Uncertainty in the analysis of the overall equipment effectiveness on the shop floor

M P Rößler and E Abele
Institute of Production Management, Technology and Machine Tools, Technische Universität Darmstadt, 64287 Darmstadt, Germany
E-mail: roessler@ptw.tu-darmstadt.de

Abstract. In this article an approach will be presented which supports transparency regarding the effectiveness of manufacturing equipment by combining the fuzzy set theory with the method of the overall equipment effectiveness analysis. One of the key principles of lean production and also a fundamental task in production optimization projects is the prior analysis of the current state of a production system by the use of key performance indicators to derive possible future states. The current state of the art in overall equipment effectiveness analysis is usually performed by cumulating different machine states by means of decentralized data collection without the consideration of uncertainty. In manual data collection or semi-automated plant data collection systems the quality of derived data often diverges and leads optimization teams to distorted conclusions about the real optimization potential of manufacturing equipment. The method discussed in this paper is to help practitioners to get more reliable results in the analysis phase and so better results of optimization projects. Under consideration of a case study obtained results are discussed.

1. Introduction
The methods of lean manufacturing derived from the Toyota production system were developed to optimize the efficiency of production systems by constantly removing everything from the value stream which adds no direct value to the customer [1, 2]. So one of the results is to free up capacity and so to create more value from existing resources with fewer additional costs [3]. To achieve this ambition in literature three “inhibitors” that indicate why the performance of a production system can be impaired, have to be overcome [4]. The first inhibitor is variability, secondly waste and thirdly inflexibility, where the driving force behind the development of lean management was and still is the elimination of waste [5, 6, 7]. In view of the above an enhanced method will be presented in this article, which will help practitioners to identify and uncover waste as well as variability on the shop floor concerning manufacturing equipment to ensure high level productivity and low costs.

The appraisal of the overall equipment effectiveness (OEE) measure of a specific manufacturing equipment usually is performed by systematically analyzing a specific time period of the working time of that device, machine or plant and so to derive conclusions how well this equipment is running and to identify losses that impair the effectiveness [8]. This analysis should first be applied to the bottlenecks of a value stream that affect throughput or at costly areas of manufacturing systems [9]. By increasing the effectiveness of a bottleneck, the capacity of the whole value stream increases with

1 To whom any correspondence should be addressed.
it until a new bottleneck occurs. This identification of e.g. a bottleneck machine can be conducted via value stream analysis which is not part of this article.

2. The overall equipment effectiveness analysis

2.1. Background and calculation

The concept of systematically measuring the overall effectiveness of a plant firstly was described by the Japan Institute of Plant Maintenance (JIPM) as one of five strategies of the Total Productive Maintenance (TPM). As a main goal here the maximization of the plant effectiveness is stated. This is to be done by examining the inputs to the production processes and identifying and eliminating the losses associated with these inputs to maximize the output. To have a measure how effective a plant is running the determination of the equipment effectiveness was stated [10].

The OEE is defined as the percentage of the planned production time, in which defect free products are produced. To identify the reasons for deviations to a value of 100 %, three categories of losses have to be considered [11]:

\[
OEE \text{ rate} = \frac{\text{availability rate} \cdot \text{performance rate} \cdot \text{quality rate}}{\text{planned production time [h]}}
\]

The following table 1 gives an overview over the categories of losses and main factors of influence addressed by the analysis of the OEE. These losses were adapted to discrete part manufacturers, which feature slightly differences to the original classification of the eight losses in the OEE out of the field of process industry; therefore see Suzuki [10].

Table 1. Loss categories and main factors of influence to the determination of the overall equipment effectiveness.

| Loss categories | Main influencing factors |
|-----------------|-------------------------|
| Availability    | 1. Failure              |
|                 | 2. Changeover           |
| Performance     | 3. Small stops          |
|                 | 4. Reduced speed        |
| Quality         | 5. Scrap                |
|                 | 6. Rework               |

2.2. Data acquisition and analysis

The elevation of the data necessary to perform an OEE analysis can be performed by the use of plant data collection systems, or for less capital-intensive equipment manually by analysing the operator’s logs [8].

When firstly implementing and performing an OEE analysis in a specific production environment for instance in the course of an optimization project at a discrete part manufacturer, data necessary usually is collected by the operators at the specific manufacturing equipment over a representative, defined period of time (e.g. one week). In that case operators have to document every relevant activity at their manufacturing equipment such as tool breakdown, changeover, oil refill, scrap, rework, etc. and also the time period associated with that activity in a semi-formal log. Regarding the operator’s recording process, different facts and circumstances have to be considered [12]:

- The data recording process itself leads to disruptions in operation cycles,
- The raising of the frequency of short-term events, such as order confirmations, minor stops or answering short questions can overburden the operator,
- The necessary data must be recorded immediately after completion of a task. Therefore the covered tasks must not be too delicate or too complex,
- Recording errors arise from self-written logs rather than from foreign surveys.

The current state of the art in OEE analysis with the use of manually collected data is done as illustrated in figure 1. This following approach results out of the fact described above, that not all short-term events could be captured by the operators. These short-term events are performance losses such as small stops and reduced speed. So these losses usually have to be calculated. The quality loss for scrap also has to be calculated by multiplication of the number of defect parts with the corresponding cycle time.

**Figure 1.** Current state of the art approach in OEE analysis for using manually collected data.

As a result of this approach the so called OEE water fall chart can be derived, see figure 2 [13]. Here the performance fractions for small stops and reduced speed were presumed to be 1:1. The data used as a basis to derive that chart was collected in a case study performed at the Center for Industrial Productivity at the TU Darmstadt, see paragraph 4.2. Therefore a special software tool was developed.

**Figure 2.** Visualization of an OEE analysis using the water fall chart.
After the visualization of collected data with the waterfall chart usually optimization potential is deduced. As a result of this analysis it is common to initiate specific optimization projects in the potential fields of loss, e.g., optimizing the changeover processes with the method of Single Minute Exchange of Die (SMED) [14].

2.3. Limitations of the OEE analysis

The method described above is used when data capturing takes place manually. If a plant data collection system is utilized instead, the OEE analysis can be performed semi-automatically. As a result of different influences the key performance indicator (KPI) of the OEE underlies statistical fluctuations. Therefore several examples can be stated:

- Human perturbation in the recording process: Especially time-referenced vagueness e.g. caused by predefined resolution in form sheets or the data collection process itself,
- Discrepancies in classification of losses: If for example a plant data collection system is employed at a machine tool without additional input from the operator this system is not in position to decide whether an interruption is either performed for changeover or caused by a tool defect. So for deriving the data necessary and in the right quality to perform an OEE analysis mostly human interaction is inevitable,
- Recognition issues, esp. of quality-related problems directly at the process: In the case of not using a plant data collection system a possible reason why fuzziness must be included in the process is that in practice not all quality defects which could lead to scrap are recognized directly at for example a machine. A not obvious quality defect caused by those instable processes often firstly is recognized at quality gates or in the course of customer reclamation after the OEE analysis is done already. In that case the operator doesn’t take a specific note in his log and so the KPI gets distorted,
- Missing recognition of sporadic occurring characteristically constitutional changes: Another distorting factor to the robustness of the OEE analysis, no matter what data collection principle is used is that the OEE analysis is based upon a specific time period that is considered during data collection. In this period perhaps characteristically constitutional changes of the analyzed manufacturing equipment do not occur. These effects are not considered in the analysis if the time period is chosen too short,
- Further the proportioning of all losses comprised in an analysis also depends on the actual product mix produced on the emblazed manufacturing equipment.

In the case of a semi-automatically data collection for instance a manufacturing execution system with the capability of interfacing machine controls could be used. Such systems usually are capable of deriving OEE analyses [15].

As carried out in this paragraph, no matter what method of data acquisition is implemented, the data used to derive OEE analyses contains fuzziness and uncertainty in the process of data collection. To include this variability in the process of the OEE analysis, the use of fuzzy logic is suggested here.

3. Fuzzy set theory

As one possible methodology regarding the mathematical handling of uncertainty, fuzzy logic has been developed, based on the theory of fuzzy sets according to Zadeh. Zadeh defines a fuzzy set as a class of objects, having a range of degrees of membership. This set is characterized by a membership function \( \mu(x) \) which assigns each object class a membership degree of between zero and one. That means that an object is not only located inside or outside of the set, but that this also may be included "a little" in the set. The membership to this set is gradually staged [16, 17]. Two fuzzy numbers respectively their membership functions are shown in figure 3.
Figure 3. Visualization of a trapezoidal and a triangular fuzzy number type LR.

The intervals described by these membership functions can be specified in different ways. In literature the standard type and the LR type are distinguished, at which in this paper the LR type will be used further. The formal notation for fuzzy numbers is displayed with a tilde over the literal [18, 19, 20]. In this context the membership functions of fuzzy numbers (e.g. $\tilde{M}$, $\tilde{N}$) can be described using a lower value ($m_l$, $n_l$), an upper value ($m_u$, $n_u$), a lower spread ($\alpha$), and an upper spread ($\beta$).

$$\tilde{M}_{LR} = (m_l; m_u; \alpha; \beta)_{LR} \quad (2)$$

Working with fuzzy numbers requires elementary fuzzy algebra. The operations stated next are used to execute different arithmetic procedures [18, 19].

**Addition**

$$\tilde{M} \oplus \tilde{N} = (m_l + n_l; m_u + n_u; \alpha + \gamma; \beta + \delta)_{LR} \quad (3)$$

**Negation**

$$\ominus \tilde{M} = (-m_u; m_l; \beta; \alpha)_{LR} \quad (4)$$

**Subtraction**

$$\tilde{M} \ominus \tilde{N} = (m_l - n_l; m_u - n_u; \alpha + \delta; \beta + \gamma)_{LR} \quad (5)$$

**Multiplication**

$$\tilde{M} \Diamond \tilde{N} = (m_l n_l; m_u n_u; m_l \alpha + n_l \gamma; m_u \beta + n_u \delta)_{LR} \quad (6)$$

**Division**

$$\tilde{M} \div \tilde{N} = \left( \frac{m_l}{n_l}; \frac{m_u}{n_u}; \frac{m_l \delta + n_u \alpha}{n_l (n_u + \delta)}; \frac{m_u \gamma + n_l \beta}{n_u (n_l + \gamma)} \right)_{LR} \quad (7)$$

To facilitate the modeling of fuzzy numbers for the use on a shop floor environment further the triangular form will be preferred. Triangular fuzzy numbers are easy to utilize and give a relatively good representation of the situations under observance. More complex membership functions (than the triangular one) cause greater computational complexity without adding significant benefits [21, 22].

4. Including uncertainty in the OEE analysis

4.1. Methodology of the Fuzzy-OEE analysis

In this paragraph the methodical enhancement of the current state of the art in OEE analysis due to the inclusion of uncertainty will be proposed. This enhancement is suggested to overcome the influences of different circumstances as stated in paragraph 2.3. The method proposed here is based on the state of the art approach of the OEE analysis and enhances it after the process of the classical loss data collection, see figure 4. Principally there are three possibilities how to capture and include additional data about variability to the process analysis:

1. Estimated general factor for mainly manually collected constitution data,
2. Specific factors for single loss categories based on precise and measurable facts,
3. Specific factors for single loss categories with the use of qualified expert estimates.

The inclusion of directly measurable influencing factors to variability mostly is not possible in practice because no additional data is available. At this time it has to be decided what principle should be used to overcome the circumstances in each specific situation, e.g. as described in paragraph 2.3.
To obtain enhanced information about the losses a combination of crisp loss data out of the state of the art analysis and variability information out of the enhanced analysis has to be performed. This can be realized by converting the crisp loss data into fuzzy numbers and the belated addition of the variability information for each category out of the enhanced analysis using the fuzzy set theory as described in paragraph 3.

For visualizing the enhanced information the use of the fuzzy OEE waterfall chart is recommended. Because the derivation of this form of visualization is a complex task which cannot be performed manually, the use of software that is able to handle fuzzy arithmetic is advised.

The last step of the enhanced method is to derive optimization projects out of the potential fields of loss to sustainable remove waste as well as variability. To give an example how this method could be realized in practice and how it benefits the process of the optimization the next paragraph contains an illustrative example.

### 4.2. Case study at the Center for Industrial Productivity

For the first time the method of the Fuzzy-OEE analysis has been applied at the Process Learning Factory CiP at the Technische Universität Darmstadt. In this realistic production environment with machining and assembly areas methods for optimizing production processes are explored, applied and taught. These methods are taught in an interactive way so a sustainable learning is achieved for students and industry staff [23, 24].

In this production environment the method of Fuzzy-OEE analysis is utilized at a turning machine which usually is used to manufacture plungers for pneumatic cylinders. According to this method the first six steps contain the state of the art in OEE analysis, which has to be performed before information about variability can be included. The data capturing in this very first phase of the enhanced analysis is executed by manually recording of data by the use of an operator’s log. Here the times for failure, changeover and scrap are captured. Rework is not possible at this kind of machine. The times for small stops and reduced speed are calculated backwards, see table 2.
Table 2. Input factors and results of the enhanced method of Fuzzy-OEE analysis at a turning machine, which has been observed over an eight hours shift using an operator’s log for data recording. During this time a total amount of 123 faultless parts with an average cycle time of 148.5 seconds are manufactured, eight parts are defect.

| Time slice             | Recorded time [h] | Variability added [h] | Resulting relative time including variability [%] |
|------------------------|-------------------|-----------------------|--------------------------------------------------|
| Total available time   | 8 ±0              | (1.14;1.14;0;0)       |                                                  |
| Planned shutdown       | 1 ±0              | (0.143;0.143;0;0)     |                                                  |
| Planned production time| 7 ±0              | (1;1;0;0)             |                                                  |
| Failure                | 0.45 ±0.045 / +0.2| (0.0643;0.0643;0.01;0.03) |                                              |
| Changeover             | 0.725 ±0          | (0.104;0.104;0.01;0.03) |                                                  |
| Operating time         | 5.825 ±0          | (0.832;0.832;0.06;0.02) |                                                  |
| Small stops            | 0.255 ±0          | (0.0364;0.0364;0;0)   |                                                  |
| Reduced speed          | 0.255 ±0          | (0.0364;0.0364;0;0)   |                                                  |
| Net operating time     | 5.315 ±0          | (0.759;0.759;0.06;0.02) |                                              |
| Scrap                  | 0.23 ±0.023 / +0.4| (0.0329;0.0329;0;0.06) |                                                  |
| Rework                 | 0 ±0              | (0;0;0;0)             |                                                  |
| Productive time        | 5.085 ±0          | (0.726;0.726;0.11;0.02) |                                              |

After performing the state of the art OEE analysis in the first phase, according to figure 4, information about variability has to be collected subsequent. To raise this kind of information, in paragraph 4.1 three possibilities were suggested which are applied here individually for each loss category.

Due to the fact that data collection is performed manually in this case an estimated general factor of 10 % of the recorded time is taken into account as variability for the loss fraction of failure. Here an extra charge of 33 % is added to the variability range because maintenance was performed the day before the analysis. Due to an interview with a maintainer the usual availability rate of the machine sinks rapidly after one week and so failure time could rise up to 45 minutes per shift.

The second observed influence factor is the changeover time, here also a general factor of 10 % is considered to be a realistic fluctuation caused by human perturbation. Additionally to that proportion the maximum possible time for changeover was calculated and considered. This is the cumulated time for changeover if after every lot a change of dies has to be performed.

The time fraction for scrap is also extended by a factor of 10 % for human perturbation, additionally to that an investigation at a quality gate comes into play. Due to the fact that not all quality issues are recognized at the turning machine, some parts with not obvious quality defects are classified as faultless parts by the operator. So they directly increase the OEE. At the quality gate after the machining area in average up to 10 parts per shift are discharged because of quality defects. This fact has to be taken into account as a variability increase at the scrap time in the Fuzzy-OEE analysis.

As a next step the crisp data captured by the operator has to be converted into fuzzy numbers and the fuzzy variability data has to be added using fuzzy arithmetic. To visualize this enhanced data the use of the fuzzy waterfall chart is suggested. In this case the OEE ratio lies between 61.6 % and 74.6 % with a maximum membership degree at 72.6 %, see figure 5 and 6.

Figure 5. Visualization of the OEE in the selected case study as a fuzzy number type LR.
As the last step of the enhanced method optimization projects have to be initiated in the potential fields to minimize waste as well as variability. At the present case study the major waste lies in the field of changeover. Here the method of SMED can be applied to lower the associated time losses. To also minimize the variability included in the process, the major observable potential lies in the area of scrap. Here for instance a quality initiative can be specifically started to minimize these fluctuations. Only under consideration of uncertainty and fuzziness, the potential in this field of action becomes transparent and improvable.

5. Conclusions
In this article the consideration of uncertainty is proposed due to the implementation of the OEE analysis on the shop floor of production companies. This is done to overcome the various deficiencies of the current state of the art. The state of the art in OEE analysis only considers the identification of waste as one of three performance inhibitors. With the use of an enhanced method proposed here more potential can be raised out of given facts considering also a second inhibitor, namely variability. To operationalize this claim in practice, the enhanced method is introduced and discussed by means of a case study. In this case study it is displayed that it is possible to bring more transparency into the analysis and so identify an expanded optimization potential with more reliable results. It is shown, that with the inclusion of the fuzzy set theory in an enhanced method the effectiveness of the OEE analysis can be augmented.

References
[1] Shingo S 1981 Study of the toyota production system: from an industrial engineering viewpoint (Tokyo: Japanese Management Association)
[2] Ohno T 1988 Toyota production system: beyond large-scale production (Tokyo: Diamond, Inc.)
[3] Braggaley B 2006 Using strategic performance measures to accelerate lean performance Cost Man. 20 36-54
[4] Liker J K 2004 The toyota way: 14 management principles from the world’s greatest manufacturer (New York: McGraw-Hill)
[5] Womack J P, Jones D T and Roos D 1990 The machine that changed the world: the story of lean production (New York: Free Press)

Figure 6. Visualization of a Fuzzy-OEE analysis at a turning machine using the fuzzy water fall chart.
[6] Sim K L and Rogers J W 2009 Implementing lean production systems: barriers to change Man. Res. News 32 37-49
[7] Bhasin S 2012 Performance of lean in large organisations J. Man. Syst. 31 349-57
[8] Productivity Development Team 2004 Oee for operators: overall equipment effectiveness (New York: Productivity Press)
[9] Hansen R C 2001 Overall equipment maintenance: a powerful production / maintenance tool (New York: Industrial Press, Inc.)
[10] Suzuki T 1994 Tpm in process industries (New York: Japan Institute of Plant Maintenance)
[11] Nicholas J M and Soni A 2006 The portal to lean production: principles and practices for doing more with less (Boca Raton: Taylor & Francis Group)
[12] Bokranz R and Landau K 2006 Produktivitätsmanagement von Arbeitssystemen (Stuttgart: Schäffer-Poeschel Verlag)
[13] Ahmad M and Benson R 1999 Benchmarking in the process industries (Rugby: Institution of Chemical Engineers)
[14] Shingo S 1986 Zero quality control: source inspection and the poka-yoke system (New York: Productivity Press)
[15] Kletti J 2006 MES Manufacturing execution system (Berlin: Springer Verlag)
[16] Zadeh L A 1965 Fuzzy Sets J. Inf. Contr. 8 338-53
[17] Zimmermann H J and Gutsche L 1991 Multi-criteria analyse (Berlin: Springer-Verlag)
[18] Chen S J, Hwang C L and Hwang C Z 1992 Fuzzy multible attribute decision making (New York: Springer-Verlag)
[19] Geldermann J, Sprengler T and Rentz O 2000 Fuzzy outranking for environmental assessment. Case study: Iron and steel making industry Fuzz. sets syst. 115 45-65
[20] Goumas M and Lygerou V 2000 An extension of the promethee method for decision making in fuzzy environment J. Oper. Res. 123 603-13
[21] Driankov D, Hellendoorn H and Reinfrank M 1993 An introduction to fuzzy control (Berlin: Springer-Verlag)
[22] Braglia M, Frosolini M and Zammori F 2009 Uncertainty in value stream mapping analysis J. Log. Res. Appl. 12 435-53
[23] Abele E, Cachay J and Wennemer J 2011 Kompetenzentwicklung und Führung bei Verbesserungsprozessen in der Produktion Industrie Management 27 14-18
[24] Abele E, Anderl R, Brungs F and Mosch C 2011 Materialflußsimulation in der schlanken Produktion Productivity Management 48-51