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The Hybrid Ant Lion and Grey Wolf Algorithm (HALGW) for Cashew Nuts Production Plan with Split Demand

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Abstract
The novel concept of split demand is introduced based on the dynamic single-level lot-sizing (DSLLS), called the DSLLS-split demand model. The hybrid algorithm based on the combination between Ant Lion Optimization (ALO) and Gray Wolf Optimization (GWO), called the HALGW algorithm is proposed in this study. The suitable cashew nut production planning is examined with the DSLLS-split demand model and the HALGW algorithm. Four monthly datasets including demand, production quantity, production cost and holding cost are collected from January 2020 to December 2020. Two main concepts with split demand and without split demand are compared with three different algorithms: ALO, GWO and HALGW. The results found that the HALGW algorithm with the concept of split demand provides the minimum cost, 507,910.11 baht with lowest RMSE value, 106.08 and lowest MAPE value, 0.0000115. Hence, this method may help the community enterprise in Tha Pla, Uttaradit, Thailand to manage their processes, efficiently.

Keywords
Split Demand, Hybrid Ant lion-Gray wolf, Lot Sizing Problem, Cashew Nuts, Production Plan.

Introduction

A cashew nut product is a main industrial drop of Tha Pla district, Uttaradit, Thailand for local consumption and global exportation. The community enterprise in Tha Pla has many orders a month. The production order is prepared from their expertise. It causes overstate inventory and high cost. Over the years, one hundred twenty-one times is the frequency of the production process in this enterprise. It is discovered that product quantity and demand are unbalanced. Therefore, the proper plan of cashew nut process may help the enterprise manage their production number, inventory and also cost of the product.

To find the suitable production planning, there are four important factors. Firstly, ordering cost, the essential cost incurs when the order is placed. Secondly, holding cost, the cost involves storing inventory before selling the product. Thirdly, shortage cost, the cost occurs when there is no stock. Finally, purchase cost, the unit cost of an item obtained either from external source or the unit replenishment cost of internal production (Onanaye & Oyebode, 2019; Luis et al., 2014). In recent years, a lot of research investigate the production plan and lot sizing problem though various methods. One of the most popular methods is metaheuristic algorithm. Wei et al. (2019) scheduled circuit board assembly production using two-stage ant colony algorithm with lot sizes (TSACAWLS). In terms of stability, computation time and output volume, the findings demonstrated that two-stage ant colony algorithm gives a better solution than others. Chung-Yuan Dye and Liang-Yuh Ouyang (2011) examined a retailer's optimal pricing and lot sizing problem for degrading products with variable demand under trade credit financing using particle swarm optimization (PSO). Duong et al. (2021) applied a metaheuristic algorithm to solve the optimal power flow problem. They found that the standard deviation of 50 independent runs of the suggested artificial ecosystem optimization (AEO) algorithm is better than equilibrium optimizer (EO), PSO, sunflower optimization (SFO) and genetic algorithm (GA) methods. In the domain of robust optimization, Ozmen et al. (2011) introduced RCMARS,

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an extension of the Conic Multivariate Adaptive Regression Splines (CMARS) method, designed to handle data uncertainty in regression models. They incorporated robust optimization techniques to mitigate the sensitivity of CMARS. The results showed that the solutions are sensitive to the limits of confidence intervals. [6] Kuter (2021) examined the suitability of machine learning algorithms such as Random Forests (RF) and Support Vector Regression (SVR) for estimating fractional snow cover (FSC) from MODIS Terra reflectance data compared to Artificial Neural Networks (ANNs) and Multivariate Adaptive Regression Splines (MARS). The results showed that all models achieved high consistency with reference FSC values and normalized difference snow index (NDSI) and normalized difference vegetation index (NDVI) had a minimal impact on improving accuracy. Maity et al. (2016) analyzed a Multi-Objective Transportation Problem (MOTP) under uncertain environments by incorporating the cost of reliability and fuzzy multi-choice goals. The results demonstrated that addressing uncertainties in supply, demand and transportation costs through reliability concepts and fuzzy multi-choice goal programming can lead to more effective and realistic solutions for complex transportation problems.

Furthermore, the hybrid metaheuristic algorithm became the suggestive method for solving production planning process and lot sizing problem. Khalilpourazari and Pasandideh (2019) presented a novel mathematical model for the Economic Order Quantity (EOQ) problem include of considerations for multiple items and operational constraints. The results showed that the hybrid algorithm handles the complexities and constraints, effectively. Mohammad Reza (2008) presented a hybrid intelligent system based on a fuzzy neural network and GA to estimate the demand rate, define material planning and choose the ideal provider. The results provided that the model can improved demand forecasting and reduced costs in the case study by 4%. EL-Sayed et al. (2020) introduced a hybrid technique between Gray Wolf Optimization and Particle Swarm Optimization called GWOPSO for feature selection problem of twelve datasets. The results found that the hybrid GWOPSO achieves data compactness and also find the best subset of features in different datasets. Bo Yang and Zihui Liu (2020) combined the Improved Gray Wolf Optimizer (IGWO) and Adaptive Neuro-Fuzzy Inference System (ANFIS) to conduct the selection of temperature-sensitivity points in improving the processing efficiency of gear production. The results discovered that the combined IGWO-ANFIS generalization performance is superior to others. Narinder Singh and S.B. Singh (2017a) enhanced the exploitation capability of Particle Swarm Optimization with the exploring capability of the Grey Wolf. The results demonstrated that the combination of the PSO and GWO variant in terms of solution quality, solution stability, convergence time and capacity to locate the global optimum. Chengzhi et al. (2020) employed a unique hybrid method referred to as HSGWO-MSOS for unmanned aerial vehicle (UAV) path planning, compared to the GWO, Symbiotic Organisms Search (SOS) and SA algorithms. As a result, the HSGWO-MSOS algorithm can acquire a viable and efficient path with more success. Narinder Singh and S.B. Singh (2017a) presented the hybrid GWO-SCA technique for optimization issues. The findings showed that the hybrid variant provided is extremely successful in tackling benchmark and real-life applications with or without confined and unknown search regions. Phromfaiy et al. (2022) introduce a new objective function by using Ant Lion Optimization (ALO), SOS, PSO and Artificial Bee Colony algorithm (ABC). The results found that the ALO algorithm delivers higher forecasting skills than others with the lowest RMSE value of 0.0913.

As mentioned previously, this study aims to develop the previous work of the authors (Phromfaiy et al., 2022) by introducing a novel concept of split demand and combining two metaheuristic algorithms between ALO and GWO to find the optimum production plan for cashew nuts. The literature review is briefly described in Section 2. In Section 3, the schematic and methods of the proposed model are detailed. Section 4 reveals and discusses the ideal production plan results. Section 5 concludes the outline of this investigation.

Literature review

Lot size problem

Lot sizing is one of the most important issues in manufacturing production plan. Karimi et al. (2003) categorize lot sizing into single or multi-level, capacitated or incapable and dynamic or stagnant. The dynamic single-level lot-sizing (DSLLS) problem is the primary form of several lot-sizing variants. The fundamental concept can be expressed mathematically as the following optimization model (Xiao et al., 2018).

$$\text{minimize} \sum_{t=1}^{T} (SY_t + hI_t)$$

$$I_t = I_{t-1} + X_t - D_t \qquad \forall_t \qquad (1)$$

$$X_t - MY_t \le 0 \qquad \forall_t \qquad (2)$$

$$I_t \ge 0 \qquad \forall_t \qquad (3)$$

$$X_t \ge 0 \qquad \forall_t \qquad (4)$$

With:
- S: Setup cost
- Y: Binary decision variables
- h: Holding cost
- I: Inventory level
- X: Production quantity
- D: Number of demands
- t: Period index

Ant lion optimization (ALO)

The ALO algorithm is inspired by the hunting behavior of ant lions in nature, in which the interaction between predator (ant lions) and prey (ant). To find food, ants utilize a stochastic movement. According to the ALO algorithm, there are six primary processes to hunting prey (Mohammad et al., 2008; Mirjalili, 2015).

- Random walk of ants: The positions of the ants are updated at each stage of the optimization procedure using a random walk. The position of ants can be updated by (5).

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t \tag{5}$$

With:
- a_i: Minimum of a random walk of i^{th}
- b_i: Maximum of a random walk of i^{th}
- c_i^t: Minimum of i^{th} variable at t^{th} iteration
- d_i^t: Maximum of i^{th} variable at t^{th} iteration

- Building traps: A roulette wheel is utilized to represent the hunting abilities of ant lions. During optimization, the ALO algorithm utilizes a roulette wheel operator to choose ant lions depending on their fitness value.
- Entrapment of ants in traps: As stated previously, the ant lion trap will influence the ants random walking. The entrapment of ants in the ant lion trenches may be expressed mathematically as follows.

$$c_i^t = Antlion_j^t + c^t \tag{6}$$

$$d_i^t = Antlion_j^t + d^t \tag{7}$$

- Sliding ants towards the ant lion: The ant lion shoots sand outwards from the middle of the pit when it detects an insect within the trap. This behavior hinders the escape attempt of a trapped ant. This mechanism mathematically modelled as follows.

$$c^t = \frac{c^t}{I} \tag{8}$$

$$d^t = \frac{d^t}{I} \tag{9}$$

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

With:
- I: Ratio
- t: Current iteration
- T: Maximum number of iterations
- w: Constant defined based on the current iteration

- Catching preys and rebuilding traps: Ant lions need to update their position to the most recent location of their prey in order to increase their chances of capturing further prey. This tendency is mathematically described by (11).

$$Antlion_j^t = Ant_i^t \text{ if } f(Ant_i^t) > f(Antlion_j^t) \tag{11}$$

With:
- $Antlion_j^t$: Position of selected j^{th} ant lion at t^{th} iteration
- Ant_i^t: Position of i^{th} ant at t^{th} iteration

- Elitism: The best solution to the optimization process next round can computed as following (12).

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{12}$$

With:
- R_A^t: Random walk around the ant lion selected at t^{th} iteration using a roulette wheel
- R_E^t: Random walk around the elitism at t^{th} iteration
- Ant_i^t: Position of i^{th} ant at t^{th} iteration

Grey wolf optimization (GWO)

The hunting behavior and social structure of grey wolves inspired the creation of the grey wolf optimizer, often known as the GWO algorithm. In the mathematical model (Mirjalili et al., 2014; Zheng-Ming & Juan, 2019; Avelina et al., 2020), the GWO algorithm for hunting prey consists of four primary phases.

- Encircling prey: Grey wolves hunting strategy encircle the prey before hunting as in following equations (13) and (14).

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{13}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{14}$$

With:

$\vec{a}$: Progressively decreasing from 2 to 0 throughout iterations

$\vec{r}_1$: Random vectors in [0, 1]

$\vec{r}_2$: Random vectors in [0, 1]

- Hunting: The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. The first three best solutions will update their positions according to the best search agents as follows.

$$\begin{aligned} \vec{D}_\alpha &= \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|, \\ \vec{D}_\beta &= \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|, \\ \vec{D}_\delta &= \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \end{aligned} \tag{15}$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{aligned} \tag{16}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{17}$$

With:

$\vec{C}_1$: Coefficient vectors of the alpha wolves

$\vec{C}_2$: Coefficient vectors of the beta wolves

$\vec{C}_3$: Coefficient vectors of the delta wolves

$\vec{X}_1$: Position vectors of the alpha wolves

$\vec{X}_2$: Position vectors of the beta wolves

$\vec{X}_3$: Position vectors of the delta wolves

- Attacking prey: The grey wolves finish the hunt when it stops moving.
- Search for Prey: The search is conducted according to the positions of the alpha, beta and delta. The wolves separate in order to look for prey and then reunite in order to attack it. This process provides an opportunity to explore and find a global solution.

Performance evaluation

The accuracy of the HALGW algorithm is measured by RMSE and MAPE. The RMSE and MAPE can be defined as follows (Botchkarev, 2019).

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2} \tag{18}$$

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\frac{|A_i - P_i|}{|A_i|} \tag{19}$$

With:

A_i: Actual values

P_i: Predicted value

N: Total number of input data

Data and Methods

Data used in this study are collected from the cashew nuts community enterprise at Tha Pla district, Uttaradit, Thailand. Four factors including demand, production volume, production cost and holding cost are examined. All factors are chosen between January 2020 and December 2020.

Dynamic single-level lot-sizing (DSLLS)

The dynamic single-level lot-sizing (DSLLS) problem is a fundamental problem in inventory management and production planning. It is based on the idea of determining the optimal production quantities for single product over a finite planning horizon. The primary objective is to minimize the total cost with three key variables including setup costs, production costs and inventory holding costs. The DSLLS is applied in Equation (1) as a constrain of lot sizing problem. The diagram of the DSLLS is shown in Figure 1.

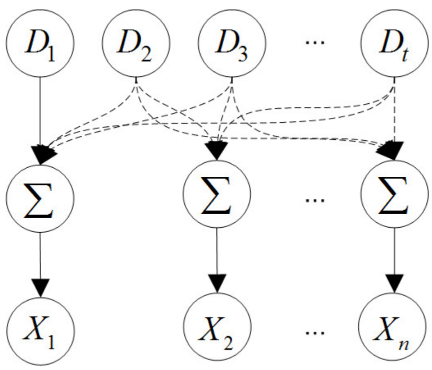

Fig. 1. The DSLLS diagram

Dynamic single-level lot-sizing split demand (DSLLS-Spd)

In this study, Dynamic Single-level Lot-Sizing Split Demand (DSLLS-Spd) is introduced as a new concept to find the suitable production plan of cashew nuts production. It is developed from the DSLLS problem by separating demand into two parts. In process of split demand, weight is applied to divide the product demand in each period into two parts before finding the optimum production plan as shown in Figure 2.

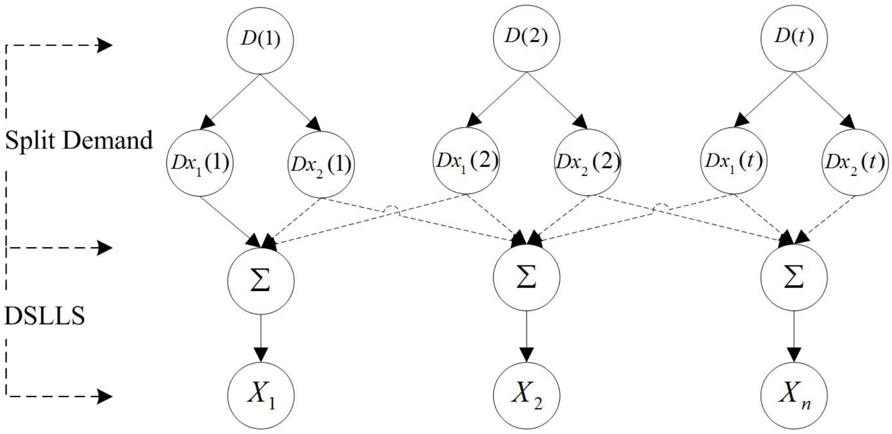

Fig. 2. The DSLLS-Split Demand diagram

The mechanistic mathematical model of split demand can be written as follows.

$$Dx_1^t = [D_t W_t] \tag{20}$$

$$Dx_2^t = D_t - Dx_1^t \tag{21}$$

With:

- D_t: Number of demands at period t^{th}
- Dx_1^t: Product demand of part 1 at period t^{th} that must be an integer
- Dx_2^t: Product demand part 2 at period t^{th}
- W_t: Weight for split demand at period t^{th}

The hybrid ALO-GWO algorithm

The hybrid ALO-GWO algorithm is implemented by combining the advantages of ALO and GWO. The ALO algorithm solves optimization problems with a small number of parameters at a rapid rate (Tian et al., 2018). The number of random and user-selected parameters has been lowered to simplify. Meanwhile, the GWO algorithm has high potential in solving a variety of optimization problems with a reduced user experience and in a manner comparable to other meta-heuristics (Precup et al., 2017). The diagram of the HALGW algorithm is shown in Figure 3.

According to Figure 3, the process of HALGW algorithm can be described as follows.

1. Determine the parameter values including the maximum iteration and the number of search agents (NSA) of ALO and GWO algorithms.
2. Random the algorithm between ALO and GWO. This mechanism mathematically modeled as in (22).

$$\text{HALGW}(t) = \begin{cases} \text{ALO} & \text{if rand} > 0.5 \\ \text{GWO} & \text{if rand} \leq 0.5 \end{cases} \tag{22}$$

With:

- t: Current iteration
- rand: Random number between 0 and 1 generated with a uniform distribution

3. Calculate fitness function.
4. Compare the production cost between the current period and the last period along with update the best fitness solution (BFS) as in (23).

$$\text{BFS}(t) = \begin{cases} X(t) & \text{if Cost}(t) < \text{Cost}(t-1) \\ X(t-1) & \text{otherwise} \end{cases} \tag{23}$$

5. Change the algorithm if production costs do not decrease.
6. Repeat step 3 to 5.

Parameter setting

DSLLS and DSLLS-Spd are solved using ALO, GWO and HALGW. Five cases of a number of search agents (NSA) for ALO, GWO and HALGW are determined as 10, 20, 30 ,40 and 50. The number of max iterations for ALO, GWO and HALGW are set as the same value of 1000. The parameter setting is shown in Table 1.

Table 1
Parameter settings of the ALO, GWO and HALGW algorithms

Parameter	Algorithms		
	ALO	GWO	HALGW
NSA	10, 20, 30, 40, 50	10, 20, 30, 40, 50	10, 20, 30, 40, 50
Iterations	1000	1000	1000

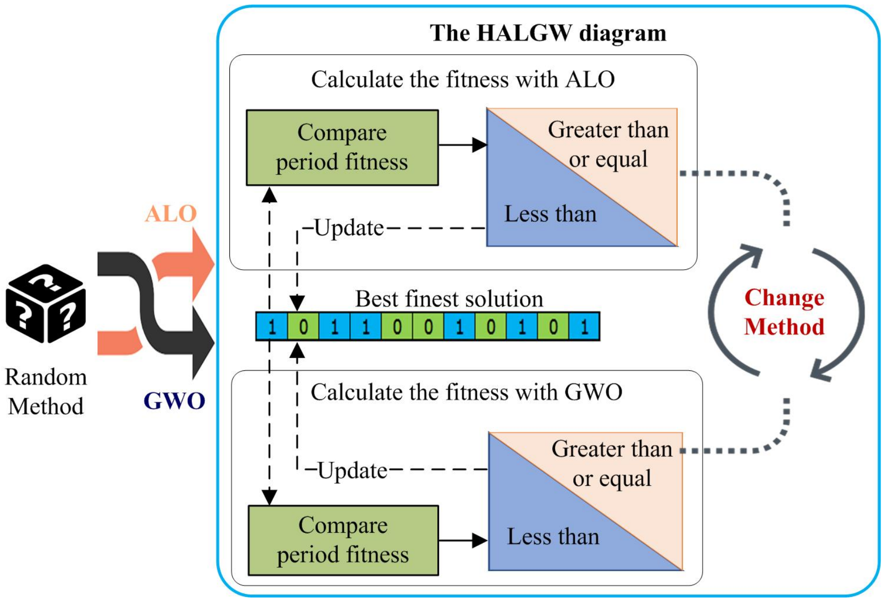

Fig. 3. The hybrid ant lion and grey wolf algorithms diagram

Results and Discussion

The optimal parameter

In this study, five different NSA in ALO, GWO and HALGW algorithm are investigated to find the suitable value for DSLLS and DSLLS-Spd. It is possible to determine the minimum cost of each algorithm by following the instructions in Table 2 and Table 3, respectively.

According to the lowest cost, the best-suited example is selected. As shown in Table 2, the ideal parameter for the HALGW algorithm with the DSLLS problem is NSA = 40, while the minimal cost is 579,644.10 THB. According to Table 3, the ideal parameter for the HALGW algorithm DSLLS-Spd problem is NSA = 40, with a minimum cost of 507,910.11 THB. The DSLLS-Spd executes the optimal production plan with the lowest RMSE value compared to the DSLLS problem.

The production plan for cashew nuts based on DSLLS-Spd problem is shown in Table 4. There are 121 times of order quantity a year. The results show that only 35 out of 121 needs to product, as in Figure 4.

DSLLS-Spd can be divided the demands into 2 sections of Dx_1^t and Dx_2^t at period t^{th}. The product quantity is suitable for production quantity and production cost. It can be seen that order quantity is 500 kilograms at periods 8, 24, 28, 53, 60, 62, 71 and 81.

As shown in Table 5, the cost reduction performance attained by ALO, GWO and HALGW using DSLLS and DSLLS-Spd are presented. It is found that the ALO, GWO and HALGW based on DSLLS-Spd can be reduced production cost 37.23%, 14.49% and 12.38% respectively.

From Figure 5, It can be seen that the HALGW algorithm with DSLLS-Spd find the optimal solution faster than DSLLS method.

Table 2
The optimal parameter of ALO, GWO and HALGW for DSLLS

Algorithms	NSA	Minimum Cost (THB)	RMSE	MAPE
ALO	40	809,302.96	85,779.00	0.00371
GWO	40	594,166.78	111,529.39	0.01034
HALGW	20	579,644.10	186,333.45	0.01940

Table 3
The optimal parameter of ALO, GWO and HALGW for DSLLS-Spd

Algorithms	NSA	Minimum Cost (THB)	RMSE	MAPE
ALO	40	508,012.79	459.76	0.0000084
GWO	20	508,057.50	1,561.21	0.0000463
HALGW	40	507,910.11	106.08	0.0000115

Table 4
The production plan for cashew nuts using HALGW algorithms base on DSLLS-Spd

	Time (t)										
	1	2	3	4	5	6	7	8	9	...	121
D	443	271	62	58	86	157	51	395	120	...	409
W	0.063	0.33	0.595	0.091	0.062	0.006	0.055	0.0370	0.039	...	0.387
Y	1	1	0	0	0	1	0	1	0	...	1
X	443	478	0	0	0	222	0	500	0	...	409
I	0	207	145	87	1	66	15	120	0	...	0

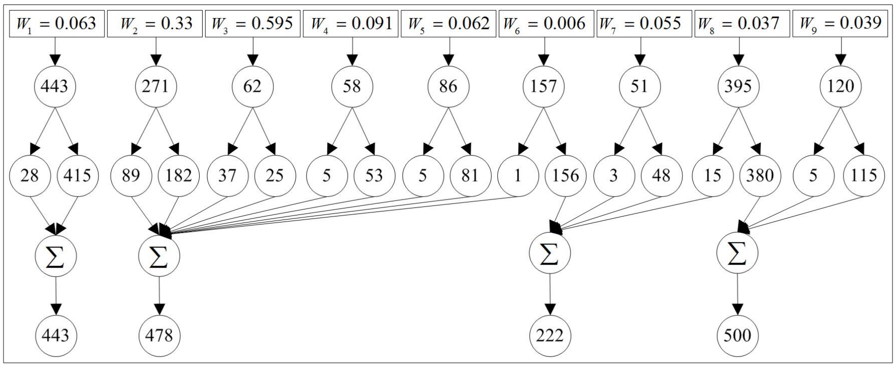

Fig. 4. The production plan for cashew nuts based on DSLLS-Spd

Table 5
The analysis of the differences in the performance of cost reduction

Algorithms	Minimum cost (THB)		Discount (%)
	DSLLS	DSLLS-Spd	
ALO	809,302.96	508,012.79	37.23
GWO	594,166.78	508,057.50	14.49
HALGW	579,644.10	507,910.11	12.38

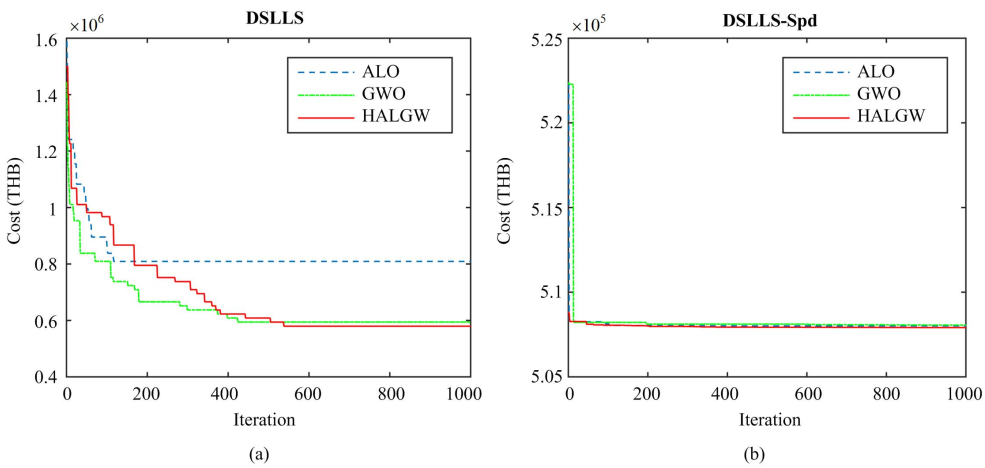

Fig. 5. The comparative performance between ALO, GWO and HALGW algorithms: (a) DSLLS. (b) DSLLS-Spd

Conclusion

In this study, the idea of split demand (DSLLS-Spd) is introduced by improving the dynamic single-level lot-sizing (DSLLS). Two metaheuristic algorithms of ALO and GWO are combined as the HALGW algorithm to find the optimal production plan of cashew nuts in Uttaradit, Thailand. The data period cover 121 times recording from January 2020 to December 2020. The performance of the HALGW algorithm is measured by RMSE and MAPE values. Two different objective functions of DSLLS-Spd and DSLLS and three algorithms of ALO, GWO and HALGW are compared. The results show that the HALGW algorithm with DSLLS-Spd gives the lowest RMSE value of 106.08. The frequency time of the production process is decreased from 121 to 35 times. Furthermore, the HALGW algorithm with DSLLS-Spd can reduce the production cost about 12.38% compared to the DSLLS method. Therefore, the HALGW algorithm based on DSLLS-Spd is the most appropriate approach in this investigation. For further research, the HALGW and DSLLS-Spd algorithms should be applied to additional industrial issues.

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