Chapter 2
Developments of Manufacturing Systems with a Focus on Product and Process Quality

In this section MS as well as recent developments in the area of holistic IM and related topics will be presented. Furthermore, certain basic aspects of manufacturing, MS and related areas are described in detail in order to allow readers to familiarize themselves with the fundamental terms and definitions used throughout this dissertation. In each subsection, concluding paragraphs summarize how the described topic is relevant to the research and putting it in perspective. Main principles and how they are utilized throughout this dissertation is summarized there.

First the manufacturing domain is illustrated, focusing on manufacturing processes, products and manufacturing itself, highlighting process monitoring, process control and process diagnostics. This first subsection is rather descriptive, building a basic understanding of the terms and definitions. As product and process quality and its understanding is used differently in varying contexts, in this section, the definitions of quality related terms and approaches fundamental to the recent developments in manufacturing systems are derived. Presenting holonic and intelligent manufacturing systems in the next subsection, as they are a widely recognized conceptual and holistic view on modern manufacturing. In the previous sections, the connection to the information and data perspective is omnipresent. Therefore, an introduction to information and data management in manufacturing, incl. Big Data and information quality is presented. Concluding, key challenges of the recent developments in MS from a product and process information perspective are discussed.

2.1 Manufacturing Terms, Definitions and Developments

In this section the principle understanding of manufacturing, manufacturing processes and products in this domain is presented. On the highest level, the term manufacturing describes the production of goods using labor and machines, tools, processing, or formulation (see Fig. 2.1) (Steven 2007; Jehle 1999). Today, manufacturing is mostly

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Fig. 2.1 Manufacturing as a transformation process to create material goods as an output

connected to industrial production. Hereby it has to be noted that while the terms production and manufacturing are frequently used interchangeably, their inherent meaning differs to some extent. Whereas it is true that every type of manufacturing is also production, not all production is necessarily manufacturing as it describes converting input to output in a broader term. An example for a production which cannot be described by manufacturing is a book. Whilst the making of the physical book itself can surely be manufactured, the content, the creative work cannot. Despite various researchers argue that manufacturing can also produce non-material products (e.g., Morris and Johnston 1987), in this research, manufacturing in understood as the making of material goods (see Fig. 2.1) in accordance with Filos (2013).

According to Filos (2013), "*manufacturing is the activity to make goods, usually on a large scale, through processes involving raw materials, components, or assemblies with different operations divided among different workers. Manufacturing encompasses equipment for materials handling and quality control and typically includes extensive engineering activity such as product and system design, modeling and simulation, as well as tools for planning, monitoring, control, automation and simulation of processes and factories. It is increasingly seen as a priority area of economic activity especially for economies that have been hit by the recent financial and economic crisis*."

There are five different manufacturing principles regarding the spatial structure of manufacturing in a facility, the workbench principle, the on-site principle, the function or job-shop principle, the cellular principle and the flow principle (Lödding 2013). Within this work the focus lies on function or job-shop principle and the flow principle. Within these, products are transported between stations where different transformation processes are conducted to change their state.

Looking at the production types, within this work, the focus lies on mass production with a large number of production runs and continuous production. Also a possible applicable area is a serial production with a large size of production runs. However, a large number of products manufactured are needed as a bases for the developed concept. Next, the basics of manufacturing processes are introduced.

Fig. 2.2 Transformation model in manufacturing and value creation

2.1.1 Manufacturing Processes[1]

A process is a pattern, designed for a certain purpose (Fig. 2.2). It can describe different variants of combinations of activities or events which are related through causal and/or timed order relations directly to a process confining and activating activity or an activating event and a connected and related result (event or state). This can happen through relations to other activities or events of the process (Hoffmann et al. 2002). This very general definition of a process can be further sharpened and related to the manufacturing domain, looking at the DIN EN ISO 9000:2005 definition of a process. There a process is defined as "set of interdependent or interrelated tasks transforming inputs in outputs" (CEN 2005).

Manufacturing techniques, used for transforming e.g., products geometry or state can be classified as follows (see Fig. 2.3).

The presented techniques are in general not applied individually but in combination. The six primary techniques are described in more detail in the following list:

- *Primary shaping*: describes the creation of material object out of shapeless matter. By applying certain processes, e.g., casting, cohesion is created. Primary shaping techniques are mostly applied in early parts of a manufacturing programme (Grote and Feldhusen 2007).
- *Forming*: this technique is changing the form of a product whilst maintaining the cohesion. Through processes like e.g., rolling the elements are restored without changing the mass or cohesion (Fritz and Schulze 2006).
- *Cutting*: describes the production through changing the form of a product by reducing the cohesion and elimination of elements. Cutting represents an important area of manufacturing (König and Klocke 2008).
- *Joining*: summarized processes to join two or more parts or products. Examples for processes are adhesive bonding or welding (Westkämper and Warnecke 2010).

[1]The content of this section has been partly published in accordance with Universität Bremen (2007) in Wuest and Thoben (2012).

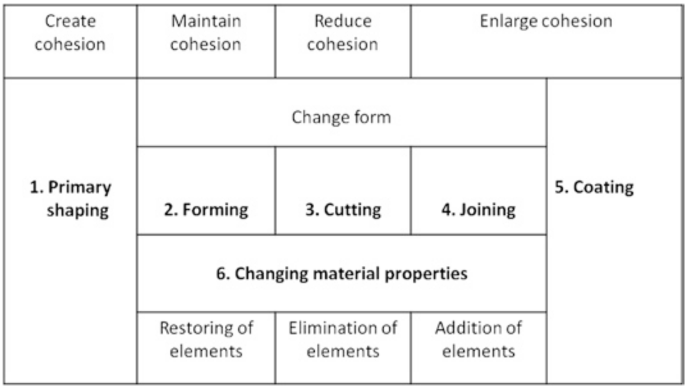

Fig. 2.3 Classification of manufacturing techniques according to DIN 8580 (CEN 2003)

- *Coating*: is realized by permanently adding a shapeless material as an outer layer on a physical body. The added layer can e.g., improve the friction behaviour (Grote and Feldhusen 2007).
- *Changing material properties*: whereas the above stated manufacturing techniques change the outer form of a product, this one changes the material properties within the product itself. The changing of properties can be done by applying physical processing, chemical processing or biological processing (Steven 2007) e.g., heat treatment.

The transformation within a manufacturing process can either be base on actions of humans or machines (Zingel 2009). This definition is already very closely related to the manufacturing definition presented above describing manufacturing as a transformation process (see Fig. 2.2). The transformation within a manufacturing process needs time; a direct production of outputs is not possible (see Fig. 2.2). This implies that a manufacturing process mostly involves more than one stage or sub-processes (Gutenberg 1970). As the result of a manufacturing process is a product, which represents the customer needs, the manufacturing process is necessarily part of a business process or a business process (Korndörfer 2003) with the goal of adding value to the product (Porter 2008; Hutton and Denham 2008).

Figure 2.4 illustrates a manufacturing programme (sequence of manufacturing processes) connecting input of process n with output of process n − 1 through interfaces. These interfaces can either be internal or external. The terminology of the process hierarchy used in this dissertation is presented in the figure as well. A manufacturing programme represents the manufacturing system with all manufacturing processes,—operations down to the individual manufacturing activity involved.

After having clarified what a manufacturing programme,—process, etc. stands for in general and having introduced the main techniques, next, a more detailed

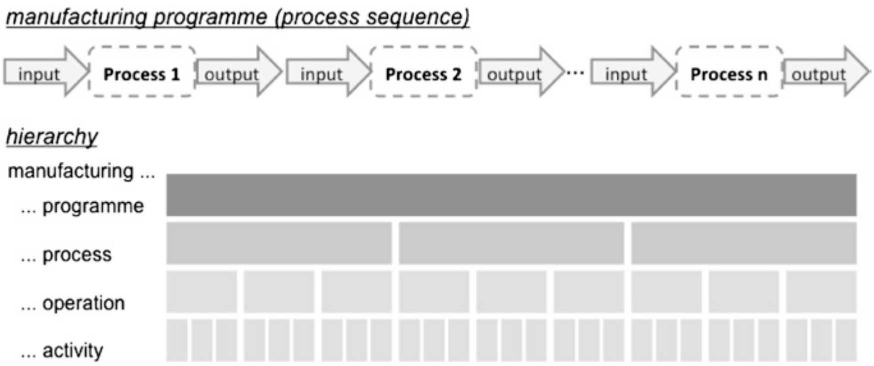

Fig. 2.4 Process sequence and hierarchy (adapted from Becker 2008)

discussion will focus on implications of a manufacturing process and its relation to quality. When looking at improving manufacturing processes, as a first step towards efficient manufacturing, it has to be ensured that the manufacturing processes, the entire manufacturing programme for that matter, design is capable to produce the desired product properties (Mohanty 2004). After this overarching requirement, a functional process design, is given, the process quality plays a major role, as it is directly connected to product quality (Brinksmeier 1991; Jacob and Petrick 2007). In every process, a certain degree of variation of the input parameters of individual products can be found even in state of the art manufacturing which can influence the product quality (Yu and Wang 2009).

The product quality can be influenced at the end of the manufacturing programme (final product quality) or during the different processes or operations. It is important to consider, that the processes and operations are often linked via process intra- and inter-relations to each other and thus, the variations can, even being tolerable from an individual (isolated) process perspective, lead to an unacceptable accumulation causing failure of the final product to meet the customer requirements (Wuest et al. 2013). Taking a closer look, some of these influences are not or just partly known today and in most cases hard or impossible to quantify (with monetary and technical restrictions) as it is mostly very specific to product and process. In this context, the system view gains importance as new research indicates that an isolated focus on single processes during monitoring or improvement initiatives may lead to an incomplete understanding of relations (Zantek et al. 2006; Jiang et al. 2012). This is further illustrated in Sect. 2.2.3. Furthermore, Viharos and Monostori (1999) state that having reliable process models is extremely important, as they are required e.g., for selecting optimal parameters during process planning, for designing and implementing adaptive control systems or model based monitoring algorithms.

Looking again at the input-output model of a manufacturing process as presented in Fig. 2.2, transformation in this case can be described as a change of the product state, and thus of one (or multiple) relevant state characteristics, from

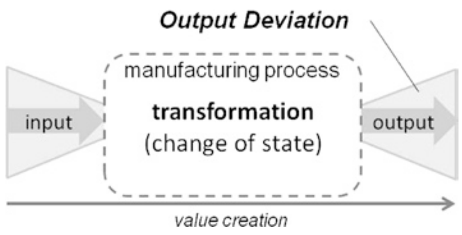

Fig. 2.5 Input and output deviation of manufacturing process

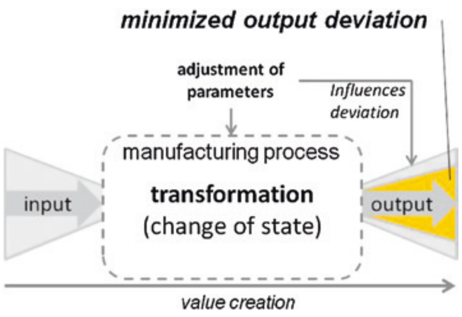

Fig. 2.6 Output deviation based on adjustment of parameters of manufacturing process

input (product state) to output (product state). Every manufacturing process has an input product state, which deviates to a certain extent from the originally planned input (see Fig. 2.5) (Ding et al. 2002). The term product state used here describes a product at a certain point during a manufacturing programme. This will be presented in greater detail in Sect. 4.2. This deviation is always there and due to some degree to process 'noise' such as machine/material variability, environmental factors, thermal effects, operator error, etc. (Kaiser 1998). The level of the deviation and with it, the impact on the product quality, however varies a lot. These deviations of the input product state have an influence on the output product state after the state change (transformation) if transformation parameters can be considered unchanged (see Fig. 2.6) (Jansen-Vullers et al. 2003).

One option is to base the adjustment of the process parameters on information of the product, for example the input product state (see Fig. 2.7). Taking known cause-effect relations and the process view into account, this information can be described by the *product state concept*, introduced in this research (see Sect. 4.2 ff.). The comprehensive approach can contain all necessary information needed by processes involved.

However, identifying this set of relevant information is not trivial. A special focus within such a concept has to be laid on the question, how can the relevant information which provides the basis for the adjustment be identified. Once this relevant information, among it being the drivers of product state, is identified, experts can apply it to adjust the process on an informed basis accordingly.

Manufacturing is an area with a constant need for efficiency and product and process quality improvement. There are many different areas in manufacturing tackling this issue. In order to structure the following findings, the areas are

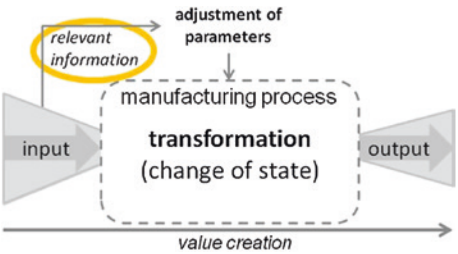

Fig. 2.7 Importance of relevant process information process parameter adjustment

grouped in different domains. These domains constitute of areas with similar requirements and challenges towards supporting techniques and technologies. However, there are various forms of semantics out there and as the areas are not sharply distinguishable in their focus, overlaps between the domains will occur. The three overarching domains are monitoring, diagnostics and control. They are complementary in as much as it is necessary to monitor in order to control and without diagnostics control is unfocused/undefined. The additional domain of scheduling stands out as it is not directly related to the above. As this work is focusing on monitoring, the domains of control, diagnostics and scheduling are briefly introduced in the following paragraph, before process monitoring is detailed in the next subsection.

The domain of ***control*** includes a wide variation of areas and is closely related to monitoring (Kang et al. 1999). Control is the action of bringing a process back into a desirable state. Harding et al. (2006) state that "[ML] and computational intelligence tools provide excellent potential for better control of manufacturing systems". The areas represented by this domain include but are not limited to (intelligent) manufacturing control (e.g., Bowden and Bullington 1996; McFarlane et al. 2003), (statistical or automated) process control (e.g., Qin et al. 2006; Jenab and Ahi 2010) and simulation (e.g., Baker 1988; Fowler 2004). The domain of ***diagnostics*** (e.g., Chinnam and Baruah 2009) compromises the areas of process analysis (e.g., Arbor 2000) and fault diagnosis (e.g., Widodo and Yang 2007). Additionally there is the domain of ***scheduling***, which is required to ensure the control and/or process actions happen in the right order. However, scheduling, as part of internal and external logistics will not be in the focus of this work. In order to present a rather complete picture, the different areas summarized under scheduling are: scheduling (e.g., Aytug et al. 1994), sequencing (e.g., Lödding 2013) and capacity planning (e.g., Lutz et al. 2012).

2.1.2 Process Monitoring

Using product and/or process data to monitor and/or forecast certain events, chains of events and/or outcomes is a topic, widely discussed among scholars for more than the last 20 years. Du et al. (1995) describe monitoring as an act of identification of characteristic changes of a process by evaluating process data without interfering running operations. Stavropoulos et al. (2013) describe monitoring as the manipulation of sensor measurements (e.g., force, vision, temperature) in determining the state of the processes. Ge et al. (2013) define process monitoring simply termed as fault detection and diagnosis, and as a tool for process safety and quality enhancement. These definitions already highlight again the connection to process control and process diagnostics as described before. The task of monitoring is to separate the normal process data samples from the faulty ones (Ge et al. 2011). The extraction of useful information from the recorded process dataset enables the monitoring and prediction of the process operation condition and the product quality (Ge et al. 2011).

Due to increased number of variables measured and monitored and the improved controllability of these variables a method of analyzing the data is required. Without an appropriate method only limited data about the processes can be extracted (Lee et al. 2004). Du et al. (1995) find in their research that monitoring based on learning from examples turns out to be more effective in manufacturing programmes than learning from instructions.

Monitoring in manufacturing includes the areas of machine performance monitoring (e.g., Spoerre et al. 1995), (machine) condition monitoring (e.g., Peng 2004; Widodo and Yang 2007), quality monitoring (e.g., Ribeiro 2005; Wuest et al. 2013) and process monitoring (e.g., Skittet al. 1993; Qin et al. 2006). More detailed application areas include the analysis of high-dimensional and correlated process data, e.g., in chemical and biological plants and products (Ge et al. 2011), wastewater treatment processes (Lee et al. 2004), model-based monitoring for fault detection and diagnosis in aerospace, engine and power systems (Ge et al. 2013), tool wear and tool breakage (Stavropoulos et al. 2013). The challenges in the domains control and monitoring are very similar, reflecting the large overlap and connection of the two domains. For example, in order to identify a faulty process, the cause-effect relations play an important role. When control kicks into get the process back on track based on the monitoring information, cause-effect relations are essential in order to take the right measures. Within the monitoring domain the challenges can be stated as follows: unclear/unknown cause-effect relations, high-dimensionality, incomplete (product and process) data. The relevant sub-domain of process monitoring, quality monitoring will be elaborated in a later section (see Sect. 3.2.2). Next, the term product and its understanding within the manufacturing domain is introduced.

2.1.3 Product in Manufacturing

In the definition of manufacturing introduced before, the purpose of manufacturing is the production of material goods. In industrial production, these goods can be referred to as products. As the term product is a central aspect of the developed

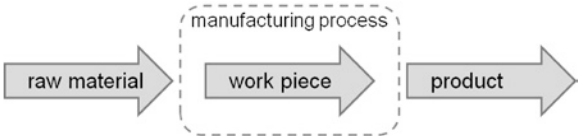

Fig. 2.8 Raw material, work piece and product in relation to a manufacturing process

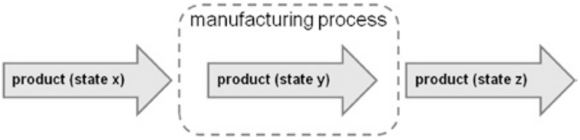

Fig. 2.9 Product with changing state during a manufacturing process

concept, first commonly accepted definitions are presented, before the agreed upon understanding of the term is presented.

A general definition describes a product as representing an output offered on the marketplace which satisfies the customer needs through specific functions and characteristics in a beneficial way. The output can be material goods, services, information or experiences (Kotler et al. 2011).

According to the Quality Management (QM) standard (DIN ISO EN 9000:2005), representing an engineering perspective, a product is defined as the final result of a process. The results of the previously discussed manufacturing processes can therefore be defined as products. During the manufacturing process, the to-be-transformed material is referred to as "work piece" (CEN 2005). Finalizing the manufacturing process, the work piece becomes a product (see Fig. 2.8). It has to be noted, that two or more work pieces can be combined to a single product (Schmachtenberg 2000).

In manufacturing, the PLM perspective is increasingly gaining attention. In closed-loop, item-level PLM, an object over all phases of its lifecycle, beginning from raw material over work piece and final result of manufacturing (product) to the to-be-recycled materials after usage are considered and referred to as product (Jun et al. 2007; Terzi et al. 2007; Taisch et al. 2011) (see Sect. 3.1).

In this research, the term product is used comprehensively to describe an artifact over various stages of its product-life-cycle replacing the more technically accurate terms e.g., raw material before and work-piece during manufacturing. Reasons include the focus on individual products (item-level) and the reduction of complexity. Based on this understanding of the term product, the product state describing a product at different stages of a manufacturing programme, will be defined later on (Sect. 4.2) (see Fig. 2.9). Next, basic quality terms and definitions are presented in the following subsections.

2.1.4 Quality in Manufacturing

Quality has been a focus area of manufacturing for several decades and the market success of companies successful in utilizing their understanding of quality and customer requirements highlight the importance of quality. De Weck et al. (2012) found in their recent study on system lifecycle properties (‘Ilities’) that quality is and was the most dominant ‘ility’ of engineering systems for over a century, rated higher than e.g., reliability and safety (De Weck et al. 2012).

In this research the term quality is understood as “the degree to which a set of inherent characteristics fulfils requirements” (DIN EN ISO 9001:2008—CEN 2008). Requirement within this context is defined as the “need or expectation that is stated, generally implied or obligatory” (DIN EN ISO 9001:2008—CEN 2008). According to this definition, quality depends on the fulfillment of requirements. The fulfillment of these requirements depends on the planning of processes (commands) and the execution of processes (executions) (see Fig. 2.10) (Masing 2007). Quality of the final product is regarded as achieved to a higher degree when more of the original customer requirements match with the achieved characteristics of the final product (Sitek 2012). The *product state concept* corresponds with this definition as it defines so called state characteristics by which the state of a product can be described at all times during its lifecycle. It has to be considered that a product can inherit different qualities, the sum of these (sub-)qualities like e.g., security, workmanship or durability finally represent the final product quality (Kamiske and Brauer 2008).

There are different definitions of quality in manufacturing available. Some researchers have a very technical view on quality in manufacturing. An example for such a technical definition is presented by Kaiser (1998), who defines quality in manufacturing as “primarily a factor of machining tolerances” This implies that quality can be achieved when the machining tolerances are controlled. This view does not reflect common problems like input deviations or environmental influence on the processes. Other researchers define quality in manufacturing more generally, as “confirming with requirements”, thus focusing on the customers (Garvin 1984). However, researchers agree, that in most cases “products with small variations in shape and size are considered high quality, while products with large variations are considered poor quality” (Kaiser 1998). This corresponds with the former definition, as “a product that deviates from specifications is likely to be poorly made and unreliable” (Garvin 1984). However, these variations have to

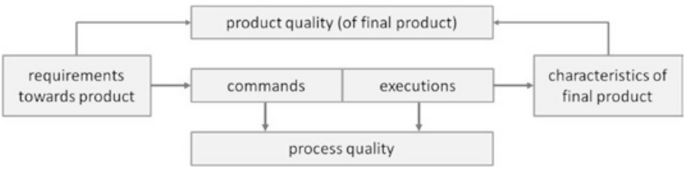

Fig. 2.10 Elements of quality (adapted from Masing 2007; Sitek 2012)

be viewed form a customer requirement perspective. Some variations of parameters not important for the customer with not impact on other important parameters have no influence on quality. As manufacturing companies constantly try to improve the quality of their products and processes, it has to be noted that quality improvement generally requires collection and analyses of data to solve quality related manufacturing problems (Köksal et al. 2011).

According to the quality definition above, the final product quality depends on the fulfillment of the customer expectations and thus the customer requirements. Overall, there are many possible reasons for a discrepancy from these requirements, e.g., the requirements of customers where not correctly retrieved or the designers interpreted and transformed the requirements differently than the customer fancies. However, within this research it is assumed that the requirements were correctly retrieved and the product will fulfill the customer expectations if it meets the specifications set by the designers and process planers. Using the terminology of Fig. 2.10, the commands are considered correct and the execution is the focus area. The reason behind this is that this research is focusing on supporting the manufacturing process and does not directly support phases like e.g., the design or product planning. Following Taguchi's (1989) six stages of activities of manufacturing companies, the focus lies on stage (4) manufacturing and partly (3) manufacturing process design, whereas the stages (1) product planning, (2) product design, (5) marketing and (6) sales will not be looked upon.

2.1.4.1 Product Quality

The term product quality has been introduced partly in the previous section. As can be seen in Fig. 2.10 product quality is determined by the fulfillment of the (quality) requirements by the characteristics of the final product. To adapt this definition to the process and system view, product quality can also be determined for processes and/or operations within a manufacturing programme. The final product is to be understood as the outcome of a process or operation instead of the overall manufacturing programme. However, the requirements are not as easily determinable because of existing cause-effect relations between different processes and/or operation during the manufacturing programme. In manufacturing programmes, a wide variety of potential errors can influence the quality characteristics of a product. The product end quality is finally determined by all stages of the manufacturing program (Zantek et al. 2006; Jiang et al. 2012). This challenge is addressed by the *product state concept,* as it is one of the pillars towards the identification of a set of relevant information (see Sect. 4.4).

Some quality characteristics can be easily measureable, for example length, depth or weight, some are hard to measure, like functions or aesthetic. Easily measurable characteristics have the advantage of being easier to monitor and control. The quality characteristics being hard to measure are mostly hindering the checking of the fulfillment of requirements. Additionally, quality characteristics are an element for control of the impact of quality management processes

(Eversheim 1997). It is however a challenge to determine the actual real life requirements according to which the product quality is finally determined (Olbertz and Otto 2001). As stated above, this question is not in the focus of this research.

2.1.4.2 Process Quality

Quality principles cannot just be applied to product but also to processes. The process quality definition depends to a large extent on the understanding of process itself. A process, e.g., a manufacturing process, inherits a specific order of transformation activities alongside temporal and spatial dimensions with a defined input and output. The quality of a manufacturing process is determined by the compliance with criteria for order, time, place, input and output (Kreutzberg 2000).

Process quality determines the product quality, given that the entire manufacturing programme and product/process design is capable of meeting the requirements, (Brinksmeier 1991; Jacob and Petrick 2007) (see Fig. 2.10). Even if a process is executed with the exact same parameters, a certain degree of variation of the input parameters of individual products can be found even in state of the art manufacturing which can influence the process quality and thus the product quality (Taguchi 1989; Yu and Wang 2009).

It is a major task of QM to ensure a high process quality in manufacturing. Continuous improvement is widely employed in order to reduce failure and to optimize manufacturing processes and the quality of the output (Eversheim 1997). This QM tasks, involving a lot of information and data and efficient handling of such, are introduced in the following subsections.

2.1.5 Example of a Manufacturing Programme[2]

A manufacturing programme consists of different processes and operations, each with a certain very specific task and goal. To transform a raw material to a final product, all processes are necessary and have to be executed in a certain order. To make the theory introduced in the previous sections more feasible, an exemplary description of the manufacturing programme of a highly stressed steel product will be presented. This example is based on an adapted manufacturing programme following (Klein et al. 2005) which consists of three process steps: forging, machining and heat treatment (Fig. 2.11).

In industrial practice, a manufacturing programme involves generally more processes and/or some have to be executed multiple times at different stages of the whole manufacturing programme. To build a foundation for the following concept,

[2]The content of this section has been partly published in accordance with Universität Bremen (2007) in Wuest et al. (2013)

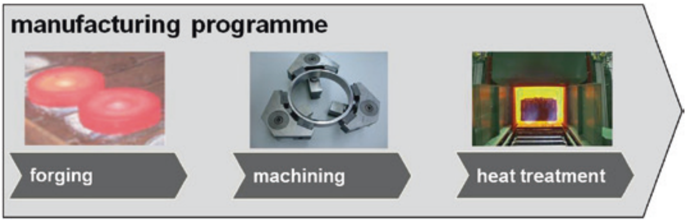

Fig. 2.11 Exemplary manufacturing programme with three processes

the author chose to use a simplified example in order to focus on the main ideas behind the concept instead of getting lost in details.

Today, it has to be taken into consideration that manufacturing programmes are not executed by a single company at a single location any longer but rather in collaboration with other companies (Seifert 2007). This includes extra interfaces and interdependencies between stakeholders as well as manufacturing and business processes. For example, could the forging (process 1) in the exemplary manufacturing programme (see Fig. 2.11) be done by company A in country X, whereas the processes machining (2) and heat treatment (3) are executed by company B's department C (country Y) and D (country Z). As this adds further complexity to the manufacturing itself by involving additional logistics and information exchange, there is an indispensible need for a clear structure to identify, share/distribute and use product and process information (Merali and Bennett 2011).

This section presented the basic terminology, e.g., manufacturing, product and process used in this research. It described how manufacturing processes transform products by adding value. This value adding can be done in various ways, e.g., machining or heat treatment. Furthermore, the importance of the availability of the right information for a manufacturing process is introduced. Together with process monitoring, which can be understood as the capturing of information in a manufacturing process this is the basic principle the *product state concept* is build upon.

2.2 Developments of Manufacturing System

A manufacturing system describes the method of manufacturing in a generalist way. A manufacturing system sub-summarizes all means necessary for the production of a certain product, including the manufacturing programme and processes, machines, production method, etc. It represents the overarching layer connecting the different stakeholders involved and is mostly complex and of large-scale (Höpf and Schaeffer 1997). Koren et al. (1998) have shown that the configuration of the manufacturing system affects the performance of the system. The effects identified include productivity, capacity scalability, and part quality and thus, influence the lifecycle cost of the manufacturing system.

Over time there have been many different methods and concepts concerning manufacturing systems. From flexible and integrated manufacturing systems (e.g., Collins 1980; Kimemia and Gershwin 1981) towards today's Holonic (HMS) and Intelligent Manufacturing Systems (IMS) (e.g., Höpf and Schaeffer 1997; McFarlane and Bussmann 2003) there are many different definitions available, each focusing on certain aspects with smaller or larger overlaps with each other. Even so some concepts were adopted in the 1980s, they are still to some extent valid and applied in their original or adapted/updated form today (ElMaraghy 2006).

Flexibility is still an important factor for today's manufacturing systems especially given the trend towards mass customization (He et al. 2013). However, the focus is increasingly shifting towards a combination of reconfigurability, flexibility and even adaptability (ElMaraghy 2006; Almeida 2011). Reconfigurability, flexibility and adaptability reflect the customer demand driven production of today's business environment. These concepts focus to a large extent on scheduling and production planning and control activities. IMS, in detail explained in Sect. 2.2.2, try expanding that view by expanding the focus on further characteristics like e.g., autonomy, learning and efficiency (Kumar 2002; Oztemel 2010; Almeida 2011). HMS, while based on the IMS concept, focus on the self organization aspects of large complex systems and how this integrates in and influences the performance of the system (McFarlane and Bussmann 2003) (see Sect. 2.2.3).

2.2.1 System View on Manufacturing

The general systems theory (Von Bertalanffy 1972) and the derived systems perspective has had an effect on various disciplines and has partly been adapted to the needs of various disciplines like operations, information systems and also engineering (Maddern et al. 2013). A System represents "a set of interacting components having well-defined (although possibly poorly understood) behavior or purpose; the concept is subjective in that what is a system to one person may not appear to be a system to another" (Magee and de Weck 2004). A complex system expands on the above system definition by being "a system with numerous components and interconnections, interactions or interdependencies that are difficult to describe, understand, predict, manage, design, and/or change" (Magee and de Weck 2004). Engineering (and thus manufacturing) systems) are "systems designed by humans having some purpose" (Magee and de Weck 2004).

However, in the manufacturing domain often the focus is on individual processes or operations, disregarding the previous or following ones, which can have an impact on the products final quality. Hoffmann et al. (2002) found that there are cause effect relations across process borders which have a significant influence on the behavior of a product during manufacturing (Sölter 2010). Such often complex process intra- and inter-relations are common in engineering systems (Giffin et al. 2009). In line with the principles of systems theory, the environment of the system also has an influence of the behavior of a system (Maddern et al. 2013).

In manufacturing programmes, a wide variety of potential errors can influence the quality characteristics of a product. The product end quality is finally determined by all stages of the manufacturing programme (Zantek et al. 2006; Jiang et al. 2012). Therefore, taking the whole system into account instead of individual, isolated processes can help to accomplish sustainable product and process quality improvements (Zoch 2009). Supply Chain Management (SCM) represents a very common variant of a system view, focusing mostly on logistics and collaboration efforts (Christopher 2005), whereas the research focus in this manuscript lays on product and process quality improvements in manufacturing.

2.2.2 Intelligent Manufacturing Systems

Increasing market pressure towards quality, efficiency and flexibility together with new developments in ICT, Artificial Intelligence (AI) and optimization techniques lead to the concept of intelligent manufacturing. Intelligent manufacturing is also known as smart manufacturing, being used almost interchangeable. A comprehensive definition of smart/intelligent manufacturing is presented by Wallace and Riddick (2013) as follows: "Smart [or intelligent] manufacturing is a data intensive application of information technology at the shop floor level and above to enable intelligent, efficient and responsive operations" (Wallace and Riddick 2013).

Another definition of intelligent manufacturing describes the concept as "an intelligent manufacturing process [that] has the ability to self-regulate and/or self-control to manufacture the product within the design specifications" (Kumar 2002). In this definition the autonomous aspect of intelligent manufacturing is highlighted. What is commonly accepted among researchers is the importance of product and process information and data, technology and (human or machine inherent) knowledge (Chand and Davis 2013). This understanding already implies that in order to make a manufacturing process intelligent, various functions of a manufacturing company have to work together, e.g., design, process planning, production planning, operations and process control. Looking at the final product, individual quality control and based on that, corrective measures are required. During manufacturing itself, monitoring, diagnostics and measures like predictive maintenance play an important role (Mazumder 2008). Overall, continuous improvement is crucial to make the system intelligent.

However, the degree of autonomous behavior is not specifically defined. Kumar (2002) defines three ways to achieve the above-defined intelligent manufacturing:

- "Existing manufacturing processes can become intelligent by monitoring and controlling the state of the manufacturing machine
- Existing processes can be made intelligent by adding sensors to monitor and control the state of product being processed.
- New processes can be intelligently designed to produce parts of desired quality without the need of sensing and control of the process."

According to these findings, existing manufacturing processes can be made "intelligent" by monitoring and control the state of the products via sensor technology and the application of ICT. This is highly relevant to the conducted research as the here stated "state of a product" is in line with the basic understanding of products and processes of the developed concept.

The intellectual father of IMS, Yoshikawa, defines them as follows: "The IMS takes intellectual activities in manufacturing and uses them to better harmonize human beings and intelligent machines. Integrating the entire corporation, from marketing through design, production and distribution, in a flexible manner which improves productivity" (Yoshikawa according to Piddington and Pegram 1993).

The global, IMS program compromises a R&D program established to develop the next generation of manufacturing and processing technologies, led by industry (Nagy et al. 2005). The first idea for IMS came up by the end of the 1970s (Hatvany and Nemes 1978) shortly after followed by early IMS definitions (Hatvany 1983). Hatvany (1983) gave the next generation of manufacturing systems a perspective combining findings of AI research "to solve, within certain limits, unprecedented, unforeseen problems on the basis of even incomplete and imprecise information". (Monostori 2002) Being widely discussed, a worldwide IMS initiative, initiated by Japan 1989 (EC 2009), was formally started in the mid 1990s with the kick off of six test cases. One of the cases were Holonic Manufacturing Systems (HMS) (TC5), which looked into the ability of companies to react to rapidly changing market conditions (see Sect. 2.2.3), others looked into knowledge systemization in product and process design (TC7), whereas others focused on clean manufacturing (TC2), concurrent engineering (TC3) and rapid product development (TC6), etc. (Kopacek 1999). Even so the impact of conducted project within the first phase of IMS was positive, there is still potential for future development in IMS especially given the rapid development in ICT (Zobel and Filos 2006).

According to Kumar (2002), "IMS

1. uses technology which can minimize the use of human brain.
2. regulation for product mix and priority production, self regulated.
3. self controlled operations with automatic feedback mechanism.
4. monitoring and control of the manufacturing machine.
5. monitoring and controlling the state of product being processed.
6. new processes with intelligence can be made to produce parts of desired quality without the need of sensing and control of process" (Kumar 2002).

One has to bear in mind that the points stated above are rather idealistic goals as a realization in the near future is unlikely due to e.g., the high dimensionality and complexity involved in modern manufacturing and PLM approaches.

IMS, being based on the intelligent manufacturing paradigm, are supposed to support various characteristics, starting with flexibility and reconfigurability combining them with ideas from the ICT domain like autonomy, decentralization, flexibility, reliability, efficiency, learning, and self-regeneration (Liu et al. 1997; Revilla and Cadena 2008; Mekid et al. 2009; Shen et al. 2006; Almeida 2011).

Looking at the above, the importance of state monitoring of both, processes and products within IMS is evident. This research is contributing to support state monitoring issues in complex manufacturing programmes to support the IMS goals.

2.2.3 Holonic Manufacturing Systems

The word “holon” is an artificially created term based on the Greek word “holos” meaning whole and the Greek suffix “on” meaning particle or part as in proton or neutron (Höpf and Schaeffer 1997; McFarlane and Bussmann 2003). A holon is understood as “an identifiable part of a system which has a unique identity, yet is made of subordinate parts and in turn is part of a larger whole” (Kopacek 1999). McFarlane and Bussmann (2003) define a holon in manufacturing as an “autonomous and cooperative building block of a manufacturing system for transforming, transporting, storing physical and information objects”. Given the above definition, a holon itself can contain a unlimited amount of holons as subsystems, providing the necessary processing, information, and human interfaces to the outside world (McFarlane and Bussmann 2003).

HMS were originally established as part of the global IMS initiative as TC5 “Holonic Manufacturing Systems” in 1989 to create “companies able to react promptly and efficiently to changes in environmental and marketing conditions” (Kopacek 1999). Especially SMEs require flexibility in their manufacturing systems to survive in the future global market environment. Holons offer allow those companies to create flexible manufacturing systems based on principles known from ICT. HMSs are supposed to be intelligent, flexible and modular (Kopacek 1999).

As a basis for this research HMS present an interesting foundation as it combines the detailed view on an “excerpt” (holon) of an overarching system and the implications of its performance/changes and inherent information/data representation. This is strongly related to the approach taken when looking at the manufacturing programme by the different product and process states and the identification of state drivers based on data from different defined sub-systems (see Sect. 5.3). The interpretation of the results strongly depends on how the findings of the analysis of sub-systems affect the manufacturing programme as the overall systems.

In conclusion, the previous subsections highlighted different approaches to describe manufacturing systems. Instead of looking at operations or processes individually, the importance of considering all elements of the manufacturing system, as there are correlations across process borders is described. The *product state concept*, describing a product holistically by its state over a manufacturing programme is a reflection of the system view on manufacturing.

2.3 Developments in Information and Data Management in Manufacturing[3]

This section presents a closer look on information and data and its handling and management in manufacturing. Most advanced manufacturing approaches, e.g., the above discussed IMS and HMS initiatives, rely strongly on information and data. The developed *product state concept,* as a holistic product focused information system is dependent on a functional information and data management as well.

Along a manufacturing programme, physical products as well as information are exchanged between the partners (Hicks et al. 2006). The availability of information is a precondition to adjust each manufacturing process in such a way that the outcome reflects the set quality requirements to a high degree. Quality, as stated before, constantly gains importance for customers and for a sustainable use of resources. At the same time, distributed production brings forth new challenges for managing quality (Sitek et al. 2010). Looking at quality improvements of manufacturing products and processes, the collection and analysis of data/information is essential to solve quality related manufacturing problems (Köksal et al. 2011).

In order to present a solid foundation and highlight the current challenges in the domain, first information and data management are presented before looking more closely into information quality and their understanding within the manufacturing domain. Based on this general introduction, selected standards and tools used in practice are presented. The widely discussed Big Data domain is briefly discussed at the end of this section; mainly to distinguish the differences and similarities of the developed concept with regard to the Big Data perspective. Two specific topics related to the domain of information and data management, namely PLM and PDM, are discussed in the next section due to the available practical applications and their close relation to the theoretical foundation of the *product state concept*.

Before focusing more closely into information and data management, Fig. 2.12 distinguishes the difference between IM (incl. data management) and Knowledge Management (KM). Overall, it can be stated, that information management is considered more technical than knowledge management and that knowledge is backed by information and data. An important differentiation, is that data and information can be stored relatively easy compared to knowledge which is always connected to a person (Probst et al. 2006). The differentiation in explicit and implicit knowledge is crucial for the transferability and applicability. They are based on Polanyis findings concerning the personalized nature of knowledge (Polanyi 1962). In comparison, information is relatively easy to transfer and data even easier. However, information itself does not foster realizations or new findings; it has to be connected to a context in order to become knowledge (Haun 2002). This is important

[3]The content of this section has been partly published in accordance with Universität Bremen (2007) in Wuest and Thoben (2012).

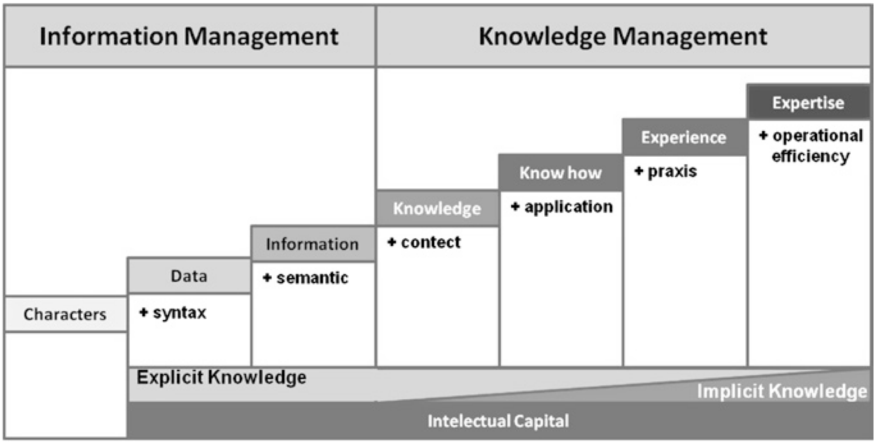

Fig. 2.12 Differentiation of knowledge and information management Wuest and Thoben (2012), inspired by North and Güldenberg (2008); Auer (2010)

for the developed concept as the process of connecting data and information with context represents a major challenge during the application.

However, the above illustrated distinctions between the different areas are not as clear as Fig. 2.12 indicates. One of the reasons is, that solid measures are missing resulting in large gray zones and overlaps between the different terms which make a clear distinction impossible at times. Within this manuscript, the focus is on information and data as a source of product state and process knowledge.

KM is the systematic and explicit control of knowledge based activities, programs and governance within the enterprise with the goal to make effective and profitable use of the intellectual capital (Wiig 1998). (Davenport et al. 1998) emphasize that KM does not only imply successful utilization of knowledge but also creation and allocation. The KM research field is a very broad one and there are various research areas involved, from social science over psychology and business to engineering. Therefore, the number of publications and available information is vast. Setting the focus on identifying knowledge, (Probst et al. 2006) with their model of knowledge building blocks defined one of them as "knowledge identification" (Probst et al. 2006). Taking a closer look, this block describes the need to increase transparency of internal and external sources of knowledge. It also is supposed to ease the way the own employees have access to knowledge needed. The pioneers in the field of KM, (Nonaka and Takeuchi 1997) created the well-known model of the "knowledge spiral", an illustration of the knowledge creating process focusing on transforming implicit to explicit knowledge. Other concepts, like e.g., process oriented KM (Mertins and Seidel 2009), are variations or combine the models of Probst et al. or Nonaka and Tekeuchi and combine it with other theories like Porter's value chain (Porter 2008). None of these approaches and models offers a defined and accepted concept clearly to identify very specific

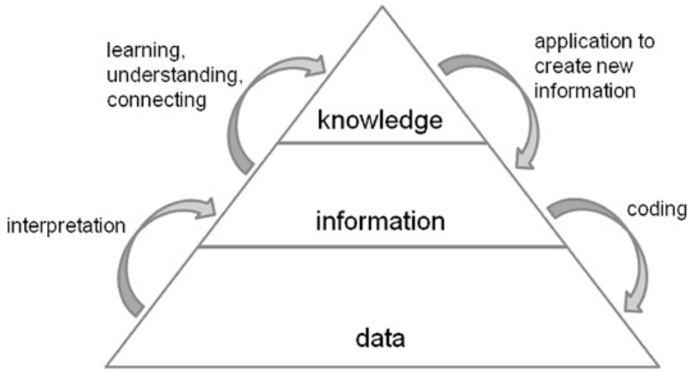

Fig. 2.13 Information pyramid (Fink et al. 2005)

sources of information or data about an individual product or process. But they all emphasize the importance of having the right knowledge or information available at the right place for all business processes. This can be seen as the overarching argumentation for the *product state concept*, as it is supposed to provide the right information/data to experts who can apply their knowledge to improve the process and thus product quality on that basis. In the future expert systems could support knowledge creation based on the *product state concept*.

Another interesting distinction of knowledge, information and data, this time including the relations among each other in both directions is presented by the information pyramid (Fink et al. 2005) (see Fig. 2.13). The highlighted relations in Fig. 2.13 between knowledge, information and data can be seen throughout this research. In order to identify a relevant set of product state information, knowledge of the manufacturing programme, the individual processes and their process intra- and inter-relations has to be applied as well as available process and product data has to be analyzed when there is a knowledge gap.

The question if process and product quality can be improved through transparent IM based on identification of relevant product state characteristics along a manufacturing programme through modeling process intra- and inter-relations between these characteristics has not yet been addressed sufficiently in literature or practice. Areas related to this question were identified as follows: knowledge, information and data management; SCM (incl. process management and related areas); research on collaborative production and quality management.

Next, the areas of IM will be explained in greater detail to clarify the domain in focus of this research and provide a solid background before including a brief explanation of the Big Data domain.

2.3.1 Information Management (Systems) in Manufacturing

IM and the more technical term IM systems are strongly linked to ICT and related technical solution in the manufacturing domain. In this area, a lot of progress has been made over the last years. As stated above the understanding of IM and IM systems in manufacturing does not distinguish itself sharply from e.g., PDM and PLM systems, also with strong links to ICT, which will be discussed in next Sect. 3.1. However, IM is closely connected to the quality of the data and information to be managed (Storey et al. 2012). Garetti and Terzi (2004) highlight that the "product" information and data management is representing a key aspect of product centric and product driven approaches, also emphasizing a strong overlap between the two areas.

Nevertheless, the research focus of IM in manufacturing is mostly focused on how already existing information has to be managed (e.g., Choe 2004; Hicks 2007) or what existing IM system should be chosen (e.g., Beach et al. 2000; Gunasekaran and Ngai 2004). The general principles of IM (e.g., Augustin 1990; Jehle 1999; Hoke 2011), the right information at the right time in the right granularity at the right place in the right quality can be seen as the general vision this research builds on without providing a problem definition for the domain or a proposed solution.

The relatively new but widely discussed topic of Big Data plays an important role in the current developments within the information and data management domain in manufacturing. The economically reasonable retrieval and usage of crucial insights from qualitatively diverse and versatile structured information, which are subject to constant change and which accumulate in large scale is defined as Big Data. The Big Data development is seen as a paradigm shift, as the importance of hard- and software diminishes, the importance of data as a value adding factor rises. The industrial domain is seen as one of the main benefactors of Big Data developments. In a digital world, Big Data is seen as a fourth production factor besides capital, labor and raw materials. The rapid increase in the amount of data is partly based on new developments in e.g., sensor technology, improved (mobile) communication and social media content. Big Data applications tackle an area where traditional approaches reach their limitations, basically to handle the sheer amount of information for decision making support.

Even so Big Data is widely used in recent times, this reflects a contrast to the fact that there is no commonly accepted general definition. One can argue that due to the rapid developments in data processing technologies, concrete numbers might not be useful within a definition. So the amount of data needed for an application to be considered Big Data is vaguely considered too big for traditional approaches to handle with acceptable effort. This is not the only defining factor of Big Data applications. The complexity of the to-be-analyzed data and the velocity of the processing are crucial (Küll 2013).

Today a lot of sensor data is lost due to missing commonly accepted standards for data communication, processing and handling. Challenges are e.g., the large data volumes accrued by continuously recording sensor solutions. It not only the large amounts that propose challenges but also the rapid development in sensors and thus continued emergence of new data types which have to be handled (Lohr 2012). Especially wireless sensor networks are prone to outliers due to various factors. As there are many different sensors active in these networks, failures can accumulate fast (Branch et al. 2013). This 'contaminated' data streams are a big challenge also for Big Data applications. Researchers look into various methods to identify and eliminate negative effects in sensor data, ranging from ML to Hopfield nets (Aggarwal 2013).

In contrast to traditional data analysis methods, where the solution space is at least sketched, Big Data principles look at large amounts of data and try to identify new findings hidden in the data in real time. The approach used within the *product state concept* can be seen in between, however leaning towards traditional analysis paradigms. The goal of the *product state concept* is stated beforehand, as of identifying a relevant set of state characteristics to support quality monitoring in manufacturing. However, as there are large knowledge gaps in regard to cause effect relations across manufacturing processes/operations. In order to define a set of relevant information for the manufacturing programme, all possible information artifacts have to be considered initially and the identification of cause effect relations, in this case applying pattern recognition shares similarities to Big Data principles.

Technically, the amount of information artifacts will most likely not be considered Big Data due to the comparable small amount. Thinking ahead, considering improvements in sensor technologies this can change in the near future. Furthermore, the interpretation of real time is different in Big Data applications, closer to milliseconds, than it is in the developed concept where real time is understood as 'available when needed'.

The importance of knowledge, information and data was already introduced as early as in the introduction of this dissertation and further detailed throughout this section by presenting existing domains and definitions. The different approach of IM, trying to gather relevant data for pre-defined problems and big data, looking at all available data in real time, trying to identify patterns in order to create new knowledge, is explained. Both approaches have an influence on the *product state concept* development. The goal of the *product state concept* is to identify a comprehensive set of relevant information to describe a product along the manufacturing programme. However, there are many unsolved issues and discrepancies between the available knowledge about the manufacturing processes and the needed knowledge. Therefore, Big Data principles of looking at available manufacturing data in order to identify patterns, which help in return to identify relevant information of the product and process, are included in the concept.

In the following sub-section, the topic of data and information quality is introduced as it plays an important role in all information based applications in manufacturing.

2.3.2 Data and Information Quality[4]

Data and information quality is a topic of great interest for many domains, be it social sciences, natural sciences or engineering. In manufacturing, especially in the area of process monitoring and control, data and information quality can play a decisive role in weather an analysis and the subsequent action is successful or not. As was stated previously within this section, information and data is not sharply distinguished in literature. From now on, to simplify the understanding, the term data quality will be used comprehensively, integrating both, information and data. In the following subsection, the current state of the art in data quality is presented from a research point of view.

Data quality is a multi-dimensional concept (Pipino et al. 2002). Data and information quality is usually defined in terms of contribution to the objectives of the end-user (Helfert 2002). It can be additionally described as the adequacy for the relevant data processing application (Naumann 2007). Poor data quality can be a major cause for damages and losses on organizational processes (Storey et al. 2012). To avoid the damages and losses data quality problems and solutions should be considered as early as possible, best at the design stage of the information system (Storey et al. 2012).

2.3.2.1 Data and Information Quality Dimensions

Pipino et al. (2002) list under the data quality dimensions the following attributes: accessibility, appropriate amount of data, believability, completeness, concise representation, consistent representation, ease of manipulation, free-of-error, interpretability, objectivity, relevancy, reputation, security, timeliness, understandability, value-added. Data quality can thus be also described as a set of quality characteristics (Naumann 2007). Many of the listed attributes contribute a lot to the overall data quality, as tested by a third-peer.

The starting point for consideration of data quality is the user-oriented quality concept. Helfert divides data quality in design and execution quality. The fulfillment of end-user requirements and specifications can be met through a choice of properties in the data design. Design quality refers as such to the collection of specific quality requirements from the user's perspective. Execution quality includes compliance with the specifications (Helfert 2002). Helfert's basic data quality criteria are: correctness, completeness, consistency and timeliness (Helfert 2002). Data quality criteria developed by English are: data standards, data definitions and information architecture (English 1999). These criteria can be understood as the access capability, timeliness and interpretability of the data and the data system.

[4]The content of this section has been partly published in accordance with Universität Bremen (2007) in Wuest et al. (2014).

Data quality as understood by Wang and Strong can be divided into internal data quality, contextual data quality, presentation, and access quality (Wang and Strong 1996). Wang and Strong focus on user-related data quality—interpretability, usefulness, credibility, time reference, and availability have been rated as important criteria (Wang and Strong 1996; Helfert 2002). Jarke, Jeusfeld, Quix and Vassilidis's data quality criteria are: completeness, credibility, accuracy, consistency, and interpretability (Jarke et al. 1999). A poll conducted by Helfert delivers additional quality criteria important to organizations: clearly defined data descriptions, formal data syntax, delivery times (for data), and specific information about selected properties of the data, e.g., number of errors (Helfert 2002).

Rohweder et al. describe data quality as the degree the characteristics suffice the requirements on the data product. The requirements for the data are determined through particular decisions and goals set on data quality. Rohweder et al. define data quality with the help of 15 IQ (Information Quality) dimensions (Rohweder et al. 2011). These can be applied to e.g., master data, to assess if the data is useful or not acceptable. The IQ dimensions have been divided into four categories and form a regulatory concept for data quality (Rohweder et al. 2011). The 15 IQ dimensions are as follows:

System support (e.g., user interface).

- **Accessibility**: accessible and easy to access.
- **Ease of manipulation**: easy to use and to change.

Inherent (content examination).

- **Reputation**: data source and processing highly trustworthy.
- **Free of error**: error free and consistent with reality.
- **Objectivity**: strictly objective and value-free.
- **Believability**: reinforced with quality standards, etc.

Representation (overall presentation, e.g., the form of statistics)

- **Understandability**: ability of users to directly understand and use information.
- **Concise representation**: clear, saved in appropriate and understandable format.
- **Consistent representation**: uniform and held in consecutive and equal manner.
- **Interpretability**: understandable in same, technically correct manner.

Purpose-dependant (data use in the processes)

- **Timeliness**: actual properties of data (described) accurately and up-to-date.
- **Value-added**: usage leads to quantifiable increase in monetary cost function.
- **Completeness**: no missing information contained.
- **Appropriate amount of data**: amount meets requirements set on data.
- **Relevancy**: provides all necessary information for user.

Overall, it is accepted, that all IQ dimensions should exhibit a high or at least sufficient quality for an information system to be functional (Rohweder et al. 2011). Looking at the IQ dimensions, it can be stated that the *product state concept* can contribute to several of those. Especially the purpose-dependant dimensions, focusing on the data usage in processes, are reflected in the development. In Sect. 4.1, features of the *product state concept* are mapped to these information quality dimensions (Table 4.1) according to how they address the issues.

2.3.2.2 Avoiding Data Errors

Data errors can be avoided most effectively and most sustainably at the moment of their emergence, e.g., throughout the manual data entry or automatic data collection (Naumann 2007). A direct capture of the data from the source to an electronic device without human interference is the best way to minimize data input errors. When human interface is unavoidable input errors may occur and consequently degrade data quality (Verma 2012). To prevent quality degradation a quality check can be performed in the moment of data delivery (here data transformation to the target system). The data can be further checked by end-users through the use of complaints-forms or other rating-systems, e.g., statistical methods (Helfert 2002). In case of data sets from external sources, it is essential for the researcher/information-manager to deal consciously with the data and the data quality; it is crucial to mark the problematic data to be able to deal consciously with it (Naumann 2007). The external party and the person responsible for integrating the data into the target system should be clear about the purpose of why the data are being collected, and it should be clearly stated (Verma 2012).

The most common data quality issues are incorrect or missing values, duplicates, and errors in the recording process (Helfert 2002; Winkler 2004; Naumann 2007; Verma 2012). Errors in data cause errors in reports generated from the data, thus reinforcing the “garbage-in-garbage-out-effect”. Errors can be found within the schema and/or the data level. The schema level describes the errors in the structural, semantic and schematic heterogeneity of the data characteristics. The data level includes value-, unit-, accuracy-, and duplicates errors (Naumann 2007).

Duplicates, one of the most costly data errors (Naumann 2007) can arise, e.g., due to typographical errors in the unique identifiers (e.g., the name of the researcher). Missing identifiers and contradictions in data indicate low quality (Winkler 2004). These issues can be prevented with data quality ensuring practices, e.g., marking of problematic data, auto correction of format errors, manual correction of the data values, troubleshooting and coordination with the data suppliers, and organizational rules (Helfert 2002). Furthermore file-linkage can be used to create “more complete” data (Winkler 2004). The traceability of data origin and documentation of discrepancies is also relevant (Helfert 2002). Semantics and identifiability, as well as the precision of the value ranges, the granularity of data models, and the technical aspects of the data are less critical for the overall data quality (Helfert 2002).

Data quality can be assessed by a third-peer. The assessment can either be task-independent, where no contextual knowledge is required, or task-dependent, with specific application context (Pipino et al. 2002). The data quality methodologies can be classified according to various criteria (Batini and Scannapieco 2006):

- Data-driven versus process-driven
- Measurement versus improvement (assessment or improvement of data quality)
- General-purpose versus specific-purpose
- Intra-organizational versus inter-organizational

The previously presented basics and subsequently described relation to the conducted research and developed concept are underpinned by an elaboration on challenges of MS from an information and system perspective in the next subsection.

2.4 Challenges of MS from a Product and Process Information Perspective

In this section the challenges in the manufacturing domain with regard to the increasing importance of product and process information are derived. This provides a broad understanding of the research area and research problem in a wider sense this dissertation is based upon. In the following Chap. 3, current concepts and approaches tackling these challenges to a certain extent will be presented. The resulting gaps between the challenges and how the current approaches tackle them further specifies the research problem.

The European Commission (EC) predicted the development of manufacturing along three paths[5]: (1) On-demand manufacturing; (2) Optimal (and sustainable) manufacturing and (3) Human-centric manufacturing (Filos 2013). Especially the second path highlights that manufacturing has to be prepared to produce high quality products with high security and durability, competitively priced without avoidable waste and scrap (Filios 2013). This focus on quality of individual products and efficient processes supports the arguments brought forth within this research.

There are several studies available proposing key challenges of manufacturing on a global level. The following key challenges most of researchers agree upon (Gordon and Sohal 2001; Shiang and Nagaraj 2011; Dingli 2012; Thomas et al. 2012):

- Adoption of advanced manufacturing technologies
- Growing importance of manufacturing of high value added products
- Utilizing advanced knowledge, information management and AI systems
- Sustainable manufacturing (processes) and products

[5]www.actionplant-project.eu/public/documents/vision.pdf (retrieved Feb. 12, 2014).

- Agile and flexible enterprise capabilities and supply chains
- Innovation in products, services and processes
- Close collaboration between industry and research to adopt new technologies
- New manufacturing management paradigms.

However, these key challenges highlight the ongoing trend of manufacturing operations growing complexity. This complexity is inherited not only in the manufacturing programmes but increasingly in the to-be-manufactured product itself as well as in the (business) processes of the companies (Wiendahl and Scholtissek 1994). Adding to the challenge is the fact that the business environment of today's manufacturing companies is affected by uncertainty (Monostori 2002).

Focusing from the global challenges towards the challenges of monitoring in manufacturing systems, the inherent complexity in manufacturing systems brings several challenges to the table when it comes to modeling and/or monitoring and control approaches of manufacturing programmes. Some of the challenges new concepts have to be able to deal with are:

- the great number of different machining operations,
- multidimensional, non-linear, stochastic nature of machining,
- partially understood (cause-effect) relations between parameters,
- lack of reliable data,
- missing parts of data sets,
- high-dimensionality and multi-variate nature of data.

(Derived from: Tönshoff et al. 1988; Van Luttervelt et al. 1998; Monostori 2002; Viharos et al. 2002; Kano and Nakagawa 2008; Wuest et al. 2012).

When trying to increase quality through a monitoring of manufacturing processes, it is tough to tackle the challenge of identifying problematic states throughout manufacturing processes by modeling cause-effect relations between product states as of these process intra- and inter-relations along the process chain due to this and other factors. The problem at hand has an inherent high complexity and high dimensionality (in this context high-dimensionality is understood as a multidimensional system with a large number of dimensions) (Suh 2005; Lu and Suh 2009; Elmaraghyet al. 2012). Optimization tools in this field need to be able to handle a large number of dimensions and variables in order to be useful in practice. Even so it would be desirable to use precise first-principle models, the development and application of such models is hindered by the complex nature and the above stated challenges of manufacturing programmes, especially when it comes to new manufacturing programmes, processes or operations (Kano and Nkagawa 2008). The NP complete nature of the problem of identifying process intra- and inter-relations is described in more detail in Sect. 4.5.1.

Kano and Nakagawa (2008) identified three functions that systems intended to improve product quality in manufacturing need to fulfill in order to be considered useful: "(1) to predict product quality from operating conditions, (2) to derive better operating conditions that can improve the product quality, and (3) to detect faults or malfunctions for preventing undesirable operation".

Tönshoff et al. (1988), outlined already in the late 1980s the necessity of sensor integration, sophisticated models, multi-model systems and learning ability in monitoring and control of manufacturing programmes, especially machining processes. A possible clustering of concepts based on the kind of knowledge applied, leaves fundamental, heuristic and empirical models that can be distinguished (Viharos et al. 2002).

In the next section, existing approaches which focus on the identified challenges are discussed. The gaps between the successful tackling of the raised issues by these approaches provide a further basis for the developed *product state concept*.

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