International Journal of Production Research

ISSN: 0020-7543 (Print) 1366-588X (Online) Journal homepage: https://www.tandfonline.com/loi/tprs20

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To cite this article: A. Mousavi & H.R.A. Siervo (2017) Automatic translation of plant data into management performance metrics: a case for real-time and predictive production control, International Journal of Production Research, 55:17, 4862-4877, DOI: 10.1080/00207543.2016.1265682

To link to this article: https://doi.org/10.1080/00207543.2016.1265682

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Published online: 13 Dec 2016.

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International Journal of Production Research, 2017
Vol. 55, No. 17, 4862–4877, https://doi.org/10.1080/00207543.2016.1265682

Automatic translation of plant data into management performance metrics: a case for real-time and predictive production control

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(*Received 26 January 2016; accepted 17 September 2016*)

A scalable and repeatable solution for linking shop-floor control system to a discrete event simulation (DES) model is presented. The key objective is to automatically translate the real-time data from the control system (e.g. supervisory control and data acquisition, SCADA) into KPI transfer functions of the production process. Such a seamless translation allows for the integration of engineering data emitted at plant level to higher level information system for decision-making. The solution provides a platform for researchers and practitioners to utilise the capabilities of real-time DAQ and control with that of discrete event simulation to accurately measure the key manufacturing systems performance metrics. In addition to the real-time capabilities, the predictive capabilities of the solution provide the managers to look ahead and to conduct *What-if* scenarios. Such capability enables line management to optimise performance and predict destabilising factors in the system ahead of time. A fully operational version of the designed solution has been deployed in a brewery's live production system for the first time. The brewhouse production line model measures the utilisation of resources, Overall Equipment Effectiveness, and Overall Line Effectiveness in real-time and fast-forward mode simulation. The results of the predictive models (*What-if-Scenarios)* have been validated and verified by statistical means and direct observations. The accuracy of the estimated parameters is highly satisfactory.

Keywords: control; real-time; predictive; overall equipment/line effectiveness; simulation; brewery

1. Introduction

The motivation for this research project was to provide a solution for filling the gap between engineering data emanating from the factory control system (i.e. flows, levels, rates, sensors, actuators, alarms) and the higher level production management data (i.e. efficiency, utilisation, effectiveness, quality, …). Such integration should facilitate effective communication between day-to-day production management and that of strategic decision-makings at board levels.

With the introduction of advanced control technologies, like other manufacturing industries, breweries are producing a large number of end products with wider variety of raw materials. Their management main goal is to decrease the cost per hectolitre and hence increase production throughput. The proposed performance measurement and control system for breweries is in direct response to the persisting shortcomings of existing ERP solutions in dealing with the uncertainties of production lines.

Every operation manager and production strategist in the Brewery sector uses a set of generic KPI for the measuring process efficiency. These KPIs are utilisation of resource, overall equipment effectiveness (OEE) and overall line effectiveness (OLE) (Leachman 1997; Oechsner et al. 2002; Nachiappan and Anantharaman 2006; Mousavi et al. 2007; Iannone and Nenni 2013). Moreover, the use of discrete event simulation (DES) as an effective tool for analysis of systems performance with respect to uncertainties of production process has a strong following (e.g. Moon and Phatak 2005; De Ugarte et al. 2006; Jahangirian et al. 2010). DES in real-time has also shown to be effective for monitoring (Viswanadham and Narahari 1992), prediction tool for testing 'what-if' scenarios, predictive process control (e.g. Onut et al. 1994) and as a scheduling tool (Gupta, Sivakumar, and Sarawgi 2002; Mousavi, Broomhead, and Devagiri 2008).

It seems that the use of existing shop-floor monitoring and control systems integrated with a DES modelling capabilities, both robust and well established in academia and industry may be a reasonable platform for measuring and

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monitoring industrial KPI. Therefore, the primary aim here is to present a feasible implementation and to illustrate the potential benefits of a real-time simulation-based application that measures key productivity metrics in the brewing industry. The solution will include a simulation model of a brewhouse line with the capability of running either in real-time or in fast modes. The fast mode simulation will use the probability distributions obtained by a curve fitting analysis of historical brewery data. It will be capable of evaluating alternative production-scheduling scenarios (*What-if*). The authors believe that the scalable solution suggested in this paper can be applied to other manufacturing processes regardless of their nature (speed and frequency of operations and product motion) with no or minimum adjustments.

The main contributions of the paper can be listed as:

(1) Development of a novel and flexible middleware that connects the shop-floor control system with higher level production management systems (Section 3.1).
(2) Introduction of the concept of OLE for measuring KPI of productivity in multiple line production environments. This is combined with the concurrent measurement of resource utilisation which the authors believe would provide a more realistic overview of performance and productivity of system (Sections 3.2 and 3.3).
(3) Provision of decision-making tool that provides real-time information about the current state of the system, but more importantly at a fingertip allows the line managers to conduct predictive *what-if-scenarios* for better decision-making.

2. Background literature

The research questions posed by the brewery management to the researchers were: ‘Could breweries decrease the cost per hectolitre of production whilst maximising resource utilisation and improve OEE and OLE at the same time?’ and ‘How can we be confident about the information we have and the decisions we make?’

The research therefore focused on answering the second question first by engineering an information architecture which makes sense of the obtained data. And then to prove that with confidence in the ‘knowns’ the company can evaluate new initiatives for reducing production costs whilst maximising productivity. The aim was therefore to test and validate the feasibility of developing and implementing real-time KPI measurement in the brewing industry. The first challenge was to explore the possibility of assessing the current capabilities and finding an effective method for estimating and monitoring productivity metrics. The next step was to explore the methods of linking such metrics with the production cost. The constraint was to find solutions within the existing technological capabilities and not to impose prohibitive new purchases on the factory. The solution should:

(1) Be able to receive and translate real-time data generated by the SCADA system into KPI.
(2) Use the real-time data to trigger the event of the process simulator.
(3) And use the capabilities of the production simulator to run predictive scenarios.

Zhang et al. (2013) emphasise the need for basic engineering data produced by equipment and other manufacturing resources from the plant into shop-floor knowledge. They offer a systematic method that facilitates this translation and transition of engineering data into management knowledge system. The knowledge as a metadata structure can then be fed into higher level performance measurement platforms. We find such an approach relevant to the proposed solution in this paper. The authors also encourage readers to review the mechanisms of engineering data and knowledge in manufacturing plants in (Tavakoli, Mousavi, and Broomhead 2013).

2.1 *Productivity measurement methods*

Productivity measurement helps to identify problems and find solutions for improving system performance (Oechsner et al. 2002; de Ron and Rooda 2005; Nachiappan and Anantharaman 2006; Braglia, Frosolini, and Zammori 2008). In the context of manufacturing, productivity seems to be linked to equipment availability and equipment utilisation. Leachman (1997) defines equipment utilisation as the equipment busy time over the total operating time (i.e. availability of equipment).

Equipment availability is defined as the fraction of total operating time that a resource was capable of performing or actually performing processing work, excluding the time used for maintenance, cleaning, or calibration. It seems that these two metrics alone cannot represent the overall equipment efficiency levels, because normally availability does not take efficiency losses caused by equipment idle times. Moreover, when measuring equipment utilisation, the speed of the Unit of Production Process (UPP) is not taken into consideration. For example, at occasions, the equipment can be reported to be fully utilised but not providing 100% of its theoretical productivity. This discrepancy can be attributed to the differences in operator handling, production line jamming or the equipment being out-of-tune or unable to operate at full speed. Braglia, Frosolini, and Zammori (2008) and Huang et al. (2003) use production productivity, throughput and equipment utilisation as indicators of performance. Their definition fits well with brewery processes that are the main concern of this article.

OEE is the ratio between what was actually manufactured and what could be ideally manufactured, or the fraction of the time in which a production entity works at its full operating capacity (Braglia, Frosolini, and Zammori 2008). OEE was proposed by Nakajima (1988) as the key metric to support Total Productive Maintenance (TPM). The TPM entails the rigorous measurement of production equipment effectiveness (PEE) (Nakajima 1988; Leachman 1997; Huang et al. 2002).

According to Jonsson and Lesshammar (1999), manufacturing losses are either chronic or sporadic. The chronic losses may be hidden and caused by several concurrent events that may not seem relevant to the untrained observer. The sporadic disturbances on the other hand are sudden and immediately observable. They cause major disturbances (deviations) to the normal state. Ljungberg (1998) believes that chronic disturbances may seem normal to the untrained eyes, and their impact can be overlooked. The most logical way to identify chronic disturbances could be to compare the actual performance with the theoretical capacity of the equipment (Jonsson and Lesshammar 1999; Nachiappan and Anantharaman 2006). But this requires a good understanding of real-time data and applying corrective actions immediately or preventatively. Such preventative actions can break the chain of events that embed themselves as chronic disturbances. A reasonable account of OEE can therefore help in reducing losses. For example, Jonsson and Lesshammar (1999) found that the main causes for low OEE were lack of material, breakdown, corrective maintenance and time for programming the flexible manufacturing systems.

Huang et al. (2003) predicted that OEE would become popular and widely used as quantitative tool for measurement of productivity in manufacturing operations. However, OEE alone would not be sufficient as no production entity is isolated in a factory, but operates in a liked and complex environment (Oechsner et al. 2002; Nachiappan and Anantharaman 2006). The evolution of OEE measurement has led to other productivity measurements such as Total Equipment Effectiveness Performance, PEE, OLE and Overall Factory Effectiveness of the entire factory (Nachiappan and Anantharaman 2006; Muchiri and Pintelon 2008). Nevertheless, research has shown that not all the overall performance metrics can be used in all manufacturing system/factory.

The OEE measurement method adopted in this work evaluates how well equipment are exploited in comparison to their theoretical potential originally suggested by Nakajima's (1988) and improved by (Leachman 1997; Nachiappan and Anantharaman 2006). The reason for this choice is that in our experience, a large number of production process control and optimisation solution providers (e.g. SAP, Harford Control, Acontrol, BrewMaxx …) has adopted OEE measurement as one of the KPI in their solutions. Thus, the popularity of such measurement is ubiquitous and well established as a KPI in the process industry

2.2 *Performance evaluation and performance modelling*

There is a difference between performance evaluation and performance modelling. Performance evaluations use factory data to monitor resources and operations and diagnose failures. By comparing the expected and the actual performance a relative evaluation of system performance is achieved (Viswanadham and Narahari 1992). Performance modelling on the other hand employs simulation or analytical techniques to study the operational and decision-making issues. Simulation and modelling have become one of the most popular analytical methods to explain performance in industrial systems (e.g. Jahangirian et al. 2010; Komashie et al. 2015). Banks et al. (2009, 14) defined DES as 'the modelling of systems in which the states variables changes only at a discrete set of points in time'. DES has proven to be able to capture the stochastic nature of manufacturing systems, shop floor control and operations (Wu and Wysk 1988; Son et al. 2002; Smith 2003; Ramakrishnan, Wysk, and Prabhu 2004; Jahangirian et al. 2010; Mousavi, Komashie, and Tavakoli 2011). According to Kelton et al. (2010) and Altiok and Melamed (2007), DES models have shown to outperform other analytical or physical models capturing the complexities manufacturing systems. The models enable managers and systems analysts to quickly evaluate production scenarios (Curry and Feldman 2009, 45). They are useful tools for optimising production processes (Gupta, Sivakumar, and Sarawgi 2002; Huang et al. 2002; Robinson 2005; Curry and Feldman 2009; Duflou et al. 2012).

One of the weaknesses of traditional DES modelling has been the time lag between input data collection and the time the modelling process produces results. Once the results are produced, the model will become obsolete, because the settings of the plant have changed already. In recent years, research into using real-time data feed, automatic curve-fitting and the application of real-time DES in predictive control have shown promising results (Harmonosky 1990, 1995; McConnell and Medeiros 1992; Son, Rodriguez-Rivera, and Wysk 1999; Son and Wysk 2001; Tavakoli, Mousavi, and Komashie 2008a; Mousavi, Komashie, and Tavakoli 2011). In the experience of authors, the automation of input data collection and analysis for the purpose of DES can reduce the DES project life cycle by 70%.

The application of multi-pass simulation-based real-time scheduling and shop-floor control system was demonstrated by (Son and Wysk 2001). The performance of this multi-pass tool yielded a throughput increase of 138% over single-pass dispatching procedures in the laboratory. Even though the solution inspired many research projects e.g. Moreno-Lizaranzu et al. (2001), Ramakrishnan and Thakur (2005), Son and Wysk (2001), Son, Wysk, and Jones (2003), Mousavi et al. (2007, 2008, 2011), Mousavi and Tavakoli (2009), Lee, Son, and Wysk (2007), Gupta et al. (2002) and De Ugarte et al. (2006) – but the solutions remained localised. To the best knowledge of the authors, a standard solution that could be implemented in day-to-day control of plants has never become available. The desire for an instrument of preventive and proactive management in food, automotive, process and aviation sector persists to date.

De Ugarte et al. (2006) presented an open architecture framework supporting real-time decision-making. This architecture involves the integration of optimisation and real-time simulation with ERP and MES systems. The solution integrated a real hybrid continuous and discrete manufacturing scenario in the aluminium industry. The core of the decision-making was a system dynamic builder (SD Builder). The SD Builder is a combination of a discrete-event simulator, a production rules-based expert system and a state-graph search-based optimisation engine. The SD Builder runs the models and initiates decision-making logics depending on the disturbing events and the current system state. The decision-making process begins by initialising the SD Builder with data from the ERP and from the MES. The demonstrator solution endeavours to prove that simulation-based decision tools can be integrated with enterprise-level activities.

Similarly, Mousavi, Hamdi, and Sarhadi (2007) argued that SCADA, MRP and ERP systems alone are not enough, and that decision-making tools are needed. They proposed a quick-response modeller for the food production process to help manager to take decisions based on the measurement of system performance within the food industry. They outlined four KPFs; resources utilisation, production efficiency, customer satisfaction and inventory levels for the purpose describing the state of the plant using real-time and historical shop-floor data. Consequently, they integrated this system with a standard simulation tool in order to provide managers with a prediction platform to improve decision-making. The objective here was to illustrate that real-time data along with high-quality information help managers to be proactive. But the solution remained case-based and not repeatable.

Tavakoli et al. (2008a, 2008b) proposed a generic-enabling protocol for quick-response decision-making. The Flexible Data Input Layer Architecture (FDILA) was used to enable the system developers to define any number of data entry points for the purpose of data integration. The solution combines real-time DAQ and discrete event simulation software. The solution was tested in automated pet food manufacturing system where key data such as process times for each machine, machinery capacity and resource utilisation were measured. The idea behind modelling this plant was not only to test the data processing module, but also to initiate a research on the measurement of KPFs as a tool to improve decision-making.

In the following sections, we will discuss the development of a generic repeatable and scalar solution that combines supervisory control and DAQ systems with DES. The technical and financial constraints of the project were to minimise any imposition of purchasing new software/hardware licences for the company. Therefore, the Brewmaxx™ control system solution holding one-fifth of global beer production was chosen as the base controller. The Arena™, one of the prevalent discrete event simulation software solutions from Rockwell Automation® was the chosen solution for the real-time and predictive modelling. The methodology and the protocols suggested in the solution can be repeated and customised for any other control systems and modelling tool.

3. Methodology

In this section, we will explain the development of a real-time DES modelling application for the purpose of translating shop-floor control signals (engineering metrics) into productivity metrics (management metrics). The solution consists of three parts:

(1) The Inter-Process-Communication (IPC) platform connects the shop-floor control system (i.e. Brewmaxx™) and the DES (i.e. Arena™). The IPC links the control system (engineering layer) to the higher level performance measurement (management layer). It is modular and can be linked with any control system and the DES applications or simply a Microsoft Excel® spreadsheet that contains the necessary formulation of transfer lines and general serial systems.

(2) The model of the brewhouse production process. The input parameters of the DES model describe the variations of raw material, order patterns, production plan, resource allocation, plan layout, capacity scheduling, mean-time

between failures, uptime and downtime of resources, processing time, production quality, material handling, and the plant layout. The output parameters of the DES model provide a very good estimation (up to 95% confidence interval) of resource utilisation, production throughput and cycle time, as well as waste. The preliminary output is then used to measure the overall equipment and line effectiveness (OEE/OLE).

(3) The OEE/OLE is expressed as the product of three efficiency parameters; product quality, availability, and performance of the resources. The efficiency of product quality is the ratio of defective products over the amount of rework (Dal, Tugwell, and Greatbanks 2000; Muchiri and Pintelon 2008; Garza-Reyes et al. 2010). Note that in continuous processes as opposed to discrete processes, the way rework is handled would be different. In continuous processes, rework and good products cannot physically be separated. Therefore, defective products need to be reworked at the same time and place as the good products (Nachiappan et al. 2006). The OEE and OLE measurement models suggested here takes this into consideration, meaning that product is not transferred to the next stations in the production line unless the quality is acceptable.

3.1 *The control system architecture and the real-time data feed*

The control systems architecture shown in Figure 1 comprises the Programmable Logic Control (PLC), the Execution Server and the Client module. The communication of the individual components with each other runs via Ethernet connections, TCP/IP and Object Linking and Embedding for Process Control (OPC). Prominent commercial control systems providers such as Brewmaxx, Rockwell Automations, AControl, National Instruments, Siemens, Harford Control, to name a few, have similar modules and functionality with minor variations.

The role of the PLC is to interconnect the set of sensors and actuations that monitor and control the operations of the plant and transfer the information to the higher level information systems. The real-time and Archive SQL database hold all recipe parameters, automation object settings, real-time process data, step-logs and historical records from the

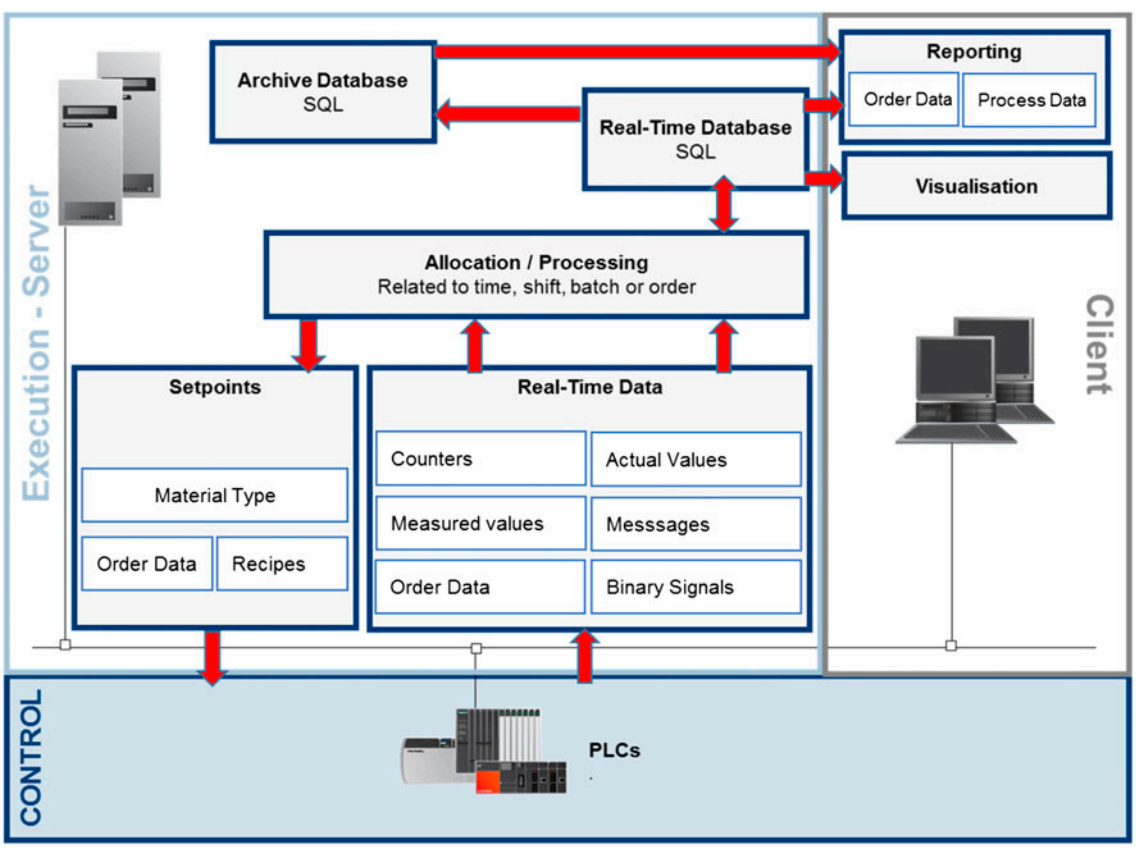

Figure 1. The control system architecture.

latest orders. Also, it is the source of information for the workstations where process visualisation and reporting are available. The step logs are the triggers of events for the DES models.

The server provides the operators, supervisors and managers with the data to customise reports on the process, add new recipes and other control functions. One capability of Brewmaxx is the Sequence-Based Recipe Control (SBRC). Such a feature facilitates process-related executions with respect to production sequences. Figure 2 shows an overview of Brewmaxx sequence-based recipe control including the step logs feature (ProLeiT 2015). Each sequence is a class instance with configurable parameters for specifying production steps. Moreover, each step encloses the activation of automation objects such as valves and pumps, monitoring analogue inputs and control of process values according to recipe parameters. A step ends when specific operations are fulfilled, for instance, maximum step time, temperature set point, operator interventions, etc. The step logs record the 'start' and the 'end' times of each step, the duration of the step, the alarms and their duration and other relevant process values. The information from the logger is used to specify the productivity metrics.

Table 1 lists a number of parameters specified for describing the system state at any given time.

3.2 *Input variable selection and process formulation*

The purpose of data selection and curve fitting process is to identify relevant information for the purpose of DES modelling. The brewery produces eight different type of beer. The input variables required for building the DES model were resource occupancy time (ROT) (busy time), the actual and the theoretical production processing time, scheduled and unscheduled downtimes, and the production plan.

It is worth noting that the product is not released by a resource unless the quality of the product reaches an acceptable level. As a result, the ROT may vary depending on the properties of the raw material and other production factors. In the case of continuous process, the ROT is a combination of waiting time, the delay time caused for unscheduled downtimes and the rework time. By recording and conducting statistical goodness-of-fit from historical data, the preliminary (default) ROT probability distribution function (PDF) is produced. This random processing time with respect to the calculated PDF will be updated continuously and automatically beyond this point. The unscheduled downtimes were

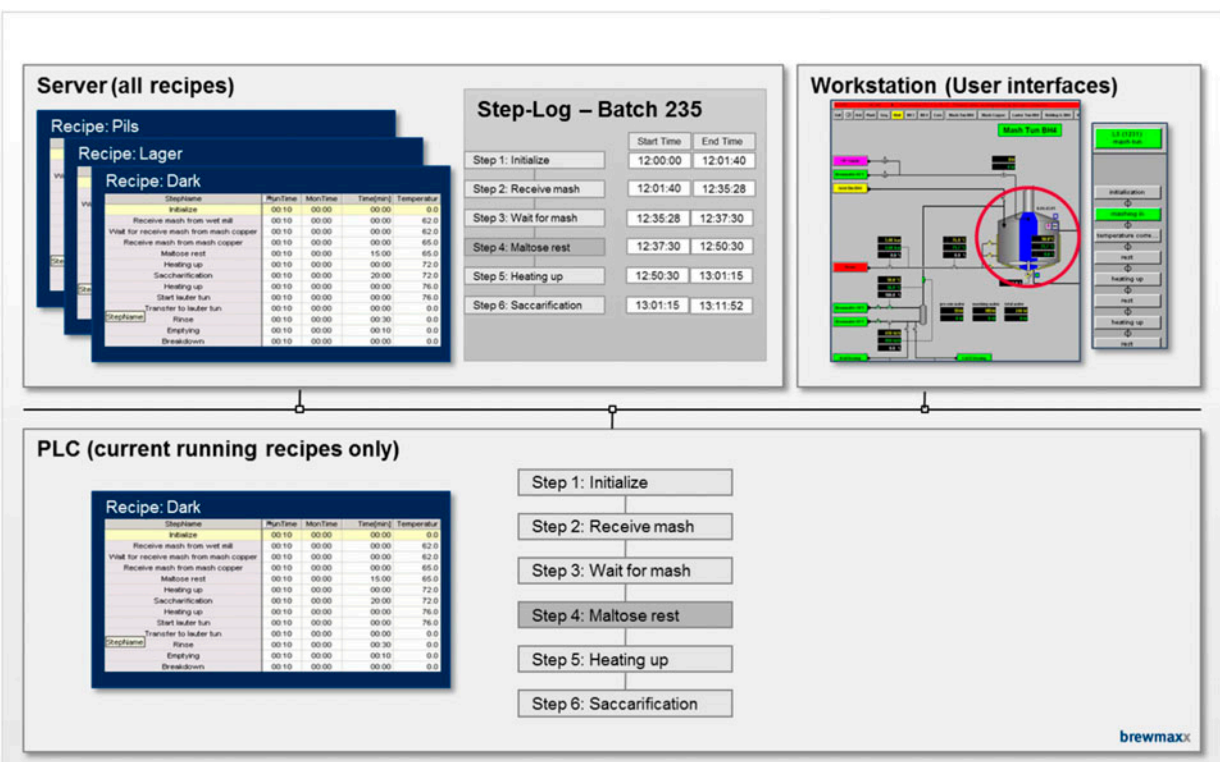

Figure 2. The Brewmaxx sequence-based recipe control.

Table 1. Sequence status description.

Status	Description
Idle	Machine/Resource is ready for use
Running	Step is active; sequence is being processed
Paused	Step is active but no automatic transitions. Automation objects could be activated. This status is not being used by the German brewery
Held	Step is active but no automatic transitions and no automation objects are activated. This is triggered normally by Alarms
Completed	Normal completion of the functional sequence
Stopped	No Normal, smooth completion of the functional sequence
Aborted	No Normal, immediate completion of the functional sequence

calculated based on the data available from the PLC and a mean-time-between-failure and out-service time probability distribution function was calculated.

Based on the ROT and scheduled and unscheduled downtimes, two types of Processing Time (PT) was calculated. PT_1 is the difference between the ROT and the unscheduled downtime.

$$\mathrm{ROT} = \mathrm{EndStep}_{\mathrm{EndTime}} - \mathrm{StartStep}_{\mathrm{StartTime}} \tag{1}$$

$$\mathrm{UDT} = \sum_{1}^{n} \mathrm{Time\ in\ Held} \tag{2}$$

$$\mathrm{PT}_1 = \mathrm{ROT} - \mathrm{UDT} \tag{3}$$

where n is the total number of alarms.

PT_2 is the duration of a sub-process which is a fraction of the resource occupation time. It is used when the ROT is a part of previous and/or subsequent operations in the production line. Equation (4) calculates the PT_2. For example, the ‘Mashing Time’ and the ‘Transfer to LS Time’ type of data.

$$\mathrm{PT}_2 = \mathrm{StepM}_{\mathrm{EndTime}} - \mathrm{StepN}_{\mathrm{StartTime}} - \mathrm{UDT}_{N \to M} \tag{4}$$

The theoretical equipment-processing time (Garza-Reyes et al. 2010) was provided by the brewery production management.

3.3 *The modelling of the system*

The logical construct of the manufacturing process was built based on Duflou et al. (2012) definitions of unit of production process (UPP), the unit factory (UF) and the facility. For example, we considered the processes in Millstar, Mashtun and Lauterstar as relevant to UPP. The brewhouse as the UF and the brewery as the facility. The equipment productivity measurement applies to the sequential operations. Also for UPP, OEE and OLE measurements, we adopted the equipment states model (Leachman 1997; Oechsner et al. 2002; de Ron and Rooda, 2005; Nachiappan et al. 2006). Accordingly:

- Idle state: the UPP is ready for processing the product, but no product is available.
- Busy state: the UPP is processing the product as planned (de Ron and Rooda 2005).
- Unscheduled down state: the UPP is not processing any product due to unplanned downtime events (e.g. random equipment failures).
- Scheduled/Inactive down state: the UPP is not processing any product due to planned downtime (e.g. planned maintenance) or the UPP is put off-line due to capacity alteration plans.

The utilisation of the resources is calculated using Equation (5) (Kelton, Sadowski, and Swets 2010).

$$U = \frac{\mathrm{Production\ time}}{\mathrm{Resource\ Available\ time}} \tag{5}$$

The OEE is expressed as the product of availability efficiency (AE), operational efficiency (OE), rate efficiency (RE) and quality efficiency (QE) (de Ron and Rooda 2005).

$$\text{OEE} = \text{AE} \times (\text{OE} \times \text{RE}) \times \text{QE} \tag{6}$$

Where,

$$\text{AE} = \frac{\text{Manufacturing time}}{\text{Total time}} \tag{7}$$

$$\text{OE} = \frac{\text{Production time}}{\text{Manufacturing time}} \tag{8}$$

$$\text{RE} = \frac{\text{Theoretical production time for actual orders}}{\text{Production time}} \tag{9}$$

$$\text{QE} = \frac{\text{Theoretical production time for effectives orders}}{\text{Theoretical production time for actual orders}} \tag{10}$$

Since brewhouses do not have separate rework areas, any quality discrepancy is detected immediately. The rework therefore occurs within the existing production processes. Therefore, the rework should be expressed as RE loss rather than quality loss. Such an approach requires modifying Equation (6) to:

$$\text{OEE} = \text{AE} \times (\text{OE} \times \text{RE}) \tag{11}$$

And for OLE calculations, Equation (12) is adopted (Nachiappan and Anantharaman 2006).

$$\text{OLE} = \text{LA} \times \text{LPQP} \tag{12}$$

where LA is the line availability efficiency, and LPQP is the line production quality-performance efficiency.

$$\text{LA} = \frac{\text{OT}_\text{n}}{(\text{Total time} - \text{SDT}_1)} \tag{13}$$

OT_n is the operation time of the nth UPP, and SDT_1 is the scheduled downtime of the first UPP. OT_i can be expressed as:

$$\text{OT}_i = [\text{OT}_i - \text{SDT}_i] - \text{UDT}_i \tag{14}$$

UDT_i is the unscheduled downtime for the UPP_i. LPDP can thus be expressed as:

$$\text{LPQP} = \frac{G_n \times \text{CYT}}{\text{OT}_1} \tag{15}$$

where G_n is the volume of good products at the nth process, (CYT) is the longest cycle time (bottleneck) amongst all processes (1 to n) and OT_1 process time of the first process.

The practical implementation of the real-time simulation requires two parts, the data integration and processing, and the simulation modelling engine (Tavakoli, Mousavi, and Komashie 2008a). The first component obtains the real-time data and the second produces the discrete event simulation (Figure 3).

The IPC application (the dashed inside square, Figure 3) acts as the link between the two parts. This framework was chosen because the Real-time Model Matching Mechanism (R3 M) (Tavakoli, Mousavi, and Komashie 2008a) offers an effective way for tracking discrete events received from the control system. Within the R3 M, the process flow of the simulation model runs continuously with respect to the discrete events received from the production line. The events associated with the start and stop of the processes (i.e. sequences) are reproduced by the simulation model. Similarly, when a new order starts in the physical model, then R3 M creates a new entity in the model with similar attributes (Figure 4).

4. Implementation and analysis of results

Figure 5 shows the components of the test platform implemented at the brewery. The brewhouse test system consists of Brewmaxx server, Brewmaxx workstation and the ABC soft PLC emulating the Simatic® S7-CPU 416 with CP443-1. The components run within a VMWare ESXi Server environment mirroring the real process. The server contains the current settings, recipes and parameters of the brewhouse. The workstation contains the latest process graphics. In addition to the standard enabling technology, the developed IPC module was embedded inside the virtual machine. The role

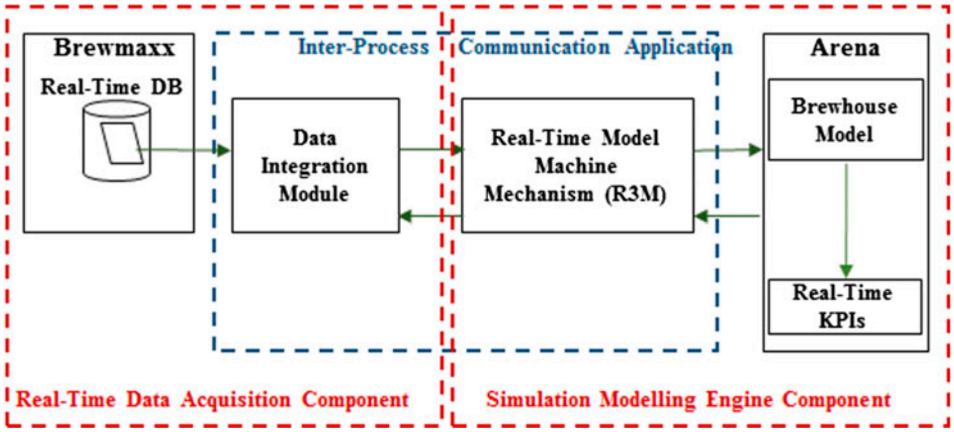

Figure 3. Components and modules for a real-time simulation platform.

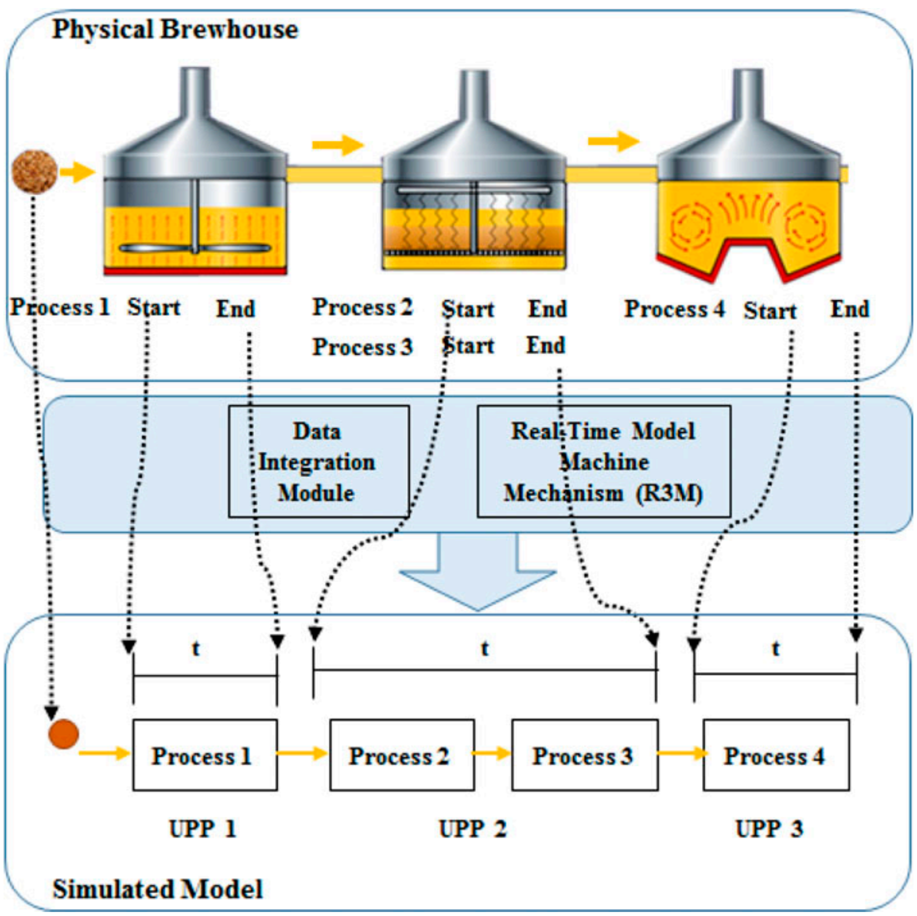

Figure 4. The R3 M diagram between physical plant and simulated model.

of the IPC is to manage the data communication between various components of the real-time and predictive simulation. Furthermore, a new graphical interface showing the scheduled utilisation was added to the Brewmaxx system. The real-time DES model (e.g. Arena) is connected to the Brewhouse test system (Figure 5).

Live tests were conducted for 20 h intervals on the production line. Two scenarios were modelled during the test. In one scenario, a single batch went through the complete production process, triggering all possible events. The second

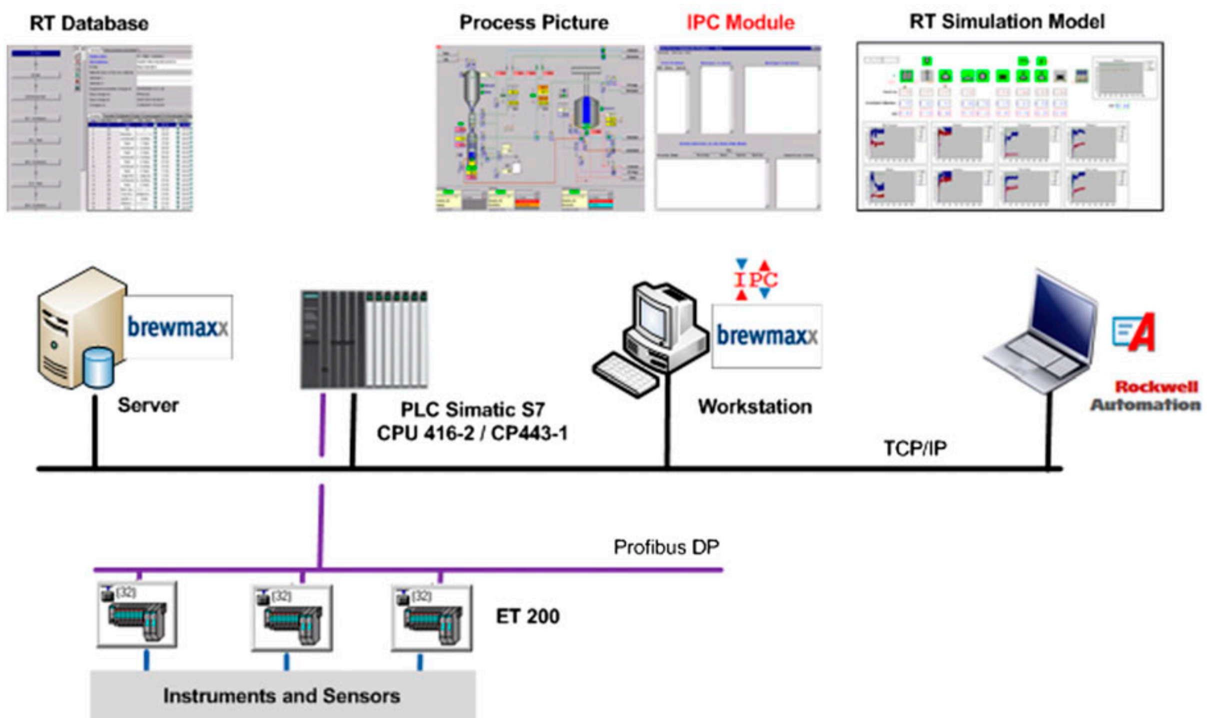

Figure 5. Components of the real brewhouse system.

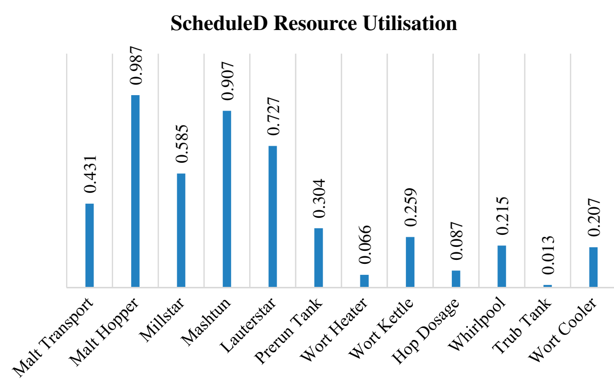

Figure 6. The results of average scheduled utilisation of resources based on real-time simulation.

scenario captured multiple batches and different beer types. Whilst the first scenario captured a special case, the second scenario encapsulated all possible events that could happen throughout a typical production shift. The tests helped to prove that R3 M could successfully cope live production and it can be repeated and scaled up. The tests for measuring OEE and OLE were verified by running a number of batches with events triggered on fixed periods so that measured OEE and OLE could be easily compared against calculated values. Figure 8 shows the architecture of the real system.

The results of the translation of engineering layer shop-floor signals into management information are demonstrated in Figures 6 and 7. Figure 6 represents scheduled utilisation of the resources. The chart displays the 'Malt Hopper' as the resource with the highest utilisation, however, it is not considered as a bottleneck of system, because it works as a buffer tank. In this example, the real bottleneck is the Mashtun with a scheduled utilisation of 0.907. Delays in the Mashtun process had an impact on the equipment at the beginning of the line, particularly with the Malt Hopper.

Figure 7 shows the OEEs of resources, and the OLE for the entire brewhouse line.

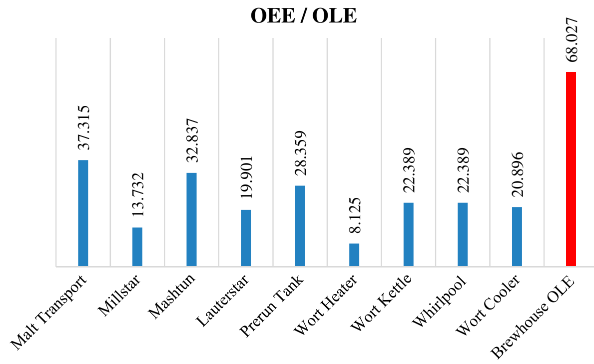

Figure 7. The results of average OEE and OLE based on real-time simulation.

Table 2. Category report – Model validation – Resource operating times – Due to commercial sensitivity the name of the operations have been changed and a few have not been listed to maintain confidentiality.

Category Overview						
Brewhouse						
No. Replications: 400 Time Units: Hours						
Tally						
Interval	Average	Half Width	Min. Average	Max. Average	Min. Value	Max. Value
Duration per Brew	4.7656	<0.47	0	9.7170	0	14.68
Operation Time R1	0.4303	<0.04	0	0.8819	0	1.68
Operation Time R2	1.2529	<0.12	0	2.5760	0	5.89
Operation Time R3	1.3568	<0.13	0	2.7923	0	5.86
Operation Time R4	0.7684	<0.08	0	1.5553	0	2.32
Operation Time R5	1.3433	<0.13	0	2.776	0	5.88
…	…	…	…	…	…	…
Operation Time R_{N-2}	0.7259	<0.07	0	1.4801	0	2.23
Operation time R_{N-1}	0.2125	<0.02	0	0.4335	0	0.73
Operation Time R_N	0.8788	<0.09	0	1.7959	0	2.94
Counters						
Count	Average	Half Width	Min. Average	Max. Average		
Completed Brews (Batches)	39.0	<3.85	0	78.0		
R1 Batches						
R2 Batches						
…	…	…	…	…		
R_N Batches	39.0	<3.85	0	78.0		

Due to the limitations of access and setting up the proposed solution live on the Shop-floor, the real-time simulation and predictive scenario builder were used at 20 h intervals of the production line.

For the purpose of model validation, the *t*-test for measuring the difference between the calculated performance means against the actual system was conducted. The modelling of the brewhouse process was developed using Arena® 14.70. It involved a curve-fitting analysis of 16 processing times for 8 different beer types. The model was validated by comparing means of simulated ROTs with historical ROTs over a 10-week period (Direct data collection). A comparison of means indicated that the probability distributions are good-fit for the brewhouse process, thus allowing us to conclude that the model is a close approximation of the actual production behaviour of the brewhouse. The validation process covered the data for two years of the production process. The Discrete Event Simulation model of the brewhouse was statistically proven to predict the production behaviour of the production plan and the results of the simulation were validated by comparing the simulated data with the existing record of production. By doing so, we confirmed that our model can estimate (i.e. predict) the production system with high levels of accuracy and with 95% confidence interval.

Tables 2 and 3 shows the results of 95% confidence interval and hypothesis tests of the operational times and the key observable system parameters after 400 replications.

Table 3. Confidence interval and hypothesis test on the operating times.

Paired-T means comparison			ROT validation			
Identifier	ESTD. mean difference	Standard deviation	0.95 C.I. half width	Minimum value	Maximum value	No. observations
ROT Malt Transport	−0.0154	0.113	0.0251	1.11	1.87	80
				1.18	2.16	80
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Malt Hopper	0.0364	0.367	0.0822	1.89	3.35	79
Real				1.19	3.4	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Millstar	−0.0245	0.236	.0525	0.463	1.17	80
				0.412	1.24	80
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Mashtun Real	−0.0276	0.475	0.106	1.13	3.4	79
				2.38	3.23	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Lauterstar Real	0.00194	0.167	0.0375	2.16	3.13	79
				2.16	3	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Prerun Tank	0.00757	0.134	0.03	1.76	2.5	79
Real				1.1	2.59	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Wort Heater	−0.00141	0.0466	0.0104	0.327	0.612	79
Real				0.342	0.618	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Wort Kettle	0.0251	0.151	0.0338	1.52	2.36	79
Real				1.67	1.9	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT HOP Dosage	−0.00242	0.108	0.0243	0.391	1.61	79
				0.409	1.5	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Whirlpool	0.0468	0.351	0.0786	1.38	3.07	79
				1.35	1.79	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Wort Cooler	−0.0276	0.144	0.0323	1.23	2.09	79
				1.29	2.06	79
Fail to reject H0 => Means are Equal at 0.05 Level						
ROT Trub Tank	0.0157	0.917	0.214	0.152	3.38	73
				1.15	3.23	73
Fail to reject H0 => Means are Equal at 0.05 Level						

The calculated KPIs of the system via the proposed real-time systems modelling were compared with the historical measurements of the system performance data. Figure 8 shows the results of the comparisons. The vertical lines on the graph represent the range of the historical data and the points are calculated for OEEs using the real-time simulation results. The calculated OEE are well within the known historical measurements and encouraging (see Figure 9).

Some of the interesting observations with regard to the the production process performance can be summarised as:

- The 'Lauterstar' is running slower than the theoretical value, whereas the 'Prerun Tank' shows an acceptable RE but a low OE. Therefore, the low RE in the 'Lauterstar' may be affecting the performance of both UPPs Mashtun and Prerun Tank (Figure 10).
- The productivity losses in the Mashtun can be attributed to the RE factor. It can be concluded that the processing time in Mashtun and Lauterstar have significant impact on the production throughput.
- The efficiency losses in Mashtun can be attributed to the faulty step times in the recipe, delayed interventions of the operators during the process and/or losses occurred in the 'Lauterstar'.
- LA of 1.0 indicates that there were not failures during the simulation period (Figure 11). Focusing on the efficiency of production quality (LPQP), the efficiency losses can be attributed to Mashtun cycle time (4.55 h). Therefore, by minimising the bottleneck in the Mashtun and Lauterstar, the OLE will increase.

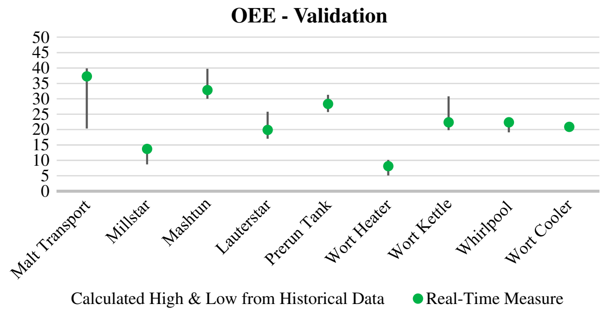

Figure 8. The validation of measured OEEs for a given type of product.

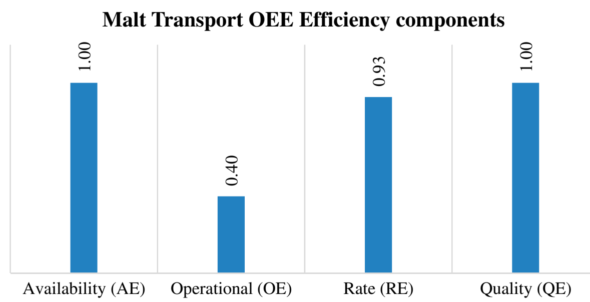

Figure 9. OEE efficiency components for the malt transport resource.

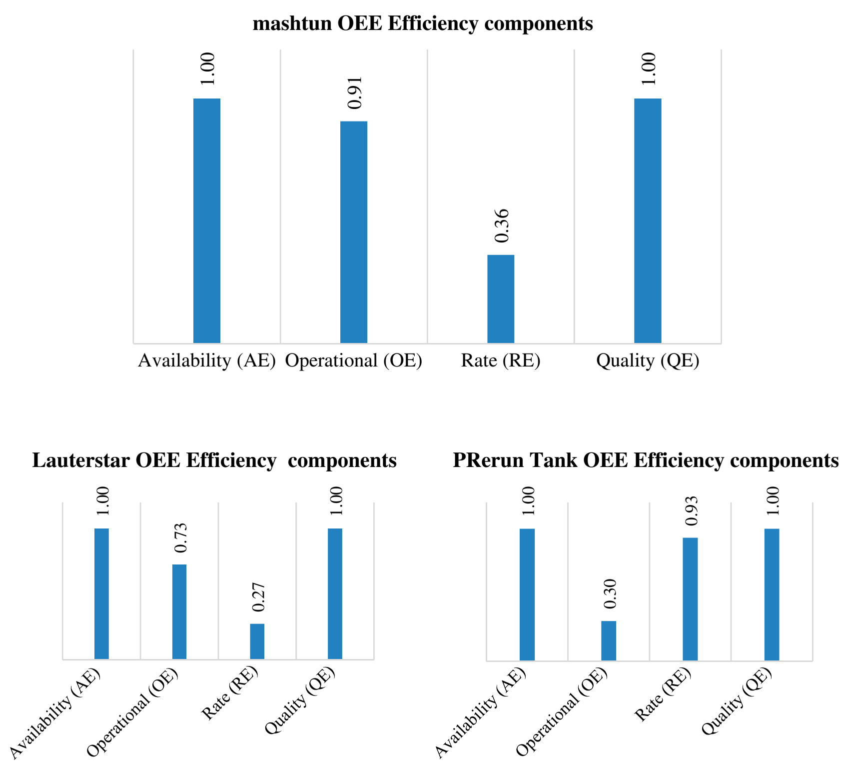

Figure 10. OEE of the Lauterstar, Prerun Tank and the Mashtun.

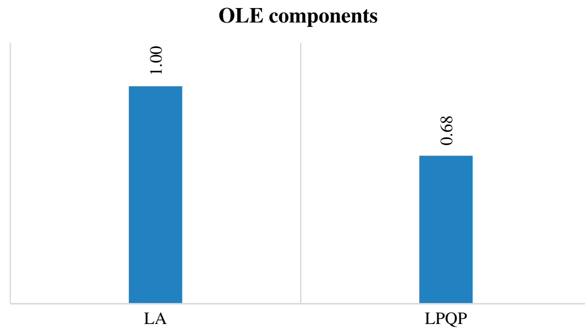

Figure 11. OLE for the brewhouse production line.

Each identified source of low effectiveness can thus be analysed and remedial actions suggested. The fast-forward *What if* scenario feature of the solution provided would allow the testing of initiatives at no cost or disturbance to the actual line.

5. Conclusions

Building a solution that is capable of automatically translating shop-floor engineering data into high-level management and decision-making information was the key motivation for this work. The design and development of a repeatable and scalable real-time information system that is enhanced with a predictive *what-if* scenario generator has been the outcome. The tool developed can now be used to answer the two questions posed by the brewery management: 'Could breweries decrease the cost per hectolitre of production whilst maximising resource utilisation and improve OEE and OLE at the same time?' and 'How can we be confident about the information we have and the decisions we make?'

Given the ability to visualise the losses and gains of control interference/non-interference more accurately, the cost of production can be reduced whilst resource utilisation reaches a balance (adjustment of capacity). Hidden capacity and capabilities have been identified that can now be utilised for improving OEE and OLE. Through predictive analysis validated and verified by statistical and analytical means action plans can be devised to reduce the gap between expected productivity and the actual productivity. The proactive line management allows better adjustments to the variations in raw material, which we found to be one of the major causes for production delay and interference with best production control settings.

The results of the look ahead 'what-if-scenarios' shown to be accurate estimation of the system state, paving the way for line managers and engineers to intervene with the process control if required. The limited run of 20-h live run of the solution was due to the software being at research and development stage, efforts are now underway to integrate the solution with actual control system of the plant in the form of a professional embedded solution.

Disclosure statement

No potential conflict of interest was reported by the authors.

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