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Integrating predictive models and sensors to manage food stability in supply chains

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A B S T R A C T

Food products move through complex supply chains, which require effective logistics to ensure food safety and to maximize shelf-life. Predictive models offer an efficient means to monitor and manage the safety and quality of perishable foods, however models require environmental data to estimate changes in microbial growth and sensory attributes. Currently, several companies produce Time-Temperature Indicators that react at rates that closely approximate predictive models; these devices are simple and cost-effective for food companies. However, even greater outcomes could be realized using sensors that transfer data to predictive models in real-time. This report describes developments in predictive models designed for supply chain management, as well as advances in environmental sensors. Important innovation can be realized in both supply chain logistics and food safety management by integrating these technologies.

1. Introduction

Today's food marketplace is highly global and complex, a fact emphasized when epidemiologists attempt to locate specific sources of contamination following an outbreak. A notable example is the 2011 *E. coli* O104:H4 outbreak in Germany, in which more than 4000 persons became ill and 54 died (Burger, 2012; Grad et al., 2012; Karch et al., 2012). After extensive investigation, seed produced in Africa two years earlier and sold to different sprouting companies in Europe, were consider a likely vehicle for the pathogen. However it could not be concluded if the seed was contaminated at production, at import, or during transport (Karch et al., 2012).

Also consider the challenge of investigating a potential foodborne illness linked to a serving of 'Chicken Kiev', a processed product in which ingredients can originate from more than 15 countries (Wall, 2010). Further compounding this situation is the complexity of the 'food highway', as described by Ercsey-Ravasz et al. (2012). They accessed very large databases of food import-export data, graphically demonstrating the complexity of the international agro-food trade network, and thus implicating the importance of logistics (e.g. time, temperature, and cross-contamination) on food safety and quality (i.e. food stability). All of these examples underline the need for effective food traceability systems.

While consumers are not normally aware of the sources of ingredients in their food, this information is vital to commercial food safety systems, where food processors must trace all ingredients back to specific suppliers (FDA, 2011). Fortunately, advances in digital technology (e.g. bar codes, radio frequency tags, wireless networks) have been used to develop sophisticated traceability systems (Regattieri et al., 2007). Yet even more valuable flows of information could be realized if sensors were coupled to predictive models, revealing in real-time how actions in the supply chain influence both the safety and quality of our food supply.

This report describes the development of predictive models, sensors and software that, when integrated, can provide participants (actors) in a food chain with the appropriate tools to monitor and predict food safety and quality (McMeekin, 2007; McMeekin et al., 2006; McMeekin and Ross, 1996).

2. Drivers of food safety

When considering the many drivers that impact food safety, the management of modern commercial supply chains is very challenging. These factors include environmental impacts such as climate change, food regulations that require companies to implement food safety systems and to accept greater responsibility for the actions of up- and down-stream suppliers, consumers who

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prefer foods with less processing, changes in consumer demographics, new food technologies, market pressures from food retailers, and emerging hazards (Hobbs et al., 2002; Tirado et al., 2010; Yapp and Fairman, 2006).

Nearly all of these drivers produce separate information flows that are relevant to food stability, and which should be digitally transmitted throughout the supply chain to prevent and control foodborne illness and product spoilage.

3. Supply chains

Food supply chains are a system of organizations, persons and events that interact—from food production to the consumption of food and food products (Kozlenkova et al., 2015). These systems support much of the world's economy, delivering important benefits to persons at all socio-economic levels of life.

Various reports describe factors that have influenced the development of modern supply chains, including market competition, regulation, procurement, supply chain strategies, economics, and technology (MacCarthy et al., 2016). Undoubtedly, technological innovation has had a major role in structuring more effective supply chain networks via digital technology, particularly in the transfer of information among supply chain actors.

Beginning in the 1990s, the Internet presented a platform for major advances in managing supply chains, facilitating highly efficient movement of information across multiple actors. Subsequently, the ability to trace the movement of food products was realized with the creation of Automatic Identification and Data Capture (AIDC) systems (Epelbaum and Martinez, 2014), recognized today as bar codes, two-dimensional Quick Response (QR) codes, and Radio Frequency Identification (RFID) tags. Each of these developments innovated supply chain systems by improving efficiencies in identifying the movement of products in time and space (Regattieri et al., 2007). However, AIDC devices alone do not convey how the environment influences food stability. Instead, they must be coupled to sensors that detect characteristics of the environment which impact food safety and quality.

While product temperature is an obvious parameter influencing microbial growth, others factors include pH, water activity, atmosphere, and nutrient level. Similar factors can also affect product quality, even in the absence of microbial growth, such as the effect of atmosphere on lipid oxidation that impacts taste and color. Food quality can also be impacted by actions earlier in the supply chain. For example, during the transport of cattle from farm to abattoir, animals can be stressed from rough transport, causing glucose levels in beef muscle to markedly decrease. This results in high pH, dark-cutting, low quality meat. In such cases, vibrational sensors embedded in trucks can identify causes of poor food quality.

In each of these cases, information from supply chain sensors must be translated into useful interfaces that show the user how environmental factors affect food safety and quality. This can be accomplished through mathematical algorithms (i.e. predictive models), which describe changes in food quality as a function of the environment.

4. Predictive tools

4.1. Predictive microbiology

Predictive microbiology, a sub-discipline of food microbiology, provides a quantitative and condensed description (i.e. mathematical equation) of the microbial ecology of food (McKellar and Lu, 2003; McMeekin et al., 1993). This is accomplished by measuring the kinetics of microbial behavior, or the probability of growth/inactivation (i.e. stochastic), under a defined set of conditions, and then translating this information into mathematical equations that describe microbial behavior as a function of the environment (Koyama et al., 2017; Mataragas et al., 2015; McMeekin et al., 1993; McKellar and Lu, 2003; Parra-Flores et al., 2016).

Predictive models are commonly produced to describe microbial growth and inactivation, as influenced by specific environmental conditions (e.g. temperature, pH, water activity). The change in microbial numbers is typically segmented into kinetic parameters, including lag time, growth rate (or inactivation rate), and maximum population density. This is most accurately and easily done using 'primary' curve-fitting software, such as DMFit (http://browser.combase.cc/DMFit.aspx).

After generating primary curves over a range of environmental conditions relevant to how the model will be applied, kinetic parameters are translated into 'secondary' models that describe changes in parameters as a function of the environment (e.g. the change in growth rate as a function of food storage temperature).

Then, based on the secondary and primary models, a 'tertiary' model is produced, which becomes the interface between the model and the end-user, in which environmental values are entered that result in estimations of microbial growth. Examples of tertiary model interfaces include Excel spreadsheets such as the American Meat Institute's process lethality calculator (http://www.amif.org/), and stand-alone software, such as ComBase Predictor (http://browser.combase.cc/ComBase_Predictor.aspx?model=1) and the USDA Pathogen Modeling Program (https://pmp.errc.ars.usda.gov/PMPOnline.aspx).

4.2. Examples of predictive models developed for supply chain management

More than 700 predictive models have been reported with potential applications for food (https://foodrisklabs.bfr.bund.de/index.php/openfsmr/). These are found in publications, in stand-alone software, and online. They include models based on microbial growth/inactivation in bacteriological media and in specific food matrices. However, few models have been applied and validated for use in supply chains (Taoukis et al., 1999; Tsironi et al., 2008), especially for food transport. The section below describes two models designed to estimate microbial growth in seafood and meat supply chains.

4.2.1. *Vibrio parahaemolyticus* in Pacific oysters (*Crassostrea gigas*)

Vibrio parahaemolyticus is a bacterium that naturally occurs in marine environments and causes human disease from the consumption of raw molluscan shellfish, most notably oysters (USFDA, 2005). Research shows that the ecology of *V. parahaemolyticus* is strongly influenced by seawater temperature and salinity (Kaspar and Tamplin, 1993). As a result, both pre- and post-harvest risk mitigation strategies have been developed to control the growth of *V. parahaemolyticus* in oysters (USFDA, 2009).

Scientists in the US conducted research to manage *V. parahaemolyticus* risk, producing a predictive model for the growth of *V. parahaemolyticus* in the American oyster (*Crassostrea virginica*) (Parveen et al., 2013). Related models estimate *V. parahaemolyticus* levels in oysters, as a function of seawater surface temperature (USFDA, 2005). These tools, as well as others, have been used as part of voluntary control plans aimed at managing *V. parahaemolyticus* levels at the time of harvest (USFDA, 2009). While these models have demonstrated utility for *V. parahaemolyticus* levels in the American oyster, it cannot be assumed that they apply to other oyster species, and/or other oyster-growing environments, without validation.

In response to this problem, Fernandez-Piquer et al. (2011) developed a predictive model for the growth of

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