# Collaborative Evolution of Process Plans in Distributed Manufacturing

Jungyub Woo, Hyunbo Cho Department of Industrial Engineering Pohang University of Science & Technology San 31 Hyoja, Pohang 790-784, Korea Phone: +82-54-279-8243; +82-54-279-2204, Email: woo@postech.ac.kr; hcho@postech.ac.kr

> Boonserm (Serm) Kulvatunyou Manufacturing Systems Integration Division National Institute of Standards & Technology Gaithersburg, MD 20899-8260, USA Phone: 301-975-6775, Email: serm@nist.gov

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## ABSTRACT

Global production has become a new trend in today's competitive business environment in pursuit of lower cost, shorter time-to-market, and better quality. This forces manufacturing enterprises to have separate design houses and manufacturing facilities. The design houses are located at the forefront of customers to respond to the rapidly changing customers' demands. The manufacturing facilities can be placed in the cost and quality-competitive areas. This physical and logical separation between designers and manufacturers (or between upstream manufacturers and downstream manufacturers), however, raises various integration issues. Particular issues addressed in this paper are the framework for representing the data necessary to communicate requirements and objectives of the designer and the methodology for utilizing such data to optimize the business objectives related to production cost and quality. The proposed representation, collaboration framework, and methodology enable design houses and manufacturing facilities to realize the actual benefits of global production. They can scale to accommodate management of loosely integrated supply chains.

## INTRODUCTION

In order to pursue both high customer satisfaction and low production cost, most manufacturers adopt a global production strategy. Careful planning for such strategy can make the value chain more competitive in terms of cost, time, and quality. The emergence of Internet-based e-business standards such as UN/CEFACT ebXML (<u>http://www.ebxml.org</u>) that allows dynamic business relationships to be established is accelerating this trend.

However, the physical and logical separation between designers and manufacturers may raise various integration issues. In a dynamic relationship environment, the designer must first be able to generate a process plan without considering the capability, capacity, and resources specific to any manufacturer. Second, the manufacturers may have difficulties in knowing precise needs of designers beforehand. Third, a proper chain among multiple manufacturers and multiple designers must be established in terms of resource allocation and delivery requirements. Integration between those design houses and manufacturing facilities becomes an issue that requires attention.

The objective of this paper is to propose 1) a framework to the representation and evolution of the designer's plan data that facilitate the integration between designers and manufacturers and 2) an approach to optimally select and allocate the manufacturers. In this paper, we scope our consideration to the process plan, which includes only material removal processes.

# **RELATED WORK**

Classical process planning generates manufacturing instructions necessary for realizing the designed product from the raw material (Cho, 1993). A process plan, represented as an AND/OR directed graph, contains sufficient information to evaluate the manufacturability, manufacturing cost, and product completion time (Wysk, Peter, and Smith, 1995). It is a primary input to the shop floor control system (SFCS), which monitors the progress of an order, makes decisions, and executes the scheduled tasks required to fill the orders (Cho and Wysk, 1995). Although several research projects identified the roles of process planning for shop floor control (Boulet *et al.*, 1991), the design, planning, and manufacturing functions were tightly coupled.

Planning frameworks within a distributed environment have been studied in various disciplines. For example, multi-agent planning is used to generate distributed plans. Coordination between agents is controlled by a global plan specifying all actions and interactions between agents (Ulieru *et al.*, 2000). Many planning strategies have also been researched. A strategy presented by Joo and colleagues in 1998 uses a real-time parameter optimization technique. This technique organizes a frame of parameters, which is then adapted based on real-time information. However, this research focused on a specific situation, in which information about target resources was known in advance.

A process plan for distributed manufacturing consists of multiple operations and processes with nonlinear ordering, each of which can be performed by several different manufacturers. In this case, the designer needs to generate a Resource Independent Process Plan (RIPP) for unknown target resources. The RIPP is used by upstream manufacturers to collaborate with downstream manufacturers in the supply chain (Kulvatunyou, 2001).

# PROCESS PLANNING IN THE DISTRIBUTED ENVIRONMENT

In the distributed manufacturing environment, the designer makes a universal process plan, since no information about specific resources of manufacturers is available. This initial plan is called a Resource Independent Process Plan (RIPP), which only indicates implicit works necessary to produce the product. The RIPP constitutes two levels: operations and their precedence relationships at the upper level, and processes and their precedence relationships within each operation.

A process is defined as an activity that changes state of being of the product. Different states of a product may be reflected by its shape, location, quality, etc. Hence, state of being of a product can be changed by machining, inspection, or transportation processes, for instance. A process corresponds to a removal feature (e.g., hole, slot, pocket, etc.) for job shop kinds of parts. For example, if a product consists of three (3) removal features (e.g., two holes and one pocket), the designer can define the three (3) corresponding processes (e.g., "First hole making process", "Second hole making process", and "Pocket making process"). The implicit steps within each of these processes can be identified to produce each feature (e.g., drill and ream or drill and bore for a hole) when manufacturer's specific information is known.

Removal features may have tolerance dependencies. The removal features having high positional repeatability requirements must be manufactured without refixturing; in other words, each of them cannot be manufactured at different manufacturing facilities. If the two hole-making processes have a positional tolerance dependency, they are bound to a single operation. Such requirements necessitate that these processes are bound to a single operation (set-up). That is, an operation consists of a set of

processes, which must be manufactured without refixturing at the same manufacturing facility. Therefore, it is noted that resource-binding (i.e., resource allocation to the RIPP) must be performed at the operation level.

A RIPP typically consists of several operations. These operations defined at the upper level of the RIPP are connected to one another in a non-linear precedence relationships using an AND/OR directed graph. An operation consists of several processes, which may also have non-linear precedence relationships to one another. Hence, a RIPP is a two-level graph. The upper level graph is called an Operation Level Graph (OLG) and the lower level graph is called a Process Level Graph (PLG). Each node in the OLG describes operation type, equipment, work-holding requirements, and a pointer to associated PLG. Each node in the PLG specifies process capability requirements such as type of process, accuracy, and associated geometric entities. An example product and its corresponding RIPP are illustrated in Figure 1.



Figure 1. An exemplary product and its RIPP

The framework used to integrate the designer and manufacturing facilities through virtual space in the dynamic and distributed supply chain environment is illustrated in Figure 2. The designer generates a RIPP corresponding to a design. Then from a public registry, the designer discovers valid manufacturers whose manufacturing capabilities and capacities matched the requirements specified in each operation. We note that manufacturers register their manufacturing capabilities and capacities at the public registry based on their manufacturing resource model. We also note that if the discovery fails, the designer may modify the design and/or regenerate the RIPP. After the discovery, the designer assigns valid manufacturers to the RIPP, which then becomes a Manufacturer-Dependent Process Plan (MDPP).



Figure 2. Planning overview for distributed manufacturing

An evolution of a partial RIPP in Figure 1 into an MDPP is illustrated in Figure 3. Each operation node in the MDPP has multiple manufacturers assigned. It is noted that a manufacturer may be eligible for producing more than one operation. The next step is determining a single manufacturer for each operation through negotiation when multiple manufacturers discovered earlier for each operation. In this step, the designer must send RFQs consisting of manufacturing requirements and then the manufacturers must reply with Quotes that contains manufacturing cost, lead-time, and quality. In order to facilitate this procedure, steps are described in the Preparation of Collaboration Data section to generate a Manufacturer-Oriented Process Plan (MOPP). The designer evaluates each manufacturer based on their quote responses. The designer uses the quote information in association with the MOPP to generate the Distributed Process Plan in the last step. In this research, a heuristic evaluation methodology is proposed and is described in the, through which the designer can obtain a final Distributed Process Plan (DPP). The DPP is the optimal sequence of manufacturers, each of which is assigned to a group of operations that provide the designer with the optimal or near optimal performances of interests such as manufacturing cost, quality, and lead-time.



Figure 3. MDPP transformed from a prototype RIPP

A node in the MOPP, which consists of operations to be produced within a single manufacturer, becomes a unit used to generate the Request for Quote (RFQ). Receiving an RFQ consisting of manufacturing requirements from the designer, the manufacturer analyzes the RFQ and returns a quote that contains manufacturing cost, lead-time, and quality. Then the designer evaluates each manufacturer based on their quote responses. In this research, a heuristic evaluation methodology is proposed and is described in the Evaluation and Determination of the Manufacturers section. The DPP is the optimal sequence of manufacturers, each of which is assigned to a group of operations that provide the designer with the optimal or near optimal performances of interests such as manufacturing cost, quality, and lead-time.

# APPLICATION TO THE AUTOMOTIVE INDUSTRY

At the present, most electronic supply chain collaborations are only possible for cataloged components using electronic catalogs such as Covisint Catalogs from an automotive supply chain hub initiative (Covisint, 2003) and Global Exchange Service Global Product Catalogs (GXS, 2003). In other words, the collaboration is performed using part identification. Such collaboration limits the savings only through management of the ordered quantity. On the other hand, the proposed collaboration approach allows collaboration based on a newly designed part that generates. In addition, it opens the designer/client to a larger set of partners. We believe that this will result in several benefits.

First, a larger and dynamic supplier base provides the designer more opportunity for saving time and cost from design to manufacturing. This opportunity derives from the higher chance to meet suppliers whose capability matched the requirements and whose capacity may be excessive.

Second, larger and dynamic supplier base may provide clients with newer technologies. This opportunity may yield clients who can produce better designs and better quality products.

Third, the capability to establish dynamic relationships enables a client to manage the fluctuating customer demand for customization more efficiently. The cost and manufacturability of a newly designed part can be quickly obtained and necessary changes made.

## PREPARATION OF COLLABORATION DATA

The preparation of collaboration data involves obtaining an MOPP for evaluation from the MDPP. It can be viewed as an information-generation function that provides instructions necessary for the negotiation between a design house and manufacturing facilities. The availability of collaboration data from a MOPP simplifies the RFQ generation process for the design house. In this research, the preparation of collaboration data is decomposed into three procedural steps as shown in Figure 4. The heuristic procedure of the preparation is as follows:

- 1. Pruning: Eliminate from the MDPP such operation nodes and/or initially invalid manufacturers that are not available or deemed uneconomical.
- 2. Expansion: Expand the manufacturer alternatives using the OR-junctions such that each operation node contains only one valid manufacturer.
- 3. Collection: Group the operation nodes that can be produced by a single manufacturer.



Figure 4. Generation of MOPP for preparation of collaboration data

The objective of the pruning step is to eliminate unavailable or uneconomical operations or manufacturer alternatives from the MDPP. As shown in Figure 5, if an MDPP has the number of operations (n) and an operation node ( $O_i$ ) is assigned to a set of manufacturer alternatives (MAS<sub>i</sub>), the designer eliminates the manufacturers that are not currently available, for example,  $M_j$  and  $M_{j+1}$ . Through this step, the size of the MDPP becomes smaller.



\*\* Each of n and m is a natural number.

#### Figure 5. Example of pruning an MDPP

The next step, the Expansion step, is to expand the pruned MDPP by duplicating operation nodes. This implies that an operation node containing multiple manufacturer alternatives is duplicated as many as the number of manufacturer alternatives. The duplicated nodes are joined together with SPLITS-OR and JOIN-OR type nodes. For example, if an operation node  $(O_i)$  in Figure 5 has *m* manufacturer alternatives, the node is duplicated *m* times into  $(O_{i1},...,O_{im})$  as shown in Figure 6. Then each duplicated operation has the same information but different manufacturer  $(M_1,...,M_m)$  assigned. The result of the expansion step is an expanded MDPP, in which each operation node is associated with only one manufacturing facility.



\*\* Each of n and m is a natural number.

#### Figure 6. Expansion of an MDPP

Next step, the collection step, the operations that can be performed at the same manufacturer are grouped together in the interest of reducing the transportation and handling costs. This step generates an MOPP, in which each node contains the set of operations to be performed at a single manufacturing facility. For example, if manufacturer  $M_1$  can manufacture two operations ( $O_a$ ,  $O_b$ ), group node  $G_j$  is generated as shown in Figure 7.



Figure 7. Generation of an MOPP

# EVALUATION AND DETERMINATION OF THE MANUFACTURERS

The last step in obtaining a DPP is to serialize the MOPP, that is, to remove AND and OR junctions. Removing AND junctions implies that all the manufacturers surrounded with AND junctions are rearranged sequentially, while removing OR junctions implies that a single path is chosen. In particular, the designer cannot request the quotes simultaneously to all the manufacturers surrounded with AND junctions, since the designer does not yet know about the exact state of input part. The part state is known to the designer only after a manufacturer is determined for an operation one by one. Therefore, the sequence of manufacturers surrounded with AND junctions must be constructed by one by one. This produces a large solution space with large amount of information that needs to be generated for each different part state. Hence, obtaining a real optimal solution to this problem can be computationally complex. A heuristic procedure based on local optima is proposed to resolve this situation. The description of the procedure is shown in Figure 8.



Figure 8. Procedure for evaluation and determination of a distributed process plan

If the minimal cost is the performance criterion of interest in serializing an AND junction, a cost matrix can be composed to represent transportation and manufacturing cost. If the number of nodes within an AND junction is n, the cost matrix has  $n \times n$  matrix. As an example in Figure 9, cost  $C_{ij}$  is the summation of the transportation cost between facilities i and j, and the manufacturing cost at facility j.



Figure 9. An exemplary cost matrix

This problem is similar to the TSP (Traveling Salesman Problem) (Murty, 1995). A TSP can be solved using greedy algorithms, one of which is the Nearest Neighbor Heuristic (NNH). The procedure of the NNH can be modified and applied as follows:

- 1) Choose an initial manufacturing facility.
- 2) Determine to the next manufacturing facility that is the most inexpensive from the current facility among the unvisited facilities.
- 3) Repeat step 2) until visiting all facilities.
- 4) Repeat the above steps until all the facilities are chosen as initial facilities.
- 5) Select the best sequence.

Once the AND junctions have been eliminated, Genetic Algorithm (GA) (Goldberg, 1989) is then used to select the best path by removing OR junctions. The GA, one of the derivative-free optimization methods such as simulated annealing and downhill simplex search, is based on the concepts of natural selection and evolutionary processes (Holland, 1975). Unlike gradient descent methods such as artificial neural networks, the GA consumes long computation time to reach the optima due to its iterative nature and randomness. Nevertheless, whether the problem is continuous or discrete, the GA finds the solutions with a proper objective function and the solutions are global optima within the solution space. This characteristic makes the application area of GA widely diverse including, for instance, facility layout design, building design, prediction model parameter estimation, and process parameter optimization. In the basic procedure, generating and evaluating new populations is repeated until a stopping criterion is met. The elitism mechanism is usually adopted to survive the elite chromosomes to the next generation with an elitism portion. The other population of the next generation is generated by the crossover and mutation operators until the total population is generated. The crossover and mutation occur with a probability equal to the crossover rate and the mutation rate, respectively. After meeting a stopping criterion, the chromosome having the best fitness value is the optimal solution.

In our problem, the decimal encoding scheme is adopted to construct a chromosome (namely, a DPP candidate).. A chromosome consists of slots, each of which is a serialized sequence (which is obtained by removing AND junctions in the previous step) among those surrounded with OR junctions. Each slot is encoded with a decimal number. A decimal number represents a serialized sequence in a layer. A population (namely, the predetermined number of chromosomes) is then generated by selecting serialized sequences randomly within each layer. An example of a chromosome encoded with decimal numbers is depicted in Figure 10. That is, a chromosome 3-1-3 represents a linearized graph in which each layer containing serialized sequence number 3, 1, and 3. If sequence number 3 of the first layer represents a sequence of operation 2 and 1, sequence number 1 of the second layer represents a sequence of operation 4, 6, then 5, and sequence number 3 of the third layer represents a sequence of operation 8 and 9, then the 3-1-3 chromosome represents an overall solution of operation sequence 2, 1, 4, 6, 5, 8, and then 9.



Figure 10. Chromosome encoding of an MOPP

Determining a proper fitness function to the target application is critical to success. In our problem, the fitness function is the total cost of each chromosome, since our objective is to minimize the total transportation and manufacturing cost to produce the designed part.

A population generation procedure usually consists of elitism, crossover, and mutation. The crossover and mutation operations in our problem are performed as Figure 11 and Figure 12, respectively. In Figure 11, two types of crossover operators are introduced including one-point crossover and two-point crossover. In addition, the mutation operator replaces some precedence with alternatives.







Figure 12. An example showing the mutation operation

Through the GA algorithm, the best chromosome (representing the DPP solution) is obtained at the last generation. The chosen chromosome must be decoded to a DPP, as shown in Figure 13. The DPP is a serialized process plan, in which each operation node is assigned to only one manufacturer. It should be noted that there might be cases where the best chromosome might not be a feasible DPP due to some dynamic parameters such as manufacturer availability. In such case, the final DPP is selected from the best feasible chromosome among the those in the last generation.



Figure 13. An example of a DPP decoded from a chromosome

# CONCLUSION

The study proposed a heuristic methodology to facilitate evolution and evaluation of process plans in the chain of distributed manufacturing facilities. The designer prepares a Resource-Independent Process Plan (RIPP) for a product. The designer then discovers a set of manufacturers to adequately produce the product based on their resource capacities and capabilities. The proposed method transforms the RIPP at the operation level into the manufacturer-dependent process plan and then the manufacturer-oriented process plan, from which the collaboration data are generated for RFQs (Request for Quotes). Receiving the RFQs, the manufacturers manipulate the process plan to evaluate manufacturability and subsequently compute the manufacturing cost, time, and product quality. Finally, the designer evaluates and determines the best operation sequence and manufacturing facilities based on responses from the manufacturers. In this last step, the traveling salesman problem algorithm and genetic algorithm are used to obtain the optimal sequence. The final operation sequence is represented as a distributed-process plan that can be used to manage the manufacturing chain of the product. The proposed methodology enables the integration of planning and manufacturing in the distributed manufacturing environment. Eventually, it can be used to rapidly and effectively form a virtual manufacturing enterprise.

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