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GENERATING OPERATING CURVES IN COMPLEX SYSTEMS USING MACHINE LEARNING

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ABSTRACT

This paper proposes using data analytic tools to generate operating curves in complex systems. Operating curves are productivity tools that benchmark factory performance based on key metrics, cycle time and throughput. We apply a machine learning approach on the flow time data gathered from a manufacturing system to derive predictive functions for these metrics. To perform this, we investigate incorporation of detailed shop-floor data typically available from manufacturing execution systems. These functions are in explicit mathematical form and have the ability to predict the operating points and operating curves. Simulation of a real system from semiconductor manufacturing is used to demonstrate the proposed approach.

1 INTRODUCTION

Effective utilization of processes (i.e. machines, toolsets) in capital intensive industries, such as, those in semiconductor manufacturing is challenging. A tool that is widely used is an operating curve (OC) to estimate cycle times in a factory or a toolset under varying conditions (i.e. utilization) and to identify the critical point in system loading. Despite their use in explaining the performance, operating curves are predicated on challengeable assumptions of aggregate models (e.g. M/G/1), which is a limitation on their application. Therefore, we propose a means to avoid assumptions and to exploit the data available from the system shop-floor to generate the operating curves.

To harvest available capacity, it is important to link system behavior to the factors that affect cycle times. These include system dynamics, considering production mixes, production rules, such as, batching, sequencing decisions (e.g. prioritization), as well as toolset characteristics. Therefore, this paper investigates the incorporation of these dimensions to construct the components of an operating curve through the use of machine learning of system data without assumptions. Through the use of data generated by processes, decisions and the toolset, predictive models for cycle time and throughput are derived by symbolic regression using genetic programming (GP). The resulting models, incorporating low granularity aspects of the system to predict its operating points, can provide strategic information in planning and control. The approach tested here on a detailed simulation model of a complex toolset (a wet bench, from an industrial case study), benchmarks the initial results while providing incentive for further investigation.

In the remainder of the article, first a literature review is carried out on OC in Section 2. Subsequently, Section 3 gives a brief description of the simulation model, the wet bench tool under study, to demonstrate the complexity of the model. Section 4 presents a synopsis of the method proposed, the parameters of the simulation model the paper focuses on, and the use of GP to perform machine learning of the manufacturing system. Section 5 presents the results, Section 6 provides a discussion and the conclusions of this paper are given in Section 7.

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2 LITERATURE RESEARCH

The Operating Curve Methodology (see Aurand and Miller (1997), also referred to Characteristic Curve as defined by the MIMAC project (cf. Fowler and Robinson (1995)), it is considered to be the standard factory productivity measurement tool and a key performance indicator (see Fowler, Brown, Gold, and Schoeming (1997) for an illustrative example) (Schoemig 1999). The purpose of the OC is to present an analysis methodology to understand and to quantify the trade-offs between cycle time performance and throughput and also to track factory performance (Aurand and Miller 1997). Queueing theory is the basis of the Operating Curve Methodology and it uses a formula based on M/G/1/ Queues.

Two parameters are inputted to measure a line's performance for an OC analysis: the line's cycle time multiplier (X) and the line's bottleneck utilization percentage (U) (Aurand and Miller 1997). X-factor, which is the ratio of actual line cycle time and total raw process time of a manufacturing, is one of the major performance measures used in the literature. X-factor is also commonly referred to as cycle time multiplier (Aurand and Miller 1997) or theoretical cycle-time multiplier (Fowler, Brown, Gold, and Schoeming 1997) or normalized cycle time (Martin 1998). In this calculation, average cycle time is normalized by dividing the raw process time. The Raw Process Time is defined as the theoretical minimum amount of time that one lot would take to move from the beginning to the end of the line. It is calculated assuming that the manufacturing line is totally empty. In other words, the lot finishes its processes without being uninterrupted from start to finish. It includes load, process and unload times for each machine. It does not include the times related with the transportation times between the operations and inspections or any delays (Aurand and Miller 1997). On the other hand, Actual Line Cycle Time can be measured in the system by the average WIP in the line divided by the average line production rate by the result of Little's Law (Little 1961). The second OC parameter is the bottleneck utilization percentage of the line, it is defined as the ratio of average line production rate and raw capacity of the bottleneck machine, which is often called design speed (DSP), which is the maximum number of units that the line could process per day (Aurand and Miller 1997).

In the semiconductor manufacturing, a major goal is to reduce cycle time. In other words, it is to reduce the cycle-time multiplier to be as close to one as possible. It includes the objective of minimizing the average cycle time and its variance since it has many positive effects in any system (Montoya-Torres 2006). In addition, it is claimed that the X-factor is a much more sensitive factor for indicating the capacity problems than throughput (Martin 1998). The main reason is that the X-factor increases in large amounts when throughput approaches the effective capacity. This sensitivity of the X-factor can be used to uncover non capacitated issues (Martin 1998). In addition, for different toolsets customized X-factor targets can be inserted. It provides both individual operating characteristics of different toolsets and also overall line objective (Martin, 1998). The X-factor can also be interpreted in the wafer fabs in a broader context as the overall manufacturing cycle time divided by theoretical cycle time (raw process time) for shipped lots (FabTime 2007). Typically, a weighted average X-factor is measured for a fab according to the current product mix in the fab.

Cheng and Kleijnen (1999) develop a nonlinear regression metamodel to generate a CT-TH curve by using a simulation model. In a more detailed study, Fayed and Dunnigan (2007) discuss four major factors and their sub-factors by comparing the effects on CT-TH curves. The four major factors are fab configuration, fab loading, flexibility and variability, and operations.

An operating curve generally exhibits two characteristics, a function of utilization and corresponding cycle time where initial slope and inflection points are modulated based on multiple additional factors. Calculation of utilization often relies on assumptions, based on a sample of products produced, rendering them too conditional for direct application. Furthermore, measuring the utilization may be an issue, especially for cluster tools, such as, the wet bench tools, in the semiconductor manufacturing. This type of tool can process multiple batches at the same time utilizing a robot arm. Therefore, cycle time analysis needs to include some other factors that primarily affect the average lot cycle time performance of this type of tool. Through such analysis, the OCs can be corrected and reflect better the operating characteristics of complex tools.

In the next section, we provide a synopsis of the wet bench tool used to generate the detailed shop-floor data before investigating the possibility of deriving OCs based on the machine learning.

3 WET BENCH TOOL DESCRIPTION

In this study, a wet bench tool studied by Kabak, Heavey, and Corbett (2010) is used for an OC curve analysis. The tool consists of six etch and six rinse tanks, an additional rinse tank for cleaning robot arms, a dryer module and a transfer module used for both loading and unloading of batches. Also, there is an auxiliary material handling robot that delivers the batch from one tank to another according to a pre-defined route under a given recipe. The operation of the wet bench tool is complicated by the operational constraints. One of these constraints is the implementation of strict no-wait (NW) or zero-wait (ZW) time constraints for etch tanks. However, these constraints are not applied for rinse tanks. That is, a batch can be overprocessed at a rinse tank. In addition, a batch is not delivered to an etch tank if the associated rinse tank is full (Kabak, Heavey, and Corbett 2010). In this study, the batch size is two lots (i.e. 50 wafers). A batch which has two lots is defined as a “Full Batch”. Similarly, a batch which has only one lot is defined as an “Half Batch”. Accordingly, “Full Batch Percentage” or “Half Batch Percentage” can be defined as the percentage of full batches or half batches when all of the batches are considered, respectively.

The wet bench simulation model taken for the analysis is highly detailed due to complex operations of the wet bench cluster tool incorporated into the model. The model has product mix inputs obtained from the real fab data. The product mix has input percentages for each product type and process data associated for each product type. The process data defines the sequence of recipes used for a particular process. A recipe defines the route a batch traverses in the wet bench and process time (i.e. bath time) at each step. Also, the model has stochastic inputs, such as, the lot interarrivals into the queue, lot priorities, are determined by an empirical distribution (Kabak, Heavey, and Corbett 2010). Similarly, the products, with associated process stages and recipe, are selected from a uniform distribution. Apart from stochastic inputs, the model additionally includes deterministic inputs in relation to robot operation, such as, robot speed, distances between each tank, robot ascending and descending times. All these deterministic inputs are adapted from real fab data.

4 METHOD

We consider a machine learning approach to derive performance curves to predict operating points. This is performed by using GP to derive approximate models which incorporate detailed information from the system. For illustrative purposes, 3 different aspects of a semiconductor manufacturing toolset, wet bench, are considered to form a structured data set. Using these data sets, throughput and cycle time models are developed to construct operating curves.

Toolsets, such as, wet bench or cluster tools in semiconductor manufacturing, have complex behavior which is comparable to job-shops due to the presence of independent and parallel processing capabilities. At the high level, the coherence among products, planning and scheduling as well as tool settings determine the overall performance. In order to incorporate more information from the system, the product, plan and toolset related data is broken down to lower granularity. For instance, the weekly loading level is considered as a matrix to account for the share of different products and the share of the different prioritization levels in the mix. Such parameters are specifically chosen from those that the engineers would have control over (See Figure 1). In order to create these scenarios, a discrete-event simulation (DES) model for the wet bench tool is used to mimic the real system as described in Kabak, Heavey, and Corbett (2010).

A 3-level experimental design of Kabak, Heavey, and Corbett (2010) was for different values of weekly loading, robot speeds and dry times. We further detailed these parameters to incorporate more information about utilization, in particular by converting the weekly loading into a matrix to show the percentages for individual product families and the percentages of different priority levels for a corresponding utilization level. While this goes beyond the amount of detail common in the current methods used to calculate

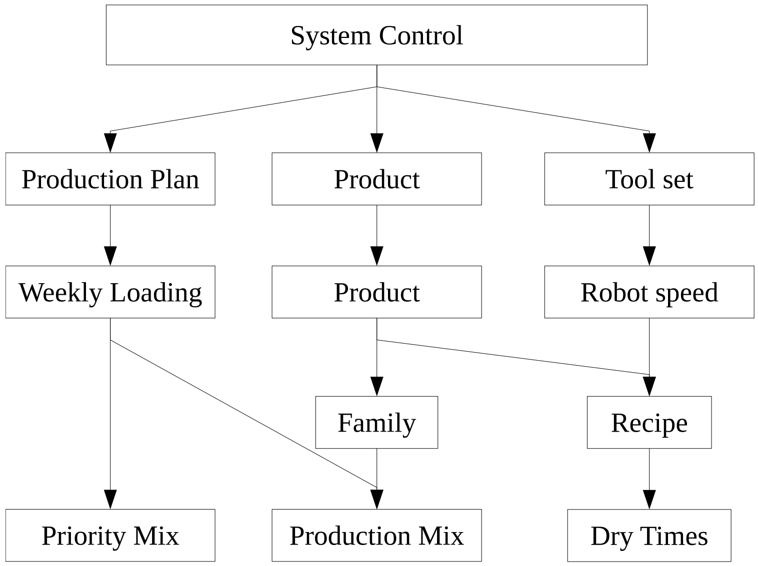


Figure 1: A top-down breakdown of the controllable factors that relate to the toolset performance in the simulation model under study. Factors are considered from abstract detail to less granularity. For example, the product mix could be incorporated as a weekly loading or at more detail level by including the details of product and priority mix.

operating curves, it ideally incorporates characteristic information to assist detailed planning of the system. In addition, we included robot speeds of the tool as a design issue in these experiments, whereas dry times are considered to represent the R&D changes on the recipes in order to verify the proposed approach works. Note that we use the simulation model only to produce these scenarios. In a real system, such data will typically be available from Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP) systems.

Subsequently, the response metrics, throughput and cycle times, for the corresponding scenarios in the experimental design are modeled individually based on the aforementioned factors as predictors (see Figure 1) in the context of metamodeling. Incorporation of further details on the product mix and lot priorities to the cycle time and throughput models, and eventually to the operating curves, requires application of advanced analytics methods to data. This mainly is due to expected complexity of the models as a consequence of the presence of high level interactions as well as the models for the response metrics may not always be known in a closed form. For these reasons, we considered an evolutionary algorithm, genetic programming (GP) (Koza 1992). We will examine these aspects in Section 5 in more detail.

GP evolves explicit analytic models underlying a dataset without any assumptions on the functional form. The use of GP to learn from a data set is referred to symbolic regression. It demonstrates desirable generalization (validity on unseen data) and abilities in modeling complex industrial systems. For more detail on GP applications in manufacturing and supply chain industries readers are referred to Can and Heavey (2012).

The process of symbolic regression is similar to a standard regression. The regression functions are developed and updated iteratively to minimize the error of the predictions made by the functions on an input data; however, in contrast, no functional form is assumed and different mathematical operators, such as, +,-,*, LN, Cos, can be used to construct the functions. This poses a great advantage when the closed form of equations are not known for the response metric being modeled. In the context of symbolic regression, these functions are the models representing a data set where the factors in the data set are the arguments of the functions. Once a function is formed, it is evaluated against the data set and the deviations (e.g. error) from the target values are used to calculate a fitness for the function. We considered mean squared error in calculation of the fitness. As an evolutionary algorithm, GP works with multiple functions in parallel in a population. The exploration of functions with better predictive performance occurs through the application of evolutionary operations, such as crossover, on the populations at each iteration of the algorithm. A generic symbolic regression process can be summarized as:

1. Randomly create a population of functions using functional primitives (e.g. +,-,*,Sin, LN).
2. Evaluate each function and assign fitness, make the initial population the current population.
3. Select two functions at random as parents, create an offspring through evolutionary operators.
4. Repeat Step 3 until the next generation population is filled.
5. Make the next generation population the current population.
6. Repeat 3 to 5 for a pre-determined number of iterations.

The method presented in this paper takes a data driven approach to characterize the two metrics, cycle time and throughput, as the components of an operating curve using GP. Providing high dimensional characteristic functions of performance metrics that encompass the trade-offs among the factors of a system is in contrast with the common means of developing operating curves. These functions, as illustrated in Section 5, which incorporates detailed information from the system, such as, product mix, priority scheme and tool configurations (see Figure 1), eventually allowing more effective exploitation of the tool behavior to assist planning and control of these systems.

5 RESULTS

In contrast with the previous studies, the method presented in this paper takes a data driven approach to characterize the two components of the system, cycle time and throughput, using machine learning. GP is used to derive approximate analytic functions of these metrics based on low granularity data collected from a simulation model of a wet bench toolset. Matrix data is incorporated to account for product mix, priority levels, line loading and tool configuration. Following the validation of the metric functions, the derived operating curves demonstrate high proximity to those obtained from the simulation model of the toolset. In the remainder of this section, first typical factors for a wet bench are examined by analysis of variance (ANOVA) at a high level. Then, exploiting the outcome of the ANOVA, we incorporate further details and apply GP to derive characteristic functions for the key metrics that are used to build the OC.

5.1 Preliminary Analysis

At a high abstraction level, ANOVA is used to identify the statistical significance of the considered main factors (see (Kabak, Heavey, and Corbett 2010)); weekly loading levels, product dry times, lot priorities, and robot speed, in relation to cycle time (see Table 1). From the P-values (see those ≤ 0.05), all the main factors and interactions such as those between utilization, product and tool characteristics with a 95% confidence at $\alpha = 0.1$ in a 3-level full factorial experimental design are statistically significant.

While a linear model incorporating the signicant factors and interactions (see the sources in bold in Table 1) may be informative, it remains explanatory since it does not transparently support production planning. To illustrate, a utilization metric as aggregate as weekly loading will include the effects of product mix and status of the batches (full and half batches). Similarly, the factor “Priority lots” takes into account the impact of high-priority and non-high priority lots alone whereas there may be more than two levels of prioritization. Modulating the production plan on a weekly basis without having to know the impact of such factors may undermine effectively harvesting the available capacity. Indeed, during the simulations of the toolset, we observed that the individual tanks are utilized not more than 60% of the time.

Table 1: Analysis of variance for a general linear model illustrating the main effects and interactions.

Source	DF	Adj SS	P-Value
Model	64	41156.8	0
Linear	8	37587.2	0
Weekly loading level	2	27743.9	0
Dry time	2	9097	0
Priority lots	2	253.2	0
Robot speed	2	493	0
2-Way Interactions	24	3064.2	0
Weekly loading level*Dry time	4	2306.5	0
Weekly loading level*Priority lots	4	398.1	0
Weekly loading level*Robot speed	4	55.5	0.172
Dry time*Priority lots	4	146.6	0.01
Dry time*Robot speed	4	103	0.034
Priority lots*Robot speed	4	54.5	0.179
3-Way Interactions	32	505.5	0.061
Weekly loading level*Dry time*Priority lots	8	228.8	0.011
Weekly loading level*Dry time*Robot speed	8	34	0.795
Weekly loading level*Priority lots*Robot speed	8	139	0.076
Dry time*Priority lots*Robot speed	8	103.7	0.172
Error	16	121.4	
Total	80	41278.2	

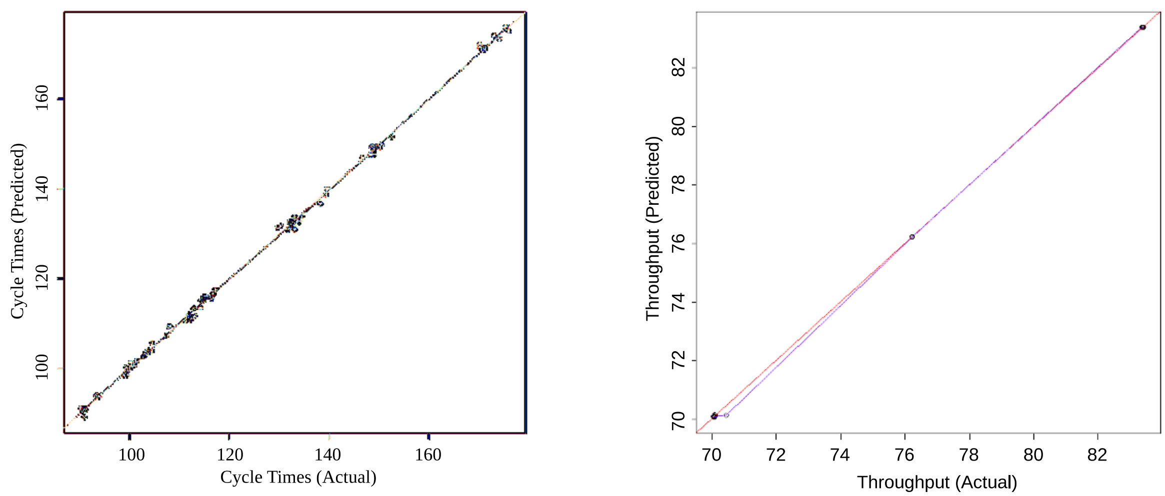
5.2 Modeling an OC through Machine Learning

Motivated by the above observations, a predictive modeling approach is considered to construct operating curves. To facilitate this, low granularity, i.e. more detailed, data, obtained from a system can be used to derive characteristic models, e.g. to predict cycle time and throughput. We demonstrate this on a DES model to motivate the discussion.

In order to derive the models characterizing metrics such as cycle time and throughput, the detailed data gathered from the system is driven by the ANOVA factors (see Table 1). In particular, the unstructured transactional data is structured to obtain utilization in the form of a data matrix of both priority (at 5 different priority levels) and product mix for 11 different products (e.g. C6, H6 representing different product families). In addition, the share (%) of the half batches in the weekly loading is also included in this data as the batches can be queued as half, or the half batches can be topped up to form a full batch. To put the predictors on a common scale, weekly loadings, dry times and robot speed are rescaled to the range of the percentages of product mix, e.g. [10-70]. The GP is configured to allow a maximum tree length of 30 and a tree depth of 12. Symbolic regression experiments are replicated 5 times and the best model from these runs are chosen for evaluation presented here. Each run of the GP, implemented in C# programming language, took less than a minute on a computer with an Intel Core i7 processor and 4GB RAM to develop the best solutions. Equation 1 illustrates a complex cycle time function explaining the behavior of the toolset including the parameters driving the cycle time as the amount (%) of half batch present (A), weekly loading levels (C), share (%) of product H6 in this loading (B), and the overall shares (%) of the lots at the three priority levels 1 (D), 2 (F), 3 (E).

$$\begin{aligned}\text{Cycle time} = \ln((0.168\times A+(-0.0743)\times B+1/((-0.467\times C+(-10.749))+1/(0.198\times A)\\ \times(-0.159)+D\times(0.689\times E+(-0.792)\times C)\times(-0.012)/(1.165\times F)))\times(-264.411)+737.179) \quad (1)\end{aligned}$$

Similarly, GP with the same configuration modeled the throughput of the system based on the same input data test, resulting in simpler functions. The daily throughput was proliferating at the three values when the system was at steady state (see the right hand side of Figure 2) for the 3-level experimental design given in Kabak, Heavey, and Corbett (2010).



(a)

(b)

Figure 2: R-squared comparisons of cycle time (left) and throughput (right) predictions against the target values obtained from the DES model show over 99% predictive performance in both cases.

In contrast with the cycle time, throughput is affected by the tool configuration in particular, as demonstrated in Equation 2 where A is share (%) of product C6, B is dry time, C is weekly loading level, and D is robot speed.

$$\text{Throughput} = -0.481 \times A + (-0.001) \times B + 0.201 \times C + \ln(1.253 \times D) \times 0.003 + 78.775 \tag{2}$$

The comparison of the predictions made by the discovered model to the actual values observed in the DES model depicts in explanation of the variation in the vicinity of 98.5% in terms of R-squared comparison for cycle times and daily throughputs (see Figure 2).

Note that using such predictive models, operating points for a system configuration can be derived on demand. While the cycle time predictions will provide the y-axis of an OC, the throughput model can be used to determine the x-axis. A similar example is found in Veeger, Etman, and Van Herk (2010) where the ratio of throughput to maximum possible throughput is used for the utilization axis, while cycle times on the y-axis were predicted through effective process times. The trend line in Figure 3 shows the operating curve obtained from the DES model, and the blue markers refer to the operating points predicted by the constructed models at different values of the factors, i.e. HalfFullBatch%, weekly loading, priority levels; 1, 2, 3, and H6% (see Equation 1). Modulating these factors will allow the method to capture the shifts on an operating curve to allow making more informed decisions based on the estimates of the operating point. We illustrate this for an example case where the product mix is modulated and the response of the system is predicted using the obtained models to calculate the new operating point (see red circled point in Figure 3). For example, the circled operating point illustrates the shift in cycle time for two different weeks. At the same weekly loading level and the share (%) of product H6 in the mix, we were able to detect the shift based on product mix changes and HalfFullBatch%. We could further see the cycle time sensitivity is high for the small changes in these factors.

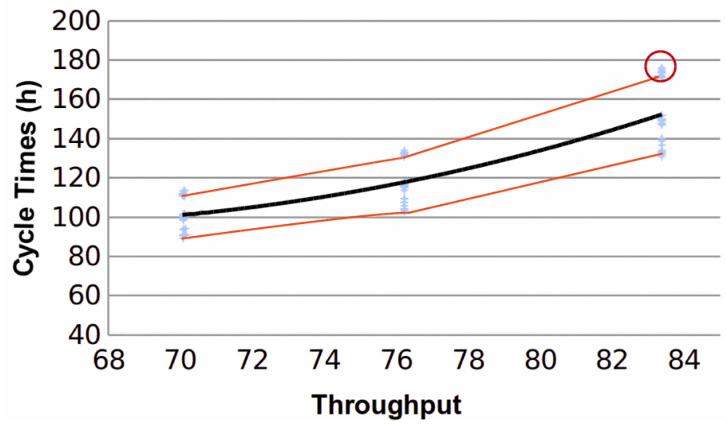


Figure 3: Operating points (blue markers) predicted by the cycle time and throughput models at different settings for the considered parameters demonstrating the shifts (orange lines) from the operating curve and the operating curve (black curve) from the simulation model. The red circle belongs the example described in Table 2.

Table 2: Prediction of shifts in the cycle time - throughput rate behavior as the factors vary.

	Weekly Loading (lots)	HalfFullBatch%	H6%	Priority 1%	Priority 2%	Priority 3%
Case 1 (baseline)	1350	75.2	26	14.4	16.5	54.5
Case 2 (red circle)	1350	78.4	26	15.0	16.0	55.8

6 DISCUSSION

We demonstrated that genetic programming can be used for symbolic regression to leverage data from a shop-floor. We first uncover the underlying relationship in a manufacturing system and production plan by evolving models for key metrics, such as cycle time and throughput. Subsequently, these models are used to predict the changes in the trade-off between the metrics to determine the shifts in operating points. We exemplify this on the simulation of a real system in semiconductor manufacturing, a wet bench toolset. Our results indicate that utilisation can be effectively represented by product and priority mix to approximate the system behavior. The resultant models are shown to have 98% proximity to the simulation model. While cycle time is shown to be more sensitive to external factors, throughput is mainly driven by the tool configuration. For the particular simulation model considered, it is evident from the throughput values settling at three different levels that the configurations restrict the variability in the toolset. However, it does motivate future study of this approach of using the shop-floor data to deploy predictive analytics.

7 CONCLUSION

Operating curves allow estimation of the time the product goes through the system and when the critical point in loading the system is approached. In this study, we presented the use of data analytic tools to demonstrate how the operating curves could be generated using shop-floor data. Through machine learning of low granularity data by genetic programming, we illustrate the operating point calculations which can assist planning industrial systems. The idea originates from the ability to develop predictive models that effectively approximate the key components of operating curves, cycle time and throughput, using machine learning on the data that is readily available from a MES system. The models that are based on the controllable factors regarding product mix, priority scheme and toolset characteristics may provide a strategic advantage to planning and controlling semiconductor systems.

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