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SYSTEMS DYNAMIC MODELING: PLANNING BEYOND THE WORKER

William J. Peck
Daniel A. Finke

The Applied Research Laboratory
The Pennsylvania State University
Applied Science Building
University Park, PA 16804, USA

ABSTRACT

Using Systems Dynamic Modeling, we propose a novel formulation that considers workers as a decision variable with other parameters that are beholden to known, but random demand. Previous applications within the literature focus on estimating manpower to meet production demand for a particular process. We extend that work by including system constraints that are more realistically represent the problem under consideration. The proposed model was used to find configurations of workers, shifts, and work stations that achieve a minimized deviation between output and demand while maintaining a near constant workforce. The system under consideration is a manufacturing environment and the model posits the production of certain product lines that are each composed of a series of disparate operations. The model was tested using real production data and the results show that Systems Dynamic Modeling is an effective method in estimating the long-run resource requirements for the variable demand profiles.

1 INTRODUCTION

Simulation Modeling is a large and varied subject whose general aim is to model a physical system in order to make generalizations about processes, to better understand complex systems, or to collect and present relevant performance statistics. In developing a model, there are many different methods a modeler might use; many of these techniques are problem dependent. To model the job shop resource allocation problem described in this paper, we focus our scope to techniques that have been used to solve production capacity, resource allocation, conventional forecasting, and manpower planning.

Simulation modeling enables realistic estimation of demand forecasts and production capacity to meet those forecasts. This is due to the ability to represent the inherent randomness of system variables. Properties, such as the central limit theorem, ensure that after a series of replications, a distribution can be created from which a better estimation of performance (capacity vs demand) is achieved. Instead of relying on a single data point, or a series of empirically gathered data points; simulation modeling can produce a seemingly unending series of forecasts that, when combined, provide a more robust and accurate estimation of demand, or any parameter in question.

1.1 Problem Statement

The problem under consideration is a job shop environment with multiple product lines each requiring multiple operations. Each product line produces an assembly of components necessary in fabricating larger units. The components themselves form a large variety of piece parts that are produced by the job shop under consideration. There are a variety of work stations in each cell required for the production of any given product line as well as a skilled and specialized workforce. Often times, a single worker will perform

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the vast majority of necessary operations in order to deliver a finished part. What additional resources are needed to meet a significant, but variable increase in demand?

The problem can be defined as follows. Given a set of J product lines where $J = \{J_1, J_2, \dots, J_n\}$, and a set of O independent operations where $O = \{O_1, O_2, \dots, O_m\}$ determine the appropriate number of workers, shifts, and work stations for each product line J. At most, there can be three shifts for each product line. A worker needs a work station so as to contribute to the total output of the shop, and each work station can process only one operation at a time. Once a process has begun on that work station, the operation must be completed without interruption. Each shift suffers some sort of productivity penalty, P_s due to various economic and working conditions. There exists a physical capacity on the number of work stations and workers that can perform work within the space. Each operation is processed in the order given by the set O for the specific job. The collective production pertaining to the combination of workers, shifts, and work stations shall be known as output. Every period l, they face a random demand that is known is advance. The goal is to solve the problem and in doing so, minimize the deviation between output and random demand per period.

2 PREVIOUS WORKS

The fundamental objective in computer simulation and simulation modeling in general, is to develop simplified software abstractions to represent the behavior of a complex system over time, which are often more difficult under more traditional means of analysis (Rothrock and Narayanan 2011). The following examines previous contributions submitted to the scientific community by other authors on the subject of systems modeling and resource allocation problems. The techniques under review are discrete event simulation, agent based modeling, dynamic systems, and systems dynamic modeling.

There are many different modeling paradigms available to researchers within the simulation community. A popular example is discrete event simulation, which models a system over time where state changes occur at separate countable points in time (Law and Kelton 2000). As the entity moves throughout the system it encounters a series of queues and activities that introduce stochasticity throughout the entire framework; thus the movement time of an item is said to be stochastic in nature (Brailsford et al. 2010). Structurally, discrete event simulations are widely used when the modeling parameters require an operational or tactical level of clarity (Tako and Robinson 2012). Practitioners of discrete event modeling tend to analyze performance over time of an interconnected system that is subject to internal and external variation (Morecroft and Robinson 2006). Discrete event simulation is a widely used and well established simulation approach especially within the areas of healthcare (Brailsford et al. 2010), lean manufacturing (Detty, Yingling 2000), and logistics (Tako and Robinson 2012). Its applications are many; though they primarily focus on estimating parameters centered on queues, and arrival/departure schedules.

Another technique is agent based modeling, whereby the aim of this technique is to analyze individual interactions among agents and how those actions shape global consequences (Scholl 2001). Agent based simulation can best be used to study how patterns and organizations unfold and to uncover structural occurrences at the system level that are not readily seen from the individual agent behaviors (Macal and North 2005). This focus on emergent behavior requires a broad and flexible rule base that agents subscribe to in their actions. Applications within agent based modeling deal with systems at the constituent level and are less focused on aggregate areas (Bonabeau 2002). The use of agent based modeling in logistics and other applications is a bottom up inductive approach derived from agent interaction as opposed to top down deductive models (Swinerd and McNaught 2012).

Models classified under dynamic systems are meant to replicate physical systems from the perspective of a time dependent model (Fishwick 2007). The principles of dynamic systems define a framework for how new and novel forms emerge and stabilize through a series of internal feedback activities (Granic and Peterson 2006). Negative and positive feedback loops drive self-organization of the dynamic system. Novelty within the system emerges through positive feedback loops whereby negative feedback loops drive stability and the system converges towards an attractor. Within this context, a dynamic systems model establishes a state space to which a series of dynamic rules are applied (van Geert 1991). Over time, attractors stabilize and a control strategy can be developed to better understand output and minimize error between the achieved and desired output.

Lastly, we come to systems dynamic modeling whose aim is to augment the structural comprehension of a system and the relationships that exist between variables considered relevant to the original problem (Brailsford and Hilton 2001). Typically, a systems dynamic model is composed of a series of interconnecting stocks and flows. Whereby flow of information or other quantities is regulated by the intensity of the flow in to or out of a stock. Specifically, the flows are regulated by a series of parameters that are often interconnected with other flows or parameters; thus creating a feedback loop. As a modeling technique, systems dynamic is designed for long-term, chronic dynamic management problems that play out over a strategic period (Vlachos et al. 2004).

Systems dynamic modeling has often been described as a top-down approach that models a system by breaking it into major components and modeling those interactions. This is opposed to bottom-up techniques that place due emphasis on entity level interactions as a pretext to global consequences as is usually seen in applications of agent based modeling (Heath et al. 2011). In this same vein, we decide against discrete event simulation due to its focus on decisions at the operational and tactical level, while also acknowledging that many of its applications lie in the realm of scheduling and process architecture. Our goal, therefore, is not to use systems dynamic modeling as a sort of control system with feedback loops, as one might see in an application associated with dynamic systems, but rather as an optimization technique that evaluates potential configurations concerning optimality.

The scope of systems dynamic modeling is wide and varied. In recent years it has been used to analyze systems that include management of water resources in river basins, (Kotir et al. 2016) diffusion of differing chemical species on a mesoscopic scale, (Leberecht et al. 2017) and implementation on social impact assessments with regards to large development projects (Karami, et al. 2017).

Past research into systems dynamic modeling have used it as tool to estimate the number of workers or people necessary for a system. One such application looked at U.S. Army enlisted personnel and used systems dynamic modeling to understand the impact of policies and the stability on manning requirements (Thomas et al. 1997). We build upon this methodology by introducing stochasticity into the systems dynamic model. Enlistment for the US Army is forecasted, but not subject to random factors, whereas the demand figure in our analysis is derived from forecasts and subject to random factors. Another example of systems dynamic modeling and staffing decision support focused on staff attrition in software development organizations (Collofello et al. 1998). The methodology considered three staffing polices for a perspective employer to consider and offers a recommendation regarding the best staffing plan. Our analysis expands this idea by presenting an optimal staffing plan with respect to the deviation between output and demand.

3 METHODOLOGY

Within the realm of a market-based economy, consumption pressures the production of goods. Market signals, such as the price of a good, conveys to manufactures a whole host of information pertaining to supply and demand of a single good. It is therefore necessary to forecast demand so as to plan production. In order for a manager to plan production and be able to meet demand targets, they must devise some sort of manufacturing plan that will allow for the production of a certain good. This type of resource planning often manifests itself in hiring workers and purchasing machines that will allow workers to convert their labor into output, which manifests itself in some sort of product. Resource planning is costly as workers require training and machines require large amounts of capital investment to be purchased in addition to training and maintenance. This, in turn, leads to two different developments. Firstly, because hiring and requisition is costly, it is best to develop a long-term staffing plan whose fluctuations over time are minimal. Secondly, in order for a long-term staffing plan to be created, demand must be forecasted over a sufficiently long planning horizon. Thus, in order to achieve a long-term staffing plan, we must have a long-term forecast regarding demand for that product.

Our methodology is a systems dynamic modeling approach. In using a systems dynamic model we create a framework for users to achieve various response variables such as the number of workers, shifts, or work stations. By executing the model, we determine the output that the configuration achieves and evaluate whether or not the solution represents an optimal or feasible solution. Optimal solutions are those that achieve a minimized deviation value, while feasible solutions are those whose output is larger than the random demand. Infeasible solutions are those whose output falls short of the demand. In an ideal world, output and demand would be equivalent, but in a practical sense, we want to achieve a minimized amount of overage with respect to output. There are multiple product lines produced by the job shop and each product line will have some portion of the total demand. Furthermore, each product line will have a number of operations that are required to create that specific product. Each work station provides the necessary tools that allow a worker to convert labor into output. We assume that each operation requires a different work station.

Our selection of systems dynamic modeling is based on the notion that its application to this problem in conjunction with other decision variables and forecasted demand is unique. Configuration decisions that are occurring happen under the auspices of random demand that fundamentally influence each decision variable. An integral aspect of systems dynamic modeling is the interplay between stocks and flows. Simply put, stocks are storage devices where units aggregate and flows regulate the intensity of units either entering or leaving the stock. The intensity of a flow is often governed by a series of parameters or variables. It is possible for multiple flows to terminate or depart from an individual stock. See Figure 1 for an example stock and flow arrangement.

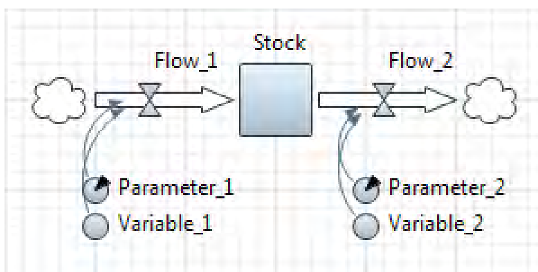

Figure 1: Simple stock/flow illustration.

A single stock and multi flow illustration are shown in Figure 1. The stock lies between two flows labeled Flow_1 and Flow 2. Each of the flows have a parameter and variable value that determines the intensity of the flow into and out of the stock. We can further develop this simple illustration into that of an operation. See Figure 2 below.

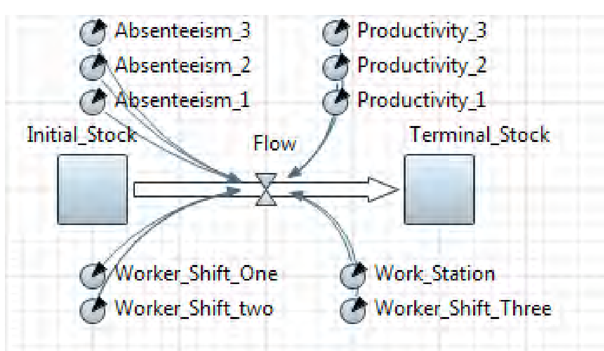

Figure 2: Sample operation.

The sample operation, presented in Figure 2, contains all the necessary elements to define an operation. Specific operational demand will flow into the initial stock on the left. The intensity of production (flow) is controlled by a variety of parameters such as the number of workers on respective shifts, the productivity of those shifts, the absenteeism of those shifts, and the number of work stations available. Output flows into the terminal stock on the right. At completion, the terminal stock will contain the output produced for that period per the configuration set in the parameters. At the operational level we are flowing hours between the stocks.

The novelty of our formulation is that we are using systems dynamic modeling to create a configuration of workers, shifts, and work stations whose output must be greater than demand. Previous applications have used systems dynamic modeling to estimate the number of workers needed due to some attrition rate, or to solely plan for the number of workers necessary in some system. In our approach, workers are a decision variable that must be considered alongside other factors to achieve an output that minimizes the deviation between output and demand. The other variables present within our model are work stations and shifts. Shifts are a practical tool to reduce downtime and raise the overall production of the shop by having workers contributing towards output around the clock. Work stations provide a physical capacity constraint on the job shop; only a certain number of work stations can physically exist in the shop before workers are unable to utilize them efficiently. Naturally, every worker on a shift needs a work station in order to convert their labor into output. Work shifts are represented as a decision variable and it is assumed that productivity on first shift is greater than second or third shifts. The number of workers on third shift is bounded by second shift, which is then bounded by first shift. Since workers on first shift represent the maximum number of workers present for any shift, we can then equate that value to the number of workers stations present for any operation.

By introducing the flow parameters we create a more realistic manufacturing environment. The rationale behind productivity penalties is to penalize the production of later shifts based on empirical evidence. It was observed that the output of the second and third shift was lacking when compared to the first shift. In this manner, a decision was made to penalize the production of these shifts as compared to the first shift. It also became apparent that not every individual scheduled for production arrived at the shop floor at the beginning of their respective shift. This led to the inclusion of an absenteeism parameter. On any given day there will be a percentage of workers who do not arrive for work. These parameters control those percentages and are geared towards individual shifts. Thus, the first shift will have an absenteeism percentage that may or may not differ from those observed for the second and third shifts. By introducing absenteeism we are “over” planning for the eventuality that not all workers will arrive at the shop floor.

Stochasticity within our model is derived from random demand that is sampled from a triangular distribution. The specific parameters for the triangular distribution are achieved via fitting a distribution to historical demand data for each product line. In this way, demand is both forecasted and stochastic in nature. Naturally, the known demand is stochastic because it is drawn from a probability distribution. Due to its derivation from a triangular distribution, it also represents a forecasted value that may or may not represent the true demand in the next period that the shop is required to meet as a quota. The reasoning behind the choice of a Triangular distribution is that they are intrinsically accommodating when it comes to specific parameters and will be known by any layperson manning the shop floor. This is in contrast to some Normal or Poisson distribution.

Replications within the model are necessary so as to allow the probability distributions to express fully themselves in terms of the range of their parameters and ability to produce a random iterate. Replications create a more comprehensive configuration assuming that they are set to a value that allows the probability distribution to achieve a series of long run values. Without replications, the analysis bases itself around a single iterate value that may nor may not represent the true demand in future periods and is thus essentially frivolous.

4 IMPLEMENTATION

Building on the concepts established in the above section, we extend to an actual systems dynamic model containing multiple product lines. What follows is a model illustration containing a single product line and two operations. In an iterative fashion, we extend that model to one that contains two product lines and multiple operations per product line to show the scalability of the methodology and to highlight the experimentation performed using the model with data obtained from the real world system. See Figure 3 below for a presentation of the single product line model with two operations.

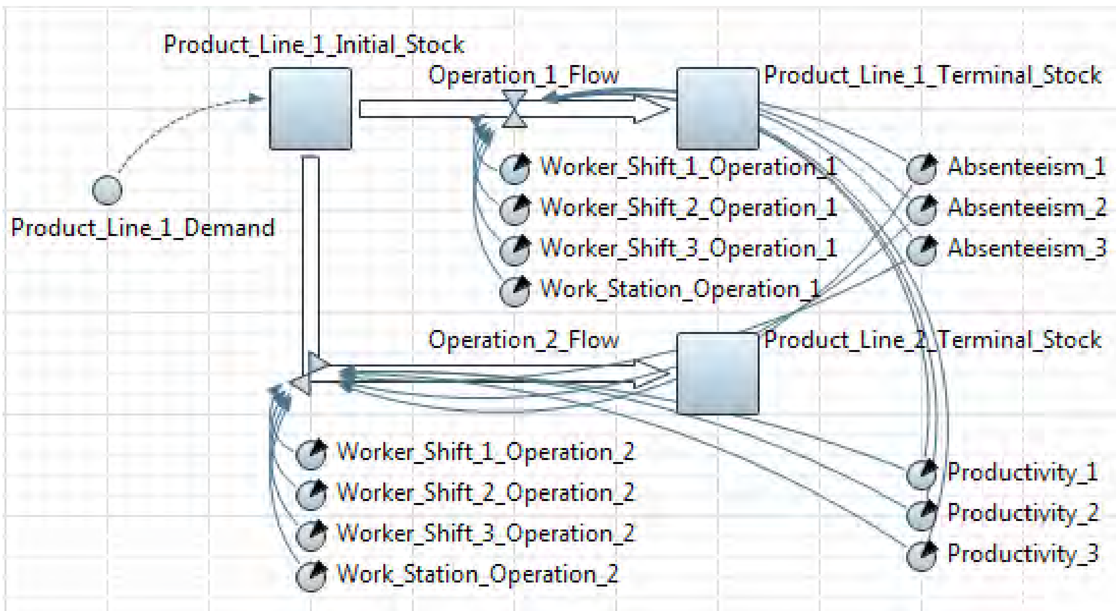

Figure 3: Single product line with two operations.

Displayed in Figure 3 is a systems dynamic model that contains a single product line and two operations. The single product line is evident by the single demand that is flowing to the initial stock. The demand value is then divided into two operational demand values as the labor profiles siphon demand, convert it into output, and store that output in the terminal stock for the respective operations. For each operation there exists distinct shift values that need to be filled by workers. The number of work stations for each operation is also unique and distinct. Productivity penalties and absenteeism percentages are shared throughout the shop floor. The first productivity penalty for shift one (Productivity 1) is set to one, which implies that it does not face any sort of penalty. The second productivity penalty (Productivity 2) is set to 90%, which reflects a ten percent decrease in productivity for the second shift as compared to the first shift. Finally, for the productivity penalty reflecting the third shift (Productivity_3) we set that value to 80% reflecting a twenty percent decrease in output as compared to the first shift.

Absenteeism percentages also extend to the shop floor and should be considered a general trend instead of an operational or even product line happenstance. Absenteeism for the first shift (Absenteeism 1) is set to 20% and implies that twenty percentage on the workforce for the first shift on any given day will not arrive. This, as was the case for productivity penalties, is based on empirical evidence. The second shift faces a slightly higher absenteeism rate (Absenteeism 2) of 25%. The ramifications are similar to what they were on the first shift. Namely, twenty-five percent of the second shift workforce will not arrive to work on any given day. The third shift sees the highest rate of absenteeism (Absenteeism 3) in the form of 30%. We assume that each shift is scheduled for eight hours a day so that the shop is continuously operating and that the number of production days is five as in any typical work week. The planning horizon is set to 52 weeks.

In order to perform proper experimentation and present useful results, real world data was collected on a process that contained two product lines and multiple operations per product line. The creation of the two product line model is relatively straight forward and is an extension of the single product line model that has been explained and examined above. See Figure 4 below for the two product and multiple operations model.

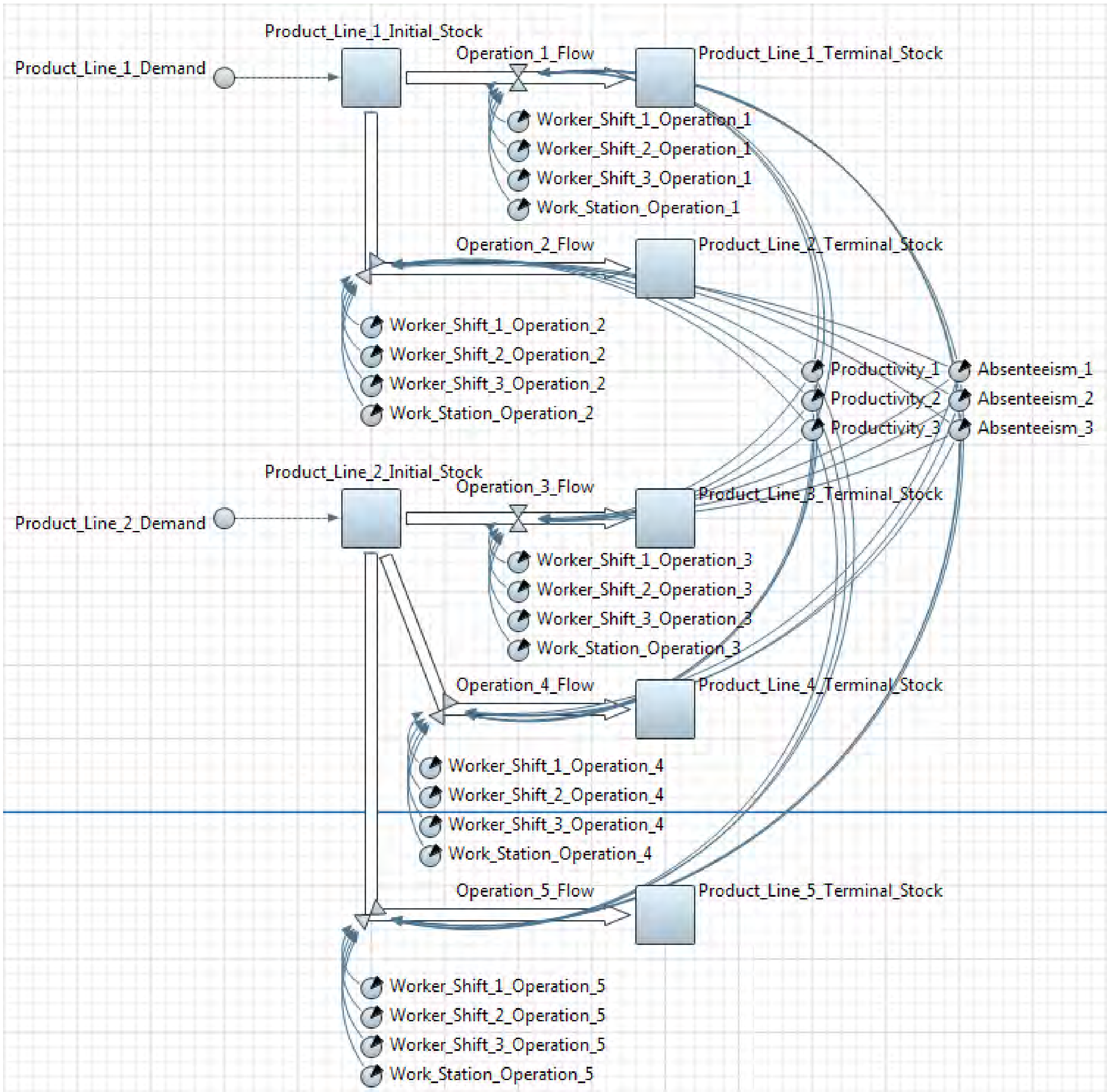

Figure 4: Two product lines and multiple operation model.

In order to adequately present and exploit our real world data we introduce Figure 4, which displays the two product line and multiple operation model. This model differs from the single product line two operation model is several ways. The largest difference in the number of product lines. The model in Figure 4 contains two product lines, while the model is Figure 3 contains only one. This is evident by the number of product line demands. Recall that each product line demand is derived from historical data and fitted to parameters corresponding to a triangular distribution. The triangular distributions for each product line are then replicated 50,000 times so as to allow the total variably within the distributions to fully express themselves. The number of replications were experimentally determined after observing the changes in the long run averages per product line. At 50,000 replications that change in long run average value for each product line was not noticeable from iteration to iteration after each replication.

Another difference between the two models are the number of operations per product line. Observe that for the first product line, the number of operations was set to one. Whereas for the second product line, the number of operations was set to three. Stylistically, the demand for the second product line requires further partitioning among three operations, which introduces a new host of workers, shifts, and work stations to the shop floor as opposed to a two operation product line. The shop floor constants pertaining to productivity penalties and absenteeism remain the same as in the single product line model presented in Figure 3. These constants are shop wide and do not pertain to individual product lines or operations.

When exercising the model and interpreting the results, the values of the initial and terminal stocks at termination is of paramount importance. In a feasible scenario, the contents of the initial stock will be negative and the contents of the terminal stock will be a relatively large positive number. There are many reasons for this. The first is that it will almost never be the case that output and demand are equivalent. Thus, we plan and require output to be larger than demand, but the deviation between the two must be minimized. This is the premise of our optimization problem. When the contents of the initial stock are negative, that indicates to the user that the configuration was able to produce an output that exceeded demand. Due to the nature of this implementation as a manual method we cannot directly guarantee optimality, but merely feasibility. Repeated implementation via manual methods will guide the user in a more feasible direction; one that minimizes the difference between output and demand.

Another possible scenario after termination is that there remains some positive value left in the initial stock. When this occurs, the configuration should not be considered feasible as output produced was unable to meet demand and the user should continue to form new configurations until a feasible one is found. Once that occurs, the user can then hone in on improving that feasible solution.

The formulation that we propose is not an optimization technique as it does not iterate through a series of feasible solutions before achieving an optimal solution. Indeed, we cannot guarantee optimality due to the manual nature of implementation and perturbation. Rather, it is a validation tool for other optimal methods that seek to find an optimal configuration of workers, shifts, and work stations subject to specific constraints. Planners and production specialists can use this formulation to better allocate workers across various shifts and purchase work station equipment in accordance with increasing demand or some other changes within the job shop.

Within the problem statement, we declare that the purpose of this model is to aid in the planning of additional resources subject to some significant, but variable, increase in demand. Given a base system that is subject to increasing demand a planner can use this formulation to obtain a sense of what additional resources, in the form of workers, shifts, and work stations, are needed to meet this demand increase. This formulation allows for a rough understanding of the changes that are needed to meet a demand increase and be compared against more traditional methods that may take longer to implement. Although, the traditional methods will likely perform better in actual estimation of specific resources; this tool is a much quicker method that produces rough estimates, which allows users to better appreciate results from more precise and time consuming methods.

4.1 Experimentation and Results

Using the real world data mentioned earlier, we exercise our modeling methodology on the model developed and presented in Figure 4. In order to illustrate experimentation via manual implementation we present results for the first product line first operation of the two product line multiple operation model. The purpose of this is to present convergence on demand within a tolerance band of 5%. We begin with an initial solution that is naively formed and continue performing perturbations until the deviation value is within five percent of the target demand value; we will use this as a stopping criteria. The results for this use case are shown in Figure 5 below.

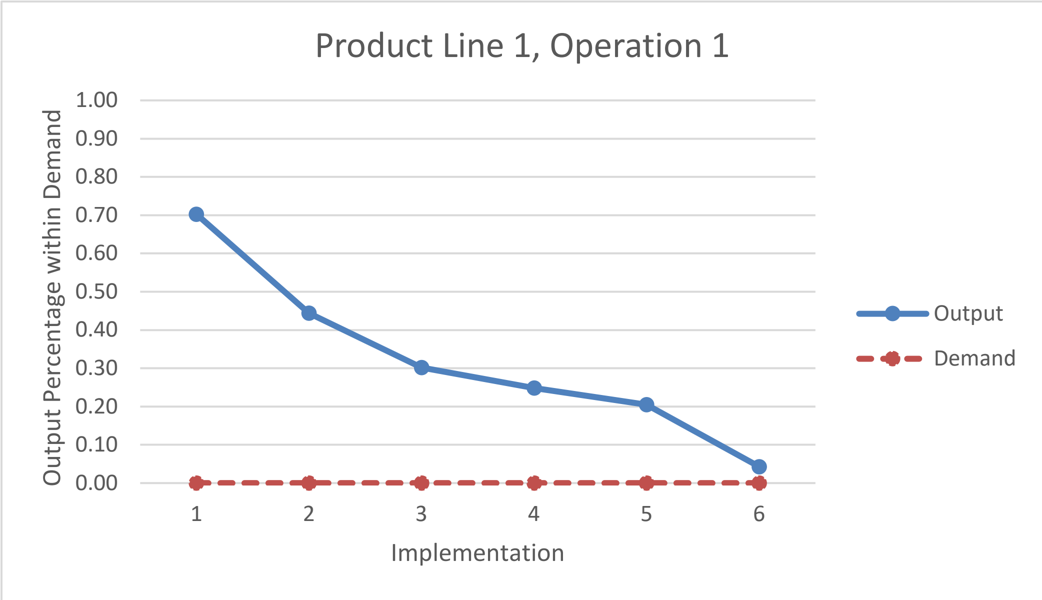

Figure 5: Sample implementation on first product line, first operation of two product line multiple operation model.

After six perturbations of the decision variables the user was able to create a configuration whose output was within 5% of the target demand; this is illustrated in Figure 5. The first iteration, which was naively formed, over produced demand by approximately 70%. It was a three shift combination consisting of 26 workers on the first shift, 15 on the second, and 12 on the third shift. Subsequent changes were able to move in a feasible direction until iteration six was able to produce an output within 5% of the target demand. Iteration six consisted of a three shift combination of 14 workers on the first shift, 13 on the second shift, and 4 on the third. Perturbations were conducted manually and consisted of removing workers from respective shifts, inputting those values into the systems dynamic model, and observing the output in the terminal stock.

In obtaining data from the real world shop and creating the systems dynamic models we were in constant communication with experts who provided their knowledge and guidance regarding the process configurations. In this manner, validation of the model and the data was accomplished. Scenarios, illustrations, and applications described within this conference proceeding reflect scaled or permuted data to not publically expose proprietary data.

5 CONCLUSIONS

In this paper, we propose a systems dynamic framework to solve a manpower-planning problem occurring within a job shop under the context of a resource allocation problem. The purpose is to allocate resources in an environment that is experiencing a significant, but variable, increase in the demand. Our framework enables users to achieve values for the various response variables that form configurations pertaining to the number of workers, shifts, and work stations. The impetus for change in the model is demand, which must be met, if not exceeded in a manner that minimizes the deviation between the output of the shop produced and the actual product line demand. In performing experimentation through manual iteration, the user creates a configuration of the response variables and then uses a systems dynamic model to measure the output of that configuration. Iterative modification of the decision variables creates a framework for moving in a direction to minimize the deviation. To the best of the author's knowledge, this type of framework is novel since it concerns itself with more than just worker values. Indeed, additional parameters and variables such as productivity penalties and absenteeism extend the state-of-the-art and create a more realistic model, more closely modeling the real world manufacturing environment. Workers are also allocated across different shifts to simulate a shop floor that is continuously in action.

By beginning with the basics of systems dynamic model we allow the reader an opportunity to observe all the nuances that went into creating a model. The final product is one that contains two product lines and multiple operations, which presented an excellent opportunity to apply real world data that was obtained from a similar process. In performing the experimentation we illustrate how manual implementation can be used to perturb configurations in an improving feasible direction until the configured output was within 5% of the target demand.

Future work includes integrating this model into a decision support system that uses an optimization tool to generate feasible configurations of workers, shifts, and work station. In doing this, we effectively remove the manual iterative manipulation of the decision variables in this framework. The optimization tool should also converge on an optimal or near optimal solution given the integer nature of the decision variables. Metaheuristics present themselves as an interesting tool for generating feasible solutions whose quality could be measured against the exact method of integer programming. We would also like to relax the constraint that each operation and worker requires a unique machine. Given the job shop nature of the problem it may be the case that multiple operations use the same machine, but for different tooling procedures. It may also be the case that one worker is not sufficient to complete the work for a given machine. Multiple workers may be needed for certain machines.

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AUTHOR BIOGRAPHIES

William J. Peck is a graduate student at the Pennsylvania State University. His research includes simulation modeling, and the use of metaheuristics and mathematical programming to solve resource allocation problems in manufacturing environments. He has a Dual M.S. in Industrial Engineering and Operations Research from the Pennsylvania State University (2019) and a B.S. with Honor in Industrial Engineering, University Honors, from New Mexico State University (2017). His e-mail address is wjp16@psu.edu.

Daniel A. Finke is an Assistant Research Professor at the Applied Research Laboratory, The Pennsylvania State University. His current research interests include simulation-based decision support, planning and scheduling, heuristic algorithm development and implementation, agent-based simulation and modeling, and process improvement. Dr. Finke received his PhD in Industrial Engineering (2010) and MS in Industrial Engineering and Operations Research (2002) from the Pennsylvania State University and BS in Industrial Engineering from New Mexico State University (2000). His e-mail address is daf903@psu.edu.