Food Supply Chains as Cyber-Physical Systems: a Path for More Sustainable Personalized Nutrition

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Abstract

Current food system evolved in a great degree because of the development of processing and food engineering technologies: people learned to bake bread long before the advent of agriculture; salting and smoking supported nomad lifestyles; canning allowed for longer military marches; etc. Food processing technologies went through evolution and significant optimization and currently rely on minor fraction of energy comparing with initial prototypes. Emerging processing technologies (high-pressure, pulsed electric fields, ohmic heating, ultrasound) and novel food systems (cultured biomass, 3-D bioprinting, cyber-physical chains) try to challenge the existing chains by developing potentially more nutritious and sustainable food solutions. However, new food systems rely on low technology readiness levels and estimation of their potential future benefits or drawbacks is a complex task mostly due to the lack of integrated data. The research is aimed for the development of conceptual guidelines of food production system structuring as cyber-physical systems. The study indicates that cyber-physical nature of modern food is a key for the engineering of more nutritious and sustainable paths for novel food systems. Implementation of machine learning methods for the collection, integration, and analysis of data associated with biomass production and processing on different levels from molecular to global, leads to the precise analysis of food systems and estimation of upscaling benefits, as well as possible negative rebound effects associated with societal attitude. Moreover, such data-integrated assessment systems allow transparency of chains, integration of nutritional and environmental properties, and construction of personalized nutrition technologies.

Keywords Cyber-physical systems · Food chains · Food systems · Traceability · Sustainability

Introduction

Food processing technologies not only influenced our lifestyle making it more comfortable and relaxed, but also became a major evolutionary force for the development of food systems and humans within it. People learned to bake bread long before the advent of agriculture; salting and smoking supported nomad lifestyles; canning allowed for longer military marches; etc. [2]. Since their invention, certain modern food processing technologies underwent long evolution and significant equipment and process optimization, exhibiting high efficiency levels compared with their initial prototypes. However, current demands for “unprocessed” or minimally processed, “clean label”, and “functional” foods call for

changes in how the food is produced and processed, where novel processing technologies and novel food systems could respond to these demands [11, 86, 91]. Emerging processing technologies often rely on other sources of energy such as mechanical, electrical, electro-magnetic, or others, compared with conventional ones using mostly thermal energy. New technologies based on application of high-pressure (static high pressure, high pressure homogenization, supercritical fluids, shockwave), electrical energy (pulsed electric fields, ohmic heating), or using electromagnetic radiation (radiofrequency, microwave, E-beam) and novel food systems (cultured biomass, 3-d bioprinting, cyber-physical chains) try to challenge the existing chains by developing potentially more nutritious and sustainable food solutions.

However, as many innovations in general, novel developments in food systems often rely on low technology readiness levels (TRL). While low TRL technologies are suitable for small-scale developments and generation of added value, they create additional challenges for the estimation of future potential benefits or drawbacks. It is becoming a complex task, mostly due to the lack of integrated data and multifaceted

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nature of food systems. In order to deal with complex data issues, developed data solutions should be applied. However, such solutions are not adapted to the specific requirements of food production and consumption due to enormous biological variations and unsuitable data acquisition [36, 82]. At the same time, food system can be foreseen as a cyber-physical system (CPS), able to reach the highest autonomy levels for self-management and self-control, but it requires special approaches and development of a framework applicable for further development of cyber and physical solutions.

This review aims for the development of conceptual guidelines of food production system structuring as cyber-physical systems. The article is structured to comprehensively review current literature dealing with improvement of food production-consumption chains perceiving them as potential cyber-physical systems, suitable for automated traceability, sustainability assessment and personalized nutrition. It starts with explaining and illustrating the concepts of cyber-physical systems (CPS) and current knowledge on CPS application in food industry. Further, the paper addresses definition of conceptual requirements for food production systems transformation into CPS, followed by requirements of food system digitalization, emerging processing technologies, traceability approaches, and personalized retail and nutrition. It is finalized with an overview on potential benefits and negative consequences of food systems transformation into CPS while applying the conceptual guidelines.

The Concepts of Cyber-Physical Systems (CPSs)

The definition of cyber-physical systems (CPSs) has emerged in the new millennium as a response to the need of developing conceptual and efficient framework dealing with constantly increasing interactions between cyber computational systems and physical hardware. CPSs therefore are defined as transformative technologies for managing interconnected systems between its physical assets and computational capabilities [8]. CPS can also be considered in more cyber domain as “a computational operation with the surrounding physical object across downstream/upstream industry in collaboration environment” [25]. This highlights a rather virtual character of the CPS. While “classical” definition describes CPS as integrated computation and physical processes or embedded computational systems and their physical environment [23, 61, 68, 75], some authors highlight the leading role for the computation core, which coordinates, operates, and monitors physical, biological, and engineered systems [8, 75, 90]. The whole variety of definitions and concepts can be arranged in 4 main groups according to the main fields of application: (1) control theory (CPSs are understood as a composition of the physical world, transducers, and control components), (2) computer sciences (CPSs are understood as a composition of the physical world, transducers, control components, and computer sciences

elements), (3) communication engineering (CPSs are understood as a combination of transducers, control components, some data analytics elements, computer science elements, and communication components), and (4) vertical systems (CPSs are understood as a combination of all the components: physical world, transducers, control components, data analytics elements, computation elements, communication components) [16]. Despite a great variety of definitions and concepts, they all acknowledge that through the connection to the advanced computational technologies, CPS can provide autonomous predictive management, self-diagnosis/maintenance mechanism for risk avoidance, and collaborative production planning for improved performance. CPSs, therefore, have all the required properties for the application in food industry for improvement of food production safety or traceability [25].

Even though there are a lot of CPS concepts and definitions, they still undergo intense evolution process. Constantly changing properties of both, physical and cyber parts, pose difficulties for the design of “smart networks”, which previously were never dealt with [3, 19, 68]. For the last 20 years physical hardware system went through accelerated developments [126], which resulted in higher availability and affordability of sensors, data storage systems, and interconnected wired and wireless systems. Such developments in its turn resulted in continuous generation of high data volumes, which received the name “Big Data” [31, 67, 87, 95, 97, 113]. CPS in such environment evolved into frameworks dealing with management of Big Data for interconnected hardware-software networks aiming to leverage intelligent, resilient, and self-adaptable machines capable to deal with complex physical world interactions [77]. CPS got a high level of implementation in industrial environment forcing the development and emergence of smart factories (“industry 4.0”) and “digital twins” [18, 103]. While CPS can be declared as a conceptual system describing “industry 4.0” and “digital twins” [88, 107], it goes beyond their scope of functioning and implementation [104, 107]. It can be applied to more diverse and extended systems beyond industrial environment.

There are plenty of concepts and definitions like embedded systems, legacy systems, industry 4.0, pervasive sensing, machine-to-machine communications, etc., related in higher or lower degree to CPS concept [16, 32, 68]. If most of the definitions can be differentiated from CPS, “Internet-of-things” (IoT) is a concept, which has a lot of similar characteristics to CPS [16]. This review supports the view that CPS belongs to IoT, in a way that the CPS is only a new pattern or a scenario of IoT [16, 76, 121]. For example, the aggregated definition of Monostori et al. [76] highlights very well the integration of CPS with Internet, pointing towards reliance of CPS systems on data-processing services available on the Internet. Such interconnection and integration could have positive and negative consequences for CPS concept applied in food industry (see next chapter).

CPSs have been long recognized as an intelligent autonomous system going through learning human behaviours with the help of artificial intelligence [12]. At the same time, intelligent autonomous cyber system requires development of extensive and advanced physical architecture-based information system [25]. The Eindhoven Institute for Research on ICT (EIRCT) identified six components of CPS architecture: physical world, transducers, control components, data analytics elements, computation elements, and communication components [16, 33]. Physical part of CPS in such grouping is limited to physical world and transducers; however, some authors separate physical world (devices or hardware) and physical environment (environment where the physical objects are located) [46, 61]. Cyber part, on the other hand, is quite well conceptualized into 5-level CPS structure [68], which provides a guideline for developing and deploying a CPS for manufacturing application. The 5C architecture connects functional levels with specific hierarchical implementation conditions from physical to higher cognition: (1) Smart Connection Level, aimed for condition based monitoring through physical sensors; (2) Data-to-Information Conversion Level, for self-aware prognostics and health management; (3) Cyber Level, for peer to peer monitoring, self-comparison, and twin modelling; (4) Cognition Level for decision support system allowing integration of simulation and synthesis, and collaborative diagnostics and decision-making; and (5) Cognition Level for resilient control system and self-functions including avoidance of error actions [68]. Such well-structured architecture allows for the guided design of CPS, especially in the cyber part of it. Physical part of CPS, especially in application to food systems, remains so far poorly covered.

Current Knowledge on CPS Application in Food Industry

Despite quite a long history [12], in many cases, CPSs are still in the early stages of development, with successful constantly working cases of application in a few areas (Fig. 1). The following main application fields of CPS were identified by the CPS Vision Statement issued by the federal Networking and Information Technology Research and Development (NITRD) CPS Senior Steering Group [76, 80]:

- Agriculture
- Building controls
- Defence
- Energy response
- Energy
- Healthcare
- Manufacturing and industry
- Society
- Transportation

Such list is rather interesting as it devotes a huge attention to energy and different forms of manufacture, which partially corresponds to the application areas set by the authors from Berkley University (Fig. 1). The last source [76], however, indicates a wider range of applications including communication, robotics as a separate industry, and physical security (as a quite wide CPS systems devoted for automated safety surveillance). Food is not precisely mentioned by either of the classifications. Potentially it relates to the huge complexity of food systems [6, 100], which cannot be easily complemented with CPS systems of one area. Food systems in their wide meaning (from biomass production to food consumption, and beyond) require implementation of CPS from diverse application areas starting from manufacture, over agriculture and aquaculture, including consumer and communication (Fig. 1).

As the literature often does not distinguish the CPS application for food systems, it is necessary to review the compliant options of CPS integration from other fields. For example, certain similarities and transfer points can be drawn from medical and agricultural CPS. Medical CPS systems are quite well developed with multiple examples. They can be aggregated into few main application groups: notable (records); daily use; medical status monitoring; medication intake control; and emerging group (e-health architecture, cloud computing solutions, CPS modelling for medical processes validation, smart living, etc.) [49].

Agriculture CPS lately got quite well researched in the topic of smart agriculture in the development of CPS systems [4, 28]. Precision agriculture is playing a major role to enhance the efficiency and resource savings [65, 89]. Precision agriculture can rely on quite specific developments such as Wireless Underground Sensor Networks, when machinery is “communicated” with sensors under soil [96, 112] or underground sensor networks controlling the quality of soils [13, 50, 81, 112]. Further developments in agricultural stage include real-time monitoring of crops growth in field and greenhouses [47, 64, 94, 105], weed control [119], and precise autonomous water or fertilizer management on the field [60, 72, 93] or frost monitoring [125]. Some authors proposed an overall method for information integration based on a service-oriented architecture (SOA) in agri-food supply chain networks, potentially enhanced with cloud systems, [25, 45, 116].

A few concepts of CPS application are proposed to enhance traceability of agricultural food systems [26] or “virtualization” of food supply chains [111]. Application of virtual models of different food systems with known parameters is an immensely popular method to develop smart management systems of food supply chains [25, 110, 111, 114, 120, 124]. Application of such systems in reality is a challenging task [1, 101, 109].

At the same time, food processing is rather poorly covered by the development of CPS systems. Literature indicates a few

Fig. 1 The concept map of CPS.
Source: Berkley University [16]

scarce examples, where CPSs are applied in the form of wireless networks for bread manufacturing process optimization [9]; robotics for packaging, picking and placing, pelletizing, inspection, testing, and serving in restaurants [54, 59]. Catering industry is more devoted to the application of smart and collaborative robots [1]. Recent literature also highlights on the potential of digital twins development for the process optimization in agri-food and especially processing factories [109]. However, first complete agri-food applications of digital twins and smart collaborative robotic networks are ought to be demonstrated [1, 109]. Existing methods oriented on niche applications of machine learning and modelling approaches are indicated in literature (Table 1).

Machine learning algorithms such as Gaussian process regression [24, 122], support vector machine [38] and nondominated sorting genetic algorithm II [34, 58] are applied in milling industry for cost reduction and energy consumption, through predictive process parameter optimization or for product quality improvements via predicting food processing properties (surface roughness, cutting force, structure deformation). Multi-objective optimization finds also cases of application development for food retail [37], food processing and food engineering [41, 42, 53, 106], and food quality control [5, 44, 73]. However, such application developments are rather sporadic and never get connected through single ICT platforms (not even CPS) due to multiple standards and lack of

Table 1 Food system functions (technologies) with potential of integration in CPS systems

Food system function or technology	CPS integration model	Source
Traceability of agri-food systems	Intuitionistic fuzzy-based case-based reasoning technology	[26]
Agri-food supply chain networks	Service-oriented architecture (SOA)	[25, 116]
Precision agriculture	Wireless sensor network	[89]
Precision agriculture	Cyber-physical system architecture model	[65]
Precision agriculture	Wireless underground sensor networks	[96, 112] [13, 50, 81, 112]
Real-time monitoring of crops growth in field and greenhouses	Sensor-based network, wireless sensor networks, monitoring, detecting, and responding-CPS	[47, 64, 94, 105]
Weed control	Automated weed mapping and variable-rate herbicide spraying (VRHS) system	[119]
Precise autonomous water and fertilizer management on the field	Agricultural cyber-physical system for solar photovoltaic water systems and wireless sensor networks	[60, 72, 93]
Bread manufacturing process optimization	Wireless networks application	[9]
Packaging, picking and placing, pelletizing, inspection and testing, and serving in restaurants	Robotics	[54, 59]
Decision support system in agri-food companies	Mind map and conceptual graph models	[21]
Robotic cooking	Batch Bayesian optimization and robotics	[56]
Drying	Gaussian process regression	[24]
Oil brands identification (food production support)	Support vector machine	[38]
Grinding, sorting	Nondominated sorting genetic algorithm II	[34, 58]
Drying	Optimization based on computational fluid dynamics, several multiphysics modelling methods (e.g. conjugate modelling), multiscale modelling, and modelling of material properties	[35]
Drying, environmental efficiency	Multi-objective optimization	[92]
Product development	Sequential quadratic programming	[27]
Olive oil bleaching	Hybrid artificial neural network-genetic algorithm technique	[7]
Food retailing	Multi-objective optimization	[37]
Food processing and food engineering	Multi-objective optimization	[41, 42, 53, 106]
Food quality control	Multi-objective optimization	[5, 44, 73]
Food quality and safety	Multi-objective optimization	[10]
Complex agri-food chain issues	Visualization, interactive learning, interactions between machine learning systems and human experts	[82]
Agri-food chains traceability and transparency	Blockchain	[30, 43]
Perishable foods active management	Extended material requirements planning (EMRP) model	[15]

interest from value chain actors for data sharing and infrastructure development [20].

The potential explanation to the low application of CPS in food system can be possibly related to the complexity of CPS construction, which is much more than developing a single robot interaction with a product. It is a comprehensive issue covering all dimensions of the control, sensing, processing, machines, communication, system engineering, and integration [98].

Division of physical component of CPS into physical world and physical environment (Kyoung-Dae [46, 61]) for food industry is of highest importance, as it poses a viable direction for the progression of cyber system interaction not only with hardware but also with food packaging.

Smart kitchens with intelligent appliances like fridges and stoves have a potential to define through packaging not only the amount of food and its safety level (expiration date) [74, 123], but also actively promote to the consumer food planning through recipes, which has a potential to reduce food waste [71, 74, 85]. Intelligent packaging therefore is foreseen as an enabling technology for the communication between smart home appliances and other agents of supply chain (consumer, retail, producer, waste treatment facilities, etc.) [39, 57, 71, 79, 108]. Intelligent and active packaging, interacting with food biomass via “Time Temperature Indicators” or other gas indicators or (bio)sensors can inform about the properties of food, picked up by smart appliances [79].

Fig. 2 Decomposition of the automation hierarchy with CPS distributed services, joined through a single network, adapted from literature [14, 76]

However, direct tracking and tracing of food biomass and determination of its properties and ongoing changes require further development of relevant physical tools not only from hardware side, but also from food processing and engineering able to change physical properties of food biomass. Food processing in this case plays a crucial role, as it not only determines the structure and properties of the end product [55, 63], but also can efficiently track and trace food structures after relevant hardware and software development.

Interaction between different CPS systems (e.g. transportation, manufacture, communication, consumer, etc.) is adding to the complexity of CPS required for food supply chains. Each of the application areas has developed its unique

properties and standards of data exchange for the specific functions, which cannot be easily combined and complemented. Such communication is required for the development of a system of systems for CPS application [117]. Up to now, no smart food chain CPS systems of the higher level are developed.

Application of existing CPS in food systems is also challenging not only due to undeveloped background physical system and higher-level cyber systems, but also due to the only one world network, which can efficiently combine the separate CPS system. Internet is a modern network system with a huge diversity of connected devices, and nodes can play a crucial role for the development and efficient evolution

Fig. 3 Overview of approaches, developed to fulfil main functions (in bold) of Food CPS ([7, 15, 29, 30, 48, 51, 68, 102]; <http://www.agrocycle.eu/>)

Fig. 4 CPS structure model for food manufacturing: cyber, control, and physical layers (adapted from [59])

of food chain CPS and its potential automation (Fig. 2). However, reliance on internet comes at a cost. Despite multiple access points to the internet through wired and wireless networks, some areas even in developed countries remain uncovered with either of the access options. Security of connection to the common pull of computational devices can pose serious cyber security risks [3, 22, 52]. Despite the multiple mentioned challenges, there are some perspectives of food CPS developments.

Conceptual Requirements of Food Production Systems Transformation into CPS

The CPS approach, even though existing for few decades [12], represents still a concept, especially when it is dealing with food system. In 2014, Wright with co-authors grouped application areas of CPS into (1) cyber physical products and assets; (2) cyber physical assembly and manufacturing automation; and (3) cyber physical ecosystems to support the life cycle of the product [117]. The first group is dealing with CPS applied to a single product or technological process such as milling or sorting and has a direct connection to food processing. The second group defines the automation of complex products and systems, and includes concepts of "automation of automation" and "assembly of assemblies" and demonstrates the work on level "system of systems" [78, 84]. It is

different from classical food processing automation, because it includes one (or more) hierarchical level of automation, which is not necessarily hierarchically structured (Fig. 2). The third and higher level of CPS integration is demonstrating dealing and tracking of product properties along the life cycle and automated adaptation to the design or manufacturing according to the responses from the lifetime of the product. Such high level cyber-physical ecosystem can collect the data from multiple products in diverse conditions and enable the analysis of data collected for the complete variety of products without giving specific attention to a single product and eliminating minor errors (Fig. 3). CPS at life cycle level (or ecosystem level) can therefore enhance the prediction errors and potential problems associated, for example, with contamination or breakage risks for the complete spectrum of products. Moreover, it can diagnose the reasons for such problems [117]. Such grouping of application areas allows to determine the requirements to food CPS.

Literature indicates two possible areas of application for the development and integration of CPS in food system. The first one (1) reviews the food engineering and manufacturing CPS as an area that has a similar automation scheme and CPS structure adopted from other sectors and termed as cyber-physical production system (CPPS). All the technology modules, like human-robot collaboration, connected CPPS physical elements, smart devices and raw-materials, big data

analytics, and real-time intelligent decision-making using artificial intelligence and cyber security, are becoming basic ingredients for the food manufacturing CPS or CPFPS (Fig. 3). Technology transfer of solutions developed and tested in other industries can enhance the overall digitalization of records and create a joined system for tracking and traceability. For example, application of developments in medical sphere for electronic records [25, 49] or blockchain approaches can generate enormous benefits for traceability, efficiency, and sustainability analysis of food systems at larger scale [6, 99].

The second application area (2) pertains to the CPS in food manufacturing and serving industry in the futuristic industry 4.0 era. In such system, food production, ordering, preparation, and serving functions exist simultaneously in close premises. This has the potential to exhibit human-robot collaboration in the cyber physical food serving system (CPFSS) model on both ends of the robotic serving process or may confine to the customer end in the future [69]. Moreover, common current connection between CPFPS and CPFSS is highlighted to be the compulsory inclusion of the human-cyber systems interactions [83]. Such approaches can easily integrate the requirements for the personalized retail and nutrition and nudge it to the implementation [17]. Both approaches indicate the need to integrate already developed and upcoming technological solutions in the food system. While being feasible, they still do not indicate how the cyber systems will be connected with the second physical level (Fig. 4) and more specifically its biomass sub-level.

We see the integration of biomass properties and cyber system as urgent requirement which should be solved before it is possible to create fully functioning food CPS—a system integrating physical environment and food biomass with computer-based system able to deal with food system organization in autonomous and self-manageable manner. While there are some examples of CPS systems integrating cyber and physical level I and even level II (packaging, sensors), no real examples exist, which would be connecting food biomass with the cyber system. Existing approaches can trace and record environmental changes around the biomass mostly [25, 40, 70], but not the change of biomass composition, structure, functional properties, or origin. At the same time, there are specific developments combining the marking and/or tracking of biomass properties directly [29, 48, 51, 62, 66, 102, 115, 118], which can enhance the food CPS systems in the future. Such developments can be performed only by the joined effort of food and computer system scientists and developers. Conceptual requirements for food CPS, therefore, should integrate not only cyber parts of the different systems (having different protocols and managed by different actors), but also further development of physical systems (sensors and biomass interaction).

Conclusions

Despite more than 50 years of CPS research and development, it remains in conceptual stage when it comes to biomass production, food processing, engineering, and consumption. Food value chains as higher hierarchical level system remain uncovered by CPS development. While CPSs are well developed in multiple spheres (automotive, manufacturing, medicine, etc.), their application in food industry is very limited due to lacking of few conceptual challenges: unification and generalization of approached in different food production areas; connection of cyber parts of food chains agents via adapted record-tracking systems (potentially blockchain-based); integration of computational component with chemical and physical properties of food biomass and transfer of such integration through supply chains; and development of efficient defence mechanisms, able to cope with potential cyber-food-safety risks and hazards. Such challenges are becoming the basis for the guidelines of food engineering, production, and consumption system structuring as cyber-physical systems. The conceptual guidelines, indicated in this work, included transfer of successful approaches for computational solutions from fields dealing with similar problems/systems (medicine, agriculture); creation of multi-hierarchical cyber and physical components, which should solve the problem of transferability and safety; and development of physical-based solutions for the physical-physical system interaction between sensors and food biomass.

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