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Towards a business and production engineering concept for individual beer brewing applying digitalization methodologies

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Abstract. Individualization is a common trend in many fields of production across the industries. Also in the food sector, significant changes can be observed. For many products, individual offerings towards the customer are meanwhile either mandatory or at least help to increase the sales and revenue. Somehow, individual product design and production contradicts scaling effects, which are especially important for food production. On the other hand, as digitalization is implemented in a fairly limited way in the food sector, currently great chances can be observed to build a unique selling proposition and consequently gain market share by implementing appropriate measures to enable a digital food factory. This is where the proposed idea comes into the game. The starting point is the idea to produce individually developed beer and ship it to the individual customer. The beer can be designed on a web page based on typical parameters, like beer type, bitterness, colour, or alcohol concentration. In an expert mode, individual beer creations may be thoughtful, allowing the creation of completely individual recipes (for sure, not guaranteeing the customer a perfect drinking experience). In any way, the data from the web page is directly fed to the brewing equipment in the brewing facility. There, using newly to be developed specialized machines, the individually ordered beer will be produced automatically. In this paper we discuss the individual challenges at each point in the production cycles and propose solutions to those.

Key words: digital factory, individual food production, smart manufacturing, gamification, industry 4.0.

INTRODUCTION

There are two trends, which also the food industry cannot withstand: automation of production (Thomas et al., 2017; Morgan & Haley, 2019; Schallmo, 2019; Sonnen, 2019) and individualization of products (Ettl et al., 2015; Neef et al., 2020). Customers request more and more individual products (e.g., cereals (mymuesli GmbH (2020), Zhou & He, 2019) or beer (Beer Engineer (2020)). In the context of competitiveness and efficiency, automation of production needs to be considered as well. The key question arising is: How to automate individual wishes? As long as the definition of the individual request is precise in the form of a formal recipe, this might be directly possible. In general, however, the description from the customer is imprecise and personally biased (Leckner et al., 2003; Kreye, 2018). Furthermore, the quality of raw material and the production processes underlay natural and statistical fluctuations. Therefore the food industry has a strong demand for approaches dealing with the question how to guarantee the satisfaction of the customer reliably and automated (Shewhart, 2012; Caroco et al., 2018). Developing (a) solution(s) to this problem is challenging, while the path to the solution marks significant milestones in the research field of food technology (Pramanik et al., 2018), as will be shown in the following. For illustrative purposes, we follow a specific real world example for immediate clarification of the argumentation chain, which is the beer brewing process alongside with a digitally transformed brew master involved in the process.

Basic Technological Challenges and Implementation Approaches

The first challenge related to individual beer brewing, for sure, is, to automate the beer production on small batches, e.g., 20–30 litres per brewing cycle. This amount is assumed to be a production quantity, which is possible to be sold to an individual customer within one single sales process. Beer Engineer (2020) use a procedure to create individual beers by creating cuvees from several base beers. However, a very limited amount of different beers can be created and – to be fair – the created beer is not really brewed individually. The customer can choose between Pils and Bock, each with two colour shades. For each of the types five grades of intensity of hops/bitterness and three/four levels of alcohol content and degree of carbonisation can be chosen only. Therefore, alternative approaches need to be developed, which allow micro quantities like 20–30 litres, to be brewed without noticeable manual supervision of the brewing process. For this purpose, newly to be developed brewing equipment needs to be installed. This mainly covers the mechanical setup in a first step.

The scheduling of a single brewing event will be organized by the smart factory on its own, potentially considering premium orders for quicker delivery. The smart production site itself will be completely automated with autonomous logistic infrastructure, secure full connectivity, and production data aware production cycles. This enables a fully remotely accessible real-time status monitoring and control of the production cycle. Any deviation, which can be captured by information technological means, will be detected. As the brewing site will be setup from scratch, early considerations of the latter will not lead to huge implementation efforts, like this would be the case for a retrofitting of an existing brewing site.

Along with the production, additional services to the customer will be derived from the anyway highly automated production site. The customer will be part of the production process, meaning the customer will receive automated feedback on its current process status of his product. Very exemplarily for a specific individual beer the inclusion of the customer could deliver the following information: order received, brewing process started, 1st settle time for sugar rest in progress, beer in maturation status. The authors are aware, that there are manifolds of different brewing approaches. The given customer output relates to only one of those many possibilities. As well, this may include: information about continuous ethanolic fermentation/breakdown of the extract, temperature profile, live pictures from brewing process.

The data provided to the customer will be accessible via a secured area on a web page or via a special app. Additionally, the order history along with personally to be added tasting notes of the customer tops the whole story of. The actual extend of usage may be activated on a payment model.

Summarized, the proposed approach may revolutionize the current view on brewing by allowing individualized brewing concepts, as a complete new setup of a brewery does not need to follow hardened process structures of established companies. First initiatives to implement an appropriate machinery are already under investigation at the University of Applied Sciences Upper Austria.

The idea combines a traditional industrial branch with modern technologies and modern business models. Especially this fact puts this research in a charming light. In future extensions, the running production site may be used for interdisciplinary educational purposes as well.

Advanced Technological Challenges

The aforementioned setup covers the automation of idealized process parameters, which can be reliably predicted, straight forward put in operation, and ideally tracked and controlled. However, problems that are more sophisticated pop up once the customers are getting involved as human beings and variations of the used raw material are considered as well. Obviously, fluctuations of quality and properties of per definition equal raw materials influence the appearance of the final product significantly. Examples include: grain and hops are natural products, therefore, every year the actual quality may vary depending on the environmental conditions. Grain, and the resulting malt, may contain more or less or different kinds of stark. Hop may be more or less aromatic and may differ in alpha acid, important for the degree of bitterness. As well, various companies can perform the procedure of malting differently, resulting in different malts from the potentially same grain unintentionally. This may lead to variations in colour and taste using the same recipe. This is not a complete list of potential issues but shall just give a first impression on common problems.

In current systems, a human brew master captures the raw material fluctuations. Applying his/her expertise and experience enables him/her to sustain product quality even in those conditions. In a highly automated production environment, also this brewing master needs to be digitalized, which marks the first extremely challenging field of research to be done. The task of gathering implicit knowledge from experts to automate certain processes is currently accomplished in several domains and often focusses on inspection and quality-preserving process tasks, i.e. OK vs. NOK checks (Puppe, 2012). For continuous production with small lot-sizes these approaches have to be extended to derive production, related parameters at the beginning of a production process (e.g. out of measurement data of raw materials).

Besides capturing the implicit knowledge from the brewing master, also the customers experience has to be involved. Customers are not professional in the field of consumption and therefore are limited in arguing using terminology and relevant parameters of the target field (in this case beer production). Consequently, customers typically use comparative terminology (e.g., should taste like …) or at least fuzzy linguistic terms (e.g., should be a bit bitter, should be very fruity) instead of hard parameters (e.g., IBU of 30 to uniquely define the bitterness of a beer). This is a well known fact within the food industry. The prove of customer satisfaction in this context is typically performed by a triangular test setup (Sinkinson, 2017; Gatchalian, 1999; TestTriangle, 2020; SSP, 2020). Traditionally, the translation of the customer voice and the food/beer production process is performed using manual polls and surveys processed by human beings. This, however, is inefficient and expensive (cost and time). Therefore, another part of this research involves the development of a translational model of the customers' demands towards food/beer production process terminology.

The next step is the translation of the hard facts derived from the customer requirements into a recipe, which works as instruction for the automated food production process. Traditionally, a specialist of the individual field of food production performs this step. As the whole process shall be automated, again an artificial instance for recipe derivation needs to be implemented. This procedure is closely linked to the digitalization of the brew master as mentioned before, while at this point traditional deterministic measures can be applied, simplifying the problem. As typically the (typical, usual) parameters of the raw materials and their individual contribution towards the final product are known, this task is easy to a certain extent, as long as the customer demands are within known limits. If the latter cannot be assumed, creative artificial instances have to be developed, which deliver useful recipes fulfilling the customers' demands autonomously. This is especially challenging and not yet well researched in the food production area. For better results, collective knowledge might be used, similar to the approach described above for the customer model.

The final problem to be solved in the process chain is the validation of the product quality with respect to the customer preferences. This step may be considered a feedback loop to crosscheck the measured parameters of the resulting product along the initial customer needs. Traditionally, the brew master, e.g., performs manual testing. Meanwhile, significant advances can be observed in that field, e.g., powered by the measurement equipment of Anton Paar (Paar, 2020). A good show case can be found in the Anton Paar Sudhaus (Sudhaus, 2020). Still, there is a significant need for manual checking and interaction, which inhibits highly automated brewing cycles. For high automation levels, all of those checks hav to be performed by a sensor-algorithm combination again involving the digitalization of human senses (Berna et al., 2010; Ciui et al., 2018; Galstyan et al., 2018; Khan et al., 2018; Fraunhofer, 2020). Electric noses and tongues are known (Haugen, 2001; Gorska-Horczyczak et al., 2016; Palmiro et al., 2017; Mohamed et al., 2018; Di Natale et al., 2000), while the processing of the data and the description of the perception is not trivial and not yet very well researched. As stated before, a mapping of the derived perception of the sensor-algorithm setup and the perception of the customer demands need to be performed. Additional difficulties are added to the objective nature of the sensor-algorithm setup perception versus the subjective nature of the customer perception description. Intelligent algorithms need to be integrated to automatically drive this part of the process.

Overall, the described research approach seems simple on first sight: trigger an automated production process based on customer requirements. However, as discussed before, hardly predictable difficulties are introduced by the nature of the problem due to

- Automatically to be considered and detected raw material quality fluctuations
- Automatically to be considered and detected process irregularities
- Transformation of human perception in hard production facts
- Transformation of hard production facts towards human perception
- Including cultural and local individual preferences and deviations of individual perception in the automation process.

Sub-fields of the research are partially investigated, while for major parts no relevant research results are published yet. For instance, the Campus of Senses (Fraunhofer, 2020) deals with the decryption of human perception alongside modelling this perception by processing data delivered by special sensors for human senses. It intends to digitally recreate human senses, especially the chemical senses of taste and smell. Research here is still at the very beginning. However, we believe our field of research based on this idea may be successful, as we do not need to exactly model human perception to match to the human brain, but to a less complex setup of machinery, the production equipment. Gathering results is very challenging, however, not impossible if drilling the problem down to its actual requirements.

MATERIALS AND METHODS

As described before, several technical challenges need to be mastered to implement the automated production approach described in the introduction. They might be categorized as mechanical, algorithmic, sensing technology, conceptual. Each of the categories are described in the following paragraphs.

Mechanical Setup

The basic mechanical setup for brewing equipment is well known. However, first, the equipment on the market is either large scale (500–2,000 + litres per brewing cycle) and semi-automated (Table 1) or it is small scale (20–50 litres) and basically non-automated. In an optimum case, the temperature ramps and rest times can be programmed. One example of highly automated small scale brewing equipment is the Brumas BrauEule III (Brumas, 2020), another the Brewie+ (Newity 2020). However, significant manual tasks have to be performed.

The main measures to take in this field are therefore as given in the following. A mechanical setup has to be developed, which allows including automation capability in the small-scale equipment already present in large-scale systems (transformation by scaling). Furthermore, new mechanical automation setups have to be developed, where the individual choice of grain, yeast, and hop is automatically chosen from a given portfolio and added as ingredient at the right point in time according to the recipe (new individualization equipment). Especially, the latter mentioned is needed to allow for automation of individual products being an important pillar of the whole concept.

Table 1. Degree of supported automation for large scale brewing

Supported	Not supported
temperature ramps	remove spent grain
grain adding	check cloudiness of to be cleared wort
water adding	removal of denaturized proteins after wort cooking
rest times	…
whirlpool	
…	

Sensing Technology

As mentioned in the previous section, some additional sensing technology needs to be included in the setup to allow for automation. Trivially, temperature sensors are needed to precisely and repeatedly enable defined sugar rests and temperature ramps given in the recipe.

Apart from that, it is very important to detect the cloudiness of the wort during the lautering process. At this point, an optical sensor including image processing is foreseen to be installed. While in comparable situations, product quality control by optical sensors is state of the art, for this specific task not many solutions can be found on the market (e.g., Mettler Toledo (Toledo 2020)). Additional sensors need to be considered for automatically measuring the alcohol and sugar concentration during the fermentation process. While the aforementioned is state of the art within the brewing industry, it is still challenging in the context of producing small batches of maximum 50 litres. This is important to forecast the perfect moment for bottling to achieve the right means of carbonisation. Finally, the individual colour scale of produced beer needs to be checked and aligned to the customer needs before shipping. A visual sensor including image processing again can perform this.

Pushing the overall research complexity further lets us end up with more complex sensors and tasks, which are currently under investigation and not yet available to the open market. This relates to sensors imitating the human's olfaction and degustation. Fraunhofer (2020) is currently performing research in that field in the context of the Campus of Senses. Enablers for this research is, e.g., the so called electronic nose (Di Natale et al., 2000; Haugen, 2001; Gorska-Horczyczak et al., 2016; Palmiro et al., 2017; Mohamed et al., 2018), which allows to digitalize the aforementioned human perceptions. For sure, this part of the research will need some more time before reaching maturity, but is included already now in the consideration of the scope of this research approach. Once the technology is ripe, it will give great top-on benefit on the overall setup.

Algorithmic Tasks

The algorithmic tasks, which have to be performed for sure, are closely related to the sensing devices. As it is the case with the sensor environment, some of the algorithms to be put in field application are state of the art and pure development work. This includes algorithms for temperature ramp implementations, mechanical manipulation tasks and any algorithm related to timing constraints. Those will not be covered in detail here.

Subsequently, there are algorithmic tasks to be performed, which are known to be manageable, however, need some training sequence of algorithms and transformation actions from related areas. This includes, e.g., image processing for cloudiness classification of cleared wort and colour determination of the wort. Furthermore, deriving optimal time-temperature curves for perfect fermentation of the product involving alcohol and rest sugar concentration sensors needs to be considered, but is state of the art.

When it comes to algorithms translating the human perception into a specific recipe including individual actions, the story is a different one. This is also valid to say for algorithms towards a digitalization of the brew master, involving a quality and status check of all raw materials and a cross check of the final product to the customer perception and wishes. The latter involves a third problem to be tackled, which involves the transformation of the digital perception of the electronic nose towards the customer (human) perception – what is needed to validate the product quality w.r.t. the desired result. This part will be the challenging one, which, however, is crucial to make the overall process highly automated. On top of this approach, geographical details about the individual human perception need to be considered as well. As described before, the same type of food and beer will trigger different naming conventions, perception levels, and preferences in different geographical locations. If there is, e.g., a region, where the mostly sold beer type tends to be 'fruity', then a slightly bitter beer might be described as ‘bitter’, while the same beer in a different region might be considered as ‘slightly bitter’. Including this, algorithms being capable of data analysis and using the intelligence of swarms (in this case distributed beer consumers) needs to be deal with as well. Concerning the more advanced algorithm application, we identified the following topics of deeper interest.

- **Human Perception to Hard Fact Conversion**
- **Hard Fact to Recipe Conversion**
- **Hard Fact to Human Perception Conversion**
- **Swarm Intelligence Inclusion**

Methodologies we have in mind to solve the problems are deep learning algorithms, fuzzy logic, or variability modelling. Today deep learning methods are broadly accepted for various problems, especially machine vision or voice recognition tasks. A general problem applying machine learning to real world problems is to gather enough valid training data. Therefore, often simulation models as well as statistical data is used to train models. Current research approaches focus on deriving taste and flavour out of online votings in recipe databases and food & nutrition webpages (Teng et al., 2012).

For the proposed approach of individual food production, i.e. individual beer brewing, it is currently hardly possible to gather enough training data to derive accurate recipes out of interviews or surveys from human people. Therefore, we would focus on Fuzzy logic which seems to be an adequate algorithmic approach, as it maps linguistic terms and variables (to be understood very well) into crisp output variables. Those variables represent the direct hard fact output, which can be used to derive the individual recipe. Input parameters might be: beer colour (light, medium, dark), alcohol concentration in %, fruitiness (low, medium, high), bitterness (low, medium, high). Fuzzy output variables might be: weight of hop of specific type (little, some, much), melanoidin malt for colouring (little, some, much). The crisp hard fact output produced by the algorithm may be: take 13 g of a specific hop and 359 g of melanoidin malt in your recipe. Fuzzy inputs and fuzzy outputs are merged by to be developed rules, achieving a deterministic control loop. The advantage is: the definition of input variables is intuitive for the customer while the hard fact output allows direct translation to a specific recipe. The developed rules will then be transformed into a feature model which enables a deterministic mapping of customer features to production assets such as different ingredients. Feature Models are originally used in the field of software engineering to model dependencies between different artefacts (i.e., Functions, Documentation, and Requirements (Kang et al., 1990)). Generally using feature models enables the creation of complete product family and a corresponding decision tree, which will be prompted to customer on the webpage during the configuration process (similar to online car configurators). This approach may also be adoptable to production assets as required for individual food production.

This sounds promising to the authors of this paper and therefore will be one scope of future research.

Optionally, additional information about the local preferences may be included. Knowing the location of the customer allows to sharpen the interpretation of his personal perception. This fact is important for the overall satisfaction of the customer need and needs to be included into the model. The model might be considered being a cognitive sensor deriving own (potentially, e.g., geographically varying) conclusions based on distributed swarm knowledge and adequate data analysis methodologies. Those are in general well known from social network business cases and can be adopted to the current need within this project.

Conceptual Tasks

The conceptual task involves social interaction with the customer. Gamification is a crucial essence, if the overall approach shall turn to be successful. Gamification can be understood as using game typical elements in a non-game-typical context, e.g., to motivate customers towards purchasing a product. Various approaches are used in the field, which mainly are based on creating some interaction base between the customer and the manufacturer. The customer shall experience some feeling of being entertained while getting involved in the product or being part of the product itself. That way, the frontiers between the actual (mainly physical) product and a virtual product (entertainment, service) disappear. In our context, this includes involving the consumer as observing person in the production process. Along with the (technical, deterministic) individualization processes, an additional ingredient comes into the game. The customer knows at each point during the production what the current status of his personal product is. This leads to more identification with the customer justifying are higher sales price from the customers' point of view. Therefore, both the costumers' individual choice of his personal product making and the involvement in the whole production process enables the customer to identify himself with the product he is going to purchase and therefore delivers a unique selling proposition.

RESULTS AND DISCUSSION

The main research work done so far is an analysis of the target market, the current technological state of the art of related fields, and identification of critical pieces in the overall puzzle of issues to be solved.

The outcome is, that the overall concept to be implemented needs to be covered in a heavily multi-disciplinary environment, involving social aspects, economical aspects, sensor and algorithm integration and development along with research in that field, mechanical development, and finally geographical information matching.

This list demonstrates the complexity of the overall project. The initial research described in this paper allows to justify on (none – little – highly) critical issues which need to be targeted.

As highly critical issues we have identified the multi-stage interface between customer wishes, customer wish articulation and transformation towards hard digital facts, validation of the real output product towards the initial customer wishes, and detection and treatment of natural raw material fluctuation.

The main outcome of the analysis is, that one important, critical, but worth to be investigated field is the digitalization of the brew master. This is, as typically the human brew master is able to translate the customer perception into successful recipes including a validation of the latter by tasting events. In addition, the determination of common perception of specific beers is done in the food industry by installing tasting polls with humans. It will be challenging, but still news braking to automate this process.

Along with the successful implementation of the investigated and anticipated field, final results of the applied research to be taken out next will help to introduce significant changes in the field of food technology. For this reason, further investigation and involvement in this field is promising.

Next steps to be undertaken are to identify both problematic or challenging and in parallel easy to solve tasks. Those may be aligned accordingly in one research and development track and one basic research track. There are for sure more tasks, which can be solved easily but need time and humans as resources, then there are challenging tasks. This conclusion can be taken by reviewing the listed issues in the previous chapter. Still, the less challenging task will need more time to be investigated, therefore the dual split sound reasonable.

To cover the field of challenging tasks, currently a research-funding proposal is under investigation.

CONCLUSIONS

In this paper we presented our results of state of the art analysis for a beer brewing process, which allows to automate the production of individual customer chosen products. We identified and described specific bottlenecks. The first investigation demonstrates the complexity of the planned project on the one hand, while it discovered the most critical puzzle pieces to focus on as well. Further steps include a deeper analysis of the latter mentioned.

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