FH Aachen

Faculty
Electrical engineering and information technology

Bachelor Thesis

Design and Implementation of a Performance Measurement System for an Industrial Sewing Machine

Nicolas Harrje
Matr.-Nr.: 3518047

Referent: **Prof. Dr-Ing. ...**

Korreferent: **Prof. Dr.-Ing. ...**

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2.1.1. Takt Time

Maximum time allowed to produce one product in order to meet customer demand

2.1.2. IoT and IIoT

The term Internet of Things was first coined by [**?**] when explaining the idea of combining RFID with the internet in an executive meeting. He explains that on the "normal" internet, most of the content is created by human beings. In contrast to this in the Internet of Things the data is generated by things and often describes things. But his emphasizes lays more on the description of things. For example to track and count them. The information to do so would come from sensors and RFID, he says. Of course in these days more of the information on the internet is generated by bots and AI. But other than that the distinction still holds true.
The Internet Society [Rose et al.,] further explains that in the Internet of Things, machines are communicating with each other and are addressable via an own IP address. This standardizes the way in which devices communicate. They also mention that "Today, the Internet of Things has become a popular term for describing scenarios in which Internet connectivity and computing capability extend to a variety of objects, devices, sensors, and everyday items."
The Industrial Internet of Things is just the description of a domain where the IoT is used. In this case in manufacturing. [Wha,]

2.2. State of the Art

2.2.1. Industrial IoT Architectures and Patterns

Due to the requirement that the solution be developed utilizing IoT technologies and is set within a production context, a review of Industrial IoT (IIoT) architectures and patterns was conducted. The Industrial Internet Reference Architecture (IIRA) [Young, 2022] serves as a comprehensive framework, offering valuable insights into various architectural models and design patterns relevant to this domain. This reference architecture describes the following patterns: IoT Component Capability Pattern, Three-Tier Architecture Pattern, Gateway-Mediated Edge Connectivity and Management architecture pattern, Digital Twin Core as a Middleware Architecture Pattern, Layered Databus Architecture Pattern, System-of-Systems Orchestrator Architecture Pattern. Of these patterns only the first two are applicable within the scope of this work. Therefore the other ones will only be described on the surface.

Architecture Patterns IoT architecture patterns define the structure and operation of various IoT systems, detailing their implementation and highlighting their unique characteristics.

IoT Component Capability Model Pattern A single component and its associated capabilities are described, with the possibility that a component may comprise multiple sub-components. Consequently, the entire system can also be regarded as a component. The specific meanings of the capabilities are illustrated in the accompanying figure.

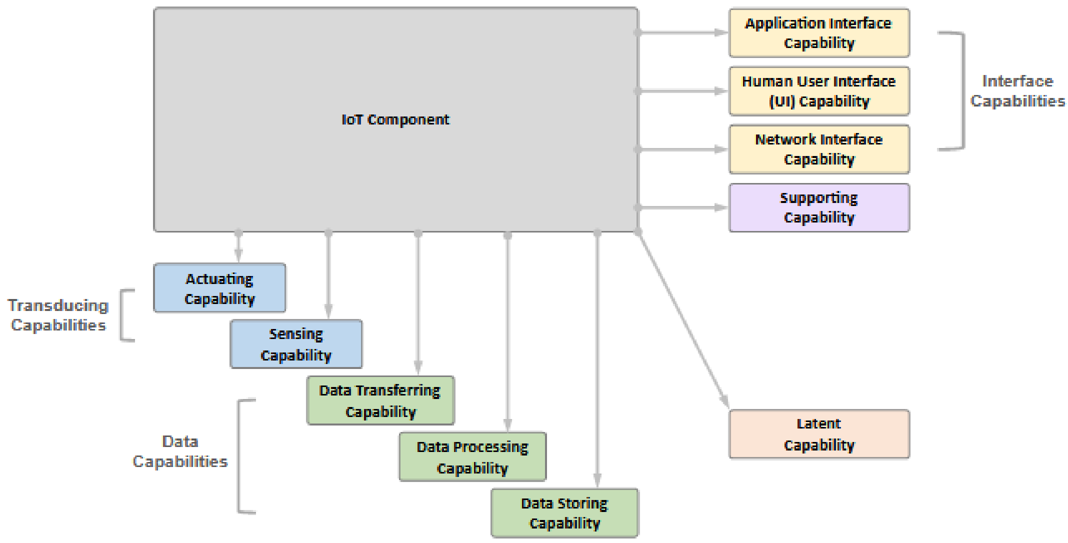

Figure 2.1.: Component Capability Pattern.
(Young et al., 2022, S. 40)

Three-Tier Architecture Pattern The system comprises the Edge, Platform, and Enterprise Tiers, as well as connecting networks. The Edge Tier contains sensors and gateways that collect data. These are connected by the Proximity Network. Data preprocessing may already be happening there.
The Platform Tier is responsible for most data processing and storage via databases. It is connected to the Edge Tier via the Access Network.
The Enterprise Tier provides domain-specific applications and interfaces for end users. These are built upon the processed data from the platform tier. It also issues controls to lower tiers. This tier is connected to the Access Network via the Service Network. The three tiers can also be further divided into different domains. That makes sense for bigger systems. But for a simple system as the one described in this work it is not necessary and therefore these domains will not be explained here.

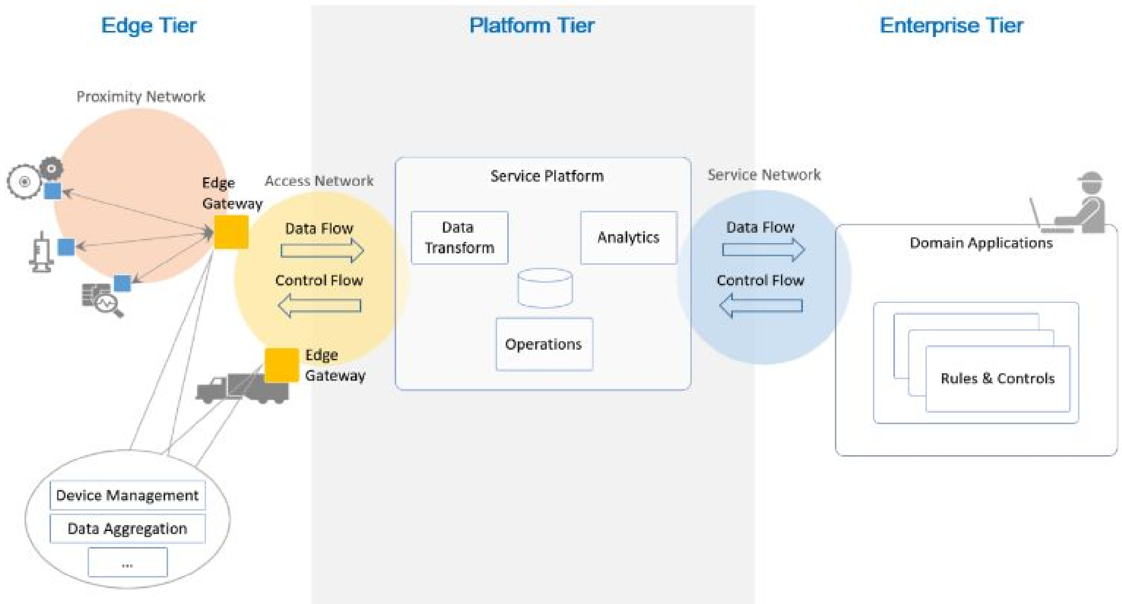

Figure 2.2.: Three Tier Architecture
(Young et al., 2022, S. 44)

2.2.2. KPIs and Metrics for Performance Evaluation in Sewing Operations

Performance measurement in the textile production industry is important due to intense competition. It enables producers to identify potential bottlenecks, provides a deeper understanding of processes, and facilitates more effective resource allocation [Alauddin, 2018].
Key performance indicators (KPIs) and metrics serve as essential tools for performance measurement. Kang et al. [Kang et al., 2016] from the National Institute of Standards and Technology in the United States analyzed the relationships among various types of KPIs and metrics used in operations management and production, based on the ISO 22400 standard. Supporting elements, referred to as metrics in this thesis, describe the measured data necessary for calculating basic KPIs. These supporting elements are categorized into time and quantity. Time elements quantify the duration of various events, such as the production time per unit. Conversely, quantity elements pertain to the number of produced items. Maintenance elements capture information about machine-related issues.
Based on the supporting elements, basic KPIs can be calculated. These KPIs are categorized into production, quality, and maintenance KPIs.
The researchers also emphasize the importance of comprehensive KPIs, which provide a broader overview of production performance. These KPIs build upon basic KPIs and include, for example, Overall Equipment Effectiveness (OEE), which is calculated by multiplying the KPIs for availability, performance, and quality ratio.
Other studies [Kiron, 2022, Alauddin, 2018] have specified KPIs specifically for the sewing section of a textile production plant. In this context, some KPIs overlap with those examined by Kang et al., while additional KPIs unique to the sewing section have also been introduced. The following table classifies these sewing-specific KPIs within the hierarchical framework proposed by Kang et al.

Table 2.1.: Classification of KPIs and Metrics in Sewing Section (based on Kang et al., 2016 and ISO 22400)

KPI/Metric	**Description**	**Classification (Kang et al., 2016 / ISO 22400)**
Supporting Element: Time		
Cycle Time	Total time taken to complete one operation, from start to start of the next piece.	Supporting Element: Time
Standard Minute Value (SMV)	Time required to complete a specific job under standard conditions and pace.	Supporting Element: Time
Allowance	Extra time permitted for personal needs, delays, and fatigue in production.	Supporting Element: Time
Idle Time/Machine	Time when operators or machines are not working, considered lost time.	Supporting Element: Time
Supporting Element: Quantity		
Operation	A step in the process required to convert materials into a finished product.	Supporting Element: Quantity
Manpower to Machine Ratio	Ratio of workers to machines, used to optimize labor and production.	Supporting Element: Quantity
Absenteeism	Rate of operator absence, which affects production and efficiency.	Supporting Element: Quantity
No of Style Change	Frequency of style changes, impacting productivity, efficiency, and quality.	Supporting Element: Quantity
Basic KPI: Production		
Efficiency	Comparison of actual output to what could be achieved with the same resources.	Basic KPI: Production
Productivity	Achievement toward goals based on the relationship between inputs and outputs.	Basic KPI: Production
Availability	Percentage of scheduled time employees or machines are productive.	Basic KPI: Production

KPI/Metric	Description	Classification (Kang et al., 2016 / ISO 22400)
Performance	Amount of product delivered relative to available productive time.	Basic KPI: Production
Line Wise Sewing Efficiency	Efficiency of sewing lines, often linked to man-to-machine ratio.	Basic KPI: Production
Basic KPI: Quality		
Defect per Hundred Units (DHU)	Number of defects found per hundred units produced.	Basic KPI: Quality
Quality	Percentage of perfect or saleable products produced.	Basic KPI: Quality
Comprehensive KPI		
Overall Labor Effectiveness (OLE)	Measures workforce utilization, performance, and quality, reflecting labor's impact on productivity.	Comprehensive KPI
Overall Equipment Effectiveness (OEE)	Quantifies how well equipment performs relative to its designed capacity, considering availability, performance, and quality.	Comprehensive KPI

2.2.3. IoT-Plattforms

The IoT is known for producing large amounts of data and for the potentials to grow these amounts even more. Therefore a scalable software infrastructure that is needed. That is where IoT-Plattforms come into play [Turki et al., 2024]. The authors also mention that IoT-Platforms help accelerating the solution development "[...] by providing foundational capabilities, avoiding the need to implement low-level infrastructure."
[Asemani et al., 2019] further highlight the different capabilities that are typical for IoT-Platforms.

Connectivity and Device Management Through various communication protocols the platforms connect with the devices, enabling them to communicate with each other, manage device status and configurations, handle software updates and provide mechanisms for error reporting.

Data Storage, Management, Analysis, Visualization Through connections to databases they store large volumes of data often in the cloud or locally. Also further data processing and analytics through various methods as well as visualizations through dashboards are possible.

Development and Deployment Tools By providing APIs and SDKs the developers are enabled to further create custom applications.

Auditing and Payments The Platforms help to have an overview over the data or compute usage and the resulting costs.

Service Management By giving an oversight over parameters like resource consumption, data requirements and access, the user can monitor vertical as well as platform internal services. The platforms also enable the communication between services or combination of basic services to create new ones.

Integration Platforms can be integrated with each other, other data sources and the cloud.

Fog/Edge Computing IoT-Platforms often support distributed data processing and storage. This can lead to less traffic due to processing close to the data source. Faster transmission would be enabled therefore and reinforced due to shorter communication distances.

The researchers go on to reveal that while commercial platforms carry all of the mentioned capabilities, open source platforms are often focused on specific capabilities. Thus in implementation sometimes need to be combined to deliver a holistic IoT-Platform.

2.2.4. Differences between Relational and Timeseries Databases

In the paper written by [Türkoğlu et al., 2024] it is analyzed how relational databases and time series databases compare regarding speed and storage efficiency when used in Grafana. First they point out the use case for relational databases is for single time data points, which can be related to other data points over various tables. Therefore enabling complex queries involving joins, aggregations and multiple tables. They make sure the data is accurate and stays consistent. Time series data bases on the other hand are made for data points with a timestamp and large volumes of data. This makes them ideal for IoT applications and real time data analytics. They are optimized to enable high speed read and write operations as well as efficient data storage. The differences in query return time are already there with small amounts of data, but when scaling up the amount they become clearly visible as can be seen in the figure below.

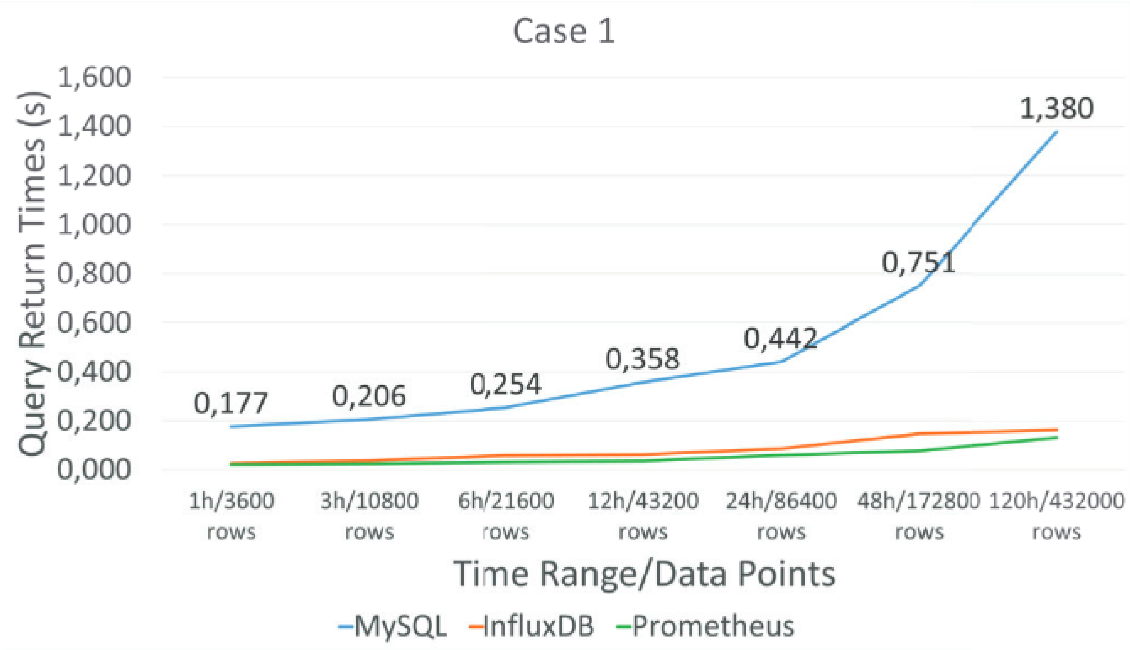

Figure 2.3.: Query Performance Relational vs. Time Series DB
(Turkoglu et. al, 2024, S. 2)

This is only one of three test cases but they all give a similar picture that shows the superiority of time series databases regarding query return times.

2.2.5. Dashboarding

3. Related Work

This section presents an overview of related solutions for sewing machines, with a focus on methods for data collection and processing in monitoring applications. It also examines general approaches to performance measurement in manufacturing. The analysis will likely address the types of metrics underlying these solutions, the sensor technologies used for data acquisition, and the strategies for data processing, storage, and analytics. This review aims to clarify the current state of the art, identify possible gaps in existing systems, and position this work within the field of automated performance measurement systems. Furthermore, the review seeks to highlight potential limitations and opportunities, including technical aspects such as hardware, software, and integration, as well as architectural considerations like standards, frameworks, and open-source approaches, which may influence the implementation of performance measurement systems.

In their seminal work, Jung et al. [Jung et al., 2020] propose a system for the analysis of sewing machine operator skill level and the complexity of the assigned sewing tasks. The present study bears a notable similarity to the aforementioned work, as both analyze the cycle time per unit. This objective is pursued by employing power consumption data of the sewing machines as the fundamental metric. To that end, a power monitoring system is employed, which is connected to the machines power plug without necessitating modifications to the sewing machine itself. Subsequently, the data is transmitted to a cloud server via wireless communication. The determination of quantity and time of work is achieved through the implementation of pattern analysis algorithms. The efficacy of the system is predicated on the non-intrusive nature of PMS. A notable disadvantage of this solution is the necessity of sufficient sample data to ensure the accuracy of the results.
Another system that uses power consumption measurement was proposed by Strazinskas [Stražinskas, 2025]. The utilization of current sensors enabled the discernment of fluctuations in motor current, which are inherently associated with the operational states of the sewing machine, including initiation, cessation, seam length, and stitch speed. The sensor is connected to an Arduino Uno microcontroller, which transmits the received data to a Raspberry Pi 3B+ microcomputer. The microcomputer is responsible for central data collection and storage. The data is stored in files, which is a disadvantage of the system because it is less efficient than storing it in an optimized time series database. Therefore, a greater quantity of space is required, and the rate of data processing is reduced. Additionally, the absence of any preprocessing mechanisms underscores the necessity for optimized data management, a crucial aspect that demands significant memory resources. Strazinskas's research indicates that the utilization of the present sensor engenders measurement errors and noise in the data.
Although adopting a divergent approach, the system proposed by Quoc et al. [Quoc et al., 2025] likewise relies on IoT devices (which were not further described) connected to the machine. The data of these devices is then transmitted to the cloud, where it is integrated with the enterprise's Management Information System (MIS). This integration facilitates the optimization of resource allocation. In light of the aforementioned data, a visualization is generated to illustrate the open positions of a contract and the extent to which it has been completed.
A divergent approach is posited by Wedanage et al. [Wedanage and Thiwanka, 2022] in their study "Fog Assisted Industrial Sewing," in which they utilize a mobile application to record the cycle

times of the sewing step.To initiate and conclude the sewing process on the workpiece, the operator is required to engage a designated button at the commencement and cessation of the operation. The data is structured in a JSON format and published via MQTT under a designated topic. A fog node, implemented using a Cisco IR829 industrial router, is subscribed to the specified topic and processes the data through a Java application. Additionally, the application utilizes a RethinkDB database, which is characterized as open-source and specifically engineered for real-time applications. The fog node is already capable of performing local data analytics. In the cloud, data from all fog nodes is combined to provide real-time alerts and analytics through dashboards. These dashboards visualize cumulative average cycle times per member and compare them to takt time (maximum time allowed to produce one product to meet customer demand). The employment of fog computing facilitates the system's notable scalability, a consequence of the distribution of computing tasks across multiple fog nodes. This configuration facilitates the system's capacity for real-time data analytics and reduced bandwidth utilization. A notable drawback of this system is its reliance on manual input from operators, which introduces a margin of error. Moreover, no historical analytics have been conducted, despite the existence of a foundation for such analyses. A notable drawback of the system in question, as well as those proposed by Jung et al. and Quoc et al., is the utilization of a cloud, which gives rise to several concerns, including but not limited to data security, latency, and ongoing costs. The merits of the aforementioned systems include their capacity for retrofitting older machines and their non-intrusive nature.

Beyond these closely related implementations, a broader perspective is provided by Tambare et al. [Tambare et al., 2022], who review various approaches to performance measurement systems. Initially, the discourse centers on two pivotal standards. The ISA-95 standard delineates entities at the shop floor level, where information technology systems such as ERP, CRM, cloud platforms, and SQL databases interact with operational technology components like sensors, actuators, microcontrollers, SCADA systems, and PLCs. Its primary function is to formalize production processes. Conversely, the ISO 22400 is employed for the formalization of performance metrics. The provided framework facilitates the definition, calculation, and dissemination of key performance indicators (KPIs), encompassing their contextual framework, formula, unit of measurement, range, and intended audience. The researchers then proceed to underscore the Scania case study, wherein these two standards are being utilized, as a paradigm of the practical implementation of international standards for performance measurement in a smart manufacturing context.
This case study by Samir et al. (samirKeyPerformanceIndicators2018) will now be examined in more detail. The system is composed of numerous autonomous, self-contained computational units that are each capable of performing independent computations and collaborating with each other. The software utilized for the processing and distribution of data has been developed using a Service Oriented Architecture (SOA) framework. This approach involves the implementation of multiple services that function independently of one another, with each service designated to specific responsibilities. The communication between the units is facilitated by an Enterprise Service Bus (ESB). The architecture further employs an Event-Driven Architecture (EDA), whereby events serve as triggers for services. This aims to address the issue of communication delays. The KPIs are designed in accordance with the ISO 22400 standard, and the IS-95 is employed to enable automated interfaces between enterprise and control systems.

Taken together, these studies illustrate a variety of approaches to IoT-based machine monitoring, each with specific strengths and limitations. In contrast to the systems examined in the aforementioned studies, the system presented in this thesis is designed to operate with a contemporary sewing machine that facilitates data extraction directly from the machine. It is also intended to provide a more comprehensive overview of the production process by means of various Key Performance Indicators (KPIs), which will be addressed in subsequent sections. The system proposed in this thesis aims to incorporate the strengths of the discussed systems while mitigating their weaknesses. The system has been designed to align more closely with the proposed model in the case study by implementing standards and service-oriented software. Therefore, this facilitates enhanced scalability and maintainability.

4. Requirements Analysis

4.0.1. Functional Requirements

4.0.2. Non-Functional Requirements

4.0.3. Constraints

4.0.4. KPI Selection and Justification

Of which the following were able to be calculated with the given metrics.

5. Zusammenfassung und Ausblick

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Abkürzungsverzeichnis

IoT	Internet of Things
$IIoT$	Industrial Internet of Things
KPI	Key Performance Indicator

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