Manufacturing Decision-Support using Interactive Meta-Goal Programming

Hao W. Lin, Sev V. Nagalingam, and Grier C. I. Lin

***Abstract*—The benefits of collaborative manufacturing are widely recognized both by the industry and the academic world. However, the engagement of collaborative manufacturing for Small and Medium Manufacturing Enterprises (SMMEs) has proven to be a challenging task due to reoccurring complex decision-making processes toward the attainment of strategic objectives for collaborative manufacturing. The focus of this paper is thus to propose an Interactive Meta-Goal Programming (IMGP) based decision-support framework to facilitate the decision-making processes for collaborative manufacturing. The proposed framework will have a critical positive impact on the operation of SMMEs engaging in collaborative manufacturing, as the accuracy and efficiency of their collaborative decision-making processes will be significantly improved.**

***Index Terms*—Collaborative Manufacturing, Goal Programming, Meta-Goal, Multi-Criteria Decision-Making, Small and Medium manufacturing enterprises.**

I. Introduction

Collaborative manufacturing is a strategic action that requires manufacturing enterprises to establish close relationships for the benefits of all participants. Forming Collaborative Manufacturing Network (CMN) enable manufacturers to exploit each other's core competencies [1]. Further, collaborative manufacturing involves allocating specific manufacturing operations to the right enterprises, this results in the improvement of overall business performance [1]. Collaborative manufacturing enables participating manufacturing enterprises to stay lean on their core competencies and thus remain competitive in their own rights. Therefore, this strategy is fast gaining momentum in the manufacturing industry worldwide [2]. This trend is especially apparent in the Small and Medium Manufacturing Enterprise (SMME) sector, as collaborative manufacturing is a promising gateway for SMMEs to compete against larger enterprises [3]. Collaborative manufacturing however, presents critical management challenges. Decision-makers of an enterprise engaged in collaborative manufacturing must continue to orchestrate the functional units within the enterprise. Furthermore, cross-organizational relationships and collaboration strategies between the business partners must be managed with similar effectiveness and efficiency. The essence of this challenge requires that each participant make decisions individually, and then these decisions are aggregated to achieve the best possible outcome for the enterprise and its business partners. To assist SMMEs to overcome this challenge, this paper proposes a decision-support framework based on Interactive Meta-Goal Programming (IMGP) be adopted. This would enable global optimal and efficient collaborative decision-making for a Small or Medium Manufacturing Enterprise (S/MME) and its business partners. In Section II, the background information on decision-making in collaborative manufacturing is discussed. In Section III, an IMGP-based decision analysis framework is proposed. In Section IV, a hypothetical example is given to justify the proposed framework.

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H. W. Lin is with the Centre for Advanced Manufacturing Research, University of South Australia, SA 5095 Australia (61-08-8302-3112; fax: 61-08-8302-5292; e-mail: hao.lin@ postgrads.unisa.edu.au).
S. V. Nagalingam is with the Centre for Advanced Manufacturing Research, University of South Australia, SA 5095 Australia (e-mail: sev.nagalingam@unisa.edu.au).
G.C. I Lin is with the Centre for Advanced Manufacturing Research, University of South Australia, SA 5095 Australia (e-mail: grier.lin@unisa.edu.au).

II. Decision-Making in Collaborative Manufacturing

In collaborative manufacturing, the essence of decision-making is to identify the unique objectives, capabilities, constraints, and commitments of all entities in the CMN. The critical goal then is to decide on how to optimally dispose the available resources to fulfil the business objectives. Under such environment, decision-making is highly complex due to large number of distributed but interrelated manufacturing variables, contradicting objectives, as well as the large number of alternatives for achieving the objectives. A systematic decision-making process is required to address this overwhelming complexity. Simon [4]has proposed a four-phase decision-making model, which has been claimed by Turban, Aronson, and Liang [5] as the most concise and yet complete characterization of a rational decision-making approach. The four decision-making phases are intelligence, design, choice, and implementation. The intelligence phase is used to simplify and make knowledgeable assumptions about the real world problem, so that decision-makers can comprehend the situations and correctly define the potential problems and/or opportunities. The design phase involves the selection of an appropriate model to analyse the decision and suggests the potential decision alternatives for the most likely scenario. The choice phase focuses on using algorithms to solve the model and find the best possible solution. Finally the implementation phase is to continuously monitor manufacturing activities against performance achievements as anticipated by the corresponding decision outcome, and if variation exists, new decision-making process is activated to rectify the underlying issues. The IMGP model focused in this paper mostly coincides with research works that cover the second and third phase of Simon's decision-making model.

III. IMGP-BASED DECISION ANALYSIS FRAMEWORK

The discussion of the IMGP-based decision analysis framework begins by recapping the fundamental concepts of Goal Programming (GP). GP is a mathematical multi-criteria optimisation technique that has been actively studied in the disciplines of Multi-Criteria Decision Making (MCDM) and Multi-Objective Programming. Furthermore, it is continuing to show promising future in theoretical developments and practical applications in industries [6]. Proposed in 1961 by Charnes and Cooper [7], GP was initially introduced as an extension to Linear Programming. Due to the simplicity in model formulation, the effectiveness in solving MCDM problems, and the suitability for conveying Simon's philosophy on satisfying or sub-optimal solution, GP has received overwhelming responses from academics and the industry. As a result, GP is now an established new branch of study in Management Science and Operational Research. In one of its most general forms, GP is modelled by Equations (3.1) – (3.3).

$$\text{Minimise}: Z = \sum_{i=1}^{r} (w^n{}_i n_i + w^p{}_i p_i) \tag{3.1}$$

Subject to:

goal functions

$$\sum_{j=1}^{s} a_{i,j} x_j + n_i - p_i = T_i, \text{for } i = 1,\ldots,r \tag{3.2}$$

hard constraints

$$\sum_{j=1}^{s} b_{k,j} x_j \le C_k, \text{for } k = 1,\ldots,t \tag{3.3}$$

non – negative constraints

$$x_j, n_i, p_i, w^n{}_i, w^p{}_i \ge 0$$
$$\text{for } i = 1,\ldots,r; \text{for } j = 1,\ldots,s; \; for\; k = 1,\ldots,t$$

r	Total number of goal functions
s	Total number of decision variables
t	Total number of hard constraints
i	Goal function index, $i = 1,\ldots,r$
j	Decision variable index, $j = 1,\ldots,s$
k	Hard constraint index, $k = 1,\ldots,t$
$w^n{}_i, w^p{}_i$	Relative weighting factors assigned to the slack and surplus goal deviations of i th goal function respectively
n_i , p_i	Slack and surplus goal deviations of the i th goal function respectively
$a_{i,j}$	Technology coefficient for the j th decision variable of i th goal function
x_j	j th decision variable
T_i	Target value of i th goal function
$b_{k,j}$	Technology coefficient for the j th decision variable of the k th hard constraint
C_k	Constraint value of the k th hard constraint

By applying a recently developed extended GP model, namely IMGP [8], this paper proposes a method to overcome the distributive decision-making challenges faced by SMMEs engaged in collaborative manufacturing. The IMGP model introduces the concepts of meta-goal and interactive process to further enrich the performance of conventional GP models. The following sub-sections discuss these two concepts, and illustrate their roles in the formulation of IMGP-based decision analysis framework.

A. *Meta-Goals*

Meta-goal is a simultaneous cognitive evaluation on the degree of achievements for original decision goals considered in a GP model. Expresses as the utility function of the model, the meta-goal evaluates undesired deviation of every existing goal function d_i to concisely communicate with decision-makers the overall status of decision outcome. Depending on the decision objective that the goal function models, the undesired deviation can be p_i (goal that needs to be equal or less than the target), n_i (goal that needs to be equal or larger than the target), or both p_i and n_i (goal that needs to be attained exactly). Conventionally, a GP model such as the one depicted by Equations (3.1) – (3.3) consists of only one meta-goal variant, where the utility function is to minimise the aggregated undesired deviations of all the goals under consideration. Different goals in fact, contribute differently to the final outcome of a decision, and thus their corresponding sensitivity for deviations is represented by appropriate weighting factors. Furthermore, normalisation is one of the most popular techniques applied to ensure all goal functions are analysed using the same scale, so that trade-offs between different decision goals can be more accurately justified [9]. Although feasible for solving simple problem models, a singular meta-goal variant model is unable to effectively and accurately portray decision-makers' perspective preferences for decisions that consist of relatively higher number of goals, and which are entangled in complex relationships spanning different operational contexts of a CMN. For decisions of such complexity, decision-makers must be presented with a model that can easily gain cognitive insights to the decision situation, and input appropriate searching parameters without extensive knowledge of the original decision model, so that the analysis process can quickly converge to the most satisfying solution within the vast solution space.

Supporting Rodriguez Uria et al. [10] and Caballero et al.'s [8] work, our study suggests that an analysis approach that incorporates multiple meta-goal variants to build a high level objective satisfying GP model for the original decision problem

GP model is an effective approach to overcome the decision analysis challenges as described. This is known as the meta-goal programming multi-objective optimisation approach. In this approach, each meta-goal variant type offers a unique way of expressing and manipulating the overall achievement of all concerning decision goals. Through the use of collective meta-goal variants, there is no need to directly manipulate the underlying original GP model when searching for the optimal solution. This is particularly important as in CMN, the operational goals are usually proposed by managers of different functional units to represent the desirable performance targets for their corresponding manufacturing contexts. Decision-makers of cross-functional analysis are not as well informed, or lacking the knowledge even, to make sound changes to the operational goal functions without possibilities of introducing errors to the model. Furthermore, the meta-goal deviations allow the CMN to more swiftly identify an overall picture on the strengths and the weaknesses of the manufacturing process under consideration. Depending on the decision-makers' preferences, the meta-goal targets can be adjusted to achieve solution that nominate better balance for those strengths and weaknesses, so that overall business performance can be improved to a desirable level. Different meta-goal variants are discussed in the following sub-sections.

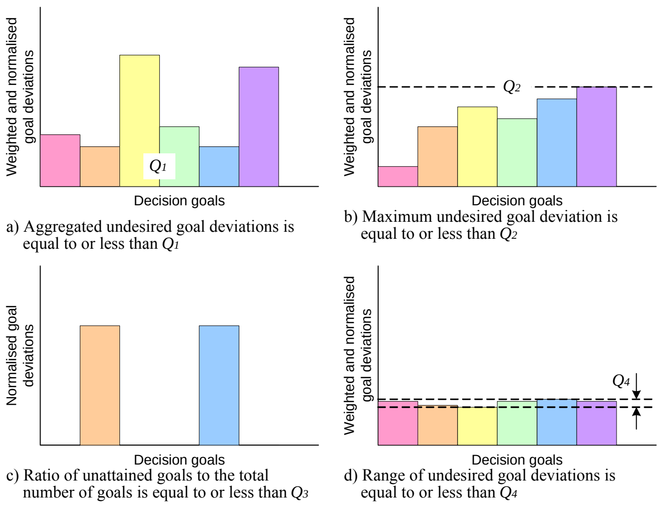

Figure 1. Meta-goal variants

1) *Meta-goal variant-1*

As introduced during the discussion of the conventional GP model earlier this section, the first meta-goal variant is the optimisation of aggregated undesired goal deviations modelled by Equation (3.4). Every undesired deviation considered d_i, is normalised by dividing its value by the corresponding target. This ratio can be verbally described as the percentage of un-achievement for the concerning decision goal. As mentioned earlier in this section, normalisation is necessary to ensure all deviations are measured under the same scale. Weighting factors w_i , are used to represent the relative importance between all undesired deviations considered. The value Q_1 is the meta-goal target that suggests the sum of the normalised undesired goal deviations must be at least equal or smaller. In term of manufacturing decision-making, this meta-goal is particular effective when analysing multiple contradicting goals that consume the same resources. Decision-makers can rank the original decision goals and let the model anticipate the best achievable manufacturing outcome with the available resources. Furthermore, decision-makers can continuously modify tradeoffs and establish new ranking scheme until the desired outcome is achieved. The solution of this particular meta-goal analysis is depicted using Figure 1.a. This figure is a bar graph with the height of every bar representing the corresponding weighted undesirable deviation of a particular goal. Consider every bar has a width of one unit, it can be concluded that the total area under the graph is equal to the result of meta-goal variant-1.

$$\sum_{i=1}^{r} w_i \frac{d_i}{T_i} \le Q_1 \tag{3.4}$$

2) *Meta-goal variant-2*

The second meta-goal variant considered in this paper is optimisation for the maximal of the undesired goal deviations, and it is mathematically modelled by Equation (3.5). Meta-goal variant-2 identifies the largest normalised and weighted deviation amongst all the goals considered, and ensures this value is kept at minimum. The meta-goal target value Q_2 , conveys the decision-maker's preference on the degree of fulfilment that every considered goal must achieve exactly or better. In term of manufacturing decision-making, this meta-goal is highly effective for analysing a set of manufacturing operations where their particular performance parameters must be maintained at a critical level. For example, a manufacturer has five different market regions for one of its products, and a successful order fulfilment target of 99% is required. Consider if all market sectors are of equal priority, thus w_j is omitted from Equation (3.5), Q_2 would take the value of 0.01. A typical analysis output is depicted by Figure 1.b, which shows all undesirable deviations fall below the meta-goal target.

$$\max_{i=1,\dots,r}\{w_i \frac{d_i}{T_i}\} \le Q_2 \tag{3.5}$$

3) *Meta-goal variant-3*

The third meta-goal variant is optimisation of the number of unattained goals, which is mathematically modelled using Equations (3.6) – (3.7). Two new variables are introduced in the equations. First, y_i is a binary variable that indicates whether a goal is satisfied, and second M_i is an arbitrary number that is considerably larger than d_i . To keep consistency between all meta-goal variants, the number of unattained goals are normalised by dividing against the total number of original decision goals considered in the model. Inherently the meta-goal target Q_3 , is simply the total percentage of unattained goals for all the goals considered. Meta-goal variant-3 does not consider optimisation of undesired deviation factors d_i , but only interested in identifying goals that are fully satisfied. In term of manufacturing decision-making, this meta-goal analysis is useful when all goals are of same priority and a decision-maker prefers to optimise the overall decision outcome by maximising the number of fully attained goals. For example, several customer orders are received within a particular time window, and since every customer is equally valuable, the manufacturer achieves optimal customer satisfaction if maximum number of customer orders can be fulfilled over the next production cycle. Figure 1.c describes a goal can either be attained (y_i = 0), or unattained (y_i = 1). Compare our model to the model proposed by Rodriguez Uria and et. al. [10], it is noticed that Equation (3.6) is slightly modified with the introduction of a lower bound parameter $-M_i$. During our experiment, we have found that this lower bound parameter is necessary to guarantee y_i to have a value of 0 when a goal is achieved (when d_i is 0).

$$-M_i < d_i - M_i y_i \leq 0,\ i = 1,...,r,\ y_i = \{0,1\} \tag{3.6}$$

$$\frac{\sum_{i=1}^{r} y_i}{r} \leq Q_3 \tag{3.7}$$

4) Other meta-goal variants

The three meta-goal variants discussed in the previous sub-sections provide the fundamental tools for decision-makers to analyse decision alternatives at an abstract level that is easier to convey by decision-makers. These tools effectively improve the accuracy of the decision outcome. Our study though, has convinced us that moreover, other meta-goal variants may be developed to further enrich the analytical features of the framework. One such example is a meta-goal that aims to minimise the differences between all the undesired goal deviations under consideration. This analysis is especially important in our work, as collaborative manufacturing often requires operational commitments, profits, risks, and other performance attributes to be shared as equally as possible between all the business partners of the CMN. The meta-goal variant must portray performance sacrificing of some goals for the improvement of other goals, and maintaining the balance in performance for all functional units. Figure 1.d depicts an expected outcome for this type of meta-goal. The formal mathematical definition of the meta-goal however, is to be considered in our future work.

B. INTERACTIVE PROCESS

In decision-making, we define interactive process as a communication algorithm between the decision-makers and the problem model in an attempt to efficiently explore the solution space and eventually towards the discovery of best possible decision outcome as desired by the decision-makers. Three stages of the interactive process used in the formulation of the IMGP-based decision analysis framework are discussed in the following sub-sections.

1) Goal function proposal

In collaborative manufacturing, a decision potentially has extensive impacts on the operation of multiple functional units spanning the enterprise, and indeed the impacts are equally sensed crossing enterprise boundaries namely the business partners. To ensure an accurate meta-goal model be built for the concerning decision problem, all entities affected by the decision are given opportunities to analyse the decision problem definition using their local analysis technique, and thus to nominate their desired local objective(s). Depending on their unique perspectives, the overall nominated local objectives would present dramatic variations. Nevertheless, the varying objectives can be largely categorised into two contradictory classes. They are the minimisation of local resource utilisation, and the maximisation of local output and service performance. The collaborative problem though is further complicated since large number of objectives can be collected from different entities, which usually compete for scarce resources and rewarding benefits, must be attained at the same time. Thus, all objectives must be concisely represented in the same fashion and then analysed together by the meta-goal functions, discussed earlier this section, to find the optimal balance as preferred by the decision-makers.

Conforming to the composition requirements of the model, every decision objective is represented by a unique linear goal function as depicted by Equation (3.2). Every technology coefficient of a goal function $a_{i,j}$, represents the degree of contribution that a decision variable put toward the corresponding decision objective. Depending on what manufacturing aspect the decision objective measures, the coefficient may anticipate the utilisation of a certain resource, production output, service quality, or other manufacturing measurements associated with the decision variable. Respectively, the right hand side of the equation T_i, represents the manufacturing performance target that the decision-makers desired to attain. Positive or negative offsets of actual achievements from desired achievements are measured by the deviation factors, n_i and p_i. They are indicators for how well each objective is attained. An entity must also supply meta-information on the goals that it proposed, which include the relative weighting factors of the goals, and if positive, negative, or zero offset is desired for every goal. This meta-information determines some of the controlling parameters that dictate how the meta-goal model is searching for the optimal decision within the properly restrained solution space. Furthermore, maximum allowable deviation for each goal function and other resource capacities are usually represented using hard constraint equations.

2) Iterative decision-maker preference entry

Interactive processes are critical to the study of MCDM. Interactive processes is an art, as it is not entirely formally scientifically based, rather the intuitions that a decision-maker has on the model and his/her ability to make correct judgments when requested upon by the model is of main focus. With the solution-searching algorithm, the decision-maker assigns priority and relative weighting factors for all the objectives, and set other controlling parameters that allow the objectives to aspire toward global optimisation. The decision-maker's preferences for the controlling parameters of every subsequent iteration is established based on the criterion matrix, which is a performance trade off summary derived from the outcomes of all previous iterations. This process is repeated until the decision-maker is satisfied with the solution. In Gardiner and Steuer's work [11], a unified interactive process algorithm is proposed for GP. This algorithm is modified for the purpose of solving meta-goal programming based decision models that our study concerns. The steps for the modified algorithm are stated as below.

1. Establish initial weighting factors: From our literature review, we have identified that Analytical Hierarchy Process (AHP) is an effective method that uses pair-wise comparison analytical techniques to derive numerical representation on relative weighting factors for up to fifteen items at a time. Satisfying consistency ratio however can be better achieved when the item size is limited to eight [12]. Considering the business characteristics of an S/MME operating in a CMN, a decision cluster that consists of more than eight objective functions are logically dissected into multi-level of sub-clusters to improve comparison consistency. Thus, the AHP model as depicted by Figure 2 is used to calculate the weighting factors for all the objectives proposed within the CMN. The actual step-by-step AHP algorithm is not described here, as it has been very well established by Satty [12], the pioneer of AHP. Furthermore, the process has been applied in problems similar to the one presented in this paper, such as the work done by Yu [13].

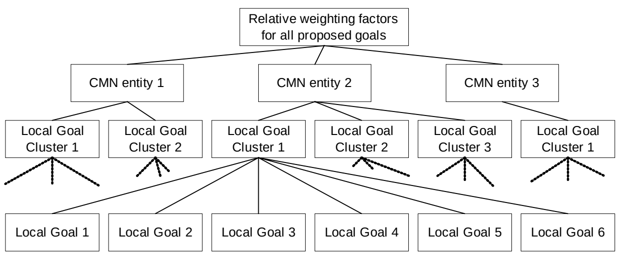

Figure 2. AHP for evaluating relative weighting factors

2. Construct initial criterion matrix: This step is to calculate an initial criterion matrix that provides the decision-maker achievement boundary information for all the existing meta-goals. Based on this information, decision-maker can make more coherent and knowledgeable selection on the target values and relative weighting factors for the meta-goals used. Inherently, more accurate trade-offs can be reinforced on existing local decision goals for the attainment of global optima. The algorithm for constructing the initial criterion matrix is presented toward the end of this sub-section.
3. Verify initial solution: Present the initial criterion matrix to the decision-maker for verification. This interactive algorithm is terminated if the decision-maker is satisfied with any of the solutions presented on the matrix. Otherwise the algorithm moves to step 4 for further analysis.
4. Establish priority levels: Depending on their contribution toward the overall performance of the decision, some decision goals must be satisfied before the others. In this step, decision-maker classifies all existing decision goals into sub-clusters, and each cluster is then assigned to a unique priority level. Cluster of higher priority level must be satisfied first. If the algorithm re-iterates from this step as satisfying result could not be found in the previous iteration, the current goal classification scheme and the corresponding priority scores can be refined to exploit better decision outcomes. This task requires decision-makers making references to the up-to-date criterion matrix, in order to achieve better trade-offs between the concerning decision goals.
5. Re-establish weighting factors: If desired by the decision-maker, the relative importance of all decision goals within their respective priority level is analysed again using AHP. Inherently every decision goal function's relative weighting factor within the model is re-established.
6. Assign meta-goal: Depending on the nature of the decision goals and how these goals should be attained, a suitable meta-goal variant is selected for each priority level to analyse the respective decision problem. The analytical strength of the four meta-goal variants used in our study has been clearly classified in Section III.A, thus it is relatively straightforward to select the most appropriate meta-goal for each priority level. Furthermore, multiple meta-goal variants maybe selected to analyse a single priority level to improve its analytical robustness.
7. Solve current meta-goal model: The decision problem model for any given priority level is solved using a Web Services based meta-goal programming solver that the authors have developed. The underlying optimisation engine used to build the meta-goal programming solver is called Lindo API, a product developed by Lindo System Inc's [14]. The mathematical model of the IMGP decision problem is introduced later in this sub-section, and the steps taken to solve multi priority level decision problems are further clarified with a hypothetical example in Section IV.
8. Present current solution and criterion matrix: The current solution and the criterion matrix, which is derived from all previous solutions, are presented to the decision-maker in a concise manner.
9. Verify current solution: If the current solution is successfully verified and accepted by the decision-maker, this solution is confirmed and the decision analysing process is ceased. Otherwise the current solution is added to the criterion matrix and the process advances to the next iteration from step 4.

To mathematically model IMGP based decision problems, the following notations are introduced to represent the parameters and variables involved in the model.

l	l th highest priority level, index for the current sub-problem of the overall meta-goal programming decision problem
ρ	Priority level index for all levels of higher priority than the l th level, $\rho = 1,\ldots,l-1$
r^l, r^ρ	Total number of goal functions in the l th and ρ th priority level respectively
s	Total number of decision variables
t	Total number of hard constraints
i	Goal function index for every existing priority level, $i = 1,\ldots,r^l$; and $i = 1,\ldots,r^\rho$
j	Decision variable index, $j = 1,\ldots,s$
k	Hard constraint index, $k = 1,\ldots,t$
$b_{k,j}$	Technology coefficient for the j th decision variable of the k th hard constraint
C_k	Constraint value of the k th hard constraint
x_j	j th decision variable
$a_{i,j}{}^l, a_{i,j}{}^\rho$	Technology coefficient for the j th decision variable of i th goal function in the l th and ρ th priority level respectively
T_i^l, T_i^ρ	Target value of i th goal function in the l th and ρ th priority level respectively
w_i^l, w_i^ρ	Relative weighting factors assigned to the undesired goal deviations of i th goal function in the l th and ρ th priority level respectively
n_i^l, n_i^ρ	Slack goal deviations of the i th goal function in the l th and ρ th priority level respectively
p_i^l, p_i^ρ	Surplus goal deviations of the i th goal function in the l th and ρ th priority level respectively
d_i^l, d_i^ρ	Undesired goal deviations of i th goal function in the l th and ρ th priority level respectively
$\alpha_{1,2,3}{}^l, \alpha_{1,2,3}{}^\rho$	Slack deviation of meta-goal variant-1, 2, or 3 in the l th and ρ th priority level respectively
$\beta_{1,2,3}{}^l, \beta_{1,2,3}{}^\rho$	Surplus deviation of meta-goal variant-1, 2, or 3 in the l th and ρ th priority level respectively
$Q_{1,2,3}{}^l, Q_{1,2,3}{}^\rho$	Target value of meta-goal variant-1, 2, or 3 in the l th and ρ th priority level respectively
D^l, D^ρ	Constraining variable for meta-goal variant-2 in the l th and ρ th priority level respectively, they represent the maximum allowed goal deviations
$M_i{}^l, M_i{}^\rho$	Constraining variable for meta-goal variant-3 in the l th and ρ th priority level respectively, their purpose in the model is discussed in Section III.A
y_i^l, y_i^ρ	Constraining variable for meta-goal variant-3 in the l th and ρ th priority level respectively, their purpose in the model is discussed in Section III.A
$\delta_{1,2,3}{}^l, \delta_{1,2,3}{}^\rho$	Undesirable deviation of meta-goal variant-1, 2, or 3 in the l th and ρ th priority level respectively
$\mu_{1,2,3}{}^l, \mu_{1,2,3}{}^\rho$	Relative weighting factors assigned to the undesired deviations of meta-goal variant-1, 2, or 3 in the l th and ρ th priority level respectively, within a priority level, the weights of all meta-goal variants must add up to 1, a weighting value of 0 represents the corresponding meta-goal is not considered
$R_{1,2,3}{}^\rho$	Undesirable deviations for meta-goal variant-1, 2, or 3 accepted by decision-makers in a higher level, ρ

Equations (3.8) – (3.24) represent the meta-goal programming decision problem for priority level l. To solve the entire decision problem model, priority levels are analysed one at a time, from the highest prioritised to the lowest. Meta-goal solutions obtained from levels higher than are converted into hard constraints during the analysis of level l. This ensures higher prioritised goals can be best achieved before the lower ones.

$$\text{Minimise}: Z = \mu_1^l \delta_1^l + \mu_2^l \delta_2^l + \mu_3^l \delta_3^l \tag{3.8}$$

Subject to:

hard constraints

$$\sum_{j=1}^{s} b_{k,j} x_j \le C_k, \text{for } k = 1,\ldots,t \tag{3.9}$$

goal functions for l^{th} priority level

$$\sum_{j=1}^{s} a_{i,j}{}^l x_j + n_i^l - p_i^l = T_i^l, \text{for } i = 1,\ldots,r^l \tag{3.10}$$

meta – goal variant 1 for l^{th} priority level

$$\sum_{i=1}^{r^l} w_i^l \frac{d_i^l}{T_i^l} + \alpha_1^l - \beta_1^l = Q_1^l \tag{3.11}$$

$$meta-goal\ variant\ 2\ for\ l^{th}\ priority\ level$$

$$w_i^l \frac{d_i^l}{T_i^l} - D^l \le 0,\ for\ i=1,...,r^l \quad (3.12)$$

$$D^l + \alpha_2^l - \beta_2^l = Q_2^l \quad (3.13)$$

$$meta-goal\ variant\ 3\ for\ l^{th}\ priority\ level$$

$$-M_i^l < d_i^l - M_i^l y_i^l \le 0,\ for\ i=1,...,r^l \quad (3.14)$$

$$\frac{\sum_{i=1}^{r^l} y_i^l}{r^l} + \alpha_3^l - \beta_3^l = Q_3^l \quad (3.15)$$

$$goal\ functions\ belonging\ to\ all\ higher\ priority\ levels$$

$$\sum_{j=1}^{s} a_{i,j}^{\rho} x_j + n_i^{\rho} - p_i^{\rho} = T_i^{\rho} \quad (3.16)$$

$$\text{for}\ i=1,...,r^{\rho},\ for\ \rho=1,...,l-1$$

$$meta-goal\ variant\ 1\ constraints$$
$$established\ in\ higher\ priority\ levels$$

$$\sum_{i=1}^{r^{\rho}} w_i^{\rho} \frac{d_i^{\rho}}{T_i^{\rho}} + \alpha_1^{\rho} - \beta_1^{\rho} = Q_1^{\rho} \quad (3.17)$$

$$\delta_1^{\rho} = R_1^{\rho} \quad for\ \rho=1,...,l-1, and\ if\ \mu_1^{\rho} > 0 \quad (3.18)$$

$$meta-goal\ variant\ 2\ constraints$$
$$established\ in\ higher\ priority\ levels$$

$$w_i^{\rho} \frac{d_i^{\rho}}{T_i^{\rho}} - D^{\rho} \le 0,\ for\ i=1,...,r^{\rho} \quad (3.19)$$

$$D^{\rho} + \alpha_2^{\rho} - \beta_2^{\rho} = Q_2^{\rho} \quad (3.20)$$

$$\delta_2^{\rho} = R_2^{\rho} \quad (3.21)$$
$$for\ \rho=1,...,l-1, and\ if\ \mu_2^{\rho} > 0$$

$$meta-goal\ variant\ 3\ constraints$$
$$established\ in\ higher\ priority\ levels$$

$$-M_i^{\rho} < d_i^{\rho} - M_i^{\rho} y_i^{\rho} \le 0,\ for\ i=1,...,r^{\rho} \quad (3.22)$$

$$\frac{\sum_{i=1}^{r^{\rho}} y_i^{\rho}}{r^{\rho}} + \alpha_3^{\rho} - \beta_3^{\rho} = Q_3^{\rho} \quad (3.23)$$

$$\delta_3^{\rho} = R_3^{\rho} \quad for\ \rho=1,...,l-1, and\ if\ \mu_3^{\rho} > 0 \quad (3.24)$$

$$variable\ constraints$$
$$x_j, n_i^l, p_i^l, \alpha_{1,2,3}^l, \alpha_{1,2,3}^{\rho}, \beta_{1,2,3}^l, \beta_{1,2,3}^{\rho} \ge 0$$
$$D^l, D^{\rho}, A^l, A^{\rho}, B^l, B^{\rho} \ge 0$$
$$0 \le \mu_{1,2,3}^l, \mu_{1,2,3}^{\rho}, w_i^l, w_i^{\rho} \le 1$$
$$y_i^l, y_i^{\rho} \in \{0,1\}$$

The calculation of initial trade-off criterion matrix mentioned in Step 2 of the interactive algorithm is a special case of the model depicted above. The trade-offs model consider all existing goals are clustered in a single priority level and thus, it is not constrained by meta-goal solutions from any higher priority level. Inherently, Equations (3.16) – (3.24) are omitted from the model. To offer a decent initial trade-off reference, the matrix is made up of best possible solutions obtained when full weight is given to one meta-goal variant at a time for the modified utility function as depicted using Equation (3.25). Since the aim of the trade-off model is to help decision-makers identify the appropriate meta-goal targets, meta-goal Equations (3.11), (3.13), and (3.15) are also omitted.

$$\text{Minimise}: Z = \mu_1^l\left(\sum_{i=1}^{r^l} w_i^l \frac{d_i^l}{T_i^l}\right) + \mu_2^l\left(D^l\right) + \mu_3^l\left(\frac{\sum_{i=1}^{r^l} y_i^l}{r^l}\right) \quad (3.25)$$

3) *Networked Delphi Process*

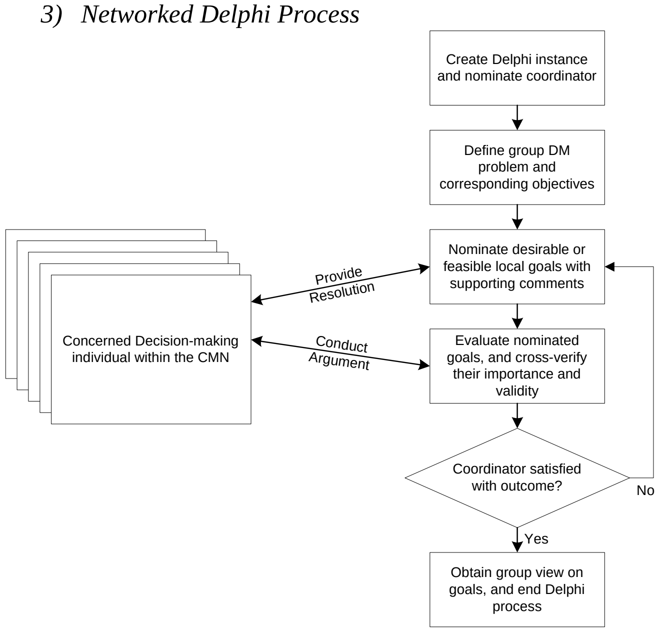

Figure 3. A networked Delphi process

So far in our discussion about the IMGP decision analysis framework, we only considered a single decision-maker's interaction with the model from the establishment of relative weighting factors to the attainment of global optimal solution. Collaborative manufacturing however requires inputs from multiple decision-makers across different entities of the CMN, whose perspectives are usually different due to their ambitions to pursue maximum performance for the corresponding manufacturing processes that they manage. These differences must be efficiently identified and eliminated to produce a group view on weighting factors and controlling parameters for the model. From our literature review, we identified that Delphi Process [15] is a suitable method to address this need. Figure 3 is a flow chart that depicts a networked Delphi Process that enables a group of decision-makers to anonymously and asynchronously participate in the IMGP-based decision analysis framework.

C. *IMGP-BASED DECISION ANALYSIS WORKFLOW*

In this section thus far, we have discussed the components that are required to setup an IMGP-based problem. Here, we demonstrate the superposition of these components to form a complete IMGP-based decision analysis framework. The process and the flow of information among each step are described in Figure 4. Each step is denoted by a numeral code above the workflow.

- Step 1 - Decision-makers retrieve important operational and performance information, identify environment and manufacturing parameters, and assigns a desired target for each parameter. A rule is then imposed on each parameter where a certain degree of deviation from its target would trigger a decision-making process. It is important that the entire set of parameters monitored could aggregate to convey the real manufacturing environment of the CMN, and that any real potential problem and or opportunity could be detected from the observation of these parameters.
- Step 2 – Upon the detection that a decision is required in Step 1, this step generates a formal statement for the decision-problem to be solved. The definition would include gathering all the associated data and information required for analysing the decision, the objectives of the CMN, the uniqueness of the decision, the knowledge domains the decision belongs to, and who is responsible to the success of the decision.
- Step 3 – Based on the decision-problem statement, the most expected scenario is defined, and a set of decision alternatives is selected for consideration. This information is then forwarded to all the entities that would be affected by the decision.
- Step 4 – The IMGP-based decision analysis framework assumes that every entity has the capabilities to analyse its local decision variables and parameters using the information received from Step 3, and then evaluate the decision with respect to the local objectives. For example, in our previous research work, a Genetic Algorithm tool [9] is used perform task scheduling, and a Game model [3] is used to select production plants to process the customer orders. The work involved in this step has been discussed in detail in Section III.B (Goal Function Proposal).
- Steps 5 to 7 – These steps constitute the IMGP model. The algorithm involved in these steps has been given in Section III.B (Iterative Decision-Maker Preference Entry).
- Step 8 – If a group decision-making environment is required, a Delphi process is activated. The Delphi process is discussed in Section III.C (Networked Delphi Process).
- Step 9 – The best possible solution is evaluated and confirmed. This solution is forwarded to the decision-maker in charge of the decision for confirmation. If not satisfied, the algorithm re-iterates from Step 7 to further refine existing model parameters and variables. Otherwise the current most satisfying solution is passed to Step 10.
- Step 10 – The decision outcome is confirmed and forwarded to all concerning entities so that all necessary resources are appropriately planned. Subsequently, manufacturing actions are performed in strict accordance to the decision outcome.
- Step 11 – As the decision is being implemented, its performance is constantly monitored, so that any negative deviation from the desired target can be detected and addressed at the earliest possible time.

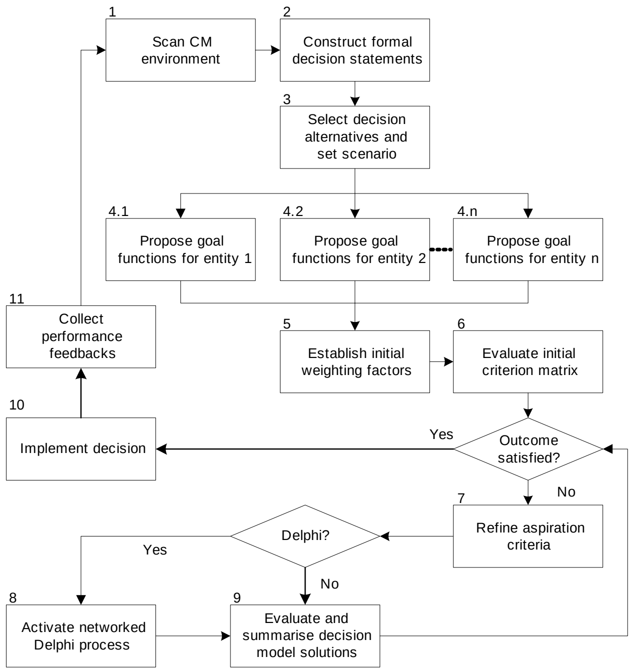

Figure 4. IMGP-based decision analysis workflow

IV. Example

In this example, we used a hypothetical decision-making problem frequently encountered by the industry partner of this project that is a suture manufacturer, to demonstrate the strength of our method. We consider four different functional units of the manufacturer participating in a collaborative manufacturing decision-making process. These units are the Sales unit that set goals on customer demands; the Finance unit that set goals on business profits and production costs; the Operational planning unit that set goals on the utilities of the available production capacity; and the Scheduling unit that set goals on the utilities of the current machine group formation. Furthermore, both the needle and thread suppliers are also participating in this process. The problem is to decide the production quantity for four different types of suture for the next production cycle. The suture production steps consist of swaging (joining the thread to the needle), packaging, and quality checking. The production lead-time for different types of suture varies, as finer needles are more difficult to handle than the coarse ones. The available swaging machines are equally divided into two groups to accommodate the two different needle sizes. Although any machine can set-up to produce the other needle size, it is not desirable by the production workers, as setting up is a time consuming process, and the slightest miss-set-up would destroy the costly die in the swaging mechanism. Table 1 summarizes the goal functions proposed by each decision-making entity.

Table 1. Goals proposed by individual collaborative manufacturing entity

Goals[1]	x_1 [2]TC	x_2 [3]TC	x_3 [4]TC	x_4[5]TC[6]	Tgt[7]	Description
G1	1	0	0	0	≥300	Production quota for each product
G2	0	1	0	0	≥350	
G3	0	0	1	0	≥420	
G4	0	0	0	1	≥325	
G5	58	51	47	41	≥70000	Sales target
G6	30	26	25	21	≤50000	Costs
G7	0.2	0.18	0.16	0.15	≤350	Swaging
G8	0.05	0.05	0.025	0.025	≤70	Packing
G9	0.025	0.025	0.025	0.025	≤35	QC[8]
G 10	0.2	0.18	0	0	≤175	Schedule for MG[9] 1 and 2
G11	0	0	0.16	0.15	≤175	
G12	12	12	0	0	≤8000	Needles to be supplied
G13	0	0	12	12	≤8000	
G14	4.8	0	4.8	0	≤3000	Thread to be supplied
G15	0	4.8	0	4.8	≤3000	

1. Goal proposed by a particular collaborative manufacturing entity,
2. Production quantity for product 1 – Fine needle and absorbable thread,
3. Production quantity for product 2 – Fine needle and non-absorbable thread, 4. Production quantity for product 3 – Coarse needle and absorbable thread,
5. Production quantity for product 4 – Coarse needle and non-absorbable thread,
6. Technical coefficient,
7. Goal target,
8. Quality Check,
9. Machine Group

Based on the goal targets, it is determined that the following deviation factors are undesirable:
$n_1, n_2, n_3, n_4, n_5, p_6, p_7, p_8, p_9, p_{10}, p_{11}, p_{12}, p_{13}, p_{14}, p_{15}$

The model represented by Equations (4.1) – (4.46) is formulated to calculate the initial trade-off criterion matrix. As mentioned in Section III.B.2, three unique solutions will be obtained as the model configures to give strict preference to meta-goal variant 1 achievement ($\mu_1 = 1$, $\mu_2 = \mu_3 = 0$), meta-goal variant 2 achievement ($\mu_2 = 1$, $\mu_1 = \mu_3 = 0$), and meta-goal variant 3 achievement ($\mu_3 = 1$, $\mu_1 = \mu_2 = 0$) respectively.

$$\begin{aligned}\text{Minimise}: Z = \mu_1(&\frac{n_1}{300}+\frac{n_2}{350}+\frac{n_3}{420}+\frac{n_4}{325}+\frac{n_5}{70000}+\\ &\frac{p_6}{50000}+\frac{p_7}{350}+\frac{p_8}{70}+\frac{p_9}{35}+\frac{p_{10}}{175}+\frac{p_{11}}{175}+\\ &\frac{p_{12}}{8000}+\frac{p_{13}}{8000}+\frac{p_{14}}{3000}+\frac{p_{15}}{3000})+\mu_2(D)+\\ &\mu_3(\frac{y_1}{15}+\frac{y_2}{15}+\frac{y_3}{15}+\frac{y_4}{15}+\frac{y_5}{15}+\frac{y_6}{15}+\frac{y_7}{15}+\frac{y_8}{15}+\\ &\frac{y_9}{15}+\frac{y_{10}}{15}+\frac{y_{11}}{15}+\frac{y_{12}}{15}+\frac{y_{13}}{15}+\frac{y_{14}}{15}+\frac{y_{15}}{15})\end{aligned} \tag{4.1}$$

Subject to:

$$x_1 + n_1 - p_1 = 300 \tag{4.2}$$
$$x_2 + n_2 - p_2 = 350 \tag{4.3}$$
$$x_3 + n_3 - p_3 = 420 \tag{4.4}$$
$$x_4 + n_4 - p_4 = 325 \tag{4.5}$$
$$58x_1 + 51x_2 + 47x_3 + 41x_4 + n_5 - p_5 = 70000 \tag{4.6}$$
$$30x_1 + 26x_2 + 25x_3 + 21x_4 + n_6 - p_6 = 50000 \tag{4.7}$$
$$0.2x_1 + 0.18x_2 + 0.16x_3 + 0.15x_4 + n_7 - p_7 = 350 \tag{4.8}$$
$$0.05(x_1 + x_2) + 0.025(x_3 + x_4) + n_8 - p_8 = 70 \tag{4.9}$$
$$0.025(x_1 + x_2 + x_3 + x_4) + n_9 - p_9 = 35 \tag{4.10}$$
$$0.2x_1 + 0.18x_2 + n_{10} - p_{10} = 175 \tag{4.11}$$
$$0.16x_3 + 0.15x_4 + n_{11} - p_{11} = 175 \tag{4.12}$$
$$12(x_1 + x_2) + n_{12} - p_{12} = 8000 \tag{4.13}$$
$$12(x_3 + x_4) + n_{13} - p_{13} = 8000 \tag{4.14}$$
$$12\times 0.4(x_1 + x_3) + n_{14} - p_{14} = 3000 \tag{4.15}$$
$$12\times 0.4(x_2 + x_4) + n_{15} - p_{15} = 3000 \tag{4.16}$$
$$n_1 - 300D \le 0 \tag{4.17}$$
$$n_2 - 350D \le 0 \tag{4.18}$$
$$n_3 - 420D \le 0 \tag{4.19}$$
$$n_4 - 325D \le 0 \tag{4.20}$$
$$n_5 - 70000D \le 0 \tag{4.21}$$
$$p_6 - 50000D \le 0 \tag{4.22}$$
$$p_7 - 350D \le 0 \tag{4.23}$$
$$p_8 - 70D \le 0 \tag{4.24}$$
$$p_9 - 35D \le 0 \tag{4.25}$$
$$p_{10} - 175D \le 0 \tag{4.26}$$
$$p_{11} - 175D \le 0 \tag{4.27}$$
$$p_{12} - 8000D \le 0 \tag{4.28}$$
$$p_{13} - 8000D \le 0 \tag{4.29}$$
$$p_{14} - 3000D \le 0 \tag{4.30}$$
$$p_{15} - 3000D \le 0 \tag{4.31}$$
$$-3000 \le n_1 - 3000y_1 \le 0 \tag{4.32}$$
$$-3500 \le n_2 - 3500y_2 \le 0 \tag{4.33}$$
$$-4200 \le n_3 - 4200y_3 \le 0 \tag{4.34}$$
$$-3250 \le n_4 - 3250y_4 \le 0 \tag{4.35}$$
$$-700000 \le n_5 - 700000y_5 \le 0 \tag{4.36}$$
$$-500000 \le p_6 - 500000y_6 \le 0 \tag{4.37}$$
$$-3500 \le p_7 - 3500y_7 \le 0 \tag{4.38}$$
$$-700 \le p_8 - 700y_8 \le 0 \tag{4.39}$$
$$-350 \le p_9 - 350y_9 \le 0 \tag{4.40}$$
$$-1750 \le p_{10} - 1750y_{10} \le 0 \tag{4.41}$$
$$-1750 \le p_{11} - 1750y_{11} \le 0 \tag{4.42}$$
$$-80000 \le p_{12} - 80000y_{12} \le 0 \tag{4.43}$$
$$-80000 \le p_{13} - 80000y_{13} \le 0 \tag{4.44}$$
$$-30000 \le p_{14} - 30000y_{14} \le 0 \tag{4.45}$$
$$-30000 \le p_{15} - 30000y_{15} \le 0 \tag{4.46}$$

variable constraints

$$x_{1,\dots,4}, n_{1,\dots,5}, p_{6,\dots,15}, D \ge 0$$
$$0 \le \mu_{1,2,3} \le 1; y_{1,\dots,15} \in \{0,1\}$$

The result of trade-off calculation is summarized in Table 2. The shaded cells indicate the best achievement for their corresponding meta-goal variant. Based on this result, the decision-makers nominate a target value for each of the meta-goal variant considered in order to analyse the decision problem further. In the new model, the meta-goal functions expressed by Equation (4.48) – (4.53) are included to the trade-off calculation model. In the current analysis, all decision goals are clustered into a single priority level, and the goals are equally weighted. Furthermore, the objective now is to minimise undesired deviations of the meta-goal functions. Thus, the objective function of the trade-off calculation model, Equation (4.1), is now replaced by Equation (4.47). The chosen meta-goal targets and their corresponding solution of this new model is summarised in Table 3. The shaded cells indicate meta-goal and original decision goals that have not met their targets.

Table 2. Initial trade-off criterion matrix

	x_1	x_2	x_3	x_4	MG variant 1 result	MG variant 2 result	MG variant 3 result
Strictly favours MG variant 1	300	350	342	325	0.37	0.19	$\frac{4}{15}$
Strictly favours MG variant 2	279	356	390	302	0.45	0.07	$\frac{7}{15}$
Strictly favours MG variant 3	300	350	342	325	0.37	0.19	$\frac{4}{15}$

MG: Meta-Goal

$$\text{Minimise}: Z = \mu_1(\beta_1) + \mu_2(\beta_2) + \mu_3(\beta_3) \qquad (4.47)$$

$$\zeta_1 - \left(\frac{n_1}{300} + \frac{n_2}{350} + \frac{n_3}{420} + \frac{n_4}{325} + \frac{n_5}{70000} + \frac{p_6}{50000} + \frac{p_7}{350} + \frac{p_8}{70} + \frac{p_9}{35} + \frac{p_{10}}{175} + \frac{p_{11}}{175} + \frac{p_{12}}{8000} + \frac{p_{13}}{8000} + \frac{p_{14}}{3000} + \frac{p_{15}}{3000}\right) = 0 \qquad (4.48)$$

$$\zeta_1 + \alpha_1 - \beta_1 = 0.38 \qquad (4.49)$$

$$\zeta_2 - D = 0 \qquad (4.50)$$

$$\zeta_2 + \alpha_2 - \beta_2 = 0.09 \qquad (4.51)$$

$$\zeta_3 - (y_1 + y_2 + y_3 + y_4 + y_5 + y_6 + y_7 + y_8 + y_9 + y_{10} + y_{11} + y_{12} + y_{13} + y_{14} + y_{15}) = 0 \qquad (4.52)$$

$$\zeta_3 + \alpha_3 - \beta_3 = 0.33 \qquad (4.53)$$

variable constraints

$$\alpha_{1,2,3}, \beta_{1,2,3} \geq 0$$

According to the interactive algorithm discussed in Section III.B, decision-makers can continue their analysis by categorise all the decision goals into prioritised sub-clusters, and then each cluster is analysed by a particular meta goal from the highest to the lowest. This would allow decision-makers to satisfy the more important goals before the less important ones, which would have less impact on the achievement of business objectives. An example of such decision model could have the following parameters:

Priority level 1: Goal 5 and 6, analysed by meta-goal variant 3, with a meta-goal target of 0
Priority level 2: Goal 12, 13, 14, and 15, analysed by meta-goal variant 2, with a meta-goal target of 0.09
Priority level 3: Goal 1, 2, 3, and 4, analysed by meta-goal variant 1, with a meta-goal target of 0.4
Priority level 4: Goal 7, 8, 9, 10, and 11, analysed by meta-goal variant 2, with a meta-goal target of 0.1

For the current decision problem however, it is clear that the constraining factors are the availability of components. Both the needle and thread suppliers are unable to supply adequate quantities to fulfil production targets. Considering these constraints, the single level analysis has provided satisfying results. If the suture manufacturer has access to other suppliers, or the current suppliers have indicated that they are capable of delivering more goods, a possible new multi priority level decision model can be constructed with the following parameters:

Priority level 1: Goal 5 and 6, analysed by meta-goal variant 3, with a meta-goal target of 0
Priority level 2: Goal 1, 2, 3, and 4, analysed by meta-goal variant 1, with a meta-goal target of 0.09
Priority level 3: Goal 7, 8, 9, 10, and 11, analysed by meta-goal variant 2, with a meta-goal target of 0.1
Priority level 4: Goal 12, 13, 14, and 15, analysed by meta-goal variant 3, with a meta-goal target of 0

The construction and evaluation of multi level meta-goal programming decision model is not discussed in this paper. However, one should appreciate this methodology allows decision-makers to accurately convey their perspective preferences in the model, and thus efficiently towards the discovery of most desired solution.

Table 3. Single priority level, equally weighted

Decision variable solution	x_1	x_2	x_3	x_4
	299	350	382	315
Goal type		Current achievement	Goal target	
Meta-goal solution	1	0.38	≤0.38	
	2	0.09	≤0.09	
	3	0.47	≤0.33	
Decision goal solution	1	299.05	≥300	
	2	350.00	≥350	
	3	382.20	≥420	
	4	314.70	≥325	
	5	66061.03	≥70000	
	6	34235.22	≤50000	
	7	231.17	≤350	
	8	49.88	≤70	
	9	33.65	≤35	
	10	122.81	≤175	
	11	108.36	≤175	
	12	7788.60	≤8000	
	13	8362.81	≤8000	
	14	3270.00	≤3000	
	15	3190.56	≤3000	

V. CONCLUSION

This paper introduced an IMGP-based decision-analysis method. The method allows individual decision-maker to first propose goals for the problem toward his/her benefits, and then the goals are cross-verified using a Delphi process before they are analysed by the IMGP model to obtain the final solution. Our work has determined that this method is suitable for handling distributed decision-making nature such as presented in collaborative manufacturing, and this suitability is verified using an example. The future work is to develop a web-based software system that allows decision-makers to utilize this system irrespective to their physical location, and engage the collaborative decision-making process through the automated procedures.

REFERENCES

[1] Danilovic, M., Winroth, M., (2005). *A tentative framework for analyzing integration in collaborative manufacturing network settings: a case study.* Journal of Engineering and Technology Management, 22 (1-2), 141-158.

[2] Johansen, K., Comstock, M., Winroth, M., (2005). *Coordination in collaborative manufacturing mega-networks: A case study.* Journal of Engineering and Technology Management, 22 (3), 226-244.

[3] Lin, H.W., Nagalingam, S.V., Chiu, M. (2005) of Conference. *Development of a Collaborative Decision-making Model for a Network of Manufacturing SMEs*. in *18th International Conference on Production Research*. Fischiano (SA) Italy: University of Salerno - Campus of Fisciano (SA) Italy.

[4] Simon, H.A., 1977. *The new science of management decision*. New Jersey, USA: Prentice-Hall, Inc.

[5] Turban, E., Aronson, J.E., Liang, T.-P., 2005. *Decision Support Systems and Intelligent Systems*. Seventh Eds. New Jersey: Pearson Education, Inc, 936.

[6] Aouni, B., Kettani, O., (2001). *Goal programming model: A glorious history and a promising future.* European Journal of Operational Research, 133 (2), 225-231.

[7] Charnes, A., Cooper, W.W., 1961. *Management models and industrial applications of linear programming*. New York: Wiley.

[8] Caballero, R., Ruiz, F., Uria, M.V.R., Romero, C., (2006). *Interactive meta-goal programming.* European Journal of Operational Research, 175 (1), 135-154.

[9] Lin, H.W., Nagalingam, S., Chiu, M. (2004) of Conference. *Development of a Dynamic Task Rescheduling Approach for Small and Medium Manufacturing Enterprises*. in *Eighth International Conference on Manufacturing & Management*. Queensland, Australia: Pacific Congress on Manufacturing & Management.

[10] Rodriguez Uria, M.V., Caballero, R., Ruiz, F., Romero, C., (2002). *Meta-goal programming.* European Journal of Operational Research, 136 (2), 422-429.

[11] Gardiner, L.R., Steuer, R.E., (1994). *Unified interactive multiple objective programming.* European Journal of Operational Research, 74 (3), 391-406.

[12] Saaty, T.L., 1980. *The Analytic Hierarchy Process*. USA: McGraw-Hill, Inc.

[13] Yu, C.-S., (2002). *A GP-AHP method for solving group decision-making fuzzy AHP problems.* Computers & Operations Research, 29 (14), 1969-2001.

[14] Lindo Systems Inc. Website, 2006. What'sBest! http://www.lindo.com/, assessed 28th April 2006

[15] Turoff, M., Hiltz, S.R., *Computer based Delphi processes*. in *Gazing Into the Oracle: The Delphi Method and Its Application to Social Policy and Public Health*, M. Adler and E. Ziglio, Editors. 1995, Jessica Kingsley Publishers: London.