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Towards a Generic Framework for the Performance Evaluation of Manufacturing Strategy: An Innovative Approach

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Abstract: To be competitive in a manufacturing environment by providing optimal performance in terms of cost-effectiveness and swiftness of system changes, there is a need for flexible production systems based on a well-defined strategy. Companies are steadily looking for methodology to evaluate, improve and update the performance of manufacturing systems for processing operations. Implementation of an adequate strategy for these systems' flexibility requires a deep understanding of the intricate interactions between the machining process parameters and the manufacturing system's operational parameters. This paper proposes a framework/generic model for one of the most common metal cutting operations—the boring process of an engine block machining system. A system dynamics modelling approach is presented for modelling the structure of machining system parameters of the boring process, key performance parameters and their intrinsic relationships. The model is based on a case study performed in a company manufacturing engine blocks for heavy vehicles. The approach could allow for performance evaluation of an engine block manufacturing system condition. The presented model enables a basis for other similar processes and industries producing discrete parts.

Keywords: performance evaluation; machining strategies; manufacturing system; manufacturing strategy; machining process interaction; dynamic modelling; performance criteria; system dynamics

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1. Introduction and Related Research

Amongst all the economic sectors, manufacturing is of high importance to the world economy. Particularly, the automotive industry, which is the largest investor in R&D, plays a crucial role in this aspect, accounting for 25% of total R&D spending; it generates an 839 billion turnover which represents 6.9% of EU GDP. In addition, 5.3% of the EU workforce is employed in this sector [1]. Almost 3 million of the world's jobs in the automotive industry represent 10% of Europe's manufacturing employment [2].

The manufacturing of engine components is vital to automotive and other vehicle production. Customarily, the manufacturing of engines is performed in automated manufacturing lines (either in flexible manufacturing lines or transfer lines). Among all processes performed in a line, machining operations have a significant effect on the performance of the manufacturing system and on the quality of the final parts. Machining is the most predominant manufacturing process in terms of volume and expenditure; furthermore, it is critical for the manufacturing system of this sector. It has been estimated that 15% of the world's mechanical component manufactured is derived from machining [3]. In developed countries, the machining process expenditure contributes approximately 5% of the total GDP while, in the US alone, it contributes approximately $250 B per year [4]. The manufacturing industries strive to achieve either a minimum cost of production or a maximum production rate, or an optimum combination of both, along with better product quality in machining [5]. In a competitive global manufacturing environment, it is necessary for every manufacturing company to optimize the machining parameters with respect to the manufacturing system's performance indicators in order to increase the productivity, decrease cost and produce parts according to design specifications.

There are two main bodies of literature that are related to the present research. The first refers to studies of models that analyze the performance of the interaction (relationship) between machining process parameters and performance measures (operational parameters) of manufacturing systems, and the second refers to system dynamics applications for the modelling and analysis of manufacturing systems.

Machining is a process in which complex and nonlinear relationships between parameters are involved. The machining process is influenced by a number of input (independent) and output (dependent) variables. The machining process input variables include capacity, cutting tool material, workpiece material, speed, feed rate, depth of cut, etc. Cutting tool life, tool wear, tool wear rate, cutting forces, material removal rate, etc., are included in the machining process output variables. The cutting technology has grown substantially over time owing to the contribution of many branches of engineering with a common goal of achieving higher machining process efficiency. Practically, in many machining processes, parameters can be varied within a wide range. Nevertheless, in many cases, the typical correlations between these parameters and the performance measures are not fully understood [3,4].

In a multi-stage machining operation, the manufacturer seeks to set the process related controllable input variables at their optimal operating conditions with minimum effect of uncontrollable variables on the levels and variability in the outputs. To implement an effective process control for machining operation by parameter optimization, the performance measures between production rate and cost at each stage of operation should be balanced to improve delivery [6,7].

Simulation and modelling are the commonly used techniques in modern manufacturing that help the process planners in reducing their efforts in selecting and optimizing machining parameters for analyzing and understanding the dynamics behavior of manufacturing systems. The use of simulation technology for analyzing the interaction of machine tool elastic structure and the cutting process is a big challenge. This is due to the fact that a large variety of phenomena exist, and they have to be modelled in great detail for the specific problems [8]. Much research has focused on calculating and predicting the fundamental cutting conditions; however, understanding the interaction between the cutting process parameters and the performance measures is not a trivial task, and it is an active research area [9]. Brecher et al. [9] described the importance of studying the interaction of machine parameters and process parameters and summarized the available modelling techniques for process and machine interactions.

Most previous research work has been done on numerical and analytical modelling of cutting process [10–13]. After determining the appropriate physical data, R.W. Ivester, et al. predicted the effect of changes in cutting conditions on decision criteria (performance criteria) (wear rate/tool life, surface quality, etc.) [4]. At the beginning of the 1990s, Teitenberg et al. [14] proposed an analytical model to predict tool-life/tool-wear during milling operations. Kannan et al. presented an analytical model for the prediction of tool flank wear progression during orthogonal machining of aluminium-based metal matrix composites (MMCs) [15]. Yen et al. proposed a model using FEM (Finite Element Method) simulation to estimate tool wear of carbide tools in orthogonal cutting [16]. Recently Attanasio et al. developed FEM-based simulation for forecasting tool wear progression during turning operations [17]. Moreover, Zel et al. implemented a similar FEM strategy and methodology to predict tool wear in turning operations in terms of crater depth and position [18].

Ribeiro et al. (2017) [19] studied the influence of each cutting parameter of feed, the depth of cut and the speed on surface roughness individually by applying an analysis of variance (ANOVA). Nalbant et al. (2007) [20], Hasçahk and Çaydas (2008) [21], Ribeiro et al. (2017) [22] used the Taguchi-based method to study the machining process in order to optimize the most controllable parameters, like feed rate, cutting speed and depth of cut. Britz and Ulbrich [23] carried out a coupled simulation of rigid and flexible multi-body machine structure models and process, and the process force was calculated by using the model.

In their work, Pang et al. [24] introduced the application of Taguchi optimization method to optimize the machining parameters of an end milling process. The depth of cut, cutting speed and feed rate were chosen to be evaluated to measure the surface roughness and the cutting force. The coupling of the modelling of processes and machines for different grinding kinematics were described by Aurich et al. [25]. Multiple modelling techniques, such as analytical methods, the finite element method, the Taguchi method boundary element method, and the multi body simulation method have been used to model the complex relationship between process and machine parameters through the prediction of forces, surface integrity, energy, and temperature. However, the interaction of the machining process parameters and performance measures in the manufacturing system and the consequences of machine life (age effect, maintenance, etc.) itself have not been considered in any of these works. In their work, Yang et al. [26] used discrete element simulation to analyze orthogonal cutting with different cutting conditions; the results of cutting force and surface cracks were studied.

Discrete event simulation (DES) is the most popular approach for simulation models of manufacturing systems [27]. It has been employed to understand and assess the impact of decisions made on the production system, including its various functional areas. DES support the engineer and decision maker to analyze each individual operation and evaluate and improve manufacturing processes and to make decisions at an early stage of implementation [28]. Kibira et al. (2009) [29] stated that, typically, DES is done to address a particular set of problems, and it does some 'what if' analyses, in which the effect of different options can be investigated. Smith, J. S. (2003) reviewed the literature on the use of DES for manufacturing system design and operation problems [30]. Caggiano, A., and Teti, R. (2018) applied DES to analyze the different manufacturing cell production strategies. DES was also employed to improve the performance of manufacturing systems in terms of throughput time, productivity, energy efficiency and resource utilization [31,32]. Application of DES can sometimes be unnecessarily complex and time consuming [33].

System Dynamics (SD) is a method for studying the world around us. It is used to study objects as a whole to understand how they interact with each other as part of a system, instead of studying each object separately [34]. In complex environments, like a manufacturing system, objects often create feedback loops, where a change in one parameter affects the others dynamically, which feeds back to the original object, and so on. The interplay among objects determines the different states that the system can assume over the course of time, which is known as the dynamic behavior of the system [35]. The dynamic complexity of the system arises not from the number of system components, but from the combination of interactions among system elements over time [36,37]. The principles of SD in manufacturing systems and how this differs from DES and applications of SD in manufacturing system modelling has been well explored [38].

2. System Dynamics and Its Application for Modelling and Analysis of Manufacturing Systems

The manufacturing of complex products requires the machining and assembly of many components. Most real-world problems are too complex to be formulated by mathematical equations [39]; therefore, a simulation approach for analyzing and optimizing a given system structure is required. The main advantages of simulation arise from the better understanding of interactions and identification of potential difficulties that simulation offers, allowing the evaluation of different alternatives and therefore, reducing the number of changes in the final system [33]. In a variety of different situations, SD shows up similar patterns of behavior. This is one of the reasons why SD is considered the most powerful of this type of problem solving method.

The work conducted by Baines and Harrison [40] demonstrated that SD has typical performance characteristics when considering strategic issues in manufacturing companies. SD has been applied to a wide range of problems. In the manufacturing industry, it is applied to analyze, evaluate and modify strategy and policy issues and to make decisions relevant to the dynamic environment of the market. SD has been widely used to understand system structure and its behavior over different time spans and to spot difficulties within a system. It has been successfully applied to a range of industrial management problems, like inventory management, logistic and supply chain management, production planning and control, demand forecasting and capacity expansion, human resource management, etc. [41].

Helo presented a SD model for strategic scenarios analysis and polices for the supply chain operations in manufacturing systems [42]. Oyarbide et al. [33] investigated the application of SD in the transfer line modelling task. Deif and ElMaraghy analyzed the concept of capacity management of the different performance measures of the manufacturing system using a SD approach under conditions of unanticipated demand fluctuations [43]. Shooshtarian and Jones used SD simulation modelling for the analysis of production line systems for the continuous model of transfer lines with unreliable machines and finite buffer stock in the system [44].

Until now, the majority of the work done for the application of SD in manufacturing systems has focused mainly on performance analysis of the supply chain. This work has mainly considered how systems are designed to respond to unexpected customer demand, considering certain performance measures of the supply chain [34,45–47]. Parnaby outlined a conceptualized SD model to manufacturing systems [48]. A manufacturing system application of SD was used by Byrne and Roberts (1994) to evaluate manufacturing performance in a Kanban-based system [49]. Until recently, in the reviewed technical literature, to the authors' knowledge, there has been no definite holistic approach available for the performance analysis of manufacturing systems that considers the interaction of machine tool elastic structure, and the process and operational parameters of a manufacturing system, while developing models for the machining processes. However, a highly automated manufacturing environment requires a powerful strategy for the control of process chain and material flow.

Most industries use the knowledge of experienced machine operators and programmers [4] to predict and control the effects of the variation of process parameters on overall manufacturing system behavior. However, this process is expensive and time consuming [4]. Thus, one of the main motivations for this research work is to develop a generic framework for manufacturing systems that considers the complex interaction of manufacturing system parameters. As a consequence, development of an appropriate evaluation tool and a sustainable framework applicable for this strategy is needed. A methodology that considers the various combinations of manufacturing system parameters and their interactions and that can also predict, optimize and analysise the outcomes of a process with respect to the performance criteria selected is required.

Manufacturing system modelling is a complex problem due to the presence of multiple decision makers, the complexity of the parts produced, demand fluctuation, continuous development of workpiece materials, technology limitations, unavailability of defined methodology and various kinds of delays. In this paper, a SD simulation and modelling approach is presented to formulate the structure and interrelationships between parameters for the machining process of an engine block. In reality, minor fluctuations in the system's initial parameters can cause significant long-term variations, which, in turn, have a significant effect on a machining system's behavior. This problem is analyzed using a SD approach. To figure out the defined problem, the present methodology studies the system as a whole rather than using an analytical approach which breaks down the problem into smaller parts. Analyzing the structure of the system as a whole makes it possible to identify the non-linear causal relationships among the system parameters and to understand the structure of the complex system [35,39].

Objectives and Outline of the Paper

In this paper, a conceptual framework for the manufacturing system of an engine block machining is developed. As a case study, a model for a boring process—one of the critical operations for the engine block machining process—is presented. This can be used as a reference model and is able to represent the relationships between manufacturing system parameters, the machine elastic structure and the selected performance measures. A flexible machine tool (FMC) is considered for the analysis.

The remainder of the paper is organized as follows: Section 3 defines some of the terms and terminology used in this paper according to the context. In Section 4, the manufacturing system process modelling is described. The basic concept of the proposed methodology, the scope of modelling and the parameters of manufacturing systems are included in this section. Section 5 describes the analysis and discussions. In Section 6, results are presented. Finally, conclusions and considerations for future research are provided in Section 7.

3. Definition of Terms Used in This Paper

3.1. Machining System

A machining system can be represented by a closed-loop system, comprising a machine tool elastic structure and the cutting process. These two subsystems are interrelated and interact with each other. The machine tool elastic structure includes a machine tool, cutting tool, workpiece, and clamping system, whereas cutting process include such example as cutting parameters (depth of cut, feed rate, cutting speed, spindle speed, etc.), tool material, cutting operation (milling, boring, turning, drilling, etc.) and cutting tool geometry [9,50].

3.2. Machining Strategy

Machining strategy is a plan for the manufacturing system's condition designed to achieve a long-term objective in conjunction with the manufacturing system's performance indicators. It can also be described as a plan or a methodology for the manufacturing system's activity to generate a series of operations that will successfully machine the part with respect to performance indicators. It also refers to the manufacturing system's conditions derived by all the decisions taken, with the objective of optimizing the machining system's parameters in respect to the pre-selected key performance criteria. To get an optimal output, the interaction of different performance measures or parameters and the detailed process level parameters should be considered.

4. Manufacturing System Process Modelling

4.1. Engine Block Machining Process Overview

An engine block has thousands of machined parts (features). Machining of the engine block requires a number of different machining operations and passes through around 20 processing stations in the manufacturing line. More than one machining operation can be conducted at each station. To evaluate and analyze the entire machining process, two possible ways/levels of evaluation technique are proposed—the system level and the process level. The choice is based on suitability in the area of application.

4.1.1. System Level Analysis

In system level analysis, all sequences of operations in the manufacturing line are hidden inside black boxes (Figure 1). The strategy for this level of analysis ignores the internal mechanism (process) of each station and focuses solely on the output of parts in response to selected inputs and execution conditions. As input parameters, only the workpiece property specifications from the foundry and the control factors from the external environment are considered. In general, this level of analysis does not concern how the inner detail process of each station is produced to achieve the desired output.

4.1.2. Process Level Analysis

In process level analysis, each station in the manufacturing line is accounted for independently, unlike in system level analysis. It is a detailed process level analysis that considers almost all of the factors at each station. To analyze the output of the part produced, each station's input parameters, the control factors, the interaction of process parameters and other activities are taken into consideration (see Figure 2). Figure 2 describes the machining process of some features at a station (station 1 from Figure 1 is taken as an example). The parallel machines in this given station, which are identical and function in exactly similar operations, indicate the possibility of adding a machine in order to cut the cycle time by half.

To evaluate the machining process for the entire manufacturing system, the working conditions of each station is analyzed independently, like in process level analysis, consequently combining and placing them in a green box. In this paper, the process for one station, boring operations, will be studied and analyzed using process level analysis.

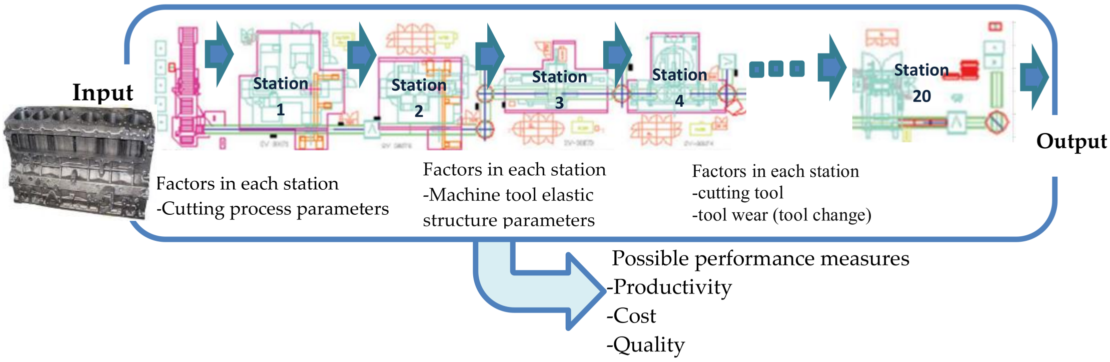

Figure 1. Sequence of stations for an engine block machining line—system level analysis.

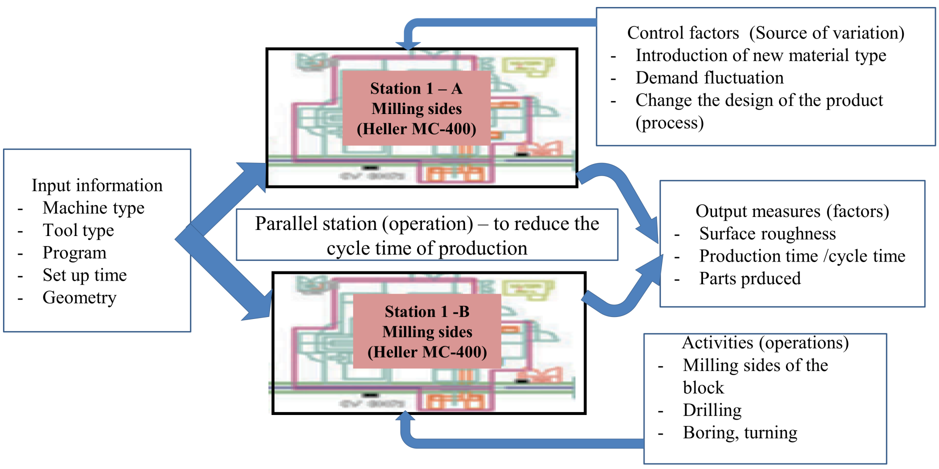

Figure 2. Machining process of features at a station with identical parallel machines—process level analysis.

4.2. Machining Process Parameters

Boring is one of the most common metal cutting operations for engine block machining and will be accounted for in this paper. It is characterized by its kinematics, productivity and dynamics. Productivity and kinematics parameters include the cutting speed, spindle speed, cutter diameter, number of teeth (inserts) in the cutter, feed per tooth, feed rate, depth of cut, number of inserts in the cut, chip thickness, feed rate adjustment, cross sectional area of uncut chips, metal removal rate, machining time, etc. The parameters of process dynamics include the tangential cutting force, torque, the machining power at the cutter and the machining power at the motor. Some of the many features in engine block machining that control the boring operation include the crankshaft bore for roughing and finishing operation, the camshaft bore for roughing and finishing operation, cylinder bores, etc.

4.3. Manufacturing System Parameters and Performance Indicators

The principal performance indicators and machining system parameters deployed in this paper are presented in Figure 3. These parameters were obtained from a literature survey and the current configuration of an actual engine block manufacturing line in the automotive industry. Due to the fluctuations in factors like demand, workpiece material, design specification, number of machines and others, the input parameters values for the machining process might be varied. However, there are parameters that might be kept constant to maintain the production flow, such as takt time, total production time, etc.

In this research, the actual cost is expected to an output dependent on values from other connected parameters, but only the main cost derived is considered.

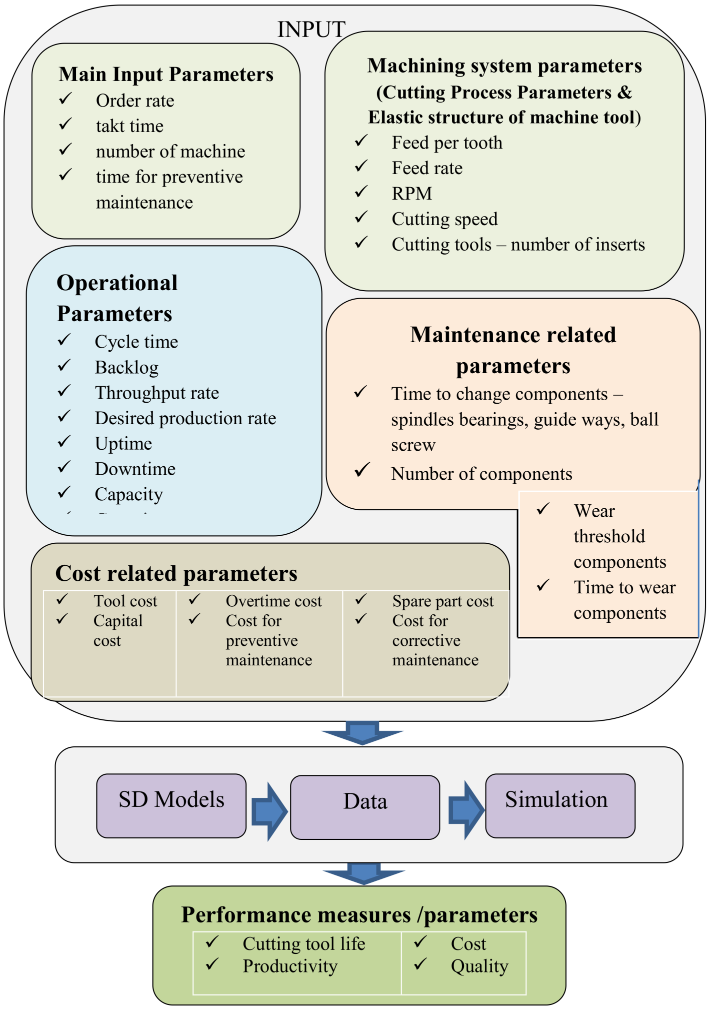

Figure 3. Modelling approach for the machining process.

4.4. Scope for Modelling

Figure 4 explicitly describes the manufacturing strategy for an engine block that is designed to be produced in-line with optimal performance criteria—PCQ (productivity, cost and quality). The manufacturing system is set up to produce the desired quantity of parts that fulfils the required quality requirement and achieves the optimum cost. To produce an optimal output for PCQ with a set of given input parameters, the manufacturing system is adjusted accordingly. This is the feedback system that closes the loop.

A specific input parameter is taken into account, and based on the variation of this parameter, the machining strategy is configured. If some adjustment in the manufacturing system behavior is required, the cutting process parameters can be varied; such requirements, for example, high/low product demand. To produce the given demand, the process can be fast/slow; thus, the total production time is varied in order to either produce overtime beyond threshold because of higher demand or reduce it because the targeted production rate has not be achieved. Moreover, the cycle time can also be reduced by adding a parallel machine to a station which is either bottlenecked or has the highest cycle time in the line.

4.5. Causal Loop Diagram

The causal loop diagram (CLD), is a tool to map the structure of a complex system. The cause effect connections in a system sometimes form loops indicating information feedback between parameters; the nature of these feedback loops determines the structure and behavior of the system. The structure of a manufacturing system's main parameters' relationship, their interaction, and feedback of the system are captured in the CLD, illustrated in Figure 5. Parameters are related by causal links, shown by arrows. Each causal link is assigned a polarity, either positive (+) or negative (−). The + and − signs represent the relationships between respective connected parameters, either in direct or inverse proportionality, respectively. They indicate also how a dependent parameter changes when an independent parameter changes. The two types of feedback loop—negative or balancing loop (B) and positive or reinforcing (R) loop—are also presented.

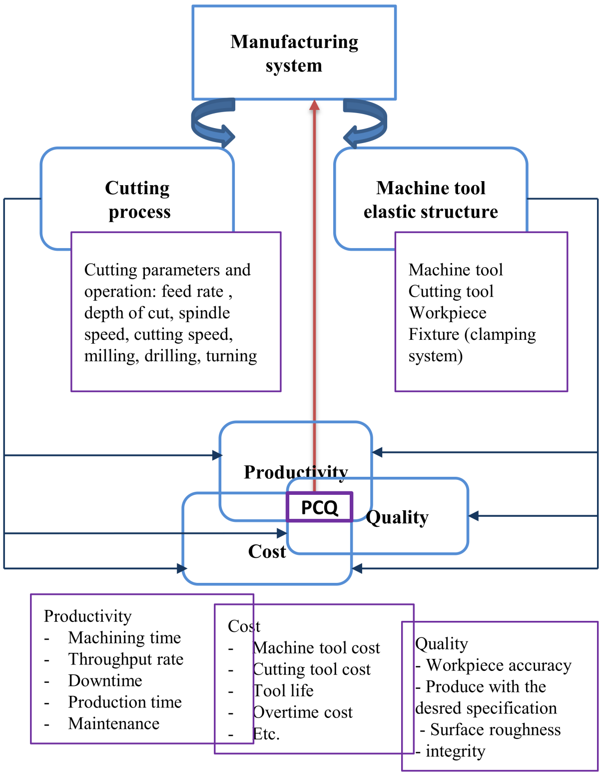

Figure 4. Conceptual map for modelling.

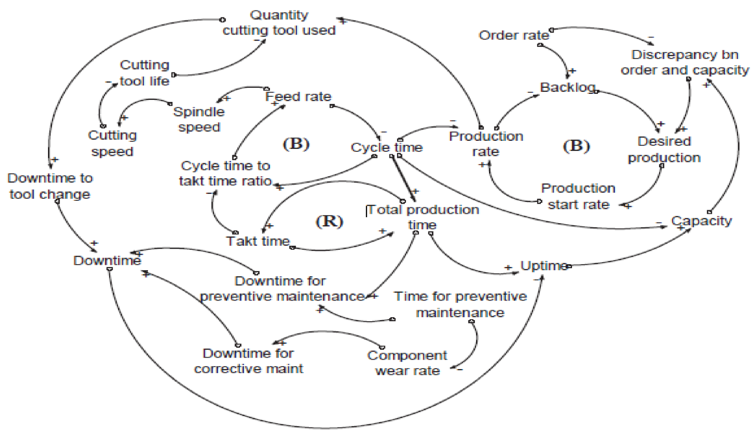

Figure 5. Causal loop diagram for the main manufacturing system parameters.

5. Analysis and Discussions

5.1. SD Modelling for Manufacturing System

As discussed earlier, the methodology implemented is based on system dynamics. To carry out a simulation and analyze the actual behavior of the model, the CLD, illustrated in Figure 5, is translated into a "stocks" and "flows" model. The structure of the model is designed based on the data from an existing manufacturing line of engine block machining of the chosen company.

5.2. Representation of Sub-Models/Modules

To have a clear understanding about the structure of the overall model of the manufacturing system, the model of this system is divided into seven sub-models: machining process, near-net shape production, operational, force and MRR (Material Removal Rate), maintenance, and cost sub-models. The model is explained in stages (sectors), and assumptions and simplifications are made, and then the structure and behavior of the system are analyzed for each module. The main modules of the SD model and their mathematical expression (expression) are explained below.

5.2.1. Modelling Machining Process

The structure of the machining process module is illustrated in Figure 6, which comprises the main manufacturing system parameters, such as takt and cycle times, and process parameters, such as feed rate, spindle speed, cutting speed, actual number of tools used, and the interactional (effect) factors—the effects of cycle time on feed rate, effect of cutting speed on tool life, etc. The figure is partitioned into zones, which are called sectors in system dynamics. This shows the specific parameters' relationships in the manufacturing system.

Two scenarios are proposed to model this module: producing the part at (1) constant takt time and (2) flexible takt time.

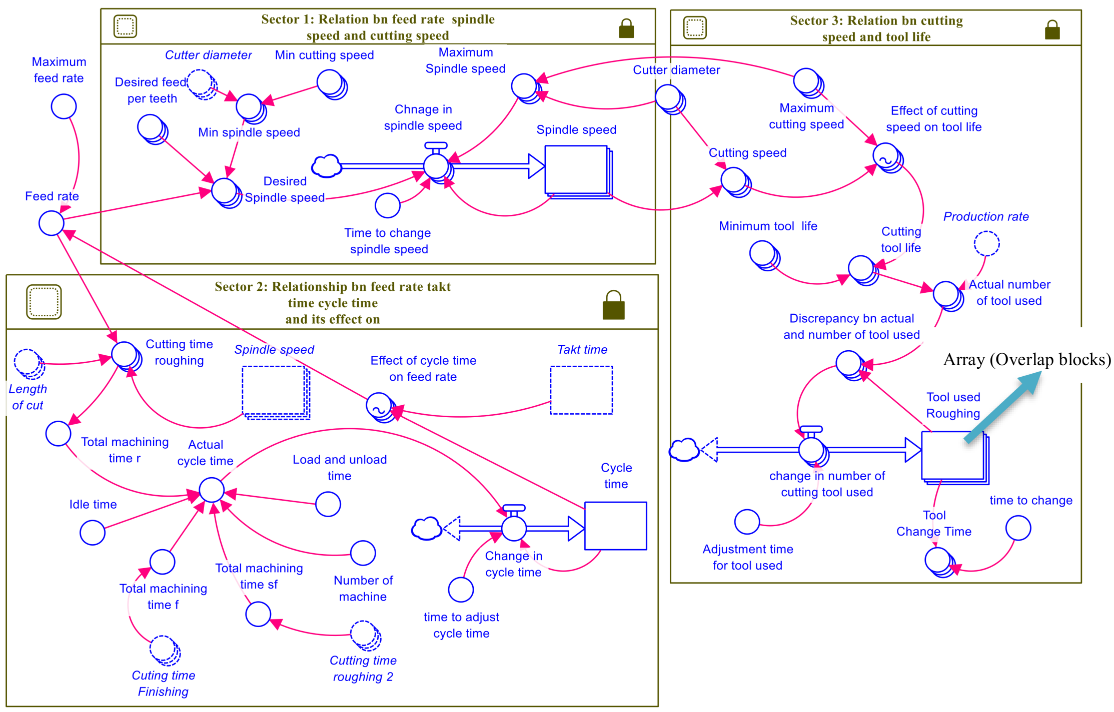

Figure 6. Machining process parameters module.

Constant Takt Time

It is obvious in a manufacturing system that if there is a fixed or targeted takt time intended to be achieved, the value of cycle time should always be less than or equal to the takt time. If there is a deviation from the normal value, the cycle time should be controlled by adjusting the process parameters, e.g., the feed rate and cutting speed in the system behavior. There is a control loop that accommodates the cycle time with respect to the takt time. A sequence of operations is performed at each station of a manufacturing line to measure the cycle time and to adjust machining parameters if needed. There is a time delay in the estimation of the cycle time and adjust its value with respect to takt time. Due to the number of operations performed, the cycle time is estimated with an information delay to determine the consecutive cutting process parameters in the next sequence of operation.

In Figure 6, arrays or overlap blocks representations are used to encapsulate parallel model structures and help to represent the essence of the situation in a simple fashion. In this model, one array represents more than one feature machined or operation conducted at each station, thus it enables modification for better future use if other scenarios are proposed.

In the machining process, three sequences of operations can be included: roughing, semi-finishing and finishing operations. The semi-finishing operation might not exist in all of the processes as it is dependent on length of cut, machine tool characteristics or the type /ability of the cutting tool to withstand high cutting forces. Each of these operations is performed with designated cutting tool types and manufacturing system parameters values.

The cycle time is adjusted with respect to the takt time under the control loop "effect of cycle time on feed rate", as presented in Figure 6. The total time needed for the production of a specific feature is called the actual cycle time and it comprises cutting time (for roughing, semi-finishing and finishing operation), loading and unloading time, idle time and time for other activities (see Equation (1)).

$$cta = \frac{mtr + mtsf + mtf + ti + t(l/u) + tO}{Nm} \tag{1}$$

The cycle time (estimated cycle time) is calculated with Equation (2):

$$ct = \int \Delta ct(t)dt + ct^{int}; \text{where } \Delta ct(t) = \frac{ct_a(t) - ct(t)}{Dt} \tag{2}$$

The time delay, Δt, is caused by an information delay and is introduced to smooth the actual value of the cycle time.

The effect of cycle time on feed rate, E_f^{ct}, is the parameter designated to control the value of feed rate in the model; it is represented as a graphical function of the time ratio between cycle time and takt time (ct/tt), as illustrated in Figure 7. If the time ratio is greater than one, the machining is performing slower than required; on the contrary, if it is less than one, there is faster production. If the cycle time is too short, it is possible to reduce the feed rate, and the feed rate can be increased if the production rate is lower than required. The feed rate is constrained between the maximum and minimum feed rates, as shown in the model. If there is a variation in the time ratio, the feed rate will be adjusted through the control loop but an efficient control should consider the given performance criteria. Obviously, finishing operations play a major role in the quality of the part, so the value of the parameters for finishing operations should be set within a certain interval to meet the required quality specification of the parts.

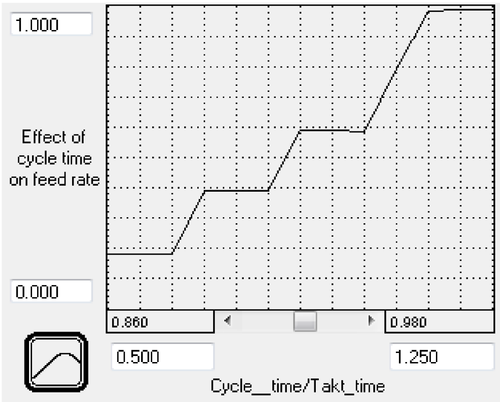

Figure 7. Behavior of the effect of cycle time on feed rate.

For the initial simulation, the input value for feed rate is initialized from the current manufacturing process conditions. For the consecutive simulation, the parameter is automatically modified in accordance with the ratio between cycle time and takt time; this effect is multiplied by the maximum allowable feed and is used as an input value for the next operation (see Equation (3)):

$$f_r = E_f^{ct} \times f_{r\ max} \tag{3}$$

The machining time required when cutting parallel to the workpiece's centerline for a given length of workpiece is described by the following equation: Equation (4). This reflects the relationships between machining time and feed rate.

$$t_m = \frac{l}{f_r \times n} \tag{4}$$

The sector "relationships between feed rate, spindle speed and cutting speed" in Figure 6 reflects the relationships between these parameters and the control on the spindle speed. The feed rate is defined as a function of spindle speed, and then the spindle speed influences the cutting speed. The equation of desired spindle speed is described by Equation (5).

$$f_r = n_{des} \times f_z^{des} \tag{5}$$

The desired spindle speed cannot be smaller than the minimum allowable spindle of the given machine tool. Hence, the desired spindle in the model is calculated as (Equation (6)).

$$n_{des} = max\,(\frac{f_r}{f_z^{des}},\ n_{min}) \tag{6}$$

There is an information delay between the desired spindle speed and the actual spindle speed. The spindle speed changes through time; that is, it is the time necessary for the number of experimental conducts to estimate the actual spindle speed. The actual spindle speed is regulated by the change in spindle speed (see Equation (7)). It is limited by maximum spindle speed; this, in turn, is limited by the maximum cutting speed.

$$n^{ch} = \frac{(min(n_{Des},\ m) - n}{t^n};\text{ where; } n_{max} = \frac{1000V_c^{max}}{\pi d} \tag{7}$$

The minimum value is taken into account; therefore, the spindle speed will not be more than the maximum speed allowable. Equation (8) estimates the actual spindle speed.

$$n = \int n^{ch}(t)d(t) + n^{init} \tag{8}$$

The life of the cutting tool is expected to be dependent on the cutting speed—in other words, for the cutting speed to influence the life of the cutting tool, this correlation is presented in Figure 6 in the 'relationships between cutting speed and tool life sector'. The cutting speed is limited by the feed rate and spindle speed, assuming the depth of cut is constant. Under these circumstances, consideration should be given when selecting the maximum cutting speed; the maximum cutting speed should not be greater than the allowable, because this leads to an increase in temperature and consequently rapid wear of the cutting tool. Mathematically, the quantitative relationships of the tool life can be expresses by the Taylors tool life equation (Equation (9); Taylor 1907),

$$Vt^{\alpha} = C \tag{9}$$

The tool life relationship can be represented by taking the two extremities of cutting speed (maximum and minimum) and considering experimental data about a tool's life and the variation between an increase or decrease in cutting speed within this range. For example, from experience, a 5 m/min decrease in cutting speed will increase tool life by 40%. The connection in the model is denoted as a non-linear effect of cutting speed on tool life as presented in Figure 8 above. The cutting speed is described by Equation (10).

$$V_c = \frac{\pi dn}{1000} \tag{10}$$

The tool wear (life of the cutting tool) in the model is calculated with Equation (11).

$$tl_{cut} = E_{tl}^{V_c} \times tl_{min} \tag{11}$$

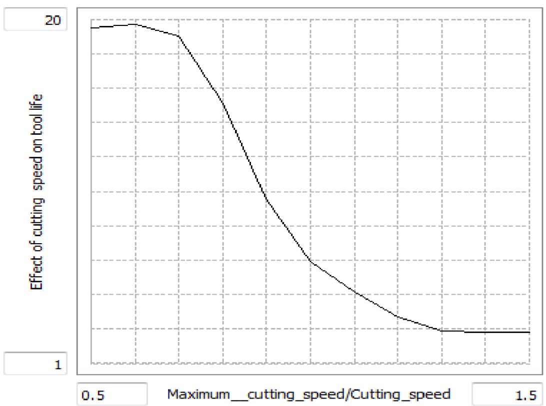

Figure 8. Behavior of the effect of the cutting speed on tool life.

Flexible Takt Time

In this situation, the takt time is not constant anymore; rather, it is determined from the total production time and the total amount of desired production available. The takt time is calculated by the general formula (see Equation (12)).

$$tt = \frac{t_a}{d} \tag{12}$$

The main objective in this case is to develop a model that relates different manufacturing system parameters during a variation in takt time. The difference from the aforementioned scenario is the variation of the takt time in accordance with the desired production demand and production time available. The structure in the model is presented in Figure 9. There is a first order information delay between the desired takt time and takt time because it takes time to achieve this value. The takt time is regulated by the change in takt time (Equation (13)):

$$tt_{ch} = \frac{tt_{des} - tt}{t^{tt}} \tag{13}$$

The desired takt time can be estimated by:

$$tt_{des} = \begin{cases} \left(\frac{t_{des}}{p_{des}}\right), & if\ t_t > t_{th} \\ (tt)_0, & if\ t_t < t_{th} \end{cases} \tag{14}$$

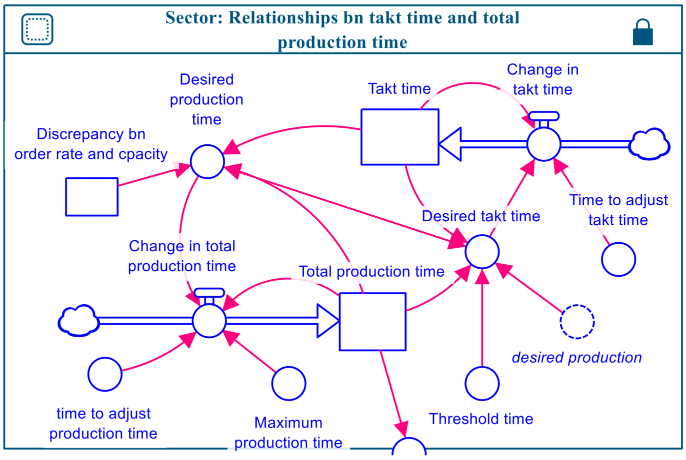

Figure 9. Structure of machining system module for flexible takt time.

When the total production time needed is greater than the threshold time, this is due to a higher discrepancy between the order rate and production capacity; the total production time available is not sufficient to produce the given order rate. To fulfil the overall demand, a parameter called desired production time is introduced, which is calculated as

$$t_{des} = t_t + (tt)_0 \times C_{gap} \tag{15}$$

The total production time needed is limited by the maximum production time allowable and the desired production time and is regulated by the change in total production time. It cannot be exceeded beyond the maximum production time. However, the change in the actual production time is limited by the maximum time capacity of the company (Equation (16)); that is, it cannot be greater than the maximum production time available:

$$t_t = \int_{i=0}^{t} t_t^{ch}(t)dt + (t_t)_0; \text{ where, } t_t^{ch} = \frac{min(t_{des}, t^{max}) - t_t}{t^p} \tag{16}$$

The capacity gap can be positive or negative, depending on the demand and on the production capacity. If it is positive, the desired time to produce is higher; otherwise, it is either equal to or less than the total production time.

As discussed earlier, the only difference is the input parameter of takt time; apart from this, all parametric relationships are also applied to this scenario.

5.2.2. Near-Net Shape Production Modelling

The concept of near-net shape modelling in this paper is used to explore possibilities to produce parts with better tolerance and accurate geometrical dimension, in order to decrease the machining efforts. Also, it is used to analyze the relationships between successive operations and to balance the resources between two processes in the sequence. It contributes to reducing the number of intermediate roughing machining processes, the manufacturing cost, and, in some industries, it even cuts more than two thirds of the production costs in regard to the casting process. The number of roughing passes required to machine a component can be determined from the given workpiece geometry and tool properties. In this case, it is investigated to determine how modelling is adapted during the variation of dimensions in the foundry irrespective of the cost incurred for casting.

Castings that are to be machined must have sufficient metal stock on all surfaces requiring machining. The 'near-net shape' modelling calculation is influenced by the geometrical dimensions of the workpiece delivered from the foundry (the amount of metal left for machining from casting)—leftover stock (stock allowance) or stock size. Roughing operations pertain more to productivity at as high of a material removal rate as possible (the purpose is to remove as much material as possible), while finishing operations are performed to attain the specified dimensional and geometrical tolerances and surface finish of the part. The necessary allowance is commonly called the required machining allowance (RMA), machine finish allowance, or machining allowance and depends on the size and shape of casting, surface to be machined, hardness of the material, roughness of casting surface, and tendency to distort. To maintain the quality of the part produced, the depth of cut (required machining allowance) for finishing operations for each feature is limited within a certain range. Considering the depth of cut for a finishing operation, the number of passes for a specific feature can be estimated by:

$$N_r = \frac{d_{St} - d_{min} + d_f}{d_R \times 2} \tag{17}$$

The machine at each station might not handle more than one roughing, semi-finishing and finishing operation. Otherwise, it might incur high costs or slow down production. Moreover, it might not withstand high cutting forces if a change in cutting tool is necessary in order to cut more material at a time. Usually, it has either a roughing and finishing operation or roughing, semi-finishing and finishing operations. This variation is from the variability of the part geometry from the foundry. The acceptable maximum variation of the stock allowance from the foundry should be limited. That is, the stock size should not be larger than the maximum allowable stock diameter. The overall model comprises three steps of operation: roughing, semi-finishing (more than one roughing process) and finishing. In this paper, it is assumed that there is always a roughing and a finishing operation and that they are active in the modelling environment; however, the semi-finishing is determined from the stock allowance and can be activated or deactivated depending on the length of the component to be cut. If deactivated, all related and interconnected parameters will be halted, and only the roughing and finishing operations will be considered. Otherwise, if there is some material left to be cut, the semi-finishing operation will be active. The depth of cut for the roughing operation is dependent on the maximum allowable depth of material to be removed for roughing and on the maximum cutting tool diameter that can withstand the cutting force (Figure 10). This is an input parameter and constant and is calculated by Equation (18).

$$d_r = \begin{cases} d_t^{max}, & d_t^{max} \le d_r^{max} \\ d_r^{max}, & d_t^{max} > d_r^{max} \end{cases} \tag{18}$$

The depth of cut for the semi-finishing operation is regulated by the stock size and expected machining allowance

$$d_{sf} = \begin{cases} 0, & if \;\; d_{st} \le d_e \\ d_{st} - d_e, & if \; d_{st} > d_e \end{cases} \tag{19}$$

If d_{sf} is zero, the semi-finishing operation is not needed in the system. Hence, in the model, the parameters interconnected with this variable become inactive; otherwise, they are active and there is a need to add the semi-finishing operation in the overall system.

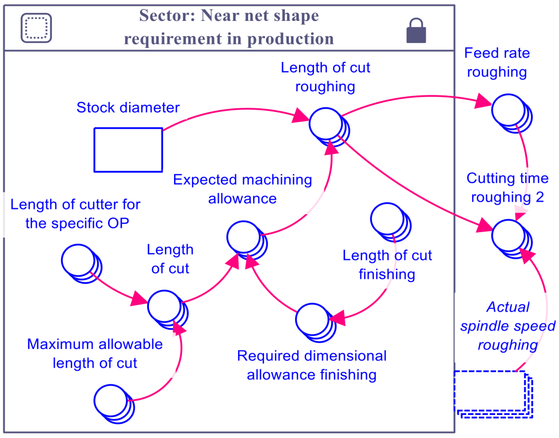

Figure 10. Structure of 'near-net shape' production modelling.

5.2.3. Modelling Production System

The production system module (Figure 12) illustrates the main dynamics behavior of an operational parameter in the manufacturing system. It is the manufacturing system of a single workstation.

The order backlog is a delay between the placement and production of an order. In other words, there is a delay between demand of the part and the time to decide production of the part. It is accumulated by the order rate and reduced by the order fulfilment rate. According to Little's Law [51], the desired production volume at any moment is calculated as in Equation (20).

$$p_d = \frac{b}{dd} \tag{20}$$

The capacity of the machine to produce the desired amount of the part is dependent on the cycle time and productive time available which is called uptime and is estimated by

$$C = \frac{t_u}{ct} \tag{21}$$

In this model, it is assumed that the production start rate is not constrained by the availability of input materials, labor force, economy, etc. It is constrained to be non-negative, and it is influenced by the capacity of the machine and desired production volume

$$p_{sr} = min(C, p_d) \tag{22}$$

Typically, production involves multiple steps that create significant inventories of work in process (WIP). The WIP is accumulated by the production start rate and depleted by the production rate. It is obvious that only one part can be machined at a time; however, the accumulation is accounted for in every DT (Delta Time) period, hence, the WIP is higher than one

$$WIP = \int_{i=0}^{t} p_{sr}(t)d(t) + (WIP)_0 \tag{23}$$

The production rate (Equation (24)) is calculated by

$$P_{rate} = dl(p_{sr},\ ct) = \frac{WIP}{ct} \tag{24}$$

The total downtime is the sum of downtime for corrective maintenance and component overhaul, tool changing, and preventive maintenance, shown in Figure 11. The uptime can be obtained in two ways:

1. It depends directly on the downtime and total production time available, Equation (25)

$$t_u = t_t - t_d \tag{25}$$

2. It is related to the overall equipment efficiency and total production time, Equation (26)

$$t_u = OEE \times t_t; \text{where, } OEE = max(0,\ min\left(1 - \frac{t_d}{t_t},\ 1\right)) \tag{26}$$

If the total production time needed is exceeds the time available for normal production days of the company, it is considered as downtime, as it exceeds the threshold of production time.

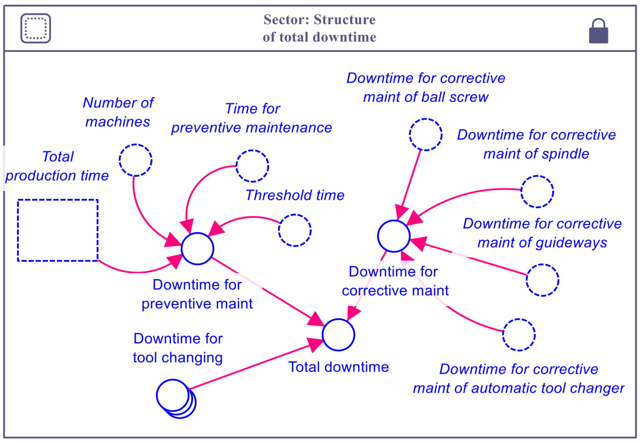

Figure 11. Structure of downtime and uptime.

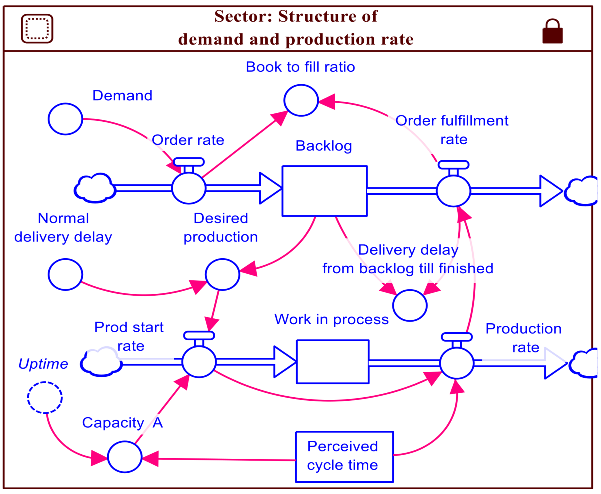

Figure 12. Structure of operational parameters module.

5.2.4. Modelling Cutting Force (MRR)

The dynamic structure of force and related parameters is described in Figure 13. The force can be calculated as follows and is dependent on the properties of the workpiece material type.

$$F = K_c a_p f \tag{27}$$

Stiffness is a measure of a structure's ability to resist loads without changes to its geometry (deformations). The deviation of the cutting tool creates deviation of the workpiece. Deformation or deviation from a workpiece is measured as a function of force and stiffness—the higher the force, the greater the deformation will be. However, the deviation should be limited within the tolerance specification values.

$$x = \frac{F}{K_c} \tag{28}$$

The material removal rate is controlled by the cutting speed, feed rate and depth of cut. It is estimated by the following equation:

$$MRR = V_c a_p f \tag{29}$$

According to Equations (27) and (29) the mean power in cutting is:

$$P = FV_c = K_c a_p f V_c = K_c MRR \tag{29a}$$

The power in cutting, P, represents a limiting factor in the machining and consequently, is a spindle selection criterion.

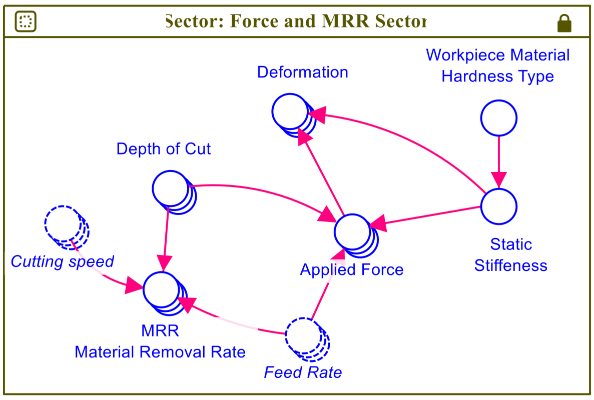

Figure 13. Structure of Force and MRR.

5.2.5. Maintenance

The different maintenance activities performed on the workstation and their structure are presented in the system dynamics module, Figure 14. The main machine components that have high probability of wearing and are considered in this paper are spindles (with gearbox, ball bearings), ball screws, guideways, and the automatic tool changer. The number and type of components selected are based on the current engine block production of the vehicle manufacturing industry. To analyze the structure of the module, only one of the machine tool components, the spindle, which is the highlighted rectangle in Figure 14, is considered. The mathematical relationships for the other components have almost a similar structure. A machine is working properly if all of the components are in proper operational conditions. A component is changed if either an unexpected failure occurs during its service life or at the end of its life; this phenomenon is related to corrective maintenance and component overhaul.

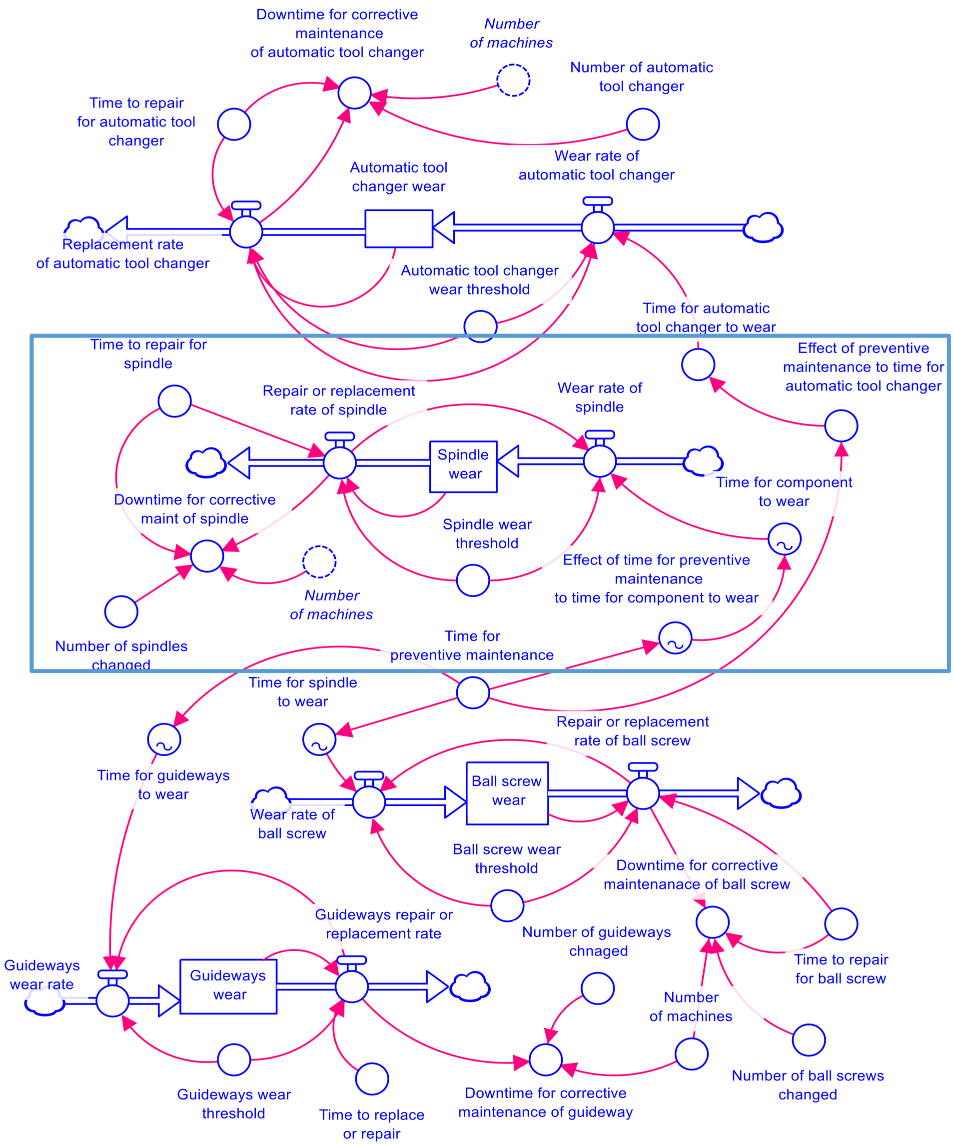

Figure 14. Structure of maintenance module.

Maintenance Model of the Machine Tool Component

The spindle wear in Figure 14 is influenced by the spindle wear rate and the replacement rate. It is determined from the spindle wear rate and the replacement rate and can be estimated by

$$w_s = \int_0^t (w_{sr} - r_r)(t)dt + (w_s)_0 \tag{30}$$

The spindle wear threshold is the maximum value of spindle wear, whereas the wear rate is the rate at which the component is deteriorating and is calculated as

$$w_{sr} = \begin{cases} 0, & if\ r_r > 0 \\ \frac{w_{st}}{t^w}, & if\ r_r \leq 0 \end{cases} \tag{31}$$

The expected life of the component—the time to wear for a spindle—can be obtained either from design specifications or from historical data. It is dependent on the time for the conduction of preventive maintenance. There is required and planned preventive maintenance for each machine tool selected. However, if the time for preventive maintenance is less than that required, then the service life of the component will be shorter than designed. There is a high probability for the component to wear; therefore, it needs to be substituted before its expected end of life. The relationship is presented in graphical function in Figure 15.

Figure 15 depicts the behavior of the average expected life of a component and the time for preventive maintenance. To achieve the maximum average expected life of the component, it should be maintained with the maximum amount of preventive maintenance. The replacement rate (Equation (32)) is the rate at which the component is corrected after failure and replaced into a state that can perform the required function.

$$r_r = \begin{cases} \frac{w_s}{T^{RS}}, & if\ w_s \geq w_{st} \\ 0, & if\ w_s < w_{st} \end{cases} \tag{32}$$

The downtime for corrective maintenance of the spindle is non-productive time that is used for replacing the worn out parts and is obtained using Equation (30)

$$t_d^{cm} = \begin{cases} t^{rs} \times N_s \times N_m, & if\ r_r > 0 \\ 0, & if\ r_r \leq 0 \end{cases} \tag{33}$$

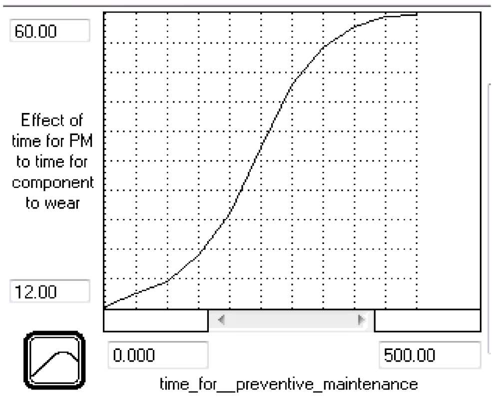

Figure 15. Effect of preventive maintenance time on the life of the component.

In the model, it is assumed that all of the components require preventive maintenance. However, for components that do not require special preventive maintenance, the time for the component to wear is independent of preventive maintenance. Scheduled overhaul is the time to inspect, to improve, innovate, make necessary repairs and restore a component to working conditions. It is the replacement time designated for a component to wear at the expected designed rate, keeping the required time of preventive maintenance. The mathematical relationships formulated for the spindle wear sub-model can also be applied to ball screws, automatic tool changers and guide ways.

Modelling Maintenance Related to Factors, MTTR and MTBF

The machines, machine cells and equipment must perform optimally in regard to technical availability and be designed for very good access for maintenance and repairs. Machines must have very good access for tool change and tool settings. To calculate equipment effectiveness, the following inputs are important:

- Preventive maintenance requirements must be described. Time needed for inspection and change of wear parts shall be specified.
- Time for tool change must be calculated and include quality check of the first piece after tool change.
- Repairs of major parts/components in the machine and equipment must be described with the calculated time needed.

The structure of maintenance activity and its related parameters can also be modelled in different ways, as shown in Figure 16.

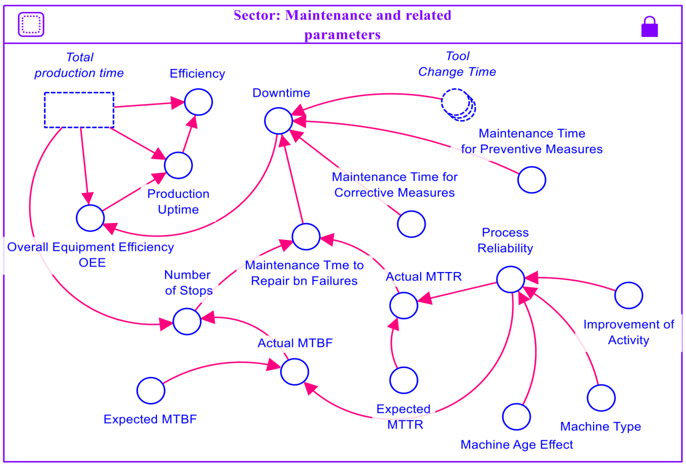

Figure 16. Structure of maintenance considering MTTR and MTBF.

Considering the availability of the company's historical data (production historical data) on MTBF (meantime between failure), MTTR (meantime to repair), and the machine age effect on process reliability, maintenance activity of the manufacturing system can be structured and formulated in Figure 16 and described as below.

The formulas for total production time and uptime are the same as described in Equations (16) and (26), respectively.

The OEE evaluates and measures how the manufacturing operations are utilized and can be estimated by

$$OEE = max(0,\ min\left(1 - \frac{t_d}{t_t},\ 1\right)) \tag{34}$$

Efficiency of the system can be calculated by:

$$E = \frac{t_u}{t_t} \tag{35}$$

The downtime in this structure includes the maintenance time between failures which is calculated by

$$t_d = t_d^{rf} + t_d^{cm} + t_d^{pm} + t^{tl} \tag{36}$$

The total maintenance time to repair between failures is dependent on the number of breakdowns (stops) and the average time it takes to repair after a failure (actual MTTR):

$$MTBF_t = MTTR_a \times N_{st};\ \text{where;}\ N_{st} = \frac{t_t}{MTBF_a};\ MTTR_a =\ MTTR_e \times R \tag{37}$$

The average time elapsed from one failure to the next is:

$$MTBF_a = MTBF_e \times R \tag{38}$$

Process reliability depends on the machine age effect, machine type and level of machine improvement (development) activity. Machine development is the maintenance activity conducted on a machine's components, for example, the structure in Figure 14 presented the maintenance conducted on spindles, guideways, ball screws, and automatic tool changers and is hence considered to be an improvement (upgrade) activity. This could possibly be used as an input to this factor:

$$R = MAE \times MT \times DA \tag{39}$$

5.2.6. Cost Model

The cost is calculated based on the output results obtained from the aforementioned modules. A change in the dynamic behavior of a system results in variation in the cost of production. It does not have a dynamic effect on the model as it stands alone, rather the dynamic effect from other key performance indicators gives rise to the variation in its output. The cost type and related parameters considered in this paper are explained in Table 1.

Table 1. Basic costs considered in the model.

Category	Related Parameters (Source of Cost)
Capital/Investment cost	Number and type of machine tools
Tool cost	Tools used for different operation types
Maintenance cost	Cost for corrective maintenance, cost for preventive maintenance, cost from external maintenance worker
Spare part cost	Replacement of the worn out part, operator overtime cost
Overtime cost	Total production time, threshold
Real estate cost	Factory adaption cost and the floor area used by the specific machine type

6. Results

6.1. Analyzed Model's Results

The proposed SD model explained in the previous section was built using Stella Professional software. Stella is a modelling tool commonly used to build, simulate and analyze system dynamics models. It provides a flexible way of building simulation models based on causal loops or stock and flow diagrams.

The model provides the structure for how the different factors of the machining process and performance parameters interact in the manufacturing system, considering a boring operation as an example. The interaction between factors in the overall manufacturing system can be developed with respect to the possible variation in demand, workpiece materials and new product design introduction for parts produced in different machines and with manufacturing systems' settings (flexible or dedicated manufacturing systems). The structure of these relationships can be modified according to the type of operation, variation and working conditions. Essentially, the model is used as a framework for other related processes. This framework is the core, which is adapted for other related machining processes within an engine block production line.

After creating the overall structure of the manufacturing system condition for a given machining process of the engine block production, the initial input parameters' values can be introduced, and the model is ready to run. The boring process parameters' relationships with performance measures and the manufacturing system's condition is taken as an example that can be used as the basis for other processes of engine block machining. The simulation results can be described and analyzed using different perspectives. However, in this paper, the simulation results of the actual working conditions are not provided; rather, only the general framework for the interrelations of the machining process parameters, performance indicators and their behaviors is studied. The general procedure to run and analyze the behavior of the simulation model result is briefly presented in Figure 17.

6.2. General Procedure to Run the Model

The proposed model can be run under every possible combination of production parameters and given performance criteria. To run and analyze the simulation results, one first determines the length of simulation, the time step size (DT) between calculations, the interval between simulation pauses, the units of time, the integration method and the run mode. A step size/time delay (DT) achieves a good compromise between accuracy of results and speed of simulation—the smaller the simulation time step, the more accurate the simulation results. However, DT should be smaller than the smallest time delay in the model. In general, a good first approximation would be to choose a step size one-half of the shortest time delay in the model. Many time delays may be apparent, though, if the shortest time delay can be determined, it is a good starting point for selecting the step size.

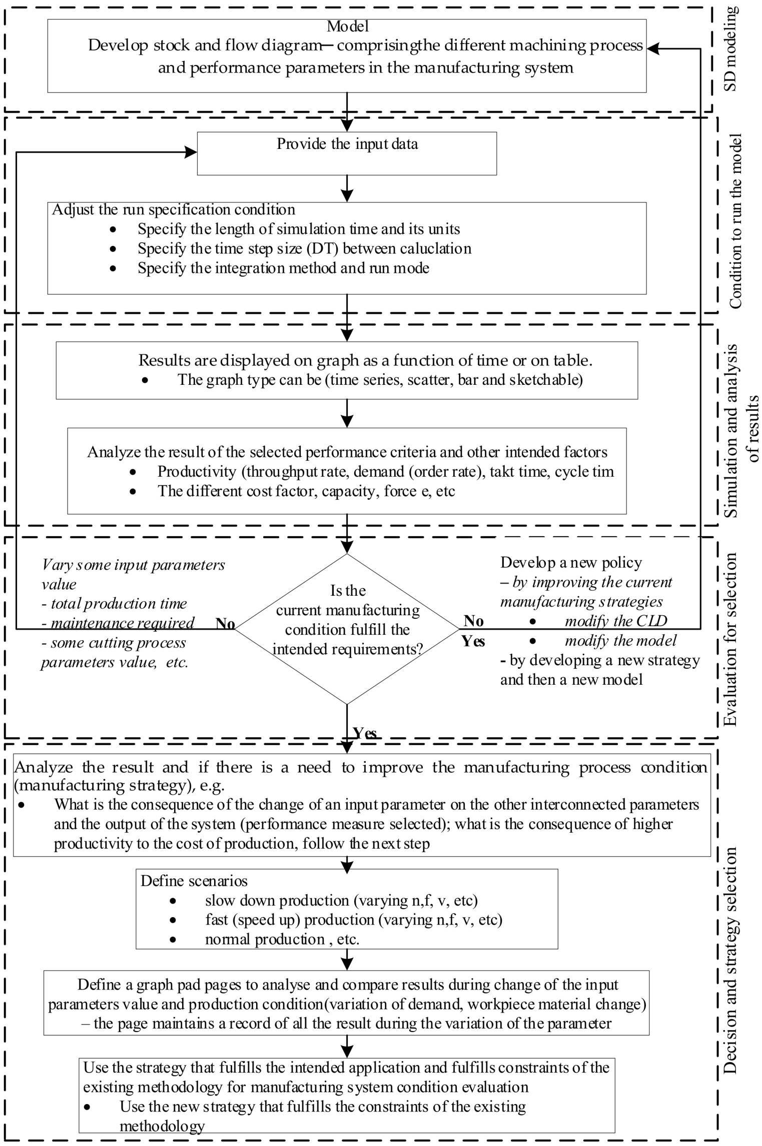

Figure 17. Procedure to run the generic model and analyze the simulation result.

6.3. The Behaviour of the System

Over the course of simulation runs, the model's structure creates the behavior of the system's performance for the designated model parameters. In order to illustrate and analyze the dynamic behavior and performance of the system, a dynamic demand patter can be considered. The dynamic behavior of the different performance criteria can be analyzed after providing the initial input parameters' values and the result is displayed in graphs as a function of time.

Consider what the dynamic behavior of the different performance measures (productivity, cost,) in the system will be if the system is disturbed by variation in demand. Is the existing manufacturing system condition capable of responding to the given demand variation? If not, will varying some of the parameters, such as feed rate, cutting speed and working time, make a change in the manufacturing system? Is it possible to optimize the manufacturing system by controlling the interaction effects of process and performance parameters? Does it require additional parallel machine tools to enhance production and achieve the target? By doing so, the behavior of the simulation result for the order rate from customers (demand) and the production rate will be illustrated by graphs/tables.

Similarly, the result for other performance indicators, like cost and quality, can be analyzed. Moreover, the interaction between these indicators will be explored with the same manufacturing strategy as well as by modifying or changing the strategy. Furthermore, it is viable to analyze the manufacturing strategy's effect on the change in parameter values on the performance indicators (criteria) chosen. By changing some parameter values, it is possible to see the effect of this change on the interconnected parameters and on performance measure—cost, productivity and quality of parts produced. Changing one parameter in system dynamics application does not mean freezing others and seeing the effect of the change only in the output. Rather, these changes will make a change on the other interconnected parameters and on the output of the system, because the system parameters are interconnected through the system in the model.

6.4. Fast and Slow Production/Performance Policy Analysis

There are conditions and scenarios where fast or slow production rates are required in the machining process. To slow down production, it is necessary to either decrease the feed rate, depth of cut, or the cutting speed, etc. A decrease in feed rate increases the cutting time and takt time and decreases the cutting speed, which induces lower cutting forces and results in smaller deformations. The lower cutting forces imply lower tool wear rates, better dimensional accuracy (due to decreased deflections/deformation) and increased machine tool life (due to reduced loads on bearings and guideways). As a consequence, the life of the cutting tool will be longer, causing a reduction in the total tool cost. Productivity might be lower if a higher demand of production is required; cost will be determined according to specifications, along with the desired product quality in machining. The intricate interaction and influence between these parameters can be analyzed in the simulation run. A similar analysis can also be applied to accelerate the machining operation.

When a change in workpiece material in the system is experienced, the machinability data that contains the recommended values of cutting speeds, feed rates and depth of cut for the respective work material can be collected in handbooks (design) or from a company's computer database. Then, the respective simulation for a change in workpiece material can be analyzed in a similar way as described for variation of demand. The main difference will be the input values of some cutting process parameters and their interrelationships. The change in workpiece material strongly influences the overall machining cost, which depends mainly on the tool life that can be achieved under the assumed production conditions.

7. Conclusions and Recommendation

Manufacturing companies are adopting various strategies to enhance the performance of the manufacturing systems. A system dynamics model is presented herein to analyze the machining operations for some specific features of the engine block production. This model forms the standpoint for the development of a generic framework for performance analysis of manufacturing systems. The core of the model is represented by the interaction between process and system parameters with respect to key technological and cost performance measures. Accordingly, the model analyzes the intricate interaction between manufacturing system parameters and the machine elastic structure in relation to the selected key performance measures. Namely, it includes the feedback loop structure of the operational parameters, machining process parameters, force/power and MRR, near-net shape production and maintenance modules. The model also encompasses the manufacturing metrics—the cost structure for capturing the cost per part for manufacturing. Input data from an engine block manufacturing process can be provided to simulate the results and validate the model. Hence, the model can be used as a performance evaluation tool for the manufacturing system of engine block machining and as a decision support system for selecting a suitable strategy for manufacturing system configuration. A sensitivity analysis could be carried out to determine the key parameters that should be taken into account for optimization or a controlling process. A new policy framework can be proposed to improve the existing system by changing the manufacturing strategy and varying the values of applicable parameters in the system. The effect of the variation of the different manufacturing system parameters and their interaction in different scenarios on the manufacturing system could be evaluated. In general, the model enables an understanding of industry relevant outcomes depending on the chosen setting and thus, can improve productivity and the performance criteria intended to be attained.

To sum up, the outcomes from the system dynamics modelling environment in this research work enable the following:

- A generic model, developed for the performance evaluation of manufacturing systems for specific machining operations which can be used for adapting the production to various market situations. However, modification according to system specifications is required.
- The model could evaluate the relationships between critical parameters in relation to the selected key performance criteria.

As described earlier, herein only the structure of the model and the procedures of how to analyze the simulation result have been presented. However, it is recommended that the simulation result of the model is analyzed by considering one process as an example; also the structure of the model should be validated.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

b	backlog
ct	cycle time
ct_a	actual cycle time
c_{gap}	discrepancy between order rate and capacity
ct^{int}	initial cycle time
C	capacity of machine
d	demand
d_{St}	stock allowance
d_f	depth of cutting /length/diameter for finishing operation
dd	delivery delay

dl	delay
d_{min}	minimum cutting size
d_R	actual length/depth of the part to be cut for roughing
d_T^{Max}	maximum capacity cutting tool can cut
d_R^{Max}	maximum allowable depth of material to be removed
d_{sf}	depth of cut for semi-finishing operation
d_e	expected total depth of the part to be removed
D	workpiece diameter or length to be cut
DT	delta time
E	efficiency
E_f^{ct}	effect of cycle time on feed rate
$E_{tl}^{V_c}$	effect of cutting speed on tool life
f_r	feed rate
$f_{r\ max}$	maximum feed rate
f_z^{des}	desired feed per teeth
FEM	finite element method
IA	improvement activity
l_{min}	minimum length of part that can be cut
l	length of the part to be cut
mtr	machining time for roughing operation
$mtsf$	machining time for semi-finishing operation
mtf	machining time for finishing operation
MT	machine type
MAE	machine age effect
$MTTR_a$	actual mean time to repair
$MTBF_a$	actual mean time between failures
$MTTR_e$	expected mean time to repair
$MTBF_e$	expected mean time between failures
$MTBF_t$	total time to repair between failures
MRR	material removal rate
$MTTR$	meantime to repair
$MTBF$	meantime between failures
n	spindle speed
n_{des}	desired spindle speed
n_{min}	minimum spindle speed
n^{ch}	change in spindle speed
n_{max}	maximum spindle speed
n^{init}	initial value of spindle speed
Nm	number of machine tools
N_r	number of rough passes
N_s	number of spindle replaced/maintained
N_{st}	number of stops due to failure
OEE	overall equipment efficiency
p_d	desired production
p_{des}	desired production demand
p_{rate}	production rate
p_{sr}	production start rate
r_r	spindle replacement rate
R	process reliability
SD	system dynamics
t_m	machining time
tl_{cut}	tool life of cutting tool
ti	idle time

$t(l/u)$	time for loading and unloading
to	time for other activities
T	tool life
tt	takt time
t_a	net available time
tt_{ch}	change in takt time
t^{tt}	takt adjustment time
tt_{des}	desired takt time
$(tt)_0$	initial takt time
t_t	total production time
t_{th}	threshold time
t_{des}	desired production time
t_u	uptime
t^n	time to change spindle speed
t_t^{ch}	change in total production time
$(t_t)_0$	initial total production time
t^p	time to change total production time
t_d	downtime
t^w	time for spindle to wear
t^{rs}	time to replace spindle
t^{cs}	time to change spindle
t^{tl}	time to change tool
t_d^{cm}	time for corrective maintenance
t_d^{pm}	time for preventive maintenance
t_d^{rf}	time to repair between failures
V_c^{max}	maximum cutting speed
V	cutting speed
w_s	spindle wear
w_{sr}	spindle wear rate
$(w_s)_0$	initial spindle wear
w_{st}	spindle wear threshold
WIP	work in process
$(WIP)_0$	initial work in process
α	exponent in Taylor's tool life equation
c & α	constant parameters depend on work material, tool material, feed and depth of cut rate, can be obtained either experimentally, statistically or from published data
Δct	change in cycle time

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