Chapter 8
Advanced Computational Tools for Enhanced Food Quality and Safety

S. Sreevathsan, Bhavana B. K., Sukumar Debnath, and Sandeep N. Mudliar

Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
CAC	Codex Alimentarius Commission
CFD	Computational Fluid Dynamics
FAO	Food and Agriculture Organization
FCM	fuzzy c-means
GA	Genetic Algorithm
GMO	Genetically Modified Organism
HACCP	Hazard Analysis and Critical Control Point
IoT	Internet of Things
ISO	International Organization for Standardization
KNN	k-Nearest Neighbour

Authors Sreevathsan S. and Bhavana B.K. have equally contributed to this chapter.

S. Sreevathsan · S. N. Mudliar (✉)
Plant Cell Biotechnology Department, CSIR – Central Food Technological Research Institute, Mysuru, Karnataka, India

Academy of Scientific and Innovative Research (AcSIR), Ghaziabad, Uttar Pradesh, India
e-mail: sandeepm@cftri.res.in

Bhavana B. K.
Food Engineering Department, CSIR – Central Food Technological Research Institute, Mysuru, Karnataka, India

S. Debnath
Academy of Scientific and Innovative Research (AcSIR), Ghaziabad, Uttar Pradesh, India

Food Engineering Department, CSIR – Central Food Technological Research Institute, Mysuru, Karnataka, India

H. U. Hebbar et al. (eds.), *Engineering Aspects of Food Quality and Safety*, Food Engineering Series, https://doi.org/10.1007/978-3-031-30683-9_8

ML	Machine Learning
OUOD	One Up One Down
QR	Quick Response
RFID	Radio Frequency Identification
SVM	Support Vector Machine
USDA	United States Department of Agriculture
US-FDA	United States-Food and Drug Administration
IR	4th Industrial Revolution
HSV	Hue, Saturation and Value
SOCIP	Self-Operating Clean-in-Place
P2P	peer-to-peer
M2M	Machine to Machine
IPFS	Interplanetary File System
PPB	parts per billion
NIR	Near Infra-Red
BSI	Biometric Signature Identification
HVAC	Heating, Ventilation and Air Conditioning
RANS	Reynolds Averaged Navier-Stokes
SST	Shear Stress Transport
SIMPLE	Semi-Implicit Method for Pressure-Linked Eq.
VCC	Virtual Cold Chain
PISO-SIMPLE	Pressure Implicit with Splitting of Operators
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
CAD	Computer-Aided Design
SDGs	Sustainable Development Goals

1 Food Quality and Safety

Food quality and safety have turned out to be the challenging aspects in the food sector, due to the ever-increasing global flows of goods, and needs to be assessed by a ‘farm to fork’ approach. Food quality and safety can be addressed from many perspectives at different stages of the food value chain, from agricultural practice and post-harvesting followed by supply chain, processing, and transport. Agricultural practices involve the irrational use of pesticides and fertilizers, which may be taken up by the agricultural produce. During post-harvest, improper maintenance of storage conditions deteriorates the quality of food products and decreases their shelf life. Supply chain is mostly recognized by a “one up, one down” (OUOD) approach, where the food supply chain participants know only the immediate supplier (one link up the chain) and the immediate customer (one link down the chain) for a product, thereby affecting food traceability (Pearson et al. 2019). During food processing, various unit operations such as drying, baking, mixing, modified atmosphere packaging, pasteurization, irradiation, and high-pressure processing are adopted to manufacture a wide range of food products like dairy products, frozen foods, meat, seafood, beverages, and processed foods. The selection of food processing methods depends on several internal and external quality and safety assessment factors. Internal factors affecting food quality such as appearance, nutrients, flavour, origin; and food safety involves assessment of pathogen, artificial colorants, pesticide residuals, toxins and heavy metal contaminants (Gao et al. 2020; Talaviya et al. 2020; Lin et al. 2018; Zhang et al. 2014; Xu et al. 2020). The selection of appropriate food processing methods is crucial for retaining the nutritional value and quality of the food product, which also depends on external factors such as temperature, relative humidity, light, gas concentration, sanitation procedure and shelf-life of food products.

1.1 Current Practices to Ensure Food Quality and Safety

In order to address these above-mentioned food quality and safety problems, several measures have already been taken by governments, regulatory bodies and food manufacturers. Quality assurance after the production step has been made mandatory at all food processing and storage units. Additionally, in order to regulate risks associated with food processing, ISO 22000 – food safety management operational guidelines are being followed. ISO also ensures best practices for managing risks in all areas of food production (Cho and Kang 2011). Similarly, Hazard Analysis and Critical Control Point (HACCP) management system, based on United States – Food and Drug Administration (US-FDA) guidelines, involves the evaluation and control of physical, chemical and biological hazards from procurement and handling of raw material to production, manufacturing, supply and consumption of the final product (https://www.iso.org/iso-22000-food-safety-management.html). The Codex Alimentarius is a collection of guidelines and standards established cooperatively by the Food and Agriculture Organization (FAO) and the World Health Organization (WHO), that defines the basic conditions and practices required to safeguard consumer health and ensure fair practices in food industries (https://www.fda.gov/food/hazard-analysis-critical-control-point-haccp/haccp-principles-application-guidelines; http://www.fao.org/fao-who-codexalimentarius/en/).

Meanwhile, the increasing demand for organic food and certification to verify its quality and origin, needs efficient traceability. Traceability of organic food is essential in the food supply chain as it can indicate any usage of pesticides, genetically modified organisms (GMOs), and track the environmental /carbon footprint. The reasons for the authenticity of organic foods include partnering with certified organic farmers, meeting global testing standards as per United States Department of Agriculture (USDA), substituting chemical fumigation with food grade CO_2 fumigation and meeting global quality and hygiene standards in state-of-the-art facilities.

Conventional methods of food quality assessment by physical, chemical, microbiological, nutritional, and sensory parameters depend on specific attributes such as sensory properties, based on colour, flavour, aroma, taste, texture and quantitative properties of the food product. The traditional microbiological detection and identification methods for food borne pathogens are time consuming and is unable to meet demands for food more rapid food testing. Further, the evaluation of internal factors as mentioned above is vital especially to fresh foods such as dairy, meat, fruits and vegetables, and processed foods. As it is difficult to quantitatively assess the factors related to the quality and safety of food products, technologies developed will require high sensitivity, high specificity, low detection limits and portable usage (Cho and Kang 2011). These demanding characteristics can be tackled by the use of robust, diverse and cost-effective computational tools, which will facilitate a significant improvement in the quality and safety of food products.

1.2 Key Issues Controlling Performance

According to the Codex Alimentarius Commission (CAC), "food safety is the guarantee that the corresponding food will not harm the consumer when prepared or eaten as per its intended use" (Trafialek 2019). However, there are several factors/ parameters responsible for food contamination which needs to be resolved by viable methods. The factors causing spoilage of food threaten its safe consumption and make it harmful to human health. Contamination of food can often occur via pathogens such as bacteria, viruses and parasites, chemical agents and toxins at almost any stage of the food supply chain, which eventually trigger foodborne diseases. These diseases sometimes lead to mortality in developing countries, due to poor personal and food hygiene. These outbreaks can be averted by maintenance of appropriate storage conditions thereby preventing microbial contamination (Uçar et al. 2016). In other cases, fallacious agricultural practices such as irrational pesticide use can be kept under control by supply-chain traceability. For example, traceability will allow a consumer to acquire data on ripening methods (natural/ chemical) and storage conditions of the mangoes purchased at a local supermarket.

As discussed earlier, post-harvest storage is a critical step for safe handling of all foods. Post-harvest losses are sometimes as high as 38% and in developing countries, the percentage may rise up to 60% due to lack of dedicated storage areas with proper temperature maintenance (Gustavsson et al. 2011). Cold-chains are employed to meet the requirements of post-harvest storage, slow down the ripening process, minimize respiratory heating, avoid moisture loss and microbial contamination. Temperature is the most critical parameter to be monitored during storage. However, analysis and improvement of these operating conditions in cold chains requires model-based evaluation by testing different designs and concepts, thereby leading to optimization of the complete process (Ambaw et al. 2013). The following subsections discuss the advent of modern numerical modeling and computational tools in the area of food quality and safety.

1.3 Computational Paradigms

Modeling and simulation tools have proven to be very effective in designing and optimizing a large variety of processes and systems across various industrial sectors. Additionally, food manufacturers have discovered and applied some of these techniques in the past decade (Padhi 2020; Misra et al. 2020; Tian 2016; Delele et al. 2010). A wide variety of factors are involved in the food supply-cum-processing chain and therefore traceability and optimization are key paradigms to effectively manage food quality and safety. With the rapidly growing concern of food safety, reliable scientific data-driven computational tools and databases are the need of the hour. Automated detection of food parameters by modern techniques generates large amount of data and hence requires efficient computational tools. Some of the tools are artificial intelligence (AI) based on artificial neural network (ANN), support vector machine (SVM), random forest, k-nearest neighbour (KNN), decision tree, fuzzy c-means (FCM), genetic algorithm (GA), and so on (Zhu et al. 2021; Zhou et al. 2019). Techniques like blockchain technology are essential for food traceability. On the other hand, computational fluid dynamics (CFD), an advanced modeling and simulation tool, can be extensively used for optimizing fluid-based problems throughout the food processing chain, especially in food storage. It is to be noted that food safety is a function of food processing and supply chain. There are very minimal reports on the application of novel and emerging computational tools for food quality and safety. In view of the above, the chapter discusses the use of AI and blockchain from a traceability and supply chain perspective along with the application of CFD from a food processing/ storage angle.

The massive generation of data by Internet of Things (IoT) devices, sensing systems, web applications and social media have contributed to the rise of Artificial Intelligence (AI) (Koch 2018). AI is a technology in which computers and machines are rendered to mimic the problem-solving and decision-making abilities of the human mind. Most of the machine learning and deep learning methods of AI are applied in various food industries with automated food processing units via sensors, Radio Frequency Identification (RFID) tags, Quick Response (QR) codes. These are primarily employed for data collection followed by data optimization using the respective AI models, which is the key driver to avoid food hazards. Further, food traceability issues can be addressed by the use of blockchain technology, which may be described as a decentralized, distributed digital ledger that records transactions across the entire network. Blockchain can be used for efficiently tracking and authenticating the agri-food products in the supply chain thereby ensuring transparency. CFD is a robust design and analysis technique that involves the simulation of fluid engineering systems. As many processes in the food industry involve fluid flow and thermal systems, CFD simulation has traditionally been employed in food processing industries for the past two decades to provide a powerful early-stage qualitative and quantitative evaluation of the performance of food processing operations, thereby allowing modification and optimization of design parameters or operating conditions for a better workflow. Therefore, CFD can also be utilized for designing and optimizing post-harvest storage systems, airflow chambers and transportation systems in order to extend shelf life and maintain quality and safety of the foods.

This chapter discusses the comprehensive applications of advanced computational tools such as AI, blockchain and CFD to enhance food quality and safety. Brief introductions on AI, blockchain, food supply management and CFD with schematic illustrations are furnished to understand the applicability of these emerging tools. Additionally, case studies pertaining to the application of AI for the prediction of food contaminants, blockchain for traceability of agri-food products, food supply chain management and CFD for cold chains, along with their challenges have been summarized. We believe this chapter will be a significant addition to the existing knowledgebase on food quality, safety and sustainability, through a better understanding of AI-enabled blockchain technology, food supply chain management, and CFD.

2 Modeling Approaches for Food Quality and Safety

2.1 Artificial Intelligence

Recent advancements in AI, machine learning (ML), big data and the era of 4th Industrial Revolution (4.0 IR) are highly influencing the methods of crop farming, cultivation, production and food processing by adhering to the regimens of food quality and safety (Younus 2017). Artificial intelligence works in integration with digital data, sensors and robotics, by analyzing large amounts of data with quick iterative processing and intelligent algorithms thus allowing the AI model to learn automatically from features or patterns in the data. The role of AI is to analyse the data from both inputs and outputs, to derive an output with an enhanced degree of precision and efficiency without the human interference.

2.1.1 Architecture and Working of AI

The basic structure of AI is the artificial neural network (ANN), a theoretical mathematical model which comprises of a number of linear or nonlinear processing elements called nodes, which are interconnected through weighted connections. ANN usually includes 3 parts – input layer, the hidden layer and the output layer, which are usually specified by architecture, learning algorithm and neuron model. The architecture characterizes the interconnection pattern between the different layers of neurons, the learning algorithm updates the weightage to model a particular task appropriately, and the neuron model which is defined by its activation function transforms a neuron's weighted input to its activated output (Njikam and Zhao 2016; Thike et al. 2020). Once the data is collected, AI performs a prediction from the data sets based on a centralized model, in which a group of servers run a specific model against training and validating datasets. The AI model will be validated and optimized for minimum error based on the experimental and predicted values. ML-based AI is more appropriate for agri-food systems, where higher accuracy is expected and frequent training of the system is not a limitation as compared to rule-based AI (model based on pre-defined outcomes).

AI-based applications are gaining attention in the food industry with respect to food safety and quality assurance due to their ability to analyze large amounts of data generated from various monitoring techniques such as X-rays, lasers, spectroscopy or cameras. The data obtained is then examined by both intrinsic and extrinsic characteristics of the produce from harvest to packaging and the output is predicted in few seconds. Some novel methods such as computer vision are used to evaluate the quality of beverages, where the usage of automated analysis techniques integrated with AI is beneficial. The advantages of AI-integrated analysis of food quality parameters include cost-effectiveness and lower time-consumption, which in turn allow accurate, consistent, and reliable results. Further, the use of drones and robots on the fields makes it possible to thoroughly assess the sorting of foods, ripening status of fruits and to monitor the use of herbicides and pesticides during agricultural practices. The following applications exemplify the use of AI in revolutionizing the process mechanism in food industry in order to maintain high standards of food quality and safety:

AI for sorting of foods

Conventional food sorting systems which work on 'programmed as "acceptable" from the "rejected" lot of food products' is being replaced with advanced systems that can make optimized decisions based on AI. AI based food sorting uses image processing technologies such as cameras and near-infrared sensors for sorting and grading according to the size and colour of food product.

The application of image processing for sorting of red and green tomatoes and red and green grapes based on colour and size was analysed for an agricultural product packaging system. The colour recognition was carried out by HSV (Hue, Saturation and Value) analysis, and the size recognition was calculated by measuring the diameter of the object/fruit in the grayscale image and setting the thresholding. The data is of fruit size and colour is fed to the microcontroller to sort the fruit by moving it to the box of red/green tomato or red/green grape (Dewi et al. 2020). To arrive at an optimized decision, effective data collection and monitoring of food processes using AI-based optical sensors, to measure and regulate temperature, humidity, pressure and time along with other areas of improvements are essential (Kosior et al. 2017).

Enhanced traceability with precision

The conventional practice of tracing the food product depended entirely on simply gathering the data from a specific region and interpreting it accurately with respect to that specific region. However, traceability across the global food supply chain requires execution of strategic safety interventions to gather data from various regions, interpretation and validation of the collected data with minimal time consumption. In this regard, AI systems have made it possible to correlate past data and predict certain events across multiple timelines from different regions (Ramírez et al. 2019).

Automation for Self-Operating Clean-in-Place systems (SOCIP)

'Smart agriculture' is a classic example of how automation is expanding the production, processing, and packaging of food products using clean-in-place (CIP) systems, which involves periodic cleaning of the equipments to maintain hygiene. The advantage of a self-operating CIP system is that it avoids human intervention, which in turn limits the risks of cross-contamination via foodborne pathogens (Garbie 2010). Martec of Whitwell Ltd. is now examining its self-optimizing CIP system which utilizes optical fluorescence and ultrasonic imaging technologies to feed data to the designed AI program for the measurement of microbial debris and residual food within the equipments. Based on the output parameters i.e., extent of fouling from the debris, the intelligent decision-making tool for CIP will stop the cleaning phase. Some of the applications of AI in food processing is summarized in Table 8.1.

Table 8.1 AI applications in the agri-food supply chain and processing industries

Artificial intelligence	Process	Reference
Bee project hive network-Oracle	Hive uses IoT sensors to remotely collect data and provide insights into the nature of relationships bees share with their environments and data is stored in Oracle's Cloud.	https://worldbeeproject.org/, https://indianexpress.com/article/cities/pune/a-sweet-success-story-in-12-years-indias-honey-production-grows-by-200-exports-by-207-5736611/
TOMRA	X-ray, NIR (Near Infra-Red) spectroscopy, lasers, cameras and a unique machine-learning algorithm for fruit and vegetable sorting	https://www.tomra.com/en/sorting/food/food-technology
Detox™	Laser sorter utilizes an optical design to identify aflatoxin contamination in nuts such as almonds, peanuts, hazelnuts and figs. The Laser technique captures the low intensity of light reflected by the fungus enabling the detection and removal of aflatoxin contaminated nuts.	https://www.tomra.com/en/sorting/food/food-technology
Genius™	Genius™ sorter offers a variety of inspection technologies in different inspection zones with high resolution cameras and lasers. Further the state-of-art guns reject the foreign materials and defective vegetables, fresh cut fruits and nuts within milliseconds and process the approved products to the processing line, ensuring food safety.	https://www.tomra.com/en/sorting/food/sorting-equipment/genius
Google's TensorFlow	Cameras, X-rays, Near Infra-Red (NIR) spectroscopy and lasers to measure and automatically detect variances in diced potatoes, applicable in baby food for ensuring safety standards. Potatoes can be	https://blog.google/products/google-cloud/how-ai-can-help-make-safer-baby-food-and-other-products/

(continued)

Table 8.1 (continued)

Artificial intelligence	Process	Reference
	sorted based on various end products such as French fries or potato chips. Additionally, it optimises and predicts the end-product which will produce the least waste when cut for specific products	
ICatador	Artificial neural network-based virtualization and analysis of organoleptic attributes of cheese using NIR spectrometry as input data for the quality control process.	García-Esteban et al. (2018)

The data stored in AI may be altered or manipulated by hacking due to storage in a centralized manner (Dinh and Thai 2018). Besides, the origin of data and the authenticity of the sources generating the data are not certain and guaranteed (Qi and Xiao 2018). This may lead to an inaccurate and risky prediction. In order to address these risks and issues in AI-based technology, the concept of blockchain was introduced.

2.2 *Blockchain Technology*

Blockchain was introduced in 2008 as a distributed ledger technology to perform digital transactions via Bitcoin, avoiding the need for intermediaries such as payment gateways, banks, etc. (Tripoli and Schmidhuber 2018). As the vigorous decentralized functionality of the blockchain technology is established and proven for global financial systems, it can also be extended to food safety management systems to resolve food traceability issues across the global food supply chain. Further, the application of blockchain to enhance quality and safety of agri-foods can be addressed by data transparency and traceability, improving food safety and quality monitoring, and reducing the cost of financial transactions.

2.2.1 Working Principle of Blockchain

The architecture of blockchain includes a decentralized model which enables secure peer-to-peer (P2P) transactions based on a cryptographically protected approach such as Hash function (#) (Steiner et al. 2015). A unique hash value (combination of numbers and strings) specific to each transaction (similar to a fingerprint) is generated and the hash algorithm is constructed. Instantaneously, each transaction which is stored in a block has to be validated and approved by computing systems following the blockchain protocol (also referred to as nodes). The nodes can detect if there is any change in transaction by reading the hash value. Each block includes its own hash value and the hash value of the immediately preceding block, thereby forming a chain of blocks. A minor change in the transaction of any previously recorded block will change its associated hash value and consequently breaks the chain. However, the information stored in the blocks are no longer changeable once they are uploaded to the blockchain. Additionally, there is an added advantage that new blocks can be integrated with the blockchain for more transactions as the blockchain can update itself periodically (Xu et al. 2020). Some of the popular decentralized storage technologies of blockchain are Filecoin, BigChainDB, Interplanetary File System (IPFS), Storj, Swarm (Protocol Labs 2017; McConaghy et al. 2016; Benet 2014; Wilkinson 2014; Hartman et al. 1999).

With advanced features of transparency and traceability, blockchain represents an emerging technology in the field of agri-foods, which may transform many aspects of the food industry and enable the improved quality and safety of agri-foods. The traceability chain from ‘farm-to-fork’ via blockchain technology is depicted in Fig. 8.1a (Borah et al. 2020). Food products that have been monitored by blockchain technology in earlier reports are summarized in Table 8.2.

2.3 Blockchain-Enabled AI Applications in Agri-food Industry for Improved Food Security

The emerging concept of decentralized AI, which is basically a combination of AI and blockchain, enables processing and analysis of the data on trusted, digital platforms (Team 2018). The data can also be secured and shared on the blockchain, in a decentralized model. The key features and benefits of block chain integration with AI are enhanced data security, improved trust on robotic decisions, collective decision making, decentralised intelligence and high efficiency (Salah et al. 2019). AI-enabled blockchain can therefore be applied in food supply chain management for simultaneous food traceability and data protection of the supply chain.

2.3.1 AI-Enabled Blockchain in Rice Supply Chain Management

The application of AI-enabled blockchain in agri-food industry to maintain food quality and safety is discussed using the rice supply chain management (Fig. 8.1b, c) (Kumar and Iyengar 2017). The rice supply chain which begins at farm land requires detailed understanding of artificial intelligence models for the optimization of agricultural applications such as smart irrigation, farming, plant data analysis, next generation farming, food processing, use of pesticides etc. The technology of smart irrigation was developed to increase the agricultural produce without the involvement of manpower by using sensors that detect the level of water, temperature of the soil, nutrient content, operation of irrigation pumps and forecast weather. Machine to Machine technology (M2M) was developed to ease the data sharing and

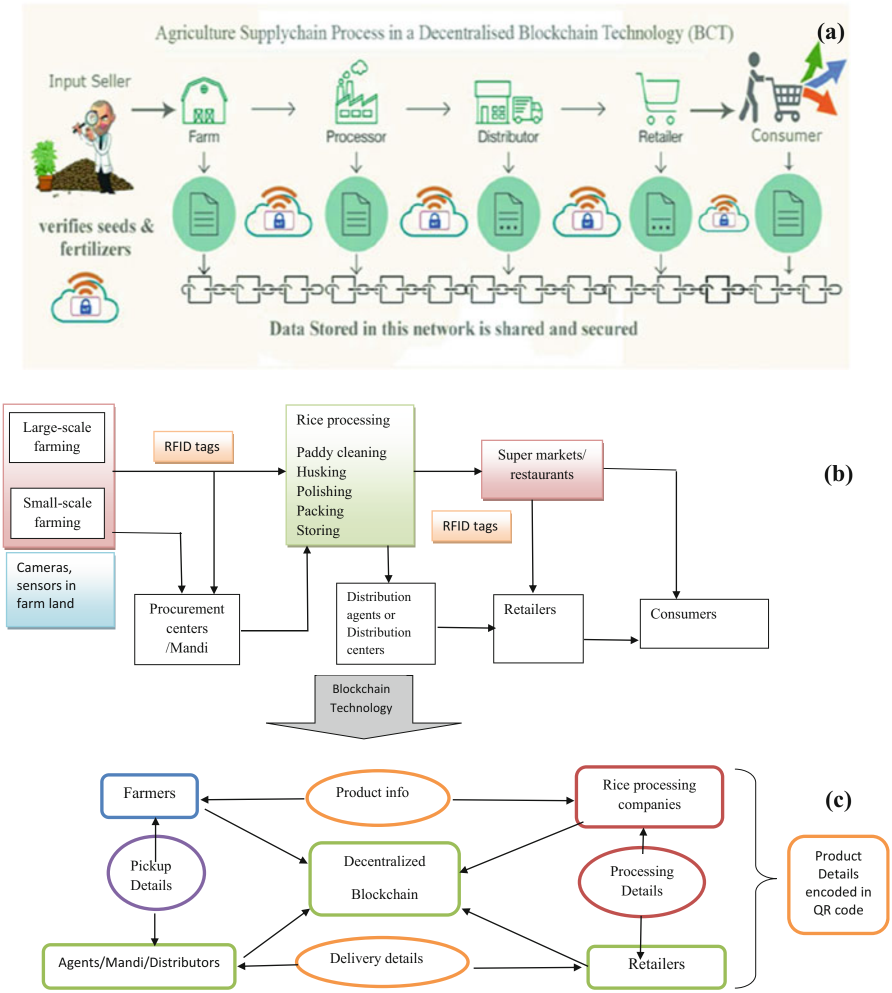


Fig. 8.1 (**a**) The traceability chain from 'farm-to-fork' by implementation of blockchain technology (Reproduced from Borah et al. (2020) with permission from Springer Nature) (**b**) Rice supply chain in India and (**c**) Blockchain framework. (Adapted and modified from Antonucci et al. (2019) and Kumar and Iyengar (2017))

communication gaps with the server or the cloud connected by a central network to all the nodes of the agricultural field (Shekhar et al. 2017). Image analysis of rice cultivation will be captured by computer vision and data collection through sensors, which will be trained, analysed in the developed model based on AI. Further, the harvested rice will be tracked during its shipping which is tagged by RFID to avoid the food fraud affecting the food safety. The traceability of rice from farm to processing unit to procurement centres followed by retailers and consumers will be encoded in a QR code, where the data collected will be stored in a decentralized blockchain.

Table 8.2 Blockchain applications in the agri-food supply chain

Food products	Aim	References
Chinese pork and Mexican mangoes	Conventional methods for back-end traceability of mangoes from supermarket to farm through the supply chain earlier took 6.5 days, whereas blockchain adapted by Walmart and Kroger could achieve the traceability within few seconds	Kamath (2018)
Turkeys	Cargill Inc. harnesses blockchain using QR code to trace the turkeys from the store back to the farm with its Honeysuckle White brand	https://fooddigital.com/food/cargill-using-blockchain-technology-trace-turkeys-farm-table
Coffee	Data (text, images, videos etc) from plantation/ processing/ transportation was uploaded into the blockchain and a unique code was assigned where the information can be shared within the supply chain by web platform or mobile application. QR code on the packaging of the product that transforms normal labels into "smart labels" provides information about the product.	San Domenico coffee (2018)
Tuna fish	Blockchain Supply Chain Traceability Project (WWF 2018) by World Wildlife Foundation (WWF) was initiated to eradicate the illegal tuna fishing, in which the fishermen can register their fish caught, on the blockchain through RFID tags and scanners. Fish caught will be registered by fishermen via SMS and will be stored in blockchain using a permanent, unique identifier such as QR, RFID or barcode. The caught fish transferred to supplier will also be registered on the blockchain and can be accessible to everyone with the unique identifier.	Provenance (2016)
Beef	Blockchain based Hyperledger where the data is stored. Scanning the QR code on the beef product using a mobile application decodes the information regarding the farm that raised the cow, section of the cow, where it was processed, and its package date, beef steak's serial number and 64-digit alphanumeric code referring to the transaction.	Huang (2017)
Beer	DOWNSTREAM beer product is a pioneer using blockchain technology with uniquely marked and authenticated smart QR code, enabling full traceability of every bottle through the brewery and the supplier network to the consumer,	https://www.down-stream.io/

(continued)

Table 8.2 (continued)

Food products	Aim	References
	providing access to information on the premium raw materials – malt, hops, yeast and water and brewing methods	
Bio and DOCG product	To ensure traceability in the agri-food chain by quality and digital identity [for bio and DOCG (Designation of Origin Controlled and Guaranteed) products]	AgriOpenData (2016)
Pork/ Beef	Arc-net is a cloud-based product authentication and traceability service to avoid food fraud involving horse meat labelled and sold as pork/ beef.	http://arc-net.io/
Fresh food	Information on origin of product including the data collection from sensors, permitting data transparency from farm to fork	https://ripe.io/
Milk	To eliminate food fraud in the dairy supply chain by automating the procurement and the registration of information	Milk CyberSecurity (2018)
Pasta	To identify the whole supply chain (i.e., manufacturer, products and flours used, type of drying, transport)	Pasta supply chain (2018)

Adapted and modified from Antonucci et al. (2019)

2.4 Computational Fluid Dynamics

Computational fluid dynamics is a refined modeling and simulation that uses powerful computers to design, analyze and predict fluid flow, phase change, heat transfer, mass transfer, chemical reactions, mechanistic movements, and solid-fluid interaction. CFD facilitates the evaluation of several different design constraints of a physical system using a specifically constructed computational model representing the system. The yardstick of success is observed by how well the results of the numerical simulations correspond with the results of the experiment, in circumstances where laboratory experiments could be performed and how proficiently the simulations can envisage highly complicated processes that cannot be established in the laboratory (Sun 2019).

CFD is a branch of knowledge primarily based on the theory of fluid mechanics. Fluid flows are defined by the conservation laws of mass, momentum and energy in the form of partial differential equations. These equations are replaced by respective algebraic equations during model development in CFD and are then numerically solved. These algebraic equations portray the relation between pressure, temperature, velocity and liquid density with respect to the fluid problem under study. CFD offers a qualitative prediction of fluid flows using: (i) precise mathematical modeling (using Navier-Stokes transport equations) (ii) numerical methods and (iii) software packages (solvers, pre- and post-processing functions) (Tu et al. 2018; Zawawi et al. 2018). The outcome of a CFD study is a function of the physics and numerics available within the software package and can deliver a comprehensive in-depth analysis of a flow system for specific application (Norton and Sun 2006).

Originally, CFD was solely associated with industries involving aerospace and mechanical activities allowing simulation of combustion processes in rocket engines and other physicochemical reactions in and around the rocket airframe. Successively, chemical engineers started employing CFD tools primarily for design of reaction vessels and fluid flow systems (Ranade 2002). Today, CFD is applied in various disciplines across several industries such as aerospace, automotive, chemical, manufacturing, food processing, biomedical, power generation, petroleum exploration, polymer processing, pulp and paper processing, meteorology, astrophysics, medical research and so on (Bayatian et al. 2021; Toparlar et al. 2017; Bakalis et al. 2015). The upcoming sub-sections discuss the equations governing CFD and its applications for enhanced food quality and safety.

2.4.1 CFD in Food Quality and Safety

The food processing sector is unique due to the wide range of distinct constraints that affect process design and development. The food products have to be desirable to the consumer in terms of visual appeal, nutrition, quality and safety. Food processing involves physicochemical and biological interactions of material and non-material components followed by storage and transportation of the manufactured product. This occurs by the means of physical, chemical and biological reactions through transformation of mass, momentum and energy. Robust modeling and simulation tools are employed to diligently study the various transformations during food processing thereby facilitating improved quality and safety (Bakalis et al. 2015).

CFD has grown to be an indispensable part of the design and analysis ecosystem of many food manufacturers due to its capability to predict and analyze the performance of new processes or designs prior to their implementation or fabrication (Padhi 2020; Parpas et al. 2017). One of the undeniable advantages of CFD modeling of food processing operations is the evaluation of the multiphase flow behaviour and prediction of the effect of different operating conditions on the overall process. Process engineers, equipment designers and researchers use CFD to improve the execution and performance of food processing operations, such as drying (Malekjani and Jafari 2018; Ramachandran et al. 2018), baking (Salish et al. 2021; Zhou and Therdthai 2019), sterilization and thermal processing (Park and Yoon 2018; Anandharamakrishnan 2013), refrigeration (Pham et al. 2021; Hoang et al. 2015), mixing (Gomes et al. 2019; Pires et al. 2017) and so on. CFD can be utilized as a robust technique for modeling and simulation of a new food processing facility or retrofitting existing facilities, leading to better performance, quality, safety and energy-optimized operation thus saving up on time, economic cost and manpower.

2.4.2 Governing Equations

The governing equations for CFD of fluid dynamics, heat and mass transfer can be regarded as mathematical expressions of the conservation laws of fluid mechanics and are referred to as the Navier-Stokes equations (Norton and Sun 2006; Farid 2010). These laws of conservation correlate the rate of change of a specific fluid property and associated external forces, when applied to a fluid continuum and can be labelled as:

1. The law of conservation of mass (continuity equation), which states that the mass flows entering a fluid element must balance exactly with those leaving.

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial xi}(\rho uj) = 0 \tag{8.1}$$

2. The law of conservation of momentum (Newton's second law of motion), which states that the sum of the external forces acting on a fluid particle is equal to its rate of change of linear momentum.

$$\frac{\partial}{\partial t}(\rho ui) + \frac{\partial}{\partial xj}(\rho uiuj) = \frac{\partial}{\partial xj}\left[-p\delta ij + \mu\left(\frac{\partial ui}{\partial xj} + \frac{\partial uj}{\partial xi}\right)\right] + \rho gi \tag{8.2}$$

3. The law of conservation of energy (the first law of thermodynamics), which states that the rate of change of energy of a fluid particle is equal to the heat addition and work done on the particle.

$$\frac{\partial}{\partial t}(\rho CaT) + \frac{\partial}{\partial xj}(\rho ujCaT) - \frac{\partial}{\partial xj}\left(\lambda\frac{\partial T}{\partial xj}\right) = sT \tag{8.3}$$

By applying these conservation laws over discrete spatial volumes in a fluid domain, a systematic interpretation of the changes in mass, momentum and energy can be obtained. The aforementioned equations and their governance on CFD can be further explored in detail from "Mathematical modeling of food processing by Farid M.M. (Ed.). 2010" (Farid 2010).

2.4.3 Numerical Analysis and Visualization

CFD code developers and researchers use a selection of diverse numerical methods to discretize the modelled fluid domain. The most significant ones are finite difference, finite element and finite volume methods. Finite difference methods are seldom used for engineering flows due to their limitations in processing of complex geometries. Finite elements are used to model arbitrary geometries such as wind and building interactions in agricultural building designs (Wang et al. 2016). However, due to the technical difficulties involved in the programming and understanding of

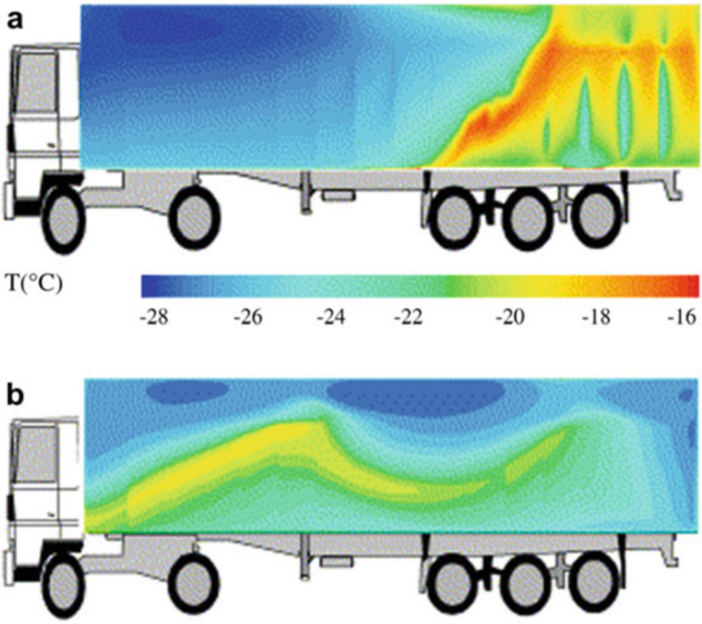


Fig. 8.2 Contours of temperature field within a refrigerated truck (a) with air and (b) without air. (Reproduced from Moureh and Flick (2004) with permission from Elsevier)

this method, a very limited number of commercial finite element packages exist. The finite volume method provides an organized report of the changes in mass, momentum and energy of the fluid across the boundaries within the computational domain (Versteeg and Malalasekera 2007). Therefore, finite volumes are most commonly used due to their ease of understanding, programming and flexibility. The model to be selected for CFD simulation may be laminar or turbulent – based on the type of fluid flow. In a turbulent model, which generally denotes the realistic fluid flow in most applications, the effect of driven forces, eddies and vorticities are incorporated.

Visualization of a CFD problem is almost always necessary to represent its accurate solution. Contour plots, vector and line plots augment the validity of simulation results and have also been employed in several studies to support design and fabrication (Ciano et al. 2021; Inostroza et al. 2021; Demissie et al. 2019). Figure 8.2 illustrates an example of the use of visualization methods to enhance the design process (Moureh and Flick 2004). Today, there are a number of commercial CFD codes and packages that are capable of addressing different problems faced in different areas of engineering (Boysan et al. 2009). Some of the most commonly used commercial CFD codes are ANSYS FLUENT, CFD-ACE, ANSYS CFX, PHOENICS, FLOTHERM and OpenFOAM. These codes incorporate almost all functionalities, employ intuitive graphical user interfaces and support Windows, UNIX and Linux platforms.

3 Applications of Advanced Computational Tools in Food Quality and Safety – Case Studies

3.1 Food Supply Chain Management

Food supply chain is a complex system involving the uninterrupted food flow from farm to consumers. However, there is a lack of transparency and traceability due to the interference of various middlemen. This interference may have significantly negative effects on the freshness of agricultural produce and food quality, and hence the information of all the processes and stages involved in the food supply chain needs to be tracked. The main stages characterizing an agri-food supply chain are agricultural production, post-harvest handling, processing, distribution, retailing and consumption (Caro et al. 2018).

The supply chain in the food industry depends on automated machines which is based on AI, machine vision, navigation technologies and sensor technologies to record the data of temperature, microbiological information and other food quality parameters over the lifecycle of the food products (Jedermann et al. 2014; Heising et al. 2014; Abad et al. 2009). For instance, Radiofrequency Identification (RFID), a sensor-based technology is being applied in food processes, agri-food supply chain industry as one of the efficient traceability systems. The use of RFID and storage of data using blockchain technology in the agri-food supply chain reduces the losses during the logistics process and also maintains food quality and safety. Various food chain traceability initiatives have been taken up and one such initiative by BigchainDB, is based on HACCP, blockchain and IoT (McConaghy et al. 2016). The system provides an information platform for all the supply chain members ensuring transparency and safety (Tian 2016). Also, a recent initiative by Walmart to track and trace the supply of leafy green vegetables by uploading the data to the blockchain using IBM Food Trust Network, can be applicable to other suppliers to ensure food safety along the supply chain. This ensured quick traceability of products back to the farms and harvest sites.

3.1.1 Foodborne Outbreaks in Supply Chain

Food sector faces additional challenges apart from food processing, such as the foodborne outbreaks in the supply chain, which needs immediate attention in the food regulatory framework. The insufficient measures adopted by food regulatory agencies to trace the origin of contamination in foodborne outbreaks affects the public health thereby losing trust of the food product in the supply chain indefinitely. Some of the foodborne outbreaks are detailed in Table 8.3. Therefore, an understanding of the significant impact of foodborne outbreaks, technological advancements and integrated measures to reduce the risks associated with future outbreaks and therefore its prevention by identification and control of hazards at critical stages of the supply chain within a limited time period should be of utmost priority.

Table 8.3 Foodborne outbreaks in agri-food supply chain

Agricultural food products	Reason	Reference
E. coli outbreak in spinach, 2006	Outbreak originated from Yuma, Arizona, and it took almost 7 days for the Walmart food safety division to identify the source of contamination across the supply chain of lettuce	Kamath (2018)
Salmonella contamination in papayas, 2017	Salmonella outbreak in US market in papayas required almost 3 weeks to trace the source to a single farm in Mexico. Papaya farmers from unaffected areas suffered economic losses because of the inability to rapidly track and trace food products	Kamath (2018)
Traceability of sliced mangoes in USA	Walmart and IBM utilized blockchain to trace sliced mangoes from South and Central America to North America highlighting the significant gap in the traceability. The conventional method of traceability took 7 days to connect the supply chain from consumer to the origin of the mangoes, however, blockchain delivered information within 2.2 seconds	Kamath (2018)
Aflatoxin detection in crops	Monitoring of biotic and abiotic conditions in crop field facilitates the identification of the areas of increased incidence of aflatoxins before the harvested crop could enter the food chain	Pillmann et al. (2006)
Poultry meat supply chain	Poultry meat supply chain needs to be restructured to prevent the spread of the avian influenza A virus (H7N9), as the government authorities enforced the closure of live bird markets (LBM) in disease-affected areas of China	Khokhar et al. (2015)

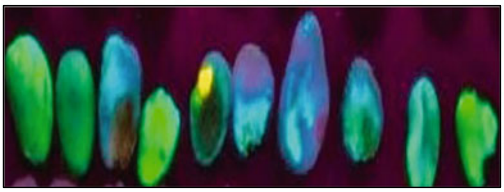
3.2 *Aflatoxin Detection in Nuts: Detox™ by TOMRA, a Case Study of AI*

Food contamination by aflatoxins, which can cause cancer is considered a major health risk to consumers and also a commercial risk to food businesses. *Aspergillus* (fungi) species present in the environment as *A. flavus* and *A. parasiticus*, are commonly found in orchards of nuts. The parasite grows when suitable conditions arise and produces a chemical compound known as aflatoxin. Aflatoxin is a secondary metabolite and a potent carcinogen. The concentration of aflatoxins is measured in parts per billion (PPB), which is equivalent to a pinch of salt to a 10-ton bag of potato chips. As aflatoxins are known to cause fever, malaise, abdominal pain, vomiting, hepatitis and cancer, they need to be addressed for food safety. Aflatoxin B1, occurs naturally in a wide range of foods and primarily infects cereal crops, spices, figs, dried fruits, cocoa beans, rice and nuts such as walnut, peanuts and tree nuts. Further, Aflatoxin M1 is sometimes present in milk taken from animals that have consumed feed contaminated by aflatoxin B1. Development of technologies for detection of aflatoxin in milk is essential as pasteurisation of milk does not protect against aflatoxin infections (https://food.tomra.com/blog/aflatoxins-in-foods).

The advanced modeling technology Detox™ using AI sensor-based sorting by TOMRA, uses fluorescent lighting, advanced lasers and near infra-red (NIR) spectroscopy to examine and identify the extremely low intensity of light reflected by the aflatoxin moulds in a variety of food types, thereby detecting aflatoxin contamination (Fig. 8.3). TOMRA's sorting machines works on the principle of unique biometric signature identification (BSI) technology. BSI works by scanning and detecting the biometric characteristics of the nuts, which is compared with the database to determine whether the items should be accepted or rejected (https://www.fareasternagriculture.com/technology/infrastructure/laser-sorting-machines-can-eliminate-the-risk-aflatoxins-in-foods). This technology detects and removes smaller defects as compared to conventional spectral technology, as false-rejection rates are exceptionally low with high yields.

(a) Aflatoxin contamination in brazil nuts and figs

(b) TOMRA Nimbus 640 with double Laser in DETOX ™ Configuration



Aflatoxin B1/B2 – blue fluorescence

G1, G2, Y – green and yellow fluorescence in UV light

(c) Aflatoxin detection using Detox^{TM} developed by TOMRA

Fig. 8.3 Aflatoxin detection in nuts using Detox™ model (**a**) Aflatoxin contamination in brazil nuts and figs (**b**) TOMRA Nimbus 640 with double Laser in DETOX ™ Configuration (**c**) Aflatoxin detection using Detox™ developed by TOMRA

3.3 Case Studies of Blockchain Technology

3.3.1 Dairy Industry: A Pioneer in the Adoption of Blockchain Technology

Milk with acceptable quality is processed into a variety of dairy products such as yoghurt, liquid milk products, butter, ice creams, cheese and ghee by food processing operations such as homogenization, pasteurization, packaging and storage (https://www.fao.org/publications/sofa/2016/en/). However, although milk is considered as an essential nutritional supplement for human beings, the quality of dairy products has been a major issue affecting the health, especially that of infants and older people. Therefore, traceability of milk and milk products is essential as it provides access to critical information about its origin and processing methods (Francisco and Swanson 2018).

Figure 8.4 illustrates the traceability of milk supply chain, which begins from the milking process at the farm and labelled with an activated QR code for each churn. The data will be updated on a blockchain and further the QR code of each milk churn can be scanned to validate the quality before combining them together in the giant tank. The transport tank will be attached with another activated QR code security seal to trace the truck movement. The activated QR code provides the information on the location of the farm where the milk was sourced, procurement time and volumes, results of onsite tests, and details of the transportation vehicle, which will be stored in a distributed ledger using blockchain technology.

Further, the raw milk arriving at the dairy industry will be scanned to access the data of milk procurement and the shipment will be accepted post-verification. The information encrypted in the QR code will be logged and the status of the milk batch will be updated on the blockchain server. If any discrepancies regarding the milk quality should arise at the processing unit, the milk batch will be traced back to the particular farm through the unique QR code. The batch of milk with inferior quality can then be rejected as it is no longer safe to be processed further.

The data of the entire dairy supply chain is automatically recorded and uploaded to the blockchain system using the various sensors installed. Finally, at the packaging/ bottling stage, a QR code will be printed on each product which provides complete information of the dairy supply chain to the end users. Each QR code, encrypted by a hash value, provides the information from farm to finished product along with additional data consisting of processing details, batch number and expiry date (Tan and Ngan 2020).

Considering the multiple processes involved in dairy supply chain, a smart contract integrated with IoT sensors will be efficient and time-saving for the transaction between the dairy industry and retailers. Smart contracts offer information on shipment details, process parameters such as temperature and humidity during shipment and shelf-life of the product. The product after delivery will be certified for maintenance of temperature and humidity during the food product shipment, so that the quality is maintained throughout the supply chain. The consumers, who are

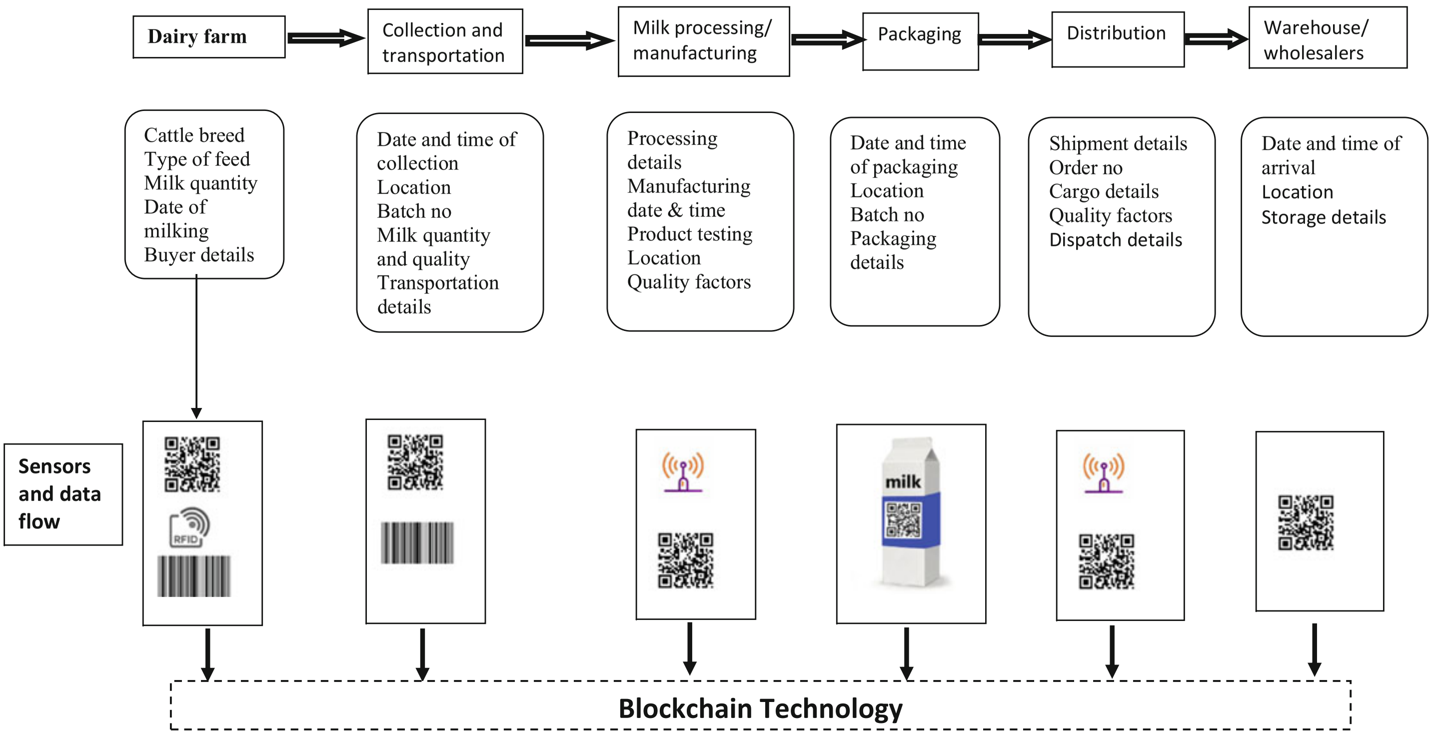


Fig. 8.4 Framework for blockchain-based traceability system in the dairy supply chain. (Adapted and modified from Tan and Ngan (2020))

the end users, can scan the QR code on the product using the respective application on their smartphones to verify its provenance and authenticity. Furthermore, the details of dairy farming, type of processing, the food safety standards regulating the supply chain (HACCP, ISO, national standards) and the manufacture and expiry date of the dairy product can also be made available by blockchain technology.

3.3.2 Hive to Tongue Traceability: Implementation of Blockchain Technology (an Emerging Case Study)

Globally, there are about 94 million beehives with an average annual honey production of about 1.77 million metric tons in 2020 (Statista 2018). Quality honey is an immunity booster, and its traceability is beneficial for both the producers and consumers. Honey is often one of the most impure or mislabelled foods as 76% of honey sold in the market is adulterated (Everstine et al. 2013). It has been observed in recent years that honey mixed with impure ingredients such as sugar, salt, corn syrup and even toxins have been found at suppliers and retailers. Although, analytical methods may detect honey adulteration, they are expensive and tedious to be performed on a regular and scalable basis (Strayer et al. 2014). As honey is currently a highly unorganised sector, due to the constant shifting of beekeepers based on the bee's movement, making it difficult to identify the source of the honey product. Also, to reduce the cost of honey, the honey suppliers and traders often blend the honey from different sources of low-grade honey with a relatively small volume of high-quality, expensive honey. The natural honey which is composed of fructose, glucose, and sucrose is commonly adulterated with corn or sugar syrup, results in a homogeneous mixture which makes it difficult to differentiate (Wang et al. 2015). The syrup or sugar residues in adulterated honey are identical to the natural residues in pure honey. Therefore, the detection of these adulterants becomes difficult, and hence new methods to distinguish the differences between pure and adulterated honey (Drummond and Sun 2010). Additionally, with the increasing demand for organic honey, the suppliers or manufacturers need to meet the criteria such as pure organic honey should not constitute any GMO based content, presence of hazardous substances like antibiotics and pesticide residue, and other chemical residue levels should be below the prescribed limits (Wang et al. 2015). With the increase of adulterated honey flooding the market, the origin and traceability of honey (via labelling) can be powered by blockchain technology.

3.3.3 Unique Identifiers to Verify the Authenticity of Honey

The sale of impure honey could be prevented by testing of adulteration in honey using blockchain-enabled supply chain and traceability. For instance, ultra-filtration is an operation used in honey processing which removes all the naturally beneficial pollen from the honey in order to extend the shelf life of the product thereby rendering it impossible to tell the origin of the honey or the location of beehive.

The collection of data comprising the unique identifiers such as health of bees, temperature of bees and the amount of honey produced can be stored in the blockchain and shared throughout the supply chain between different parties. These unique identifiers can then be identified by the label on the product and can be traced for its origin to verify the authenticity of the honey.

3.3.4 Future of Honey Verification with Blockchain

The tampering of honey with adulterants can be validated by contemplating the locality of the bee hives where the honey was harvested. The analysis of the locality and type of farms surrounding the hives can uncover evidence on the adulteration of honey. For example, if the sample of honey contains maple pollen but the hive is at a location where there are no maple trees, it is understood that the honey is probably adulterated. It is more likely and economically practical that any "standard" applied to honey would be based on how the farm is being managed – for example, the farmer is setting aside a portion of the land to grow pollinator friendly plants all year round. The same can be monitored by capturing aerial images of the land and analysing the division of the lands.

3.4 CFD in Cold Food Chains

3.4.1 Cold Food Chains

A large variety of raw, partially cooked or ready-to-eat chilled and frozen foods are available to consumers all over the world. As the demand for innovative food products and ready-to-eat meals increases, the need for enhanced food safety and improved, optimized cold chain facilities also increases. In order to maintain the quality and extend shelf life of a large number of food products, temperature control is crucial at almost every stage of the food processing chain (Tassou et al. 2015). A chain that comprises the production and distribution of frozen and chilled food products is usually described as a 'cold food chain'. Cold food chains involve heating, ventilation and air conditioning (HVAC) systems, frozen and chilled food display cabinets and refrigerated storage systems: low-temperature (−30 to −40 °C) for frozen foods and medium/ high temperature (−8 to −15 °C) for chilled foods storage. It also includes refrigerated transportation that refers to the conveyance of food by land, sea and air via refrigerated containers (Brown 2008). In the subsequent sections, the effects of freezing and chilling on the quality and safety of fresh and processed foods are explored along with special reference to three case studies, wherein CFD tool is used to enable significant reduction of post-harvest losses and facilitate improved food quality and safety.

3.4.2 Food Quality and Safety Issues at Low Temperatures

Food quality and safety is essential to all fresh and processed foods especially meat, fruits and vegetables. The main objective of chilling or freezing is to extend the shelf life of the food product thereby maintaining its quality. However, certain variation in the characteristics of the food product are often expected due to mismanagement of the cold storage. Oxidation and enzymatic biochemical reactions, especially in fruits, vegetables and sea-food lead to off-flavours and odours. In other cases, the effect of unoptimized cold room conditions is responsible for the degradation of product appearance, palatability and texture (Tassou et al. 2015; Darwesh and Elmetwalli 2015). Additionally, several factors influence the cold chain process efficacy such as temperature distribution, air flow rates, cooling method, storage conditions, thermal-physical interactions, physiological properties, packing design and stacking pattern (Delele et al. 2013a; Chourasia and Goswami 2007a; Pathare et al. 2012).

In order to analyze and improve the existing process and design of the cold chain, modeling of fluid flow, heat and mass transfer is essential during cooling, storage and transportation operations (Ambaw et al. 2013; Delele et al. 2010). CFD solves the governing equations (Eqs. 8.1, 8.2, and 8.3) for cold chain operations to a high degree of accuracy using a very fine mesh of the geometry under study. CFD is also reported to be the most suitable and commonly used technique to analyze the aerodynamics and thermal distributions inside cold storages (Brown 2008; de Albuquerque et al. 2019). Table 8.4 recapitulates the recent use of CFD for design and evaluation of post-harvest cold storages.

3.4.3 Case Study I – CFD Based Optimization of Precooling Conditions of Dates in Cold Room

Ghiloufi and Khir (2019) studied the modeling and optimization of precooling process for dates using CFD. The cold storage (5.6 × 3.62 × 3.3) was designed to preserve about 11 tons of dates at 5 °C. Compression vapor refrigeration system, with 3 axial fans of 45 cm diameter and rotating velocity of 1500 RPM, was used to deliver the necessary cooling capacity. The dates were packed in 432 plastic bins (62 × 32 × 15 cm) and arranged in 3 rows; each row containing 84 bins with 2 m height and circulation corridors were provided. Simulation was performed considering three designs of the cold storage: (1) normal cold room, (2) cold room with single deflector and (3) cold room with three aerodynamic deflectors.

Model Development

The Reynolds Averaged Navier-Stokes (RANS) equations were resolved in three dimensions to determine the air flow profiles. The turbulent model used was the k-ω (SST) developed by Menter (Liu et al. 2012) to study the airflow inside the cold room. This model is best suited to describe the air spinning patterns in a cold room (Nahor et al. 2005). The governing equations for the study have already been

Table 8.4 Recent applications of CFD in design of post-harvest storage facilities

Food product/ replica	Modelled system	CFD Modeling			Reference
		Turbulence model	Numerical technique	Validation	
Beef	Microbial inactivation of pasteurized foods	No	Finite element	3D-heat transfer model, thermal and microbial inactivation kinetics	Delele et al. (2019a)
Beef carcasses	Industrial cooling system Heat and Mass transfer during Industrial cooling	k-ω SST	Finite element	Temperature profile, heat and mass transfer coefficient	Delele et al. (2019b)
Dates	Precooling system and cold storage design	k-ω SST	Finite volume	Design validated with airflow and temperature distribution profiles	Ghiloufi and Khir (2019)
Apple	Heat transfer between product and air	k-ω SST	Finite volume	Anemometry – air velocity and temperature measurements	Hoang et al. (2015)
Citrus fruit	Forced convective cooling conditions, energy consumption	k-ω SST	Finite volume	Cooling rate and heat transfer distribution across packaging	Delele et al. (2012)
Apple	Thermonebulisation fungicide fogging system	SST	Finite volume	Particle deposition as a function of stack positioning	Ambaw et al. (2011)
Apple	Diffusion and adsorption of gas during cold storage	SST	Finite volume	1-MCP concentration measurements	Ferrua and Singh (2011)
Strawberry	Forced-air cooling process of fresh strawberry packages	No (laminar)	Finite volume	Particle image velocimetry, temperature measurements	Arêdes Martins et al. (2011)
Apple	Forced air cooling of fruits	No (laminar)	Finite volume	Comparison of model calculated Nusselt number against literature	Ho et al. (2006)
Pear	Gas permeation, diffusion and respiration kinetics	No	Finite element	Gas concentration profiles and fluxes	Ho et al. (2008, 2010); Cuesta and Lamúa (2009)

(continued)

Table 8.4 (continued)

Food product/ replica	Modelled system	CFD Modeling			Reference
		Turbulence model	Numerical technique	Validation	
Not specific	Heat conduction during chilling of fruit and vegetables	No	Empirical correlation (Fourier series)	No validation	Delele et al. (2009)
Chicory root	Evaluation of chicory root cold store humidification	SST	Finite volume	Mean air velocity	Moureh et al. (2009a)
Cheese and meat products	Mist flow process in refrigerated display cabinets	RNG k-ε	Empirical correlation	Velocity and temperature measurements	Moureh et al. (2009b); Amara et al. (2008)
Not specific	Flow field inside domestic refrigerator	No (laminar)	Finite volume	Particle image velocimetry	Alvarez and Flick (2007)
PVC spheres	Cooling of stack of food products	Macroscopic	Empirical correlation + finite volume	Air velocity and temperature measurements	Chourasia and Goswami (2007b)
Potato	Airflow, heat and mass transfer	No	Finite volume	Time-temperature history and weight loss of product	Allais et al. (2006)
Gel-filled celluloid spheres	Mist-chilling of a stack of spheres	No	Empirical correlation + finite volume	Air velocity and water mass flow rate measurement	Menter (1993)

discussed under Sect. 2.4.2 (Eqs. 8.1, 8.2, and 8.3) of this chapter. Precooling process for dates takes place immediately after harvest from 35 to 40 h depending on initial temperature and refrigeration conditions. Several earlier reports have indicated that the heat respiration of the product during this precooling period is extremely minimal and hence can be neglected (Delele et al. 2012; Gowda et al. 1997; Qiu and Wang 2015). Therefore, the heat respiration and mass losses of dates were not considered for the actual simulation. Assuming each bin of dates to be a solid block, the convective heat transfer coefficient h_{cv} related to the convective flux $q_{dates\text{-}air}$ can be obtained by:

$$\mathrm{hcv} = \frac{\mathrm{qdates} - \mathrm{air}}{\mathrm{Td} - \mathrm{TS}} \tag{8.4}$$

where T_d is the initial temperature of dates and T_S is the storage temperature.

The model was established using CFD code ANSYS FLUENT 17 using second-order discretization method and SIMPLE algorithm for pressure-velocity coupling. Steady-state simulations are performed to study the airflow distribution, temperature distribution and convective heat transfer coefficient at date-air interface. The cold room space was divided into 16 million cells using the ANSYS Mesher with additional finned meshing near the interfaces. Further details on the model, boundary conditions, geometry and meshing can be found in Ghiloufi and Khir (2019).

Simulation Results

The established CFD model was validated considering earlier studies performed on cold storage of apples (Hoang et al. 2015). The simulation results for the three different cold storage designs are detailed below.

Normal cold room

Figure 8.5a displays the air flow circulation. The air velocity has a swirling profile due to the rotation of the fans. The velocity is maximum (7.5 m s^{-1}) at the extremities and almost zero at the centre. A recirculation zone is observed due to the air turbulences near the walls. This air flow distribution affects the cooling behaviour of the product in the cold storage. In order to obtain high and uniform air velocity, a steady temperature distribution throughout the cold storage needs to be established. The temperature distribution after 25 h of cooling was observed in three different planes. A large variation in the cooling zones can be observed in the normal room due to the heterogeneous cooling rate causing poor air flux distribution. This will lead to increased biological and mass losses and deteriorate the quality of the stored product.

Cold room *with single deflector*

The air flow after 25 h of cooling inside the cold room using a single deflector (baffle) is depicted in Fig. 8.5b. Although most of the zones are optimally cooled, several bins remain at temperatures >15 °C. It can be observed that although the usage of a single baffle improves the product refrigeration, the arrangement was not able to ensure uniform cooling of the product.

Cold room with three aerodynamic deflectors

A better airflow distribution was obtained with the three deflector design (Fig. 8.5c). Several recirculation zones were observed above the bins due to the increased turbulence developed by the deflectors. A uniform temperature distribution was observed inside the cold room with three aerodynamic deflectors. All the product bins are cooled to temperature < 10 °C in all the planes which validates the effectiveness of the arrangement. Additionally, results indicate that the new design significantly reduces the precooling period by 6 h compared to cold room with single deflector and by 10 h compared to normal cold room. The new arrangement with three deflectors also considerably minimizes the energy consumption and therefore the operating cost of the cold storage.

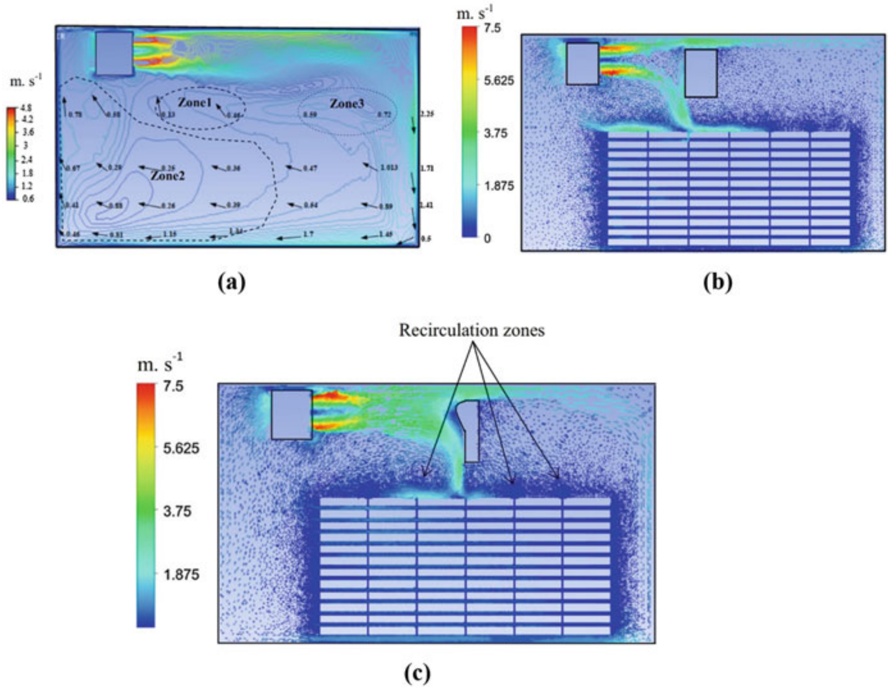


Fig. 8.5 Temperature distribution in (**a**) normal cold room (**b**) cold room with single deflector (**c**) cold room with three deflectors. (Reproduced from Ghiloufi and Khir (2019) with permission from Springer Nature)

3.4.4 Case Study II – Virtual Cold Chain (VCC) Method to Model Post-harvest Temperature History and Quality Loss of Citrus Fruit

Loss of quality is a growing concern in the fruit industry. Post-harvest losses are often as high as 13–38% (Gustavsson et al. 2011). During the preservation and storage of fresh produce, temperature is the most important parameter affecting their quality, shelf life and spoilage rates. It is essential to maintain optimum temperature throughout the supply chain (Pelletier et al. 2011). Therefore, quality observation throughout the cold chain is crucial to track the temperature history of the fruit. Conventionally, temperature monitoring is performed using point probes at specific locations on the pallets or cartons and it does not accurately represent overall fruit quality (Delele et al. 2013b). A better alternative would be to apply numerical modeling via computational fluid dynamics and calculate the core temperatures of each fruit by modeling the heat transfer within the fruit and the surrounding airflow (Wu et al. 2018). This can be accomplished by the use of a virtual cold chain (VCC) strategy wherein, temperatures of packed fruit can be tracked throughout different unit operations of a cold chain. By definition, a virtual cold chain employs a CFD-based workflow to obtain the thermal history and predict the quality evolution of every product going through the different operations of a cold chain. With the help of VCCs, post-harvest losses in the fruit and vegetable industry can be significantly reduced (Menter 1994).

Wu et al. (2018) developed a VCC method for tracking the temperature of packed citrus fruit through various unit operations in different cold chain scenarios using CFD modeling. The temperature information of individual fruits are collated to predict fruit quality loss throughout the entire post-harvest supply chain. The VCC method for citrus fruit (oranges) is discussed in the case study for a conventional cold chain entailing three operations – precooling, refrigerated transport and cold storage. Although only a single carton is used for this study, it is adequate to show the efficacy of the VCC method and can be later extended to other complex models.

Cold Chain Strategies

The VCC method in the present study is used to comparatively assess the temperature history and fruit quality loss throughout the five cold chain strategies. The VCC method recreates five different cold chain strategies used in the fruit industry using different combinations of the above-mentioned unit operations. The different cold chain strategies and their operating parameters are illustrated in the form of a flow chart in Fig. 8.6a. The baseline cold chain (I) is chosen as the control/ representative scenario as it is the most widely used cold chain in the fruit industry; it involves partial precooling to remove fruit heat followed by further heat removal during transport. The cold-disinfestation precooling (II) consists of lower temperatures required for markets demanding a disinfestation protocol to kill insect larvae in fruit. The third cold chain – ambient cooling (III) does not include a precooling step. The fruits are instead stored in static cold storage for 5 days before shipment, establishing a slow cooling process. In the ambient loading (IV) cold chain model, the fruits are directly loaded to the refrigerated container for transport after packing. The final cold chain strategy – holding after precooling (V) contains an additional cold storage before shipment and simulates the scenario where fruits are stored for few days after precooling before being transported.

Model Development

A fibreboard carton (0.4 × 0.3 × 0.27 m) filled with 64 orange fruits according to a predetermined pattern was selected as a model for the study. The fruits are discretely modelled as spheres (d = 7.5 cm) with the total weight of the carton being 13.6 kg. Three separate computational models are developed for precooling, refrigerated transport and storage (Fig. 8.6b). The air flow rates are 1 L kg^{-1} s^{-1}, 0.02 L kg^{-1} s^{-1} and 0.002 L kg^{-1} s^{-1} for precooling, transport and storage, respectively. The initial temperature of the fruit and cardboard is assumed to be 21 °C.

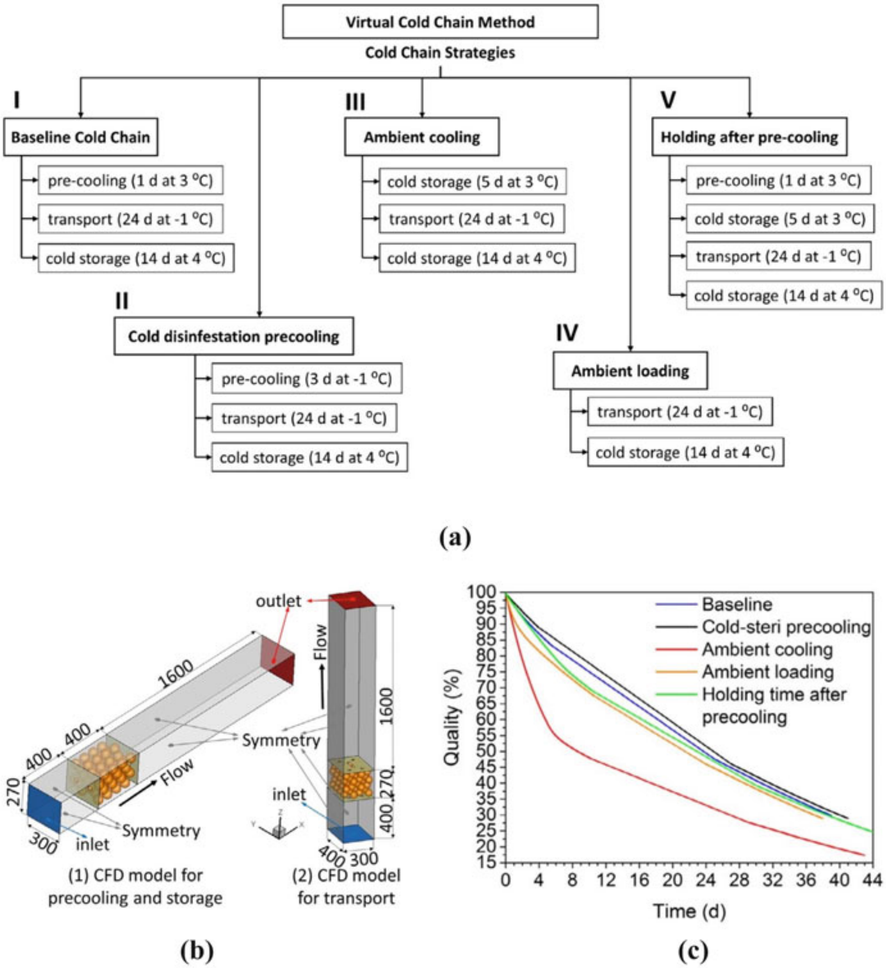


Fig. 8.6 (**a**) Virtual cold chain strategies (**b**) computational models for the VCC method (**c**) average quality loss of fruits in the five cold chains. (Reproduced from Wu et al. (2018) with permission from Elsevier)

The simulations are performed using RANS equations with the shear stress (SST) k-ω turbulence model on the open source CFD code OpenFOAM 2.4.0 (Robertson 2016). All CFD models are meshed using tetrahedral cells. The latent heat of evaporation and heat of respiration have negligible effect on the cooling rate of the oranges and hence are not incorporated in the model. SIMPLE and merged PISO-SIMPLE (PIMPLE) algorithms are used for steady state and time-dependent simulations, respectively. A standard model for predicting the disparity in overall fruit quality over time is developed based on the kinetic rate law (Dermesonlouoglou et al. 2008):

$$-\frac{dA}{dt} = kAn \tag{8.5}$$

where t is the time [s], k is the rate constant [s^{-1}], n is the order of the reaction and A is the change in overall fruit quality estimated by the simulated virtual cold chains. First order reactions are assumed for the overall quality change (A) of oranges. Therefore, Eq. (8.5) can be integrated as:

$$A = A0e - kt \tag{8.6}$$

Arrhenius equation gives the temperature dependency of overall fruit quality loss (Delele et al. 2019b):

$$k(T) = k0e^{\frac{-Ea}{RT}} \tag{8.7}$$

where k_0 is a constant [d^{-1}], E_a is the activation energy [J mol^{-1}], R is the ideal gas constant [8.314 J mol^{-1} K^{-1}], T is the absolute temperature [K].

Simulation Results

The average temperature history of all fruits reveals the differences amongst the five cold chains in a comprehensive manner. The cold disinfestation precooling (II) cold chain is observed to be the most efficiency strategy to lower the fruit temperature. Due to the effects of precooling, the baseline cold chain (I) and holding time after precooling (V) chain are also efficient to cool the fruit quickly to 3 °C. On the contrary, the ambient cooling (III) and loading (IV) cold chains take longer duration to cool the fruit due to lower air flow rates.

The quality degradation of all fruits, based on first order kinetics is illustrated in Fig. 8.6c. The remaining quality after baseline (I), cold-disinfestation precooling (II), ambient cooling (III), ambient loading (IV) and holding time after precooling (V) cold chains are 30%, 29%, 17%, 29%, and 25%, respectively. The ambient cooling cold chain has the lowest residual quality, almost 23% elevated quality loss as compared to the baseline cold chain. This may be attributed to the longer duration of initial cold storage (5 d) before shipment, leading to a significant quality loss. A maximum variation of 2% in quality loss is estimated between individual fruits in the cold-disinfestation after precooling (II) cold chain making it the most effective strategy. Conversely, a maximum difference in quality loss of 5% is observed among the fruits in ambient cooling (III) cold chain, making it the least effective strategy.

3.4.5 Case Study III – Performance Improvement of the Industrial Cooling Process of Large Beef Carcasses by CFD Modeling

Beef is usually stored in cold rooms as carcasses, before being processed to the consumer's preferred size and shape, thereby maintaining hygiene, quality and visual appeal. During industrial air blast cooling in the cold rooms, the carcasses are exposed to the cooling air at a specific temperature, velocity, flow direction and relative humidity which determine the cooling rate of the beef; which in turn affects weight loss, moisture loss, shelf life, rate of biochemical reactions within the carcass and final meat quality (Hamoen et al. 2013). As both very fast and very slow cooling rates have side effects on final meat quality, modern slaughterhouses use controlled cooling methods with an aim to produce meat with desired quality in the shortest possible cooling time. The following case study is discussed in brief as it is fairly similar to the case study discussed in Sect. 3.3.3. on pre-cooling operation during cold storage.

Delele et al. (2019a) evaluated the optimization of industrial cooling of large beef carcasses using CFD. The CFD model allows combination of airflow, temperature, moisture transport, energy transport, weight loss and quality aspects to optimize the cooling efficiency (Kuffi et al. 2016). The study was performed using a validated model of beef carcass developed by Kuffi et al. [142] and solved using commercial CFD code ANSYS-CFX. The cooling problem was solved using the commonly used RANS equations based on the governing equations using a turbulence model. Further details on the model, mesh and computational boundary conditions can be found in Delele et al. (2019a). The study analyzed the effect of pre-cooling temperature and air flow rate on the cooling time quality loss of the beef carcass.

Simulation results indicated that precooling air temperature and duration have a major effect on the cooling time and weight loss, whereas air velocity was not considered a critical factor. Low air velocity was found to be optimal for both energy consumption and retaining overall meat quality. Additionally, low temperature was noted to be the optimum operating condition for the pre-cooling process. If quick drying of the product is desired, high velocity with high temperature is more appropriate with limitations of higher weight and colour loss. However, as low weight loss was aimed in the current study, low velocity and low temperature pre-cooling were deemed ideal. For further discussions on the simulation results, Delele et al. (2019a) can be referred. Therefore, the study summarises that comprehensive CFD models are capable of predicting the optimum operating conditions of industrial cooling of beef carcasses and the approach can be extended to similar cooling operations in the cold chain industry.

4 Challenges, Summary and Outlook

4.1 Challenges

AI and blockchain have been gaining increasing significance due to the recent change in food safety regulations. AI and blockchain focus on the prediction and prevention model rather than the reaction and response model for early prediction of future foodborne outbreaks and other food safety issues. Although the data of food traceability being stored in a decentralized blockchain ledger looks promising, it does not possess a verification system to check the authenticity of the data collected from RFID tags or barcodes. Additionally, as blockchain involves P2P interactions, there is a need to standardize the protocols used in blockchain and its integration with AI for ensuring transparency and data security.

The application of CFD simulations reveals that products can be processed and stored in more efficient systems thereby improving its quality and shelf life. Though CFD provides significant data on the performance of food processing operations and storage environments, the simulation process is time-consuming and requires powerful supercomputers with large storage databases. In recent years, 3D image data from computed tomography (CT) and magnetic resonance imaging (MRI) provides realistic high quality 3D models. However, most existing meshing tools can only operate with models developed by computer-aided design (CAD) tools and have difficulty meshing 3D images. Image-based meshing is expected to open new avenues of modeling in food processing and storage that were earlier challenging due to unavailability of suitable models thereby enabling enhanced food safety.

4.2 Summary

In this chapter, an overview on the current state-of-the-art of AI and blockchain technology in food supply chain management, and CFD for optimization of post-harvest cold storage rooms is reviewed. The applicability of AI and blockchain in gathering the data of agricultural practices and tracing of food products from 'farm to plate approach' is discussed. The role of CFD in food processing as an enabling tool for enhanced food quality and safety is outlined. As a case study, the application of AI in aflatoxin detection in nuts is presented using the Detox™ model by TOMRA. Additionally, the implementation of blockchain technology in the dairy industry is discussed along with an emerging case study of honey traceability. A case study on the application of CFD for optimization of pre-cooling conditions for dates storage in a cold room is reviewed, wherein it was observed that cold room with three deflectors proved to be the most suitable configuration with the best airflow and temperature distribution. In another case study, the development of a virtual cold chain method for tracking the temperature of individual fruits in the cold chain and its simulation using CFD is evaluated. The optimization of industrial pre-cooling of beef carcasses using a comprehensive CFD model is also reviewed as another case study.

AI-enabled blockchain, with its added advantage of decentralized, distributed data storage, enables better agri-food management with enhanced traceability and transparency. The food industry is also exploring the benefits of blockchain technology and next generation genome sequencing for traceability of pathogen outbreaks to ensure food safety. Even though CFD has been a conventional modeling tool in food processing for the last decade, recent computational advancements will enable CFD to be an obligatory tool for optimization of food quality and safety operations. Further, CFD can also facilitate food industries to expand and develop new process strategies corresponding to the demands in the market, while also maintaining high levels of product quality. Therefore, quantitative assessment of the quality and safety of food products is deemed to be highly essential for both the manufacturers and consumers.

4.3 Outlook

Future food safety guidelines to ensure food quality and safety insist on embracing advanced computational tools as an essential part of the global food supply-cum-processing chain. AI-enabled blockchain has the potential to address the challenges of sustainable development goals (SDG) to achieve food security, improve nutrition and promote sustainable agriculture by predicting the environmental effects on nutritional quality and safety of food. In this regard, there is a need to focus on the emerging concern of micropollutants such as heavy metals, pesticides and its end-to-end traceability in vegetables and seafoods across the food chain, in order to predict any foodborne outbreaks. Further, from a policy perspective, a stringent regulatory framework has to be mandated for providing the quality standards information for primary processed food products such as rice, cereals, fruits, vegetables etc. sold by the retail chain along with back-end traceability to locate the agricultural practices of fruits and vegetables. Additionally, usage of big data analytics, though currently in its infancy, will be highly useful in food safety and quality in near future, as it can improve the efficiency of the entire food processing chain by providing predictive insights, correlations, hidden patterns and taking real-time decisions.

CFD aids food manufacturers to stay in complete control of every aspect of food production from the initial to the final stage, thereby delivering a high quality product that is most desirable to the consumer. The continuous advancements in computational technology, parallel processing, advances in numerical methods and persistent effort from CFD researchers are the key factors that will make integration of CFD in food processing conceivable in the near future. Deep machine learning will also be an enabling tool to improve the speed, accuracy, applicability and user-friendliness of the CFD software. Although the modeling platforms of AI, blockchain and CFD have been rigorously adopted in other domains, it is still in its infancy in the agri-food supply chain sector and requires implementation supported by strong research. The advancements in traceability of agri-food products, effective maintenance of operating conditions, and monitoring the quality and integrity of foods pre- and post- processing using emerging advanced computational tools are key to minimize quality issues in the food industry to ensure overall food safety.

Acknowledgments The authors are immensely thankful to Prof. V.V. Ranade for his insights, suggestions and comments on the chapter.

References

Abad E, Palacio F, Nuin M, De Zarate AG, Juarros A, Gómez JM, Marco S (2009) RFID smart tag for traceability and cold chain monitoring of foods: demonstration in an intercontinental fresh fish logistic chain. J Food Eng 93(4):394–399. https://doi.org/10.1016/j.jfoodeng.2009.02.004

AgriOpenData (2016) https://www.youtube.com/watch?v=7o3245dZ_gk. Accessed 24 June 2021

Allais I, Alvarez G, Flick D (2006) Modelling cooling kinetics of a stack of spheres during mist chilling. J Food Eng 72(2):197–209. https://doi.org/10.1016/j.jfoodeng.2004.11.010

Alvarez G, Flick D (2007) Modelling turbulent flow and heat transfer using macro-porous media approach used to predict cooling kinetics of stack of food products. J Food Eng 80(2):391–401. https://doi.org/10.1016/j.jfoodeng.2005.12.052

Amara SB, Laguerre O, Charrier-Mojtabi MC, Lartigue B, Flick D (2008) PIV measurement of the flow field in a domestic refrigerator model: comparison with 3D simulations. Int J Refrig 31(8): 1328–1340. https://doi.org/10.1016/j.ijrefrig.2008.04.005

Ambaw A, Beaudry R, Bulens I, Delele MA, Ho QT, Schenk A, Nicolai BM, Verboven P (2011) Modeling the diffusion–adsorption kinetics of 1-methylcyclopropene (1-MCP) in apple fruit and non-target materials in storage rooms. J Food Eng 102(3):257–265. https://doi.org/10.1016/j.jfoodeng.2010.08.028

Ambaw A, Delele MA, Defraeye T, Ho QT, Opara LU, Nicolaï BM, Verboven P (2013) The use of CFD to characterize and design post-harvest storage facilities: past, present and future. Comput Electron Agric 93:184–194. https://doi.org/10.1016/j.compag.2012.05.009

Anandharamakrishnan C (2013) Applications of computational fluid dynamics in the thermal processing of canned foods. In: Computational fluid dynamics applications in food processing. Springer, New York, NY, pp 27–36

Antonucci F, Figorilli S, Costa C, Pallottino F, Raso L, Menesatti P (2019) A review on blockchain applications in the Agri-food sector. J Sci Food Agric 99(14):6129–6138. https://doi.org/10.1002/jsfa.9912

Arêdes Martins M, Soares de Oliveira L, Osorio Saraz JA (2011) Numerical study of apple cooling in tandem arrangement. Dyna 78(166):158–165

Bakalis S, Knoerzer K, Fryer PJ (eds) (2015) Modeling food processing operations. Elsevier

Bayatian M, Azari MR, Ashrafi K, Jafari MJ, Mehrabi Y (2021) CFD simulation for dispersion of benzene at a petroleum refinery in diverse atmospheric conditions. Environ Sci Pollut Res 1-12: 32973–32984. https://doi.org/10.1007/s11356-020-12254-1

Benet J (2014) IPFS-content addressed, versioned, P2P file system. [Online]. Available: https://arxiv.org/abs/1407.3561. Accessed 24 June 2021

Borah MD, Naik VB, Patgiri R, Bhargav A, Phukan B, Basani SG (2020) Supply chain management in agriculture using blockchain and IoT. In: Advanced applications of blockchain technology. Springer, Singapore, pp 227–242. https://doi.org/10.1007/978-981-13-8775-3_11

Boysan HF, Choudhury D, Engelman MS (2009) Commercial CFD in the service of industry: the first 25 years. In: 100 volumes of 'notes on numerical fluid mechanics'. Springer, Berlin, Heidelberg, pp 451–461. https://doi.org/10.1007/978-3-540-70805-6_35

Brown M (ed) (2008) Chilled foods: a comprehensive guide. Elsevier

Caro MP, Ali MS, Vecchio M, Giaffreda R (2018, May) Blockchain-based traceability in Agri-food supply chain management: a practical implementation. In: 2018 IoT vertical and topical summit on agriculture-Tuscany (IOT Tuscany). IEEE, pp 1–4. https://doi.org/10.1109/IOT-TUSCANY.2018.8373021

Cho YJ, Kang S (eds) (2011) Emerging technologies for food quality and food safety evaluation. CRC Press. https://doi.org/10.1201/b10710

Chourasia MK, Goswami TK (2007a) Simulation of effect of stack dimensions and stacking arrangement on cool-down characteristics of potato in a cold store by computational fluid dynamics. Biosyst Eng 96(4):503–515. https://doi.org/10.1016/j.biosystemseng.2006.12.010

Chourasia MK, Goswami TK (2007b) Steady state CFD modeling of airflow, heat transfer and moisture loss in a commercial potato cold store. Int J Refrig 30(4):672–689. https://doi.org/10.1016/j.ijrefrig.2006.10.002

Ciano T, Ferrara M, Babanezhad M, Khan A, Marjani A (2021) Prediction of velocity profile of water based copper nanofluid in a heated porous tube using CFD and genetic algorithm. Sci Rep 11(1):1–12. https://doi.org/10.1038/s41598-021-90201-x

Cuesta FJ, Lamúa M (2009) Fourier series solution to the heat conduction equation with an internal heat source linearly dependent on temperature: application to chilling of fruit and vegetables. J Food Eng 90(2):291–299. https://doi.org/10.1016/j.jfoodeng.2008.06.036

Darwesh M, Elmetwalli AH (2015) Effect of cold storage conditions on physical properties of potato tubers. Misr J Agric Eng 32(2):789–806. https://doi.org/10.21608/mjae.2015.98640

de Albuquerque CD, Curet S, Boillereaux L (2019) A 3D-CFD-heat-transfer-based model for the microbial inactivation of pasteurized food products. Innovative Food Sci Emerg Technol 54: 172–181. https://doi.org/10.1016/j.ifset.2019.04.007

Delele MA, Schenk A, Ramon H, Nicolaï BM, Verboven P (2009) Evaluation of a chicory root cold store humidification system using computational fluid dynamics. J Food Eng 94(1):110–121. https://doi.org/10.1016/j.jfoodeng.2009.03.004

Delele MA, Verboven P, Ho QT, Nicolai B (2010) Advances in mathematical modelling of postharvest refrigeration processes. Stewart Postharvest Rev 2(1):1–8. https://doi.org/10.2212/spr.2010.2.1

Delele MA, Vorstermans B, Creemers P, Tsige AA, Tijskens E, Schenk A, Opara UL, Nicolaï BM, Verboven P (2012) CFD model development and validation of a thermonebulisation fungicide fogging system for postharvest storage of fruit. J Food Eng 108(1):59–68. https://doi.org/10.1016/j.jfoodeng.2011.07.030

Delele MA, Ngcobo ME, Opara UL, Meyer CJ (2013a) Investigating the effects of table grape package components and stacking on airflow, heat and mass transfer using 3-D CFD modelling. Food Bioprocess Technol 6(9):2571–2585. https://doi.org/10.1007/s11947-012-0895-5

Delele MA, Ngcobo MEK, Getahun ST, Chen L, Mellmann J, Opara UL (2013b) Studying airflow and heat transfer characteristics of a horticultural produce packaging system using a 3-D CFD model. Part I: model development and validation. Postharvest Biol Technol 86:536–545. https://doi.org/10.1016/j.postharvbio.2013.08.014

Delele MA, Kuffi KD, Geeraerd A, De Smet S, Nicolai BM, Verboven P (2019a) Optimizing precooling of large beef carcasses using a comprehensive computational fluid dynamics model. J Food Process Eng 42(4):e13053. https://doi.org/10.1111/jfpe.13053

Delele MA, Kuffi KD, Nicolai B, Verboven P (2019b) CFD modeling to improve the performance of industrial cooling of large beef carcasses. In: Computational fluid dynamics in food processing. CRC Press, p 61

Demissie P, Hayelom M, Kassaye A, Hailesilassie A, Gebrehiwot M, Vanierschot M (2019) Design, development and CFD modeling of indirect solar food dryer. Energy Procedia 158: 1128–1134. https://doi.org/10.1016/j.egypro.2019.01.278

Dermesonlouoglou EK, Pourgouri S, Taoukis PS (2008) Kinetic study of the effect of the osmotic dehydration pre-treatment to the shelf life of frozen cucumber. Innovative Food Sci Emerg Technol 9(4):542–549. https://doi.org/10.1016/j.ifset.2008.01.002

Dewi T, Risma P, Oktarina Y (2020) Fruit sorting robot based on color and size for an agricultural product packaging system. Bull Electr Eng Inform 9(4):1438–1445. https://doi.org/10.11591/eei.v9i4.2353

Dinh TN, Thai MT (2018) AI and blockchain: a disruptive integration. Computer 51(9):48–53. https://doi.org/10.1109/MC.2018.3620971

Drummond L, Sun DW (2010) Effects of chilling and freezing on safety and quality of food products. In: Processing effects on safety and quality of foods. CRC Press, pp 295–322

Everstine K, Spink J, Kennedy S (2013) Economically motivated adulteration (EMA) of food: common characteristics of EMA incidents. J Food Prot 76(4):723–735. https://doi.org/10.4315/0362-028X.JFP-12-399

Farid MM (ed) (2010) Mathematical modeling of food processing. CRC Press. https://doi.org/10.1201/9781420053548

Ferrua MJ, Singh RP (2011) Improved airflow method and packaging system for forced-air cooling of strawberries. Int J Refrig 34(4):1162–1173. https://doi.org/10.1016/j.ijrefrig.2011.01.018

Francisco K, Swanson D (2018) The supply chain has no clothes: technology adoption of blockchain for supply chain transparency. Logistics 2(1):2. https://doi.org/10.3390/logistics2010002

Gao Z, Shao Y, Xuan G, Wang Y, Liu Y, Han X (2020) Real-time hyperspectral imaging for the in-field estimation of strawberry ripeness with deep learning. Artif Intell Agric 4:31–38. https://doi.org/10.1016/j.aiia.2020.04.003

Garbie IH (2010) Enhancing the performance of industrial firms through implementation of lean techniques. In: IIE annual conference. Proceedings. Institute of Industrial and Systems Engineers (IISE), p 1

García-Esteban JA, Curto B, Moreno V, González-Martín I, Revilla I, Vivar-Quintana A (2018) A digitalization strategy for quality control in food industry based on artificial intelligence techniques. In: 2018 IEEE 16th international conference on industrial informatics (INDIN). IEEE, pp 221–226. https://doi.org/10.1109/INDIN.2018.8471994

Ghiloufi Z, Khir T (2019) CFD modeling and optimization of pre-cooling conditions in a cold room located in the south of Tunisia and filled with dates. J Food Sci Technol 56(8):3668–3676. https://doi.org/10.1007/s13197-019-03812-8

Gomes LC, Miranda J, Mergulhão FJ (2019) Operation of biofilm reactors for the food industry using CFD. In: Computational fluid dynamics in food processing. CRC Press, pp 561–590

Gowda BS, Narasimham GSVL, Murthy MK (1997) Forced-air precooling of spherical foods in bulk: a parametric study. Int J Heat Fluid Flow 18(6):613–624. https://doi.org/10.1016/S0142-727X(97)00028-3

Gustavsson J, Cederberg C, Sonesson U, van Otterdijk R, Meybec A (2011) Global food losses and food wastes–extent, causes and prevention. FAO, Rome. http://www.fao.org/3/mb060e/mb060e00.htm. Accessed 25 June 2021

Hamoen JR, Vollebregt HM, Van Der Sman RGM (2013) Prediction of the time evolution of pH in meat. Food Chem 141(3):2363–2372. https://doi.org/10.1016/j.foodchem.2013.04.127

Hartman JH, Murdock I, Spalink T (1999) The swarm scalable storage system. In: Proceedings 19th IEEE International Conference on Distributed Computing Systems. IEEE, pp 74–81

Heising JK, Dekker M, Bartels PV, Van Boekel MAJS (2014) Monitoring the quality of perishable foods: opportunities for intelligent packaging. Crit Rev Food Sci Nutr 54(5):645–654. https://doi.org/10.1080/10408398.2011.600477

Ho QT, Verlinden BE, Verboven P, Nicolaï BM (2006) Gas diffusion properties at different positions in the pear. Postharvest Biol Technol 41(2):113–120. https://doi.org/10.1016/j.postharvbio.2006.04.002

Ho QT, Verboven P, Verlinden BE, Lammertyn J, Vandewalle S, Nicolaï BM (2008) A continuum model for metabolic gas exchange in pear fruit. PLoS Comput Biol 4(3):e1000023. https://doi.org/10.1371/journal.pcbi.1000023

Ho QT, Verboven P, Verlinden BE, Nicolaï BM (2010) A model for gas transport in pear fruit at multiple scales. J Exp Bot 61(8):2071–2081. https://doi.org/10.1093/jxb/erq026

Hoang HM, Duret S, Flick D, Laguerre O (2015) Preliminary study of airflow and heat transfer in a cold room filled with apple pallets: comparison between two modelling approaches and experimental results. Appl Therm Eng 76:367–381. https://doi.org/10.1016/j.applthermaleng.2014.11.012

http://arc-net.io/. Accessed 24 June 2021
http://www.fao.org/fao-who-codexalimentarius/en/. Accessed 24 June 2021
https://blog.google/products/google-cloud/how-ai-can-help-make-safer-baby-food-and-other-products/. Accessed 25 June 2021
https://food.tomra.com/blog/aflatoxins-in-foods. Accessed 24 June 2021
https://fooddigital.com/food/cargill-using-blockchain-technology-trace-turkeys-farm-table. Accessed 24 June 2021
https://ripe.io/. Accessed 24 June 2021
https://worldbeeproject.org/. Accessed 25 June 2021, https://indianexpress.com/article/cities/pune/a-sweet-success-story-in-12-years-indias-honey-production-grows-by-200-exports-by-207-5736611/
https://www.down-stream.io/. Accessed 24 June 2021
https://www.fao.org/publications/sofa/2016/en/. Accessed 24 June 2021
https://www.fareasternagriculture.com/technology/infrastructure/laser-sorting-machines-can-eliminate-the-risk-aflatoxins-in-foods. Accessed 24 June 2021
https://www.fda.gov/food/hazard-analysis-critical-control-point-haccp/haccp-principles-application-guidelines. Accessed 24 June 2021
https://www.iso.org/iso-22000-food-safety-management.html. Accessed 24 June 2021
https://www.tomra.com/en/sorting/food/food-technology. Accessed 25 June 2021
https://www.tomra.com/en/sorting/food/sorting-equipment/genius. Accessed 25 June 2021
Huang E (2017) Blockchain could fix a key problem in China's food industry: the fear of food made in China. Quartz. Available: https://qz.com/1031861/blockchain-could-fix-a-key-problemin-chinasfood-industry-the-fear-of-food-made-in-china/. Accessed 24 June 2021
Inostroza C, Solimeno A, García J, Fernández-Sevilla JM, Acién FG (2021) Improvement of real-scale raceway bioreactors for microalgae production using computational fluid dynamics (CFD). Algal Res 54:102207. https://doi.org/10.1016/j.algal.2021.102207
Jedermann R, Pötsch T, Lloyd C (2014) Communication techniques and challenges for wireless food quality monitoring. Philos Trans R Soc A Math Phys Eng Sci 372(2017):20130304. https://doi.org/10.1098/rsta.2013.0304
Kamath R (2018) Food traceability on blockchain: Walmart's pork and mango pilots with IBM. J Br Blockchain Assoc 1(1):3712. https://doi.org/10.31585/jbba-1-1-(10)2018
Khokhar SG, Min Q, Su C (2015) Bird flu (H7N9) outbreak and its implications on the supply chain of poultry meat in China. J Appl Poult Res 24(2):215–221. https://doi.org/10.3382/japr/pfv007
Koch M (2018) Artificial intelligence is becoming natural. Cell 173(3):531–533. https://doi.org/10.1016/j.cell.2018.04.007
Kosior E, Mitchell J, Davies K, Kay M, Ahmad R, Billiet E, Silver J (2017) Plastic packaging recycling using intelligent separation technologies for materials. In: Proceedings of the annual technical conference, Hyatt Regency, Santa Clara, CA, USA, 12–14 July 2017, pp 500–506
Kuffi KD, Defraeye T, Nicolai BM, De Smet S, Geeraerd A, Verboven P (2016) CFD modeling of industrial cooling of large beef carcasses. Int J Refrig 69:324–339. https://doi.org/10.1016/j.ijrefrig.2016.06.013
Kumar MV, Iyengar NCS (2017) A framework for Blockchain technology in rice supply chain management. Adv Sci Technol Lett 146:125–130. https://doi.org/10.14257/ASTL.2017.146.22
Lin J, Shen Z, Zhang A, Chai Y (2018, July) Blockchain and IoT based food traceability for smart agriculture. In: Proceedings of the 3rd international conference on crowd science and engineering, pp 1–6. https://doi.org/10.1145/3265689.3265692
Liu CC, Ferng YM, Shih CK (2012) CFD evaluation of turbulence models for flow simulation of the fuel rod bundle with a spacer assembly. Appl Therm Eng 40:389–396. https://doi.org/10.1016/j.applthermaleng.2012.02.027
Malekjani N, Jafari SM (2018) Simulation of food drying processes by computational fluid dynamics (CFD); recent advances and approaches. Trends Food Sci Technol 78:206–223. https://doi.org/10.1016/j.tifs.2018.06.006

McConaghy T, Marques R, Müller A, De Jonghe D, McConaghy T, McMullen G, Henderson R, Bellemare S, Granzotto A (2016) Bigchaindb: a scalable blockchain database. White paper, BigChainDB

Menter F (1993) Zonal two equation kw turbulence models for aerodynamic flows. In: *23rd fluid dynamics, plasmadynamics, and lasers conference*, p 2906. https://doi.org/10.2514/6.1993-2906

Menter FR (1994) Two-equation eddy-viscosity turbulence models for engineering applications. AIAA J 32(8):1598–1605. https://doi.org/10.2514/3.12149

Milk CyberSecurity (2018) Available: https://www.greatitalianfoodtrade.it/consum-attori/blockchain-nella-filiera-alimentare-il-prototipo-di-bari/. Accessed 24 June 2021

Misra NN, Dixit Y, Al-Mallahi A, Bhullar MS, Upadhyay R, Martynenko A (2020) IoT, big data and artificial intelligence in agriculture and food industry. IEEE Internet Things J 9:6305–6324. https://doi.org/10.1109/JIOT.2020.2998584

Moureh J, Flick D (2004) Airflow pattern and temperature distribution in a typical refrigerated truck configuration loaded with pallets. Int J Refrig 27(5):464–474. https://doi.org/10.1016/j.ijrefrig.2004.03.003

Moureh J, Tapsoba S, Derens E, Flick D (2009a) Air velocity characteristics within vented pallets loaded in a refrigerated vehicle with and without air ducts. Int J Refrig 32(2):220–234. https://doi.org/10.1016/j.ijrefrig.2008.06.006

Moureh J, Létang G, Palvadeau B, Boisson H (2009b) Numerical and experimental investigations on the use of mist flow process in refrigerated display cabinets. Int J Refrig 32(2):203–219. https://doi.org/10.1016/j.ijrefrig.2008.06.005

Nahor HB, Hoang ML, Verboven P, Baelmans M, Nicolai BM (2005) CFD model of the airflow, heat and mass transfer in cool stores. Int J Refrig 28(3):368–380. https://doi.org/10.1016/j.ijrefrig.2004.08.014

Njikam ANS, Zhao H (2016) A novel activation function for multilayer feed-forward neural networks. Appl Intell 45(1):75–82. https://doi.org/10.1007/s10489-015-0744-0

Norton T, Sun DW (2006) Computational fluid dynamics (CFD)–an effective and efficient design and analysis tool for the food industry: a review. Trends Food Sci Technol 17(11):600–620. https://doi.org/10.1016/j.tifs.2006.05.004

Padhi MR (2020) A review on applications of computational fluid dynamics (CFD) in the food industry. PalArch's J Archaeol Egypt/Egyptol 17(7):10159–10169

Park HW, Yoon WB (2018) Computational fluid dynamics (CFD) modelling and application for sterilization of foods: a review. PRO 6(6):62. https://doi.org/10.3390/pr6060062

Parpas D, Amaris C, Tassou SA (2017) Experimental investigation and modelling of thermal environment control of air distribution systems for chilled food manufacturing facilities. Appl Therm Eng 127:1326–1339. https://doi.org/10.1016/j.applthermaleng.2017.08.134

Pasta supply chain (2018) Available: https://www.aldocozzi.it/news/lablockchain-sbarca-nel-settore-alimentare-la-confezione-di-pastaporta-con-se-tutta-la-sua-storia/. Accessed 24 June 2021

Pathare PB, Opara UL, Vigneault C, Delele MA, Al-Said FAJ (2012) Design of packaging vents for cooling fresh horticultural produce. Food Bioprocess Technol 5(6):2031–2045. https://doi.org/10.1007/s11947-012-0883-9

Pearson S, May D, Leontidis G, Swainson M, Brewer S, Bidaut L, Frey JG, Parr G, Maull R, Zisman A (2019) Are distributed ledger technologies the panacea for food traceability? Glob Food Sec 20:145–149. https://doi.org/10.1016/j.gfs.2019.02.002

Pelletier W, Brecht JK, do Nascimento Nunes MC, Emond JP (2011) Quality of strawberries shipped by truck from California to Florida as influenced by postharvest temperature management practices. HortTechnology 21(4):482–493. https://doi.org/10.21273/HORTTECH.21.4.482

Pham AT, Moureh J, Belaidi M, Flick D (2021) CFD modelling of a pallet of heat-generating product applied to a cheese product. Int J Refrig 128:163–176. https://doi.org/10.1016/j.ijrefrig.2021.03.011

Pillmann W, Geiger W, Isenmann R (2006) Informatics for environmental protection, sustainable development, and risk management 20 years technical committee on environmental informatics. In: Managing Environmental Knowledge. Shaker Verlag. http://enviroinfo.eu/sites/default/files/pdfs/vol114/0001.pdf. Accessed 24 June 2021

Pires JC, Alvim-Ferraz MC, Martins FG (2017) Photobioreactor design for microalgae production through computational fluid dynamics: a review. Renew Sust Energ Rev 79:248–254. https://doi.org/10.1016/j.rser.2017.05.064

Protocol Labs (2017) Filecoin: a decentralized storage network. [Online]. Available: https://filecoin.io/filecoin.pdf. Accessed 24 June 2021

Provenance (2016) Available: https://www.provenance.org/trackingtuna-on-the-blockchain#pilot-phase-2/. Accessed 24 June 2021

Qi Y, Xiao J (2018) Fintech: AI powers financial services to improve people's lives. Commun ACM 61(11):65–69. https://doi.org/10.1145/3239550

Qiu S, Wang J (2015) Effects of storage temperature and time on internal quality of Satsuma mandarin (Citrus unshiu marc.) by means of E-nose and E-tongue based on two-way MANOVA analysis and random forest. Innovative Food Sci Emerg Technol 31:139–150. https://doi.org/10.1016/j.ifset.2015.08.005

Ramachandran RP, Akbarzadeh M, Paliwal J, Cenkowski S (2018) Computational fluid dynamics in drying process modelling—a technical review. Food Bioprocess Technol 11(2):271–292. https://doi.org/10.1007/s11947-017-2040-y

Ramírez EC, Albarrán JC, Salazar LAC (2019, October) The control of water distribution systems as a Holonic system. In: International workshop on service orientation in Holonic and multi-agent manufacturing. Springer, Cham, pp 352–365. https://doi.org/10.1007/978-3-030-27477-1_27

Ranade VV (2002) Computational flow modeling for chemical reactor engineering, vol 5. Academic

Robertson GL (ed) (2016) Food packaging: principles and practice, 3rd edn. CRC Press. https://doi.org/10.1201/b21347

Salah K, Rehman MHU, Nizamuddin N, Al-Fuqaha A (2019) Blockchain for AI: review and open research challenges. IEEE Access 7:10127–10149. https://doi.org/10.1109/ACCESS.2018.2890507

Salish K, Pushpadass HA, Franklin MEE, Mitra H, Muniandy S, Ghosh BC (2021) Three-dimensional computational fluid dynamics modeling of baking of chhana podo (milk cake). J Food Process Eng 44(1):e13587. https://doi.org/10.1111/jfpe.13587

San Domenico coffee (2018) Available: https://www.blockchain4innovation.it/mercati/agrifood/dalla-piantagionealla-tazzina-la-blockchain-entra-nel-caffe/. Accessed 24 June 2021

Shekhar Y, Dagur E, Mishra S, Sankaranarayanan S (2017) Intelligent IoT based automated irrigation system. Int J Appl Eng Res 12(18):7306–7320

Statista (2018) Honey Market Worldwide and in the US. Retrieved Nov 15, 2019 from https://www.statista.com/topics/5090/honey-market-worldwide/

Steiner J, Baker J, Wood G, Meiklejohn S (2015) Blockchain: the solution for transparency in product supply chains. https://www.provenance.org/whitepaper. Accessed 24 June 2021

Strayer SE, Everstine K, Kennedy S (2014) Economically motivated adulteration of honey: quality control vulnerabilities in the international honey market. Food Prot Trends 34(1):8–14. https://www.cropin.com/blogs/following-the-hive-to-honey-trail-using-digital-traceability/

Sun D-W (ed) (2019) Computational fluid dynamics in food processing, 2nd edn. CRC Press. https://doi.org/10.1201/9781351263481

Talaviya T, Shah D, Patel N, Yagnik H, Shah M (2020) Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. Artif Intell Agric 4:58–73. https://doi.org/10.1016/j.aiia.2020.04.002

Tan A, Ngan PT (2020) A proposed framework model for dairy supply chain traceability. Sustain Futures 2:100034. https://doi.org/10.1016/j.sftr.2020.100034

Tassou SA, Gowreesunker BL, Parpas D, Raeisi A (2015) Modelling cold food chain processing and display environments. In: Modeling food processing operations. Elsevier, pp 185–208. https://doi.org/10.1016/B978-1-78242-284-6.00007-6

Team NA (2018) NEBULA AI (NBAI) – decentralized AI blockchain whitepaper. https://neironix.io/documents/whitepaper/4082/NBAI_whitepaper_EN.pdf. Accessed 24 June 2021

Thike PH, Zhao Z, Shi P, Jin Y (2020) Significance of artificial neural network analytical models in materials' performance prediction. Bull Mater Sci 43(1):1–22. https://doi.org/10.1007/s12034-020-02154-y

Tian F (2016) An agri-food supply chain traceability system for China based on RFID & blockchain technology. In: 2016 13th international conference on service systems and service management (ICSSSM). IEEE, pp 1–6. https://doi.org/10.1109/ICSSSM.2016.7538424

Toparlar Y, Blocken B, Maiheu B, Van Heijst GJF (2017) A review on the CFD analysis of urban microclimate. Renew Sust Energ Rev 80:1613–1640. https://doi.org/10.1016/j.rser.2017.05.248

Trafialek J (2019) The role of suppliers of raw materials in ensuring food safety. Glob J Nutr Food Sci 1(4):1–2. https://doi.org/10.33552/GJNFS.2019.01.000517

Tripoli M, Schmidhuber J (2018) Emerging opportunities for the application of Blockchain in the agri-food industry. FAO and ICTSD: Rome and Geneva. Licence: CC BY-NC-SA, 3. http://www.fao.org/publications/card/en/c/CA9934EN/. Accessed 24 June 2021

Tu J, Yeoh GH, Liu C (2018) Computational fluid dynamics: a practical approach. Butterworth-Heinemann. https://doi.org/10.1016/C2015-0-06135-4

Uçar A, Yilmaz MV, Cakiroglu FP (2016) Food safety–problems and solutions. Significance, prevention and control of food related diseases. IntechOpen, pp 1–26. https://doi.org/10.5772/63176

Versteeg HK, Malalasekera W (2007) An introduction to computational fluid dynamics: the finite volume method. Pearson Education

Wang S, Guo Q, Wang L, Lin L, Shi H, Cao H, Cao B (2015) Detection of honey adulteration with starch syrup by high performance liquid chromatography. Food Chem 172:669–674. https://doi.org/10.1016/j.foodchem.2014.09.044

Wang L, Quant R, Kolios A (2016) Fluid structure interaction modelling of horizontal-axis wind turbine blades based on CFD and FEA. J Wind Eng Ind Aerodyn 158:11–25. https://doi.org/10.1016/j.jweia.2016.09.006

Wilkinson S (2014) Storj a peer-to-peer cloud storage network. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.693.785. Accessed 24 June 2021

Wu W, Cronjé P, Nicolai B, Verboven P, Opara UL, Defraeye T (2018) Virtual cold chain method to model the postharvest temperature history and quality evolution of fresh fruit–a case study for citrus fruit packed in a single carton. Comput Electron Agric 144:199–208. https://doi.org/10.1016/j.compag.2017.11.034

Xu J, Guo S, Xie D, Yan Y (2020) Blockchain: a new safeguard for Agri-foods. Artif Intell Agric 4:153–161. https://doi.org/10.1016/j.aiia.2020.08.002

Younus UM (2017) Fourth industrial revolution. https://www.dawn.com/news/1331909. Accessed 25 June 2021

Zawawi MH, Saleha A, Salwa A, Hassan NH, Zahari NM, Ramli MZ, Muda ZC (2018, November) A review: fundamentals of computational fluid dynamics (CFD). In: AIP conference proceedings, vol. 2030, no. 1. AIP Publishing LLC, pp 020252. https://doi.org/10.1063/1.5066893

Zhang B, Huang W, Li J, Zhao C, Fan S, Wu J, Liu C (2014) Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: a review. Food Res Int 62:326–343. https://doi.org/10.1016/j.foodres.2014.03.012

Zhou W, Therdthai N (2019) Three-dimensional CFD modeling of continuous industrial baking process. In: Computational fluid dynamics in food processing. CRC Press, pp 193–224

Zhou L, Zhang C, Liu F, Qiu Z, He Y (2019) Application of deep learning in food: a review. Compr Rev Food Sci Food Saf 18(6):1793–1811. https://doi.org/10.1111/1541-4337.12492

Zhu L, Spachos P, Pensini E, Plataniotis KN (2021) Deep learning and machine vision for food processing: a survey. Curr Res Food Sci 4:233–249. https://doi.org/10.1016/j.crfs.2021.03.009