Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia CIRP 3 (2012) 55 – 60

www.elsevier.com/locate/procedia

45th CIRP Conference on Manufacturing Systems 2012

Integral Analysis of Labor Productivity

T. Czumanski[a,]*, H. Lödding[a]

[a]*Hamburg University of Technology*, *Denickestr. 17*, *Hamburg D-22765*, *Germany*

* Corresponding author. Tel.: +49-40-42878-3677; fax: +49-40-42878-2295. *E-mail address*: czumanski@tuhh.de

Abstract

Analyzing and improving the productivity of labor-intensive manufacturing and assembly operations remains a crucial task for industrial companies. Because of the heterogeneous causes for productivity losses, the analysis requires a comprehensive data acquisition and evaluation. With this paper we introduce a state-oriented approach providing the possibility to identify and prioritize the different impacts on labor productivity for subsequent process enhancements. With a case study, we show how to visualize and evaluate state data of an assembly cell to establish a goal-oriented improvement process.

Keywords: Productivity analysis; Labor productivity; State-oriented modeling; Continuous improvement process

1. Introduction

Especially companies with manufacturing and assembly processes aim at adapting methods and tools provided through the lean production philosophy and other classical approaches to analyze and optimize their production [1]. A common goal is to establish a continuous improvement process to achieve the same added value with reduced resource utilization [2]. The decision on which optimization approaches are to be used as well as the order of their application is often based on the management's experience or actual trends in the practice of production management or lean production. This lack of transparency is a reason for ineffective improvement processes, applying methods and tools to selected areas of a production site without previous prioritization [3].

These shortcomings lead to the question, how transparency over productivity losses can be achieved in a way that enables the production manager to decide which problems should be approached with priority. This article presents a method for the comprehensive analysis of labor productivity in manufacturing or assembly environments.

2. Productivity analysis

The productivity is defined as relation between the output and the input of a production process [4]. The labor productivity as a partial productivity index typically describes the relation of the output of a process to the used capacity given in time units or the number of persons involved. The productivity management cycle formulated by Sink [5] consists of the four phases Measurement, Evaluation, Planning, and Improvement. For the purpose of this research work, productivity analysis is assigned to the first two phases.

Common productivity measurement techniques include productivity indices, econometric models and linear programming [6]. Measuring the total or partial factor productivity with indices enables the implicit description of a production function of any industrial company. The factor quantities and corresponding weighting coefficients may be determined empirically [7]. Econometric models also belong to the parametric measurement methods. In these models, specific characteristics for a company are formulated through altered error terms and both systematic and random deviations from an average production function [8].

doi:10.1016/j.procir.2012.07.011

With nonparametric approaches, in particular the data envelopment analysis (DEA), the production function is derived from empirically collected input/output data and subsequent linear programming [9].

A problem with total and partial productivity indices is that the optimization potential is not indicated. Econometric models are equally based on assumptions regarding the form of the production function and require estimations of mathematical terms for company-specific adaptations. The data evaluation as part of the DEA is not suitable for prioritization of improvement projects without further considerable analysis effort.

Beside the named measurement methods, the relative productivity of a company may be determined through benchmark studies based on the analysis of financial key figures and through extensive acquisition of empirical data [10]. Transferring the introduced approaches to manufacturing systems is generally possible and has been done for example by Wan using the DEA [11].

However, two main disadvantages regarding the practical implementation of the methods remain: they yield abstract results through theoretic assumptions, i.e. assigning identified productivity losses to optimization fields is suggestive, and, with a low level of detail, they are only suitable for the mid-term and long-term adaptation of production processes.

In contrast, operational methods for the analysis and optimization of production processes rely on a high level of detail. A selection of methods includes predetermined time systems, set-up time analysis, sickness records, and breakdown time analysis. The approaches enable detailed analyses and, to some extent, the operational optimization of labor-intensive production environments with respect to productivity. However, these methods do not provide the data required for a comprehensive analysis of the labor productivity.

In summary, the two groups of methods yield results that are either too superficial or too focused. Additionally, both necessitate high effort for the data acquisition and evaluation. The designated method thus is designed for productivity analyses based on data with an above-average level of detail and a reduced level of data acquisition and analysis effort (see Fig. 1).

For a structured implementation of the designated method, an analysis framework has been developed. The scope of this paper includes the methodical elements data acquisition, data aggregation and data evaluation.

3. State-oriented modeling

State-oriented modeling focuses on the analysis of input data, i.e. the activities of the personnel employed in the production processes measured in time units. For a comprehensive description of the input in the form of human work, the concept of worker states is introduced.

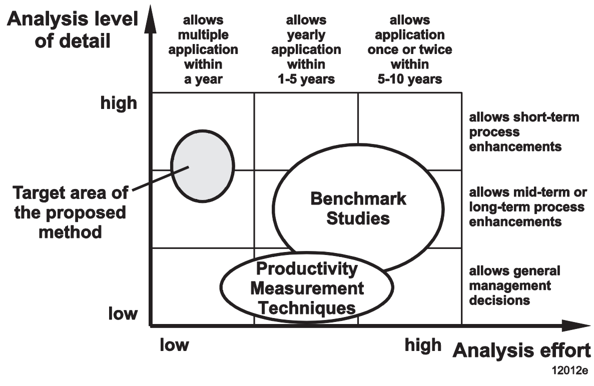

Fig. 1. Classification of the analysis approach

Worker states represent any planned or unplanned activities occurring for each person engaged in a production process. So far, state-oriented efficiency or productivity analyses have mainly been applied to machines or interlinked manufacturing systems [12, 13].

To realize a comprehensive analysis, the worker states need to cover the whole time span the personnel is paid by the company. Value-adding tasks as well as for example waiting and repair times can equally be a source for reduced labor productivity.

As a fundamental structure, a state hierarchy has been formulated to differentiate between certain types of worker states. They are grouped into four categories: cycle-bound, batch-bound, periodical, and irregular. In Table 1 the state categories are specified.

Table 1. Specification of worker state categories

State category	Description	Example
Cycle-bound	Represents all activities of workers occurring within one working cycle	Manual assembly step in a paced production line
Batch-bound	Represents all activities of workers occurring for each produced batch	Transport of material before and after the production of a batch
Periodical	Represents all activities of workers occurring periodically	Group meetings or planned breaks
Irregular	Represents all activities of workers occurring irregularly	Waiting time caused by equipment breakdown; absenteeism

Each category contains typical worker states. The worker state may be refined to enable the data acquisition and evaluation with a variable level of detail. The hierarchy of selected worker states of the cycle-bound category is depicted in Fig. 2. The sum of the state durations per category plus a term for not recorded activities equals the paid working time (equation 1).

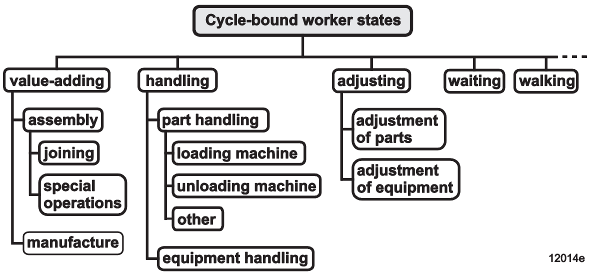

Fig.2. Hierarchy of cycle-bound worker states

$$T_{paid} = T_{cyc} + T_{bat} + T_{per} + T_{irr} + T_{NR} \qquad (1)$$

T_{paid}	paid working time [hrs]
T_{cyc}	cumulative duration of cycle-bound states [hrs]
T_{bat}	cumulative duration of batch-bound states [hrs]
T_{per}	cumulative duration of periodical states [hrs]
T_{irr}	cumulative duration of irregular states [hrs]
T_{NR}	duration of not recorded activities [hrs]

A comprehensive data acquisition aims at minimizing the term T_{NR}. Based on the state-oriented approach, the data acquisition method is described in the following.

4. Data acquisition

Acquiring time data for serial production processes is typically done to establish detailed working plans. For every production step, target times must be defined. Common analysis techniques include time studies and predetermined time systems which both require high acquisition efforts [14]. The method of work sampling is particularly applicable to non-repetitive or irregularly occurring activities [15]. In general, the aforementioned three techniques measure activities related directly to the workplace. For a comprehensive analysis, additional data must be documented for which the above mentioned methods are not suitable. For example, times for group meetings, planned breaks, absenteeism or waiting caused by equipment downtime need to be determined.

4.1. Recording modes

For the acquisition of state data, an integral approach has been defined, comprising the following recording modes:

- Reduced time studies (RTS)
- Self-recording (SR)
- Operating and machine data (OMD)

Combining these modes offers the possibility to gather data with reduced effort. It provides alternatives for the user who can choose a mix of appropriate methods depending on the availability of data and specific procedures applied within a company. The recording modes are described in the following.

As one part of the data acquisition, the actual durations of operations directly related to the workplace need to be measured. A reduced variant of time studies offers the possibility to gather these data with lowered effort. Compared to classical time studies employed for detailed work descriptions, the effort for setting up time standards is omitted and the sample size n can be reduced. The desired accuracy may be evaluated by calculating confidence intervals for small sample sizes ($n < 30$) using the t-distribution:

$$\left[T_{cyc,i,m} - t \frac{s}{\sqrt{n}} \,,\, T_{cyc,i,m} + t \frac{s}{\sqrt{n}} \right] \qquad (2)$$

$T_{cyc,i,m}$	mean duration of cycle-bound state i [hrs]
t	t-distribution value [-]
s	sample standard deviation [hrs]
n	sample size [-]

Among the recording modes described, self-recording is probably the most conventional technique. The workers themselves document activities or events with effect on the labor productivity. Especially when there are no information systems employed, this mode is a useful means to record irregular states such as waiting times due to equipment breakdowns or absence of workers due to further qualification.

Many manufacturing companies today use information systems to gather and evaluate production data. Manufacturing Execution Systems typically comprise a variety of data, e.g. regarding labor, machines, tools or material [16]. Operation and machine data may be extracted and incorporated in the productivity analysis. Times of labor attendance and product volumes as data basis are typically available.

4.2. Acquisition procedure

In every case, cycle-bound state data is documented manually with reduced time studies for single workplaces or workers, depending on the production process. This recording mode is also applicable to states belonging to the batch-bound category. Other state data are rather captured through self-recording and operating and machine data systems. The acquisition procedure consists of the following steps:

1. Selection of the area to be analyzed
2. ABC-analysis of the product portfolio
3. Selection of a product group or variant
4. Assignment of recording modes to state categories

5. Recording plan for reduced time studies
6. Reduced time studies per work station or worker
7. Documentation of self-recording data
8. Documentation of operating and machine data

After an area is selected, an ABC-analysis may be used to select a product group or single variants to be analyzed. To start the analysis for the most relevant products, useful criteria are the output quantity or the sales volume per product. A low profit margin might also indicate the need for analysis. The assignment of recording modes requires an estimation of which state categories are expected. The recording plan for reduced time studies includes the definition of sample sizes per work station or worker. Data collected through self-recording and operating and machine data must be considered. The procedure then generates cycle-bound or batch-bound data related to a certain product group or variant plus documentations or extracts of data captured by company data systems or the personnel.

4.3. Horizontal data aggregation

The data acquisition yields the durations per state for a work system. To minimize the acquisition effort, the states can be differentiated by the regularity of their appearance (see also Table 1):

- State appears with the processing of every part
- State appears once for each batch
- State appears periodically

There are two possibilities for horizontal aggregation of data, i.e. the aggregation of state durations over the paid working time.

Firstly, if the states have been recorded in samples, the duration per sample is multiplied with the appearance frequency of the specific state within the selected time period. For cycle-bound states this is usually the number of produced items (see equation 3), for batch-bound states the number of batches accomplished, and for periodically arising states for example the number of shifts in the evaluation period. To aggregate these state durations within a certain state category, they need to be summed up across all states belonging to that category, as equation 4 describes for cycle-bound states.

$$T_{cyc,i} = T_{cyc,i,m} \cdot OUT_{act} \tag{3}$$

$$T_{cyc} = \sum_{i=1}^{v} T_{cyc,i,m} \cdot OUT_{act} = \sum_{i=1}^{v} T_{cyc,i} \tag{4}$$

$T_{cyc,i}$	cumulative duration of cycle-bound state i [hrs]
$T_{cyc,i,m}$	mean duration of cycle-bound state i [hrs/pc.]
OUT_{act}	actual output [pcs.]
T_{cyc}	cumulative duration of cycle-bound states [hrs]
v	number of cycle-bound states [-]

Secondly, if *m* states are documented through self-recording or extracted from operation or machine data systems, they simply add up to the cumulative state duration of a category. This is exemplified for irregularly appearing states with equation 5.

$$T_{irr} = \sum_{i=1}^{m} T_{irr,i} \tag{5}$$

T_{irr}	cumulative duration of irregular states [hrs]
$T_{irr,i}$	cumulative duration of irregular state i [hrs]
m	number of irregularly appearing states [-]

Having determined the cumulative state durations per category, they can be integrated using equation 1. If the data acquisition considers all product variants produced, the duration of not recorded activities T_{NR} can be calculated. If only selected variants are included, as determined by the ABC-analysis, durations for unconsidered variants need to be estimated.

4.4. Vertical data aggregation

The vertical aggregation of state data means to condense data to higher system levels. Above the workplace level, the cell or line level may be next, followed by the production area and the plant level. The levels are formally assigned by the index *e*, with $e = 0$ representing the lowest. Equation 6 describes the vertical aggregation of batch-bound state data across system levels.

$$T_{bat,i,q,e} = \sum_{p=1}^{r} T_{bat,i,p,e-1} \quad ; \ e \geq 1 \tag{6}$$

$T_{bat,i,q,e}$	duration of batch-bound state i in work system q on system level e [hrs]
$T_{bat,i,p,e-1}$	duration of batch-bound state i in work system p (sub-system of q) on system level e-1[hrs]
r	number of sub-systems of work system q [-]

It has to be considered, that the data required may be not available on the lowest system level. This means that the integral analysis of aggregated data then is only possible from level 1.

5. Data evaluation

For the evaluation, the collected data need to be processed and illustrated. Few but meaningful standard key figures and diagrams allow to determine priorities and to derive improvement projects through subsequent root cause analysis. Because of the comprehensive character of the data acquisition and the horizontal and vertical aggregation, the same diagrams and key figures can be used on different system levels. Two main key figures are introduced in the following.

The state portion SP_i gives the percentage of the paid working time used for a specific activity (equation 7).

$$SP_i = \frac{T_i}{T_{paid}} \tag{7}$$

SP_i	time portion of state i [-]
T_i	cumulative duration of a state i [hrs]
T_{paid}	paid working time [hrs]

This enables prioritization of the largest time portions, independent of their category affiliation. If the data acquisition covers selected variants, the certain state durations can be related to the sum of all durations.

While SP_i describes the portion of any state, the portion of irregular activities per piece I_{irr} relates irregular state durations to the number of completed parts within the evaluation period (equation 8).

$$I_{irr} = \frac{T_{irr}}{OUT_{act}} \tag{8}$$

I_{irr}	portion of irregular activities per piece [hrs/pc.]
T_{irr}	cumulative duration of irregular states [hrs]
OUT_{act}	actual output [pcs.]

The category of irregular states includes activities as rework, idle times through machine breakdowns, or unplanned absence of personnel. Evaluating these state durations with respect to the output provides further details regarding productivity losses.

Furthermore, the worker state distribution can be displayed with a ranking list to show the pareto values or as circle diagram indicating the duration of not recorded activities. Both diagrams are included in the following case study.

6. Case study

The proposed method has been applied to an assembly cell producing motor-driven devices. The cell consists of 13 workstations, additional two stations for inspection and testing as well as one workplace for packaging. Nine workers including one line leader build the assembly team, producing devices in a one-piece flow as described by Black and Chen [17] as Rabbit Chase. The product portfolio is limited to two variants, each built by the same assembly steps.

State	State category	Aquisition mode	absolute value [hrs]	Portion [%]
Manual assembly	cycle-bound	RTS	270.4	24.0
Screwing	cycle-bound	RTS	159.4	14.1
Sickness	irregular	OMD	140.0	12.4
Vacation	irregular	OMD	119.0	10.6
Part handling	cycle-bound	RTS	98.8	8.8
Final inspection	cycle-bound	RTS	84.2	7.5
Cell feeding	periodical	SR	57.6	5.1
Packaging	cycle-bound	RTS	35.4	3.1
Labeling	cycle-bound	RTS	28.8	2.6
...	...	...	...	... ...
not recorded			45.9	4.1

12015e

Fig. 3. Pareto ranking of state durations in the case study

The worker state hierarchy has been tailored on the basis of working plans for the respective workstations. Accordingly, the three data acquisition modes have been assigned.

Reduced time studies (RTS) have been done for each workstation. A software tool was used that included the worker states as predefined structure. Other data have been self-recorded (SR), such as the time for cell feeding, or taken from the company's production data system (OMD), such as the times of presence and absence.

The evaluation period was one calendar month. The state data recorded through reduced time studies have been horizontally aggregated over the output quantity within the chosen month and vertically integrated on the cell level. The data acquisition required an effort of three eight-hour working days, including the adaptation of the state hierarchy and a first data visualization and evaluation. SR and OMD state data had been prepared by the company. Once the state hierarchy had been tailored to the observed work system, the acquisition effort with RTS was significantly reduced.

Fig. 3 shows the pareto ranking of the recorded states for the assembly cell. The reduced time studies have been done with four samples for each work station. Assuming a t-distribution of the recorded states, an analysis of the confidence intervals has shown no ranking permutation from rank 1 to 7 with an error probability of 5%.

The data evaluation explicitly includes all activities, value-adding and non value-adding, since all of them are sources for productivity losses. From the data it can be seen, that the highest state portions SP_i are the ones for manual assembly and screwing operations with 24 %

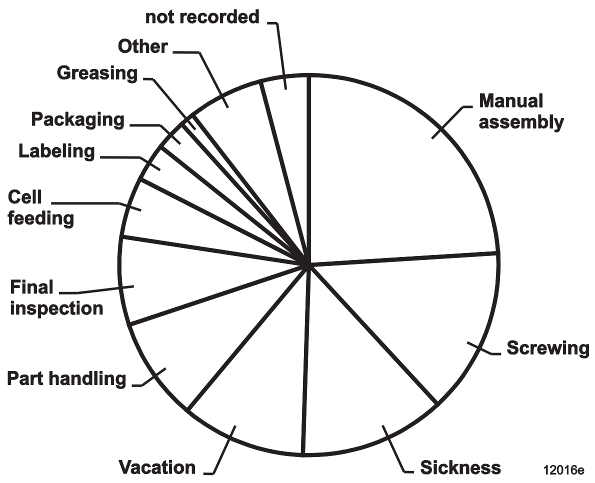

Fig. 4. Integral state distribution in the case study

and 14.1 % of the paid working time, respectively. The sickness rate for the evaluated assembly cell is very high with a value of 12.4 %. On the cell level, these states would be addressed with highest priority through subsequent root cause analysis.

The time portion of irregular activities for the case example has been calculated to 7.2 minutes per piece. Non value-adding states might also be analyzed. The portion of non value-adding states adds up to 56 %.

Fig. 4 shows the state distribution in the form of a circle diagram displaying the time portion of not recorded activities. In the case example T_{NR} is 4.1 %, showing that the approach is capable to cover a relatively high portion of the paid working time.

For the definition of improvement activities, the cycle-bound data can also be evaluated on the work station level. A subsequent root cause analysis enables the production manager to establish an effective and efficient improvement process, addressing the states with adequate priority.

7. Conclusion

We have introduced a method for the integral analysis of labor productivity for prioritization of optimization fields using a state-oriented approach. With the proposed method production managers can enhance the effectiveness and efficiency of their improvement activities, once a suitable worker state hierarchy is defined. The approach enables the user to conduct a comprehensive analysis of worker states using different data sources depending on the acquisition methods and specific procedures applied within a company. It leads to high transparency over productivity potentials with a relatively low data acquisition effort. Its applicability has been shown with a case example. The ongoing studies at the IPMT include the definition of an accurate sample size for reduced time studies. Furthermore, the evaluation is to be done with other industrial partners to cover different types of production, such as multi-machine operations and tact-based assembly lines. A next research step will be to link obtained state distributions with standard optimization methods as decision aid for production managers.

Acknowledgment

We thank Deutsche Forschungsgemeinschaft for funding the project (Lo 858/5-1).

References

[1] Pavnaskar, S.J., Gershenson, J.K., Jambekar, A.B., 2003. Classification scheme for lean manufacturing tools, International Journal of Production Research, 41/13:3075-3090.

[2] Womack, J.P., Jones, D.T., Lean Thinking, 2003, Free Press, New York.

[3] Lorentzen, K., Maschek, T., Richter, R., Deuse, J., 2011. Entwicklung einer Variabilitätstypologie, Zeitschrift für wirtschaftlichen Fabrikbetrieb, 106/4:214-218.

[4] Tangen, S., 2005. Demystifying productivity and performance, International Journal of Productivity and Performance Management, 54/1:34-46.

[5] Sink, D.S., 1985. Productivity Management: planning, measurement and evaluation, control and improvement. Wiley, New York.

[6] Singh, H., Motwani, J., Kumar, A., 2000. A review and analysis of the state-of-the-art research on productivity measurement, Industrial Management & Data Systems, 100/5:234-241.

[7] Craig, C. E., Harris, R. C., 1973. Total Productivity Measurement at the Firm Level, Sloan Management Review, 14/3:13-29.

[8] Sudit, E.F., 1995. Productivity measurement in industrial operations, European Journal of Operational Research, 85/3:435-453.

[9] Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units, European Journal of Operational Research, 2/6:429-444.

[10] Hayes, R.H., Clark, K.B., 1986. Why some factories are more productive than others, Harvard Business Review, 64/5:66-73.

[11] Wan, H.D., Chen, F.F., 2008. A leanness measure of manufacturing systems for quantifying impacts of lean initiatives, International Journal of Production Research, 46/23:6567-6584.

[12] Wiendahl, H.P., Hegenscheidt, M., 2001. Produktivität komplexer Produktionsanlagen, Zeitschrift für wirtschaftlichen Fabrikbetrieb, 96/4:160-163.

[13] Grando, A., Turco, F., 2005. Modelling plant capacity and productivity: conceptual framework in a single-machine case, Production Planning & Control, 16/3:309-322.

[14] Niebel, B.W., Freivalds, A., 2003. Methods, standards, and work design, 11. ed., McGraw-Hill, Boston, Mass.

[15] Pape, E.-S., 1992. Work Sampling, In: Handbook of Industrial Engineering, 2nd edition, Ed. Salvendy, G., John Wiley & Sons, New York.

[16] Kletti, J., 2007. Manufacturing Execution System – MES, Springer, Berlin.

[17] Black, J.T., Chen, J.C., 1995. The role of decouplers in JIT pull apparel cells, International Journal of Clothing Science and Technology, 7/1:17-35.