

# Overall Equipment Effectiveness and Overall Line Efficiency Measurement using Fuzzy Inference Systems

Hasan Moradizadeh and Rene V. Mayorga  
*Faculty of Engineering, University of Regina, Regina, Canada*

**Keywords:** Intelligent Systems, Fuzzy Inference Systems, Overall Equipment Effectiveness, Overall Line Efficiency, Six Major Losses in Industry.

**Abstract:** Increasingly, Intelligent Systems (IS) techniques are being used to solve both complex problems and industrial problems with uncertainty. They also can implement the operator's knowledge (experience) into the system. This Paper aims to improve and compute the well-known manufacturing metrics: the Overall Equipment Effectiveness (OEE), and Overall Line Efficiency (OLE), using IS techniques. The proposed methodologies to improve the OEE and OLE weakness are based on Fuzzy Inference Systems. These techniques result in an effective way to measure OEE and OLE considering different weight of losses and also the difference in machine's weight factors. Moreover, they allow the operator's knowledge to be taken into account in the measurement using uncertain input and output with implementation of linguistic terms.

## 1 INTRODUCTION

In the existing intense competitive economic environment, manufacturing plants intend to reduce their manufacturing costs as well as maintaining the quality of their products. Total Productive Maintenance (TPM) is normally implemented to optimize the manufacturing equipment effectiveness and improve their reliability as a result of eliminating six major losses in industry (I.P.S. Ahuja and J.S. Khamba, 2008). These losses include breakdown, adjustment losses, idle times and small stops, start up and yield, and defect and rework. Overall Equipment Effectiveness (OEE) is one of the most important TPM's key performance indicators that has been increasingly used in industry not only for controlling and monitoring the productivity of production equipment but also as an indicator and driver of process and performance improvements (Jose Arturo Garza-Reyes et al., 2010). Overall Line Efficiency (OLE) is also being used to show how well a manufacturing line is running compared to how well it could be running. This metric take into account each of the machine's OEE.

Recent studies (D. Kotze, 1993; M. Lesshammar, 1999; R. Wudhikarn and W. Manopiniwes, 2010)

been done and major improvements have been achieved to measure OEE; however this metric has some flaws. First, for continuous flow processes such as oil refinery, metal smelting and power stations calculating the performance rate is more difficult due to lack of cycle time of their products. Also weighting of each OEE element is different in different industries or processes. For example quality losses may have a different contribution in OEE in processes where the material is expensive and the product cannot be reworked rather than in manufacturing line with short cycle time and cheap raw material. Also operator/user knowledge can be implementing in measuring OEE using linguistic term in Fuzzy Inference Systems. Furthermore, OLE cannot be measured easily in complex manufacturing lines where each machine has a different weight factor. As an example, an unbalanced manufacturing line is assumed. A machine that is the bottleneck has a more effect on the line efficiency rather than a machine that barely operates.

This study aims to improve and calculate the OEE and OLE weaknesses by implementing Intelligent Systems (IS) techniques. To do so, the proposed methodology is presented and its experimental results are analyzed.

## 2 OEE & OLE

Overall Equipment Effectiveness (OEE) can be implemented to benchmark, analyze and improve a production process by measuring inefficiencies and groups them in different categories (B. Dal et al., 2000). The most common inefficiency causes in industry are those called “six big losses.” These losses can be categorized in downtime losses, speed losses, and quality losses. To find a way to monitor and improve a manufacturing process, six big losses are addressed as follows.

(1) Downtime losses: Downtime is the most important loss for equipment effectiveness improvement since other metrics cannot be addressed if the manufacturing process is down. Tooling failures, unplanned maintenance, equipment breakdowns are some examples of downtime losses.

(2) Setup and Adjustment: This loss is the time between the last acceptable part produced before setup to the first consistent acceptable parts produced after setup and adjustment. This is often a set of adjustments to machines and/or equipment in order to produce a product that meets the standard requirements. Warm up time and changeovers can be represented as setup and adjustment losses in a manufacturing process. These losses are considered in calculation of the availability factor.

(3) Small Stops: These stoppages occur when the machine stops due to a temporary problem such as an activated sensor that shuts the machine down automatically. These minor stoppages are usually less than 10 minutes and can be dealt with by the operator and generally there is no need to call a maintenance team.

(4) Reduced Speed: Knowing the ideal cycle time of a machine and comparing it with the actual cycle time, it will be possible to monitor low running or reduced speed losses. Machines may run at the speed less than the ideal run rate for various reasons. Training level of operators, and worn equipment can be categorized as the aforementioned reasons. Small stops and reduced speed are known as speed losses and are taken into account in performance factor calculation.

(5) Start up Rejects: Startup losses occur in the initial start of a machine up to the stabilization of its products quality. A root cause analysis can be done to pinpoint the potential causes of rejects and to prevent similar losses from occurring in the future. It is necessary to note that reworks, scraps and incorrect assembly, all are considered as rejects in the production processes.

(6) Production Rejects: This loss occurs in a

steady-state production and is not attributed to start up. Damage, scraps, and reworks, are some examples of production reject losses.

The last two losses are considered quality losses and affect the quality factor of OEE.

The traditional method of OEE calculation considers *availability*, *performance*, and *quality* factors as follows:

*Availability*: Availability is the ratio of actual production time that a machine is working divided by the time the machine is planned to work.

$$A = \frac{\text{Operation time}}{\text{Planned production time}}$$

*Performance*: Performance of a machine is the percentage of total number of parts on that machine to its production rate. In simple words, performance measures the ratio of actual operating speed of the equipment and the ideal speed (M. Lesshammar, 1999).

$$P = \frac{\text{Ideal cycle time}}{\frac{\text{Operation time}}{\text{Total pieces}}}$$

*Quality*: To gain insight into the quality aspect of a production process the quality portion of OEE is defined. The Quality metric represents good (acceptable) units produced by machine divided by the total units produced by that machine in the production time.

$$Q = \frac{\text{Acceptable Pieces}}{\text{Total Pieces}}$$

Given the above, the OEE is normally calculated as follows:

$$OEE = A \times P \times Q$$

Therefore OEE takes into account the six major losses. Significant improvement can be achieved within a short period by eliminating these losses in industry as a result of enhanced maintenance activities and equipment management (M. Maran et al., 2012).

In a situation where a manufacturing line consists of unbalanced/decoupled machines OEE alone is not sufficient (Braglia et al., 2009). Also OEE is measured for an isolated individual equipment and controlling a single tool does not seem to be effective (Richard Oechsner et al., 2002). OLE evaluates the line Efficiency in the production phase and takes into account of effectiveness (OEE)

of machines in a manufacturing line. For a manufacturing line with  $n$  machines where all machines have same weight factors OLE is computed as:

$$OLE = \frac{OEE_1 + OEE_2 + \dots + OEE_n}{n}$$

However, in a case where machines have different weight factors and cycle times, OLE calculation is more complex. This study also aims to improve accuracy of the OLE measurement by implementing user/expert knowledge into the system using IS techniques.

### 3 METHODOLOGY

Implementing Fuzzy Inference Systems in OEE and OLE measurement as proposed in this Paper it is a truly novel methodology and offers several advantages over traditional methods. First, measurement can be done for all production processes in different industries regardless of their products. Moreover, different weight factors can be allocated to OEE factors involved in the measurement depending on the process. Also, OLE can be measured for factories with a variety of production lines and machines with various weight factors. In this Paper the Mamdani and Sugeno Fuzzy Inference Systems are used to improve the OEE weaknesses and also to take advantage of the operator’s knowledge of the process. Also Mamdani FIS is used to measure OLE in unbalanced manufacturing line where machines have different contribution in the line efficiency.

#### 3.1 OEE Measurement using Mamdani FIS:

In this method, availability, performance, and quality, are calculated based on their associated losses involved in an equipment effectiveness reduction. Here Matlab Fuzzy Toolbox is used to examine the accuracy of the proposed methodology. In order to complete the OEE measurement, the six main losses in industry are considered as inputs of the FIS. As mentioned earlier; breakdowns, and setup and adjustment are two losses associated with the availability factor. Small stops and reduced speed cause inefficiency and performance reduction. Finally start-up and process rejects are quality losses that are involved in overall equipment effectiveness. Given the six losses as inputs, the OEE of the

machine is the sole output of Mamdani FIS System. Once inputs and output of the system are determined, the next step for the system to reach its goal is to set antecedent-consequent (if-then) rules. Like determining inputs and outputs, operator experience/knowledge plays an important role in this step by applying weight factors to each input into the system. Setting inaccurate rules has a big negative impact on results. Using linguistic terms [low, average, high] for input parameters helps to measure OEE when inputs cannot be measured accurately. Note that the number of membership functions of each input is not limited and may be varied depend on the process and possibility of measuring inputs. Here 3 Generalized bell-shaped membership functions [low, average, high] are assigned to each input and 5 Generalized bell-shaped membership functions [very low, low, average, high, very high] are output, here OEE, qualifiers. Center of area (COA) diffuzification method is used to convert the fuzzy output to crisp output. Also, 729 if-then rules are set to represent the real system more accurately.

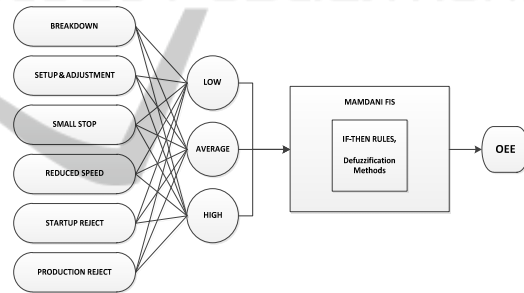


Figure 1: OEE measurement using Mamdani FIS.

#### 3.2 OEE Measurement using Sugeno FIS:

The Sugeno FIS is also implemented to measure OEE in processes that weight factor of inputs can be described in coefficients of an equation. For instance if all associated inputs of OEE measurement (six big losses) have the same weight factor, the OEE can be presented as follows:

$$OEE = \frac{Brk + Stad + Sml + Red + Str + Prr}{6}$$

This can be modeled as a first order Sugeno fuzzy model. In a case where the quality factor has a severe impact on OEE; the Sugeno fuzzy Inference System can be modeled with more concentration on quality losses as follows:

$$OEE = \frac{Brk + Stad + Sml + Red + (2 \times Str) + (4 \times Prr)}{10}$$

Like the Mamdani FIS, Matlab Fuzzy Toolbox is used here. After determining the inputs and their weight factors in OEE measurement and also outputs of the Sugeno FIS; the operator knowledge of the manufacturing process can be applied to the system by setting fuzzy if-then rules. This system can be implemented in the processes where six major losses (inputs) cannot be measured accurately, however each input can get a weight factor depends on the contribution in OEE measurement. In this case 3 generalized bell-shaped membership functions [low, average, high] are assigned to each input and 3 outputs are considered as functions of inputs and their weight factors. Also 3 if then rules are set to represent the real system.

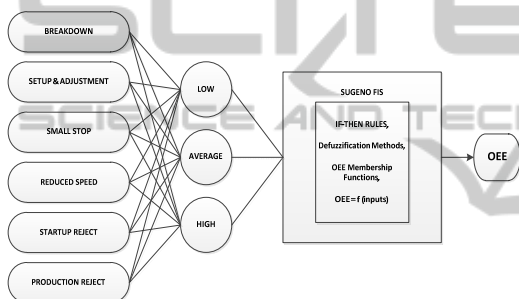


Figure 2: OEE measurement using Sugeno FIS.

### 3.3 OLE Measurement using Mamdani FIS:

The OLE can also be calculated, taking into account each machine’s OEE in the manufacturing line. Due to complexity of OLE calculation in manufacturing lines with different types of machines, different cycle times, and also different weigh factors; Fuzzy Inference Systems are also proposed here to measure the Overall Line Efficiency. This method, the effectiveness (OEE) of every single machine in the manufacturing line is an input of the FIS. Inputs can get linguistic terms [low, average, high] that are presented as Generalized bell membership functions. Also, OLE is the output of the Mamdani FIS that is resulted in Fuzzy linguistic terms [low, average, high] and is diffuzified in crisp output using COA method. The operator’s knowledge of the system can be best applied into the FIS with setting accurate if-then rules that represent the real life system. The weight factor of each machine in the manufacturing line can be taken into account in rule setting. For instance, if we assume a manufacturing line with 3

machines where machine 2 is the bottleneck in this process, and its cycle time is noticeably higher in comparison to machine 1 and machine 3, the following rule can be set to assure that machine 2 has a bigger impact on this line efficiency.

*If  $OEE_{Machine2}$  is low then OLE is low (regardless of  $OEE_{Machine1}$  and  $OEE_{Machine3}$ )*

Here 29 rules are set to represent the production process in the real system.

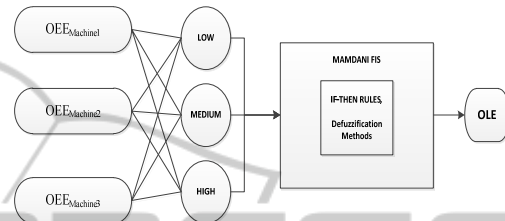


Figure 3: OLE measurement using Mamdani FIS.

## 4 EXPERIMENTAL RESULTS

First, common situations in industry are considered and values of inputs are given to the system and the OEE and OLE are obtained. Also, the considered scenarios are compared to demonstrate the accuracy of the proposed methodologies (M. Moradizadeh, 2014). Here, a brief explanation of each scenario along with a table of inputs and results is presented. Please note that these methodologies can be implemented for general and diverse production systems (M. Moradizadeh, 2014), regardless of manufacturing process and variation and vagueness of the inputs.

### 4.1 OEE Measurement using Mamdani FIS

Here a typical (but general) industrial scenario is presented. Some other industrial scenarios are also presented in (M. Moradizadeh, 2014). A machine in a manufacturing plant has been selected and its OEE is to be measured. Assume there are qualitative losses associated with this machine in the past month; however, its performance rate is average and also the machine was available to operate properly (no major downtime) in this period. Therefore the following assumptions are considered:

- Although a minor breakdown occurred in this period; the machine was running continually and its operator considers the value of breakdown loss as low.



- There were not setup and adjustment losses involved with the machine, and these losses are considered to be low.
- Within the last month small stops occurred during running time and have been fixed by the operator so small stops loss is considered average for this machine.
- Machines' ideal cycle time for pressing the metal part is 12 seconds however its actual cycle time is measured as 15 seconds and reduced speed loss has considered average by operator.
- There was not a considerable amount of startup rejects and this loss considered low in this period.
- Qualitative issues have been observed and noticeable number of non-conforming parts has been produced by this machine within last month. Therefore the process reject loss is considered to be high in this period.
- In this manufacturing plant the availability factor has a higher weight factor rather than performance and quality due to the short cycle time and inexpensive material. Also, the Total Productive Maintenance (TPM) and Single Minute Exchange of Die (SMED) are being implemented to increase the running time of machines and reduce the setup and adjustment time.

The following Table presents the results considering the aforementioned parameters as inputs of Mamdani FIS to measure OEE:

Table 1: OEE measurement using Mamdani FIS, Experimental results.

Inputs	Linguistic Term	Input Value	Output	Deffuzified Output Value
Brk	Low	15	OEE	74.8
Stad	Low	10		
Sml	Average	38		
Red	Average	36		
Str	Low	18		
Prr	High	65		

Note that, in traditional methods of OEE calculation, the result, which is the average of inputs, is 69.67%.

#### 4.2 OEE Measurement using Sugeno FIS

Three pneumatic presses (scenarios) are assumed in a manufacturing plant and their OEE are to be measured using a Sugeno FIS.

Following assumptions are considered as inputs to the Sugeno FIS system:

- Due to its material price, quality losses must be identified and reduced in this manufacturing plant.
- Qualitative loss costs are drastically more than other losses associated with OEE.

Table 2: OEE measurement using Sugeno FIS, Experimental results.

Inputs	Weight Factor	Scenario 1	Scenario 2	Scenario 3
Brk	2	14	32	8
Stad	1	8	4	6
Sml	1	31	28	31
Red	1	17	11	21
Str	3	9	26	6
Prr	4	77	12	8
OEE		65.08%	80.58%	89.67%

In order to measure the OEE more accurately this company decided to assign different weight factors to inputs. The Table above shows the weight factor for each input, the value of each input for these scenarios, and also the obtained OEE for each scenario.

#### 4.3 OLE Measurement using Mamdani FIS

A manufacturing line is assumed with three different machines. Each machine contributes in Overall Line Efficiency; however, the machine 2 is the bottleneck on this line and plays a more important role in the OLE measurement. Therefore, the operator uses his/her knowledge to set rules in the Mamdani FIS in order to measure the OLE more efficiently. Also it is necessary to note that this technique can be used for any type of manufacturing line with a variety of machines to measure its efficiency.

The following Table provides experimental results obtained for different scenarios (represented each by a row) from the Mamdani FIS:

Table 3: OLE measurement using Mamdani FIS, Experimental results.

Scenario	OEE <sub>1</sub>	OEE <sub>2</sub>	OEE <sub>3</sub>	OLE
1	0.68	0.75	0.69	0.639
2	0.97	0.84	0.76	0.749
3	0.81	0.62	0.69	0.656
4	0.81	0.77	0.7	0.68
5	0.89	0.53	0.76	0.656
6	0.85	0.85	0.56	0.703
7	0.74	0.81	0.74	0.676
8	0.79	0.84	0.61	0.692

## 5 CONCLUSIONS

This Paper presents truly novel Intelligent Systems (IS), in particular Fuzzy Inference Systems, approaches and methodologies to measure the commonly used indicators in many industries: Overall Equipment Effectiveness and Overall Line Efficiency. The proposed techniques can be easily implemented to improve the accuracy and reduce the limitations of the OEE and the OLE measurements. These IS techniques, in particular the Fuzzy Inference Systems (FIS) offer valuable and significant new ways to measure the OEE and the OLE in industry. Dealing with uncertainty and vague data, taking advantage of user’s knowledge of the system, and also the ability of adding weight factors of inputs to the system, are some of the great advantages of applying FIS in the OEE and the OLE measurement.

## REFERENCES

I. P. S. Ahuja, J. S. Khamba, "Total productive maintenance: literature review and directions", *International Journal of Quality & Reliability Management*, Vol. 25 Iss: 7, (2008) 709 – 756.

Jose Arturo Garza-Reyes, Steve Eldridge, Kevin D. Barber, Horacio Soriano-Meier, "Overall equipment effectiveness (OEE) and process capability (PC) measures: A relationship analysis", *International Journal of Quality & Reliability Management*, Vol. 27 Iss: 1, (2010), 48 – 62.

D. Kotze, "Consistency, accuracy lead to maximum OEE benefits", *TPM Newsletter*, vol. 4, no. 2, 1993.

M. Lesshammar, "Evaluation and improvement of manufacturing performance measurement systems –

the role of OEE", *International Journal of Operations and Production Management*, vol. 19, no. 1, pp. 55-78, (1999).

R. Wudhikarn and W. Manopiniwes, "Autonomous maintenance using total productive maintenance approach: A case study of synthetic wood plank factory", *Technology Innovation & Industrial Management Conference, TIIM2010, Pattaya, Thailand*, in press.

B. Dal, P. Tugwell and R. Greatbanks, "Overall Equipment effectiveness as a measure of operational Improvement", *International Journal of Operations & Production Management*, vol. 20, no. 12, (2000), 1488–1520.

M. Maran, G. Manikandan, K.Thiagarajan, "Overall Equipment Effectiveness Measurement By Weighted Approach Method", *International Association of Engineers Vol. 2.*,(2012).

M. Moradzadeh, "Overall Equipment Effectiveness and Overall Line Efficiency Measurement Using Intelligent Systems Techniques" M.A.Sc. Thesis, Faculty of Engineering, University of Regina, Canada, April, 2014.

Braglia, M., Frosolini, M., & Zammori, F., "Overall equipment effectiveness of a manufacturing line (OEEML)". *Journal of Manufacturing Technology Management*, Vol. 20 Iss: 1, (2009), 8 – 29.

Richard Oechsner, Markus Pfeffer, Lothar Pfitzner, Harald Binder, Eckhard Müller, Thomas Vonderstrass, "From overall equipment efficiency (OEE) to overall Fab effectiveness (OFE)", *Materials Science in Semiconductor Processing*, Vol. 5, Iss 4–5, (2002), 333-339.

## LIST OF ACRONYMS

IS	Intelligent Systems
FIS	Fuzzy Inference Systems
OEE	Overall Equipment Effectiveness
OLE	Overall Line Efficiency
Brk	Breakdowns
Stad	Setup & adjustment
Sml	Small stops
Red	Reduced speed
Str	Start-up rejects
Prr	Production rejects
Coa	Center of area