The Development of Assessment and Control Systems for the Brewery

Based on Real-Time Measurement of Biological Parameters and Expert System Technology

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ABSTRACT

The use of sophisticated analytical techniques to monitor quality and process control in breweries is well established. High-level parameters such as pH, gravity, turbidity, and conductivity are monitored for process management.

Measurement of biological parameters, such as yeast vitality, functional protein distribution and polyphenol profiles, may allow more responsive assessment and control of the brewing process and product quality.

Computational intelligence technology provides mechanisms by which human expertise and learning capacity can be embedded and implemented to solve problems, provide assessment of process from input data and provide intelligent control.

This paper summarizes the investigation into, and articulation of, the ideas of real-time measurement of biological parameters and computational intelligence system technology applied to the brewery.

Keywords: computational intelligence, artificial intelligence, expert system, biosensors, intelligent control

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SINTÉSIS

El uso de técnicas analíticas sofisticadas para controlar la calidad y el proceso de control en las cervecerías está bien establecido. Los parámetros de alto nivel tales como pH, gravedad, turbiedad y conductividad son controlados para el proceso de administración.

La medida de parámetros biológicos, tales como la viabilidad de la levadura, la distribución de proteína funcional y los perfiles de los polifenoles, podrían permitir una evaluación y control, mas sensible del proceso de la elaboración de la cerveza y la calidad del producto.

La tecnología de inteligencia computacional provee mecanismos por los cuales la habilidad humana y la capacidad de aprendizaje pueden ser empotrados e implementados para solucionar problemas, para proveer una evaluación del proceso de la captura de datos y proveer un control inteligente.

Este documento resume la investigación y articulación de ideas de la medida en tiempo real de parámetros biológicos y de la tecnología de sistema de inteligencia computacional aplicada a la cervecería.

INTRODUCTION

There are common issues emerging that affect most food and beverage manufacturers. These include: the rationalisation of human resources, the appreciation of and increasingly sophisticated nature of automation and sensing; and the management of knowledge and technical skills. We are developing a concept which couples the capture of knowledge and experience with the application of intelligent computation to address some of these concerns. This paper addresses the use of automation and computational intelligence in the brewery, and the development of sensor technology, particularly biosensor technology for these
powerful systems. These two components of automated assessment and control are usually not discussed together.

**AUTOMATION**

Automated systems and expert systems in breweries have traditionally interacted with physical or chemical control points and parameters of the process (e.g., pressure, temperature, flow rate, pH). A plant process controller based on these types of parameters is inherently sub-optimal as these parameters are related to the process itself and are only indirectly linked to the wort or beer. The development of novel sensor technology should enable the development of advanced assessment and control systems which are capable of directly assessing biochemical parameters of the wort or beer. The integration of on-line biosensors within intelligent real-time assessment and control systems, should provide a much greater level of control from the research effort into artificial intelligence (AI). The four and parameters of the process (e.g., optimisation of resource usage, etc.), and the quality of the beer. Originally, automation was aimed at minimising the labour intensive operations. The introduction of the cylindro-conical fermenting tank, and the introduction of CIP systems are typical examples of labour saving innovations. [351]

Very early control systems consisted of hard-wired switches and contactors. The introduction of microprocessors and micro-controllers offered a substantial improvement over hard-wired systems, as process alterations could be made in software which was simpler and less costly.

The PLC provided a significant breakthrough. Its companion, ladder logic programming, was higher level and more focussed towards process control than were the lower level languages that were often used to write programs for microcontrollers. The PLC offered a simpler input/output (I/O) interface, robust modular architecture, and a more standardised system. (Footnote: Although many different PLC standards existed, each brand had a so called standard. In contrast with the earlier ‘custom designed’ microcontrollers which, usually had unique characteristics.)

PLC operations often used some form of embedded graphical screen display. These human-machine interfaces (HMI), meant the operator had convenient control of the PLC, although they had limited functionality. The introduction of supervisory control and data acquisition (SCADA) systems substantially improved operator interaction with the plant control systems. The SCADA delivers such things as: live plant data to custom built graphical displays over computer networks, the display of plant operation on web sites, the logging of sensor data for future reference, supervisory control of the PLC, recipe management and batch control.

SCADA systems offer some impressive tools for information management and representation, but fall short in the area of intelligent automation of plant processes. They provide operators with useful information about the process but they are not designed to make high level decisions. They still depend on operator interaction to run the process equipment.

**INTELLIGENT SYSTEMS**

An intelligent system may be regarded as a culmination of a number of computationally intelligent methodologies arising from the research effort into artificial intelligence (AI). The four most pertinent of these are expert systems, fuzzy logic, neural networks and evolutionary computing. Expert systems are knowledge-based reasoning systems used for diagnosis, design and control. Fuzzy logic can be regarded as an extension to conventional binary crisp logic and provides a means of computing with words. This enables system designs to embed reasoning to mimick that of humans. Neural networks comprise networks of artificial non-linear neurons, similar in concept to biological neurons. They can perform non-linear operations and are capable of learning and self-organisation. Evolutionary computing encompasses genetic algorithms and is based on mechanisms of natural evolution such as biological genetics and natural selection. [19] These systems are therefore able to evolve, adapt and self-modify, and are often used in advanced optimisation applications.

Individually, each method has advantages and disadvantages. Hybrid systems provide means of overcoming these disadvantages. For example, neuro-fuzzy systems allow fuzzy systems to learn and self-organise, and yet retain the ability to compute with words. In general terms, an intelligent system is therefore best realised as a hybridisation of the four computationally intelligent techniques discussed (as illustrated in figure 1) [20]. This gives greater scope in the methodologies and capabilities available to cope with the relatively complex and diverse decision making requirements inherent in brewing automation.

![FIGURE 1](image-url)

Intelligent systems may be best realised through hybridisation of artificial intelligence borne computation techniques such as expert systems (ES), neural networks (NN), fuzzy logic (FL) and evolutionary computing (EC).

There are significant differences between the purpose and functionality of SCADA systems and on-line expert systems or intelligent systems. SCADA systems deal primarily with information and information management. They can present live data to HMI screens anywhere on a network in real-time (ie. information accessibility). They have the ability to log data, record information and can be configured to automatically generate reports. They can also provide high level supervisory control functions through the use of pre-programmed control sequences. In comparison, intelligent systems deal with knowledge and the application of knowledge. Knowledge can be derived directly from the process using various machine learning techniques, or the knowledge from human experts can be implemented as rule-
based expert systems. Intelligent systems do not simply process information. Embedded intelligence enables these systems to act on the information. Although there is no hard-limit to the potential capability of an intelligent system, the required development effort increases considerably with the required functionality.

**TABLE 1**

<table>
<thead>
<tr>
<th>Year</th>
<th>Milestone</th>
</tr>
</thead>
<tbody>
<tr>
<td>1900's</td>
<td>(Early 1900's), Lukasiewics developed the maths required to operate the 'ternary' or three value logic system.</td>
</tr>
<tr>
<td>1937</td>
<td>Max Black defined the first fuzzy set [8]</td>
</tr>
<tr>
<td>1943</td>
<td>McCulloch and Pitts propose neural-network architectures for intelligence [33]</td>
</tr>
<tr>
<td>1950's</td>
<td>Origins of evolutionary computing (Bremermann, Friedberg, Box) [6]</td>
</tr>
<tr>
<td>1955</td>
<td>Newell, Shaw, and Simon develop ‘IPL-11’, first AI language [33]</td>
</tr>
<tr>
<td>1956</td>
<td>Newell, Shaw, and Simon create “The Logic Theorist”, solves maths problems [33]</td>
</tr>
<tr>
<td>1956</td>
<td>Ulam develops “MANIAC I”, the first chess program to beat a human being [33]</td>
</tr>
<tr>
<td>1958</td>
<td>LISP AI programming language (McCarthy) [22]</td>
</tr>
<tr>
<td>1962</td>
<td>Genetic algorithms were introduced (Holland) [6]</td>
</tr>
<tr>
<td>1962</td>
<td>First commercial industrial robots [33]</td>
</tr>
<tr>
<td>1965</td>
<td>Lotfi Zadeh introduced the concepts of fuzzy logic and fuzzy systems [65]</td>
</tr>
<tr>
<td>1970's</td>
<td>Fundamental work on evolutionary computing (including genetic algorithms) served to overcome initial computing and methodology limitations to bring these techniques to the wider community (Holland, Rechenberg, Schwefel, Fogel) [6]</td>
</tr>
<tr>
<td>1970</td>
<td>Work begins on PROLOG AI programming language (Colmerauer, Roussel, et al.) [22]</td>
</tr>
<tr>
<td>1973</td>
<td>Lotfi Zadeh introduced the concept of the <em>linguistic variable</em>, which enabled the computation and classification of variables using words instead of being only restricted to numbers. [66]</td>
</tr>
<tr>
<td>1977</td>
<td>One of the first successful commercial applications of fuzzy logic. (A fuzzy logic controlled cement kiln run by the F. L. Smidth Corp. in Denmark). [84]</td>
</tr>
<tr>
<td>1977</td>
<td>MYCIN, a program for diagnosing bacterial infections (Shortliffe, et al.) [22]</td>
</tr>
<tr>
<td>1979</td>
<td>CRYsalis, a program for determining protein structure (Englemore and Terry) [43]</td>
</tr>
<tr>
<td>1980</td>
<td>Expert systems up to 1000 rules [33]</td>
</tr>
<tr>
<td>1982</td>
<td>IBC PC [33]</td>
</tr>
<tr>
<td>1986</td>
<td>AI industry revenue now $1,000,000,000 [33]</td>
</tr>
<tr>
<td>1993</td>
<td>Establishment of the journal <em>IEEE Transactions on Fuzzy Systems</em>, indicating wide spread acceptance of the field in the western world.</td>
</tr>
</tbody>
</table>

Some of the more significant milestones that have been achieved, and some significant applications that have resulted, during the progression and development of the field of intelligent computing, are given in table 1.

There are a number of commercially available tools for developing intelligent systems. These tools/systems are usually categorised as either off-line or on-line systems. The off-line systems are typically stand-alone computer applications which are often used for diagnostic or predictive purposes. The on-line systems are usually more sophisticated as they must incorporate the connectivity required for communicating with sensors, actuators, PLCs and control equipment. Due to the inherent time demands associated with the on-line control of processes, such intelligent systems must be real-time systems. They must be able to receive data from the on-line sensors, process the information with intelligent computing algorithms, and then deliver a response to the system, within a time period considered to be real-time for the given process. There are a number of commercial intelligent system development environments available as illustrated in table 2.

**TABLE 2**

<table>
<thead>
<tr>
<th>AI/Intelligent computing development platform</th>
<th>Company contact details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogsys</td>
<td>Cogsys Ltd. 26-28 Leslie Hough Way, Salford M6 6AJ UK. <a href="http://www.cogsys.co.uk">http://www.cogsys.co.uk</a></td>
</tr>
<tr>
<td>Connoisseur</td>
<td>Predictive Control Ltd. Richmond House, Gadbrook Business Centre, Northwich, Cheshire CW 7TN <a href="http://www.predictive.co.uk">http://www.predictive.co.uk</a></td>
</tr>
<tr>
<td>G2</td>
<td>Gensym Corporation, 125 Cambridge Park Drive, Cambridge, MA 02140 USA <a href="http://www.gensym.com">http://www.gensym.com</a></td>
</tr>
<tr>
<td>MatrixX</td>
<td>WindRiver Systems Inc. 201 Moffett Park Drive, Sunnyvale, CA 94089-1322 <a href="http://www.windriver.com">http://www.windriver.com</a></td>
</tr>
<tr>
<td>RTWorks</td>
<td>Talarian Corporation <a href="http://www.talarian.com">http://www.talarian.com</a></td>
</tr>
</tbody>
</table>

We have selected the G2 intelligent operations system as an R&D tool for assessment and control of particular brewery operations, some of which are described in this paper.
The Intelligent Brewery

The intelligent brewery is an overarching concept using a network of interacting intelligent systems for data acquisition, assessment, interpretation, decision support and control, to provide efficiency savings and to assure consistent quality of product. These intelligent systems are based on quantitative information, rules-of-thumb and tacit knowledge. The system ideally captures and retains intellectual capital.

Other food industries have also used intelligent systems to improve their processes. The Campbell Soup company applied these systems to hydrostatic sterilizer decision making and control in the 1980’s. A rule-base containing over 150 rules, encapsulated over 30 years of tacit knowledge within the company. The system provided trouble shooting capability, and was subsequently expanded to include quality and safety assurance. The system could decide whether faults had the potential to affect quality, and then subsequently whether product should be released to the market.

In the corn industry, a prototype fuzzy logic expert system was developed to control corn breakage during the drying process. This system included quantitative data on predicted levels of breakage in response to drying regimes, as well as the tacit knowledge or experiential knowledge of experts in the field and in the company.

A notable and widely publicised application is Nabisco’s implementation of Gensym’s G2 intelligent system technology for advanced control of their baked biscuit processes. Nabisco have reported that the G2 installation, which manages the baking process through simple input entries (biscuit dimensions, colour, water content and weight), has significantly increased plant efficiency and almost eliminated product returns.

Aarts et al described an expert system for use in enzyme production control. A hierarchical rule and frame-based expert system was used for a glucoamylase production process. This was built to be an on-line system so as to provide real-time data that could be used to predict faults, and then to provide diagnosis and apply corrections. A refinement was applied to on-line diagnosis and control for a lactic acid production process. This used an expert system rule-base to determine the progress and outcomes of a fermentation after input evaluation and inference. This system could provide dialogue for the operators to both assist with their judgements, and to improve their understanding of the complex operational system.

A number of similar systems were reported for microbial cultivation, real-time fermentation control, cell status during bioreactor fermentations, and fermentation management. For baker’s yeast production, the optimal process state is based on yeast yield and dissolved oxygen concentration. Sterbacek and Votrubu developed an expert system to analyse and control the production strategy for a commercial 500HL bioreactor.

There have also been some intelligent systems developed for the brewing industry. Bull et al developed an expert system for malt allocation. However it is the fermentation process which has attracted the most interest. Yorke et al have developed a real-time expert system for fermentation. The learning and corresponding predictive abilities of neural networks have made them a popular basis for fermentation intelligent systems.

The application of fuzzy systems to yeast behaviour during fermentation has been studied by Vassileva et al. Postlethwaite developed a fuzzy state estimation system for fed-batch fermentation. Venkateswarlu experimented with varying fuzzy system rule-bases for modeling and control of batch beer fermentation. An interesting three stage fuzzy system was developed by Whitnell et al. The first stage was a four-input single-output fuzzy module which used pitch rate, total pitched volume, viability, and average conversion temperature in the brewhouse to provide an initial estimate of the fermentation time. The second stage was a two-input single-output module which used pH and specific gravity to predict the level of vicinal diketone (VDK). The third stage was also a two-input single-output module which used the outputs of the first two stages (ie. initial prediction of fermentation time, and the predicted level of VDK respectively), to provide an updated prediction of the fermentation time.

There has also been some interest in the application of hybrid systems to the brewing industry. Teissier et al developed a hybrid neural network - ‘linear correlation model’ based system for state prediction during yeast production in wine and Simutis et al have investigated the use of hybrid neuro-fuzzy systems for state estimation and prediction during the fermentation process.

Kashihara et al described an expert system for the control of beer fermentation using a pH input as one of the key input elements. The system was based on the Gensym G2 development tool. It has also been reported that Eli Lilley is using an expert system to assess respiratory events during fermentations to provide expert assistance to the operators. Simutis et al have developed an expert system for planning the mashing temperature process. More recently, this work was extended to a fuzzy case-based reasoning system for mashing in brewery applications and for rye bread baking.

The literature shows that machine intelligence can be enhanced by intelligent system technology. The development of intelligent systems based on biological data inputs such as protein concentration, enzyme activity, polyphenol oxidation states, volatile production, the activity of specific metabolic pathways, has the potential to expand the application of expert systems. The development of biosensors and their miniaturisation and mass production should provide the opportunity for this development.

Technical Framework

We have proposed the plant-wide ‘virtual brewer’ intelligent system concept. It has a hierarchical structure which is comprised of a series of expert nodes (enodes) (depicted in figure 2). Expert physical nodes interact directly with individual sensors and process control systems, and are referred to as $P$-enodes. Their function is highly localised. An intermediate array of $l$-nodes is used as an expert system overlay for major processing stages such as the wort complex, or fermentation. These nodes are responsible for integrating information to and from the respective $P$-enodes and also for interacting with the broad overlaying super expert node, referred to as the $S$-enode.

An array of quality expert nodes ($Q$-enodes) provide the necessary connectivity and assessment capabilities based on quality parameters. They will evaluate the product at key stages during the process to determine/predict final beer quality in
terms of sensory and physical properties such as flavour, foam, mouth-feel, colour, bitterness, volatiles and haze. The development of Q-enodes relies on real-time measurement of biological parameters.

The Q-enode receives inputs from on-line (bio)sensors from relevant parts of the process. The Q-enode interacts with a real-time database, stores and obtains access to historical information as required, and can perform a number of intelligent operations using a series of embedded expert systems (as depicted in figure 3). The Q-enode also requires information regarding the target specifications of the current brew. The outcomes of the Q-enode are linked into the system through the S-enode.

Q-enodes depend on the acquisition of data in real-time to make assessment and processing decisions. In figure 2, one of the Q-enodes refers to haze, that is physical stability. Reversible and permanent haze are produced by reactions

**FIGURE 2**
Structure of the intelligent brewery. A hierarchical structure has been used for the intelligent system, with modular sub-systems being allocated to specific component functions. Four types of expert-nodes are shown: P-enodes deal directly with the operation of individual pieces of process equipment, I-enodes deal with an entire area of the process, Q-enodes deal with particular quality issues that are related to the final beer product (and rely on sensory input from all stages of the brewing process), the S-enode is the overarching intelligent system that co-ordinates all other expert nodes.

**FIGURE 3**
The Q-enode receives inputs from on-line (bio)sensors from relevant parts of the process. The Q-enode can interact with corporate databases and can perform a number of intelligent operations using a series of embedded intelligent systems, all in real-time.
between haze active proteins and polyphenols. Beer may be stabilised by removing polyphenols and acidic proteins with polyvinylpyrrolidone and silica gel respectively. The Q-enode that is dedicated to haze analysis, would constantly monitor haze related parameters in real-time. Any significant variations of these parameters would be reported to the S-enode.

The S-enode would then identify the I-enodes that are affected by the situation, and the I-enodes that are able to rectify the situation. The I-enodes would in-turn direct the relevant P-enodes to take the required action (ie. adjust storage temperature or time, PVPP or Silica Gel dosage rates). The interaction between the various types of enodes and how they manage the process, is shown in figure 4.

The intelligent system interacts with existing plant PLC and control equipment. For instance, Gensym’s G2 software system can be coupled to existing SCADA systems and PLC’s, as shown in figure 5. It can also be linked to corporate databases and data concentrators.

**PROGRESS**

We started with the premise that sophisticated sensor technology will become robust and cheap in the near future. Machine intelligence and sensor developments for process assessment and control, simulation and education purposes, and for capturing the company’s tacit knowledge have been examined. Progress at Carlton & United Breweries (CUB) has been made on a number of fronts and can be depicted within the context of the technical framework as shown in figure 6.

These developments have been mainly within the P-enodes and Q-enodes of the hierarchical structure, although some I-enode progress has also been made. One development is an intelligent system for controlling beer filtration.[13] Diatomaceous earth (DE) filtration removes yeast cells, chill haze and particles from storage beer. DE is added to the beer prior to filtration. Green beer generally varies in solids content and composition. Typically, DE is overdosed to compensate for any unforeseen large changes in the incoming feed beer quality. A three-input, single-output fuzzy logic controller embeds expert knowledge and experience of the process in the form of IF-THEN rules, as illustrated in figure 7.

The DE fuzzy control system (shown in figure 8) derives the filter differential pressure change and the differential pressure change trend from the filter differential pressure. Coupled with the beer inlet turbidity, the fuzzy controller calculates the dosing pump speed using the embedded fuzzy rules. It is important to distinguish this action from a conventional expert system since the rules in the fuzzy controller are acting on fuzzy variables, not crisp variables. This system has undergone plant trials and optimises DE consumption, leading to consistent beer quality and increased filter-run duration. [13,40]

Typical plant data from a trial run is shown in figure 9. The system was used to control body feed dosing of beer for filtration by an autojet filter. Differential pressure, change in differential pressure, the trend in the change of differential pressure, inlet-turbidity and recommended dose change are plotted. In the data excerpt shown, the change in differential pressure was low (ie. < 30kPa/hr), therefore the controller recommended that the DE dosing be reduced to increase the kPa/hr value towards the experimental optimum of 30kPa/hr. This mode of operation alone resulted in a significant saving of DE. In this example the turbidity of the feed was low, hence the controller was making decisions primarily based on the change in differential pressure.

Another P-enode development is an intelligent system that estimates the stand-time of the mashing process; that is, the time required to extract and digest the starch to the appropriate ratio.
Some work has commenced on numerous components within the distributed virtual brewer, including biosensor analysis and intelligent system development.

**FIGURE 6**

Architecture of the fuzzy controller for DE filtration: The relation between the input and output variables are shown relative to an example rule-base. The expert knowledge has been implemented in the form of ‘IF-THEN’ rules. As the observable and controllable parameters of the filtration system are ‘crisp’ (non-fuzzy) values, the fuzzy system must perform domain transformations in order to interact with these values. The first of these transformations is commonly known as fuzzification, and is the process through which the crisp input parameters are converted into their fuzzy equivalents. The second domain transformation (defuzzification) occurs at the output of the fuzzy system, where the fuzzy output of the rule inference processor must be converted into its equivalent crisp value, (as a crisp/numerical value is required to control the dosing pump).
Intelligent control of DE based filtration using fuzzy logic embeds expert knowledge of the process within the fuzzy rule set. The dosing pump is controlled by the fuzzy controller taking main-line turbidity, filter pressure differential and the corresponding trend, as input variables.

The bodyfeed controller manages injection of diatomaceous earth into the beer prior to filtration. [40]. The incoming turbidity (ppm) has remained reasonably low throughout this portion of the filter run and hence (in this case) has had very little influence on the control of the bodyfeed dosing rate. Under conditions of low turbidity, the controller will modulate the bodyfeed dosing rate, so as to maintain a rise in differential pressure of around 30kPa/hr.
of fermentable and non-fermentable sugars. This system will replace the present practice whereby an operator estimates the stand-time required for each brew. For most breweries, seasonal and varietal changes in malt characteristics mean that the mashing-in process requires constant revision for each brew. The intelligent mash stand-time prediction system eliminates the subjectiveness of the process, maintains repeatability and offers a pathway towards automation in the brewhouse.

Some work has also commenced on the fermentation I-enode. It contains several modules, some of which are shown in figure 10.

![Fermentation I-enode](image)

**FIGURE 10**

The fermentation I-enode manages all aspects of the fermentation process, including the fermentation itself, yeast propagation and harvest and carbon dioxide recovery. It is also responsible for interfacing the S-enode to the individual P-nodes, facilitating the implementation of any high level requirements determined by the S-enode.

The internal modules of the fermentation I-enode deal with yeast metabolism, CO₂ recovery, yeast propagation and yeast “cropping and recovery”. Despite this complexity, there is a large amount of available quantitative data to describe these processes. The effects of temperature, pressure and nutrient concentration, for instance, on the yeast metabolism of brewing strains are reasonably well known, although not necessarily well understood. However, the predictive power of the knowledge base, in conjunction with the available tacit knowledge of the process, gives brewers a strong predictive capability. This information can be used to develop the knowledge trees of expert systems. As there are multiple variables that impact on the outcome of any one fermentation parameter, the dimensionality of an intelligent system for fermentation is quite high. Hence an intelligent system that was based on analytical information and machine learning techniques would require massive amounts of data. An alternative approach that is more approximate but considerably more practical and expedient, is to base the intelligent system on tacit knowledge. The intelligent system for fermentation has been partitioned into a series of smaller independent modules as illustrated in figure 11.

![Intelligent System for Fermentation](image)

**FIGURE 11**

The intelligent system that governs the fermentation biochemistry can be partitioned into a series of modular units. This breakdown of the complicated multiple-input multiple-output (MIMO) module into a series of multiple-input single-output modules (MISO), simplifies the design and testing of the intelligent system and enables multiple modules to be developed simultaneously and independently.

The hydrogen sulphide module (as illustrated in figure 12), was based on the tacit knowledge of human experts in the field. This enabled the extrapolation of an approximate control surface over the entire range of the variables.

![Hydrogen Sulphide Module](image)

**FIGURE 12**

The hydrogen sulphide module is a three-input single-output module. A control surface is shown, illustrating the relation between pitching-rate and oxygen, and their influence on the level of hydrogen sulphide that is produced. Being a four dimensional system, the displayed control surface is only valid for a single temperature.
The fermentation 1-enode may receive information about the progress of fermentations from gravity changes, ethanol and CO₂ formation and from the production of volatile compounds. If the data indicated that a fermentation was trending out of specification, remedial action could be applied by, for example, alterations to temperature, agitation and cation balance. Up-stream 1-enodes would be alerted of the problem so that additional action could be considered to validate prior processes and ensure the quality of product being sent forward. In addition, the fermentation 1-enode would undertake a risk assessment on quality parameters such as foam stability (proteins), protease activity, flavour production etc, and take appropriate production scheduling decisions to minimise impact on the plant. Some inputs would be accumulated on-line, other information would be obtained through communication with the operator, and additional data could be collated by at-line analysis or off-line laboratory work if required. Similarly, other issues such as yeast vitality and viability management would be handled by the fermentation 1-enode.

Biosensors

The intelligent systems described require inputs for assessment and prediction. Some of these are provided by existing sensors for pH, temperature, gravity, O₂, CO₂, turbidity and so on. However, if the system is to describe the biological status of the product in transit, it needs information about protein, carbohydrate, polyphenols, enzymes and flavour and taste components during the process. The authors believe that this will be possible within a relatively short time-frame as a result of the new sensor technology that is now emerging. A selection of these developments is described in the following section. Some technologies, including near infrared (NIR) analysis, have not been included because it is conjectured that precise analytical information rather than data predictions provide information that will in the long term be of greater value for intelligent systems.

Amphometric

Amphometric biosensors were originally used to describe analytical tools that combined a biochemical recognition component with a physical transducer (αβ) (figure 13).

The biological recognition component could be an enzyme, a protein, an antibody, a microbe or DNA [26]. The transducer converts the biological event-recognition reaction to a measurable signal which can be sequentially recorded. The field has largely been dominated by enzyme based biosensors [55] and well known examples are the disposable enzyme electrodes that are used for blood glucose measurement [56]. These first-generation amphometric enzyme sensors use glucose oxidase to oxidize glucose with oxygen, which is detected by a pO₂ electrode (see equations below) [59]. The enzyme in solution was retained at the sequence above with an alternative electron carrier such as a quinone, ferrocene, a viologen or an organic conducting salt [26].

Second generation biosensors replaced the O₂ as a reactant in the sequence above with an alternative electron carrier such as a quinone, ferrocene, a viologen or an organic conducting salt [26]. Third generation electrodes immobilised both the enzymes and the electron carrier on the electrode surface [27]. Some polymers have redox properties, so they can ferry electrons and are suitable for direct chemical coupling to the enzyme (figure 14). The immobilised, reductive enzyme, GOX - FADH₂, transfers electrons to immobilised redox sites along the polymer to the electrode. The perceived benefits are greater stability, continuous measurements, and lower cost of production. Similar sensors for sarcosine, lactate, amino acids, triose phosphate, celllobiose and other sugars are reportedly under construction. Many others can also be produced for low molecular weight compounds using enzymes that have been identified for some time.

Fourth generation electrodes eliminate the enzyme by replacing it with polymers or molecules that mimic the catalytic site and provide a more stable but fast chemical pathway for amphometric sensing [24, 46].

While there are various synthetic small-molecules and polymer receptors for carbohydrate recognition and binding, very few are capable of transducing binding into an amphometric event. Chen et al [14], however, have prepared a polymer that binds glucose and instantly releases protons in proportion to the amount of glucose bound.
**MOLECULAR RECOGNITION**

There is an increasing number of reports describing biosensors that are capable of measuring biological molecules with accuracy at low concentration. Most of these sensors are based on biological recognition systems, such as the binding of an antibody with its particular antigen. Molecular recognition technologies are usually degenerate, meaning that there are often many ligands that can target different structured domains of the same analyte. In addition, the ligands can be designed to maximise stability under aggressive conditions. This will allow miniature sensors with multianalyte analytical capability to be developed to discriminate between very similar compounds. Ideally these systems should operate on-line, but even if at best they operate only as at-line systems, they will still allow the development and testing of intelligent systems to manage brewing quality and control.

**FLUORESCENCE**

The most common approach has been to couple a reporter group, such as a fluorophore to a protein which acts as the ligand for the analyte. The environment of the reporter group is altered by the binding event which provides a fluorophore response. Sensors have been developed for different metal ions, phosphate, maltose, glucose and cereal macromolecules and many of these can be used for real-time measurement. The maltose sensor uses an engineered maltose binding protein from *Escherichia coli* cells, which has fluorophores positioned where they experience environmental changes when maltose is bound to the protein. The same approach can be used with glucose and galactose binding proteins and phosphate binding protein. Metalloproteins show very selective binding and high affinity to zinc and calcium. Zinc fingers are small peptides, around 25 amino acids in length that selectively bind zinc with dissociation constants in the nM to pM range. The peptides unfold when Zn is removed. The Zn dependent folding can be followed by tracking the changes in the fluorescence of an attached reporter fluorophore.

**ION CHANNELS**

Cornell et al have developed a generic sensor technology which is based on membrane channel switches using an affinity reaction to open a gate or switch in a membrane. The sensor is based on the conductance of a population of molecular ion channels which is switched by a binding or recognition reaction, as illustrated in figure 16.
The ion channel receptor is based on a 2-site sandwich assay. A lipid bilayer contains tethered (lower) and free gramicidin. The free gramicidin is attached to active affinity groups. The dimeric gramicidin complex forms an ion channel (A). The target analyte has multiple sites for the active groups. Binding (B), uncouples the gramicidin channel, and disrupts the current, (C) \( C_m \) is the membrane capacitance, \( C_h \) is the Helmholtz capacitance at the gold surface; \( G_m \) is the conductance of the ion channel (after Cornel et al).

The ion channels form when two gramicidin molecules line up to form a conducting channel that spans the biosensor membrane.

This system has several advantages. Firstly, it is generic and can be tailored to target a wide range of analytes. Secondly, it produces an exceedingly high flux for individual events. It should also be possible to fabricate ion channel sensors in miniature and as assemblies of sensor arrays which will respond to a wide range of analytes. It has been suggested \(^{157}\) that the availability of antibody libraries for ligands, or a combination of synthetic receptors will allow the use of a diverse range of binding ligands to target an analyte. The “profile” response from these arrays could be interpreted by using a neural-network or neural-fuzzy approach in much the same way as described earlier, to produce a response capable of discriminating between similar molecules. The arrays therefore can be likened to an electronic version of a biological tongue, having multiple sites recognising different epitopes and providing shades of interpretation. These devices are suitable for affinity assays in medicine, the environment, food, monitoring, security, and defence. It should be possible to produce them cheaply and tailor them for specific markets including brewing.

**PLASMON RESONANCE**

Another technique based on molecular recognition uses plasmon membrane technology. **Biacore AB**, Sweden has developed a flow through sensor cell that uses plasmon resonance technology. Surface plasmon resonance (SPR) occurs when surface plasmon waves are excited at a metal-liquid interface. The interface or sensor surface forms one wall of a flow cell, and sample is injected over the surface at a known flow rate. Light is directed towards and reflected from the opposite side of the sensor wall. SPR reduces the reflected light intensity for a given angle and wave-length when molecules attach to the sensor surface (such as when proteins are captured by immobilised antibodies on the sensor, as illustrated in figure 17). Changes in the refractive index close to the wall occur, producing a change in the SPR signal (resonance units). A change in surface concentration of attached molecules by 1 picogram per square millimeter, would correspond to a signal change of 1 resonance unit (RU). The system works well for analytes that have high molecular weights. For smaller molecules, competitive sandwich reactions can be used to increase the mass attached to the sensor surface. The system is available as a small probe and as a flow through cell, and provides rapid at-line analysis. We have collaborated with the Biacore company in Australia to evaluate the technology’s suitability for analysing beer proteins.

**FIGURE 17**

Biacore technology is based on capture of analytes by affinity ligands. Analyte binds to the immobilised ligand and saturates the binding site. The Biacore plasmon resonance sensor responds in resonance units which increase in proportion to the mass of analyte bound. Regeneration of analyte-free ligand is performed with an alkali solution.
We have used this technology to determine specific proteins in beer, including the Z7 protein, and also to measure polyphenols. When the pAb (polyclonal antibody to the Z7 protein) was attached to the sensor surface, the antibody protein was bound to the sensor and exhibited saturation kinetics. The comparison between the Z7 antibody and the control is clearly illustrated by the sensorgram in (figure 18).

The upper trace shows the sensor’s response to the Z7 protein when the pAb antibody was attached to the sensor’s surface. The lower trace is that of the control, whose response was clearly at least an order of magnitude lower than that of the pAb antibody. The control sensor surface did not bind the protein. Regeneration of the polyclonal-Antibody pAb surface was achieved using phosphoric acid, which removed bound Z7 barley protein without affecting the activity of the immobilised surface. Competition studies showed that there was no non-specific binding to free carboxyl groups on the carboxymethyl dextran surface. Dose response studies showed that the technology could be used to predict the concentration of Z7 in wort and beer, over a reasonable concentration span and in real-time. This relation between the concentration of Z7 protein and the magnitude of the SPR signal, is depicted in (figure 19).

The degree of binding of Z7 protein to the surface antibody was not affected by changes in the carrier medium (eg. protein levels), but the kinetics of binding were sensitive to changes in the medium. Polyphenols can also be determined using a sandwich reaction technique, to amplify the surface binding phenomenon.

<figure>
<image>
<figcaption>FIGURE 19</figcaption>
Barley protein Z7 was estimated in dosed beer samples using the Biacore plasmon resonance technique. Resonance units (the measure of output), have been plotted against the concentration of authentic Z7.
</figure>

**OLFATORY MODELS**

The olfactory system of mammals has been used as a model for another group of sensors. On the one hand, the biological basis of the olfactory system could possibly be mimicked, which would be a formidable task. Alternatively, an electronic equivalent of the olfactory system can be developed using sensors based on metal oxides, conducting polymers, surface acoustic waves, gas chromatograph (GC), mass spectrometry and the light spectrum. Some of these technologies are traditionally visualised as large items of equipment, rather than as small and versatile sensor technology. However, small sensor devices that combine several discriminatory technologies are being developed. Miniature versions of the quartz microbalance are already part of the conventional electronic nose technologies. The microbalance is based on the fact that the resonance frequency of a spring is dampened when a mass is added to it. Capacitance changes occur when polymer coatings absorb molecules and can consequently be used as a sensor. The development of micro arrays will provide another dimension that incorporates these sensor systems as well as separation systems, on a microscale. The integrated systems should include sensors, actuators, electronics, fluids and optics. In these micro-systems, analytes passing through a micro-channel will be separated due to dissimilar solid mobile phase partitioning effects. Acoustic wave technology can be miniaturised to provide detection systems. The integrated sensor will therefore contain regions for concentration of analytes, channels for separation and arrays of sensors that will be equivalent to a micro-chemistry laboratory (figure 20). These systems hold out the utopian dream of cheap, independent sensing technology, with the limitations of conventional laboratory based analytical tasks largely eliminated.
phenomena for example), and a compartment for chemical­ly selective detection

A micro-biosensor which includes compartments for sample collection and concentration, separation (by partitioning

collection and concentration, Separation (b y partitioning
cisers and phospholipids. These sensors can be used in
tongue. Olfactory systems for example, capture target odours

Nature has theref ore provided a model showing how nose tech­
nology can be transferred to wet chemi stry sensing. Sato et al [45]
with membrane bound receptors to produce cascade ef f ects.

"real-time" information on process, quality sensitive compounds and sensory quality, together with intelligent system technology, shows great potential in approaching this ideal.

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