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SIMULATION OPTIMIZATION DECISION SUPPORT SYSTEM FOR SHIP PANEL SHOP OPERATIONS

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ABSTRACT

Simulation is a powerful tool that is used to understand and analyze the effect of changes on real systems. However, developing and using simulation models requires high-level engineering skills. The objective of this research is to put state-of-the-art problem-solving technologies into the hands of decision makers, e.g. planners and supervisors. This paper presents a Decision Support System (DSS) that utilizes discrete-event simulation models and heuristic optimization, yet permits effective use without detailed knowledge of the methodologies. The system is developed for the Panel Shop at Northrop Grumman Ship Systems' (NGSS) Pascagoula Operations; the shop is considered the bottleneck for the shipyard. This system focuses on two key opportunities for improvement: sequencing panel production and resource allocation among steps in the production processes. The DSS is designed to be reused in similar operations at other shipyards and portions of the DSS may be used to apply simulation optimization to most industries.

1 INTRODUCTION

Management of a panel shop in a shipyard is a complex process that involves many decisions. This paper focuses on the panel shop at Northrop Grumman Ship Systems' (NGSS) Pascagoula Operations. The shop is considered the bottleneck of the shipyard since every panel for every ship must be processed through the shop. With the advent of management information systems and data processing, the ability of planners to control the whole panel shop process has greatly improved. However, shop-floor supervisors and planners still do not have enough information to effectively analyze shop operations.

Simulation models have proven to be a reliable and convenient tool to support decision makers that manage daily operations and those making longer range planning decisions. These models capture the salient behavior of the system and provide a test-bed to assess changes in operations and managerial policies, troubleshoot problems, and analyze resource conflicts. Simulation tools also provide a basis to address "what-if" questions, such as "how can the time it takes to process each job be minimized or which job should be started next?" However, understanding the mechanics of these models requires high-level engineering skills. Planners and shop managers typically do not possess these essential skills.

A DSS can be an effective link between the sophisticated technologies and operations personnel. The DSS couples simulation and optimization models, provides access to the data sources that drive the models, and creates effective user-interfaces. The interfaces provide an easy means for the planners and shop managers to enter information into the models and generate output reports that increase understanding of the behavior of the system, indicate the effect of changes, and enhance decision making.

2 PROBLEM DESCRIPTION AND SOLUTION APPROACH

Operations in a shipyard panel shop are complex. The following sections describe the operations, typical problems, and an approach for addressing the problems.

2.1 Problem Description

All panels for all ships are fabricated and assembled in the panel shop. Each panel goes through the same sequence of processing steps, although the work content varies greatly at each step. The shop primarily operates as an assembly line. Once production starts on a panel, the sequence is not changed. The panels are composed of very large plates of steel and it is extremely difficult, if not impossible, to off-load or route panels around production steps. Most panels are unique and vary considerably in terms of their physical attributes and work content. Due to this uniqueness, panels require varying amounts of resources and processing times. Figure 1 illustrates the variability in work content for a sample sequence of 150 panels in two of the six key processing steps within the panel shop.

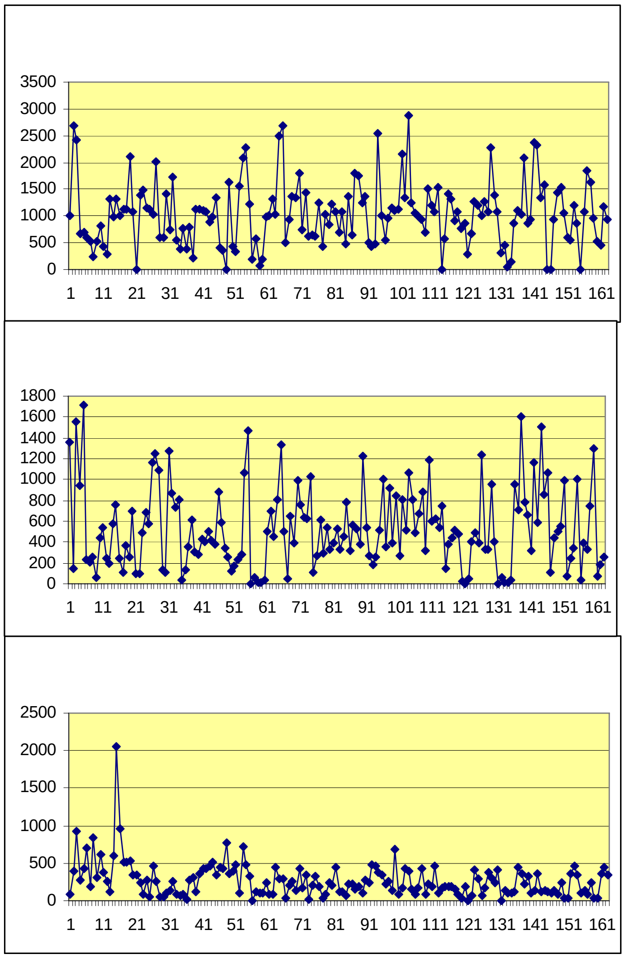


Figure 1: Variability of Work Content in Panels

This high level of temporal variability makes it extremely difficult to estimate the capacity of the shop. Therefore, it is difficult to effectively plan or schedule the panels through the production process. The variability in panel characteristics, in conjunction with the resource allocations that are made to each process step, causes the bottleneck to shift within the shop. That is, the bottleneck can shift depending on the processing sequence of the panels. As a result, some areas of the line become overcommitted, while others are underutilized. When the panel shop becomes over committed, panels must be constructed offline or subcontracted in order to meet upstream demand, resulting in higher costs and longer lead times.

2.2 Solution Approach

One means to address the problems described above is to design and manage the processes with the help of models (abstractions or representations of a real system). According to the Oak Ridge Center for Manufacturing Technologies, "modeling and simulation (M&S) are emerging as key technologies to support manufacturing in the 21st century, and no other technology offers more than a fraction of the potential that M&S does for improving products, perfecting processes, reducing design-to-manufacturing cycle time, and reducing product realization costs" (McLean 1998). Since the panel shop is a set of complex, interdependent, stochastic and dynamic processes, multiple types of models need to be applied in order to effectively manage the shop. These models, the data that drive them and the interfaces needed for lay users to interact with the models demand an integrated analysis system. This system needs to represent and simulate the behavior of the panel shop operations and provide an "analysis platform" or "test bed" for experimenting with and testing alternatives (e.g. work rules, processing plans, construction schedules, equipment investments, facilities layout) for operating the line.

3 PANEL SHOP DECISION SUPPORT SYSTEM

The DSS provides a means for panel shop managers and planners to improve shop and shipyard operations by better understanding and assessing the impact of changes in resources, operational practices, panel attributes, sequence etc. on shop performance. While this particular DSS is built to improve the performance of a shipbuilder's panel shop, it is designed such that key components can be reused in similar operations at any shipyard or in any industry. A high-level representation of the Simulation-Optimization DSS is shown in Figure 2. It illustrates how the planning data, operational parameters, etc. are transformed to predicted measures of system performance through the interaction of simulation and optimization models.

As Figure 3 illustrates, the DSS pulls information from the real system and users and provides information back to the users that facilitate making decisions about the real system. In that role, the DSS is an integrated system of three primary components: controllers, models (discrete-event simulation of the panel shop and optimization algorithms), and a variety of interfaces.

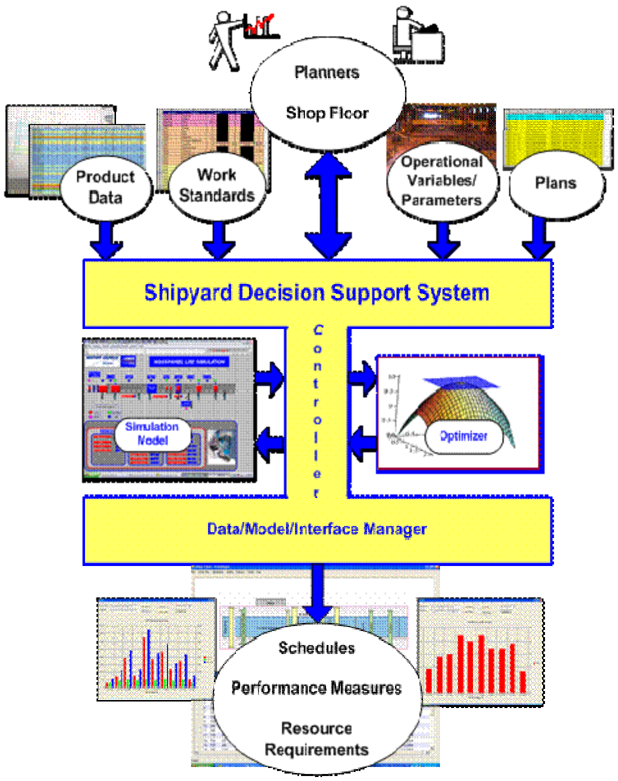


Figure 2: DSS Overview

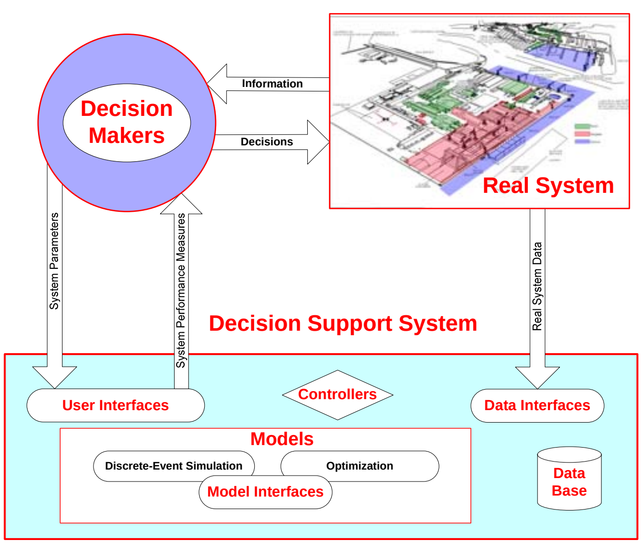


Figure 3: DSS Process Flow

3.1 DSS Controller

The DSS controller handles all of the processes that need to be carried out between the users, the data, and the models. The basic process flow of the DSS is illustrated in Figure 4 The DSS takes in such data as the current production schedule, panel attributes, and work standards. That data is then transformed into a simulation-usable format and the simulation model is executed to evaluate the performance of the system. An alternative solution is generated by the optimizer and its performance is determined by the simulation model. This process continues until there is no longer significant improvement. Once the process is complete, output reports and graphs are generated from the data and simulation outputs. The simulation model and optimization operations are transparent to the users.

3.2 Models

As indicated above, two types of models are integrated within the DSS: discrete-event simulation that is used to represent the operational behavior of the panel line, and optimization, that is used to determine the best sequence for producing panels. Each type of model is briefly explained below.

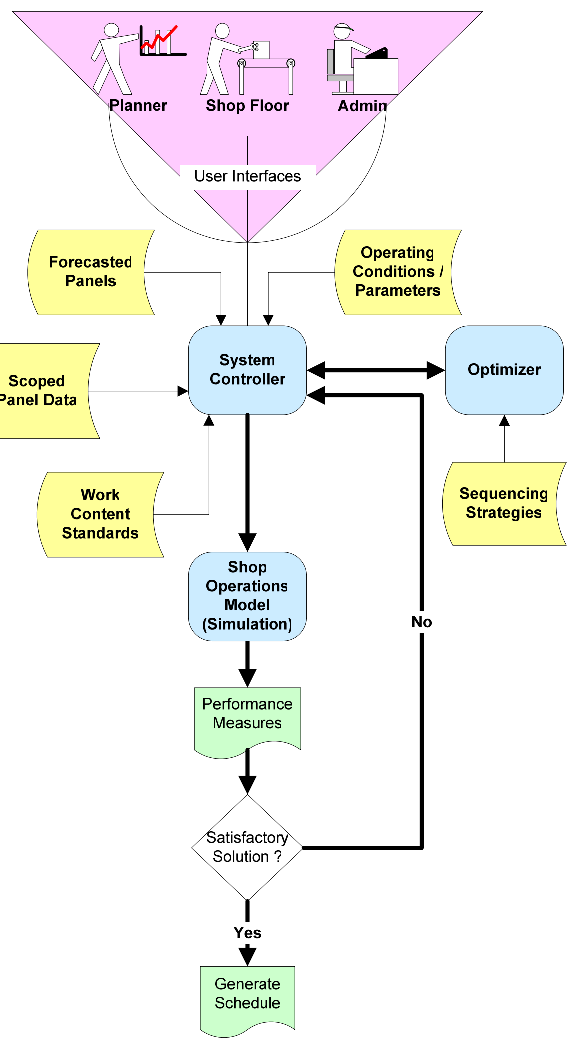


Figure 4: Overall DSS Process Flow

3.2.1 Discrete-Event Simulation Model

The objective of many simulation studies is to assess the effect of resource allocation on system performance, considering such things as the number of resources available, downtime, resource selection rules, the use of priority and preemption, etc. The DSS is design to execute models developed either in *ProModel*® (developed by ProModel Corporation) or *QUEST*® (developed by Dassault Systems). NGSS's Pascagoula panel shop model was developed by MSU using *ProModel*®; NGSS's New Orleans panel shop model was developed by the University of New Orleans' Simulation Based Design Center in *QUEST*®. Both models have similar functionality and are incorporated into the DSS to allow for cross-yard analysis. Screenshots of the *ProModel*® and *QUEST*® simulation models are provided in Figure 5 and Figure 6, respectively.

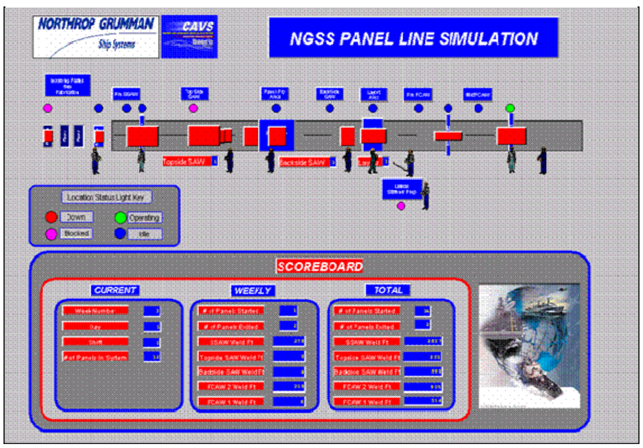


Figure 5: *ProModel*® Simulation Model

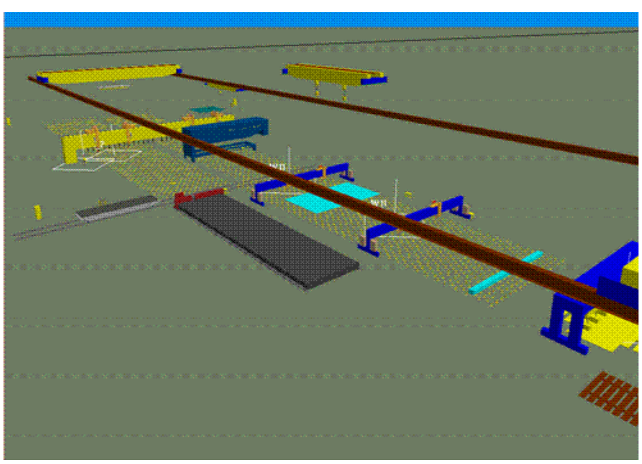
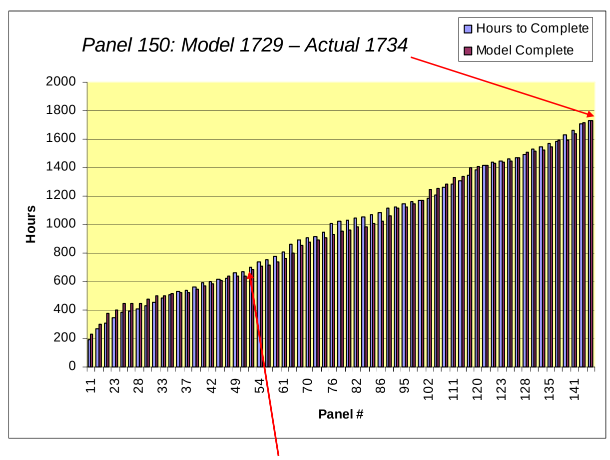


Figure 6: *QUEST*® Simulation Model

Since both models are similar in design, only the *ProModel*® simulation model is discussed. The panel shop contains seven work areas in series; each panel travels through the shop on a large conveyor. Each work area is responsible for a different aspect of panel construction. The first work area grinds the edges of plates and preps them for welding. The next work area welds the transverse seams. The third work area is responsible for welding the longitudinal seams and any additional material to the topside of the panel. The next work area flips each panel. The fifth work area handles welding the backside of all topside welds. Next, the positions of the stiffeners are mapped onto the panel and finally the stiffeners are positioned and welded.

The DSS interfaces with the simulation model through *ActiveX* (or *QUEST*® BCL) and *Microsoft*® *Excel* files. The data contained in the *Excel* files include the parametric data associated with each panel and number of resources available. The sequence of the panels entering the system is determined by the order in the *Excel* file. The simulation model considers panel size, conveyor capacities, work content, resource availability, work assignments, operational rules, equipment downtime, task variability, shift schedule, and a variety of measures of performance.

The simulation model was validated using a four-month production run. As shown in Figure 7, the model results compared very favorably to the actual system performance. At the end of the four-month period, the real system and the model differed by only five hours and the differences that occurred over time were also quite small. The simulation results are the mean of ten replications of the model.



Hours to complete is based on observation; the number of panels that had exited at a specified time; e.g., at time 697, 52 panels had been competed. *Model Complete* is the time a panel left the system in the model; e.g. Panel 52 was completed at time 681.

Figure 7: Validation of Model Behavior

Some of the labor resources in the panel shop are pooled so that certain work areas can pull from the pool to perform work. The simulation model performs dynamic resource allocations during the simulation run. That is, the simulation tries to make any non-bottleneck work area subservient to the bottleneck process. As illustrated in Figure

8, the simulation model does this by looking ahead at the work being performed downstream and allocates the minimum number of resources – within the constraints of the total number of resources available – to the non-bottleneck processes. The allocation is made such that the bottleneck is not starved. The number of resources that the simulation model assigns to each panel is recorded and output so that it can be used as a prescription for shop floor personnel.

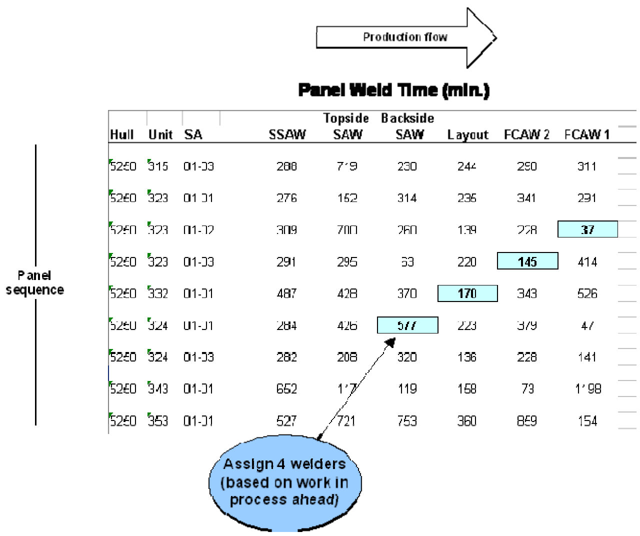


Figure 8: Dynamic Resource Allocation Example

3.2.2 Optimization Approach

For the panel shop problem the objective is to find the "best" sequence in which to produce the panels, subject to material availability and downstream process due dates. "Best" is evaluated in terms of the throughput of the shop; i.e., get as many panels through the shop as possible, given the operational, physical, and programmatic restrictions.

The following is a brief description of the optimization algorithm that is utilized by the DSS and some current work that is underway to improve its performance.

An Evolution Strategies (ES) algorithm is employed to "optimize" the panel shop-sequencing problem. An ES works on real-value objective function variables by applying recombination and mutation (Mitchell 1991). A solution is represented in a gene format consisting of function variables and strategy parameters. Function variables represent the solution where as the strategy parameters help the algorithm traverse the solution space more effectively by mutating function variables. The core algorithm is described in the following pseudo code:

1. START
2. Generate initial population
   (a) Randomly generate values for variables
   (b) Initialize strategy parameters for each variable defined
   (c) Evaluate initial population
3. Generate next generation
   (a) Select two parent members at random
   (b) Create an offspring solution by selecting each variable value from either of the parent's corresponding variable.
   (c) Define strategy parameters for the offspring as an average of the corresponding two parent values.
   (d) Mutate strategy parameters
   (e) Mutate each variable of the offspring based on the new strategy parameter.
4. Evaluate the objective function
5. Sort the solutions
6. Repeat from step 3 until desired tolerance is achieved.
7. END

Since the panel shop optimization model involves sequences of non-repetitive integers that are used to represent a panel, a real-value algorithm cannot be used directly. Therefore, there is an encoding and decoding of real values and integer sequences (Rudolph 1991). Encoding is achieved by assigning randomly generated numbers [0,1) to the sequence after sorting. The assignment ensures that the least number is assigned to the least job ID, and proceeds until all integers are mapped. Similarly, each ES solution is decoded by assigning ranks to the real values. Ranking also ensures that no duplicates are created. Since the algorithm as designed, passes on the complete real-value solution set to the next generation, there is no need for any further encoding. Encoding is performed only for the parent population.

An objective function value is associated with each gene. This objective value is the sum of the number of days each panel is late and makespan of all panels in days. The simulation model is used to evaluate the objective function. The simulation model's output is then used to calculate the number of days late and makespan. The optimizer attempts to minimize this objective function.

Generally, initial population members are generated randomly in order to enable a wide range of solutions. However, this variety may slow down the optimization process. Therefore, in order to achieve faster improvement, the initial population is generated using established efficient heuristic scheduling rules. The following four common scheduling algorithms – Earliest Start Date (ESD), Shortest Processing Time (SPT), Earliest Due Date (EDD) and Critical Ratio (CR) are used. SPT is near optimal for finding the minimum total completion time and weighted completion time. CR is the ratio of time remaining to the work remaining and works well on minimizing average lateness. The initial population is comprised of one sequence based on each of these heuristics.

These algorithms are used since the panel shop can be viewed as a flow shop problem where all jobs follow the same sequence of machines. That is, a machine can only process one job at a time and once a job starts on a machine, it must be processed to completion. Each job has a due date associated with it; a job is ready for processing at or after its release time and must be completed by its due date. This type of flow shop problem is NP-hard.

These heuristics as expected were not perfect, but provided a good starting point to look for the better solutions. Further improvements are sought by using heuristics that are more efficient. Sarin's approach minimizes the idle time on the last machine (Sarin 1993). Campbell modifies the well-known Johnson's rule such that if the shortest time is for the first machine, do the job first, if the shortest time is for the second machine, do the job last. (Campbell 1970). EEDF (Earliest Expected Due Date First) is a classical algorithm, which assigns priorities to jobs according to their effective deadline (Bettati 1992).

Table 1 compares the performance of the four traditional algorithms and the new heuristics, in terms of improved schedule sequence. Values have been standardized. The objective function that measures the quality of the sequence is based on ten replications of the simulation model using the prescribed sequence. Three different sets of panel are used, consisting of 31, 64 and 154 panels.

Table 1: Heuristics Comparisons

	ESD	**SPT**	**EDD**	**CR**	**Sarin**	**Camp**	**EEDF**
Set 1 (31)							
Makespan	1.00	1.01	1.03	1.01	1.01	1.03	1.01
Days Late	1.37	1.00	1.22	1.33	1.33	1.41	1.33
Overall Fitness	1.29	1.00	1.17	1.26	1.26	1.37	1.26
Set 2 (64)							
Makespan	1.04	1.03	1.00	1.03	1.04	1.02	1.09
Days Late	1.47	1.00	1.35	1.85	1.9	1.44	1.51
Overall Fitness	1.37	1.00	1.26	1.74	1.89	1.42	1.41
Set 3 (154)							
Makespan	1.01	1.00	1.01	1.01	1.00	1.00	1.01
Days Late	1.06	1.00	1.06	1.45	1.49	1.44	1.12
Overall Fitness	1.00	1.03	1.00	1.39	1.54	1.46	1.05

The results are mixed. For example, Sarin's heuristic provides the best makespan for Set 3. SPT shows better results for days late for most of the panel sets. Therefore, if one heuristic excels over the other in makespan, the other improves the overall fitness value. The heuristics are situation sensitive; i.e., one heuristic provides a good solution in one case, but is worse solution in a different situation. The use of additional heuristics and enabling the optimizer to select the best for the initial population could improve the performance of the optimization algorithm.

3.3 DSS Interfaces

The DSS must manage a number of types of interfaces, e.g. between the users and the models, between the data and the models, between the models themselves.

The models in the DSS require a large amount of data, including: physical characteristics of each panel (e.g. dimensional data, the amount of weld-feet, the number of tie downs), work standards for each production step to determine the work content at each work area, production plan, operational parameters (resource level and schedule), etc.

Since a primary objective of the DSS is to make sophisticated models readily available to decision makers, as much data as possible must read directly into the DSS. Similarly, the interactions between the various users and the DSS must be effective. Figure 9 shows one of the DSS's easy-to-use interfaces. This view is comprised of three main areas. The area represented by the graphical image of the shop floor allows the user to select any work area and set resource levels and availability. The schedule area (lower left portion of Figure 9) displays the set of panels that will be optimized. The user can easily modify the contents of that set, the planned release dates, etc. The third area (lower right portion of Figure 9) displays the optimized sequence of panels. Other interfaces allow the user to specify the source of information for the set of panels to load, modify the shift schedule for the shop, number of replications of the simulation model to use during optimization, select output reports, etc.

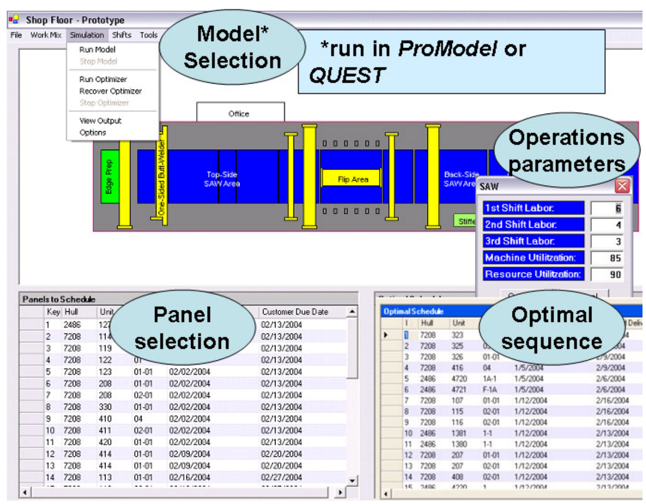


Figure 9: DSS Interface

The DSS provides a variety of outputs including a measure of simulated makespan, a comparison of the planned schedule to the simulated schedule, a prescription of resource allocations, simulated dwell times for each panel at each work area, etc. A sample of the output generated by the DSS is shown in Figure 10.

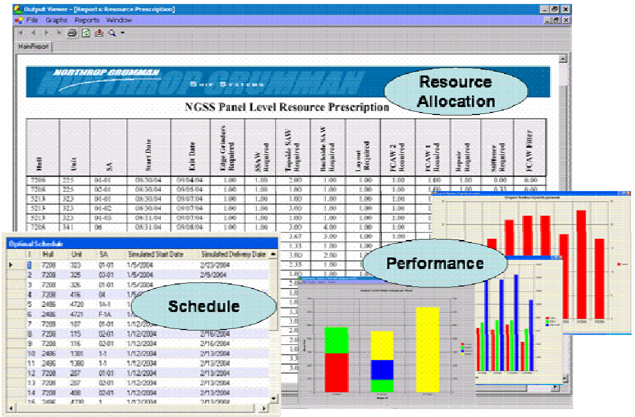


Figure 10: Example DSS Outputs

4 APPLICATION OF THE DSS

The following provides two example analyses that are performed by applying the DSS. One involves a sensitivity analysis on the impact of various operations variables on makespan. The other analysis shows the effect of the optimization on makespan and lateness. Makespan is defined as the difference between the starting time of the first panel and the ending time for the last panel in a specified set.

A sensitivity analysis was performed to determine the percent change in makespan with changes in machine effectiveness, personnel effectiveness and process variability. Machine and personnel effectiveness are composite measures that reflect both availability (i.e., uptime) and efficiency of the corresponding resource. A base-line case is considered for comparisons with other cases when effectiveness and process variability are modified.

Table 2 shows the percentage change in makespan that results from changes in machine effectiveness and personnel effectiveness. For example, if personnel effectiveness is increased from the baseline (85% personnel effectiveness and 100% machine effectiveness) to 100%, then makespan improves by 6.0%.

Table 2: Personnel vs. Machine Effectiveness

		Machine Effectiveness				
		100	**90**	**80**	**70**	**60**
Personnel Effectiveness	**100**	6.0%	5.8%	5.7%	5.2%	4.4%
	95	3.9%	3.9%	3.8%	3.2%	2.7%
	85	0.0%	-0.6%	-0.6%	-1.6%	-1.1%
	70	-7.7%	-7.4%	-8.3%	-8.5%	-9.0%

Table 3 similarly shows that the sensitivity of personnel effectiveness and process variability on makespan. As expected, as personnel effectiveness increases and process variability decreases, makespan improves.

Table 3: Personnel Effectiveness vs. Process Variability

		Process Variability				
		None	**-5/+10**	**-10/+20**	**-25/+50**	**-25/+100**
Personnel Effectiveness	**100**	6.5%	6.0%	5.4%	3.0%	-4.8%
	85	-0.1%	0.0%	-1.2%	-3.4%	-11.7%
	70	7.1%	-7.7%	-8.4%	-11.5%	-20.0%

The second example analysis shows the effect of optimization of the panel sequence on makespan and lateness. The percentage improvement with the optimized sequences are shown in Table 4. The analysis is performed for five sizes of panel sets: 19, 43, 64, 82 and 103 panels.

Table 4: Sequence Improvement

	Improvement (%)
Set 1 (19)	
Makespan	1.2
Days Late	41.5
% Jobs Late	21.4
Overall Fitness	31.9
Set 2 (43)	
Makespan	-0.4
Days Late	39.5
% Jobs Late	6.1
Overall Fitness	34.6
Set 3 (64)	
Makespan	-0.3
Days Late	21.2
% Jobs Late	33.3
Overall Fitness	19.1
Set 4 (82)	
Makespan	-0.2
Days Late	2.9
% Jobs Late	5.7
Overall Fitness	2.6
Set 5 (103)	
Makespan	-0.1
Days Late	4.8
% Jobs Late	16.5
Overall Fitness	4.3

While one would expect makespan to decrease with an improved sequence, makespan is basically unchanged in these cases because the shop is so overscheduled. However, the optimized sequence greatly reduces lateness (to the next major step in the ship construction process).

Days late is a cumulative measure of panel delays to the next major production process. The improvement tends to decrease as the number of panels in the set increases. This is due to the increasing solution space as the number of panels increase.

The overall fitness value is a combination of makespan and the number of days late. In this case, the number of days late is dominant in the objective function; therefore, this result is similar to that of days late.

5 CONCLUSIONS

This paper demonstrates that a DSS can effectively integrate simulation models and optimization algorithms to aid planners and shop floor managers in their decision-making processes. The DSS uses simulation to measure the quality of alternative sequences for producing ship panels that exhibit significant variations in physical characteristics and resulting work content. The system is used to more efficiently schedule the panel shop operations, assess alternative sequencing strategies, determine the shop capacity based on a set of panels, estimate shop performance based on resource availability and make outsourcing decisions. The DSS is easy-to-use and requires very little knowledge of advanced engineering methodologies and tools, such as simulation and optimization. In addition, the system is able to utilize multiple simulation packages and existing models can be adapted to fit into the DSS framework.

6 FUTURE RESEARCH

Future research for this project should focus on two key components—the DSS and the optimization algorithm. Future DSS work should focus on making the system more general in order to extend it to other shops in the shipyard and to other industries. In addition, expanding the types of simulation models that can be utilized will be done. Optimization algorithm research should investigate further improvements in the initial population for the existing algorithm. Other techniques, such as simulated annealing and neural networks, could be applied to improve the algorithm itself. Finally, the composition and form of the objective function needs to be examined and improved.

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