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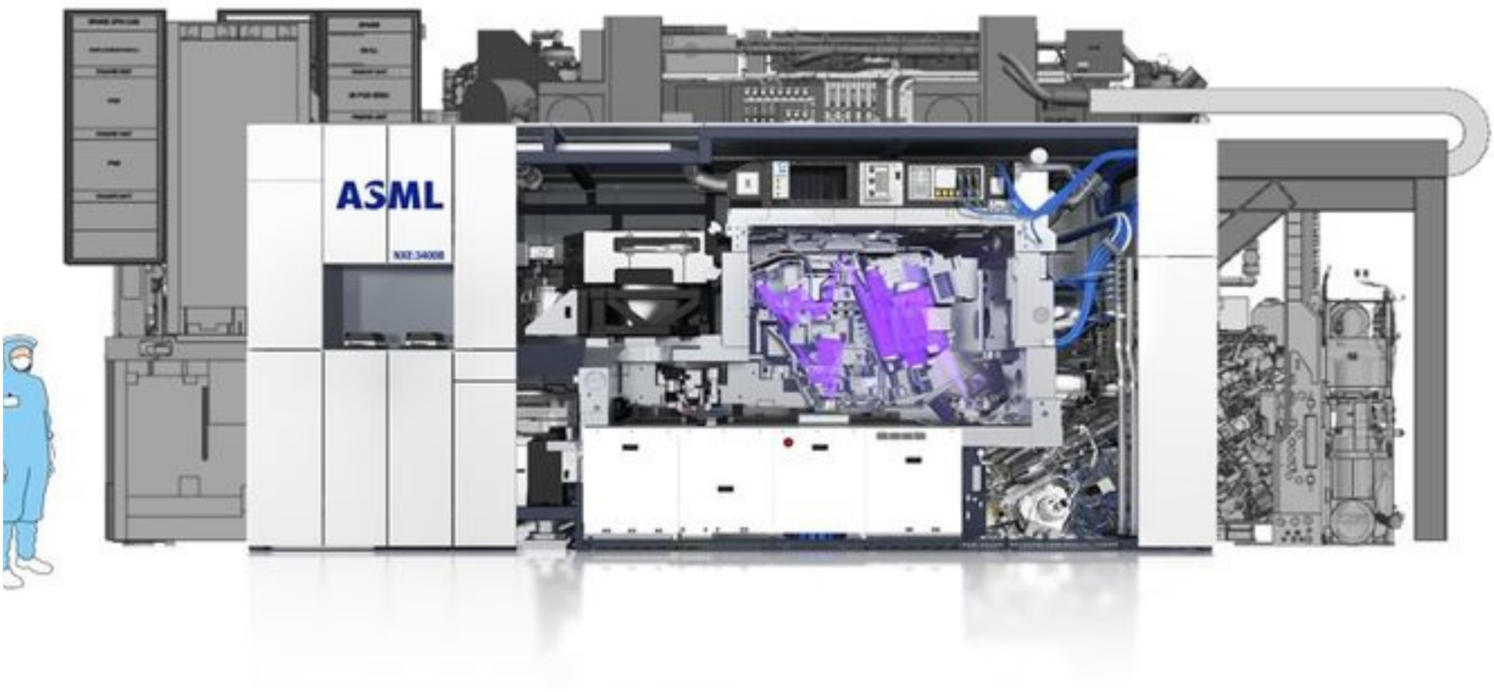
Enhancing Semiconductor Technology Development by Co-Development and Supply Chain Integration



TU Delft Delft University of Technology

ASML

MARCH 26, 2024

Enhancing Semiconductor Technology Development by Co-Development and Supply Chain Integration

by

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Graduation Project

in partial fulfilment of the requirements for the degree of

Master of Science
in Mechanical Engineering

at the Department Maritime and Transport Technology of Faculty Mechanical, Maritime and Materials Engineering of
Delft University of Technology
to be defended publicly on Tuesday March 26, 2024 at 03:00 PM

Student number:	4580265	
MSc track:	Multi-Machine Engineering	
Report number:	2023.MME.8874	
Thesis Committee:	Dr. A. Napoleone (Alessia)	TU Delft Supervisor
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Date:	March 26, 2024	

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Abstract

Semiconductor product development becomes increasingly challenging due to diminishing product life cycles, miniaturization, introduction of new physical principles, and new manufacturing processes. These problems are compounded in the absence of standardized development processes for the most complex semiconductor products like MEMS technologies, because the manufacturing of these products is often outsourced. Suppliers play a pivoting role in the realization of the product, from product design until process design and ramp-up. The supplier selection problem in this industry denotes the challenges in finding the right supplier while meeting all the technical, process and business requirements. The contribution of this research is in presenting how to develop a generic methodology for data-driven co-development. Thereby, this work presents a novel product development framework that leverages co-development and supply chain integration through data-driven decision-making. Co-development is reached through standardized methods for generating the required engineering output for supplier selection. Supply chain integration is introduced in the early stages of product development. This synthesizes with the outsourced manufacturing processes. Clustering algorithms are used to effectively shortlist suppliers based on their competences, and provide insights into supplier profiles and gaps. The latter is used to draw strategies for developing unattainable technologies. Using the framework, the required engineering output for supplier selection was generated in 77% less time while reducing information asymmetries between actors in the product development process. Furthermore, the framework made it possible to quantify decisions, allowed for supplier profile recognition and gap identification through its hybrid automated approach, and supplier shortlisting in 95% less time. This efficiency does not only showcase the immediate benefits of the proposed methodology, but also lays the foundation for future research towards a fully automated approach in semiconductor product development. The developed framework includes information flows between actors and steps in the product development process, their interfaces and demonstrates its added value and potential for a fully automated yet efficient future approach in semiconductor product development.

Keywords: Semiconductor industry, product development, co-development, modularity, supplier selection problem, machine learning, clustering, decision-making

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Introduction

1.1. Problem description

Semiconductor technology development is a highly competitive and rapidly evolving industry where time-to-market for new technologies and products plays a crucial role in providing superior products with more applications and functions. New product development is becoming increasingly complex, due to shorter life cycles, miniaturization, and the translation of new physical principles to new products. These innovations not only introduce new products, but also make the development of new manufacturing processes necessary to accommodate their unique features and functionalities. The semiconductor industry faces challenges to develop and mass produce these emerging technologies. The misalignment between the development of the products and their manufacturing processes with the supply chain plays a key role in the challenges of realizing these new technologies within desired time frames. This is also denoted as the supplier selection problem in literature. The important KPI's in this industry are time to market and the innovative nature of their new technologies for increasing their products performances.

The conventional approach to product development consists of discrete steps, supplier selection challenges, inefficient transitioning between product and process design and supply chain management challenges. As a result, bringing new semiconductor technologies to mass production within the desired time frames remains a complex and resource-intensive task. The developments of products and their manufacturing processes are not synthesized, resulting in lots of rework to account for this misalignment. Additionally, the supply chain is not integrated sufficiently during these development processes. That is because there is no knowledge about the interfaces between the steps of the product development process and their interfaces. This hinders the smooth transition from features to product and process design, towards supply chain integration and mass production.

To address this problem, there is a need for an integrated framework that combines product process co-development incorporating modularity, with efficient supply chain integration. This framework can support decision-making regarding product development, improving supplier selection processes using data-driven approaches, and reducing time-to-market for new technologies. The efficiency of product development processes in this industry is highly dependent to the complexity of the technologies being developed and the information availability at each stage of product development. It determines the smooth progression between phases in the product development process. Due to the complexity and the differences between the types of semiconductor products products, the framework was unified for the whole industry. That is why the interfaces between the steps in product development are important. This framework was verified and validated at ASML, the case company.

1.2. Literature gaps and motivation

The aim of this research is to contribute to the field of knowledge transfer and data-driven approaches to be incorporated in the early stages of product development. The current literature lacks information on methods that support design decisions aided by data, for generating the required engineering output towards supplier selection. There is no concrete information on the different steps taken during product development, their interfaces, information flows across stakeholders and how they could potentially be arranged and combined to reduce time to market, labour, and intellectual property losses. The lack of literature further extends to the absence of a standardized methodology guiding the translation of a desired set features for new technologies to a physical product. This gap also includes the design of manufacturing processes, supply chain integration, and other potential sequential or alternative orders during the product development process. Another notable gap in the literature is the insufficiency of information on how supplier selection and supplier capabilities can be mapped and strategically leveraged to enhance product development within the context of co-development and modularity approaches.

The semiconductor industry is a relevant example of an industry where these gaps apply. This is due to the large amount of stakeholders involved, the lack of methods for integration amongst them, complexity of the products, complexity in their manufacturing processes, and the intellectual property sensitivities involved. This work aims to contribute to the literature and practitioners in the semiconductor product development field by filling these gaps in a concrete an comprehensive manner.

1.3. Research objectives and scope

The research objective is to formulate how to develop a unified framework for the semiconductor industry to streamline complex semiconductor product development and enhance supplier selection by integrating product development with supply chain, using co-development and data-driven approaches. The scope of the framework is complex semiconductor products like MEMS, due to the lack of standardised methods for their product development, as will be explained in Section 2. The aim is thereby to be able to make reliable decisions when developing new technologies and explore how to leverage supplier selection for this process. The goal is to reduce the time to market (TTM), labour, and risks of IP loss by semiconductor companies.

In line with the motivation for this report, a research question was formulated in order to clarify how to make a framework for the semiconductor industry to streamline semiconductor product development, ultimately to reduce time to market, labour, and IP loss. This report specifically focuses on the decision-making steps and interdependencies of the steps in the new product development framework. The aim is to establish a framework on how the steps taken during product development should be standardised and how this can enhance supplier selection towards realising new technologies and products.

The following main research question was formulated for this research:

RQ: How to develop a comprehensive product development framework to enhance future technology development for the semiconductor industry?

This research question was decomposed into subquestions to make an assessment of the semiconductor industry, the state of practice for product development, and its limitations. Followingly, the state of the art methods for product development, drawn from literature in other industries, were explored to enhance efficiency within the semiconductor industry. Subsequently various methods on how supply chain integration could be effectively applied to enhance time to market were researched and a state of the future framework was designed. Additionally, data-driven approaches for decision-making were researched and applied in the context of the framework.

The following subquestions were formulated for this research:

SQ1: How can the semiconductor industry be described, and what are the crucial manufacturing processes involved?

SQ2: What are the state of the practice methods for developing new technologies in the semiconductor industry that affect the time to market?

SQ3: What are the state of the art methods for improving product development processes in the semiconductor industry?

SQ4: How can co-development strategies and modularity principles be effectively integrated into product and process design for semiconductor technologies?

SQ5:How can supply chain integration be effectively leveraged to enhance the development of new technologies?

SQ6:How can modularization impact the supplier selection problem?

SQ7:How to map the necessary steps and information flows that improve the time to market for future technologies?

SQ8:How can modeling, simulation, and data-driven approaches contribute to optimizing the strategic decision-making process in supplier selection for product development in the semiconductor industry?

SQ9:What machine learning algorithms can be effectively employed to address the supplier selection problem in the industry for strategic decision-making?

SQ10:How to verify and validate the developed models?

SQ11:What are the key aspects and interfaces to consider in the product development framework and its application?

1.4. Research methodology and structure

Throughout this research and in the subsequent sections, the outcomes from thorough literature studies are explored initially. After establishing the current information base from literature, a reflection of the findings from the case study followed at the end of the subsections. These findings were used to reflect on the earlier established knowledge from literature. The literature studies were based on papers about the semiconductor industry, and in the absence thereof, papers about different but yet comparable complex manufacturing focused industries. This approach was undertaken to build up a well-founded contribution to the existing literature, with strong foundations and robust scientific principles.

First, an extensive literature study of industry publications, relevant academic literature, journals, and books was conducted. The aim hereby, was to identify traditionally used frameworks, the semiconductor industry practices, and proven methodologies for co-development, modularization, supplier selection, and data driven decision making methods. This was done in order to understand the state of the practice and state of the art of product development approaches.

A case study at the case company was conducted to gather information on the state of practice methods applied in a real-world context. The choice for conducting a case study was driven by the need to gain insights into the specific practices, challenges, and dynamics present in the industry, specifically within the case company. By zooming in on the real-world operations of the case company, this research aimed to understand why certain methods were adopted, how they were implemented, and the corresponding outcomes. Due to this qualitative approach, a more nuanced exploration of context-specific factors influencing the semiconductor industry could be drawn. Furthermore, the case study was conducted in order to reflect on the information available in existing literature. The findings and reflections provided a foundation for the development of hypotheses in the run up to a comprehensive framework.

Multiple MEMS products from the case company were identified. Specifically MEMS products were chosen because, as opposed to other semiconductor products, their product development processes are less standardised in the industry. Furthermore, literature review reveals that no significant breakthroughs have been accomplished in standardising these development processes. Hence in this report, the term 'MEMS' will be used to address the MEMS case products. The term 'semiconductor product' will encompass all semiconductor products, including MEMS. This was done in order to validate various parts and tools developed as part of the framework. The reasoning behind this was to capture different ranges of challenges and intricacies related to the different MEMS products. This enhanced the understanding of the interfaces between the types of products and the product development processes as a result thereof. The developed co-development strategies were applied on these case studies as follows. A visual representation of a typical MEMS product architecture was made in order to breakdown the MEMS into distinct components and their functionalities. Modular breakdown tables were designed to detail out components, technical requirements, process requirements, interfaces, key-challenges, and co-development considerations. This analysis and breakdown aimed to understand the interactions between the components, and to withdraw useful information needed from the MEMS products. This information was crucial for formulating requirements and questionnaires for the supplier selection process in the next stages, also denoted as the required engineering output in the context of this research. This was the first step towards the development of a data-driven decision-making tool for supplier selection.

Different modeling and data-driven methodologies used in literature were evaluated. This was done to enhance the effectiveness of the supplier selection process within the framework. By doing so, the aim was to identify suitable methodologies for leveraging the available data during supplier selection.

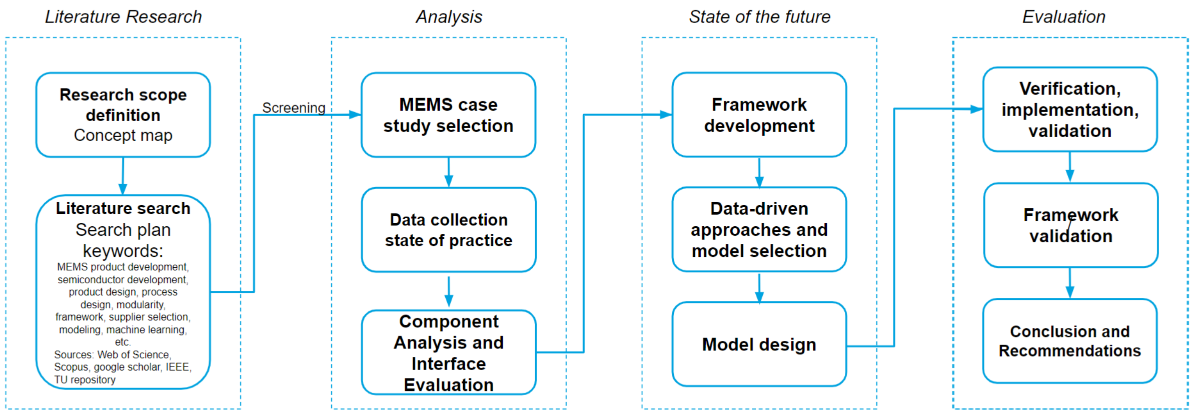


Figure 1.1: Research methodology

The developed data-driven decision-making tools were applied to the case study. Methods to translate this information to useful data were developed and applied for supplier selection, while taking into account the position and objectives of the models in the framework. A machine learning model was chosen and applied to analyse the case study. This model was then compared to different models for validation, to understand if it was the right model for the type of problem. This included a comparison with alternative models to validate the effectiveness of the chosen model in the context of supplier selection.

The developed framework and models were verified and applied to real-world scenarios within the semiconductor industry, on various types of MEMS devices from the case study. Validation processes followed to assess the efficiency of these methodologies, as a state of the future approach in product development. This was done by peer-reviews and evaluating the savings in terms of time and labor for the crucial decision-making processes during product development.

Finally, the execution of the methodology, the analyses, and validations were summarized. Recommendations for industry practitioners and suggestions for future research were provided based on this studies outcomes.

The outline of this report is as follows. Section 2 provides and overview of the semiconductor industry and the state of practice approaches and limitations for product development by answering SQ1 and SQ2. Section 3 explores the state of the art methods for enhancing product development in the semiconductor industry and answers SQ3 and SQ4. Section 4 elaborates on how supply chain integration can enhance product development by answering SQ5, SQ6, and SQ7. Section 5 builds further on this by implementing data-driven approaches for optimizing strategic decision-making processes. Hereby answering SQ8, SQ9, SQ10 and SQ11. Concludingly the findings, results and discussion are formalized and opportunities for future research are outlined. Figure 1.1 outlines the methodology and gives insights into the approach with the case study.

2

The state of practice and limitations in the semiconductor industry

This section describes the current state of the semiconductor industry and formalizes a comprehensive definition. This definition is build up by establishing an understanding of semiconductor products and their core characteristics. Followingly, delving into the analysis of the semiconductor industry, specific sectors and types of companies within the industry were distinguished. Subsequently, the industry is described from a manufacturing point of view, as a hybrid of discrete and process manufacturing with a strong emphasis on flexibility and complex supply chain management.

After providing this context, the critical MEMS manufacturing processes are described. Consequently, state of practice methods for developing new technologies are described. The supplier selection problem is elaborated upon, together with the state of practice information flows in product development. The reason behind this is approach is to provide clarity and context by presenting the state of practice of the semiconductor industry. The purpose behind this is to offer a foundational understanding of the industry's dynamics and challenges.

2.1. The semiconductor industry

The semiconductor industry stands as one of the world's most advanced manufacturing and R&D industries. It plays a pivoting role in driving innovation in various other domains, including computing, automotive, and healthcare [30]. The main products produced by the semiconductor industry are computer chips, integrated circuits (IC's), and MEMS devices. Computer chips and IC's are the backbone of electronic devices. They allow for complex functionalities in the digital world in a compact space. MEMS products are distinguished from the other semiconductor industry products, because they offer a bridge between the digital and physical worlds, enabling the integration of miniature mechanical systems with electronic circuits [33]. The supply chain and manufacturing infrastructure of MEMS devices are also distinguishable. And likewise, the product development of MEMS products is also different.

The physical differences between MEMS and electronic semiconductor devices are one of the major reasons for this distinction. Their physical differences come from the differences in capabilities and functions. MEMS devices, such as found in smartphones, automobiles, and high-tech machines, are used as actuators, sensors, or as miniaturized structural components. To achieve these capabilities, MEMS devices consist of materials with dimensions uncommon to semiconductor electronics. Piezoelectric materials, magnetic materials, structural polymers, and noble metals are MEMS-specific materials that are less well represented in semiconductor electronics. These materials are used because of their unique capabilities and require special tools in the manufacturing processes for MEMS manufacturing. Another difference with MEMS devices, is that they often have empty spaces, openings, or slits in them that enable the interface with a certain medium. For example photons, or pressure. The need for an interface and hence an empty space marks another contrast with semiconductor electronics, which are more often monolithic. In MEMS devices, this is less common, because the components can allow for physical movement [33]. Typical MEMS devices are gyroscopes, pressure sensors, inkjet printer heads, and optical switches [70].

To accomplish these functions, a greater variety of geometries are used in MEMS devices. Figure 2.1 shows that electronic devices are mostly composed of planar, rectangular shapes. Figure 2.2 shows that MEMS devices are composed of more complex three-dimensional shapes with curves and protrusions. The distinct shapes of MEMS results in differences in the tools used in the manufacturing processes. Wafer bonding, deep reactive ion etching, vapor hydrofluoric acid etching, and front-to-backside lithographic alignment are among the processes used specifically for manufacturing MEMS. Furthermore, due to the three-dimensional shapes, lithography processes are performed across nonplanar surface topologies. Hence the MEMS need to be aligned to features on the opposite side of a wafer, in contrast to generic semiconductor manufacturing.

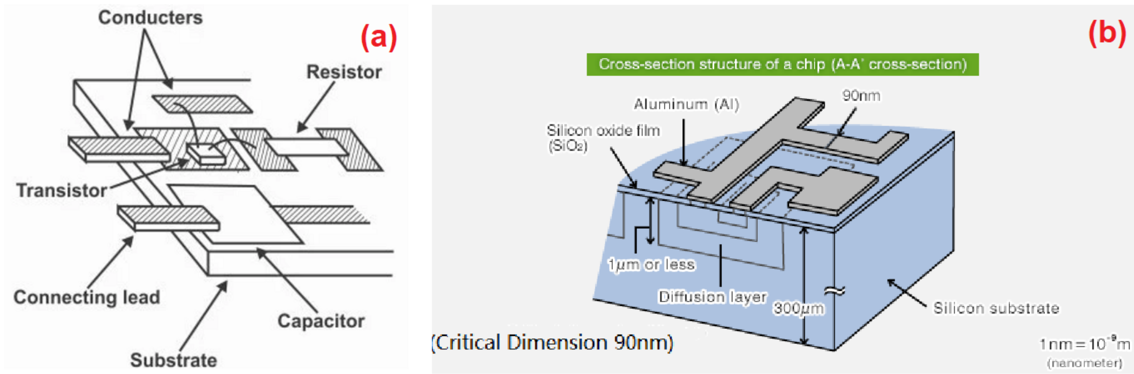


Figure 2.1: (a) IC with capacitors, resistors and conductors on a ceramic substrate [32], (b) cross-section of an IC chip [24]

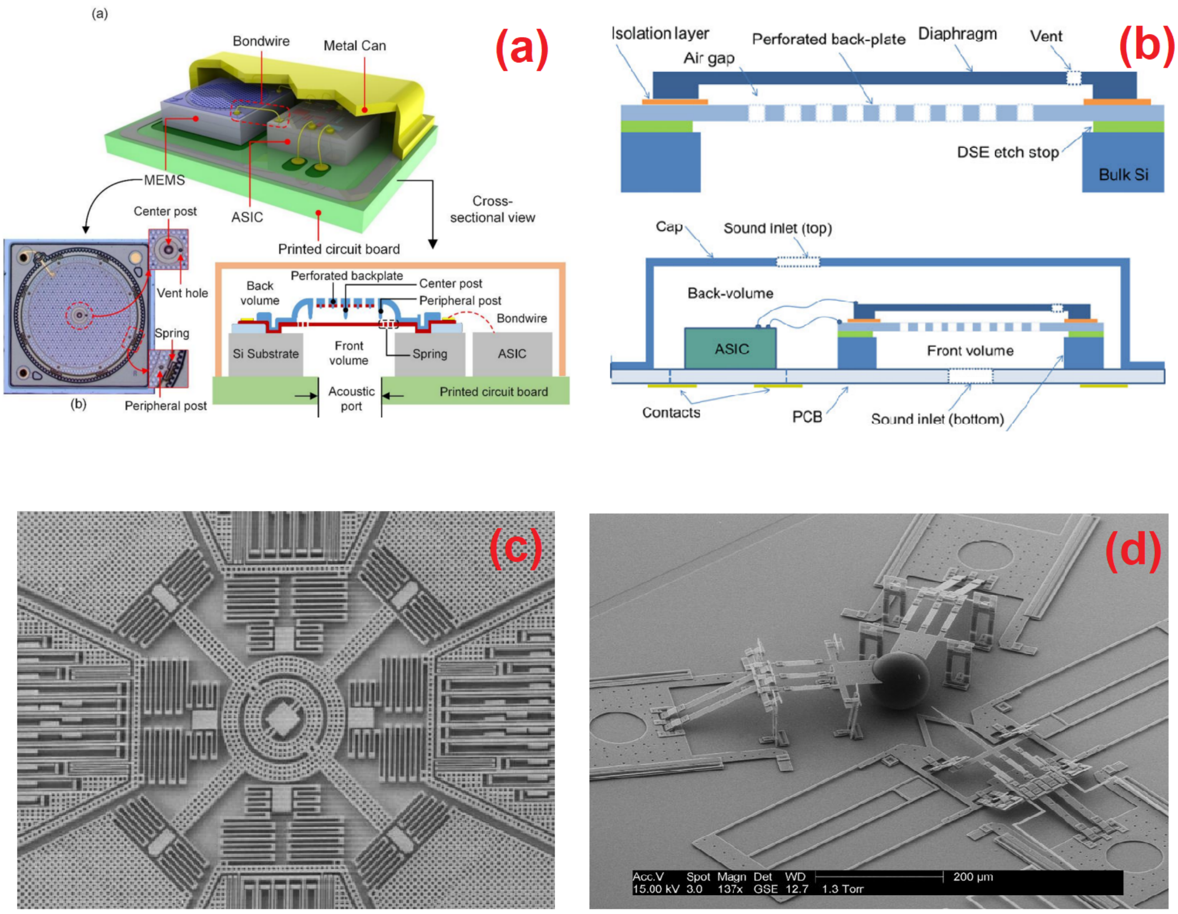


Figure 2.2: (a) A generic MEMS microphone package [98], (b) Electrostatic MEMS microphone [45], (c) MEMS pressure sensor [71], (d) MEMS DNA nanoinjector for cells [104]

MEMS and conventional semiconductor manufacturing techniques differ significantly from one another. MEMS design and manufacturing processes are less standardised, compared to for example IC processes. The latter can be standardised because the core components are transistors, capacitors, diodes, and resistors. Manufacturers can then combine these components and create various products. MEMS devices, on the other hand, are distinct and hence need different sets of procedures [33]. As a result, even after decades, no significant breakthroughs have been accomplished in the industry, nor in research to standardise these manufacturing processes, nor the development processes beforehand. And that amplifies the significance of MEMS devices in this research.

MEMS manufacturers need to make large investments to realise the manufacturing processes and the product designs of each unique MEMS device. Every MEMS product requires a unique process, which takes time and resources away from the supplier for other semiconductor products that may share a common process. Moreover, compared to larger-scale semiconductor products, MEMS products often have smaller wafer quantities per process. This lesser volume is due to the particular needs of MEMS devices, their smaller physical size, and their specialization in particular applications. Their specialization in applications makes that for some high-tailored MEMS devices, a customer needs lesser volumes. Consequently, MEMS development costs rise as a result of the fragmentation of manufacturing volume and the inability to reuse methods across devices [33]. This is the result of a single-product-oriented approach in the product design and process design phases of new MEMS devices. These aspects affect the entire cost of production as well as the expenses related to the total MEMS product development.

To get a deeper understanding into the analysis of the semiconductor industry, specific sectors of the semiconductor industry can be distinguished.

Integrated Device Manufacturers (IDMs) are companies in the semiconductor industry that handle all aspects of the manufacturing process in-house, from design and fabrication to assembly, testing, and sales. These companies show a high degree of integration and take ownership and management of their whole product development process [33]. Intel, Texas Instruments, Infineon, SK Hynx, Micron, STMicroelectronics, Bosch and Samsung are examples of IDMs [55, 48]. These companies own and run captive fabs that are focused on their own product lines. These captive fabs are used for the unique manufacturing needs of their own tailored semiconductor products, and make optimal use of the facility's production capabilities [33]. IDMs make for a substantial contribution to the global economic activity within the semiconductor industry. In 2012, the IDM sector was responsible for a contribution to employment and direct economic effect of $ 135 billion across the world. That is two-thirds of the direct GDP. Their influence on employment was also noteworthy, as IDM companies provided support for almost 801,000 jobs, or 62% of the benefits directly related to employment [30]. The fundamental characteristics of the IDM model, which sets these companies apart from others in the market, are their independence and ability to have complete control over the design and production of semiconductors. Because of their capacity to oversee and carry out every step of the product development process, IDMs are regarded as major forces behind innovation, global economic expansion, and job creation in the semiconductor sector.

Foundries are another powerful sector in the industry that revolutionized semiconductor manufacturing with their unique business model. Unlike IDMs, foundries are essential because they own and run fabs that are only used to manufacture semiconductor product designs for other businesses. This helps them meet the needs of organizations who cannot or will not finance or maintain their own fabs [48, 33]. TSMC, GlobalFoundries, SMIC, and UMC are examples of well know foundries in the industry.

Fabless semiconductor companies use foundries as specialized manufacturing hubs to produce their ideas. NVIDIA, AMD, Qualcomm, Broadcom, and MediaTek are well-known fabless companies in the industry [55, 48]. Foundries are hired to create chip designs and utilize their infrastructure and experience.

Semiconductor equipment manufacturers focus on the development of specialized machinery that is essential for the creation of semiconductor devices. Examples of such companies are Applied Materials, ASML, Lam Research, Tokyo Electron, and KLA. They design and develop the machines and tools for processes such as lithography, etching, deposition, and metrology. These companies manufacture precise machines to the highest standards, constantly research and develop to improve semiconductor device production techniques, and keep up with technology developments to satisfy changing market demands [55]. For the development of these machines, they work together with other semiconductor companies, their suppliers. The suppliers provide them with necessary semiconductor devices like

MEMS devices, to make their machines.

The semiconductor value chain is complex and consists of various types of companies. It ranges from manufacturers, designers, and service providers with IDMs, fabless companies, foundries, and equipment manufacturers. There is an interdependence between those companies where they rely on each other as suppliers for the design, fabrication, and supply of semiconductor products. This convoluted network underlines the diverse roles and collaborations within the value chain and emphasizes the necessity for coordination in supplier relationships. Because the core of their interdependencies and intricacies is in the development of new semiconductor products. This can be either within each type of semiconductor company, between foundries and equipment manufacturers, or between other types of companies. The interdependencies make for the necessity of a standardised framework to allow for collaboration amongst semiconductor companies and suppliers to enhance product development.

This collaboration amongst companies introduced a new phenomena, the division of intellectual property ownership. This concept transformed the semiconductor industry. Foundries invested in their own manufacturing processes, while their consumers kept ownership of their designs. This division allowed smaller design-oriented companies to thrive without having to bear the heavy financial burden of owning and running high-tailored manufacturing facilities. This paradigm promoted innovation and industry competitiveness by facilitating access to state-of-the-art semiconductor manufacturing processes. With over 200 foundries operating worldwide, the foundry concept has seen a sharp increase in popularity over time. TSMC is the driving force behind this paradigm and this model has been continued after their success [48, 33].

From a manufacturing point of view, the semiconductor industry can be seen as a hybrid of discrete and process manufacturing with a strong emphasis on flexibility and complex supply chain management. As described earlier, this is due to complexity of the value chain, and the product development processes.

The semiconductor industry includes discrete manufacturing, because this form of manufacturing deals with the manufacturing of discrete units. It deals with orders and parts, and the output is easily identifiable things, for example, chips, cars, and computers [108]. In the context of the semiconductor industry, this is also the case. Because the industry is involved in creating individual components such as chips, ICs and MEMS. This also includes the assembly of discrete components such as transistors, capacitors, sensors, MEMS into the final semiconductor product. This statement is backed up in [111, 86]. Discrete event simulation models were found to be effective in simulating the complex manufacturing processes in the semiconductor industry according to [35, 95, 22, 122]. These studies underline the significance of discrete-event simulation in improving performance and decision-making in the semiconductor industry's discrete manufacturing processes.

The industry also includes process manufacturing, because of the chemical and physical processes applied such as deposition, lithography, and etching. These processes have to be performed sequentially, after one another. They convert materials into complex semiconductor parts. These permanent changes applied throughout production are another core characteristic of process manufacturing [7].

MEMS manufacturing follows similar patterns and can therefore also be seen as a hybrid of discrete and process manufacturing, depending on the features of the MEMS device. The discrete manufacturing processes tailored for each MEMS device follow sequential steps. The processes involved in making the layers of individual components of the MEMS are mostly irreversibly merged on a substrate like silicone. This makes it impossible to disassemble complex MEMS devices without sacrificing their functionalities. Hence, MEMS manufacturing is a hybrid of discrete and process manufacturing processes.

2.2. The core processes in semiconductor manufacturing

In this subsection, the core processes of semiconductor manufacturing are described. This is important because it provides context and understanding to the processes discussed in the following sections of this report. The six core processes for semiconductor manufacturing that also apply on MEMS manufacturing are: deposition, photoresist coating, lithography, etching, ion implantation and packaging. The semiconductor manufacturing process starts with a silicon wafer that is sliced from a cylindrical shaped pure silicon bar. Followingly, the thin wafers are polished to reach a desired level of smoothness before the next processes start.

Deposition

Film deposition is used to deposit thin films onto these polished wafers. These thin films consist of conducting, semiconducting or isolating materials. Deposition is not only done in the first step in semiconductor manufacturing. In the next steps during the manufacturing process, metal or dielectric layers are deposited as well. A semiconductor device such as a MEMS may contain multiple deposition layers. Several techniques, including metalization, chemical vapor deposition (CVD), physical vapor deposition (PVD), and epitaxy, can be used to carry out deposition [77].

Photoresist coating

A photoresist is applied onto the metal layer through a spinning process. This coating is sensitive to light-induced chemical changes. The photomask, a transparent plate with opaque areas, is placed between a light source and the wafer. This mask is used to selectively expose sections of the substrate to light. Photoresist typically exists in two types: "positive" and "negative." In positive resists, masked areas on the photomask correspond to where the photoresist remains after development. Conversely, negative resists leave exposed areas intact, developing the unexposed sections. This developed resist is usually hard-baked before entering a chemical etching process to remove the underlying metal [59].

Lithography

The primary processes during photolithography include exposure, development, and process control. This process starts with the thin film coated wafer from the latter step. Followingly, an Integrated Circuit (IC) design is transferred via a photo mask, or reticle, onto the photosensitive polymer. By doing so, accurate and precise three-dimensional patterns are created on the silicon wafer's surface. Exposure tools, like steppers, project light through the reticle to expose the wafer with ultraviolet light, transferring the pattern onto the wafer. Subsequently, the exposed wafer undergoes development, eliminating polymerized sections of the photoresist [77].

Etching

In the next step, the exposed areas on the wafer surface are selectively removed through chemical or physical etching processes. The etch step creates the desired, patterned layout that was created during the earlier lithography step. The precise removal of material is crucial in shaping the final features and structures on the wafer. Etching processes are distinguished in wet and dry etching. For wet etching, liquids are used to remove material. In the latter case, gases are used [77].

Ion implantation

Ion implantation is done by applying dopant (positive or negative) ions to the etched areas on the surface of the wafer. This is done in order to adjust the patterns electrical conducting characteristics. The silicon material of the wafer is not an ideal insulator, nor a conductor. It is important to adjust this in order to control the flow of electricity and create transistors in the semiconductor products such as e.g. MEMS, microchips, or others [77, 63].

Packaging

In the last steps, the wafer must first be singulated into individual die. The spacing in between the die depends on the dicing method. Mechanical sawing using a dicing saw, laser cutting, and scribing and breaking are typically used dicing methods. All die are singulated and individually assembled and packaged. The interface between the MEMS die, the environment, and the system is in this packaging. Packages vary based on their materials, which are often ceramics, metals, and plastics. There are numerous different shapes for packages, including overmolded and hollow containers. Examples of packages are: plastic molded case, ceramic open, or Wafer-level encapsulation [33]. Further details on the descriptions of all MEMS packages available are beyond the scope of this paper and can be found in [61, 60].

2.3. State of practice methods for developing new technologies

This section aims to elaborate on the critical steps in the MEMS product development and their interdependencies, limitations, information flows, and introduces the supplier selection problem in the semiconductor industry affecting new product development. Despite no comprehensive product development model could be found in literature, an extensive literature study and a case study resulted in a state of practice model describing each step in MEMS product development with its corresponding actors, information flows and limitations.

2.3.1. MEMS product development

An extensive literature study has been performed on the critical steps in the development of new MEMS technologies in the semiconductor industry. MEMS product development falls behind on other semiconductor product development, because for MEMS, the industry has not yet been able to fully standardise process flows and automation tools to consequently design and produce new chips at high yield [33], like explained earlier in this chapter. Automated MEMS design processes are described as a sequential process in Fig. 2.3, where the biggest challenges are in process design by foundries.

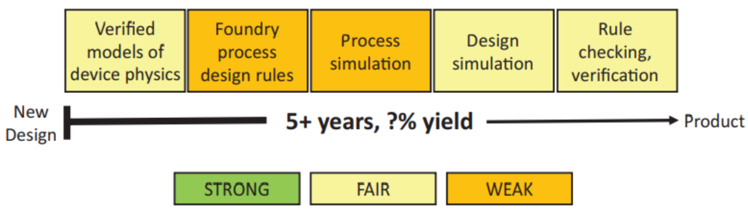


Figure 2.3: The key elements of an automated MEMS design environment [33]

The book [33] further defines five stages of commercialising MEMS products as: proof-of-concept prototype, advanced prototypes, foundry feasibility, foundry pilot production, and foundry production in Fig. 2.4. The authors discuss that the foundry feasibility step is for transferring the MEMS process to the foundry and to determine the feasibility of making the unique MEMS device at the foundry [33]. This step includes lots of feedback loops and other risk mitigation steps. These feedback loops are not only between engineering and design teams of the buyer and the supplier, but also inside of the procuring company between product design teams and process design teams. These complexities arise from the level of novelty of the MEMS technologies being designed, as well as the need for finding the suitable manufacturing processes for them. These discrepancies result in longer product and process design durations, necessitate numerous design alterations due to supplier shortcomings, and consequently make it highly challenging to identify the right supplier.

No clear overview of product development steps could be found. Nor did the authors in [33] provide a comprehensive overview of the information flows between different actors in this ecosystem, e.g., departments, or engineers that design the MEMS products and their manufacturing processes before selecting foundries or suppliers.

The authors in [101] gave a generic overview of the steps in product development in the general domain of complex manufacturing technologies. The authors in [85] summarized this classical linear model for product development in their study about design for manufacturing in the semiconductor industry. The representation of the process flow of product development steps according to [101] and [85] can be seen in Fig. 2.5.

According to [40], the high-level phases in the semiconductor product development were: evaluation of product proposals from customers, the development phase, and production ramp. The first phase included the identification of the type of technology to be used, the technical requirements, and the expected resource requirements. The authors do however mention that for new products, very limited information is available in this phase. This came also forth from a case study of the author of this report. The model derived from a case study will be evaluated using this extensive literature study at the end of this section.

In the second phase according to [40], the product development begins upon approval of the semiconductor company. The authors emphasize the need for investments to develop new IP. The completed designs are transformed into designs and prototypes. After approval of the prototypes, the

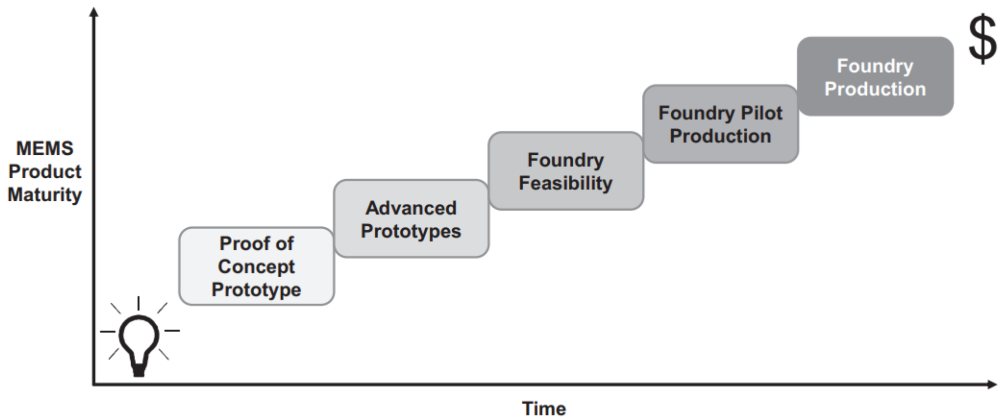


Figure 2.4: The five stages of development to commercialize a MEMS product [33]

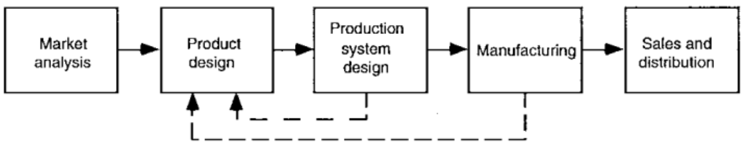


Figure 2.5: Classical (linear) model for product development [85, 101]

product design is evaluated and the final phase can start. In the production ramp phase, the production process starts and capacity related risks are evaluated due to unforeseen developments affecting the availability of resources [40]. It is very important to note that [40] was focused on the semiconductor industry overall. It shows discrepancies with other information found in literature about MEMS product development, classical product development and the case study at the company about MEMS product development. The discrepancies are in the process design phase, which happens after the prototypes are approved. In the case study of this work, and for complex semiconductor products like MEMS, the design of MEMS manufacturing processes take place after the product design phase. The prototyping phase follows subsequently.

Based on a case study at the case company of this research, it was found that the product development process is more nuanced. Therefore, the author of this report developed the linear model of MEMS product development in Fig. 2.6. This model shows the state of practice product development process flow, build by combining information from literature as described earlier and empirical research at the case company. This process flow is composed of the agents and the deliverables of each step during product development, until supplier selection. The process starts with the research department (RES) at the company. They define the features of the new MEMS device according to customer needs or in-company defined requirements. These features are then translated into products by the development and engineering department (D&E). Followingly, the process engineers (also D&E) design the manufacturing processes to make the physical MEMS product. Lastly, these designs are communicated with suppliers, and after that follows the iterative design refinement of the product and its process towards realising the final MEMS product. The translation of product designs to process designs, and the communication with and selection of suppliers require lots time and resources. All in all, these processes require lots of iterative changes, rework, and manual labor.

Moreover, there is a significant concern regarding intellectual property (IP) sensitivity. Semiconductor companies may vendor lock-in challenges when sharing crucial IP with suppliers during the initial phases of product development. This situation arises when suppliers lack engineering expertise or incentive to commit to contractual agreements. Nevertheless, semiconductor companies are reluctant to switch to alternative suppliers due to the risks of forfeiting valuable IP and potentially exposing themselves to further IP loss with other suppliers. This dilemma is compounded by the competitive nature of the semiconductor industry. These inefficient processes affect the time to market significantly. Section 4 will elaborate further on how to improve these inefficiencies.

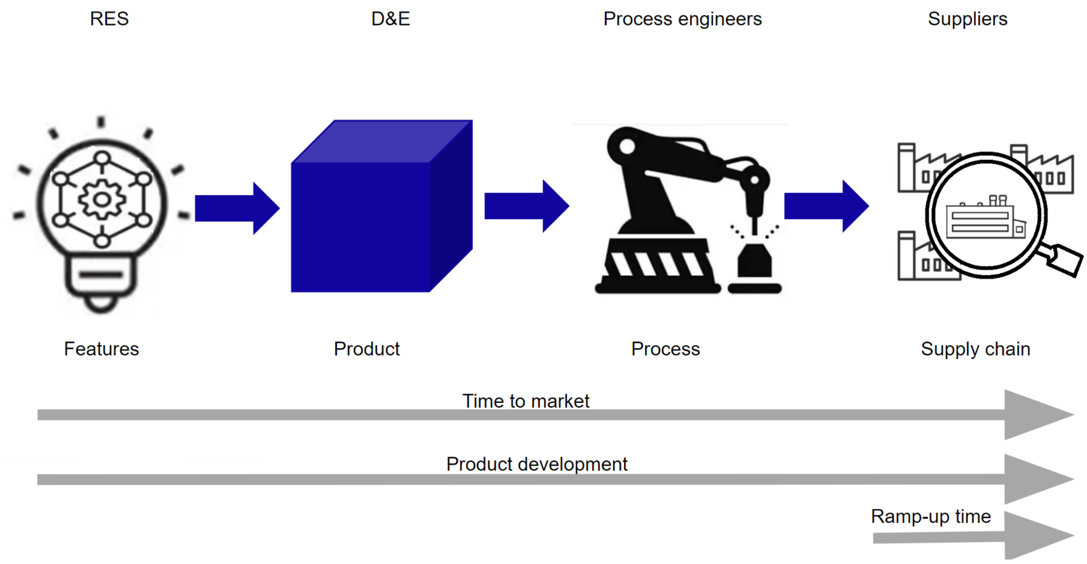


Figure 2.6: Own elaboration of steps in product development

2.3.2. The supplier selection problem

The limitation that overarches the design and realisation of the product at a semiconductor company is best described as the supplier selection problem. This problem makes new technology development even more challenging and increases time to market further. This term is used in various researches [110, 15]. Various papers denote that selecting the suppliers is one of the most critical aspects of the supply chain in the semiconductor industry [4, 49, 78]. The driving force of the semiconductor industry is the new technologies that are developed that go beyond the existing technologies with regards to innovation, performance, and system compliance. And as a result thereof, these new technologies require technical requirements and manufacturing requirements that have not yet been proven or are not executed by semiconductor suppliers. The realisation of these new technologies is influenced by suppliers. In the semiconductor industry, the suppliers play a pivoting role in all inputs of the designs, processes, manufacturing flow and the end products of the technologies [110]. Therefore, these suppliers are of direct influence for the profitability [69, 12] and the innovation capability of the procuring company. This influence encompasses the industry from a technology level, company level, but hence also on an industrial level. All major semiconductor companies recognize this supplier selection problem through various steps in their new product development processes.

Furthermore, the suppliers have an impact on the timely fulfillment of the orders of the products and modules [4]. This again has consequences for the design and prototyping phases at a company, and its competitive position. And because of the high competitiveness, this affects the industry as a whole [78].

The authors in [4] highlighted that the existing supplier selection processes have proven to be insufficient. The determination of the optimal selection criteria to identify the most suitable suppliers was always a challenge [52]. This is because the supplier selection process consists of a multitude of criteria [47, 121, 29]. A possible solution often recognized in literature to this multitude of criteria is in the comprehensive evaluation of the various qualitative and quantitative elements. These diverse factors significantly impact the supplier selection process, and make it important to find a balance among them to identify and engage the most suitable supplier [4].

However still, these methodologies introduce new challenges in balancing various criteria. It can be often complex to trade-off all the possible factors in the supplier selection process. One could recognize that not all criteria contribute equally in supplier selection, while an indiscriminate approach can complicate the process. This then can potentially lead to errors and adverse effects on the selection process and thus company profits and performance [4].

The main criteria for selecting suppliers across different industries are given in table 2.1. A problem that arises with these criteria, is due to their generic nature. The technology criteria is mentioned in a few papers, but only severely and without context. The majority of these criteria are not tailored for new technological and manufacturing challenges that arise because of the innovative nature of the semiconductor industry. They are universal criteria. Even though these criteria introduce a glance of what should be taken into account during supplier selection, they are not technology focused. Meaning that, when using these requirements at the end of a design process, no conclusions can be drawn about whether or not a supplier is really capable of realising new technologies or manufacturing methods. This is because that has not yet been proven. And this is a huge gap, specifically for the semiconductor industry, that has not yet been challenged in literature, nor by professionals in the industry itself. This means that it should first be researched when exactly in the product development process one should apply any supplier selection criteria. And secondly, which criteria and how any criteria should be used in supplier selection. This allows for making informed decisions during supplier selection, proactively.

Table 2.1: The main criteria for selecting suppliers across different industries

Criteria	Sub-criteria	Industry (Semiconductor, General manufacturing, Automotive, High-tech)	References
Price	Competitive cost, cost information	S, G, A, H	[17, 59, 66]
Quality	Factory audit, yield, rejection rate	S, G, A	[119, 113, 16, 29]
Delivery	Distance, delivery speed, safe stock	S, G, H, A	[113, 119, 17, 8, 29],
Service	Response time, reliability, joint development, information sharing	S, G, A	[119, 17, 53, 67, 29]
Flexibility	modification, volume	S, G, H	[17, 4, 27, 8]
Technology	product innovation, capability of R&D	S, H, G	[17, 8, 16]

Numerous decision-making models have been proposed in the literature, such as multi-objective optimization problems (MOP), data envelopment analysis (DEA), simple multi-attribute rating technique (SMART), and total cost approaches. While these models offer systematic approaches, they often present implementation difficulties. They require decision-makers to specify precise weights for individual criteria or present challenges in involving decision-makers effectively [43].

The authors of [53] address the limitations of existing supplier selection methods by pointing on the need for technology planning using a technology roadmap. In the context of semiconductor manufacturing, the rapid pace of technological innovation necessitates strategic technology planning, including timely investments and equipment upgrades. The paper proposes an extended, four-layered technology roadmap (TRM) that integrates supplier selection as a critical factor. The TRM incorporates a layer specifically focused on equipment suppliers, selected through an evaluation process using the analytic hierarchy process (AHP). This approach aims to enhance technology planning by integrating considerations for equipment supplier selection into semiconductor manufacturing companies. The problem however with the approach of integrating an equipment supplier is that it makes the supply chain practically even more complex, due to the challenges in coordinating between suppliers and the very little amount of understanding on the needed equipment for the manufacturing process of a semiconductor device.

Therefore, in the context of a more comprehensive but holistic approach, and because this supplier selection problem is part of a bigger challenge, that is to enhance the development of future technologies, the solution for this supplier selection problem should not only be sought in the criteria or the quantification, like in the papers cited earlier. The solution should encompass the broader scope of the problem instead. That is, in the context of product development steps and the integration of the supplier selection, the integration of the design process with the supply chain. For that, there should be a good understanding of the technology needs from a client perspective and the capabilities from a supplier perspective. The problem with the current proposed methods in literature is in the fact that they do not emphasize the need for a more inclusive and technology driven supplier selection process. Moreover, they portray this supplier selection process as a problem in itself and not as part of the whole product development process. This is definitely not in line with the widely accepted view that supplier selection has a major influence on the development of new technologies, and should therefore be addressed in a new product development framework.

2.3.3. State of practice steps and information flows in product development

Given the biggest challenges for developing new technologies and MEMS products in the semiconductor industry, and now that there is a more comprehensive overview of the currently used process steps in the product development of new MEMS technologies, the important information flows in between these steps can be researched. This topic is a gap in the existing literature and hence the information in this subsection was derived from an in-depth literature study and findings from the case study. A very limited amount of papers does show the disjoint between the design and manufacturing phase, and thus the transfer of information, like in [68]. The amount of detailed knowledge into the information needed for transfer is scarce, as shown in Fig. 2.7.

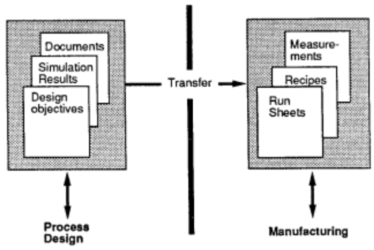


Figure 2.7: The disjoint between design and manufacturing and sparse amount of information that is needed to transfer between both [68]

In order to provide a comprehensive overview, and to fill this gap in the literature, all findings from literature and empirical research were summarized at the end of this chapter for the state of practice information flows. As stated earlier in this chapter, MEMS product development follows a linear process flow with the following sequential steps: (1) formalising features, (2) translating those into a product design, (3) the process design thereof and lastly, (4) the supplier selection process with the supply chain integration step.

The formalisation of the features of the new MEMS device is dependent on the technology push and market pull principles according to [41]. In the technology push principle, the existing IP at and the technological core competences within the company are evaluated. This is an important aspect describing the semiconductor industry. Followingly, the market trends and opportunities are evaluated. In the market pull principle, the market, customers, and high-level product definition are evaluated. From a case study, it was seen that the research department is responsible for this early idea generation and conceptualisation phase. The decisions made in this phase were more technology push focused and the market pull was realised after new technology markets were discovered. The information flow to the next step here according to [41] and the extensive case study was based on the definition of the features of the new MEMS device, limited to the high-level product definition. This was based on the objectives to be reached with the MEMS device. This phase forms the foundation for the sequential product development stages. This phase includes information on the dimensionality in 2D; isotropic material properties; idealized boundary conditions; expected thin film stress; calculated parameters such as voltage, current and power; and a course accuracy according to [33].

In the product design phase, the 3D designs with dimensions and anisotropic material properties are defined. Furthermore, the boundary conditions and measured thin film stress from test wafers are formulated. Followingly, MATLAB and Simulink models are made to test the device performance. Lastly, the accuracies are calculated within 15 % and 30 % of reality according to [33].

In order to proceed to the process design phase, the detailed MEMS requirements and specifications need to be known. This includes the detailed dimensions, materials used, and the design criteria and features resulting from the MATLAB and Simulink simulations. The process engineers need to have a clear understanding of the components, features, and design of the product in order to design the manufacturing processes. That is in order to select: the types of materials to deposit, lithography equipment to use, feature sizes and etching methods to apply. For lithography, for example, the two tools most commonly used for MEMS are contact lithography and stepper lithography. Contact lithography, can expose features down to 2μm . On the other hand, stepper lithography tools can achieve 0.5 μm linewidths [33].

It is possible that, during the process design of the devices, some external factors of the manufacturing processes could affect the other components of the MEMS device. Other external factors could also affect the MEMS while in operation. These types of external effects should be taken into account during the preliminary product designs and process designs, in order to come to a detailed design of the products and processes. Examples of these external factors are: dimensional tolerances; influences of other manufacturing processes; electrical signal input; thermal input from other components; stresses induced by chip-mounting methods; location and type of mechanical, electrical, optical, and fluidic interfaces [33].

The information gathered from literature is combined with the information gathered from the case study. An overview of the information flows in between product development steps in the state of practice is given in Fig. 2.8. This is the first attempt towards standardization of the information flows as part of the framework.

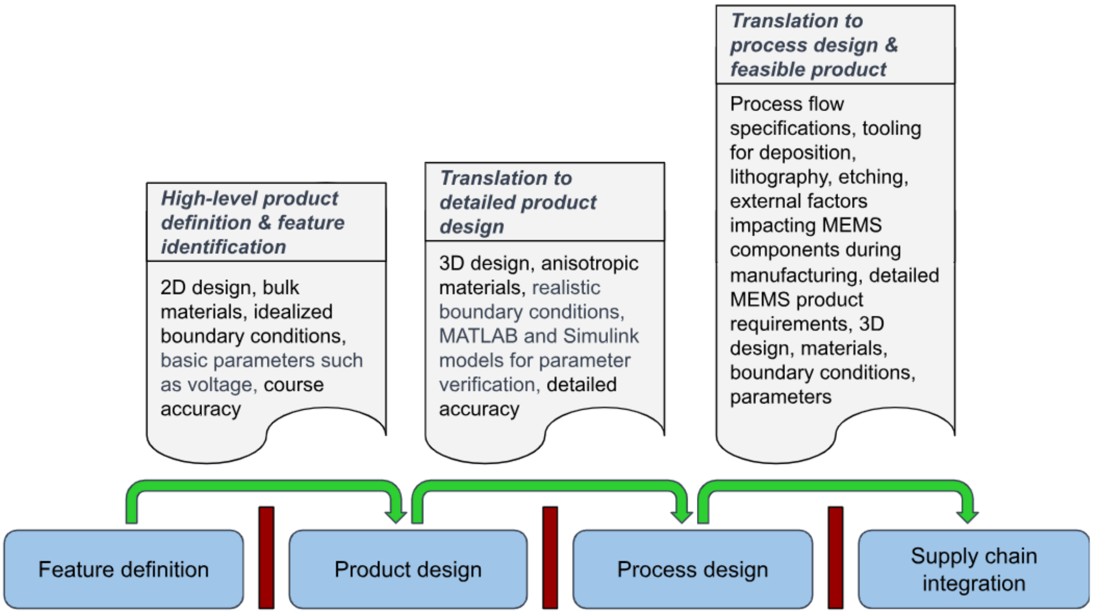


Figure 2.8: Own elaboration of information flows across product development steps

2.4. Concluding remarks

This chapter provided a comprehensive explanation of the semiconductor industry by explaining the uniqueness and lack of a standardised process for MEMS product development. The industry is composed of different types of companies, such as IDMs, foundries, fabless, and equipment manufacturers. Currently, product development is typically done by employing a linear sequential process with limited amount of standardized information flows between the steps, resulting in information asymmetries. The supplier selection problem is the main limitation that overarchers the design of the product, its manufacturing processes and their execution in the semiconductor industry. Supplier selection in literature is done through standard criteria and has proven to be insufficient in the context of a new all encompassing framework. This is because these criteria are too general and no sufficient models are developed that proactively incorporate the design choices of the products and processes using these criteria. In this context, the information flows between the design and manufacturing phases are proven to be sparse. Hereby, the answers to subquestion 1 and subquestions 2 are established comprehensively. The next chapter focuses on exploring state of the art methods that are proven to be sufficient for product development, according to literature about other industries and fields.

3

State of the art methods for semiconductor product development

The aim of this chapter is to elaborate on the state of the art methods for enhancing semiconductor product development, recalling the major challenges in product development from chapter 2. This is done by analysing MEMS products, due to the lack of standardized development processes and their higher level of complexity compared to other semiconductor products such as wafers or reticles. The measure of enhancements is in the nature of the problems that limit product development and increase time to market. The nature of the problems arise from the discrepancies between product design and process design steps, and the lack of knowledge on how and which suppliers to select for outsourcing the physical MEMS products and components. The solutions to these problems are sought in literature from the semiconductor industry, literature from other manufacturing-dependent industries, and from empirical research through a case study. By doing so, the objective is to slice and dice the current problems, and ultimately answer subquestion 3: "What are the state of the art methods for improving product development processes in the semiconductor industry?". Additionally, subquestion 4: "How can co-development strategies and modularity principles be effectively integrated into product and process design for semiconductor technologies?" was addressed. The enhancements are measured by ensuring the smooth transition to the next steps of product development. This included reduced labor, rework, time needed to complete activities, and improved information flows, thereby reducing information asymmetries through standardization.

3.1. Co-development strategies

As seen in earlier sections, the interaction of design and manufacturing is becoming increasingly important for the semiconductor industry due to the complexities of emerging technologies, the need for efficient resource utilization, shorter life cycles, and the demand in reducing TTM due to the competitive nature of the industry. The knowledge from the manufacturing domain in general should be leveraged for the design of the processes and the products to increase product success. Furthermore, this can reduce rework and design changes afterwards, ultimately reducing TTM. This statement is backed up in [13], where the authors integrated operations and product development methodologies for improved product success using advanced product quality planning. However like the authors stated, it is impossible to plan for every possible issue during semiconductor development.

In order to adapt to volatile markets, greater product variety, and shorter product life cycles, literature and industry noted that platform-based co-development of goods and manufacturing systems, as well as flexible manufacturing, are becoming increasingly important. However, managing the relationships between the manufacturing and product domains is essential to platform-based co-development. The definition of co-development according to [11], is making sure that decisions about the manufacturing platform's capabilities are taken into account while designing the product platform, and vice versa. Co-development and managing both product and process (or manufacturing) domains can be applied internally within one company if the process designs are made internally.

In the semiconductor industry however, the product domain is carried out internally and the manufacturing domain is outsourced. Hence, the manufacturing processes are predominantly handled by external suppliers. And because the capabilities and knowledge on manufacturing processes are at these suppliers, the semiconductor company finds itself in a disadvantaged position, lacking leverage over these crucial processes and relying heavily on the expertise and capabilities of the suppliers. While for most semiconductor products, the process requirements allow for flexibility as long as the final product meets the technical requirements, this dependency on suppliers introduces the risk of IP loss, extended product development timelines due to many iterative refinements, and hence consequently increasing costs. Ultimately, this reliance diminishes the semiconductor company's control and strategic advantage in manufacturing-related decisions and operations.

In the automotive industry, the implementation of co-development strategies extends to outsourced manufacturing domains as well. The authors in [31] state that in co-development, it is essential to go from antagonistic to collaborative partnerships, which will promote open communication between the supplier and the procuring company. Synchronizing processes through uniform methods, shared information, and cooperative milestone coordination is essential for success of both companies. This coordination also includes the organization, followed by mutual synchronization toward predetermined milestones, and collaborative ongoing process improvement. The resulting improved communication and inter-company cooperation was proven in [31] using an illustrative model for process synchronisation between suppliers and procuring companies, as shown in Fig. 3.1.

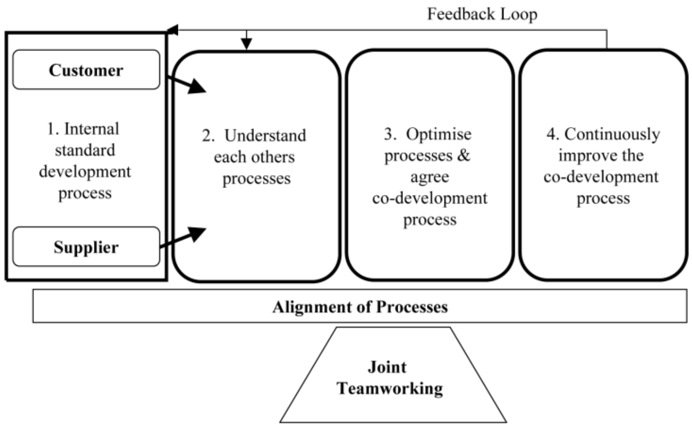


Figure 3.1: Process synchronisation model [31]

This model was taken up by 88 co-development teams. A co-development wallchart with milestones for coordination provided an adaptable method for process synchronisation. The teams shared their processes and this facilitated discussions and optimizations. The method's adaptability to changing procedures promoted cooperation between companies by concentrating on important benchmarks and identifying bottlenecks for improvement. This strategy, which is built on increased communication, aimed to streamline the product development and significantly cut the time and expenses for the suppliers involved.

The main learning from this study is that any co-development partnership should internally adopt a standard method for developing products, preferably by integrating teamwork and involving multiple functional areas. The co-developing partners must then exchange information in order to comprehend each other's development processes. The organizations' operational procedures are still a more important focus point than their joint ventures. Companies have to implement strategies and tools such as the co-development synchronization wallchart, to encourage cooperation amongst product development teams. This also gives management the backing they need to internalize the necessary improvements within their team. The automotive companies from the study met their goals of reducing development time by 30%, development cost by 40%, and overall part cost by 30% among 88 suppliers [31], demonstrating the potential advantages of standardized methods for co-development in an industry where the product domain is carried out internally and the manufacturing domain is outsourced, such as is the case in the semiconductor industry.

According to [74], the current manufacturing problems are related to product variation. The change of products encourage collaborative product and production system development, in other words co-development. The paper viewed co-development in the context of several platform techniques. The authors discussed how to characterize the various situations for the co-development of products and manufacturing systems. They distinguished between Product-Platform-Based Co-Development, Manufacturing-Platform-Based Co-Development, or Platform-Based Co-Development and also denoted that combining the three is possible. The needs of the system to be designed determines how much and where co-development is ought to be implemented.

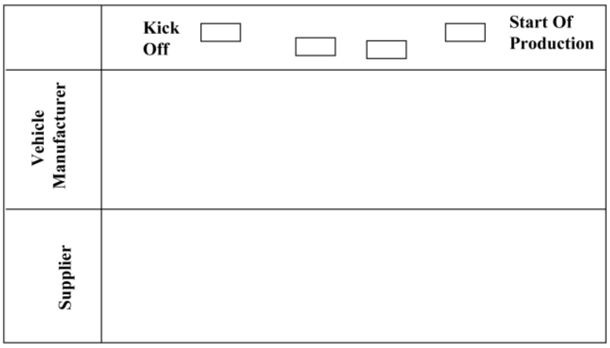


Figure 3.2: Co-development process synchronisation wallchart [31]

Although functional modeling can serve as a foundation for illustrating system designs, [74] focuses on the varying levels of emphasis on the interfaces and interactions of these systems. In general, several scopes can be used to zoom in on the interactions and interfaces. As a result, the three models to capture the interactions and interfaces are identified as follows: within the product, so between the product's components; within the manufacturing system, so between machines and robots; a hybrid between the products and the manufacturing systems. It is important to note that the authors assume that a system consists of subsystems. As a result, various models illustrating the composition of products and production systems were composed [74, 23, 39]. Figure 3.3 shows the three models and the interactions for developing and synchronising design solutions between the systems, consisting of the product or manufacturing platforms. The blue color relates to the product system, while the orange color refers to the manufacturing system. The areas captured by the continuous line are a set of design solutions. The requirements and constraints for the design solutions are shown by the dashed lines [74].

The main learning from this study is that co-development is an effective strategy for addressing product and manufacturing based problems. It is important to recognize the different types of co-development and on whether it applies on the product platform, the manufacturing platform, or both. Thereby Product-Platform-Based Co-Development, Manufacturing-Platform-Based Co-Development, and Platform-Based Co-Development are distinguished. The decision on the extend and scope of co-development implementation depends on the specific needs of the system or product to be designed.

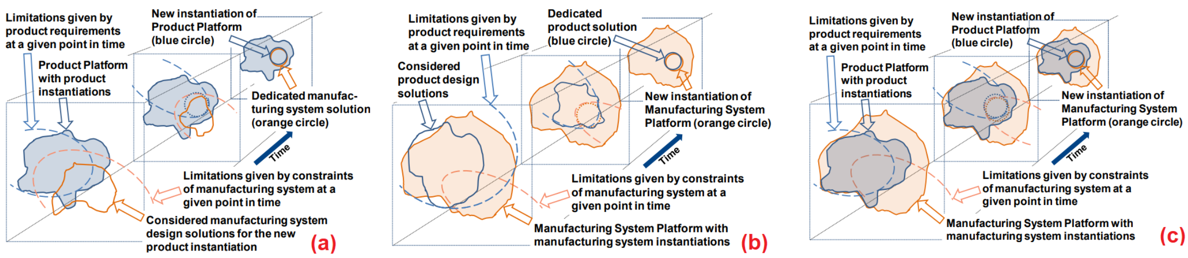


Figure 3.3: (a) Product-Platform-Based Co-Development, (b)Manufacturing-Platform-Based Co-Development, (c) Platform-Based Co-Development [74]

3.1.1. Modularity principles

Modularity is an enabler of co-development and an emerging methodology to be applied in the context of product development [5]. Due to the rising complexity of modern technology, the interests in modularity have grown both in literature and by management of technology companies [75, 76]. It is the approach of designing a system so that its operational functions are divided into independent, readily integrable modules that can be put together in many configurations according to [5]. Likewise, the authors in [76] define modularity as a technique for effectively arranging complicated processes and products by breaking them down into smaller, more manageable tasks. Without sacrificing system integrity, modularity enables components to be manufactured independently and utilized interchangeably in various product configurations [9, 37, 38, 19, 76].

According to [76], a rising number of companies, such as in the consumer electronics and automobile industries are facing challenges keeping up with the growing diversity of products and mixes of product models [115]. It is challenging for these companies to find strategies to replace items and occasionally expanding product lines with creative, high-quality models that reduce development and production costs [25]. Many companies are adopting modular product architecture design concepts in order to reduce the time needed for new product development, and thus the time to market. Furthermore, modularity is used in offering different models of their products fast at lower cost, and the introduction of different versions of a product line with increased performance levels [76]. For instance, in the automotive sector, an OEM in car manufacturing can offer a specific model with a range of different options for driving assistance, comfort features, engine variations, or under-body structures as shown in Fig. 3.4. This could be applied while the other parts of the chassis of the car, and the majority of the components used are the same across the range of different versions of the product line.

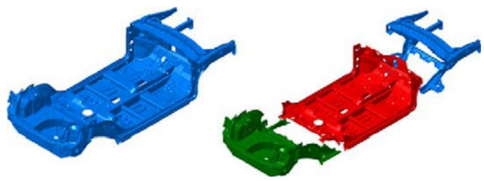


Figure 3.4: Integral under-body (left) and modular under-body (right) structures [80]

It is important to note, that the definition of modularity depends on the context in which it is used. According to the authors in [99], this can be at a product level, system level, or even component level. The authors illustrated this hierarchical architecture in Fig. 3.5.

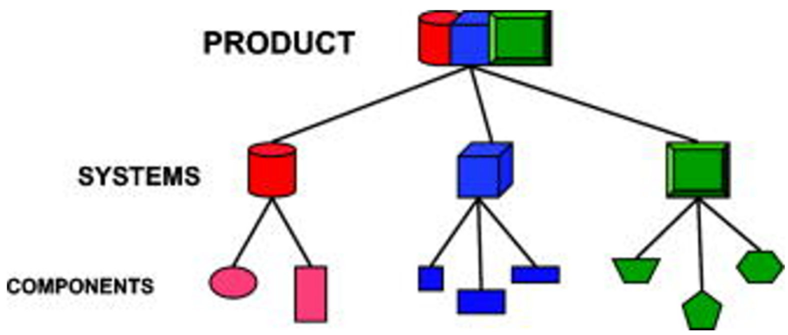


Figure 3.5: Hierarchical decomposition of a product [99]

On a product level, modularity is described as having "de-coupled component interfaces" and arising from a one-to-one mapping between functional elements and physical components at the product level [106]. Modularity on a system level is described in the literature as a clustering of similarly dependent components that are loosely coupled with other clusters and firmly connected inside the cluster [51, 102, 20, 99]. On a component level, [99] views complex products as a network of interconnected components sharing technical interfaces. The definition of interfaces, is further elaborated upon in [75].

Interfaces are connections that are shared by the parts, sections, and subsystems of a certain product architecture. Interface standards are the basic protocol for all of the interfaces and parts that make up a technological product or system. The tolerance specification of the components with regard to manufacturing processes, operating frequency bandwidths, maximum heat dissipation threshold, voltage and current requirements, and packaging dimensions are typical interface specifications for a consumer electronics product at the new product development level.

Product architecture is the grouping of a product's functional components into physical building blocks and the specification of the interfaces between the interacting physical components and the mapping of functional elements to physical components. Thereby, the goal is to specify the functions and interfaces of the product's core physical building components in relation to the rest of the device [107, 106]. There are two types of product architectures: integrated and modular, like shown earlier in Fig.3.4. In order to make it possible to create product variations, modular product architectures are used as flexible platforms [72, 73, 42, 91, 90, 88]. This allows a company to introduce technologically improved products more quickly and achieve cost savings through leveraging existing inventory and logistic solutions [75], and component commonalities, and shared manufacturing processes.

The authors in [109] distinguished between product modularity and process modularity. But in essence recalled the same general definition of modularity in line with the papers referred earlier. A process or manufacturing system that is modular is made up of smaller subsystems that can be built separately and still work together as a whole [106, 107].

According to [54], process modularity means modularity-in-production whereas product modularity relates to modularity-in-design. The fundamental aspects of modularity are formulated as functional binding, interface standardization, and decomposability [81].

Functional binding is the breakdown of a system's intended functions [9, 34, 46, 89, 107, 106, 109]. The main idea is that functions can be added or removed from a product (or process) by adding or deleting components (or sub-processes), as there is a one-to-one mapping of functions to physical components (or sub-processes). This means that each function is associated with a physical component or manufacturing process. This is advantageous, because it reduces the interdependencies of components and enhances their autonomous design [109].

Interface standardization relates to the shared, accepted methods via which complementary product or process components of a system communicate with each other. These interfaces are widely accepted standards among all parties involved. They are often referred to as the "visible" rules of design [9] and allow complimentary system components to be easily exchanged. These standardized interfaces drive coordination in product development processes [91].

Decomposability refers to the measure of how easily a system may be divided into its individual components, enabling easy component swapping [3, 6, 65, 105, 117]. Since decomposability makes component swapping practical [93, 10], it is most often associated with a flexibility advantage. Decomposability allows a system to be readily reconfigured using the same, similar, or supplementary components without affecting its performance. Decomposability prevents performance degradation and enables a system to be easily reconfigured with comparable, or other components [109].

The main learning from this study is that modularity plays a pivotal role as an enabler for co-developing increasingly complex technologies at various levels of product diversity. It can be used to breakdown complex products into distinct, interchangeable components through interfaces. Therefore it allows for reuse when designing new products or new versions of existing products and reduces development and production timelines and costs. These insights were used to build further upon in a semiconductor product development context in the next subsection.

3.2. Co-development and modularity in the semiconductor industry

In the earlier subsections, the significance of modularity within product development, particularly in industries with technological complexity were elaborated. Furthermore various co-development strategies were shared from different industry perspectives. In this subsection these state of the art methodologies were applied to the domain of semiconductor product development, specifically MEMS development. This was done in order to improve product development processes in this specialized field within the semiconductor industry.

Recalling from Section 2, MEMS devices are characterized by their miniaturized sizes and multi-functional capabilities. MEMS devices present challenges during product development phases, are made using complex manufacturing methods, and have no standard development process in contrast to other semiconductor products. The complexities are a result of the interdependent nature of various components of the MEMS device, each of which have distinct functions and requirements while being interconnected.

The modularity approach is applied to MEMS in this section to disassemble the system into distinct components, each with their own functionalities and requirements. A visual representation of a MEMS device was made in order to achieve this. In Fig. 3.6, various types of components within a MEMS device are shown. Each of these components is broken down into functions and requirements. By doing so, it is possible to highlight their interconnections through interfaces. This is done in order to be able to withdraw each components' technical requirements, process requirements, critical interfaces, and the interactions within the MEMS device in later steps.

This standardized approach aims to streamline co-development processes between product design engineers and process design engineers, by providing a better understanding of the technical and process requirements, and their flexibilities, to ultimately result in the required engineering output for streamlining the supplier selection process.

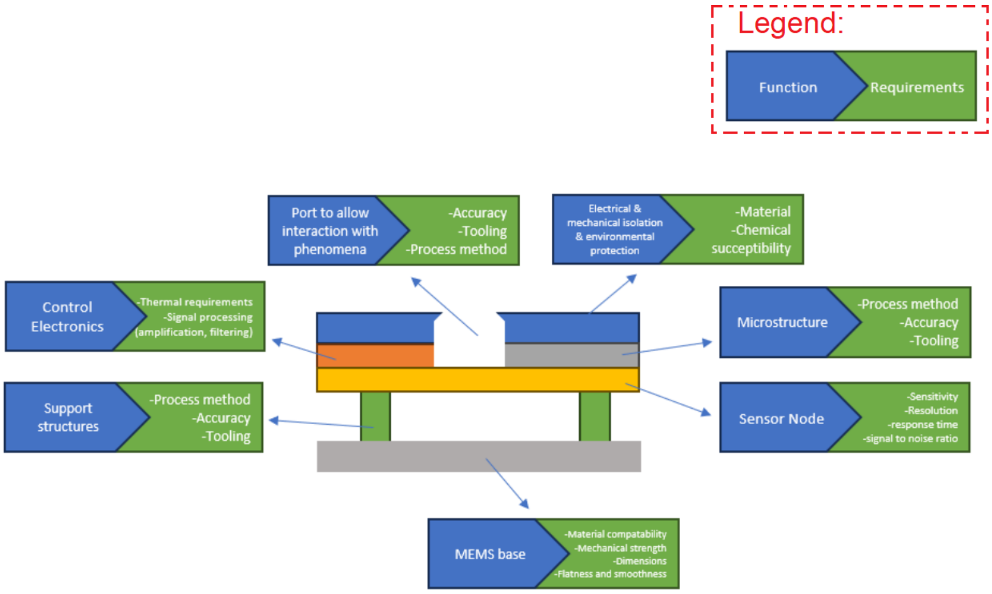


Figure 3.6: Modular MEMS product architecture

The breakdown of the MEMS architecture to modules in Fig. 3.6 resulted in a better understanding of the functions and requirements of the components. The visualisation helped to deconstruct the MEMS device and the creation of a table format, encapsulating the intricate details of the MEMS device. This table format is shown in Table 3.1, and functions as a standardized tool for enabling co-development of the product and its intricate processes. The columns of the table outlined the following characteristics of a semiconductor device: functionality, technical requirements, process requirements, interfaces, challenges, and co-development considerations. .

For researchers in this field, the table emphasizes the relationships in between the types of characteristics and how they affect the product and process design processes through co-development. Moreover, it shows how to develop a generic standardized methodology to enable co-development. For practitioners in the industry, it serves as a comprehensive reference tool and facilitates the understanding of the MEMS characteristics across stakeholders during co-development. Moreover, commonalities between the requirements of different components and MEMS products were identified for reuse.

Furthermore, it assures that all components are being taken into account, thus preventing rework later on because of forgotten requirements of components. It gives nuances to the needs and interfaces and interactions between components, aiding in streamlined co-development between product design and process design phases through collaborative design efforts. This is done by formalizing the technical and process requirements. Moreover, it addresses key challenges in MEMS device manufacturing, to enable a better understanding and information flows between all stakeholders during product development of new complex technologies. The specific co-development considerations to take into account are also taken into account. This standardized method for generating crucial information is also advantageous for supplier selection, which is a form of inter-company co-development between the procuring company and suppliers.

These standardized methods and tools are beneficial for non-standardised, complex semiconductor product development due to the challenges in designing the right manufacturing process, while keeping in mind the capabilities of suppliers. The complexity of MEMS products and the dependencies on suppliers highlight the necessity of knowledge generation and sharing between actors in the product development process. This is achieved through co-development by employing the modular breakdown of components in a semiconductor device, and leveraging this information for formalizing questionnaires for supplier selection.

In addition to this standardized method of designing questionnaires, the method of how suppliers answer the questions was also standardized. This is advantageous for the automation of the supplier selection process through data-driven approaches, as will be elaborated upon in Section 5. Therefore, examples of possible answers to choose from should be provided with the questionnaires, while also providing room for additional comments in text format. This method with predefined answers makes it easier to standardize and quantify the assessment procedure of the suppliers later on. This is, because now values can be assigned based on the answers. Table 3.2 provides an overview of how the provided answers should be labeled. Examples of categorical answers that could be provided can be seen in Table 3.3.

Table 3.1: Template for Modular breakdown of components in a MEMS device

Component	Functionality	Technical Requirements	Process Requirements	Interfaces	Key Challenges	Co-Development Considerations	Question
MEMS Base							
Support Structure							
Control Electronics							
Port for Interaction							
Electrical & Mechanical Insulation and Environmental Protection							
Microstructure							
Sensor Node							

Table 3.2: Labeling the types of answers

Label	Type	Value
Yes/No	Binary	1 / 0
High / medium / low / none	Quantitative	3 / 2 / 1 / 0
Multi-options (e.g., type of machines)	Categorical	5 / 4 / 3 / 2 / 1 / 0

Table 3.3: Questionnaire format with dimensions and answers

Question dimension	Question	Answers to choose from
Technical	At what cleanroom class do you operate?	Class 1, 10, 100, 1000, 1000
Process	What processing capabilities do you have?	Deep Reactive Ion Etching, e-beam lithography, other
Business	What types of semiconductor products are you specialized in?	Integrated circuits, MEMS, memory chips

Concludingly, this standardized method serves as a comprehensive guide in formalizing the required engineering output for supplier selection. This includes the formalization of conceptual product and process designs, before assessing suppliers on these capabilities. By zooming in on specific functionalities, technical requirements, process requirements, and outlining the interfaces, key challenges, and co-development considerations it enables a precise synchronisation between a procuring company's needs and a supplier's capabilities. Potential suppliers can be evaluated based on their ability to meet these requirements and contribute to collaborative design and development efforts. This structured breakdown facilitates an informed assessment, ensuring the selected supplier matches with the intricate demands for MEMS development, fostering a more efficient inter-company collaboration. An example of a completed modular breakdown table can be seen in Table 3.4. By breaking down the MEMS device into its distinct components, the overlapping requirements between components, and between devices were also more easily visible. The modular breakdown of devices allows for reuse of components through their commonalities in terms of requirements. This reduces the development times of new products, new versions, or enhancements of existing products, eliminating the need to invest time and resources in designing and manufacturing entirely new solutions for each iteration.

Table 3.4: Completed modular breakdown of components in a MEMS device

Component	Functionality	Technical Requirements	Process Requirements	Interfaces	Key Challenges	Co-Development Considerations
MEMS Base	Provides foundation for MEMS assembly	Stability, precision, flatness requirements, material, temperature	Specific base geometry requirements, wafer size, tools for base material processing	Interface with support structure, microstructure	Ensuring compatibility, precision manufacturing	Co-development for compatibility, processing temperatures
Support Structure	Provides structural integrity	Material comparability, mechanical strength, stability, dimensions, flatness	Tooling for precision fabrication, material-specific processing requirements	Interface with MEMS base, environmental compatibility	Miniaturization while maintaining strength, material selection	Co-development for structural optimization
Control Electronics	Processes sensor data	Thermal requirements, signal processing, amplification, filtering	Specific semiconductor fabrication tools, substrate preparation needs	Connectivity with main processing unit, sensor and actuator interfaces	Integration with different sensor types, thermal management	Co-development for low-power circuitry, synchronization with communication interfaces
Port for Interaction	Enables external interactions with phenomena	Versatile interface, accuracy, compatibility with external stimuli, geometry	Etching tools for Specific geometry, tooling for external connections	Integration with other system components	Ensuring compatibility, standardization	Co-development for flexible interface design, joint testing with external systems
Electrical & Mechanical Insulation and Environmental Protection	Ensures electrical and mechanical integrity	Materials, chemical requirements, acceptable susceptibility to environmental factors	Deposition methods of materials for insulation, tooling for sealing	Interface with microstructure, environmental compatibility	Maintaining integrity in harsh conditions, sealing effectiveness	Co-development for insulation and protection, joint testing for durability
Microstructure	Defines component's functional features	Dimensional precision, design, surface area, susceptibility to other processes	Etching tools for precise feature creation, lithography tools, specific layer deposition tools	Integration with other MEMS components, precise positioning	Achieving accuracy in micro-features, surface optimization	Co-development for functionality, collaborative design for precision
Sensor Node	Detects specific phenomena	High sensitivity, accuracy, signal processing, response time	Tooling for sensor placement, bonding machines for sensor integration on top of wafer	Data output to control electronics, power management	Miniaturization without compromising accuracy, environmental robustness	Co-development for sensitivity, synchronization with other sensors
Other Components	Various specialized functionalities	Specific to component type	Tooling for component-specific fabrication needs	Interface with other system components	Component-specific challenges	Co-development for functionality, joint testing with system

3.2.1. Challenges in adopting co-development during product development

This subsection aims to reflect on the challenges in adopting new methodologies, like co-development in the industry. The challenges in adopting co-development approaches are analyzed from different perspectives. Management attitude towards new operational procedures is an important factor to take into account. The challenges revolve around the need to root this new product development approach into a theoretical framework. The literature on this topic distinguishes between transactional and transformational leadership. In the former, the emphasis is on outward job performance. This is seen as a more practical approach because of its emphasis on meeting specific objectives. The latter forges a vision and motivates people to go beyond expectations [2]. It allows for organizational openness and the necessary awareness for co-development. Therefore allowing for better identification of demands, dependencies and builds and maintains better interfaces with the actors involved in product development. Co-developing teams interact intensively. Hence transformational leadership, allowing for new operational methodologies, supports these teams [100]. These statements are backed up by literature about the relationship of transactional leadership with innovation generation in [84, 79]. If the management attitude does not allow for new methodologies and approaches to be implemented for reaching product success, implementing co-development is doomed to fail in all realms of the industry and within a company. Whether it is between product and process development teams, between research and sourcing, or between engineers of different companies in buyer-supplier relationships.

Co-development further requires collaboration and a shared incentive for collaboration between engineering disciplines within the company. Without good communication and a shared incentive to work together for the greater good, a technically feasible MEMS product for example, this could result in challenging design and manufacturability trade-offs. Product engineers for example focus on the design of new MEMS devices to meet and surpass functionalities and performance requirements. The process engineers focus on the manufacturing feasibility, complexity, and processing time. Balancing design requirements with process requirements can be challenging. However, good knowledge on why certain requirements are needed overcomes these challenges.

Challenges in co-development between companies arise from an increased dependency on suppliers, when the suppliers are in full control on product specifications. In the current situation, the lack of knowledge on the reasoning behind and necessity of certain requirements leaves a gap for supplier to fill. However this problem can be prevented if module knowledge, gathered using Fig. 3.6 or Table 3.1, is generated first and shared with suppliers. This helps in formalizing why certain specifications and requirements are formalized, because of the interdependencies, filling the information gaps before suppliers do.

3.3. Concluding remarks

This chapter focused on the exploration of state of the art methods for enhancing product development as described in scientific contributions from comparable manufacturing-focused industries. Co-development strategies were adopted to the semiconductor industry, by using modularity as an enabler thereof. A concrete standardized method to translate functions into the most important requirements for complex MEMS products was developed and facilitated using Fig. 3.6 and Table 3.1. This advanced modular breakdown of components of the MEMS device formed the basis to formulate the right requirements and questions, to be later used in the supplier selection process. Concludingly, this chapter has provided answers to the subquestions 3 and 4 by showing the state of art methods for product development to improve efficiency in the semiconductor industry, and the standardized tools and methods to integrate co-development strategies and modularity principles into product and process design for semiconductor technologies. In this context, modularity can be used to distinguish the components, revealing commonalities between the technical or process related requirements of a product. Thereby modularity allows for reuse in the design of new products, new versions, or enhancements of existing products. The standardized tools developed in this section enhance the level of detail of information necessary for generating the required engineering output for supplier selection. For the research field, this section provided insights into the method how to develop the tools for a generic standardized methodology to enable co-development. Moreover, it showed the relationships between the types of characteristics of a product in development, with regards to the product and process designs and the corresponding interfaces. These methodologies for generating such detailed information on the product and process requirements were not available in the state of the art and existing literature. Therefore, the gaps addressed in this section contribute to the information flows between different actors in the early stages of product development, allowing for a structured and comprehensive way for combining information to formalize the required engineering output for realising complex semiconductor products. The next section explores how this new knowledge contributes to streamlining the subsequent product development processes, by means supply chain integration.

4
Supply chain integration

This section explains how supply chain integration can be effectively leveraged to enhance product development and reduce time to market for new technologies, answering subquestion 5. Followingly, this section explores subquestion 6, explaining the contexts in which modularization impacts the supplier selection problem in the semiconductor industry. Subsequently, the information gathered is synthesized into a mapping of the necessary steps and information flows that improve the time to market for future technologies. Thereby this section concludes with answering subquestion 7, providing insights into the strategic integration of supply chain integration and modularization in the semiconductor industry.

4.1. Leveraging supply chain integration to enhance time to market

Because of the dependencies on the outsourced manufacturing platform, supply chain integration plays a pivotal role in enhancing time-to-market for emerging semiconductor products. A well-integrated supply chain facilitates the right match and collaboration between the semiconductor company and its suppliers. This results in easy translations of the product design to process design, and ramp-up. The supplier selection problem is the initial crucial step of supply chain integration. The semiconductor companies face challenges with this initial crucial step, because of the lack of an information-driven standardized approach for selecting suppliers. The literature on this topic lacks a comprehensive method to make informed decisions for engaging with suppliers in the early stages of product development. Moreover, there is no standardized method to withdraw requirements that suppliers need to be assessed on for new technologies early on in the process. The preparations and supplier selection processes take up to months. Suppliers are often chosen based on anecdotal or subjective information, where a single promising aspect, such as the presence of new machinery at a previously engaged supplier from earlier projects, becomes the determining factor in the selection process for new technologies.

Information gathering to assess the capabilities of suppliers for manufacturing the devices relies on questionnaires. However, there is a lack of knowledge on a standardized method for crafting these questionnaires both in industry and in the literature. This leads to a time-consuming process, often taking up to two months to formalize the requirements and questionnaires. Followingly, revisions become necessary to cover for overlooked requirements and components of the MEMS device that initially seemed unimportant, or to eliminate aspects that prove to be less critical in later stages of product development.

As a result of the lack of knowledge for integrating the supply chain, supplier selection processes follow challenging and long procedures. Consequently, semiconductor companies engage and share IP about the concept designs with suppliers having hidden shortcomings, either technically or in terms of business aspects. For example when suppliers do not have the engineering competence to help and co-develop the designs, or when suppliers lack incentive to commit to contractual agreements, as mentioned in Section 2. This results in many meetings for rework and solving the initiated problems related to the product design, the process design, and contractual agreements. Ultimately, the cost of goods for delivering finished products for ramp-up rise, resulting in additional financial expanses in the order of tens of millions of euros. Furthermore, due to the required rework needed and additional efforts needed to proceed with the product development the time to market for new technologies increases.

Table 3.4 from Section 3 forms the foundation for crafting an all-encompassing questionnaire, essential for supplier selection and supply chain integration in the early stages of product development. The functionalities, technical requirements, and process requirements of each component are outlined in the table and serve as focal point for creating targeted questions. The questionnaires should encompass inquiries about a supplier's experience in meeting these specific requirements and their capability to fulfill the technical competences. Furthermore it should be assessed whether suppliers can meet the required process capabilities with the corresponding processing recipes, experience, tools, and machinery requirements. The key challenges and co-development considerations formalized using Table 3.4 help to formulate questions for examining the strategies of suppliers to overcome these challenges and their willingness to engage in collaborative development. Concludingly, the table acts as a blueprint, guiding the formulation of precise and comprehensive questionnaires with the aim to assess potential supplier's capabilities to match the complex needs of MEMS product development and manufacturing. This is done proactively, in the initial stages of product development, preventing extended time to market timelines due to necessary rework and lots of iterative design changes due to suppliers lacking key competences. Involving suppliers early on by making informed decisions enhances co-development, which also reduces unnecessary rework and design iterations.

4.2. The impact of modularization on the supplier selection problem

The impact of modularization on the supplier selection problem was measured using the methodologies developed in earlier chapters, based on different criteria to account for the differences between MEMS products. Three MEMS products from the case study were distinguished based on product complexity, process complexity, and IP sensitivity.

Product complexity refers to the challenges related to the technical requirements of the product. Examples of technical requirements affecting the product complexity are: geometries, critical dimensions, material properties, coatings, stacking of components and layers, aspect ratios, and sensitivity to performance (e.g. through alignment of layers).

Process complexities refer to the challenges regarding the manufacturing process requirements to make the physical product. For example through the process steps described in Section 2, such as lithography and etching. Examples of criteria affecting the level of process complexities are: the number of process steps required, multi-material integration, changes of recipes compared to existing processing methods, cleanroom contamination requirements, advanced processing techniques and sensitivity of process steps.

IP sensitivity refers to the level of importance for protection of IP associated with the product and its corresponding processes. It is important in supplier selection, because it complicates the supplier selection process. This is because in the early stages of development, a very limited amount of information can be shared with suppliers. But at the same time, supplier assessments need to be employed by using all the necessary information to make informed decisions and prevent faulty decisions resulting in increasing development timelines. Examples of criteria affecting the IP sensitivity level are: special or patented processing recipes, IP ownership of the co-developed product, IP ownership of the co-developed process and uniqueness of the product. This makes it challenging to assess the already small number of suppliers and choose the right supplier. Suppliers want more clarity on requirements and the reasoning behind requirements before engaging in contractual agreements with the procuring company.

Table 4.1 shows an overview of the selected MEMS products from the case study. MEMS products with different levels of complexity were selected to be able to draw a fair reasoning behind the effects of the methods designed in this research, and to draw a touchstone of the currently used methodologies.

MEMS Product	Product Complexity	Process Complexity	IP Sensitivity
Product 1	Medium	Medium	Low
Product 2	Medium	High	Medium
Product 3	High	High	High

Table 4.1: MEMS Product Complexity and IP Sensitivity Levels

To emphasize on this and to make the nuances between the levels of complexity even more clear Fig. 4.1 was made. When analysing the ranges of time required for each step in MEMS product development for these three products, it was found that the initial product development steps require between 5 to 10 months, depending on the complexity of the product. The subsequent process development step takes between 4 to 6 months. During these timelines, lots of iterative design changes are required. Followingly, supplier scouting and engagement of the first supplier takes between 2 to 6 months. Detailed information on the stages of product development was formalized in Fig. 4.2.

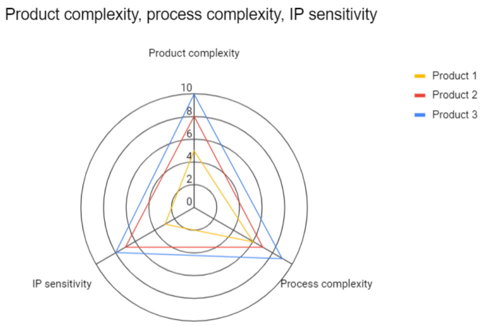


Figure 4.1: Product complexity, process complexity and IP sensitivity for three MEMS products

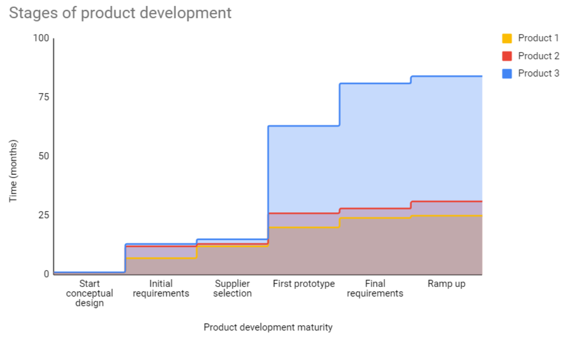


Figure 4.2: Stages of product development versus time for three MEMS products

Combining the information extracted from Fig. 4.2, and the information gathered through empirical research at the case company, it was concluded that increasing product complexities also induce increasing process complexities. That is where the need for more information and a framework to account for these complexities become more evident. The correlation between increasing product and process complexities and IP sensitivity of new products with an increased need for a framework is shown in Fig. 4.3. Each dot is a reference to a real MEMS product developed at the case company. The size of the dot distinguishes the level of IP sensitivity, giving this diagram third dimension.

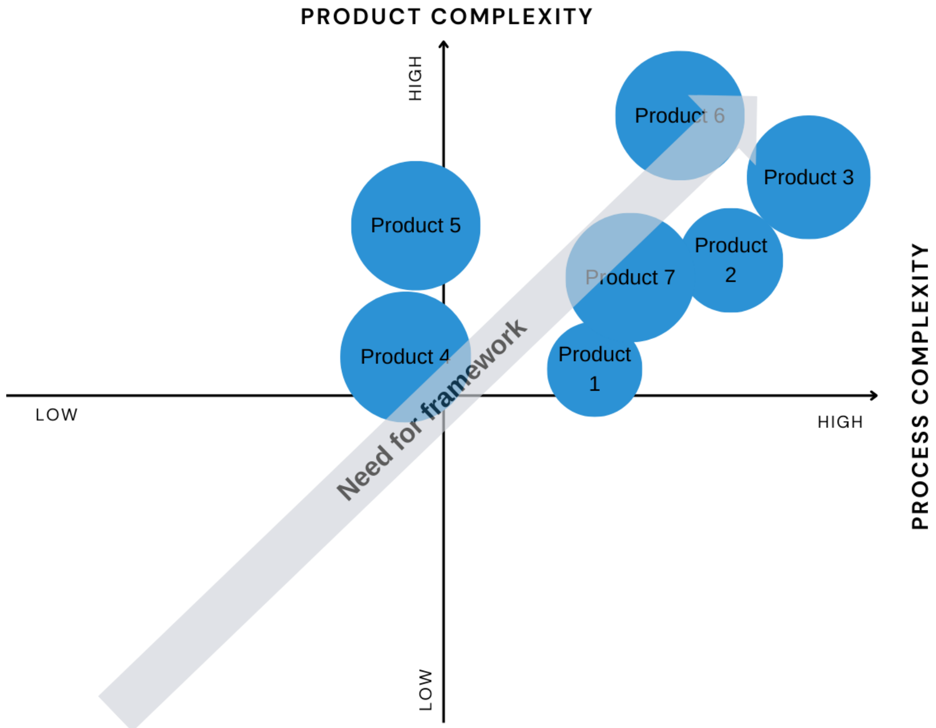


Figure 4.3: Four quadrant diagram showing the relation between product complexity, process complexity and IP sensitivity with the need for a framework

The supplier selection process is done in a non-standardized way, sometimes through short communication lines with previously contacted suppliers and limited information sharing to really comprehend the capability levels of suppliers in the early stages. The following observations were made in order to assess the impact of the currently employed approaches. After initial contact, the first meetings with suppliers followed. From the case study, it became clear that most of the time these initially contacted suppliers prove to be insufficient because of lacking competencies. This results in losses in the form of time and recourse allocation, because of unnecessary meetings with incompetent suppliers. As a result, a loss of at least two to three meetings, each with four to five engineers was observed. That is between 8 and 15 engineering hours lost, spanning over a period of one month of time. From the case study, it became clear that with a comprehensive assessment or screening upfront, this loss in time and resources could have been prevented. This is, because the necessary questions to assess these suppliers on the right capabilities followed quickly from the modular breakdown table introduced in Section 3. Questionnaire designs typically take between one to two months with weekly meetings, again with four to five engineers. The questionnaires are then revised, which again takes between three to four meetings with the same engineering teams. During these revisions, the overlooked questions are added and the unnecessary questions are removed. These observed non-standardized methods are inefficient and time consuming. The losses in time up to months due to rework and the engagement with incompetent suppliers can be prevented with the standardized approaches proposed in this report as a result of the completed thorough literature study and the design of the new methodologies.

The impact of modularization and the methodologies introduced in Section 3 on the supplier selection problem is in the added values it gives for generating the required engineering output for supplier selection. This output includes the detailed requirements and commonalities between components, allowing for reuse. Due to modularization, co-development was enabled to follow the standardized approach for collecting information to be used for supplier selection. This standardized method has to do with the modular product architecture and enables the design of a comprehensive questionnaire including all the components of the semiconductor device. This standardized methodology for mapping a comprehensive questionnaire forms the integration layer between the procuring company and the supplier, the two actors in the supply chain. Consequently, this allows for inter-company co-development by anticipating product and process designs in the early stages of product development. That is important because the manufacturing platform is outsourced.

Using these standardized methods, the design of the questionnaire was accomplished after only two meetings involving two engineers each. The revisions and final validations were completed in a single meeting with three engineers. This streamlined approach resulted in a 70% reduction in the number of questions compared to a questionnaire made by practitioners using the current approach. Through previous experiences with questionnaires, suppliers had revealed that they faced challenges in answering the large number of questions. Furthermore, the lack of clarity on the necessity and relationships between questions presented challenges for suppliers. In contrast, With the new methodology, resulting in a shorter and more comprehensive coherent questionnaire, these inconveniences of suppliers were limited. The savings in time when employing the developed new methodology can be seen in Table 4.2. Combined, the time needed for the generation of the required engineering output for supplier selection, in the form of technical and process requirements, and the design of comprehensive questionnaires was reduced by 77%.

Table 4.2: Comparison of Current and Proposed Approaches

Item	Design Time (hrs)	Rework Time (hrs)	Cost (EUR)	Rework in FTEs
Current Approach	20	15	1750	1.7
Proposed Approach	5	3	400	-
Savings (%)	75	80	80	-

4.3. State of the future product development and information flows

The current steps in product development were given in Fig. 2.6. The application of co-development led to a new process flow. This new product development process flow is shown in Fig. 5.15. It includes both vertical co-development within the procuring company, and horizontal co-development with suppliers. The vertical information flows include product, process, and business related requirements for the semiconductor product. This information is shared between researchers, development and engineering teams, process engineers, and the sourcing department. The horizontal information flows outward of the procuring company include the engineering output for supplier selection, the questionnaire. This questionnaire is used to gather data on supplier capabilities. The backward information flow, from suppliers to the procuring company, include the suppliers' capabilities or responses to the questionnaire.

This method is easily scalable and allows for the procuring company to easily expand their supply base, rather than having to choose from the limited amount of suppliers in their current supply base. Followingly, after suppliers' responses are collected and potential interesting suppliers are chosen, the procuring company engages with suppliers. In those engagements, both companies can collaboratively enhance the product and process design of the device. These collaborative efforts will be led by the gaps, which are now easily identified using the modular breakdown table as a blueprint, and with the responses to the questionnaire.

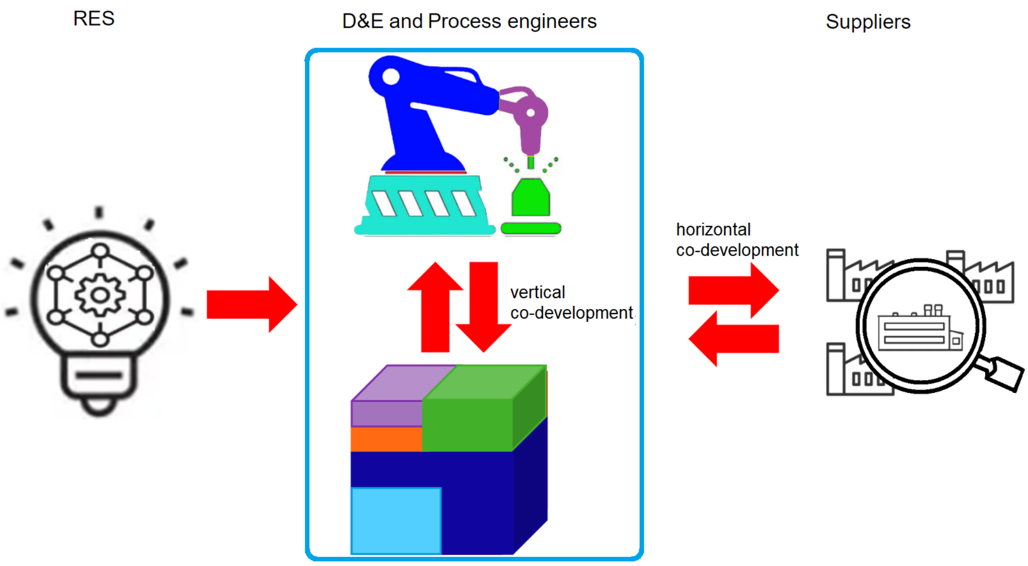


Figure 4.4: State of the future MEMS product development process flow

4.4. Concluding remarks

Supply chain integration is crucial in the semiconductor industry for product development, because the manufacturing platform is outsourced. In the current situation, semiconductor companies face challenges in finding the right suppliers for their products. They rely on a supply base with limited amounts of suppliers known from earlier product development collaborations. Because of this reliance, technology development is hindered and the semiconductor companies may end up in vendor-lock. Supply chain integration helps to prevent this situation. This is because with this integration, the supply base can be expanded and the right suppliers can be included early on in the product development process, reducing the large amount of rework and design changes afterwards. And if semiconductor companies want to reach out to many new suppliers to expand their supply base, lots of information and data will need to be collected both internally and at the vast amount of suppliers. The information gathering process is streamlined through the standardized methods as shown earlier using Table 3.1. Therefore, supply chain integration can be effectively leveraged to enhance the development of new technologies by reducing time to market and unnecessary prolonged timelines by employing the standardized methods for supplier selection developed during this research. That is because these methods allow to make informed decisions on the requirements and competences to assess suppliers in the early stages of product development. Early engagement with multiple suppliers results in an expansion of the supply base, providing more suppliers with more competences to choose from. Furthermore, earlier engagements with suppliers reduce unnecessary rework and design changes afterwards, as early co-development initiatives facilitate smoother collaboration. Subquestion 5 is thereby answered.

The effects of modularization on supplier selection were also explored, answering subquestion 6. Because of the modular breakdown of the MEMS device, it was possible to formalize a comprehensive overview of requirements and challenges for the new products. Applying these developed standardized methodologies on real MEMS products from the case study revealed the correlation between increasing product complexity, process complexity and IP sensitivity, with the need for a framework to gather the right information both internally and at the potential suppliers, in order to expand the supply base and engage with the right suppliers. The necessary steps and information flows that improve time to market for new technologies include vertical and horizontal co-development. The vertical information flows are within the procuring company, and the horizontal information flows are between the procuring company and suppliers. Thereby subquestion 7 is also answered. The next section explores how the interpretation of the large amounts of data from suppliers can be analyzed and used in data-driven decision making.

5

Implementation of data-driven approaches for strategic decision-making

This section elaborates on methods to improve the strategic decision-making in supplier selection. The literature lacked a standardized methodology to leverage data-driven co-development with supply chain integration like in the early stages of product development. Additionally, this topic was researched because of the highly competitive nature of the semiconductor industry, the rapid technological advancements and the complexity of supply chains. This section build further upon the significance of the supplier selection problem on new technology development, as introduced in the earlier sections of this report. This is done to explore the contribution of modeling, simulation and data-driven approaches for supplier selection in the semiconductor industry and other industries. Thereby subquestion 8 is resolved. It shows how the key information, collected through a standardized way as described in sections 3 and 4, is leveraged for supplier selection. Subsequently, the positioning of the modeling approach within the framework is assessed, while considering the available data at that stage. Followingly, the right modeling approach is selected, answering subquestion 9. Finally, a decision-support tool is designed, applied, verified, and validated in a case study. Thereby subquestion 10 is addressed. The key aspects to consider in the final product development framework, the corresponding information flows and their interfaces are elaborated upon at the end of this section, thereby answering subquestion 11.

5.1. Modeling and data-driven approaches for supplier selection

Simulation modeling approaches are used in supplier selection for describing the supply chain process, its system dynamics, and comparing alternatives in [103, 18]. The authors in [62] describe how simulation offers a lot of potential for showing how supply chains evolve dynamically and providing useful decision support to deal with problems arising from high variability and stochastic uncertainty. Stochastic uncertainty here refers to the unpredictability of systems in relation to future states.

The authors in [120] emphasize the essence of supplier selection in the semiconductor industry. Research has been done on supplier selection from a transactional perspective, strategic partnership perspective, and the effects of peak and off seasons on supplier selection in [120]. The authors used an analytic hierarchy process (AHP) with flexible integers for peak and off seasons to see if the supplier selection decisions would differ. After ranking their suppliers on quality, cost, delivery, service, environment, and inconsistency, they concluded that this method was of added value for supplier selection by reducing the average price per wafer with 45 cents (or 0,89% in their case).

It is important to mention that this paper took into account a relative low complexity, high volume product where the peak or off seasons have an effect on the price of raw materials and the possibility that a supplier with higher pricing may consistently receive the highest rating due to its quality and service niches, potentially increasing operational costs during off seasons. And on the other hand, a lower-ranked supplier might have weaknesses in quality and delivery but could offer cost-effective materials and actively support joint development of new technologies. This is an interesting approach, but for high-complex, low volume MEMS products, for which the product design and process design is of significant importance and also affected by supplier selection, this method is not sufficient.

Model predictive control (MPC) is another interesting modeling approach for supplier selection. It is a well known method among researchers and used to solve many control problems. Model predictive control is an optimal control approach where a constrained dynamical system's cost function is minimized over a finite receding horizon. An MPC controller obtains or guesses the current status of the plant at each time step. Then, by solving a restricted optimization problem that depends on the present system state and an internal plant model, it determines the order of control operations that minimizes the cost over the horizon. Next, the controller applies the first calculated control action to the plant, ignoring the subsequent ones. The procedure is repeated in the subsequent time step [114]. So by predicting the state and input variables on the prediction horizon, and by substituting these predictions into the objective function and solving it using optimization, the optimal control action is determined [116]. The MPC control loop is shown in 5.1.

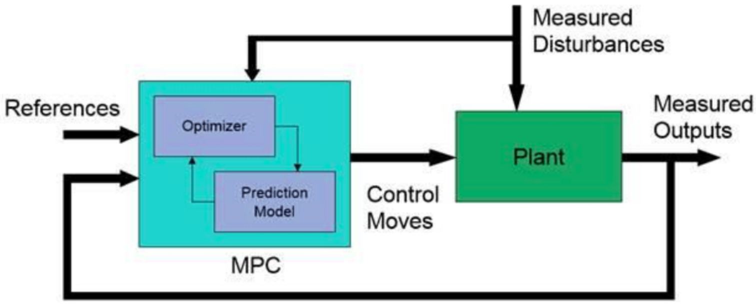


Figure 5.1: MPC control loop [114]

This method can be applied in dynamic modeling of supplier performance over time, for example. Relevant supplier criteria for this approach are cost, quality, delivery time, and reliability in the model. Using this method, the way of change of these criteria in response to different market conditions or external factors could be evaluated.

MPC could also be employed to determine the optimal strategy for managing stock levels in a multi-product inventory system through supplier selection, in case of many alternatives, while minimizing the total cost. This was done in [116] for a multi-supplier multi-product system, where the authors showed how the total cost can be minimized through employing MPC.

The authors in [83] presented how MPC can be employed in single stage batch factories and multi-product distribution networks servicing numerous clients. A mixed integer linear programming (MILP) model was used as a basis, in order to analyse the full supply chain. MILP is an efficient mathematical modeling technique for solving complex optimization problems and determining the possible trade-offs between conflicting objectives [44]. The primary features of the MILP included the analysis of the whole supply chain, taking into account suppliers, production, distribution, and clients all at once. Furthermore, the information and material flows across the supply chain, as well as the transportation and processing durations associated with each were taken into account. The MILP uses a rolling horizon, similar to that of MPC, to update choices in response to changes that impact the supply chain [83]. The input of the dynamic model consisted of the production schedule, the raw material acquisition plan, and the upstream orders between nodes. These variables can be modified or controlled by decision makers to operate the system. These decisions are made to reduce the effect of disturbances to the system, such as incoming orders. The supply chain's dynamic performance is determined by the inputs (decisions) and disturbances (demands), and the resulting inventory and order levels in each distribution node. In order to fulfill the orders, the system will reply by sending the proper shipments from node to node [83].

As shown with the described examples, modeling approaches such as MPC and MILP can be applied in problems with large amounts of variables and information available on the broader supply chain dynamics. This can include historical, inventory, distribution, and client data with the aim to optimize a cost function, as shown in Fig. 5.2.

In contrast, within the scope of this research, the principle challenges in supplier selection are during the product development phase for low-volume, high-complexity products. Furthermore, the distinction is made by analysing the nature of the problem, which occurs during the early stages of product development, as opposed to after its completion in the earlier mentioned modeling approaches. This introduces unique challenges to the supplier selection process in the context of this research. The widely recognized state of the art methods for supplier selection such as MPC and MILP rely on extensive information about the supply chain dynamics, or historical data. This information is not available in the early stages of product development, where the product design and process design are crucial and strongly influenced by supplier selection outcomes. Therefore, for these high-complexity

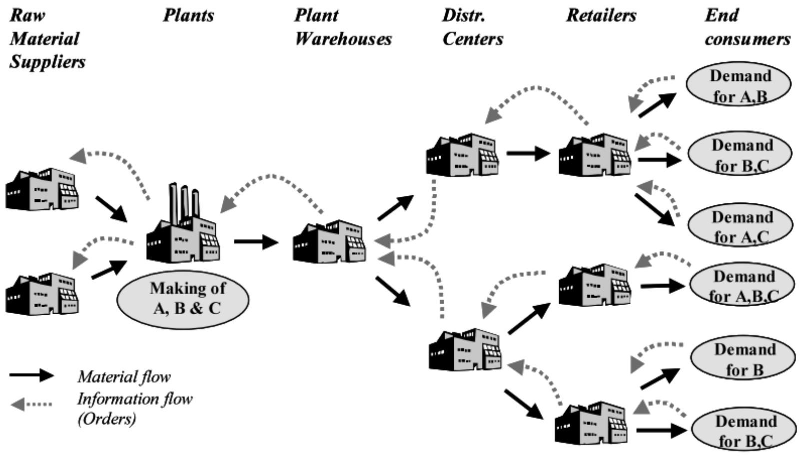


Figure 5.2: Broad supply chain dynamics used in MPC and MILP approaches [83]

MEMS products, the conditions for the effective application of MPC or MILP are not met, making their use redundant in this case. The next subsection explores which modeling approach could aid the strategic decision-making for supplier selection, given the constraints and limitations mentioned in this subsection.

5.2. Machine learning models for supplier selection

In recent years, the application of machine learning techniques has increased for solving complex business related challenges. This section provides an overview of various machine learning models, categorized into unsupervised and supervised learning for solving the supplier selection problem. In the context of supplier selection, classification, regression, and clustering tasks were considered within the scope of this research.

Supervised learning algorithms are applied to datasets where the outputs and the inputs are known and hence can be used to establish the model. The input vector and output vector of the samples are fed into the algorithm. This algorithm then produces a solution space that predicts the expected output for all the samples. So supervised learning involves training a model on a labeled dataset, where the algorithm learns from historical examples to make predictions on new data. However, this approach is not suitable in case of absence of historical data, and the desired outcomes are unknown. Examples of supervised learning algorithms are: linear regression, logistics regression, decision trees, nearest neighbour, naive bayes, random forest, neural networks, and support vector machines [58].

Unsupervised learning is a class of machine learning algorithms where the model is trained on unlabeled data. These self-organized algorithms find unknown patterns or structures in the datasets, without the need for pre-set labels [36]. In the context of supplier selection, unsupervised learning can help identify natural groupings within the provided dataset. Examples of unsupervised learning algorithms are: K-Means clustering, fuzzy c-means clustering, hierarchical clustering, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and principle component analysis (PCA) [57].

Machine learning methods can further be distinguished based on tasks. In literature, the following tasks are specified.

Classification tasks are supervised learning tasks where the algorithm is trained on the categories in the provided dataset. In this dataset, each observation or sample in linked to a category. The dataset can consist of two or more categories. These categories are often also referred to as label or class. The algorithm is then used to mathematically categorize data into a label. This is done by mapping a function (f) with input variables (X) to output variables (Y) as labels [57, 92]. Classification can be used, for example to classify customer reviews for a product into "positive," or "negative" sentiments.

Regression tasks are supervised learning tasks used to predict the target variable by determining a linear or nonlinear relation between variables. The difference with classification is that classification predicts a distinct class, and regression predicts a continuous quantity. Regression models are used for (financial) forecasting, trend analysis, time series estimation, and more [92].

Clustering tasks are unsupervised learning tasks that identify and group similar data points in large datasets together based on their shared characteristics. This can be particularly useful for segmenting suppliers with similar profiles or competencies. The data grouped in the same cluster share more similarities amongst each other, compared to with data in other clusters [92]. Clustering is used in data analysis to discover the trends or patterns in data, e.g. by grouping customers based on their behaviour, or data center location optimization based on network traffic patterns.

The choice for the machine learning models to be used depends on several factors. This includes the availability of data at the applied step in product development, so in its early phases or later on, the expertise of the staff, and the willingness of management to adopt these advanced decision-support techniques. Each model has its strengths and limitations, and a thoughtful consideration of these factors is crucial for successful implementation. In the following sections, the process of choosing and developing the right machine learning model in the context of supplier selection will be explored. Followingly, the best practices will be highlighted and the developed models will be evaluated.

5.3. Model and experiments

In this section, the selection process of the best machine learning model for supplier selection in the product development framework is elaborated upon. To ensure the validity of the chosen model, this was done by first comprehending the position of the model in the new product development framework. Additionally, the goals and available data from the case company played a pivotal role in this selection process. Within the context of the new product development framework, it was evident that the potential modeling approach should be applied in the early stages of product development. In this early stage, the model can only be composed using the information that is available, or gathered using the tools developed as part of the new framework in this report.

5.3.1. Purpose of the model

In the early stages of product development, like shown in Fig. 5.15, the model is used to facilitate future convergence of the product and process designs during co-development with suppliers. This enhancement should be initialized in the early stages of product development. Therefore, in order to be able to synthesize the required competences between the semiconductor company and suppliers, there should be initial information available on the needs of the semiconductor company. This information is generated and withdrawn using this developed framework and using the modular breakdown table provided in Table 3.1. With the generated information using this table, the semiconductor company can withdraw the necessary competences to use for the initial supplier selection process.

These competences were broken down into three dimensions, being technical competences, process competences, and business competences. This breakdown was made because of the nature of the requirements of various different MEMS products in the case study, and because the manufacturing platform is outsourced. This also helps in generalization of the framework. In the specific case of the case company where there is a layer that separates the design from manufacturing, it makes sense to include the third dimension of business competences. In the absence of any business related competences needed in supplier assessment, for example if the manufacturing was fully done in-house, the need for a third business axis connecting the supply chain would have been redundant. Thereby, this third dimension is the also the layer that separates the design from production.

Based on the levels of complexity, and initial business requirements such as those covering intellectual property, process ownership and volume production capabilities, the questionnaires for four complex semiconductor products, including MEMS, were formalized in a case study. Because of the breakdown of functions, requirements, and interfaces of the requirements in 3.1, the answers of suppliers to these questions can be reused as a basis for future MEMS products as well.

The questionnaires were composed for suppliers, while taking into account the ease for suppliers answer them, and to be able to standardise the translation of the answers to a dataset as an input for the model. The questionnaires followed the standardized rules from Table 3.2, including binary questions, qualitative questions, and categorical questions. These outputs were translated to data as input for the model.

Given that the model was to be used in the early phases of product development, in order to understand supplier competences early on to later synthesize the product design and process designs for MEMS, clustering algorithms were selected. Because of the limited amount of data in these early stages and in order for the models to be easily applicable by the case company, unsupervised clustering algorithms were selected. Clustering algorithms are also advantageous to draw conclusions for assessing a multitude of suppliers based on many requirements.

5.3.2. Data-input

The data-input for the developed models consisted of two datasets. Firstly, real-world information from the case company was translated into a usable data file. The available data was analyzed and supplemented where needed. The dataset contained information about the capabilities of 21 semiconductor suppliers. This would later serve as an input for the machine learning model to be developed as part of the case study. The case company's goals through supplier clustering were identified. Three cluster dimensions, detailed criteria, and performance metrics were formalized to evaluate suppliers.

Followingly, this data was expanded for experimentation, verification, and validation purposes. A larger dataset provided a different representation of the distribution of the data, enhancing generalization and increasing the robustness of the developed model. For example, it was seen that the neighbouring suppliers from different clusters in the initial dataset were close to each other. This resulted in ambiguity in the sense of how good suppliers were assigned to each cluster, as will be elaborated further upon in the next section about fuzzy clustering.

The dataset was expanded to generate an artificial dataset with information about 50 suppliers in a systematic way using web-based data collection, industry reports, and generative adversarial networks (GAN). Relevant competences were identified and categorized into the three dimensions of product, process, and business competences as described earlier in this section. Feature analysis was applied to eliminate redundant data. Subsequently, the dataset was normalized to scale the remaining features of the dataset. Both the extended dataset and initial dataset were developed to later allow for clustering suppliers based on the predefined three dimensions: technical, process, business competences, as will be explained in the next sections. The resulting extended dataset and the initial dataset are shown in Fig. 5.3. The artificially extended dataset is correlated with the real-world data. This provides more diverse representation of types of supplier competences across the three provided dimensions. When experimenting with the dataset, this will be of added value for more robust and nuanced clustering analysis. It will also help practitioners better understand the scalability of this solution in supplier selection.

Figures 5.4 and 5.5 provide different perspectives, showing the correlation between the two datasets. The extended dataset does not solely mirror the initial dataset, but also includes additional nuances in the data with outliers. The added value of this when experimenting, within the context of this scientific research, will be elaborated upon in the following sections.

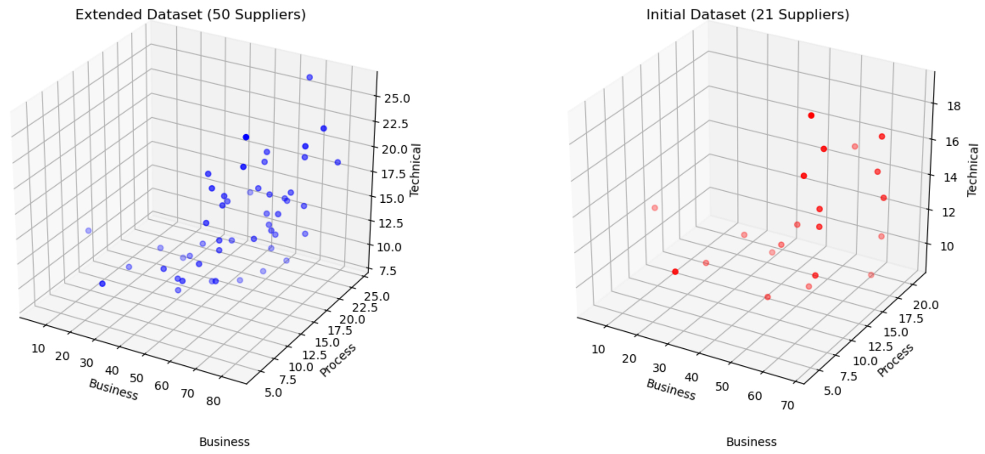


Figure 5.3: The extended dataset (left) and the initial dataset (right)

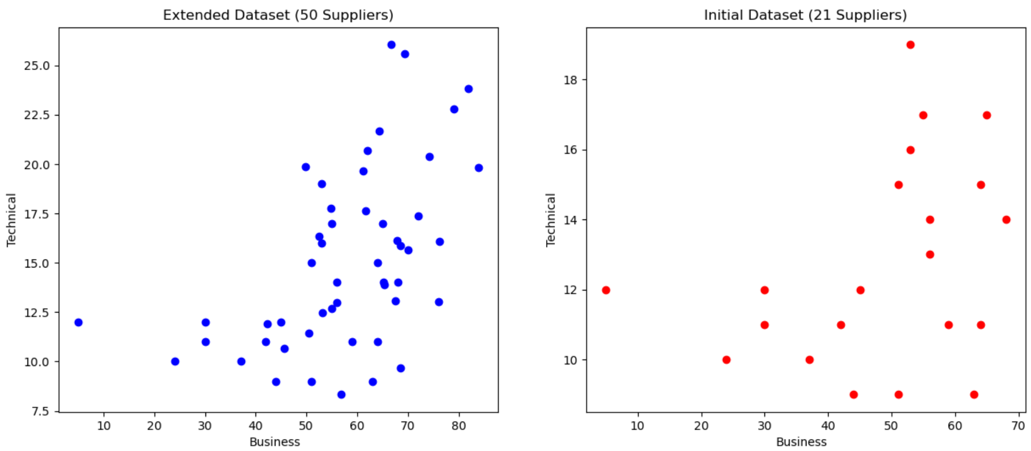


Figure 5.4: Technical and Business capabilities of suppliers in the extended dataset (left) and the initial dataset (right)

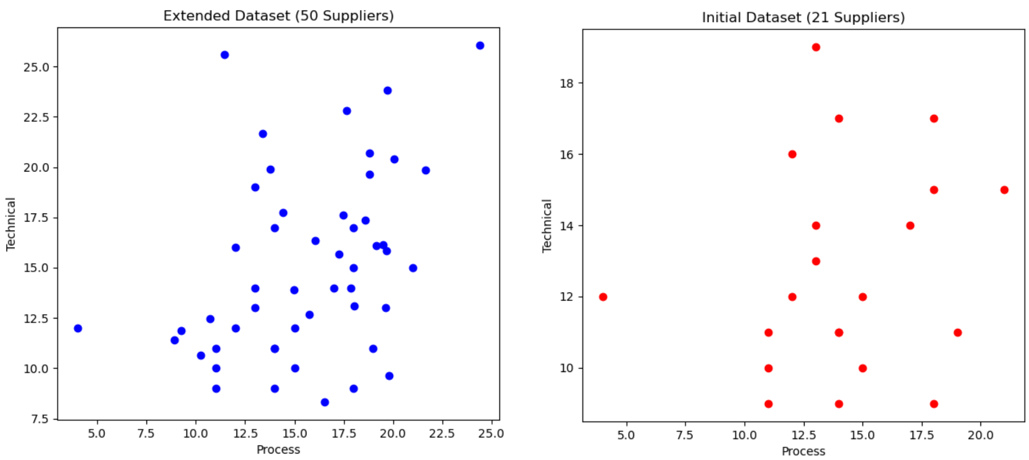


Figure 5.5: Technical and process capabilities of suppliers in the extended dataset (left) and the initial dataset (right)

5.3.3. K-means clustering

K-Means clustering is an unsupervised machine learning algorithm. It is used for grouping data points into distinct clusters based on their similarities [26]. The K-means algorithm used is a partitioning clustering algorithm. It is used to classify the input data into K different clusters using an iterative process. First, the algorithm randomly initializes K number of cluster centers, also called the centroids.

All data points are then assigned to the nearest centroids by calculating the euclidean distances. The Euclidean distance between two points x_i and c_j in a d-dimensional space is given by:

$$d_{Euclidean}(x, \mu) = \sqrt{\sum_{k=1}^{d} (x_i - \mu_k)^2} \tag{5.1}$$

Where:
x_i is the i-th data point.
μ_k is the centroid of the cluster to which x_i is assigned.

Each data point is assigned to a cluster whose centroid is the closes using the formula:

$$\mathrm{J}(c_k) = \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \tag{5.2}$$

The centroid of the cluster μ_k is calculated by the mean of the samples of the cluster using:

$$\mu_k = \frac{1}{|C_k|} \sum_{x \in C_k} x \tag{5.3}$$

Where:
μ_k is the centroid of the k-th cluster.
C_k is the set of data points assigned to centroid c_k.
$|C_k|$ is the number of data points in cluster k.

The algorithm aims to minimize the within-cluster sum of squares, also known as the inertia. To be more specific, it is calculated as the sum of squared distances between each data point and its assigned centroid. The objective function, inertia (J), of the k-means algorithm is given by:

$$\mathrm{J(C)} = \sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \tag{5.4}$$

Where:
k is the number of clusters.

This process of assigning data points to clusters repeats until convergence, when a minimum is reached [94, 97, 1, 50]. The minimum is reached when either the assignment of data points to clusters no longer changes significantly. Or after a fixed number of iterations is reached. Hence it is called a local minimum.

In order to determine the optimal number of clusters k, the elbow method is used. With this method, the k-means algorithm is run for different values of k while calculating the inertia. This heuristic method does not guarantee to provide an optimal solution [94]. However, it is a practical and efficient problem-solving strategy. The results are plotted and the elbow is identified as the point where the rate of decrease of the inertia value sharply changes. In Fig. 5.6, k=4 is the elbow point.

The K-Means algorithm categorized suppliers into distinct clusters based on their shared attributes. The results offer insights into suppliers and their clusters characteristics, revealing patterns and similarities that were not apparent through traditional or manual methods of interpreting supplier capabilities.

Using the same methodology, the extended dataset was clustered. The optimum number of clusters found for this artificial dataset using the elbow method was k=3, to prevent overfitting. This overfitting is shown in Fig. 5.10. Due to the complexity of the model, it captures noise in the data allowing for too

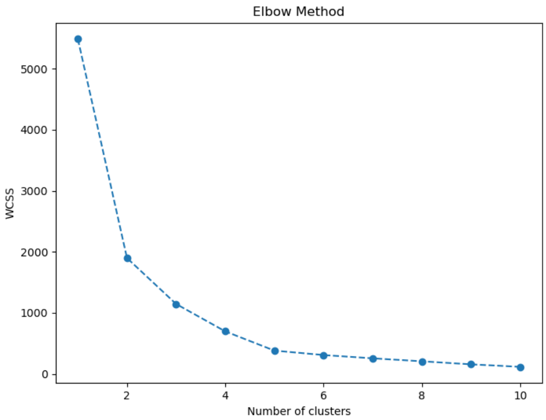


Figure 5.6: Elbow method applied on initial dataset

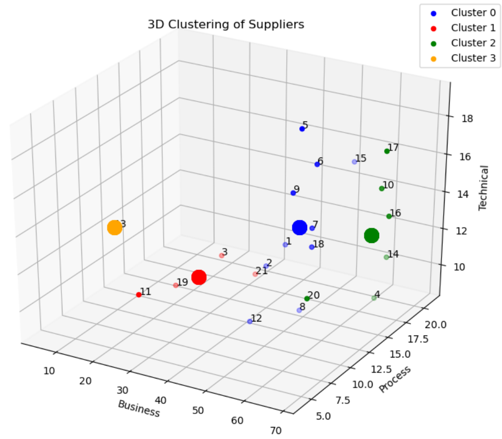


Figure 5.7: K-means clustering with k=4 clusters applied on initial dataset

many clusters where the data points are correlated too much to draw meaningful conclusions from. In these examples, the models typically find clusters based on small variations in the data rather than meaningful underlying structures.

Comparing the clustering results of the real-world dataset (with k=4) and the generated dataset (with k=3) reveals that the initial dataset may reveal a higher degree of diversity, resulting in a slightly larger number of distinct clusters. The artificial dataset does not capture the same level of diversity, resulting in a lower number of clusters. Although the extended dataset seems to show similar patterns in Fig. 5.4 and Fig. 5.5, an important insight from this analysis is that the GAN still shows limitations in its ability to capture all of the intricate patterns within the real-world dataset and the diversity of the generated data. The constraints of the training dataset for the GAN impact its ability to generate fully representative samples. Furthermore, the limited number of suppliers with a lower density of data points also results in a higher diversity among the data points, as can be seen in Fig. 5.3. This then leads to an increased number of clusters.

Therefore, it is important to also consider the characteristics of the used datasets when interpreting the results of the clustering algorithm. Alternative clustering methods, like c-means clustering, can provide additional insights into how data-points are assigned to distinct clusters.

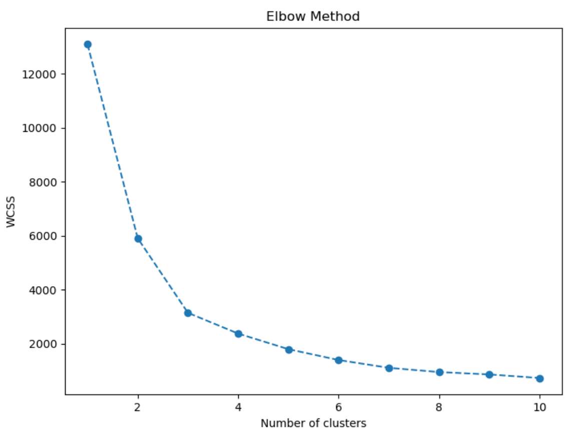


Figure 5.8: Elbow method applied on extended dataset

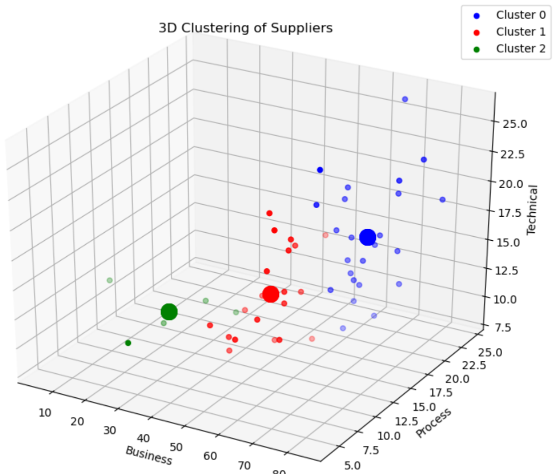


Figure 5.9: K-means clustering with k=3 clusters applied on the extended dataset

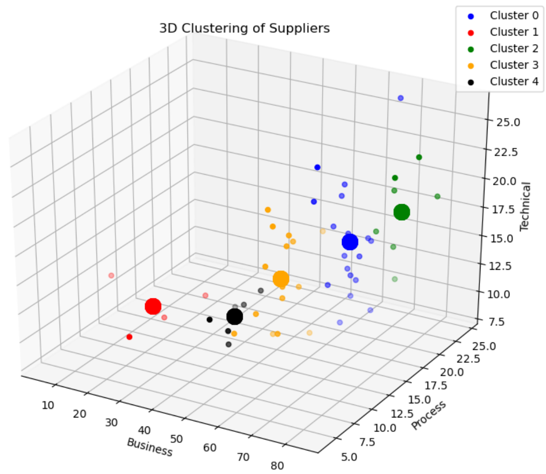


Figure 5.10: K-means clustering with k=5 clusters applied on the extended dataset

5.3.4. Fuzzy c-means clustering

It is important to note that the data collected through the case study and utilized for k-means clustering includes uncertainty and ambiguity. This is because it is collected through an old questionnaire that was not set up with the intention of using its output for making a machine learning decision-support tool. In order to understand the effects of this ambiguity and uncertainty in the real-world data, fuzzy clustering was also considered in this research.

The fuzzy equivalence relation used in fuzzy clustering stands out from other clustering techniques [112, 118, 56, 64]. In contrast to k-means which is a form of hard clustering, fuzzy clustering enables soft clustering [21, 87]. Overlapping clusters are managed by the fuzzy clustering algorithm by providing a detailed representation of the relationships between the data points and the clusters [96]. The flexibility provided by fuzzy clustering allows data points in the dataset to have partial memberships in multiple clusters. This allows for and gives insight into the ambiguity and uncertainties that are frequently seen in real-world data [14]. In the context of this research this reflects to the answers provided to the questionnaires and the ambiguity of the questionnaire provided by the case company. By doing so, fuzzy clustering enables the representation of uncertainty in clustering and imprecise clusters. In the context of supplier selection, this algorithm groups suppliers into clusters and assigns membership values to each cluster. This enables a more nuanced understanding of the shared characteristics between the suppliers for different clusters. A fuzzy clustering algorithm was developed and applied on the dataset. Figure 5.11 shows the visual representation after fuzzy clustering. Figure 5.12 shows the resulting clusters and membership values of the data points.

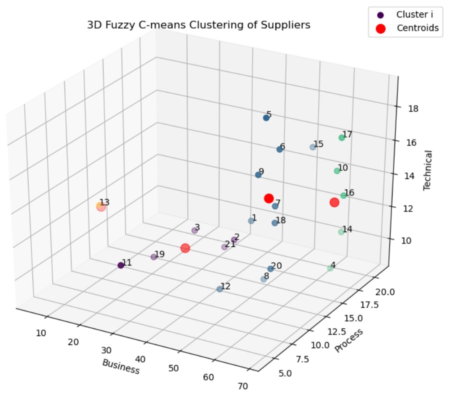
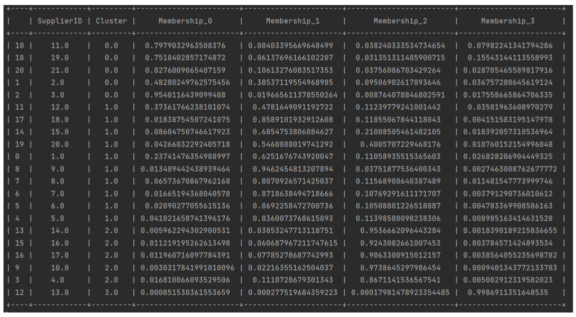


Figure 5.11: Fuzzy c-means clustering applied on initial dataset



	SupplierID	Cluster	Membership_0	Membership_1	Membership_2	Membership_3
10	11.0	0.0	0.7979032963508376	0.08403395669648499	0.038240333534734654	0.07982241341794286
18	19.0	0.0	0.7518402857174872	0.06137696166102207	0.031351311485900715	0.15543144113558993
20	21.0	0.0	0.8276009065407159	0.10613276083517353	0.03756086703429264	0.028705465589817916
1	2.0	0.0	0.48280249762575456	0.38537119554968985	0.09506902617893646	0.036757280645619124
2	3.0	0.0	0.9540116439099408	0.019665611378550264	0.008764078846802591	0.017558665864706335
11	12.0	1.0	0.37361766238101074	0.4781649091192722	0.11239779241001442	0.03581963608970279
17	18.0	1.0	0.01838754507241075	0.8589101932912608	0.11855067844118043	0.004151583195147978
14	15.0	1.0	0.08604750746617923	0.6854753806084627	0.21008505461482105	0.018392057310536964
19	20.0	1.0	0.04266032292405718	0.5460088019741292	0.4005707229468176	0.010760152154996048
0	1.0	1.0	0.23741476354988997	0.6251676743920047	0.11058935515365603	0.026828206904449325
8	9.0	1.0	0.013489442438939464	0.9462454813207894	0.03751877536400343	0.0027463008762677772
7	8.0	1.0	0.06573670867962168	0.8070926571425037	0.11568908640387489	0.011481547773999746
6	7.0	1.0	0.01665194368040578	0.8718638494718666	0.10769291611171707	0.003791290736010612
5	6.0	1.0	0.02090277055615136	0.8692258472700736	0.10508801226518887	0.004783369908586163
4	5.0	1.0	0.041021658741396176	0.8360073768615893	0.11398580098238306	0.008985163414631528
13	14.0	2.0	0.005962294302900531	0.03853247713118751	0.9536662096443284	0.0018390189215836655
15	16.0	2.0	0.011219195262613498	0.060687967211747615	0.9243082661007453	0.003784571424893534
16	17.0	2.0	0.011960716097784391	0.07785278687742993	0.9063300915012157	0.0038564055235698782
9	10.0	2.0	0.0030317841991010096	0.02216355162504037	0.9738645297986454	0.0009401343772133783
3	4.0	2.0	0.016810066093529506	0.1110728679301343	0.8671141536567541	0.005002912319582023
12	13.0	3.0	0.000851530361553659	0.000277519684359223	0.00017981478923354485	0.9986911351648535

Figure 5.12: Fuzzy c-means clustering output with clusters and membership values

5.3.5. Evaluation of clustering methods

When comparing the results of the the K-means (Fig. 5.7) and fuzzy clustering algorithms (Fig. 5.11), a level of consistency was observed. Most suppliers were assigned to similar clusters. However, a closer examination showed a discrepancy for suppliers 2 and 20. The k-means clustering algorithm assigned these suppliers to cluster 0 and 2, whereas fuzzy clustering assigned it to cluster 1 and 0. This difference in cluster assignment between the two methods outlines that a nuanced interpretation of the supplier's characteristics is needed, if one relies solely on the clusters for shortlisting the suppliers.

The membership values for supplier 20 in the fuzzy clustering method emphasizes its association with different clusters. The membership values were 0.54 for cluster 1 and 0.4 for cluster 3. This indicated why this supplier was assigned to cluster 1, but also showed a notable presence in cluster 3. The nuances outlined by the membership information enhances the understanding of the supplier's relationship with multiple clusters. This provides valuable insights into the level complexity of its categorization to certain clusters. When shortlisting suppliers, it is therefore advised to not solely rely on selecting suppliers from one specific cluster. The relevance and effects of the nuances between clusters are hereby proven. Hence selecting neighbouring suppliers from other clusters could provide additional options, if the data points are close to each other.

5.3.6. Model Verification

Followingly, conclusions were drawn from this visual representation by analyzing the characteristics of each cluster. Commonalities between suppliers in the dataset were identified in terms of technical, process and business competences. For the real-world dataset, cluster 0 showed high technical and business capabilities. Zooming in on the dataset and the suppliers in this cluster, it was seen that indeed these suppliers scored high on technical capability questions. It was seen that the suppliers in this cluster were able to reach certain technical requirements such as geometry, critical dimensions, and aspect ratios better compared to the suppliers from other clusters. The suppliers in cluster 2 showed higher process competences overall. Looking at the datasets of these suppliers, it was found that these suppliers indeed had better process competences than the other suppliers because they had certain critical machinery and had developed their own recipes for MEMS processing. Clusters 3 and 4 scored lower on all three competences. Looking at their questionnaire output, it was seen that these suppliers could not meet the necessary business requirements related to contractual agreements or supply chain continuity measures. Hereby, the developed clustering model passed the first verification test, showing results that can be withdrawn from the real-world data. An overview of the clusters and their distinct characteristics for both the real-world data and the artificial dataset can be found in Table 5.1 and 5.2.

Cluster	Business Competence	Technical Competence	Process Competence
0	Medium	High	Medium
1	Low	Low	Low
2	High	Medium	High
3	Low	Low	Low

Table 5.1: Cluster characteristics in the real-world dataset

Cluster	Business Competence	Technical Competence	Process Competence
0	High	High	High
1	Medium	Medium	Medium
2	Low	Low	Low

Table 5.2: Cluster characteristics in the extended dataset

Furthermore, the model was verified by trying to revoke errors by setting negative numbers for the number of clusters k. As a result of this test, ValueErrors followed appointing that negative dimensions for k are not possible. Similarly, the model showed errors when trying to set the number of clusters to 0 or at unreasonably large numbers such as 100. It was impossible to set the number of clusters k higher that the number of data points. The model returned the error given in 5.13. These verification tests applied on both the dataset with 21 data points and 50 data points. In order to observe the central locations of each cluster visually, the cluster centroids were also plotted. No discrepancies or outliers between the centroids and the data points could be found.

```
  File "C:\Users\Sezer V\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py", line 998, in fit
    _num_samples(X), self.n_clusters))
ValueError: n_samples=50 should be >= n_clusters=100
```

Figure 5.13: Error returned during verification

5.3.7. Model Validation

in order to validate the model, the real-world data was clustered as shown earlier. The resulting clusters per supplier are shown in Fig. 5.14. This cluster data was used to make quick and data-driven decisions for shortlisting suppliers for further consideration during product development. Suppliers from clusters matching the desired criteria were shortlisted. By doing so, five important observations validating the added value of this method, also for practitioners, were made.

Firstly, this shortlist of suppliers included the suppliers known from the best practices by the case company. Secondly, this shortlist excluded a so called 'high-risk' supplier known at the case company. This was, because this method gives its users tunable buttons in the form of weight-factors for each competence used to assess suppliers. Furthermore, this method was validated by its proven speed and ease of use for practitioners in interpreting large scale information. In the case study, the dataset consisted of the responses of 21 suppliers to a questionnaire with 53 questions. Subsequently, this methodology proved to make it able to understand trends of supplier characteristics and benchmark suppliers quantitatively against each other. Using this method, the gaps of suppliers were more easily identified. Lastly, after the identification of these gaps, strategies could be drawn do develop suppliers further to move up on the axis of business, technical or process competences. To give an example, it was now possible to bring to light that a certain supplier did have the necessary machinery and tooling available from its relative high process competences. However, this supplier did not have the recipes and experience in place for complying to the technical requirement of reaching the desired critical dimensions with that tooling. A strategy for enhancing this suppliers capabilities could be to invest in them by sending engineering teams and developing the recipes together.

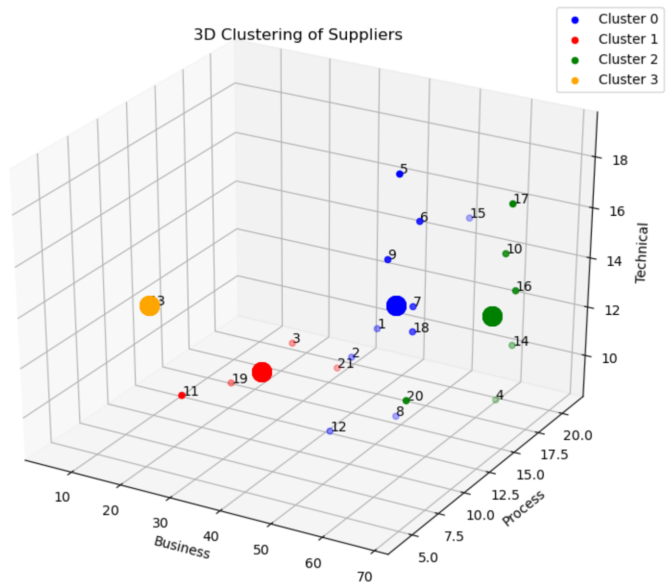


Figure 5.14: K-means clustering applied on initial dataset

5.4. The new product development framework

In this section, the designed novel product developed framework is elaborated upon. The definition of a framework varies depending on the disciplines, whether it is used for research or applied in industry. Therefore, this section distinguishes between the scientific framework and the practical application thereof for practitioners in the semiconductor industry. Frameworks are seen as a supportive structure around which something can be build. This can be a system of rules, ideas, or beliefs that is used to plan or decide something [28]. In the context of scientific research, frameworks aid researchers in getting enhanced understandings in their field of research. This is because frameworks help in distinguishing and slicing complex processes and operations into smaller manageable parts, revealing the relationships and interfaces in between them. This also reveals the core concepts, interesting for further research [82]. This is achieved by zooming out and distinguishing between the different parts of the framework. The literature on this topic contains little discussion on how frameworks can be used to bridge between the theory of science and practitioners in the industry.

Product development needs to be viewed with a more integral perspective, starting with generating a deeper understanding of the product development challenges. These challenges start from the early conceptualization phases and expand through supplier selection until ramp up and mass production. In this context, a holistic framework is developed, taking into account its generalizability for later application in other semiconductor products as well as by practitioners.

The framework serves to pinpoint the crucial role of product development steps and modular tools for synthesizing and communicating knowledge between steps and actors. Its primary objective is to elaborate how the mechanisms in product development stimulate information flows and what the interfaces are in-between them. The framework does not only serves as a theoretical model but also provides practical insights for practitioners, assisting them in enhancing their product development processes' efficiency to ultimately reduce time to market for their products.

The framework distinguishes between the distinct phases of product development. It maps the information flows needed to translate from the early conceptualisation phases, where features of technologies are translated to product and process designs, and links these steps to supply chain integration, thereby allowing for co-development.

The information flows from feature definition to product design include information about the key features and functions of the product, which relate to its requirements and the relations between these requirements. These key features, functions and requirements are used to make the translation to the product design and process design. For the translation to the supplier selection process, supplier capability information is needed to map their overall technical competences, process competences, and business competences.

An important interface to note here is for cases where commonalities exist between earlier developed technologies and the new to be developed ones. For those cases, supplier capabilities are already known. The earlier gathered supplier capabilities can be used to reflect on the initial product requirements. This information is used to proceed to the detailed design in co-development with suppliers towards ramp-up.

The practical application of the framework and its procedure are shown in Fig. 5.15. This elaboration aims to show the process of applying the framework for an ideal situation that allows to use the steps as shown. In the application process of the framework, four phases of product development are distinguished. Firstly, the idea generation and conceptualisation phase, where new technologies are in the research phase and potential purposes and applications are being explored. In the design phase, the features and initial requirements of the product and the process are defined by making a modular breakdown of the MEMS product. This helps in formalizing the function and the requirements of each component (module). Using the modular breakdown table, the components, functionalities, technical requirements, process requirements, interfaces between components, key challenges, and co-development considerations are formalized.

In case of absence of information about suppliers' capabilities to reach these requirements, this standardized method allows for mapping a comprehensive questionnaire. A dataset with responses of suppliers to this questionnaire is used as input for a machine learning model. The output of this model is a visual representation of various clusters to which suppliers with comparable competences are assigned. This visualisation shows an overall overview of the supplier competences for three dimensions: technical, process, and business. Depending on the most important competences needed for the product, suppliers can shortlisted.

Followingly, the detailed competences of these suppliers can be extracted. Depending on the key supplier capabilities of these shortlisted suppliers, a supplier can be selected for consideration. With knowledge of these capabilities, the engineers responsible for the product design and the engineers responsible for the process design can consider different design choices depending on what is possible from supplier side (the manufacturing platform). Combining this information with the initially generated requirements, a concept design can be formalized. Followingly a verification step follows to examine whether the technical, process, and business requirements for the product are met.

If gaps persist, the process iterates with reevaluation and selection of alternatively shortlisted suppliers. Once the requirements are satisfied, the design refinement phase starts. In this phase, the best potential supplier is contacted before further engagement. In this contact, the final gaps of the supplier according to their questionnaire output are discussed. The modular breakdown table can be used in these discussions as a guide pointing out the requirements and the interdependencies of the requirements. The detailed design and re-evaluation of product and process designs can start. Followingly, a convolution of the designs of both parties follows, based on a well-considered evaluation of the requirements from the procuring company's perspective and the capabilities from the supplier's perspective. This results in a preliminary definition of the requirements and supplier selection. Subsequently, a proof of concept prototype follows. If necessary, a feedback loop allows to re-evaluate and alter the requirements. In case of sufficiently performing prototypes, a ramp-up plan can be made to prepare for mass production.

5.4.1. Framework validation

Because of the comprehensiveness of the framework and because it is generalized, it can be used for product development of all sorts of semiconductor products, irrespective of their complexity levels. The tools developed for its application can be used independently from each other, similar to the steps as shown in Fig. 5.15. If a new product is developed, containing commonalities with an earlier product, and hence no new questionnaire needs to be mapped, the old output of the machine learning model can be consulted for shortlisting suppliers already.

Typically the stages of product development take anywhere between 3 months to several years. Hence, within the scope of this project it was impossible to go through each step and compare the TTM with and without applying this framework, let alone following both the state of practice and the state of the future approach for one product. Therefore within the scope of this research, the time consuming, resource intensive tasks were extracted. Followingly, the tools developed in this research were applied to measure the savings and other added values compared to the touchstone. The results are shown in Table 5.3. This table summarizes the key aspects improved in the current situation by applying the developed framework. The proposed approach functions as an intermediate step towards fully automated activities for supplier selection. The term intermediate is used, because in the state of practice everything is done manually. Whereas the approaches proposed by this research are partially automated, by using the machine learning model.

Shortlisting suppliers from a multitude of supplier questionnaire responses is not a standard approach at the case company. However, the time needed to make a shortlist manually based on 21 questionnaires, taking into account the time needed to assess the suppliers together with a professional at the case company was estimated between 10 and 15 hours in total. In the proposed approach, the machine learning model visualized an overview of the suppliers and their competence ratings immediately after running the model. From this visualization, the suppliers were shortlisted based on their competences and gaps in 30 minutes. That is a reduction of 95% in time. In a theoretical future approach this final step can also be automated if needed. For now a visual representation does exactly what is needed, namely visualizing the overview of suppliers and their overall competences, and providing a measure to shortlist suppliers easily by the look at a graph.

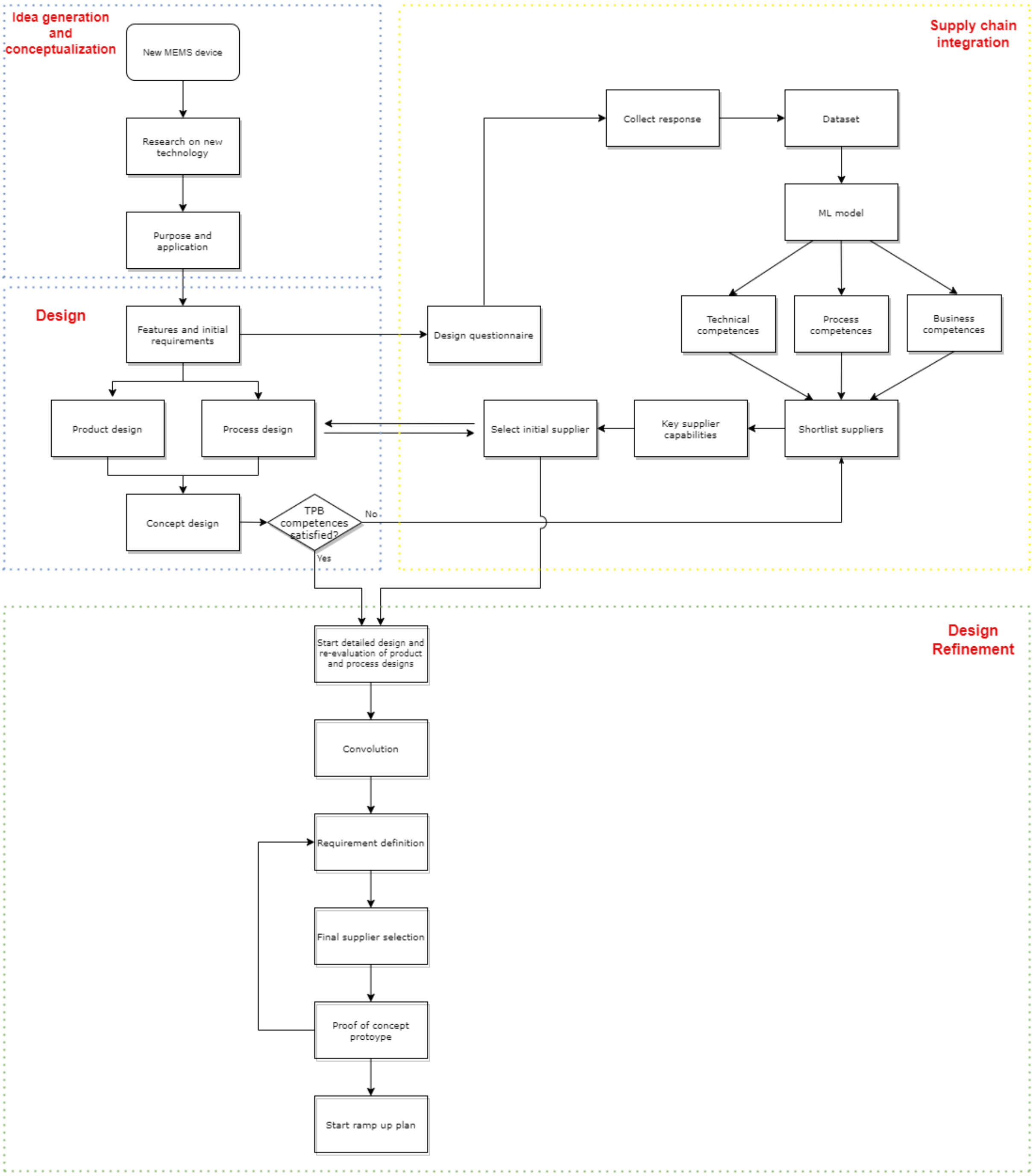


Figure 5.15: Application of MEMS product development framework

Cluster profiling by identifying their characteristics, generating insights into the types of supplier groupings and their trends, is not possible in the current approach. With the proposed approach, this was possible, as shown earlier in this section and in Table 5.3. In a fully automated virtual environment, a full report can be derived from the cluster characteristics by employing Natural Language Processing (NLP) models.

Identifying supplier gaps in the current approach from a large pool of suppliers was approximated to take up to 10 hours. This is because of the large amounts of questions and supplier responses that the analyst would have to go through one by one. Another problem with analyzing this output by hand, was that suppliers sometimes provided different types of answers, making it hard to compare and rank the suppliers and extract a good understanding of their gaps. The non-standardized way of answering, made this analysis even more labor intensive and time consuming. The standardized answers in the proposed approach mitigate these time consuming tasks. In the proposed approach, the gaps of the suppliers can be extracted from the visual representation that is provided by the machine learning model. The finest details, are now more easily visible because this visual representation points out which suppliers' questionnaire output should be taken into account. In a theoretical future approach, again using NLPs a detailed report can be extracted from the questionnaires, pointing out the gaps and competences of suppliers.

Supplier profile recognition, showing insights into the types of suppliers, is not possible in the current approach. This is possible in the proposed approach based on three dimensions. In a fully automated future approach, if there is enough data to work with, models can be developed that provide extensive reports on the supplier profiles, if desired.

The design and refinement of questionnaires was a time consuming process including multiple people and required lots of refinement steps. In the proposed approach, the hours needed to come to a comprehensive questionnaire without overseeing requirements was reduced significantly. In a theoretical future approach, questionnaires can be automatically designed by models based on data-input containing the necessary requirements.

In order for the theoretical future approach to work, tailored machine learning models should be developed and all information that passes through the product development steps should be registered in large data files, to create a fully virtual environment. Furthermore, NLPs should be trained to give the desired level of quality and nuance when generating the reports mentioned above. The theoretical future approach requires a high maturity level in data-management from companies and practitioners to create this virtual environment. However that is another research topic on its own and hence it is out of the scope of this project. This proposed hybrid approach is the first step towards a theoretical future approach where the activities for product development are fully automated.

Table 5.3: Comparison of supplier selection approaches

Activity	Current Approach	Proposed Approach	Theoretical Future Approach
Supplier shortlisting (hr)	10-15	Intermediate, $\frac{1}{2}$	Automated
Cluster profiling	Not possible	Possible	Automated
Identifying supplier gaps (hr)	10	Intermediate, 1	Automated
Supplier profile recognition	Not possible	Possible	Automated
Questionnaire design and refinement (hr)	35	8	Automated

5.5. Concluding remarks

Modeling approaches like MILP and MPC require extensive information about the supply chain dynamics, or historical data. This level of detail in information is not available in the early stages of product development, where supplier selection plays a crucial role and affects the product design and process design. As a result, subquestion 8 "How can modeling, simulation, and data-driven approaches contribute to optimizing the strategic decision-making process in supplier selection for product development in the semiconductor industry?" has been addressed. The limited amount of information that can be generated through the standardized method described in the earlier sections, can be leveraged for supplier selection through clustering algorithms. These algorithms save time when efficiently organizing large numbers of suppliers based on their overall performances from technical, process, and business perspective. This enabled the focused shortlisting of suppliers without extensive manual evaluations per supplier. And it provided insights into supplier profiles and gaps by formalizing design challenges to be used when engaging with suppliers, reducing the unnecessary meetings with insufficient suppliers and IP leakage. This led to resolution of subquestion 9: "What machine learning algorithms can be effectively employed to address the supplier selection problem in the industry for strategic decision-making?". Furthermore, this overview enables the design of strategies for missing technologies for suppliers based on competence gaps, such as investing in the development of suppliers that have certain machinery but lack the experience in using those. In this way, suppliers can be developed to meet otherwise unattainable technical requirements. The model was verified and validated in a case study, answering subquestion 10. It revealed that the model is right, and it is the correct model for the purpose of its application, while making good use of the available information in the early stages of product development.

The developed framework includes insights into the information flows between steps and actors through the product development process. Furthermore, interfaces are described in the framework to make it all-encompassing and to account for changes during practical application. Finally, an evaluation is made by comparing the proposed framework in relation to the current approach and the theoretical future approach. Insights on what this future approach would consist of were also shared. Concludingly subquestion 11 has also been resolved as well.

6

Conclusions and Future Research

In this report, a novel product development framework was developed employing co-development and supply chain integration through data-driven decision-making. A thorough literature study, supported by empirical research conducted in a case study formed the foundation of the assumptions and findings of this work. In the analysis of describing the current situation and practices of the semiconductor industry, it was found that it is composed of different types of companies being: IDMs, foundries, fabless, and equipment manufacturers. The state of practice product development processes follow a sequential process with limited standardized information flows. This results in information asymmetries between actors of this system. The main overarching limitation in product development is the supplier selection problem.

The state of the art methods for improving product development are co-development, facilitated its key enablers modularity, comprehensive information flows, and standardization of processes. The standardization is reached through the utilization of the tools and methods developed during this research for the co-development of products and their corresponding processes. The developed tools include the modular MEMS product architecture, emphasizing functions and requirements; the modular breakdown table for generating the required engineering output for supplier selection and mapping questionnaires; the standardized labels for questionnaire responses; the three dimensions of business, process, and technical competences through which suppliers are assessed; the machine learning model for interpreting the vast amount of data; and ultimately the developed framework and its approach procedure.

Supply chain integration can be effectively leveraged to enhance product development by inclusion in the early stages of product development. This is because suppliers play a pivotal role in product development, because the manufacturing platform is often outsourced in this industry. Modularization and the standardized methods described earlier can be used to gather the necessary information from suppliers for supplier selection. Increasing product complexity, process complexity, and IP sensitivity correlate with the need for a framework to gather and analyze the requirements and data internally and at the potential suppliers, to expand the supply base. The vertical information flows, internally between research, engineering and sourcing departments in semiconductor companies are focused on requirement generation for the products and processes. This is also called vertical co-development. The external, horizontal information flows with the suppliers focus on understanding their capabilities for horizontal co-development. The engineering output generated through vertical co-development is used to enable this horizontal co-development. The potential matches with suppliers are explored using data-driven decision-making methods, the clustering algorithms.

Strategic decision making in supplier selection processes was improved using the developed machine learning models, specifically the clustering algorithms. The models proved to save time and labor in shortlisting suppliers, provided insights into supplier profiles and gaps, and enabled the otherwise impossible development of informed strategies on suppliers for missing technologies. The machine learning model was verified and validated in the case study. The savings in time for shortlisting suppliers and identifying supplier gaps was up to 95% for the most complex semiconductor products.

The novel product development framework presented in this work includes knowledge about information flows between stages and actors during the product development process. The interfaces in-between are also included in this work. An evaluation of the framework in relation to the current approach and the theoretical future approach revealed its added values and pivoting role in going towards a fully automated approach. The time needed for the generation of the required engineering output for supplier selection, in the form of technical and process requirements, and the design of comprehensive questionnaires was reduced by 77%.

The limitations of this study were in the limited amount of real-world data to provide a touchstone and reference for the currently applied practices. These challenges were mitigated through extensive empirical research and the employment of a new validation plan. In practical application, this framework acts as a strategy towards enhanced product development.

Considering the scope of the project and the substantial timelines up to many years needed to undergo one full product development cycle, spanning from conceptualization until ramp-up, a dedicated validation plan was established and executed. The added values of this novel framework were formalized and supported by extensive empirical research and industry professionals. The most important, measurable actions were extracted from the product development process. Generating the required engineering output in the form of technical and process requirements, and translating that to a comprehensive questionnaire was one of these actions. Another action was the process of identifying the missing competences, or gaps of suppliers. Additionally the analysis of large amounts of information on supplier competences to be able to shortlist suppliers was an important action that affects time to market and could prevent rework if done properly while taking into account a multitude of criteria at once. These were the actions of most influence for the initial phases during product development. Therefore, these actions were executed using the tools and methodologies from the new product development framework. This allowed to examine the savings in time on critical processes and added values that could be achieved, together with new insights in this field of research.

The aim of this research was to contribute to the field of knowledge transfer and data-driven approaches to be incorporated in the early stages of product development. The literature lacked information on how to develop a methodology for data-driven co-development. This gap was filled by elaborating on the design of a standardized framework for product development incorporating co-development and its cross-function with supply chain. There was no concrete information on the different steps taken during product development and their interfaces, and how to arrange those to reduce time to market, labour, and intellectual property losses. Another gap in literature filled by this research was the absence of a standardized methodology guiding the translation of a desired set features for new technologies to a product design and its corresponding process design. Furthermore the literature included insufficient information on how supplier selection processes and supplier capabilities can be mapped and leveraged to enhance product development within the context of co-development and modularity approaches, already in the early stages of product development.

The contribution of this work is twofold. It contributes to the literature and the research field by filling the existing gaps in a concrete an comprehensive manner. For practitioners it provides insights into the necessary procedures to enhance decision-making processes during the product development process. This was achieved through a detailed literature study and a case study. This resulted in a novel validated product development framework, enhancing time to market by reducing the timelines, resources and labor needed for generating the required engineering output for supplier selection and the supplier selection process itself. Additionally, this framework provides data-driven decision-making tools for supplier selection. This paves the way for future research on a future approach where all actions and processes are fully automated in a virtual environment, reducing the time needed to proceed in the product development process even more.

Future research could also focus on the next phases in product development. This includes the phases after supplier selection, where design choices and the corresponding consequences for the two semiconductor companies can be evaluated through modeling to enable a quicker convolution of designs and reduce the time needed to start with the prototyping phase. Variable design choices on dimensions, materials used, and the needed processes can be evaluated together while taking into account their effects on product performance in optimization models. This can be done to assess the necessities for the complex technical and process requirements, where design flexibilities are necessary for otherwise unattainable technologies. Consequently, the process of design convolution can be speed up by filtering out the the unattainable product or process requirements, facilitating quicker prototyping of the products.

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