Analyzing Multiple Product Development Projects Based On Information and Resource Constraints

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Abstract

Product development (PD) and engineering design processes are often characterized by the information flowing among activities. In PD, this flow forms a complex activity web—a process that can be viewed as a complex system. Most literature on the subject of information flow in PD focuses on a single project, where precedence information constraints (based solely on necessary information and possible assumptions) determine the execution sequence for the activities and the resultant project lead-time. In this paper, we consider multiple PD projects that share a common set of design resources. Especially in this setting, precedence information availability is insufficient to assure that activities will execute on time. We extend the information flow modeling literature by including resource availability. We model several PD projects as a portfolio, where activity execution is based on both information and resource availability. We demonstrate the effects of accounting for resource constraints on both individual projects' and portfolio lead-time distributions.

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1. Introduction

A fast product development (PD) process can provide a source of competitive advantage [17, 23]. The speed of a PD process is largely influenced by how it is structured and managed. However, managing PD projects has always been a challenge in the manufacturing industry due to the unpredictable nature of engineering design, where design iterations are a pervasive phenomenon. Successful project completion requires repetition and updating of many development activities. Iteration influences PD cost and schedule immensely. Even though particular iterations are not necessarily known with certainty prior to project execution, a skilled manger (equipped with the right tools) can identify many potentially iterative development activities and plan accordingly. Understanding the web of information flow in a project can help identify potential iterations. Unfortunately, many PD managers fail to plan for iterations; consequently, PD projects incur schedule and cost overruns [2, 5] - often forcing them ultimately to sacrifice scope or to fail.

The PD process management problem is compounded when companies manage a portfolio of PD projects at once. In a multi-project PD environment, organizations tend to micromanage their PD portfolio [9, 11, 26]. That is, managers direct attention to one project at a time and allocate resources accordingly, ignoring the interactions and interdependencies between projects. Instead, scarce development resources should be managed from a PD system perspective and allocated to maximize the value of the whole portfolio.

Researchers have suggested many models, tools, and techniques to help managers plan and control PD projects more effectively [22]. One such tool is the Design Structure Matrix (DSM), which provides a means of representing a complex system (such as a process) based on its constituent elements (activities) and their relationships (information flow). DSM-based methods show promising results in managing complex PD processes [10]. However, the DSM literature focuses on a single project and the flow of information within. In the DSM methodology, precedence constraints based on information dependencies determine the optimal execution sequence for a set of activities. In this paper, we introduce an important, new constraint, resources, into the DSM analysis. When we consider multiple, simultaneous development projects within an organization (sharing a common set of design resources), the availability of predecessor information is insufficient to assure that activities will be executed on time. We address resource availability through a project portfolio plan that constrains activity execution based on both information and resource availability.

This paper has two primary purposes. First, we demonstrate that a DSM model can meaningfully represent both multiple PD projects and resource constraints. Second, based on this extension, we develop a simulation model of multiple PD projects, which results in the development of performance measures for each individual project and for the portfolio as a whole.

Resource constraints force choices about which activities to support at a given time. To make this decision, we define a preference function that determines the insertion points of resource constraints in an aggregate DSM representing the entire portfolio of projects. The preference function is used to simulate the mental decision-making process that resources (i.e., project participants or processors) go through when dealing with multiple projects, thereby allowing us to simulate the execution of activities in a multi-tasking environment.

The simulation model presented in this paper provides organizations with an analytical tool to analyze the impact of multi-tasking and resource allocation policies on project and portfolio lead times. This will ultimately assist organizations in the development of better multi-tasking and resource allocation policies.

The paper is organized as follows. Section 2 surveys the literature for existing single and multi-project modeling and management techniques, and Section 3 reviews the DSM methodology. In Section 4, we introduce several modeling constructs that are essential for the building the multi-project model. Section 5 describes how the model is simulated, and Section 6 provides an example with simulation results and sensitivity analysis of some important model parameters. Finally, Section 7 summarizes and concludes the paper.

2. Literature review

A review of project management literature in general, and PD management in particular, reveals the existence of numerous models addressing both single and multiple projects. Perhaps the most visited problem is the well-known resource-constrained-project-scheduling problem (RCPSP) resulting in many exact solutions (all based on a 0-1 integer linear programming formulation) and numerous heuristic procedures. Brucker *et al*. [6] provide a recent, comprehensive review. A natural extension to the RCPSP deals with multiple projects [13]. The major deficiency of the RCPSP formulations in dealing with PD management problems is their inability to address feedback loops that result in the rework of some activities.[1] This literature differs from our paper in a major way. While RCPSP techniques seek to optimize the scheduling of activities based on generic precedence and resource constraints, we are evaluating project lead times using predetermined and fixed project architectures and schedules based on a fuller characterization of information flow.

Other researchers suggest the use of queuing networks [20], Petri nets [14], or stochastic dynamic programming [3] to capture the stochastic nature of information flows in PD processes

[1] Methods such as GERT (Graphical Evaluation and Review Technique) addressed this deficiency by accounting for uncertainties in the sequence of activities in the project (Neumann, 1990). However, GERT charts provide poor visualization of the full information flow in a design process and do not account for multiple projects.

and build corresponding simulation models. For instance, Adler *et al*. [1] analyze an activity network allowing for reentrant queues (to model rework) using a discrete event simulation. The simulation allowed them to identify bottleneck activities and several other process characteristics. Our paper is closely related to this research stream, but contrary to these models that assume stochastic arrivals of activities, instead we assume, at the outset of the simulation, that the number of projects and activities are planned; uncertainty is only found in rework occurrence and activity duration.

Simulation of PD projects has also been used in computational, micro-contingency organization theory by Levitt *et al*. [15]. This research relates to our work even though we focus on project management and Levitt's research focuses on organizational design. Levitt's research employs simulation techniques to understand and predict the effects of alternative organization and work process designs on project performance in complex organizations. In order to simulate a project in an organizational setting, Levitt and his research team define a set of attributes that describe the project activities, the project participants, communication between participants, and the organizational structure. Similarly, our simulation employs attributes for activities, projects, and personal preferences to build the processor preference function. We are interested in understanding how the preference dynamics of PD participants involved in multiple projects influences PD performance.

Another related research stream is multi-criteria methods for project selection [4], usually in R&D environments [16, 24]. These techniques utilize a set of measures to evaluate each project within a portfolio and then calculate a weighted utility measure for each. This allows the prioritization of the projects. However, this approach utilizes little if any information about the efficiency of each project's PD process architecture. In this paper, we utilize a similar technique to build a preference function that determines resource priorities at each time step of the simulation, thus combining these multi-criteria techniques with information flow simulation techniques.

Finally, our model relates to the critical chain methodology developed by Goldratt [11]. Goldratt established a set of generic rules to improve multi-project performance that include, in addition to buffer management, avoidance of resource multitasking. He conjectured that resource multitasking results in lead time increase due to the lack of clear priority, but he did not show how to measure these priorities in order to eliminate possible resource confusion. In this paper, we explicitly account for different priorities in a multitasking environment.

3. The Design Structure Matrix (DSM) Model

DSM-based models have been used to represent the technical relationships between design activities in complex PD projects. The simplest DSM model of a design project is a binary, square matrix with n rows and columns, and m non-zero elements, where n is the number of activities and m is the number of dependencies between the activities. Activity names are listed down the left side of the matrix as row headings and across the top as column headings in the same order. If activity i depends on activity j, then the value of element ij (row i, column j) is unity (or marked with a '■"). Otherwise, the value of the element is zero (or left empty). In the binary matrix representation, the diagonal elements of the matrix do not have any interpretation in describing the project, so they are usually either left empty or blacked out. Sample DSMs are shown in Figure 1. In this convention, subdiagonal elements in the DSM represent feed-forward information flows among the activities and superdiagonal elements represent feedbacks.[2] Feedback information flow captures much of the iteration and rework potential in a design project.

[2] Some DSMs use the opposite convention—showing feedback below the diagonal—which conveys equivalent information.

The DSM model can be used to determine an improved sequence for the design activities [10]. Reordering the activities within the DSM can eliminate or reduce the number and impact of feedback loops in the project. Partitioning[3] is the process of resequencing the DSM rows and columns such that the new DSM arrangement contains minimal feedback marks—i.e., towards lower-triangular form. For complex engineering projects, it is highly unlikely that mere row and column manipulation will achieve a complete lower-triangular form. Therefore, the analyst's objective changes from eliminating the feedback marks to moving them as close as possible to the diagonal (this form of the matrix is known as block triangular). In doing so, fewer activities will be involved in iteration cycles, resulting in a faster and more predictable development process. Figure 1b shows the result of partitioning the DSM in Figure 1a.

The partitioned DSM (Figure 1b) shows the existence of three iterative blocks (the highlighted squares along the diagonal): A-E-J, B-H-I, and D-G. The activities included in a block are coupled and are candidates for iteration. For example, consider the execution of the activities within block (B-H-I) and assume that all activities prior to activity B are completed. Activity B requires inputs from activities C and A (already completed) and activity I, which is not completed yet. Therefore, activity B starts with missing information (perhaps making a guess on the value required from activity I). Once activity B is completed, it delivers its output information to both activities H and I. When activity I finishes its original work, it delivers its output information back to activity B (as represented by the feedback mark in the block). At this point, activity B reevaluates its earlier results in light of the new information received; thus, activity B might or might not need to perform another iteration (some rework). If iteration is performed by activity B, then we refer to it as first-order rework. Due to the coupled nature of the block, second-order rework is also possible. That is, if activity B, which feeds activities H

[3] Also referred to as block diagonalization or block triangularization of the DSM.

and I, is reworked, then there is a chance that either activity H, activity I, or both will also need to be repeated. This is called second-order rework. If activity I is reworked, then the iterative process, described above, might be repeated several times, resulting in higher-order rework.

Several extensions to the base DSM model have been proposed to include more information in the matrix (e.g., [5, 7, 28]). Reviewing all of these extensions is outside the scope of this paper. However, one such extension directly related to this paper is a method to perform Monte Carlo simulation on the DSM [28]. The DSM simulation model characterizes the design process as being composed of activities that depend on each other for information. Changes in that information cause rework. As discussed earlier, rework in one activity can cause a chain reaction through supposedly finished and in-progress activities. Activity rework is a function of rework risk, which combines the probability of a change in inputs and the impact this change might have on the dependent activities. The impact measure used in the simulation represents the fraction of the original work (i.e., activity duration) that needs to be repeated or reworked. Both probabilities and impacts are numbers between 0 and 1 and they replace the marks in the binary DSM. Thus, the simulation model is represented by two identical DSMs, one containing probabilities of information change and the other containing the impacts of change. In the probability DSM, the superdiagonal marks are replaced by first-order rework probabilities, and the lower-diagonal marks are replaced by second-order rework probabilities. The simulation also accounts for stochastic activity duration by using three point estimates (optimistic, most likely, and pessimistic) to form a triangle distribution. In this paper, we utilize a similar simulation; however, we expand the simulation into multiple projects and include the impact of resource constraints.

4. A Framework for Multi-Project Simulation

This section discusses three modeling constructs employed: aggregate DSMs, project queues, and processor preference functions.

4.1 The Multi-Project DSM Model

In this subsection, we discuss the extension of the single-project DSM to include multiple projects and resource constraints. We refer to the multi-project DSM as the aggregate DSM. Building the aggregate DSM is best illustrated through a simple example. Consider three development projects occurring simultaneously (projects 1, 2, and 3) and involving four development resources/processors (A, B, C, and D), as shown in the top part of Figure 2. Processor A is assigned to all projects as depicted in the Figure by A1, A2, and A3. Processor B is assigned to projects 1 and 2 as depicted in the Figure by B1 and B2. The same representation holds for processors C and D.

The aggregate DSM, shown in the lower part of Figure 2, combines the DSMs for each project. The square marks ("■") inside the aggregate DSM represent information constraints, while the diamond marks ("❖") represent resource constraints. Note that the diamond marks shown in the figure represent only one possible resource constraint profile. The arrangement shown assumes that activities in project 1 are preferred to activities in project 2, and activities in project 2 are preferred to activities in project 3. For example, the diamond mark in row 5 and column 1 conveys that A2 depends on A1 finish for its execution. Inserting this mark in row 1 column 5, instead, would reverse the resource dependency. In general, if a processor is assigned to *p* projects, then there are (*p*!) possible priority profiles for that processor.

The aggregate DSM provides managers of multiple projects a simple snapshot of the whole development portfolio, allowing them to clearly see and trace information dependencies within projects and across multiple projects, while explicitly accounting for resource contention.[4] Partitioning the aggregate DSM reveals an improved information flow and clear resource prioritization across the whole PD portfolio as compared to independently partitioning the individual project DSMs.

4.2 Project Queues

Each processor can be involved in multiple activities (from the same or different projects), but they can only work on one project's activity at any given moment. The list of activities from different projects is called the project queue for a processor. We will refer to each processor's project queue as Q_i, where i is the processor index. At any time, t, $Q_i(t)$ consists of two mutually exclusive and collectively exhaustive partitions: $A_i(t)$ and $I_i(t)$.

The processor's active queue, $A_i(t)$, contains a subset of $Q_i(t)$ that is readily available for work (based on predecessor information availability only) at time t. The processor must choose one of these activities to work on. The inactive queue, $I_i(t)$, contains all other activities. Recall that coupled activities are those activities involved in an iterative block. A work policy is used to allocate coupled activities to either $A_i(t)$ or $I_i(t)$ based on how the activities are sequenced in the DSM (the process architecture determined by partitioning). The first activities in the coupled block make assumptions about the later activities' inputs and are assigned to $A_i(t)$.

[4] In this paper we assume no information dependencies (only resource constraints) between projects, but the aggregate DSM can accommodate such dependencies by allowing the insertion of a combination of square and diamond marks outside the individual projects blocks.

4.3 The Preference Function

If a processor is assigned to two projects and it can perform work on either one, at a given instant in time, the choice is made based on a preference function that includes activity, project, and processor characteristics. The preference function addresses the following concerns:

a. When faced with a choice, which activity (in which project) should a processor work on?

b. What is the impact of the above decision on PD time?

The preference function (or priority profile) ranks the activities in processors' active queues, so that the activity with the highest priority is selected to work on. Preference or priority is a function of activity, project, and processor attributes. The attribute hierarchy is shown in the tree of Figure 3. Determining how to weight the attributes requires conducting interviews with the processors involved in the different projects to solicit their mental value model they use when determining activity priorities. For an extensive explanation of the method we used for building the attribute hierarchy and selecting convenient attribute measures, the reader is referred to Keeney's book on value focused thinking [12]. Our preference function consists of a weighted combination of the eight attributes listed and discussed in Table 1.

Each branch, i, in the attribute hierarchy (Figure 3) has a weight, k_i, and a utility or preference value, U_i, which is a function of the attribute level, x_i. The utility functions or curves used are shown in Figure 5. To arrive at an overall preference index for each activity, we use a weighted sum: $U(x_1, \ldots, x_n) = \sum_{i=1}^{n} k_i U_i(x_i)$. Each utility curve is defined over [0,1], and all of the weights are positive and sum to one, so the overall preference index is also defined over [0,1]. Once a preference index is calculated for each activity in a processor's active queue, the activity with the highest preference index is preferred.

Assessing the weight and utility curve for each attribute requires interviews with the different processors. There are numerous assessment techniques suggested in the decision analysis literature. Discussing all such techniques is outside the scope of this paper; however, the interested reader is referred to [8]. The simplest technique is the direct assessment technique, where participants are asked to score each attribute on a scale (say from 0 to 100). Then, these scores are normalized through dividing each attribute's score by the sum of all scores. A more sophisticated assessment can be employed using the AHP method of pair-wise comparisons [27]. Table 2 provides the attribute weights directly assessed by conducting a set of structured interviews with PD project managers from a chemical products manufacturing firm.[5] The single attribute utility functions shown in Figure 5 were assessed during the same interview process using the mid-level splitting method [8].[6]

It is worth noting that we have run our simulations using one set of attribute weights and the same utility curves for all the processors because we recommend conducting interviews for their assessment in a group environment. This will eliminate any biases in the assessment process and achieve group consensus on the attribute weights and the shape of the utility curves. Alternatively, the model can easily be modified to allow for different weights and utility curves for each processor; however, multiple one-on-one interviews will be required instead of the group assessments.

[5] The authors gratefully acknowledge the help of Brad Boersen, an SDM Masters student at MIT, in conducting the interviews for determining the set of relevant attributes, assessing the attributes' weights, and soliciting the shapes of the single utility functions.
[6] Initally, it might be more practical to use linear utility functions (after assessing the end points) instead of expending effort during an interview to solicit non-linear ones. After performing the first round of simulations and conducting some sensitivity analysis to determine if lead times are highly sensitive to the shape of the utility functions, then it will be worth going back to the participants to reassess their utility functions. Otherwise, linear utility functions may suffice.

4.4 Model Assumptions

a. Each project is important to somebody (no consensus on the most important project to work on), so processors must choose which activities to work on based on various criteria.

b. There is a one-to-one correspondence between activities and processors.

c. Projects are independent except for resource constraints (i.e., all marks in the aggregate DSM, outside of the individual project blocks, represent resource constraints).

d. Initially, switching costs / penalties are not considered. However, we later remove this assumption by accounting for switching penalties when a processor begins working on a new activity.

5. Simulating the Model

The simulation is implemented in a spreadsheet model using Excel Visual Basic macro programming.[7] All input information (i.e. project data and the corresponding activity details) is entered into the Excel spreadsheet. Then, the simulation starts by executing the simulation macros. The results of the simulation are displayed as a set of lead-time distributions for each project and for the whole portfolio.

In our simulation, project execution is guided by a specific work policy. We use a simple work policy that requires all predecessor activities to be completed before an activity is eligible to begin work. However, coupled activities can begin work without inputs from downstream activities within their block (by making assumptions about the nature of those inputs). Prior to the beginning of the simulation, the aggregate DSM is partitioned in order to the minimal set of coupled activities.[8] Then, a nominal duration for each activity is randomly sampled from its

[7] The multi-project DSM simulation program can be downloaded from <http://web.mit.edu/dsm/Tutorial/Multiple-DSMs.htm>
[8] We use the partitioning algorithm described in Warfield (1973).

triangular distribution.[9] These sampled durations are saved in a temporary vector for later use within a single simulation run.

Once the DSM is partitioned and nominal activity durations are sampled, the simulation proceeds through increments of time, Dt.[10] At each time step, the simulation must (a) determine which activities are worked on (b) record the amount of work accomplished, and (c) check for possible rework. Determining which activities can be worked requires two steps:

a. Determine which activities are eligible to do work based only on information constraints. Activities that have work to do and for which all predecessor activities are completed (i.e., for which all upstream input information is available) are eligible.
b. Assign eligible activities to their processors, thereby determining each processor's active queue. If any processor has more than one activity in their active queue, then the preference algorithm is invoked to select the activity the processor will address in the current time step. This step essentially entails temporarily inserting additional marks into the DSM that represent processors' preferences for eligible activities.

Each processor's active queue is redetermined at each time step. If it is empty, then the processor is idle. If it contains a single activity, then the processor works on that activity. If the active queue contains more than one activity, then the preference function is invoked to determine which activity the processor will work on. At each time step, the simulation deducts a fraction of "work to be done" from each working activity. Finally, at the end of each time step, the simulation macro notes all activities that have just finished (nominal duration or rework). The macro performs another check to determine the coupled ones by inspecting the partitioned aggregate DSM. For each one of these finished and coupled activities, a probabilistic call is

[9] The triangular distribution for each activity duration is represented by the minimum, likely, and maximum duration values in the input spreadsheet

made to determine whether this activity will trigger rework for other coupled activities within its block. If rework is triggered, then the amount of rework is determined from the impact DSM and added to the "work to be done" on the impacted activity.

A simulation run provides a simulated duration for each project in the portfolio, and for the portfolio as a whole. The simulation is run many times (e.g., 1000 times) to provide a distribution of duration outcomes. A pictorial flowchart for the above algorithm is shown in Figure 6.

6. Example

In this section we illustrate the application of the simulation model. This example consists of three PD projects (numbered 1, 2, and 3) sharing eight development resources (named A through H). The aggregate DSMs showing information dependencies, feedback probabilities, and rework impacts are shown in Figure 7. The three-point duration estimates for each activity and its deadline are shown in Table 3. Table 4 contains project-related input data such as project type, deadline, budget, and cost of delay.

6.1 Simulation Results

The simulation output is represented by a series of lead-time distributions as shown in Figure 8.[11] The first chart (Figure 8a) represents the development time distribution for the whole PD portfolio. The other three charts (Figures 8b, 8c, and 8d) represent lead-time distributions for the individual projects. The solid curves represent time distributions when resource constraints are not accounted for—i.e., assuming unlimited resources. The dashed curves, however,

[10] A discrete event simulation was considered (and could provide a superior approach) but would be more difficult to implement in a spreadsheet without substantial additional coding and/or third party software. The simple, time-advancing simulation suffices to demonstrate the insights of the model.

represent time distributions when activities compete for resources and priorities are assigned to them based on the eight attributes discussed earlier. The shift form the solid curves to the dashed curves represents the strength of resource contention and the degree of error in information flow models that do not account for resource contention. For example, inspecting Figure 8d shows that project 3 was minimally impacted by the resource constraints as compared to projects 1 and 2. Similarly, inspecting Figure 8b reveals that project 1 was the most impacted. The means and standard deviations for all distributions are shown in Table 5.

6.2 Sensitivity Analysis

Sensitivity analysis can be performed on any of the model parameters including activity duration, probabilities of feedback, and rework impacts. In this paper, however, we restrict the sensitivity analyses to those parameters that directly relate to the preference attributes and resource constraints. See [5] for additional sensitivity analyses.

6.2.1 Project Versus Activity Priority Rules

In this scenario, we simulated the example problem using only the *project* attributes in the preference function (i.e., all attributes within the project category were equally weighted, while activity and processor attributes were set to zero). Then, we reversed this scenario by considering only *activity* attributes in the preference function. The results of both simulations are shown in Figure 9a. The figure does not show a major difference between the scenarios. Testing did not show any significant statistical difference between both means and variances.

[11] Simulation used 1000 runs with $Dt = 1$.

6.2.2 Faster Versus Slower Rework Policy

In a similar fashion, the model was modified to shed light on whether processors should react to design changes faster or slower (i.e., rework schedule) and its impact on development lead times. This was accomplished by assigning a relatively high weight to the "rework risk" attribute (other attributes were scaled back) and then running the simulation with two different utility shapes: increasing and decreasing utility functions. That is, at each time step (and for all processors), if there is rework to be done, then it will be a priority to work on. The reverse scenario implements a work policy that prohibits processors from doing rework on any activity unless they have no other work to do. The results of both simulations are shown in Figure 9b. The figure shows that if faster rework policy is implemented in this development environment, then a more predictable development process will be achieved (dashed curve has a relatively smaller variance compared to the solid curve).

6.2.3 Effect of Adding Resources

To assess the impact of adding an extra processor of a specific type (i.e., of type A, B, or C, etc.) on portfolio and projects' lead times, we simulated the portfolio eight times. Each of these eight simulations assumes that there are two processors of a certain type.[12] We increase the capacity of the processors one at a time, while keeping the capacity of the rest of the processors at their nominal values (i.e., one processor of each type). For the processor that has a capacity of two, when faced with a choice to work on more than one activity, it works on the one with the highest priority and the second processor is called upon to perform work on the activity with the second highest priority.[13]

[12] The number of processors available for each type is entered by the user as part of the simulation inputs.
[13] It is worth noting that if the processor with a capacity of two has only one activity to work on at a certain time, then having two processors available to work on the same activity does not reduce the duration of that activity. Only one processor does the work required.

Figure 10 shows the results of the eight different simulations compared to the base case (one processor of each type). The figure shows that the addition of an extra processor (of any type) does not really benefit the project portfolio in general (i.e., reduce mean lead-time). In this example, at the portfolio level, no one single processor is significantly responsible for the delay due to multi-tasking.[14] Similarly, at the project level, projects 1 and 3 would not benefit from such an increase in resources.[15] However, project 2 benefits from adding a second processor of type B (significant reduction in project 2 lead time as marked by the ellipse in the figure).

6.3 Including Switching Costs

Switching between activities typically causes a period of reduced productivity as the processor begins the new activity. We account for this phenomenon by allowing a percentage of the new activity's duration to proceed at 50% efficiency. This percentage (10% for the example)[16] is converted into a number of time steps in which the reduction of the activity's remaining work is only reduced by half its normal amount.

Including the 10% switching penalty resulted in the distributions shown in Figure 11. Contrary to expectation, the lead-time distribution was not shifted to the right due to switching cost penalty. Instead, the two distributions (i.e. "without switching penalty" and "with switching") overlap. The reason for this is due to the fact that none of the activities were preempted during execution and that there was a consistent priority for each activity at every time step of the simulation. Therefore, in this graph, the magnitude of a shift can be viewed as a measure for the amount of preemption that occurred during the execution of the projects.

[14] Of course, this is only true in the case of this example problem, not for any project portfolio.
[15] No statistically significant difference was detected in the means of projects 1 or 3 under the eight different resource configurations.
[16] This percentage is set by the user as part of the simulation inputs.

7. Summary and Conclusion

This paper discusses an extension to information flow modeling to analyze the performance of multiple PD projects sharing a common set of development resources. We utilize a set of activity, project, and personal attributes in order to prioritize executable activities. This preference function is imbedded in a DSM simulation model to build lead-time distributions for the project portfolio and the individual projects.

Some of the model limitations, which could be overcome by possible extensions, are as follows. First, the model assumes that all the projects and their activities are known prior to running the simulation. In some organizations, their PD portfolio evolves dynamically over time and projects are continuously added to and deleted from the portfolio. This situation could be accounted for by revisiting the model at whenever such an event occurs. In fact, the model could help with the analysis of the impacts of such events. Second, projects within the same portfolio might be interdependent through more than shared resources. That is, the success or failure of, or rework in, one project might influence other projects. Our model assumes that projects are only interdependent through shared resources. However, additional dependencies could also be included. Another extension can address PD performance issues resulting from placing a ceiling on the number of projects a processor can be involved in at any point in time. Furthermore, our model does not currently explore overlapping of dependent activities or other alternative work policies. However, the work policy we use could be modified. Finally, the sensitivity of development lead time to changes in attributes' weights could be assessed in more details by designing a full-blown factorial experiment (where each attribute is treated as a factor) and running the simulation for the different factor configurations [18].

In conclusion, the main advantage of the methodology presented in this paper over other traditional multi-project techniques is it allows users to simulate a wide range of possible scenarios in a multi-project environment. These scenarios can include all, or a subset, of the following: (a) feedback structure and process architecture within individual projects, (b) the use of partitioning to arrive at an improved information flow, (c) limited resources shared among multiple projects, (d) project switching penalties or costs, and (e) different preference profiles for activity executions. All of the above features are implemented in a user-friendly, Excel-based environment allowing users to interact with the simulation, adjust its parameters, and perform sensitivity analysis in a very simple manner.

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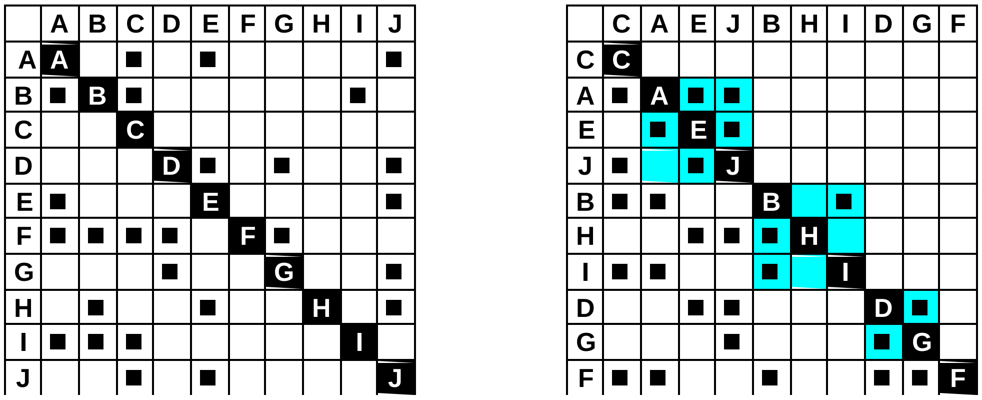


(a) Original DSM

(b) Partitioned DSM

Figure 1: DSM Example

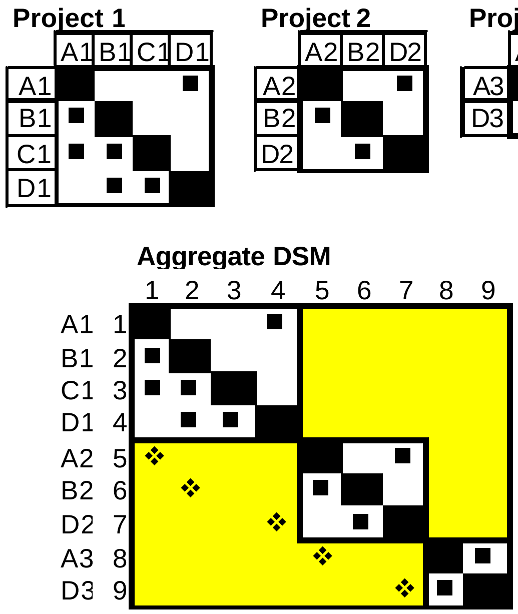


Figure 2: DSM Representation of Three Projects and Their Aggregate DSM

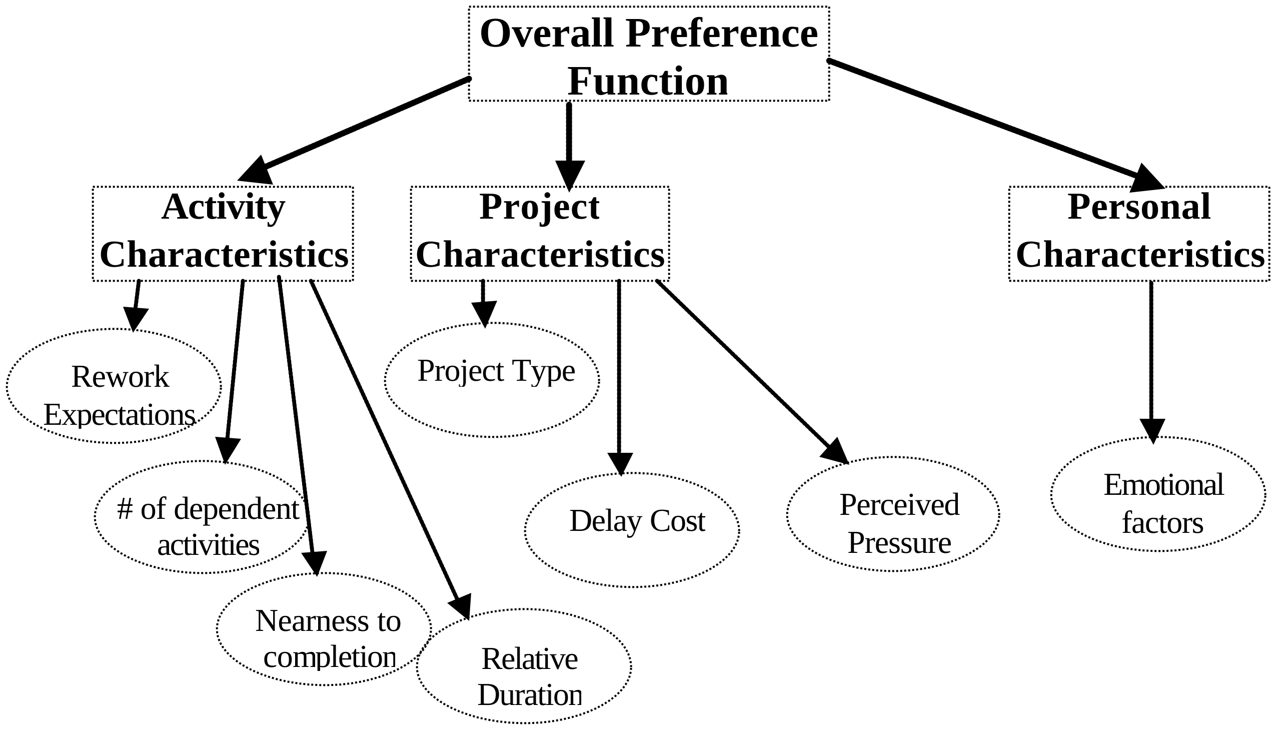


Figure 3: Attribute Hierarchy Tree

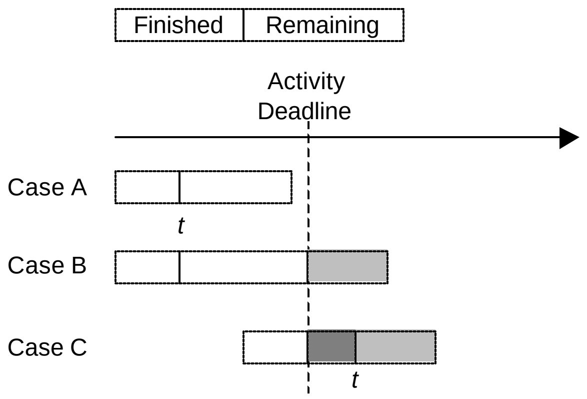
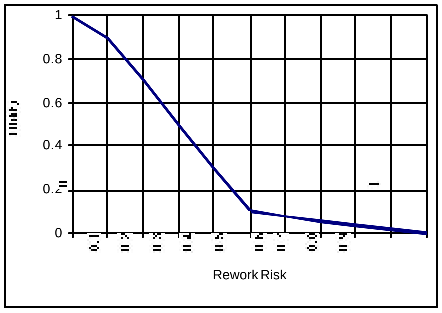
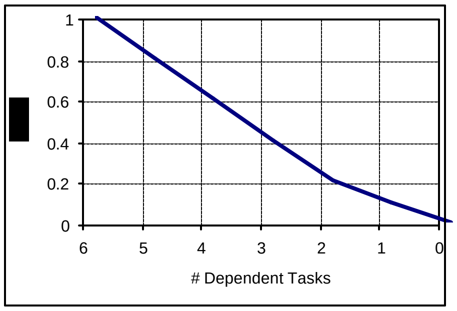


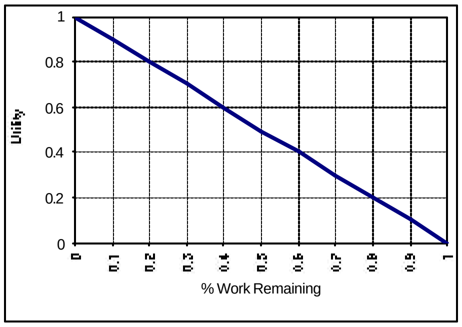
Figure 4: Schedule Pre ssure Calculation



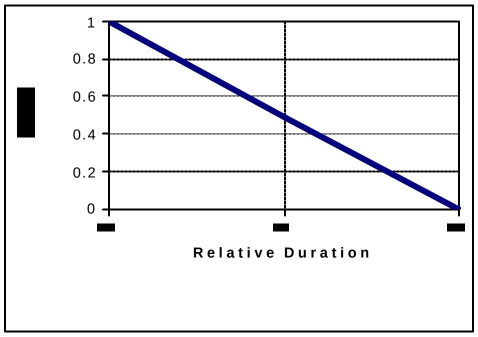
(a) Rework Risk



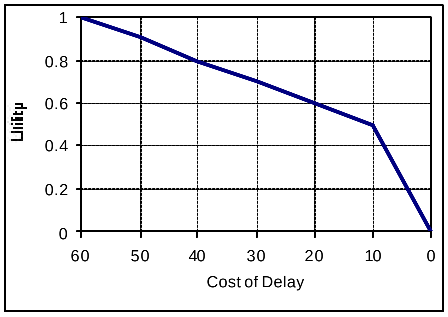
(b) Number of dependent activities



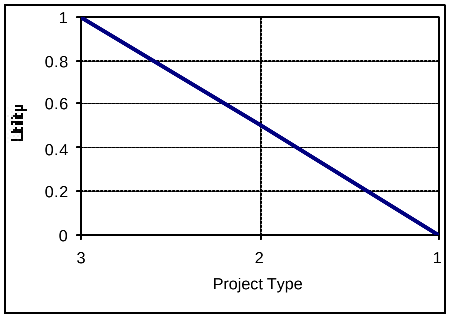
(c) Nearness to completion



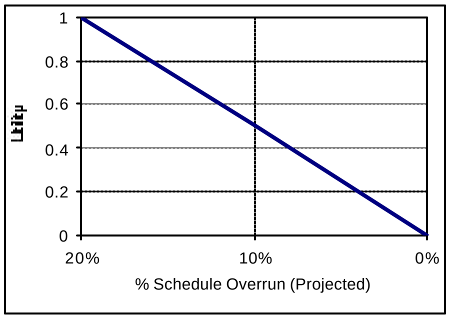
(d) Relative duration



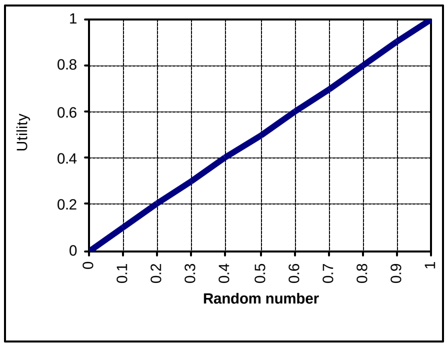
(e) Cost of project delay



(f) Project type



(g) Schedule pressure



(h) Personal / Random factors

Figure 5: Utility Curves Used in the Simulation

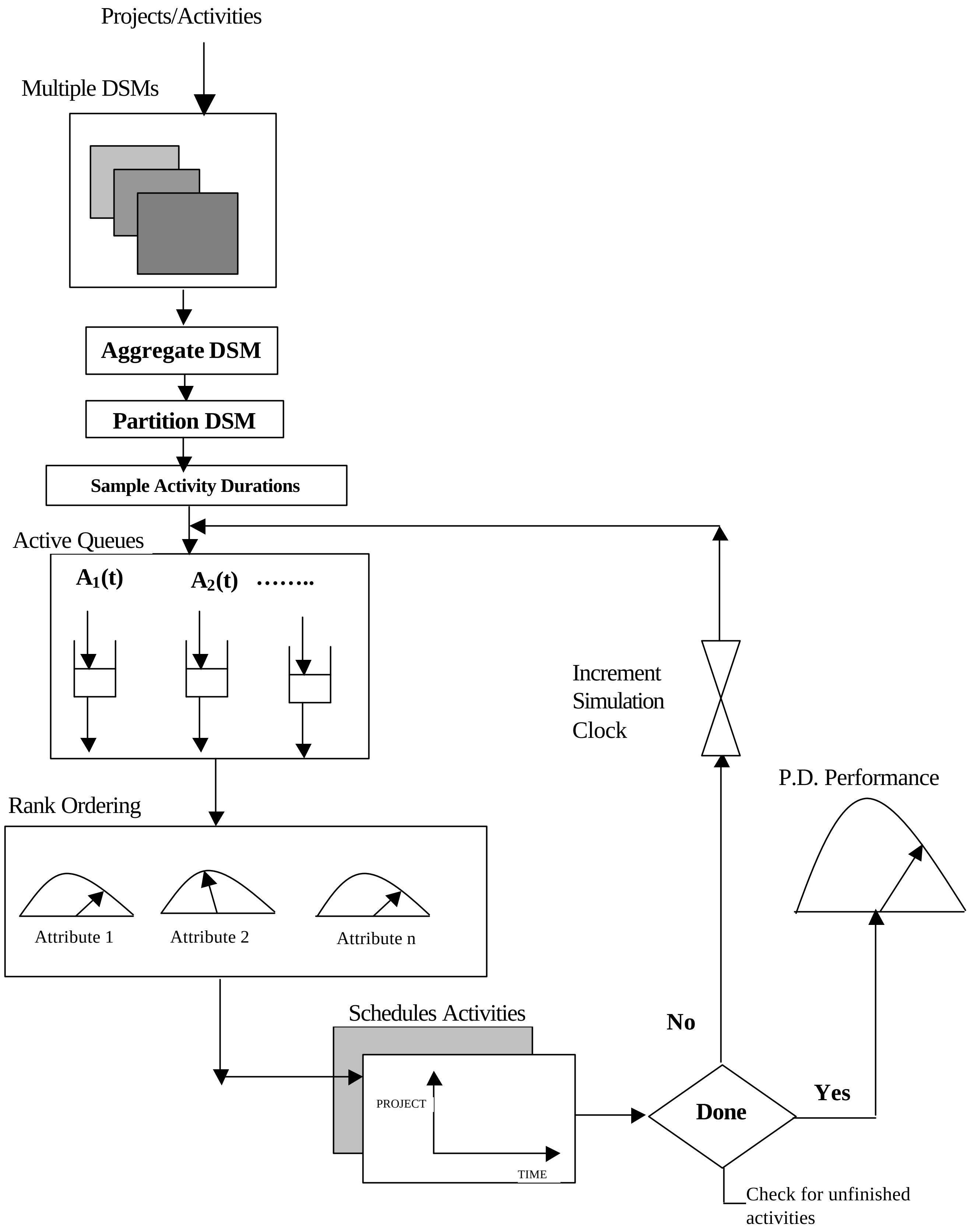


Figure 6: The Simulation Model

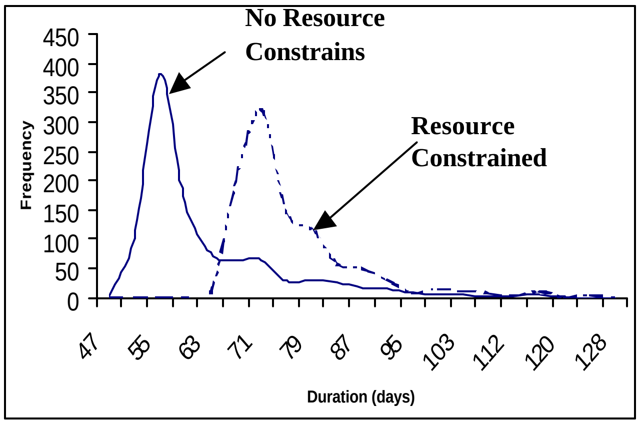
	A1	B1	C1	D1	E1	F1	G1	H1	A2	B2	C2	F2	D2	H2	B3	D3	A3	C3	G3	H3
A1	■				.2															
B1	.5	■																		
C1		.7	■																	
D1		.9		■	.4		.3													
E1					■															
F1		.6				■														
G1			.5			.5	■													
H1		.9			.6	.8	.8	■												
A2									■				.1							
B2										■	.4			.4						
C2										.5	■									
F2										.9	.7	■								
D2									.5			.6	■							
H2										.4		.3	.7	■						
B3															■	.3		.2		.3
D3															.5	■			.4	
A3																	■			
C3																.7	.8	■		
G3															.8		.8	.9	■	
H3																	.8		.9	■

(a) Rework probabilities

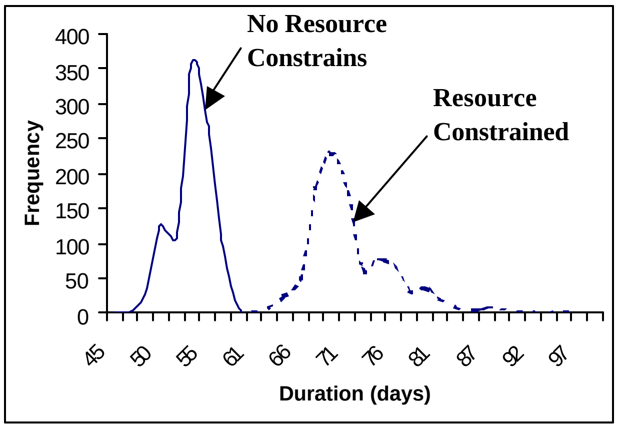
	A1	B1	C1	D1	E1	F1	G1	H1	A2	B2	C2	F2	D2	H2	B3	D3	A3	C3	G3	H3
A1	■				.9															
B1	.5	■																		
C1		.5	■																	
D1		.9		■	.5		.4													
E1					■															
F1		.9				■														
G1			.5			.4	■													
H1		.8			.5	.8	.9	■												
A2									■				.4							
B2										■	.4			.5						
C2										.5	■									
F2										.9	.7	■								
D2									.5			.6	■							
H2										1.0		.6	.7	■						
B3															■	.4		.4		.2
D3															.2	■			.6	
A3																	■			
C3																.7	.5	■		
G3															.9		.6	.5	■	
H3																	1.0		.7	■

(a) Rework Impacts

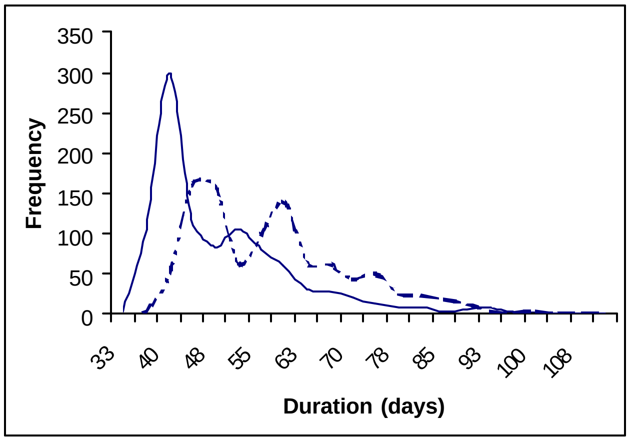
Figure 7: Aggregate DSMs for Example Problem



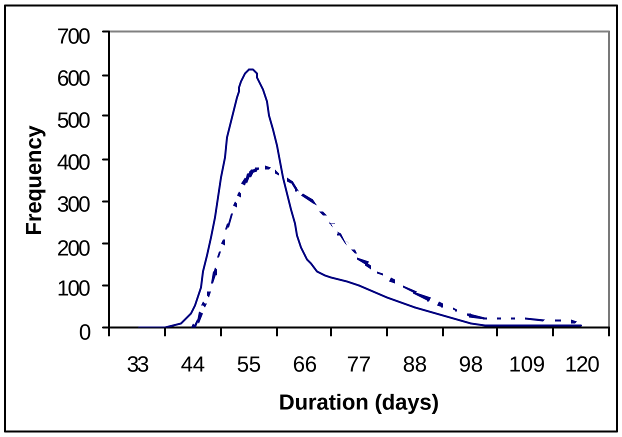
(a) Lead time distributions for the overall project portfolio: with and without resource constraints



(b) Lead time distributions for Project 1: with and without resource constraints

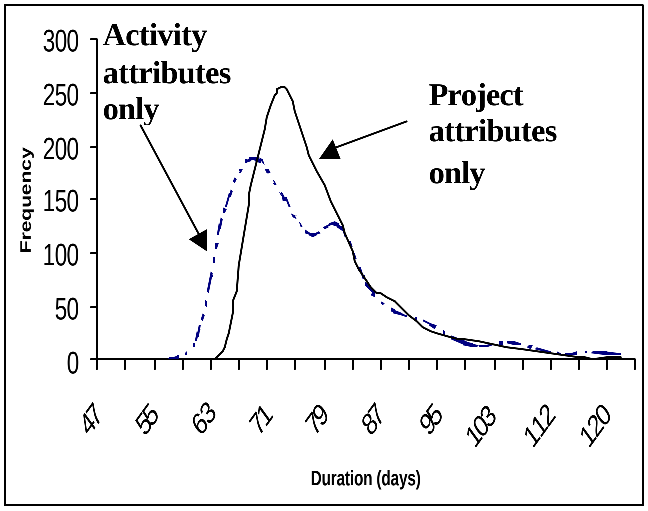


(c) Lead time distributions for Project 2

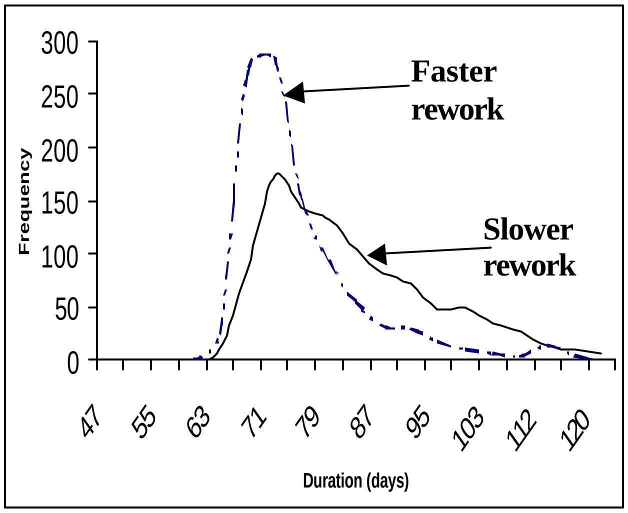


(d) Lead time distributions for Project 3

Figure 8: Simulation Results



(a) Project versus Activity Attributes



(b) Slower versus faster rework

Figure 9: Scenario Analysis

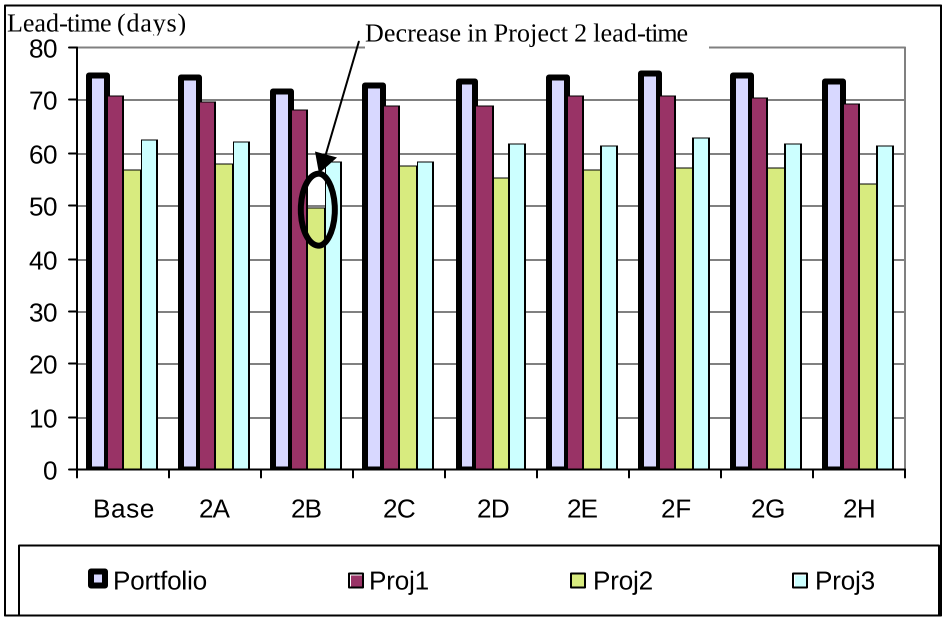


Figure 10: Sensitivity of Lead Time to Resource Addition

("2A" denotes the availability of two processors of type "A"

and one processor of each of the other remaining types)

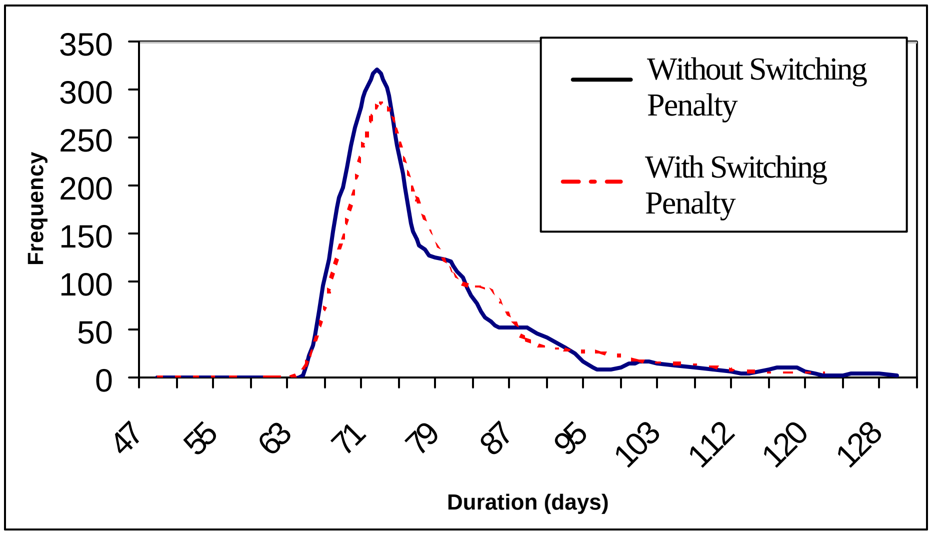


Figure 11: Including Switching Penalties

Table 1: The Eight Attributes Used in Developing the Preference Function

<u>Activity Attributes</u>	1. *Expectations for activity rework (Rework Risk).* People's choice of whether or not to work on an activity can be influenced by their knowledge of the likelihood of that activity to change or be reworked later. What is the point of working on something that is likely to have to be changed? Prior to running the simulation, a "rework risk" is estimated for each activity based on the likelihood and the impact of changes in the activity's inputs. The estimate combines the impacts of both first- and second-order rework. First-order rework is caused by changes in inputs from downstream activities and is the sum of the product of rework probability and rework impact for all such inputs. Second-order rework is caused by changes in inputs from upstream activities which themselves have some risk of first-order rework. Second-order rework is the sum of the product of rework probability and rework impact for all such inputs, where each such product is further multiplied by the upstream activity's estimated rework risk. For examp le, if the first activity in a DSM has two feedback inputs (P(rework) = .3 and .5; Impact(rework) = .3 and .4), then Risk(rework) = 1 - [1 – (..3)(.3)][1 – (.5)(.4)] = .27. Then, say activity two has no inputs from downstream activities, but it depends on activity one (P(rework) = .1; Impact(rework) = 1). In this case, the rework risk for activity two stems only from second-order rework: Risk(rework) = (.1)(1)(.27) = .027. Higher-order rework possibilities are usually small and are not included in the estimate (a realistic assumption in practice).
	2. *Number of dependent activities*. People are more likely to work on activities upon which a large number of other people depend. The number of marks in each column of the binary DSM is counted to determine the number of dependent activities.
	3. *Nearness to completion*. This attribute is a function of the amount of work remaining for the activity. It assumes that people would rather finish nearly complete activities than begin new activities[17] [14].
	4. *Relative duration*. This attribute assumes that shorter activities will be preferred to longer ones. Prior to running the simulation (but after a random sample has been obtained for each activity's duration), the relative duration of each processor's activities is determined. Each processor's

[17] The attribute can also be set to reflect the reverse situation.

	activities are classified as either the shortest or the longest duration activity for that processor, or else in-between. (This attribute can also be set to prefer longer activities.)
Project Attributes	5. *Cost of project delay* [21]. A cost of delay is supplied for each project as an input to the simulation. Activities in projects with higher costs of delay are given greater priority.
	6. *Project type*. Project type is also given for each project as an input to the simulation. We classify project type based on project visibility and/or priority—which is either "high," "medium/normal," or "low."
	7. *Schedule pressure*. As a project falls behind schedule, pressure builds to finish its activities. Each project and each activity within it have scheduled completion times or deadlines, which are provided as inputs to the simulation. Project schedule pressure is the sum of the schedule pressure contributions of all of its activities. The schedule pressure contribution of each activity is calculated depending on which of three cases it falls into, as shown in Figure 4. In Case A, the activity is running ahead of schedule, and it makes no contribution to its project's schedule pressure. In Case B, the activity has not yet missed its deadline, but it is projected to do so. In this case, the schedule pressure contribution is proportional to the amount of projected overrun. In Case C, the activity has already missed its deadline. The entire, remaining portion of the activity contributes to the schedule pressure, along with the amount by which the activity is running behind its deadline. The schedule pressure contributions of all activities in a project are summed to arrive at a number, which is normalized against the deadline to arrive at a percentage of anticipated schedule overrun. As this percentage grows, schedule pressure increases. Thus, delinquent activities with early deadlines contribute much more to schedule pressure than activities with later deadlines.
Processor Attribute	8. *Personal and interpersonal factors*. It is impossible to represent the comprehensive set of factors that influence a processor's choice of projects and activities. Therefore, we utilize a random factor to represent other influences, including personal and interpersonal (and even irrational) factors. The random factor can represent personality, risk propensity or averseness, interpersonal relationships—really anything not attributable to the other attributes.

Attribute Name	Weight
1. Rework Expectation	0.20
2. Number of Dependencies	0.06
3. Nearness to completion	0.17
4. Relative Duration	0.07
5. Project delay cost	0.16
6. Project Type	0.16
7. Schedule pressure	0.16
8. Emotional factors	0.02

Table 2: Attribute Weights

	Duration (days)			
Activity Name	**Min.**	**Likely**	**Max.**	**Activity Deadlines**
A1	5	10	15	10
B1	3	5	7	15
C1	6	7	8	22
D1	15	17	20	32
E1	6	7	8	7
F1	3	4	5	19
G1	5	7	10	29
H1	10	11	12	40
A2	5	8	10	8
B2	3	5	7	13
C2	10	13	15	26
F2	2	4	6	30
D2	8	10	14	40
H2	4	6	8	46
B3	6	7	8	7
D3	10	12	15	19
A3	8	12	15	12
C3	4	6	9	25
G3	10	10	12	35
H3	8	10	13	45

Table 3: Activity Data

Project Number	**Project Type**	**Deadline**	**Budget**	**Cost of Delay ($k/day)**
1	3 = Low visibility	40	80	50
2	2 = Normal	46	50	40
3	2 = Normal	45	40	50

Table 4: Project Data

		Without Resource Constraints (Unconstrained)	With Resource Constraints & Considering all Attributes	Considering all Attributes & 10% Switching Penalty
Portfolio	**Mean**	60.29	76.94	76.55
	95% CI*	2.65	3.51	3.60
	Std. Dev.	17.62	17.71	17.22
Project 1	**Mean**	52.86	70.79	72.17
	95% CI*	0.49	10.18	0.45
	Std. Dev.	2.26	2.23	2.27
Project 2	**Mean**	46.86	57.61	58.96
	95% CI*	3.30	2.45	3.09
	Std. Dev.	15.48	11.52	14.26
Project 3	**Mean**	54.04	64.76	63.32
	95% CI*	3.16	3.04	3.97
	Std. Dev.	14.57	19.11	19.65

Table 5: Simulation Results and Comparison of Means

*(95% Confidence Interval around the mean based on 100 observations/simulation)