Evaluation of SCOR KPIs using a Predictive MILP Model under Fuzzy Parameters.

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***Abstract*— The Supply Chain Operations Reference (SCOR) model is a well-recognized process reference model in the supply chain management field. Based on the literature, there is no research work that proposes a method to estimate and predict SCOR key performance indicators (KPIs) of a company. The objective of this paper is to propose a methodology to assess the SCOR KPIs under uncertainties based on level 2 of the SCOR-Make process metric, including nine KPIs. The proposed methodology consists of predictive MILP models with fuzzy parameters and some algorithms to assess the KPIs related to agility. The novelty of this paper is to relate the manufacturing parameters to the SCOR KPIs, and use the MILP model with fuzzy parameters to enable the performance prediction process in many what-if scenarios. This method is new in the performance evaluation framework by using a SCOR model. A case study of a bottled-water factory is conducted to demonstrate the application of the proposed methodology. The originality of this paper is we establish the relationship between the manufacturing parameters to the SCOR KPIs to enable the performance prediction process in many what-if scenarios. The findings indicate that the proposed methodology is capable of developing the relationship between the manufacturing parameters and the SCOR KPIs, which enable the effective prediction process especially when the manufacturing parameters are changed or improved.**

***Keywords*—** *SCOR, Performance measurement, MILP Model, Fuzzy, Supply Chain Management*

1. Introduction

The Supply Chain Operations Reference (SCOR) Model is a well-established process reference model which is supported by the APICS Supply Chain Council [1]. It is organized into five main processes. SCOR Model is comprised of performance attributes and the measurement metrics in a hierarchical structure. These organized features allow the framework to be widely adopted in the supply chain research, and practically adapted to various industries. To evaluate the performance using the SCOR KPIs, the model has provided a definition that is ready to be used, and it is possible to assess the values of these KPIs based on business outcomes. This method, even though it is quick and easy to use, lacks a procedural methodology, and the obtained KPIs cannot be further analyzed. The disadvantages of direct assessment of the SCOR KPIs are:

1. The relationships between the values of SCOR KPIs and manufacturing parameters are not known. Hence, it is not possible to predict the consequences of the SCOR KPIs when the manufacturing parameters are changed or improved.
2. There are agility measures in the SCOR KPIs. Without a procedural method and model, the evaluation of the agility measures is unclear and non-systematic.

Based on the above reasons, this paper proposes a model and a procedural methodology to assess these SCOR KPIs. For supply chain planning, there is an increasing interest to incorporate uncertainties into the models. This challenge leads to an application of stochastic programing and fuzzy mathematical programing [7]. However, when the statistical data is unavailable or not reliable, stochastic modelling may not be the best choice to deal with uncertainties. The fuzzy set theory (FST), is the alternative modelling technique that is effectively applied to model sources of uncertainty since it requires less data, compared with the probability theory that requires sufficient historical data. FST may be applied with the mixed integer linear programing (MILP) model to incorporate uncertainties into optimization capabilities [29]. The constraints and goals can be formulated and optimized to find the best allocation of resources that satisfy the objective function. The popularity of the fuzzy MILP model has broadly appeared in the supply chain research field such as: Inventory management [4], Vendor selection [12], [35], Transport planning [19], [24], Production-distribution planning [26], [33], and Procurement-distribution planning [32], [38]. With the successful implementation of the MILP model with fuzzy parameters that has contributed to various research fields, it is also expected that the MILP model with fuzzy parameters provides a good foundation as a predictive model that is used to systematically assess the SCOR KPIs according to the proposed methodology that is outlined in this paper.

The objectives of this paper are:

1. To propose a predictive model and a procedural methodology to assess the SCOR KPIs using fuzzy parameters.
2. To demonstrate the effectiveness of the proposed method by using a case study of a bottled drinking water factory.

The originality of this paper is to establish a method to assess the SCOR KPIs using the predictive MILP model. The developed methodology involves the manufacturing, supply, and demand related parameters that contribute to the assessment of the SCOR KPIs. Also, there are some procedures to assess agility metrics that are difficult to evaluate. The FST is used to handle process, demand, and supply uncertainties of the supply chain system.

The paper is organized as follows. Section 2 presents a literature review on (i) the foundation of SCOR model and its application in research, and (ii) the fundamentals of fuzzy set theory and its use in MILP model. Section 3 proposes the MILP model and the methodology to assess the SCOR KPIs, where a case study with numerical example is provided in Section 4. In section 5, the results are exhibited and discussed. Finally, the conclusion, limitations, and recommendations for further research are presented in Section 6.

2. Literature review

2.1 Foundation of SCOR model and its application

The SCOR model is a process reference model that provides a unified framework to manage a supply chain under the same standards and format. The model was first introduced in 1996 by the Supply Chain Council, and has been continuously revised to the 11th edition [1]. The model consists of three parts; (i) a SCOR model with standardized supply chain processes, (ii) a set of performance attributes and metrics, and (iii) benchmarking standards where the best practices are discussed. The model enables the company to establish communication using a standard terminology, and eliminates the wasteful practices along the chain, resulting in the improvement of the overall processes. [17], [18]. The application of the SCOR model has been reported in several industries. For example, the service industry [14], IT and technology consulting [40], transistor-LCD [16], the construction industry [9], [28], automotive industry [31], and in shipbuilding [47].

Based on literature reviews, the model is connected to many research methodologies to broaden their application. For example, the model is integrated with the AHP techniques for prioritization and evaluation purposes [6], [8], [27]. Fuzzy theory is combined with the SCOR model to address the issues of uncertainty. [13], [21]. Discrete event simulation is introduced to the SCOR model to create a template to use as a decision support tool [22], [30]. Lastly, case studies are applied to the SCOR model to investigate problems in the particular decision area such as in environmental considerations [3], [43], delivery processes [37], inventory management [15], and the footwear industry [34].

From the current literature, it is recognized that the APICS SCOR model is a globally accepted model that has been used by most of the academicians and practitioners to address many supply chain issues. However, the literature review discloses that the method for estimation of the SCOR KPIs is still limited in the literature, and without the method to estimate the performance that can be linked from the manufacturing system to the SCOR model, the direction for performance improvement is mostly obscured. This article aims to address this research gap by proposing a method with some models to evaluate the SCOR KPIs of a company by applying the model with the method of predictive modelling. The predictive model to evaluate the SCOR KPIs is useful since it helps the company to determine the relationship between manufacturing system and supply chain performances. The model is also capable to perform what-if analysis to foresee the new SCOR KPIs when the manufacturing parameters are changed or improved. Thus, it notifies changes to the management team before making decison, without conducting a real experiment on the manufacturing system.

2.2 Applications of Fuzzy Set Theory to handle uncertainties.

Uncertainty in a production planning environment is usually modelled as randomness, fuzziness, and epistemic uncertainty. Randomness came from the random nature of events and is described as a membership or non-membership element in a set. Fuzziness is related to the fuzzy constraints in fuzzy sets, and epistemic uncertainty is concerned with the unknown parameters modelled by fuzzy numbers in the setting of possibility theory [11]. Uncertainties in a supply chain system serves as one of the main factors that can influence the effectiveness of operations, therefore, many researchers have addressed this issue by different modelling techniques, such as a probabilistic distribution. [2], [36]. However, this technique requires evidence in the past, which is sometimes unavailable and not reliable. Fuzzy set theory (FST) is an alternative modelling technique, where a membership function describes the uncertainty parameters to generate the model's objective function, and constraints [5].

Fuzzy set theory (FST) was introduced by Zadeh, [46] as a technique to deal with the imprecise data and uncertainty that cannot be avoided in a practical situation. FST involves a set with element x that has the degree of membership valued in the real unit interval $[0,1]$, and the membership function is expressed as $\mu(x)$. The degree of membership is interpreted as the level of belonging of a particular element x to the set, which represents the nature of uncertainty that is commonly found in the studied environment. FST has provided an efficient evaluation of a system, and was continuously used until the present, for example, in a control system [42], [48], resource allocation [20], cellular manufacturing for small batch production [44], performance evaluation [41], planning and scheduling [23], supply chain production planning [7], [25], supplier selection [10], [21], [45] and system design [39].

In this study, the MILP model with fuzzy parameters is used to solve the production planning problem of a case study and to evaluate the SCOR KPIs of the company according to the proposed methodology. The aim of the MILP model is to determine the optimal plan for the limited production resources that satisfy the market demands at a minimum cost. Fuzzy parameters are used to represent the sources of uncertainty in the production system, and they are described as triangular fuzzy numbers (TFNs). The TFNs are denoted by fuzzy set $\tilde{A}$, and they are defined as *(a ,b, c)*. The A_λ is a crisp set that used to represent uncertainty, and it is derived from the parent fuzzy set $\tilde{A}$, where $0 \le \lambda \le 1$ and $A_\lambda = \{x \mid \mu_{\tilde{A}}(x) = \lambda\}$. The membership function $\mu_{\tilde{A}}(x)$ is shown in Eq. (1), where the crisp set A_λ is exhibited in Fig 1.

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

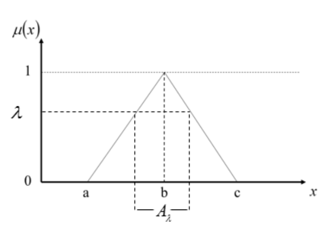

Figure 1: A fuzzy set with λ cut

3. The proposed methodology

The proposed methodology for SCOR KPIs evaluation consists of two parts. The first part is to formulate the predictive MILP model with fuzzy parameters, and the second part is to propose the method to evaluate the SCOR KPIs based on level 2 of the SCOR-Make process metric, including nine KPIs. Before the methodology is presented, we present a block diagram to explain the overall research procedure, and this is exhibited in Fig 2.

Develop the MILP model (predictive model) to represent the manufacturing system under consideration.

↓

Apply uncertainties in the manufacturing system to the MILP model, using TFNs, and solve the model for the optimal outputs based on uncertainties.

↓

Evaluate the level 2 SCOR KPIs, based on the outputs of the MILP with fuzzy parameters, and the proposed methodology.

Figure 2: Block diagram of the overall research procedure

3.1 The predictive model

In this study, a predictive model is used because the relationships between the values of SCOR KPIs and the manufacturing parameters are not known. The aim of the predictive model is to represent the manufacturing system to be studied. This is used as a foundation to assess the SCOR KPIs of the SCOR-make process. Also, there are agility measures in the study, and without the procedural methodology, the measurement of agility is almost impossible. The structure of the manufacturing system, the MILP model, and the fuzzy parameters are described as follows.

3.1.1 The MILP model

The MILP model is used to determine optimal plans that are most favourable to the stated objective function. In this case, the optimal plans involve raw material ordering, production, and inventory planning that meet the demand requirements in each period. The structure of the manufacturing system is presented in the Fig 3. In this paper, the manufacturing system is a make to stock flow shop. It produces I products to fulfill the demand D_{it} over T planning periods. The manufacturing process consists of K production stages. The raw material is planned and ordered using a material requirement planning (MRP) system. The amount of plastic resin in grams to produce each size of the plastic bottle is τ_i. The machine at each stage is specific to the operation and there are n_k identical machines at each production stage k. There is a work in-

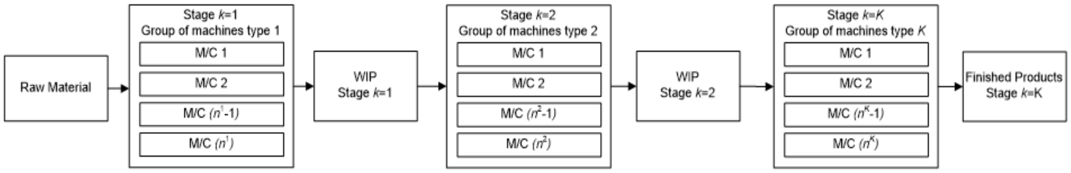

Figure 3: Structure of manufacturing system

-process (WIP) between production stages, and W_t workers are available in period t. The manufacturing system operates h_t shifts in period t, and each shift has δ working hours. The parameters, decision variables, objective function, and constraints of the model are defined as follows.

Parameters

i	Product index $i=1,2,..,I$
t	Period index $t=1,2,..,T$
k	Production stage index $k=1,2,..K$
n^k	Number of machines at production stage k.
cm_i	Material cost of product i (Baht/pack)
cu_i	Utility and production overhead cost of product i (Baht/pack)
cr	Labour cost per one shift (Baht/person)
ci_i	Inventory carrying cost of product i (Baht/pack/period)
cj_i	WIP Inventory carrying cost of product i (Baht/bag/period)
cl	Raw material Inventory carrying cost (Baht/ton/period)
cs_i	Subcontract cost of product i (Baht/pack)
cb_i	Backorder cost of product i (Baht/pack)
ck_i	Standard cost of WIP inventory of product i (Baht/bottle)
cn_t	Standard cost of Raw Material inventory of product i (Baht/kg)
e_i	Hours of labour per unit of product i (man-hour/unit)
W_t	Total workforce in period t (workers)
δ	Working time per one worker per shift (hours/shift)
γ	Machine operating hours per day (hours/day)
C^k	Production capacity of each machine in stage k (units/hour)
h_t	Number of shifts per day in period t
d_t	1 if period t is a working day, 0 otherwise
ρ_i	Number of units per pack of product i
θ	Number of units per bag of WIP of product i
D_{it}	Demand of product i at period t (packs)
ΦD_i	Total number of order of product i in all periods (orders)
R_i	Selling price of product i (Baht/pack)
$\underline{I}_i$	Level of safety stock of product i, according to company policy (packs)
Sm_{it}	Maximum allowable subcontract amount of product i at period t (packs)
$\overline{M_t}$	Maximum raw material inventory at the end of period t: beyond this level there is a cost penalty (tonnes)
$\overline{J_{it}}$	Maximum WIP inventory of product i at the end of period t in any stage: beyond this level there is a cost penalty (units)
$\overline{I_{it}}$	Maximum finished product inventory of product i at the end of period t: beyond this level there is a cost penalty (packs)
$\underline{M_t}$	Safety stock of raw material at the end of period t (tonnes)
$\underline{J_{it}}$	Safety stock at of WIP of product i at the end of period t in any stage (units)
$\underline{I_{it}}$	Safety stock of finished product i at the end of period t (packs)
$\hat{I}_i$	Target ending inventory of product i according to company policy (packs)
G_t	Amount of raw material based on MRP system to be received at period t (tonnes)
τ_i	Amount of raw material used to produce product i (grams per unit)
TF_i	Fixed component cycle time i.e. schedule time, issue material time, and release product time per lot of product i (min)
L_{ik}	Lot size of product i at process k (packs)
T_{ik}	Unit processing time of product i at process k

Decision Variables

P_{it}^k	Amount of product i produced at period t in stage k (units)
S_{it}	Subcontract amount of product i at period t (packs)
I_{it}	Inventory of product i at the end of period t (packs)
J_{it}^k	WIP Inventory of product i at the end of period t in stage k (units)
B_{it}	Backorder amount of product i at period t (packs)
M_t	Raw material inventory left at the end of period t (tonnes)
ΦB_i	Total number of orders, with backorder of product i in all period (orders)

Objective Function

$$MAX = \sum_{i=1}^{I}\sum_{t=1}^{T} R_i D_{it} - \sum_{t=1}^{T} cr\, W_t d_t - \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=K}\left((cm_i + cu_i)\frac{P_{it}^k}{\rho_i}\right) + \sum_{i=1}^{I}\sum_{t=1}^{T} ci_i I_{it} + \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=1}^{K-1} cj_i \frac{J_{it}^K}{\theta_i} - \sum_{i=1}^{I}\sum_{t=1}^{T}\left(cs_i S_{it} + cb_i B_{it}\right) - \sum_{t=1}^{T} clM_t \tag{2}$$

Constraints

1. Raw material balance

$$10^{-6}\sum_{i=1}^{I}\tau_i P_{it}^{k} = M_{t-1} + G_t - M_t \quad ,\forall t,\ k=1 \qquad (3)$$

2. Inventory balance

$$J_{it}^{k} = J_{i(t-1)}^{k} + P_{it}^{k} - P_{it}^{k+1},\ \forall i,\forall t,\quad k=1,..,K\text{-}1 \qquad (4)$$

$$I_{it} - B_{it} = I_{i(t-1)} - B_{i(t-1)} + \frac{P_{it}^{k}}{\rho_i} + S_{it} - D_{it} \quad ,\forall i,\forall t,\ k=K \qquad (5)$$

3. Production capacity constraint

$$\sum_{i=1}^{I} P_{it}^{k} \le \gamma C^{k} d_t n^{k} \qquad ,\ \forall t,\ \forall k \qquad (6)$$

4. Workforce- production constraint

$$\sum_{i=1}^{I} e_i P_{it}^{k} \le \delta d_t h_t W_t \qquad ,\forall t,\ k=K \qquad (7)$$

5. Safety stock and maximum inventory policies

5.1 Raw material inventory

$$\underline{M_t} < M_t < \overline{M_t} \qquad ,\ \forall t \qquad (8)$$

5.2 WIP inventory

$$\underline{J_{it}} < J_{it}^{k} < \overline{J_{it}} \quad ,\forall i,\forall t, k=1,..,K\text{-}1 \qquad (9)$$

5.3 Finished goods inventory

$$\underline{I_{it}} < I_{it} < \overline{I_{it}} \qquad ,\ \forall i\ \ \forall t \qquad (10)$$

6. Target ending inventory of finished products

$$I_{it} = \hat{I}_i \qquad ,\ \forall i,\ t=T \qquad (11)$$

7. Subcontracting limitation

$$S_{it} \le Sm_{it} \qquad ,\forall i,\forall t \qquad (12)$$

8. Backordering is not allowed at the end of planning horizon

$$B_{it} = 0 \qquad ,\forall i,\ t=T \qquad (13)$$

The objective function in Eq. (2) is to maximize profit, which consists of total sale revenues minus total manufacturing costs, including the labor cost, direct material and production overhead costs, inventory holding cost for all production stages, subcontracting cost, and backordering cost. Constraints (3-5) explain the inventory balance of raw materials, WIP, and finished products. Note that constraint (5) allows backordering of finished products. Constraint (6) represents a machine capacity that limits the production quantity of each stage based on the machine operating hours, machine capacity, workday per period, and number of machines at each stage. Constraint (7) limits production quantity of finished products, based on available workforce level. Constraints (8-10) control raw material, WIP, and finished product inventory levels based on the safety stock and maximum stock policies of the company. Constraint (11) sets the target finished product inventory at the end of planning horizon, based on the company policy. Constraint (12) restricts the subcontracting level in each period. Constraint (13) states that backordering is allowed in all periods except at the end of the planning horizon, to ensure that all demands must be satisfied, although it may be satisfied late.

3.1.2 The MILP model with fuzzy parameters.

The output obtained from the MILP model is the optimal plans that the company should follow to get the maximum profit, but in reality, there are uncertainties in the manufacturing system that prevent the manufacturing process from reaching the planned outputs. In this study, we consider uncertainties from manufacturing processes, demand, and supply. The crisp set A_λ at $\lambda=0.8$, based on the fuzzy set $\tilde{A}$, is used to represent uncertainty. Zadeh's notation is used to present a

crisp set $A_{0.8}$ according to Eq. (14).

$$A_{0.8} = \{a, b, c\} \qquad (14)$$

Equation 14 explains that each fuzzy parameter contains three finite numbers, which represent uncertainties of three scenarios. The MILP model with *a*, *b*, and *c* values of fuzzy parameters is solved separately to obtain the outputs under uncertainties. To be specific, three MILP models with three sets of parameters are solved to determine the company's actual output in this case. The fuzzy parameters and decision variables are defined below.

Fuzzy parameters for uncertainty

Uncertainties from the manufacturing process

$\tilde{n}^{k}$	Number of machines in working conditions at production stage *k*
$\tilde{W}_t$	Total workforce that is really available in period *t* (workers)
$\tilde{\delta}$	Working time that one worker really works per shift (hours/shift)
$\tilde{\gamma}$	Number of hours that a machine really operates per day (hours/day)
$\tilde{M}_0$	Real initial raw material inventory (tonnes)
$\tilde{J}^{k}{}_{i0}$	Real initial WIP inventory of product *i* at stage *k* (bottles)
$\tilde{I}^{k}{}_{i0}$	Real initial finished product inventory of product *i* (packs)

Uncertainties from the supply side

$\tilde{G}_t$	Amount of raw material really received at period *t* (tonnes)
$\tilde{Sm}_{it}$	Real maximum allowable subcontract amount of product *i* at period *t* (packs)

Uncertainties from the demand side

$\tilde{D}_{it}$	Real demand of product *i* at period *t* (packs)

Fuzzy decision variables for uncertainty

$\tilde{P}_{it}{}^{k}$	Finished product *i*, which is really produced at period *t* in stage *k* (units)
$\tilde{J}_{it}{}^{k}$	Real WIP Inventory of product *i* at the end of period *t* in stage *k* (units)

$\tilde{I}_{it}$	Real inventory of product i at the end of period t (packs)
$\tilde{S}_{it}$	Real subcontracting amount of product i at period t (packs)
$\tilde{B}_{it}$	Real backorder amount of product i at period t (packs)
$\tilde{M}_{t}$	Real raw material inventory left at the end of period t (tonnes)

The fuzzy set of parameters and the decision variables are replaced in the MILP model to solve for the optimal outputs under uncertainties. However, we input the additional constraints to the MILP model with fuzzy parameters to ensure that the cumulative production quantities under uncertainties do not exceed the cumulative planned production quantity in each period. The reason is that the company cannot practically produce faster than the production plan to compensate for the delay that may occur in the future, which is not known at the present time. This is explained by constraint (15)

$$\sum_{t=1}^{T} \tilde{P}_{it}^{k} \leq \sum_{t=1}^{T} P_{it}^{k} \qquad ,\forall i \ ,\forall t \ ,\ \forall k \qquad (15)$$

The outputs from the MILP model with fuzzy parameters are then defuzzified using a centroid method which is presented by Chou and Chang (2008). For TFNs, the centroid of $\tilde{A} = [a, b, c]$ is determined by Eq.(16)

$$C_{\tilde{A}} = \frac{a+b+c}{3} \qquad (16)$$

3.2 The proposed methodology to evaluate the SCOR KPIs.

This part consists of the proposed methodology to evaluate the SCOR KPIs based on SCOR version 10.0 (APICS,2016), and a mechanism to assess the agility measures. The scope of this paper is the manufacturing process, therefore, the level 2 SCOR KPIs of the make process are focused on. Table 1 illustrates the SCOR performance attributes, level 1 strategic metrics, and the level 2 SCOR KPIs, used in this paper.

Table 1: SCOR performance attributes and level 2 KPIs used in this paper

Performance Attributes	Level 1 Strategic metrics	Level 2 SCOR KPIs (make process)
Supply chain reliability	Perfect Order Fulfillment (RL. 1.1)	(1). Percent of Orders Delivered in Full (RL.2.1)
Supply chain responsiveness	Order Fulfillment Cycle Time (RS. 1.1)	(2). Make Cycle Time (RS.2.2)
Supply chain agility	Upside Supply Chain Flexibility (AG.1.1)	(3). Upside Make Flexibility (AG.2.2)
	Upside Supply Chain Adaptability (AG.1.2)	(4). Upside Make Adaptability (AG.2.7)
	Downsize Supply Chain Adaptability (AG.1.2)	(5). Downsize Make Adaptability (AG.2.12)
Supply chain cost	Supply Chain Management Cost (CO.1.1)	(6). Cost to Make (CO.2.3)
	Cost of Goods Sold (CO.1.2)	
Supply chain asset management	Cash to Cash Cycle Time (AM.1.1)	(7). Inventory Days of Supply (AM.2.2)
	Return on Supply Chain Fixed Assets (AM.1.2)	(8). Return on make fixed assets
	Return on Working Capital	(9). Return on make working capital

RL 2.1 measures the percentage of orders of each product that is delivered in full with a committed quantity within the period. It is computed as:

$$\frac{\phi D_i - \phi B_i}{\phi D_i} \times 100\% \qquad ,\forall i \qquad (17)$$

3.2.2 Make cycle time (RS2.2)

Make cycle time is the average cycle time associated with the make process. It consists of the fixed component cycle time and the variable cycle time per lot. The calculation is expressed in Eq. (18)

$$\sum_{i=1}^{I} TF_i + \sum_{k=1}^{K} \sum_{i=1}^{I} (L_{ik} \rho_i T_{ik}) \qquad (18)$$

3.3.3. Upside Make Flexibility (AG2.2)

Upside make flexibility is the average number of days that a company requires to satisfy a demand increase of 20% from the current level. The proposed procedural methodology to evaluate AG2.2 is presented in Fig 5.

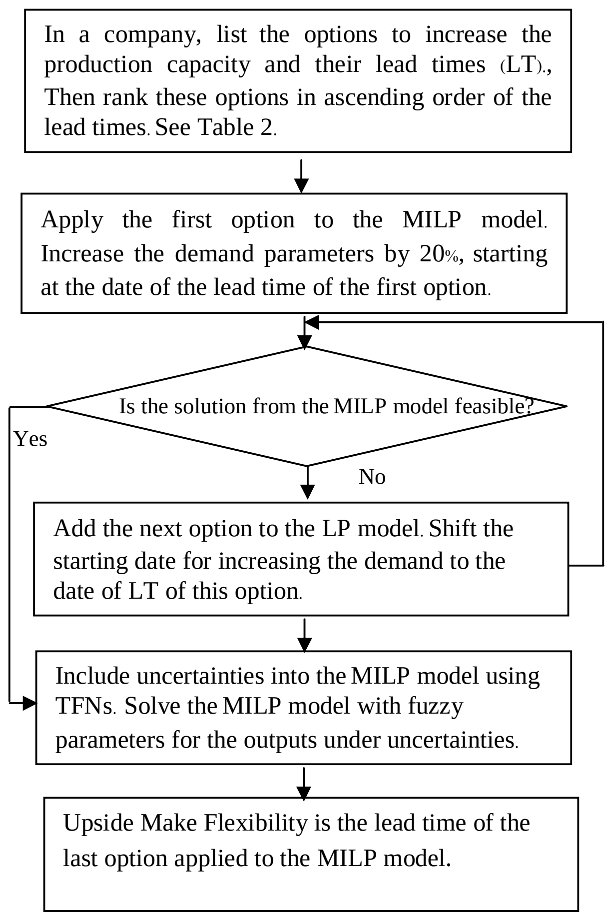

Figure 5: The proposed procedure to evaluate Upside Make Flexibility

Table 2: Options to increase production capacity and the estimated lead time.

Resources	Options	Lead Time
Raw material	Order additional raw material using MRP	10 days
Workforce	Add four more skilled workers for production.	15 days
Subcontract	Increase subcontracting by 10% from current subcontract level	21 days
Safety Stock	Increase safety stock of finished products by 25% from the current level.	21 days.
Machines	Purchase more production machines.	Up to 4 months.

3.3.4. Upside Make Adaptability (AG2.7)

Upside make adaptability is the maximum sustainable increased percentage of the demand that the company can satisfy given a preparation time of 30 days. The proposed methodology to evaluate this agility measures is explained by Fig 6.

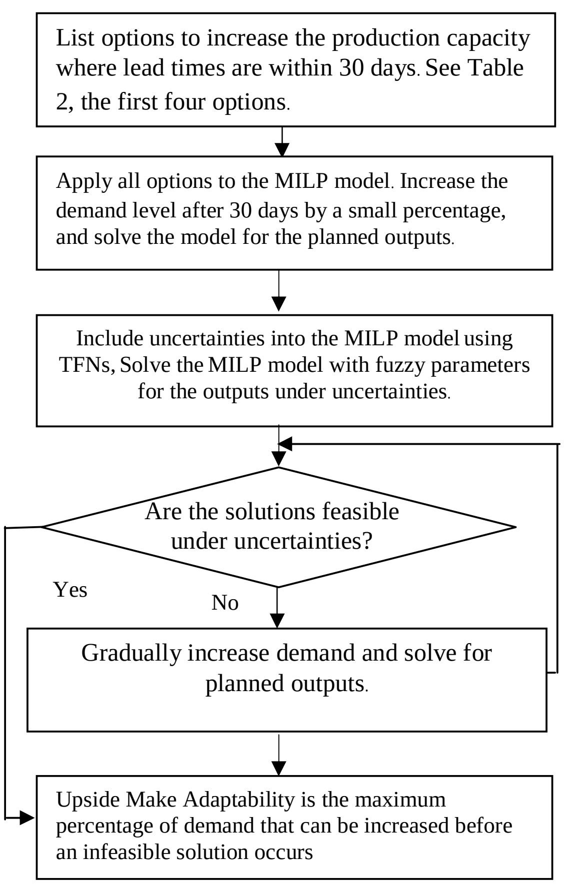

Figure 6: The proposed procedure to evaluate Upside Make Adaptability

3.3.5. Downsize Make Adaptability (AG2.12)

Downsize make adaptability is the maximum reduction percentage of demand that the company can achieve within a preparation time of 30 days, and the reduction must not incur extra cost on inventory holding and other penalties. The procedural evaluation of AG2.12 is presented in Fig 7.

Table 3: Options to decrease production capacity and the estimated lead time.

Resources	Options	Lead Time
Workforce	Move three skilled workers to other activities in the factory	15 days
Working time	Reduce working time from 12 to 8 hours/shift	15 days
Subcontracting	Reduce subcontract level up to 10% of the initial demand	21 days

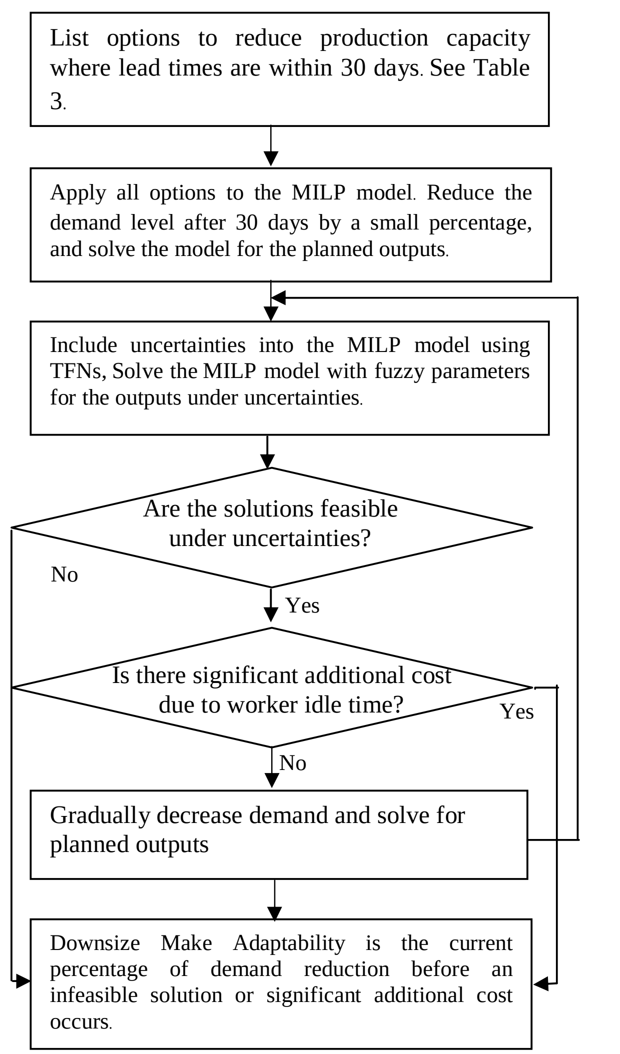

Figure 7: The proposed procedure to evaluate Downsize Make Adaptability

3.3.4. Cost to make (CO2.3)

Cost to make or Cost of goods sold, measured in percentage of sales revenue, is the cost associated with buying raw materials and producing the finished goods. It includes the direct cost of labor and materials, and the indirect cost of overhead. The evaluation is explained by Eq.(19).

$$\left(\begin{array}{l}\sum_{t=1}^{T} cr\, W_t d_t + \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=K}\left((cm_i + cu_i)\frac{P_{it}^{k}}{\rho_i}\right) + \\ \sum_{i=1}^{I}\sum_{t=1}^{T} ci_i I_{it} + \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=1}^{K-1} cj_i \frac{J_{it}^{K}}{\theta_i} \\ -\sum_{i=1}^{I}\sum_{t=1}^{T}\left(cs_i S_{it} + cb_i B_{it}\right) + \sum_{t=1}^{T} clM_t \end{array}\right) / \sum_{i=1}^{I}\sum_{t=1}^{T} R_i D_{it} \tag{19}$$

3.3.5. Inventory days of supply (AM2.2)

The measure of cash-to-cash cycle time actually includes the inventory days of supply, days sales outstanding (DSO), and days payable outstanding (DPO). However, this paper aims to predict the SCOR KPIs from the MILP model, so we neglect the effect of DSO and DPO. This is expressed by Eq. (20).

$$\frac{\frac{1}{T}\left[\sum_{t=1}^{T}\sum_{i=1}^{I} I_{it}\left(cm_i + cu_i\right) + \sum_{t=1}^{T}\sum_{i=1}^{I} J_{it}(ck_i) + \sum_{m=1}^{M} M_t\left(cn_t\right)\right]}{\text{Cost to make per period (Baht)}} \tag{20}$$

3.3.6. Return on make fixed assets

The return on make fixed assets indicates the return on the capital invested to the make fixed assets. It is calculated as the fraction of the net profit to the fixed assets in manufacturing facilities. The formula is presented by Eq. (21).

$$\frac{\left(\sum_{i=1}^{I}\sum_{t=1}^{T} R_i D_{it} - \text{Cost to make (Baht)} - \text{Sales and admin costs}\right)}{\text{Total make fixed assets}} \tag{21}$$

3.3.7. Return on make working capital

The return on make working capital compares the revenue generated from the manufacturing facilities to the amount of working capital. The computation is expressed by Eq. (22), while the AP and AR are assumed to be constant in this case.

$$\frac{\left(\sum_{i=1}^{I}\sum_{t=1}^{T} R_i D_{it} - \text{Cost to make (Baht)} - \text{Sales and admin costs}\right)}{\frac{1}{T}\left[\sum_{t=1}^{T}\sum_{i=1}^{I} I_{it}\left(cm_i + cu_i\right) + \sum_{t=1}^{T}\sum_{i=1}^{I} J_{it}(ck_i) + \sum_{m=1}^{M} M_t\left(cn_t\right)\right] + \text{AR} - \text{AP}} \tag{22}$$

In this work, since the SCOR KPIs are evaluated based on the outputs of the MILP model with fuzzy parameters, the outputs are also fuzzy numbers. The SCOR KPIs need to be defuzzifed using the centroid method in Eq. (16). Results from the proposed methodology is presented in Section 5.

4. Case study

To demonstrate an application of the method, this paper conducts a real case study in a small flow shop producing bottled water since its manufacturing process is easy to understand and the degree of complexity is suitable to clarify how the proposed method and models are applied in a real situation. It is expected that the readers of this paper will be able to apply the proposed method to more complicated cases afterward. The bottled drinking water factory under consideration has the manufacturing process configured according to Fig 8. The company produces 2 sizes (i_1 = 1500cc, i_2 =600 cc) of drinking water in bottles. The amount of plastic resin in grams to produce each size of the bottle is τ_1 = 4.17 and τ_2 = 1.58, respectively. The manufacturing facilities are arranged as a flow shop that consists of 2 stages (K=2), which are a bottle blowing process and a water filling process. The company orders raw material of plastic resin to produce the bottles based on the material requirement planning (MRP) at an amount of 2 tonnes per lot. There are 4 blowing machines for producing bottles (n^1 = 4). Each has a capacity of 1,600 bottles per hour (C^1= 1,600), and they are operated for 24 hours a day (γ=24). Empty bottles, which are a work-in-process (WIP), are stored between two production stages, and wait to be transferred to a fill line. The water filling line is operated by a conveyor system. The empty bottles are conveyed to a wash, filled with water, covered with a cap, seal, inspected, shrink-wrapped into bundles, and transferred to stock in a warehouse area. There are two fill lines (n^2 = 2). Each line has a capacity of 2,400 bottles per hour (C^2= 2,400), and they are operated for 24 hours per day. Currently, 13 workers are involved in the production (W_t = 13). Each unit of bottles requires on average 0.05 man-hours (e_i=0.05) and the employees work two shifts per day (h_t=2), at 12 hours/shift from Monday to Friday (δ=8). The labor cost (cr) is 300 Baht/day. The company is now subcontracting for extra capacity on average at 30% of the current demand. The cost structure, inventory holding policy, options to increase and decrease capacity, and total asset values are discussed next.

4.1 Cost structure and inventory holding policy.

The finished products are sold in packs, which are 6 bottles per pack for 1,500 cc (ρ_1=6), and 12 bottles per pack for 600 cc (ρ_2=12). Estimated demand per day is 805 bottles per day for 1,500 cc (D_{1t} = 805), and 3,198 bottles per day for 600 cc (D_{2t} = 3,198). The selling price (R_i) is 40 Baht/pack for both products. Table 4 shows the related operating costs. The unit for all costs is Baht/pack except the finished product and WIP inventory holding cost,

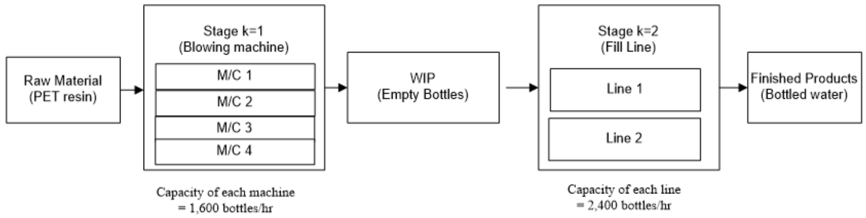

Figure 8: The manufacturing process of a case study

which are Baht/pack/period, and Baht/bag/period, respectively. The standard cost for WIP inventory is in Baht/bottle, and standard cost for raw material inventory (cn_t) is 60 Baht/kg. The raw material inventory holding cost (cl) is 20 Baht/tonne/period.

Table 4: Operating cost information

Bottle (CC)	Material Cost cm_i	Overhead Cost cu_i	Subcontracting Cost cs_i	Backorder Cost cb_i	FP Inventory holding Cost ci_i	WIP Inventory holding Cost cj_i	Standard Cost of WIP Inventory ck_i
1,500	21.68	3	35.96	7	0.72	0.8	1.35
600	23.2	4	37.13	9	0.8	0.833	2.95

4.2 Current fixed assets, estimated accounts receivable, and accounts payable

From the collected data, the company can estimate total fixed assets as shown in Table 6. In this case study, the estimated accounts receivable and accounts payable are 5,286,107 Baht and 2,509,905 Baht, respectively.

The company's inventory holding policy is shown in Table 5.

Inventory	Maximum inventory limit		Minimum inventory limit	
	1,500 cc	600 cc	1,500 cc	600 cc
WIP (bottles)	19,000 ($\overline{J_{1t}}$)	50,000 ($\overline{J_{2t}}$)	0 ($\underline{J_{1t}}$)	15,000 ($\underline{J_{2t}}$)
Finish goods (packs)	2,500 ($\overline{I_{1t}}$)	5,000 ($\overline{I_{2t}}$)	375 ($\underline{I_{1t}}$)	600 ($\underline{I_{2t}}$)
Raw materials	0.82 tonnes ($\overline{M_t}$)		0.13 tonnes ($\underline{M_t}$)	

The WIP in between the process is stored and transferred in bags, which are 380 bottles per bag for 1,500 cc (Θ_1=380), and 720 bottles per bag for 600 cc (Θ_2=720). The options to increase and decrease production capacity to analyse the agility measures are presented in Tables 2 and 3.

Table 6: Estimated company's total fixed assets.

Make Fixed Assets	Value (THB)
1. Land	15,000,000
2. Building, factory, office, and warehouse	5,000,000
3. Four blowing machines at current book value	2,200,000
4. Two fill lines at current book value	2,800,000
Estimated Total Make Fixed Assets	25,000,000

The sources of uncertainty are presented by TFNs, using a crisp set A_λ at λ=0.8. The fuzzy parameters used in the MILP model are presented in Table 7.

5. Results and discussion

The proposed methodology is applied to the case study to demonstrate the practicality of the method. Results are presented in two parts; first is the outputs from the predictive model and second is the outcomes of the SCOR KPIs based on the proposed method.

Table 7: The fuzzy parameters used in the MILP model

Fuzzy Parameters	$A_{0.8}$
Number of blowing machines in working condition (n^1)	$\{3, 4, 4\}$
Number of fills line in working condition (n^2)	$\{1, 2, 2\}$
Total workforce that is available (W'_t)	$\{12, 13, 13\}$
Working time for one worker work per shift (δ')	$\{11, 12, 12\}$
Number of hours that a machine operates per day (γ')	$\{22, 24, 24\}$
Real initial raw material inventory (M'_0)	$\{0.47, 0.5, 0.53\}$
Real initial WIP inventory of product 1 at stage 1 (J'^1_{10})	$\{8{,}600, 9{,}000, 9{,}400\}$
Real initial WIP inventory of product 2 at stage 1 (J'^1_{20})	$\{34{,}400, 36{,}000, 37{,}600\}$
Real initial finished product inventory of product 1 (I'_{10})	$\{980, 1{,}000, 1{,}020\}$
Real initial finished product inventory of product 2 (I'_{20})	$\{5{,}860, 6{,}000, 6{,}140\}$
*Amount of raw material really received at period t (G'_t)	$\{1.179, 1.451, 1.632\}$
Real maximum allowable subcontract amount of product 1 at period t (Sm'_{1t})	$\{760, 792, 824\}$
Real maximum allowable subcontract amount of product 2 at period t (Sm'_{2t})	$\{2{,}822, 2{,}940, 3{,}058\}$
Real demand of product 1 at period t (D'_{1t})	$\{734, 805, 875\}$
Real demand of product 2 at period t (D'_{2t})	$\{3{,}009, 3{,}200, 3{,}390\}$

5.1 Outputs from the predictive mode

The optimal outputs based on the provided data and MILP model are presented in Table 8 in terms of the total cost structure, according to the stated objective functions and model constraints.

Table 8: Outputs from the MILP model, and MILP model with fuzzy parameters.

	MILP model	Defuzzified outputs of MILP model with fuzzy parameters.
Total Revenue	7,689,600 (Baht)	7,688,883 (Baht)
Total Cost		
1) Production	5,131,522	5,022,173
2) FP Inventory cost	3,447	3,548
3) Backorder cost	-	2,234
4) Subcontract cost	45	149,742
5) Labor cost	187,200	184,320
6) WIP Inventory	1,138	1,156
7) Raw material inventory	841	855
Total (COGS)	5,324,193	5,364,028
Gross Profit	2,365,407	2,324,856
Operating expenses (10% of revenue)	768,960	768,888
Net Profit	1,596,447	1,555,967

The revenue and cost structure of the planned outputs from the MILP model is compared to the outputs under uncertainties. The results indicate that the average net profit is decreased when uncertainties exist. This is because there is a variation in the production resources, which is sometimes up or down, and the company cannot manage to produce according to the plan. Therefore, to meet the required demand in each period, subcontracting is needed and backordering is unavoidable, which result in higher subcontracting and backorder costs.

5.2 The SCOR KPIs

From the outputs of the predictive model and the proposed methodology to evaluate the SCOR KPIs, the performance of the company is presented in Table 9, and illustrated graphically in Fig 9.

Table 9: SCOR KPIs of the company

Level 2 SCOR KPIs (make process)	Outputs of the SCOR KPIs at $A_{0.8}$	Defuzzified SCOR KPIs	Value of each scale in the web diagram
Percent of Orders Delivered in Full (i=1)	$\{98.33\%, 100\%, 100\%\}$	99.44 %	0, 80, 85, 90, 95, 100
Percent of Orders Delivered in Full (i=2)	$\{96.67\%, 100\%, 100\%\}$	98.89%	0, 80, 85, 90, 95, 100
Make Cycle Time	$\{23.47, 25.00, 25.00\}$	24.49 mins	40, 35, 30, 25, 20, 0
Upside Make Flexibility	$\{5, 5, 1\}$	3.67 days	7,6,5,4,3, 0
Upside make adaptability	$\{60\%, 132\%, 129\%\}$	107%	0, 30, 60, 90, 120, 150
Downsize make adaptability	$\{43\%, 37\%, 20\%\}$	33%	0 ,10, 20, 30, 40, 50
Cost to serve	$\{80.59\%, 79.24\%, 79.38\%\}$	79.74%	90, 85, 80, 75, 70, 0
Inventory Days of Supply	$\{1.74, 1.78, 1.90\}$	1.81 days	2.5, 2.0, 1.5, 1.0, 0.5, 0
Return on make fixed assets	$\{0.0636, 0.0639, 0.0593\}$	0.0622	0, 0.02, 0.04, 0.06, 0.08,0.1
Return on make working capital	$\{0.262, 0.27, 0.274\}$	0.27	0, 0.1,0.15,0.20,0.25,0.30

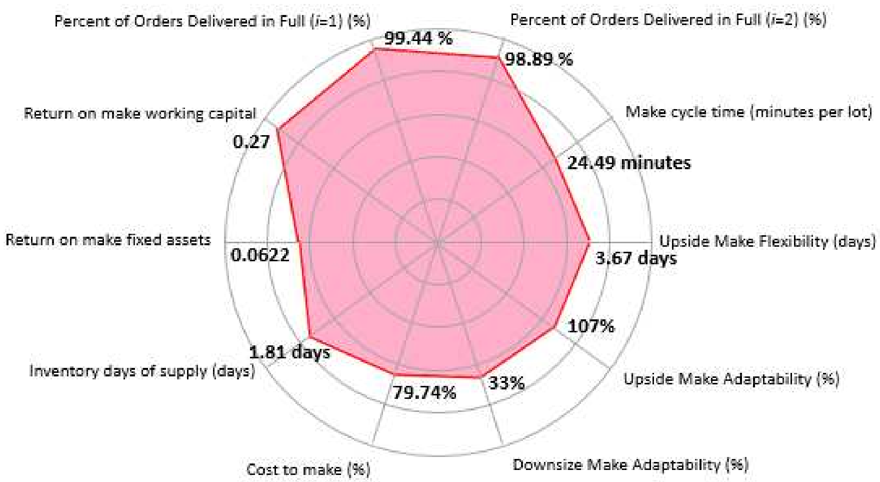

Figure9: Graphical representation of the SCOR KPIs

Since the MILP model with fuzzy parameters is used to determine the output under uncertainty, the SCOR KPIs derived from the proposed methodology are TFNs, as depicted in column 2 of Table 9. The advantage of the TFNs is that they allow a management team to understand the ranges of SCOR KPIs under uncertainties that occur in the manufacturing system. The fuzzy solution is defuzzified as shown in column 3. The SCOR KPIs based on the proposed method and above case study indicates that the company can now fulfil 99.44%, and 98.89% of orders for 1,500 cc and 600 cc bottles, respectively. The actual cycle time to produce bottles of water is approximately 24.49 minutes per lot. When the demand is suddenly increased by 20%, the company takes around 4 days to response to this change. Due to a sufficient capacity and given a preparation time of 30 days, the upside make adaptability or the ability that the company can cope with the increase in demand is 107%. In contrast, the company can reduce the production capacity by 33% without an additional cost or inventory penalty. The cost to make, calculated as a percentage of total revenue, is 79.74%. The inventory day of supply is only 1.81 days. The return on make fixed assets, and return on make working capital are estimated at 6.22% and 27%, respectively. From the numerical results, a web diagram is presented to display the value of SCOR KPIs based on the 9 metrics. The scale in column 4 of Table 9 is obtained from the opinion of the management team, based on a satisfaction level for each KPI. The diagram is also used for comparison when there is an improvement of KPIs in the future. For example, the scale of the percent of orders delivered in full starts from 80% because the management team feels that 80% is the minimum acceptable level for their company. The scale of some KPIs starts from the maximum to the minimum, such as the total cost to serve, because lower is the better. According to the web diagram, it is seen that most of the KPIs are located quite far from the center. This indicates that the operating performance, based on the SCOR KPIs of this company, is satisfactory. Based on the results obtained from the predictive model and the achievement of SCOR KPIs from the proposed method, the findings indicate that the proposed method is effective to predict the SCOR performances in a real situation. Moreover, since the MILP model is a predictive model, it can be used to perform a what-if analysis to estimate the KPIs under different situations. For example, when the management team needs to invest in more assets and needs to know the consequences of future performances. For a measurement of agility, as flexibility analysis is a key strategic role to improve responsiveness, the proposed method here can be applied to answer other agility questions that may be different from the definitions of the SCOR model. However, the MILP model presented in this paper is only applied to the current situation. It is suggested that the model should be further applied to various situations to establish a stronger relationship between the predictive model and the SCOR KPIs, to make the evaluation of SCOR KPIs more accurate. Lastly, the model and proposed methodology can be a good foundation to evaluate performance in a supply chain system that is not limited to the make process.

6. Conclusion

The SCOR model is a process reference model that is widely recognized in the supply chain research field, and the framework has been successfully used to improve businesses in various industries. However, among the current research works, the method for evaluation of the SCOR KPIs is still limited. The SCOR model has provided a definition to assess these KPIs directly, but without a procedural methodology, the resulting KPIs cannot be further analyzed. This paper proposes a method to evaluate the SCOR KPIs based on the predictive model. It consists of the MILP model that is used to represent the operations of the company, the MILP model with fuzzy parameters to address the uncertainties from the operations, and a methodology to evaluate the SCOR KPIs based on the level 2 of the SCOR-Make process with some algorithms to assess the KPIs related to agility. TFNs with a specific crisp set are used to represent uncertainties. A case study of a make-to-stock, bottled water manufacturer is used to demonstrate an application of the method. The proposed methodology provides theoretical and practical contributions to the field of supply chain management and performance measurements as follows:

1. The proposed methodology to evaluate the SCOR KPIs based on the predictive model is new and original.
2. The proposed approach is capable of establishing the relationship between the SCOR KPIs and manufacturing parameters. Thus, it enables the prediction of the performance when the manufacturing parameters are changed.
3. The proposed methodology consists of a procedural method and a model to evaluate the agility in the SCOR metrics.
4. A real industrial case study is used to demonstrate that the SCOR KPIs of the company can be evaluated based on the proposed approach.

This paper still has some limitations that can be improved further. First, when the characteristics of the manufacturing system are changed, the parameters and constraints of the MILP models need to be adjusted to the particular case. A further research to construct a software to automatically generate the MILP model based on manufacturing system structure and parameters is recommended. Second, the value of each scale of the web diagram is obtained based on an opinion of the management team of the company. Thus, it should be revised when applied to other companies. In this case, it is suggested that some visualization technique such as R-statistical modelling can be applied to the web diagram to demonstrate a real-time performance comparison when the manufacturing parameters are changes. And lastly, the current scope of this paper considers only the manufacturing aspect of the SCOR-Make process, therefore further research can be extended to cover the evaluation of other processes, namely, plan source deliver, and return, in a supply chain system.

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