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A Framework for Designing Robust Supply Chains considering Product Development Issues

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The primary objective of the design of a supply chain (DFSC) is the selection of an appropriate product family. Moreover, it deals with the selection of the optimal combination among the different conflicting criteria while making a trade-off between the supply chain cost, sales profit and the product design complexities. In this research, to address the DFSC issues a product platform approach has been proposed which amalgamates the component modularity as well as the function modularity in the product design. The optimization model proposed in this paper for the product development and the supply chain design is based on a Generic Bill of Materials (GBOM) representation. The complete framework includes a vital decision-making needed for designing a robust supply chain such as locating plants to alleviate the likely dominance of production cost and market mediation cost on product variety and imparting process flexibility of the located plants. The optimization model proposed in this paper, models the supply chain cost, sales profit and product design complexity as three criteria that altogether determine the robustness of the supply chain and the underlying product development approach. The certain parameters like process flexibility, flow types and drivers of the product variety dominance have been controlled in the design framework. To resolve the complexity of the proposed model a Genetic Algorithm (GA) technique has been proposed. The proposed GA adopts an arithmetic crossover, a dynamic mutation and a variable penalty strategy to produce optimal results in a very short computational time. To validate the proposed model, a simulated case study of the wiring harness supplier of an AGV manufacturer has been studied.

Keywords: Design for supply chain (DFSC), Genetic Algorithm, GBOM, optimization, Platform based product development

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1. Introduction

The Design for Supply Chain (DFSC) problems deal with designing a supply chain and quite often involve resolving some decisions regarding the product development. The urgency to ensure necessary product variety in a diversified market and the simultaneous consideration of its associated supply chain structure cannot be overlooked by any firm which intends to compete in a long run. Many hypotheses have been proposed in literature to deal with the various aspects of DFSC such as the product variety, supply chain relationship, and the profit issues (Lee et al. 1998; Randall and Ulrich, 2001; Desai et al. 2001). However, the literature indicates that the different aspects of the DFSC need to be efficiently handled to optimize the product development processes.

Graves and Tomlin (2003) found that supply chains with higher values of process flexibility enhances the overall scale efficiency of the plants and helps to imitate high production dominant strategy. However, the production plants with the lower degrees of flexibility suffer more from the shortfalls. Blackhurst et al. (2004) point out that the supply chain faces uncertainties, such as the uncertainty of its network operations apart from the demand uncertainty. Supplier performance also plays a crucial role in the success of a supply chain. Though, the cost is a key parameter in the research pertaining to supply chain, yet in an interdependent environment, a supplier is evaluated in terms of not only the supply chain cost, but also the delivery performance and the quality assurance.

Jain et al. (2004) argued that a fuzzy set approach can be implemented to evaluate a suppliers' performance. Concerned with the juxtaposition of the product variety and the supply chain, Randall and Ulrich (2001) have proposed some hypotheses which reflect that plants with large scale efficiency and local nature, with respect to the target market have a least dominance of the production cost or market mediation cost in altering the product varieties. Lamothe et al. (2005) proposed a mixed integer linear programming model to select a diverse product family with an optimum supply chain cost using the market segment design strategy, modular design strategy or the combination of the both

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3 strategies. These findings suggest that supply chain is an integral part of the production
4 process and hence must be handled efficiently.
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9 Modularity compels a designer to create a higher level of independence between the
10 components by redefining their interface details (Sanchez, 1997). Depending upon the
11 intricacy of the technological development or production capacity, modules can be either
12 function or component modules (Pahl and Beitz, 1988). That is, the component modules
13 refer to combining/standardizing different components into a module, while the function
14 module means relating different functional requirements and meeting them through the
15 modularization. The function modules become very important while designing a product
16 that has several intricate functional requirements. Wang et al. (1998) proposed a
17 Concurrent Engineering (CE) driven design for a mechanical system by studying the
18 correlation of functions in the product development. Although, the consideration of the
19 component modularity in a product design, along with its supply chain parameters may
20 be found in the literature, function modularity is rarely considered in a product driven
21 DFSC problem. Therefore, there are some gaps that give designers difficulties in
22 including a comprehensive set of criteria for the supply chain. This paper attempts to
23 bridge this gap by proposing a framework for designing a robust supply chain that deals
24 with various products and supply chain design parameters.
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39 Converting the abstract ideas into a concrete one is a key stage of designing a product,
40 and nearly 75% of the manufacturing cost can be anticipated and committed in particular
41 product concepts (Ulman, 1992). Different models and mode of bills of materials such as
42 planning bills (Braker, 1996), modular bills, kit bills (Oden et al., 1993), and Generic Bill
43 of Material (Jiao et al., 2000) are available in literature and industry, that that can be
44 utilized in various design problems. Products can be designed in accordance with the
45 existing customer diversity by designing products for different market segments with
46 optimum profit and differentiation. This can be accomplished using a platform approach,
47 leveraging the design cost between the lower and higher market segments. Although, this
48 platform-based product development has a low unit variable cost, it often results in an
49 optimal profit and larger product differentiation (Krishnan and Gupta, 2001; Bernard and
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Xu, 2009). In case of highly diverse customer requirements, platform-based product development can also be implemented using Internet-based reconfiguration systems (Xie et al., 2005).

The challenges highlighted above in the literature can be overcome by considering a multi-criteria 'DFSC' (Design for Supply Chain) problem dealing with a diverse product family selection and its supply chain design. A tree representation for the product family of the supply chain has been adopted from the work of Lamothe et al., (2006), while taking into account a hybrid market segment and modularity technique for the diversification. At the same time, component modularity vis-à-vis functional modularity has also been considered in the product design part of the problem. In this paper, a comprehensive optimization framework has been proposed considering various control factors such as process flexibility, production or market mediation dominance on product variety, supply chain cost, profit and product design complexity.

The framework inherits number of decision variables such as (a) which and how much items to choose, (b) the existence, location and capacities of plants, (c) the shipping channels to use, (d) products performance levels, and (e) product prices. The DFSC problem studied in this paper also considers number of constraints such as (i) demand and flow conservations, (ii) safety inventories, (iii) feasible product flows, (iv) resource lines, (v) market segmentation, and (vi) product differentiation. Additionally, the framework integrates the optimization of the objective function and a few supply chain performance hypotheses. The framework also imparts process flexibility to the supply chain, to tackle the demand uncertainties to a remarkable extent. Broadly, the optimization problem to DFSC in this paper can be divided into two parts,

1. Product family selection
2. Design of supply chain.

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Prior to the optimization model for DFSC problem, the control parameters such as scale efficiency and plant location, and process flexibility are discussed as a part of the design framework. The optimization model aims to meet the following three objectives, i.e.

- Minimize supply chain cost,
- Maximize sales profit of end products and
- Minimize product design complexity

To handle this kind of complex DFSC problem literature identifies the use of constrained based heuristic algorithms such as the mixed integer linear programming or the branch and bound method. However, the existing methods are not applicable for large size problems, as they fail to generate solutions in a real time. In order to overcome these limitations, this paper proposes a Genetic Algorithm (GA) based approach. GA is capable of searching many optimum points in parallel and reaching to a global optimum with high probability in less computational time. To experimentally evaluate the propositions, a problem of wiring harness supplier of an AGV manufacturer is considered. The main objective is to achieve a trade-off between the supply chain cost, sales profit and the design complexity.

2. Model development:

This section presents a model for the development of a product family, while simultaneously designing its supply chain. The model places an emphasis on developing an optimum variety through modular platform product development. We firstly discuss the conceptual development of the model and then present the mathematical formulations and explanations. Notations and symbols used in the model are explained in Appendix A.

<<Insert Appendix A here>>

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2.1. Model conceptualization

Product variety is necessary to cater for diverse and ever changing customer demands. This paper is aimed at proposing a model for selecting the optimal product family based on the Generic Bill of Materials (GOBM) model developed by Lamothe et al. (2006). In the proposed model the logical and physical items are represented as nodes. The logical items in the model are the hypothetical one and they can neither be manufactured in the plants nor be stored or shipped. Whereas, the physical items can be manufactured, stored and shipped. These nodes are connected with each other through an AND and Ex-OR nodes. AND nodes are those which flourish over the contributions from each and every one of their children, whereas the Ex-OR nodes flourish over the contribution from one and only one of its children.

The market is a logical item. It has various demands from the point of view of performance levels and it consists of a number of market segments. Market segmentation is conducted using suitable technologies and principles according to different performance levels demanded by different consumer segments (Lamothe et al., 2006). This paper adopts a hybrid market-modular approach that has been adopted for the product development. By this approach, the market is first divided into several segments by fixing specific performance levels for the each function. The market segmentation is shown in Figure 1 (a) and 1 (b). At least one module variant is then designed as per the function technology per performance level, so as to assemble the desired modular variants. However, we assume this modularization to be a one component. The component modularization is shown in Figure 1 (c). This hybrid market-modular strategy helps to reach a compromise between high equipment cost, excessive level of satisfaction, and high management costs (Lamothe et al., 2006).

<< Include Figure 1(a), (b) and (c) about here >>

In Figure 1, we have considered a product with two functional requirements, function 1 and function 2. A functional requirement can be met at one or more performance level as

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shown. *MFx* or *Market frag.x* indicates a market segment formed by fixing a specific performance level (P-level) for each of the functional requirements. P-level 'x/y' means meeting x^{th} functional requirement at service level 'y', demanded for that function. A product variant encompasses all the functional requirements with a given specific service level. A variant 'x.y' satisfies functional requirement 1 at performance level '1/x' and functional requirement 2 at performance level 'y'. Module X/Y-i represents the design principle 'i' for function X with a performance level Y. 'BOM X.Y' or 'X/Y' means the bill of material for the corresponding item.

Different children choices at Ex-OR nodes result in the different combinations of product families. An optimal product family is selected based on the objective function. In our model, we assume that the market is segmented into two segments (lower and higher). We also assume that consumers in a market segment are homogenous, i.e., their valuation is a linear function of products performance level. Different products offered to the two consumers' segments with different performance levels share a common platform which is defined as components and subsystem assets shared across a product family (Krishnan and Gupta, 2001). A product platform reduces product development cost, imparts greater degree of reuse and enhances the responsiveness of firms, but may incur over or under design cost of the lower and the higher market segment respectively. The three criterion addressed in this paper are sales profit, supply chain cost and product design complexity. The mathematical modeling is described in the next paragraph.

The fixed and unit variable costs incurred in the product design and development with performance level ρ from a base product of performance level ρ_o is assumed to be the functions of $g(\rho^b - \rho_o^b)$ and $k\rho^c$ respectively (Krishnan and Gupta, 2001). At the same time, the fixed cost for a modular platform development contributing a quantity ρ_p ($\rho_p \leq \rho_l \leq \rho_h$) as a performance to the product is a polynomial function of ρ_p^b , i.e., $h(\rho_p^b)$. The total fixed cost to develop the product family is $g(\rho_h^b - \rho_p^b) + g(\rho_l^b - \rho_p^b) = g(\rho_h^b) - g(\rho_l^b) + (h-2g)(\rho_p^b)$ where, ' $h(\rho)$ ' is a polynomial

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function and $g(\rho)$ is not necessarily a polynomial function. Realizing the scale of economies ($\alpha, 0 < \alpha < 1$) of non-platform units, when the firm produces $\sum_f N_{s_{END}^{ft}}$, the unit variable cost is given by $Ik[1 - ((1 - \alpha)/\eta_{max})^{\frac{F}{f}} N_{s_{ft}}] \rho^c$, where η_{max} is the maximum number of products the firm can produce and is equal to $\eta_{max} = \sum_f N_{s_{ENDL}^{ft}} + \sum_f N_{s_{ENDH}^{ft}}$.

In the GBOM, the products are simply considered as the leaves of the tree. The supply chain cost comprises of the fixed costs and the variable cost terms (Lamothe et al., 2006).

Fixed costs are the costs incurred on the selection of items $\sum_s \Phi_{s_i}^e \delta_s$, opening of facilities $\sum_f \Psi_{fn}^o \chi_f$, building of shipping channels $\sum_f \sum_{e \neq f} \Pi_{fh}^p \lambda_f$, and opening of resource lines $\sum_r \sum_f \psi_{rf}^{open} \varepsilon_{rf}$. The variable costs include the costs incurred in manufacturing $\sum_s \sum_f \sum_t \Omega_{sf}^{req} N_{s_{ft}}$, storing $\sum_s \sum_f \sum_t \Delta_{sf}^{req} S_{s_{ft}}$ and shipping $\sum_s \sum_f \sum_t \sum_{e \neq f} \Gamma_{sfe}^{req} H_{s_{fet}}$.

A module is generated using the combinations of individual parts or assemblies. These modules are given maximum possible orthogonality, so as to reduce the complexity. While deploying the functional modularity concepts, a module can be made an absolutely coupled module or an independent one, based on the coordination level of the different function, which ultimately depends upon whether the effect of one function becomes the cause of the other or not (Tsai and Wang, 1999). This cause-effect coordination may be defined on several grounds, such as the geometry constraint (size, shape, tolerance etc.), mechanical strength (load, stress distribution, etc.), energy flow (kinematics variables, inertia, etc.) and signal flow (sensing, transmission, etc.). Dividing 'n' number of functions into 'm' number of modules is on the one hand influenced by the coordination level between different functions, and on the other hand, is ultimately restricted and optimized by different types of manufacturing complexity,

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$comp_{mf} = -1 / \theta_l \sum_i^n (d_i \ln d_i + (1 - d_i) \ln (1 - d_i))$ and assembling complexity;

$comp_{as} = -\sum_i^{\theta_l} ((u_l(i) / \eta_i) \ln (u_l(i) / \eta_i))$. As evident from the expression, manufacturing

complexity decreases with the increase in the number of modules however at the same time the assembly complexity increases. So we are compelled to reach a trade-off in order to minimize the overall design complexity given by the number of modules at a given correlative level (l), feasibility for all the functional technologies, and the number of functions in each of the modules. The correlative level can be set using an α -cut method (Tsai and Wang, 1999; Zimmermann, 1991). That is, the complexity in designing the functional topology is given by $COMP_{des} = comp_{as} + comp_{mf}$.

These criteria are combined to form a measure for the supply chain effectiveness. The objective function OBJ can then be written as $OBJ = w_1 SC \text{ Cost} - w_2 PRF + w_3 COMP_{des}$ where w_1 , w_2 and w_3 are the magnitude of the three weights corresponding to the supply chain cost ($SC \text{ Cost}$), profit (PRF) and the design complexity ($COMP_{des}$) respectively. Coefficients of w_1 and w_2 are positive, while that of w_3 is negative, because the intention is to minimize $SC \text{ Cost}$ and $COMP_{des}$, whereas PRF needs to be maximized. The expressions for $SC \text{ Cost}$, PRF and $COMP_{des}$ backed by the above discussions are given as follows:

$$SC \text{ Cost} = \sum_s^S \Phi_s^{exist} . \delta_s + \sum_f^F \Psi_f^{open} \chi_f + \sum_f^F \sum_{e \neq f}^{F \cup F^C} \Pi_{fe}^{path} \lambda_{fe} + \sum_r^R \sum_f^F \Psi_{rf}^{open} \epsilon_{rf}$$
 (1)

$$+ \sum_s^S \sum_f^F \sum_t^T [\Omega_{sf}^{req} N_{sft} + \Delta_{sf}^{req} S_{sft} + \sum_{e \neq f}^{F \cup F^C} \Lambda_{sf}^{req} H_{sfet}]$$

$$PRF = \sum_t^T (\sum_f^F N_{s_{ENDL}ft} [p_l - c_o Ik\{1 - ((1 - \alpha) / \eta_{\max}) \sum_f^F N_{s_{ENDL}ft} \} \rho_l^c] + \sum_f^F N_{s_{ENDH}ft} [p_h - Ik\{1 - ((1 - \alpha) / \eta_{\max}) \sum_f^F N_{s_{ENDH}ft} \} \rho_h^c])$$

$$- g(\rho_h^b) - g(\rho_l^b) - (h - 2g)(\rho_p^b))$$
 (2)

The profit term PRF comprises of the sum of contributions from the individual market segments product minus the fixed cost of developing the platform based product family. The decision variables involved in this term are the total number of end products manufactured for each of the market segments, the performance levels and the selling

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prices. The performance level (currency per valuation of a market segment) of a member of the product family is assumed to be determined from the supply chain cost incurred in manufacturing a single piece during a given time period, i.e.

$$COMP_{des} = -1/\theta_l \sum_i^{\eta} (d_i \ln d_i + (1-d_i) \ln(1-d_i)) + -\sum_i^{\theta_l} ((u_l(i)/\eta) \ln((u_l(i)/\eta)) \quad (3).$$

The objective function is combined so as to give a best trade-off between the supply chain cost, sales profit and the design complexity, in building the functional topography.

2.2 Mathematical Formulations

The objective function does restrict its decision variables due to number of factors such as, the limitation imposed on the resources, market targeting and customer valuation, and more product differentiation than the non-platform approach. It also follows the policies of GBOM and avoids the cost incurred on the excess or unsafe inventory. So, the constrained non-linear programming DFSC problem is given as follows.

$$\text{Minimize } OBJ = w_1 SC \text{ Cost} - w_2 PRF + w_3 COMP_{des} \quad (4)$$

Subjected to

$$N_{sft} \leq N_{\max} \delta_s \text{ and } N_{sft} \leq N_{\max} \chi_f \quad \forall s \in S, f \in F, t \in T \quad (5)$$

$$\delta_s \leq \sum_p^{PRNT_p} \delta_p + \sum_p^{PRNT_p} \delta_{sp} \quad \forall s \in S - S_c \quad (6)$$

$$\delta_{sp} \leq \delta_s \text{ and } \delta_{sp} \leq \delta_p \quad \forall p \in S^+, s \in CHLD_p \quad (7)$$

$$\sum_s^{CHLD_p} \delta_{sp} = \delta_s \quad \forall p \in S^+, \quad (8)$$

$$\sum_s^{CHLD_p} N_{spft} = N_{pft} \quad \forall p \in S^+, f \in F, t \in T, \quad (9)$$

$$N_{spft} \leq N_{\max} \delta_{sp} \quad \forall p \in S^+, s \in CHLD_p, f \in F, t \in T \quad (10)$$

$$\delta_s \geq \delta_p \quad \forall p \in S^*, s \in CHLD_p, f \in F, t \in T \quad (11)$$

$$S_{sft} - S_{sft-l} = N_{sft} + \sum_{e \neq f}^F H_{seft} - \sum_{e \neq f}^{F \cup F^c} H_{sfet} - \sum_p^{S^+ \cap PRNT_s} \sigma_{sp} N_{spft} - \sum_p^{S^+ \cap PRNT_s} \sigma_{sp} N_{pft} \quad \forall s \in A, f \in F, t \in T, \quad (12)$$

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$$0 = N_{sft} - \sum_p^{S^+ \cap PRNT_s} \sigma_{sp} N_{spft} - \sum_p^{S^+ \cap PRNT_s} \sigma_{sp} N_{pft} \quad \forall s \in C, f \in F, t \in T, \quad (13)$$

$$Dmd_{sf^c t} = \sum_e^F H_{sef^c t} - \sum_p^{S^+ \cap PRNT_s} \sigma_{sp} N_{spft} - \sum_p^{S^+ \cap PRNT_s} \sigma_{sp} N_{pft} \quad \forall s \in C, f^c \in F^c, t \in T \quad (14)$$

$$Dmd_{sf^c t} = N_{sf^c t} - \sum_p^{S^+ \cap PRNT_s} \sigma_{sp} N_{spft} - \sum_p^{S^+ \cap PRNT_s} \sigma_{sp} N_{pft} \quad s \in A, f \in F^c, t \in T \quad (15)$$

$$\lambda_{fe} \leq \chi_f \text{ and } \lambda_{fe} \leq \chi_e, \quad \forall f \in F, e \in F - \{f\} \cup F^c \quad (16)$$

$$0 \leq H_{sft} \leq N_{\max} \lambda_{fe} \text{ and } H_{sft} \leq N_{\max} \delta_s \quad \forall s \in C, f \in F, e \in F - \{e\} \cup F^c, t \in T \quad (17)$$

$$S_{sft} \leq N_{\max} \chi_f \text{ and } S_{sft} \leq N_{\max} \delta_s \quad \forall s \in C, f \in F, t \in T \quad (18)$$

$$S_{sft} \geq \tau_{sf}^{get} (\tau_{sf}^{manuf} N_{sft} + \sum_{e \neq f}^F \tau_{sef}^{ship} H_{seft} + \sum_{f^c}^F \tau_{sef^c}^{ship} H_{seff^c t}) \quad \forall s \in S, f \in F, t \in T \quad (19)$$

$$\sum_s^{S_r} N_{sft} \pi_{rs} \leq \pi^T \varepsilon_{rf} \leq \pi^T \text{Max}_{rf} \chi_f \quad \forall r \in R, f \in F, t \in T \quad (20)$$

$$\chi_f, \lambda_{fe}, \delta_s \in \{0,1\}, \varepsilon_{rf} \in N, \quad \forall f \in F, e \in F - \{e\} \cap F^c, \quad \forall s \in S \quad (21)$$

$$\text{and } \delta_{sp} \in \{0,1\} \quad \forall p \in S^+, s \in CHLD_p$$

$$v_l \rho_l - p_l \geq v_l \rho_h - p_h \quad (22)$$

$$v_h \rho_h - p_h \geq v_h \rho_l - p_l \quad (23)$$

$$v_l \rho_l \geq p_l \quad (24)$$

$$v_h \rho_h \geq p_h \quad (25)$$

$$\rho_h \geq \rho_l, \quad (26)$$

$$\rho_l \geq \rho_p, \quad (27)$$

$$\begin{aligned} \rho_h - \rho_l \geq & \left[\sum_f^F N_{s_{ENDH}ft} v_h / b(g + \sum_f^F N_{s_{ENDH}ft} k \{1 - ((1-\alpha)/\eta_{\max}) \sum_f^F N_{s_{ENDH}ft}\}) \right]^{1/b-1} \\ & - \left[\sum_f^F N_{s_{ENDL}ft} v_l - \sum_f^F N_{s_{ENDH}ft} (v_h - v_l) / b(g + \sum_f^F N_{s_{ENDL}ft} k \{1 - ((1-\alpha)/\eta_{\max}) \sum_f^F N_{s_{ENDL}ft}\}) \right]^{1/b-1} \end{aligned} \quad (28)$$

Constraints from (5) to (11) are GBOM constraints, since they express the conditions to draw a consensus on the implementation of GBOM concepts. Constraint (5) and (6) are defined for all the nodes. Constraint (5) stipulates that a net requirement associated to an item compels it to exist. Constraint (6) specifies that the selection of an item (without external demand) requires either the existence of one of its parents as an AND node or

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the existence of a relevant link to an Ex-OR node. Constraints from (7) to (10) are defined only for Ex-OR nodes. Constraint (7) stands that the existence of a link to an Ex-OR node forces the existence of concerned child and parent. Constraint (8) reveals that the existence of an Ex-OR node ' p ' compels the selection of one and only one relevant link. Moreover, constraint (9) ensures that a net requirement on an Ex-OR item ' p ' induces a gross requirement on its child item. Constraint (10) implies that whenever a link p - s exists, the net quantity required for ' p ' requires the child item ' s '. Constraint (11) defined only for the AND nodes, says that the existence of an AND node rely on the existence of the each and everyone of its child.

Constraints from (12) to (15) are defined in order to conserve the flow of items. The amount by which we may vary the inventory of a physical item ' p ', is bound to be equal to the sum of the amounts produced in the facility and shipped to this facility from other facilities, and minus the sum of the amounts used in the plant to satisfy the gross requirement associated with the parent items as depicted in the constraint (12). Moreover, these flow conservation constraints consider the GBOM's restriction over the physical and logical items. Constraint (13) restricts logical items not to be manufactured, stored or shipped in any kind of facility, and constraint (14) defines physical items coming from manufacturing or storing in a customer facility.

Constraint (16) and (17) are shipping constraints, indicating that the amount of an item shipped for the existing plants, shipping channels and items. Constraints (18) and (19) are the inventory constraints. Constraint (18) confirms that the storage of an item at a facility is possible only when both the items and the facility exist. Constraint (19) reflects that the safety stock maintained for an item should be modeled as a percentage of flows (internal manufacturing flow, supplying flow from other facility and delivery flow to the customer facilities) during the item's lead time. τ_{sf}^{manuf} and τ_{sefc}^{ship} are the manufacturing and shipping lead times of item ' s ' at facility $f \in F$ and up to facility $f^c \in F^c$. Both are expressed as the percentage of the duration of the time period ' π^T ', while τ_{sf}^{get} is the percentage of manufacturing and shipping lead time of an item ' s ' at facility $f \in F$.

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Constraint (20) is a capacity constraint which ensures that sufficient resource lines should be opened to match the desired amounts. π_{rs} is the time for which resource line ‘ r ’ is used for item $s \in S_r$ and Max_{rf} is the maximum number of resource lines of type ‘ r ’ at a facility ‘ f ’. Constraint (21) includes binary variable constraints.

Constraint (22) ensures that a low-segment customer purchases a product targeted to their segment only. This is done by maintaining the utility from the lower segment more than or equal to its utility from high segment product. Constraint (23) stands likewise for the higher-segment product. Constraints (24) and (25) make sure that a products utility is greater than its price. While constraint (26) and (27) are obvious, constraint (28) stipulates that the product differentiation from the platform approach is more than any non-platform approach (single product, standardized product or niche product approach). However, the profit return is confirmed to be greater than the independent development by maintaining $c_o I \leq 1$.

3. Factors influencing the supply chain Performance

In addition to the factors incorporated into the above mathematical model, several other factors are also considered in the framework to improve the performance of the supply chain, though not necessarily in the optimization. They are discussed in this section.

3.1. Process Flexibility in the supply chain: The Concept of Chaining

A firm sets its plant capacities in an attempt to anticipate the future volatile and uncertain demand of the products. This can be done either by planning plant capacity efficiently to meet maximum possible demand, or by imparting the process flexibility.

The investment strategy is costlier and posses a low utilization of the capacity whereas, the process flexible strategy meets the demand efficiently and economically. In this paper, flexibility can be encoded by a bi-partite graph (Jordan and Graves 1995), so that the product assignment decisions are represented through the direct product-plant links.

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Determination of flexibility configuration may be done using a random vector $Dmd =$

$$\left\{ \sum_{f^c}^{F^c} Dmd_{s_{ENDL}} f^c t, \sum_{f^c}^{F^c} Dmd_{s_{ENDH}} f^c t \right\} \text{ and a random variable SF } (Dmd, Arc), \text{ depending on the}$$

demand distribution and flexibility configuration, where Arc_k is the set of all the item-plant links at stage k . A stage corresponds to the processing of a particular kind of physical items of the GBOM, e.g. product variants, function modules, component modules or bill of materials etc. The shortfall is calculated by solving a linear problem for a particular demand realization and a particular determination of the flexibility configuration 'A'. The configuration inefficiency may be defined as a relative increase in the anticipated shortfall due to the interaction of the different stages in the supply chain while configuration loss is due to the inability of the supply chain to be totally flexible (Graves and Tomlin, 2003).

If we consider our supply chain to be a single stage process where we have to process our products at 'Q' number of plants with the total stage capacity 'W' ($= \sum_f^F N_{max}$). Then, an

equal allocation would be to carry the product capacity for each market segment equal to $W/2$. For many subsets of products M , the available capacity in the supply chain $\sum_{q \in L(M)} w_q$ (q is a plant, w_q is the capacity of this plant and $L(M)$ is the set of plants that can process one or more product in the set M), may be greater than that corresponding to the equal allocation. This excess capacity (for subset M) over the equal allocation may be measured in the unit of equal allocation. The excess capacity ($\omega(M)$) can be increased by increasing the product-plant links. The minimum value of the excess capacity, over all the product subsets, for which the number of plants in the set $L(M)$ is less than Q , is defined as the degree of flexibility (μ), i.e.

$$\mu = \min \{ \omega(M) \} : L(M) < Q \quad (29)$$

The configuration loss and the configuration inefficiency undergoes drastic downfall when this degree of flexibility increases from 0 to 1 and minor downfall for further increase (Graves and Tomlin, 2003). So, while designing one should avoid the value of μ

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below 1, so that it makes the configuration inefficiency insignificant. This degree of flexibility can be increased by increasing the number of plants processing any product so that it leads to chaining. In the optimization framework, we keep on increasing the degree of flexibility till we get a value of μ greater than or equal to 1.

3.2 Product and market variety in the supply chain structure

Variety has two basic classes of costs within a supply chain i.e. production and market mediation costs. These costs depend on the structure of the supply chain and the product variety.

An attempt to enhance the product variety is accompanied by an increase in both the production costs and the market mediation costs. The former increases, as the volume splits among the different products while, the latter increases as the demand uncertainty peaks, causing either an increase in replenishment lead time or maintenance of a large quantity of finished goods inventory (Eppen, 1979). The variety is production dominant if an increase in product variety is accompanied by an increase in the production cost which is more than that of the market mediation cost e.g. the variation in the body styles of an automobile. Conversely, the variety is market mediation dominant when an attempt to increase the variety is accompanied by a greater increase in the market mediation costs than the production costs e.g. the variation in color of an automobile.

The structure of a supply chain can be determined by location and scale (operations model approach) or by the degree of outsourcing (economists' approach) (Randall and Ulrich, 2001). Some of the few hypotheses from the literature on the supply chain structure are outlined below that has been adapted in this paper (Randall and Ulrich, 2001);

- a. Greater scale efficiency leads to greater production dominant variety than lesser scale efficiency
- b. Local plants with respect to target markets generates larger market mediation dominant variety

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- c. Matching of production dominant variety with the scale efficient production and matching of the market mediation dominant variety with local plants leads to firm's better performance.

Table 1 shows the impact of the scale efficiency and location of the plants and facilities with respect to the target market. Coefficient of scale economy may be used to distinguish between scale efficient ($\alpha \geq .6, say$) and scale inefficient ($\alpha \leq .3, say$) plants. Local and distant location may be distinguished using a mean distance strategy. In this strategy, the sums of the distances between each of the different manufacturing facilities and the customer facilities are calculated. Thereafter, the mean of these sums are computed, which is denoted by DIS_{mean} . This parameter is utilized to evaluate the location of a facility in terms of the market mediation variety that it will impart to the product. That is, those combinations of the manufacturing facilities are preferred, which have lower values of DIS_{mean} . These are used in the designing of the supply chain discussed later in the sub-section 3.5.

<<Insert Table 1 here>>

3.3 Different flow types in the supply chain

The material flow types between the different facilities for a given supply chain is predefined and must be feasible (Srinivas *et. al.*, 2005). For example, a supplier firm assembles the basic components and the automated components of a product (an AGV in our case) and is finally shipped to the customer facilities (Lamothe et al., 2005). Dani (2006) proposed a new technique, to network the flow of material in the supply chain. At synchronous facilities, component manufacturing, inventory and assembly of the finished products is carried out with the decision of the suppliers. For example, for a supplier connecting the electrical components of a car or an AGV, the supply chain has three kinds of feasible flow types in the supply chain as explained in Table 2.

- a. From automated (computer) and sub-assembly facility to a synchronous facility (ASTS flow).

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- b. From automated (computer) to sub-assembly facility and then from sub-assembly to a synchronous facility (ATSTS flow)
- c. From automated (computer) to a synchronous facility (ATS flow)

<<Include Table 2 about here >>

In Table 2, the existence and direction of the flow between different types of facilities is imitated through the flow indices, 1, 0 or -1, indicating flow from a facility in the row (arranged vertically) to a facility in a column (arranged horizontally). The flow index ‘0’ shows that no material flow takes place between the two facilities, whereas ‘1’ indicates that a flow is in order. The flow index ‘-1’ also indicates the existence of flow, but in the opposite direction.

3.4. Market Diversity parameter

A non-dimensional measure for the market diversity can be defined to indicate the degree of complexity. It incorporates the customer valuation concepts as well as the scale difference between the low and high market segments. Moorthy and Png (1992) were the first to devise this parameter which is mathematically represented as, $Div = (\sum_f N_{s_{ENDH}ft} / \sum_f N_{s_{ENDL}ft}) ((v_h - v_l) / v_l)$. The quantity manufactured of both the consumer products affect the ability of the product architecture to be in agreement with the product diversity in the context of our model. We incorporate the concept of market diversity parameter to measure the performance of the optimization framework and are discussed in Section 6.

3.5. Order of activities for designing the robust supply chain framework

We use GBOM representation to study the different alternatives for the product family, depending upon the child items chosen for the Ex-OR nodes. Then, all the potential and possible locations for each kind of facilities are marked. We term these combinations as

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possible combinations of facilities. Thereafter, the market mediation costs (including the inventory holding costs, product mark down costs and lost sales costs) can be leveraged along with the production costs by evaluating the locations of the facilities with respect to the distance from the customer location and the scale efficiency. Scale efficiency is virtually dependent on the location, since proper scale efficiency can be attained by outsourcing the production to a scale efficient firm. The combinations of the location of the plants are evaluated with respect to the scale efficiency and plant location until the dominated strategy is avoided to enter into the leveraging compromise between the market mediation and production dominant strategy. This is done by evaluating DIS_{mean} and the scale efficiency for the different combinations of locations of manufacturing facilities and finally choosing the one, when a trade-off between the production dominant and the market mediation dominant variety is reached. That is, both kinds of varieties are increased until we escape the dominated strategy (low production dominant variety and low market mediation dominant variety). A benchmark is set for the dominance of the market mediation by making DIS_{mean} bounded above by a limit. So is done for the dominance of the production on the product variety by making the scale efficiency bounded below by a limit. This leads to the combination of plant location which can be taken as a part of the sample space and from which selection of the plants, facilities, shipping paths, etc. is to be done. We term this combination as a variable combination of facilities, as our decision variables are encompassed in this combination.

Thereafter, the process flexibility is imparted to the supply chain by increasing the product plant links under chaining strategy and the degree of flexibility is measured. This is continued until we get a value of the degree of flexibility greater than or equal to 1. In addition to the process flexibility, it also grants scale efficiency. It increases the production capacity of the supply chain, but enables the firm to enjoy the ability to suffer huge configuration losses (Graves and Tomlin, 2003). Then, the algorithm is implemented to compute the optimal values through the implementation of Genetic Algorithm. Finally, one or more of the flow types are deployed to design the supply chain so as to materialize the manufacturing and supply activities. These activities are shown via a flow chart in Figure 2.

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<<Include Figure 2 about here >>

4. Experimental Evaluation

Some experiments have been carried out on a wiring harness supplier problem of an AGV manufacturer that performs the task of connecting all the electrical and electronic components of the AGV. The components include connectors, relays, fuses, computer etc. that are to be connected and assembled. The fundamental set of these components is very large and same is the functional diversity. There are five functional requirements of an AGV i.e. driving system, carrying system, supporting system, monitoring system and sustaining system. The tasks performed by these functional requirements are indicated in Figure 3.

The wiring harness supplier connects all the electrical and electronic components of the AGV. Therefore, in order to simplify the calculations we make an assumption that three grand functional requirements are to be considered in the problem. The three main functional requirements assumed are, the driving and carrying function (F1), the supporting function (F2) and the monitoring and controlling functions (F3) as depicted in Figure 3. The consideration of the modular function architecture becomes even more vital in the case of a highly automated product like AGV. To interlink the optimum number of function modules in a determination problem with the GBOM, we assume that the latter to be a combinatorial problem, in which three combinations are possible viz. F1, F2 and F3 in a single module; two modules, one with F1 and F3 and other with F2; and the three modules each comprising of one functional requirement (Figure 4). This can be done by setting the correlation level at $l=2$ (with number modules at this correlative level, $\theta_l=2$). Among some of the other nodes in the GBOM, *P-level* denotes the performance level corresponding to a functional module and C-module denotes the corresponding component module.

<<Include Figure 3 about here >>

<<Include Figure 4 about here >>

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While designing the product family, we are left with many design choices (such as one or several computers, motors, etc. with different options for its location) and location or functional based decomposition of the wiring harness. That is, whether to connect computers with the bus or not, to use two or more computers for signal receiving and launching, multiple choices for auxiliary device, etc. Hence, there are many possible variants for the each market segment or each sub-assembly. The proposed model is implemented to resolve this problem in which two types of AGV are manufactured, one targeted to the lower market segment (*Market frag.1*) and other to the higher segment(*Market frag.1*). This is done by limiting the number of versions of computers, for example, more for the lower segment than for the higher segment and likewise. The effective performance level for each of the lower segment AGV and the higher segment AGV are to be determined by making children choices for the Ex-OR nodes.

As evident from the GBOM, the higher segment can be served at any one of the two possible performance levels (corresponding to the two variants denoted), while the lower segment can be served at any one of the four possible values of performance levels. Overall, we have eight possible product families that are possible, from which one having the best trade-off between the supply chain cost, sales profit and the design complexity (functional) is to be selected. The variants are materialized by assembling it from the basic components (from 1 to 10) and the computer components (11 to 15).

Different combinations of these numbers in the GBOM indicate the bill of materials of the components of AGV connected by the wiring harness supplier. These combinations are made to be located at the leaves of the GBOM. Different versions of computers are used for the lower and higher segments, though some are common along with other basic components. The common components include platform components manufactured on common platforms whereas the unique ones represent the non-platform components in the GBOM.

The simulated problem gathers 7 manufacturing facilities (for basic components) and 2 synchronous facilities, each dedicated to a customer and the time periods over which

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demands are made and are taken to be 2. The mandatory data is simulated and the optimization task is performed through genetic algorithm, with arithmetic genetic operators and variable penalty over the simulated data, as discussed later in section 5.

Before solving the optimization problem, the planning involved in setting the locations for all the 7 manufacturing facilities (basic as well as computer facilities) are be done to strengthen the product variety using the hypotheses proposed by Randall and Ulrich (2001). Given the location for customer facilities, all the possible locations for opening sub-assembly, computer and synchronous facilities are marked and the scale efficiency for different combinations of facility location is also evaluated. The different values of DIS_{mean} corresponding to each of the combination of facility locations are calculated. A benchmark is set for the dominance of market mediation by making DIS_{mean} bounded above by a limit. So is done for the dominance of the production on product variety by making the scale efficiency bounded below by a limit. Different possibilities of locations are evaluated based on these benchmarks, till the dominated strategy is escaped. This task can be accomplished through a linear programming. Thereafter, chaining is done to impart the process flexibility to the supply chain by assuming that each of the items can be processed in at most three plants, to realize the process flexibility with a degree greater than or equal to 1. This can be done using equation 29 and the methodology discussed in sub-section 3.3.1.

After imparting the process flexibility, the value of η_{max} changes, i.e., the production capacity of the AGV wiring harness supplier also changes. This task can be accomplished manually or through the computer programming. Though increasing the value leads to a higher investment cost, but it also strengthens their ability to tackle those effects of the lost sales. Particularly, by attaining a flexibility measure greater than or equal to 1 reduces the configuration losses drastically (Graves and Tomlin, 2003). Further, the final computation of the optimized value of the objective function (through GA as discussed in the next section) and corresponding decision variables are exploited to realize the facilities, shipping paths, items selected and the net requirement of different items associated (manufactured or stored as the case may be) with each of the items at each

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facility or shipped from one facility to the other. Genuine flow types are utilized to emulate the shipping and the flow conservation of different items in the finally designed supply chain.

5. Methodology and Measures

In the large size DFSC problems, optimization techniques such as the mixed integer linear programming may face oscillatory problems leading to a slower solution time. Genetic algorithm has been applied to resolve many optimization problems and hence can be applied to this problem. In GA, stochastic instead of the deterministic rules searches the solution (Stockton, 2008). This helps to escape from the local optima in which other stochastic algorithms might get entrapped (Goldberg, 1989; Onwubolu and Kumalo, 2001; Millas and Vosniakos, 2008; Chan and Kumar, 2009).

Genetic Algorithm, which combines the adaptive nature of the natural genetics or the evolution procedure of the organs with its functional optimization, searches the best chromosome using “the survival for the best” strategy and the random information exchange. The resolution of the solution depends upon the number of bits used to encode a solution. However, the larger the number of encoding bits, the slower is the convergence. To ensure a speedy convergence, as well as a large resolution, we utilize an integer coding scheme for the chromosome representation. The different nodes in the GBOM, the facility location and the shipping paths are all numbered and coded along with other decision variables as per the scheme.

The cross-over operation is in fact a structured recombination operation and a very crucial component of the GA. Our approach applies to a special case of arithmetical cross-over viz. intermediate crossover (Schwefel and Rudolph, 1995). If $\mathbf{x} = \{x_1, x_2, \dots, x_n\}$ and $\mathbf{y} = \{y_1, y_2, \dots, y_n\}$ be two parent chromosomes then the offsprings are

$$\mathbf{x}' = \lfloor \lambda_1 \mathbf{x} + \lambda_2 \mathbf{y} \rfloor \quad (29)$$

$$\mathbf{y}' = \lfloor \lambda_2 \mathbf{x} + \lambda_1 \mathbf{y} \rfloor \quad (30)$$

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$$\lambda_1 + \lambda_2 = 1, \quad \lambda_1 > 0, \lambda_2 > 0 \tag{31}$$

Where, λ_1 and λ_2 are multipliers and $\lfloor \cdot \rfloor$ denotes the greatest integer function such that the chromosome $\mathbf{x}' = \{\lfloor \lambda_1 x_1 + \lambda_2 y_1 \rfloor, \lfloor \lambda_1 x_2 + \lambda_2 y_2 \rfloor, \dots, \lfloor \lambda_1 x_n + \lambda_2 y_n \rfloor\}$ and likewise for the $\mathbf{y}'$. In case of intermediate crossover, we have $\lambda_1 = \lambda_2 = 0.5$ so that the probability of generating infeasible offspring is less than the other arithmetical crossover operators.

Though random information exchange takes place during the crossover but the creation of new genetic material is deficient. However, this purpose is served by the mutation operator. Mutation can be uniform or non-uniform or dynamic. For a given parent $\mathbf{x}$, if the element x_k is selected for mutation, the resulting offspring is $\mathbf{x}' = \{x_1, \dots, x'_k, \dots, x_n\}$ where x'_k is randomly selected from two the possible choices,

$$x'_k = x_k + \nabla(\text{gen}, x_k^U - x_k) \quad \text{or} \quad x'_k = x_k - \nabla(\text{gen}, x_k - x_k^L) \tag{32}$$

The function $\nabla(\text{gen}, y)$ is given as follows

$$\nabla(\text{gen}, y) = \lfloor y.r. (1 - \text{gen}/\text{gen}_m) \rfloor \tag{33}$$

Where ‘gen’ is the generation number or iteration number, gen_m is the maximal generation number, r is a random number from $[0, 1]$ and d is the degree of non-uniformity. As evident from the expression of $\nabla(\text{gen}, y)$, the mutation operator initially searches uniformly and locally at later generations.

The implementation in the GA is done through fitness functions. Constraints have to be handled using the rejection, repairing or penalty strategy. Penalty strategy can be implemented via constant penalty or variable penalty. We engage a variable dynamic penalty function devised by Joines and Houck (1994). Let our DFSC problem be represented in terms of the chromosome (vector) $\mathbf{x}$ as follows,

$$\text{Minimize } F(\mathbf{x}) \tag{34}$$

$$\text{Such that } G_i(\mathbf{x}) \geq 0, \quad i = 1, 2, \dots, m_1 \tag{35}$$

$$H_i(\mathbf{x}) = 0, \quad i = m_1 + 1, m_1 + 2, \dots, m (= m_1 + m_2) \tag{36}.$$

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Then the addition form is taken as the evaluation function,

$$eval(\mathbf{x}) = F(\mathbf{x}) + P(\text{gen}, \mathbf{x}), \quad (37)$$

Where $P(\text{gen}, \mathbf{x})$ is given by

$$P(\text{gen}, \mathbf{x}) = \Gamma_{\text{gen}}^A \prod_{i=1}^m D_i^B(\mathbf{x}) \quad (38)$$

and A and B are the parameters to adjust the scale of penalty value. The term Γ_{gen} and

$D_i^B(\mathbf{x})$ stands for the variable penalty factor and the penalty for violation of constraints such that they are given respectively by,

$$\Gamma_{\text{gen}} = C \cdot \text{gen} \quad (39)$$

$$\begin{aligned} D_i^B(\mathbf{x}) &= 0, && \text{if } \mathbf{x} \text{ is feasible,} \\ &= |G_i(\mathbf{x})|, && \text{otherwise for } 1 \leq i \leq m_1, \\ &= |H_i(\mathbf{x})|, && \text{otherwise for } m_1 + 1 \leq i \leq m \end{aligned} \quad (40)$$

Where C is a constant

The penalty on infeasible chromosome is increased along with the evolutionary process because the variable penalty factor varies with the iteration of the GA. In order to put emphasis on the “best” chromosome and speed up the convergence, fitness value is normalized as follows.

$$FIT = K/eval(\mathbf{x}) \quad (41)$$

Where ‘K’ denotes the scaling constant

The necessary data for the wiring harness supplier problem for an AGV manufacturer are simulated. While designing, the coefficient of the AGV targeted at the lower market segment is considered to be 3. The integration coefficient and the coefficient of scale economy of non-platform units of AGV are considered to be 0.5 and 0.4 respectively. In the supply chain, the manufacturing facilities for basic components or the sub-assembly facilities are indexed from 1 to 5, while the computer facilities are indexed 6 and 7. The synchronous and the correspondingly dedicated customer facilities are indexed through 8, 9, 10, and 11 respectively. The feasibility of the three functional technologies viz. F1, F2 and F3 of the AGV are taken to be 0.6, 0.8 and 0.7 respectively. The duration of the time

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period for the DFSC problem is taken as 365 days. The other mandatory data are simulated randomly using a uniform distribution. The costs are measured in millions of a currency and time in days or fraction of π^T . The ranges for different parameters are as follows.

$$\begin{aligned} \Phi^e &\in [1,10], \quad \Psi_f^{open} \in (131,150), \quad \Psi_{rf}^{open} \in [7,21], \quad \Pi_{fe}^{path} \in [40,70], \quad \Omega_{sf}^{req} \in [12,25], \\ \Gamma_{sf}^{req} &\in [5,13], \\ \Delta_{sf}^{req} &\in [8,20], \tau_{sf}^{manuf} \in [0.05,0.15], \tau_{sf}^{get} \in [0.1,0.7], \tau_{sfe}^{ship} \in [0.02,0.07], Dmd_{sf^c_t} \in [21,60], \text{ and} \\ \pi_{rs} &\in [0.20,0.52] \end{aligned}$$

The Cross-over and mutation rates were set at 0.6 and 0.03 respectively, and an exclusive strategy was followed. This algorithm was coded in C++ language and the results obtained are discussed in the next section. The optimal decision variables obtained are utilized to design the supply chain using an appropriate flow types.

6. Result and Discussions

For the convenience during the experimentation, the objective function value for each solution was converted into a fitness value. The optimal fitness value after converging through the GA in 1000 generations was found to be 164.051. The optimum product family of AGV selected for this solution is shown in Figure 5. The optimum number of modules is found to be 2, in which one module comprises of the driving and carrying function (F1) and the monitoring and controlling functions (F3) whereas the other one comprises of the supporting function (F2). Therefore, the intuition that implementing the component modularity as well as the function modularity raises the complexities in design is overcome by the minimization of the complexities, which strengthens the designing strategy by choosing an optimal function module type. The market diversity parameter is found to be 0.24, i.e. the optimal quantity of the products manufactured has low relative amount and the higher end product per unit difference valuation of the two market segments. For the supply chain, the binary decision variables corresponding to the existing facilities, shipping channels, etc. obtained after optimization are exploited to design the supply chain. The designed supply chain is shown is Figure 6.

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The weighted objective function is optimized using the GA as described in the last section. The corresponding convergence curve is shown in Figure 7.

<<Include Figure 5 about here >>

<<Include Figure 6 about here >>

<<Include Figure 7 about here >>

For the product development issue, a computational analysis of the proposed DFSC problem is done by studying the variation in the market diversity attained by varying the coefficient of the scale of economy of non-platform units.

The value of market diversity parameter is found to increase, as the value of coefficient of scale of economy for non-platform units of AGV is increased. This affirms the trade-off benefits of the platform based product development with the elements of function as well as the component modularity as shown in Figure 8. However, at very large non-platform economies of scale market, diversity suffers some falls indicating the lesser suitability of the platform based product development in ensuring the appropriate market diversity. In this situation the optimum fitness value obtained decreases, resulting in undesirable increase in the supply chain cost and decrease in the profit. Computing the values of the market diversity for three different values of the lower and higher AGV consumer segment valuation (v_l and v_h respectively), the variation of the market diversity parameter is observed. Consequently, the most competent value of the market diversity is observed at the intermediate difference between the valuations of two consumer segments and intermediate scale of economies. However, promising results are obtained in the case of intermediate values for differences even at high non platform economies of scale, as compared to the results obtained for a very small or large valuation difference at large economy of scale.

<<Include Figure 8 about here >>

6. Conclusions

In this research a design framework for the robust supply chain considering the process flexibility, dominance of production planning and marketing mediation over the product variety has been proposed. The main objective of the proposed framework was to minimize the supply chain costs, the degree of design complexity and maximize the sales profits of the end products. The paper also proposes a platform based product development strategy to reduce the product development cost by using mixed market-modular strategies. The corresponding model helps to target the products to an appropriate market segment and select optimum prices. The outcome from the simulated case study can be utilized to design the supply chain and select the product family. The framework, thus, certainly acts as a decision support system while designing a robust supply chain from several viewpoints.

The computation has been kept flexible using a stochastic algorithm i.e. GA, for which several other algorithm can also be used that obviously draws further research attention. In future, the model can be extended considering the time and cost functions. The effect of financial costs (duties, taxes, exchange rates) may also be incorporated in the model. Moreover, the information flow plays a significant role in the different aspects of the supply chain and in the product development. Hence, the future work may involve designing a multi-agent supply chain framework for the product development.

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REFERENCES

- Bernard, A. and Xu, Y., An integrated knowledge reference system for product development, *CIRP Annals - Manufacturing Technology*, 2009, 58 (1), 119-122
- Blackhurst, J., Wu, T., O'Grady, P., Network-based approach to modeling uncertainty in a supply chain, *International Journal of Production Research*, 2004, 42 (8), 1639-1658
- Stonebraker, P. W., Restructuring the bill of material for productivity: a strategic evaluation of product configuration, *International Journal of Production Economics*, 1996, 45 (1-3), 251-260
- Chan, F. T. S. and Kumar, V., Performance optimization of a leagility inspired supply chain model: a CFGTSA algorithm based approach, *International Journal of Production Research*, 2009, 47 (3), 777-799
- Dani, S., Supply Chain Architecture-A Blueprint for Networking the Flow of Material, Information and Cash, *International Journal of Production Research*, 2006, 44 (2), 417-418
- Desai, P., Kekre, S., Radhakrishnan, S., Srinivasan, K., Product differentiation and commonality in design: balancing revenue and cost drivers. *Management Science*, 2001, 47 (1), 37-51
- Eppen, G., Effects of centralization on expected costs in a multi-location newsboy problem, *Management Science*, 1979, 25, 498-501
- Goldberg, D. E., Genetic Algorithms in Search, Optimization and Machine Learning, *Addison-Wesley Longman Publishing Co., Inc.*, 1989, Boston, MA
- Graves, S. C. and Tomlin, B. T., Process flexibility in supply chains, *Management Science*, 2003, 49 (7), 907-919
- Jain, V., Tiwari, M. K, and Chan F. T. S., Evaluation of Supplier performance using a fuzzy based approach, *Journal Manufacturing Technology Management*, 2004, 8, 735-744
- Jiao, J., Tseng, M. M., Ma, Q., and Zou, Y., Generic bill-of-materials-and-operations for high-variety production management, *Concurrent Engineering*, 2000, 8 (4), 297-321
- Joines, J., and Houck C. R., On the use of non-stationary penalty functions to solve nonlinear constrained optimization problems with GA's, *Proceedings of the First IEEE*

Yadav et al.

Conference on Evolutionary Computation, IEEE World Congress on Computational Intelligence, Orlando, FL, 1994, 2, 579-584

Jordan, W. C., and Graves, S. C., Principle on the benefits of manufacturing process flexibility, *Management Science*, 1995, 41 (4), 577-594

Krishnan, V., and Gupta, S., Appropriateness and impact of platform based product development, *Management Science*, 2001, 47 (1), 52-68

Lamothe J., Hadj-Hamou, K., and Aldanondo, M., An optimization model for selecting a product family and designing its supply chain, *European Journal of Operational Research*, 2006, 169 (3), 1030-1047

Robertson, D., and Ulrich, K., Planning for product platforms, *Sloan Management Review* (summer), 1998, 39 (4), 19-31

Millas, V. S. and Vosniakos, G. C., Transfer batch scheduling using genetic algorithms, *International Journal of Production Research*, 2008, 46 (4), 993 - 1016

Moorthy, K. S. and Png, I. P. L., Market Segmentation, Cannibalization, and the Timing of Product Introductions, *Management Science*, 1992, 38 (3), 345-359

Oden, H., Langenwalter, G., and Lucier, R., Handbook of material and capacity requirements planning. *McGraw-Hill*, 1993, *London*

Onwubolu, G. C. and Kumalo, T., Optimization of multipass turning operations with genetic algorithms, *International Journal of Production Research*, 2001, 39 (16), 3727 - 3745

Pahl, G., and Beitz, W., Engineering design: a systematic approach. 1988, *Springer, London*

Randall, T. and Ulrich, K., Product variety, supply chain structure, and firm performance: analysis of the U.S. bicycle industry, *Management Science*, 2001, 47 (12), 1588-1604

Sanchez, R. and Mahoney, J. T., Modularity, flexibility, and knowledge management in product and organization design, *Strategic Management Journal*, 1996, 17 (10), 63-67

Schwefel, H. P. and Rudolph, G., Contemporary evolution strategies, Advances in artificial life, in *Advances in Artificial Life. 3rd Int. Conf. on Artificial Life* (LectureNotes in Artificial Intelligence, vol. 929), F. Mor'an, A. Moreno, J. J. Merelo, and P. Chac'on, Eds. Berlin, Germany: Springer, 1995, 893-907

Yadav et al.

Srinivas, Dashora, Y., Choudhary, A. K., Harding, J. A., Tiwari, M. K., A cooperative multi colony ant optimization based approach to efficiently allocate customers to multiple distribution centers in a supply chain network, *ICCSA, Lecture Notes in Computer Science*, 2005, 3483, 680-691

Stockton, D. J., Khalil, R. and Finch, J. A., Control point policy optimization using genetic algorithms, *International Journal of Production Research*, 2008, 46 (10), 2785 - 2795

Tsai, Y. T. and Wang, K. S., The development of modular-based design in considering technology complexity, *European Journal of Operational Research*, 1999, 119 (3), 692-703

Ulman, D. G., The mechanical design process, *McGraw-Hill*, 1992, New York

Xie, S. Q., Xu, X., and Tu, Y. L., A reconfigurable platform in support of one-of-a-kind product development, *International Journal of Production Research*, 2005, 43 (9), 1889-1910

Zimmermann, H. J., Fuzzy set theory and its applications, 2nd ed., *Kluwer Academic Publishers, Boston, Dordrecht, London*, 1991

Figure 1: A tree representation of the Market and modular approaches

Figure 2: Flow chart of the order of activities in designing the supply chain

Figure 3: Functional representation of an AGV

Figure 4: A GBOM for AGV product family selection

Italics - logical items
Normal - physical items

Figure 5: A PF-Tree for AGV

Figure 6: The designed supply chain for the best solution

Figure 7: The convergence plot

Figure 8: Market Diversity versus Economies of Scale by the supplier

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Table 1: Impact of scale efficiency and plant location on variety

	Scale efficiency/location w.r.t market			
	Distant /inefficient	Distant	Local/inefficient	Local/efficient
	(Dominated strategy)	/efficient		(Dominant strategy)
Production dominant variety	0	1	0	1
Market mediation dominant variety	0	0	1	1

Table 2: Flow types in the Supply Chain**(a)ASTS flow**

	sub-assembly facility	computer facility	synchronous facility	customer facility
Sub-assembly Facility	0	0	1	0
Computer facility	0	0	1	0
synchronous facility	-1	-1	0	1
Customer facility	0	0	-1	0

(b) ATSTS

	sub-assembly facility	computer facility	synchronous facility	customer facility
Sub-assembly facility	0	-1	1	0
Computer facility	1	0	0	0
synchronous facility	-1	0	0	1
Customer facility	0	0	-1	0

(c) ATS flow

	sub-assembly facility	computer facility	synchronous facility	customer facility
sub-assembly facility	-	-	-	-
Computer facility	-	0	1	0
synchronous facility	-	-1	1	1
Customer facility	-	0	-1	0

Appendix A: Notations list

A	Set of all the logical items
α	Coefficient of scale economy of non platform units
b	Constant
c	Constant
C	Set of all the physical items
$CHLD_p$	Set of all the child items of an item p
d_i	Certainty of i^{th} function technology
c_{req}	Variable cost in storing an item s at a facility f
Δ_{sf}	
δ_s	Binary decision variable for the existence of an item s
e	Index for any manufacturing, inventory facilities or customer facilities
η	Number of modules of all the functions
η_{max}	The maximum number of product the firm can produce
ε_{rf}	Number of resource lines of type r opened at facility f
f	Index for a manufacturing or inventory facilities
f^c	Index for the customer facility
F	Set of production or inventory facilities
F^c	Set of customer facilities
Φ_s^e	Fixed cost of existence an item s
$\bar{H}_{sft}$	Quantity of a physical item s
sI	Coefficient of integration, accounting for integration benefits of platform based product
t	development
k	Constant
χ_f	Binary decision variable for the existence of a facility f
λ_{fe}	Binary decision variable for the existence of a shipping path between facilities f and e
N_{max}	Maximum quantity of any item that can be manufactured, stored or shipped on a time period
N_{sft}	Decision variable corresponding to the net quantity of requirement relevant to an item s at a facility f
N_{spft}	Net quantity required of an item p to make from the child item s
v_h	Valuations of high market segment customer per unit of performance
v_l	Valuations of low market segment customer per unit of performance
Ω_{sf}^{req}	denotes the costs incurred in making an item s at a facility f
p	Index for any item in the GBOM
$PRNT_p$	Set of parent items of an item p
π_{rs}	Time for which resource line r is used for item $s \in S_r$
π^T	Duration of the time period T
Π_{fe}^{path}	Fixed cost of building a shipping path between facility f
r	Index for a resource line type
R	Set of all types of resource lines
ρ	Performance level of product in general
ρ_0	Performance level of the base product (base product is one from which concerned product is derived)
ρ_p	Performance level of the common platform (i.e., performance level delivered through

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	modular components)
ρ_l	Performance level of the product target to the lower market segment (having contributions from platform components as well as non-platform components)
ρ_h	Performance level of the product target to the higher market segment (having contributions from platform components as well as non-platform components)
s	Index for any item (node) in the GBOM
S	Set of items(nodes) in the GBOM
S^+	Set of all the Ex-OR nodes
S^*	Set of all the AND nodes
S_c	Set of those items which have relevance to a customer, i.e, relevance to a customer facility f^c
S_r	Set of physical items requiring resource type r
S_{sft}	Decision variable corresponding to amount of an item s stored at facility f during the time phase t
Ψ_f^{open}	Fixed cost of opening a facility f
Ψ_{rf}^{open}	Fixed cost of opening a resource line of type r at facility f
t	Index of a time period
T	Set of time periods considered
τ_{sf}^{get}	The percentage of manufacturing and shipping lead time of an item s at facility $f \in F$
τ_{sf}^{manuf}	Manufacturing lead time of item s at facility $f \in F$
τ_{sfe}^{ship}	Shipping lead time of item s at facility $f \in F$ and up to facility $f^c \in F^c$
Γ_{sf}^{req}	Cost of shipping item s between facilities f and e
θ_l	Number of modules at a functional coordination level l
$u_l(i)$	Number of functions contained in i^{th} function module