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A Robust credibility-based fuzzy programming for supply chain optimization in lean manufacturing environment

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Abstract*- Lean manufacturing is a strategic concern for companies which conduct mass production and it has become even more significant for those producing in a project-oriented way by modularization. In this paper, a bi-objective optimization model is proposed to design and plan a supply chain up to the final assembly centre. The delivery time and the quality in the procurement and low fluctuation of the production are the most important lean production principles that are considered. Because of the long-horizon planning and the subjective data gathered, it is necessary to handle uncertainty. Therefore, a robust credibility-based fuzzy programming (RCFP) approach is proposed to perform the robust optimization and to obtain the crisp equivalent of an MILP model using the chance constraint programming method in terms of simultaneous credibility measurement. A real industrial case study is provided to present the usefulness and applicability of the proposed model and programming approach.*

Keywords**:** *Lean manufacturing, supply chain network design, robust optimization, credibility measure, fuzzy programming*

I. INTRODUCTION

Today lean manufacturing is a high priority for companies which aim to have high efficiency in production, eliminate as much waste as possible and achieve just-in-time production. In the definition by Naylor et al. (1999), ‘lean thinking means deployment of a value-driven stream to eliminate time, material and work wastes, and to ensure a level schedule of production volume’. Lean manufacturing states that all non-value-adding activities (Muda) must be eliminated (Naylor et al., 1999). Lean thinking and lean principles include the identification of the value stream, removing wastes and stable production (Womack and Jones, 1996). Waste can be related to the quality of the inputs and outputs. The evaluation of suppliers of raw materials is one of the practices which is required in order to observe the second principle. Paying attention to TQC (Time, Quality and Cost) is the rule to achieve lean production (Womack et al., 1990). By reducing the delivery times in cases where non-value-adding activities are eliminated or processes with less run time are alternated, we can progress to lean production, and lean procurement is of interest to all companies. A stable flow of production means using resources with low fluctuation, as reducing the fluctuations in production gives greater stability in resource consumption, increasing the production rate and reducing wastage of time (Altiparmak et al., 2006), and ultimately reducing the fluctuations in the sourcing, which leads to reduced levels of material inventory (Melton, 2005).

II. LITERATURE REVIEW

For the supply chain in the lean manufacturing environment, a number of conceptual, definitional models, as well as discrete multi-criteria decision models have been developed. Gupta and Jain (2013) presented an extensive literature review of lean manufacturing. They also discussed widely the benefits and barriers towards lean implementation. Salem

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et al. (2015) investigated the level of recognition of lean concepts, principles, tools, and techniques in different industrial sectors in Qatar. Sharma et al. (2016) discussed the modelling of lean implementation for the manufacturing sector. Delivery time, quality and waste removal are the main criteria of leanness as postulated by Agerwall et al. (2006). Also, Towill and Christopher (2002) acknowledged that the quality and lead times in the lean side have to be improved. Naim and Gosling (2011) placed more emphasis on the final assembly. Also, they recognise the postponement strategy in the design phase as well as assembly to achieve leanness and agility. Abdollahi et al. (2015) presented a framework for supplier selection based on leanness and agility concepts. Lin and Wang (2011) designed a BTO SC network that included two types of manufacturing process: producing semi-fabricated modules and assembling them and making final products. Pan and Nagi (2010) tried to manage cost variability due to the uncertainty of demand, through robust optimization. Susilawati et al. (2015) presented a fuzzy logic based method to measure the degree of lean activity in the manufacturing industry. Farahani and Elahipanah (2008) developed a model in the JIT environment so as, firstly, to enhance the earliness and tardiness measures on the constraints and, secondly, to decrease shortage and inventory levels through the OF. Wang et al. (2004) provided a distribution plan with a JIT approach where they considered the delivery time of raw materials to be important, because it impacts on the tardiness penalty in meeting customer demand from the lean point of view. Chan and Kumar (2009) indicate lean principles like reducing the Muda time (waiting time) and shortening the delivery time. Houshmand and Jamshidnezhad (2006) describe fortifying lean principles through some of the identified process variables in the design of a manufacturing system, using an axiomatic model. For example, maximizing customer satisfaction as a lean principle could be fortified through on-time delivery of best quality products as a process variable. Safaei (2014) proposes a multi-objective model to optimize a supply chain in a lean environment that reduces the waste and inventory level of materials and products. Arbos et al. (2011) use operation time-chart tools for modelling manufacturing systems and tracking activities that visually evaluate the impact of different scenarios on the system performance in terms of lean criteria such as lead-time, downtime and inventory. Melton (2005) explains the benefits of lean manufacturing through lean manufacturing standards and obstacles encountered in lean production. He recognises value-added flow, preventing seven types of waste in the lean production base, because 60% of activities add no value. Rubio and Corominas (2008) determine the optimum production and order sizes and the optimum order point for a manufacturing-remanufacturing (forward-reverse) system using an EOQ technique which satisfies lean production metrics like reducing the inventory level and delivery time. Powell et al. (2014) define a newly adopted lean principle set with an engineer-to-order strategy like modularization, which is in compliance with basic principles developed by Toyota.

III. Problem description

In the problem concerned, the demand data are assumed to be possibilistic parameters which are obtained by prediction. Since satisfaction and capacity constraints are taken into account through robust optimization to cover all the predictions, it is assumed that there is no lost sale. Of course, these products are sent straight to the final assembly centre. The SC is capacitated. There are some functional products which are produced and transferred to storage at the assembly centre. In this lean manufacturing plan, the raw material and components have to be procured to satisfy predicted demands and estimated semi-finished common boards requirements. It is assumed that the inventory control system occurred at the beginning of the period and that the product is sent to the assembly centre at the end of the period. In the first phase, the planning horizon is considered to be one year with monthly periods, and in the second phase, the planning horizon is considered seasonal with weekly periods. The innovative products through customer design consist of a common board or common sub-product and a series of specific elements, which have been formed by adding specific elements to the common board in final assembly.

In this paper, the most important principles of lean manufacturing are captured and applied in the proposed bi-objective mathematical model for production planning of the real case study. Also, because of the uncertain nature of some parameters in the real case, a robust credibility-based fuzzy programming (RCFP) approach is proposed to perform the robust optimization and to obtain the crisp equivalent of the MILP model. The outline of the proposed mathematical model and solution procedure is illustrated in Fig. 1.

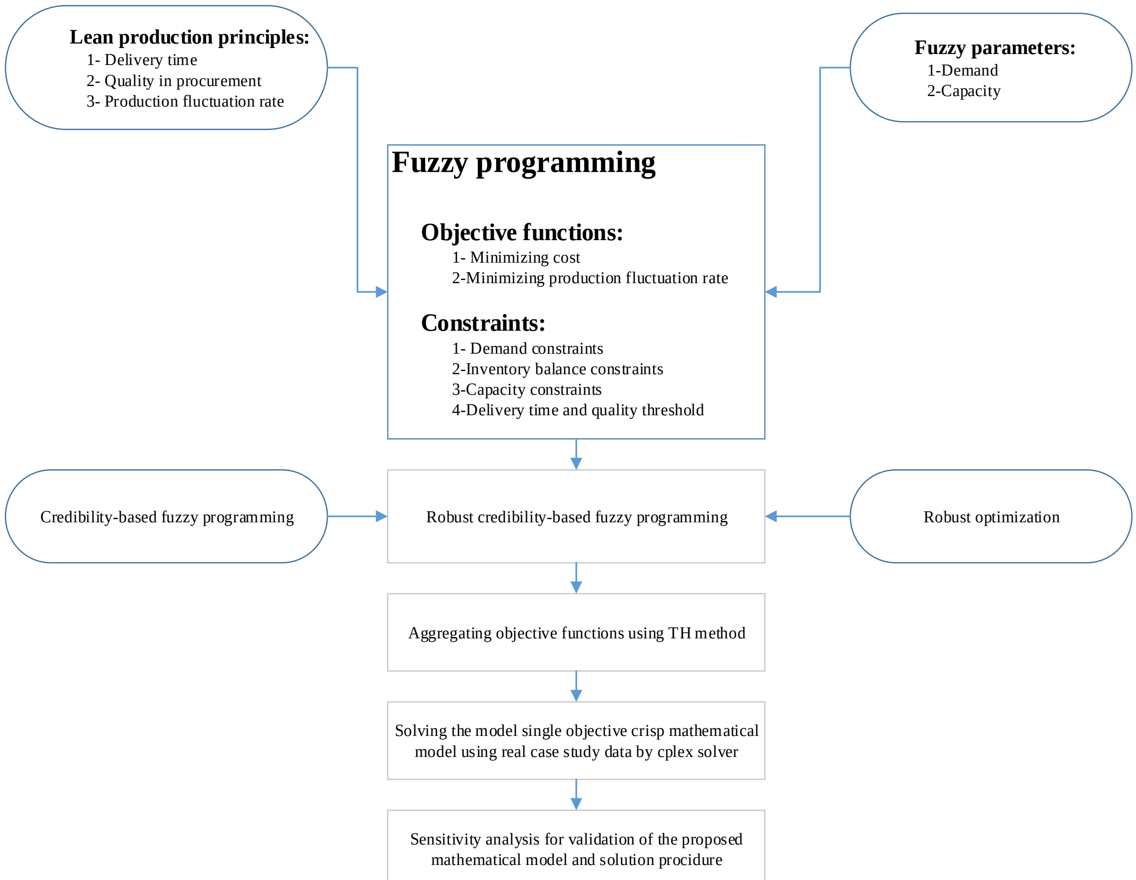

Fig. 1. Outline of the proposed mathematical model and solution procedure

A. Proposed mathematical modeling

The presented mathematical model determines optimal outsource and production quantity for joint sub-products and functional products. Since planning time horizon is long and also are parameters are subjective, we will inevitably lead to uncertainty programming to reach the crisp equivalent model that will be discussed in Section IV.

Notations:

Indices:

i	Index of suppliers, (i= 1,2, ..., I)
j	Index of main production centers, (j= 1,2, ..., J)
r	Index of common parts (as raw material) types, (r= 1,2, ..., R)
f	Index of functional product types, (f= 1,2, ..., F)
t	Index of time periods, (t= 1,2, ..., T)

Parameters:

oc_{irt}	Fixed cost to order part r from supplier i in period t
c^{C}_{ir}	Unit cost of purchasing part r from supplier i
cp^{F}_{jf}	Unit production cost to produce functional product f in production center j

cp_j^C	Unit production and assembly cost of common board in production center j
ct_{ij}^c	Unit cost for transporting common parts from supplier i to production center j
ct_j^C	Unit cost for transporting common parts from production center j to assembly center
ct_{jf}^F	Unit cost for transporting functional part f from production center j to assembly center
co_f^F	Unit cost for transporting functional part f from outsourced center to assembly center
co^C	Unit cost for transporting common parts from outsourced center to assembly center
ch_{jr}^c	Unit cost for holding common part r in the production center j
γ_r^C	Usage rate of common board/part r in assembling common board
$\widetilde{dem}_{ft}^F$	Predicted demand of functional product f in period t
$\widetilde{need}_t^C$	Predicted required common boards in period t
$\widetilde{DR}_{ir}^C$	Defective rate of part r at period t
$\overline{DR}_r^c$	Maximum allowable defectiveness rate for part r
$\widetilde{DT}_{ir}^C$	Delivery time of supplier i for part r at period t
$\overline{DT}_r^c$	Maximum allowable delivery time for part r
γ_r^F	Usage rate of part r in assembling functional product f
$SC_{ir}^{C\_Max/Min}$	Maximum /minimum available part r for supplying by supplier i
uv_r^C	Required space to store common part r
WS_j^L	Available space in production center j
Ss_{jrt}^C	Required safety stock of part r in production center j at period t
$\widetilde{Cap}_j$	capacity of production center j

Decision variables:

O_{irt}	1, if supplier i is selected to supply part r at period t , and 0 otherwise
X_{ijrt}^C	Quantity of common parts r shipped from supplier r to production center j at period t
Y_{jft}^F	Quantity of functional products f shipped from production center j to assembly center at period t
Y_{jt}^C	Quantity of common boards shipped from production center j to assembly center at period t
OS_{jt}^C	Quantity of common boards shipped from outsourced center j to assembly center at period t
OS_{jft}^F	Quantity of functional products f shipped from outsourced center j to assembly center at period t
Q_{jt}^C	Quantity of common boards shipped from production or outsourced center j to assembly center at period t
Q_{jft}^F	Quantity of functional products f shipped from production or outsourced center j to assembly center at period t
I_{jrt}^C	Inventory level of part r in production center j at period t

$$\begin{aligned}\text{Min}\quad TC = &\sum_t\sum_i\sum_r oc_{irt}O_{irt} + \sum_t\sum_i\sum_j\left[\sum_r c^c_{ir}X^c_{ijrt}\right] + \sum_t\sum_i\sum_j\left[ct^c_{ij}\sum_r X^c_{ijrt}\right]\\ &+\sum_t\sum_j\left[cp^F_{jf}\sum_f Y^F_{jft} + cp^C_j Y^C_{jt}\right] + \sum_t\sum_j\left[\sum_f ct^F_{jf}Y^F_{jft} + ct^C_j Y^C_{jt}\right]\\ &+\sum_t\sum_j\left[\sum_r ch^c_{jr}I^c_{jrt}\right] + \sum_j\sum_t co^C OS^C_{jt} + \sum_j\sum_t\sum_f co^F_f OS^F_{jft}\end{aligned} \tag{1}$$

$$\text{Min}\quad MRUBF = \frac{\sum_j RUBF_j}{|J|} \tag{2}$$

$$RUBF_j = \frac{\sum_t \left|\left(\frac{\sum_f Y^F_{jft} + Y^C_{jt}}{\widetilde{Cap}_j}\right) - \left(\frac{\sum_f\sum_t Y^F_{jft} + \sum_t Y^C_{jt}}{|T|\,\widetilde{Cap}_j}\right)\right|}{|T|} \tag{3}$$

$$\sum_j OS^C_{jt} + \sum_j Y^C_{jt} \geq \widetilde{need}^C_t \tag{4}$$

$$\sum_j OS^F_{jft} + \sum_j Y^F_{jft} \geq \widetilde{dem}^F_{ft} \tag{5}$$

$$\sum_i (1-\widetilde{DR}^C_{ir})X^C_{ijrt} + I^C_{jr,t-1} = I^C_{jrt} + \gamma^C_r Y^C_{jt} + \gamma^F_r \sum_f Y^F_{jft} \qquad \forall j,r,t \tag{6}$$

$$O_{irt}SC^{C\_Min}_{ir} \leq \sum_j X^C_{ijrt} \leq O_{irt}SC^{C\_Max}_{ir} \qquad \forall i,r,t \tag{7}$$

$$\sum_r\sum_i uv^C_r(X^C_{ijrt} + I^C_{jr,t-1}) \leq WS^L_j \qquad \forall j,t \tag{8}$$

$$Y^C_{jt} + \sum_f Y^F_{jft} \leq \widetilde{Cap}_j \qquad \forall j,t \tag{9}$$

$$I^C_{jrt} \geq \widetilde{Ss}^C_{jrt} \qquad \forall j,r,t \tag{10}$$

$$OS^C_{jt} + Y^C_{jt} = Q^C_{jt} \qquad \forall j,t \tag{11}$$

$$OS^F_{jft} + Y^F_{jft} = Q^F_{jft} \qquad \forall j,f,t \tag{12}$$

Equation (1) shows the operational costs up to final assembly, which includes fixed and variable procurement costs like contract dealing and purchasing costs, transportation costs and other costs such as production, holding of raw elements –note that the production centre has only raw material storage–, and outsourcing. Equation (2) presents the second objective function which minimizes the expected resource usage balance factor (RUBF) in production sites, which is defined in Equation (3). Equation (3) presents the mean absolute error (MAE) for production divided by capacity in time periods. This objective function reduces the fluctuation in production in periods. Expression (4) ensures that the required common boards are manufactured and outsourced at a rate that is estimated. Inequality (5) ensures that functional products satisfy the anticipated demand. Equation (6) establishes the dynamic balance between inventory and purchasing redeemable parts and the production amount. Expression (7) ensures that the amount of purchases from suppliers is within the determined ranges. Expression (8) ensures the availability of space at the warehouse. Expression

(9) ensures that the amount of output per period does not exceed the fixed capacity of each site. Inequality (10) guarantees that the available inventory of purchased parts should be at least as much as the safety stock. Equations (11) and (12) calculate the amount of produced or outsourced functional and semi-finished products.

In order to achieve a lean purchase plan, a thereshold is determined by the supply management for the quality and delivery of raw materials. Equation (13) shows that if the delivery time or defective rate of the part is greater than the defined threshold for each of them, the cost of purchasing the part from that supplier is considered a large number. In other words, suppliers that do not meet the predefined threshold for quality and delivery time will not be selected for trade.

$$\begin{cases} c_{ir}^{c} = M & \text{if} \quad \widetilde{DR_{ir}^{C}} \geq \overline{DR_{r}}^{C} \cup \widetilde{DT_{ir}^{C}} \geq \overline{DT_{r}}^{C} \\ c_{ir}^{c} = c_{ir}^{c} & O.W. \end{cases} \tag{13}$$

IV. Uncertainty handling

The objective of the paper is production planning for a long time horizon in a real case study. It is emphatically required to perform a robust optimization and get a crisp equivalent model, due to the vague and subjective nature of some parameters and the lack of knowledge. Since the data are acquired by asking the experts and future predictions, the data are necessarily uncertain and according to their nature, preferably have to be considered as possibilistic (e.g. see Peidro et al., 2009). Therefore, it is crucial to make the obtained solution more realistic by addressing the uncertainties. To this end, three types of modelling techniques, namely stochastic programming, fuzzy programming and robust optimization are introduced in the literature. In this paper, a robust possibilistic programming (RPP) approach that benefits from both advantages of fuzzy and robust programming approaches is used (Rabbani et al, 2016). The possibilistic parameters in the model can be demonstrated with four prominent values, so trapezoidal possibilistic distribution is accommodated for them.

To explain how the distribution for the parameters can be defined, see Inuiguchi et al. (2000). To simply describe RFCP, first, the theoretical model (14) is considered.

A. Credibility-based fuzzy programming

$$\begin{aligned} &\text{Min } Obj = \tilde{\mathbf{c}}\boldsymbol{x} \\ &s.t. \quad \mathbf{A}\boldsymbol{x} \geq \tilde{\mathbf{d}} \\ &\qquad \mathbf{A}'\boldsymbol{x} \leq \tilde{\mathbf{c}} \\ &\qquad \tilde{\mathbf{B}}\boldsymbol{x} = \boldsymbol{y} \\ &\qquad \boldsymbol{x}, \boldsymbol{y} \geq 0 \end{aligned} \tag{14}$$

Pishvaee et al. (2012) have brought up robust possibilistic programming approach which they used chance constrained programming method to implement their approach based on necessity degree. As it is seen in the model (15), in this study, possibilistic programming is defined based on credibility degree.

$$\begin{aligned}
&\text{Min} \quad E(Obj) = E(\tilde{\mathbf{c}})\boldsymbol{x} \\
&S.t. \quad \text{Cr}\left\{\mathbf{A}\boldsymbol{x} \ge \tilde{\mathbf{d}}\right\} \ge \alpha \\
&\qquad\ \ \text{Cr}\left\{\mathbf{A}'\boldsymbol{x} \le \tilde{\mathbf{c}}\right\} \ge \beta \\
&\qquad\ \ \text{Cr}\left\{\tilde{\mathbf{B}}\boldsymbol{x} = \boldsymbol{y}\right\} \ge \pi \\
&\qquad\ \ \boldsymbol{x}, \boldsymbol{y} \ge 0
\end{aligned} \tag{15}$$

To acquire the crisp equivalent of constraints in the model (14), the definitions delineated by Liu and Liu (2002) are used: Let

$\tilde{a} = (a^1, a^2, a^3, a^4)$ be a trapezoidal fuzzy number and r is a real number.

$$Cr\left\{\tilde{a} \le r\right\} \ge \alpha \Leftrightarrow r \ge (2-2\alpha)a^3 + (2\alpha-1)a^4, \tag{16}$$

$$Cr\left\{\tilde{a} \ge r\right\} \ge \alpha \Leftrightarrow r \le (2-2\alpha)a^2 + (2\alpha-1)a^1. \tag{17}$$

$$Cr\left\{\tilde{a} = r\right\} \ge \pi \quad \Leftrightarrow \quad a^2 \le r \le a^3 \tag{18}$$

According to formulas (16), (17) and (18) and assuming $\alpha, \beta \ge 0.5$, the crisp equivalent of the model (15) is transformed:

$$\begin{aligned}
&\text{Min} \quad E(Obj) = \left(\frac{\mathbf{c_1} + \mathbf{c_2} + \mathbf{c_3} + \mathbf{c_4}}{4}\right)\boldsymbol{x} \\
&S.t. \\
&\qquad \mathbf{A}\boldsymbol{x} \ge (2-2\alpha)\,\mathbf{d_3} + (2\alpha-1)\,\mathbf{d_4} \\
&\qquad \mathbf{A}'\boldsymbol{x} \le (2\beta-1)\,\mathbf{c_1} + (2-2\beta)\,\mathbf{c_2} \\
&\qquad \mathbf{B_3}\boldsymbol{x} \ge \boldsymbol{y} \\
&\qquad \mathbf{B_2}\boldsymbol{x} \le \boldsymbol{y} \\
&\qquad \boldsymbol{x}, \boldsymbol{y} \ge 0
\end{aligned} \tag{19}$$

B. Robust credibility-based fuzzy programming

Robust optimization has been applied several times for handling infeasibility risks in production planning and supply chain optimization in recent works by, for example, Pishvaee et al. (2011), Pan and Nagi (2010), Yu and Li (2000), Leung et al. (2007), Adida and Perakis (2006), Babazadeh et al. (2011) etc. Also robust optimization in agile SC management has been important in previous research. For example, Pan and Nagi (2010) resolved uncertainty of demand in an AM environment through robust optimization, while Hasani et al. (2011) applied robust optimization to handle uncertain parameters in agile SC at a strategic level. In the planning system proposed in this paper, although with the lean thinking vision the proposed model in the first phase has to minimize the variation effects of non-deterministic parameters, especially demands, on the production rate and reduce deviations from lean objectives, it requires robustness, but since this phase covers a strategic level of planning and provides inputs of an agile sub-system, it furthermore needs robust optimization in the planning environment. According to the theory of robust optimization stated in Ben-Tal et al.'s work (2009), the model should be sensitive to deviations from the optimal value in the OF (optimality robustness) and deviations from constraints feasibility (feasibility robustness) and for this reason the cost of robustness should be mentioned in the objective function of the model (see Bertsimas and Sim, 2004; Pishvaee et al., 2012).

$$\begin{aligned}
\text{Min } & E(Obj) + \delta\left(Obj_{\max} - E(Obj)\right) + \\
& \sigma(\mathbf{d}_4 - (2-2\alpha)\,\mathbf{d}_3 - (2\alpha-1)\,\mathbf{d}_4) + \\
& \lambda\left((2\beta-1)\,\mathbf{c}_1 + (2-2\beta)\,\mathbf{c}_2 - \mathbf{c}_1\right) \\
S.t.\ & \\
& \mathbf{A}x \ge (2-2\alpha)\,\mathbf{d}_3 + (2\alpha-1)\,\mathbf{d}_4 \\
& \mathbf{A}'x \le (2\beta-1)\,\mathbf{c}_1 + (2-2\beta)\,\mathbf{c}_2 \\
& \mathbf{B}_3\boldsymbol{x} \ge \boldsymbol{y} \\
& \mathbf{B}_2\boldsymbol{x} \le \boldsymbol{y} \\
& \boldsymbol{x}, \boldsymbol{y} \ge 0, \quad 0.5 \le \alpha, \beta \le 1
\end{aligned} \tag{20}$$

In model (20), the cost of deviation from the expected optimality is shown along with coefficient δ, and the penalty for deviations from feasibility is shown along with coefficients σ and λ. We use the proposed RCFP model to write the crisp equivalent MILP model for the uncertain model of the lean phase, and the RCFP formulation is used for both of the OFs. The parameters of the first objective function are deterministic, but the second OF has a non-deterministic parameter of $\widetilde{Cap}_j$ that is handled by multiplying the penalty coefficient of δ by the amount of difference between $Obj_{\max}$ and $E(Obj)$. $Obj_{\max}$ is calculated using the coefficient of $1/Cap_{j\,(1)}$ and if $\widetilde{Cap}_j$ is a positive fuzzy number then $\dfrac{1}{\widetilde{Cap}_j}$ is a positive fuzzy number too, with the following distribution:

$$\widetilde{Cap}_j = (Cap_{j(1)}, Cap_{j(2)}, Cap_{j(3)}, Cap_{j(4)}) \to \frac{1}{\widetilde{Cap}_j} = \left(\frac{1}{Cap_{j(4)}}, \frac{1}{Cap_{j(3)}}, \frac{1}{Cap_{j(2)}}, \frac{1}{Cap_{j(1)}}\right).$$

The expected value of MRUBF can be calculated regarding the value of $E(\widetilde{Cap}_j^{-1})$ in formula (21).

$$\begin{aligned}
& E(\widetilde{Cap}_j) = \frac{Cap_{j(1)} + Cap_{j(2)} + Cap_{j(3)} + Cap_{j(4)}}{4} \to \\
& \to E\left(\frac{1}{\widetilde{Cap}_j}\right) = \frac{\frac{1}{Cap_{j(4)}} + \frac{1}{Cap_{j(3)}} + \frac{1}{Cap_{j(2)}} + \frac{1}{Cap_{j(1)}}}{4} = \\
& = \frac{\left(\begin{array}{c} Cap_{j(1)}Cap_{j(2)}Cap_{j(3)} + Cap_{j(1)}Cap_{j(3)}Cap_{j(4)} + Cap_{j(1)}Cap_{j(2)}Cap_{j(4)} \\ + Cap_{j(2)}Cap_{j(3)}Cap_{j(4)} \end{array}\right)}{4 \times Cap_{j(4)}Cap_{j(3)}Cap_{j(2)}Cap_{j(1)}}
\end{aligned} \tag{21}$$

Both the main OF and the robustness penalties should have the same unit to be collected, otherwise they need to be normalized, So the robustness penalty term in the second OF should be multiplied by $E(|T|^{-1}|J|^{-1}\widetilde{Cap}_j^{-1})$ to have the same unit as R_2. In the following model, in the first OF, the unit of R_1 and TC is the cost unit (i.e. US $). Thus the unit of σ, η, ψ, and τ will be item/$. Since MRUBF is the MAE of production volume, then MRUBF, R_2 and the corresponding robustness coefficients have no unit. The robustness coefficients of the R_2 mean:

$$
\begin{aligned}
\text{Min} \quad R_1 = TC &+ \sigma \sum_t \left[need^C_{t\,(4)} - \left(2 - 2\alpha_t^C\right) need^C_{t\,(3)} - \left(2\alpha_t^C - 1\right) need^C_{t\,(4)} \right] \\
&+ \eta \sum_f \sum_t \left[dem^F_{ft(4)} - \left(2 - 2\alpha_{ft}^F\right) dem^F_{ft(3)} - \left(2\alpha_{ft}^F - 1\right) dem^F_{ft(4)} \right] \\
&+ \psi \sum_j \left((2\beta_j - 1)\, Cap_{j\,(1)} + (2 - 2\beta_j)\, Cap_{j\,(2)} - Cap_{j\,(1)} \right) \\
&+ \tau \sum_j \sum_r \sum_t \left[Ss^C_{jrt(4)} - \left(2 - 2\alpha_{jrt}^{SS}\right) Ss^C_{jrt(3)} - \left(2\alpha_{jrt}^{SS} - 1\right) Ss^C_{jrt(4)} \right]
\end{aligned}
\tag{22}
$$

$$
\begin{aligned}
\text{Min} \quad R_2 = E\,(MRUBF) &+ \delta \left[\frac{\sum_j \frac{1}{Cap_{j\,(1)}} \sum_t \left| \left(\sum_f Y^F_{jft} + Y^C_{jt} \right) - \left(\frac{\sum_f \sum_t Y^F_{jft} + \sum_t Y^C_{jt}}{|T|} \right) \right|}{|T||J|} - E\,(MRUBF) \right] \\
&+ \sum_j E\left(\frac{1}{|T||J|\widetilde{Cap}_j}\right) \sigma' \sum_t \left[need^C_{t\,(4)} - \left(2 - 2\alpha_t^C\right) need^C_{t\,(3)} - \left(2\alpha_t^C - 1\right) need^C_{t\,(4)} \right] \\
&+ \sum_j E\left(\frac{1}{|T||J|\widetilde{Cap}_j}\right) \eta' \sum_f \sum_t \left[dem^F_{ft(4)} - \left(2 - 2\alpha_{ft}^F\right) dem^F_{ft(3)} - \left(2\alpha_{ft}^F - 1\right) dem^F_{ft(4)} \right] \\
&+ \sum_j E\left(\frac{1}{|T||J|\widetilde{Cap}_j}\right) \psi' \sum_j \left((2\beta_j - 1)\, Cap_{j(1)} + (2 - 2\beta_j)\, Cap_{j(2)} - Cap_{j(1)} \right) \\
&+ \sum_j E\left(\frac{1}{|T||J|\widetilde{Cap}_j}\right) \tau' \sum_j \sum_r \frac{1}{\gamma_r^C} \sum_t \left[Ss^C_{jrt(4)} - \left(2 - 2\alpha_{jrt}^{SS}\right) Ss^C_{jrt(3)} - \left(2\alpha_{jrt}^{SS} - 1\right) Ss^C_{jrt(4)} \right] \\
&+ E\,(MRUBF) = \sum_j \sum_t \left\{ E\left(\frac{1}{\widetilde{Cap}_j}\right) \times \frac{\left| \left(\sum_f Y^F_{jft} + Y^C_{jt} \right) - \left(\frac{\sum_f \sum_t Y^F_{jft} + \sum_t Y^C_{jt}}{|T|} \right) \right|}{|T||J|} \right\}
\end{aligned}
\tag{23}
$$

$$
\sum_j OS^C_{jt} + \sum_j Y^C_{jt} \geq \left(2 - 2\alpha_t^C\right) need^C_{t\,(3)} + \left(2\alpha_t^C - 1\right) need^C_{t\,(4)} \quad \forall t \tag{24}
$$

$$
\sum_j OS^F_{jft} + \sum_j Y^F_{jft} \geq \left(2 - 2\alpha_{ft}^F\right) dem^F_{ft(3)} + \left(2\alpha_{ft}^F - 1\right) dem^F_{ft(4)} \; \forall f, t \tag{25}
$$

$$
\sum_i \left(1 - DR^C_{ir\,(2)}\right) X^C_{ijrt} \geq I^C_{jrt} + \gamma^C_r Y^C_{jt} + \gamma^F_r \sum_f Y^F_{jft} - I^C_{jr,t-1} \quad \forall j, r, t \tag{26}
$$

$$\sum_i \left(1 - DR^C_{ir\,(3)}\right) X^C_{ijrt} \le I^C_{jrt} + \gamma^C_r Y^C_{jt} + \gamma^F_r \sum_f Y^F_{jft} - I^C_{jr,t-1} \quad \forall j,r,t \tag{27}$$

$$O_{irt} SC^{C\_Min}_{ir} \le \sum_j X^C_{ijrt} \le O_{irt} SC^{C\_Max}_{ir} \qquad \forall i,r,t \tag{28}$$

$$\sum_r \sum_i uv^C_r (X^C_{ijrt} + I^C_{jr,t-1}) \le WS^L_j \qquad \forall j,t \tag{29}$$

$$Y^C_{jt} + \sum_f Y^F_{jft} \le (2\beta_j - 1) Cap_{j\,(1)} + (2 - 2\beta_j) Cap_{j\,(2)} \qquad \forall j,t \tag{30}$$

$$I^C_{jrt} \ge \left(2 - 2\alpha^{SS}_{jrt}\right) Ss^C_{jrt(3)} + \left(2\alpha^{SS}_{jrt} - 1\right) Ss^C_{jrt(4)} \qquad \forall j,r,t \tag{31}$$

$$OS^C_{jt} + Y^C_{jt} = Q^C_{jt} \quad \forall j,t \tag{32}$$

$$OS^F_{jft} + Y^F_{jft} = Q^F_{jft} \quad \forall j,f,t \tag{33}$$

$$X, Y, Q, OS \ge 0, \quad O \in \{0,1\} \tag{34}$$

V. SOLUTION PROCEDURE

Given that, in this model, the optimal minimum confidence levels are obtained, it is not considered to be an interactive model. Given the confidence levels (e.g. $\alpha^C_t, \alpha^F_{ft}, \beta_j, \alpha^{SS}_{jrt}$), to analyze and find the best solution, the problem needs to be solved many times, so we consider them as variables and their optimal values are achieved through the final solution. In the solution method, the TH approach as a fuzzy multi-objective programming approach is used (see Torabi and Hassini, 2008).

If the optimal plan resulting from the chosen solution is not satisfactory in the view of senior management, switchable robustness parameters will be changed and the Pareto optimal sets will be produced again. Figure 5 shows the process described step by step, used to solve the whole problem. The robustness parameters such as σ, η, ψ, τ and δ are usually meaningful and their initialization is generally consistent with expert opinion or can be obtained through some calculations. So it is generally not appropriate to change the optimum solution and achieve an interactive model through them. For example, the σ and η parameters can be regarded as penalties for not satisfying customer demands, which is familiar to the sales management, marketing and CRM departments. And the τ parameter can be calculated as follows: the probability of an inventory shortage multiplied by the unit cost of lost sales divided by the corresponding usage coefficient in BOM, these mentioned data being available to the inventory and warehouse management and sales management, respectively. ψ means the imposed cost on the company for increasing a unit of capacity. However, if a small change in a robustness parameter is negligible in terms of management, it can also be considered as an interactive parameter; for example, on the robustness coefficients in the second OF, which we call “flexible robustness coefficients”, small changes can be applied to analyze the sensitivity of the solutions and find the preferred solutions.

VI. Case study implementation

In this section, to evaluate and demonstrate the applicability of the proposed structure, data extracted from a real industrial case study which is appropriate to the suggested SC is placed in the model. The case study concerned is one of the main manufacturers of analog and digital equipment and radio transmitters that meet the demand of domestic governmental and non-governmental customers. The company has a mechanical manufacturing site which is also responsible for assembling common boards and some analog low-power 10 Watt transmitters, for which it is assumed as a production centre in the SC. The company has an active assembly facility within two miles of the production site that purchases certain new components such as the demodulator tuner DVBT2/DVBS2/DVBC, a new customized demodulator with an integrated fractional for 100 to 1000 MHz frequencies, optimizer sensors with 66 mv/A sensitivity and some other special parts. For reasons of space limitations, we refrain from naming the complete list, but this is available upon request. These elements are used for the final assembly of more specifically customized products compared to the low-power analog transmitters. The specifically ordered products manufactured at this facility include high-power 100 and 200 Watt transmitters, Remux DVBT2/DVBS2 receivers and PVRs (personal video recorder) whose main distribution boards, main sub-racks and exciters are assembled in the production centre. The SC optimization problem was modelled when the company was on the verge of a tender for Iran Broadcasting (IRIB) as the employer. The tender object was the production and delivery of radio and television transmitters and receivers to three provinces. At the time, the contract was adjudicated for the contractor to deliver the products at the end of the sixth and twelfth months. It was possible to change some proportion of the demand for the products until the end of the third month and that is why the demand of the consumer was estimated by a team of project managers and contracting experts and then, as the result, the four prominent points of the corresponding trapezoidal numbers were determined. In Table I, the required amount of semi-manufactured products (common boards) that is a combination of the main sub-racks and boards and the low-power analog transmitter required are presented.

Some parts are provided by foreign purchasing, and some are available in the domestic market, therefore the unit of costs is considered in dollars. The unit costs of production, transportation and outsourcing as well as the capacity of the production site are shown in Table II. Given that the production capacity is calculated along a one-year planning horizon, and on the other hand, that there is the possibility of increasing capacity due to the company’s development policies, eventually the experts and production managers identify four prominent points of the corresponding trapezoidal fuzzy number.

Due to the fact that the production of a low-power transmitter and the merging common sub-product require the same capacity, the capacity parameters for the production of common boards and functional products have not been separated. Because of space limitation, we do not adduce the other parameters, such as the purchase price of raw elements and specified components, but these are available on request.

TABLE I. Estimated required common boards and demand of low power analog transmitter in moths

Period (month)	Predicted need of common board	Predicted demand of 10 Watt Transmitter
1	(0, 0, 0, 0)	(0, 0, 0, 0)
2	(0, 0, 0, 0)	(0, 0, 0, 0)
3	(0, 0, 0, 0)	(0, 0, 0, 0)
4	(0, 0, 0, 0)	(0, 0, 0, 0)
5	(0, 0, 0, 0)	(0, 0, 0, 0)
6	(112, 130, 135, 140)	(224, 228, 230, 235)
7	(0, 0, 0, 0)	(0, 0, 0, 0)
8	(0, 0, 0, 0)	(0, 0, 0, 0)
9	(0, 0, 0, 0)	(0, 0, 0, 0)
10	(0, 0, 0, 0)	(0, 0, 0, 0)
11	(0, 0, 0, 0)	(0, 0, 0, 0)
12	(110, 120, 124, 132)	(220, 230, 240, 245)

TABLE II. Cost and capacity data

costs	Common board	10 Watt Transmitter
Production cost ($/unit)	61.8	30.25
Transportation cost to assembly plant ($/unit)	5	3
Outsourcing cost ($/unit)	600	250
Capacity of production shop $(Cap_{j(1)}, Cap_{j(2)}, Cap_{j(3)}, Cap_{j(4)})$	(135, 140, 150, 154)	

The extracted data is used to explain and validate the optimization model and the presented solution method is coded by GAMS 23.5 optimization software, while the IBM CPLEX solver is used to solve on a Core 2 Duo processor PC with 2.53 GHz CPU and 4 GB RAM. The average CPU time spent for each run was 10 seconds. In all the numerical tests carried out, the fixed robustness coefficient values were set as follows: σ = 200 \$, η = 250 \$, ψ = 40 \$, and τ = 20 \$, which are recommended by the experts based on knowledge and experience.

VIII. COMPUTATIONAL RESLT AND SENSITIVITY ANALYSIS

In this section, several sensitivity analyses are performed in order to validate the presented model and investigate the effect of the data parameters on the case study. The results are discussed in depth to provide some managerial implications.

In converting a bi-objective problem to a single-objective one using the TH method, two parameters, the relative importance of the objective function and the coefficient of compensation, have to be specified. The relative importance of the objective function (θ) is determined based on the preferences of the decision maker. The coefficient of compensation determines the balancing amount of a compromise solution. Higher values for the coefficient of compensation lead to more balanced compromise solutions, while lower values lead to more unbalanced compromise solutions (Torabi & Hassini, 2008). Therefore, in order to obtain a solution which satisfies the decision maker, a sensitivity analysis is conducted on the coefficient of compensation. Table III shows the results of the sensitivity analysis on the considered case study.

As shown in Table III, increasing the value of ρ resulted in a higher value for the minimum of membership functions and a lower value for the weighted average of membership functions. In other words, by increasing ρ the difference between the satisfaction of the objective functions becomes less.

Also Table III shows the results of the sensitivity analysis on the robustness parameters which is performed in terms of the optimal degree of credibility of the constraints.

The results presented in Table III help the manager to compare the impacts of the objective functions, their minimum satisfaction and the robustness priorities on the results and make a decision based on his preferences.

TABLE III. Summary of results obtained by solving proposed model

Flexible robustness coefficients					**Compensation coefficient**	**Importance of OFs**		**Satisfaction degree of objectives**		**OF values**		**Optimal minimum confidence levels ***			
δ	σ'	η'	ψ'	τ'	ρ	θ_1	θ_2	μ_1^π	μ_2^π	R_1 *(TC)*	R_2 *(MRUBF)*	$\bar{\alpha}_t^C$	$\bar{\alpha}_{ft}^F$	$\bar{\beta}_j$	$\bar{\alpha}_{jrt}^{SS}$
0.1	0.001	0.001	5×10^{-4}	2×10^{-4}	0.2	0.95	0.05	1	0.6012	5160221	0.4949	0.62	0.60	0.50	0.55
						0.9	0.1	0.99	0.6726	5199422	0.4850	0.63	0.59	0.51	0.55
						0.8-.5	0.2-.5	0.9637	0.7122	5304119	0.4750	0.63	0.59	0.50	0.55
						0.45-.1	0.55-.9	0.9433	0.8431	5365351	0.4594	0.62	0.59	0.51	0.54
						0.2-.05	0.8-.95	0.9332	0.8955	5401462	0.3382	0.63	0.60	0.51	0.55
					0.5	0.45	0.55	0.9820	0.6996	5226916	0.4763	0.62	0.60	0.52	0.54
						0.3-.25	0.7-.75	0.9637	0.7122	5304119	0.4750	0.62	0.60	0.50	0.55
						0.15	0.85	0.9545	0.7374	5321532	0.4710	0.62	0.59	0.51	0.55
					0.8	0.6	0.4	0.9545	0.7374	5321532	0.4710	0.63	0.60	0.50	0.55
						0.5-0.3	0.5-.7	0.9433	0.8431	5365351	0.4594	0.63	0.60	0.52	0.55
						0.25-.2	0.75-0.8	0.9332	0.8955	5401462	0.3382	0.63	0.60	0.52	0.54
						0.15-.05	0.85-.95	0.9225	0.9171	5512116	0.2231	0.63	0.60	0.52	0.54
0.1	8×10^{-4}	8×10^{-4}	5×10^{-4}	2×10^{-4}	0.2	0.95	0.05	0.991	0.6678	5000227	0.4262	0.59	0.57	0.52	0.55
						0.9	0.1	0.982	0.6728	5032084	0.4189	0.58	0.57	0.51	0.56
						0.8-.65	0.2-.35	0.9612	0.6902	5183521	0.4129	0.60	0.58	0.51	0.55
						0.6-.2	0.4-.8	0. 9545	0.7141	5173903	0.4087	0.59	0.56	0.52	0.54
						0.1	0.9	0. 9124	0.9284	5347086	0.1928	0.60	0.55	0.52	0.55
					0.5	0.45	0.55	0.991	0.6678	5000227	0.4262	0.57	0.56	0.52	0.54
						0.3-.25	0.7-.75	0. 9647	0.6859	5168192	0.4211	0.59	0.57	0.52	0.56
						0.15	0.85	0. 9545	0.7141	5173903	0.4087	0.60	0.55	0.52	0.55
					0.8	0.6	0.4	0. 9124	0.9284	5347086	0.1928	0.59	0.56	0.52	0.54
						0.55-.1	0.45-.9	0.8908	0.9491	5437141	0.1653	0.60	0.55	0.51	0.54

*** The mean of minimum confidence level of constraints (e.g.).** (e.g. $\bar{\alpha}_{ft}^F = \dfrac{\sum_f \sum_t \alpha_{ft}^F}{|F||T|}$).

VIII. CONCLUSIONS

Lean procurement enables the selection of suppliers of high quality materials with a short delivery time. Another important principle of lean manufacturing is sustainable production, which is improved through the second objective function. Planning for the realization of the long-term horizon and subjective parameters inevitably suffer from uncertainty and, because of the high cost of infeasibility, the RCFP approach was developed. The proposed mathematical model is developed and solved using a real industrial case study that is related to the production of a radio transmitter. The proposed model and solving approach is evaluated and a sensitivity analysis was performed on the robustness parameters in terms of the optimal degree of credibility of the constraints.

As guidance for future research, robust optimization could be aggregated with soft fuzzy programming. The concepts of earliness and tardiness could be covered in tactical supply chain planning for the engineer-to-order strategy in the JIT and lean manufacturing environment.

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