

52nd CIRP Conference on Manufacturing Systems

Automatic Estimate of OEE Considering Uncertainty

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Abstract

Overall Equipment Effectiveness (OEE), which is commonly used for production performance monitoring, can mislead decision makers with low accuracy when a large amount of losses remains unclassified. This paper is to study the critical factors and potential pitfalls when trying to automatically estimate the OEE of a manufacturing system, considering uncertainty. Two methods based on fuzzy arithmetic and interval arithmetic respectively are proposed to manage the uncertainty in estimating the production speed, the stoppage duration, and the quality losses. Datasets from real-world settings are used to illustrate the concepts and the benefits of the methods in practice.

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Peer-review under responsibility of the scientific committee of the 52nd CIRP Conference on Manufacturing Systems.

Keywords: overall equipment effectiveness; uncertainty; fuzzy arithmetic; interval arithmetic

1. Introduction

Overall Equipment Effectiveness (OEE) has been widely used as a quantitative tool essential for the measurement of productivity in manufacturing industries. It is designed to identify and eliminate the related losses to improve the performance and reliability between facilities.

As the development of industrial digitalization, automatic OEE measurement has been a central part in Manufacturing Execution Systems (MES). The validity and usefulness of OEE estimate are highly dependent on the data collection which needs both availability and accuracy of data especially the accuracy which determines the OEE values [1-4]. However, there can be numerous sources of uncertainties that influence the accuracy of data in a real-world manufacturing environment. Due to manual or semi-automatic data collection, data like some minor stoppage, idling and speed losses et al. can be often overlooked. Moreover, the loss categories, which are lacked or with poor descriptions, cannot be grouped into the classified losses for OEE estimation and derive the inaccurate OEE. Furthermore, there is no apparent cause and effect relationship between change in either factor

(availability, performance and quality) and the OEE [5]. Hence, conventional formulation of OEE, which is based on accurate data and results in a single value, may perform with low accuracy to mislead decision makers. Then uncertainties should be considered into account.

Zammori et al. [6] considered OEE as a stochastic random variable, and of which the probability density function is generated through the aggregation of the probability density function of the underlying causes of waste. Furthermore, Zammori [7] decomposed the manufacturing losses into primary causes and modeled as LR fuzzy numbers. Sousa et al. [8] studied the fuzzy performance measures to represent uncertainties and proposed a method to calculate an indicator of the compliance between a fuzzy PM and its target value. Busert and Fay [9] used fuzzy logic to model the uncertainty in information under consideration of information quality dimensions. Sonmenz et al. [10] studied the existence and determination of uncertainties in stoppage duration and production speed, which can be handled as fuzzy-type uncertainties and interval-type uncertainties. However, uncertainties occur not only due to the measurement of realized stoppage duration and realized production speed, but

also due to misjudgment of production inspection, which is an inevitable risk result from human factor, limitation of measurement instrument and flaws in data collection processes. Chen et al. [11] and Akkerhuis et al. [12] proposed the quantitative estimation methods of misjudgment risk of product inspection.

Based on the studies above, this paper focuses on the automatic OEE estimation considering the uncertainties of stoppage duration, production speed, and quality losses. By analyzing the critical factors and potential pitfalls when calculating OEE of discrete manufacturing systems, two methods based on fuzzy arithmetic and interval arithmetic respectively are proposed to manage the uncertainties in estimating. Then it is followed by modeling and analysis of the datasets from real-world settings to illustrate the concepts and the benefits of the methods in practice.

2. Problem Modeling

2.1 Components and Uncertainties in OEE Estimate

OEE is an analysis tool based on a multiplication of three components, which are availability (A), performance (P) and quality (Q) respectively, as Eqs. (1) shows. Moreover, these three components aim to capture and eliminate the 6 significant losses in the production defined by Nakajima [1].

$$OEE = A \cdot P \cdot Q \tag{1}$$

Where:

1) A is the ratio of the operating time T_A to the planned operating time T_P and indicates the unplanned production stoppages losses TL_{ST} , as Eqs. (2) shows;

2) P indicates the performance efficiency of equipment and it is the ratio of the planned cycle time CT_P to the realized average cycle time CT_A which can be obtained by T_A over the actual number of products produced P_A , as Eqs. (3) shows;

3) Q is the ratio of the qualified products number P_Q to P_A and indicates the quality losses PL_Q , as Eqs. (4) shows.

$$A = \frac{T_A}{T_P} = \frac{T_P - TL_{ST}}{T_P} \tag{2}$$

$$P = \frac{CT_P}{CT_A} = \frac{CT_P}{\left(\frac{T_A}{P_A}\right)} \tag{3}$$

$$Q = \frac{P_Q}{P_A} = \frac{P_A - PL_Q}{P_A} \tag{4}$$

Fig. 1 shows the classification and relationships of production and production losses of equipment.

Define the corresponding production losses obtained by the three types of the losses as PL_{ST} , PL_{SP} and PL_Q . Then the relationship between planned production P_P , P_Q , and the production losses PL_{ST} , PL_{SP} and PL_Q is shown as Eqs. (5).

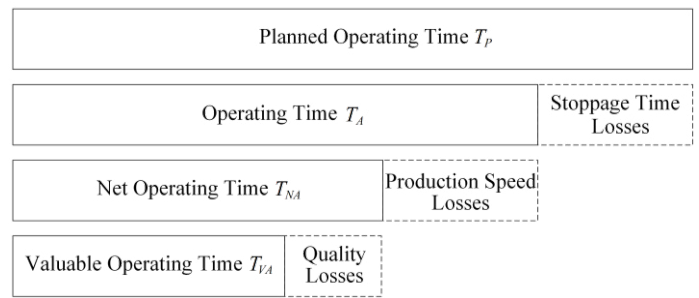


Fig. 1. The classification and relationships of production and production losses of equipment.

$$P_P = P_Q + PL_{ST} + PL_{SP} + PL_Q \tag{5}$$

However, by analyzing the data of a tightening station of a powertrain assembly line from MES, which covers 30 days of production, it is found that the sum of P_Q , PL_{ST} , PL_{SP} and PL_Q is not equal to P_P , as Eqs. (6) shows. There are 750 parts of unexplained losses.

$$\begin{aligned} P_Q + PL_{ST} + PL_{SP} + PL_Q &= P_A + PL_{ST} + PL_{SP} \\ &= P_A + 0 + \left(\frac{T_P}{CT_P} - \frac{T_P}{CT_A} \right) \\ &= 27330 \text{ parts} \\ &\neq P_P \end{aligned} \tag{6}$$

Where, the planned cycle time is 75 s/part, and the planned production P_P is 28080 parts with the production scheduling of 3 shift/day, 7.5 h/shift, then $T_P = 28080 \times 75 = 2.106 \times 10^6 s$. Moreover, in the MES, the recorded actual average cycle time counted is 81.9167 s, there is no stoppage record, the number of actual products is 24959 parts, and the number of the qualified is 24667 parts.

There are various uncertain factors during the operating of manufacturing systems, which lead to data inaccurate and cause deviation of data analysis subsequently to influence the decision. Sousa et al. [9] point out the main uncertainties in performance measurements, as Fig. 2 shows. Meanwhile, it demands a considerable investment of time and effort to filter erroneous data from the massive amount of data. Moreover, in fact, it is difficult to find out all abnormal data.

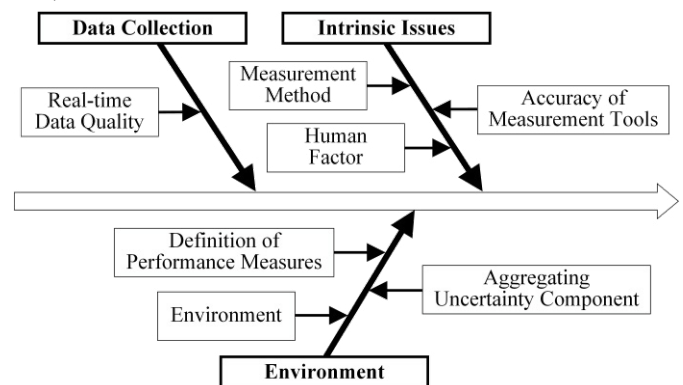


Fig. 2. The classification and causes of uncertainties in OEE estimate.

In this study, we not only consider the uncertainties of unplanned production stoppage and production speed losses but also focus on the uncertainties of quality losses which results from random misjudgment of quality inspection equipment. Affected by zero shift of sensors, some qualified products may be misjudged as the defective as well as some defective may be falsely accepted as the qualified. Therefore, there is also a particular error in quality statistics.

2.2 OEE Estimate with Fuzzy Type Measurements

Distinguished from the determined mathematical model and random mathematical model, the fuzzy mathematic model can more precisely reflect the uncertainties of the relevant data for OEE estimate [8,10,13]. In this section, fuzzy triangular numbers are used for the expression of stoppage duration, production speed and quality losses with uncertainties.

Considering the fuzzy stoppage duration losses \widetilde{TL}_{ST} as a triangular fuzzy number. The left spread TL_{ST}^L of \widetilde{TL}_{ST} is zero as there may be no stoppage. The right spread TL_{ST}^R is $(T_P - P_A CT_P)$ with the considering of an assumption that if the production speed is as planned during the production of the actual production amount P_A and there are no production speed losses. Therefore, \widetilde{TL}_{ST} can be expressed as Eqs. (7) shows. Moreover, Eqs. (8) is the corresponding membership function.

$$\widetilde{TL}_{ST} = (TL_{ST}^L, TL_{ST}^M, TL_{ST}^R) = (0, TL_{ST}, T_P - P_A CT_P) \quad (7)$$

$$\mu_{\widetilde{TL}_{ST}}(x) = \begin{cases} 0, & x < 0 \\ \frac{x-0}{TL_{ST}-0}, & 0 \leq x < TL_{ST} \\ \frac{(T_P - P_A CT_P) - x}{(T_P - P_A CT_P) - TL_{ST}}, & TL_{ST} \leq x < (T_P - P_A CT_P) \\ 0, & (T_P - P_A CT_P) \leq x \end{cases} \quad (8)$$

$$\widetilde{CT}_A = (\overline{CT}_A^L, \overline{CT}_A^M, \overline{CT}_A^R) = (CT_P, \overline{CT}_A, \frac{T_P}{P_A}) \quad (9)$$

$$\mu_{\widetilde{CT}_A}(x) = \begin{cases} 0, & x < CT_P \\ \frac{x-CT_P}{\overline{CT}_A-CT_P}, & CT_P \leq x < \overline{CT}_A \\ \frac{\frac{T_P}{P_A}-x}{\frac{T_P}{P_A}-\overline{CT}_A}, & \overline{CT}_A \leq x < \frac{T_P}{P_A} \\ 0, & \frac{T_P}{P_A} \leq x \end{cases} \quad (10)$$

Meanwhile, the fuzzy actual average cycle time $\widetilde{\overline{CT}}_A$ can be expressed as Eqs. (9) shows. The left spread \overline{CT}_A^L is $\frac{T_P}{P_A}$ under

$$\widetilde{OEE} = \left(\frac{(P_A \cdot CT_P)^2 \cdot (P_A(1-Q_2) - PL_Q)}{T_P^2 \cdot P_A}, \frac{(T_P - TL_{ST}) \cdot CT_P \cdot (P_A - PL_Q)}{T_P \cdot \overline{CT}_A \cdot P_A}, \frac{P_A(1+Q_1) - PL_Q}{P_A} \right) \quad (18)$$

$$\widetilde{TL}_{ST} = [TL_{ST}^L, TL_{ST}^U] \quad (19)$$

$$\widetilde{CT}_A = [CT_A^L, CT_A^U] \quad (20)$$

$$\widetilde{PL}_Q = [PL_Q^L, PL_Q^U] \quad (21)$$

the situation of P_A is produced without any stoppage. Moreover, the right spread \overline{CT}_A^R is the planned cycle time which also is the minimum cycle time of the equipment. Then the membership function of \overline{CT}_A is shown as Eqs. (10).

For the quality losses, consider the false acceptance of defective products and the false rejection of qualified products due to sensor error. Define the probability of false rejection as Q_1 and the probability of false acceptance as Q_2 , which are shown as Eqs. (10) and Eqs. (11) respectively. In reality, the misjudgment can be found out and corrected by the inspection downstream or the rework offline. Nevertheless, the data of the station recorded will not be updated.

$$Q_1 = 2 \left(1 - \int_{|x-a| \leq \frac{T}{2}} \varphi_x(x) dx \right) \int_0^{\frac{T}{2}} \varphi_{z_1}(z) dz \quad (11)$$

$$Q_2 = 2 \left(1 - \int_{|x-a| \leq \frac{T}{2}} \varphi_x(x) dx \right) \int_0^{\frac{T}{2}} \varphi_{z_2}(z) dz \quad (12)$$

Where x is the realized value, z is the measurement, a is the standard reference value and T is the process capability index.

Then the left spread is the quality losses $(PL_Q - P_A Q_1)$ considering false acceptance, as well as the right spread is $(PL_Q + P_A Q_2)$ with the consideration of a false rejection. Then the fuzzy production losses \widetilde{PL}_Q and the membership function are as Eqs. (13) and Eqs. (14) show respectively.

$$\widetilde{PL}_Q = (PL_Q^L, PL_Q^M, PL_Q^R) = (PL_Q - P_A Q_1, PL_Q, PL_Q + P_A Q_2) \quad (13)$$

$$\mu_{\widetilde{PL}_Q} = \begin{cases} 0, & x < PL_Q - P_A Q_1 \\ \frac{x - (PL_Q - P_A Q_1)}{PL_Q - (PL_Q - P_A Q_1)}, & PL_Q - P_A Q_1 \leq x < PL_Q \\ \frac{PL_Q + P_A Q_2 - x}{PL_Q + P_A Q_2 - PL_Q}, & PL_Q \leq x < PL_Q + P_A Q_2 \\ 0, & PL_Q + P_A Q_2 \leq x \end{cases} \quad (14)$$

Consequently, the components of OEE can be reformulated by using the fuzzy values above. Eqs. (15), Eqs. (16) and Eqs. (17) show the fuzzy availability \widetilde{A} , fuzzy performance \widetilde{P} , and fuzzy quality \widetilde{Q} respectively. Finally, the fuzzy OEE can be expressed as a triangular fuzzy number as Eqs. (18) shows.

$$\widetilde{A} = \frac{T_P - \widetilde{TL}_{ST}}{T_P} = \left(\frac{P_A \cdot CT_P}{T_P}, \frac{T_P - TL_{ST}}{T_P}, 1 \right) \quad (15)$$

$$\widetilde{P} = \frac{CT_P}{\overline{CT}_A} = \left(\frac{CT_P}{\frac{T_P}{P_A}}, \frac{CT_P}{\overline{CT}_A}, 1 \right) = \left(\frac{CT_P P_A}{T_P}, \frac{CT_P}{\overline{CT}_A}, 1 \right) \quad (16)$$

$$\widetilde{Q} = \frac{P_A - \widetilde{PL}_Q}{P_A} = \left(\frac{P_A(1-Q_2) - PL_Q}{P_A}, \frac{P_A - PL_Q}{P_A}, \frac{P_A(1+Q_1) - PL_Q}{P_A} \right) \quad (17)$$

$$\widetilde{A} = \left[\frac{T_A - TL_{ST}^U}{T_P}, \frac{T_A - TL_{ST}^L}{T_P} \right] \quad (22)$$

$$\widetilde{P} = \left[\frac{CT_P}{CT_A^U}, \frac{CT_P}{CT_A^L} \right] \quad (23)$$

$$\tilde{Q} = \left[\frac{P_A - PL_Q^U}{P_A}, \frac{P_A - PL_Q^L}{P_A} \right] \quad (24)$$

2.3 OEE Estimate with Interval Type Measurement

In this section, stoppage duration, production speed, and quality losses are reformulated by interval numbers with the consideration of uncertainties due to lower accuracy of data collections, given by the physical values or the empirical data. The interval number can be defined as $X = [a, b]$ which is a

$$\overline{OEE} = \left[\frac{T_A - TL_{ST}^U}{T_P}, \frac{T_A - TL_{ST}^L}{T_P} \right] \cdot \left[\frac{CT_P}{CT_A^U}, \frac{CT_P}{CT_A^L} \right] \cdot \left[\frac{P_A - PL_Q^U}{P_A}, \frac{P_A - PL_Q^L}{P_A} \right] = \frac{[T_A - TL_{ST}^U, T_A - TL_{ST}^L] \cdot \left[\frac{1}{CT_A^U}, \frac{1}{CT_A^L} \right] \cdot [P_A - PL_Q^U, P_A - PL_Q^L]}{P_P P_A} \quad (25)$$

$$\overline{OEE} = \left[\frac{P_A \cdot CT_P}{T_P}, 1 \right] \cdot \left[\frac{CT_P \cdot P_A}{T_P}, 1 \right] \cdot \left[\frac{P_A(1 - Q_2) - PL_Q}{P_A}, \frac{P_A(1 + Q_1) - PL_Q}{P_A} \right] = \left[\frac{P_A \cdot (P_A(1 - Q_2) - PL_Q)}{(P_P)^2}, \frac{P_A(1 + Q_1) - PL_Q}{P_A} \right] \quad (26)$$

Table 1. The component data for OEE estimate of a manual tightening station.

Name	Value
T_P	2025000 s
TL_{ST}	600 s
CT_P	75 s
\overline{CT}_A	78.7765 s
P_A	24431 parts
P_Q	23799 parts
Q_1	0.019 %
Q_2	0.374 %
PL_Q	632 parts
PL_Q' full consideration with misjudgment of inspection.	546 parts
PL_Q'' combined with the statistics from the inspection downstream and rework offline.	542 parts
PL_{ST}	1294 parts
PL_{SP}	7 parts
Actual Losses recorded by MES.	3201 parts
Calculated Losses	1933 parts
Unexplained Losses	1268 parts

3. Case Study and Application

3.1 Case Study

The proposed methods have been applied in analyzation of a manual tightening station of a powertrain assembly line. The data of the planned, measured and calculated is as shown in Table 1. As the value of unexplained losses shows, there are some uncertainties in the measurement system.

By implementing the proposed fuzzy method, the fuzzy stoppage duration losses are $\overline{TL}_{ST} = (0, 600, 192675)$, the fuzzy average cycle time is $\overline{CT}_A = (75, 78.7765, 82.8865)$, and the fuzzy quality losses is $\overline{PL}_Q = (541, 632, 637)$. Then the fuzzy availability component of OEE estimate is calculated as $\tilde{A} = (0.9049, 0.9997, 1)$, the fuzzy performance component is $\tilde{P} = (0.9048, 0.9520, 1)$ and the fuzzy quality component is $\tilde{Q} = (0.9778, 0.9852, 0.9889)$. Furthermore, The fuzzy OEE is $\overline{OEE} = (0.8006, 0.9376, 0.9889)$, where the modal value is equal to the conventional OEE.

set of all real number between and including endpoints. The interval numbers of the losses can be expressed as Eqs. (19), Eqs. (20), Eqs. (21) show. Then the interval components in OEE estimate are shown as Eqs. (22), Eqs. (23), Eqs. (24). And the interval OEE can be obtained as Eqs. (25) shows.

If one considers the situation where the physical limits considered in Section 2.2, the interval OEE can be estimated as Eqs. (26) shows.

Defuzzy the fuzzy OEE by Eqs. (27). Moreover, take $\lambda = 0.5$ as the risk is neutral, then $E(\overline{OEE})$ is 0.9162.

$$E(\overline{OEE}) = \frac{(1 - \lambda)OEE^L + OEE^M + OEE^U}{2} \quad (27)$$

Where λ is the risk index and the value depends on the risk attitude of the decision makers.

To contrast, use interval arithmetic to estimate the OEE of the station. The lower and upper physical limits of interval stoppage losses \overline{TL}_{ST} are $TL_{ST}^L = 300$ sas being reduced by using the standby device, and $TL_{ST}^U = 47400$ s by adding the data of the minor stoppage which may be overlooked according to the industrial engineering supervisor. Moreover, the interval realized average cycle time can be given as $\overline{CT}_A = [78.7765, 80]$. With the full consideration of the misjudgment of torque sensors, the interval quality losses are $\overline{PL}_Q = [PL_Q - P_A Q_1, PL_Q + P_A Q_2] = [541, 637]$. Then the interval components are calculated as $\tilde{A} = [0.9766, 0.9998]$, $\tilde{P} = [0.9375, 0.9520]$ and $\tilde{Q} = [0.9778, 0.9889]$ respectively. Therefore, the interval OEE is $\overline{OEE} = [0.8952, 0.9412]$ with the closer interval compared to the fuzzy type OEE.

As Fig. 3 shows, with the full consideration of uncertainties in estimating the stoppage duration, production speed and quality losses, the left and right spread value of the fuzzy OEE estimate can be more explicit to show the worst and best possible value to decision makers. To contrast, the interval of the interval OEE can be tighter, and the estimate can be more convenient on the premise of good experience and data accumulation of engineers.

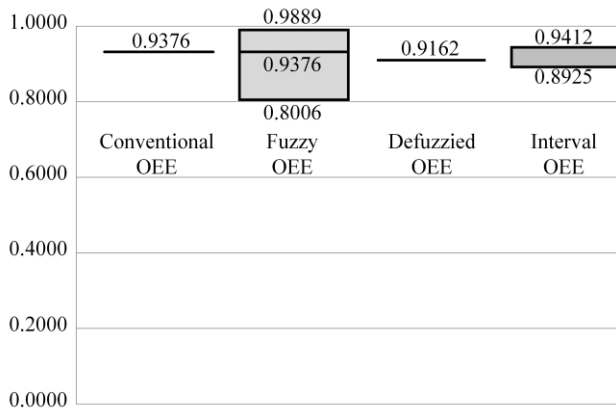


Fig. 3. The different OEE results of a manual tightening station.

3.2 Fuzzy OEE Automatic Estimate in Plant Simulation

The fuzzy OEE estimate method has been programmed and built as an automatic OEE calculation module in Plant Simulation. The components of conventional OEE can be calculated in Plant Simulation by the equations as Table 2 shows. Then A, P, Q and OEE can be obtained by Eqs. (2), Eqs. (3), Eqs. (4) and Eqs. (1) respectively.

However, it is hard to count the minor stoppages which cannot be described as availability and MTTR in Plant Simulation as well as the planned downtime used for production due to the different user definitions. Meanwhile, it is also difficult to count out the number of misjudgments of quality sensors which need to be shown in the simulation as in the beginning and the end of a period the misjudgments will break out.

Hence, the fuzzy method is applied for OEE estimate considering the uncertainties. The improved approach of OEE components is shown in Table 3. Then the fuzzy components $\tilde{A}, \tilde{P}, \tilde{Q}$ and the fuzzy OEE can be reformulated as Eqs. (7), Eqs. (9) Eqs. (13) and Eqs. (18). Fig. 4 shows the dialog window of the OEE automatic estimate module and the chart of the fuzzy OEE result of a station in Plant Simulation.

Table 2. OEE components calculated in Plant Simulation.

Name	Equation
T_p	$T_p = \text{Eventcontorller.SimTime} - \text{Eventcontroller.StartStat} - \langle \text{path} \rangle.\text{statUnplannedTime} - \langle \text{path} \rangle.\text{statPausingTime}$
TL_{ST}	$TL_{ST} = \langle \text{path} \rangle.\text{PlannedDownTimeUsedforProduction} + \langle \text{path} \rangle.\text{statBlockingTime} + \langle \text{path} \rangle.\text{statWaitingTime} + \langle \text{path} \rangle.\text{statFailTime}$
CT_p	$CT_p = \langle \text{path} \rangle.\text{DefaultProcTime}$
P_A	$P_A = \langle \text{path} \rangle.\text{statNumOut}$
PL_Q	$PL_Q = \langle \text{path} \rangle.\text{statNumUnqualified}$

Note: $\langle \text{path} \rangle.\text{PlannedDownTimeUsedforProduction}$, $\langle \text{path} \rangle.\text{DefaultProcTime}$ and $\langle \text{path} \rangle.\text{statNumUnqualified}$ are user-defined attributes.

Table 3. Fuzzy OEE components calculated in Plant Simulation.

Name	Equation
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T_p	$T_p = \text{Eventcontorller.SimTime} - \text{Eventcontroller.StartStat} - \langle \text{path} \rangle.\text{statUnplannedTime} - \langle \text{path} \rangle.\text{statPausingTime}$
\tilde{TL}_{ST}	$\tilde{TL}_{ST} = (0, TL_{ST}, \langle \text{path} \rangle.\text{statNumOut} \cdot \langle \text{path} \rangle.\text{DefaultProcTime})$
CT_p	$CT_p = \langle \text{path} \rangle.\text{DefaultProcTime}$
P_A	$P_A = \langle \text{path} \rangle.\text{statNumOut}$
\tilde{PL}_Q	$\tilde{PL}_Q = (PL_Q - P_A Q_1, PL_Q, PL_Q + P_A Q_2)$

Note: TL_{ST} and PL_Q are shown in Table 2.

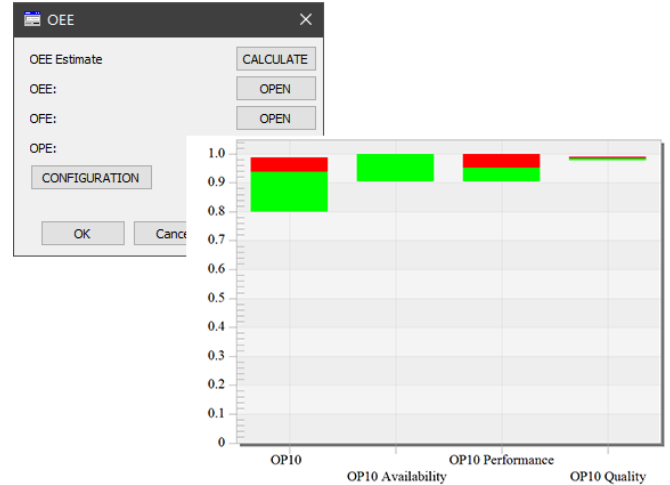


Fig. 4. The dialog window of OEE automatic estimate module and the chart of the fuzzy OEE result of a station in Plant Simulation.

4. Conclusions

This paper studies the automatic OEE estimation with the consideration of uncertainties of stoppage duration, production speed and quality losses compared to the conventional OEE calculation which is based on accurate data. Due to various uncertain factors which can not be avoided during the operating of manufacturing systems, the data collected may be inaccurate and lead to deviation of system control. By analyzing the critical factors and potential pitfalls when calculating OEE of systems, two methods based on fuzzy arithmetic and interval arithmetic respectively are proposed to manage the uncertainties in estimating. Moreover, a dataset from real-world is used to illustrate the concepts and the benefits of the methods in practice. Moreover, the fuzzy method proposed has been applied to modify the OEE automatic estimate module in Plant Simulation.

The future work is to extend the methods to estimate Overall Line Effectiveness (OLE) and Overall Plant Effectiveness (OPE) which are used to measure the line-level and plant-level effectiveness respectively. Moreover, different statistical distribution will be considered for the development of the approach.

Acknowledgements

This research is supported by National Science and Technology Major Project of the Ministry of Science and Technology of China (2011ZX04015-22).

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