A Decision Support Framework for Robust Multilevel Co-Design Exploration of Manufacturing Supply Networks

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ABSTRACT

The design of a manufacturing supply network (MSN) requires the consideration of decisions made by different groups at multiple levels and their interactions that include potential conflicts. Decisions are typically made based on information from computational simulations that are abstractions of reality and, therefore, embody uncertainty. This necessitates focusing on design space exploration to identify robust satisficing solution sets that are relatively insensitive to uncertainty. Current frameworks that support robust satisficing design space exploration are limited by their capability to support the efficient exploration of multilevel design spaces simultaneously.

In this paper, we present the ***F****ramework for* ***Ro****bust* ***M****ultilevel* ***Co****-****D****esign* ***E****xploration (FRoMCoDE), a decision support framework that allows designers to i) model decision problems across multiple levels and their interactions, ii) consider uncertainties in the decision problems, and ii) visualize and systematically carry out simultaneous exploration of multilevel design spaces, termed co-design exploration. In FRoMCoDE, we combine the coupled compromise Decision Support Problem construct, where a combination of the Preemptive and Archimedean formulations is used, with robust design constructs and interpretable-Self Organizing Maps (iSOM) based visualization to facilitate robust co-design. We use a steel MSN problem with decisions made at two levels to test the framework. Using the problem, we demonstrate FRoMCoDE's efficacy in supporting designers in i) modeling multilevel decision problems and their interactions, considering the uncertainties, and ii) the efficient co-design exploration of multilevel design spaces. FRoMCoDE is generic and supports designers in the robust co-design exploration of multilevel systems.*

Keywords: Multilevel systems, Robust Co-design, Robust satisficing solutions, Manufacturing Supply Networks

GLOSSARY

Manufacturing Supply Network (MSN): A network of independent, interrelated stakeholders, such as suppliers, manufacturers, and customers, that work collaboratively to produce products.

Group: Collection of all stakeholders that perform the same role in the MSN. Example: Collection of all suppliers that provide the materials required by manufacturers constitute the 'Supplier Group.'

Level: Group or groups in the MSN that occupy the same position in a design decision-making hierarchy.

Robust Design: A design that is relatively insensitive to uncertainties.

Co-design: A design that facilitates collaboration among a network of stakeholders distributed across multiple levels by supporting the consideration of their interrelations to ensure the satisfaction of the stakeholder's goals.

Robust Co-design: A co-design that is relatively insensitive to uncertainties.

Robust Satisficing Solutions: Solutions that are relatively insensitive to uncertainties and 'satisfy' and 'suffice' the design requirements.

Service Level (SL): A measure of the capability to meet delivery expectations in terms of lead times. Mathematically, SL is defined as the ratio of expected lead time to actual lead time, where actual lead time is computed as the sum of the order processing time and time for transporting materials or products from the source to the destination.

1. FRAME OF REFERENCE

Manufacturing systems are characterized by multiple stakeholders, such as suppliers, manufacturers, and customers, interacting and making decisions to meet individual and system goals. These stakeholders are interdependent by the flow of materials and information, forming a network, which we define as a manufacturing supply network (MSN). We define the collection of all stakeholders that perform the same role in an MSN as 'groups.' For example, the set of all manufacturers is termed as "Manufacturer Group." In Figure 1, we depict an MSN composed of manufacturer, supplier, and customer groups interrelated by the flow of information and materials.

The design of MSN is complex as it involves formulating and solving independent but interdependent design problems focused on the different stakeholders across multiple levels of the design hierarchy. We consider a 'level' in the MSN to be composed of a group or a set of groups that occupy the same position in the design hierarchy. For example, in the MSN depicted in Figure 1, manufacturer group decisions are being made first and, therefore, are categorized as design level 1. Supplier and customer groups are depicted as making independent decisions based on level 1 decisions, hence categorized as design level 2. The design of such MSN's is challenging as it requires designers with specialized knowledge to focus on the different stakeholder disciplines, consider their interactions, and coordinate the multilevel couplings to identify solutions that satisfy the individual stakeholder and overall system goals.

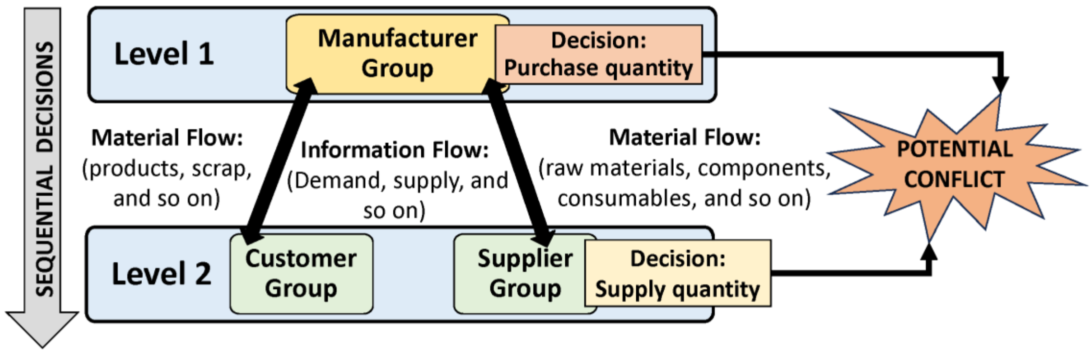


FIGURE 1: An example of an MSN that includes manufacturer, supplier, and customer groups located across two design levels and their interactions in terms of the flow of material and information

1.1 Requirements for the simulation-based design of MSN's

We identify the following issues in the simulation-based design of MSN's:

(1) Given the group interrelations, decisions made by one group impact the decisions of other related groups and thereby define the overall MSN performance. Hence, the satisfaction of the group's goals and ensuring MSN performance requires facilitating collaboration between groups.

(2) Independent group decisions across levels can lead to design conflicts, where decisions made by a group may not align with the decisions of an interrelated group. For example, the purchase quantity decisions by the manufacturer group at level 1 may differ from the supply quantity decisions by the supplier group at level 2, leading to design conflicts, see Figure 1. These conflicts adversely impact MSN performance.

(3) The simulation-supported design of MSN's is subject to various uncertainties [10], including (i) natural uncertainty inherent in the system, (ii) model parameter uncertainty associated with the parameters in the MSN models, (iii) model structure uncertainty associated with the models used in the MSN design problem, and the (iv) propagation of these uncertainties across design levels.

Hence, the design of MSN's requires support for the consideration of group interrelations and management of conflicts and uncertainties to ensure identifying solutions that satisfy MSN performance.

Towards this, we identify the need to facilitate '*robust co-design*' that supports MSN designers (group decision-makers) distributed across multiple levels to consider their interrelations and the various uncertainties involved in MSN design. Robust co-design facilitates collaboration among group decision-makers and thereby ensures the satisfaction of the group's goals and the MSN performance under conditions of uncertainty. Collaboration is achieved by supporting '*co-design exploration*' - the simultaneous exploration of the multilevel design spaces to identify a set of common '*robust satisficing solutions*' for the groups across different levels. Robust satisficing solutions are solutions that are relatively insensitive to uncertainties and 'satisfy' and 'suffice' the design requirements.

1.2 Design foundations and constructs

From a systems design perspective, we consider design a goal-oriented, decision-based process supported by simulations. We, therefore, follow the Decision-Based Design (DBD) paradigm advocated by Mistree and co-authors [1], where designing is considered a decision-making process wherein designers make a series of decisions, some sequentially while others concurrently. We anchor our work in the Decision Support Problem Technique [2, 3], rooted in the notion of bounded rationality proposed by Herbert A. Simon [4]. Given that the models employed in simulations are incomplete, inaccurate, of different fidelity, and are approximations of reality, designers seek 'satisficing solutions' for the design problem at hand by exploring the solution space. A satisficing solution [5] 'satisfies' and 'suffices' the design requirements often specified by many conflicting goals. The compromise Decision Support Problem (cDSP) [6] is a well-established construct in the literature to model decision problems involving many conflicting goals and explore satisficing solutions. The use of the coupled cDSP (c-cDSP) construct to model multilevel decision problems and their interactions, with multiple conflicting goals at each level, has been discussed in the literature [7, 8]. The coupling is vertical when the decisions are made sequentially along a hierarchy or horizontal when the decisions are made concurrently. The solution spaces generated by executing Decision Support Problems (DSP's) are explored to identify satisficing solutions.

Management of uncertainties is achieved by designing the system to be relatively insensitive to uncertainties without reducing or eliminating them, which is termed as '*robust design*'. Three types of robust designs - Type I, Type II, and Type III are discussed in the literature to deal with uncertainties related to noise, design variables, and models, respectively; see [9]. The use of robust design indices, namely, the Design Capability Index (DCI) [10] and Error Margin Index (EMI) [11], in conjunction with the DSP construct, has been proposed to help designers identify robust satisficing solutions. DCI is employed for Type I and II robust designs, whereas EMI is employed for Type III robust designs.

1.3. Existing approaches in the literature for the design of multilevel systems

Different approaches have been proposed in the literature to support the co-design of multilevel systems. This includes approaches like bi-level integrated system synthesis (BLISS), analytical target cascading (ATC), and collaborative optimization (CO) from the multi-disciplinary optimization (MDO) [12] domain. Sobieski and co-authors [13-15] present BLISS, where multilevel engineering systems are designed by decomposing the system-level optimization into many subsystem optimizations that seek to minimize their contribution to the system-level objective under local constraint. Kim and co-authors propose the ATC [16] approach that embodies a hierarchical multilevel optimization formulation where the objective at each level is to minimize the discrepancy between the targeted optimal values calculated at the previous level and the response at the level. Kroo and co-authors [17] present CO, where multilevel systems are modeled using a bi-level optimization formulation consisting of system-level and subspace optimizations, with the sub-space objectives related to the system objective being satisfied while also satisfying constraints locally. The computationally expensive nature of MDO approaches [18] arising from repeated iterations of passing single-point solutions between the levels makes them unsuitable for supporting early-stage design exploration when the information is incomplete and inaccurate, and models are not of equal fidelity. All-in-one (AIO) optimization formulations [19, 20] are also proposed to design MSN's, where multiple levels of the MSN are designed simultaneously and in an integrated manner. The AIO approach fails to consider the decision-making independence of groups across different levels in the MSN. The MDO and AIO approaches are based on optimization formulations where the fundamental assumption is that the models used are complete, all the required information is available, and the objective function is perfect. Given that during the early stages of the design of MSN's, the models employed are incomplete and inaccurate, the information available is incomplete, and the objective functions are imperfect, optimization approaches are not suitable for the early-stage design. Our focus is on ‘satisficing’ rather than ‘optimizing,’ and we seek a ranged set of ‘*robust satisficing solutions*’ during the early-stage design of MSN’s.

Different approaches have been proposed from the satisficing domain that support the identification of robust satisficing solution sets during multilevel system design. Choi and co-authors propose the Inductive Design Exploration Method (IDEM) [21] to support multilevel system design, where a ranged set of robust satisficing solutions are identified individually at each level and subsequently propagated sequentially between the multiple levels. IDEM has limitations such as restrictions on the number of design variables that can be considered, discretization errors, increased computational expense for improved accuracy, and limited design flexibility, as discussed in [22]. Nellippallil and co-authors [23] present an inverse robust design method - Goal-oriented Inverse Design (GoID), that supports the integrated multilevel design of the material, product, and associated manufacturing processes. In GoID, the focus is on design exploration of the individual levels separately to identify satisficing solutions and propagating these solutions as targets in an inverse manner along the hierarchical process chain. The sequential nature of decisions in the IDEM and GoID approach can result in design conflicts. This is because these sequential design exploration methods do not sufficiently consider the couplings across the multilevel, such as shared variables, related constraints, and many conflicting objectives. Due to these limitations, the existing approaches do not facilitate co-design exploration, resulting in design conflicts and reduced system performance across levels. Sharma and co-authors [7, 24] propose using coupled DSP to facilitate the consideration of the coupling across levels and thereby support the co-design of multilevel engineered systems. Here, ternary plots are employed to visualize and explore the design spaces separately at each level to identify satisficing solutions for the level. This sequential nature of design exploration can still result in design conflicts. The approach also does not support co-design exploration. All the above approaches only allow consideration of goal relations and tradeoffs at a level and do not support the consideration of tradeoffs among the goals across multiple levels of the decision hierarchy. Hence, these approaches require compromises on lower-level goals to satisfy the requirements identified at higher levels, thereby limiting design flexibility. These approaches are also limited to simultaneously visualizing and exploring a maximum of three design goals, hence unsuitable for many goal scenarios.

1.4. Framework to support robust, multilevel, co-design exploration

In this paper, we focus on supporting various group decision-makers in making decisions during the simulation-supported design of MSN's operating under uncertainty. From a DBD perspective, we hypothesize that this can be achieved by facilitating robust co-design using a decision support framework that supports i) modeling individual group decision problems and their interactions across levels in terms of the flow of information, ii) consideration of uncertainties in the decision problems, and iii) co-design exploration of the multilevel design spaces to identify common robust satisficing solutions and thereby manage conflicts and uncertainties. We propose modeling the group decision problems and their interactions using the c-cDSP construct, where a combination of Preemptive and Archimedean formulations is used, see Section 3.1.1. Using the Preemptive formulation, designers are able to consider hierarchical relations among group decision problems at multiple levels. Using the Archimedean formulation, designers can consider many conflicting goals for decision problems at a level. By combining the two, group decision-makers are able to account for many conflicting goals at a level and group relations across levels in a single coupled decision problem formulation. The DCI metric is employed in c-cDSP to identify robust satisficing solutions across multiple levels, see Section 3.1.2. The multilevel design spaces are visualized using interpretable-Self Organizing Maps (iSOM) [25] to facilitate co-design exploration, see Section 3.1.3. In this paper, we present the Framework for Robust Multilevel Co-Design Exploration (FRoMCoDE), a decision support framework that enables group decision-makers to i) model group decision problems across multiple levels and their interactions, ii) consider uncertainties, and iii) visualize and efficiently explore multilevel design spaces simultaneously to support robust co-design. The novelty of FRoMCoDE lies in two aspects: a) facilitating the formulation of multilevel design problems that involve many conflicting goals at a level and group interactions across levels, using a coupled decision problem formulation that combines the Preemptive and Archimedean formulations, and b) supporting the combined management of conflicts and uncertainties across multiple levels by facilitating co-design exploration - the simultaneous exploration of high-dimensional (more than 3) design spaces across multiple levels to identify common robust satisficing solutions across the levels. Co-design exploration is realized by exploiting the correlated nature and inherent interpretability of iSOM plots to efficiently identify common robust satisficing solution regions. Co-design exploration also helps enhance design flexibility by allowing designers to consider tradeoffs among goals across multiple levels rather than just goals at the same level, as in sequential multilevel design exploration approaches presented in Section 1.3.

In Section 2, a description of the problem is presented. The FRoMCoDE framework to support the robust co-design of multilevel MSN's is presented in Section 3. In Section 4, we showcase the efficacy of FRoMCoDE in supporting robust co-design using a steel MSN test problem. In the test problem, we focus on the interactions between supplier and manufacturer groups. We end the paper with our key findings and closing remarks in Section 5. In Appendix A, we present the mathematical models that relate the design variables and goals in the coupled manufacturer-supplier cDSP formulation.

2. PROBLEM DESCRIPTION

Consider a MSN comprising the Manufacturer group (j), Supplier group (i), and Customer group (k) located across two levels: i) Level 1: composed of the Manufacturer group, and ii) Level 2: composed of the Supplier and Customer groups, see Figure 2. The customers in the customer group are considered to be individual enterprises.

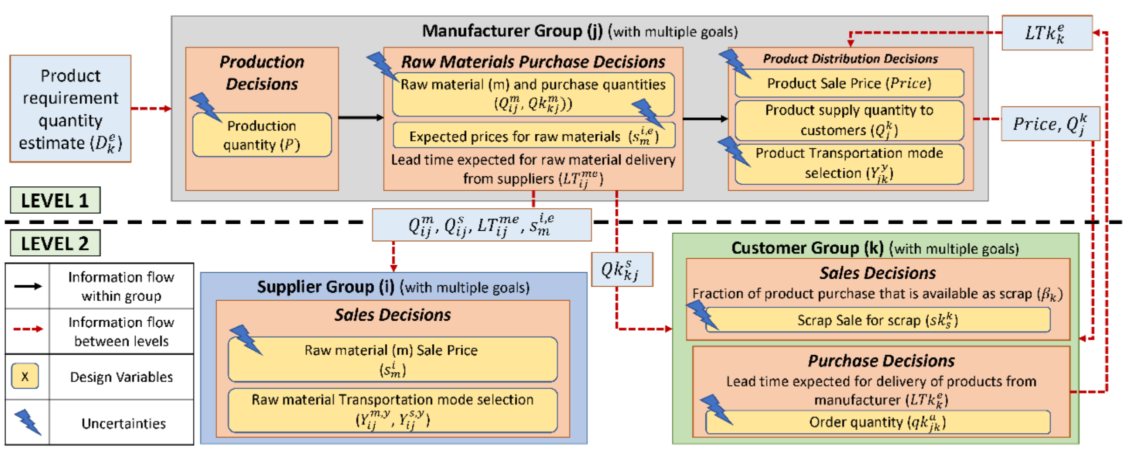


FIGURE 2: Flow of information connecting the Manufacturer, Supplier, and Customer groups across Levels 1 and 2 in a Manufacturing Supply Network (MSN)

The design of MSN involves the different group decision-makers across two levels making decisions to achieve group-specific goals. The groups are interrelated by the flow of information within and between groups, as depicted in Figure 2. In Figure 2, the flow of information within a group is indicated by solid arrows at Level 1, and the dashed arrows connecting Levels 1 and 2 show the flow of information between groups at different levels. The manufacturer group at Level 1, based on the estimates of the customer product requirement quantity (D_k^e) and expected product delivery lead times (LTk_k^e) from the customers, makes decisions related to production, raw-material (m) sourcing, and product distribution to customers. The production decision involves estimating the production quantity (P). The product distribution decisions include estimating the sale price for products ($Price$), determining the product supply quantities (Q_j^k), and selecting the mode of transportation to deliver the products to the customers (Y_{jk}^y). The raw-material sourcing decisions include the estimation of the amount of different raw materials to be procured (Q_{ij}^m, Q_{ij}^s, Qk_{kj}^s) and the estimation of the prices at which the raw materials should be purchased ($s_m^{i,e}$). We assume that part of the raw material required is sourced from the customers and is transported using the same mode as the products. At the supplier group at Level 2, sales decisions are made related to the choice of mode of transportation ($Y_{ij}^{m,y}$) and sale prices (s_m^i) for the various raw materials (m). The above decisions are made based on the expected delivery lead times for raw materials from suppliers (LT_{ij}^{me}), expected prices for raw materials ($s_m^{i,e}$), and order quantities for different raw materials from the manufacturer level (Q_{ij}^m, Q_{ij}^s). Hence, the supplier and manufacturer groups at Levels 2 and 1, respectively, are interrelated by the flow of information, see Figure 2. At the customer group, sales decisions are made with regard to the prices at which products at the end of life or scrap are returned to the manufacturer (sk_s^k). Based on the price that the product is sold to the customers by the manufacturer ($Price$) and the quantity available for sale from the manufacturers (Q_j^k), the customers make purchase decisions in terms of quantity of product to be purchased (qk_{jk}^a). Hence, the manufacturer and customer groups at Levels 1 and 2, respectively, are interrelated by the flow of information, see Figure 2. Given the relations between the group decision problems (modeled as cDSP's) across different levels (two) in the MSN, decisions by a group decision-maker can adversely impact the decision of another group decision-maker, resulting in design conflicts. Hence, there is a need to facilitate '*co-design*' to consider the relations between the multilevel decision problems. A summary of the variables for each group is provided in Table 1.

TABLE 1: List of variables, their notations, and descriptions for the different groups

Supplier Group
1. *i* (supplier index) ϵ I, set of all suppliers
2. *m* ϵ M, set of all raw materials
3. $Y_{ij}^{m,y}$, selection of transportation mode for raw materials 'm' from supplier 'i' to manufacturer 'j'
4. s_m^i, sale price for raw materials 'm' at supplier 'i'
Manufacturer Group
1. *j* (manufacturer index) ϵ J, set of all manufacturers
2. *P*, production quantity
3. Q_{ij}^m, quantity of raw material '*m*' to be procured from supplier '*i*' by manufacturer 'j'
4. Q_{ij}^s, quantity of scrap 's' to be procured from supplier '*i*' by manufacturer 'j'
5. Qk_{kj}^s, quantity of scrap 's' to be procured from customer '*k*' by manufacturer 'j'
6. Y_{jk}^y, selection of transportation mode for: i) raw materials procurement from customer 'k,' and ii) product delivery to the customer 'k'
7. $s_m^{i,e}$, estimated price for raw materials 'm' sourced from supplier 'i'
8. $Price$, estimated sale price of the product

9. Q_j^k, product supply quantities to customer ‘k’ from manufacturer ‘j’
10. LT_{ij}^{me}, expected delivery lead times for raw material ‘m’ from supplier ‘i’ by manufacturer ‘j’
Customer Group
1. k (customer index) ϵ K, set of all customers
2. D_k^e, product requirement quantity estimate from customer ‘k’
3. LTk_k^e, expected product delivery lead times from the customers ‘k’
4. sk_s^k, estimated sale prices of scrap ‘s’ by customers ‘k’
5. qk_{jk}^a, the quantity of product purchased by customer ‘k’ from manufacturer ‘j’

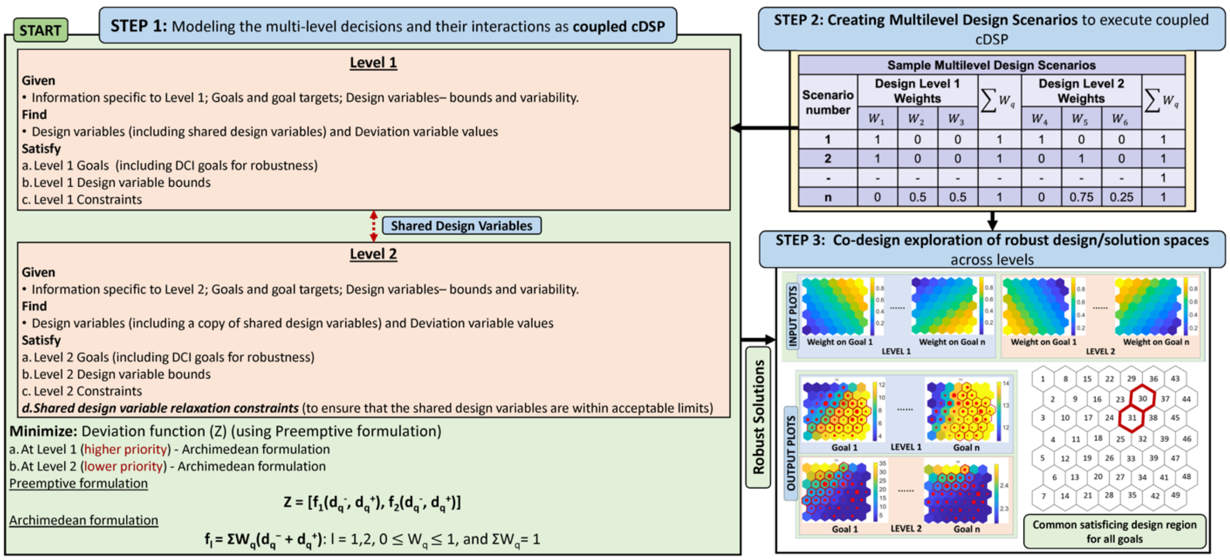
The design variables in the group cDSP’s are subject to uncertainties arising from i) production variability due to machine breakdowns and labor shortages and ii) supply variability due to material shortages at suppliers and transportation delays. These uncertainties impact the achievement of the group’s goals and MSN performance. Hence, there exists the need to manage these uncertainties by identifying ‘*robust solutions.*’ The focus in the simulation-supported design of MSN’s operating under uncertainty is on design exploration to identify a ranged set of ‘robust satisficing solutions.’ Therefore, the need is for the facilitation of robust co-design and co-design exploration of the group design spaces across different levels.

3. A DECISION SUPPORT FRAMEWORK FOR ROBUST MULTILEVEL CO-DESIGN EXPLORATION OF MSN’s

The Framework for Robust Multilevel Co-Design Exploration (FRoMCoDE) to support robust co-design of multilevel MSN’s is presented in this section. The various constructs and tools used in FRoMCoDE are discussed first, followed by a discussion on decision support using FRoMCoDE.

3.1. Constructs and tools used in FRoMCoDE

We use three constructs/tools in FRoMCoDE, namely, the coupled-compromise Decision Support Problem (c-cDSP) construct, the Design Capability Index (DCI) robust design construct, and the interpretable Self-Organizing Map (iSOM) visualization tool. They are discussed in detail as follows. In Figure 3, we depict how the constructs/tools are combined in FRoMCoDE.



Scenario number	W_1	W_2	W_3	$\sum W_q$	W_4	W_5	W_6	$\sum W_q$
1	1	0	0	1	1	0	0	1
2	1	0	0	1	0	1	0	1
-	-	-	-	-	-	-	-	1
n	0	0.5	0.5	1	0	0.75	0.25	1

FIGURE 3: Framework for Robust Multilevel Co-Design Exploration (FRoMCoDE)

i. coupled-compromise Decision Support Problem (c-cDSP) construct

The c-cDSP [7, 24] is a DSP construct used to model the relations among group compromise decision problems at different levels, some of which are made sequentially across a hierarchy and others concurrently. The relations between individual-level cDSP's in the c-cDSP, see Levels 1 and 2 in Step 1 of Figure 3, are modeled as either a vertical or horizontal coupling [7, 8]. Vertical coupling is used for decisions made sequentially along a hierarchy, whereas horizontal coupling is used for decisions made concurrently.

In c-cDSP's, the level-specific information in MSN's, such as design variables, goals, and constraints, is captured using the keywords – '*Given, Find,* and *Satisfy*.' The focus in using the c-cDSP is to find solutions that '*Minimize*' the total deviation of all the goals from their target values, termed the '*deviation function,*' Z; see Minimize in Step 1 of Figure 3. The deviation function is a function of deviation variables (d_q) that represent the distance (deviation) between the set goal target (aspiration level) and the actual attainment of the goal. The deviations can be either i) under-achievements (d_q^-), where the achieved goal values are less than set goal targets, or ii) over-achievements (d_q^+), where the achieved goal values are greater than set goal targets. The deviation function in the c-cDSP is modeled using the combination of Preemptive and Archimedean formulations based on the coupling between the multilevel decision problems. A Preemptive formulation [6] is used when the coupling is vertical, and this permits the assignment of different priority levels for the goals at different levels, as depicted in Step 1 of Figure 3. A higher priority level signifies the need for the goals at that level to be achieved first before looking at achieving the goals at any of the lower priority levels. At a priority level, the Archimedean formulation allows assigning different weights to the many goals at a level with a higher weight value indicating greater relative importance; see expression for 'f_l' in Step 1 of Figure 3.

ii. Design Capability Index (DCI) construct

Uncertainty in design variables can be considered in decision problems using the DCI [10] construct. The DCI value is computed as per Equation 1 for a 'larger is better' case where the designer aims to keep the mean response away from a lower requirement limit, see Figure 4.

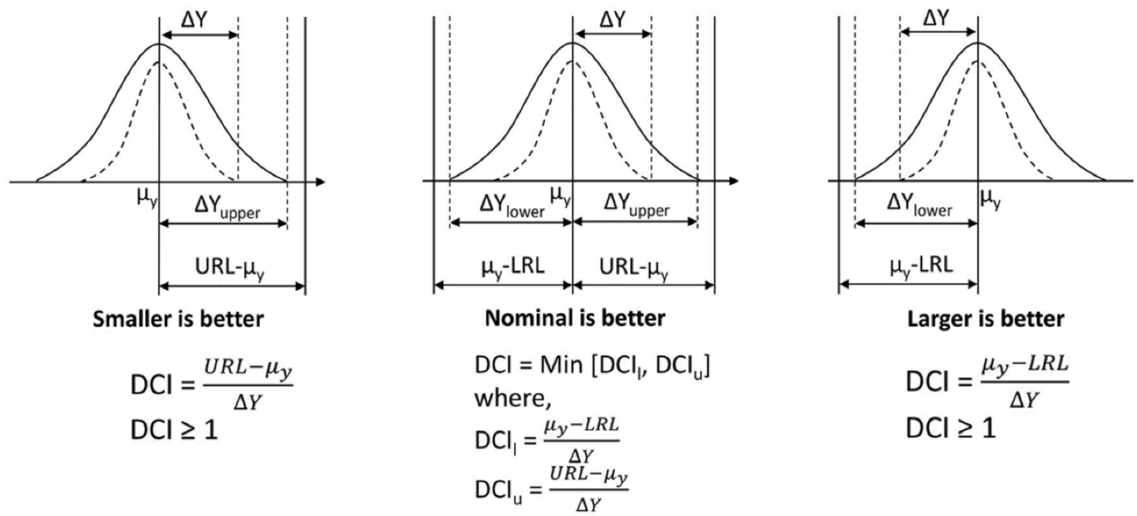


FIGURE 4: Mathematical constructs of DCI [23]

$$DCI = \frac{\mu_y - LRL}{\Delta Y} \quad (1)$$

where,

ΔY: response variation for small variations in design variables

μ_y: Mean responses

LRL: Lower requirement limit

ΔY is computed as per Equation 2.

$$Y = \sum_{p=1}^{n} |\frac{\partial f}{\partial x_p}| . \Delta x_p \quad (2)$$

where,

p= 1,2,…,n (index of design variables)

Δx_p: variation (uncertainty) in design variable x_p

$\frac{\partial f}{\partial x_p}$: variation of the response, f, with respect to the design variable x_p

A value of DCI ≥1 is required for the solutions identified to be robust. The higher the value of DCI, the higher the measure of safety against failure due to design variable uncertainties. The equations for computing DCI value for the smaller is better and nominal is better cases are shown in Figure 4. In FRoMCoDE, we use DCI in conjunction with the c-cDSP construct to identify robust satisficing solutions across multiple levels; see Levels 1 and 2 in Step 1 of Figure 3.

iii. Interpretable-Self Organizing Maps (iSOM)

iSOM [25] is used as a tool to visualize high-dimensional data in 2D. It is an unsupervised learning algorithm – an artificial neural network and a modified form of the conventional SOM (cSOM) [26]. Modifications to cSOM help avoid self-intersection of the iSOM grid, thus preserving the co-relatability among the 2D iSOM plots and making them inherently interpretable. Using the iSOM plots, designers can visualize the relations among input design variables and output responses. By exploiting the above characteristics, designers are able to carry out forward (from inputs to outputs) and inverse (from outputs to inputs) design exploration. The utility of the tool in visualizing i) high dimensional design spaces and ii) the relations among inputs and outputs in multilevel systems is demonstrated in the work by Sushil and co-authors [27]. More details on iSOM and its application for decision support in design can be found in [28, 29]. In FRoMCoDE, we use iSOM to support the co-design exploration of multiple levels in the MSN; see Step 3 in Figure 3.

3.2. Decision support using FRoMCoDE

The use of FRoMCoDE is described in this section. FRoMCoDE is executed in three steps, as depicted in Figure 3 and described in detail below. In the framework, we only consider the interactions between two levels to demonstrate the idea.

a. ***Step 1:*** In this step, the decision problems (cDSP's) at two levels - Level 1 and 2, and their interactions are modeled as a c-cDSP. This requires the different group decision-makers (designers corresponding to the level) to first establish the individual cDSP's for the two interacting levels by identifying the decision problem-specific information at each level using the keywords - Given, Find, and Satisfy, as shown in Step 1, Figure 3. The problem-specific information at each level includes i) design variables - their bounds and variability or uncertainty estimate, ii) goals - DCI formulation used for goals impacted by design variable uncertainty, iii) goal targets, and iv) level-specific constraints.

Next, the group decision-makers establish the flow of information connecting the two cDSP's by identifying any shared design variables between the two levels and sharing the same between the levels; see the dashed arrow connecting Levels 1 and 2 in Step 1, Figure 3. At the lower level - Level 2, copies of the shared design variables are used as the level-specific design variable. In FRoMCoDE, the group decision-makers seek to propagate a ranged set of shared design variables rather than single-point values to allow increased design flexibility. To facilitate the same, '*shared design variable relaxation constraints*' are added to the cDSP at Level 2. This allows the shared design variable copy at Level 2 to take a value between a predefined upper and lower percentage (as per designer preference) of the original shared design variable value identified at Level 1. The shared design variable relaxation constraint is mathematically represented as in Equation 3.

$$J_z * X_{z,shared} \leq X_{z,shared}^{copy} \leq K_z * X_{z,shared} \quad (3)$$

where,

z: index of the shared design variable, z= 1,2, …,n

$X_{z,shared}$: shared design variable at Level 1

$X_{z,shared}^{copy}$: copy of the shared design variable at Level 2

J_z: lower relaxation bound multiplier ($0 < J_z < 1$)

K_z: upper relaxation bound multiplier ($K_z > 1$)

Using the above information, the c-cDSP for the MSN is established with the deviation function modeled using a combination of Preemptive and Archimedean formulations. We consider vertical coupling between the cDSP's at Levels 1 and 2, given the sequential manner in which group decisions are made across the hierarchy. Hence, the Preemptive formulation is used to assign two separate priority levels for the goals at the two levels; see 'Minimize' in Step 1 of Figure 3. Level 1 cDSP is given higher priority as it is at the top of the hierarchy, followed by the cDSP at Level 2. The difference in preferences of the many goals in a level is modeled using the Archimedean formulation, where different weights (values between 0 and 1, such that the sum of the weights assigned on all goals is equal to 1) are assigned to the goals at a level to indicate differences in preference, see 'Archimedean formulation' in Step 1 of Figure 3. Hence, the deviation function (Z) of the c-cDSP is modeled as an ordered set (Preemptive) of Archimedean formulations for Levels 1 and 2, respectively; see

Step 1 of Figure 3. By combining the Preemptive and Archimedean formulations in the c-cDSP, designers are able to account for many conflicting design goals at a level, and relations across levels into a single coupled decision problem formulation, which is further executed, and the solution space is explored.

b. ***Step 2:*** The c-cDSP from Step 1 is executed for different multilevel design scenarios to generate design solutions across the levels, including robust solutions. The multilevel design scenarios are created by combining individual-level (Levels 1 and 2) design scenarios. Level 1 and 2 design scenarios are created by assigning different weights (values between 0 and 1, such that the sum of the weights assigned on all goals at a level is equal to 1) to the different goals at the level using uniform sampling. Using the individual-level design scenarios, designers are able to account for differences in preference among the many conflicting goals in the Archimedean formulations at Levels 1 and 2 of the c-cDSP; see 'Archimedean formulation' in Step 1 of Figure 3. Level 1 and 2 design scenarios are combined in all possible combinations to generate multilevel design scenarios; see Step 2 in Figure 3 (for two levels). If there are 'a' distinct individual level design scenarios across two levels, a^2 distinct multilevel (two) design scenarios can be generated. Using the multilevel design scenarios, designers are able to consider different combinations of individual-level design scenarios at Levels 1 and 2 in the Preemptive formulation of the c-cDSP. By considering a combination of individual-level design scenarios, designers are able to account for differences in goal preferences across multiple levels simultaneously. The solutions generated by executing the c-cDSP for the multilevel design scenarios, therefore, account for the coupling among the decisions at multiple levels.

c. ***Step 3:*** The design spaces corresponding to the solutions generated by executing the c-cDSP for the multilevel design scenarios are visualized by the group decision-makers (designers) using iSOM. By combining iSOM with the c-cDSP (that uses the combined Preemptive and Archimedean formulations), designers are able to simultaneously visualize the individual design spaces across multiple levels. Using iSOM, separate 2-dimensional (2D) plots are generated for each of the inputs (weights corresponding to the multilevel design scenarios of the c-cDSP) and outputs (achieved values of individual goals) across the levels. First, the c-cDSP is executed for different multilevel design scenarios defined in terms of the different weights assigned to the goals at each level (as detailed in Step 2). iSOM is trained for the input c-cDSP weight combinations and the output goal values generated for the different multilevel design scenarios. Using the iSOM plots for the goals, the group decision-makers explore the solution spaces to identify satisficing solution regions (identified by the hexagonal iSOM grid points) for the individual goals by setting satisficing limits. Only the grid points with multilevel design scenarios mapped against them, indicated by the dots at the center of the hexagonal iSOM grid points, are considered. The larger the size of the dots, the greater the number of multilevel design scenarios being mapped to the iSOM grid point; see Step 3 iSOM plots in Figure 3. Using the solution space visualization capability offered by iSOM, designers are able to seek common satisficing regions for all goals across multiple levels. If no common satisficing region is identified, the designers are able to make necessary relaxations to the satisficing limits of the individual goals across the levels till a common satisficing region is realized; see the plot labeled 'common satisficing design region for all goals' in Step 3, Figure 3. A '*systematic approach for satisficing limit relaxation of goals*' is discussed below.

The designer begins by identifying a single goal whose satisficing limit cannot be relaxed due to its critical nature. The critical goal is chosen based on the designer's preference from amongst i) goals formulated as DCI's or EMI's with low satisficing limit values, typically less than 1.5, or ii) other goals deemed critical by the designers. All the remaining goals, collectively called 'non-excluded' goals, are grouped into two sets: i) Set 1 - all non-excluded goals formulated as DCI's or EMI's with satisficing limit values greater than 1.5, and ii) Set 2 - all remaining non-excluded goals. The relaxation of satisficing limits of non-excluded goals begins with Set 1 non-excluded goals, followed by Set 2 non-excluded goals. In Set 1, the goal with the highest DCI or EMI satisficing limit value is relaxed first, followed by the goals with subsequently lower DCI or EMI satisficing limit values. Next, goals in Set 2 are relaxed similarly, starting with the goal that has the largest scope for relaxation as determined by the designer. The satisficing limit of every goal in Sets 1 and 2 is relaxed one goal at a time until a common satisficing region (iSOM grid points) with the critical goal is identified.

For the common satisficing region identified, designers are further able to identify the corresponding satisficing multilevel design scenarios (identified by the weights assigned to the c-cDSP) and the corresponding design variable values. Using iSOM, designers are able to simultaneously visualize and explore the multilevel solution spaces and thereby facilitate efficient co-design exploration. This is a distinct advantage over the conventional approaches for multilevel design exploration, where design exploration is carried out sequentially across the individual levels.

4. TEST PROBLEM: STEEL MANUFACTURING SUPPLY NETWORK

The test problem considered is a steel MSN composed of the steel manufacturer group (j) at Level 1 that produces steel slabs, the supplier group composed of the suppliers (i) of raw materials (m) for steel production, and the customer group composed of the individual enterprise customers (k) for the steel slabs at Level 2, see Figure 5.

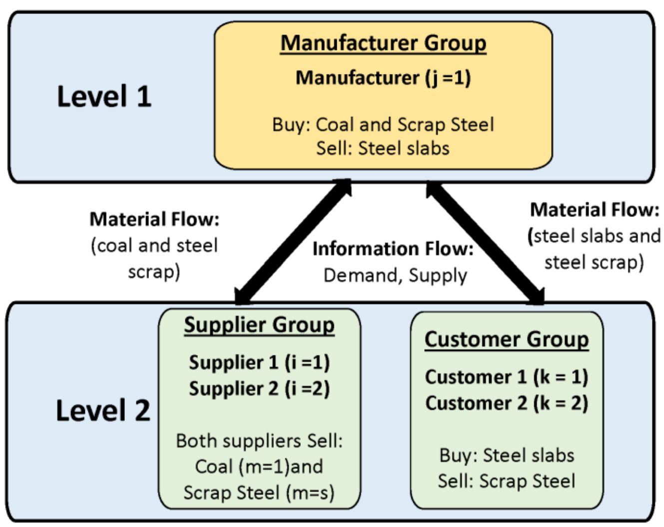


FIGURE 5: Flow of material and information between levels in the Steel Manufacturing Supply Network

The steel manufacturer purchases raw materials from suppliers to produce steel slabs, which are then sold directly to the customers. The steel production quantity is determined based on an estimate of expected customer requirement that is assumed to be known. We consider the supplier group at Level 2 to be composed of 2 suppliers ($i = 1,2$) capable of supplying both coal and steel scrap. At Level 1, we consider a single manufacturer ($j = 1$) operating a single manufacturing facility to manufacture steel slabs using the integrated Blast Furnace (BF) – Basic Oxygen Furnace (BOF) technology [30, 31]. We consider the customer group at Level 2 to be constituted by two customers ($k = 1, 2$) who purchase steel slabs from the manufacturer and sell steel scrap produced after their use back to the manufacturer. The material flow between the groups at the two levels is facilitated by employing logistics services, the cost for which is borne by one of the interacting groups. The group's decision-makers have a choice between 2 modes of transportation: i) Road – faster but relatively expensive ($y = 2$), and ii) Rail - less expensive but slower ($y = 1$).

Decisions are made by the manufacturer, supplier, and customer group decision-makers at Levels 1 and 2 to meet their goals and satisfy their constraints, see Section 4.1. Hence, the steel MSN is characterized by decisions being made by various group decision-makers across multiple levels. The multilevel group decisions are connected by the flow of information and materials, see Figure 5. Hence, group decisions made at one Level will impact the group decisions at another level and can result in conflicts that adversely affect the steel MSN performance. Therefore, it becomes vital to consider the group interactions across Levels 1 and 2 and manage conflicts to ensure steel MSN performance. This requires the facilitation of '*co-design*' of the multilevel steel MSN. Uncertainties in design variables that arise from production delays, quality control issues, and damage to products in transit impact the steel MSN performance. Hence, it is also necessary to manage these uncertainties to ensure steel MSN performance. Therefore, a need exists to support the '*robust co-design*' of the multilevel steel MSN to help manage uncertainties and conflicts and thereby ensure steel MSN performance.

In this paper, we demonstrate the efficacy of FRoMCoDE in facilitating the robust co-design of the multilevel steel MSN by considering the interactions between the manufacturer and supplier groups across Levels 1 and 2. We consider the group decision to be made sequentially across a hierarchy, with the manufacturer group at Level 1 being the lead decision-maker.

4.1. Group decisions across multiple levels and their interactions in the steel MSN

The decisions made by the manufacturer and supplier groups at Levels 1 and 2, respectively, and their interactions are discussed below.

4.1.1. Decisions at Level 1

The manufacturer group at Level 1 is involved in manufacturing and supplying the products required by the customers by using raw materials sourced from the supplier and customers. Hence, interactions at this level occur with both the supplier and customer groups at Level 2, see the dashed arrows depicting the flow of information between Levels 1 and 2 in Figure 6. The solid arrows within the manufacturer group in Figure 6 depict the flow of information within Level 1. The dashed arrows represent the flow of information from external sources, including other interacting groups.

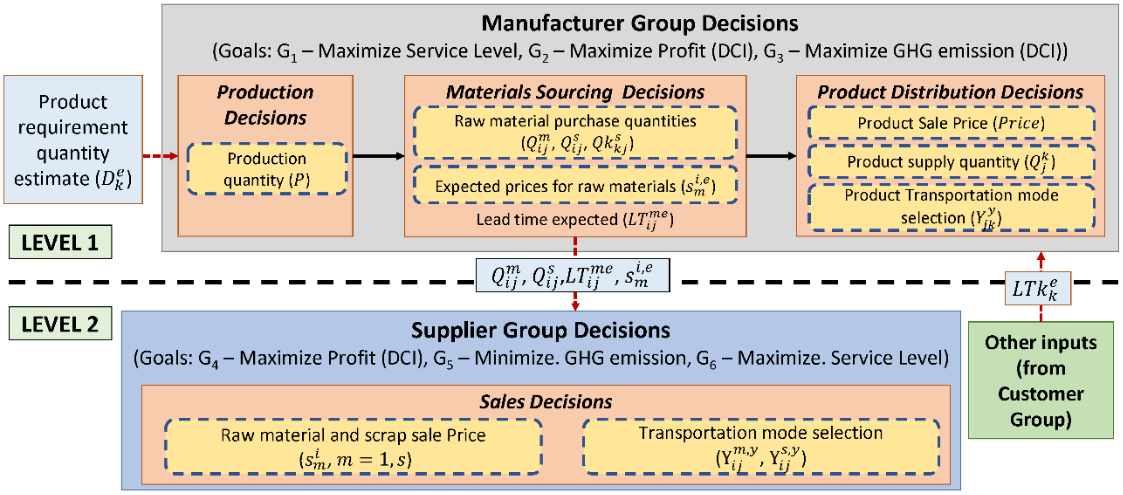


FIGURE 6: Flow of information connecting the manufacturer and supplier groups at Levels 1 and 2, respectively, in the steel MSN

The manufacturer group decision-maker at Level 1 makes production, materials sourcing, and product distribution decisions; see manufacturer group decisions at Level 1 in Figure 6. These decisions are aimed at fulfilling three level-specific end-requirements: i) maximization of service level (SL), ii) maximization of profits, and iii) minimization of greenhouse gas (GHG) emissions, which are conflicting in nature. A focus on maximizing the SL results in the reduction of profits and an increase in GHG emissions. The quantities indicated in the dashed boxes at the manufacturer group in Figure 6 depict the design variables at Level 1. We consider a 2 percent variability (of the variable value range) in all the continuous design variables.

The basic assumptions for group decisions at Level 1 follow.

a) The manufacturer employs the Made-to-Stock (MTS) approach to manufacturing and makes products based on customer demand estimates.
b) The cost of transportation of products to customers and the steel scrap from the customers are borne by the manufacturer.

c) The mode of transport used to deliver products is also used to transport scrap purchased from customers.
d) There is sufficient capacity at the suppliers to meet the manufacturer's demand.
e) Scrap availability from customers is 10% of the sale quantity to customers.
f) All modes of transportation have sufficient capacity to supply the required quantity of products together.

Next, we describe the decisions made by group decision-makers for the supplier group at Level 2.

4.1.2. Decisions at Level 2

The supplier group at Level 2 supplies the required raw materials - coal and steel scrap, to the manufacturer as per requirement. Hence, the supplier group interacts only with the manufacturer group at Level 1. These interactions are represented by the flow of information, as depicted in Figure 6. The arrow flowing into the supplier group shows the flow of information from Level 1. The decisions at Level 2 are aimed at fulfilling three level-specific end-requirements: i) maximization of profit, ii) maximization of SL, and iii) minimization of GHG emissions, which are conflicting in nature as described for Level 1. The quantities indicated in the dashed boxes at the supplier group in Figure 6 depict design variables at Level 2. We consider a 2 percent variability in all the continuous design variables at Level 2.

The basic assumptions for supplier group decisions made at Level 2 follow.

a) There is sufficient capacity at the suppliers to meet the manufacturer's demand.
b) The cost of transportation of raw materials to the manufacturer is borne by the suppliers.

c) All the suppliers can supply both coal and steel scrap as required.

d) All modes of transportation have sufficient capacity to supply the required quantity of raw materials together.

The manufacturer and supplier groups at Levels 1 and 2 in the steel MSN are related by the shared design variables (prices for the raw materials) and propagated parameters (raw material purchase quantities and expected lead times); see the arrow connecting the manufacturer and supplier groups in Figure 6

4.2. Steel MSN: Decision support using FRoMCoDE

We demonstrate the efficacy of FRoMCoDE in supporting the robust co-design of multilevel MSN's by applying it to the steel MSN test problem described in Sections 4 and 4.1. The group decision-makers start with Step 1, where the decisions at manufacturer and supplier groups at Levels 1 and 2 and their interactions described in Section 4.1 are modeled as a c-cDSP.

4.2.1. Step 1

Given that decisions are made sequentially across a hierarchy, with the manufacturer group at Level 1 making decisions first, followed by the supplier group at Level 2, to meet their many conflicting goals, the decision problem is modeled as a vertically coupled cDSP. The goals in the c-cDSP impacted by design variable uncertainties are formulated as robust goals using the DCI construct. The deviation function of the c-cDSP is modeled using a combination of Preemptive and Archimedean formulation, with Level 1 goals taking higher priority than Level 2 goals. A condensed version of the c-cDSP word formulation for the steel MSN follows, with additional details provided in Appendix A.

<u>Given</u>

a) Level 1 specific information (see Appendix A3 for details)

- Manufacturer group (j) and Customer group (k) Information

b) Level 2 specific information (see Appendix A3 for details)

- Manufacturer group (j) and Customer group (k) Information

c) Design variables, their bounds, and variability

- At Level 1: Sixteen continuous and four binary variables.
- At Level 2: Four continuous and eight binary variables.

The design variables and their bounds at Levels 1 and 2 are provided in Appendix A4.

Assuming a +/- 2% variability in the continuous design variables at Levels 1 and 2.

d) End requirements at Level 1

i. Maximize Service Level (SL)
ii. Maximize Profit (in $)
iii. Minimize GHG emissions (in kgs of CO_2)

Corresponding requirements on the cDSP goals (G_q)

i. Goal G_1: Maximize Service Level (SL)
ii. Goal G_2: Maximize DCI for Profit
iii. Goal G_3: Maximize DCI for GHG emission

End requirements at Level 2

i. Maximize Profit (in $)
ii. Minimize GHG emissions (in kgs of CO_2)
iii. Maximize Service Level (SL)

Corresponding requirements on the cDSP goals at Level 2 (G_q)

i. Goal G_4: Maximize DCI for Profit

ii. Goal G_5: Minimize GHG emission

iii. Goal G_6: Maximize Service Level (SL)

The mathematical equations for the end requirements at Levels 1 and 2 are provided in Appendix A1 and A2, respectively.

e) At Level 1: Lower Requirement Limit (LRL) for profit goal ($400,000), and Upper Requirement Limit (URL) for GHG emission goal (3,250 tons of CO_2)

At Level 2: LRL for the profit goal ($575,000).

<u>Find</u>

At Level 1:

a) Design variable values:

i. Continuous: Production quantity in tons (P), Coal and scrap purchase quantities from suppliers in tons (Q_{ij}^{m}), Scrap purchase quantities from customers in tons (Qk_{kj}^{s}), Product supply quantities to customers in tons (Q_{j}^{k}), Steel selling price (Price) in $, Estimated selling price of material '$\boldsymbol{m}$' at supplier '$\boldsymbol{i}$' in $ ($\boldsymbol{s_{m}^{ie}}$), and estimated selling price of material 'm' at customer 'k' in $ (sk_{m}^{ke})

ii. Binary: Transportation mode selection (Y_{jk}^{y})

Here, $i = 1, 2$, $j = 1$, $k = 1, 2$, $y = 1, 2$ and $m = 1$, s.

b) Deviation variable values: (d_q^+, d_q^-) for all $q = 1, 2, 3$

At Level 2:

a) Design variable values:

i. Continuous: Selling price of material **'$\boldsymbol{m}$'** at supplier 'i' ($\boldsymbol{s_{m}^{i}}$)

ii. Binary: Transportation mode selection (Y_{ij}^{my})

Here, $m = 1$, s, $i = 1, 2$, $j = 1$ and $y = 1, 2$

b) Deviation variable values: (d_q^+, d_q^-) for all $q = 4, 5, 6$

<u>Shared Design variables</u>: $\boldsymbol{s_m^{ie}}$ and $\boldsymbol{s_m^{i}}$ are the shared design variables. $\boldsymbol{s_m^{i}}$ is a copy of $\boldsymbol{s_m^{ie}}$ at the supplier group.

<u>Satisfy</u>

a) Constraints at Level 1: (ten linear and four non-linear constraints)

i. Total production less than production capacity: $P \leq Capacity$

ii. Total production greater than total demand/demand forecast: $P \geq \sum_{k=1}^{2} D_k^e$

iii. and iv. Scrap purchased from customers less than the scrap available at customers: $Qk_{kj}^s \leq B_k Q_j^k$, for $k = 1, 2$

v. Minimum amount of coal ($m = 1$) to be purchased: $\sum_{i=1}^{2} Q_{ij}^m \geq A_m * P$

vi. Minimum amount of scrap (m=s) to be purchased: $\sum_{i=1}^{2} Q_{ij}^m + \sum_{k=1}^{2} Qk_{kj}^s \geq A_m * P$

vii. and viii Product supply quantity equal to demand/demand forecast: $Q_j^k = D_k^e$, for $k = 1, 2$

ix. and x. Only one mode of transportation can be selected for product/scrap shipment (to both customers): $\sum_{y=1}^{2} Y_{jk}^y = 1$, for $k = 1, 2$

xi. Minimum DCI for Profit, $G_2 \geq 1$

xii. Minimum DCI for GHG emission, $G_3 \geq 1$

xiii. Minimum value of Profit= $400,000

xiv. Maximum value of GHG emissions= 3,250 tons of CO_2

b) Design variable bounds at Level 1; see Appendix A4

c) Constraints at Level 2: (twelve linear and two non-linear constraints)

i. to iv. Only one mode of transportation can be selected for coal/steel scrap shipment:

$$\sum_{y=1}^{2} Y_{ij}^{my} = 1, \text{ for I =1,2 and all m=1}$$

v. to xii. Maximum and minimum value for all shared design variables (Shared design variable relaxation constraints: Assuming +/- 10 % relaxation)

- $0.9s_1^{1e} \leq s_1^1 \leq 1.1s_1^{1e}$
- $0.9s_1^{2e} \leq s_1^2 \leq 1.1s_1^{2e}$
- $0.9s_s^{1e} \leq s_s^1 \leq 1.1s_s^{1e}$
- $0.9s_s^{2e} \leq s_s^2 \leq 1.1s_s^{2e}$

xiii. Minimum DCI for Profit, $G_4 \geq 1$

xiv. Minimum value of Profit= $575,000

d) Design variable bounds at Level 2; see Appendix A4.

<u>Minimize</u>

Deviation function, *Z*: a combination of Preemptive and Archimedean formulations.

Level 1 is at higher priority - Priority 1, followed by Level 2 at lower priority - Priority 2.

$$\mathrm{Z} = [\, f_1, f_2 \,]$$

where,

f_1 and f_2 are the Archimedean formulation at Levels 1 and 2, respectively.

$$f_1 = \sum_{q=1}^{3} W_q \, (d_q^+ + d_q^-) \text{ where } \boldsymbol{\Sigma}\, \mathrm{W_q} = 1 \text{ and q =1,2,3}$$

$$f_2 = \sum_{q=4}^{6} W_q \, (d_q^+ + d_q^-) \text{ where } \boldsymbol{\Sigma}\, \mathrm{W_q} = 1 \text{ and q =4,5,6}$$

4.2.2. *Step 2*

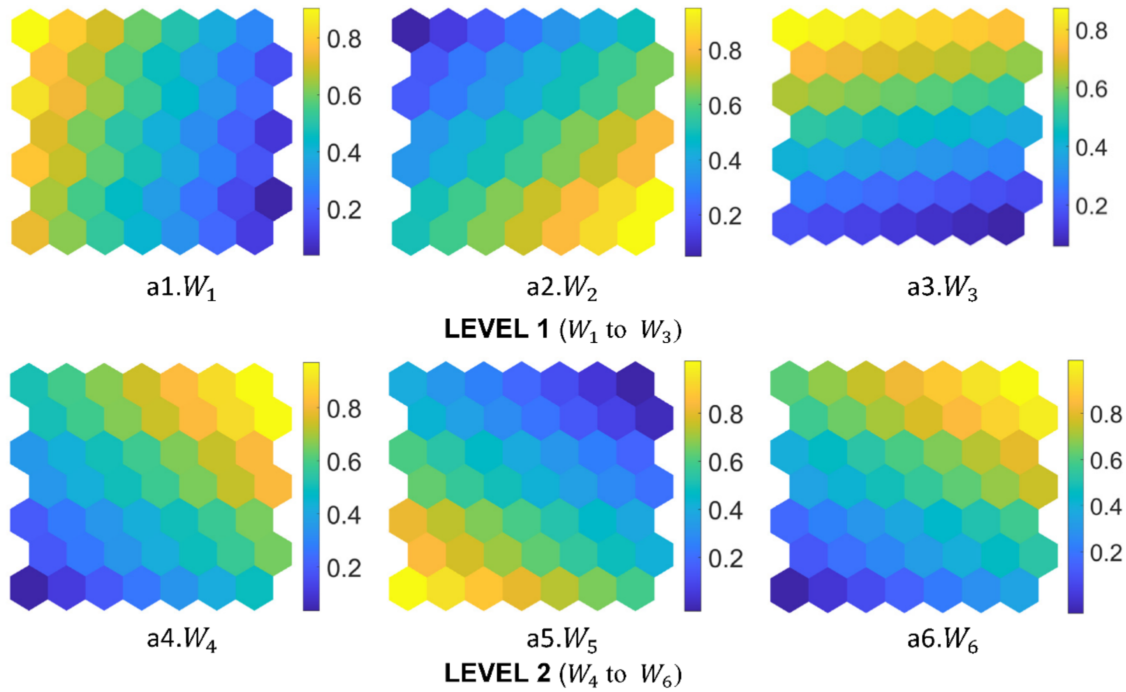
The multilevel design scenarios for executing the c-cDSP are created by combining the design scenarios at Levels 1 and 2 created using uniform sampling. A total of 132 multilevel design scenarios are created and used in the Preemptive formulation of the c-cDSP established in Step 1. The c-cDSP is executed for these 132 multilevel design scenarios to generate design solutions across the levels. Some sample multilevel design scenarios are listed in Table 2.

TABLE 2: Sample multilevel design scenarios

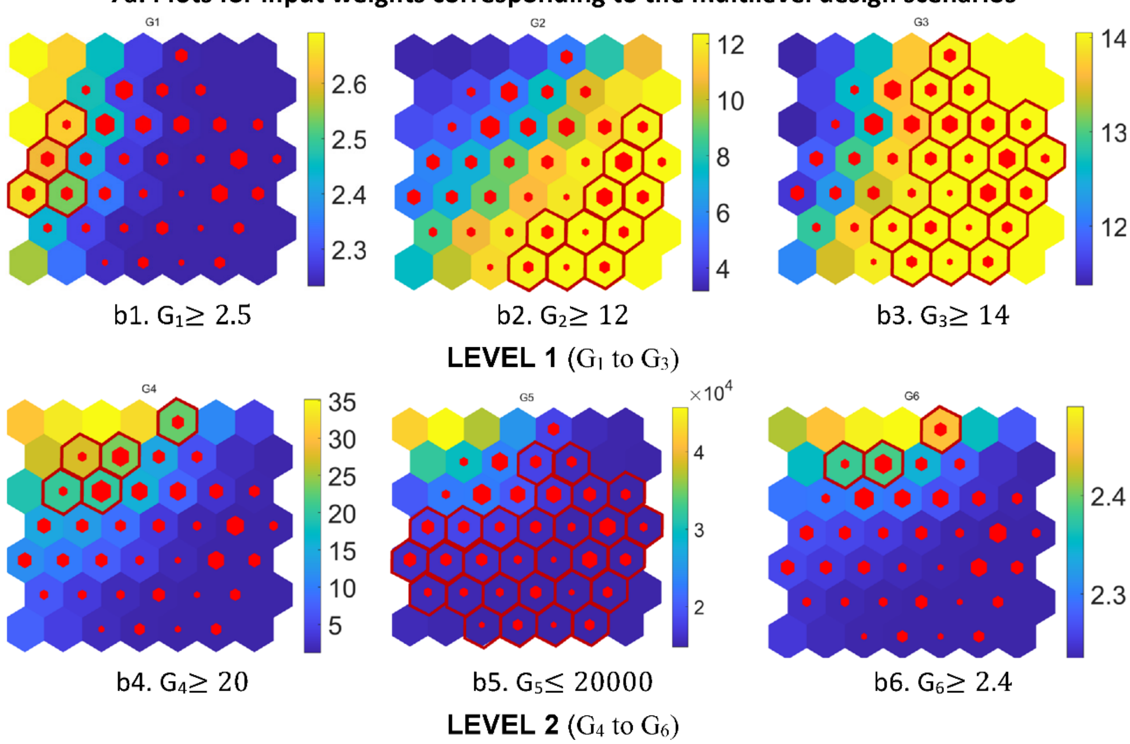
Scenario number	**Level 1 Weights**			$\boldsymbol{\Sigma}\ W_q$	**Level 2 Weights**			$\boldsymbol{\Sigma}\ W_q$
	W_1	W_2	W_3		W_4	W_5	W_6	
1	1	0	0	1	1	0	0	1
2	1	0	0	1	0	1	0	1
-	-	-	-	-	-	-	-	-
55	0	0.5	0.5	1	0	0.75	0.25	1
-	-	-	-	-	-	-	-	-
131	0.33	0.34	0.33	1	0	0.25	0.75	1
132	0.33	0.34	0.33	1	0	0.75	0.25	1

4.2.3. *Step 3*

Using iSOM, the design solutions corresponding to the 132 multilevel design scenarios across the manufacturer and supplier groups at Levels 1 and 2 are simultaneously visualized for co-design exploration. Six input plots corresponding to the design scenarios weights - W_1 to W_6, and six output plots corresponding to the six goals across Levels 1 and 2 are generated; see Figures 7a and 7b, respectively.



7a. Plots for input weights corresponding to the multilevel design scenarios



7b. Plots for goals before relaxation of satisficing limits. The satisficing region for each goal is identified and represented using the red hexagonal borders on the iSOM grids

FIGURE 7: The iSOM plots for input (design scenario weights, W_i) and output (Goals, G_i) for the steel MSN problem before relaxation of satisficing limits.

NOTE: For DCI Goals G_2, G_3, and G_4, the yellow regions indicate regions of high robustness, and the blue regions indicate regions of comparatively lower robustness

The co-design exploration starts with the group decision-makers identifying the satisficing limits for the goals across the levels to identify satisficing solution regions for each goal (indicated by the iSOM grid points highlighted with red hexagonal border), as shown in Figure 7b. For the DCI goals at Levels 1 and 2, the designer focuses on higher DCI value regions to ensure a greater degree of safety against design variables uncertainties. The designer seeks to maximize the SL and hence picks regions where the values are high. Regions of low values of GHG emission are preferred at Level 2 to reduce GHG emissions. Initially, the satisficing limits for the goals at Levels 1 and 2 are set as follows.

At Level 1

i. SL, $G_1 \geq 2.5$
ii. DCI Profit, $G_2 \geq 12$
iii. DCI GHG emission, $G_3 \geq 14$

At Level 2

i. DCI Profit, $G_4 \geq 20$
ii. GHG emission, $G_5 \leq 20000$ kg of CO_2
iii. SL, $G_6 \geq 2.4$

No common regions are identified for all goals across Levels 1 and 2 for the above satisficing limits. Hence, the group decision-makers look at relaxing the satisficing limits for the goals using the '*systematic approach for satisficing limit relaxation of goals*.'

The group decision-makers start by identifying a critical goal whose satisficing limits cannot be relaxed. Here, G_5 is identified as the critical goal. Goals formulated as DCI goals

- G_2, G_3, and G_4 fall into 'Set 1' and remaining goals - Goals G_1 and G_6 fall into 'Set 2.' To begin, the satisficing limits of Set 1 goals are relaxed in the order of decreasing satisficing limits ($G_4 > G_3 > G_2$), until common iSOM grid points are identified with G_5. G_4's limit of 20 is first relaxed to 10. G_3, with a limit of 14, has common grid points with G_5, and hence its limit is not relaxed. G_2's limit of 12 is then relaxed to 9. Next, the satisficing limits of Set 2 goals are relaxed, starting with the goal with the largest scope for relaxation according to the decision-makers ($G_1 > G_6$). First, G_1's limit of 2.5 is relaxed to 2.2. Finally, G_6's limit of 2.4 is relaxed to 2.3. With the relaxed satisficing limits, the updated satisficing regions for all the goals are identified, see Figure 8.

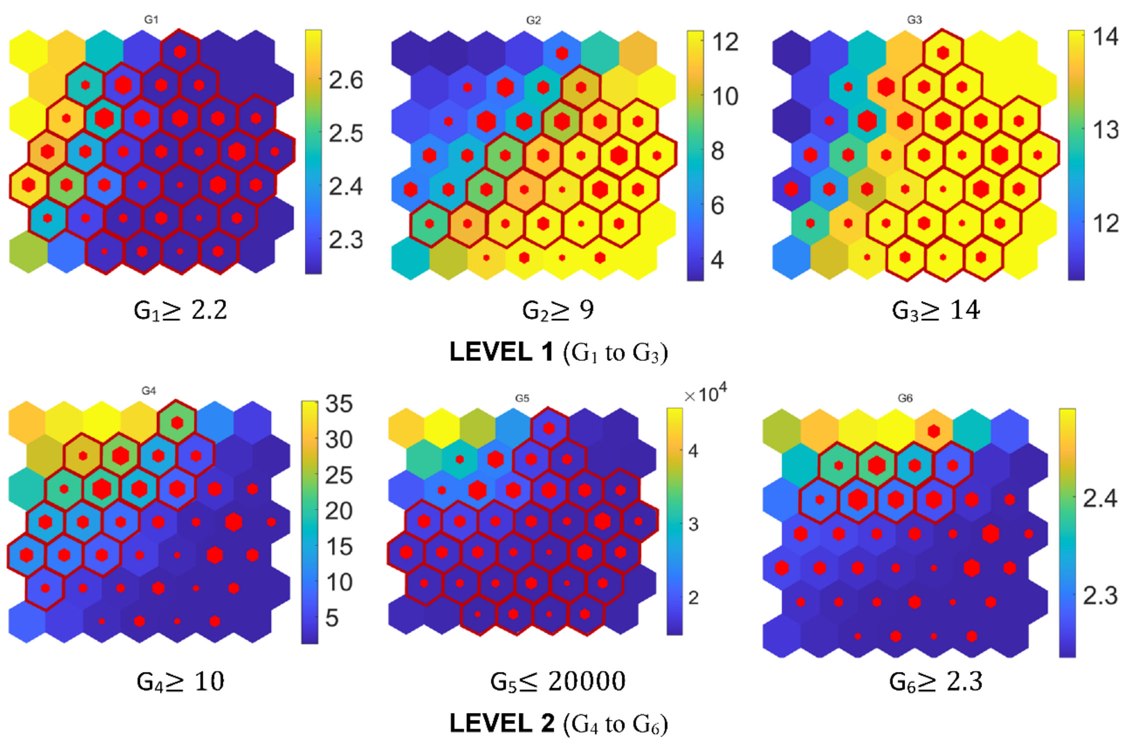


FIGURE 8: iSOM plots depicting the satisficing solution regions for goals after relaxation of satisficing limits; see iSOM grid points highlighted using red hexagonal border

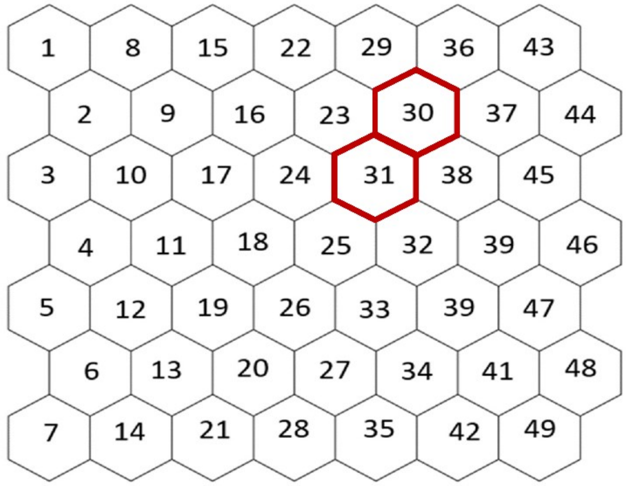


FIGURE 9: Common satisficing solution region for all goals after relaxation of satisficing limits; see iSOM grid points 30 and 31 highlighted using thick hexagonal borders

NOTE:

- iSOM grid point locations are indicated by the number in the hexagons.
- Common satisficing regions are identified by the iSOM grid numbers of the common grid points (30 and 31, in this example)

With the updated satisficing regions, iSOM grid points 30 and 31, see Figure. 9, are identified to be the common satisficing region for all the goals. Grid points 30 and 31 have two and seven multilevel design scenarios mapped against them, respectively. Therefore, nine common robust satisficing solutions are identified for Levels 1 and 2 of the steel MSN design problem. The nine design scenarios and the corresponding goal values at Levels 1 and 2 are listed in Table 3. Hence, using the iSOM plots, designers are able to simultaneously explore the solution spaces across Levels 1 and 2 and thereby support the co-design exploration of the steel MSN.

TABLE 3. Goal values at the manufacturer and supplier groups for the common robust satisficing solutions identified

Multilevel design scenarios	Level 1			Level 2			Level 1			Level 2		
	W_1	W_2	W_3	W_4	W_5	W_6	G_1	G_2	G_3	G_4	G_5 (Kgs of CO_2)	G_6
105	0	0.25	0.75	0	0	1	2.23	12.35	14.05	1.37	14793.16	2.23
107	0	0.25	0.75	0.25	0	0.75	2.23	12.35	14.05	1.37	14793.16	2.23

108	0	0.25	0.75	0	0.25	0.75	2.23	12.35	14.05	1.61	14787.02	2.23
123	0.33	0.34	0.33	1	0	0	2.23	12.36	14.05	1.09	14777.69	2.23
125	0.33	0.34	0.33	0	0	1	2.23	12.35	14.05	1.37	14793.16	2.23
127	0.33	0.34	0.33	0.5	0	0.5	2.23	12.35	14.05	1.19	14782.91	2.23
129	0.33	0.34	0.33	0.25	0	0.75	2.23	12.35	14.05	1.37	14793.16	2.23
130	0.33	0.34	0.33	0.75	0	0.25	2.23	12.36	14.05	1.09	14777.69	2.23
131	0.33	0.34	0.33	0	0.25	0.75	2.23	12.35	14.05	1.36	14793.37	2.23

In Table 3, each multilevel design scenario depicts the differences in the various group decision-makers preferences for their respective goals. For example, Multilevel Design Scenario 123 represents a situation where manufacturer group decision-makers at Level 1 have equal preference for all their goals - G_1, G_2, and G_3, as indicated by the weight values of 0.33, 0.34, and 0.33, respectively. For the same scenario, at Level 2, the supplier group decision-makers have a full preference for one goal and zero on the other two; see weight values of 1, 0, and 0 on their goals G_4, G_5, and G_6, respectively. Analyzing the goal values for the manufacturer group at Level 1 in Table 3, it is observed that the relaxed satisficing limits for all the goals were satisfied. This is due to the higher priority assigned to Level 1 in the c-cDSP, using the Preemptive formulation. From the goal values achieved for the supplier group at Level 2, see G_4 to G_6 in Table 3, it is observed that G_5 and G_6 values meet the relaxed satisficing limits, and G_4 (Profit DCI maximization) failed to satisfy the relaxed satisficing limit of $G_4 \geq 10$. This is expected as the LRL for profit at the supplier group is set high, see Section 4.2.1, which results in low DCI values. However, the solutions identified are still robust since the DCI values are greater than 1. The design variables values corresponding to the nine common robust satisficing solutions are listed in Tables 4 and 5, respectively.

TABLE 4. Key design variable values for the manufacturer group corresponding to robust satisficing solutions identified

Design Scenario	P (tons)	Q_{11}^{1} (tons)	Q_{21}^{1} (tons)	Q_{11}^{s} (tons)	Q_{21}^{s} (tons)	Qk_{11}^{s} (tons)	Qk_{21}^{s} (tons)	Q_{1}^{1} (tons)	Q_{1}^{2} (tons)	Price ($/ton)	Y_{11}^{1}	Y_{11}^{2}	Y_{12}^{1}	Y_{12}^{2}
105	2040	1.6	1610.5	0.6	612.0	0.1	0.1	1020.0	1020.0	1199.9	1	0	1	0
107	2040	1.6	1610.5	0.6	612.0	0.1	0.1	1020.0	1020.0	1199.9	1	0	1	0
108	2040	0.1	1612.6	0.0	612.0	0.0	0.0	1020.0	1020.0	1200.0	1	0	1	0
123	2040	0.4	1610.7	0.1	612.0	0.0	0.0	1020.0	1020.0	1200.0	1	0	1	0
125	2040	1.6	1610.5	0.6	612.0	0.1	0.1	1020.0	1020.0	1199.9	1	0	1	0
127	2040	0.8	1610.6	0.3	612.0	0.0	0.0	1020.0	1020.0	1200.0	1	0	1	0
129	2040	1.6	1610.5	0.6	612.0	0.1	0.1	1020.0	1020.0	1199.9	1	0	1	0
130	2040	0.4	1610.7	0.1	612.0	0.0	0.0	1020.0	1020.0	1200.0	1	0	1	0
131	2040	1.6	1610.5	0.6	611.9	0.1	0.2	1020.0	1020.0	1199.9	1	0	1	0

TABLE 5. Design variable values for the supplier group corresponding to robust satisficing solutions identified

Design Scenario	s_{1}^{1} ($/ton)	s_{1}^{2} ($/ton)	s_{s}^{1} ($/ton)	s_{s}^{2} ($/ton)	Y_{11}^{11}	Y_{11}^{12}	Y_{21}^{11}	Y_{21}^{12}	Y_{11}^{s1}	Y_{11}^{s2}	Y_{21}^{s1}	Y_{21}^{s2}
105	319.9	330.0	210.0	220.0	1	0	1	0	1	0	1	0
107	319.9	330.0	210.0	220.0	1	0	1	0	1	0	1	0
108	300.0	330.0	209.9	220.0	1	0	1	0	1	0	1	0
123	320.0	330.0	210.0	220.0	1	0	1	0	1	0	1	0
125	319.9	330.0	210.0	220.0	1	0	1	0	1	0	1	0
127	320.0	330.0	210.0	220.0	1	0	1	0	1	0	1	0
129	319.9	330.0	210.0	220.0	1	0	1	0	1	0	1	0
130	320.0	330.0	210.0	220.0	1	0	1	0	1	0	1	0
131	319.9	330.0	210.0	220.0	1	0	1	0	1	0	1	0

The design variable values corresponding to the common robust satisficing solutions identified are similar to each other, see Tables 4 and 5. For the manufacturer group at Level 1 to meet the large satisficing limits for G_2 and G_3, the group decision-makers look at design scenarios with higher weightage on G_2 and G_3. This results in designers choosing solutions that have similar design variable values. For the supplier group at Level 2, the decisions made at Level 1 by the manufacturer group, along with the high LRL set for G_4, will restrict the design space at Level 2. This will lead to the choice of design solutions that will result in similar design variable values.

Based on the design variables values for the manufacturer group in Table 4, the manufacturer group decisions are as follows: (i) produce 2040 tons of steel slab (see, P) by sourcing almost all of the coal and scrap steel required from Supplier 2 in the Supplier group (see Q_{21}^{1} and Q_{21}^{s}), (ii) use the slower mode of transportation to transport the steel slabs to the customers and steel scrap from the customers to the manufacturer group (see Y_{11}^{1} and Y_{12}^{1}), and (iii) sell 1020 tons of steel slabs each to Customers 1 and 2 in the customer group (see Q_{1}^{1} and Q_{1}^{2}), at a selling price of $1200 per ton (see Price).

Based on the design variables values for the supplier group in Table 5, the following decisions are made by the suppliers in the supplier group: (i) Supplier 1 estimates a selling price of $320 per ton for coal and $210 per ton for steel (see s_{1}^{1} and s_{s}^{1}), (ii) Supplier 2 estimates a selling price of $330 per ton for coal and $220 per ton for steel (see s_{1}^{2} and s_{s}^{2}), (iii) Suppliers 1 and 2 choose the slower mode of transportation to transport coal and steel scrap to the manufacturer group (see Y_{11}^{11}, Y_{21}^{11}, $Y_{11}^{s1}$and Y_{21}^{s1}).

Using FRoMCoDE, group decision-makers are able to model the decision problem in the steel MSN using a single c-cDSP with a combination of Preemptive and Archimedean formulations, considering the decisions made at Levels 1 and 2 and their interactions. Uncertainties in design variables are accounted for by formulating goals affected by design variable uncertainties as robust DCI goals in the c-cDSP. Shared design variable relaxation constraints are used in the c-cDSP to facilitate the sharing of a ranged set of shared design variable values from Level 1 to Level 2. By exercising the c-cDSP for various multilevel design scenarios, the design and solution spaces are generated across Levels 1 and 2. The solution spaces across Levels 1 and 2, including robust solution space for DCI goals, are simultaneously visualized using iSOM plots. By setting satisficing limits for each goal and simultaneously exploring the solutions spaces across the levels using the iSOM plots, designers are able to carry out co-design exploration and identify '*satisficing or robust satisficing solutions*' for all the goals across Levels 1 and 2 in the steel MSN. Conflicts that occur when no common solutions are identified across Levels 1 and 2 are managed during co-design exploration by relaxing the satisficing limits for the goals as deemed appropriate by the group decision-makers till a common solution region is identified. Hence, using FRoMCoDE, the robust co-design of the multilevel steel MSN is achieved.

5. CLOSING REMARKS

The simulation-supported design of MSN's requires support for consideration of the group interaction across multiple levels and the management of uncertainties and design conflicts that influence MSN performance. Computational models employed in the simulation-supported design of MSN's are abstractions of reality. Hence, our focus is on design exploration to identify a ranged set of robust satisficing solutions. This requires the facilitation of visualization and co-design exploration.

In this paper, we present the decision support framework, namely 'FRoMCoDE,' where we combine the following construct or tools: i) the c-cDCP construct, ii) DCI robust design construct, and iii) iSOM-based visualization to support the '*robust co-design*' of MSN's. Using FRoMCoDE, the group decision-makers are able to i) model group decision problems across multiple levels and their interactions using a single coupled decision problem formulation, ii) consider uncertainties, and iii) visualize and efficiently explore multilevel design spaces simultaneously to support robust co-design.

The key contributions in this paper are the functionalities offered by FRoMCoDE, which include:

a) Facilitating the formulation of multilevel design problems involving many conflicting goals at each level and interactions among multiple decision levels. The functionality is achieved by combining the Preemptive and Archimedean formulations in the c-cDSP. By combining the Preemptive and Archimedean formulations in the c-cDSP, designers are able to account for many conflicting design goals at a level and relations across levels into a single coupled decision problem formulation.

b) Facilitating the co-design visualization and exploration of high-dimensional (more than 3) design spaces across multiple levels. Efficient co-design exploration is realized by simultaneously exploring the multilevel design spaces formulated using the coupled cDSP (c-cDSP) by means of the interpretable self-organizing map (iSOM) construct. This is achieved by training iSOM using the input c-cDSP weight combinations (weights corresponding to the multilevel design scenarios of the c-cDSP) and the generated output design goal values (achieved values of individual goals) for different multilevel design scenarios. Two-dimensional (2D) plots for each of the inputs and outputs across the levels are generated via iSOM. Using the simultaneous design space visualization capability offered by iSOM, designers are further able to explore and seek common satisficing robust regions for the many goals across multiple levels. The co-design exploration approach supports the management of design conflicts and uncertainties across levels, ensuring system performance. Co-design exploration also allows designers to consider tradeoffs among goals across multiple levels. This enhances design flexibility by allowing designers to compromise goals at any level in the design hierarchy while still accounting for the impact of such compromises on goals at other levels. These are advantages over other multilevel design exploration approaches that are based on the sequential exploration of the individual levels, as discussed in Section 1.

The efficacy of FRoMCoDE is tested for the above functionalities using the steel MSN problem. Using FRoMCoDE, robust co-design of the steel MSN with interactions between the manufacturer and supplier groups at Levels 1 and 2 is demonstrated. The conflicts arising between manufacturer and supplier groups at different levels are managed by simultaneously exploring the solution spaces to identify common robust satisficing solutions for all the goals across the levels. Using the framework, we facilitate the robust co-design of multilevel systems characterized by hierarchical relations across multiple levels.

The FRoMCoDE framework is flexible and can be adapted to model and solve a variety of design problems involving decisions being made across one or more levels of a decision hierarchy, with each level constituted by one or more decision-makers. The flexibility of the framework comes from i) the inherent flexibility in modeling the deviation function of the c-cDSP construct using the Preemptive and Archimedean formulations to suit the problem structure and ii) the generic nature of the tools and constructs used. The framework can be modified to account for additional design levels in the MSN (more than the two depicted in Figure 3) by appropriately adding the required priority levels in the Preemptive formulation of the deviation function. Consequently, the multilevel design scenarios need to be modified to account for the new design levels in the MSN. The goals of multiple groups at the same level can be considered using the Archimedean formulation at each Preemptive priority level in the deviation function. The ability to support modeling and solving a variety of design problems makes FRoMCoDE framework generic.

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APPENDIX A: Mathematical models for the end requirements, level-specific information, and design variables at Levels 1 and 2 of the c-cDSP for the steel MSN problem

What follows is an amplification of what is presented in Section 4.2. The mathematical models for the end requirements of the manufacturer and supplier groups at Levels 1 and 2 of the steel MSN c-cDSP are listed below in A1 and A2, respectively. In A3, the information specific to Levels 1 and 2 of the c-cDSP for the steel MSN is provided. In A4, we list the design variables and their bounds for Levels 1 and 2 of the c-cDSP for the steel MSN.

A1. Models for the Manufacturer Group end requirements at Level 1 in the steel MSN c-cDSP (see Given in Section 4.2.1)

i. Maximize Service Level (SL)

$$G_1 = \sum_{k=1}^{2}\{LTk_k^e/(\sum_{y=1}^{2}\frac{D_{jk}^y}{Speed^y} * Y_{jk}^y + LT_o^j)\}$$

ii. Maximize Profit (in \$)

$$G_2 = (Price * \{\sum_{k=1}^{2} Q_j^k\}) - (P * Cost^n + \sum_{m=1,s}\sum_{i=1}^{2} s_m^i\, Q_{ij}^m + \sum_{k=1}^{2} sk_s^k\, Qk_{kj}^s +$$

$$\sum_{i=1}^{2}\sum_{y=1}^{2} Q_j^k D_{jk}^y T_{jk}^y Y_{jk}^y + \sum_{k=1}^{2}\sum_{y=1}^{2} Qk_{kj}^s D_{jk}^y T_{jk}^y Y_{jk}^y$$

iii. Minimize GHG emissions (in kgs of CO_2)

$$G_3 = (P * E + \sum_{i=1}^{2}\sum_{y=1}^{2} Q_j^k D_{jk}^y E_{jk}^y Y_{jk}^y + \sum_{k=1}^{2}\sum_{y=1}^{2} Qk_{kj}^s D_{jk}^y E_{jk}^y Y_{jk}^y)$$

A2. Models for the Supplier Group end requirements at Level 2 in the steel MSN c-cDSP (see Given in Section 4.2.1)

i. Maximize Profit (in \$)

$$G_4 = \sum_{m=1,s}(\sum_{i=1}^{2} s_m^i q_{ij}^m - (C_m^i q_{ij}^m + \sum_{y=1}^{2} d_{ij}^{my}\, q_{ij}^m\, t_{ij}^{my} Y_{ij}^{my}))$$

ii. Minimize GHG emissions (in kgs of CO_2)

$$G_5 = \sum_{m=1,s}\sum_{i=1}^{2}\sum_{y=1}^{2} d_{ij}^{my}\, q_{ij}^{m}\, e_{ij}^{my}\, Y_{ij}^{my}$$

iii. Maximize Service Level (SL)

$$G_6 = \{\sum_{i=1}^{2}(\frac{1}{m} * \sum_{m=1,s}(\frac{LT_{ij}^{me}}{\sum_{y=1}^{2}(\frac{D_{ij}^{my}}{Speed^{y}} * Y_{ij}^{my} + LT_{o}^{i})}))\}$$

A3. Level Specific information for the c-cDSP (see Given in Section 4.2.1)

At Level 1

- Manufacturer group (*j*) Information: Set of manufacturers (*j* = 1), Production capacity (Capacity) in tons, Production cost ($Cost$) in \$ per ton, the raw material (*m*) requirement in tons per ton of steel produced $\{A_m\}$ (coal, *m*=1 and steel scrap, *m*=s), transportation information – (modes {*y = 1,2*}, speed in km/hr. $\{Speed^{y}\}$, distance to customers in km $\{D_{jk}^{y}\}$, transportation costs in \$ per ton per km $\{T_{jk}^{y}\}$, Greenhouse gas {GHG} emission in kgs of CO_2 per ton transported per km $\{E_{jk}^{y}\}$), and demand estimate at customer k (D_k^e).
- Customer group (*k*) Information: Set of customers (*k* = 1, 2), Steel scrap availability – a fraction of tons of steel purchased (B_k), steel scrap prices in \$ per ton (sk_s^k), and expected lead time in hrs. (LTk_k^e).

At Level 2

- Manufacturer group Information: Actual order quantity of material m (Q_{ij}^{m}), expected lead time for material m in hrs (LT_{ij}^{me}) from supplier i
- Supplier group Information: Set of suppliers (*i* = 1, 2), Materials supplied $\{m$, = 1 (coal), = s (scrap)}, forecasted demand estimate for material 'm' at manufacturer

in tons (d_m^e), Material cost of material ‘m’ in \$ per ton, (C_m^i), transportation information – (modes {*y = 1,2*}, speed in km/hr $\{Speed^y\}$, distance to customers in km $\{d_{ij}^{my}\}$, transportation costs in \$ per ton per km $\{t_{ij}^{my}\}$, Greenhouse gas {GHG} emission in kgs of CO_2 per ton transported per km $\{e_{ij}^{my}\}$)

<u>**A4.** Design variables and their bounds at Levels 1 and 2 of the c-cDSP for steel MSN</u> (see, Given in Section 4.2.1)

<u>**At Level 1**</u>

- 2000 ≤ Production quantity in tons (*P*) ≤ 4000
- Coal and steel scrap purchase quantities from suppliers in tons (Q_{ij}^m), where $i = 1, 2; j = 1$; and $m = 1, s$
  - $0 \leq Q_{11}^1, Q_{21}^1 \leq 3200$
  - $0 \leq Q_{11}^s, Q_{21}^s \leq 1600$
- Scrap purchase quantities from customers in tons (Qk_{kj}^s), where $k = 1, 2; j = 1$
  - $0 \leq Qk_{11}^s, Qk_{21}^s \leq 500$
- Product supply quantities to customers in tons (Q_j^k), where $k = 1, 2; j = 1$
  - $1000 \leq Q_1^1, Q_1^2 \leq 1200$
- $1000 \leq$ Steel selling price in \$ per ton (*Price*) ≤ 1200
- The estimated selling price of material ‘m’ at supplier ‘i’ (s_m^{ie}) in \$ per ton, for all $m = 1, s$ and $i = 1, 2$
  - $310 \leq s_1^{1e}, s_1^{2e} \leq 330$
  - $210 \leq s_s^{1e}, s_s^{2e} \leq 230$

- The estimated selling price of material 'm' at customer 'k' (sk_m^{ke}) in \$ per ton, for all $m = s$ and $k = 1, 2$
  - $30 \leq sk_s^{1e} \leq 50$
  - $40 \leq sk_s^{2e} \leq 60$
- Transportation mode selection (Y_{jk}^{y}) for transporting the products to customers and steel scrap from customers, where $k = 1, 2$; $j = 1$; and $y = 1, 2$
  - $Y_{11}^1, Y_{11}^2, Y_{12}^1, Y_{12}^2 = 0, 1$

<u>At Level 2</u>

- The selling price of material 'm' at supplier 'i' (s_m^i) in \$ per ton, for all $m = 1, s$ and $i = 1, 2$
  - $300 \leq s_1^1 \leq 320$
  - $310 \leq s_1^2 \leq 330$
  - $190 \leq s_s^1 \leq 210$
  - $200 \leq s_s^2 \leq 220$
- Transportation mode selection (Y_{ij}^{my}) for transportation of materials to the manufacturer, for all $m = 1, s$; $i = 1, 2$, and $y = 1, 2$
  - $Y_{11}^{11}, Y_{11}^{12}, Y_{11}^{s1}, Y_{11}^{s2} = 0, 1$
  - $Y_{21}^{11}, Y_{21}^{12}, Y_{21}^{s1}, Y_{21}^{s2} = 0, 1$