Chapter 7
Mechatronic and Cyber-Physical Systems within the Domain of the Internet of Things

Peter Hehenberger, David Bradley, Abbas Dehghani and Patrick Traxler

Abstract There has been a shift in emphasis within systems from hardware-oriented to more software-oriented topics integrated in an overlaying communication framework (e.g., cloud-based services). This chapter presents current research in the field of the interaction between mechatronic and cyber-physical systems. It presents solution basics design methods that are illustrated by some real-world applications. The discussed case studies (Smart Home, Bio-mechatronic Systems, Cyber-Physical Production System, Data-driven analysis) provide illustration of applications involving different functional distributions of activity between the 4 key elements of people, data, mechatronics and cyber-physical system.

Keywords Mechatronics · Cyber-physical system · Design methods · Smart home · Bio-mechatronics · Cyber-physical production system · Data-driven analysis

7.1 Introduction

Recent years have seen the development of the concepts of Cyber-Physical Systems and the Internet of Things, both of which impact in related but different ways on the design, development and implementation of mechatronic components and devices, as well as on larger systems resulting from the combination and integration of these. In the case of Cyber-Physical Systems, individual components, often but not always

P. Hehenberger (✉)
School of Engineering, University of Applied Sciences Upper Austria, 4600 Wels, Austria
e-mail: peter.hehenberger@fh-wels.at

D. Bradley
Abertay University, Dundee, UK

A. Dehghani
School of Mechanical Engineering, Institute of Design, Robotics and Optimisation (iDRO), University of Leeds, Leeds, UK

P. Traxler
Software Competence Center Hagenberg, Hagenberg im Mühlkreis, Austria

mechatronic in nature, are combined and integrated through the use of advanced intelligent software. The Internet of Things, then, provides a domain structured around access to and exchange of information, to further aggregate both mechatronic and Cyber-Physical Systems to create new and novel systems focused on users.

Beginning with Mechatronics, itself an interdisciplinary construct within engineering science structured around the integration of mechanical engineering, electrical engineering/electronics and information technology across a range of applications and products, the chapter considers associated design issues and discusses the product development process from both a Mechatronic and a Cyber-Physical System (CPS) point of view, using a model-based approach within the overall domain of the Internet of Things[1] (IoT). In this context, an important requirement in both the modelling and simulation of the interactions between systems at different hierarchical levels is that the product model is consistent across all phases of the design process and across all sub-systems considered.

Where such complex systems are concerned, achieving highly accurate system modelling is often prohibitive both in cost and time. As such, simplified modelling approaches become preferable. Further, an interdisciplinary model-based approach of the system-level models needs the provision of specific methods, languages and tools to support such a multi-view approach, as for instance multi-agent modelling based on an engineering cloud structure.

The chapter begins by looking at the relationships between mechatronics, Cyber-Physical Systems and the Internet of Things, including consideration on the potential impact on associated design methods and strategies in areas such as user-centred design and system modelling. It then uses a series of case studies in Smart Home technologies, Bio-mechatronics, CPS-based production systems and data-driven analysis to provide context for the discussion.

7.2 Mechatronics, Cyber-Physical Systems (CPS) and the Internet of Things (IoT)

While mechatronics has become well established as an engineering discipline, the more recent constructs of Cyber-Physical Systems and the Internet of Things are still evolving both technically and conceptually as well as in respect of their relationships with each other.

In the case of CPS a particular challenge is that of integrating design practice to support the interdisciplinary nature of a CPS, particularly in the allocation of functionality between software and physical elements at a level beyond that generally associated with mechatronics [2, 3].

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[1]"The Internet of Things refers to a state where Things (i.e. objects, environments, vehicles and clothing) will have more and more information associated with them and the ability to sense, communicate, network and produce new information, becoming an integral part of the Internet" [1].
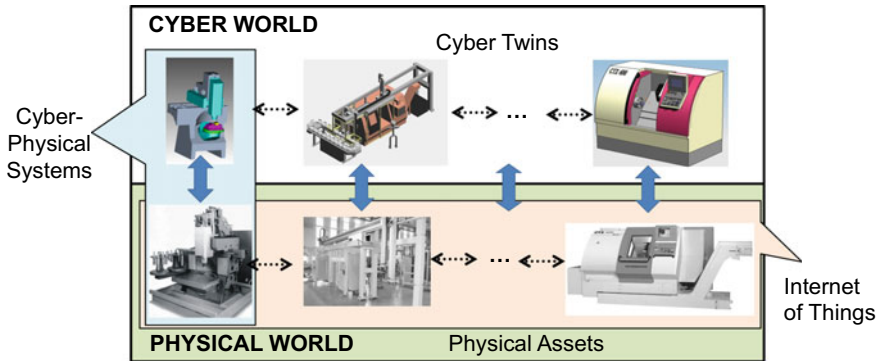
Fig. 7.1 Cyber-physical systems and internet of things (after [3])

An important element in Fig. 7.1 is the "Digital Twin", Digital Twin was brought to the general public for the first time in NASA's integrated technology roadmap and is defined as follows (see [4]):

> A Digital Twin is an integrated multiphysics, multiscale simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin. The Digital Twin is ultra-realistic and may consider one or more important and interdependent vehicle systems, including propulsion/energy storage, avionics, life support, vehicle structure, thermal management, etc. Manufacturing anomalies that may affect the vehicle may also be explicitly considered.

In contrast, the Internet of Things is a much more abstract concept structured around a dynamic network of system artefacts to enable these to collect and exchange data. In 2013 the International Telecommunications Union (ITU) Global Standards Initiative on Internet of Things (IoT-GSI) [5] described the IoT as being "*the infrastructure of the information society.*" The IoT thus supports the integration of remote and disparate smart objects as part of a dynamic system configured according to both context and need. In a system structured around the IoT, each individual smart object remains uniquely identifiable while integrating and exchanging data with other such objects through the infrastructure of the internet. From a design perspective, the abstraction of the IoT presents a particular challenge through its ability to incorporate as required both hardware and software elements of defined functionality but of unknown origin given that they can be autonomously selected by the system on the basis of context and need.

7.2.1 Characteristics of Systems

Mechatronic systems integrate sub-systems and components from mechanics, electrical engineering, electronics and software and constitute the basis for the design of products ranging from domestic appliances to machine tools and vehicles [6–8].

In a mechatronic design process the conceptual design phase is especially important. Here, the functional interactions between discipline-specific sub-systems are determined, and therefore have to be carefully considered. This implies that during the phases of conceptual and preliminary design, the designer should be able to quickly and accurately evaluate those system properties and interactions that result from design changes to mechanical components as well as to other components. The successful development of complex mechatronic systems is thus only made possible by close cooperation between specialists in the different disciplines involved. Consequently, design activities take place in a multidisciplinary environment involving engineers and others with different backgrounds [9, 10]. The interactions between product developers from these different disciplines are, however, often hindered by an insufficient understanding of the interactions between the disciplines, and by failing to utilise common platforms for the modelling of complex systems [11]. In respect of Cyber-Physical Systems, these are defined by Lee [12] as resulting from the:

> …. integration of computation and physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa.

Thus, a CPS could be considered as being structured around an aggregation and assembly of mechatronic components and devices. Such systems can be found in areas such as aerospace, automotive, energy, healthcare, manufacturing, entertainment and consumer appliances.

For the easy validation of requirements during the overall product development process, methods are needed for the decomposition of high-level system requirements into criteria for design decisions. This will in the future be an increasingly important issue as new system architectures such as those of Cyber-Physical Systems are introduced [13, 14]. As has been seen, the Internet of Things (IoT) then provides access to information, context dependent and otherwise, as well as sourcing a range of software, platforms and infrastructure services and functions. In many cases, these will be autonomously sourced by the system on demand without necessarily any a priori knowledge by the designer or user as to their origins or structure. Thus, individual systems may communicate with each other to establish a network and determine optimum solutions for themselves as well as with other systems.

Referring to Fig. 7.2, within the context of the chapter the relationship between the various system layers of mechatronics, Cyber Physical systems and the Internet of Things can be expressed in terms of increasing levels of abstraction, to which must then be added the user whose primary role becomes that of defining system functionality and the context within which it operates [4].

7.2.2 From Design for All to Design by All

Design for All (DfA) refers to a design philosophy which aims to support access to and use of products, services and systems by individuals without the need for adaptation
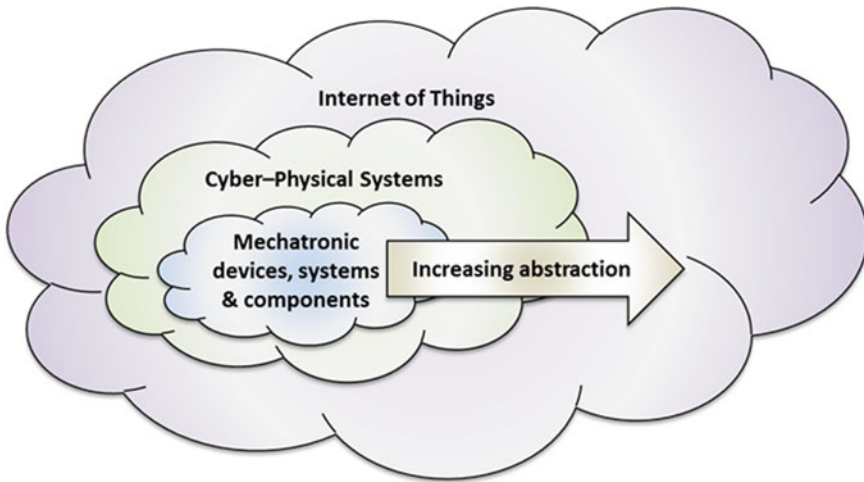
Fig. 7.2 Abstraction of systems [4]

[15]. Further, Design for All is often considered as an aspect of Universal Design (also Inclusive Design and Barrier Free Design), an approach to the physical and aesthetic design of buildings, products and environments accessible to all irrespective of age or physical capability [16–19]. Conceptually, Design for All also forms a part of the Digital Inclusion agenda which aims to ensure equivalent access to information [20].

Conventionally, problems of accessibility have been solved through a combination of adaptation and the use of assistive technologies. Within Digital Inclusion, the concept of Universal Access implies access by anyone, anywhere and at any time. Associated products and services must therefore be capable of accommodating individual user requirements across the full range of contexts of use while being independent of location, hardware or runtime environment, increasingly within an IoT construct [21–25].

In the context of mechatronics, the design process conventionally encompasses a continuum of activities ranging from needs identification and conceptual design to the detailed design of individual components. The advent of cloud-based systems such as those represented by the Internet of Things and its related concepts raises specific design-related issues and questions by increasingly treating information as a commodity whose value to the system will vary according to both context and demand.

A particular aspect of cloud-based systems is the implied integration and transfer between the information and physical domains, and the potential for decisions made in relation to one domain to impact upon, define and influence decisions made in the other. For instance, real-time information on traffic conditions may be assigned a high value by an individual only if it affects his or her intended journey, while that same information, when integrated with traffic flow management options such

as traffic light sequencing, can help to mitigate problems of traffic flow within the urban environment.

The ability to influence the physical environment is a key consideration with Design **FOR** All where, as has been seen, the aim is to ensure access and facilitate use across as wide a spectrum of individuals as is possible. However, it may be argued that at one level, that of the system, which itself can be considered at a number of different levels as suggested by Table 7.1, the introduction of cloud-based technologies means that responsibility for the design of the system is devolved to the user, opening up the concept of Design **BY** All.

The considerations above are in direct contrast and contradiction with a classical approach to design which concentrates on first establishing user needs and then transfers the responsibility for the design to an, often remote, individual or group. With Design **BY** All, that specific expertise still needs to be present, but in a form and format which is accessible by, and transparent to, the user. Located in the cloud, as may be much of the system software and management tools, this expertise then serves to underpin decisions and to inform and guide users in relation to their choice based around the selection of suitable components. Specifically, there is a need to support non-expert users in achieving their goals without their being aware of the underlying technologies and its operation. Such transparency of operation in which the user specifies context, requirements and outcomes is increasingly a feature of CPS and IoT based systems such as those of Table 7.1. Thus, a user seeking to control their domestic environment to maximise comfort and minimise energy consumption will focus, with the aid of appropriate smart tools, on the determination and confirmation of outcomes rather than the detail of the control of individual devices.

Structurally, the resulting system is likely to be what is increasingly being referred to as a participatory system such as that shown in Fig. 7.3. The key components of which are:

Table 7.1 System levels

System level	Notes
Mechatronic	The individual components making up the physical structure of the system. In the case of a vehicle, these would range from individual sensors and actuators to smart sub-systems such as engine management, traction control, braking systems and environmental control
CPS	Operating under the control of the intelligent cyber component, the individual vehicle systems are brought together as a Cyber-Physical System. This enables the individual (e.g. mechatronic) components and sub-systems to operate together to facilitate and optimize system behaviour, for instance by linking the engine management, traction control and smart gear boxes to minimize fuel consumption
IoT	Supports information exchange between individual vehicles as well as with other locations. For instance, direct communication between vehicles can be linked to traffic light control to manage traffic flow and, if required, provide clear path routing for emergency vehicles
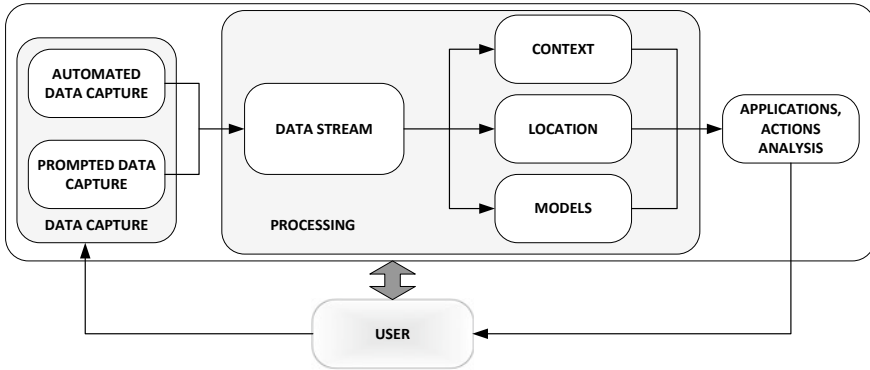
Fig. 7.3 Participatory system

- **Data Capture**: As its name implies, this is associated with the provision of the source data to the system and itself comprises two components as follows:

    - *Automated data* capture implies generic system-level data which is provided on a regular basis from a defined sensor set.
    - *Prompted data* capture then implies data which is not necessarily captured on a regular basis but only in response to a prompt generated by the system user.

- **Processing**: Data is merged into a data stream and evaluated in relation to parameters such as established context and location along with being used as input to relevant system models, as for instance the heat transfer model of a house referred to earlier.

- **Applications, Actions and Analysis**: The outputs from the processing element are taken and used as appropriate in relation to the system outputs, which may themselves be expressed in terms of:

    - *Applications*—As for instance the operation of environmental controls, lighting systems or domestic security.
    - *Actions*—As for instance the turning on or off of a heating system.
    - *Analysis*—As for instance the refinement of the models used in processing the data.

- **User**: Sets and defines the system-level functions including context and constraints, including issues such as the privacy and security of the user and their data.

## 7.3   Methods for Modelling and Evaluation of (Mechatronic) Systems

The role and importance of modelling in relation to the incorporation of mechatronic components and sub-systems with Cyber-Physical System constructs and their subsequent incorporation as smart objects within the Internet of Things has been introduced earlier in the chapter. This section therefore focuses on two important topics in relation to the modelling and evaluation of mechatronic systems, namely system decomposition and system modelling, including integration with biological systems.

A number of methods currently exists for the modelling and evaluation of systems, including, among others, Design Methodology for Mechatronic Systems [8], Axiomatic Design [26], Property-Driven Development/Design (PDD) [27] and Model Integrated Mechatronics MIM) [28].

7.3.1   Decomposition of Mechatronic Systems

To describe and evaluate complex mechatronic systems, it is necessary to decompose the total system into a hierarchical structure of mechatronic sub-systems and modules. Figure 7.4 provides an example of the hierarchical decomposition of an overall

Fig. 7.4 Hierarchical structure of a complex mechatronic system [29]
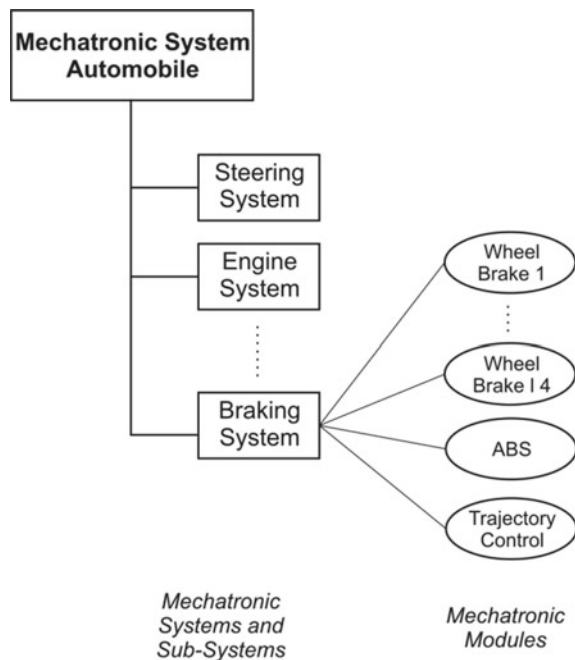
mechatronic system, in this instance the braking system of a passenger car [29].

In this system, the brake-by-wire mechatronic braking system is structured into four individual mechatronic wheel brake modules. The information from the brake pedal to the modules is transferred electronically and power is transferred to the brake modules via the vehicle's electrical system. As both information and power may be transmitted independently from one another, additional functions as for example, ABS and traction control system can be implemented more flexibly.

The design and optimisation of the mechatronic module 'wheel brake' is a complex task, in part because of the multi-discipline characteristics of mechatronics but also due to the safety-critical and reliability aspects of such systems. The hierarchical structuring supports the recognition and description of internal interactions along with the coupling and integration of all systems at all levels. In this way all relevant interactions, interdependencies and interfaces become transparent.

These characteristics and requirements in combination with cost savings, call for new methods for design, evaluation, optimization and specification of such mechatronic modules building upon and supported by established modelling techniques such as those mentioned in the previous section.

A mechatronic module (according to [29, 30]) invokes several different disciplines, e.g. mechanics, automatic control and sensors, requiring discipline-specific components to be integrated and merged to provide the desired functionality. Thus at the lowest level, a mechatronic module can be decomposed only into discipline-specific (non-mechatronic) components, and not into other mechatronic modules or sub-systems.

A mechatronic module therefore defines the lowest hierarchical level of a mechatronic system and is indivisible within the set of mechatronic sub-systems. With the mechatronic system design model, all couplings between the individual mechatronic disciplines need to be described with the elements or pillars of the model then representing a discipline-specific sub-component or assembly. This in turn is structured into several hierarchical levels corresponding to the degree of detailing as in Fig. 7.5.

This implies that only the first or highest level has an interface to the other disciplines (compare with encapsulated modelling) via the mechatronic coupling level. All couplings between the discipline-specific models (e.g. design parameters and requirement parameters affecting multiple disciplines) are thus captured and described at the mechatronic coupling level.

The model structure has to be adapted if additional couplings between discipline-specific components are detected during a design iteration (design, analysis, integration, performance check, etc.). This is also true if new or additional disciplines come into consideration.

It should also be noted that the Mechatronic System Design Model may also be seen as a representation of a project organization in which each pillar represents a (discipline-)specific group or team. In this context, the Mechatronic Coupling Level may be seen as representing a coordination function within project management. The design of mechatronic systems is an iterative process, as designers often have to move back and forth between steps to redesign or tune what they had previously created. Accordingly, for the process of product modelling of Fig. 7.5, there is a
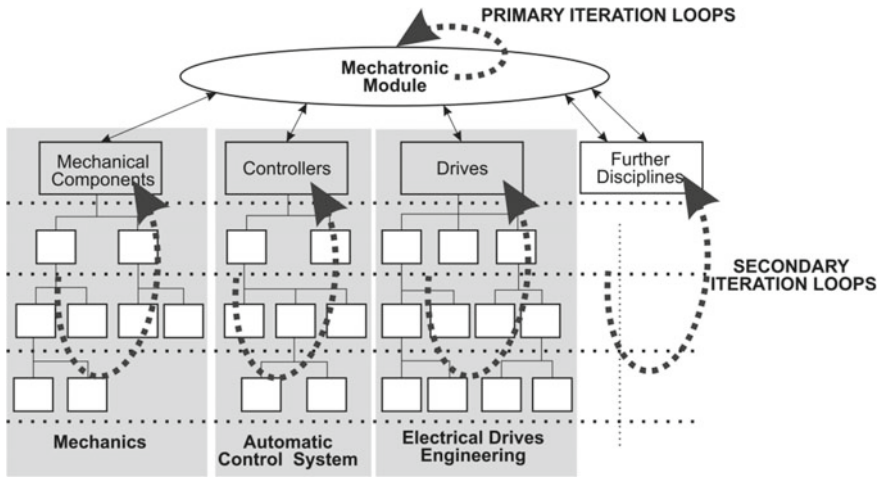
Fig. 7.5 Mechatronic module and design iterations [29]

distinction between two qualitatively different types of iterative loops: one for the different mechatronic disciplines (secondary iteration loops) and one for the couplings between them (primary iteration loops).

Iterations become primary loops if they are characterized mainly by changes in the coupling of the individual sub-systems. Here the requirements and dependencies between the design parameters at the beginning of the development are specified, from which the intersections between the different disciplines are established. It is clear that later changes usually have large effects on the overall operational sequence, thus it should be ensured that subsequent changes are avoided as much as possible, leading to the smallest number of necessary iterations.

The progressive development in the individual partial disciplines is then later characterized by secondary loops. Here, a higher number of iteration runs can be accepted in contrast to the primary loops, as these modifications affect only the requirements and parameters of the specific discipline, and thus have no direct effect on other model pillars as long as the definitions at the coupling level do not need to be changed [31]. The iterative structure of the model allows for a standardized procedure for the development process in subsequent steps.

7.3.2 Bio-mechatronic System Modelling

As has been seen, modelling a mechatronic system is a challenging process. This is due to the fact that such a system comprises mechanical modules (system elements or sub-systems), electronic modules and software to provide the required level of intelligence (including control) for the system operation. The complexity of the modelling

is further compounded by the need for the modelling to take into consideration not just the models for individual subsystems/elements of the system, but also interaction between and among them.

A bio-mechatronic system such as has been developed to interact with the human neuromuscular-skeletal system to assist with impaired human motor control [32] thus consists of an integration of biological and mechatronic systems. Biological systems are themselves inherently complex, and as a result the modelling and simulation of bio-mechatronic systems is generally associated with a high level of assumptions and simplifications while taking into consideration the interaction of the two systems.

There is a suggestion for the modelling of such systems using "*a conceptual model for systems design in bio-mechatronics based on the ideas of mathematics and cybernetics originated by systems theory*". It is argued that "*…traditional mathematical models and models of artificial intelligence do not allow describing bio-mechatronic systems being designed on all its levels in one common formal basis*" [33].

Considering a lower limb prosthetic system as a typical example where the ultimate goal is to replace a lost limb of an amputee with an intelligent device to ideally resemble a biological limb both in terms of functionality and aesthetics. Figure 7.6 shows the elements and interactions in this typical example in a very simplified form.

An intelligent prosthetic device as a mechatronic system should have the required sensors, actuators and control to function as expected. In a bio-mechatronic system, as shown in Fig. 7.6, the additional interaction with the biological system which has its own sensors i.e., receptors, actuators or muscles and control (the central nervous system) adds another layer of complexity to the whole system since static and dynamic interactions should also be taken into consideration. This will make the modelling and simulation more challenging. Another example of a bio-mechatronic system is a robotic exoskeleton, which should also interact with the human body but as a separate device. In such a system the interaction should provide some feedback to the system for control purposes. This should also be taken into consideration in the modelling process.

Fig. 7.6 An example of a bio-mechatronic system
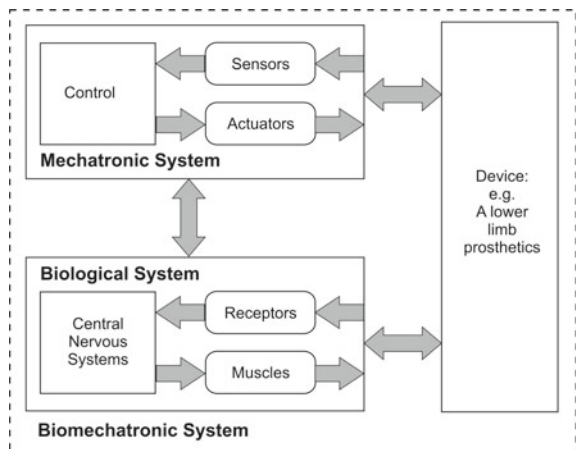
The presented methods are only two examples for methods used in mechatronic design processes. In the authors point of view, these play an important role in the first (conceptual) design phases.

7.4 Case Studies

The following case studies provide illustration of applications involving different functional distributions of activity between the 4 key elements of people, data, mechatronics and cyber-physical system. In order to place these case studies into context, each one has been evaluated (on a scale of 0 (minimum) to 5 (maximum)) concerning their design content in respect of these four key elements as follows:

Design content	Assessment criteria
Data	The significance and importance of data in relation to function and operation of the overall system and to the IoT
CPS	The extent to which the system conforms to the general definition of a CPS presented earlier in terms of the balance between the physical and cyber components
People	The expression of the interface between the system and its users, and the importance of that interaction to its operation
Mechatronics	The contribution of mechatronics, generally in the form of components, modules and sub-systems in achieving overall system functionality

Once the individual case studies have been scored by the system designers, the results can be plotted to create the web diagrams of functional distribution of Fig. 7.7 in order to provide a visual representation of the contribution of each of these four elements to overall system functionality. In doing so it needs to be recognised that the result is intended to be informative as to the relative weight of each element at the system level and not definitive in terms of defining its contribution to system operation.

7.4.1 Smart Home

Smart Home technologies and systems for home automation were introduced in the latter part of the 20th century. The advent of the internet then supported new concepts such as the Digital Home, eHome or iHome [34, 35] and saw traditional automation services evolve to include entertainment and communication supported by home networks and residential gateways as suggested by Fig. 7.8 [36–38].
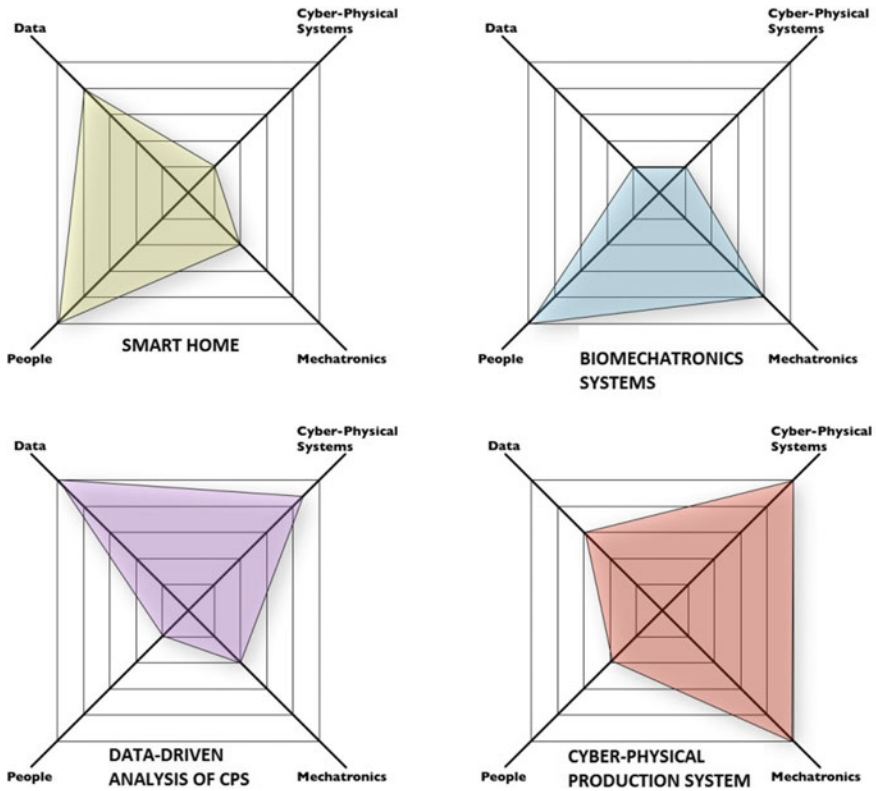
Fig. 7.7 Functional distribution

The 21st century also brought with it new paradigms such as "*ubiquitous comput-ing*" [39] and "*ambient intelligence*". In the case of ambient intelligence, this defines a context in which people will be surrounded by intelligent and intuitive interfaces embedded in everyday objects which recognize and respond to their presence in ways which are context dependent and autonomously and intelligently adapt and respond to the user [40, 41].

This trend of adding intelligence to devices is moving to wider environments as exemplified by the Internet of Things and Smart Cities. The resulting Web of Everything will then integrate Smart Cyber-Physical Systems with the Internet of Things to provide new forms of integrated service [42, 43]. It must also be recognised that this shift brings with it a number of associated risks in relation to matters of individual security and privacy, in particular associated with the collection and use of personal data and the ability to draw inferences about the individual and their personal environment from this. In considering the privacy of the individual it is also necessary to distinguish between the *hard* security issues of Table 7.2 aimed at preventing access to private information, and the *soft* or people oriented aspects of
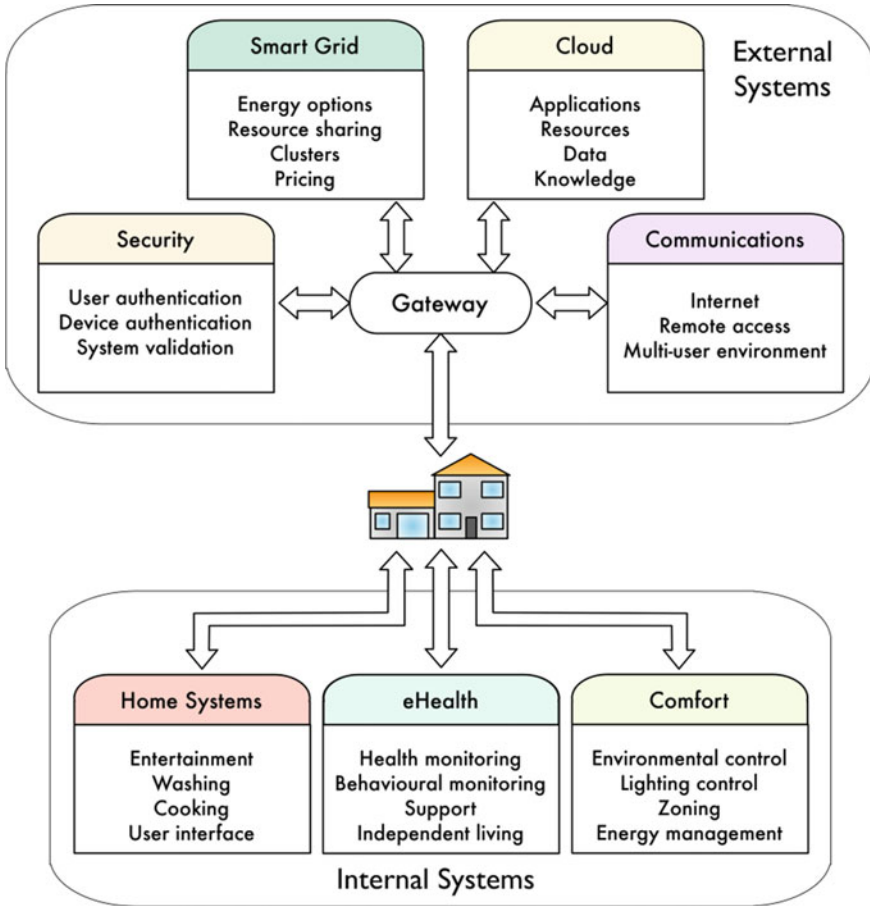
Fig. 7.8 Smart home constructs

Table 7.2 Hard security measures

Measure	Notes
Cryptography	Techniques such as public/private key encryption, digital signatures, steganography, secret sharing, key management, escrow and public and private certificates
Firewalls	Establishes a logical barrier between a trusted and secure network and any external networks
Passwords	Security depends on the passwords being difficult to guess or discover

privacy associated with concepts such as privacy by design [44] aimed at ensuring an individual's right to control over their own data as suggested by Fig. 7.9.

As Information and Communication Technologies (ICTs) develop, individual devices and systems need to communicate with each other in order to support increasingly complex services which involve both co-operation and competition for resources. In this context, the control, multimedia and data functions can be considered according to Table 7.3.

Initially, services were specialized and strongly coupled to the technology that supported them. As the level of embedded intelligence has increased, systems have
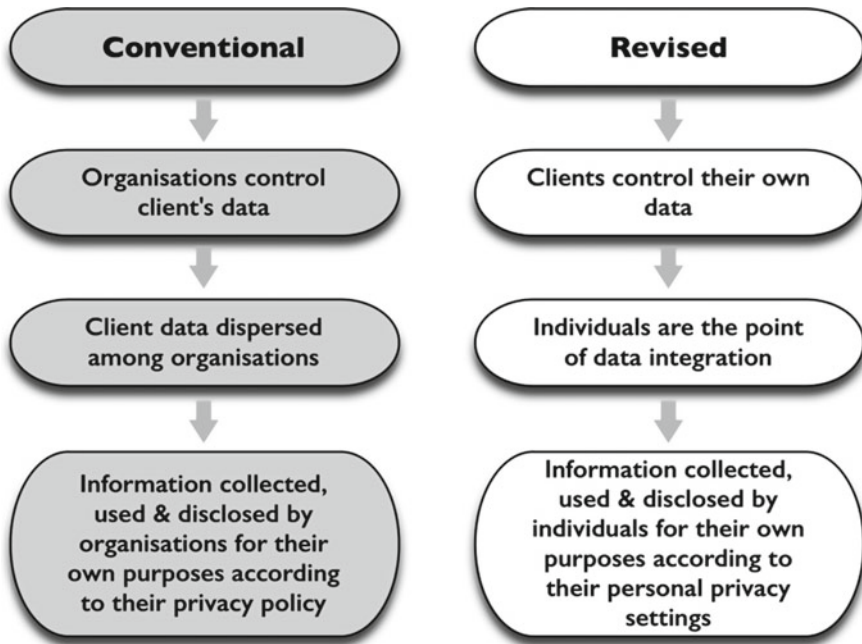

Fig. 7.9 Conventional and revised approaches to client privacy (after [44])

Table 7.3 Input-output transactions table

Control	This provides the infrastructure for the management the home system. Requirements include low cost, ease of installation and reconfiguration, ease of expansion and fault tolerance
Multimedia	This supports the distribution of audio and video media to televisions, HiFi equipment and other media systems. Requirements relate to the volume of data and the quality of service provision required
Data	The data network must provide access to information from anywhere within the home environment for all data sharing devices. Requirements include high bandwidth and low cost

evolved towards a distributed structure in which the gateway supports any device or service with the necessary intelligence [45].

The most important issue is that of enabling individually intelligent devices to communicate and interact with the other devices and actors in the environment. It also needs to take into account the increasing volumes of information home systems are being required to manage, particularly within the context of the Internet of Things where the CONNECT forum has suggested that [46]:

> … the integration of 'Things' as actors in the Internet via massive and innovative sensors, actuators, and real-time reactivity will cause another order-of-magnitude data explosion with challenges that we have yet to understand and deal with.

The underlying concepts of the smart home can be expanded to that of a smart grid environment such as that suggested by Fig. 7.10 where shared resources might, at some future time, encompass local energy systems such as micro-CHP or fuel cells [47, 48]. In such a scenario, the individual houses would be required to negotiate with each other, and with external systems, to balance user requirements, for instance with respect to energy utilization and system level efficiency.

For the user, the requirement is for effective interfaces which adapt to the user and which integrate with context-based approaches to the programming of the system and the requirements for the Design for All and Digital Inclusion agendas introduced in Sect. 7.2 [49–52]. Thus the user interface has to support autonomy while learning to perform tasks for their users and providing proactive assistance as required.

Smart Homes, and their Smart Grid extension, can be considered as constituting a participatory system of the form shown in Fig. 7.3. In order to better understand this relationship, consider the following scenario based around the configuration of a domestic environmental control system for both heating and lighting.

- The first stage of the process would be to first capture the physical layout of the environment and to display this to the user in a suitable form and format. This

Fig. 7.10 Smart grid
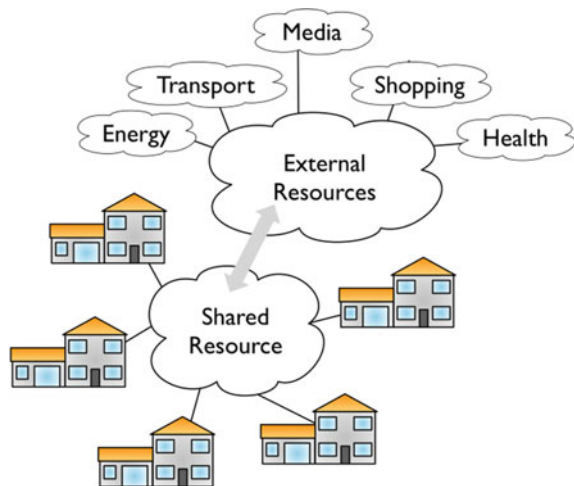
could, but not necessarily, be supported by information on physical properties such as the heat-transfer properties of the walls and ceilings and access to the physical spaces.

- Having defined the environment, then the details of each space can be established along with the use to which that space is put. For instance, do people gather to watch television or listen to music, to eat or to simply sit quietly? This feeds into the modelling of resource utilisation such as heating and lighting, which is in turn reflected into the model of the physical environment.
- Where information such as the heat transfer properties are not available, the system could instead construct over time a model of the profiles for the heating and cooling of the individual spaces, and hence adjust its operation accordingly, taking into account parameters such as the external temperature.

In the above the role of the user is that of data provision and capture, as for instance of the physical dimensions.

- Once the user is satisfied with the needs definition and specification, the design process then devolves to that of component selection structured around user defined criteria such as cost, size, power limitations and so on. This implies an intelligent search function based on some form of recommender system to suggest alternatives to the user from which they can then make a selection.
- Following the selection of components, the system is then required to autonomously generate system-level data such as the optimum location for sensors controlling heating and lighting and the necessary system level functional coding (software) for each device.
- System assembly then evolves to the installation of the components within the environment on a plug, download and play basis. This applies both to individual devices and to the system controller, which may be any combination of smart phone, tablet PC, laptop or panel, and must support external communications for remote operation and diagnostics.

While Smart Home and related technologies are still evolving, it is clear that they present both significant challenges and opportunities across a wide range of technologies from sensors to actuators as well as in relation to context-based approaches to system management structured around the concepts of ubiquitous computing and ambient intelligence. Many of these technologies, and in particular the user interface, are of significance in relation to the requirements of Design for All and Digital Inclusion considered earlier [53–57].

7.4.2 Bio-mechatronic Systems

As introduced in Sect. 7.3.2, bio-mechatronic systems result from the integration of mechatronic and biological systems, usually to assist or support some functionalities of the biological system. Most commonly used examples are prosthetic devices where

they are expected to become an integral part of the human body. Robotic exoskeletons, though not becoming part of the human body, integrate and interact with the human body externally to form a bio-mechatronic system. These robotic exoskeletons are traditionally made of hard materials. However, more recently a lot of attention is being given towards soft materials in the design and development of soft robotic systems.

A robotic exoskeleton has a spectrum of applications ranging from individuals with weak body segments or those suffering from a body part pathology, to those involved in heavy duty work such as in the construction industry, to those involved in search and rescue operations after natural and other disasters, and so on. This spectrum of applications can generally be divided into assistive and enhancive robotic exoskeletons.

Taking an overview of the population, and considering normal behaviours and functions, it is possible to identify three core groups of individuals associated with lower than normal physical capacity and capability:

(i)   Those with some form of congenital disability from birth;
(ii) Those who due to illness, disease or accident lose some portion of their physical capacity and capability and
(iii) The elderly, a growing proportion of the population who gradually lose capacity and capability as a result of the ageing process.

Recent advances in technology afford opportunities for the design, development and implementation of a range of modular bio-mechatronic systems to address a range of problems associated with all of these categories.

The focus here will be on bio-mechatronic prosthetic systems with particular attention on an above knee lower limb prosthetic device. For the development of a bio-mechatronic prosthetic system, it is important to note that a key feature of human locomotion is its adaptability and robustness to changing situations. For the cases of standing, walking, turning, ascending and descending steps/ramps, and sitting, the lower limb segments and body centre of mass require a sophisticated intelligent sensory-motor-control system to ensure adaptability. This complex system is non-linear with all segments affecting each other [58]. Hence, a sophisticated bio-mechatronic system is needed to be designed and developed to provide full fidelity for a human body segment.

The last decades have seen a technological revolution in the prostheses industry due to technical advances in materials, electronics, sensors and actuators. Current lower limb prostheses are divided into three groups:

(1)   Purely passive,
(2)   Actively controlled, and
(3)   Actively driven or powered prostheses.

Purely passive devices are essentially mechanical systems and require significant voluntary control effort from amputees. The first actively controlled prosthesis was the C-leg, including the first microprocessor knee controlled damping with a hydraulic cylinder. Other prostheses (Smart IP) use pneumatic swing control or the

REHO knee using magnetorheological fluid stance and swing control. More intelligent actively controlled prostheses are now available, such as the *Orion* and *Genium* microprocessor knees. But, these do not provide positive energy for stair ascending and other tasks. Actively driven prostheses are fully actuated and are known as *Power Knees* [59]. These are typically actuated using either brushless dc motors [60] or pneumatic actuators [61]. Although these supply power, they consume more than the human muscles because the muscles of the lower limb are not continuously activated during normal walking. To mimic this behaviour, a hybrid hydraulic lower limb prosthetic based on a semi-active approach was developed [62], but hydraulic systems are inefficient.

In a bio-mechatronic system, dynamic coupling interaction between the segments can be used to produce more efficient and comfortable walking for above knee amputees, with power applied appropriately to the prosthetic knee. The advantage of this is the avoidance of the stiff control of a powered knee, which is often uncomfortable due to the dynamic interaction between the amputee and the prosthetic. Also, using the dynamic natural behaviour of the mechanism provides more energy-efficient walking.

With the user-centred design approach in mind (and also to appreciate the current short-comings in the lower limb prosthetic devices) it can be considered what amputees expect from the next generation of such devices. The following comments are referred to as a sample of lower limb amputees' views:

> adaptability in the foot standing and balance is more difficult than walking; adaptability and sensory feedback in the foot shell; ankle movement is very important; current knees are less adaptable to variable speeds; walking on uneven ground is difficult; turning towards amputated side quite difficult; socket is extremely important; smart socket to relax or firm up according to activity; heat sensitivity; more flexibility at joints particularly ankle joint; shock absorbing mechanism; smart limb alignment; interaction with user feedback is definitely needed (amputees currently use visual feedback, they need to look at the foot); contact feedback: heal, toe, rough ground, driving; do not know where the foot is; comfort of socket fit; adaptable socket for different activities/time of the day; aesthetics are also important; energy expenditure is currently too high; affordable prostheses; a fully integrated limb is needed as part of the body (forgotten limb); powered ankle and knee are essential for some activities; prosthetic leg should adapt to the patient not the patient to the prosthesis; reliable and easy to maintain; to be robust for different environments; learning, training and rehabilitation issues.

Examples of challenges include:

i. In terms of the design and development of bio-mechatronic systems, modelling and simulation is a big issue.
ii. For a lower limb prosthetic bio-mechatronic system to function towards the ideal goal, the interaction at high level is very critical. This means that the user intent should be captured by the system well in advance of an action. Only limited advances have been made in this area.
iii. Static and dynamic coupling between the device and human body is another very important parameter for proper functioning of a prosthetic system. This requires arrays of sensors to be used at appropriate locations in the system.

iv. Currently, there is a bottleneck in a two-way interaction between the human body and the prosthetic device. Feedback to the user is required to allow a natural interaction and hence proper system functionality.
v.   Energy efficiency is also crucial for the next generation of such bio-mechatronic systems to allow longer battery life.
vi. Interaction between the bio-mechatronic system and the environment could provide a much better performance. This requires the use of appropriate sensors and more connectivity with the aim of achieving a cyber-physical system. Prevention of falls could be a typical outcome of such systems for example.

In order to design and develop an intelligent lower limb bio-mechatronic device the following processes may be used:

(a) To adopt a user-centered design approach a user community can be set up to allow interaction with the relevant end users.
(b) Detailed biomechanical analysis of human body segment kinetics and kinematics characteristic of common locomotor tasks.
(c) Biomechanical simulation of a human body and lower limb prosthetics, its control and optimization.
(d) Design of optimum prosthetic device and relevant physical experimental work.
(e) Experimental investigation into energy efficiency, recovery and dynamic coupling effect.
(f) Experimental measurement of gait dynamics using appropriate sensors.
(g) Development of algorithms to predict user intent and self-tune to user parameters.
(h) Haptic feedback and its effect on prosthetic performance and consideration of neural connectivity.
(i) Prototype design, development and validation.

Figure 7.11 shows a block diagram of the outcome of such a development. A typical prosthetic system designed and developed using such approach is shown in Fig. 7.12.

Although great advances have already been made in various areas of technology, there are still challenging aspects that require close attention. Two important areas which could greatly advance bio-mechatronic systems including connectivity with the user (neural connectivity) and also with the surrounding environment. Prosthetic devices could be considered as a typical example of such bio-mechatronic systems. User intent is crucially important for proper integration with human body. Interaction with the environment could provide an additional dimension to enhance the performance of such systems as well.
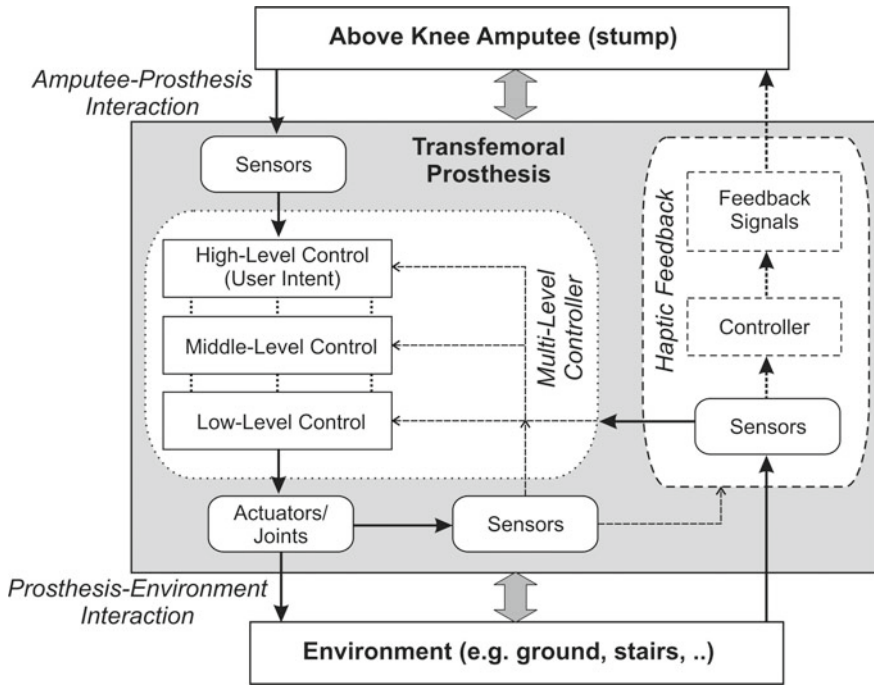
Fig. 7.11   A bio-mechatronic system with user and environment interaction

Fig. 7.12   A prosthetic knee during initial user evaluation process

7.4.3   Cyber-Physical Production System (CPPS)

This section discusses improvements to the development of a Cyber-Physical Production System (CPPS) using ontologies. Future research into the efficiency and quality improvement of CPPS engineering faces numerous challenges [63, 64]:
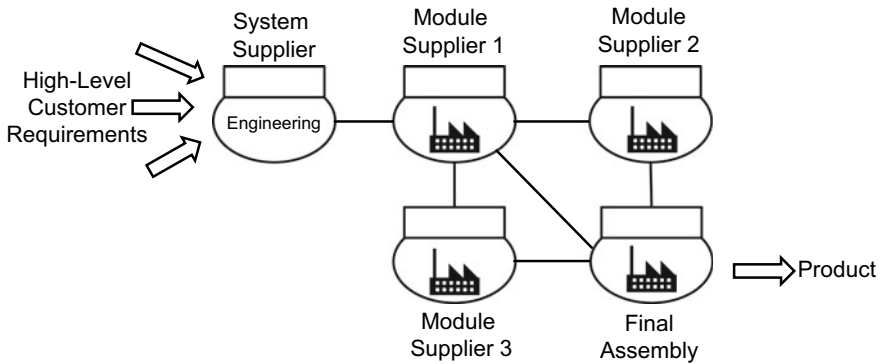
Fig. 7.13 Example of a cyber-physical production system

- Since CPPS use a multitude of systems and subsystems from many different domains, the number of both possible and viable solutions to a particular problem is large. Methods that generate solutions in the synthesis phase would therefore be helpful.
- As there exits a multitude of sustainably solutions to particular design problems, reasonably accurate methods for their evaluation are needed. Including early concept optimization in the methods that support this evaluation saves time.

One solution for tackling these problems is the strict usage of models in different degrees of detail. Since design models can be complex, and their creation and maintenance is often distributed across multiple disciplines, it is difficult to ensure their consistency and correctness.

In the scenario shown in Fig. 7.13, the customers communicate their needs to the system supplier manufacturer (final assembly) and are thus the first link in the supply chain. Depending on the percentage of modules and components manufactured in-house, the process occurs at multiple levels and involves components, component assemblies, mechatronic systems and their integration into the target environment. Based on high-level customer requirements, engineers select and configure standardized mechatronic modules. Building on these modules, the suppliers manage their assembly lines including standardized and user-defined components in the mechatronic module. The manufacturers have to extract internal requirements for their own production process, and must also ensure the consistency of component and module interfaces.

For the optimization of such processes data integration and model consistency play an important role. The involved companies have often problems to guarantee the correctness of data (often embedded in models and their parameters) over time [65]. The aim is now to tackle this challenge by using a semantically-based description of the CPPS to support information and product data exchange.

The knowledge needs to be structured according to a semantic representation. Based on a mechatronic ontology (in [65]) using basic concepts (such as
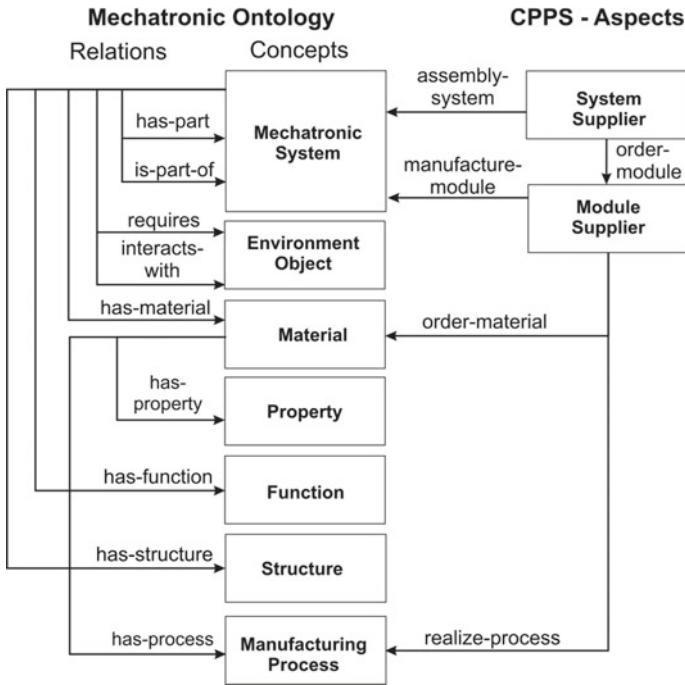
Fig. 7.14 Mechatronic ontology of the CPPS

"*mechatronic system*", "*environment object*", "*material*", "*property*", "*function*", "*structure*" and "*manufacturing process*") and relations (such as "*has-part*", "*is-part-of*", "*requires*", "*interacts-with*", "*has-material*", "*has-property*", "*has-function*", "*has-structure*" and "*has-process*") the relevant knowledge of a CPPS can be presented ("*assembly-system*", "*manufacture-module*", "*order material*" and "*realize-process*"). Figure 7.14 shows the concept of the ontology by means of the above example. This semantic model can be seen as the main element for the horizontal and vertical integration within a CPPS. The wide range of information available to the suppliers can be handled by the described meta-model in a clear and consistent way.

7.4.4   Data-Driven Analysis of Cyber-Physical Systems (CPS)

Asset health and asset performance are essential for efficient and trouble-free operation of CPS. Modern information systems continuously communicate with CPS to analyse and forecast their state of health and performance. In this chapter, a data-driven approach to CPS using the example of the health management of photovoltaic (PV) systems is described.

The scientific foundation of health management applications are the models and algorithms for detecting system faults (fault detection, FD), identifying their possible causes (fault diagnosis, FDD), and the analysis of system performance (performance analysis, PA). Current research assumes the a priori availability of exact models of the target CPS (model-based or knowledge-based diagnosis [66–68]). Manual modelling of systems is however time-consuming in practice and of high costs. Many projects are therefore often not realized.

One goal of data-driven analysis of CPS is thus to automate FD, FDD, and PA and consequently to avoid the need for tedious a priori model building. Robust learning algorithms (RLA) are an important step towards achieving this goal. Robust algorithms learn the necessary model from available observational data. Due to their robustness, they can learn from data of poor quality such as data that itself contains faults. Robust learning and estimation is a current challenge in statistics and machine learning.

The motivation or enabling technology of this research is the Internet of Things (IoT). New technologies for the IoT facilitate the collection and evaluation of data at continuously decreasing costs even for large amounts of data. Technology foundations are cheap and accurate sensors, low-cost internet connections, geo-information systems, cloud-based IoT services. Example applications of learning-based FD, FDD, and PA in the IoT are:

- **Fault message generation and prioritization**. Prioritizing fault messages according to their relevance. This enables the monitoring of a large amount of CPS, e.g. PV systems.
- **Real-time FDD**. Instantaneous identification of possible faults after sudden failures to guide maintenance.
- **Performance analysis**. Analyzing the performance of CPS for use in business planning and in particular planning maintenance.
- **Predictive maintenance**. Forecasting downtimes, system and component failures.

The increasing number of CPS connected to the internet raises new challenges and possibilities. Health management is one of the major benefits the IoT enables. Health management encompasses mere system monitoring and at its core the scientific, data-analytic problems of FD, FDD, and PA. The IoT raises new scientific challenges for data analysis research due to the following reasons:

- **A large number of different system types**—From mobile devices (such as smartphones or tablets) through every kind of vehicle (car or a mobile crusher), household appliances (washing machine or a roof-mounted PV system), sensors for measuring temperature and other environmental parameters and entire facilities for industrial production.
- **A large number of systems**—Besides the large number of different system types, the number of CPS of a particular type itself can be huge. E.g., all cars of a leading manufacturer. Due to the large number of systems, a possible massive amount of data needs to be processed and analyzed (big data).
- **The variety of system configurations**—CPS may exist in different configurations. For example, two PV systems of the same type can have different sets of

sensors. This problem closely relates to the problem of faulty sensors. If a sensor is malfunctioning, its measurements are useless.

- **Incomplete system knowledge**—Knowledge about the system design is often incomplete. Moreover, systems and thus the system models change over time.
- **Unreliable data connections**—Data is often unavailable due to unreliable or slow data connections.

Most of these aspects are new, especially the vast number of system types. Current data analysis algorithms and information systems are often not capable to deal with this new situation without time-consuming manual system modelling. Mastering this situation is the major challenge for scientific disciplines such as machine learning, knowledge discovery, statistics, and fault diagnosis.

Data-driven analysis of CPS relies on methods from machine learning, statistics, and knowledge discovery. The choice of the method depends primary on the CPS, available data, and the analysis task. In the use case of PV systems, the aim is to analyze PV systems to detect and classify faults (FD) [69–72]. Figure 7.15 shows the data-analytic parts of such a health management application. Data is collected from a possible large amount of PV systems. The random process is the conversion of solar energy into electrical energy. Robust learning takes historical data as input and delivers a (linear) model of the PV system to FD. The model relates the system output

(a) Photovoltaic system

(c) Data analysis process

(b) Energy conversion (random process)
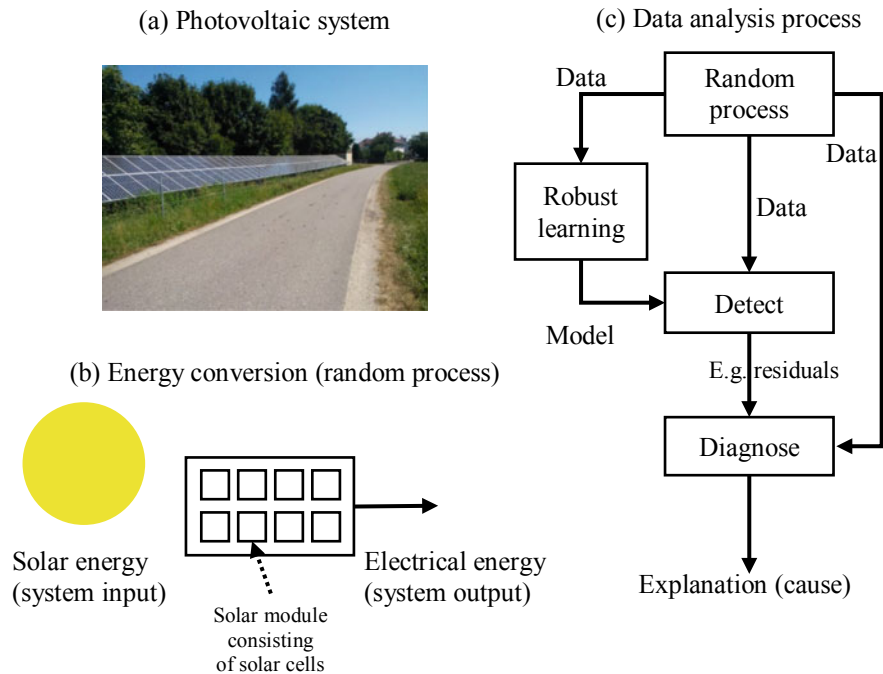
Fig. 7.15 **a** Photo of a mid-sized PV system. **b** Schematic picture of the random process to be analyzed. **c** Overview of the data analysis process based on observations of the random process

(power) to its system input (plane-of-array irradiance) and system state parameters (e.g. module temperature). FD takes current data and the model as input and checks for strong deviations of the observations from the model. FDD tries to identify and explain the faults. One way is to classify faults as melting snow, shading, etc.

The pattern in Fig. 7.15 applies to many other situations in data-driven analysis of CPS. Robust learning assumes that all but k data samples are independent and identically distributed. The remaining k data samples can be arbitrary faults. This notion closely relates to the breakdown point of robust statistics [73]. Any algorithm for computing an estimation with a high breakdown point is a robust learning algorithm (RLA). Such algorithms and heuristics are known for classical statistical problems such as location, dispersion, and linear regression [73], but not known e.g. for decision tree learning or learning artificial neural networks. RLA are necessary if historical data contains faults, which is usually the case in practice.

Fault detection (FD) often reduces to computing residuals, i.e. the model output minus the observed output, and identifying large residuals. Despite some difficulties due to randomness in the data, FD is often a simple task. Fault diagnosis (FDD) however is more involved. The main reason is that learned models are sometimes considerable less accurate than models enriched with expert knowledge. One reason is the existence of critical system components that are not monitored by sensors. In the use case of photovoltaics, a PV system behaves roughly as a linear system. It still does so if a solar module fails. A fault can be detected but its cause cannot be identified if the module is not monitored by a sensor. How to conduct FDD based on learned models is a current challenge. One way is to learn subsystems or cause-effect relations, e.g. via causal discovery algorithms [74]. Another approach tries to include expert knowledge, e.g. learning causal graphical models [75]. Finally, it is possible to concentrate entirely on components, assuming that the necessary sensors are installed. This is done e.g. in [76], which is based on hybrid time automata learning [77].

To meet the challenges of data-driven CPS, several problems had to be solved. There is large variety of PV system configurations due to different solar cell technologies, various common circuit designs, and so on. Thus, linear system models due to their generality were considered [69] noting that they are less accurate than models, which capture the exact non-linear system dynamics.

Because of the large number of PV systems, a fast algorithm especially for model learning for FD [69] was designed and analysed. FDD algorithms are only applied if a fault is detected. This allows to invest more computation time in FDD. FDD algorithms analyse the residuals of robustly learned models. The algorithm in [69] locates faults in residuals, i.e. it estimates the starting time and end time of a fault. Several fault types such as shading or melting snow have typical time patterns. For example, a shading event may happen in the morning over a couple of months. FDD is thus fault classification. In practice, these classifications help to explain the faults.

A common difficulty in data-driven analysis of CPS is the lack of sensors. In the case of PV systems, a plane-of-array irradiance sensor is not present (probable the most critical parameter besides the power output). The idea in [78] is to learn relations (associations) between PV systems that work under similar conditions. The

learning method is a robust alternative to correlation networks, a so-called fitness graph. Correlation networks are an important type of associative graphical models. The fitness graph is employed to detect and identify faulty systems. The difficulty here is to learn enough relations to increase the accuracy and reliability of FD.

Most recently, in [79] it is showed how to design fast and parallel RLA for the problem of linear regression, i.e. learning linear models. This method is called Median-of-Means (MoM). MoM is a meta-algorithm following the divide-and-conquer principle. MoM uses the fact that input data is independent and identically (i.i.d.) distributed. It can speedup algorithms. It is robust. It can boost the confidence of algorithms. In addition, it can parallelize sequential algorithms. This last property of MoM in combination with practical algorithms for linear regression is used for analyzing PV systems data.

7.5   Discussion and Conclusions

Mechatronics is an established engineering discipline for which proven and demonstrable design methods and tools are available. However, with the advent of both Cyber-Physical Systems and the Internet of Things, while these methods and tools can continue to be used as the basis of the design of mechatronic modules and subsystems, an extension is needed to accommodate particular requirements for integration at the system level (characterized by the integration of components) that characterises CPS as well as the information exchange and sharing associated with the IoT.

Starting from the fundamentals of mechatronics design, the chapter has considered the extension of the associated methods, and particularly modelling approaches, to support the inclusion of the resulting mechatronics components within the larger integrated system concepts of both CPS and the IoT. Particularly emphasis is given to four design areas, namely data (the IoT), CPS, mechatronics and people (including not just users but others impacted both directly and indirectly by the system) chosen to characterise, and differentiate between, categories of system.

Building on this, four case studies have been presented, each of which focuses primarily on one but encompasses all domains. The nature of the case studies is such that they not only illustrate the design decisions associated with them, but the interaction with and between the various hierarchical levels. This then allows consideration to be given to design elements invisible to the designer of the individual systems components, as for instance the autonomous selection at the level of the IoT of system elements based on context and need.

Thus viewed from the perspective of both a CPS and the IoT, mechatronic design approaches can be considered as a key driver for the development of a wide range and variety of future systems. The concepts present designers with the challenge of implementing structures within information rich environments where information and communications are increasingly the drivers of the design process. This in turn requires designers to have access to new and novel means of simulation capable of representing such situations.

What is also clear is that the advent of both CPS and the IoT is introducing a new range of challenges for designers and the design process, many of which are centred around the need to ensure the privacy of individual users whilst supporting the integration of data across multiple users, as for instance in healthcare, to facilitate the early detection of situations and conditions and the appropriate responses to these. In doing so, designers are obliged to consider not only the hard aspects of privacy, namely ensuring the security of data during storage and transmission, but the soft or people oriented aspects of ensuring an individual's control over their own data. These are increasingly important consideration when considering the increasingly distributed nature of data, and the dynamic nature of systems, particularly at the level of the Internet of Things.

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