D6.2

Public IT Architecture & Model: the Holistic Information Model HIM

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Abstract:	This deliverable describes the architectural model and design for a real-time information system, with regard to smart manufacturing framework, and integrated into the ADMONT project scope. This holistic informational model HIM is developed within the strictness of a physical framework.
Keywords:	Requirement analysis, real-time factory analysis and control, architectural requirements, detailed information concept

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Executive Summary

This document provides the D6.2: Public IT component and architectual model. This document is related to IT & automation topics and activities anticipated within WP6. The focus of this document is the detailed model and design of how data gets transformed in information in real-time, including continuous aggregation of more meaningful information on different levels of abstraction. The conceptual background is further related to the official ITRS roadmap (International Technology Roadmap for Semiconductor 2.0: 2015 [1]): “Real-time data collection, analysis and consequent disposition of wafers via a fully automated material handling system will remain the goals of the High Volume Factory in the next decade until ‘full light out’ operation is reached.” ([1], pp. Exec. Sum. 2).

The gap between data volume on the one hand and effective analytical methods on the other hand opens up gravely. Production sites have to deal with Terabytes of Data, and the data volume continues to grow. Not only Intel reports explosion of data volumes, but also smaller manufacturing sites have to deal with higher automation, higher product mix and the need to analyse big data volumes in real-time [2].

The core concept to close this gap is to introduce a concept of information, which is designed with the same strictness as physical laws, but also offering a very fine granularity and constructivist usability. The *key point* is that all those single atomic data is *in a holistic manner inherently interlinked* – from a physical and engineering perspective – with other atomic data. This linkage expresses any kind of information, which is required in terms of [1], and in terms of the ADMONT WP6 project, and can be used to create solutions with best algorithmic efficiency – a so far “undecidable” task. We propose to build new kinds of applications, which are capable to enable the requirements of a future real-time information system, and according to the requirements specified in this document.

It is reported already on international conferences, that within the next 10 years, formerly separated applications and application domains need to work together. It is one highlight of the ADMONT project that the WP6 project could contribute to such a conference with an own presentation [3]. Our approach has been discussed by and gained commitment from the international audience [3].

State-of-the-art solutions support the creation and delivery of information based on complicated data extraction, transformation and aggregation processes. Additionally, such applications do not offer inherent real-time capability, because those processes are disadvantageous executed posterior to the period which should be inspected and steered in real-time.

Contrary to this, the proposed approach is based on the concept to continuously create information in the context of any single atomic fab event [3], [4]. Information spaces are used to store those information components, which brings the corresponding information system on a new and unseen level of efficiency (best algorithmic efficiency), and enabling at the same time new production analysis and optimization capabilities. Any information component is ready to be aggregated and further analysed within multiple dimensions – and vice versa: drill down from any created information to the root events (root cause analysis). The informational spaces are enabled by the invented Holistic Information Model HIM.

The Introduction chapter gives an overview about the document, and outlines the investigations described in this deliverable. The most significant barriers of the state-of-the-art solutions are explained.

Chapter 2 describes the requirements for main real-time scenarios and functionalities. Those scenarios refer to the demonstrators, which will be built in the project. The new architecture enables new domains of functionality.

Those requirements clearly show and motivate the need for a new architectural approach, in order to realize and implement an innovative, real-time based Production Methodology.

Chapter 3 introduces the major innovation of this architectural description:

- a Holistic Information Model HIM,
- which is based on a corresponding structuring of information components in linear information spaces,
- whereas those information spaces are enabling best algorithmic efficiency and deployability to standard hardware and software environments, and – based on this efficiency – new domains of functionality.

The next chapter 4 describes the basic design of an architecture, which implements the holistic information model.

This is done in a stepwise approach, in order lay down in detail how data is handled and transformed to information in a given computing architecture, and how the system enables inherent real-time capability. It is shown, how fab events (such as equipment state change, material movements) are gathered and transformed in real-time to information fundamentals and fractals.

It is further shown, how functional scenarios and data processing mechanisms will become directly mappable to data views, materialized data views or other efficient data management capabilities. The detailed design of the holistic information model HIM enables best algorithmic efficiency and is the *key innovation of the current research*.

Next, it is shown, how the 3-layerd requirements architecture is implemented, covering the operational, the engineering, and the optimisation layer. This design refers to those in chapter 2's described requirements.

The next chapter 5 describes the deployment concept of this architectural approach. This concept takes an example deployment structure into account, which is based on standard hardware and software infrastructure.

Contents

List of Figures

1 Introduction

Strong production capacity growth is a reality, especially for 200 mm fabs. This trend leads to dramatically increased requirements for production information systems. Manufacturing Execution Systems (MES) addressed the functions and tasks between the ERP level and the equipment automation level, including functionalities like management of work in progress, equipment utilization, dispatch/scheduling, manufacturing job management and others. Besides these, additional, mostly bottom-up grown applications and frameworks like SPC, FDC, and others led and are still leading to an ever growing degree of diversification in the application landscape of modern semiconductor production sites.

All those applications create growing amounts of data volumes, while maintaining their own data schemes. Consequently, the overall system lacks the availability of integrated and comprehensive information, but provide instead numerous and growing sources of data. Additionally, such data is of reduced value, because only the correlation to other data creates the required information.

Following drawbacks need to be overcome:

a) **First drawback: Lacking informational Integration of the Application landscape.** The industrial processes are lacking fundamental concepts to realize integrated information from within a fab-wide perspective. This fab-wide informational consistency, and corresponding control and analysis functionalities are required to continuously steer and improve the production process (scope of ADMONT and of ITRS as well). Currently, partly inhomogeneous architectures with growing complexity on different scales *hinder* the ability to easily introduce new functionalities and to continuously develop and optimize the production process (for example a functionality to additionally manage energy efficiency of production equipment and corresponding process steps).

b) **Second drawback: no Real-Time capability.** Usually, important information such as key performance indicators of the manufacturing process are calculated after the actual event occurs, or even after a certain period of time (such as shift end). That is, all this data lacks real-time cadence, and for this reason it is not usable for further Real-time analytics and control.

c) **Third drawback: Lack of support for Root-cause Analysis and continuous Knowledge Discovery.** Another major drawback is that the original FAB events and atomic data sets are not available from within an overall perspective, such as required by Business Intelligence. Only aggregated views and reports are maintained. For this reason, the state-of-the-art solution fails to enable root cause analysis. Any root cause analysis requires access to original FAB events and atomic data sets.

The research design of the proposed solution is based on the concept to overcome such blocking points through the introduction of a new informational model and corresponding methodology: the Holographic Information Model HIM.

The core concept of HIM is based on the finding, that all required information in order to enable meaningful real-time capability can be modelled based on a system state model, as already outlined by Wand / Weber 1995 [5]. The production methodology and process itself is modelled using such state models [1]. The main innovation of the new architectural design shows how traces of state transitions of corresponding models and sub-models will be captured in new informational structures, called fundamentals and fractals.

Those informational structures are creating linear informational spaces. It is well understood that complex production systems may show complicate, non-linear behaviour (such as unplanned WIP waves, which may disturb delivery dates of productive material). The core invention of HIM is that even such non-linear behaviour gets mapped without any loss of information into linear information spaces, which enable best algorithmic efficiency, and most reliable deployability of the architectural design with standard hardware and software components.

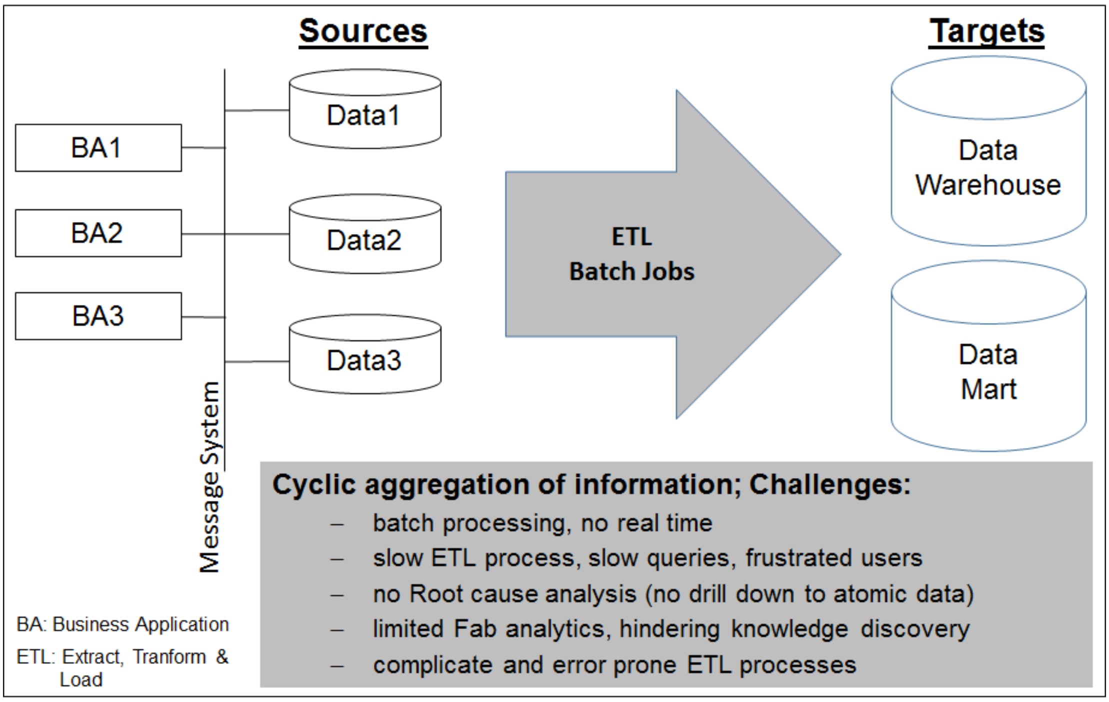


Figure 1.1: State-of-the-art Date Storage and Integration Technology

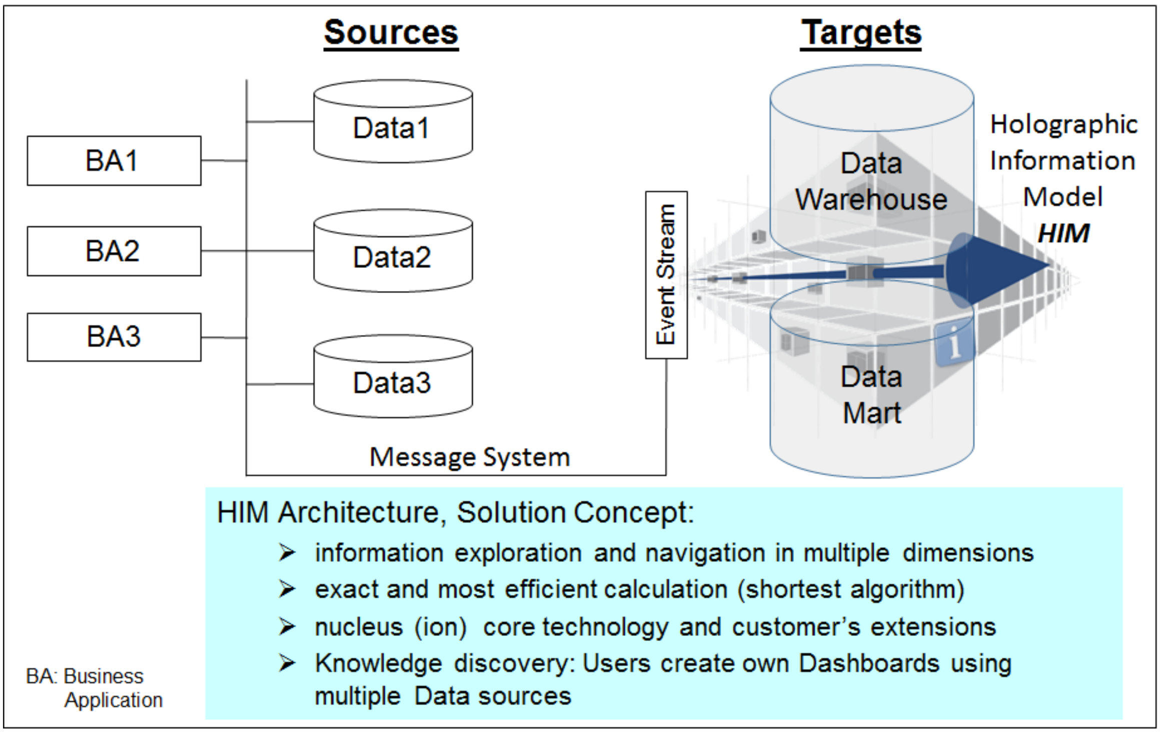


Figure 1.2: Overview of the Holistic Information Concept

Figure 1.1shows the ETL-Job-Centric perspective of state-of-the-art implementations. Complicate and load-intense ETL Batch Jobs are replaced by lean Event Stream Processing. Figure 1.2 gives the first impression, how the internal structure of the Holistic Information Model enables best algorithmic efficiency. The blue flash indicates, that any aggregation of information is done by simple summations, which are executable in highest parallelism, and for this reason optimal distributable on standard multi-cpu hardware systems.

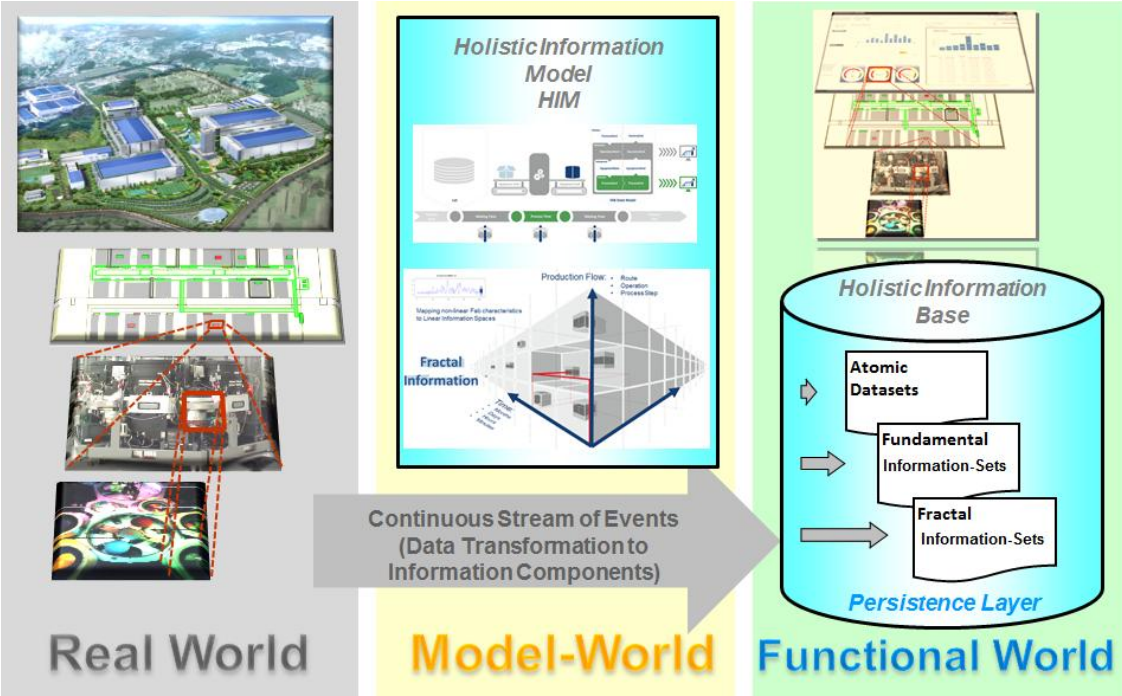


Figure 1.3: Holistic Information Model HIM, Data and Information Flow Overview: Data will be immediately stored (Atomic Datasets) and continuously transformed to Information Components (Fundamental Information-Sets, Fractal Information-Sets)

Figure 1.3 exemplifies from within a symbolic perspective, how any fab event gets immediately transformed to information. This is done via an immediate analysis of the continuous stream of events. Any movement of a machine, or a transport unit, a measurement process is on the one side created by the control units of those devices. On the other side those events are distributed on a fab-wide message bus, and any who has interest on such events can register itself for any of those events. This is the so-called “message-oriented production steer and control methodology”, which is a core concept in ITRS [1].

Semiconductor industry has traditionally played a lead role in setting up this technological approach.

It is of most interest for this study, to take advantage of this lead, and to further focus on a core concept which enables the capability to immediately transform any fab event into meaningful information.

2 Requirements for main real-time scenarios and functionalities

2.1 Overview and Objectives

Comprehensive production control systems which are capable to report and visualize the fab performance in real-time are still a vision for most existing fabs, especially in the 200mm area.

Baseline for overcoming this gap is to enable the factories to provide and process real time data for each atomic step in the value chain.

Besides smart software solutions for data processing, the fabs need to be empowered to provide this real-time data and corresponding events by appropriate solutions for equipment integration, manufacturing execution systems and hardware automation topics.

The objectives for the part “Real Time Factory Analysis and control” are visualized in the following figure and will be discussed in the next sub-chapters.

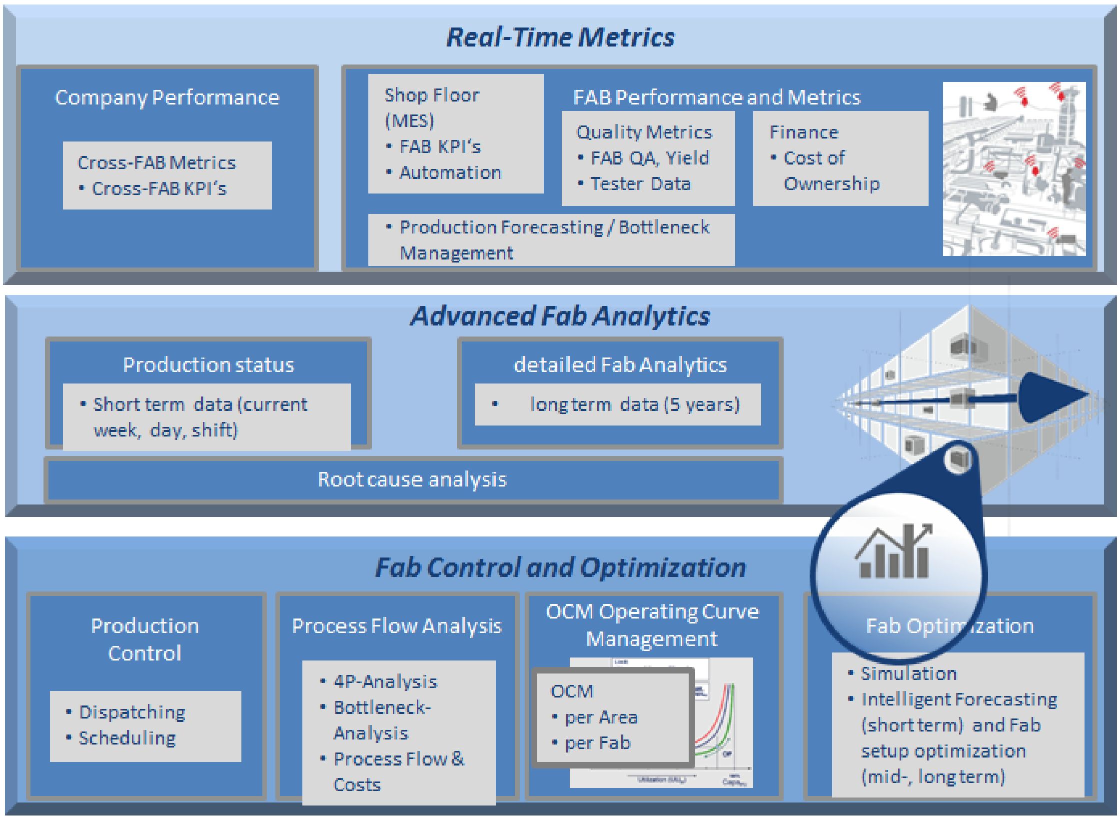


Figure 2.1: Objectives for Real Time Factory Analysis and control; Level 1: operational level -> Real-Time Metrics; Level 2: Engineering Level -> Advanced Fab Analytics; Level 3: Fab Optimization Level

Such kind of data might be available within the MES, or in other systems (such as automation systems). In state-of-the-art systems it is complicated or impossible to identify and extract the corresponding data sets at a belated time. This drawback hinders or disables the requirements to continuously monitor and improve the production value chain.

The main requirement is the introduction of smart IT systems for fab and pilot-line simulation, reporting and decision making that fulfil the real-time requirements and provide "Real-Time Fab Intelligence".

To summarize, the solution has to provide

- real-time capability in all its consequences,
- support complex and ad-hoc interrogation,
- and, finally, to enable continuous learning and knowledge discovery of the entire organisation, in order to be ready to face the future.

2.2 Business requirements for Future Smart Production in Real-Time

2.2.1 Operational Level

The state-of-the-art solutions offer reports for production figures (such as cycle time, flow factor, factory throughput), after certain periods have been finished. Shift reports are created, after the shift has ended. This paradigm has to be replaced by inherent real-time capability: any fab event should continuously update all those figures in real-time. Production bottlenecks have to be identified immediately, and not after a shift have ended. In next steps, such critical situations should become visible and highlighted in forecasts.

The basic requirement of this level is to store the necessary information for reporting, and to provide a functionality to continuously update the predefined reports in real-time. A real-time Transformation Process has to replace the classical ETL process (ETL: Extract, Transform & Load the data). All incoming data has to be stored, in order to enable root cause analysis

In order to enable this, those incoming datasets have to be immediately enriched and turned to information components. That is, the informational content and contribution of any event has to be immediately extracted and stored. Example: any lot movement has to update immediately the flow factor of the fab, etc.

Data as such does not hold any meaning (semantics). In order to turn data into information, any data needs to be embedded immediately in an information model, so that the data a) finds its correct place, and b) then becomes transformable according to the rules given by the information model. In classical architectures, this process took place in a belated time (not in real-time), by so-called ETL processes. Additionally, those ETL processes are complicated and error-prone batch jobs. They create peaks of load on the production system when they are executed. IT staff is often called in when those batch jobs – which usually run in the night shift – fail.

A solution has to be found how information can be created immediately with any fab event.

It must be possible to integrate a customized Fab Model (as explained in ITRS) into this immediate data transformation process.

This level has to concentrate on the replacement of classical reporting services by the core components of a real-time information system.

Target users of this level are production shifts and teams / team leaders.

2.2.2 Engineering Level

There is a huge amount of requirements and pressure on the production department to answer following kinds of questions. Those questions represent structural requirements to the new solutions, and are to be understood as examples. Not all those questions are, or only with huge amounts of effort answerable by state-of-the-art solutions:

- What is the current, detailed Flow Factor / Cycle Time / WIP distribution in Lithography and Backend Facilities during the performance problems this morning (drill down to lot / equipment events etc.)?
- What was and is the impact of this incident on the important fab figures, such as production cycle time, flow factor, delivery dates?
- What will this incident cost?
- How did the line behave in detail during last year‘s similar event?
- Show the detailed trend of Flow Factor, WIP distribution and Inline-Yield during the ramp of the new product, and highlight the margins covered by the new equipment; compare to last year’s ramp, and highlight the differences.
- Include detailed figures of cost center calculation and show the costs / benefit caused by the new equipment (show / calculate break-even). Include energy efficiency.
- Show forecast for bottleneck equipment for the next 3 shifts. Give an Ad-hoc analysis of all bottleneck equipment during the last fiscal year.
- Create an Ad-hoc Analysis showing Equipment-Non-Utilization due to preceding Bottleneck-Equipment.
- Provide a simplified creation tool for users, so that anybody can create her/his own charts – including automated warning limits.
- Make the information available on tablets, smartphones.

Target user groups of this level are production engineers, industrial engineering.

2.2.3 Production Optimization Level

Companies have to be competitive and manoeuvrable in a global world. The biggest challenge in order to face and facilitate the future is to be capable to continuously learn and discover new knowledge and capabilities.

Especially semiconductor manufacturers are pushing their own strategic requirements: “the more IC the more I see!”

It is reported already in international conferences, that within the next 10 years, formerly separated applications and applications domains need to work together (as reported in the introduction). It is one highlight of the ADMONT project that the WP6 project could contribute to this conference with an own speech and presentation [3].

Goals and details of the methodology and overall architecture have been presented and discussed on this important international conference. The goals and also the new mind-set of our new technical approach have been discussed and committed by the audience. Special focus has been given to the production optimization level. First of all, the systematics of our approach – covering the three level: operations, engineering, optimization – have been understood and their scopes have been committed.

For the production optimization level, the proposed solution concept gives plausible figures and arguments to support the following main requirements

1. Integrate and enable Operating Curve Management (OCM) in real-time
2. Integrate Fab simulation, so that the engineering process for simulation can be substantially simplified and streamlined for higher user-friendliness and user acceptance

3. Provide an architectural platform and methodology which enables simplified integratability of multiple applications with regard to a common informational model, including real-time capability

Ad 1): Operating Curve Management (OCM)

The OCM methodology is known in many production sites and industries. The goals of this methodology are commonly appreciated, but the current toolsets do not enable the required real-time capability.

Main requirement for the proposed architecture is to enable the required information functions in order to support Operating Curve management in real-time.

Ad 2) Integrate fab simulation

Many attempts have already been made to use fab simulation tools. The main requirements are:

- Simulate modified or new equipment setup / equipment positioning in cleanroom
- Simulate dispatching or other production scenarios
- Forecast production
- Simulate entire fabs with regard to fab planning, modification of fabs etc.

As of today, the engineering process is complex and complicated for the following reasons:

- It is difficult to extract the required data out of runtime-applications (usually, such application are always loaded and are not designed to extract amounts of data out of them)
- It is difficult to build a similar model as used in a productive environment (usually those models are not documented with the required details)
- It is difficult to design an architecture which is capable to enable fab simulation in real-time (usually simulation task are scheduled for specific points in time; for example a production forecast may be executed at midnight – it is not possible in a simple manner to start an ad-hoc simulation – but this is required when a real incident happens in a fab)

The main requirement is to create and design an architecture, which overcomes those limitations.

Ad 3) Integrated Information Model

The remaining document will explain the methodology and architecture to address this topic.

2.3 Outlook

Within the remaining project, a demonstrator will be developed out of already existing functional models, to proof feasibility and usability of the sketched architecture and solution concept, and to clarify further requirements and approaches.

3 The Holistic Information Model HIM

3.1 Overview and Objectives: Information Systems with lowest Complexity, and highest Informativeness, and deployable on standard hardware and software platforms

The vision of an integrated data collection and information processing system goes back to the 1990's, and SEMATECH is still maintaining its CIM Data Model. For different reasons the initial, very ambitious CIM concept failed, and was replaced by data collection and processing systems on defined functional scopes. Manufacturing Execution Systems (MES) addressed the functions and tasks between the ERP level and the equipment automation level, including functionalities like management of work in progress, equipment utilization, dispatch/scheduling, manufacturing job management and others.

Those different applications maintain their own data schemes. Consequently, data correlation and further creation of information out of different data sources shows a couple of challenges. Given this background it has even been mentioned, that data mining / warehousing has become an art (Faloutsos, [6]). Faloutsos already mentioned the need for good models, in order to reduce and control the cardinality of the data spaces. The Kolmogorov complexity is seen as the measure of the complexity of an algorithm. Faloutsos argues, that data mining is equivalent to data compression and Kolmogorov complexity, which is undecidable. The Kolmogorov complexity of a text, or other kind of data is the length of the shortest computer program (an algorithm) that produces the text or data as output. In the words of Faloutsos, data mining and data modeling will remain as an art, and does not have a logical or physical foundation. This conclusion is a direct outcome of today's widespread thinking and attitude in computer science, that "information" does not exist from within a physical perspective, and gets only conceptualized during the thought process of a recipient. This would indeed block and disable any endeavor to find and evaluate those architectures showing best margins from a physical perspective.

Contrary to this, the mathematician Yuri I. Manin shows that natural laws are the algorithms which reduce data spaces to algorithms with lowest Kolmogorov complexity (Manin, [7]).

The aim of this overview is to motivate a new approach and mind-set for the proposed architecture. The key element for this approach is a unified concept of "information". At first glance, this may sound a bit strange and overweening. However, we will explain step-by-step the logic and the need for this approach.

An ad-hoc comment could be formulated as followed: "All the deficiencies and requirements which have been written down are somehow known, and companies like Intel – as documented in [2] – may have already similar approaches." It is true that such requirements are, for example, also mentioned in the "Industry 4.0" approach [8].

However, the main point is that this approach must enable highest algorithmic efficiency, so that the required real-time capability of this new approach can be deployed on standard hardware and software platforms. It is known that companies like Intel use very big computing farms and sophisticated data distribution architectures, in order to achieve the reported functionalities in [2]. Target of the current approach is to be more efficient.

What is the key topic to address the issue of algorithmic efficiency?

The answer comes from the fact, that the concept of information is disambiguated and not used in a straightforward and efficient manner. However, this disadvantage will be overcome while using "information" with the same strictness as the concept of "physical laws". Then we will become capable of designing and handling applications within a sustainably improved architecture, and providing the required and inherent real-time capability at the same time.

Where does this disambiguation in the concept of information come from?

In the broader context of computer science, “information” is seen as a sensory input that has meaning for its receiver. When stored in computers, it is called “data”. When data is processed (including computing, data mining etc.), its output can be perceived as information. That is, “information” seems to appear only in the subjectiveness of a receiver.

Contrary to this, Claude Shannon, one of the founding fathers of information theory, wanted to measure the exact amount of information, which a certain message contains. This measure should be – at least to a certain degree – independent from the subjectiveness of the receiver of this message. He considered the number of answerable questions with yes/no as a fundamental measure of the information content of a message, or a structure. Hence, many questions are necessary to "scrutinize" a complex, unknown structure. In simpler systems such as a dice, if we want to inquire about one of the numbers on the rolled dice (given a 2 was thrown), the following strategy can, for example, be followed: 1st question: "is the number of points between/inclusive of 4 and 6?" Answer: no. 2nd question: "is the number of points between/inclusive of 1 and 2?" Answer: yes. 3rd question: "is it 1?" Answer: no. Now it is clear that it must have been a 2. Usually the logarithm of base 2 (with yes/no as so-called binary questions to be answered) is needed for questions about a system with n possible outcomes (for the dice, n = 6): $\log_2(6) = 2.58$ bit. But Shannon’s concept does not take into account any information about the system itself (in our case: the dice). We will keep Shannon’s idea how to measure all states of a system, but we need to add how physical information (or more complex information) can be taken into account as well.

We see two different usages of the concept of information: While Shannon and others try to measure and categorize “information” independent from its meaning to a receiver, computer science sees “information” linked to the meaning of data for a receiver:

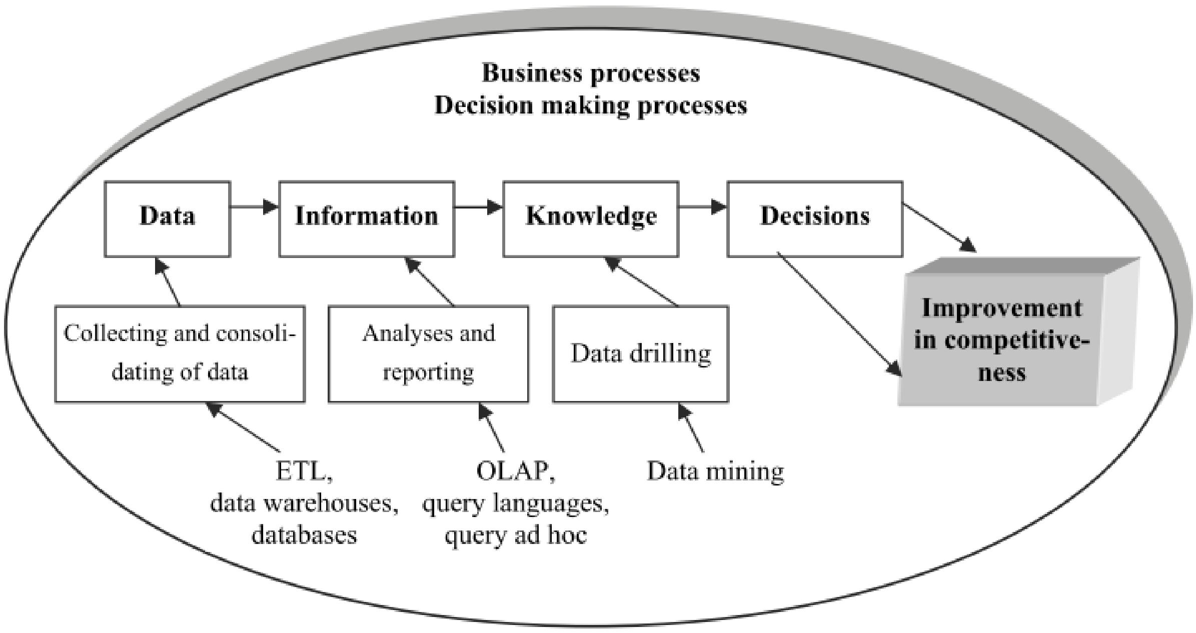


Figure 3.1: The concept of information as seen in computer science: data, when perceived by a receiver, may create information, which may be transformed to knowledge and to decisions (Olszak & Ziemba [9], Figure 2, p.137)

According to Gibson et al. [10], the role of business intelligence is to extract the information deemed central to the business and to present or manipulate that data into information: "Better information, better strategies, better tactics and decisions, and more efficient processes" ([10] pp. 296]. However, data volumes are exploding, and many additional applications and application domains are developed (for example in the IoT context).

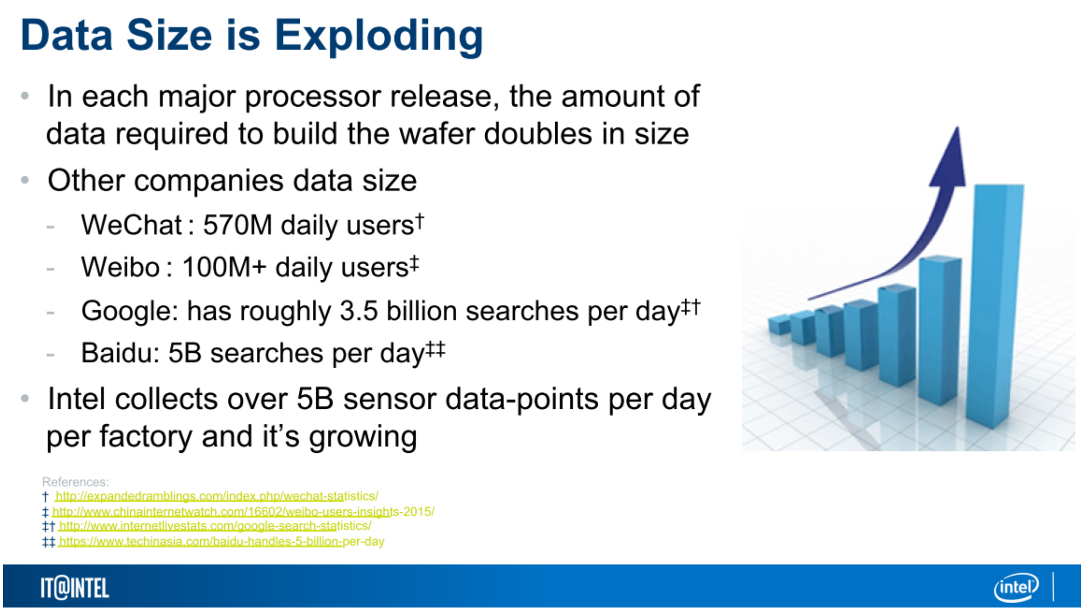


Figure 3.2: Exploding Data Volume (Chadwick [2])

Figure 3.2 is a well known picture, which represents the pros and cons of the nowadays exploding data volumes. More data does not a priori deliver more information. What is the crucial point in order to get this data managed? Data scientists know that good models help to reduce huge amounts of data, because all this data can easily be understood and created by applying the abstract information model to appropriate boundary conditions.

However, we all know that such models grow and evolve within the historical background of our companies. Many projects have been done in order to harmonize company data models. Practitioners know that those projects have often been only of limited success.

Which way helps out of this dilemma? Couldn't there be a more fundamental principle in order to not be drowned in "oceans of data" (D. Chadwick, Intel [2])?

We propose that "information" does not only appear as such in our minds, but is grounded on a more fundamental principle. This fundamental principle should enable to organize data in informational data spaces, so that such spaces are reduce to systems with lowest Kolmogorov complexity. It will be shown in detail that this is to be done by the core principle, how any data is interlinked to other data in the strictness of physical laws (including engineering modeling).

This enables also to invent and develop new information functions, which cannot be designed in systems based on state-of-the-art architecture. This new design enables a system-inherent real-time capability. The goal is to deliver a new quality of a real-time capable information system architecture.

Practitioners know that, for example, the data model of the OEE application maybe similar or related to the data model of the MES application. Also, the simulation model should be similar to those. But in detail the things differ, and interoperability is complicated.

What we want to do is to design a model which offers the strictness of physical laws, so that very advanced performance characteristics of the new architecture are achievable (in order to handle exploding data volumes with standard software and hardware systems, and to achieve the required real-time capability), and to simplify the interoperability of systems as well.

The objective of the next chapters is to lay down this principle, so that the key innovation can be derived out of it.

3.2 The Holistic Information Model HIM

3.2.1 Information is data plus most meaningful transformations

According to Manin [7], the most meaningful transformations are programs or algorithms providing systems of the lowest complexity, and highest informational content at the same time. The goal is to design computing systems in a manner, so that computer programs run as stable and efficient as natural laws. Additionally, shortest and most efficient programs are also those, which are most easy to understand.

Is “information” fundamental in such a physical sense?

Meanwhile, a couple of scientists are arguing that “information” may be a fundamental category in nature. The so called “holographic principle” holds that the universe has an unexpectedly limited capacity to store and process information. Any system, including living systems “create order”. The physicist John Archibald Wheeler proposes a participatory role of any observer of this world, even with regard to the emergence of physical laws [11]. To put it another way around: the universe is highly structured in a sense, that any movement, any transformation of bigger down to the smallest parts of the universe takes place in very restricted informational spaces. Chaotic behaviour is restricted to transformational phases between different dominant physical phase spaces. Life always creates order, and is capable to do so, because life continuously incorporates its environment (nurture, coordinated actions etc.).

The measure for the restrictedness of any such informational space is the Kolmogorov complexity, as we have already seen: any physical law is an exemplification of an informational space, whereas those laws are descriptions of the corresponding informational spaces with lowest Kolmogorov complexity.

The conclusion out of those preconditions is twofold: Information = Data + Transformation Rules, which interlink any data and create corresponding fundamental information:

a) <u>Information covers the laws / rules</u> how systems are transformed in a manner, that the descriptions (traces) of those transformations are reducible to a minimal complexity (the so-called Kolmogorov complexity). For example, the trace of a moving object in its simplest form contains the data of the starting coordinates, and the ending coordinates. Now, any information always comes out of the interlinkage of data entries. In order to retrieve this information, rules have to be given (physical rules, engineering rules). By applying such rules, the data can be interlinked. If the moving object is a freely falling ball, then the rule to apply is Newton’s law ($s = ½ g t^2$; s: distance, g: gravitational constant, t: time). If measures are taken, covering starting time / coordinates, and ending time / coordinates, those measures can be interlinked. It is easy to see that additional measures (maybe between start and end) can be interlinked as well. The physical model gives the information of how out of all those interlinkages many different types of information can be retrieved. For example, the median travelled distance between two measures (multiple movements assumed). Then, as the physical framework is given, the description of all movements can be reduced to the physical formula, and important statistical information can be calculated (standard deviation etc.). Those topics seem somehow trivial, but it is important to note that the application of the physical law guarantees best algorithmic efficiency, because it holds smallest Kolmogorov complexity. This needs to be considered with regards to the next steps.

b) Information covers the data of any kind of system behaviour, which has appeared (typically in traces of data); this may include possible future traces as well. The concept of information covers correspondingly the capability to extract or create out of the data traces of all elements aggregated physical descriptions of the behaviour and characteristics of those systems, of which the elements which have been traced are made of (example: the movements of all parts of a system together define the movement of the system itself).

The following example will guide step-by-step through this idea.

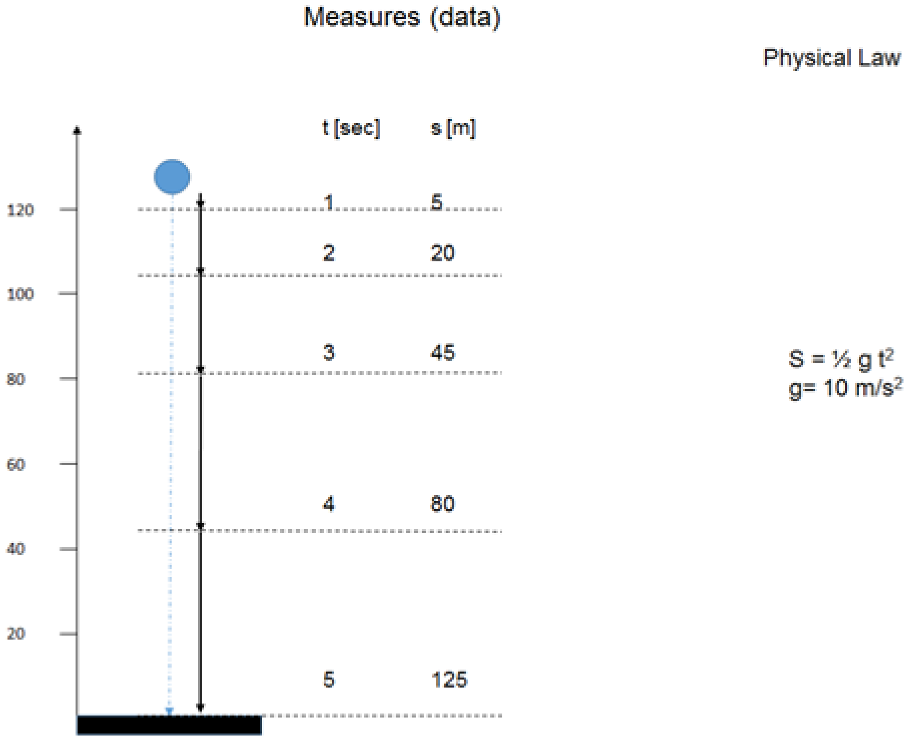


Figure 3.3: Physical law and Data

Figure 3.3 illustrates a blue ball which falls down the dotted line. The total distance is 125 meter. Measures are taken every second the ball is falling down. Touch-down is after 5 seconds. Now, if the physical formula is applied, any detail of the movement can also be calculated. When we take measures, the real values may differ from the ideal values.

In this case, all data values can be reduced to the simple physical law.

This model seems trivial, but it can be extended with regard to a complex production system. In order to envision this, we see the flight of the ball as the production process (the ball could fly through a specific atmosphere, or even through a fluid, and a specific interaction between the ball and its environment may represent the production process). Additionally, many balls, and of different size and material may fly through the production tunnel. Turbulences in the tunnel may occur (if the tunnel is filled with a fluid, and the fluid partially streams upward, then a ball may also fly partially upward).

The production process has now to control and to monitor the movements of all balls in real-time. The next figures show how this can be done in a strict physical sense.

3.2.2 Fundamental and Fractal Information: lowest Kolmogorov complexity and lowest algorithmic complexity enabled by the Principle of Holistic Information

The next step is to figure out how the formula "Information = Data plus meaningful Transformations" can be mapped to and exploited for engineering science / production systems. To achieve this, we rely on the classical system approach: systems are made of components or elements, which are structurally coupled. If we conceptualize those couplings, then we will interlink all data entries, enabling descriptions of minimal complexity.

Given the initial conditions of a certain system (including boundary conditions), then only a very limited set of structurally coupled data will create the trace of the system. If a system moves in a certain direction, then all its parts move in a structurally coupled manner. For the example of the ball, all elements of the ball are tight together. Additionally, the ball might rotate as well. The goal is to structure the data so that the information which represents any kind of movement or other desired information can be aggregated in the simplest manner (shortest algorithm) out of those data sets. Two different phenomena need to be considered:

1. Information about states of physical systems (static aspect): The ball finds itself on different locations, depending on the time it is under way. If we now inspect the system for a certain time, the information about the distance which the ball has flown can directly be written down. We call this information "Fundamental Information". On the other side, it is also possible to drill down to the exact staring point and ending of this specific flight. We call this date "Atomic Data". *Fundamental Information is the link between all Atomic Data.* Another example might be a magnet, which emits a magnetic field. Now, the magnetic force of any point in the space, which creates the environment of the magnet, can directly be calculated. The information for this point can directly be written down. It is also possible to calculate magnetic forces for more complex elements, for example a surface. The calculation is simple: a summation of all values of all points, which create this surface.

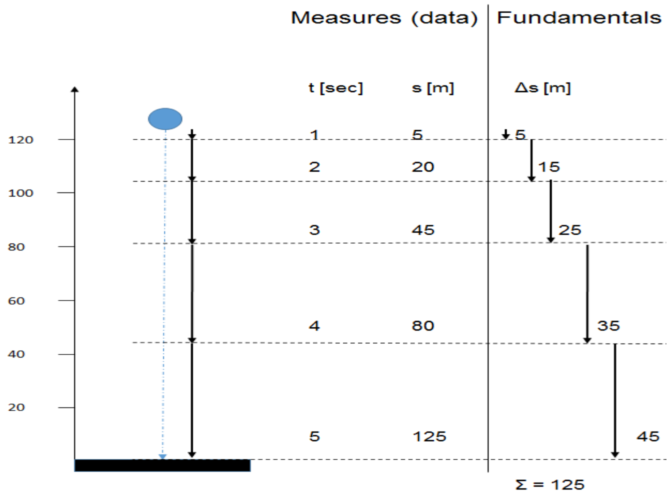


Figure 3.4: Fundamental Information; those fundamentals interlink the data (the measures)

Figure 3.4 shows examples of "fundamental information". Each fundamental represents the distance which the ball has flown during 1 second. Other, different time measures are also possible. The granularity depends on the required accuracy of the information system.

However, with this simple example we can already explain the production cycle time of products. It is the sum of all fundamentals (in this example the value of each time fundamental is 1 sec). Another fundamental is the flown distance. Here, the values of the fundamentals differ.

A next requirement could be – with regard to the characteristics of a production system – to measure how the material is distributed over the production line. We want to know how long the material remains in similar part of the production line (let's say in parts of similar length). We know already that the speed of the balls increase, and that the balls will remain longer time in the upper part of the tube. Therefore, it is important to retrieve this kind of information, in order to design the production line adequately (for example including room for stocking etc.).

2. Information about dynamic state changes and transformations of physical systems (dynamic aspect): We have to divide the system into adequate parts (e.g. parts of similar importance). Then we measure how long the balls remain in the different areas. We may also calculate statistical values (for example the median, the standard deviation, other statistical values). It can be shown that if we want to evaluate a specific time period (a specific sample size), then the concept of summation holds in the same manner. Based on Manin's idea, it becomes clear that this is the most simples way to calculate any more aggregated information. Because scenarios can be nested into each other, we call this information "Fractal Information".

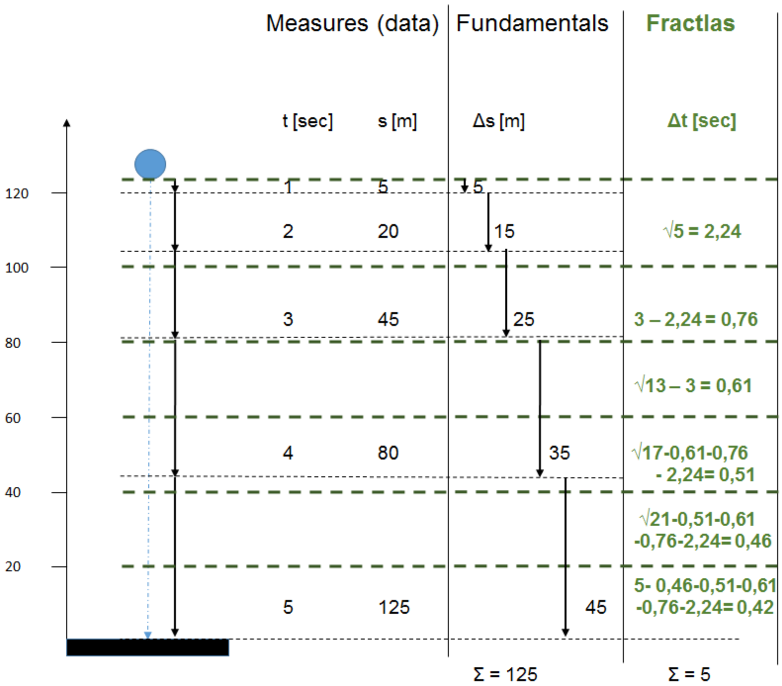


Figure 3.5: Fractal Information; those fractals interlink the data (measures) as well

The path of the ball has been divided into 6 fractals, each of them representing a certain part of the path (the production line, or tube). The upper one holds the size of 25 meters, the other 20 meters each (one could also have chosen identical lengths). In the column "Fractals" the time length of being in this element is noted. The upper one holds the value 2,24 sec, the last one holds the value 0,42 sec. We see now in a glance, how the material is distributed over the production line. (Rem.: in this Figure, Fractals have been calculated; this calculation has only been done in order to give the reader an idea about those numbers; in real systems all or most of those numbers will be measured).

The important topic is now that values from many balls can be super positioned in the simplest manner: the values just need to be summed up (of course, we might take into account, if different balls had different starting times: but this is just another summand).

This concept covers also complex, non-linear physical scenarios, like waves, swirls or bottlenecks. If we maintain the relationship between the different information types (atomic data, fundamentals, fractals), then any kind of root-cause analysis is always possible.

What does that mean in terms of the physical framework?

SYSTEMA has already conducted an analysis of the mathematical structure describing how information is derived from these scenarios. This study has concluded that if the systems are described in terms of a decompositional system model (as introduced by Wand / Weber [5]), then an informational model as described by fundamental and fractal information creates linear spaces. That is, the superposition principle holds.

A physical law, or an engineering law (as based on systems theory, including the model of Wand / Weber) is a statement abstracted (or inferred) from particular facts (and corresponding data), which can be applied to a class of phenomena, so that a particular phenomenon (fact) always occurs if certain conditions be present. Those laws are descriptions of regularities in the behaviour of real systems.

To bring it into the perspective of *information:* There are only two different perspectives within any physical or engineering scenario:

a) *The perspective of an object in its environment:* those are in our example the blue balls. In physics and engineering, such objects are atoms, atomic structures, fluids, mechanical systems etc. This perspective is covered by *Fundamentals*.
b) *The perspective of an environment, covering certain objects:* such environments are for example geometric or any somewhat physical volume or in general any kind of space-time conglomerate. This perspective is covered by *Fractals*.
c) Now, any kind of *information* can be composed through any desired combination (superposition) of Fundamentals and Fractals.

The superposition principle states that for all linear systems, the net response at a given place and time caused by two or more stimuli is the sum of the responses which would have been caused by each stimulus individually [12]. So that if input A produces response X and input B produces response Y then input (A + B) produces response (X + Y).

The homogeneity and additivity properties together are called the superposition principle. A linear function is one that satisfies the properties of superposition. It is defined as

$F(x_1 + x_2) = F(x_1) + F(x_2)$ Additivity

$F(\alpha x) = \alpha F(x)$ Homogeneity
for scalar α.

Within the context of this study, Fundamentals and Fractals are to be taken as parameter x.

This principle has many applications in physics and engineering because many physical / engineering systems can be modelled as linear systems. And now we can apply this principle in a most advantageous manner for the concept of fundamental and fractal information.

The physicist Richard Feynman has pointed to a next fact. He is arguing for the fundamental status of quantum mechanics. He is arguing that the entire universe can be described by base vectors. The required equations are creating linear spaces as well (Feynman, 2005 [17]). What he is intending to say is that all natural phenomena are holding the form of a linear space. Any nonlinear system behaviour appears on the macroscopic physical level. See the theory of weather, which is based on a deterministic multipart system.

Weather reports are becoming of better and better quality by transforming the required equations into strictly linear computer programs.

However, non-linear effects have already been studied in production science [26]. A simple example is the degree of filling of a subsequent buffer. If this buffer tends to be full, this might hinder the previous process step to send material to this subsequent process step. From the systems model perspective this establishes a non-linearity.

Scholz-Reiter mentions that within production systems, macroscopic measures like mean cycle time, work-in-progress (wip) and others can easily be calculated. However, he claims that – because of the huge amounts of data – for each object not all the corresponding locations or state changes can be tracked. But this is exactly what will be achieved with the holistic information model. Any microscopic, that is atomic data is well maintained and serves as linked object for drill down, and root cause analysis.

Therefore, it has to be highlighted, that from the perspective of the holistic information system non-linear behaviour can be studied in all detail, while the HIM concept preserves its grounding linear structure, including all its advantages for detailed studies.

This approach summarizes in the following *Principle of Holistic Information:*

- If physical and/or engineering descriptions of systems hold the superposition principle (which is in principle true for any physical system, but which is especially true for all figures used in production methodology and in operations research), then any kind of *compositional information* (such as aggregates, statistical numbers) can be created through direct combination (summation) of the corresponding information components (fundamentals, fractals).
- The linearity (including the superposition principle) of this structure enables lowest algorithmic complexity.

At first, we have to bear in mind that we are speaking of an *information system*. Even if underlying systems expose nonlinear behaviour, then never the less the system behaviour is captured by a trace of data. An object moving though a non-linear turbulence leaves a linearly ordered trace, showing fundamentals and fractals. Now, further analysis can be done based on those fundamentals and fractals.

The cycle time of a product is the sum of all the fundamentals representing the time of each production step. The cycle time of a group of products is the sum of all the fundamentals representing the time of each production step of all those products. The cycle time of a specific product route (part of the production process) is the sum of all the fundamentals representing the time of each production step in this route.

The OEE factor (Overall Equipment Effectiveness) is a multiplication of three sums:

OEE = Availability * Performance * Quality

The multiplicands Availability and Performance can directly be retrieved out of sums of specific equipment states. “Quality” might refer to measures. Those measures can also be mapped to linear spaces, but are not in scope of this project phase.

To summarize, the linearity of the aforementioned information spaces offer very important and advantageous properties, because any data component can be processed independently and enables the desired best algorithmic efficiency of the overall system. As an example, different fundamentals and fractals can be summed, and the corresponding information can be retrieved immediately (this is an example for an ad-hoc interrogation).

For this reason, any further information on such data components – all performance indicators, KPIs and the like are calculated based on such singular atomic information components (fundamentals, fractals) – can be calculated in real-time. The decompositional base system model is consistently defining linear information spaces, without loss of information, and preserving the capability of integrating such information across the whole business / industrial process, including financial processes, and the like as well. The concept of hierarchical system decomposition includes the capability of chaining and hierarchically nesting such base systems, while preserving the linearity of the informational spaces.

There are three main theoretical and methodological points which are hindering state-of-the-art solutions to conceptualize information systems showing best algorithmic efficiency, and real-time capability as outlined above:

1. One main field of application is the calculation of key performance indicators, in order to characterize and steer production lines. Methodologies are developed in operations research. A Key Performance Indicator (KPI) is a measure of performance, commonly used to help an organization define and evaluate how successful it is, typically in terms of making progress towards its long-term organizational goals (Rafal Los, [14]). In the tradition of operations research, KPI's are always calculated after the period of interest has ended. "Within Business Intelligence (BI) systems, an industrial Key Performance Indicator (KPI) is a measurement of how well the industrial process (i.e. an operational activity that is critical for the current and future success of that organization) performs within the organization." (Peng, 2008 [15])
2. Those methodologies are related to mathematical and statistical analytics. It is important to understand that statistical evaluations are always related to periods of evaluation (samples). Important figures like standard deviation require the sample size as input, and are usually calculated after the period has finished.
3. However, a couple of attempts have been made to support real-time data aggregation in different application domains. Nevertheless, all those attempts are restricted to single application domains, and are of restricted performance and flexibility (see following Patents: [16]). As outlined in chapter 2, further aggregation on corporate business level of different data sources are required, generating an ever growing amount of aggregation processes in order to support the managerial decision process and numerous other business related activities from / within a highly integrative, flexible and performant perspective. Such summarized and compressed data are typically calculated through aggregation mechanisms provided by Data Warehouse architectures and systems. Such data may be aggregated automatically for example based on timely scheduled aggregation jobs. Additionally, there is a growing demand for ad-hoc requested creation of further information, and real-time aggregation (Knowledge Discovery).

Now it is important to see and understand that within the scope of points 1., 2., 3., and also based on the understanding that the physical and engineering processes to be modelled are complex and often expose non-linear characteristics, the underlying informational field in terms of fundamental and fractal information holds, physically, a strictly linear structure.

That is, if we apply basic and known physical principles to the field of information systems, then the algorithmic complexity of such systems will be reduced systematically. The precondition is that data in form of atomic data is available, and that fundamental and fractal information can be generated immediately out of any new atomic event. But all this is true for manufacturing, because we are relying on an event based manufacturing philosophy.

On the other side we have to bear in mind that as of today, each application (like OEE, APC, Finance, MES) is keeping its own data structure.

That is, “fundamental information-sets” and ”fractal information-sets” are not foreseen in state-of-the-art Information systems. Figures like OEE or cycle time are always calculated after the corresponding time period has ended. But it is even more significant that all requirements as outlined in chapter 2 – because of the linearity of the information – can be most advantageously calculated with fundamentals and fractals.

And even more important, functionalities like real-time forecasting or real-time OCM are not at all possible using standard methodologies and technologies.

Any corresponding system model in all the different domains and applications must incorporate the structure of the decompositional system model, as defined above. That is, because of the compositional characteristics, any parameter or data component, which describes the behaviour of subsystems on the lowest level of granularity, can be grouped and aggregated with corresponding parameters using historical records, and within the mathematical concept of linear information spaces. The decompositional system model preserves the linearity of the overall model, and defines the corresponding linear relations of the historical records.

To summarize, if we use information described in the physical framework above, and calculate more complex information out of atomic data (fundamental and fractal information), then we will create a system which enables most efficient algorithms , or – put it another way around – smallest Kolmogorov complexity. This is the major precondition in order to create most efficient computing architectures. It is a holistic concept, in the following sense. Usually, a hologram is a recording of a light field, instead of an image formed by a lens. The term “hologram” roots back to the Greek words for “whole” and “drawing”. A hologram is a “drawing” which can be viewed from different angles, and showing the respective information of the original object. A lot of research has been done with this light-field-technology. However, there is another, straightforward physical mirror system which clearly shows the concept of a hologram, and which serves us as a basis to illustrate the holistic information model.

This physical system is made of a double parabolic mirror to create real 3D hologram in space. The system uses two opposed concave parabolic mirrors which are placed on top of each other to create a holographic space. The mirrors are concaved in such a way that the reflection of the image floats above the actual image:

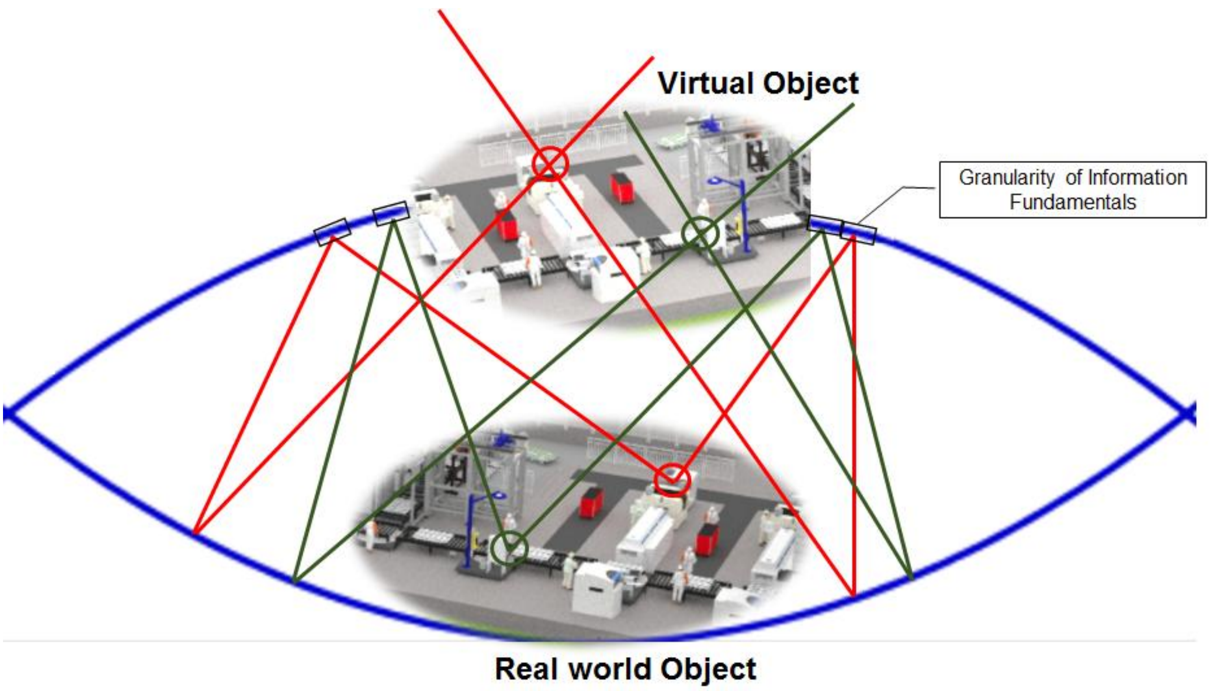


Figure 3.6: Mirror system made of concave mirrors (blue lines). The real world Object is reflected, and a virtual object appears (which is less bright, and of inverse orientation).

More than one virtual objects may appear, depending on the distance between the bottom and top mirror. However, the objects fade in relation to the distance of the two mirrors. The bigger the distance, the vaguer the virtual object. Nevertheless, the precision of the mirror determines the quality of the virtual object. In Fig. 3.6 the black boxes may represent the granularity of the system. Best information can only be achieved if the shape of the mirrors (blue lines) are full covered by mirror elements. Any mirror element creates fundamental information in the above mentioned sense.

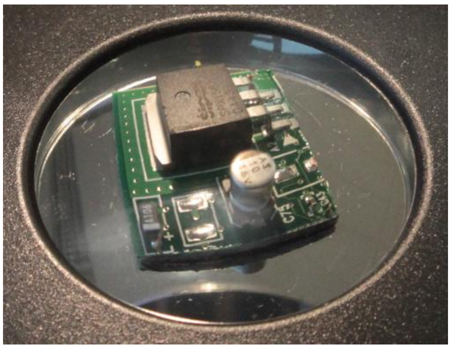
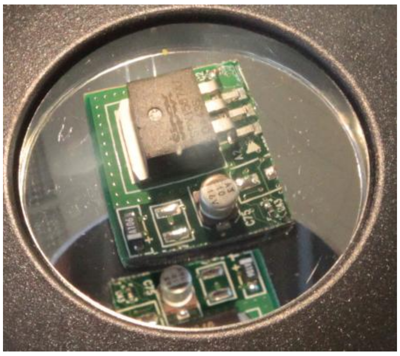



Figure 3.7: 3D image of a technical object (left); the original object can be partly seen under the 3D image (right) – it is placed on the bottom in the mirror system (inverse orientation)

A detailed example and basic setup of the usage of this concept in the context of the ADMONT project will be given in the next chapters.

3.2.3 Three Basic Architectural Principles to design HIM

The key idea of the HIM concept is that complex system behaviour like those of complex production systems can be most efficiently analysed, if we use a base engineering concept in addition to “physical laws”. This is the concept of a system state model, as already outlined by Wand / Weber 1995 [5]. They use the term “deep structure characteristics of an information system”, which manifest the meaning of the real-world system that the information system is intended to model. “For example, the rules embodied in an accounting system that indicate how transactions are to be posted to ledgers are deep-structure characteristics.” ([5] pp. 62). In our approach we are considering models of production systems as the deep structure of the information system. Accounting information or monetary information is included as well (for example, an information about the costs of the usage of an equipment over a certain time). Wand / Weber then propose a working premise, which defines an information system as a state-tracking mechanism for the real-world system it is intended to model. Such state models are of huge interest for engineering science. They are widely used in production science as well, including ITRS. A popular example is OEE: the measure of overall equipment efficiency. Additionally, the software to steer and control production units (from single machines up to an entire production site) is designed by using the state machine concept.

The application of this approach to the HIM concept is straightforward: Systems are conceptualized by state models, whereas each state is an aggregate of a number of a more detailed physical (chemical, electrical etc.) states. Each state conceptualizes a “field of control”, which needs to be monitored and steered. Then, when specific events occur, the state of the system may change. In our approach it is of interest to include also primary, detailed system sates, in order to support root cause analysis (for example the temperature and its change of a certain device). Given this physical grounding, we map the more abstract system model from Wand / Weber to physical phase spaces. Examples are locations of different materials, their main physical/chemical characteristics (including definition of how to measure those characteristics), target values etc. Given this approach, we can be sure that any complex system behaviour is decomposable into underlying, fundamental information. Or the other way around: any desired more complex information can be composed out of aggregates of most simple fundamental information.

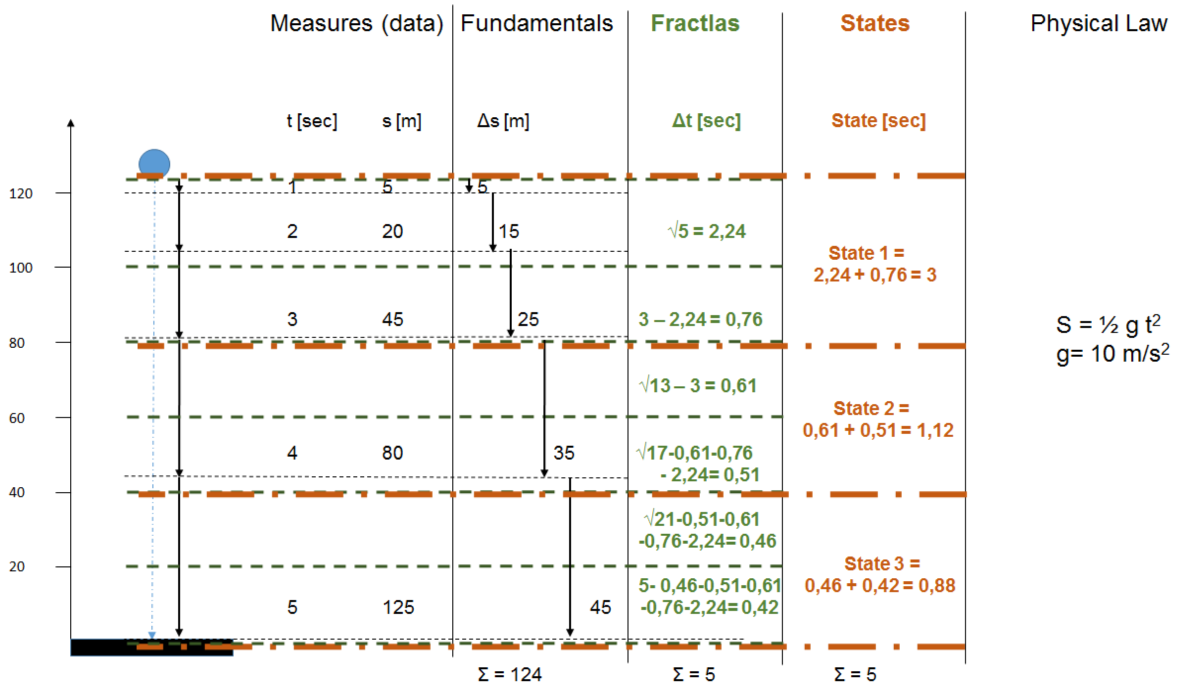


Figure 3.8: Mapping of the physical model to an engineering model by the concept of system states

Figure 3.8 shows one possibility to implement the relationship between the physical and the engineering abstraction level of the description of a system. In this example it is assumed that a number of fractals map to a specific system state. For example, if a ball finds itself in the upper and one further down fractal, the ball has the attribute “state 1”. And so on. Then following information can be created: How many balls are in “state 1” at this time? How many have been in “state 3”, last Friday 5:15 pm? The main point is that based and fundamental and fractal information, all requirements as outlined in chapter 2 can be answered. A couple of interesting examples will be given in the next chapter.

Summary of the Holistic Information Model:

a) Holistic information components (atomic, fundamental, fractal information): incoming atomic data gets immediately transformed into fundamental and fractal information.

b) Holistic aggregation: Manage a deep-structured information model, which incorporates the capability to get continuously actualized and updated. Local events, such as a termination of a lot, may immediately update global performance measures, such as cycle time, delivery ratio etc.

c) Holistic computing: Best mapping of information processing to standard hardware and software architecture through best algorithmic efficiency (maximal parallelization, minimal runtime, best usage of system resources).

Based on the linear information spaces, functional scenarios and data processing mechanisms will become directly mappable to computerized data views, materialised data views or other efficient data management capabilities. This enables best algorithmic efficiency and all elements together create the key innovation of the current research.

The synergism of modern, multi-cpu based computing algorithms together with the set-theoretical approach in database systems, and their corresponding programmability enables a computing methodology, which exposes best algorithmic efficiency. In order to achieve this, we need to derive principles of how to use atomic, fundamental, and fractal information.

1. Principle of transactional closure: system traces need to be immediately stored and coupled with corresponding partial state transformations (atomic, fundamental, fractal information).
2. Principle of superpositioning: any information can be created through simple aggregation (superpositioning) of those partial state change transformation,
3. Principle of Parallel Execution: any aggregation process can be executed by any desired combination of all information components. This enables best distributability of simplest computing tasks (mostly simple summations) on computing systems.

Those principles enable that data can be continuously transformed into information on standard, multi-cpu based computing platforms in the most efficient manner (best algorithmic efficiency).

The physicist Richard Feynman investigated in parallel processing, in reversible computing and he predicted modern Nano technology. He also saw, that nature holds the capability of computing [17][18]. His example was a magnet. The magnetic force (as a physical law) causes a specific field. The structure and force of this field is calculated by this physical law, continuously and in parallel, for any point in space. Fundamental Information covers a picture-in-time of the magnet. Fractal information covers the dynamic aspect, including induction of electrical current etc., within a given volume. Another pioneer in this area is Konrad Zuse, who developed a similar concept named “calculating space” [18].

To summarize, the Holistic Information Concept has been designed in front of the background of a physical conceptualization of information. Information is equal to “data” plus the “interlinkage of data”. The power of this concept has been measured in some detail. State-of-the-art technologies do not cover fundamental and fractal information components. As a consequence, queries delivering identical results may take 100 to 1000 times longer, or even more.

The next chapter will give a more detailed example with regard to a real-time capable production information system and architecture.

3.3 Basic Model for Production Methodology

An entry-point to the multi-level deep structure of the information system, Basic Atomic-Datasets are defined; the first level of the deep structure of the system model. A major characteristic of the structure of basic data sets is its linearity, holding an isomorphic relationship to the underlying production model, and guaranteeing and enabling at the same time the linearity of the Information Framework. New sets of data – as for example using ad-hoc queries – can be created on this level. For this reason – through a guaranteed overall linear system structure – the creation of new and relevant information in a most advantageous manner. On a succeeding level of the deep structure of the information system, such basic atomic-datasets are used as input data in order to create / update fundamental information-sets, second level of the deep structure of the system model. The corresponding data will be automatically processed and stored in fractal information-sets; third level of the deep structure of the system model.

To sum up, two main functionalities are enabled: a) automated and real-time, continuous processing of predefined key performance indicators (KPI's); and b) required interfaces in order to create ad-hoc required information directly with regard to immediate request of the user, also with regard for further knowledge discovery in databases.

While fundamental datasets cover finest granular information with regard to types of events (for example duration of single processes), the fractal datasets cover information with regard to an overall time grid. For a typical configuration, such fractals may cover information with regard to a time grid of 1 hour. Consequently, key performance indicators such as cycle time or throughput are continuously aggregated with regard to this time grid. This includes also further statistical characterization, such as standard deviation etc. Fractals may be composed out of other components, and may be grouped in hierarchical levels. Fractal production principles have been introduced by H.-J. Warnecke already in 1993, and are now regaining importance with regard to the initiative “Industrie 4.0” [23][24]

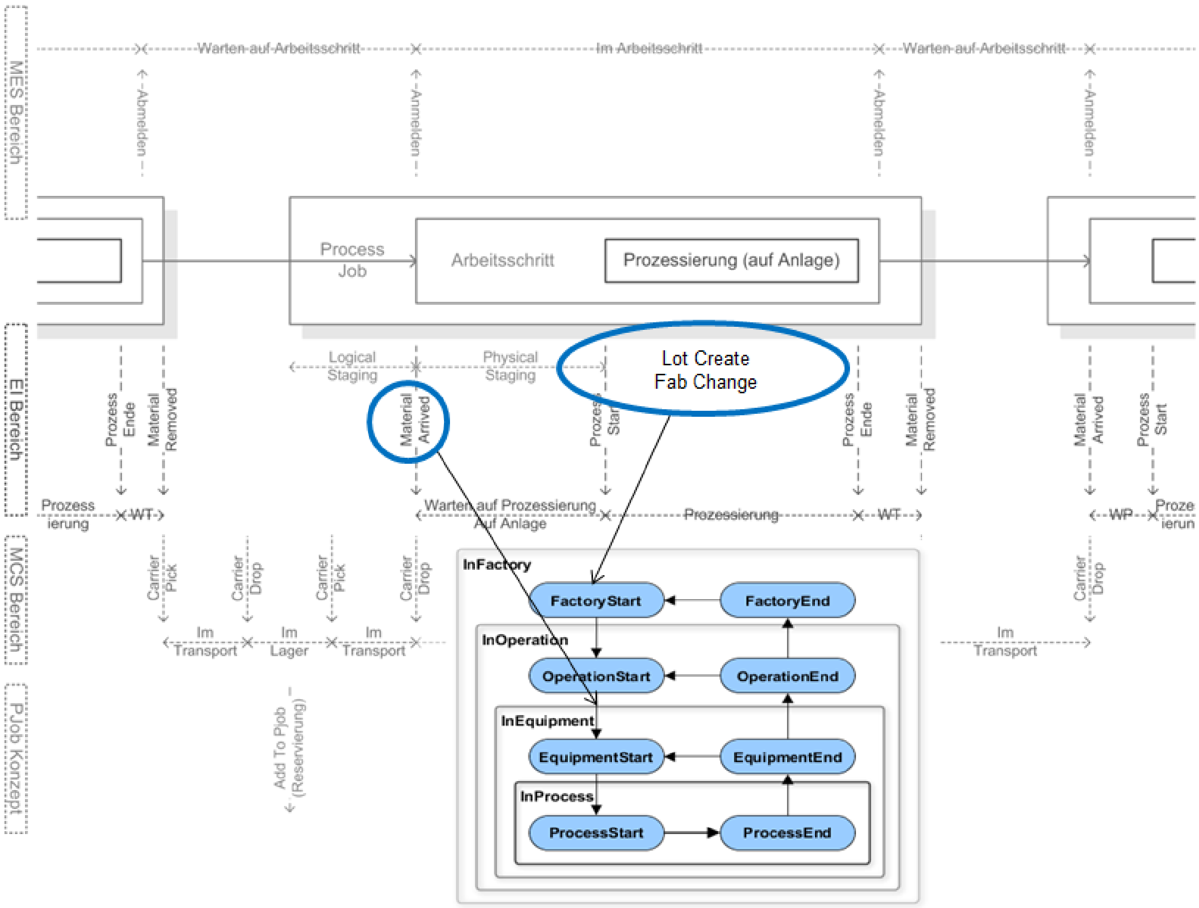


Figure 3.9: Mapping of production events to a normalized fab state model

Figure 3.9 shows an example how fab production events are mapped to a normalized fab state model. The first example (blue circle: “Material Approved”) represents an event indicating that a wafer cassette has successfully been read, and its content approved via the fab control system.

The next Figure 3.10 shows an example, where Fractal information is used in order to continuously update predefined reports. If for example a shift report exposes the throughput of certain products, then the corresponding figures can be continuously aggregated.

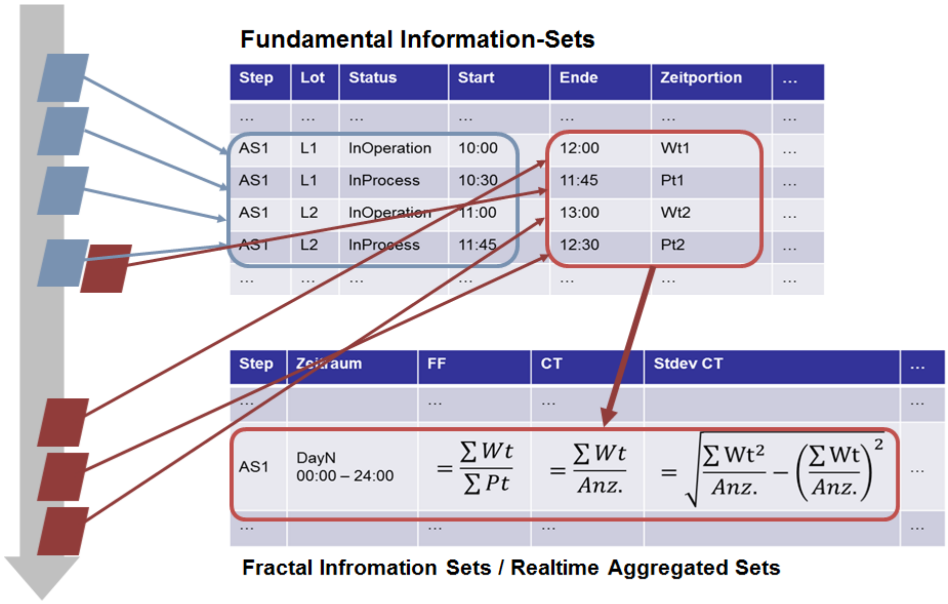


Figure 3.10: Basic production model: informational structures

Figure 3.10 shows on the left side events coming from the fab. Those events are used to immediately update fundamental and fractal information. In this example the fractal information set has been extended to a predefined report, which gets continuously updated in a real-time aggregated dataset.

3.4 Basic System Architecture

3.4.1 System Architecture of the Real-time Information System

In state-of-the-art solutions, the same information is accessed multiple times during the conventional ETL and aggregation steps. In particular, these systems first transform and store operational data and then re-access the data during the aggregation processes, and finally calculate performance indicators [22]. Each of these steps causes corresponding CPU-load, I/O-load and communication effort – systems are known for their error-prone behavior [21].

For this reason prior art systems hinder Real-Time aggregation because data extraction and further transformation and aggregation processes are holding a sequentialised, non-parallel structure, which conflicts with the goal of parallel-processed Real-Time Data Warehousing.
The basic conflict arises from the problem that in prior art systems the aggregation procedures which are required to calculate the KPIs are started in batch mode. This barrier still exists even if the refresh and updating cycles are minimized or redesigned to run incrementally. Data Warehouse updates cannot be executed anymore during off-peak hours. Some authors argue that update anomalies may arise when base tables are affected by updates that have not been captured by the incremental loading process [25]. The next incremental load could, but must not necessarily resolve such anomalies. Similar anomalies may arise for deletes and inserts. As a consequence ETL jobs have to be modified and extended in order to prevent such anomalies and to approach at least a Real-Time characteristics of the system.

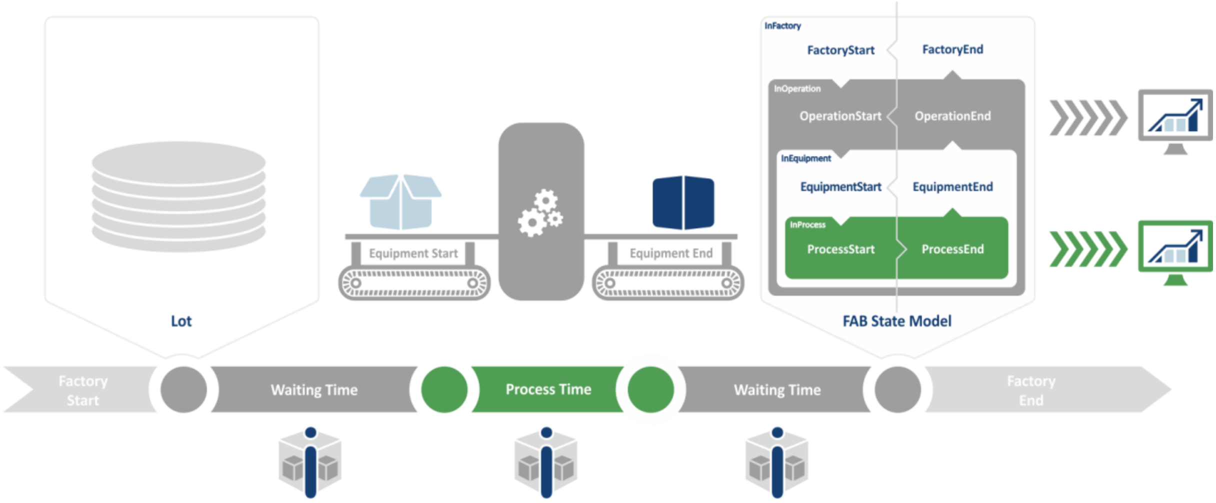


Figure 3.11: Mapping of Production Model to System State Model

Figure 3.11 shows how any fab event gets mapped to a corresponding system state / system state change. In the example the information about the waiting time of certain productive material gets collected and immediately stored. The material itself holds the state “Waiting”. Then, the material gets processed. During this time, the material holds the state “inProcess”. Then, the material is waiting again, or gets transported, all information as outlined in chapter 3.3. gets continuously stored.

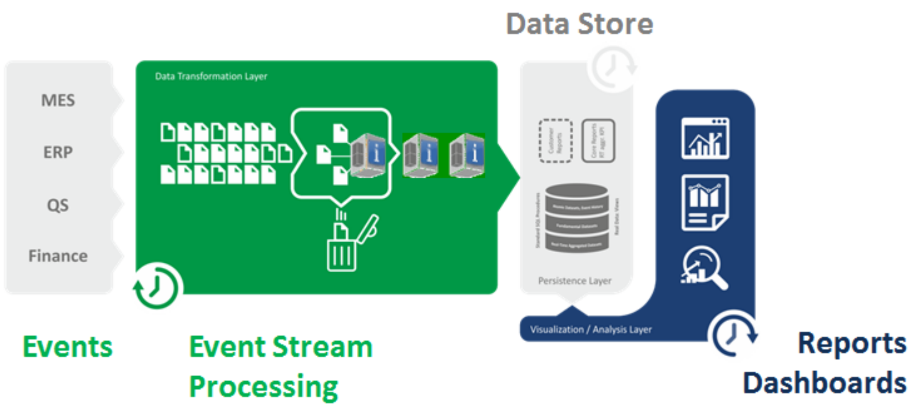


Figure 3.12: Continuous processing of all fab events’ transformation to information components

Figure 3.12 relies to Figure 1.2 and Figure 3.11. While each event gets immediately processed and mapped to the production model, inconsistencies will immediately become known. For example, if an event triggers the event “transport start”, this event should not occur before an event “process end”. It may happen for example that the “process end” event is missing (maybe due to an update of the automation software). If the system now receives the signal “transport start”, then an error can be reported immediately. In some cases it might also be tolerated, that the “process end” event is missing. Then, a warning will be reported, and the process continues.

To summarize, this concept enable another approach to engineer the entire production system: any deviation from the production model gets immediately known, and can be eliminated immediately. In ETL-based systems this is not possible!

Within a first functional pattern, the load capacity of the new solution has been evaluated and compared with a prior-art-solution. The next Figure 3.13 visualizes the advantages of the new solution. This indicates also, that the architecture of the target production system will change. Classical solutions require special hardware, where information is typically processed in batches. The new solution does not require any more batch concepts, because information gets continuously processed.

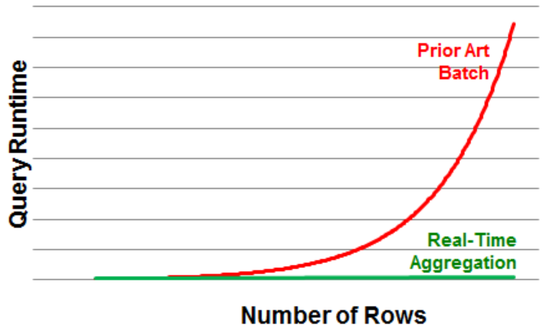


Figure 3.13: Real-time vs. batch aggregation performance

Figure 3.13 shows an aggregation run over 10.000 data sets. The classical, batch-oriented solution (red color) requires 900 sec. runtime. The Real-Time aggregated solution requires 8 sec. runtime. This indicates a runtime reduction of factor hundred.

The main topic and key innovation of this concept of information is, that it enables to overcome the dilemma of being drowned in oceans of data by design of a corresponding architecture. While the algorithmic complexity grows for state-of-the-art systems within a quadratic relationship, the holistic information model enables minimal algorithmic complexity, and only linear growth usage of resources and query runtime.

3.4.2 Overview of an Integrated Information System

Any data which characterizes the business and production processes can already be created and extracted out of any single fab event during current execution time (and will be stored in fundamental and fractal information components. This leads to following new system architecture; please note that the BI-level is now integrated into the communication infrastructure (via the messaging service).

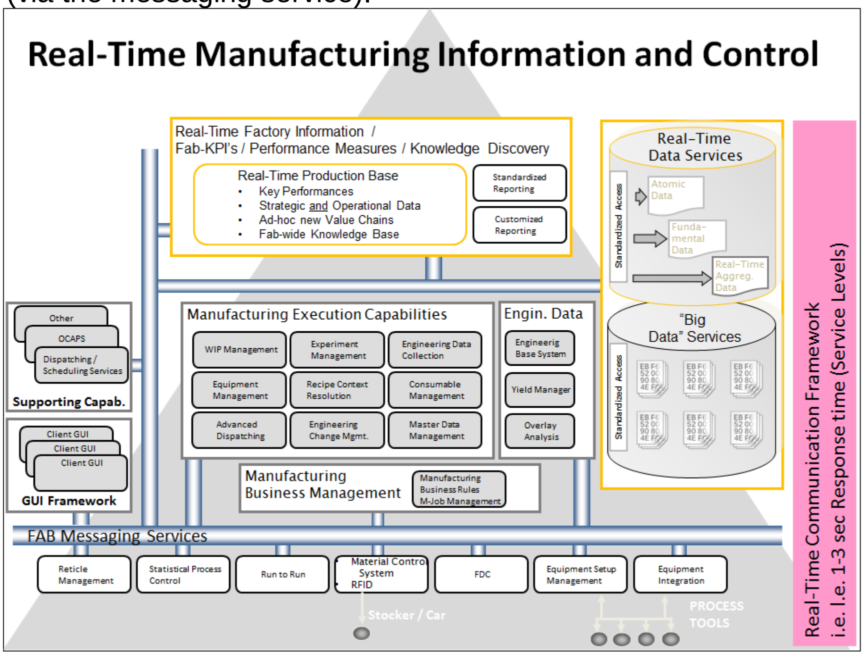


Figure 3.14: Anticipated overall Fab IT Architecture

Figure 3.14 shows an overall information system architecture, which incorporates the real-time information system (yellow boxes).
The new solution will cover suitable interfaces for data mining functionalities. In contrast to existing solutions, the anticipated new technology will provide new insights, because data mining tools will most advantageously utilize fundamental and fractal datasets.

Efficient and comprehensible analytics for short term requests (shifts, weeks) have to be supported, as well as long term analytics (years of Fab history).

Besides Real-Time Metrics and Fab Analytics, a main requirement is to continuously improve and engineer the value chain (production chain).

One of the major innovative factors of the new solution is the interoperability of the new data model. The discovered information components (atomics, fundamentals, fractals) are structure-identic transformable between different engineering domains, such as:

- Manufacturing (Dispatching, Scheduling)
- Planning (Fab Planning, Equipment planning): Simulation
- Continuous Fab Optimization (OCM: Operating Curve Management)

Classical approaches are suffering from different data formats/contents or media breaks between those different engineering domains. Although already anticipated within “digital factory” concepts, the problem regarding an efficient and integrated information model between those domains has never been solved. Consequently, requirements like Online-Simulation and Fab Optimization in Real-Time are still hard or impossible to be solved.

The new methodology is capable of solving this issue. It is planned that the anticipated demonstrators should cover functionalities, such as functions for Operating Curve Management.

3.5 Outlook

The functional pattern covers functionalities of the Operational Level (Real-time Productivity Metrics) and of the Engineering level (Fab Analytics Metrics).

Within the next steps, besides further specifications and research activities, functional pattern will be extended toward the Strategic Level (Fab Control and Optimization). This will lay the foundation in order to specify and implement within the next project cycles the anticipated demonstrators.

4 Data structures and design principles for real-time information

4.1 Design Principles

The objective of this chapter is to capture the guidelines and domains which have to be considered when the outcome of the ADMONT Smart Manufacturing Demonstrators should become a product.

These principles and guidelines should support current and future business requirements.

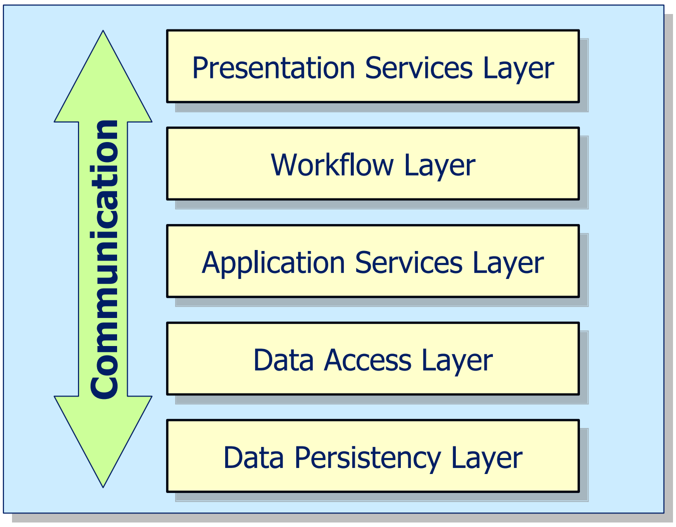


Figure 4.1: Example of a layered system architecture

Figure 4.1 gives an example of a layered architecture. It is not in the scope of this document to specify the details. This must be done during product development. But the product should adhere such components and structuring.

Figure 4.2: Example of a communication model

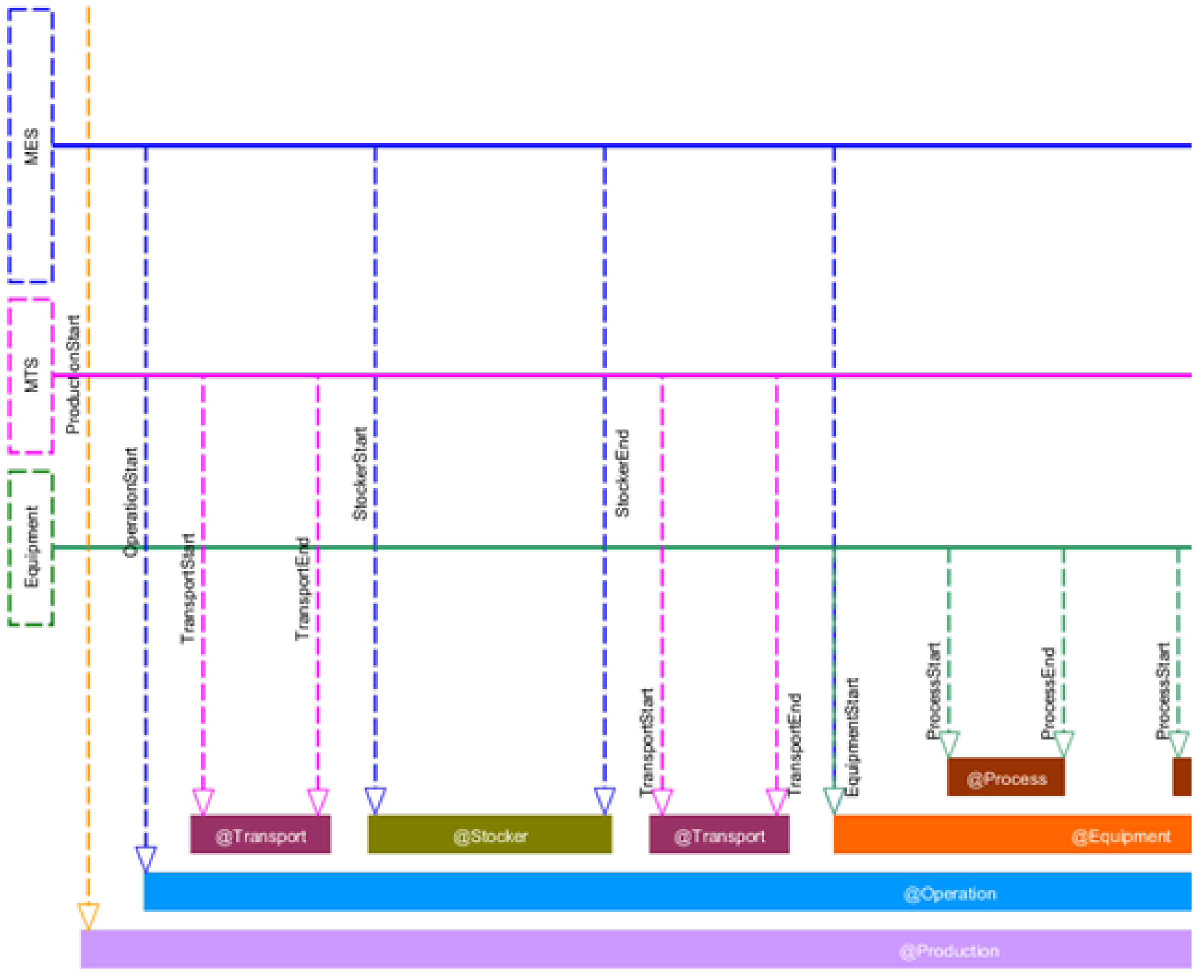


Figure 4.3: Example of a communication scenario

SYSTEMA wants to make usage of a service-oriented architecture (SOA) based on distributed components for online transaction processing (OLTP) systems (Fig. 4.1). However, this architecture should be open to integrate customers' architectures and requirements. The detailed architectural specification has to be done during product development, but should adhere the concept presented in Fig. 4.2, 4.3.

During the ADMONT project the specification which describe the demonstrators have to adhere this concept as well. Examples for architectural design principles and guidelines are flexibility and configurability.

Flexibility and configurability are grounded on:

- a solid generic system architecture and framework
- well defined interfaces, protocols and components
- well defined services based on replaceable, location transparent components
- an extensible data model
- flexible and extensible business rules
- scripting capabilities
- event driven mechanisms
- abstraction layers which encapsulate things to be changed or enhanced without impact to other layers

4.2 Data Structures

The next Figures describe in detail the following data structures. Those structures are based on the requirements (chapter 2), and on the holistic information model HIM, including the basic production model and methodology (chapter 3).

When designing a database, depending on the expected use, two organizational principles of the database technology have to be selected, which are often presented as a contrasting pair in the literature. With Online Transactional Processing (OLTP), the database is optimized for different query variants, which not only read the data stock, but also regularly change it by adding, updating or deleting data records. However, this transaction flexibility must be payed by not being able to create indexes that are designed for a long-term existence of the current data stock.

For the aggregation of large data sets and comparable queries, which read very large parts of the data stock or a large result quantity, OLTP systems based on classic models were therefore not suitable. However, the holistic information model HIM compensates such disadvantages in important points. Queries are already made on pre-aggregated data, e.g. which are deposited in the fundamentals and the fractals. The queries show a linear correlation to the result space, while classical methods have a quadratic correlation. They are reduced to simple summaries and counts.

It has already been shown that improvements in performance are possible by a factor of 100 or more.

In addition, OLAP technology can also be an advantage. For Online Analytical Processing (OLAP) the database is optimized using permanent and durable indexing strategies for fast, mainly reading access to large amounts of data. This is a precondition for data-warehouse based analyzes. As a disadvantage, however, a classic OLAP system has to accept the fact that the addition of data should be sporadic and block-wise, changes of data records are complex and data record deletions, if at all, are possible only by extensive reorganization of the index structures.

Our investigations show that classic database systems with limits of mechanical data storage under the requirements of today's BI systems do not meet the requirements independently of the database architecture, which cannot be raised arbitrarily by a high optimization effort on the database. The data model created in the project already enables rapid evaluations over large time periods on a large but not permanently changing data basis.

The improvements that are imperative for current load behavior and the associated real-time coverage will be achieved by using other technologies, such as the context of the "big data" activities. On the other hand, in addition to such technological improvements, a re-examination of the underlying data structures is necessary.

The aim is, by analyzing and exploiting basic interrelationships through all data layers, to solve the complications which have been previously encountered in the systems (ex.: the complex and error-prone ETL processes), and to enable and assure the intended real-time ability by a fundamental property (linearity) inherent in the information system. This newly discovered basic property not only simplifies the contexts, and overall system relationships, but also supports optimal implementation in modern, distributed and parallel computing architectures through basic features of linear systems.

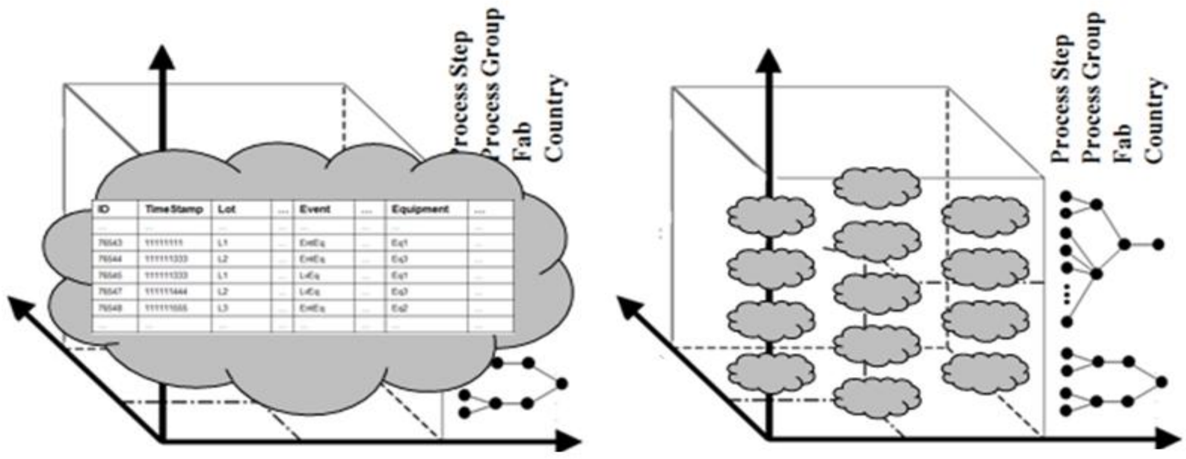


Figure 4.4: left: creation of a classical report by histories; right: multitude of different reports, whereas all those reports are created without using the potentials to reduce significantly the algorithmic complexity through the usage of fundamental and fractal information (lengthy and error-prone ETL processes)

Classic reports are usually created today on an event history in which no functional relationship is modeled between individual entries. Fig. 4.4. (left): history without functional connection between individual events.

Figure 4.4 (right): Also according to several dimensions, reports are generated whose ranges are, however, fixed and can only be changed by a repetition of the generation process so that they cannot be changed over time.

Much of the time for the nightly batch runs, must therefore be used to establish these relationships after predefined dimensions and questions. The associated ETL processes are lengthy, complicated and error-prone, since no corrections are possible in the case of missing or incorrect history entries. Moreover, such processes are not viable.

In preparing the holistic model, obvious errors are corrected "on the fly" so that the generated aggregates are always logically consistent. In addition, there is a functional relationship between the generated information components that is already guaranteed by the model, which in real-time allows a simple, flexible and fast linkage according to any question.

In summary, the holistic model allows flexible ad-hoc evaluations, for which not only the value ranges, but also the dimensions used, can be changed in real-time. In addition, the model can benefit from OLAP technologies, which are designed to provide fast access to the physical database.

The following chapters show some example analyses which are based on each of the tiers of aggregation maintained by the holistic data model (“Atomics”, “Fundamentals”, “Fractals”). As described previously, it is generally possible to generate these structures for every occurring data dimension or set of dimensions. However, a high number of analyses on a dynamic system are based on a time component. For example, key performance indicators (KPI) of a production line usually aggregate shifts, days, weeks, months, or years, but always report the performance during a certain timespan.

The examples below have directly been taken from a proof-of-concept implementation of the holistic data model using several months of production data of a semiconductor fab (X-FAB Dresden GmbH & Co. KG).

The core data structures, which are not meant to be directly queried or in other ways accessed by the user, are exposed through well-defined views that will be documented in the user's manual and supported. This allows for further optimizations and enhancements in the generated information components while the user will still be able to retrieve data in an unchanged format. If necessary, these customer accessible views can be materialized in order to improve query runtime performance by operating on the view data itself instead of a representation of the core data structures. With views being a standardized, well known concept supported by every modern relational database system, this also simplifies the future implementation on other operating systems and database servers. While features such as certain kinds of indices, physical partitions etc. of concrete database systems can be utilized to improve query answer times when aggregating information components, the basic concept the holistic information model does not depend or rely on certain features of the underlying database system.

The available views are grouped by namespaces which are labeled with the tier of aggregation they provide access to. In addition to these “Atomics”, “Fundamentals” and “Fractals” namespaces, which will be explained in more detail within the following examples, there are two other pre-defined namespaces: “Recents” provides views on unfinished states or ongoing incidents, where an initializing event has been received, but the finishing event that marks the concluding of a certain fundamental information component is still missing. Examples of such views are “all lots that are currently in line and not yet shipped”, “throughput of the current shift up to now”, “names and durations so far of lots currently being processed on a certain equipment” and so on. The other namespace is “Custom”, where user-specific queries can be stored and joined with custom master data obtained from external sources.

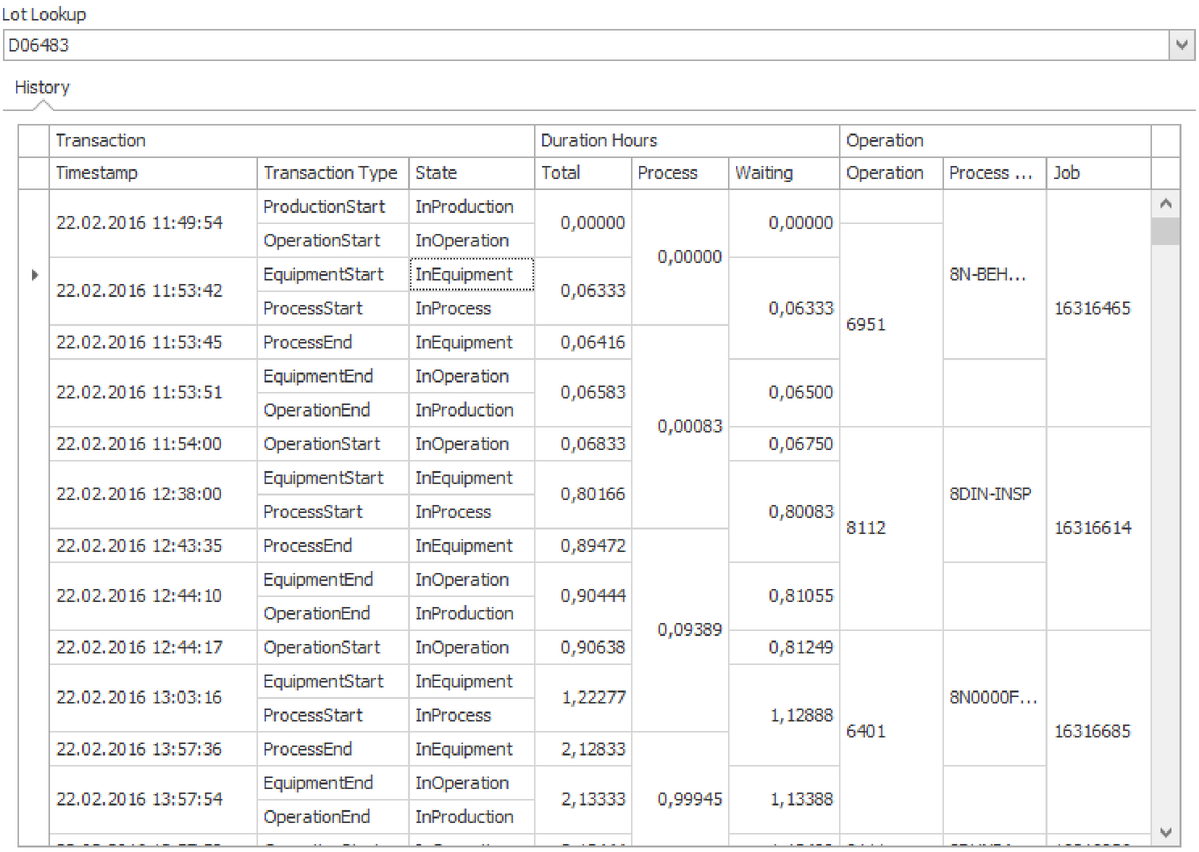
Each of the queries in the following examples demonstrate a typical use case for one of the aggregation tiers.

4.2.1 Atomic Datasets

The atomic tier represents the single events that are in any way considered within the domain model and hold information for the Fundamental or Fractal components. Each registered event is assigned a transaction ID when it is received. Then the information is being extracted from the user-specific format and written to a corresponding table column.

Queries within the Atomics namespace are usually executed to gain an overview of what happened in general shortly before and after a certain point of time. The most common use case would be a drill-down from one of the higher aggregation tiers when queries executed there indicate unusual behavior.

Figure 4.5 shows the first lines of a complete history for one selected lot (D06483), the same we will use for most of the following examples. The GUI framework summarizes cells with equal values within the same column, making it easy to identify changes to a certain value. This however, is a sole visualization feature while the data structures itself contain every event information in every single line.



Lot Lookup

D06483

History

Transaction			Duration Hours			Operation		
Timestamp	Transaction Type	State	Total	Process	Waiting	Operation	Process ...	Job
22.02.2016 11:49:54	ProductionStart	InProduction	0,00000	0,00000	0,00000			16316465
	OperationStart	InOperation				6951	8N-BEH...	
22.02.2016 11:53:42	EquipmentStart	InEquipment	0,06333		0,06333			
	ProcessStart	InProcess						
22.02.2016 11:53:45	ProcessEnd	InEquipment	0,06416	0,00083				
22.02.2016 11:53:51	EquipmentEnd	InOperation	0,06583		0,06500			
	OperationEnd	InProduction						
22.02.2016 11:54:00	OperationStart	InOperation	0,06833		0,06750	8112	8DIN-INSP	16316614
22.02.2016 12:38:00	EquipmentStart	InEquipment	0,80166		0,80083			
	ProcessStart	InProcess						
22.02.2016 12:43:35	ProcessEnd	InEquipment	0,89472	0,09389				
22.02.2016 12:44:10	EquipmentEnd	InOperation	0,90444		0,81055			
	OperationEnd	InProduction						
22.02.2016 12:44:17	OperationStart	InOperation	0,90638		0,81249	6401	8N0000F...	16316685
22.02.2016 13:03:16	EquipmentStart	InEquipment	1,22277		1,12888			
	ProcessStart	InProcess						
22.02.2016 13:57:36	ProcessEnd	InEquipment	2,12833	0,99945				
22.02.2016 13:57:54	EquipmentEnd	InOperation	2,13333		1,13388			
	OperationEnd	InProduction						

Figure 4.5: The beginning of the history for one selected lot, ordered by timestamp

This makes it easy to filter the result set of a query either before or after retrieving it from the database, reducing the data size to be operated with on the one hand, while on the other hand providing enough information to monitor the results of further reductions locally, without the need to query the database again. The example uses a combination of both filter methods: The events of the given lot are selected from the database, internally using a query very similar to the one depicted in Figure 4.6. As this already reduces the amount of data to a size that can easily be handled by a local desktop client, further filters are applied locally, e.g. by entering a filter string into a textbox that can be reached by clicking on the caption of a column. In Figure 4.7, the events for the example lot have been reduced to those that are linked to the equipment PHOT-0600. Additionally to applying filters, it is also possible to locally sort the columns by their value. Initially, the history is ordered by timestamp.

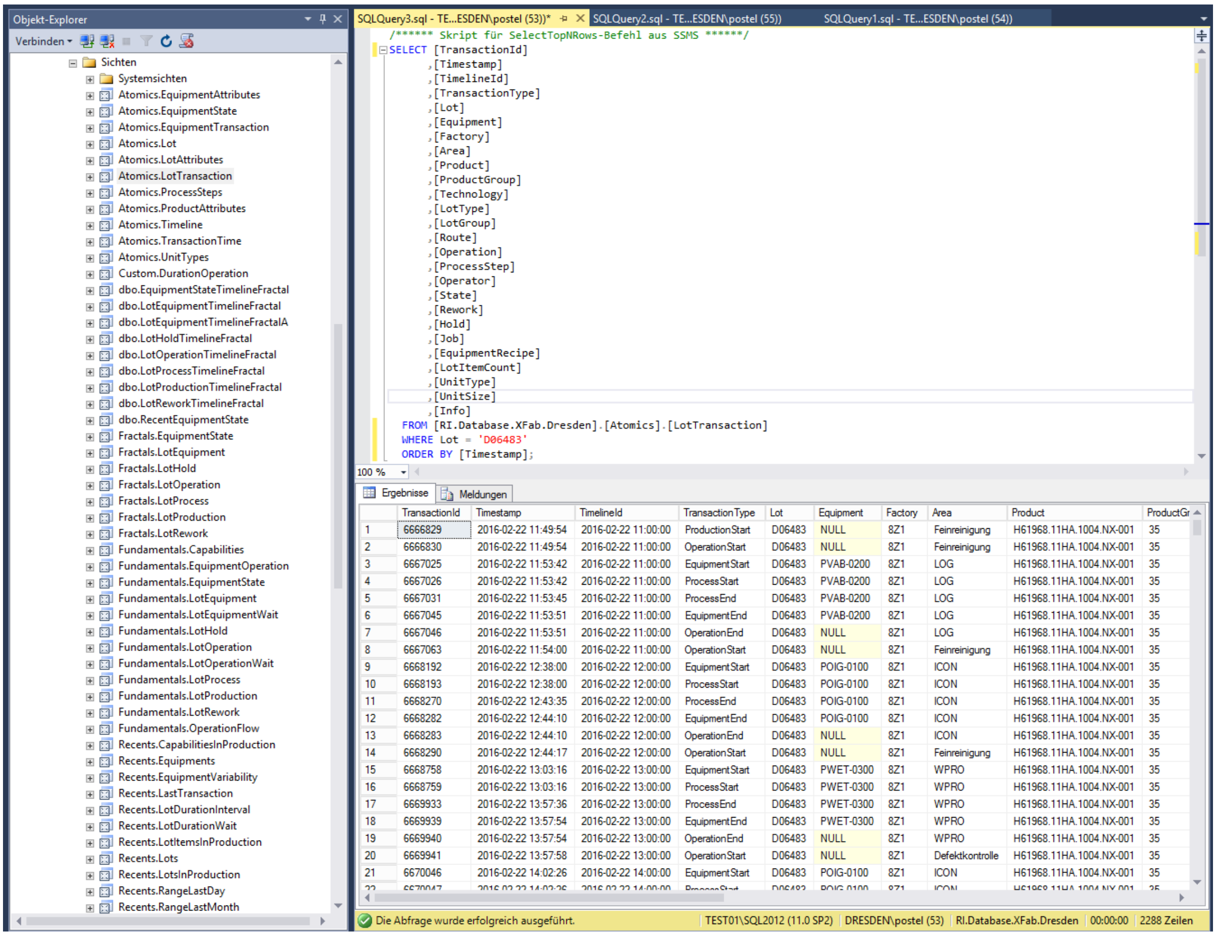
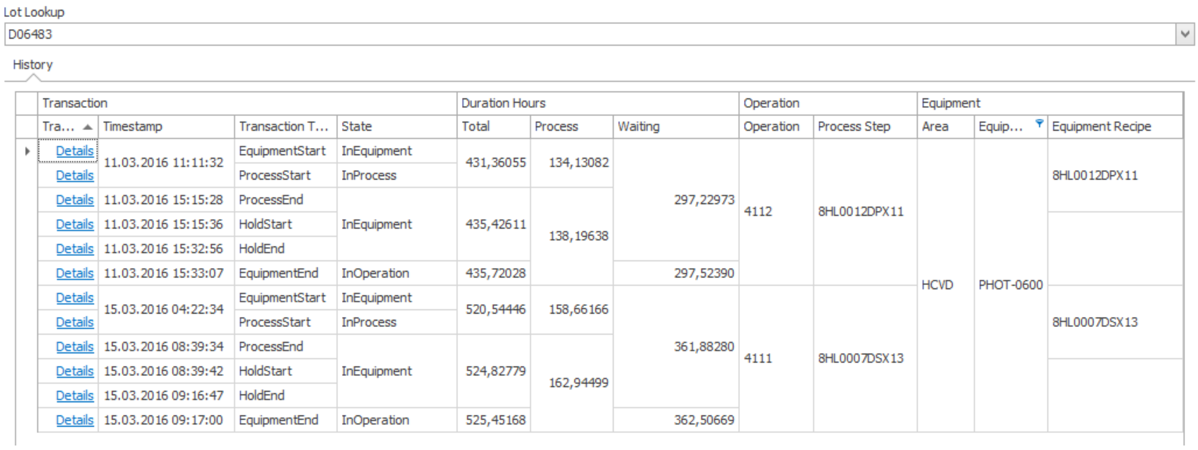


Figure 4.6: The first lines of the same history as before, queried directly on the database


Lot Lookup
D06483
History

Transaction				Duration Hours			Operation		Equipment		
Tra…	Timestamp	Transaction T…	State	Total	Process	Waiting	Operation	Process Step	Area	Equip…	Equipment Recipe
Details	11.03.2016 11:11:32	EquipmentStart	InEquipment	431,36055	134,13082		4112	8HL0012DPX11	HCVD	PHOT-0600	8HL0012DPX11
Details		ProcessStart	InProcess								
Details	11.03.2016 15:15:28	ProcessEnd				297,22973					
Details	11.03.2016 15:15:36	HoldStart	InEquipment	435,42611	138,19638						
Details	11.03.2016 15:32:56	HoldEnd									
Details	11.03.2016 15:33:07	EquipmentEnd	InOperation	435,72028		297,52390					
Details	15.03.2016 04:22:34	EquipmentStart	InEquipment	520,54446	158,66166		4111	8HL0007DSX13			8HL0007DSX13
Details		ProcessStart	InProcess								
Details	15.03.2016 08:39:34	ProcessEnd				361,88280					
Details	15.03.2016 08:39:42	HoldStart	InEquipment	524,82779	162,94499						
Details	15.03.2016 09:16:47	HoldEnd									
Details	15.03.2016 09:17:00	EquipmentEnd	InOperation	525,45168		362,50669					

Figure 4.7: The same lot history as before with additionally applied filter by a certain equipment

4.2.2 Fundamental Information-Sets

The Fundamentals namespace is the first aggregation tier of the holistic model that collates the information of several events into information components.

Figure 4.8 shows a combination of two typical queries that utilize the Fundamental aggregation layer: For a given equipment and timespan, it shows the equipment states (productive, standby, and down) and for all lots that have been processed on that equipment the durations of being assigned to that equipment and the actual processing time. In the example, we find that the equipment PHOT-0600 has been in productive state from c. 1.30 AM until c. 3.30 PM, and that, among others, the previously mentioned lot D06483 has been processed from 4.22 AM until 8.39 AM, and afterwards has been waiting for unloading until 9.17 AM, which can be verified by the lot history (Figure 4.7).

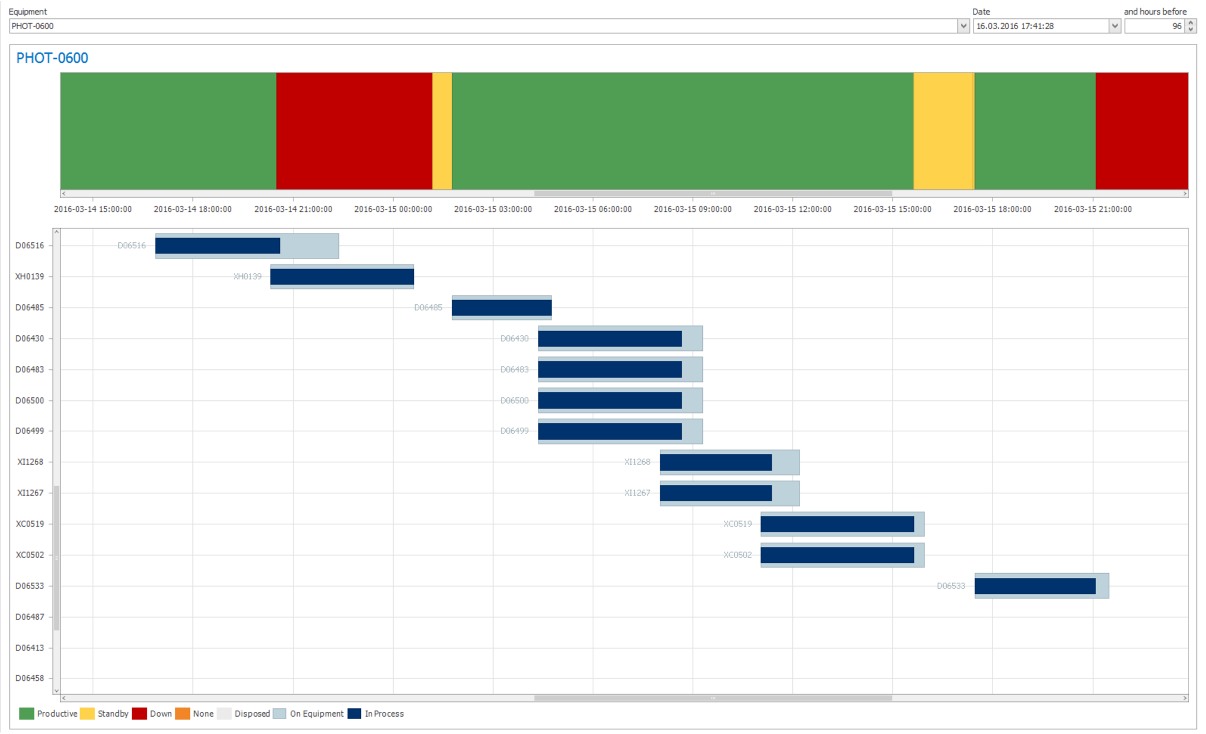


Figure 4.8: A dashboard that correlates lot processing and “on equipment” durations with the durations of SEMI E10 equipment states

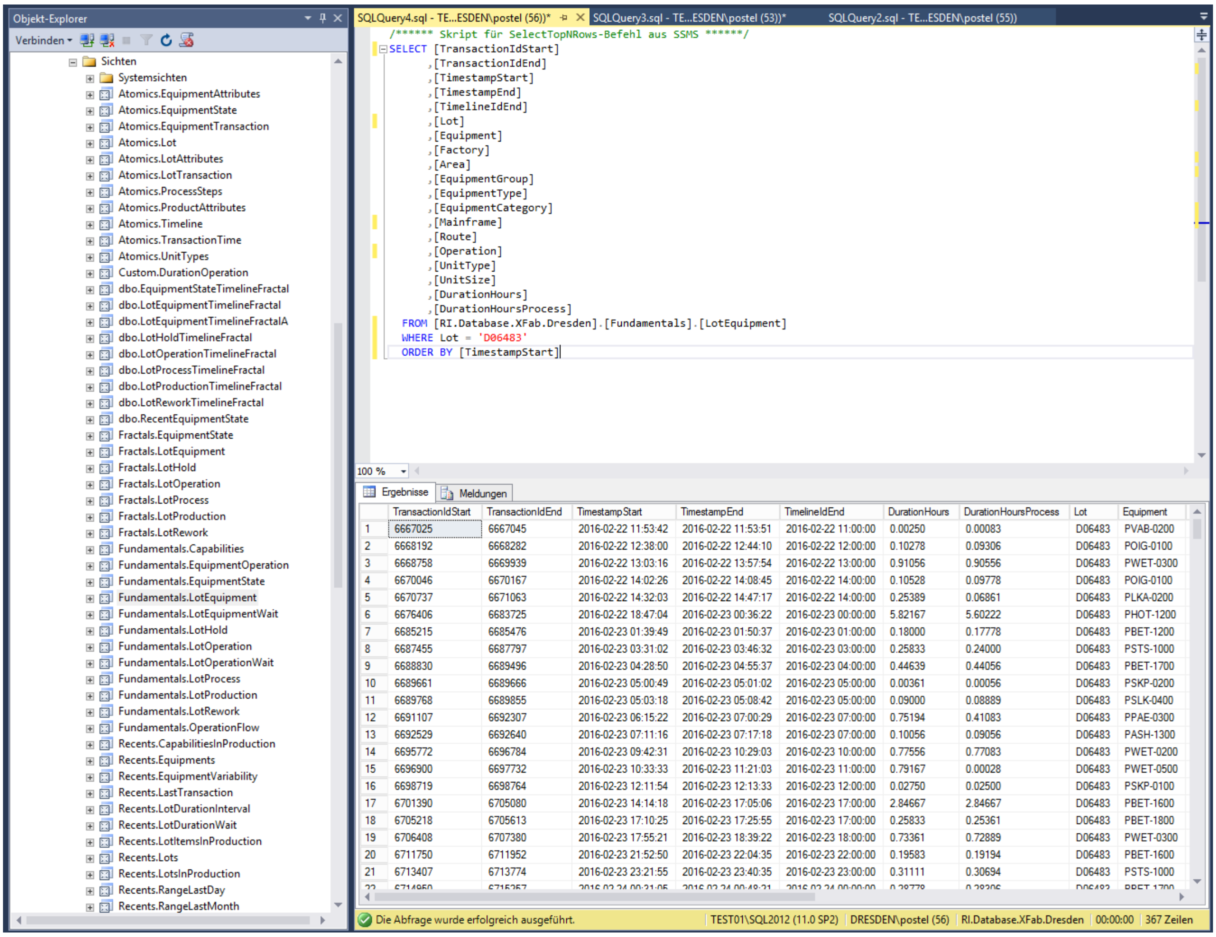


Figure 4.9: Query on the “InEquipment” Fundamentals of a certain lot, executed directly on the database system

In this case, the report utilizes the “InEquipment” fundamentls, i.e. fundamentals that were computed on the dimentsion of the equipment. If all the “InEquipment” Fundamentals for one certain lot are queried as shown in Figure 4.9, all the durations on all passed equipments are immediately available, without the need to manually unify corresponding events that mark the beginning and end of an equipment transaction. The Fundamentals also contain a TransactionId as a foreign key to the related Atomics table, which allows for direct drill-down to the events whose components were unified in the Fundamental information component. In the example, double-clicking on the lot entry opens the lot history table shown in Figure 4.7.

4.2.3 Fractal Information-Sets

In the Fractal namespace, the information portions of multiple single events are arranged into a time grid that significantly reduces the complexity of aggregations. In the example of XFAB Dresden’s production data, the Fractals are underlain by an hourly grid, i.e. for every lot, the Fractals computed on the “InOperation” dimension provide one information component for every hour and every operation the lot was assigned to during that hour.

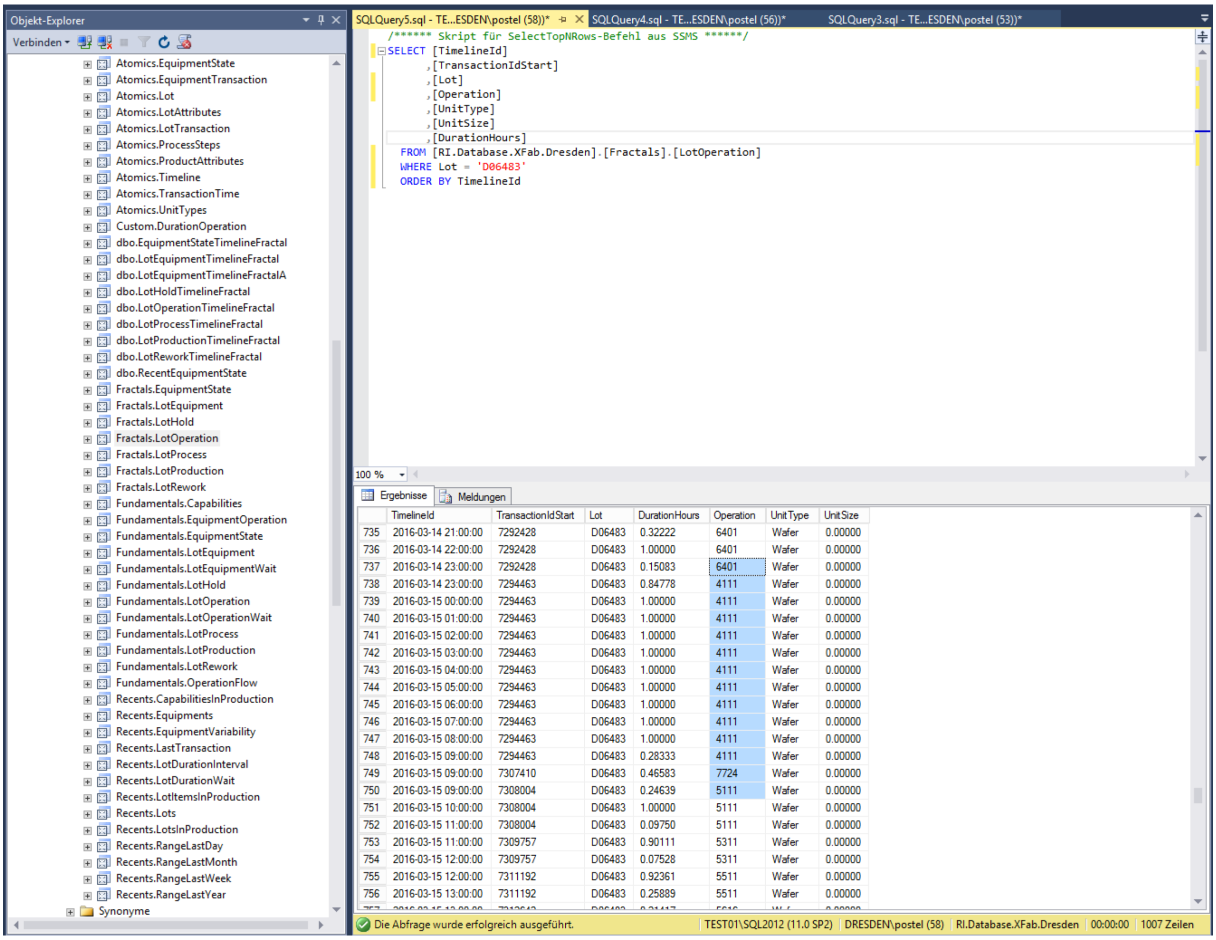


Figure 4.10: “InOperation“ Fractals queried for a certain lot and ordered by timestamp

Figure 4.10 shows the general structure of the Fractal aggregation tier. In this case, all the “InOperation” Fractals for one lot have been retrieved and ordered by the grid timestamp. In The example, the lot D06483 has been assigned to operation 4111 between a timespan that starts within the 24^{th} hour (11 PM – 12 AM) of March 14, 2016 and ends within the 10^{th} hour (9 AM – 10 AM) of March 15. From 12 AM until 8 AM, the lot did not change its current operations, so for every hour within this timespan, the operation 4111 has a fraction of 1 hours per hour. In the first quarter of the hour 11 PM – 12 AM, the lot entered the operation 4111 by leaving operation 6401. So for this hour, there are two Fractal entries, one with a fraction 0,15 and one with 0,85 hours per hour. With this structure, it is very straightforward to calculate, for example, the duration of every operation for the selected lot, even if operations have been visited more than once: For every operation in the result set, only the sum of the hourly fractions needs to be computed.

In most cases however, queries on the Fractals will not be performed for the whole living time of one lot, but on every lot that exists within a defined timespan. Figure 4.11 shows for a selected timespan and an ordered operation flow (which can be a user-supplied master route or a computed list of the most frequent operation transitions, optionally grouped by product group, technology etc.) the average number of lots that have been assigned to the displayed operation. In this example, the average WIP for operation 4111 together with their nearest two predecessors (6551, 6401) and successors (7724, 5111) has been retrieved for the first half of May 15, 2016. While it would be extremely complex and time-consuming to compute such data on a traditional lot history with no intrinsic connection between corresponding events, the holistic data model is able to return the result set needed to populate the table almost immediately. As shown in Figure 4.12 and explained in the previous paragraph, all that needs to be done is to compute the sum of all fractions for each hour. In the example, the query took less than 1 second on one year of productive data, while experiences show that on a traditional lot history, even computing average values by day can take up to several hours as part of a batch process executed at night time, with no opportunity to update the values for the current day.

Operation	15 00	15 01	15 02	15 03	15 04	15 05	15 06	15 07	15 08	15 09	15 10	15 11
6551	10,6	4,8	4,7	3,6	3,0	4,9	8,1	4,3	2,2	2,5	4,8	6,4
6401	12,8	12,7	8,2	9,1	8,2	8,5	10,5	12,2	10,8	7,4	1,6	1,6
4111	4,4	5,0	4,8	4,8	4,8	4,0	4,0	4,3	5,0	2,9	2,0	2,0
7724	3,5	2,1	1,9	2,4	2,8	2,4	4,3	4,0	2,6	4,1	4,1	3,2
5111	12,9	15,0	13,6	12,7	6,3	7,0	9,5	9,8	10,0	8,0	12,9	5,2

Technology | Product Group | Product | Route

Figure 4.11: Average hourly WIP by operation, shown for a part of the “golden operation flow“

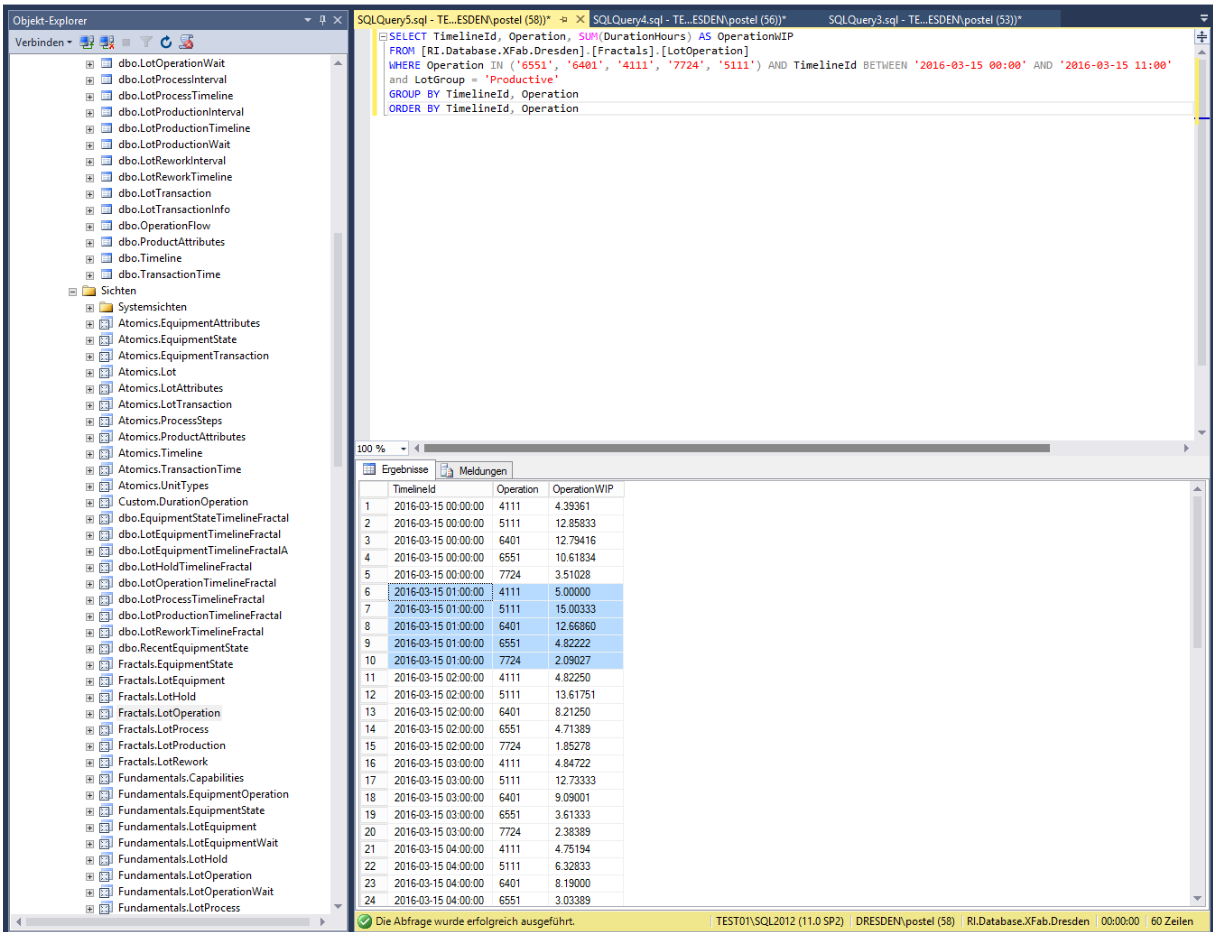


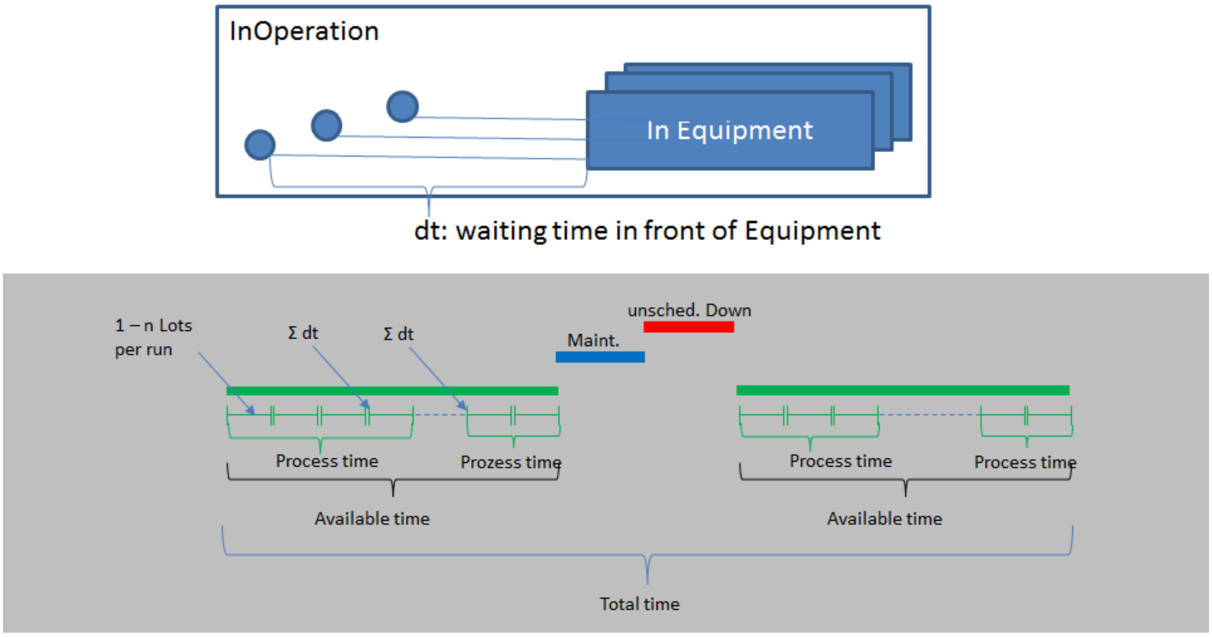
Figure 4.12: Average lots in operation per hour, queried for a given timespan and filtered on productive lots and a set of operations

4.3 Implementation of the 3-Layered System Architecture

First functional patterns have been implemented to show and evaluate the fulfilment of the requirements (chapter 2). Those functional patterns make direct use of the data structures as defined before.

The first functional pattern was used to test performance aspects (chapter 3).

A second functional pattern evaluates a functional requirement of XFAB production: analysis of production bottlenecks. For this functional pattern, 6 months of productive data have been transferred into the new model, and corresponding analysis has been done:



$$\text{Bottleneck Likelihood} = \frac{\Sigma \text{ wait time dt}}{\text{total time}} \times \frac{\Sigma \text{ Process time Eqp}}{\Sigma \text{ available time}}$$

Figure 4.13 Data model and bottleneck formula

The bottleneck likelihood has been defined and implemented as a real-time functional pattern. Full functionality and flexibility has been demonstrated with 6 months of productive data. Results have been evaluated:

- Bottleneck likelihood information has been correctly calculated
- System performance and response times of the functional pattern is excellent

A third functional pattern demonstrates “User experience” topics (Fig 4.14):

- Drill down capability
- Configurable by user
- Dynamic refresh
- Multiple dimensions and “deepness” of information

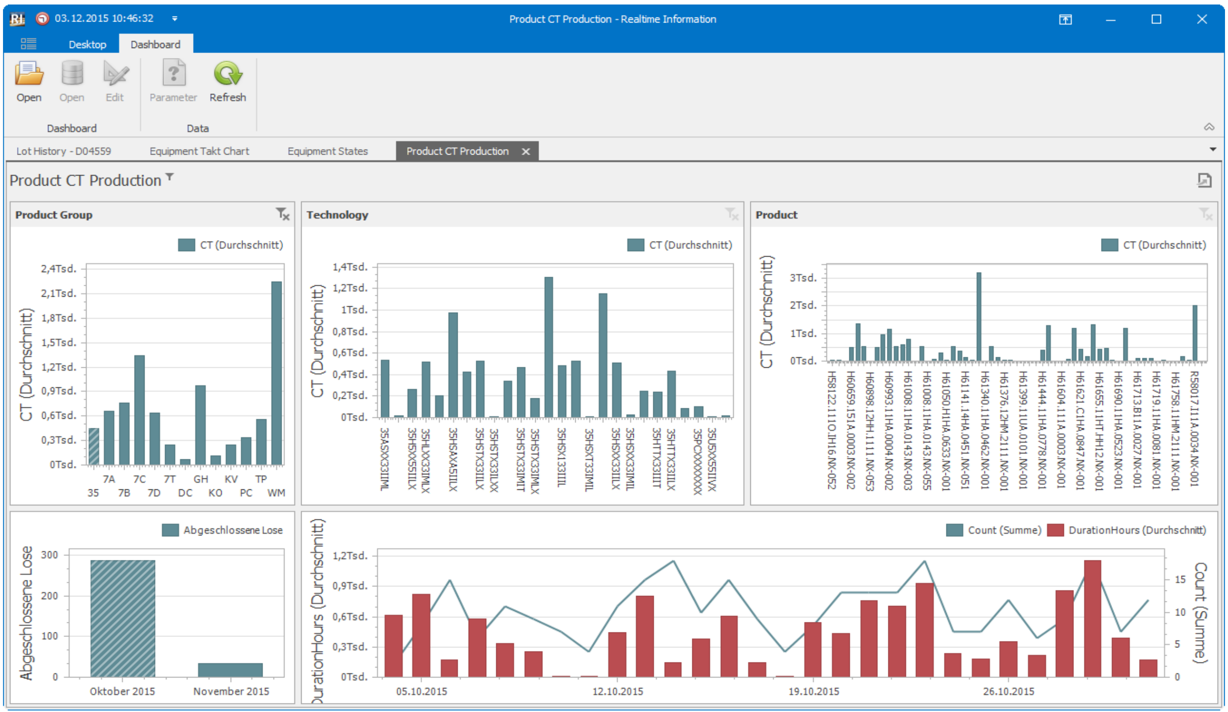


Figure 4.14 Dashboard example user interface

5 Deployment Structure

The next Figure 5.1 shows an example of a deployment structure. This structure is also planned for the demonstrator to be installed at XFAB location.

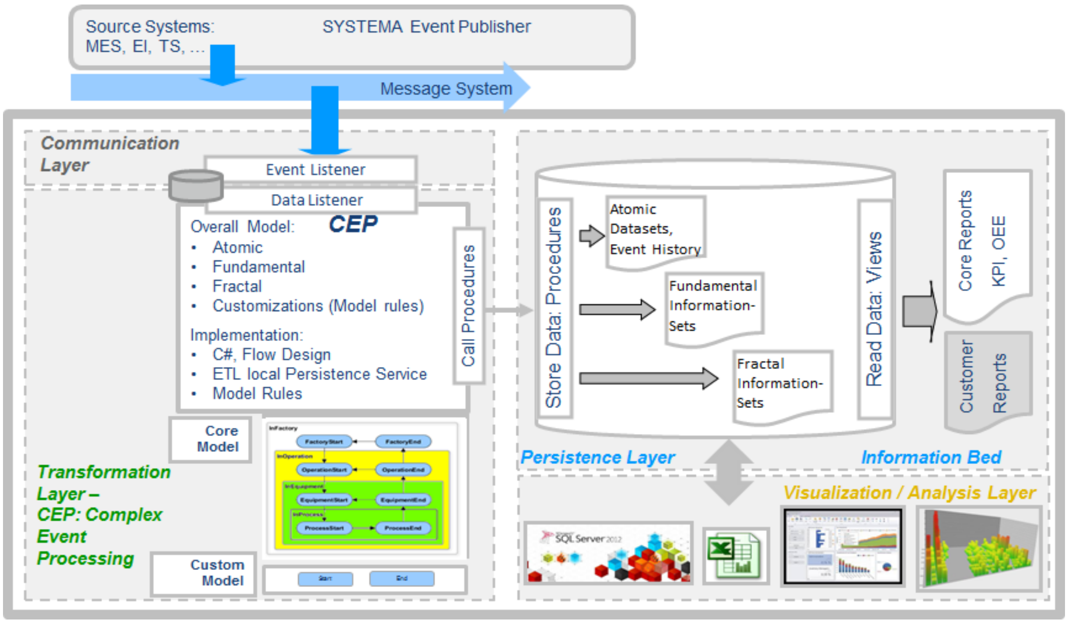


Figure 5.1: Real-time Information System Architecture

Figure 5.1 shows and highlights that the real-time information functionality can be implemented using standard hardware and software components. A functional pattern has already been implemented in the ADMONT project, and will be extended to demonstrator. All components have been developed and deployed using following standard components:

Deployment Figures:

Server:

- Hardware: standard server configuration (e.g. Xeon)
- Microsoft Windows 2003, 2008

Database:

- MS SQL

Middleware (MOM):

- Bus: ActiveMQ / TIBCO RV
- Protocol: VFEI / XML string message

Client (Visualization):

- Hardware: standard PC
- Windows 7

The components of the Event Processing Layer have been implemented using C# Windows technology. The Persistency Layer has been implemented using Microsoft MS SQL database system.

6 List of Abbreviations

Abbreviation	Explanation
BI	Business Intelligence
CIM	Computer Integrated Manufacturing
CMOS	Complementary metal–oxide–semiconductor
DDS	data distribution system
DWH	Data Warehouse System
ERP	Enterprise resource planning
ETL	Extract, Transform, Load
GDS	Graphic Database System
HC	Head count
HV	High Voltage
KPI	Key Performance Indicators
LITH	Lithography
MEMS	Microelectromechanical systems
MES	Manufacturing Execution System
OCM	Operating Curve Management
OEE	Overall Equipment Efficiency
OLAP	online analytical processing
PCM	Process Control Monitoring
ROI	Return on Investment
SBNO	Standby No Operator
SEMI	Semiconductor Equipment and Materials International
SIPOC	Supplier, Input, Process, Output, Customer
SPC	Statistical Process Control
UHV	Ultra High Voltage
WAT	Wafer Acceptance Test
WET	Wet Etching
WIP	wafer in progress
WI/WO	wafer in / wafer out
WP	work package

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