

WEB-BASED SIMULATION WORKFLOW OPTIMIZATION ALGORITHM APPLIED IN AERONAUTICS: MANUFACTURING OF CONTROL SURFACES

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Abstract. *Simulation workflow optimization has become an important investigation area as it allows users to process large scale & heterogeneous problems in distributed environments in a more flexible way. The most characteristic category of such problems comes from the aerospace industry. In this work a specially developed Simulation Workflow Optimization (SWO) algorithm that is based on heuristic optimization techniques (Genetic Algorithms) and delivers an optimized workflow implementation of an initial plan or workflow schedule, will be applied on an aerospace manufacturing problem in order to demonstrate its potentials. The algorithm has been developed under the ‘iProd’ EU project and the application use case refers to the manufacturing of an airplane tail rudder from FAE. The SWO tool helps the user to select the optimal use of local and external resources that will satisfy the product requirements under the specific time & cost constraints. The tool is customized for the specific domain/application and it is remotely invoked via web GUI & services under the ‘iProd’ collaborative framework.*

1 INTRODUCTION

Data and knowledge management technologies are of strategic importance for industrial innovation, provided they are integrated in the company processes, in the organizational structure, and can be flexibly adapted to company evolution. In particular the Product Development Process (PDP) of manufacturing companies requires the efficient management of huge amounts of data from different sources and their integration in the sub-processes that compose the product chain. The efficient use of information lifecycle, by the large adoption of virtual testing and by the inter-functional management of related data in the product management is expected to become a strategic advantage for the innovation race.

The aim of the EU Project “Integrated management of PROduct heterogeneous Data” (iProd) [1] is to improve the efficiency and quality of the Product Development Process developing a flexible, service oriented, customer driven software framework that will be the backbone of computer systems associated with current and new development processes. To achieve these goals, iProd relies on knowledge management (KM), knowledge based engineering (KBE) and process integration & automation technologies and optimization. The knowledge base along with a reasoning engine support information sharing, collaboration across companies, and promote efficient decision taking. The iProd framework will impact the product development process in order to reduce drastically product development costs by means of an optimized testing process, support knowledge and competencies extraction, structuring and sharing also with suppliers, improve focus of new product development with a fast and structured management of competitor and market analysis data (figure 1).

The work for PDP improvement involves the development and application of test planning and optimization methodologies, which are part of the iProd Reasoning Engine, their end result being detailed optimal workflows for applications areas such as Aerospace, Automotive and Appliances.

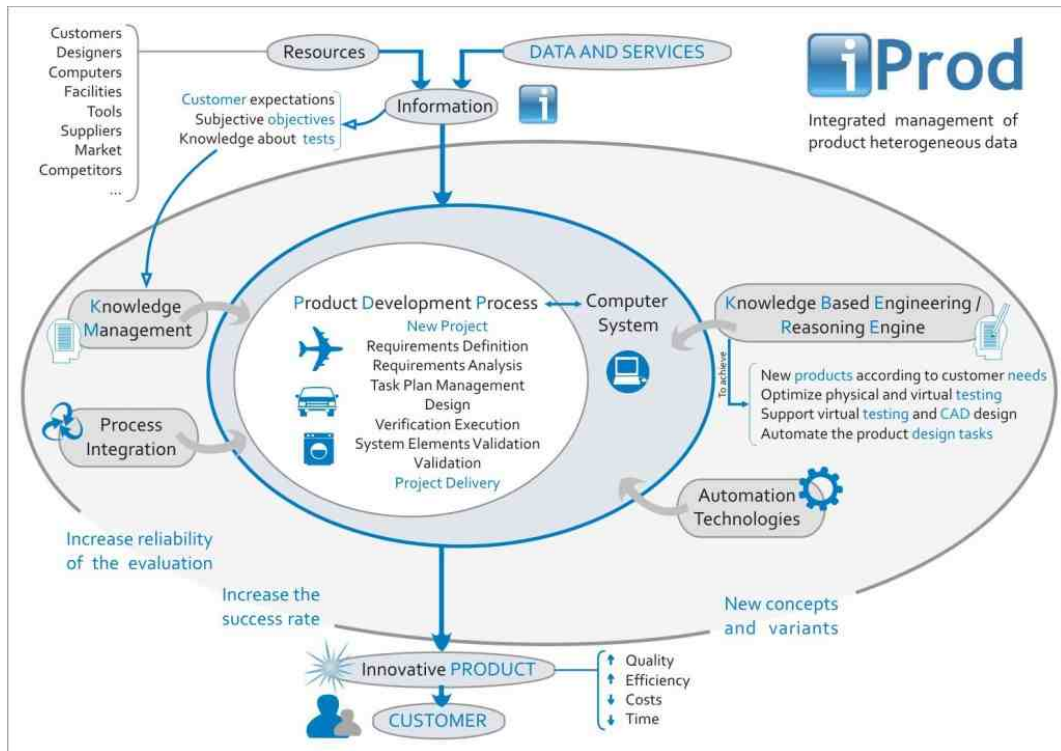


Figure 1. The iProd Framework

A main function of the reasoning engine is the optimization of the physical and virtual tests of a PDP. Product testing and verification procedures need optimization techniques in order to achieve the most efficient schedule of both simulated and physical tests required. Today's Product Development Processes (PDPs) are becoming more and more decentralized and distributed. As a result, the corresponding physical & virtual (i.e. human & simulation) test workflows are also becoming more complex as well as, distributed and heterogeneous and thus, the overall PDP optimization problem becomes more complex, with multiple & contradictory objectives and requires powerful and/or specially designed optimization tools [2].

Under iProd framework a special tool for Simulation Workflow Optimization (SWO) was developed in order to support the optimization of virtual (simulation) workflows in cases of distributed and heterogeneous networks of collaborating systems. The aim is to present a flexible web based tool [3] that will be able to promote a simulation workflow optimization method, make it available to a remote application or another service, and support a wider automated collaboration between heterogeneous design & simulation tools (figure 2).

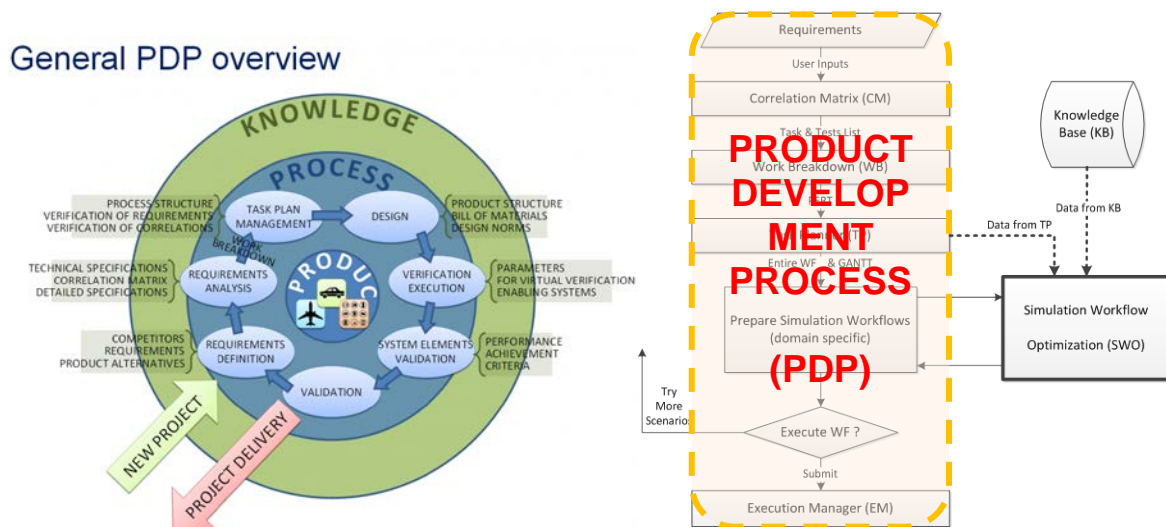


Figure 2. The role of SWO in the PDP process

A more detailed description of the SWO module can be found in [4]. In this work we will present the results of

the SWO tool when used for a sample complex and heterogeneous manufacturing process from the aerospace domain that requires a significant number of virtual tests.

2 THE FAE USE CASE

Aircraft box structures are a perfect compromise between weight and price. The conceptual design process of these structures is a typical Multi-disciplinary Design and Optimization effort, mostly performed by human engineers. The iterative nature of MDO turns the development of such components into a long and costly process. Fokker Aerostructures (FAE) is focusing on a number of Key Technologies, like thermoplastic composites and on Operational Excellence to offer their customers short lead times and affordable costs on such highly innovative products. The current climate for suppliers of aircraft structures is very competitive. Besides low cost and low weight, aircraft OEMs demand a shorter time-to-market. This requires the ability to develop aircraft parts quickly and cost effectively.

The process of developing an aircraft part usually starts with a Request for Proposal (RFP) by the aircraft integrator. After the proposal phase, two phases follow (figure 3) in which the design is detailed further: the preliminary and the detailed design phase. In each phase models are used with different level of fidelity. The challenge in each of these phases is the iterative nature between design, stress analysis, sizing and performance analysis. After a design is made, linear and non-linear stress analysis is performed on the design to check if stress limits are not exceeded. Based on that analysis the structural elements are sized in order to stay within limits. Based on the sizing a performance analysis can be made with respect to weight and cost.

Another challenge lies in the use of a common geometric model of the aircraft part, usually by means of a CAD model. This CAD model is used for Finite Element Analyses and also provides information for the recurring and non-recurring cost estimations. It is extremely important that all disciplines use the same basis. Currently the design of a rudder is time-consuming and costly. It requires a lead time in the order of several months. Also time and resource constraints do not allow for many design iterations, such that a feasible but sub-optimal design is achieved.

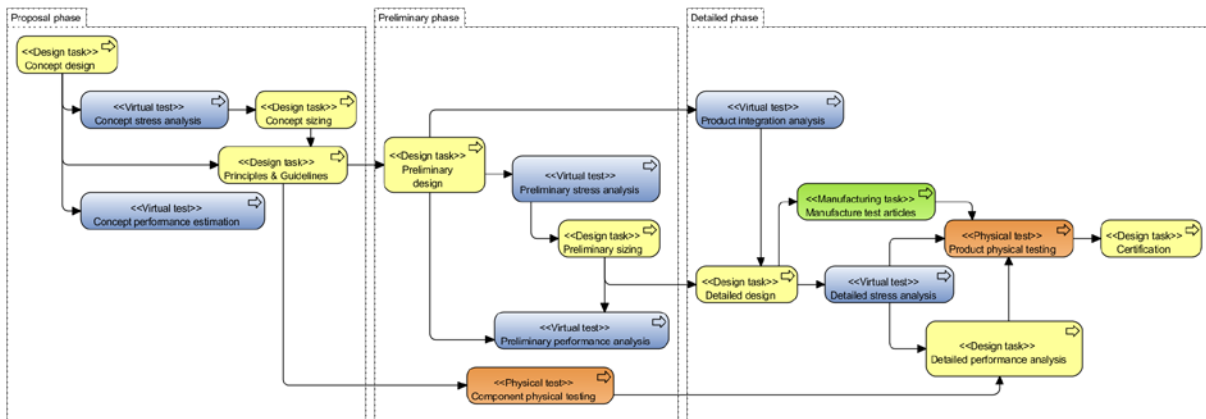


Figure 3: As-is design process of a rudder at Fokker Aerostructures

The Fokker Aerostructures (rudder) use case involves the search for an optimal rudder design through investigation of multiple repeated simulations of varying configurations while trying to satisfy conflicting requirements such as: customer satisfaction, weight minimization, manufacturing cost minimization.

As shown in figure 3, a number of physical and virtual test procedures are required for the design & analysis of the product. Each “virtual test” (shown in blue) is composed of a large number of simulations & analysis runs that need to be executed, in order to find a better or the optimal product design.

The duration of these virtual tests varies from a few days to several weeks or months. For instance, the “Update FEM analysis” subtask requires 60 days to complete all required simulations (figure 4). By using SWO on each one of these virtual tests and by optimizing each simulation workflow, a significant amount of time can be saved, or alternatively, a larger set of product variations could be tested, both resulting to increased customer satisfaction. The only requirement is the detailed knowledge of the specific task and the availability of the involved resources together with the objective that the designer wants to achieve.

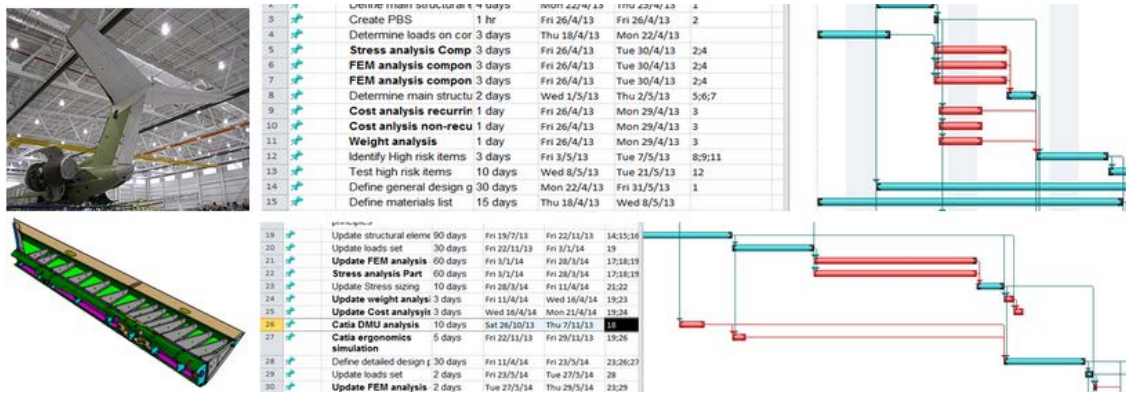


Figure 4. Sample list of various virtual tests in a Gantt form.

3 SWO APPLICATION

For the specific aerospace industry and the rudder manufacturing use case, five main parameters were selected as they may characterize the proposed designs: the material, the geometry or complexity of the rudder, the weight, the task duration and the cost.

The SWO tool was assigned to optimize a “virtual test”, the one that is dealing with the Finite Elements analysis (“Update FEM Analysis”). It is a test that requires many smaller jobs to run and it is using a more complex infrastructure of parallel resources that may allow more space for optimization. SWO calculates an optimal simulation workflow for those jobs that satisfies the user objectives. The major task details and subtask parameters involved are divided in three categories: the user objectives, the use case specific and the SWO tool specific. Typical relationships between controlling parameters and resulting indices & scores are shown in figure 5. All parameters are retrieved from the KB where the use case details are stored and updated. Some of the parameters are fixed but others are user defined, such as (Table 1):

- The objectives that describe the main goal the designer is trying to achieve,
- The use case parameters that describe the availability and the capability of the resources, and,
- The SWO tool parameters that control the function of the Genetic Algorithm

Table 1. User Defined Parameters for the FAE use case

USER PARAMETERS	DESCRIPTION
OBJECTIVES PRIORITY	
Minimize Weight	Set the user priority of minimizing the product weight. From 1 (highest) to 5 (lower), default = 1.
Minimize Cost	Set the user priority of minimizing the product cost. From 1 (highest) to 5 (lower), default = 1.
Minimize Duration	Set the user priority of minimizing the required time. From 1 (highest) to 5 (lower), default = 1.
USE CASE OPTIONS	
Avail. FE Tracks	Set the Maximum number of available FEM Parallel Computing Tracks. From 2 to 8, default = 8, 1 = no parallel support.
Avail. Tokens	Set the Maximum number of Tokens available to run the simulations. From 300 to 1000, default = 1000.
Avail. Memory	Set the Maximum GB of available Memory. From 30 to 100, default 100.
GA TOOL OPTIONS	
Population	Set the Size of Initial Population for the Genetic Algorithm (GA). Default = 13. (<15)
Generations	Set the Maximum number of Genetic Algorithm (GA) generations. Default = 120. (<200)

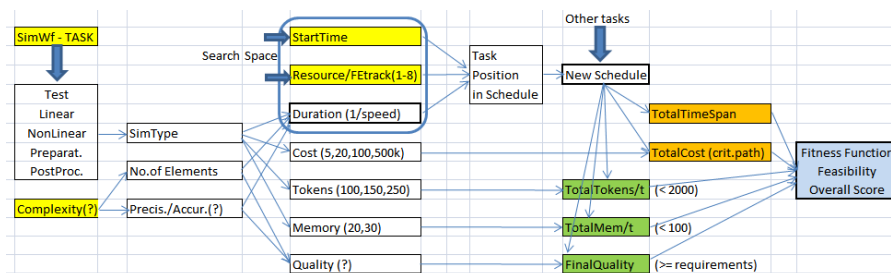


Figure 5. Relationships between controlling parameters and final indices & scores.

4 SWO RESULTS

The iProd framework offers the supporting platform for PDP improvement and the connection to the SWO tool. The entire setup is connecting several distributed modules and web services in one user interface. The user selects the domain and the product of interest, and proceeds with the Correlation matrix, Work Breakdown & Task Planning tasks (figure 6). At the end the user is provided with a workflow of physical (human) & virtual (simulation) tasks to execute.

Before executing the simulation tasks on its computer resources, the user can now use SWO and attempt to further optimize internally these tasks. From the Virtual Test Manager tab the user selects the SWO tool and uses the SWO GUI to prepare and submit the request.

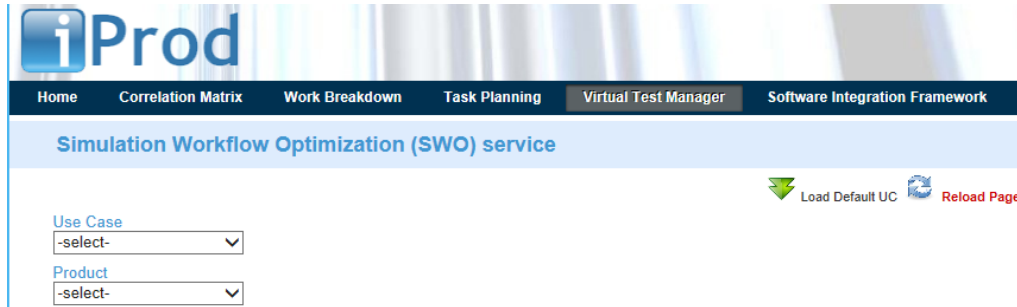


Figure 6. The SWO page in the software integration framework of iProd.

The next steps for the user are: load the UC data from the KB, adjust the user defined parameters and then pass to the execution phase by calling the optimization service. When the SWO run is finished, the following information is returned (figure 7): A table containing the top 5 simulation cases selected by the SWO tool that best satisfy the UC data and the user criteria, and, a plot showing the convergence of the GA algorithm to these solutions.

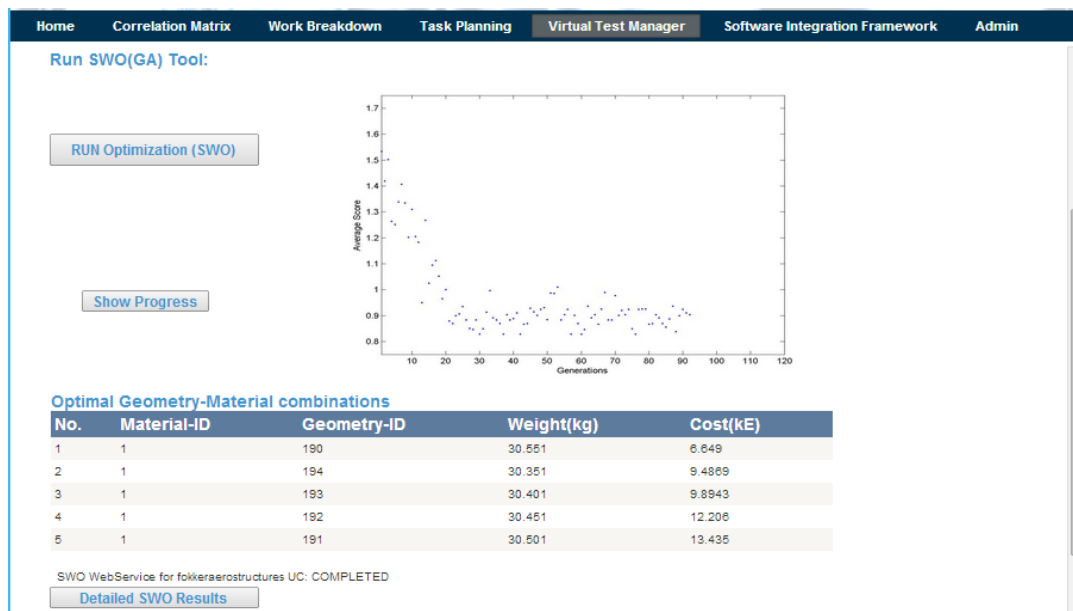


Figure 7. The first SWO results with the top 5 of the calculated solutions.

The user may ask to view in more detail the SWO results, in tables showing the GA populations of the simulation cases selected at specific phases of the optimization procedure. The three tables contain the population from the final solution (100% convergence) as well as the populations (fittest cases) from two earlier runs, at a convergence rate of 60% and 30% (Figure 8). The tables contain the IDs that define the various simulation tests and the estimated objective values.



Figure 7. The detailed SWO results with the fittest individuals at three instances.

The final step for the user is to display the proposed plan of simulation tests based on the above results (figure 8). From the four plots, the first plot shows the entire simulation plan as proposed by SWO, showing the estimated duration and its relation to the initially expected schedule.

The three other plots below show in detail the three phases of the simulation plan. Each phase contains Linear & Non-Linear FE Analysis runs of the simulation test selected by the tool and shows how they have been arranged to run (submitted for execution) by the user. The potential use of parallel tracks is also shown in these plots.

Additionally, the user may retrieve the above details in a text file reporting the proposed list of simulation runs to execute and their schedule, in order to prepare the corresponding simulation workflows for execution by the virtual test manager (Figure 9).

From the above results it is clear that by using SWO and the parallel FEM capability to optimize the simulation workflow a significant amount of time can be saved (aprox. 40%) that would permit either to finish earlier or to try more solutions.

5 CONCLUSIONS

In this document, the application of the Simulation Workflow Optimization tool developed in the iProd project in the domain of the aerospace manufacturing was presented. The Simulation workflow optimization is used to optimize the individual simulation parameters and configurations for the specific application, based on the overall PDP requirements and objectives. The result of SWO is a proposed list of simulation tasks that will converge to the optimal solution but in a shorter time. The significant amount of time saved will permit the user either to finish earlier the design phase or to try more solutions towards customer satisfaction.

6 ACKNOWLEDGMENTS

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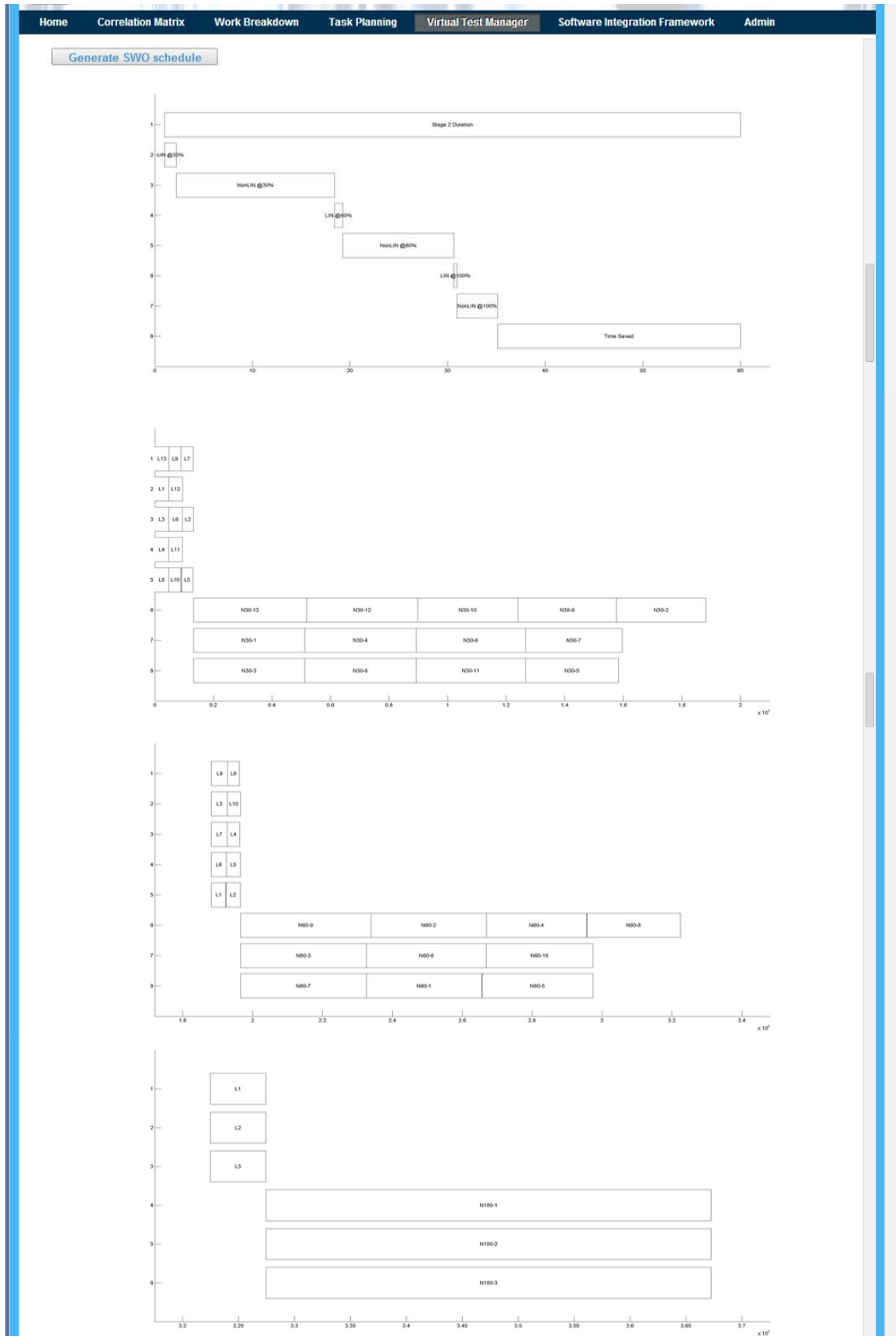


Figure 8. The proposed plan of simulation tests and the corresponding Gantt charts.

SIM	SCHEDULE		DESIGN CASE TO SimWF			ESTIMATED RESULTS		
	FTrack	StartTime	Material	Geometry	MeshDetail	Weight	Cost	Duration
LIN	2	1	M1	G070	N61	36.6 kg	8.1 k\$	475 min
LIN	3	943	M2	G039	N49	34.3 kg	11.8 k\$	382 min
LIN	3	1	M2	G069	N61	32.9 kg	9.1 k\$	475 min
LIN	4	1	M2	G096	N61	31.7 kg	9.4 k\$	475 min
LIN	5	904	M2	G118	N51	30.7 kg	15.6 k\$	397 min
LIN	3	476	M2	G136	N60	29.9 kg	8.8 k\$	467 min
LIN	1	903	M2	G152	N53	29.2 kg	14.4 k\$	413 min
LIN	5	1	M2	G159	N61	28.9 kg	17.2 k\$	475 min
LIN	1	483	M2	G160	N54	28.8 kg	9.4 k\$	420 min
LIN	5	476	M2	G161	N55	28.8 kg	8.1 k\$	428 min
LIN	4	476	M2	G169	N60	28.4 kg	9.3 k\$	467 min
LIN	2	476	M2	G169	N61	28.4 kg	9.3 k\$	475 min
LIN	1	1	M3	G190	N62	22.9 kg	14.9 k\$	482 min
FTrack StartTime Material Geometry MeshDetail Weight Cost Duration								
NLN	2	1325	M1	G070	N61	36.6 kg	8.1 k\$	3800 min
NLN	1	15765	M2	G039	N49	34.3 kg	11.8 k\$	3056 min
NLN	3	1325	M2	G069	N61	32.9 kg	9.1 k\$	3800 min
NLN	2	5125	M2	G096	N61	31.7 kg	9.4 k\$	3800 min
NLN	3	12661	M2	G118	N51	30.7 kg	15.6 k\$	3176 min
NLN	2	8925	M2	G136	N60	29.9 kg	8.8 k\$	3736 min
NLN	2	12661	M2	G152	N53	29.2 kg	14.4 k\$	3304 min
NLN	3	5125	M2	G159	N61	28.9 kg	17.2 k\$	3800 min
NLN	1	12405	M2	G160	N54	28.8 kg	9.4 k\$	3360 min
NLN	1	8981	M2	G161	N55	28.8 kg	8.1 k\$	3424 min
NLN	3	8925	M2	G169	N60	28.4 kg	9.3 k\$	3736 min
NLN	1	5181	M2	G169	N61	28.4 kg	9.3 k\$	3800 min
NLN	1	1325	M3	G190	N62	22.9 kg	14.9 k\$	3856 min
FTrack StartTime Material Geometry MeshDetail Weight Cost Duration								
LIN	5	18821	M1	G150	N53	32.6 kg	7.9 k\$	413 min
LIN	5	19234	M1	G174	N53	31.4 kg	6.1 k\$	413 min
LIN	2	18821	M2	G160	N58	28.8 kg	9.4 k\$	451 min
LIN	3	19272	M2	G161	N46	28.8 kg	8.1 k\$	359 min
LIN	4	19249	M2	G161	N51	28.8 kg	8.1 k\$	397 min
LIN	4	18821	M2	G161	N55	28.8 kg	8.1 k\$	428 min
LIN	3	18821	M2	G161	N58	28.8 kg	8.1 k\$	451 min
LIN	1	19288	M2	G162	N43	28.8 kg	13.1 k\$	335 min
LIN	1	18821	M2	G167	N60	28.5 kg	12.1 k\$	467 min
LIN	2	19272	M2	G190	N49	27.5 kg	8.8 k\$	382 min
FTrack StartTime Material Geometry MeshDetail Weight Cost Duration								
NLN	3	23262	M1	G150	N53	32.6 kg	7.9 k\$	3304 min
NLN	1	23390	M1	G174	N53	31.4 kg	6.1 k\$	3304 min
NLN	2	19654	M2	G160	N58	28.8 kg	9.4 k\$	3608 min
NLN	1	26694	M2	G161	N46	28.8 kg	8.1 k\$	2872 min
NLN	3	26566	M2	G161	N51	28.8 kg	8.1 k\$	3176 min
NLN	2	23262	M2	G161	N55	28.8 kg	8.1 k\$	3424 min
NLN	3	19654	M2	G161	N58	28.8 kg	8.1 k\$	3608 min
NLN	1	29566	M2	G162	N43	28.8 kg	13.1 k\$	2680 min
NLN	1	19654	M2	G167	N60	28.5 kg	12.1 k\$	3736 min
NLN	2	26686	M2	G190	N49	27.5 kg	8.8 k\$	3056 min
FTrack StartTime Material Geometry MeshDetail Weight Cost Duration								
LIN	1	32246	M1	G190	N64	30.6 kg	6.6 k\$	498 min
LIN	2	32246	M1	G191	N64	30.5 kg	13.4 k\$	498 min
LIN	3	32246	M1	G193	N64	30.4 kg	9.9 k\$	498 min
FTrack StartTime Material Geometry MeshDetail Weight Cost Duration								
NLN	1	32744	M1	G190	N64	30.6 kg	6.6 k\$	3984 min
NLN	2	32744	M1	G191	N64	30.5 kg	13.4 k\$	3984 min
NLN	3	32744	M1	G193	N64	30.4 kg	9.9 k\$	3984 min

Figure 9. The proposed list of simulation runs