Part One

Introduction

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On Concepts and Challenges of Realizing Material-Integrated Intelligent Systems

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1.1 Introduction

Material-integrated intelligent systems constitute materials that are able to "feel." This is the shortest possible definition at hand for the subject of the present book. What it implies will be discussed below, while detailed descriptions of individual aspects and application scenarios will follow in its main parts.

As a concept, material-integrated intelligent systems have implicitly been around for quite some time. To a considerable degree, this is because the concept as such is not so much a human invention, but rather something that is deeply rooted in nature: The human skin and the human nervous system are the typical examples cited pertaining to material-integrated intelligent systems, such as sensorial materials [1–3], robotic materials [4], nervous materials [5], or sensor-array materials [6].

These natural models taken together nicely illustrate the differences between materials with integrated sensor(s) and material-integrated intelligent systems: For one thing, the skin contains a multitude of sensors which do not only capture force or pressure, but also additional aspects like the first and second derivative of pressure or temperature. At the same time, the impression we get when we touch an arbitrary surface is not that of a separate awareness of these factors, but a combined one that is derived from fusion of sensory information.

Besides, we do not base the decisions we make in response to a tactile sensation on quantitative values of pressure, temperature, and so on, and on a deterministic model that links these values to an intended action and its potential outcome. Instead, we rely on experience, that is, on a learned relationship between an action and its outcome in relation to the associated sensory information in one way or another. Translated to technical terms, we thus follow a model-free approach.

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Having said this, we can derive a list of characteristics a material would need for us to concede that it can actually "feel." Such a material must be capable of

- capturing sensory data;
- aggregating data through some local preprocessing, performing data reduction of individual data points;
- further processing this data to derive some higher-level information, gaining knowledge;
- using this knowledge for decision-making, putting it to some internal/local use, or communicating it to higher system levels;
- coping with damage by being dynamic and reconfigurable; and
- achieving a state of awareness of host material and environment, that is, the derivation of a context knowledge.

If the above list represents a functionality-centered perspective, the question that immediately arises is how a technical implementation of this concept could be achieved, and which research domains would need to contribute to it.

On a generic level, material-integrated intelligent systems follow the universal trend in the microelectronics industry, which is typically described as having two orthogonal, primary directions: on the one hand, miniaturization or the "more Moore" development line, and on the other, diversification through the integration of additional, usually analog, functionalities such as sensing, energy supply, and so on – the "more than Moore" approach. In both cases, reference is made to Moore's law, which predicts (from a 1965 point of view) that transistor count in densely packed integrated circuits would double every 2 years, and which has since then approximately been met by actual developments, although with some indications of slowing down since about 2011. Technologically, "more Moore" is usually associated with system on chip (SoC) solutions, whereas "more than Moore" is linked to system in package (SiP) technologies. However, both merge diagonally combining both SoC and SiP approaches to create higher value systems. Clearly, this is the domain into which material-integrated intelligent systems fall. As a consequence, the following research topics need to be addressed in their development:

- miniaturization on component and system level to limit "footprint" within host material;
- system resilience against effects of processing conditions during integration;
- system compliance with host material properties in the embedded state;
- energy supply solutions that support autonomy, like cooperative energy harvesting and storage, and (intelligent) management of resources;
- reliable and robust low power internally and externally directed communication approaches;
- distributed, reliable, and robust low power data evaluation; and
- multiscale design methodologies that span the scope from chip design to smart products and environments.

Mark Weiser, in his landmark 1991 article that predicted many evolutions in computer science we have witnessed since, has set the scene by stating that "in the 21st century, the technology revolution will move into the everyday, the small and the invisible" [7]. Weiser thus anticipated a development that is connected to terms such as ambient intelligence and ubiquitous or pervasive computing.

Material-integrated intelligent systems will both profit from and contribute to the realization of this prediction through their potential of endowing many of the passive materials surrounding us today with perceptive capabilities, and ultimately even adaptive behavior. A large part of the novelty of this approach has its foundations in the notion that miniaturization of systems will allow integration on a level that provides the added functionality without compromising suitability for the primary role to be fulfilled by the material in question. A prominent example in this respect is structural health monitoring (SHM). This application scenario is relevant for safety-critical, load-bearing structures. Safety can be enhanced, or safety factors relaxed, if the exact structural state is known at any moment in time. If material-integrated intelligent systems were selected for this task, a necessary prerequisite would be that the systems themselves do not adversely affect mechanical characteristics of the host material. In other words, the materials designed thus should not afford considering any property degradation caused by the material-integrated systems during the layout of the structure for its primary task. In a further evolution of the concept, the materials themselves could thus be envisaged as semifinished materials in the same way as sheet metal: Their capabilities, including their smartness, would be available as an asset not necessarily targeted at a specific application, but providing for several ones. For production of material-integrated intelligent systems, such a scenario could open up economy of scale effects significantly enhancing their economic viability. At the same time, this would afford production techniques able to cope with the associated large production volume.

It has been suggested that the implementation of material-integrated sensing can either follow a top-down or a bottom-up approach [2]. Focusing specifically on the sensing function, Lang *et al.* [8] propose an even finer distinction, which demarcates a top-down as opposed to a bottom-up approach:

- top-down approach:
  - hybrid integration
  - local additive buildup
- bottom-up approach:
  - generic (intrinsic) sensing properties of materials
  - local growth of sensors using, for example, bioinspired processes

From our current perspective, Lang *et al.*'s proposal excludes the intelligent side of material-integrated intelligent systems and its prerequisites like energy supply by concentrating on the transducer effect and the hardware to implement it. Specifically, the bottom-up approaches still fail to offer solutions that could provide these system components. This is apparent particularly for the generic sensing properties of materials, which remain ineffectual even as sensor until at least some means of detecting (i.e., sensing) the intrinsic effect is added.

The example shows that at least on the level of full intelligent systems, bottom-up approaches do not yet respond satisfactorily to the questions of realization.

An exception, though a theoretical one, is the notion of programmable matter proposed by Toffoli and Margolus. Their original concept assumes spatially distributed computing elements similar to smart sensor nodes capable of nearest neighbor interaction only. Together, they form a material with the inherent capability of information processing. Practically, this concept is reminiscent of physical realizations of cellular or lattice gas automata [9,10].

Later, alternative or extended definitions of programmable matter stress the ability of such materials to alter their physical characteristics in a controlled fashion – controlled either by a user from the outside or autonomously from within the material. In the latter case, the programmable matter makes use of its data evaluation capabilities to respond, for example, to sensor signals. Under this headline, several materials have been understood to represent forms of programmable matter. Material-integrated intelligent systems would fall into this category, too. Since the wider definitions of programmable matter include spatial reconfiguration building on autonomous objects (cells) as building blocks besides information processing, sensing, actuation, and adaptivity, both sensorial materials [1] and robotic materials [4] can be seen as intermediate-level representatives of this overall class of intelligent materials.

Realization of programmable matter thus depends on the scope of properties and the definition adopted. The full spectrum is usually represented by the material being built up of individual, autonomous units of microscopic scale that form the matter itself by docking to each other in different configurations, an ability that requires some relative locomotion, too. “Utility fog” is another designation for a system of microscale autonomous units having such abilities, with the spatial rearrangement not based on the so-called “foglets” as the smart units, but on the flow of the fluid in which they move. Reaching a certain macroscopic shape thus does not have to depend on deliberately moving to a certain location, but can rely on making or refusing connections once the opportunity is there [11]. To date, to the knowledge of the authors, no physical material is available that combines the full set of characteristics envisaged by Toffoli or Hall [10,11].

Obviously, much nearer to implementation is the top-down approach, which essentially coincides with the intermediate, diagonal path in between the pure “more Moore” and the “more than Moore” trend: What the term top-down implies is a hybrid integration approach in which suitable components are adapted to material integration needs and combined to form the required smart sensor network.

First practical developments leading toward sensor nodes combining subsets of the features required by material-integrated intelligent systems – above all, a minute size, a certain level of energy autonomy, and data evaluation as well as communication capabilities – sailed under the “smart dust” flag from the end of the 1990s to the early twenty-first century [12]. Warneke *et al.* concentrated on developing, as they termed it, a “cubic millimeter-sized computer” fully endowed with sensing, energy storage, and data evaluation, plus communication that could create an *ad hoc* network when dispersed, like dust, in a given environment. Clearly, a handful of smart dust sensor nodes embedded in a host material would conform to our own definition of material-integrated intelligent systems and sensorial materials.

Figure 1.1 provides an overview of the main elements of such a system, which mostly form part of the smart dust mote concept, too. The sensorial material as such consists of a material-integrated network of smart sensor nodes that may

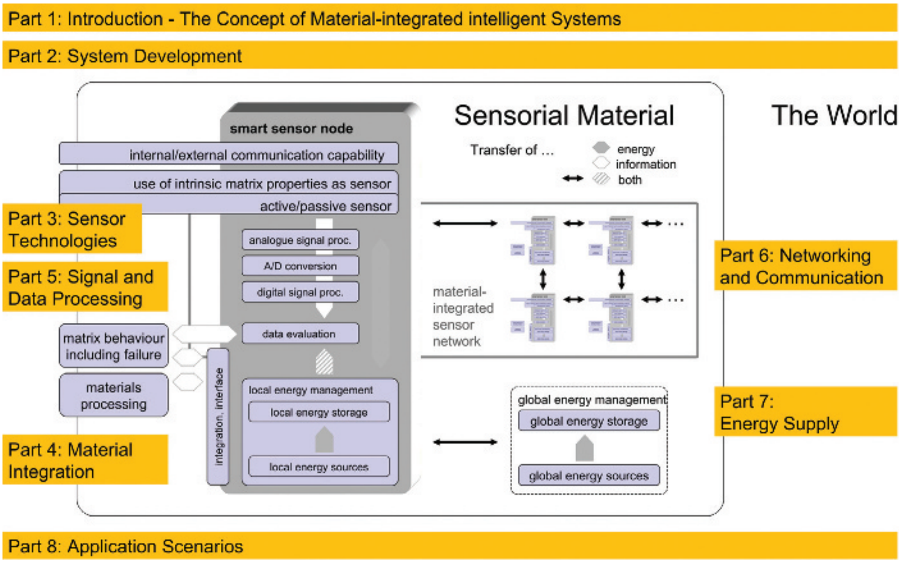

Figure 1.1 The fundamental elements of a material-integrated intelligent system, also called sensorial material, as envisaged by Lehmhus *et al.* [2] – the aspect of material integration and the resulting interactions between integrated system and host material during production and life cycle are included, as well as the link to the environment in which the system exists: The world may be the source or cause of sensor data, but may also provide communication partners, both as recipients and as suppliers of information, the latter, for example, if the material-integrated system is embedded in a higher-ranking IoT solution. Besides, it may exchange energy with the sensorial material, acting either as source or sink.

incorporate features like data evaluation and energy supply on local as well as global level. Figure 1.1 also links the various technological aspects to the respective parts of the present book.

1.2 System Development Methodologies and Tools (Part Two)

Basing a product on material-integrated intelligent systems leads to increased complexity in product development. Whereas in more conventional solutions, development of smart system and component can follow parallel paths for much of the design process, material integration affords a tighter coupling: Peters *et al.* [13] have highlighted this problem in an aerospace SHM context.

This calls for adapted design methodologies and tools that reflect the multidisciplinary, multidomain nature of the topic. In order to do so, such tools must incorporate simulation capabilities that address the various scientific disciplines involved and at least allow transferring results between them, if not even integrating them. As has been pointed out, for example, by Lehmhus *et al.* [14,15], this requirement does incorporate multiscale and multiphysics aspects, but extends beyond these in some respects by linking the process of gathering data and turning it first into information, and then using these to make decisions on physical aspects of the structure: Examples include adaptive structures that allow property change in response to loads or damage reconstructed from sensor signals, and base their decisions on incremental learning approaches [16]. Assessing the safety of such structures will have to include considerations about physical effects within the material potentially causing damage, the probability of detection of damage both of the structure itself and the sensors employed, and the developing nature of the learned model. Besides, energy issues may have to be considered if, for example, energy management adapts the number of sensors interrogated, the communication activity between sensor nodes, or the algorithms used in load or damage assessment in relation to the energy status of sensor nodes and network. If energy harvesting is used to beef up energy resources, probability of detection and so on may even be influenced by the past, present, and predicted (if a forward-looking energy management algorithm is used) service life of the structure, which determines the amount of energy available for scavenging. For such factors to have an impact, strictly speaking not even adaptivity is needed.

Design methodologies will be discussed on a global level and from the point of view of smart system design in part two of the present work.

1.3 Sensor Technologies and Material Integration (Part Three and Four)

The variety of sensors used in material-integrated sensing echoes the variety of application scenarios. Classification of sensors can, for example, be based on the manufacturing process (printed sensors, MEMS sensors, etc.), the material group (organic versus silicon sensors and electronics), the nature of the measurand (mechanical sensors, temperature sensors, chemical sensors, etc.), and the underlying principle of measurement (optical sensors, piezoresistive sensors, piezoelectric sensors, etc.). All the above classes, and more, have relevance for material-integrated intelligent systems and will be discussed in part three of this book.

For the case of sensors, material integration itself is typically described by means of several different levels. Figure 1.2 provides an overview in this respect, starting with an entirely external observation, in this case represented by a camera (level I). Surface application of sensors is the next step: The sensor is applied, usually via its substrate, to the material to be monitored (II). Surface integration in contrast assumes a tighter coupling between sensor and material or part (III). Examples in this respect include sensors directly printed onto a part or material surface, implying in situ production of the device. In materials featuring a layered buildup, as is the case for continuous fiber reinforced polymers or the so-called fiber metal laminates, surface integration realized on an internal surface can turn into volume integration (IV). Also frequently discussed is the use of intrinsic material properties for material-integrated sensing. The drawback of this approach is that it does not replace the smart sensor node, but at best the transducer element that translates the measurand into an electrical signal. From a material-integrated intelligent system point of view, this is a minor contribution that may be bought at the expense of compromising material properties.

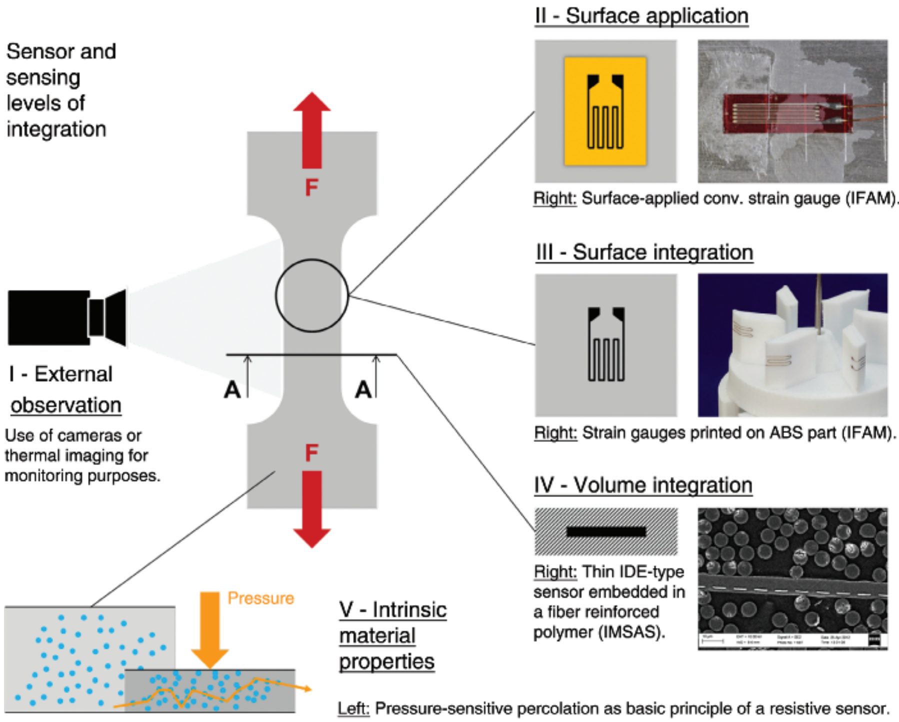

Figure 1.2 Sensor integration as a model for explaining the various levels of material integration, using a tensile test and associated sample as example. (Images courtesy of Fraunhofer IFAM – top and center right – and IMSAS, University of Bremen – bottom right.)

In terms of the challenges of integration, a distinction between life cycle phases is helpful. The beginning-of-life (BoL) phase and especially the production processes typically stress the material beyond the limits it can be expected to see in the middle-of-life (MoL) or application phase. However, unless production process monitoring is among its tasks, the system is only expected to survive in this phase, and not to deliver accurate and reliable information, which simplifies the task to some degree.

The hardships of integration themselves very much depend on the nature of the underlying manufacturing process. Casting or molding processes are typically characterized by higher processing temperature, but generally lower mechanical loads. Forming processes usually involve higher mechanical loads. Processing of polymers naturally occurs at lower temperatures than that of metals. However, in some cases, like the integration of sensors in metal casting, it is not only the absolute temperature that is of interest but also the cooling rate after mold filling: Despite the much higher mechanical loads, it is easier to integrate a sensor in high-pressure die casting than in sand casting because the former reaches cooling rates orders of magnitude higher than the latter. Figure 1.3 illustrates these differences in a qualitative manner. As a consequence, in high-pressure die casting, a thermal protection solution for the sensor system only needs to withstand the elevated temperatures for seconds or minutes at most [17–22].

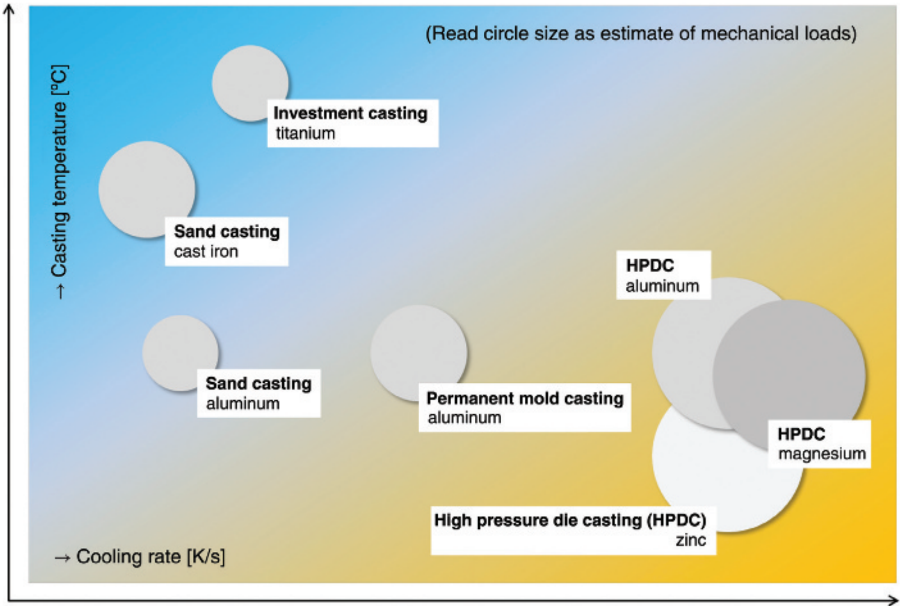

Figure 1.3 Qualitative comparison of production processes (here metal casting processes) in terms of thermal loads exerted on embedded sensors and sensor system components, showing temperature level versus cooling rates reached following mold filling.

Coming to terms with thermal loads can be discussed based on structural state consideration and thus oriented at the melting point of the various materials found in a sensor system for functionality reason. However, in many cases, the maximum sustainable temperature is not defined by this criterion, but by lower boundaries that mark the loss of core functional capabilities. Examples in this respect are semiconductor devices that depend on doping, which may be irreversibly lost if activation energies for dopant diffusion are reached and sufficient time (here the process-dependent cooling rate comes in once again) at elevated temperature is available. Since diffusion paths are short due to the high resolution of current semiconductor device technology, even limited time intervals may already harm the system. Similarly, as ceramics, piezoelectric materials like lead zirconate titanate or PZT can, in principle, withstand high temperatures, but lose their polarization once the Curie temperature (roughly between 230 and 500 °C for PZT, depending on exact composition) is passed. Naturally, polarization of an already integrated PZT sensor is difficult if the encasement is of metallic nature. Both examples underline that material integration may have to rely on specific materials with properties adapted to the integration process. Figure 1.4 enumerates solutions discussed in the field of high-temperature electronics (HTE) and contrasts their application temperatures with typical casting temperatures, illustrating the fact that not only the active components must be considered but also passives and supporting materials like solders.

If thermal stability cannot be guaranteed via an adjusted choice of materials, thermal protection is a second option. A drawback of this solution is that in case of a

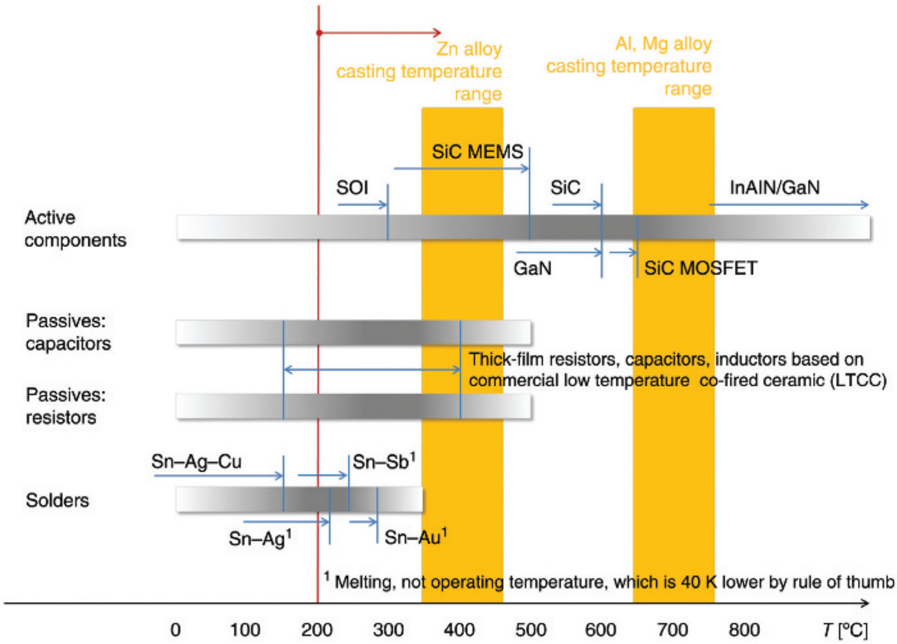

Figure 1.4 Exemplary overview of high temperature electronics material choices for different types of components (active and passive components, solders) contrasted to thermal conditions in metal casting [23–28].

sensor, it means detaching it from the structure to be monitored, which complicates the interpretation of signals gathered. In case of an electronic component, a reversal of the heat flux direction can be observed if usage of the component generates waste heat: In this case, the protective insulation designed against the requirements of the BoL phase will counteract heat dissipation during the MoL phase, that is, the product's service life (see Figure 1.5 for an schematic illustration of the problem).

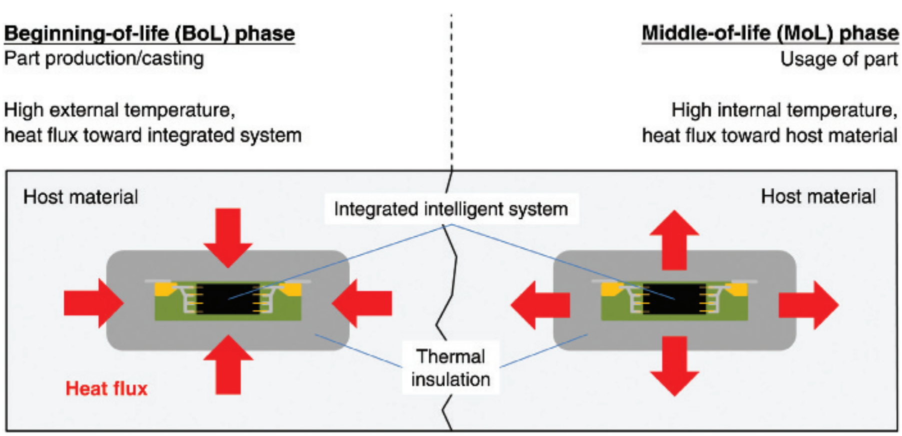

Figure 1.5 Heat flux reversal from beginning-of-life (BoL) to middle-of-life (MoL): Can being too protective do harm?

Thus, once the production process is over, service life emerges as a challenge in its own right. Already in the later phases of thermal production processes, compliance of the typical host and sensor system – functional and packaging – materials become an issue. The main aspects to consider are thermal and mechanical compliance. Differences in the coefficient of thermal expansion (CTE) on the one hand and the Young's modulus on the other affect internal stress distribution in host material and sensor system. If applied deliberately and in a controlled manner, these effects can actually be employed to improve system performance. An elegant example of such a strategy has been presented by Heber *et al.*, who have integrated piezoceramic elements at elevated temperatures in polymers with different CTE values. As a consequence, after cooling, the higher CTE of the enclosing polymers results in compressive residual stresses in the piezoceramic and tensile ones in the polymer. The main benefit is a certain alleviation of the brittle fracture behavior of the piezoceramic material [29]. In a somewhat similar approach, Choi *et al.* have deposited a low-CTE conductive material on a high-CTE substrate at an adjusted temperature to create compressively prestressed interconnects able to better sustain tensile loads and even allow some amount of stretching. A comparable, but mechanical rather than thermal effect has been reported by the same authors relying on deposition of the conductive material on a mechanically prestressed substrate that is released afterward [30].

In contrast to the above examples, deviations in the Young's modulus typically come into effect as soon as mechanical loads are applied. In a fiber-reinforced composite material, the high stiffness fibers rather than the low stiffness matrix see the highest stress levels. The same will happen in a complex material-integrated intelligent system. On a larger length scale, the effect is observable between host material and embedded device. Dumstorff *et al.* [31] have demonstrated this via FEM simulations of an assumed silicon-based device in a "virtual" matrix with varied elastic properties. Similar studies have been performed by Lecavelliers des Etangs-Lavellois *et al.* [32], who looked on a much smaller length scale at the stress distribution caused by external loads like bending within the various materials and subcomponents that together constitute a silicon-based device.

Naturally, selection of materials is neither entirely free on the functional and packaging side nor on that of the host material: The choice is always dominated by the main functional and structural requirements imposed by the product specifications. Product designers must thus attempt to reach a best compromise in terms of the compliance issue, including all system levels, essentially solving a multiobjective optimization problem across several scientific and engineering disciplines. Once again, this stresses the need for dedicated design methodologies and tools. Besides, it motivates further efforts toward limiting, at least, the mechanical loads acting on material-integrated intelligent system in structures subjected to external loads. Naturally, the solution to be adopted in this respect depends on the actual loading conditions. Nevertheless, three main groups of approaches can be distinguished:

- neutral plane engineering
- flexible/bendable/stretchable materials
- rigid islands, flexible interconnects

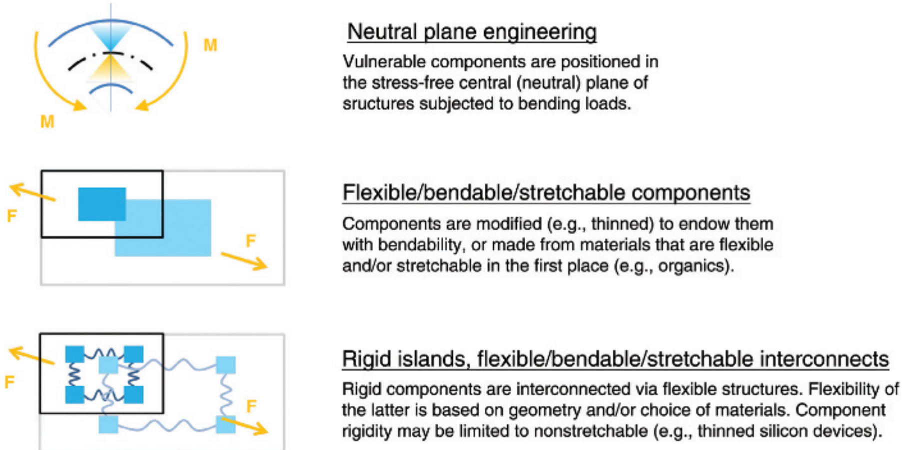

Figure 1.6 Mechanical compliance: schematic representation of fundamental concepts.

These fundamental concepts, which can partially overlap in practice, are illustrated schematically in Figure 1.6.

Flexibility can stand for several characteristics in this context: In some cases, it is meant to be understood as "bendability," in other cases as "stretchability." Furthermore, it is important to keep in mind that the benchmark for flexibility usually is a silicon device, which is characterized by brittle failure and a high Young's modulus and strength, which together translate into a very limited elongation at break. The level of flexibility that needs to be attained is thus comparatively low for most applications under consideration: Stretchability of a few percent is very often more than satisfactory.

Neutral plane engineering is specifically relevant for flat products subjected to bending loads: In this case, a stress-free (neutral) plane exists in or near which vulnerable components can be positioned. Naturally, if the task of the integrated system encompasses strain measurement, at least the sensors should be placed outside the neutral plane. Neutral plane engineering ideally requires very thin systems because the neutral plane itself, that is, the stress-free zone, has zero thickness. Thus, the thinner the system is, the lower are stress and strain in its top and bottom layer. This effect is, for example, used in ultrathin chip packaging and similar approaches that reduce the substrate thickness of silicon devices, which is not determined by function, but by the need for certain handling characteristics of the silicon wafers, leaving little more than the structured layers. The resulting flexibility in bending has been described by Wagner and Bauer, stating that "like any other stiff material, circuits become flexible and rollable when their thickness is reduced to 1/1000 of the desired radius of curvature" [33]. Since it is possible, as Lecavelliers des Etangs-Lavellois *et al.* [32] have shown, to reduce a complementary metal-oxide-semiconductor (CMOS) microchip to a mere 5.7 μm thickness, bending radii of a few millimeters can be realized this way.

Use of materials that inherently offer flexibility and/or stretchability is an approach that can either be extended to the full system, or limited to the interconnects between components like sensors, microprocessor, or energy

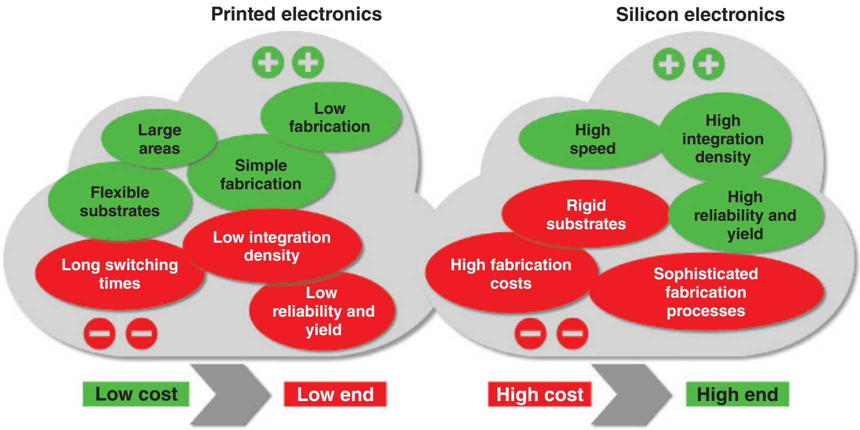

Figure 1.7 Qualitative comparison of organic printed and conventional silicon microelectronics.

harvesting and storage devices. The latter case is essentially the rigid island/flexible interconnect solution. Flexibility of interconnects can be achieved in different ways, of which some, that is, the introduction of residual stresses and/or deformation via mechanical measures or CTE mismatch, have already been described above. Further options have been summarized by Lang *et al.* [8]. In contrast, stretchability of functional devices is usually associated with organic solutions. A secondary advantage of these, besides a certain level of stretchability linked to low values of Young's modulus, is the fact that for these materials, cost-efficient large area manufacturing processes like roll-to-roll printing techniques exist. The price to be paid for these characteristics is related to performance. For one thing, taking microprocessors as an example, the resolution achievable via printed and organic electronics processes falls short of the CMOS process by roughly three orders of magnitude. In other words, on a given unit of area, the CMOS process would deliver 10^6 times the number of, say, transistors a printing process could. Furthermore, signal delays and clock rates associated with organic devices are once again orders of magnitude lower than those common for silicon microelectronics devices. These differences are illustrated in Figure 1.7.

Despite their obvious deficiencies in performance, organic electronics remain very interesting for material-integrated intelligent systems when it comes to simple tasks in signal and data preprocessing or for realizing interconnects on large areas. The printing processes available for this area also favor System-in-Foil packaging approaches, which yield full sensor systems in the form of thin, bendable foils. These can, in principle, be integrated very easily in a broad variety of materials that share a layered buildup, like continuous fiber reinforced composites or fiber metal laminates.

However, even if full compliance was achieved, sensor systems integrated in structural material would still represent a potential failure initiation side: Thus, the systems that are meant to survey structural health may become a danger to it themselves. For this reason, many efforts beyond compliance are being pursued with the aim of reducing the footprint of the sensor system within the host

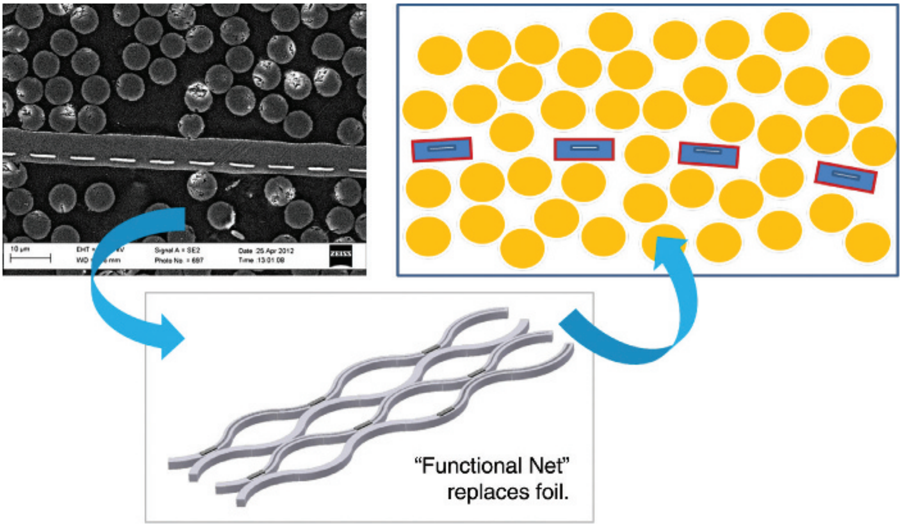

Figure 1.8 A sensor or sensor network realized as functional net, shown here to illustrate this principle. The wavy shape of remaining substrate and interconnects between the actual sensors is meant to provide stretchability. (Image courtesy of Institute of Microsensors, -Actuators and -Systems (IMSAS), University of Bremen.)

material. Elimination of substrate volume, either by continued thinning or by matching substrate and host material to allow the joining of both during integration, is one possibility to approach this aim. One step further in this direction is the layout of sensors as so-called functional nets as exemplified in Figure 1.8. Lang *et al.* [8] have coined the term "function scale integration" for such measures, highlighting that the substrate, which is needed in production only, should ideally not form a major part of the final, integrated system to the performance of which it does not contribute.

Part three of this book includes a section on sensor, electronics, and interconnect adaptation for material integration. Specific solutions for incorporation of sensors in fiber-reinforced polymers, sheet metal, and structures produced via additive manufacturing techniques are discussed in more detail in part four.

1.4 Signal and Data Processing (Part Five)

An active (aka. smart) sensor node should be able to operate autonomously and independently of the environment and other sensor nodes. It consists of different modules and units:

1) Digital signal processing and Data processing units (DSP/DPU: microprocessor, virtual machine, and digital logic and Register-Transfer Level architectures)
2) Communication units (CMU: physical, link, and data level)
3) Digital storage (DS)
4) Energy management units (EM: hardware and software control)

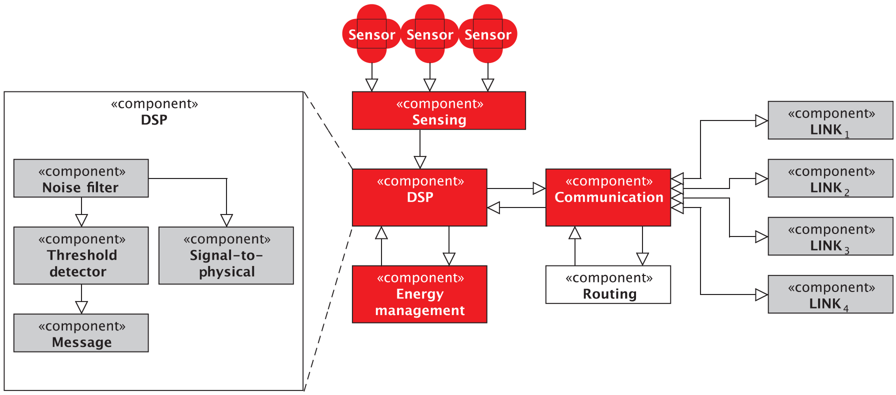

Figure 1.9 The information communication technology (ICT) architecture of a Smart Sensor Node consisting of analog and digital components.

5) Analog signal processing (ASP: analog electronics)
6) Analog-digital conversion (ADC)
7) Energy supply and Energy storage (ES)

The relation of the single units and the data flow is illustrated schematically in Figure 1.9. Typically, a sensor node processes low-level sensor data, improving the quality and accuracy using noise and fusion filter techniques. The sensor data or preprocessed information is passed from this information source to an information sink node by using message passing routed in some kind of communication network.

A smart sensor node integrated in materials must operate under harsh environmental conditions, especially concerning power, size, and technical failure constraints. Smart and distributed sensing systems are technological cornerstones of the Internet-of-Things (IoTs), wearable electronic devices, future transportation, environmental monitoring, and smart cities, shifting toward the Internet-of-Everything.

On the one hand, cloud computing relies on large-scale computers and reliable distributed services, whereas computing in materials focuses on low-scale computers, low power consumption, and technical failures as the usual case, not an exception. But both computing paradigms have to deal with a large amount of data (big data), and efficient algorithms suitable for information and pattern extraction (data mining). The Internet-of-Things is layered between material computing and cloud computing, and can be already considered as a bridge technology, but today still consisting of a diversity of solutions for specific situations and environments using traditional generic computer algorithms and paradigms.

An ongoing trend in microsystem technologies enables the integration of computational units in materials and technical structures, but they are characterized by limited computation power, storage, and reliability. Usually such a computational unit consists of a single microchip integrating the entire information and communication technologies (ICTs), and commonly performing sensing with integrated or attached sensors. The size can be reduced to the mm^3 range, with densities up to 10 million loosely coupled computing units per m^3 (e.g., smart dust [12,34,35]).

Traditional information processing methodologies using generic computers and computer networks cannot be applied and transferred directly to material-integrated embedded system networks due to their insufficient scaling, adaptability, configuration, and reliability. Material computing (not to be confused with computing of materials or materials informatics) facing the special constraints of digital computation in materials is distinct from traditional computing. This concerns programming, communication, and processing architecture models.

The deployment of digital logic enables the optimized application-specific design and implementation of various data processing architectures far beyond traditional generic microprocessor systems, though they are commonly implemented with large-scale digital logic, too. Digital logic itself is inherently parallel. Functional units can be easily parallelized on data path level, requiring only a data dependency analysis. But a parallel system on control level usually requires synchronization for resolving competition (due to concurrent access of shared resources) and providing coordination [36], demanding automated high-level synthesis approaches far beyond traditional software compilers.

Today, the CMOS technology is the prominent transistor architecture used for digital logic designs. A CMOS cell consists of two complementary field-effect transistors (FETs). The IC fabrication process requires clean-room conditions and is divided into multiple cycles of lithography, doping, material deposition and etching. The design of semi- or fully customized ASICs requires expert knowledge.

Due to the expensive and time-consuming ASIC fabrication process, rapid prototyping processes are very attractive, that is, using field programmable gate arrays (FPGA) not only during the development phase of digital logic circuits but also for the deployment in the production phase of small-lot productions.

Low-power design of all modules of a sensor node is mandatory. But low-power design of sensor nodes is not limited to the component view; it is moreover facing the algorithmic view by optimizing the data processing and communication algorithms. Energy-aware Algorithmic Scaling to microchip level can be considered as an important design methodology. At run-time, power management is performed on hardware and software level trying to minimize the energy consumption by guaranteeing the system liveliness.

Reliability necessitates robustness of the entire system in the presence of sensor, entire node, connection, data processing, and communication failures. Interaction between nodes is required to manage and distribute information.

Sensor fusion can improve the overall sensing quality and certainty significantly. It can be performed locally on node level by combining different sensors attached to the node or globally on network level by including neighborhood data, too.

To summarize, this part outlines the principles of different components of a sensor node and the challenges to integrate sensor nodes in materials and mechanical structures.

1.5 Networking and Communication (Part Six)

A smart sensor network is composed of a set of smart sensor nodes, as already discussed in part five, arranged in some kind of a regular communication structure (the network topology). A smart sensor node operates basically on locally acquired sensor data, whereas a smart sensor network can be seen as big virtual machine operating on global sensor data, possibly segmented. The network composition requires different processing and communication layers:

1) Communication hardware – the physical layer
2) Network communication protocols for messaging
3) Message passing and routing in arbitrary network topologies
4) Distributed and cloud computing addressing large-scale networks, distributed storage, and distributed data processing.
5) Agent-based computing addressing autonomous and reliable communication and data processing in large-scale networks with a unified programming and execution model.

Since the advent of networked computing in the 1960s, using simple peer-to-peer networks, there was a rapid advancement of computer and network technologies regarding increasing computational power and decreasing size – initially driven by Moore's law predicting an exponential increase in transistor density and an expected growth in storage and computational power, which is currently nearing saturating. Parallel and distributed computing is considered as solution to overcome well-known limitations of single-threaded computing. Moreover, single-point-of-failure (SPoF) issues must be avoided to ensure reliable operation of the entire system. In the past two decades, there was a shift from powerful centralized to distributed computing consisting of a wide range of different computer and communication technologies making the WEB a big virtual machine, recently driven by the advent of the IoT and cloud-based computing. These large-scale networks consisting of billions of devices demand for new communication and coordination methodologies with loosely coupled distributed information processing and big-data management, shown in Figure 1.10. There is a seamless transition from high-level computing in clouds to data processing performed in sensor networks.

The growing complexity of computer networks and their heterogeneous composition with devices ranging from servers with high computational power and high resource volumes down to low-resource mobile devices with low computational power demands unified and scalable new data processing paradigms and methodologies.

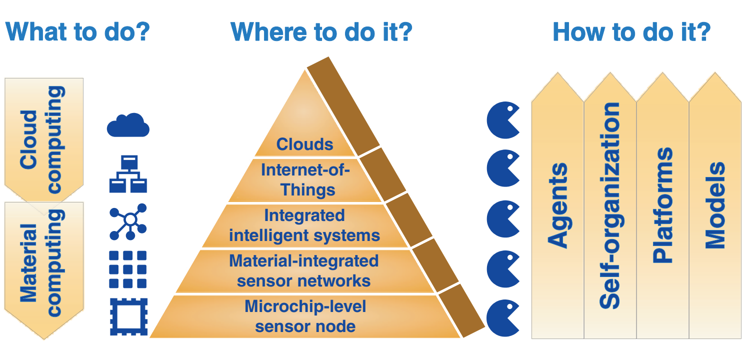

Figure 1.10 The progress: from material-integrated intelligent systems to Internet clouds with one unified information processing and coordination methodology using mobile agents.

The IoT is one major example and use-case emerging in the past decade, strongly correlated with cloud computing and big data concepts, and extending the Internet cloud domain with distributed autonomous sensor networks consisting of miniaturized low-power smart sensors. These smart sensors, for example, embedded in technical structures, are pushed by new trends emerging in engineering and microsystem applications.

Today, sensor nodes equipped with computation and communication capabilities can be scaled down to the cubic millimeter range (e.g., the smart dust mote), enabling the design of large-scale sensor network with loosely coupled nodes and reconfiguration at run-time.

Smart and distributed sensing systems are one of the technological cornerstones of the Internet-of-Things, wearable electronic devices, future transportation, environmental monitoring, and smart cities.

Furthermore, these sensor networks are used for sensorial perception or structural monitoring (load and health monitoring), deployed, for example, in cyber-physical systems (CPS) or Artificial Skin.

In the past decades there was a shift from passive sensors to smart sensor nodes, accompanied by an exponential increase of the sensor node density, shown in Figure 1.11. Distributed material-embedded sensor networks used in technical structures and systems require new data processing and communication paradigms, supporting fundamentally different architectures, establishing core concepts of Informatics in Materials (as with the new emerging Materials Informatics discipline, originally meaning Informatics for the design of materials).

Self-organizing capabilities, robustness, and adaptation to changing environmental conditions, like technical failures of components of the sensor network

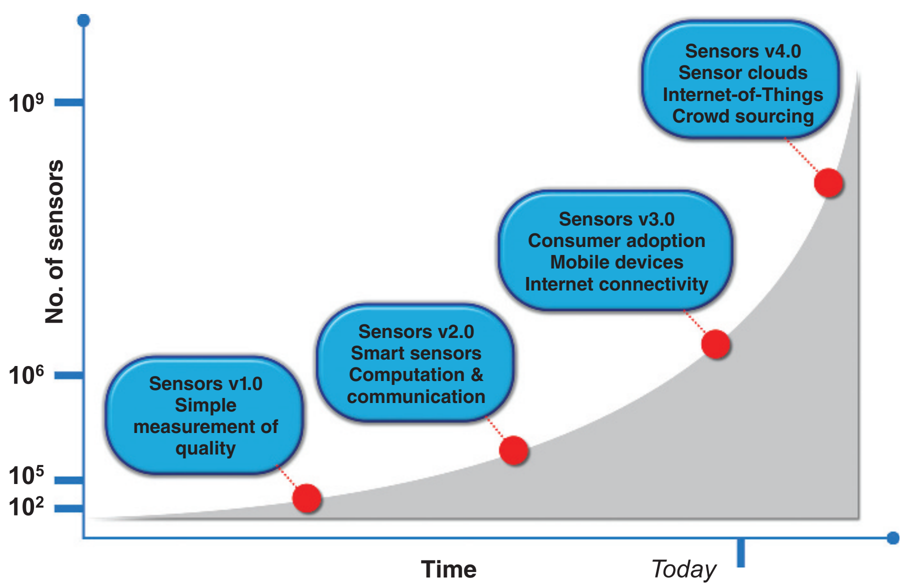

Figure 1.11 From passive sensors to networks of smart sensor nodes.

or a reconfiguration, can be caught by the deployment of mobile multiagent systems (MAS), a well-known concept of artificial intelligence (AI) [37–39].

It can be shown that agent-based computing can be used to partition typical sensing and computation in off-line and online (e.g., in-network and real-time) parts resulting in an increased overall system efficiency (performance and energy demands) and a unified programming interface between off- and online parts [40,41].

The agent model is also capable of providing a programming model for distributed heterogeneous systems crossing different network boundaries. The deployment of MAS in heterogeneous environments is often addressed on the organizational layer.

Multiagent systems are used to enable a paradigm shift from traditionally continuous-data-stream based to event-driven sensor data processing, resulting in increased robustness, performance, and efficiency.

Internet-of-Everything systems [42] require a programming model that is capable of dynamic composition, in conjunction with resource management, which can be provided by MAS.

The design of large-scale sensing networks requires contributions from different disciplines and model levels, shown in Figure 1.12. Beyond the bare sensor processing, self-estimation of the state of the entire system or a device to be monitored using Artificial Intelligence concepts will transform measuring systems in smart perceptive systems. One example is the prediction of the trust in measured

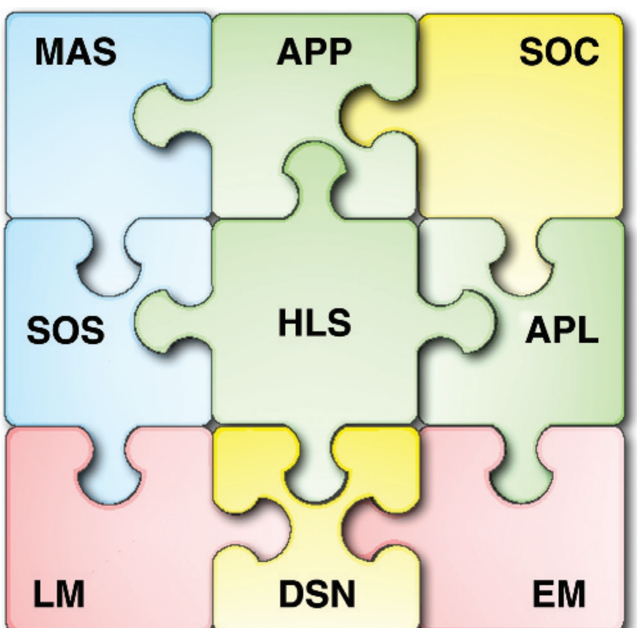

Figure 1.12 Modules contributing to the design of intelligent sensing systems from a computer science viewpoint: multiagent systems (MASs), agent processing platforms (APPs), system-on-chip design (SOC), high-level synthesis (HLS), agent programming model and language (APL), self-organizing systems (SOSs), load monitoring (LM), energy management (EM), distributed sensor networks (DSNs).

and computed results delivered with machine learning (ML). Often, measuring systems deliver ambiguous information that must be further classified. State estimation and ML can require a large amount of computing power. In biological systems like humans a brain with a complex neuronal network is used, not available in sensor networks. But distributed and decentralized state estimation, which can be deployed in large-scale sensor networks, can relax this requirement and can be performed by the low-resource sensor nodes themselves.

1.6 Energy Supply and Management (Part Seven)

Today, one major challenge in deploying smart wireless and material-integrated wired sensors in real use case and environments is related to energy consumption and guaranteeing adequate lifetime. Besides classical external energy supply, self-supply by using energy harvesting technologies gains importance. But energy harvesters still provide only low electrical power, requiring energy storage and repeating active-sleep cycles of the sensor node.

Energy management can be implemented on hardware and software level. In contrast to various commonly deployed energy management approaches, targeting microprocessor and operating system control, *smart algorithmic energy management* (SAEM), can be performed at run-time by applying a dynamic selection from a set of different (implemented) algorithms classified by their demand of computational power, and temporally by varying data processing rates. The smart energy management can be implemented, for example, with decision trees, based on quality-of-service (QoS) and energy constraints. It can be shown that the power and energy consumption of an application-specific SoC design strongly depends on the computational complexity of the used algorithms.

For example, a classical proportional–integral–differential (PID) controller used for the feedback position control of an actuator requires basically only the *P*-part; the *I*- and *D*-parts only increase position accuracy and response dynamics, which are selectable. Depending on the actual state of the system and the actual and estimated future energy deposit, suitable algorithms can be selected and executed optimizing the QoS and the trade-off between accuracy and economy. Energy analysis of data processing systems can be performed at run-time or at design time using simulation techniques, delivering valuable information for the optimization of sensor nodes.

1.7 Applications (Part Eight)

The final part eight of the present work is dedicated to the question of where, in which industries and for which specific purposes, material-integrated intelligent systems can be expected to see commercialization.

SHM has, for a significant time, been considered the killer application for large-scale introduction of material-integrated intelligent systems [43]. The interest in SHM, and thus also in new, more tightly coupled monitoring solutions, has been fueled by independent parallel developments in the receiving industries like the much extended use of fiber-reinforced composites rather than aluminum in the aerospace sector, exemplified by aircraft like the Boeing 787 Dreamliner or the Airbus A350-XWB [44]. Similar interest has been voiced by the wind energy sector, especially since the broader introduction of offshore wind turbines. In both cases, a major motivation is the reduction of maintenance costs that can be achieved through successful implementation of maintenance on demand or predictive maintenance systems supported by a powerful sensor network. Development in these fields is ongoing. One characteristic aspect of contemporary solutions is that in most cases data evaluation is not foreseen as part of the material-integrated system. On the contrary, in many cases it does not even form part of the on-board set of system components. As a consequence, data evaluation tends to be organized in a centralized manner. The vision, however, is clearly oriented toward materials that truly "feel" in our own sense [45], and beyond the structural monitoring aspect to scenarios like "fly-by-feel" [46].

Beyond SHM, production engineering is increasingly becoming aware of the promises of availability of sensorial information at new levels of depths. The term Industry 4.0 is very much en vogue today in Germany and increasingly so in other parts of the world. What it originally implies is that, following the original industrial revolution in the eighteenth century, the advent of mass manufacturing and the emergence of computer numerical control (CNC) and computer-integrated manufacturing (CIM), we are now standing at the verge of a further paradigm shift of comparable importance that is linked to terms like cloud-based design and manufacturing (CBDM) or intelligent production systems. The advent of additive manufacturing with its unparalleled flexibility is an accompanying development, providing a major support to what is at the heart of Industry 4.0: increased autonomy of production systems. In additive manufacturing, geometry representation is entirely digital and not contained in tools as in the case of most conventional manufacturing processes. Needless to say, these systems need information to base their decisions on; they need a connection to the world in which they are meant to function; in other words, they need sensory information and the capability to make sense of it. Ultimately, material-integrated intelligent systems will cover this demand. In conjunction with additive manufacturing, this will facilitate new ways of organizing production systems and product design [47–49].

Similar to the generation-based line of thought behind the term Industry 4.0, Meyendorf *et al.* have suggested a distinction between different ages in the development of a wider industrial world, or maybe even of human society as a whole. Their perspective considers the industrial revolution, set at the turn of the eighteenth century and based, for example, on the availability of iron and steel in large amounts, the steam engine and early complex though still mechanically controlled manufacturing systems, as the first step: Machines replace human muscular power. Electricity, communication and first sensors, and finally the development of computers in the twentieth century herald the next phase, the age of information, in which electronic machines replace human memory. Following this rationale, the twenty-first century becomes the age of machine decision: Smart systems assume the role of humans in decision-making in more and more natural environments. Figure 1.13 graphically depicts some of the major

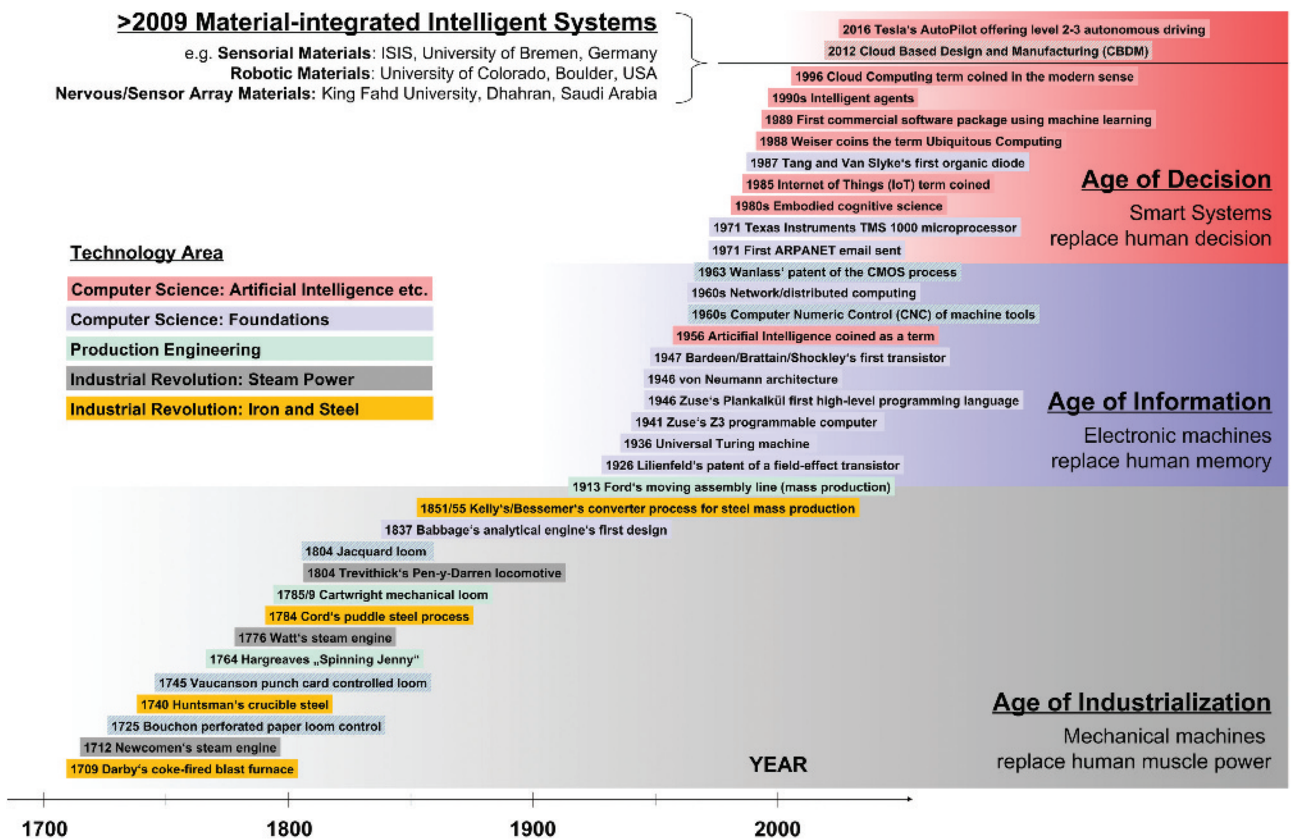

Figure 1.13 Development stages of the industrialized society. (Inspired by an image from Meyendorf *et al.* [50].)

developments that have become the hallmarks of these distinct ages, partially taking over Meyendorf *et al.*'s original thoughts [50].

The concept of an age of machine decision leads back to the introductory statement by Weiser that the technology revolution would move into the everyday, the small and the invisible [7]. In terms of application scenarios, this notion evokes the IoT, meant to provide the products surrounding us with the ability to interact and exchange information via the Internet or a similar structure. Such capabilities will open up new ways of using and interacting with objects. Tactile skins as currently used primarily in the field of robotics may have an important part in this, but human–machine interaction may profit on more generic levels, too [51]. Besides, the wide availability of product life cycle data will facilitate new business models, provided that regulatory issues like privacy and ownership of data can be solved. Such questions are treated in part eight of this book.

Looking forward, what will the future hold in store, assuming that material-integrated intelligent systems will prevail?

The vision of the ISIS Sensorial Materials Scientific Centre reads as follows:

"Five senses support us in exploring our world. Engineering components lack such natural abilities. Sensorial materials will help to bridge this gap".

Further to sensing, viable solutions for adaptivity may emerge. Locally initiated and controlled property or shape change will certainly open up additional fields of application [52,53].

What we foresee as a long-term objective linked to the introduction of material-integrated intelligent systems is nothing less than the step from the Internet-of-Things to the Internet-of-Everything – and all that this entails.

To conclude, maybe the single most important lesson learned from the past years of research on material-integrated intelligent systems is the need to establish an interdisciplinary design approach, bringing together five major scientific communities:

- Materials science
- Production engineering
- Electrical and microsystems engineering
- Computer science and artificial intelligence
- Mathematics

This is what the present book is about.

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