72,308.25	86,759.36
	20	86,656.85	57,940.44	86,738.28
	30	86,667.56	72,286.83	86,725.87
	40	86,656.85	57,942.48	86,725.87
	50	86,656.85	57,942.48	86,725.87
1500	10	86,740.32	72,286.83	86,725.87
	20	86,667.56	72,288.87	86,738.28
	30	86,656.85	72,286.83	86,725.87
	40	86,656.85	72,318.96	86,725.87
	50	86,729.61	57,940.44	86,725.87

Table 6. The optimal parameters of ABC algorithm

Maxiter	BN	Minimum cost of JAN (THB.)	Minimum cost of FEB (THB.)	Minimum cost of MAR (THB.)
500	10	86,776.02	57,942.48	86,759.36
	20	72,349.73	72,305.87	86,759.36

As seen in Table 3, the minimum costs of January, February and March are 72,349.73, 57,940.44 and 86,725.87, respectively. For January, the optimal value of Maxiter is 1500 iterations and the optimal NSA can be 30 and 50. For February, all cases of Maxiter can provide a minimum cost with different NSA values, the case of 500 iterations with NSA 20, 30, 40 and 50, the case of 1000 iterations with NSA 30 and 40 and the case of 1500 iterations with NSA 20. In March, the case of Maxiter = 500, NSA = 10, 30, the case of Maxiter 1000 with NSA 20, 30 and 40 and the case of Maxiter 1500 iterations with NSA 10, 20, 40 and 50 are performed the optimal parameters.

Simultaneously, for SOS algorithm, there are many optimal parameters. For January, all cases of MaxFE can provide a minimum cost with different ECS values, the case of 500 iterations with ECS 40 and 50, the case of 1000 iterations with ECS 40 and 50 and the case of 1500 iterations with ECS 10, 30, 40 and 50. In February, the case of 500 iterations with ECS 20, 30 and 50, the case of 1000 iterations with ECS 20 and 30 and the case of 1500 iterations. In March, the case of MaxFE = 500, ECS = 10, 20, 30, 40, the case of 1000 iterations with ECS 10, 20, 30 and 40 and the case of 1500 iterations with ECS 20, 30, 40 and 50 are performed the optimal parameters.

Likewise, for PSO algorithm, only one experiment case with 500 iterations and nPop = 20 provides the optimal parameter on January. In February, three cases of nPop 30, 40 and 50 with 500 iterations, the case of 1000 iterations with nPop 20 and the case of 1500 iterations with nPop 50 are the optimal parameters. In March, many experiment cases perform the optimal parameter.

For ABC algorithm, the optimal case in January are the case of 500 iterations with BN 20 and 40. Moreover, there are six optimal cases in February and seven cases in March.

Table 7. The optimal parameter of ALO algorithm

Month	Minimum cost (THB.)	Maxiter	NSA	RMSE
JAN	72,349.73	1500	30	2,259.89
			50	4,653.79
FEB	57,940.44	500	20	1,438.85
			30	1,822.09
			40	644.04
			50	1,575.86
		1000	30	2,141.99
			40	0.0913
		1500	20	2,133.03
MAR	86,725.87	500	10	3,340.42
			30	5.49
		1000	20	2,766.23
			30	2.57
			40	2,312.58
		1500	10	7,464.84
			20	371.25
			40	639.49
			50	368.7060

It is obviously that four algorithms have sufficient ability to compute the minimum cost. However, there are various cases of the optimal parameter. It is difficult to identify what the best algorithm should be. The RMSE value is then applied to select the most suitable case as shown in the following Tables.

Table 8. The optimal parameter of SOS algorithm

Month	Minimum cost (THB.)	MaxFE	ECS	RMSE
JAN	72,349.73	500	40	12,851.77
			50	12,420.77
		1000	40	11,159.01
			50	14,971.70
		1500	10	15,429.41
			30	6,283.85
			40	8,472.34
			50	8,927.80
FEB	57,940.44	500	20	4,708.59
			30	12,270.61
			50	6,637.86
		1000	20	5,538.90
			30	4,702.42
		1500	10	11,732.44
			20	8,407.58
			30	8,609.89
			40	1,901.20
			50	7,890.52
MAR	86,725.87	500	10	4,700.38
			20	9,755.19
			30	10.28
			40	12.13
		1000	10	5,851.85
			20	4,944.62
			30	10,579.15
			40	4,363.21
		1500	20	3,029.31
			30	5,631.95
			40	6,434.53
			50	6,069.44

Table 9. The optimal parameter of PSO algorithm

Month	Minimum cost (THB.)	Maxiter	nPop	RMSE
JAN	72,349.73	500	20	6,780.15
FEB	57,940.44	500	30	1,926.65
			40	642.08
			50	908.37
		1000	20	1,574.07
		1500	50	525.53
MAR	86,725.87	500	20	1,105.75
			30	2,018.81
			40	642.81
			50	902.84
		1000	30	640.95
			40	453.16
			50	453.77
		1500	10	524.85
			30	1,692.25
			40	371.98
			50	369.80

Table 10. The optimal parameter of ABC algorithm

Month	Minimum cost (THB.)	Maxiter	BN	RMSE
JAN	72,349.73	500	20	2,806.86
			40	4,343.11
		1000	10	3,404.80
			40	2,868.33
		1500	10	4,398.77
			20	2,373.99
FEB	57,940.44	500	30	1,927.20
			40	1,285.18
		1000	30	2,270.54
			50	1,116.21
		1500	20	829.78
			30	980.55

Table 10 continued on next page

Table 10 continued

Month	Minimum cost (THB.)	Maxiter	BN	RMSE
MAR	86,725.87	500	30	907.96
			40	1,108.85
			50	907.74
		1000	30	1,111.01
			40	3.67
		1500	20	638.40
			30	526.07

The most suitable case is selected based on the lowest RMSE value. From Table 7, the optimal parameter of the ALO algorithm on January is the case of 1500 iterations with NSA = 30. The optimal parameter on February is the case of 1000 iterations with NSA = 40. In March, the optimal parameter is the case of 1000 iterations with NSA = 30. According to Table 8, the optimal parameter of the SOS algorithm on January is the case of 1500 iterations with ECS = 30. The optimal parameter on February is the case of 1500 iterations with ECS = 40. In March, the optimal parameter is the case of 500 iterations with ECS = 30.

As shown in Table 9, the optimal parameter of PSO algorithm on January is the case of 500 iterations with nPop = 20. The optimal parameter on February is the case of 1500 iterations with nPop = 50. In March, the optimal parameter is the case of 1500 iterations with nPop = 50.

From Table 10, the optimal parameter of the ABC algorithm on January is the case of 1500 iterations with BN = 20. The optimal parameter on February is the case of 1500 iterations with BN = 20. In March, the optimal parameter is the case of 1000 iterations with BN = 40.

The simulation results of ALO, SOS, PSO and ABC algorithms for cashew nuts production plan with optimal parameter between January and March are indicated in Table 11.

Table 11. The production plan for cashew nuts using ALO, SOS, PSO and ABC algorithms

Month	Minimum cost (THB.)		Time(t)														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
JAN	72,349.73	D	249	98	110	51	256	128	111	295	38	195	30	328	70	12	48
		Y	1	0	0	1	0	0	1	0	0	1	0	1	0	0	0
		X	457	0	0	435	0	0	444	0	0	225	0	458	0	0	0
		I	208	110	0	384	128	0	333	38	0	30	0	130	60	48	0
FEB	57,940.44	D	83	192	165	224	26	68	369	24	98	96	149	61	123	-	-
		Y	1	0	1	0	0	0	1	0	0	1	0	0	0	-	-
		X	275	0	483	0	0	0	491	0	0	429	0	0	0	-	-
		I	192	0	318	94	68	0	122	98	0	333	184	123	0	-	-

Table 11 continued on next page

Table 11 continued

Month	Minimum cost (THB.)		Time(t)														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
MAR	86,725.87	*D*	426	81	46	84	216	68	345	444	194	274	77	-	-	-	-
		Y	1	1	0	0	0	0	1	1	1	1	0	-	-	-	-
		X	426	495	0	0	0	0	345	444	194	351	0	-	-	-	-
		I	0	414	368	284	68	0	0	0	0	77	0	-	-	-	-

According to Table 11, the production quantity derived from ALO, SOS, PSO and ABC algorithms with their optimal parameters provides the same results under the minimum cost condition. The result has not exceeded the performance in producing cashew nuts. Nevertheless, the traditional frequency of production plan for cashew nuts from January to March are 15, 13 and 11, respectively. This study can reduce the frequency of production plan to 5, 4 and 6 times.

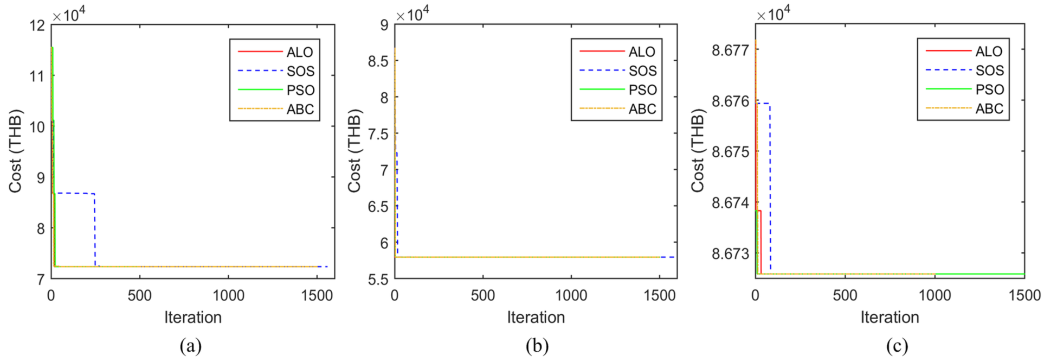
The Performance of Cost Reduction

The performances in cost reduction reached by ALO, SOS, PSO and ABC are compared to the total cost of local production plant as in Table 12. Four algorithms can attain the suitable scale of production proficiently impacted the cost reduction about 66.95% for January, 69.45% for February and 45.64% for March, respectively. However, by investigating RMSE value, ALO algorithm is superior to others as illustrated in Table 12.

Table 12. The comparison between the performances of cost reduction

Month	Algorithms	Minimum cost (THB.)	Discount (%)	RMSE	MAPE
JAN	Traditional	218,938.74	-	-	
	SOS	72,349.73	66.95	6,283.85	2.7679
	ALO	72,349.73	66.95	2,259.89	0.2324
	PSO	72,349.73	66.95	6,780.15	1.2133
	ABC	72,349.73	66.95	2,373.99	0.2055
FEB	Traditional	189,632.77	-	-	
	SOS	57,940.44	69.45	1,901.20	0.2322
	ALO	57,940.44	69.45	0.0913	0.000007
	PSO	57,940.44	69.45	525.53	0.0265
	ABC	57,940.44	69.45	829.78	0.0354
MAR	Traditional	159,545.48	-	-	
	SOS	86,725.87	45.64	12.13	0.0051
	ALO	86,725.87	45.64	2.57	0.0005
	PSO	86,725.87	45.64	369.8	0.0095
	ABC	86,725.87	45.64	3.67	0.00044

Figure 2. *The comparison performance between ALO, SOS, PSO and ABC algorithms (a) January (b) February (c) March*



From Figure 2, it can be seen that the production cost remains the same within the range of iteration 500 onward while ALO uses shortest time to access the optimal results. It is therefore suggested that ALO can be the best algorithm applied to this study.

CONCLUSION

In this study, the novel objective function is constructed to find the optimal production plan for cashew nuts processing in Uttaradit, Thailand. Four metaheuristic optimization methods, including ALO, SOS, PSO and ABC algorithms are investigated and compared the performance. The data used in this study consist of the production cost, holding cost, the frequency of production and the inventory number. It covers three months in 2019 from January to March. As a result, all algorithms establish the same results by reducing the production cost from January to March about 66.95%, 69.45% and 45.64%, respectively. It shows that the production cost has lower than the cost before using four algorithms for 60.67% per month. Therefore, ALO, SOS, PSO and ABC algorithms are capable to find the optimal production plan for cashew nuts in Uttaradit, Thailand. However, the ALO algorithm gives the smaller RMES than others. It can be summarized that ALO is the most suitable method applied to this study. For future study, different data, such as the demand of product are investigated to find the optimal case for cashew nuts.

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