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Target-Oriented Compromised Sales and Profit Approach for Production and Distribution Planning in a Supply Chain

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ABSTRACT

This paper aims to determine optimal aggregate production and distribution plans in a supply chain system that simultaneously achieve two business targets of total profit and total sales, with uncertain parameters, e.g., production rate during regular time and overtime, inventory holding costs for a manufacturer and distribution centers, and transportation cost. A fuzzy multi-objective linear programming (FMOLP) model is developed to represent the planning problem. The proposed method that minimizes maximum deviation from satisfaction targets of fuzzy profits and sales is more effective, compared with the method that maximizes minimum satisfaction of fuzzy profits and sale, to determine various compromised solutions, which are Pareto-optimal, and to allow a planner to select the most desirable solution based on his/her opinion. This paper has made a significant contribution since it is the first one that proposes the FMOLP approach to determine compromised solutions with two target-based objectives of simultaneously achieving total fuzzy profit targets and total sales target.

KEYWORDS

Compromised Solution, FMOLP, Fuzzy Multi-Objective Linear Programming, Supply Chain, Production and Distribution Planning, Profit and Sales, Seasonal Demand, Target-Oriented, Uncertainty

1. INTRODUCTION

Aggregate production and distribution planning in a supply chain (APDP-SC) problem involves determination of production quantities, workforce levels, inventory levels for a manufacturer and distribution centers, and transportation quantities among supply chain members under seasonal demands over a planning horizon of 6 to 12 months (Nam & Logendran, 1992; Djordjevica et al., 2019). Typically, APDP-SC is performed under seasonal demands and limited resources and it aims to best utilize the resources (Spitter et al., 2005).

Linear programming (LP) model is a popular technique to solve APDP-SC problem. It determines optimal production, inventory, and transportation quantities under limitations of materials, workforce,

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and inventory spaces. For single-objective problems, it may aim to achieve a maximum profit or minimum cost. For multiple-objective problems, it may determine compromised solutions between two or more conflicting objectives, e.g., minimizing cost and maximizing customer satisfaction. The LP model for multiple objective problems is called multiple objective linear programming (MOLP) model. It has two or more objective functions and parameters in the model are constant parameters (Tavakkoli et al., 2010; Horng & Yenradee, 2020). Practically, it is difficult to accurately determine the values of some parameters as constants since the parameters are uncertain (Akkawuttiwanich, & Yenradee, 2020). In order to handle this situation, MOLP model is extended to fuzzy multiple objective linear programming (FMOLP) model by changing constant parameters to fuzzy ones (Su, 2017; Azadeh et al., 2015; Rezakhani, 2012; Tansakul & Yenradee, 2020).

This research work is developed to satisfy real needs of small Thai industries with five characteristics as follows: First, many small Thai industries have limited production and distribution capacities, and investment budget. They cannot economically manage to completely satisfy demands of all customers. Thus, they accept to partially satisfy the demands, and the leftover demands are lost. Second, objectives of most available models are to minimize total related costs, or to maximize a total profit. These objectives are not practical in business. Real businesses are neither attempted to get the highest sales nor the highest profit. They want to achieve the sales target and the profit target simultaneously. They do not want to significantly achieve over the targets since the targets of the next year will be significantly increased too. Third, the total profit and total sales are not necessarily maximized at the same time because increasing sales volume may not always lead to an increase in profits. When a company increases its sales volume, it incurs additional costs to produce and market those products, which can include costs such as labor, materials, and advertising expenses. As a result, the marginal cost of each additional unit sold may be higher than the marginal revenue earned from selling that unit. In such cases, the company may be better off selling fewer units at a higher price, rather than increasing sales volume and incurring higher costs. At low production level, the profit and sales will grow together. But at high production level, to further increase sales, it may need excessive costly overtime and holding cost that may reduce the profit. In practice when sales and profit targets are high, achieving the sales and profit targets simultaneously may not be possible and compromised solutions are needed. Fourth, there are many compromised solutions and planning managers want to manipulate solutions. They want to generate a number of different solutions and personally select the one that they like most. Finally, some unit cost parameters are uncertain and should be represented by fuzzy numbers instead of constants. Therefore, the profit which is affected by the fuzzy unit cost parameters are also uncertain and should be represented by the fuzzy numbers.

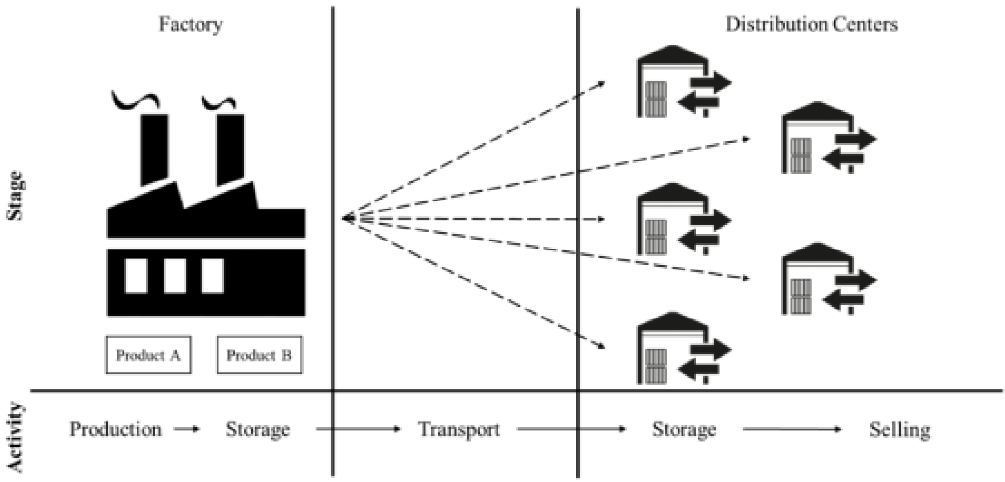
To satisfy real needs with five characteristics, the APDP-SC model is developed to determine compromised solutions between achieving sales target and profit target where the demands can be partially satisfied. Some parameters, e.g., productivity rates under regular time and overtime, unit transportation cost, and unit inventory holding cost, are fuzzy numbers. Some techniques are developed to generate a number of different compromised solutions, and allow the planning managers to select the preferable compromised solution.

This paper considers a supply chain structure as shown in Figure 1. The supply chain has 2 stages of a manufacturer and distribution centers. The manufacturer makes two decisions of production and storage. The distribution centers make two decisions of storage and sales. Transportation decision from the manufacturer and distribution centers is also required. The manufacturer produces 2 product types.

This paper has specific objectives as follows:

1. To develop the FMOLP model for APDP-SC problem to simultaneously achieve sales and profit targets.
2. To propose some methods for defuzzification of fuzzy constraints and fuzzy objective function coefficients, and for determining compromised solutions for two target-oriented objectives of achieving sales and profit targets.

Figure 1.
Supply chain structure



3. To demonstrate using a real case study in Thai industry that the proposed FMOLP model and the method for determining compromised solutions are effective to generate non-dominated (Pareto optimal) solutions.

The scope of this paper is as follows: It considers aggregate production and distribution planning in a two-stage supply chain with two product types. It does not consider detailed planning, scheduling, and purchased part planning. Some parameters including unit transportation cost, unit inventory holding cost, and regular time and overtime productivity rates are uncertain and are estimated by triangular fuzzy numbers. The customer demands are constant but the demands may be partially satisfied. Therefore, the proposed model is not restricted by the constant demands. It has similar effect to uncertain demands.

This paper has contributions as follows: First, the proposed FMOLP model is realistic and practical for APDP in supply chain because it is developed based on needs and normal practice of industries that have sales and profit targets to be simultaneously achieved. Second, the proposed methods to handle fuzzy constraints and multiple fuzzy objectives are effective to generate various compromised solutions and allow a planner select the most preferable one. Third, the profit from the model is a fuzzy number, which is more useful for the supply chain planner than a constant profit since the fuzzy profit warns the planner of a low profit under the pessimistic situation.

This paper is organized as follows: Review of previous works and how this paper is different from others are presented in the next section. Section 3 explains methodological steps for conducting this research, FMOLP model, and methods to defuzzify fuzzy constraints and handle fuzzy objective functions. Section 4 presents validation of results, solutions of single objective models, and compromised solutions. Finally, results are concluded in Section 5.

2. LITERATURE REVIEW

Table 1 compares previous works that are related to supply chain optimization problems in production, distribution, and transportation planning. The table presents types of objective function, objectives, decision variables, and solution methods. Note that LP, FLP, FMOLP, GP, and FGP stand for linear programming, fuzzy linear programming, fuzzy multi objective linear programming, goal programming, and fuzzy goal programming, respectively.

Most previous research works related to aggregate production planning (APP) consider issues of customer demand, processing time, production quantity, labor level, inventory level, and lead time. Most APP models are linear that aim to reduce total costs, including production, inventory holding, labor, overtime, and other cost components (Nam & Logendran, 1992; Spitter et al., 2005; Geetha & Elizabeth Shanthi 2020).

For real-world problems, some parameters related to APP are uncertain and unable to predict or control exactly, such as, customer demand, productivity rates, and various related unit costs. (Djordjevica et al., 2019; Peidro et al., 2010; Wong & Lai, 2011). Most APP problems consider multiple products and multiple periods. (Wang & Liang, 2005).

Some APP models focus on only workforce capacity, which is not sufficient for managing related production processes because the production quantities are limited by material constraints and production resource capacity as well. Thus, an integrated planning for production and resource capacity is a key success factor in industries. This problem is more complicated because we need to manage many factors, and then mathematical models are suitable to determine the best possible combination of the capacity, workforce, and inventory for multi-product and multi-stage production system (Sivasundari et al., 2019).

In supply chain context, a distribution stage is as important as the production stage since it significantly affects the profit and costs of the supply chain. The distribution planning is important because this stage must receive the products to store in a distribution center for sales to customers. In the distribution stage, it usually considers all parameters that are related to distribution planning, such as, customer demand, inventory at the distribution center, holding cost, inbound and outbound transportation, lead time, and available warehouse space (Pongsathornwiwat et al., 2017; Alnaggar et al., 2020; Liang, 2006).

Most articles that focus on transportation planning tend to assume that the transportation cost is directly calculated from a unit transportation cost since it is easy to calculate the cost (Ali & Yang, 2012; Pant et al., 2018; Huynh & Yenradee, 2020). However, the unit transportation cost is difficult to be precisely estimated as a constant since it is dependent on economic and environmental conditions (Liu & Xin, 2011).

Related research works of APP model with fuzzy parameters suggest that these problems should be formulated as fuzzy linear programming models with fuzzy objective function or fuzzy constraints, or both (Spitter et al., 2005; Ren et al., 2015; Charongrattanasakul & Pongpullponsak, 2017). In order to determine optimal decisions of the APP, fuzzy constraints and fuzzy objective function are defuzzified by some techniques to be equivalent constraints and objective function with only constant parameters (Rommelfanger, 1996; Kaplanski et al., 2016; Nuchpho et al., 2019).

Some research works in APP consider multiple objectives, such as minimize total production cost, minimize rate of change in labor levels, minimize holding cost, minimize backorder cost, and maximize profit (Kabak & Ülengin, 2011). A subset of these works considers both multiple objectives and uncertain (fuzzy) parameters in objective function or constraints. Fuzzy parameters are, for example, forecasted demand and production capacity. Mathematical models for this type of problems are called FMOLP (fuzzy multiple objective linear programming) model (Wang & Liang, 2004).

For multiple objectives problems, the objectives are conflicting. It is not possible to achieve the best values for all objectives at the same time. When there are targets or goals to be achieved for each objective, a goal programming (GP) technique can be used to determine compromised solutions (Broz et al., 2019; Da Silva & Marins, 2014; Ighravwe & Oke, 2015). When decision makers consider that objectives have different weights, the compromised solutions can be determined by maximizing a weighted average of satisfactions of all objectives (Javadian et al., 2009). Note that the objective values are converted to a common scale from 0.0 to 1.0, which is called “satisfaction level”, to prevent the objective that has high value, such as sales, to dominate other objective with low value, such as profit.

Table 1 shows that previous research works do not consider maximizing sales. This paper is unique that it considers two objectives of maximizing total profits and total sales at the same time. Moreover, this paper determines compromised solutions by simultaneously achieving profit target and sales target.

Table 1. Comparison of previous works that are related to supply chain optimization problems in production, distribution, and transportation planning

Related works	Obj. types		Objective Functions													Decision Variables							Methods				
	Single Objective	Multi Objectives	Minimize production time	Minimize total cost	Minimize production cost	Minimize carry, backorder cost	Minimize transport cost	Minimize inventory	Minimize unsatisfied demand	Minimize inventory cost	Minimize DC cost	Minimize delivery time	Maximize production	Maximize profit	Maximize sales	Production quantity	OT production quantity	Transport quantity	No. of worker hired	No. of worker fired	Sales quantity	Inventory	LP	FLP	FMOLP	GP	FGP
Wang and Liang (2005)	√		√													√		√						√			
Sivasundari et al. (2019)	√			√												√	√		√	√		√		√			
Wang and Liang (2004)		√			√	√										√	√		√	√		√			√		
Alnaggar et al. (2020)	√						√											√					√				
Broz et al. (2019)		√						√	√					√		√						√				√	
Pant et al. (2018)	√			√														√					√				
Ali and Yang (2012)	√						√											√					√				
Peidro et al. (2010)	√			√												√	√	√				√		√			
Spitter et al. (2005)	√					√																√	√				
Ren et al. (2015)		√								√	√		√			√		√				√					√
Liang (2006)		√									√	√						√							√		
This paper		√												√	√	√	√	√	√	√	√	√			√		

3. METHODOLOGY

In this section, methodological steps of this paper are presented, followed by mathematical models and data of a case study.

3.1. Methodological Steps

The methodological steps are presented in Figure 2. First, real business requirements of Thai supply chain are collected and FMOLP model is constructed based on the requirements. Second, methods to defuzzify fuzzy constraints and to handle multiple fuzzy objectives are developed to convert the FMOLP model to an equivalent single objective crisp LP model. Third, the model is verified and validated by determining the solution from the LP model that maximizes sales, and demonstrate that the solution is reasonable. Fourth, after the model is validated, the solutions from single objective models that maximize profit and maximize sales separately are determined. These solutions are extreme, not compromised one. Fifth, various compromised solutions between achieving profit target and sales target are determined by two methods. Finally, results are compared and the suitable method to determine the compromised solutions is recommended.

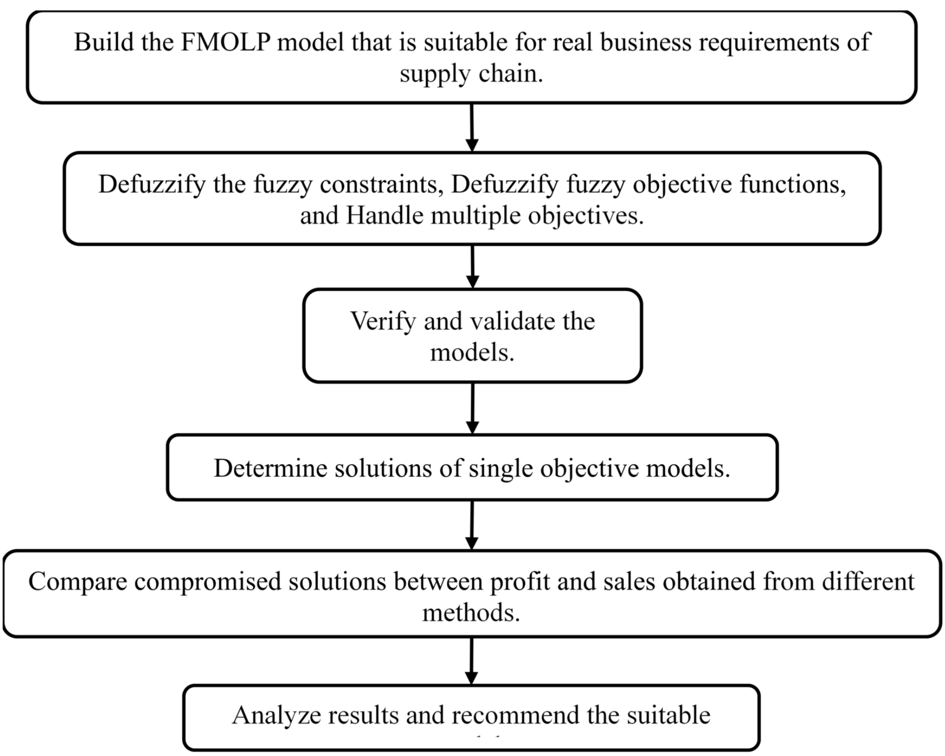
3.2. Notations

Indices, parameters, decision variables are defined as follows.

3.2.1. Indices

I: Set of products ($i = 1,2,3,\ldots,I$)

Figure 2. Methodological steps



J: Set of distribution centers ($j = 1,2,3,\ldots,J$)
T: Set of time periods (month) ($t = 1,2,3,\ldots,T$)

3.2.2. Parameters

TI : Maximum inventory capacity at the manufacturer (unit)
MW : Minimum workforce (person)
TW : Maximum workforce (person)
w_0 : Initial workforce level (person)
EC : Unit employee cost per period (Baht/person-period)
$\widetilde{IC}$: Fuzzy unit inventory holding cost per period (Baht/unit-period)
OTC : Unit overtime cost per period (Baht/person-period)
HC : Unit hiring cost (Baht/person)
FC : Unit firing cost (Baht/person)
$\widetilde{RU}_i$: Fuzzy productivity rate during regular time for product *i* (unit/person)
$\widetilde{OU}_i$: Fuzzy productivity rate during overtime for product *i* (unit/person)
$\widetilde{TC}_{ijt}$: Fuzzy unit transport cost of product *i* to distribution center *j* in period *t* (Baht/unit)
D_{ijt} : Demand of product *i* at distribution center *j* in period *t* (unit)
EI_{i0} : Initial inventory of product *i* (unit)
EDC_{ij0} : Initial inventory of product *i* at distribution center *j* (unit)
p_i : Selling price of product *i* (Baht/unit)
SM_i : Safety stock of product *i* at manufacturer (unit)
SDC_{ij} : Safety stock of product *i* at distribution center *j* (unit)
MDC_j : Maximum inventory capacity of distribution center *j* (unit)
$\widetilde{HDCC}_{ij}$: Fuzzy unit inventory holding cost of product *i* at distribution center *j* (Baht/unit)
$\widehat{TP}_{sat}^{p}$: Satisfaction target of total profit in pessimistic situation (unitless)
$\widehat{TP}_{sat}^{m}$: Satisfaction target of total profit in most likely situation (unitless)
$\widehat{TP}_{sat}^{o}$: Satisfaction target of total profit in optimistic situation (unitless)
$\widehat{TS}_{sat}$: Satisfaction target of total sales (unitless)

3.2.3. Decision Variables

x_{it}^{rt} : Production quantity of product i in period t during regular time (unit)
x_{it}^{ot} : Production quantity of product i in period t during overtime (unit)
x_{ijt} : Transport quantity of product i to distribution center j in period t (unit)
s_{ijt} : Sales quantity of product *i* at distribution center *j* in period *t* (unit)
h_t : Number of workers hired in period *t* (person)
f_t : Number of workers fired in period *t* (person)

3.2.4. Intermediate Variables

w_t : Workforce level in period t (person)
EDC_{ijt} : Ending inventory of product *i* at distribution center *j* in period *t* (unit)
EI_{it} : Ending inventory of product *i* in period *t* at manufacturer (unit)
TS : Total sales (Baht)
$\widetilde{TP}$: Fuzzy total profit (Baht)
TP^p : Total profit in pessimistic situation (Baht)
TP^m : Total profit in most likely situation (Baht)
TP^o : Total profit in optimistic situation (Baht)
TS_{sat} : Satisfaction of sales (unitless)
TP^p_{sat} : Satisfaction of total profit in pessimistic situation (unitless)
TP^m_{sat} : Satisfaction of total profit in most likely situation (unitless)
TP^o_{sat} : Satisfaction of total profit in optimistic scenario (unitless)
$\overleftrightarrow{TP^p_{sat}}$: Deviation from satisfaction target of total profit in pessimistic situation (unitless)
$\overleftrightarrow{TP^m_{sat}}$: Deviation from satisfaction target of total profit in most likely situation (unitless)
$\overleftrightarrow{TP^o_{sat}}$: Deviation from satisfaction target of total profit in optimistic situation (unitless)
$\overleftrightarrow{TS_{sat}}$: Deviation from satisfaction target of total sales (unitless)
$TS_{\max}$: Maximum total sales (Baht)
$TP^p_{\max}$: Maximum total profit in pessimistic situation (Baht)
$TP^m_{\max}$: Maximum total profit in most likely situation (Baht)
$TP^o_{\max}$: Maximum total profit in optimistic situation (Baht)
$TS_{\max}$: Minimum total sales (Baht)
$TP^p_{\min}$: Minimum total profit in pessimistic situation (Baht)
$TP^m_{\min}$: Minimum total profit in most likely situation (Baht)
$TP^o_{\min}$: Minimum total profit in optimistic situation (Baht)

3.3. Fuzzy Multi-Objective Linear Programming (FMOLP) Model

3.3.1. Objective Functions

Maximize total sales

The sales value represented by Eq. (1) is referred to as total sales. This encompasses the sales of all products across all distribution centers for all periods. It’s worth noting that total sales is a precise number, as the company can set the selling price exactly:

$$TS = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} p_i \cdot s_{ijt} \tag{1}$$

Maximize total profit

Total profit is the difference between total sales and total costs including hiring cost, firing cost, regular employee cost, overtime cost, inventory holding cost at manufacturer, transportation cost, and inventory holding cost at distribution centers, as specified by Eq. (2). From Eq. (2), some parameters are fuzzy numbers therefore the total profit is also a fuzzy number:

$$\widetilde{TP} = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} p_i \cdot s_{ijt} - HC \cdot \sum_{t\in T} h_t + FC \cdot \sum_{t\in T} h_t + EC \cdot \sum_{t\in T} w_t + OTC \cdot \sum_{i\in I}\sum_{t\in T} x_{it}^{ot} + \widetilde{IC} \cdot \sum_{i\in I}\sum_{t\in T} EI_{it} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} \widetilde{TC}_{ijt} \cdot x_{ijt} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} \widetilde{HDCC}_{ij} \cdot EDC_{ijt} \quad (2)$$

3.3.2. Constraints

$$w_t = w_{t-1} + h_t - f_t, \ \forall t \in T \quad (3)$$

$$w_t \geq MW, \ \forall t \in T \quad (4)$$

$$w_t \leq TW, \ \forall t \in T \quad (5)$$

$$EI_{it} = x_{it}^{rt} + x_{it}^{ot} + EI_{it-1} - \sum_j x_{ijt}, \ \forall i \in I, \forall t \in T \quad (6)$$

$$\sum_{i\in I} EI_{it} \leq TI, \ \forall t \in T \quad (7)$$

$$EI_{it} \geq SM_i, \ \forall i \in I, \forall t \in T \quad (8)$$

$$x_{it}^{rt} \leq w_t \widetilde{RU}_i, \ \forall i \in I, \forall t \in T \quad (9)$$

$$x_{it}^{ot} \leq w_t \widetilde{OU}_i, \ \forall i \in I, \forall t \in T \quad (10)$$

$$S_{ijt} \leq D_{ijt}, \ \forall i \in I, \forall j \in J, \forall t \in T \quad (11)$$

$$EDC_{ijt} = EDC_{ij(t-1)} + x_{ijt} - S_{ijt}, \ \forall i \in I, \forall j \in J, \forall t \in T \quad (12)$$

$$\sum_{i\in I} EDC_{ijt} \leq MDC_j, \ \forall j \in J, \forall t \in T \quad (13)$$

$$EDC_{ijt} \geq SDC_{ij}, \ \forall i \in I, \forall j \in J, \forall t \in T \quad (14)$$

$$x_{it}^{rt}, x_{it}^{ot}, w_t, h_i, f_i, x_{ijt} \geq 0, \ \forall i \in I, \forall j \in J, \forall t \in T \quad (15)$$

$$x_{it}^{rt}, x_{it}^{ot}, w_t, h_i, f_i, x_{ijt} \in int, \ \forall i \in I, \forall j \in J, \forall t \in T \quad (16)$$

Constraint (3) is a workforce balance constraint. Constraints (4 and 5) limit minimum and maximum levels of workforce. Constraint (6) is inventory balance constraint at the manufacturer. Constraint (7) controls total inventory at the manufacturer not to exceed the available space. Constraint (8) maintains the safety stock at the manufacturer. Constraints (9 and 10) relate production quantities during regular time and overtime with the number of workers and productivity rates. Since the productivity rates are fuzzy numbers, these constraints are also fuzzy. Note that the overtime work will not be used until the production quantity during regular time reaches its capacity since the overtime work has additional cost. Constraint (11) ensures that the sales quantity does not exceed the demand, demand may not be satisfied, and unsatisfied demand is a lost-sales. Constraint (12) is the inventory balance constraint at the distribution centers. Constraint (13) controls total inventory at the distribution centers not to exceed the available space. Constraint (14) maintains the safety stock at the distribution centers. Non-negativity and integer conditions are specified by constraints (15 and 16), respectively.

3.4. Defuzzification of Uncertain Constraints and How to Handle Multiple Uncertain Objectives

3.4.1. Defuzzification of Fuzzy Constraints

Constraints (9 and 10) are fuzzy constraints. They must be defuzzified before solving. Only right side of constraints (9 and 10) are fuzzy with fuzzy parameters of $\widetilde{RU}_i$ and $\widetilde{OU}_i$. A suitable method to defuzzify these fuzzy constraints is to defuzzify $\widetilde{RU}_i$ and $\widetilde{OU}_i$ to become constant of $\overline{RU}_i$ and $\overline{OU}_i$. Therefore, constraints (9 and 10) are defuzzified as constraints (9' and 10'). Note that $\widetilde{RU}_i$ is a fuzzy number with three components $\left(RU_i^p, RU_i^m, RU_i^o\right)$ and $\overline{RU}_i = \left(RU_i^p + 2RU_i^m + RU_i^o\right)/4$. Similarly, $\widetilde{OU}_i$ is a fuzzy number with three components $\left(OU_i^p, OU_i^m, OU_i^o\right)$ and $\overline{OU}_i = \left(OU_i^p + 2OU_i^m + OU_i^o\right)/4$. This defuzzification method is also applied by some research works (Nuchpho et al., 2019). Another well-known method for defuzzification of fuzzy constraint is a ranking method (Fortemps & Roubens, 1996). This method is suitable when both left- and right-hand sides of the constraint are fuzzy:

$x_{it}^{rt} \le w_t \overline{RU}_i$ or $x_{it}^{rt} \le w_t \left(RU_i^p + 2RU_i^m + RU_i^o\right)/4$ (9')

$x_{it}^{ot} \le w_t \overline{OU}_i$ or $x_{it}^{ot} \le w_t \left(OU_i^p + 2OU_i^m + OU_i^o\right)/4$ (10')

3.4.2. How to Handle Multiple Uncertain Objectives

This paper proposes two methods to handle multiple uncertain objectives, which are maximize minimum satisfaction method, and minimize maximum deviation from satisfaction targets method. Both methods involve two objectives with significantly different values. The total sales is much higher than the total profit. To prevent the objective that has higher value from dominating another objective, both total sales and total profit are converted to "satisfaction levels" with a common scale from 0.0 to 1.0, see constraints (22-25). There are four satisfaction measures, which are satisfactions of pessimistic profit, most likely profit, optimistic profit, and sales.

Method 1: Maximize minimum satisfaction method.

The concept of Method 1 is to avoid the lowest value in any satisfaction measures. It maximizes the minimum value among four satisfaction measures. This method is widely applied by previous works (Rubin, 1989). It is used to compared with the proposed method:

$$\text{Max } z_1 \tag{17}$$

where:

$$z_1 \le TP_{sat}^p \tag{18}$$
$$z_1 \le TP_{sat}^m \tag{19}$$
$$z_1 \le TP_{sat}^o \tag{20}$$
$$z_1 \le TS_{sat} \tag{21}$$
$$TP_{sat}^p = 1 - (TP_{\max}^p - TP^p) / (TP_{\max}^p - TP_{\min}^p) \tag{22}$$

$$TP_{sat}^{m} = 1 - (TP_{\max}^{m} - TP^{m}) / (TP_{\max}^{m} - TP_{\min}^{m}) \tag{23}$$

$$TP_{sat}^{o} = 1 - (TP_{\max}^{o} - TP^{o}) / (TP_{\max}^{o} - TP_{\min}^{o}) \tag{24}$$

$$TS_{sat} = 1 - (TS_{\max} - TS) / (TS_{\max} - TS_{\min}) \tag{25}$$

$$TP^{p} = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} p_i s_{itj} - \Big(HC\cdot\sum_{i\in I} h_i + FC\cdot\sum_{i\in I} h_i + EC\cdot\sum_{i\in I} w_t + OTC\cdot\sum_{i\in I}\sum_{t\in T} x_{it}^{ot} + IC^{p}\cdot\sum_{i\in I}\sum_{t\in T} EI_{it} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} TC_{itj}^{p}\cdot x_{itj} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} HDCC_{ij}^{p}\cdot IDC_{itj}\Big) \tag{26}$$

$$TP^{m} = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} p_i s_{itj} - \Big(HC\cdot\sum_{i\in I} h_i + FC\cdot\sum_{i\in I} h_i + EC\cdot\sum_{i\in I} w_t + OTC\cdot\sum_{i\in I}\sum_{t\in T} x_{it}^{ot} + IC^{m}\cdot\sum_{i\in I}\sum_{t\in T} EI_{it} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} TC_{itj}^{m}\cdot x_{itj} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} HDCC_{ij}^{m}\cdot IDC_{itj}\Big) \tag{27}$$

$$TP^{o} = \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} p_i s_{itj} - (HC\cdot\sum_{i\in I} h_i + FC\cdot\sum_{i\in I} h_i + EC\cdot\sum_{i\in I} w_t + OTC\cdot\sum_{i\in I}\sum_{t\in T} x_{it}^{ot} + IC^{o}\cdot\sum_{i\in I}\sum_{t\in T} EI_{it} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} TC_{itj}^{o}\cdot x_{itj} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} HDCC_{ij}^{o}\cdot IDC_{itj}\Big) \tag{28}$$

and constraints (1, 3-8, 9’, 10’, and 11-16).

The objective function (17) and constraints (18-21) are applied to maximize minimum satisfaction of total sales and total profit under three fuzzy (pessimistic, most likely, and optimistic) scenarios. Constraints (22-25) transform the total sales and total profit to satisfaction levels with a common scale from 0.0 to 1.0, to prevent the total sales that has higher value from dominating the total profit that has lower value. Objective function (2) which is the fuzzy objective function is defuzzified into three constraints with constant parameters, which are presented by constraints (26-28).

Method 2: Minimize maximum deviation from satisfaction targets (proposed method).

Method 2 is proposed since the business practice under consideration sets targets of total sales and total profit. Although both targets are relatively high and fully achievement of both targets may be difficult, this method attempts to satisfy both targets as much as possible. “To satisfy targets as much as possible” has the same meaning as “to minimize maximum deviation from the targets”. This concept is similar to a non-preemptive goal programming concept where the target is the goal and the method tries to minimize the deviation from the goal. When there are multiple goals, the method minimizes maximum deviation from multiple goals. Moreover, the target of sales has higher values than the target of profit. To prevent one target from dominating another, the targets are converted to the satisfaction targets with a common scale from 0.0 to 1.0. Finally, this method minimizes maximum deviation from satisfaction targets.

Unlike Method 1 that can generate only one compromised solution, Method 2 can generate various compromised solutions by setting different sets of satisfaction targets, and allows the supply chain planner select the solution that is the most preferable based on his/her opinion. This proposed approach is novel:

$$\text{Min } z_2 \tag{29}$$

where:

$$z_2 \geq \overleftrightarrow{TP}_{sat}^{p} \tag{30}$$

$$z_2 \geq \overleftrightarrow{TP}^{m}_{sat} \tag{31}$$

$$z_2 \geq \overleftrightarrow{TP}^{o}_{sat} \tag{32}$$

$$z_2 \geq \overleftrightarrow{TS}_{sat} \tag{33}$$

$$\overleftrightarrow{TP}^{p}_{sat} = \widehat{TP}^{p}_{sat} - TP^{p}_{sat} \tag{34}$$

$$\overleftrightarrow{TP}^{m}_{sat} = \widehat{TP}^{m}_{sat} - TP^{m}_{sat} \tag{35}$$

$$\overleftrightarrow{TP}^{o}_{sat} = \widehat{TP}^{o}_{sat} - TP^{o}_{sat} \tag{36}$$

$$\overleftrightarrow{TS}_{sat} = \widehat{TS}_{sat} - TS_{sat} \tag{37}$$

and constraints (1, 3-8, 9', 10', 11-16, and 22-28).

The objective function (29) and constraints (30-33) are applied to minimize maximum deviation of satisfaction form target of total sales and target of total profits under three fuzzy (pessimistic, most likely, and optimistic) scenarios. Constraints (34-37) determine the deviation from targets of total profits and total sales.

3.5. Data of the Case Study

This section provides data of the case study including demand of each product in each period, production capacity that relates to workforce level, limit of inventory for the manufacturer and distribution centers, and transportation cost.

According to Table 2, the demands of both products are seasonal, which is common for real industrial demands. Each product has different peak period of demand. The customer demands are relatively high when compared with the production capacity. It may not be economical to satisfy all demands.

Table 3 shows safety stock, beginning inventory, and maximum inventory for the manufacturer and distribution centers.

Table 4 presents workforce parameters including minimum workforce, maximum workforce, and beginning workforce.

According to the Table 5, the productivity rate during regular time and over time for each product are presented. They are uncertain because labor productivity has variability. Therefore, the data are presented as fuzzy numbers under pessimistic, most likely and optimistic situations.

Table 2. Product demand in each period

Period	Product 1(D_{1t}), (Units)	Product 2 (D_{2t}), (Units)
Period 1	9,983	13,090
Period 2	5,345	20,716
Period 3	3,365	5,663
Period 4	16,005	3,491
Period 5	20,607	7,922
Period 6	5,605	16,910

Table 3. Inventory capacity

	Safety Stock $\left(SM_i \ / \ SDC_{ij}\right)$, (Units)		Beginning $\left(EI_{0t} \ / \ EDC_{0tj}\right)$, (Units)		Inventory $\left(TI \ / \ MDC_j\right)$, (Units)
	Product 1	Product 2	Product 1	Product 2	For both products
Manufacturer Inventory	508	565	2,000	2,000	12,000
DC 1 Inventory	98	109	1,050	1,160	8,000
DC 2 Inventory	102	116	860	1,010	10,000
DC 3 Inventory	102	117	910	990	7,500
DC 4 Inventory	107	110	1,210	1,110	12,000
DC 5 Inventory	99	112	960	880	9,500

Table 4. Workforce capacity

	Minimum (MW) (Person)	Maximum (TW) (Person)	Beginning (w_t) (Person)
Workforce	50	300	75

Table 5. Production capacity

	Product type (i)	Productivity rates (Unit/Month-Employee)		
		Pessimistic	Most likely	Optimistic
Regular time $\left(\widetilde{RU}_i\right)$	Product 1	21	24	25
	Product 2	19	22	23
Over time $\left(\widetilde{OU}_i\right)$	Product 1	10	12	13
	Product 2	9	11	12

Table 6 presents regular labor cost, overtime cost, and hiring and firing costs. The overtime cost per piece of product is more expensive than the regular time cost for 10%.

Tables 7-9 show the transportation cost, manufacture inventory holding cost, and distribution center inventory holding cost, respectively. All costs are uncertain and represented by fuzzy numbers under pessimistic, most likely, and optimistic situations.

4. RESULTS AND DISCUSSION

In this section, model verification and validation are presented, followed by the result of single objective models, and the compromised solutions of multiple objective models.

4.1. Model Verification and Validation

The single objective model that maximizes total sales is used to verify that the model is correct and the results are reasonable. The model uses the objective function (1) and constraints (3-8, 9’, 10’,

Table 6. Labor, hiring and firing costs

	Cost (Baht)
Employee cost $\left(EC\right)$, (cost/month-employee)	15,000
Overtime cost $\left(OTC\right)$, (cost/unit-month)	725
Hiring cost $\left(HC\right)$, (cost/employee)	10,000
Firing cost $\left(FC\right)$, (cost/employee)	15,000

Table 7. Transportation costs

	Transportation Cost ($\widetilde{TC}_{ijt}$) (Baht/unit)			
	Product type	**Pessimistic**	**Most likely**	**Optimistic**
DC 1	Product 1	69	60	51
	Product 2	83.95	73	62.05
DC 2	Product 1	62.1	54	45.9
	Product 2	77.05	67	56.95
DC 3	Product 1	56.35	49	41.65
	Product 2	81.65	71	60.35
DC 4	Product 1	77.05	67	56.95
	Product 2	73.6	64	54.4
DC 5	Product 1	82.8	72	61.2
	Product 2	70.15	61	51.85

and 11-16). The optimal decisions in each period from the model are summarized in Figures 3 and 4 The sales and cost elements in each period are presented in Figures 5 and 6.

Figures 3 and 4 show that the demands of both products are seasonal with different peak periods. Since the model is to maximize total sales, the sales of both products for all periods are the same as the demands, except the sales of product 2 in period 1 that is lower than the demand. The production quantities are smoother than the demands that is highly seasonal. The optimal decisions from the model suggest that the inventory at the distribution centers is built up before the peak demand periods and it is used to satisfy the demands that is higher than the production quantities during peak demand periods. The inventory levels at the manufacturer are less than those at the distribution centers because the unit inventory holding cost at the manufacturer is more expensive than at the distribution centers. These observations convince that the model is correct and the results are reasonable.

Figures 5 and 6 clearly show that when the total sales is maximized, the sales in each periods of both products are highly fluctuated (similar to the demand fluctuations). The total cost is higher than the sales for some periods. This means that it has a loss in some periods. The regular labor costs (employee costs) are quite constant for all periods. The overtime labor costs (OT costs) are high for most periods, except for period 5 of product 2 since the production quantities are set at high levels to

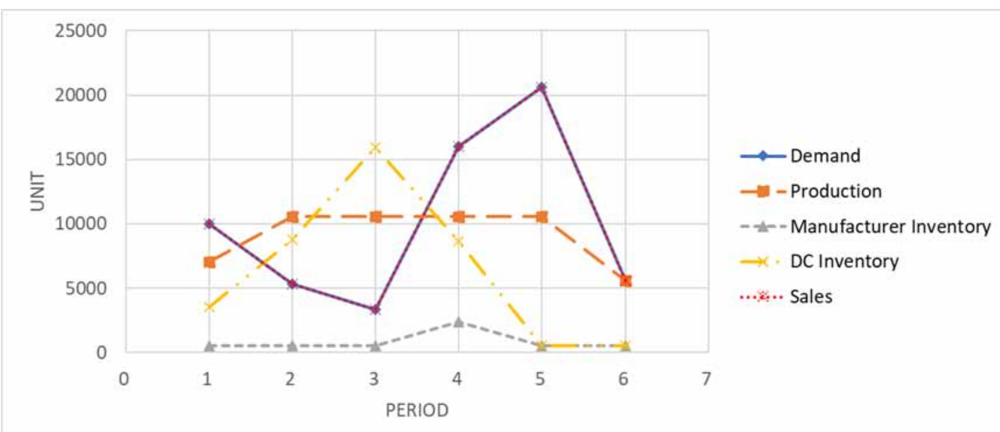
Table 8. DC inventory holding costs

	DC Inventory Cost ($\widetilde{HDCC}_{ij}$) (Baht/unit)			
	Product type	**Pessimistic**	**Most likely**	**Optimistic**
DC 1	Product 1	104.5	95	85.5
	Product 2	92.4	84	75.6
DC 2	Product 1	132	120	108
	Product 2	100.1	91	81.9
DC 3	Product 1	148.5	135	121.5
	Product 2	84.7	77	69.3
DC 4	Product 1	96.8	88	79.2
	Product 2	102.3	93	83.7
DC 5	Product 1	89.1	81	72.9
	Product 2	105.6	96	86.4

Table 9. Manufacturer inventory holding costs

	Manufacturer inventory cost ($\widetilde{IC}$) (Baht/unit)		
	Pessimistic	**Most likely**	**Optimistic**
Manufacturer Inventory cost	230	200	170

Figure 3. Optimal decisions related to product 1



satisfy most demands for maximizing total sales. The inventory holding costs at distribution centers are relatively high and fluctuated following the inventory levels at the distribution centers. These behaviors are reasonable for the model that maximizes the total sales.

Figure 4. Optimal decisions related to product 2

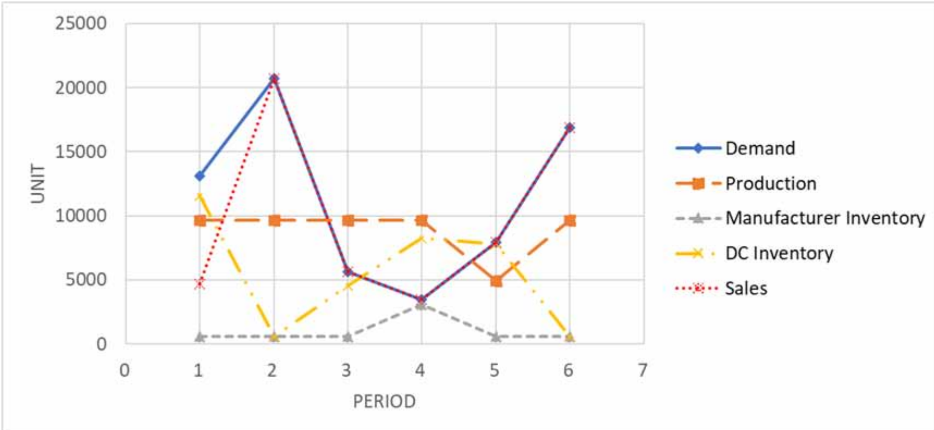
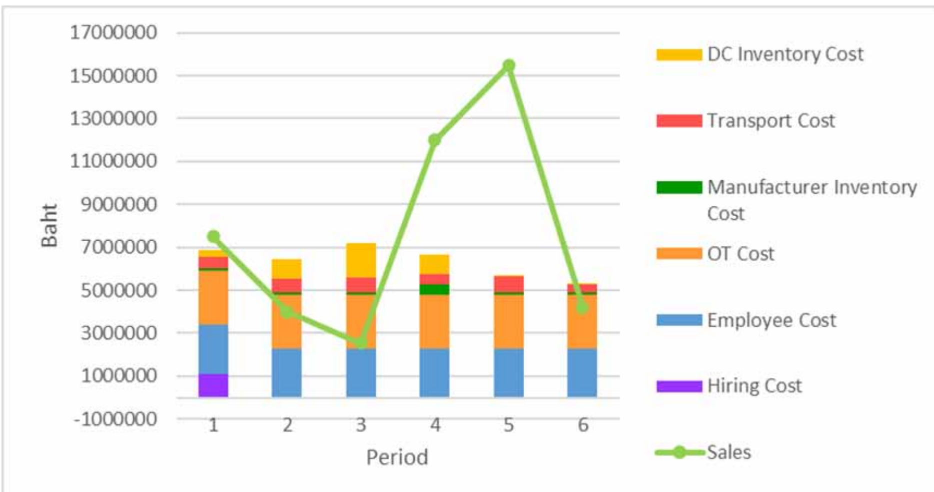


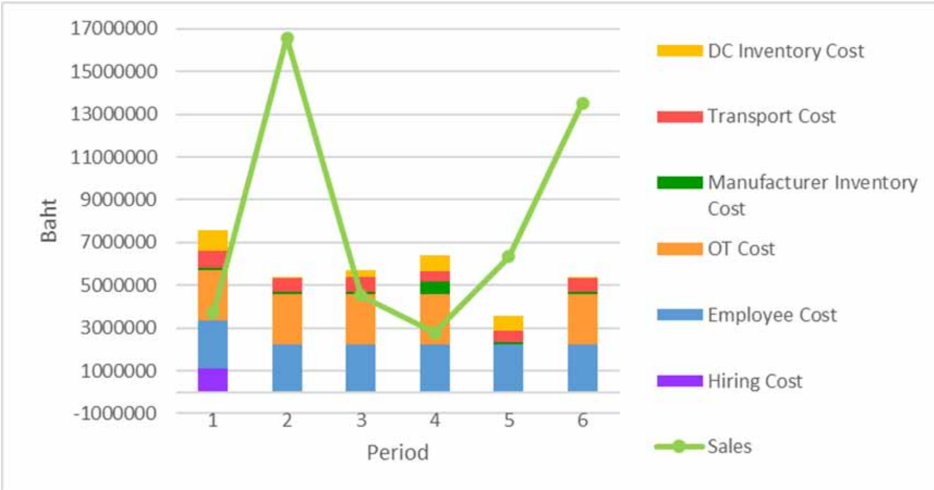
Figure 5. Cost elements and sales of product 1



4.2. Results of Single Objective Models

From Section 3.3, there are two objective functions, namely, maximizing total profit and maximizing total sales. The total profit function (Eq. 2) is a triangular fuzzy number under pessimistic, most likely, and optimistic scenarios while the total sales function (Eq. 1) is constant. Thus, there are four single objective models that maximize pessimistic profit (Eq. 26), maximize most likely profit (Eq. 27), maximize optimistic profit (Eq. 28), and maximize total sales (Eq. 1). All models have the same set of constraints (Eq. 3-8, 9', 10', and 11-16). The optimal objective values from all single objective models are presented in Table 9. From Table 9, when the objective is to maximize sales, the sales is 93.2 million Baht and the fuzzy profits range from 18.8 to 23.0 million Baht. When the objective is to maximize profits under three scenarios, the sales range from 76.6 to 71.7 and the fuzzy profits range from 31.5 to 34.1 million Baht. It clearly shows that the objectives of maximizing sales and maximizing profit are conflicting. It is not possible to get the maximum profit and maximum sales at the same time. The solutions from single objective models are extreme and are not compromised.

Figure 6. Cost elements and sales of product 2



Practically, businesses prefer compromised solutions that offer "reasonably good" sales and profits at the same time. The compromised solutions from FMOLP models will be determined in Section 4.3.

The FMOLP models need some parameters to calculate the satisfaction levels of fuzzy profit and sales, which are maximum and minimum values of fuzzy profit and sales. These parameters can be determined by experiences of a supply chain planner based on historical data or determined from the results of single objective models. This paper applies the latter method where the maximum and minimum values in each column of Table 10 are used. Therefore, $TP^p_{\max}$, $TP^p_{\min}$, $TP^m_{\max}$, $TP^m_{\min}$, $TP^o_{\max}$, $TP^o_{\min}$, $TS_{\max}$, and $TS_{\min}$ are 31,508,665, 18,839,575, 32,775,894, 20,900,588, 34,060,026, 22,961,600, 93,165,700, and 71,702,650, respectively.

4.3. Compromised Solutions

The compromised solutions from Methods 1 and 2 are presented in Table 11. The satisfaction measures are graphically shown in Figure 7. Method 1 does not need the satisfaction targets as inputs. It determines the compromised solution that maximize the lowest level of four satisfaction measures. From Table 10, the actual satisfaction of sales has the lowest level at 0.79 while the actual satisfactions of fuzzy profits are 0.86, 0.87, and 0.89. The satisfaction of sales is relatively low compared with those of fuzzy profits. Disadvantages of Method 1 are that it has only one compromised solution that cannot be controlled by the planner, and a satisfaction measure may be lower than others.

Method 2 needs the satisfaction targets of fuzzy profits and sales as inputs. When these satisfaction targets are set differently, the compromised solutions are also different. Table 11 shows that the actual

Table 10. Results from single objective models

Objectives	Pessimistic Profit (Baht)	Most likely Profit (Baht)	Optimistic Profit (Baht)	Sales (Baht)
Maximize pessimistic profit	31,508,665	32,731,130	33,953,595	71,702,650
Maximize most likely profit	31,491,946	32,775,894	34,059,842	76,552,250
Maximize optimistic profit	31,491,762	32,775,894	34,060,026	76,552,250
Maximize sales	18,839,575	20,900,588	22,961,600	93,165,700

Table 11. Compromised solutions

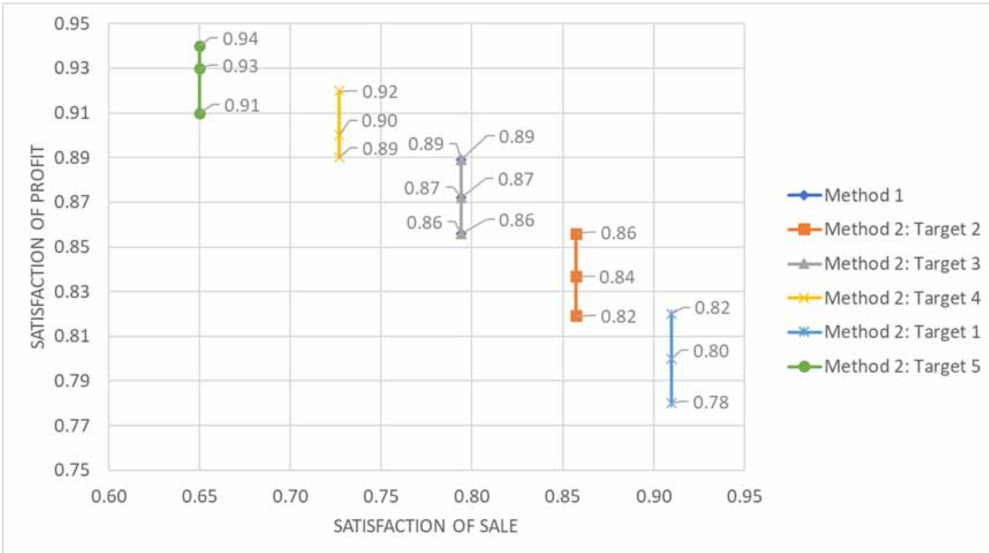
Method	Situation	Satisfaction target	Actual Satisfaction	Value (Baht)
Method 1:	Pessimistic profit	None	0.86	29,684,666
	Most likely profit		0.87	31,255,734
	Optimistic profit		0.89	32,826,802
	Sales		0.79	88,748,950
Method 2: Target 1	Pessimistic profit	0.75	0.78	28,738,784
	Most likely profit	0.75	0.80	30,411,756
	Optimistic profit	0.75	0.82	32,084,754
	Sales	0.95	0.91	91,286,950
Method 2: Target 2	Pessimistic profit	0.80	0.82	29,217,239
	Most likely profit	0.80	0.84	30,839,627
	Optimistic profit	0.80	0.86	32,462,015
	Sales	0.90	0.86	90,104,200
Method 2: Target 3	Pessimistic profit	0.85	0.86	29,684,677
	Most likely profit	0.85	0.87	31,255,739
	Optimistic profit	0.85	0.89	32,826,801
	Sales	0.85	0.79	88,748,900
Method 2: Target 4	Pessimistic profit	0.90	0.89	30,096,238
	Most likely profit	0.90	0.90	31,616,337
	Optimistic profit	0.90	0.92	33,136,436
	Sales	0.80	0.73	87,300,550
Method 2: Target 5	Pessimistic profit	0.95	0.91	30,421,955
	Most likely profit	0.95	0.93	31,896,829
	Optimistic profit	0.95	0.94	33,371,702
	Sales	0.75	0.65	85,705,600

satisfactions of Method 2 tend to be closed to the satisfaction targets. For example, Method 2 with satisfaction target set 1 (high satisfaction target of sales and low satisfaction targets of profit) has high actual satisfaction of sales and low actual satisfactions of profits. Figure 7 can clearly show that Method 2 with different sets of satisfaction targets have different levels of satisfaction of fuzzy profits and sales. There exists a clear trade-off between satisfactions of fuzzy profits and satisfaction of sales.

The supply chain planner can select the most preferable compromised solution form Method 2. From Figure 7, when very high profit is needed but the sales can be tolerated, Method 2 with satisfaction target sets 4 and 5 should be applied. When very high sales is needed but the profit can be tolerated, Method 2 with satisfaction target set 1 should be applied. It is also possible to achieve a well balance between satisfactions of fuzzy profits and satisfaction of sales, which is shown by the compromised solution of Method 2 with satisfaction target set 2. Note that Method 2 with some sets of satisfaction targets may generate the same compromised solution as that of Method 1 (see Method 2 with satisfaction target set 3).

The proposed method (Method 2) that minimize maximum deviation from satisfaction targets has advantages as follows: First, it allows the planner to generate various compromised solutions, and

Figure 7. Comparison of satisfaction measures of methods 1 and 2



select the most desirable one. Second, the compromised solution from Method 2 can be controlled by setting the satisfaction targets of fuzzy profits and satisfaction target of sales. Third, various compromised solutions from Method 2 are non-dominated solutions, which means that there is no compromised solution that is worse than another compromised solution for both profit and sales. Finally, Method 2 satisfies a need of real business that has targets of profit and sales to be achieved. Note that the targets of profit and sales can be converted to a common scale from 0.0 to 1.0, which is called the satisfaction targets.

5. CONCLUSION

In this paper, the aggregate production and distribution planning in a supply chain (APDP-SC) problem is considered and the appropriate fuzzy multi-objective linear programming model is developed with the aim of maximizing total sales and total fuzzy profits. To deal with uncertain parameters (in constraints and objective functions) and conflicting objectives, some methods to handle the fuzzy constraint and multiple fuzzy objectives are proposed. The methods include Method 1: maximizing minimum satisfaction method, and Method 2: minimizing maximum deviation from satisfaction targets method. Based on the experimental results of a case study, Method 1 provide only one compromised solution while Method 2 is effective to provide a number of different compromised solutions, and allows a supply chain planner select the most desirable compromised solution. The compromised solutions from Method 2 are responsive to the adjustments of targets of sales and fuzzy profits. This means that the actual satisfaction levels tend to be closed to the satisfaction targets.

The contributions of this paper are discussed. Theoretical contributions include:

1. This paper is the first one that proposes the FMOLP approach to determine compromised solutions for APDP-SC problem with two target-based objectives of simultaneously achieving total fuzzy profit targets and total sales target. Although many real businesses have targets of sales and profit to be achieved, there is no previous work in this field that develops the models with the same objectives.

2. The Method 2: minimizing maximum deviation from satisfaction targets, which is proposed in this paper, is effective to determine various compromised solutions and allow the supply chain planner select the most desirable one. The compromised solutions have actual satisfactions that are closed to the satisfaction targets. Moreover, the compromised solutions are Pareto-optimal or non-dominated solutions.

Additionally, practical contributions of this paper include:

1. The supply chain planner can manipulate the compromised solutions by adjusting satisfaction targets of fuzzy profits and sales. The compromised solutions will be changed following the targets. In practice, the model may not accurately represent the real situation. The planner needs the model that can generate various approximate solutions. The final decision is dependent on the planner. The proposed Method 2 satisfies the practical need of the planner.
2. The total profit from the model is a fuzzy number, which is more useful for the supply chain planner than a constant profit since the fuzzy profits warn the planner that it has a possibility that the profit will not follow the target. Therefore, this paper allows the supply chain planner set three different targets for optimistic, most likely, and pessimistic profits.

Limitations of this paper and recommendations for further studies are represented as follows: The first limitation is that the proposed model in this paper is the aggregate planning model, which does not show details of production and distribution activities, such as, a workstation, raw material, a component of the product, production schedule, and operations in distribution centers. The second limitation is that this paper considers only production and distribution stage in the supply chain system. It does not consider retailers and suppliers. Further studies should consider some disaggregation models to determine detailed plans of operations in the supply chain. The scope of supply chain under consideration should be expanded to cover retailers and suppliers as well.

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