PROPOSING A PERFORMANCE METRIC FOR AN AGILE MANUFACTURING SYSTEM

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Abstract
The company Welltec has an agile manufacturing system due to their dynamic and complex mix of production orders. Therefore, commonly used performance metrics such as utilization of machinery and *Overall Equipment Effectiveness* (OEE) do not prove to be reliable indicators of the production's performance. Hence, this paper aims to develop and propose a more reliable production metric which Welltec can use to evaluate the performance of their production. Thus allowing Welltec to more accurately determine the effect of investments in their numerous processes and agree upon their asset distribution. The metric is based upon parameters such as order type, size, part complexity, and the order composition. Estimating process parameters allowed for a Discrete Event Simulation to calculate the theoretically possible output of the production, which is compared to the actual production. The result is a ratio that more accurately depicts the efficiency of the production, with the current and/or expected order composition.

Keywords: Discrete Event Simulation, Digitization, Operation Optimization, Production metric

1. Issues with the currently used metric

Welltec delivers intervention and completion solutions as a service to the oil well industry. Their original product is the Well Tractor® which serves the purpose of tool transportation through oil pipelines. Welltec produces most of the mechanical parts required for their products in-house. Therefore, the production department has to be able to produce batches of parts from a catalogue which covers a vast amount of different part designs. Hence, the work distribution between the production processes shifts periodically which complicates evaluating the production's performance. Currently, Welltec uses utilization of their CNC machines as a performance metric. This metric is used to monitor and evaluate past production by the Component Production Manager and upper management. However, utilization of specific resources may not be an accurate measure for production performance as the measure is not directly linked to value adding activities, which result in closing production orders. For instance, a production may achieve high utilization of their resources by producing excess parts to stock. These issues also apply to the performance metric *Overall Equipment Effectiveness* (OEE) which is commonly used to assess the performance in mass production. OEE incorporates the production's availability, performance, and quality into a single metric which provides a reliable measure for productivity. However, it is still possible to achieve a high OEE by producing excess parts to stock.

Welltec has a complex order composition which covers planned, R&D, and urgent orders. These orders differ on factors such as order size, part size, and complexity. This highly dynamic order composition affects the operators' work distribution. For each production order, the operators must prepare tools and setup the CNC. Furthermore, if the order has not been produced previously, the operator also has to program CAM files for the CNC and conduct a possibly more time-consuming tool preparation and setup of the CNC than if the order has been produced previously.

As seen below on Figure 1, this complex order composition leads to periods where Welltec's production achieves vastly differing levels of utilization on their resources. In these periods, the operators may have had the same productivity, however, this can not be seen from the utilization of the CNC resources. Thus, the upper management can have a difficult time grasping the production's productivity. Therefore, there is a need for

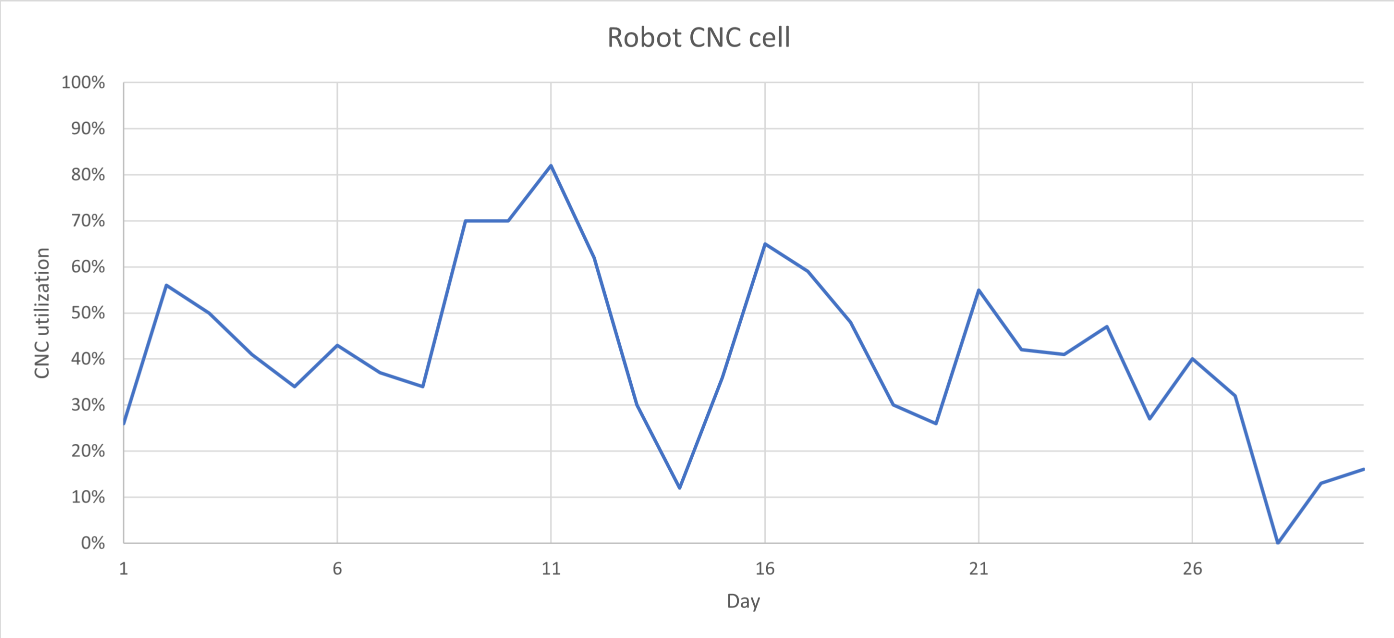

Fig. 1 Average utilization of CNC machines in a single cell over a 30-day period.

a production metric which takes the order composition for a given period into account. Such a metric should provide a more reliable indicator of the production's performance.

2. Developing and proposing a production metric

The order composition's effect on the production's output can be simulated with Discrete Event Simulations (DES). Therefore, this section describes how DES can be utilized to devise a performance metric for Welltec's production.

2.1 Explanation of the devised production metric

One important indication concerning the production's performance is the number of closed production orders. At Welltec, this number is highly affected by the order mix over a certain period of time. Therefore, due to the high variability in order mix, it is difficult to determine if the production's output over a given period is relatively low or high. However, if an ideal output is obtainable, then the ratio between the actual output and the ideal output can be used to predict the performance of the production's resources for a given order mix. The formula seen in Equation 1, can be used to compute the performance of the production's resources.

$$\text{Performance} = \frac{\text{Actual \# of orders closed}}{\text{Ideal \# of orders closed}} \cdot 100\% \quad (1)$$

However, to use the equation above, it is necessary to know the ideal number of closed orders. Fortunately, it is possible to predict the ideal output within a simulation. If the order composition and historical data are logged from the production, statistical tools can be used on the data to extract empirical distributions describing the relationship between the time spent on the individual production processes and the order composition. Hereby, these empirical distributions can be used in connection with a new order composition to predict an estimate for the ideal number of closed orders.

In the DES, an empirical distribution can be determined and used as input, alongside with an arbitrary order composition. Thus, the DES can be used to simulate the production's flow for a given order mix and output the ideal number of closed orders. Furthermore, it would be ideal if the devised performance metric can be used both as an operational and developmental tool. Meaning, that the simulation can be used to evaluate the performance of past production as well as test future adjustments conducted to the production before implementation. In both cases, the same DES can be used but with two differing data sets describing the production's characteristics. By having two data sets, the first data set can be used to simulate the behavior of the current setup whereas another data set can be used to simulate the behavior of the optimal production or an implementation of future changes. The methodology proposed in this report for using DES as an operational tool to determine the production's performance is illustrated by Figure 2.

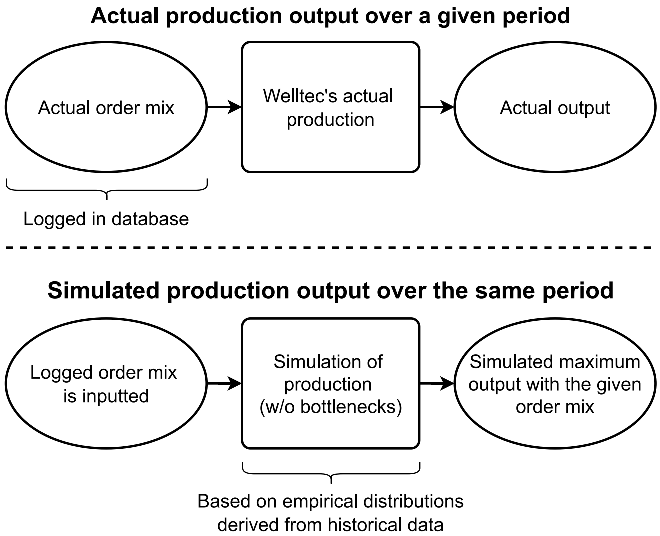

Fig. 2 The figure illustrates the methodology proposed for using the DES as an operational tool for evaluating past production.

As seen from Figure 2, the actual order mix and output of the production is logged for a given period. Once this period is over, the logged order mix is then used as input for the simulation. Hereby, the empirical distributions without bottlenecks can be used to simulate the maximum output for the given order mix. Once the actual output and simulated output has been achieved, these numbers are inserted into Equation 1. Using the formula, the performance should result in a percentage between 0% and 100%. The determined performance can then be used by the component production manager and upper management as a measure for assessing the production's operation. For this metric to work, relevant input parameters and empirical data of high quality must be available. Therefore, the next section covers determining these input parameters as well as determining necessary data which must be logged from the production.

2.2 Relevant input parameters for the DES

The process of identifying, specifying, and gathering relevant input parameters for the DES is inspired by the methodology presented in *"A methodology for input data management in DES projects"*[1]. In the article, four steps precede the creation of a input data sheet for the DES. These steps include identifying relevant input parameters, specifying the parameters' accuracy, and determining availability of the parameters. Furthermore, if relevant, the fourth step is selecting data collection tools for gathering unavailable parameters. In this report, these four steps are conducted for the input parameters related to order mix as well as the production parameters of the individual processes conducted by Welltec. The parameters listed below have been identified to describe Welltec's production in the DES at a sufficient level of detail.

Input parameters related to the order mix:

- Order type
- Order size
- Recurring part
- Part size
- Part complexity

Process parameters related to the production:

- CAM-programming
- Tool preparation
- Precutting of materials
- CNC setup
- CNC milling

The identified input and process parameters are described more in-depth below.

Input parameters related to the order mix:
The input parameters describe the specifics of an order composition. These are the parameters which change the operators' work distribution between processes from time to time. Thus, it is important to identify and collect data for relevant input parameters to achieve a DES which can simulate Welltec's production with sufficient quality and accuracy. Firstly, the relevant input parameters are described below.

Order type: Welltec has three types of production orders. These include: planned orders, R&D, and urgent orders. Thus, the production order type has significant impact on the probabilities and distributions within each production process. For instance, it is more likely that a planned order contains parts with small changes - and therefore might on average require less CAM and setup time. Similarly, the order type affects other parameters; an order is more likely to contain recurring parts if it was planned compared to a R&D order. Also, the order size is more likely to be larger if the order is planned, compared to R&D and especially urgent orders. All the mentioned relationships require data gathering in order to get representative distributions describing the cycle times for each. The input parameter is available for the DES as Welltec already logs an order's type.

Order size: The order size impacts the total amount of required CNC time. The total CNC time is assumed to be the CNC time for a single part multiplied by the order size, and the relationship is thus known to be proportional. The same principle applies to the precutting process which is also affected by the order size. The order size is also a value which is logged by Welltec. Therefore, this value is available for simulation.

Recurring part: If a part is recurring and has been produced before it affects primarily the CAM-time, as it is assumed no CAM-work is required. It also affects setup time as there are fewer unknowns with recurring parts, and therefore less careful setup is needed. It might also slightly affect CNC time as the CAM-program might have been optimized during the previous productions. The setup and CNC relationships require data gathering in order to build distributions for both recurring and new parts. Currently, Welltec already logs whether a part has previously been produced. Therefore, no additional logging is required to obtain the input parameter.

Part size: Another input parameter which affects the production's productivity is the size of the parts in an order. This parameter directly affects the CNC time as larger parts generally would need more processing. Welltec has the CAD-files for their production orders, thus, it is possible to gather this parameter.

Part complexity: The complexity of the produced parts impacts all the processes in the production. A more complex part will require more CAM-time, more setup time, and the CNC mill will generally take longer to finish a part. The part might also need several passes in the CNC mill if it needs to be rotated in order to reach all surfaces which require machining. As the complexity impacts so many processes it is crucial to implement in the DES in order to get an accurate simulation. Most importantly - and contrary to the previously mentioned parameters - no readily available measure for part complexity exists for data gathering. It is therefore important to find a way to measure complexity in order to observe the impact it has on the aforementioned processes. The complexity itself is initially assumed to be independent from all other parameters, but it is important to verify this when gathering data. As the quality of the DES heavily relies on this parameter, Section 2.2.1 is dedicated to researching part complexity further.

Process parameters related to the production:
An array of process parameters such as cycle time of the individual processes are affected by the composition of production orders. Thus, to achieve a DES that can simulate production output based on order composition, data from these processes must be logged in relation to the individual orders. Statistical tools can then be applied to the logged data over a given period of time, to determine the relation between the individual production processes and specific order parameters. The relevant production parameters are described below.

CAM-programming, tool preparation, and precutting of materials: The cycle time of the CAM-programming, tool preparation, and precutting processes for the individual orders must be logged to determine the processes' correlation to the parameters listed for order mix. Currently, this parameter is not logged by Welltec. However, a solution is under implementation which will enable Welltec to log the operators' time spent on these orders. For the collected data to be usable for the DES, the time spent must be logged and associated with the ongoing production order.

CNC setup: CNC setup must also be logged to obtain empirical distributions for the various order mixes. This metric is not obtainable yet, however, Welltec is in the process of implementing a solution which enables the operators to specify the setup time used on the CNC machines. The logged setup time should include placing precut parts in vices, installation of CNC tools, and actual setup of the CNC. Furthermore, the logged data should also be associated to the order that is being worked on by the operator.

CNC milling: Currently, an event log of the CNC is logged by a sub-contractor's Manufacturing Data Collection (MDC) software. This event log includes information such as the program being run on the CNC mills as well as part processing cycle times. Therefore, this parameter is collectable and can be used in the DES.

The input and process parameters have now been identified and described. Part complexity has not been fully defined yet, this is the subject of the next section.

2.2.1 Complexity measure

Part complexity is directly linked to factors such as the part's geometry. A complex geometry commonly requires more CAM time, setup time, and milling time. Since the parts on the CNC machines are designed in CAD, it is preferable to base the measure of complexity on the information available in the CAD-part. Thus, the measure of complexity can be obtained prior to starting production. Currently, there is no standard for defining CAD-model complexity. An array of parameters which can be a measure of a part's complexity include, but is not limited to[2]:

- Number of triangles/vertices in an STL-file of the part
- The surface area of the part
- The volume of the part
- The volume of the part's bounding box
- The number of features used to create the part
- The time used to draw the part
- The ratios between respective parameters

One article studying CAD complexity is *"An investigation and evaluation of computer-aided design model complexity metrics"*[2]. In this article, an array of CAD-models varying in complexity were evaluated by 169 respondents. These CAD-models' complexity ratings were then compared to a set of geometric complexity metrics such as surface area and cube ratio. The article found that the geometric complexity metric which was most positively correlated with the respondents' rating of part complexity, was the ratio between the part's volume and the volume of a bounding box fitted to the part. Equation 2 illustrates this ratio.

$$CV = 1 - \frac{V_P}{V_B}, \tag{2}$$

where V_P is part volume, V_B is bounding box volume

Using the formula results in a complexity value (CV) between 0 and 1, where a higher number represents a more complex part. It is evident from the construction of the equation, that a large bounding box and a small part volume would result in a complex part. Roughly, this means that a part that requires removal of a large percentage of material is deemed a complex part.

However, this is based upon a paper which investigates CAD-files in general. It is therefore desirable to confirm whether the same correspondence is present in parts relevant to Welltec's production. As the exact designs of Welltec's components are secret, a number of standard components has been chosen. 12 components that could typically be produced by turning or milling operations have been chosen. These are:

1) Compressor impeller
2) 48-teeth gear
3) Hydraulic manifold
4) Weld flange
5) Pulley wheel
6) Worm gear housing
7) Arm bracket
8) Timing belt clamp
9) Shaft coupler
10) Linear rail bracket
11) Spindle motor bracket
12) Worm gear

Illustrations of the 12 components can be seen on Figure 8 in the Appendix. Two parts have been deliberately chosen to challenge the formula, as examples of what types of parts could produce misleading results. Part no. 3, the hydraulic manifold, is expected to produce a lower complexity value than the part requires. Conversely, part no. 4, the weld flange, is expected to produce a higher complexity value than the part requires.

To be able to evaluate the precision of the complexity value, all parts have been evaluated and given a score between 1 and 3, with 3 being the most difficult to produce. The evaluation has been conducted in cooperation with an independent machinist with relevant CNC and CAM experience. On Table I, the results can be seen sorted by increasing evaluated difficulty.

The difficulty of each part is plotted against the complexity value, in order to give an idea of the correlation between the two. The result can be seen on Figure 3. There are three data points which are clear outliers. Two of those were deliberate as mentioned earlier (Marked with blue no. 2 and no. 3) the third one (no. 1) was however not intentional. This is the Linear Rail Bracket (part no. 10) and it is most likely due to the fact that the component has both a large hole as well as two small flanges which result in a higher-than-expected CV.

The hydraulic manifold is more complex than the complexity value would suggest. This is due to the fact that not much material is removed from the block, which additionally fits neatly inside the parts bounding box. However, the many long canals in the block require several changeovers in the CNC-machine, and while the CAM-program is not necessarily difficult, the machining operation is time consuming.

The weld flange is less complex than the complexity value would suggest. The flange is a simple geometry, but the circular shape paired with its large hole results in a volume much lower than its bounding box, in turn resulting in a high complexity value.

If the outliers are omitted however, there is a clear correlation between complexity value and assessed difficulty. The complexity has initially been sorted into three categories for ease of implementation in the DES. This is due to the fact that no such data exists from Welltec's production, and the data used in the DES will be estimates. When the actual data will be logged it could be beneficial to break down the categories even further and score them on a scale with smaller increments. For the initial DES, the three categories has been scored by visually fitting the two graphs by adjusting the axes. Afterwards, the categories were defined by dividing halfway between the assessed difficulty levels. This results in the following intervals: (visually illustrated on Figure 4):

- Category 1: CV of 0-0.42 (marked green)
- Category 2: CV of 0.43-0.70 (marked yellow)
- Category 3: CV of 0.71-1 (marked red)

It is important to be aware of instances like the mentioned outliers. These outliers are a testimony to the fact that, while the complexity value does provide a useful guideline, it cannot stand alone. Thus, it is important to have an engineer or machinist with relevant experience evaluate parts which could produce misleading complexity values. The complexity value could be modified, as the formula presented in [2] addresses CAD parts in general, whereas only parts for CNC machining have relevance for this project. Such a modification could for instance be to use the volume of the raw material rather than the bounding box. This

Tab. I Data of CAD-parts sorted by increasing evaluated difficulty.

No.	**Description**	**Volume** ($mm^3 \cdot 10^3$)	**Bounding box** ($mm^3 \cdot 10^3$)	**CV**	**Difficulty**
8	Timing Belt Clamp	1.5	1.8	0,16	1
9	Shaft Coupler	6.4	9.9	0,35	1
10	Linear Rail Bracket	9.5	21.5	0,56	1
4	Weld Flange	152.3	1012.5	0,85	1
3	Hydraulic Manifold	2273.2	2508.0	0,09	2
5	Pulley Wheel	1.8	3.6	0,50	2
11	Spindle Motor Bracket	152.9	403.0	0,62	2
12	Worm Gear	822.7	2263.3	0,64	2
2	48-teeth Gear	415.6	1381.4	0,70	2
6	Worm Gear Housing	307.9	1152.2	0,73	3
7	Arm Bracket	24.1	162.3	0,85	3
1	Impeller	39.8	396.0	0,90	3

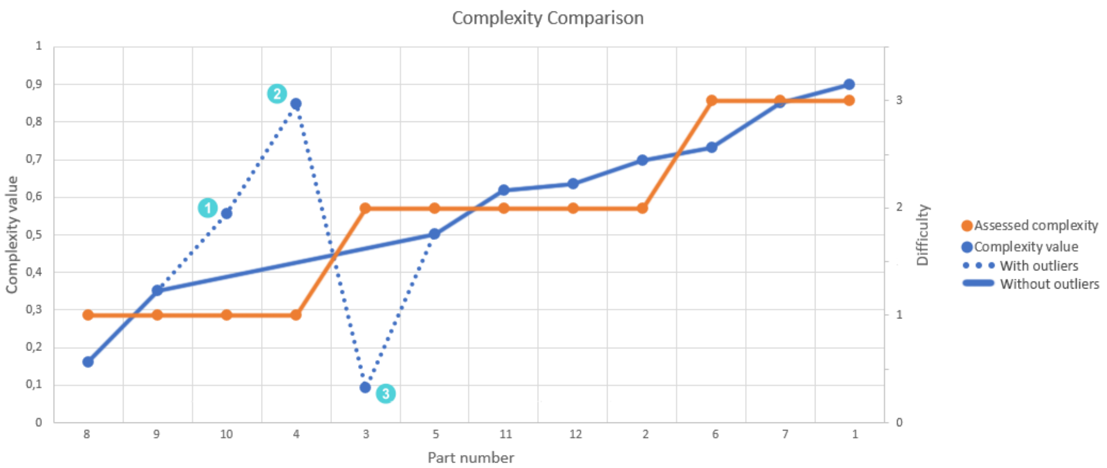

Fig. 3 Comparison of complexity value and actual difficulty.

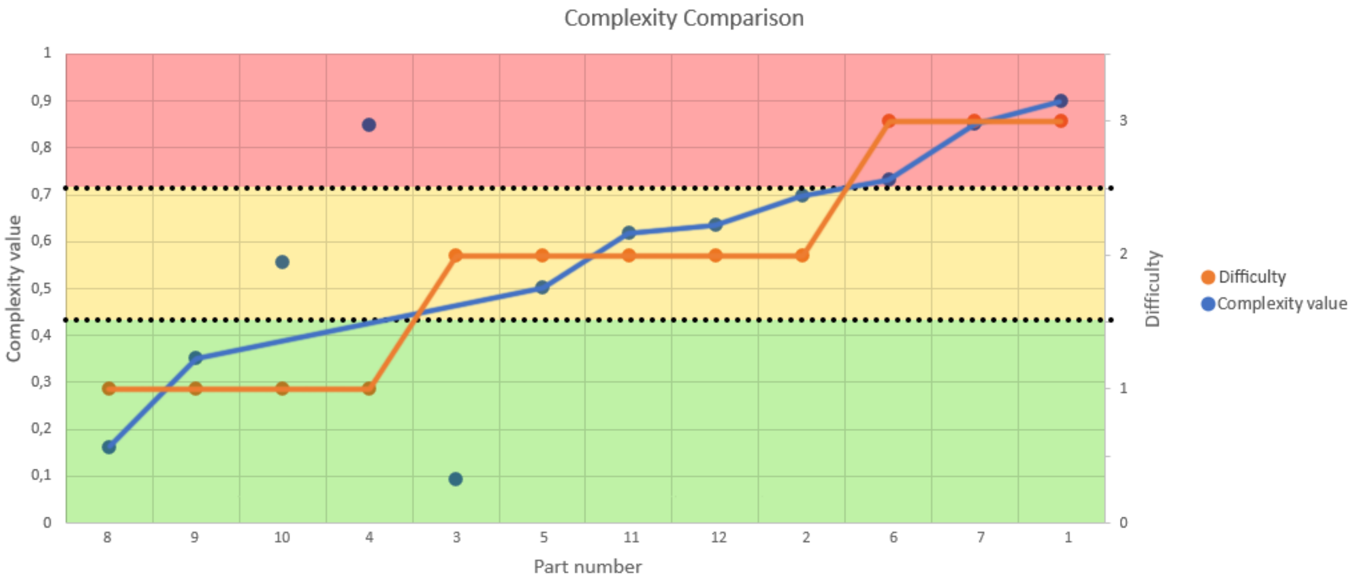

Fig. 4 Division of the Complexity Value into three complexity categories.

would likely catch unreasonably high complexity values such as the weld flange. Such parts would likely be manufactured from a hollow bar which already contains the hole in the flange. It is however important to note that if the raw material is larger than the bounding box, the bounding box should still be used. This is in order to not get exaggerated complexity values on parts which use larger-than-needed raw material due to low stock, odd dimensions etc.
The presented complexity value provides a sturdy backbone for evaluating the complexity of parts, and expanding the metrics used could result in a formula which would not require human interaction. With the use of machine learning additional data such as those mentioned earlier (STL triangles, surface area, time consumption during CAD-drawing etc.) could be logged and compared to an evaluation of the difficulty by a professional, eventually resulting in an automatic and precise calculation of a complexity value.

2.3 Modelling the DES for predicting output based on order composition

The input and process parameters required to compute the production metric have now been identified. Thus, a DES which can predict the output of Welltec's production based on order mix can now be modelled.

Following the methodology presented in the previously mentioned article[1] regarding input data management, the next step is to create a data sheet for the DES. Since the data to describe the important but complex interdependency between the identified input and production parameters is not available, it has been decided to generate this data sheet. The generated data has been estimated based on the group's knowledge about Welltec's production as well as logical decisions such as complex parts requires more milling time than lesser complex parts.

The DES that was modelled in Enterprise Dynamics can be seen in Figure 6. This DES provides Welltec with an indication of what potentially can be gained in terms of future operational and development decisions by adopting the proposed production metric. Welltec has a complicated flow and available resources which varies in periods, for instance, at a given point in time two operators could be assigned to the same task which can lower the individual processes' cycle times. As it is not trivial to simulate this kind of behavior, the DES is only valid for one scenario. This scenario is devised for the purpose of this paper, where one operator has the responsibility for the CAM-programming, tool preparation, and setup of an order. This operator prepares both recurring and new orders for production in the time interval 07:00 to 13:00. After 13:00, the same operator only prepares known orders for 2 hours. In the devised scenario, this results in 1-2 orders which are ready for the CNC. These orders can then be processed by the CNC in the time span from 15:00 to 07:00. Thus, if the production flow changes and does not correspond to this scenario, then the simulation has to be changed.

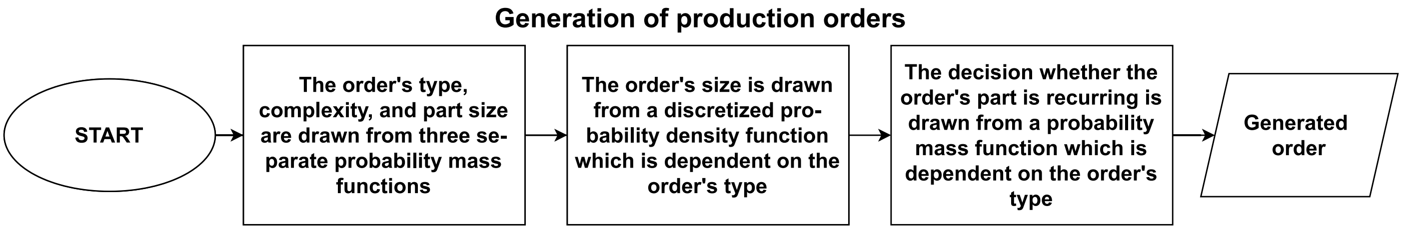

Fig. 5 The figure illustrates the method used to generate production orders. The specific probability mass functions and probability density functions used in the method have been estimated by the authors.

A scenario for the DES representing the ideal production is also required to compute the performance metric presented in Equation 1. In the scenario for the ideal production, the operator can perform orders with recurring parts and orders with new parts between 07:00 and 15:00. After 15:00, the production system works autonomously on prepared orders and orders with recurring parts until the operators arrive the next morning.

If the performance metric is to be used as an operational tool, the input parameters related to the order mix should be based on historical data. However, as it has not been possible to acquire such data from Welltec, the order composition has been generated based on probability tools. Figure 5 illustrates how data was generated for the two DES's. The probability tools described in the figure aim to generate production orders which mimic tendencies which are expected in Welltec's order composition. For instance, if the generated order is of the planned type, then it is more likely to be a large order with a recurring part than if the order type was R&D or urgent.

To generate the DES's process parameters, a method which is similar to the one presented above is used. The generated process parameters are directly affected by the currently processed order's composition. For example, if the order's complexity level is high, then CAM, tool preparation, setup, and CNC milling is likely to require more time than orders of lower complexity. The method for generating the process parameters can be seen on Figure 7. The probability density functions seen in the figure, should be based on the true relationship between the order composition and process parameters. This relationship can be extracted from data which Welltec should log in their production processes. Since the relationship is not obtainable yet, the probability density functions used in the DES's have been estimated by the paper's authors.

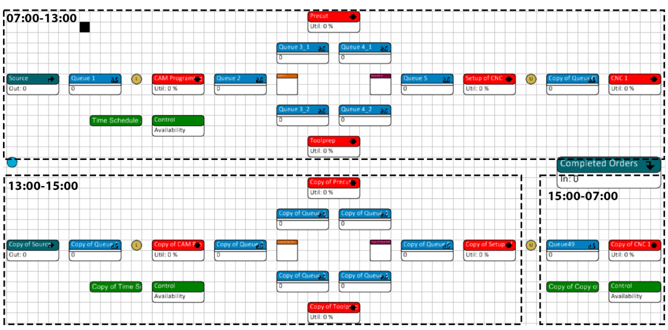

Fig. 6 Screenshot of the devised metric Discrete Event Simulation

The DES of the current and ideal production has been modeled. Therefore, it is now possible to use the production metric as an operational tool and compare performance for the different order mixes to test the metric.

3. Testing the production metric

A set of scenarios has been formed to test the devised production metric. These scenarios differ in order composition to test if the production metric is able to reliably produce a viable indicator which can be used to evaluate the production's performance. In the scenarios, the probability mass function (see Figure 5) used to draw an order's type has been altered which implicitly also affects the generated order's size and if the order's part is recurring. Therefore, the production orders in the scenarios are dominated by specific order types to test how this affects the production metric. The six devised scenarios are shown in Table II.

The six scenarios presented in the table have been inputted individually into the DES for the current and ideal production. The results can be seen in Table III, and show that the current performance is close to identical for the six scenarios. This is due to the inherent positive correlation between the current and ideal models as they have been formed with the same

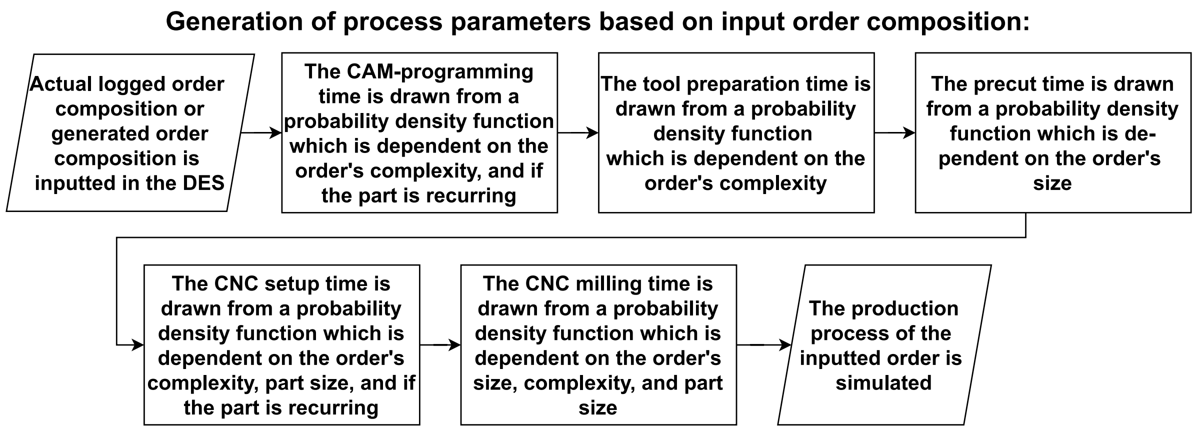

Fig. 7 Illustration of the method used to generate process parameters based on order composition. The specific probability density functions used in the method have been estimated by the authors.

production processes and flow, while being inputted with identical order compositions. The DES's have different distributions for process parameters, but since identical order compositions are inputted to the system, the process parameters of the simulated current and ideal production are affected by a similar proportion. Therefore, when an identical order composition is inputted to the two DES's, the number of closed orders remains correlated. This indicates that the devised production metric can be utilized by management to estimate the performance of an agile production setup with varying order compositions.

As seen from Table III, the current CNC utilization is greatly affected by the varying order composition. However, as the order composition was the only parameters which was altered in the simulation, the current and ideal production had the same resources available in the six scenarios but with different process work distributions. Therefore, the CNC utilization may provide management with an unreliable performance indicator which does not reflect the value added by the operators in the production.

The simulated results also provide an interesting point which highlights an additional benefit of using the devised production metric as a performance indicator instead of CNC utilization which is currently used by Welltec. Scenario 2 is highly dominated with orders of the planned order type. In the simulations, orders of this type are more likely be large size orders with recurring parts. Therefore, the CAM programming process is expected to be negligible while the CNC milling process may be more time-consuming as a large number of parts have to be produced. This facilitates a relatively high utilization of the CNC but with a lower number of closed orders. Therefore, as seen in Table III, the current production setup only closes 26 orders while having a CNC utilization of 29%. This is contradictory to scenario 2, as it has the lowest number of closed orders but the highest CNC utilization of all the simulated scenarios. Hence, there is a poor connection between CNC utilization and the number of production orders closed.

4. Conclusion

A new production performance metric has been devised in this paper which can be used as an operational and development tool. The metric takes the order composition for a given period of time into account, and thus, it is more robust to the changes in work distribution which can be experienced in a highly agile production like Welltec's. As a result of this robustness, the metric can be used by management as a "speedometer" for

	Planned [%]	R&D [%]	Urgent orders [%]
Senario 1:	33.33	33.33	33.33
Senario 2:	80	10	10
Senario 3:	10	80	10
Senario 4:	10	10	80
Senario 5:	45	10	45
Senario 6:	10	45	45

Tab. II The six devised scenarios with differing probability mass function for order type.

	Current Output [order]	Ideal Output [order]	Current Performance [%]	Current CNC utilization [%]
Scenario 1:	31	57	54%	22%
Scenario 2:	26	47	56%	29%
Scenario 3:	31	60	52%	19%
Scenario 4:	41	76	54%	17%
Scenario 5:	32	55	58%	23%
Scenario 6:	35	66	53%	18%

Tab. III The simulated number of closed orders for the current and ideal production in the six scenarios. The performance of the current production setup has been computed with the formula presented in Equation 1. Additionally, the current CNC utilization in the six scenarios is also presented. The results are based on 1000 observations with a 1-week warmup followed by a 4-week simulation period.

evaluating the performance of the production. Further work must be conducted before the metric is ready and can be implemented. The cycle time distributions for different processes in the DES are all based on estimates made by the group, and must be updated with real-world data before the metric is implemented. This update of cycle time distributions should be conducted once a month for at least 1-1.5 years to ensure that the DES uses the right distributions when calculating the performance of the production. The part complexity metric must be tested to determine if the proposed metric is also applicable to the parts produced. If not, further work should be conducted to determine a more sufficient definition of the complexity metric. Once these tasks have been completed, it is believed that the devised production metric can be used as an operational and development tool.

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Appendix

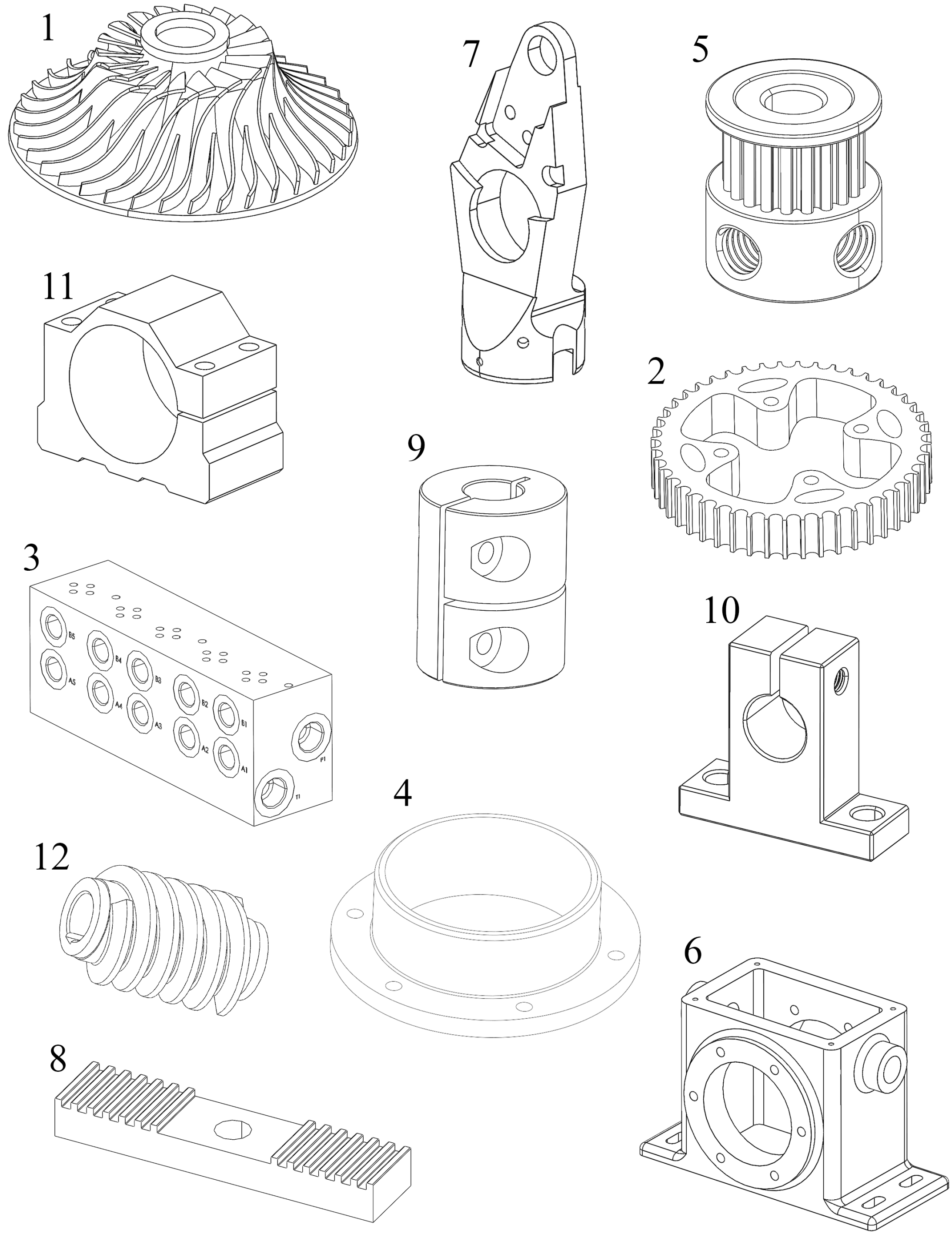

Fig. 8 The 12 different CAD files used for evaluating complexity.