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# Computer-Integrated Food Manufacturing


## Abstract

Computer-Integrated Food Manufacturing (CIFM) is part of the digital transformation of food industry that has been underway for some time but is now accelerating. While it can include all aspects of food manufacturing, including planning and design, operations, manufacturing, and customer engagement, this article focuses on computer-aided food engineering (CAFE). CAFE typically involves the building of a physics-based virtual model of the product, process, or equipment. Such a model enables understanding and quick extraction of design sensitivity for improved optimization, faster time-to-market, and higher-level innovation. Although CAFE is challenging because of complexity and variability in foods, the changes it undergoes during processing, and its multidisciplinary nature, these challenges can be overcome, particularly due to the advances in mechanistic understanding and computing resources. Digital tools in CIFM, such as CAFE, digital twins, 3-D food printing, Internet of Things, and tools for systems-level decision-making, should improve efficiency, ensure food safety and security, and minimize energy usage and food waste. Industry-university collaborations, building virtual communities and investing of governmental resources can help accelerate CIFM.


## Computer-Integrated Manufacturing

Computer-integrated manufacturing (CIM) can be broadly defined as the integration of computers in all aspects of manufacturing, including product design, production planning, process control, and information processing. CIM includes computer-aided manufacturing (CAM), a closely related term that typically refers more directly to computer-controlled manufacturing, but these terms are often used interchangeably. Still, more closely related terms include computer-aided design (CAD) that primarily deals with geometrical aspects of a design, and computer-aided engineering (CAE) that incorporates engineering analysis in addition to geometry in CAD. CIM in the food industry, or CIFM, supports all functions in a food manufacturing company, thereby enhancing its business opportunities [1]. Thus, by some definitions, CIFM includes everything from smart appliances, to monitoring and control, to design, to electronic scales, to drawing software. For brevity, CIFM, in this article, is focusing primarily on CAE in a food context, or computer-aided food engineering (CAFE[2]), with brief mention of a few broader topics.

## Computer-Integrated Food Manufacturing

Computer-integrated food manufacturing is part of the digital transformation of the food industry that enables us to: 1) uncover invisible insights, 2)  predict the future, 3) optimize design, 4) upskill humans, 5) automate, and 6) make information accessible [3]. These activities impact most areas in the food industry, including planning and design, operations, manufacturing, and customer engagement. Additionally, the use of digital tools (e.g., AI, blockchain, IoT, digital twin) across the food supply chain will undoubtedly play an important role in improving commercial efficiency, ensuring food safety and food security, and minimizing energy usage and food waste at a global scale [4, 5]. These expected improvements are part of the transition from Industry 4.0 to 5.0 [6]. Significant activity is underway in CIFM [7].

CAFE, the primary interest of this article as part of CIFM, enables uncovering invisible insights and optimization and can be a part of design and manufacturing. Food manufacturing is broadly defined here to include farm-to-fork-to-health. It includes the design and control of food products, processes, packaging, and equipment for quality and safety. CAFE can involve all these operations and indicators, from the molecular scale to that of an entire food plant or a farm (or a collection of plants/farms). Much of this article refers to the scale of a food product/process/equipment. CAFE distinguishes itself from the older prototype-based manufacturing that relied primarily on building and testing. Benefits of computer integration can be reduced making of prototypes (product/process/ equipment), thus minimizing trial-and-error experimentation, faster time-to-market, easier personalization, higher-level innovation, and less energy and resource use (more sustainable). It would be fair to say that the use of CAFE in design and manufacturing lags behind other digital tools (as part of CIFM) in use in food industry [3].

While automotive, aerospace, and defense sectors have been the largest users of CAE, the food industry has seen a small penetration of CAFE. The potential, however, is immense, as it can help the food industry innovate faster to produce healthier, more sustainable, and personalized food, as demanded by today's consumers. Such digital tools (as in CAFE) can also find their way into building smart appliances for home use [8]. Yet another use of such digital tools is in multidisciplinary training and education [9], as part of upskilling humans mentioned earlier.

## Engines of Computer-Aided Food Engineering

The main ingredient in CAFE (as part of CIFM) is a computer model that is an accurate virtual representation of a real product or process. A model can be mechanistic, data-driven, or a combination of both. Processes such as heating, drying, baking, puffing, and packaging are examples for which models have been developed. A mechanistic model uses geometry, physics, material properties, and processing conditions as close as possible to reality, without making the computations unnecessarily complex. Simulation of such a model allows one to truly understand the process that in turn provides directionality in manufacturing. The downside of this is the complexity in building such a model and the need for significant computing resources. In contrast, in data-driven models, the model is built-up from input and output data with the product and the process as black box. Data-driven models are advantageous in that they do not require the complex mechanistic understanding, so they are easier to build. On the downside, they require large amounts of real data, they do not provide the mechanistic insights, they are not as transferrable between products and processes (consequence of not being mechanistic), and the directionality is also more limited.

Today, mechanistic models (as opposed to data-driven models, not counting simple correlations) have the highest level of maturity, although these models are mostly developed in a research context. Historically, models started with analytical solutions for simple physics (as in canning) and moved into complex processes (as in microwave drying or high-pressure processing), becoming increasingly sophisticated and realistic, leading the way to CAFE possibilities. Being primarily in a research context, the models emphasized understanding, distinguishing them from use in industrial product and process design. While understanding is also a goal in industry, design sensitivity (providing a direction to optimize in product or process design), their prime objective, typically needs less mechanistic details but more rapid simulation to cover many factors and levels.

A relatively significant number of academic researchers are active in building models of food processes and product transformations. To effectively build mechanistic models, we need a framework to describe the physical and chemical changes the food is undergoing, an ability to include realistic geometry, and the ability to easily predict food physicochemical properties as function of composition, temperature, and other factors. There have been significant advances in all these fronts—several matured physics-based frameworks exist [10-12] that are readily usable, of which the porous media-based framework has been the most versatile. Realistic geometries at multiple scales can be captured and imported for model building [13]. Properties can be predicted with reasonable accuracy from existing prediction formulas [14] or predicted from complementary simulations (the same product/process but at different spatial or time scales) [15-17]. Combining the geometry, physics, and properties, a virtual model of the process is developed, typically on a commercial software, that facilitates ready inclusion of needed food physics. The model is then simulated for ranges of product and process parameters to obtain mechanistic understanding (uncover invisible insights) and directionality toward optimum design (optimize).

## Bottlenecks and Workarounds in Computer-Aided Food Engineering

In the CAFE arena of CIFM, unique challenges exist as compared to non-food manufacturing. Foods are too numerous, they are structurally and compositionally complex and highly variable, they undergo drastic changes during processing, their physics-based understanding is less developed due to their multidisciplinary nature, and they have poorly understood relationships between sensory qualities and physical and chemical characteristics.

### Complexity of foods

Foods are structurally and compositionally complex with tremendous natural variability. Their physical, chemical, biological, and sensory properties are hard to predict. Still, for the purposes of CAFE, simple models can estimate some of the material properties from composition with reasonable accuracy. Depending on the application, their structure can be acquired at multiple levels of detail. Imaging techniques [13] can provide details all the way down to nanometer scale, if needed. For many applications, homogenized (averaged) properties are good enough. Thus, the porous media-based models[11, 18], that ignore the detailed structure but use averages over a small region, while still providing local variations, have been successful for CAFE.

### Drastic changes in foods during processing

When processed, foods go through drastic changes (think of flour-to-dough-to-bread) that are not entirely mechanistically understood. The final quality is not just a function of local temperature, moisture, and other quantities, but possibly their histories during processing. Many reactions happen during processing and storage (and they matter in predicting the final sensory attributes of the food) but their rate constants needed for CAFE often have not been identified. However, a combination of mechanistic approaches to describe some of the changes (e.g., how moisture is lost during a French fry process) with semi-empirical or empirical information for the hard-to-describe ones (e.g., how moisture loss relates to crispness) can get us around this.

### Food physics is as varied as foods

Foods are numerous. When pursuing CAFE, a food process simulation within a realistic timeframe (so it does not become a research project) requires software-implementable mechanistic frameworks that describe changes in the food for entire classes of processes (e.g., drying and baking belong to the same class). The framework then can be customized easily for a specific product or process within that class by using minor parameter changes. Physics-based frameworks [10, 18, 19] that have been under development have reached a level of maturity and are now readily implementable in available commercial software, thereby making CAFE a realistic option. These frameworks treat the food product transformation in somewhat equivalent ways and the user can choose between them depending on the level of comfort with the underlying physics.

### Multidisciplinary and multiphysics background is necessary

Food processes often involve multiphysics; for example, a drying process involves heat transfer, water transport, together with the complex solid mechanics of shrinkage. Of course, food processing already combines food science with engineering. To effectively work with such processes in CAFE, a highly interdisciplinary background is needed that is hard to find in typical educational programs. Thus, there is a strong need for capacity development. While more specialized educational programs may be coming [20], a more sustainable approach through dedicated short courses [21] and their web-based delivery [22] can bridge the gap for now. Even modest resources made available for such activities can speed-up this process. Collaborative community resources are also being built that will accelerate the CAFE adoption. This includes building of computational modules that are reusable, databases (compositional, property, and safety), websites, and networks(e.g., [23]).

## The Road Ahead: CIFM in the Horizon

Product, process, and equipment design will be the primary application of CAFE within CIFM. Increasingly, larger food companies have dedicated modeling and simulation groups, as is the case in other industries. As the overall market for CAE is expected to double by 2028, the food sector can potentially benefit from this wave. The CIFM tools can enable the food industry to meet its continuing need to diversify more, use more novel processing techniques, such as high pressure and cold plasma, emphasize personalization, reduce the cost of food safety, increase emphasis on quality, and reduce time-to-market.

Several trends on the horizon are likely to become part of CIFM or influence it in a significant way. A few examples might be the following.

### Greater integration of CAFE with more accessible computing

The significant demand for computing, when the underlying models are physics-based, is constantly being addressed with improved computational capabilities that bring them closer to food-specific needs (e.g., [24]). An approach that holds great potential is to build reduced-order and surrogate models from the simulation results of the more detailed physics but are orders of magnitude faster [25]. These surrogate models can be conveniently used for problems requiring many simulations such as optimization studies or Monte Carlo simulations. Newer computing methods [26] also can greatly reduce the computing time for typical food process-related applications. The computing advances are translating into increased use of CAFE in manufacturing (e.g., [27]) and this trend is accelerating.

Data-driven models, an alternate approach that bypasses physics-based models is also gaining ground in food [28, 29] and shows great potential as the method is flexible while it is also inherently simple, demanding less formal training from the model builder in physics and computation.

### Digital twins

A digital twin is a virtual representation of the food product or process that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning, and reasoning to help decision-making [30-

32]. Digital twins have attracted significant interest due to the increasing availability, diversity, and accessibility of sensors, data, cloud-based infrastructure, and computing algorithms. As part of CIFM, digital twins potentially can improve the quality and safety of food production, storage, and transportation [32, 33].

## 3-D food printing

In this approach, the food is printed layer by layer, opening the possibility to personalize food in terms of its quality attributes like shape, color, and texture, but also its health attributes such as vitamins. Significant activities are currently underway in this area [34]. Personalized nutrition is being touted as the next frontier and 3-D food printing is likely to play a very significant role[35] in CIFM.

## Internet of Things

The Internet of Things (IoT) provides connectivity between objects using internet protocols. These objects can be a variety and multitude of different sensors and devices where the internet connection between them provides a means to use them more intelligently. A massive connection of things through IoT could mean that the processes and events can be anticipated in a more versatile way, leading to cost reduction, improved uniformity and quality, minimized use of resources (energy, water, land), reduction of losses and waste, and increased consumer confidence. IoT has made it possible to implement precision technology, automation, and robotics more efficiently and effectively in agri-food applications, ranging from integrating crop health, satellites, drones and climate data for better pest, energy and water management in agriculture, to livestock monitoring for preventive disease and yield management [36]. Critical supply-chain wide applications of IoT are related to tracking and tracing, helping to ensure consumer trust and public health[37]. IoT is expected to be a significant part of CIFM [38].

## Artificial Intelligence (AI)

Among decision-making tools, an increasing role is being played by Artificial Intelligence (AI). The application of AI in the food industry has been gaining momentum in recent years in food sorting, classification, prediction of the parameters, food safety, and quality control. Different data modeling approaches are being used in the food industry, including expert systems, fuzzy logic, artificial neural network (ANN), adaptive neuro-fuzzy inference systems (ANFIS), and machine learning [39]. For example, machine learning techniques (ML) have reduced the sensory evaluation cost, enhanced business strategies, and provided reliable support in decision making. Such approaches methods are often used in combination with sensors to enhance results.

## Decision-making tools at larger scales: efficiency and sustainability

CAFE, as described above, will be used for decision making (e.g., directionality for optimization) at the individual product or process scale, while multiple scales are possible [40]. At the industry or even larger scale, CIFM can include integration of the entire supply chain from growing to distribution and storage, together with packaging and waste management [41]; it is essential to the circular economy. Large amounts of data are available, and their integration will provide a boost in business, reduction of expenses, and better predictability. At a still larger scale, a sustainable agri-food sector that reduces its contribution to global warming poses a great challenge due to factors that include its multiscale, multi-disciplinary, and uncertain nature[42]. Models integrating these factors can provide decision-making tools for such complex systems, the computational frameworks for which are underway [43]. Such frameworks will embed the CAFE framework for transformation from raw material to final product, as discussed earlier. Additional resources [44] in building decision making tools at the systems level should expedite their development.

## Concluding Remarks

Computer-integrated food manufacturing is a broad field and only a part of it has been touched upon in this contribution. With the technological development of hardware and ICT infrastructure, many aspects in food production and processing are being automated or simplified by using computational tools beyond the food processing itself, including logistics, sorting, storage and packaging, workforce management, supply chain coordination, and management of resources. We expect that CAFE will eventually have to fit into larger CIFM frameworks that link all these aspects together to run a factory using advanced digital tools.

## Disclaimer

The views expressed in this manuscript are those of the authors and do not necessarily reflect the position or policy of PepsiCo, Inc.

Dedication

We dedicate this article to the memory of Professor Ricardo Simpson, Universidad Técnica Federico Santa María, Valparaíso, Chile. He was our friend and a passionate food engineer who has greatly contributed to computer-aided food manufacturing.

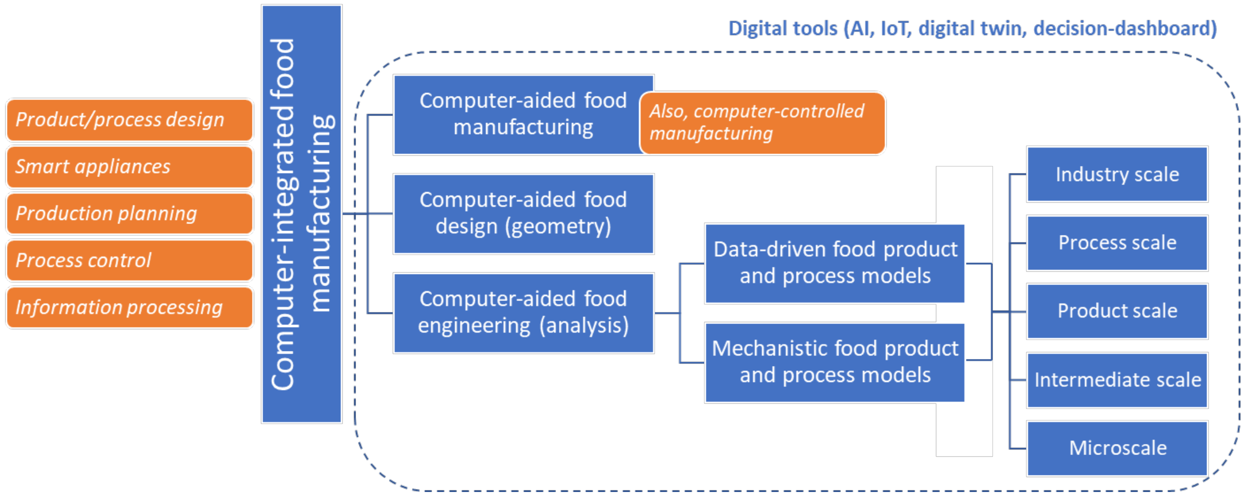


Figure 1. An approximate visual representation of how various terms related to computer-integrated food manufacturing relate to each other. The boundary of each domain is somewhat arbitrary with significant overlap between them.

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