Multi-Objective Entropy Optimization Model for Agricultural Product Price Recommendation Problem

Fajar Delli Wihartiko, Sri Nurdiati, Agus Buono, and Edi Santosa

Abstract*—This study was used to integrate the entropy and multi-objective optimization problems to produce the multi-objective entropy optimization model (MOEOM) for the agricultural product price recommendation problem (APPRP). The process was achieved by comparing several classical approaches. APPRP was used to determine the best selling price at the farm level such that a significantly high price would not allow the products to sell while a very low price could cause losses for farmers. This study was limited to the factors considered in APPRP including business profit/loss conditions, risk, business competition, production level, and product quality. The algorithm performance comparison results showed that the non-dominated genetic sorting algorithm (NSGA- II) had the best performance based on the dominance of fitness value, number of iterations, execution time, percentage of feasible solutions, and level of precision of the solution. Meanwhile, based on the dominance of the solution on the objective function, the i-NSGA algorithm was observed to have a better solution than the NSGA-II despite its limited accuracy on the equation constraints. The i-NSGA was an improved version of NSGA with the inclusion of elitism and comparison of objective functions. Therefore, it was recommended that the smart reading algorithms, NSGA-II and i-NSGA, should be used to solve APPRP when accuracy is needed within the equation constraints. The implementation results also showed that the entropy optimization function produced price recommendations to farmers based on production and agricultural product quality. The entropy optimization function in the MOEOM significantly influenced the solutions produced through standard deviation and entropy, as well as the ANOVA test at a significance level of 0.05. This means it is possible to develop the MOEOM to determine optimal solutions in multiple objectives with uniformity (or diversity) in different fields.

***Index Terms*—entropy optimization; fresh agricultural products; multi-objective optimization.**

I. INTRODUCTION

ARTIFICIAL intelligence is a continuously advancing technology that has been widely implemented to solve optimization problems in agriculture [1]. This optimization process is a problem-solving concept applied in different scientific study to determine the best solution [2][3]. Several models such as linear, nonlinear, and stochastic programming as well as fuzzy models have been employed to solve optimization problems in agriculture [4]. Another alternative model observed to have been applied is the multi-objective entropy optimization model (MOEOM) which is a development of entropy optimization problem (EOP) [5] in the form of a multi-objective optimization (MOO) model [6].

In information theory, entropy is a criterion normally used to determine the level of uncertainty represented by a discrete probability distribution [7]. The concept has also been applied in agriculture to measure the diversity or uniformity in relevant data or events for further analysis [8]–[14]. EOP is an entropy-based single-objective optimization problem in the form of nonlinear programming considered useful for image reconstruction, queuing theory, transportation planning, and portfolio optimization [5]. Meanwhile, there are some optimization cases with more than one objective function requiring a nonlinear programming model such as MOO [6].

Optimization problems are observed in supply chain management, land use, irrigation, and planning as well as those related to the managerial aspect of agriculture [4], [15], [16]. The MOO model has been specifically applied to crop patterns [17], irrigation with due consideration for weather [18], and light control in greenhouses [19]. Meanwhile, another problem majorly faced by farmers is the determination of the optimum selling price for agricultural products.

The agricultural product price recommendation problem (APPRP) is a concept developed concerning the challenges associated with determining the optimal price of products at the farm level. The problem needs to be solved to ensure sustainability in the businesses of farmers. It is considered necessary because an unreasonably low price can lead to losses while overpricing has the ability to cause low demand by consumers. This means farmers also gave economic challenges in selling their products.

Most studies on APPRP are generally dominated by predictive models using time series data while the remaining are conducted through mathematical modeling [20] such as stochastic, dynamic, and deterministic models. For example, the study by [21] used a deterministic approach to determine the optimal price based on the supply chain management (SCM) of a community support agriculture. SCM was also applied to determine the prices of products based on different approaches such as fuzzy [22], game theory [23], and optimization [24]. This APPRP was proposed to be solved in this study using the entropy-based multi-objective optimization model.

The sustainability of farming practices can be influenced by certain economic factors such as costs, capital, risks,

Manuscript received November 13, 2022; revised July 23, 2023. This research was funded by Ministry of Research and Higher Education, Republic of Indonesia through Penelitian Disertasi Doktor (Grant No. 1994/IT3.L1/PN/2021).

Fajar Delli Wihartiko is a doctoral candidate in computer science at IPB University, Bogor 16680, Indonesia. He is also a lecturer in computer science at Pakuan University. Bogor 16129, Indonesia. (email: fajardelli@apps.ipb.ac.id / fajardelli@unpak.ac.id).

Sri Nurdiati is a Professor in the Department of Mathematics, IPB University, Bogor 16680, Indonesia (email: nurdiati@ipb.ac.id).

Agus Buono is a Professor in the Department of Computer Science, IPB University, Bogor 16680, Indonesia (email: agusbuono@apps.ipb.ac.id).

Edi Santosa is a Professor in the Department of Agronomy and Horticulture, IPB University, Bogor 16680, Indonesia (edisang@gmail.com).

and business competition among farmers [25]. Farmers are always interested in having a high income to cover the expenses incurred during the implementation of farming activities. Food products have very unique characteristics as indicated by their perishability and the need to be traded fresh [26], thereby influencing the selling price. This means the variation in the quality and selection of products can further lead to differences in selling prices, even for the same commodity [27], [28]. Farm products can be sorted manually or through the application of computers, depending on the availability of existing technology [29]. This background information shows the need to develop a recommendation model to determine the selling prices of agricultural products with due consideration for important factors such as costs, income, risks, business competition, and product sorting.

Several studies have been conducted to basically develop entropy optimization. Maximum entropy (MaxEnt) concept was initialized in [23], further evolved to solve decision tree-based classification problems [31] and clustering [32], [33]. Minimum cross-entropy (MinxEnt) was also initiated in [34] and widely applied to several concepts and methods such as maximum log probability [35], the cross-entropy method to solve MOO problems [36] and pattern recognition [37]. In addition, MaxEnt and MinxEnt were developed based on entropy theory [30].

The entropy theory has also been applied to improve the performance of algorithms [38], multi-objective particle swarm optimization algorithms [39], and multi-objective genetic algorithms in terms of termination criteria [40]. It was also combined with other concepts in a model in several other studies. Furthermore, fuzzy entropy [33] was used for feature selection [42]. This means the entropy optimization model [5] can be developed to solve planning problems in the transportation sector, queuing, image recognition, and stock portfolio. A relative optimization programming model [35] was also applied to geometric programming while an entropy-based multi-objective interval stochastic programming (EMISP) was developed for irrigation problems [44].

The EMISP is a MOO model that involves entropy-based interval analysis. Therefore, this study focuses on developing MOEOM by combining the MOO and EOP contrary to related previous studies. The MOEOM is a non-linear optimization model with multiple objectives, including the entropy optimization function. Moreover, the entropy maximization function can be used to ensure uniformity of results obtained from the searched variable while the entropy minimization function focuses on the retrieval of diverse results. The MOEOM model constraints normally limit the problems in the process to ensure the effectiveness of the entropy optimization function.

This study was conducted to solve APPRP using the MOEOM. The main factors indicated to be influencing the price were operating profit or loss and product characteristics. Primary data were obtained from Statistics Indonesia (SI) and the commodities selected to be analyzed were red chili and cayenne pepper. Moreover, the problem-solving process involved the application of a non-dominated sorting genetic algorithm (NSGA-II, i-NSGA, NSGA), multi-objective particle swarm optimization (MOPSO), and ε-constraints which is a classical method commonly used to solve MOO problems [45]-[47].

This article was structured into six sections including introduction in Section 1, related research in Section 2, model development in Section 3, APPRP formulation in Section 4, results and discussion in Section 5, and conclusions in Section 6.

II. RELATED RESEARCH

The concept of information theory – entropy – was first presented by Shannon [38]. The entropy concept was defined as a tool to measure uncertainty [7] and has attracted significant attention as the basis for modern science and technology [48]. Entropy theory was developed based on the principles of MaxEnt [30] and MinxEnt [34]. The MaxEnt principle was focused on the determination of the probability distribution that maximizes the Shannon size at a linear constraint. Moreover, the constraints were used to determine the distribution features to be explored such as the mean and variance. The Kullback principle was used to find two close distributions by minimizing the size of the difference between them [49]. The MaxEnt and MinxEnt concepts have been applied widely in different fields such as operations, pattern recognition, economics, finance, marketing, as well as urban and transportation planning [49].

The principles of entropy were also observed to have been applied to improve the performance of an algorithm or method [39], [40]. mathematical modeling, fuzzy entropy [41], EOP [5], relative optimization programming [43], and EMISP [44].

A previous study used the mind mapping approach [50] in entropy study and optimization and the results are presented in the following Figure 1.The results of the bibliometric analysis [51] based on the papers found are presented in Figure 2. These results have a pattern that aligns with the results of the thought mapping in Figure 1. The word ”Entropy” is closely related to ”optimization,” ”performance,” and ”model,” which are also the main branches in Figure 1.

III. MODEL DEVELOPMENT

A. Multi-Objective Entropy Optimization Model

Suppose $F(x)$ is an objective function of a number of k functions ($k \in Z^+$), and x is a vector of size n. Let $H(p(x))$ be an entropy function where p is a probability function of the event x. In this case $H(p(x)) = -\sum_{j=1}^{n} p_j(x)ln(p_j(x))$. The multi-objective entropy optimization model (MOEOM) is defined as follows:

Maximize

$$F(x) = [f_1(x), ..., f_k(x), H_1(p(x)), ..., H_l(p(x))]^T \quad (1)$$

Subject To

$$w_q(x) \leq 0; \qquad q \in Z^+ \cup \{0\} \quad (2)$$

$$\sum_{l \in Z} p_l g_i(x_l) = d_i; \qquad l \in Z^+ \cup \{0\}, i \in Z \cup \{0\} \quad (3)$$

$$\sum_{l \in Z} p_l = 1; \qquad l \in Z^+ \cup \{0\} \quad (4)$$

$$p_l \geq 0 = 1; \qquad l \in Z^+ \cup \{0\} \quad (5)$$

Here, Function (1) is multiple objective functions where $f(x)$ denotes the model optimization function of k and $H(x)$

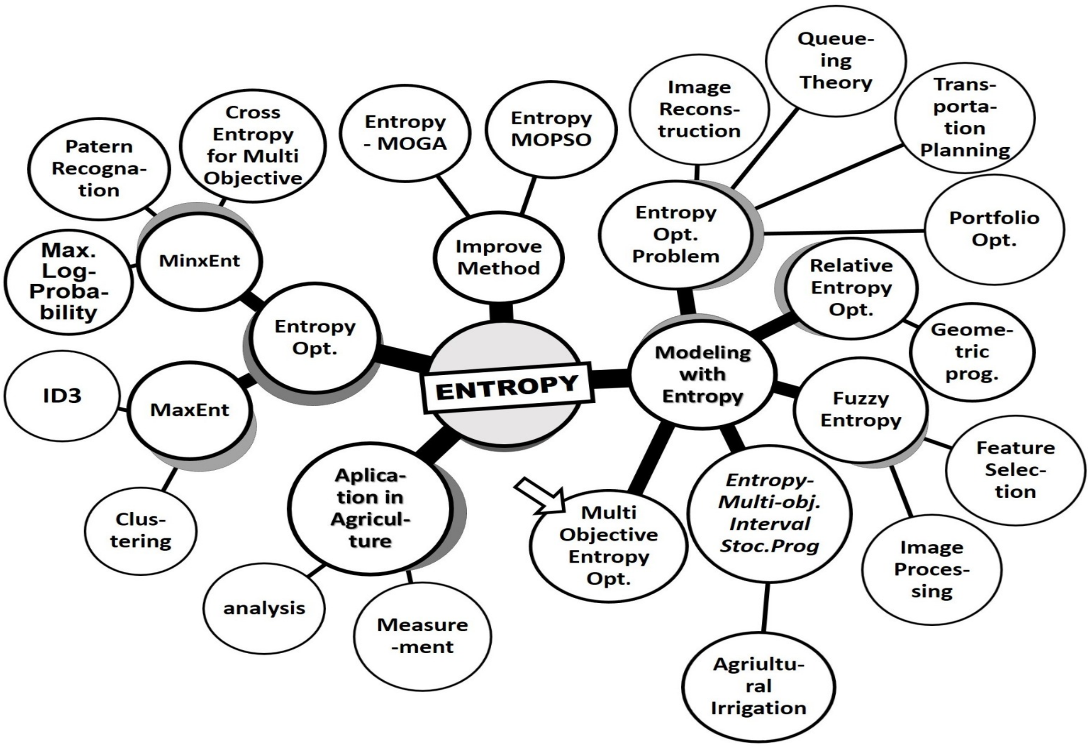

Fig. 1. Mind Mapping Results

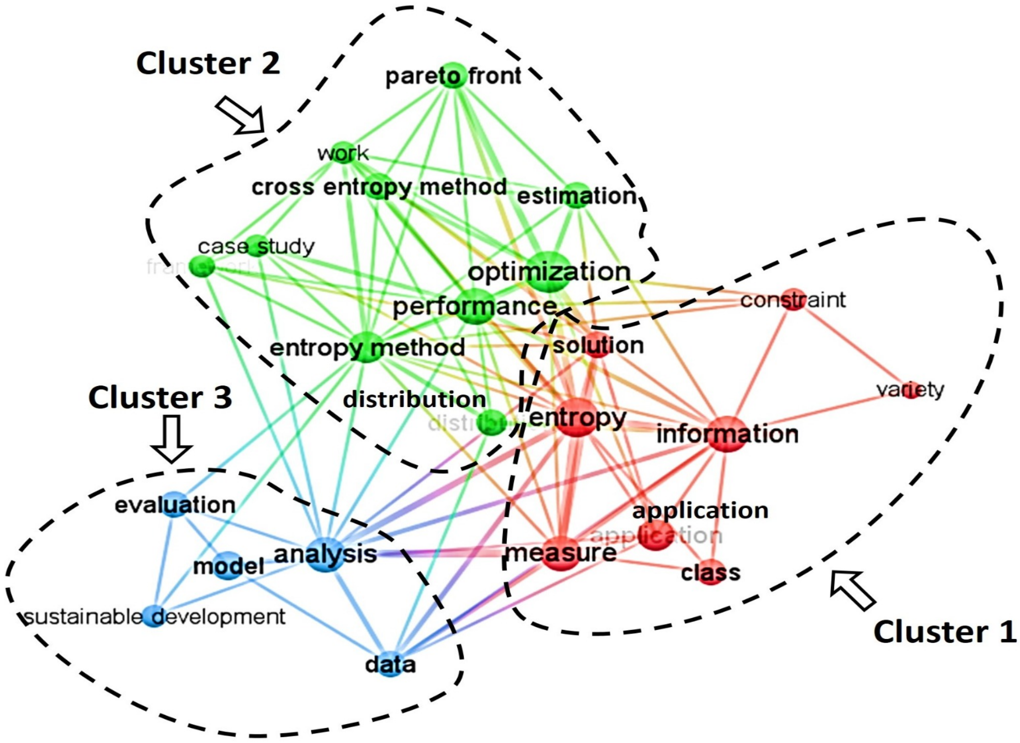

Fig. 2. The Bibliometric Result

is an entropy function of l. Constraint (2) is an inequality constraint in the form of a function $w(x)$ of a number of q constraint functions. Constraint (3) is a constraint based on the expected value of $E[g_i(X)] = d_i$. Constraint (4) guarantees that the sum of the probabilities is equal to one. Constraint (5) ensures that the probability value is always positive.

B. Agricultural Product Price Recommendation Problem

Some of the assumptions used in APPRP are stated as follows:

a) The quality of agricultural products is categorized by farmers based on time, size, taste, freshness level, and product maturity.

b) Farmers use the model with relatively similar sales or

harvest times for products.
c) The initial development of the price recommendation model considers the condition of farm profit or loss, competitor product prices, product quality, and business risks.
d) The costs incurred by farmers are accumulated into the total price.

The APPRP model was defined in the MOEOM by defining a set containing agricultural food products, a set of product quality, and several variables as follows:
a) $A = \{1, 2, ..., a|a \in N\}$, is a collection of agricultural food products (abbreviated agricultural products).
b) $B_a = \{1, 2, ..., b_a|b \in N, a \in A\}$, is a set of qualities of agricultural products $a \in A$ which are categorized sequentially based on the level of product quality.
c) x_{a,b_a}, is the price of an agricultural product $a \in A$ with quality $b_a \in B_a$ for one unit.
d) TC, is the total costs incurred by farmers for all products $a \in A$ from the production process to distribution.
e) $Profit$, as the profit the farmer expects on the sale of the entire product $a \in A$.
f) q_{a,b_a}, as a quantity of agricultural products $a \in A$ with quality $b_a \in B_a$ per unit.
g) h_{a,b_a}, the lowest selling price of agricultural products $a \in A$ with quality $b_a \in B_a$ from other competitors at the same level.
h) $\mathcal{H}_{a,b_a}$, the highest selling price of agricultural products $a \in A$ with quality $b_a \in B_a$ from other competitors at the same level.
i) r, as the value of the risk of failure to sell agricultural products due to product distribution in percentage.
j) p_{a,b_a}, as the probability to apply sales revenue of a product from x_{a,b_a} the total of all product sales $a \in A, \forall b_a \in B_a$. In this case $p_{a,b_a} = \frac{q_{a,b_a}.x_{a,b_a}}{\sum_{\forall b_a \in B_a} q_{a,b_a}.x_{a,b_a}}$; for $a \in A$.
k) $\overline{h}_a$, is the average selling price of the product $a \in A$ is expected by the farmer.

The recommendation model for the price of agricultural food products with the concept of multi-objective entropy optimization problem (MOEOM) is presented as follows.

$$\mathbf{Max} f(x_{a,b_a}) = \sum_{\forall a \in A} \sum_{\forall b_a \in B} q_{a,b_a}.x_{a,b_a} \tag{6}$$

$$\mathbf{Min} H_a(p(x_{a,b_a})) = -\sum_{\forall b_a \in B_a} p_{a,b_a}(x_{a,b_a}) \; ln(p_{a,b_a}(x_{a,b_a})); \forall a \in A \tag{7}$$

Subject To:

$$TC + Profit \leq (1 - r) f(x_{a,b_a}) \tag{8}$$

$$h_{a,b_a} \leq x_{a,b_a} \leq \mathcal{H}_{a,b_a} \qquad ; \forall a \in A, \forall b_a \in B_a \tag{9}$$

$$x_{a,1} > x_{a,2} > ... > x_{a,b_a} \qquad ; \forall a \in A \tag{10}$$

$$\frac{\sum_{\forall b_a \in B_a} q_{a,b_a}.x_{a,b_a}}{\sum_{\forall b_a \in B_a} q_{a,b_a}} = \overline{h}_a \qquad ; \forall a \in A \tag{11}$$

$$\sum_{\forall b_a \in B_a} p_{a,b_a} = 1 \qquad ; \forall a \in A \tag{12}$$

$$p_{a,b_a} \geq 0 \qquad ; \forall a \in A, \forall b_a \in B_a \tag{13}$$

$$x_{a,b_a} \geq 0 \qquad ; \forall a \in A, \forall b_a \in B_a \tag{14}$$

The objective function (6) determines the maximum value of the total revenue or gross income from farmers. The objective function (7) minimizes the entropy value to obtain a price with a low uniformity level according to the quantity of crops produced by the farmers. This means several prices are obtained for the same commodity with different qualities.

Constraints (8) are used to ensure that the income received can cover all costs and profits expected by farmers by considering the risks faced by them. Constraint (9) is used so that the price of agricultural products ranges from the prices prevailing in traditional and digital markets depending on farmers' selection of distribution systems. Constraint (10) is used so that the price determined is proportional to the quality of the price. In the case of a product $a \in A$, sequentially the quality of b_1 is better than b_2, the quality of b_2 is better than b_3 and soon.

Constraint (11) is a constraint used so that the average weighted price for an agricultural product approaches farmers' expectations ($\overline{h}_a$). This constraint is in EOP but is optional in this price recommendation problem. In real problems, the weighted average price result is quite far from the value $\overline{h}_a$. This is because of the zigzagging phenomenon where the APPRP model has constraints in the form of equations and inequalities [52].

Constraint (12) ensures the total probability value is equal to 1 for the same commodity while Constraints (13) and (14) indicate non-negativity. The APPRP model guarantees its solution as long as it has a feasible area based on the Weierstrass theorem [53].

IV. Formulation and Problem Solving

A. Data

The data used were sourced from Statistics Indonesia [54], [55], National Standardization Agency [56], National Strategic Food Price Information Center [57] and research [58]. The available data were processed and summarized as in the Table 1.

TABLE I
DATA DESCRIPTION

Data	Descryption	Source
Commodity (A)	1.Red Chili; 2.Chili Cayenne	
Quality (B)	1,2,3	[56]
TC_a	$TC_a = 10.007(q_a)$; $TC_b = 10.651(q_b)$	[54]
Profit	50.98% (TC_a) + 63.41% (TC_b)	[54]
q_{a,b_a}	$q_{1,1}$= 10, $q_{1,2}$=90, $q_{1,3}$ =50, $q_{2,1}$ = 50, $q_{2,2}$ = 40, $q_{2,3}$ =60	[58]
r	3%	[58]
h_{a,b_a}	h_1= 20,756, h_2=24,040	[57],[55]
$\mathcal{H}_{a,b_a}$	$\mathcal{H}_1$= 33,440, $\mathcal{H}_2$= 36,166	[57],[55]
$\overline{h}_a$	$\overline{h}_1$= 26,110, $\overline{h}_2$ = 28,612	[57],[55]

B. Problem Formulation

This subsection presents the process of inputting data into the available modeland this led to three objective functions which include finding the maximum income value (max $f(x)$) and the minimum entropy value of each commodity (min H_1 and min H_2). The results obtained from the APPRP model developed using the data in Table 1 are presented in the following implementation model/Model (IM):

$$\textbf{Max}(q_{1,1}x_{1,1} + q_{1,2}x_{1,2} + q_{1,3}x_{1,3} + q_{2,1}x_{2,1} + q_{2,2}x_{2,2} + q_{2,3}x_{2,3}) \quad (15)$$

$$\textbf{Min} - (p_{1,1}.ln(p_{1,1}) + p_{1,2}.ln(p_{1,2}) + p_{1,3}.ln(p_{1,3})) \quad (16)$$

$$\textbf{Min} - (p_{2,1}.ln(p_{2,1}) + p_{21,2}.ln(p_{2,2}) + p_{2,3}.ln(p_{2,3})) \quad (17)$$

Subject To

$$TC + Profit \leq (1-r)(q_{1,1}x_{1,1} + q_{1,2}x_{1,2} + q_{1,3}x_{1,3} + q_{2,1}x_{2,1} + q_{2,2}x_{2,2} + q_{2,3}x_{2,3}) \quad (18)$$

$$h_1 \leq x_{1,b_1} \leq \mathcal{H}_1; \forall b_1 \in B_1 \quad (19)$$

$$h_2 \leq x_{2,b_2} \leq \mathcal{H}_2; \forall b_2 \in B_2 \quad (20)$$

$$x_{1,1} > x_{1,2} > x_{1,3} \quad (21)$$

$$x_{2,1} > x_{2,2} > x_{2,3} \quad (22)$$

$$\frac{q_{1,1}x_{1,1} + q_{1,2}x_{1,2} + q_{1,3}x_{1,3}}{q_{1,1} + q_{1,2} + q_{1,3}} = \overline{h}_1 \quad (23)$$

$$\frac{q_{2,1}x_{2,1} + q_{2,2}x_{2,2} + q_{2,3}x_{2,3}}{q_{2,1} + q_{2,2} + q_{2,3}} = \overline{h}_2 \quad (24)$$

$$p_{1,1} + p_{1,2} + p_{1,3} = 1 \quad (25)$$

$$p_{2,1} + p_{2,2} + p_{2,3} = 1 \quad (26)$$

$$p_{1,1}, p_{1,2}, p_{1,3}, p_{2,1}, p_{2,2}, p_{2,3} \geq 0 \quad (27)$$

$$x_{1,1}, x_{1,2}, x_{1,3}, x_{2,1}, x_{2,2}, x_{2,3} \geq 0 \quad (28)$$

C. Problem Solving Method

APPRP was completed by comparing the performance of several classical algorithms designed to solve multi-objective optimization problems. The focus was on the solution dominance values, precision levels, feasibility, number of iterations, and program execution time. The domination value of the solution was compared based on the fitness and the objective function values. Moreover, the precision level was searched using the ANOVA test [59] at a significance level of 0.05. The feasibility of solutions was compared based on the probability of an algorithm to determine a feasible solution in a population. The algorithms used to solve APPRP were ε-Constraints [47], MOPSO [45] and several variants of NSGA, including the NSGA II algorithm [60], NSGA [61] and an improved version in the form of i-NSGA.

The parameters used include a population of 50 individuals, a crossover probability of 0.6, and a mutation probability of 0.01 [62]. The i-NSGA was developed by adding an elitism function, comparing the value of the objective function in non-dominated rank (NDR), and adding a penalty function [63],[64]. The elitism process used was based on five of the best individuals. Furthermore, the objective function proportion ratio for $(f : H_1 : H_2)$ was 2:1:1, and the penalty function was applied to determine the fitness value of an individual. This was achieved by subtracting the penalty value from the objective function ($f(x)$) when an individual violated the APPRP constraints.The summary of the i-NSGA formulation process is presented in the following Figure 3.

The best search criterion for the solution was based on the non-dominance value with the highest closeness between populations. Moreover, optimal pareto was visualized using fitness (fit, H_1, H_2) and objective function ($f(x), H_1, H_2$). Experiments were also conducted to determine the effect of EOP in the APPRP model. The process led to the elimination of the Function (7), Constraints (11), (12), and (13), as well as the effect of constraint (10). The model was subsequently tested using ANOVA [59] at an actual level of 0.05. The summary of the results obtained by comparing the performance of the APPRP solving algorithm was later presented in the form of a smart reading algorithm (SRA) [65].

V. RESULTS AND DISCUSSION

A. Result

The results of the problem-solving method obtained from the Model (IM) are presented in Table 2 as well as Figures 4 and 5. Table 2 shows that both ε-constraints and NSGA were unable to solve the APPRP problem as indicated by the zero-probability value recorded for the feasible solution in the best population. This was observed to be in line with several studies related to NSGA, where improvements were needed to search for optimal pareto [66]. The ε-constraints method was discovered to continuously provide the same value in every repetition, even for the price of similar products with different qualities. The phenomenon was confirmed by the value of $x_{1,1} = x_{1,2} = x_{1,3}$ and $x_{1,1} = x_{1,2} = x_{1,3}$ in Table 2, thereby indicating the inability to use the entropy minimization function in the ε-constraints method to provide price recommendations for different product qualities.

Figure 4 compares the optimal pareto based on the fitness value found in the first rank of each settlement using NSGA-II, i-NSGA, and MOPSO. The results showed that NSGA-II was in the first rank followed by MOPSO and i-NSGA. Moreover, the MOPSO was unable to form an optimal pareto set but the points produced were clustered and close to the NSGA-II results.

Figure 5 compares the optimal pareto based on the objective function and the results showed that the i-NSGA produced better $f(x)$ and $H_1(x)$ values than the NSGA-II and MOPSO. The difference between Figures 4 and 5 was associated with the ability of NSGA-II to produce variables that are close to equation constraints in APPRP, particularly Constraint (11) which was used to ensure the average price of a product met the expectations of the farmers.

The evaluation of the best populations in the NSGA-II and i- NSGA showed an error value as indicated in Table 3 which had the ability to reduce the objective function in the fitness value. Meanwhile, NSGA-II provided a solution with an error of 0.5% and this was much smaller than the 12.35% generated by i-NSGA. The best population results were also evaluated using ANOVA in order to determine the average difference at a confidence level of 0.05. The hypotheses developed for the test are as follows:

Ho: The average result of the population is the same.

H1: The average population are not all the same.

The critical region was at $F > (F_{crit} = 1.40538)$. and the results presented in Table 3 showed that all algorithms

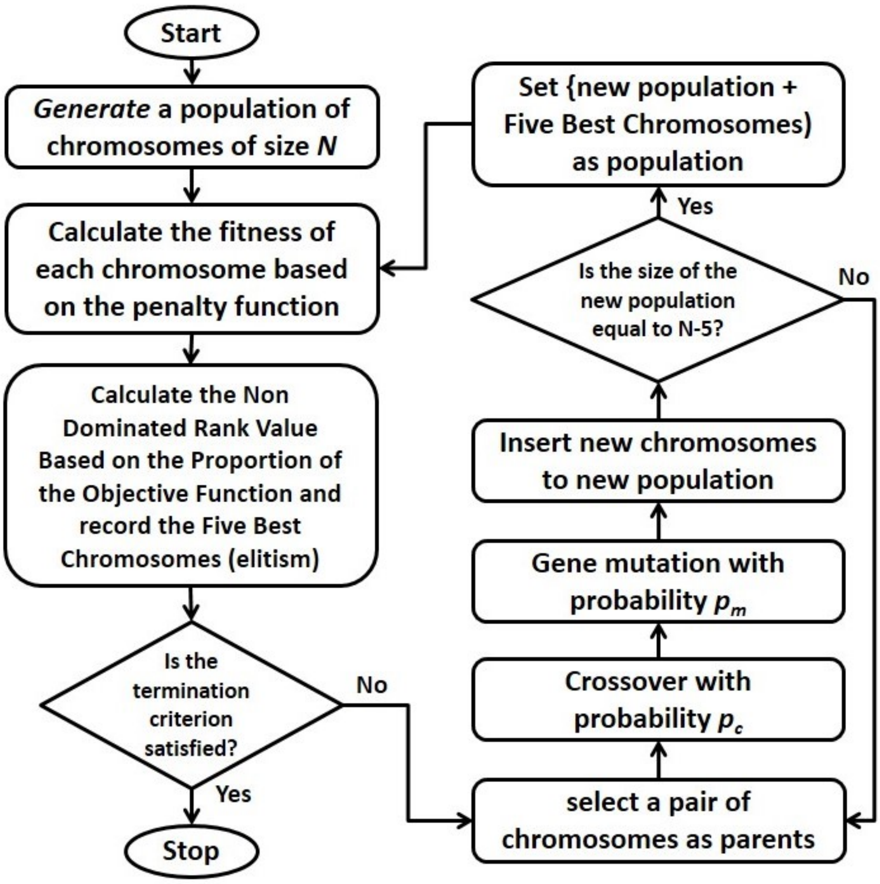

Fig. 3. i-NSGA flow chart

TABLE II
RESULTS OF IMPLEMENTATION MODEL/MODEL (IM)

Method	$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	fit	$f(x)$	$H_1(x)$	$H_2(x)$	feasible
NSGAII	26,144	26,143	26,042	36,078	24,884	24,877	8,207,871	8,208,355	0.853	1.071	0.94
i-NSGA	33,444	33,440	20,782	32,801	29,887	27,350	7,119,578	8,859,638	0.796	1.088	0.50
MOPSO	28,372	28,329	21,515	28,901	28,345	28,335	8,120,776	8,188,102	0.824	1.085	0.12
NSGA	24,705	29,909	28,819	25,721	26,115	31,941	7,433,351	8,626,950	0.827	1.066	0
ε-Cons.	33,449	33,449	33,449	36,116	36,116	36,116	3,013,250	10,434,750	0.853	1.085	0

had a high level of precision based on the ANOVA test. This was associated with the fact that their F value were smaller than F_{crit}. However, the NSGA- II algorithm had a better level of solution precision when compared to i-NSGA and MOPSO as indicated by the F_{NSGAII} (0.00022) which was smaller than the F_{iNSGA} (0.0773) and F_{MOPSO} (0.9974). The results also showed that NSGA-II was superior in terms of processing time and the number of iterations in determining the best solution.

TABLE III
PERFORMANCE COMPARISON OF APPRP SOLVING ALGORITHMS

Methods	ANOVA(F)	Iteration	RT
NSGA-II	0.00022	118	103
i-NSGA	0.07731	3783	348
MOPSO	0.99741	998	874
Methods	NDR(fit)	NDR($f(x)$)	Max Error
NSGA-II	1	2	0.50%
i-NSGA	3	1	12.35%
MOPSO	2	3	32,42%

RT = running time (second)
NDR(fit) = non-dominated rank based on fitness value
NDR($f(x)$) = non-dominated rank based on objective function

Figure 6 compares the output of the feasible population for the best generation of NSGA-II and i-NSGA in box plot form. The results showed that NSGA-II produced a more diverse range of solutions compared to i-NSGA as indicated in Figures 6(a) and 6(b) and this was consistent with Figures 4 and 5 where the NSGA-II had an optimal pareto with a wider range compared to the i-NSGA. The phenomenon also affected the range of fitness values and the objective functions formed. Based on product prices, the i-NSGA recommended a higher price than NSGA-II, especially for high-quality products in each commodity.

B. Discussion

The experimental process to evaluate the EOP performance was conducted using Model (IM). Case 1 was a condition where several EOP functions were removed from the APPRP model as in Function (7) as well as Constraints (11), (12), and (13). Case 2 was used to observe the effect of the order constraints of a solution on APPRP without EOP. This means Case 2 was Case 1 without Constraint (10). Both cases were

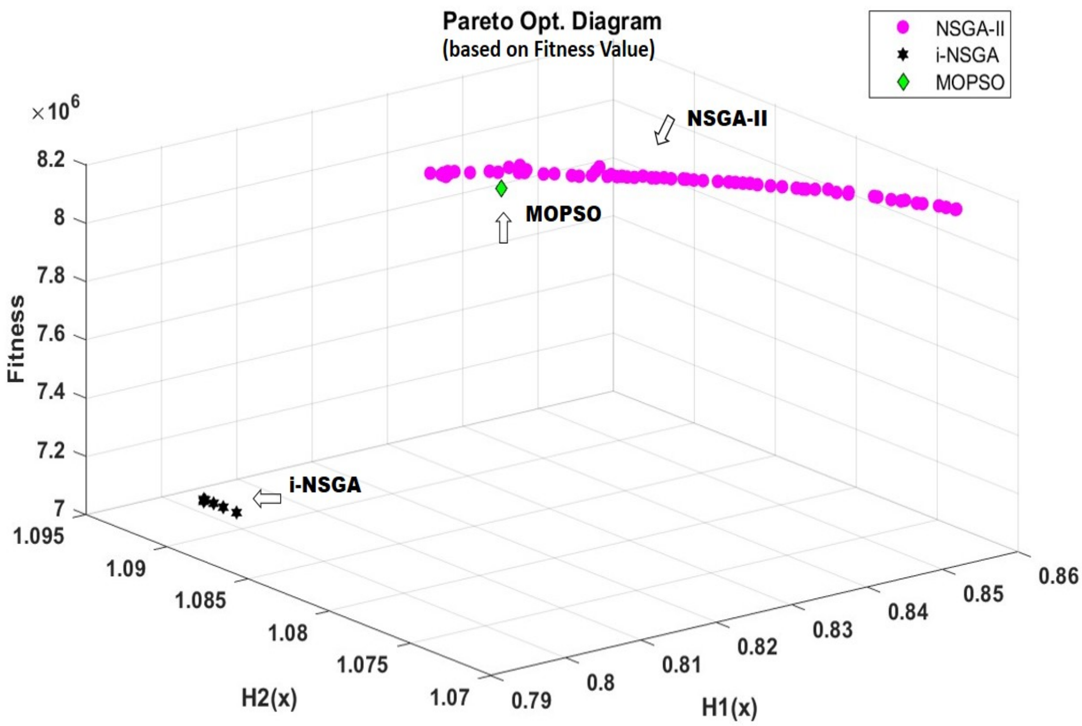

Fig. 4. Pareto optimal comparison of MOPSO, i-NSGA and NSGA-II based on fitness value

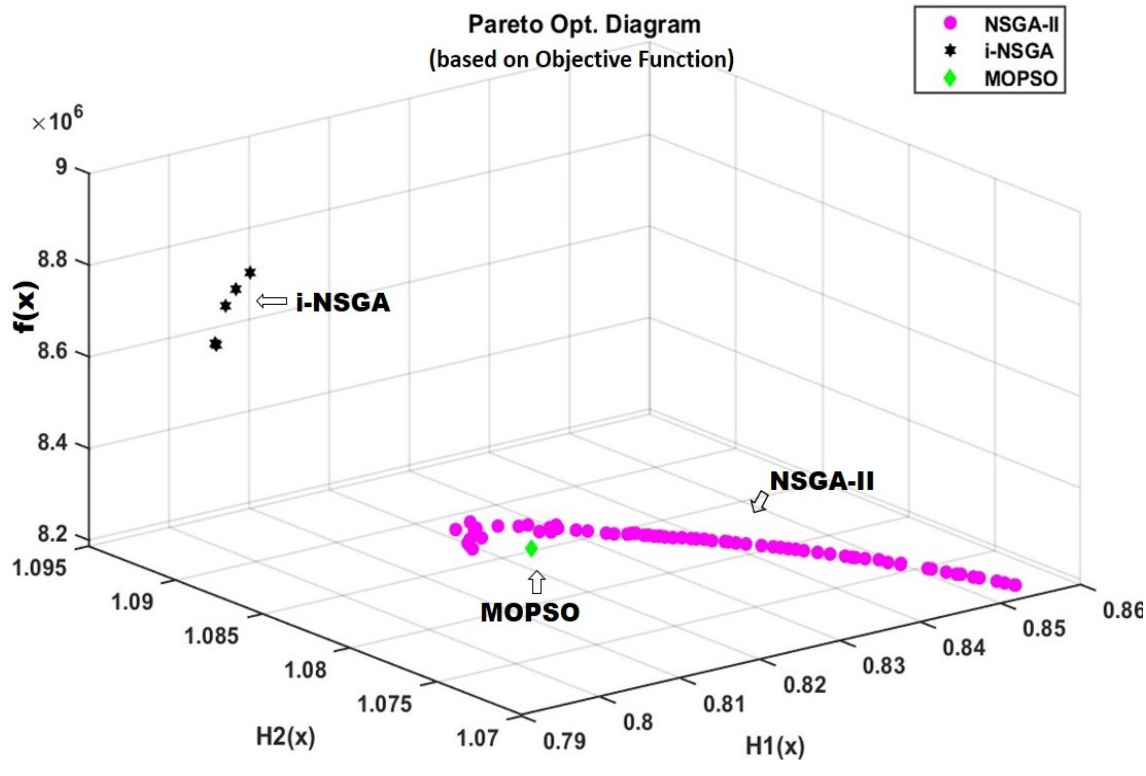

Fig. 5. Pareto optimal comparison of MOPSO, i-NSGA and NSGA-II based on objective function

solved using a genetic algorithm [67] with the same data and parameters according to the solution in the Model (IM).

The determination of the optimal solution in each generation for the two cases is presented in Figures 7 and 8 respectively. Moreover, the solutions obtained for each case were compared with those in the Model (IM) in Table 4. The results showed that the EOP was able to reduce the final objective function $f(x)$ value in the form of the operating income. This was associated with the movement of the price towards a high value but not matched by the difference based on the product quality as indicated by the low deviation in the prices in Cases 1 and 2. The application of this trend in both cases showed the possibility of lesser demand for low-quality products because they had high prices close to those

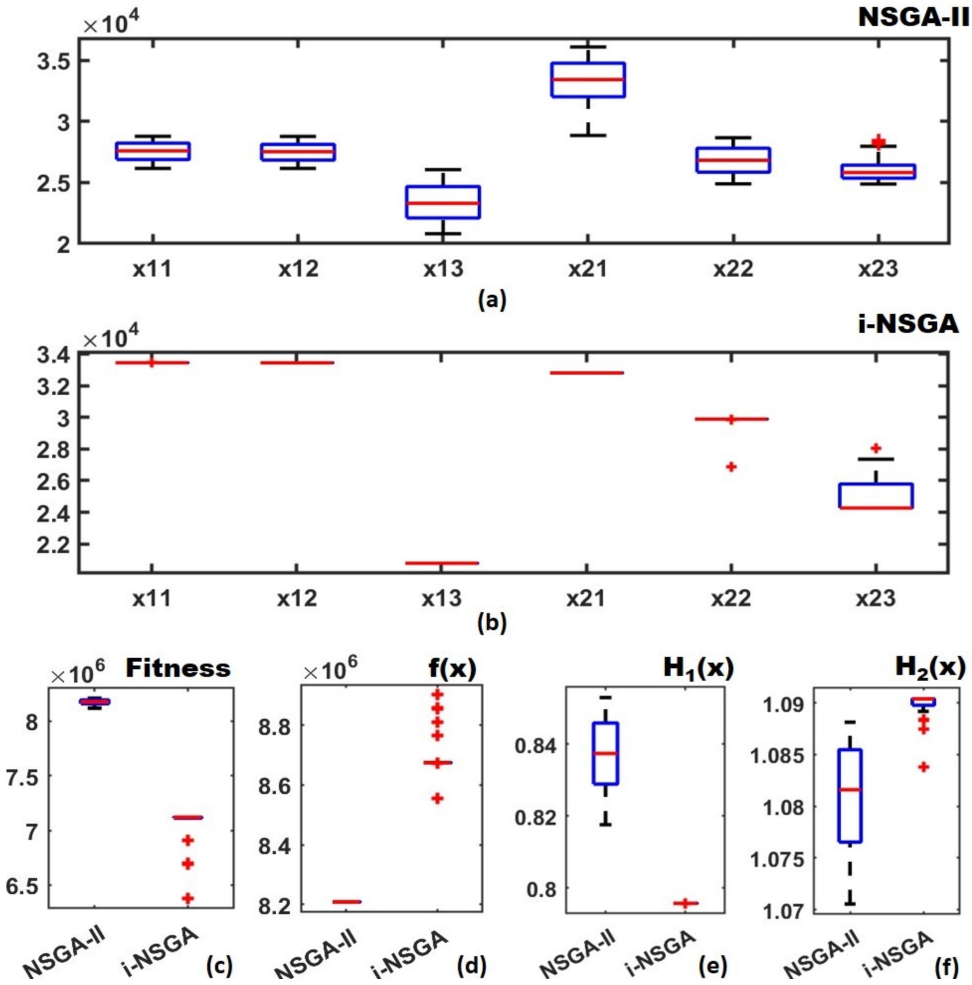

Fig. 6. Comparison of results in each variable between NSGA-II and i-NSGA

of high-quality products.

TABLE IV
COMPARISON OF EXPERIMENT RESULTS

Variable	NSGA-II	Case 1	Case 2
$x_{1,1}$	26,144	33,420	33,449
$x_{1,2}$	26,143	33,325	33,447
$x_{1,3}$	26,042	33,174	33,448
$x_{2,1}$	36,078	36,164	36,153
$x_{2,2}$	24,884	36,159	36,166
$x_{2,3}$	24,877	36,158	36,165
$\overline{x}_1$	26,144	33306.21	33448.1
$\overline{x}_2$	28,613	36160.57	36161.56
σ_1	58.78	124.1	0.9
σ_2	6465.09	2.8	7.1
$f(x)$	8,208,355	10,115,291	10,441,369
$H_1(x)$	0.853	0.853	0.853
$H_2(x)$	1.071	1.086	1.085
ANOVA(F)	-	15.73	15.45

The results in Table 4 also showed that the entropy minimization function worked effectively. This was confirmed by the comparison of the entropy values in each case where the Model (IM) was observed to have the lowest entropy value, especially for Commodity 2. The experimental results were also evaluated to determine the difference in the mean at a confidence level of 0.05. This was conducted using the same hypothesis as the previous test and a critical area of $F > (F_{crit} = 4.9646)$. The placement of this value in the critical region $(F > F_{crit})$ showed that the average

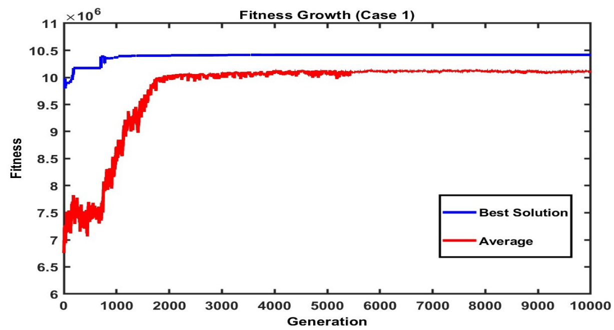

Fig. 7. Result of Case 1

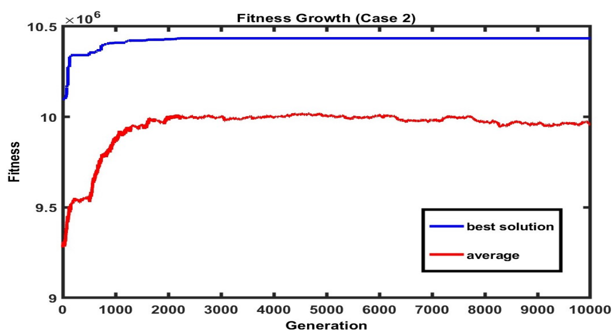

Fig. 8. Result of Case 2

TABLE V
SRA-APPRP-MOEOM COMPONENT

i	Techniques (Ξ_i)	Goal	Criteria (Φ_i)
1. (users need high accuracy)	NSGA-II	Looking for the best selling price with an average price equal (or very close) to user expectations	high accuracy [95%:100%]
2. (users do not need high accuracy)	i-NSGA	Looking for the best selling price with an average price close to user expectations	low accuracy (0%:95%)

experimental results in Model (IM) and Case 1 were not the same. This means the EOP function produced results considered different from those in Case 1. Moreover, the comparison between Case 2 and Model (IM) showed that the addition of the quality order in Constraint (10) did not affect the results when the EOP function was not included in the model. The assessment and tests conducted showed that the EOP function in MOEOM was able to effectively regulate diverse solution values based on the amount of production and due consideration for the main goal which was to maximize the income of farmers.

C. Smart Reading Algorithm for APPRP

The results obtained from the experiments and algorithm performance evaluation were summarized in the smart reading algorithm (SRA). The SRA was considered useful to determine the correct solution algorithm for the problem based on the available criteria. Let Θ be the APPRP problem in MOEOM form, the scope was stated as follows:
a) The APPRP model used was to maximize revenue and minimize the entropy value with constraints in the form of linear equations and inequalities.
b) APPRP had Constraint (11) formulated to determine the average price of similar products with different quality.
c) The user (farmer) was able to define an acceptable error rate or specify the desired level of accuracy for Constraint (11).

The components required for the SRA are presented in Table 5. This was indicated by the fact that each step had different completion techniques in the form of objectives and criteria. A combination of all existing criteria was also able to resolve all APPRP cases with Constraint (11). The existence of a case ϑ in the Θ problem ($\vartheta \in \Theta$) with the criterion (Φ_ϑ) led to the presentation of the SRA for APPRP in the following simple terms:

Smart Reading Algorithm for APPRP
Input : Φ_ϑ (criteria from user)
Output : Ξ_ϑ (problem solving technique)
Algorithm :
1. if Φ_ϑ is equal to the Criteria 1 ($\Phi_\vartheta = \Phi_1$)
2. $then$ use NSGA-II to solve ϑ.
3. $else$ use i-NSGA to solve ϑ.
4. end if.

The SRA for APPRP was applied based on the criteria selected by the user. The selection of a high accuracy on the average expected product price would lead to the application of the NSGA- II as the APPRP problem-solving technique. The system also used i-NSGA to obtain prices with better objective function values. The SRA was observed to be dynamic and this means it can be developed continuously in line with the findings of several relevant studies. The complexity of SRA is $O(i) + O(mn^3)$ where i is the number of criteria in the SRA, m is the number of objective functions, and n is the number of population [60],[65].

D. Price Evaluation Based on Benefits and Risks

The MOEOP model will be evaluated by calculating the value of the benefits and risks that might arise if the solution is implemented (or not implemented). The calculation process is done through research experiments by looking for a selling price range that farmers can use. The search for the sales price range is carried out by eliminating Constraints (11). The APPRP model without Constraints (11) will produce the highest price recommendations that farmers can sell. The recommendation for the lowest selling price is calculated by changing the objective function to search for the minimum function with a minimum price limit of IDR 0.-. Evaluation of the value of the benefits and risks of the price recommendation model can be seen in Table 6.

TABLE VI
PRICE EVALUATION

Variable	Highest Price	Lowest Price
$x_{1,1}$	30,226	18,823
$x_{1,2}$	29,629	13,618
$x_{1,3}$	28,837	6,443
$x_{2,1}$	35,841	33,950
$x_{2,2}$	35,133	28,739
$x_{2,3}$	26,547	7,413
$f(x)$	10,115,291	5,027,840
Profit(loss)	4,047,865	0

Table 6 shows that the recommended selling price of agricultural products from Model (IM) can generate a profit of IDR 3,085,055 if all of these products can be sold in full and with a risk of loss of 3%. Farmers can sell their products in the lowest to the highest price range. Determining the price below the lowest selling price will be at risk of farming losses, while pricing above the highest is at risk of high farming competitiveness.

VI. CONCLUSION

In conclusion, this study developed MOEOM as a multipurpose optimization model with due consideration for the diversity or uniformity of the solutions provided. The entropy maximization function was used to obtain consistent results while entropy minimization was employed to vary the solution.

The MOEOM model was applied to solve the price recommendation problem for agricultural food products and it was discovered to have worked effectively. This was confirmed by comparing the solutions provided with the model developed without entropy and ordered constraints. The algorithm performance was evaluated and the results showed that NSGA-II worked better than i-NSGA, NSGA, MOPSO, and ε-constraints. The i-NSGA algorithm specifically outperformed NSGA-II to dominate the objective function solution. This was associated with the fact that the NSGA-II produced solutions with a higher level of accuracy on equational constraints than i-NSGA. Moreover, the EOP function performed effectively in MOEOM as indicated by the ANOVA test at a 0.05 significance level.

The results are expected to be improved through the conduct of further studies to modify the price recommendation model using other attributes, variables, or constraints. The MOEOM is also expected to be continuously developed and implemented in different fields.

REFERENCES

[1] Y. Hidayat, B. Subartini, N. Khairunnisa, A. Sambas, and T. Purwandari, "An Estimated Analysis of Willingness to Wait Time to Pay Rice Agricultural Insurance Premiums Using Cox's Proportional Hazards Model," Mathematics, vol. 10, no. 21, art. id. 3935, 2021.
[2] A. A. Naim and N. I. Ghali, "New Optimization Algorithm Based on Venus Flytrap Plant," IAENG International Journal of Computer Science, vol. 48, no. 3, pp. 487-495, 2021.
[3] Z. Tian, G. Wang, and Y. Ren, "AMOAIA: adaptive multi-objective optimization artificial immune algorithm," IAENG International Journal of Applied Mathematics, vol. 49, no. 1, pp. 14–21, 2019.
[4] T.-D. Nguyen, T. Nguyen-Quang, U. Venkatadri, C. Diallo, and M. Adams, "Mathematical Programming Models for Fresh Fruit Supply Chain Optimization: A Review of the Literature and Emerging Trends," Agriculture Engineering, vol. 3, no. 3, pp. 519–541, 2021.
[5] I. Manzoor, H. Waqas, U. Farooq, T. Muhammad, and M. Imran. "Entropy optimization of Marangoni flow of hybrid nanofluid under the influence of viscous dissipation and activation energy: With melting phenomenon," ZAMM-Journal of Applied Mathematics and Mechanics/Zeitschrift für Angewandte Mathematik und Mechanik, vol. 103, no. 5, art. id. e202100416, 2023.
[6] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," Cogent Engineering, vol. 5, no. 1, art. id. 1502242, 2018.
[7] F. J. Cesario, "A Primer on Entropy Modeling," Journal of the American Institute of Planners, vol. 41, no. 1, pp. 40-48, 1975.
[8] M. Wang, X. Zhao, Q. Gong, and Z. Ji, "Measurement of regional green economy sustainable development ability based on entropy weight-topsis-coupling coordination degree—A case study in Shandong Province, China," Sustainability, vol. 11, no. 1, art. id. 280, 2019.
[9] V. Moutinho, M. Robaina, and P. Macedo, "Economic-environmental efficiency of European agriculture – A generalized maximum entropy approach," Agricultural Economics, vol. 64, no. 10, pp. 423-435, 2018.
[10] A. Xavier, R. Fragoso, M. de B. C. Freitas, M. do S. Rosário, and F. Valente, "A minimum cross-entropy approach to disaggregate agricultural data at the field level," Land, vol. 7, no. 2, art. id. 62, 2018.
[11] F. D. Wihartiko, E. T. Tosida, and R. Amin, "Diagnostic analysis of rice productivity using classification based on shannon and renyi entropy," International Journal of Scientific and Technology Research, vol. 9, no. 3, pp. 1223-1226, 2020.
[12] W. Juan and S. Pengjuan, "The measure of agricultural modernization level in Shanxi Province based on entropy method," IOP Conference Series: Earth and Environmental Science, vol. 657, no. 1, art. id. 12060, 2021.
[13] Sukono, A. Sambas, S. He, H. Liu, S. Vaidyanathan, Y. Hidayat, and J. Saputra. "Dynamical analysis and adaptive fuzzy control for the fractional-order financial risk chaotic system," Advances in Difference Equations, vol. 2020, art. id. 674, 2020.
[14] Z. Wang, J. Wang, G. Zhang, and Z. Wang, "Evaluation of Agricultural Extension Service for Sustainable Agricultural Development Using a Hybrid Entropy and TOPSIS Method," Sustainability, vol. 13, no. 1, art. id. 347, 2021.
[15] A. Singh, "An overview of the optimization modelling applications," Journal of Hydrology, vol. 466, pp. 167–182, 2012.
[16] T. Taskiner and B. Bilgen, "Optimization Models for Harvest and Production Planning in Agri-Food Supply Chain: A Systematic Review," Logistics, vol. 5, no. 3, art. id. 52, 2021.
[17] S. Jain, D. Ramesh, and D. Bhattacharya, "A multi-objective algorithm for crop pattern optimization in agriculture," Applied Soft Computing, vol. 112, art. id. 107772, 2021.
[18] D. Merkulov, A. Nikitin, S. Matveev, N. Stasenko, A. Petrovskaia and I. Oseledets, "A New Multi-objective Approach to Optimize Irrigation Using a Crop Simulation Model and Weather History," Computational Science–ICCS 2021: 21st International Conference 2021, 16-18, June, Krakow, Poland, pp. 75-88.
[19] Q. Yuan and T. Liu, "Multi-objective optimization of greenhouse light environment based on NSGA-II algorithm," 40th Chinese Control Conference 2021, 26-28 July, 2021, Shanghai, China, pp. 1856–1861.
[20] F. D. Wihartiko, S. Nurdiati, A. Buono, and E. Santosa, "Agricultural Price Prediction Models:A Systematic Literature Review," Proceedings of the 11th Annual International Conference on Industrial Engineering and Operations Management 2021, 7-11 March, 2021, Singapore, pp. 2927-2934.
[21] Y. Ye and Z. Cao, "Supply Chain Channel Decision Making based on the Community Supported Agricultural Mode," IAENG International Journal of Applied Mathematics, vol. 46, no. 1, pp.1-5, 2016.
[22] S. Wang, "A Manufacturer Stackelberg Game in Price Competition Supply Chain under a Fuzzy Decision Environment," IAENG International Journal of Applied Mathematics, vol. 47, no. 1, pp. 49-55, 2017.
[23] S. Sang, "The cost sharing contract of greening level and pricing policies in a green supply chain," IAENG International Journal of Applied Mathematics, vol. 49, no. 3, pp. 299–306, 2019.
[24] C.-T. Zhang, Y. Ye, and M.-M. Wang, "Production Mode and Pricing Strategy of a Two-period Closed-loop Supply Chain Considering Fairness Concerns," IAENG International Journal of Applied Mathematics, vol. 50, no. 2, pp. 409-420, 2020.
[25] M. Melina, H. Napitupulu, A. Sambas, A. Murniati, and V. A. Kusumaningtyas, "Artificial Neural Network-Based Machine Learning Approach to Stock Market Prediction Model on the Indonesia Stock Exchange During the COVID-19," Engineering Letters, vol. 30, no. 3, pp. 988-1000, 2022.
[26] X. Ma, Q. Bai, S. M. Islam, S. Wang, and X. Liu, "Coordinating a three-echelon fresh agricultural products supply chain considering freshness-keeping effort with asymmetric information," Applied Mathematical Modelling, vol. 67, pp. 337-356, 2019.
[27] A. Vohra, N. Pandey, and S. K. Khatri, "Decision Making Support System for Prediction of Prices in Agricultural Commodity," Amity International Conference on Artificial Intelligences 2019, 4-6 February, 2019, Dubai, United Arab Emirates, pp. 345–348,
[28] D. Jizhong, L. Shan, Z. Jianling, C. Wenkai, and J. Enchen, "Design and test of small-scale sorting machine of agricultural products," Transactions of the Chinese Society for Aricultural Machinery, vol. 46, no. 9, pp. 245–250, 2015.
[29] Y. Herdiyeni, A. Haristu, M. Hardhienata, and others, "Chilli Quality Classification using Deep Learning, International Conference on Computer Science and Its Application in Agriculture 2020, 16-17 September, 2020, Bogor, Indonesia, pp. 1–5.
[30] E. T. Jaynes, "Information theory and statistical mechanics," Physical review, vol. 106, no. 4, art. id. 620.
[31] R. Rivera-Lopez, J. Canul-Reich, E. Mezura-Montes, and M. A. Cruz-Chávez, "nduction of decision trees as classification models through metaheuristics," Swarm and Evolutionary Computation, vol. 69, art. id. 101006.
[32] E. A. Bobadilla and A. K. Morales, "A clustering method based on the maximum entropy principle," Entropy, vol. 17, no. 1, pp. 151-180, 2015.
[33] Q. Duan, Y. L. Yang, and Y. Li, "Rough K-modes clustering algorithm based on entropy," IAENG International Journal of Computer Science, vol. 44, no. 1, pp. 13–18, 2017.
[34] L. Van de Velde, V. Vandermeulen, G. Van Huylenbroeck, and W. Verbeke, "Consumer information (in) sufficiency in relation to biofuels: determinants and impact," Biofuels, Bioproducts and Biorefining, vol. 5, no. 2, pp. 125–131, 2011.
[35] A. E. Abbas, A. H. Cadenbach, and E. Salimi, "A Kullback–Leibler view of maximum entropy and maximum log-probability methods," Entropy, vol. 19, no. 5, art. id. 232, 2017.
[36] A. Ünveren and A. Acan, "Multi-objective optimization with cross entropy method: Stochastic learning with clustered pareto fronts," IEEE Congress on Evolutionary Computation 2007, 25-28 September, 2007, Singapore, pp. 3065-3071.
[37] S. Watanabe, "Pattern recognition as a quest for minimum entropy," Pattern Recognition, vol. 13, no. 5, pp. 381-387, 1981.
[38] C. E. Shannon, "A Mathematical Theory of Communication," ACM SIGMOBILE mobile computing and communications review, vol. 5, no. 1, pp. 39-55, 2001.

[39] E. J. S. Pires, J. A. T. Machado, and P. B. de Moura Oliveira, "Entropy diversity in multi-objective particle swarm optimization," Entropy, vol. 15, no. 12, pp. 5475-5491, 2013.
[40] S. Gunawan, A. Farhang-Mehr, and S. Azarm, "Multi-level multi-objective genetic algorithm using entropy to preserve diversity," Evolutionary Multi-Criterion Optimization: Second International Conference 2003, 8-11 April, 2003, Faro, Portugal, pp. 148-161.
[41] A. Sambas, A. Mohammadzadeh, S. Vaidyanathan, A. F. Ayob, A. Aziz, M. A. Mohamed, I. M. Sulaiman and M. A. A. Nawi, "Investigation of chaotic behavior and adaptive type-2 fuzzy controller approach for Permanent Magnet Synchronous Generator (PMSG) wind turbine system," AIMS Mathematics, vol. 8, no. 3, pp. 5670-5686, 2023.
[42] P. Luukka, "Feature selection using fuzzy entropy measures with similarity classifier," Expert Systems with Applications, vol. 38, no. 4, pp. 4600-4607, 2011.
[43] V. Chandrasekaran and P. Shah, "Relative entropy optimization and its applications," Mathematical Programming, vol. 161, pp. 1-32, 2017.
[44] S. Zhang, Q. Tan, Y. Cai, T. Zhang, and G. Song, "Mathematical analyses of ecological and economic tradeoffs in irrigated agriculture based on inexact optimization principles and hierarchical crop projections," Journal of cleaner production, vol. 235, pp. 69-84, 2019.
[45] N. Nedjah and D. M. M. Luiza, "Evolutionary multi-objective optimisation: A survey," International Journal of Bio-Inspired Computation, vol. 7, no. 1, pp. 1–25, 2015.
[46] G. Chen, Q. Qin, Z. Ping, K. Peng, X. Zeng, H. Long, and M. Zou, "A Novel Approach Based on Modified and Hybrid Flower Pollination Algorithm to Solve Multi-objective Optimal Power Flow," IAENG International Journal of Applied Mathematics, vol. 51, no. 4, pp. 966-983, 2021.
[47] M. B. Horasan, and H. S. Kilic, "A multi-objective decision-making model for renewable energy planning: The case of Turkey," Renewable Energy, vol. 193, pp. 484-504, 2022.
[48] O. M. Parkash, P. K. Sharma, and R. Mahajan, "New measures of weighted fuzzy entropy and their applications for the study of maximum weighted fuzzy entropy principle," Information Sciences, vol. 178, no. 11, pp. 2389-2395, 2008.
[49] R. S. de Mattos and Á. Veiga, "Otimização de entropia: implementação computacional dos princípios Maxent e Minxent," Pesquisa Operacional, vol. 22, pp. 37-59, 2002.
[50] V. Kokotovich, "Problem analysis and thinking tools: an empirical study of non-hierarchical mind mapping," Design studies, vol. 29, no. 1, pp. 49-69, 2008.
[51] N. Donthu, S. Kumar, D. Mukherjee, N. Pandey and W.M. Lim. 2021. How to conduct a bibliometric analysis: An overview and guidelines. J. Bus. Res. 133:285–296
[52] I. Antonau, M. Hojjat, and K.-U. Bletzinger, "Relaxed gradient projection algorithm for constrained node-based shape optimization," Structural and Multidisciplinary Optimization, vol. 63, pp. 1633-1651, 2021.
[53] V. Bhaskar, S. K. Gupta, and A. K. Ray,"Applications of multiobjective optimization in chemical engineering," Reviews in chemical engineering, vol. 16, no. 1, pp. 1-54, 2000.
[54] Statistics of Horticulture Establishment and Other Horticulture Business. Jakarta: BPS-Statistics Indonesia, 2018.
[55] Indonesian Red Chili Commodity Trade Distribution, Jakarta: BPS-Statistics Indonesia, 2019.
[56] Decision of the Head of the National Standardization Agency concerning the Establishment of Revision Five of the Indonesian National Standard, Jakarta: BPS-Statistics Indonesia, 2016.
[57] M. Najib, U. Sumarwan, S. Septiani, H. Waibel, D. Suhartanto, and F. Fahma, "Individual and socio-cultural factors as driving forces of the purchase intention for organic food by middle class consumers in Indonesia," Journal of International Food & Agribusiness Marketing, vol. 34, no. 3, pp. 320-341, 2022.
[58] J. R. Saragih, "Socioeconomic and ecological dimension of certified and conventional arabica coffee production in North Sumatra, Indonesia," Asian Journal of Agriculture and Rural Development, vol. 3, no. 3, pp. 93-107, 2013.
[59] A. Gavioli, E. G. de Souza, C. L. Bazzi, K. Schenatto, and N. M. Betzek, "Identification of management zones in precision agriculture: An evaluation of alternative cluster analysis methods," Biosystems engineering, vol. 181, pp. 86-102, 2019.
[60] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," IEEE transactions on evolutionary computation, vol. 6, no. 2, pp. 182-197, 2002.
[61] A. H. Dias, and J. A. De Vasconcelos, "Multiobjective genetic algorithms applied to solve optimization problems," IEEE Transactions on Magnetics, vol. 38, no. 2, pp. 1133-1136, 2002.
[62] M. G. P. de Lacerda, L. F. de Araujo Pessoa, F. B. de Lima Neto, T. B. Ludermir, and H. Kuchen, "A systematic literature review on general parameter control for evolutionary and swarm-based algorithms," Swarm and Evolutionary Computation, vol. 60, art. id. 100777, 2021.
[63] E. Zitzler, K. Deb, and L. Thiele, "Comparison of multiobjective evolutionary algorithms: Empirical results," Evolutionary computation, vol. 8, no. 2, pp. 173–195, 2000.
[64] F. D. Wihartiko, H. Wijayanti, and F. Virgantari, "Performance comparison of genetic algorithms and particle swarm optimization for model integer programming bus timetabling problem," IOP Conference Series: Materials Science and Engineering, vol. 332, no. 1, art. id. 012020, 2018.
[65] F. D. Wihartiko, S. Nurdiati, A. Buono, and E. Santosa, "Solving Agricultural Price Recommendation Problem Using Smart Reading Algorithms," Procedia Computer Science, vol. 217, pp. 784–795, 2023.
[66] S. Verma, M. Pant, and V. Snasel, "A comprehensive review on NSGA-II for multi-objective combinatorial optimization problems," IEEE ACCESS, vol. 9, pp. 57757–57791, 2021.
[67] S. D. Dao, K. Abhary, and R. Marian, "Maximising Performance of Genetic Algorithm Solver in Matlab.," Engineering Letters, vol. 24, no. 1, pp. 75-83, 2016.