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DEVELOPMENT OF A DATA-DRIVEN SIMULATION MODEL FOR AN ASSEMBLY-TO-ORDER SYSTEM

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ABSTRACT

This paper presents the development of a simulation model for an Assembly-To-Order (ATO) system. The model can be used to identify potential conflicts or bottlenecks in the system, to assist in the decision-making process, and to improve on the existing manual orders planning process. The process flow in the ATO system is complex as the system needs to handle a variety of products, different process routings, high product mix, and shared resources. The simulation model is developed using an existing commercial software platform. The model is designed to be fully data-driven, with sets of input and output data schema tables. This approach will make the simulation modeling more accessible to manufacturing community, and enable integration to factory's Manufacturing Execution System (MES) for real-time data and Real Time Dashboard (RTD) for displaying multiple scenarios of simulation results. The integration is accomplished through a central database server via Application Programming Interface (API).

1 INTRODUCTION

In most manufacturing systems, changes of factory layout, introduction of new equipment, changes of product mix, and flow controls are very common practices. These changes require careful planning for maximizing production throughput without sacrificing product quality or factory reliability. Further, with growing competition, rapidly changing technology and customer requirements, there is also an increasing demand for rapid solution techniques that can improve on the efficiency of manufacturing systems. There is therefore a need for a powerful and effective approach that can help to capture, analyze and improve manufacturing systems for the support of the system changes.

Simulation is one of the powerful analytical tools for visualizing, understanding, and analyzing the dynamics of complex systems. Simulation can be defined as the process of designing a model of a system and conducting experiments with the model in order to understand the behavior of the system or to evaluate various operating strategies on it (Pegden et al. 1995). A system is a collection of entities, or resources such as production materials, processing tools, space, people, etc., that act and interact toward the accomplishment of some logical end (Law and Kelton 2013). There are three commonly used simulation methods: Discrete Event Simulation (DES), System Dynamics (SD), and Agent-based (AB) simulation. Examples on the use of these methods can be found in Schroer et al. (1988), Gupta et al. (1993), Law and McComas (1997).

Simulation is widely used and provides an effective vehicle to support the decision-making process for designing or experimenting with manufacturing systems. Indeed, simulation can help to reduce the risk of unforeseen bottlenecks, under- or over-utilization of resources, and failure to meet specified system requirements, before actual system implementation. Often, it is cheaper and faster to build or configure a model and experiment with different scenarios compared to trial and error with the actual system. In fact, simulation is an indispensable tool when:

- Experimentation with the real system is disruptive or infeasible,
- Other approaches, e.g. mathematical or analytical methods, do not work,
- Evaluation of alternative designs, e.g. system designs or operating policies for a system, is required

We have developed a simulation model to fulfill the analytical requirements for an Assembly-To-Order (ATO) system. To ensure the simulation model is more accessible to manufacturing community rather than simulation community, the model is designed to be completely data-driven, with sets of input and output data schema tables. The input data sets can be rapidly configured to make a better choice to questions on resource and tool requirements, flow and release control, layout changes, etc. of the factory. Additional layout module, computational package, and intuitive visual charts are incorporated into the model to enhance its appeal to the general manufacturing practitioners. It is hoped that through this approach, the use of simulation in manufacturing industry can be more widespread, for tackling problems of our increasingly complex manufacturing world.

2 LITERATURE REVIEW

There is no lack of interest in simulation modeling research and application in the literature. Simulation papers related to manufacturing have explored applications, associated issues, or approaches to using simulations, and there is also a growing trend in using simulation to support design decision-making (McGinnis and Rose 2017).

Gan et al. (2005) developed a High level Architecture (HLA) Borderless Fab with a distributed simulation model using a commercial wafer fabrication simulator. The model comprises two factory models, integrated into a supply chain model to form a borderless fab model for improving production performance. It was found that the HLA supply chain model can achieve a significant speed-up as compared to a sequential supply chain model on a similar hardware configuration.

Ridzuan et al. (2013) built a simulation model, using an existing commercial software platform, for work-in-process (WIP) management in semiconductor fabrication. This model could be used to perform what-if analysis to understand impacts on cycle time and overall output. The authors made use of the built-in functionalities in the commercial software, to handle the complexity in the semiconductor fabrication, and to perform what-if analysis for decision-making purposes.

Kundu et al. (2019) constructed a DES model, integrated with a mathematical model based on particle swarm optimization (PSO). The simulation model is used to simulate real-life scenarios, while the meta-heuristic algorithm is applied to find the best values for each decisional variable. The hybrid model is used to analyze the impact of different Kanban settings on the performance of the assembly line feeding system. Kanban is an inventory control system used in just-in-time (JIT) manufacturing, the goal of which is to limit the buildup of excess inventory at any point on the production line. Savsar and Abdulmalek (2008) developed an assembly line simulation model built with Kanban-based JIT pull/push production control. Several costs, such as inventory holding, demand delay, and late shipment costs are considered in the search for the optimum number of Kanbans.

Fowler and Rose (2004) identified grand challenges for modeling and simulation in manufacturing, one of the challenges is to reduce existing problem solving cycles. One aspect of this is reducing the time required to create the simulation models. Most of the simulation models in the literature are built for specific research objectives, and thus models are often simplified or abstracted for solving the very specific issue on hand. These models can be quick to configure for problem solving cycles; however most of these models can only be used for tackling the designated issue. Our data-driven model is developed to be a Digital Twin of the factory, incorporating broad operations details such as operators and Automated Guided Vehicles (AGVs) traveling speeds, traveling paths, part binning, orders batching, etc., and is therefore suitable for simulating what-if scenarios of most commonly occurring factory changes.

3 MANUFACTURING MODEL

Simulation is used in our project because it is the most powerful and used operations research (OR) method in manufacturing literature. Considering the complexity and stochastic behavior of manufacturing system, a pure analytical approach is unable to obtain reliable results (Kumar and Panneerselvam 2007, Hao and Shen 2008). The Discrete-Event Simulation (DES) method is selected as it is the most appropriate for our work. We have categorized input data into two sets for the data-driven model: 1) Layout data; 2) Product and process data. The former is associated with the characteristics and attributes of physical resources in the factory, for example, the location and size of machines, queues, conveyors, operators, AGVs, network nodes, and so on (Refer to Table 1 for further details). To achieve a high fidelity simulation model, the exact locations of production resources are a must-have requirement for simulating operations of operators, AGVs, and other types of transporters. This set of data is best captured through drag-and-drop placement of production resources in a model layout. The latter input data set is shown in Table 2 and it is the data relating to the product and process such as orders plan, Bill-of-Materials (BOMs), process and setup times, part routings, etc. This set of data can either be retrieved from the existing factory database or manually input. Both data sets are pre-defined with data schema tables for ease of portability across different storage media such as plain text files and databases.

Table 1: Layout data set.

Data Type	Data Table	Description
Station	station	Name of processor and its family, operation type (by piece or batch), capacity, priority, name of operating time table and mean-time-between-failure (MTBF)
Conveyor	conveyor, conveyor_detail	Name of conveyor and its family, type of conveyor, capacity, speed, priority, and sections of conveyors
Location	location	Name of location and its family, location type, capacity, priority, associated input and output
Rack	rack, rack_detail	Name of rack and its family, type of rack, capacity, rack details of bays and levels, and the capacity
Resource	resource, resource_group	Name of operator, technician, or AGV and its group, type, capacity, speed, acceleration, deceleration, name of home node, z orientation, name of operating time table, and mean-time-between-failure (MTBF)
Node and Network	network, node	Name of network nodes and its paths, maximum number of transporters at each node, type and speed limit of path
Resource Visual	visual	Name of station, location or resource, and its department, area, size, coordinates, associated 3D shape file, and color

Table 2: Product and process data set.

Data Type	Data Table	Description
Plan	order_plan, mold_plan	Name of order, product or part type, order quantity, assembly line, and production quantity for each day
BOM	bom	Name of product with its part and quantity, part set of product's part
Process and Setup	changeover_time, process_time, part_mold	Setup time, process time or cycle time, process name, batch size, part and station name, mold name for molding machine and mold cavity
Part and Route	part, route	Part and its routing, step, process name, and type
Part Bin and Trolley	part_qty_bin	Number of units of part per bin, per trolley, etc.
Part Box and Pallet	master_data	Number of units of product per box, per pallet for shipment
Kanban and Space Limit	kanban_size	Name of Kanban location, assigned part, and space limit
Work-In-Process (WIP)	part_qty_bin_wip, wip	Initial WIP for each Kanban location and other locations
Resource Task	resource_task	Operator, AGV, or other resource task requirement for each process e.g. operator requirement for assembly operation
Part Movement	movement	Transport requirements for part movement including source and destination location, related part, resource group required, loading and unloading times
Work Shift	work_shift	Work shift definition i.e. number of shifts, name of shift, start and end times
Machine Down	down_schedule, down_unscheduled	Scheduled and unscheduled down (MTBF) definition including station name, start time and duration, distribution function and its parameters, required resource group for repair
Reject	reject	Process reject definition including process name, station, product, part and reject rate
State	state	Initial state for each station, part and its details on station including start date and time
Time Table	time_table, time_table_repeat	Time table definition including start time and duration, resource group required
Settings	options	Various settings for simulation model e.g. run length, warm-up period, date, and time for recorded factory states

To make the simulation model more user-friendly and accessible to those unfamiliar with simulation, we have developed two 'models': 1) 3D layout model; 2) simulation model. The layout model is used to capture factory layout related data. This 3D layout module enables factory layout to be created and edited by using existing drag-and-drop features within the commercial simulator platform. Once the factory layout changes are done, a one-button-click will generate the layout input data set for the simulation model. This 3D layout module can readily support constant changes in factory layout.

The conceptual overall architecture of the ATO model, with the two models is shown in Figure 1. The standard steps for a simulation process (Refer to Table 3 for simulation steps) are as follows: Users prepare layout data set, as well as product and process data set for simulation. The simulation model can then be built, reset and run with the prepared data sets. Simulation output will be generated when the simulation run length is reached.

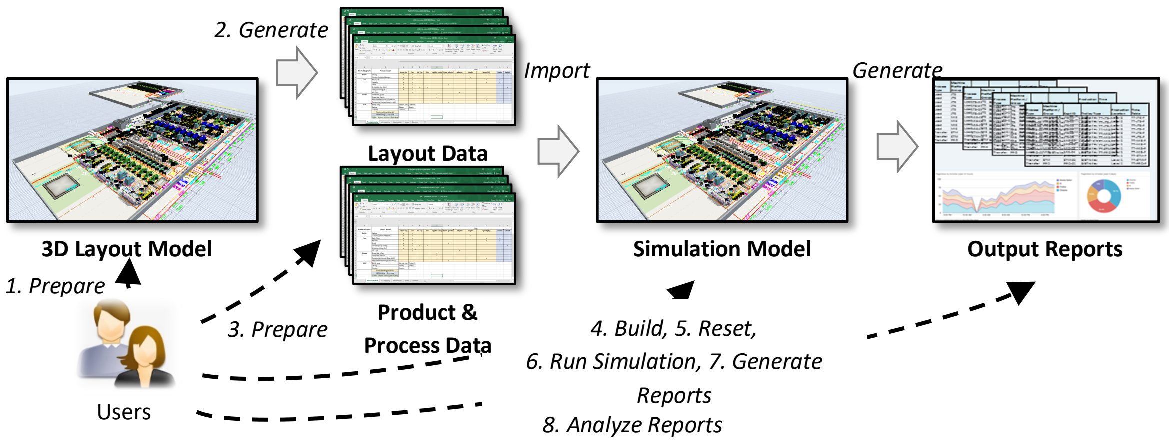

Figure 1: Overall architecture of ATO model with 3D layout and simulation models.

Most of the simulation steps are implemented in the ATO model as a one-click command execution, except for steps 1, 3 and 8. These three steps are important for what-if experiment and analysis. Steps 1 and 3 are for users to make any changes relating to factory layout, equipment, product mix, and flow controls, etc. These changes will be automatically incorporated into the simulation model when the 'Build' command is executed.

Table 3: Standard steps of simulation process.

Model	Step	Description
3D Layout Model	1. Prepare factory layout	Prepare factory layout using simulator's features
	2. Auto generate data set	Generate layout input data
Simulation Model	3. Prepare product and process data	Prepare input data relating to products and processes
	4. Build model	Build model dynamically from input data sets
	5. Reset model	Reset objects, variables and statistics
	6. Run model	Run simulation model
	7. Generate reports	Generate output reports
	8. Analyze reports	Analyze output report to identify conflicts or bottlenecks

Output reports are generated from the simulation model after each simulation run. Similar to input data, these reports have pre-defined data schemas and can either be stored in a plain text file or database. The reports cover order fulfillment, states, and output of production resources at event times or specific pre-defined time interval. The types of output reports are shown in Table 4. This simulation output reports can later be used to plot a variety of visual charts such as production volume charts, Gantt charts, state charts, etc.

Table 4: Output reports.

Report Type	Report Name	Statistics
Orders	REP_ORDERS, REP_MOLDING	Release time, start time, completion time for orders
Orders Trace	REP_ORDERS_TRACE, REP_MOLDING_TRACE	Process & setup start and end times, etc. for orders
Station States	REP_STATION_STATE	States of stations at event times, hourly and average states for machine
Resource States	REP_RESOURCE_STATE	States of resources at event times, hourly and average states for operators and AGVs
Station Output	REP_STATION_QTY	Hourly output of machines
Location Qty	REP_LOCATION_QTY	Quantities at locations or queues at event times, e.g. on entry, on exit
Location State	REP_LOCATION_STATE	Average content, input, output, and states for queues
Task Qty	REP_RESOURCE_TASK_QTY	Total distance traveled, pending number of tasks, executed number of tasks for operators and AGVs

Our data-driven simulation modeling approach, which distinguishes data capture of layout data from product and process data, has several advantages over other simulation modeling methods:

- Making full use of the drag and drop features of the commercial simulator, Flexsim. The built-in feature is intuitive, easy to use, and powerful for novice simulation users,
- Supporting detailed simulation with 3D animation, which can be a great help for verifying and validating the simulation model,
- Providing display support to Real-Time Dashboard (RTD). The sets of input data as well as output reports from 3D layout model can be stored in database server for RTD display,
- Keeping all complex modeling logic and programming code from users. For example, the production resources are dynamically created and product routing linkages are automatically generated during model building step.

Work is still ongoing to enhance the simulation model to be more intuitive for manufacturing practitioners to make what-if scenario changes and to readily identify conflicts or bottlenecks in the simulation model. For example, we have incorporated a heuristic module into the model to compute production and consumption quantities for each part to help planners to identify planning issues. We have also enhanced the output reporting with visual charts. Further description of these enhancements is in the next section.

4 APPLICATION STUDY

The model has been designed to be used for general manufacturing simulation. However, to support requests from ATO industry, effort has been spent to customize the model so that it can support ATO system. The process flow of the ATO manufacturing system under consideration is shown in Figure 2. The part Kanban storage is used to buffer between the molding production flow and the assembly line flow. Molding production flow consists of molding, oven curing, and vision processes. Not all parts are required to go through all three steps. The assembly line flow comprises molding, label printing, and assembly operations. Similar to molding production flow, Not all parts are required to be processed by all the steps. For example, a customer order may not need molding or printing step. The process routing of each part can be defined in Part and Route data tables.

Orders plan, which consists of weekly customer orders, is prepared by a planner. The orders plan is the primary source that drives the simulation for the assembly line flow. While molding plan, which is prepared manually based on the orders plan, is the secondary source that drives the molding production flow of the simulation model. The part types that are needed for each customer order are defined in the BOM data table. For this case study, the simulation is set to run for seven days with one replication run as all the input data is deterministic. Warm-up period is set to zero.

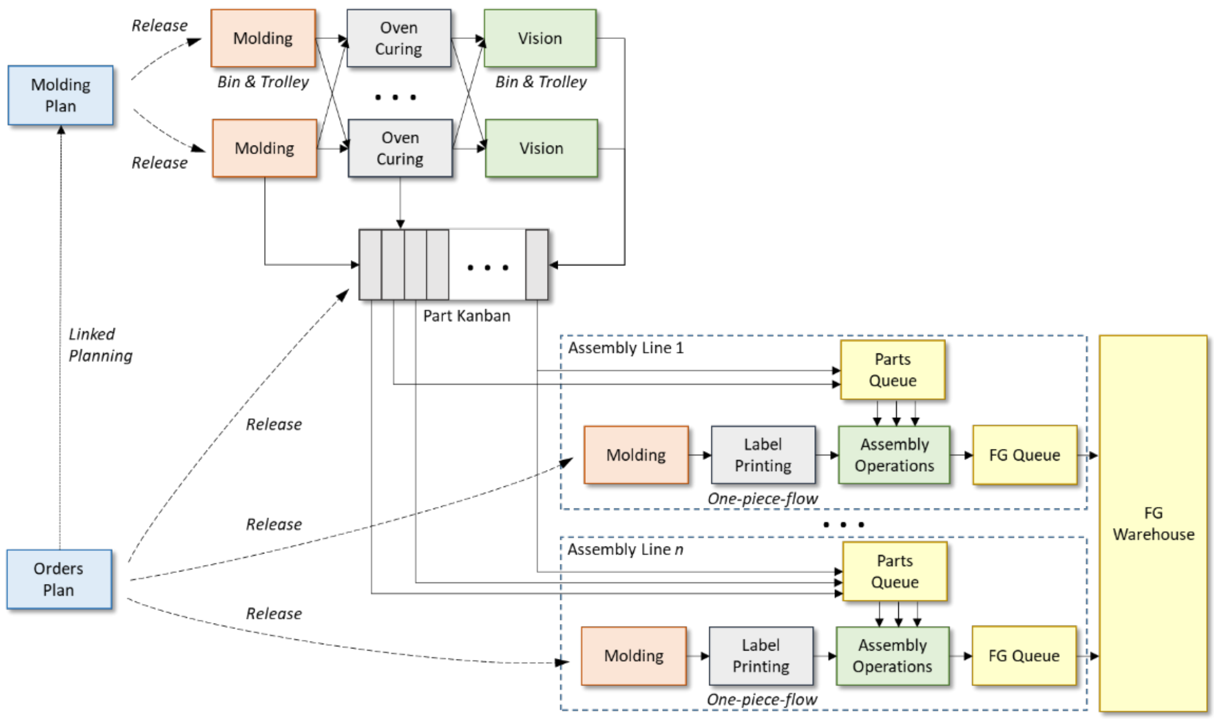

Figure 2: Process flow of the Assembly-to-Order (ATO) system.

The assembly line flow is a one-piece-flow, whereby units of a part are moving through the processes piece-by-piece, whereas for the molding production flow, bins of standard sizes are used to keep a specific number of units, with each trolley carrying 8 bins. The trolleys are used to transfer parts among the mold production processes, Kanban storages and parts queues in the assembly lines. The only exception is oven curing process. In this process, units are manually transferred to oven compatible containers for specific hours of curing process, and later transferred back to the standard bins before being transferred to the next process defined in the part routing.

The smooth operation of the ATO system is heavily dependent on the production and consumption rates, buffered by Kanban storage space, for each part. Assuming a fixed consumption rate of parts, the production and consumption rates chart of a part can be plotted, with the consideration of setup, part binning, movement, and delivery operations, as shown in Figure 3. From the chart, it can be observed that WIP inventory of the parts plays a major role in buffering the inventory required for the smooth operation of assembly line flow from unanticipated disruptions. If there is a delay in delivering any of the required parts to an assembly line, the line will have to stop its operation until the required part is delivered. This delay can be caused by machine breakdown, busy material operators (e.g. feeders), temporary part shortage, etc. As for major part shortage caused by improper planning of the molding plan against the orders plan, Kanban inventory may not be able to resolve the shortage issue completely, in particular, for major shortage mismatch of production and consumption rates of part quantities.

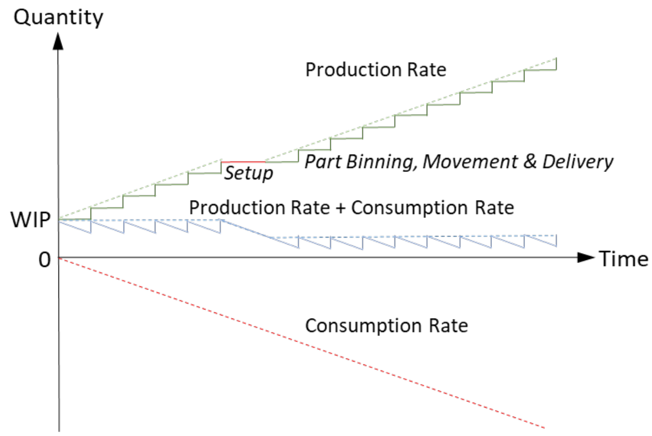

Figure 3: Production and consumption rates of a part, considering setup, part binning, movement, and delivery.

To detect the major part shortage due to planning mismatch, we have incorporated a heuristic module, to compute shortage statistics based on the production and consumption rates of each part, into the simulation model. This module is based on the concept described earlier and considers the following parameters for the rates computation:

1. Part processing and setup times for molding, curing, and vision processes
2. Part binning size and trolley transfer between processes

Five major steps are involved in the computational heuristic:

1. Compute the production time line for each mold machine based on the molding plan, considering the processing and setup times of molding, curing, and vision processes, and part binning quantity for the maximum of eight bins per trolley,
2. Sort out all production time lines of mold machine into production time line for each part, and add in the initial WIP for the part,
3. Compute the consumption time line for each assembly line based on the order plan, considering the processing, setup, and assembly times,
4. Sort out all consumption time lines of assembly lines into consumption time line for each part, considering BOM,
5. Match the consumption time line with production time line for each part, and identify shortage quantity, time, and location.

In the module, a time line is a set of non-decreasing time sorted records, with each record containing attributes of event time, quantity, and location (i.e. mold machine or assembly line). The heuristic module will be automatically executed on 'Build' command, and will generate the following statistics: starting and ending inventory, potential shortage quantity, and times of occurrences for each part. Refer to Table 5 for a typical computed output for a part. The table shows that the ending WIP is -50736 for part 'Part 1' and thus is unable to meet the quantity requirement for assembly line consumption for the planning period. The output also displays potential quantity shortages of the part for two time periods for the specified assembly lines. This information identifies planning conflicts, and can help the production planner to refine the molding plan.

Table 5: A typical computed shortage report for a part.

Part	Type	Quantity	Max Quantity	Start Time	End Time	Location
Part 1	Start WIP	15840	15840	0	0	
Part 1	End WIP	-50736	-50736	7700	7700	
Part 1	Total Production	132000	132000	168	7700	
Part 1	Total Consumption	-198576	-198576	0	6842.5	
Part 1	Shortage	-624	-624	806	840	Final Assy 13, Final Assy 14
Part 1	Shortage	-624	-76688	888.8	7700	Final Assy 14, Final Assy 13, Final Assy 10

The computational results are confirmed with an actual detailed simulation model run (Refer to Figure 4). The Gantt chart, which has been designed to help identify delays in the assembly line flow, display results visually from the simulation model output. Figure 4 illustrates that there are many assembly operation delays caused by insufficient part quantity for the specific assembly lines. The delays are extended to the end of simulation period, due to insufficient production of the part. Based on the simulation result displayed on the Gantt chart, the production planner is able to observe the impact of part shortage on customer orders fulfillment and can take appropriate action to mitigate the issue.

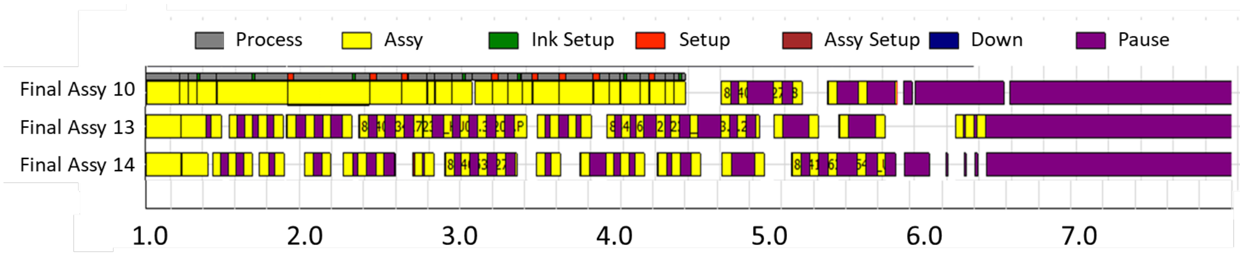

Figure 4: Gantt chart for Assembly lines 10, 13 and 14 showing pauses or delays in assembly operations before molding plan change.

To identify the part that causes the delays, the planner can use computer mouse to click on any of the 'Pause' blocks in the Gantt chart. A window will pop up to show more detailed information of the block. Table 6 shows an example of the data display. Equipped with this information, the planner can revise the molding plan for the part to be produced on more mold machines.

Table 6: An example of the data display for the 'Pause' block.

Object	Event	Start Time	End Time	Part
Final Assy 10	Pause	7143.136	7964.7382	Part 1

After several plan adjustments and simulation iterations, the planner is able to eliminate the part shortage problem (Refer to Figure 5).

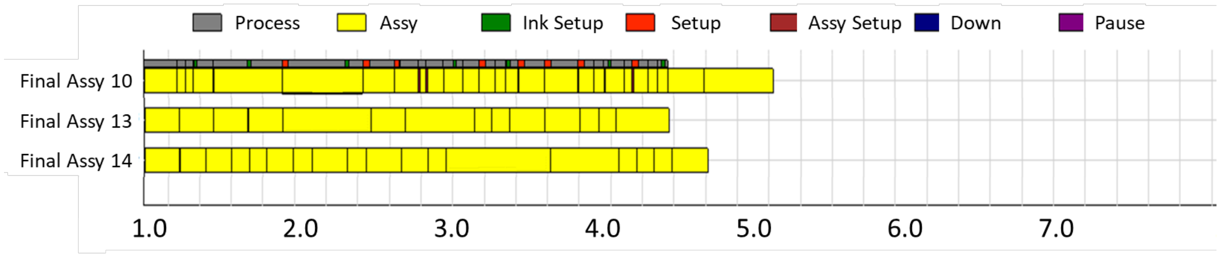

Figure 5: Gantt chart for Assembly lines 10, 13, and 14 showing no delay in assembly operations after molding plan improvement.

5 CONCLUSIONS

We have developed a high-fidelity manufacturing simulation model, customized for a case of Assembly-To-Order (ATO) system for an MNC of consumer products. The model is designed to support the most commonly encountered changes in manufacturing. These changes cover factory layout, equipment, product mix, and flow controls. The model, with its heuristic module and visual charts, is able to help planners to determine the orders fulfillment performance, and identify the potential issue for poor production performance. The model can also be used by managers to plan for capacity expansion through factory re-layout and addition of new equipment, by using the drag-and-drop features in the commercial simulator.

We have achieved our objective of making simulation more accessible to manufacturing practitioners. With data-driven simulation modeling approach, the problem solving cycles for complex manufacturing systems can be improved. We believe that data schema tables and visual charts can be designed to be more user-friendly to novice simulation users than modeling via programming scripts. For most companies, maintaining a full-time simulation expert is expensive, as years of simulation knowledge and experience may often be required for a fresh engineer to build up competency in the simulation methodologies and technologies.

6 FUTURE WORKS

This project is still ongoing, and many functionalities can be incorporated into the model. Automating molding planning is one of the most likely further work. This can be performed in two stages. The first stage is to determine the overall consumption rates of each part, and then allocate appropriate number of mold machines to meet the consumption rates. The second stage is to determine the optimum number of Kanban spaces for each part, based on the production and consumption rates, and the process flow of the parts.

The next potential work is to go through commonly found what-if scenarios and design more intuitive visual aids such as charts or graphs that can help users readily identify issues. Examples of the what-if scenarios include:

1. Loading plan and its estimated order fulfillment
2. Layout change and its impact on order fulfillment
3. Impact on factory performance when equipment is not available
4. Process flow change and analysis
5. Cycle Time, utilization, and WIP improvement
6. Capacity validation analysis

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