IDENTIFICATION OF RELATIONSHIPS BETWEEN OPERATOR UTILIZATION AND REAL PROCESS CAPACITY IN AUTOMATED MANUFACTURING

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In automated manufacturing there is continuous interaction between humans and machines. The utilization of those resources affects the capacity of manufacturing processes and consequently the performance of manufacturing systems. This paper presents an approach that incorporates productivity analysis tools and techniques to explain how manufacturing resource utilization relates to capacity and how the capacity can be improved. The findings are relevant for both academics and practitioners that are interested in understanding the effects of shop floor productivity improvements on capacity.

Keywords: Productivity, capacity, manufacturing resource utilization.

1. INTRODUCTION

The fundamental objective of a production system is to transform raw material into finished products or components. Improvement of capacity is therefore central for the improvement of production systems. The required capacity of a manufacturing process determines the amount of resources, i.e. humans and equipment, needed to perform the transformation activities. Production systems are, however, always subject to losses due to the endless variations of both external and internal features (Hopp & Spearman, 2008; Schmenner & Swink, 1998). These variations prevent resources from being utilized in the most efficient way. Naturally, this has negative effects on the capacity. In order to improve, it is therefore necessary to understand how the utilization of resources affects manufacturing processes' capacity and to show where the actual improvement potential exists.

Several researchers have studied man-machine interaction and especially the machine interference problem, often referred to as the "machine repairman problem" (Haque & Armstrong, 2007; Stecke & Aronson, 1985). The phenomenon interference is defined as the undesirable and unnecessary machine idleness caused by allowing one (or more) operators to tend several machines (Stecke & Aronson, 1985). Unwanted machine idleness is a loss that reduces the capacity of manufacturing processes and consequently reduces the production system performance. The dominant methodologies that have evolved in machine interference research are, according to Stecke and Aronson (1985), stochastic modelling and queuing theory. Furthermore, the overall equipment effectiveness (OEE) measure is a well-established metric that captures different types of production losses and indicates areas of improvement (Jonsson & Lesshammar, 1999; Nakajima, 1988). Nevertheless, the OEE measure is limited to measurement of individual equipment (Huang et al., 2003) and, as pointed out by Muchiri and Pintelon (2008), it is necessary to lift focus from individual equipment towards the performance of a factory as a whole. As a result, several factory level measures, based on OEE, have been developed. For instance overall factory effectiveness (OFE), overall throughput effectiveness (OTE), production equipment effectiveness (PEE), and overall asset effectiveness (OAE) (Muchiri & Pintelon, 2008).

Even in automated manufacturing does the overall production system performance depend on human decisions and actions (Baines et al., 2005). The equipment oriented measures and machine interference models incorporate powerful means for evaluating and improving the performance of automated processes. They are, however, limited when it comes to representing the areas of improvement for manual work tasks that are directly related to automated manufacturing (e.g. changeover activities) and, subsequently, the capacity of automated processes. Identifying the improvement potential of manual activities is done through work studies. Research has shown that there is great uncertainty in the measurement and assessment of manual work tasks (Almström & Winroth, 2010; Bailey & Barley, 2005; Kuhlang et al., 2013) and this uncertainty results in a hidden improvement potential which is not captured by using only equipment oriented measures.

Identification of relationships between operator utilization and process capacity is presented by applying a generic approach that shows how to measure and model capacity in automated manufacturing. It combines established work study techniques for analysis of manual work with a framework to assess the capabilities of equipment resources. The next chapter provides the theoretical background to capacity modelling and how it relates to productivity variables of both equipment and humans. It is followed by an industrial example where the approach has been applied.

2. MODELLING OF PROCESS CAPACITY

Capacity is intended to measure output that can be produced with the available resources of a manufacturing facility. Capacity data is central for operations researchers in the field of production planning and control. Naturally, it is also of interest to the majority of practitioners in manufacturing, including everyone from workers and engineers to managers and investors (Johnson & Montgomery, 1974). The data is thus used in several contexts, such as strategic considerations, i.e. where, what, and how much to produce, and considerations concerning the daily planning of operations (Coelli et al., 2002). Modelling of capacity data is necessary to perform in order to understand how well manufacturing resources are being utilized, to ensure feasible production schedules, and to quote realistic product delivery commitments (Witte, 1996). There are, however, numerous definitions of capacity measures which can result in confusion and misconceptions (Coelli et al., 2002; Perry, 1973). Elmaghraby (1991) states that most manufacturing firms cannot measure capacity and argues that if the basic data is available, it usually measures the wrong entity. Elmaghraby (1991) further says that the inaccuracy in measurement of capacity are caused by problems related to product mix, setup times, varying efficiency, and quality yield. In addition, Menipaz (1984) concludes that capacity typically is easy to define but hard to measure. As a result, the importance of defining capacity measures and to properly show how they are measured cannot be neglected. Following sections introduces two capacity definitions; ideal capacity and real capacity, and presents an approach for how related resource data is measured and modelled in the context of automated manufacturing.

2.1 Ideal capacity vs. real capacity

Ideal capacity and real capacity have been defined in a manufacturing resource modelling approach (Hedman, 2013) aimed at quantifying and visualizing shop floor productivity improvement potentials. The modelling approach, along with the capacity definitions, have been incorporated and elaborated in a refined theory that describes how investments affect organizational efficiency and effectiveness in manufacturing companies (Sundkvist, 2014). Both ideal and real capacities are related to the capacity of a production process and are therefore also referred to as process capacity. A process can be seen as the entire chain of activities in a factory that converts raw material into finished goods. For analytical purposes it is, however, more convenient to decompose the chain into more manageable sections. In the approach, these sections are described as facilities of a production system and are arranged hierarchically with factory as the highest level. The factory consists of subsystems, e.g. departments in a factory that in turn consists of one or several workstations.

The ideal capacity of a process is a design parameter. It is determined by the current standard of how the ingoing activities shall be performed. Thus, each activity has a defined standard time which corresponds to its ideal time duration. For manual activities is the standard time set by applying a predetermined time system, for instance Methods Time Measurement (MTM), Maynard Operation Sequence Technique (MOST) or a simplified version of MTM such as Sequence based Activity and Method analysis (SAM) (IMD, 2004; Maynard et al., 1948). For automatic activities can the standard time be set by production planning software, for instance a computer aided manufacturing (CAM) software, or based on information from the equipment supplier. It can also be determined empirically by measuring the time duration for each produced unit when the individual equipment resource is operated isolated and during stable processing conditions, i.e. not affected by factors such as blocking, starvation or disturbances. Consequently, the ideal capacity of a process is equal to its ideal throughput rate and is given by inverting the standard time duration of the process' constraining activity. It is vital to not interpret ideal capacity as equal to optimal capacity. The ideal capacity is in relation to the current standard and the standard can always be improved, striving towards an optimal state. The real capacity is equal to the *actual* throughput rate of the process. It is therefore a direct result of production system design, different disturbances, and of how resources' skill and motivation affect how well the activities are being performed in relation to the ideal capacity.

2.2 Improving process capacity

Capacity can be improved by increasing productivity. That is the underlying rationale of the proposed approach. Productivity is a relative measure often expressed as the ratio between output and input, i.e. throughput and resource consumption. Output oriented capacity improvements are focused on increasing the throughput rate of a process. In comparison, input oriented capacity improvements are aimed at reducing resource consumption, thereby reducing the amount of allocated resources needed. Saito (2001) and Helmrich (2003) describes three productivity factors developed to better understand what to focus on when improving productivity on an activity level. The first factor is the method (M) and it is defined as the inverse of the ideal time duration of an activity. Naturally, this is the core of the definition for ideal process capacity. The performance factor (P) corresponds to the speed the work is carried out at in relation to the ideal time duration of the activity. The utilization factor (U) represents the time a resource spends on performing planned activities in relation the planned production time. The three productivity factors constitute the foundation of the proposed approach.

Outputs from applying the approach are AS IS models of selected production processes. Each model defines the ideal and real capacity of a process. In short, the generation of models is initiated by breaking down the selected processes into activities and sub-activities in order to determine their standard times and thus the ideal capacity of the processes. Thereafter, the activities are re-integrated into the system as processes on one of the system levels (workstation, subsystem, or factory). The real capacity is, as stated, given by measuring the actual throughput rate of each process. The purpose of the approach is to capture the improvement potential of the production processes considering all three productivity factors. The first improvement potential corresponds to the difference between the actual throughput of the process (real capacity) and the theoretical throughput according to the current standard (ideal capacity), as seen in Figure 1. It refers to the improvement of resource's capability of performing activities and is equal to increasing the real capacity by reducing performance (P) and utilization (U) losses. The second improvement potential concerns the ideal capacity of a process which can be increased by improving activity design, i.e. develop a new standard. Typically, for manual activities this is done following an methods engineering approach (Niebel et al., 2003). For automatic activities, however, is the approach not as straight forward. Improving automated activities requires a deeper technical knowledge in potential machine re-design and in the type of manufacturing process that is assessed (e.g. machining, casting, or welding etc.).

Improvement of capacity over time can be visualized in a capacity-time diagram (Figure 1). It shows the relation between ideal capacity and real capacity. The result of improvements depends on several factors, including learning effects, firm characteristics, technology adaption and scale effects (Sundkvist, 2014).

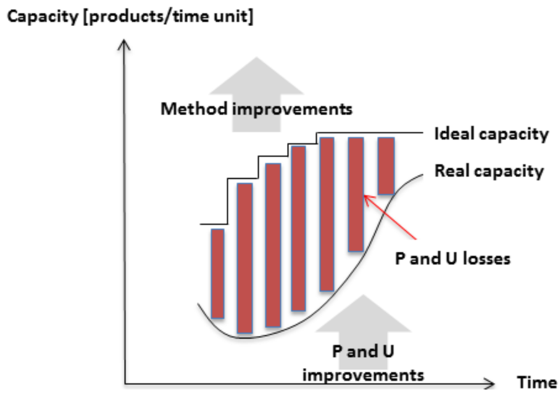

Figure 1. Capacity-time diagram, showing the relation between ideal capacity and real capacity over time.

In order to measure improvements of real capacity for manual activities have the P and U factors been further elaborated into labour productivity variables (Almström, 2013; R. Hedman et al., 2013) that are used in the proposed modelling approach, see Table 1. Processes with equipment resources can be assessed and modelled using a similar set of performance and utilization variables, see Table 2.

Table 1 Labour productivity variables.

Variable	Explanation
Personal performance rate (P_P)	The personal performance rate is affected by the individual's physical ability and his or her motivation to work at a high speed (relative the standard time) independent of work task.
Skill based performance rate (P_S)	The skill based performance rate is measuring the individual's speed of performing a specific work task depending on previous training and experiences the individual has for accomplishing the task.
Need-based utilization rate (U_N)	The need based utilization rate depends on the need for relaxation and personal time. It is often regulated by agreements at the work place. It includes paid breaks and losses before and after a break.
System designed utilization rate (U_S)	The system design utilization rate is defined as balance losses designed into the system. These balance losses can be found at assembly line as well as losses in semi-automated workstations.
Disturbance-affected utilization rate (U_D)	Disturbance affected utilization rate corresponds to the losses caused by different random disturbances. It includes the time from discovery of the disturbance until the work is performed at full speed again.

Table 2 Equipment productivity variables.

Variable	Explanation
Equipment performance rate (P_E)	Equipment performance losses occur when actual operating speed falls below the given standard speed of the equipment. It is affected by the operating status (condition) of the equipment. Also, it is affected by the operator's skill and knowledge of operating the equipment according to the defined speed standard.
Need-based utilization rate (U_N)	Need-based utilization losses are the portion of time when the equipment is idle due to preventive maintenance and tool changes.
System designed utilization rate (U_S)	System designed utilization losses corresponds to equipment idle time caused by balancing losses (i.e. blocked or starved) and idle time during setups. It also includes idle time during operator meetings, breaks and shift changes if they occur during planned production time.
Disturbance-affected utilization rate (U_D)	Disturbance-affected losses refer to downtime due to equipment breakdowns. It also includes running time when the equipment is producing defect units (if applicable).

The definition of equipment performance rate differs from the OEE definition of speed losses. The speed losses in OEE includes idling and minor stoppages (Nakajima, 1988) which here is considered as a utilization loss. Other typical losses that are considered as performance related are ramp-up and ramp-down time (Muchiri & Pintelon, 2008). The definition differs here as well. The ramp-down time before a setup and the ramp-up time after a setup is part of the setup activity and thus included in the system designed utilization rate. In addition, if they are part of the normal machine cycle then they are part of the current standard and thus an issue for activity improvement rather than a speed loss.

There is an important distinction to be made regarding the different utilization rates. The disturbance-affected utilization rate concerns pre-emptive outages. They typically occur beyond direct control which, besides breakdowns, can be power outages or operators being called away on emergencies etc. Since they have similar effects on the behaviour of the production line they can be combined and treated as breakdowns (Hopp & Spearman, 2008). Need-based and system designed utilization losses are, on the other hand, categorised as non-pre-emptive outages. They inevitably occur, but it is possible to have some control of exactly when. Typically, they occur between jobs rather than in the middle of them, so the equipment is not stopped in the middle of a cycle, which can be the case for pre-emptive outages (Hopp & Spearman, 2008). System designed utilization losses related to operator meetings, breaks etc. are only recorded if they occur during planned production time, for instance paid breaks. Changeover activities between production batches are, or at least, should be planned activities which consequently do not occur beyond control. The time duration can then fairly easy be measured from when the equipment is shut down until it can operate fully again. That proportion of time is, as stated, part of a system designed utilization loss. The SMED methodology (Shingo, 1985) is a common improvement approach to reduce equipment idle time during setups (McIntosh et al., 2000; Singh & Khanduja, 2009).

Furthermore, some clarification is necessary for why the idle time or downtime that occurs when equipment is waiting to be tended by operators has not been assigned to any of the utilization loss categories. It is included in the utilization category for which the actual cause of the stop belongs. For example, a disturbance-affected utilization loss recorded when a breakdown has occurred starts when the equipment breaks down and does not stop until the automatic activity is performed at full speed again. That includes the time before an operator detects the breakdown, until the operator is able to attend the equipment, and of course the time it takes to resolve the breakdown. Same reasoning is applied for need-based utilization losses when equipment, for instance, is waiting for tool change. Similarities can be found in measures, such as MTD (Mean Down Time) and MTTR (Mean Time To Repair), typically used in machine interference models and discrete event simulations (Banks, 2010; Stecke & Aronson, 1985). Idle times and downtimes for equipment are normally recorded by automated collection systems (Usman et al., 2013). The data collection technique in those systems can be based on timestamps registered by PLCs (Programmable Logic Controllers) or machine clients (Jasperneite & Neumann, 2000). However, the data collection systems cannot distinguish if the waiting time is caused by lack of attention by an operator, if the operator is busy tending other equipment, or if the operator is not present. This requires that the manual work of operators is studied as well.

3. INDUSTRIAL EXAMPLE

This example is taken from a case study where the approach has been applied. It was conducted at a medium-sized electronics manufacturer that produces electronic motors and drives, customized electronics, and other integrated solutions. The study was delimited to the company's automatic surface mount assembly (ASM) department where electronic components are placed on circuit boards by pick-and-place machines. The department was defined as a subsystem within the facility consisting of four pick-and-place machines arranged tightly and connected in a line. The subsystem has four defined workstations for manual activities A-D. At workstation A component rolls and component packages are warehoused in an automatic high storage. The operator orders components from the storage for each batch. Components are transported to workstation B where they are prepared and loaded onto carriers. During changeovers the carriers are loaded into the pick-and-place machines. Workstation C and D are mainly used as workbenches during changeovers of the ASM line. They are also used when operators perform activities related to the screen printer that is positioned before the ASM line. The ASM line is operated during two shifts, five days a week. The number of assigned operators varies from 2-4 individuals dependent on workload.

3.1 Data collection and analysis

Manufacturing resource data from operators and equipment was collected during a period of three weeks. Utilization of operators (Figure 2) was measured through a work sampling study. It is an industrial engineering technique where the distribution of work is measured and analysed by taking observations at random time intervals (Niebel et al., 2003). In total, 60 manual activities were mapped and included in the work sampling study. The activities were grouped in two categories; planned activities and activities that can be categorized according to the labor utilization variables (Table 1). During the data collection period 6346 samples were recorded (workstation A was not included). The work sampling sessions were randomly distributed during both shifts and samples were taken every 30 second during the sessions. That corresponds to approximately 53 hours spent on the factory floor observing and recording the distribution of manual work.

Data for determining equipment utilization was extracted from an automatic collection system that recorded stop times for each ASM machine. Thereafter, the data was categorized according to the defined equipment productivity variables (Table 2). Correction of data (i.e. removals of errors) and a deeper analysis of the automated collection system's definitions of data were also necessary during the categorization. Equipment utilization presented in Figure 4 represents the constraining machine positioned last in the line. Consequently, a larger proportion of balancing losses was present for the non-constraining machines.

The distribution of disturbance-affected utilization losses for operators (Figure 2) and for equipment (Figure 4) is of similar proportions. This relationship is no surprise since operators typically tend the machines when they break down. Thus, the downtime of equipment and the time operators spend on repairing equipment should then roughly correspond. Disturbance-affected losses for operators were, however, not entirely related to equipment breakdowns. Approximately eight percentage points of the disturbance-affected utilization losses relate to when operators interrupt their work to search for tools, material, and documents. That is a clear indication of an additional improvement potential, in this case concerning workplace design and standards. In Figure 3, it is shown that preparing components and setup related activities constitutes the majority of planned activities performed by operators. That can be seen as characteristic for automated manufacturing processes with high product variance. This is further confirmed in Figure 4 where the idle time during setup related activities constitutes for over half of the systems designed utilization losses. However, there was no defined standard for how setup operations should be performed. Additionally, it was recorded during the work sampling study that preparations of components and preparations for setup was often performed when the machines in the ASM line were idle, waiting for changeover. Several of those preparing activities could have been performed external when the ASM machines are running. This indicates a further improvement potential.

The ASM machines were turned off when operators went on break. This does, as shown in Figure 4 and Figure 5, significantly affect the system design utilization losses for equipment. Furthermore, almost one third of the proportion of utilization losses due to operators being on break is startup losses that, in turn, are a direct result of shutting down the equipment during breaks.

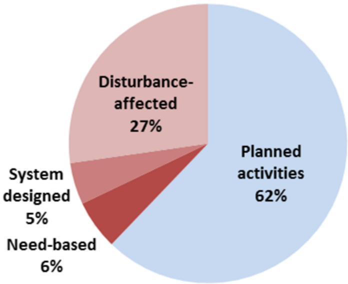

Figure 2. Operator utilization.

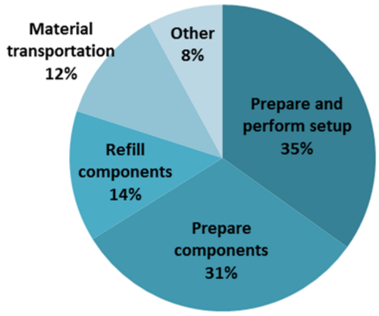

Figure 3. Distribution of *planned activities*.

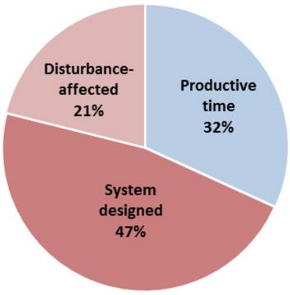

Figure 4. Equipment utilization.

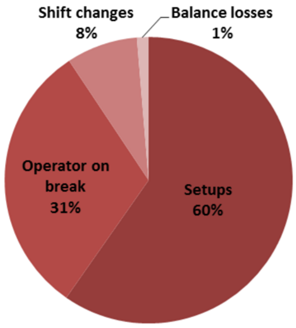

Figure 5. Distribution of *system designed utilization* losses.

No distinction was made between paid or unpaid breaks and this deviates from the definition given in Table 2. However, it shows the potential of introducing a policy with parallel breaks so that the subsystem always is manned. Thereby can system designed utilization losses be significantly reduced. The current policy involves scheduled breaks, independent of the current situation in production and where all operators go to break simultaneously. A decision of policy change should be taken based on what effects it with have on operators working conditions together with the potential benefits of an increase in productive time for equipment and consequently the capacity of the subsystem. These factors do not necessarily counteract each other.

3.2 Formulation of ideal capacity and real capacity

The ideal capacity of a process is determined by the ideal capacity of the ASM line, i.e. the constraining machine. It is defined based on the line takt time which currently is calculated by CAM software. Accordingly, one ideal process capacity measure per circuit board panel (product) can be formulated. However, in order to get the ideal process capacity of the subsystem, the product mix and consequently the setups must be considered. This was not possible due to the lack of standardized work for changeover activities. During the data collection period setup times were measured and the results showed that they varied consistently from a couple of minutes to several hours. Observations made during the work sampling study further confirmed this. The ASM line is a new investment and according to the company, standardized routines are yet to be established. It is, by definition, impossible to have a correctly defined standard time unless there is a defined standard. This also meant that the performance factors for operators could not be determined since the actual times could not be compared with any norm times. The purpose of applying the proposed approach in this case was, however, not to define the ideal capacity of processes. Even though that is necessary and indeed desirable in order to further develop target conditions and action plans for improvement. Instead, the focus of the paper was to identify relationships between the utilization of operators and equipment. Thus, utilization losses for both operators and equipment were captured. The results show how the utilization of operators affects the utilization of equipment and vice versa. They also show how the real capacity of the process can be improved. The most illustrative example is found by looking at the utilization losses for equipment (Figure 4). As shown, the largest proportion is the system designed losses. In Figure 5 these are presented in more detail and it can be seen that more or less all of the losses (except 1% balancing losses) are related to manual work and human factors such as setups, breaks and shift changes. Consequently, the real capacity of this automated process can be increased significantly by improving the related manual work and to do policy changes. This means to develop work and time standards for the manual activities. As a result, the variation and time consumption for setups can be reduced. Furthermore, accurate time data enables a better planning of activities which means that equipment can be productive even when operators are on break or during shift changes.

4. DISCUSSION AND CONCLUSION

An approach of how to measure and model capacity in automated manufacturing has been presented. By applying the proposed approach in a case study, it has been described how productivity data, mainly concerning utilization, of both manual and equipment resources is measured and organized to improve real capacity. Standardized work is frequently cited in the LEAN literature as the foundation for improvement and it was shown that standardized work is required in order to fully model the effects of improvement efforts and relation between ideal capacity and real capacity over time. Related research in machine interference (Cigolini & Grando, 2009; Haque & Armstrong, 2007; Stecke & Aronson, 1985) and performance measurement in automated manufacturing (Mathur et al., 2011; Muchiri & Pintelon, 2008; Nachiappan & Anantharaman, 2006) have previously confirmed that there is indeed a link between utilization of operators and process capacity. However, the performance measures and interference models only show the effects of operator utilization on capacity and are thereby insufficient when it comes to explaining the underlying causes related to the manual activities. The proposed approach is generic and can be applied in any type of discrete manufacturing. It is not dependent on particular systems for automatic data collection.

Future research will be focused on formulating and structuring a mathematical description of the relations between utilization and capacity, based on the approach. The case company will also be revisited to follow up the effects on real capacity when standardized work has been introduced. Also, it will then be possible to get the ideal capacity of the subsystem. The ambition is to further develop the approach making it possible for practitioners to evaluate how investments in improvement efforts, such as workforce training and engineering changes, affect the real and ideal capacity of processes. In addition, academics could use the approach to further understand and to build knowledge about the effects of different types of shop floor improvements.

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