Measuring the product configuration complexity and cost for mass-customization of automobiles:

A qualitative and quantitative study of the product variant complexity, its associated cost

by

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Abstract

This thesis presents an integrated model for analyzing product configuration complexity and cost, aiming to provide a comprehensive framework for decision-making in product configuration management. The research begins with a literature review to identify relevant complexity metrics, narrowing down to two primary metrics: structural and organizational complexity. The selected metrics are integrated into a hybrid model that conceptualizes product configuration complexity as a function of these factors. The model incorporates mathematical formulations for assessing structural and organizational complexities, allowing for a nuanced understanding of the challenges inherent in product configuration. Furthermore, a cost model is developed to quantify the financial implications of product configuration decisions, considering factors such as transport, assembly, and quality control costs. The model is applied to hypothetical scenarios, demonstrating utility in informing decision-making processes within original equipment manufacturers (OEMs). Future work is proposed to enhance the model by incorporating risk and uncertainties, conducting cost-benefit analyses, and refining the algorithm for optimal performance. Overall, this thesis contributes to the advancement of product configuration management practices by providing a comprehensive framework for analyzing complexity and cost in product configuration.

Certified by: **Eric Rebentisch**
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Sincerely,
Chetan Vidhate

<u>Note on the use of Generative AI:</u>

I have leveraged ChatGPT to enhance the clarity of my explanations by correcting spelling, voice, and grammatical errors. Additionally, Grammarly was used for final grammar adjustments, ensuring adherence to academic writing conventions.

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List of Abbreviations

ADAS	Advanced driver-assistance systems
ANSI	American National Standards Institute
BOM	Bill of Materials
BTO	Build to Order
BTS	Build to Stock
CDIO	Conceive-Design-Implement-Operate
CM	Configuration Management
COGS	Cost of Goods Sold
DSM	Design Structure matrix
EBOM	Engineering Bill of Material
EIA	Energy Information Administration
EV	Electric vehicle
GM	General Motors
GPT	Generative Pre-training Transformer
GSP	Graph Signal Process
IAQG	International Aerospace Quality Group
IEEE	Institute of Electrical and Electronics Engineers, Inc.
IFAC	International Federation of Accountants
INCOSE	International Council on Systems Engineering
ISO	International Standards of Organization
ISSE	Information Systems Security Engineer/Engineering
ITS	Intelligent Transport System
IVIS	In-vehicle Information System
JMTM	Journal of Manufacturing Technology Management
KBB	Kelly Blue Brook
LCCE	Lifecycle Cost Estimate
MBOM	Manufacturing Bill of Material
MES	Manufacturing Engineering System
OEE	Overall Equipment Effectiveness
OEM	Original Equipment Manufacturer
PC	Product Configuration
PDM	Product Data Management
PLM	Product Lifecycle Management
PMBOK	Project Management Body of Knowledge
RFLP	Requirement Functional Logical Physical
ROI	Return on Investment
SCM	Supply Chain Management
SE	Systems Engineering
SEBok	Systems Engineering Body of Knowledge
TPS	Total Productive Maintenance
TSSC	Toyota System Support Center

Chapter 1: Introduction

Since the start of this century, the product varieties offered in the automobile industry have significantly increased. Earlier, the automobile OEM sold a limited variety of cars with minimal customization or configuration options choices to the consumer. In the past two decades, the options for a vehicle configuration have grown exponentially. Consumers now have options to customize their cars to a component level. Refer to the [Appendix: A1], which shows a global trend practiced by the top 15 global car manufacturers, corresponding to 75% of the vehicles sold worldwide (“Global Vehicle Sales Top 92 Million Units in 2023; December Volume Up 11%” 2024). For automotive systems engineering, the complexity and number of variants are very high; exemplarily, 1,5x109 variants are present for current vehicles of one brand (Knippel and Schulz 2004). Technological advancements, environmental concerns, and evolving consumer preferences drive this transformation in the automobile configuration. For example, the Ford F-150 truck is now available in gas, hybrid, and fully electric models. Each of these models then has at least three trims. Each trim can be configured with at least eight colors, three powertrains, over 20 exterior components like wheels and tires, sensing system, mirrors, and several dozens of interior components like seating, sound System, dashcam, roof, interior color, steering types and many more. Many features, such as adaptive cruise control, lane-keeping assistance, self-parking, and FSD, are available for selection.

On top of that, there are 50+ accessories that the buyer can choose from. In 2000, the Ford-150 had only two variations, and there was no option to build your own car (KBB 2000).

When the consumer builds the configuration of his car, he has to select one or more options from these categories. The possible unique combinations of such configurations are enormous. The 2008 F-150 could be ordered in billions of combinations ("Automotive News" 2008). In 2016, this number was close to over one billion, and F150 can be built in different ways (Appel 2016). This flexibility allows consumers to customize their cars. From the customer's perspective, the complexity is largely invisible. From the manufacturer's perspective, there are a lot of implications of all this variety. This complexity is tricked down every part of the car product lifecycle. Introducing an option to a car impacts requirements, functions, design, manufacturing, supply chain, post-sales services, consumer adoption, regulation, and every aspect of the automobile lifecycle. People can now choose even the raw material sustainably produced for their cars. The result is that car manufacturing is getting costlier. The increase in product complexity increases the total cost of car manufacturing by up to 20 % (Marti, 2007). There is a limited capacity for producing cars in a factory. With more variation in factory planning, it is becoming difficult. It challenges the flexibility of product, operation, process, volume, expansion, and labor. Some common challenges are:

1) Managing the intricate design requirements of highly configurable products can lead to increased development time and entail significant upfront investments in research, development, and testing.

2) Producing diverse product configurations requires flexible manufacturing processes, which can be costly to implement and maintain.

3) Dealing with a wide range of components and suppliers adds complexity to supply chain management, leading to potential delays, increased and logistics costs, involves

increased inventory holding costs, transportation costs, and potential costs associated with supplier coordination and management.

4) Maintaining an efficient operational process becomes challenging due to the need to handle a variety of product configurations, leading to higher labor and training costs. Training employees to handle a wide range of product configurations and maintaining efficient operational processes result in higher labor and operational costs.

5) Providing after-sales service and maintenance for diverse product configurations requires specialized knowledge and resources, increasing service costs due to specialized technicians and spare parts inventory requirements.

Current approaches to managing these challenges with the product configuration complexity include:

1) Modular Design: Manufacturers are increasingly adopting modular design approaches to create products from standardized modules, thereby reducing complexity and cost.

2) Standardization and commonization: Standardizing components common across models or product lines are widely used. (Boas and Crawley 2011) found the potential benefits of commonality: shorter lead times, lower fixed development, sourcing, and variable costs, and higher product reliability.

3) Product Planforms: To reduce development time and procurement and operating costs of

product platform-based variants, the product platform can be designed after considering several characteristics, such as modularity, flexibility, sustainability, and complexity (Kim et al. 2016).

4) Product Lifecycle Management (PLM) Systems: PLM systems help streamline product development processes and manage product configurations throughout the lifecycle (Dassault Systèmes 2022).

5) Supply Chain Optimization: Implementing advanced supply chain management practices and technologies can help mitigate supply chain complexity.

However, some of these approaches may lack scalability, making it challenging to manage increasing complexity as product portfolios expand. Implementing advanced technologies and process changes can involve significant upfront costs and may not be feasible for all manufacturers. Integrating different systems and technologies across the value chain can be complex and may require significant time, training, and resources. Resistance from employees and stakeholders to adopt new processes and technologies can hinder the effectiveness of current approaches.

Manufacturers who fail to effectively manage increasing configuration complexity risk losing market competitiveness, facing higher production costs, and experiencing reduced profitability. Ineffective practices to cope with product configuration complexity may lead to delayed time-to-market, increased product recalls higher warranty costs, and ultimately, loss of customer trust and brand reputation.

Structural Complexity: Modern cars have thousands of components and millions of lines of software code. The vehicle product structure can go as deep as 15 levels in the structure tree. Many of these components are interconnected. From the chassis and body frame to the intricate network of electrical wiring and onboard computer systems, every aspect is coupled and connected with many other internal and external components of the car system. Moreover, integrating safety features such as airbags, collision avoidance systems, and information and entertainment systems adds another layer of complexity.

These components are defined as a Bill of material. A bill of materials (BOM), sometimes referred to as a product structure, is a list of the raw materials, sub-assemblies, intermediate assemblies, sub-components, parts, and quantities needed to manufacture an end item. BOMs inform production orders as teams assemble and/or requisition the materials needed to execute a production plan ("Bills of Material (BOM) for DMSMS | Www.Dau.Edu" 2024).

The offerings by car companies to configure and customize cars have resulted in millions of end products (Chatras et al., 2015.) In the automotive industry, the diversity of end products that result from this combinatorial process (several million) is such that no solution proposed in the literature allows a quick list of the BOMs for all these vehicles (Chatras, Giard, and Sali 2016).

Manufacturing Complexity: Each build-to-order car comes to manufacturing in a factory with a build and a unique assembly plan. There is a specific sequence of assembling these cars, and it could vary from car to car. Many of these cars are assembled on production lines built around mass-producing standardized vehicles. Each unique car will need specific components that are available at the correct time and in the proper order to assemble. The process of assembling each car must be monitored carefully because of this variation. The assembler needs to be trained on various tasks, as the assembly instructions could differ from car to car.

Organizational Complexity: The organization complexity inherent in car manufacturing. An intricate coordination is required to bring a vehicle from a customer's build-to-order to reality. Car manufacturers operate within vast networks of suppliers, production facilities, and distribution channels, each playing a crucial role in the overall process. From sourcing raw materials to assembling the correct components and conducting quality control checks, every step demands meticulous planning and execution. For a mass customization style of manufacturing, every car assembled on an identical product line could be different. The organization involved in getting the components and materials could be different. This puts pressure on the organization to effectively communicate and collaborate among diverse teams, including production planners, assembly teams, supply chain managers, and marketing specialists, for the timely delivery of products. The car manufacturers leverage advanced MES technologies and lean manufacturing principles to optimize their operations and efficiency throughout the entire production chain to meet consumer expectations.

Quality implications: While many of the verifications and validation methods at a components level can be shared, the vehicle system level testing needs to be performed individually to ensure the unique car build works perfectly together. The mass customization puts pressure on maintaining the quality of the cars.

Sourcing Complexity: One significant challenge for car makers in building custom cars lies in the sourcing of components. Procuring unique or specialized parts for assembly from mainstream suppliers can lead to delays in production and increased costs as manufacturers must either store a variety of components or have to disturb their manufacturing plan to accommodate custom orders. The supply chain disrupted by natural disasters, geopolitical tensions, or pandemics can lead to further delays and cost overruns. Carmakers have to keep a closer relationship with their suppliers, invest significantly in advanced inventory management systems, and even consider the in-house production of critical components to ensure a reliable supply chain for building custom cars.

Service: The cars have a long lifecycle. It can last up to 300000 miles and spans over 14 years (“What Is a Reasonable Life Span for a Modern Car?” 2024) (United States. Department of Transportation. Bureau of Transportation Statistics 2019). The car needs maintenance and service in its useful life. The skills need to be developed to maintain and repair unique car builds with repair procedures. The dealership and car garages must have the correct repair guides and training. They must also be able to procure replacement components that match the specific build. The training of the workforce. Difficulty procuring components, a tailored approach to service the cars can be costly and time-consuming and may require specialized skills, parts, and facilities.

Before any option or feature is introduced in a car for the consumer to choose in their car build, it undergoes various system design and system integration tasks. This typically follows the product development cycle.

Requirement complexity: When the architects must accommodate the new requirements to a car, a careful review and analysis is performed to see if the new requirement impacts any other requirement. It requires thorough research and development to ensure that the new requirement aligns with existing vehicle systems and technologies, industry standards, safety regulations, and consumer expectations. This often involves defining extensive functional, performance, interface, operational, and illities requirements. Secondly, integrating the new requirement into existing vehicle designs may necessitate significant modifications to the engineering and manufacturing processes, potentially leading to changing the tooling and testing requirements.

Functional Complexity: Functional decomposition may be impacted by adding a new option to the car. For example, adding a new hybrid gas+battery option to a car impacts the vehicle's intended purpose, design objectives, and operating conditions. While incorporating advanced features such as autonomous driving capabilities, connectivity, and electrification requires interactions between different subsystems, such as powertrain, steering, braking, chassis, and electronics. This introduces a significant complexity as the unique car variants need a unique multi-disciplinary functional analysis.

Design Complexity: After the requirements are addressed, the design teams incorporate the configuration changes in the existing or future model. The changes, as simple as adding a heated side mirror option to a trim, will likely impact the power model, electrical harness, vehicle control system, software, and display panel, at the least. Design changes will be required to all of these impacted subsystems or components. The manufacturing processes, tooling, and assembly plan will also need to be decided during design.

The changing customer requirements and technology changes have played a significant role in the increasing complexity of automobiles. "Major production systems – flow line, Toyota production system (TPS), job shop, cell, flexible manufacturing system, and seru – have been developed and applied to supplies to match different demand dimensions over time (Yin et al., 2018)." 45% of cars manufactured in 2015 were Level 0 Automation level, compared to 60% of cars today in 2024 are Level1 Automation Readiness Level and 33% are Level 2 (Buchholz, 2023). This increase in autonomous driving is technology-driven in AI, ML, Sensors, cameras, semiconductors, and the computing industry. For example, systems such as in-vehicle information systems (IVIS) and advanced driver assistance systems (ADAS) offer a broad spectrum of information to drivers (Palac, Scully, and Jonas 2021). This research paper found out, "Advanced intelligent vehicle technologies provide various types of in-vehicle information to drivers. This phenomenon leads to increasing amount of the information, which intensify the complexity of in-vehicle interface (Hwangbo, Lee, and Ji 2016)."

Introducing a new option or feature to a vehicle significantly influences every stage of its development process, from initial requirement assessment to manufacturing. Firstly, the addition necessitates a thorough reevaluation of the vehicle's specifications and performance criteria to accommodate the new element seamlessly. Designers must then meticulously conceptualize and integrate the feature into the existing framework, ensuring compatibility with the vehicle's overall aesthetic and functionality. This often entails extensive iterations and simulations to optimize performance and maintain safety standards. Concurrently, manufacturing processes undergo adaptation to incorporate the production of the new component efficiently, often involving retooling and reconfiguration of assembly lines. Quality control measures are heightened to ensure consistency and reliability throughout manufacturing. Every change has design, validation, manufacturing, and service costs. To understand this impact, there is a need to take a systemic view of product complexity and its impact on the product lifecycle from concept to service. The mass customization and build-to-order approaches are pushing the boundaries of how vehicles are manufactured in dynamic conditions. This paper explores how much impact the introduction of a feature has on the vehicle's lifecycle, from design to manufacturing to servicing the automobile. In this research, various methods developed and tested by other scholars are explored. The research takes a holistic approach to put together every possible dimension impacted by the complexity of the product configuration. The systems thinking approach is used in this paper to review the impact of changes in the vehicle's options.

The area covered by this research spans the requirement, functional, logical, and physical (RFLP) (Tao Li et al., 2020) models of the car to manufacturing and service BOM to see the impact of introducing the option in a vehicle.

This research also tries to estimate the lifecycle cost of manufacturing a complex car configuration and analyze it with the application offered by product complexity measure. This thesis works on System thinking principles and the CDIO approach (Crawley, 2007).

Sample data was developed to test the concepts, and case studies were performed on near real-time data in the car industry. The test data has over 19000 BOM parts in the car and has over 60 options to choose from. This test data also has a connected logical, physical, and manufacturing BOM model. Four widely used models measuring product complexity are used to compare the results. Tests are performed by carefully selecting options ranging from a small impact to a significant impact on car design.

This research shows that product complexity has a broad impact on every aspect of car manufacturing and can contribute significantly to the cost of product configuration management. While the revenue stays the same, the automobile industry is growing into unmanageable manufacturing complexity.

1.1 Motivation

The changing needs of the customer, industry trends, innovation, and regulations have transformed the automotive industry in the last few decades. Now, auto manufacturers offer their customers more configurable and customizable vehicles. For example, Model T by Ford has only three variants and four color options in 1925 and sold over 15 million cars, while the F-150 truck has seven models and billions of configuration options (Automotive News, 2008), which have sold over 41 million vehicles. As the variety of F-150 available to the customer has increased in the last 15 years, Ford's revenue has yet to impact the margins positively. Figure 1 shows Ford's revenue for the past 15 years compared to the number of F-150 models sold in the USA and COGS.

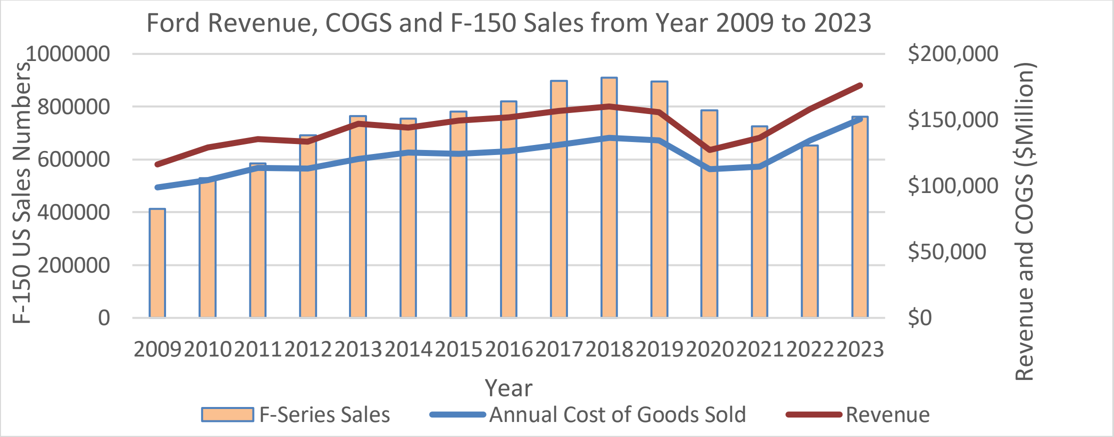


Figure 1 : Ford Sales Figures Vs F-150 US Sales Numbers ("2024 Ford F-Series Sales Figures" 2024)

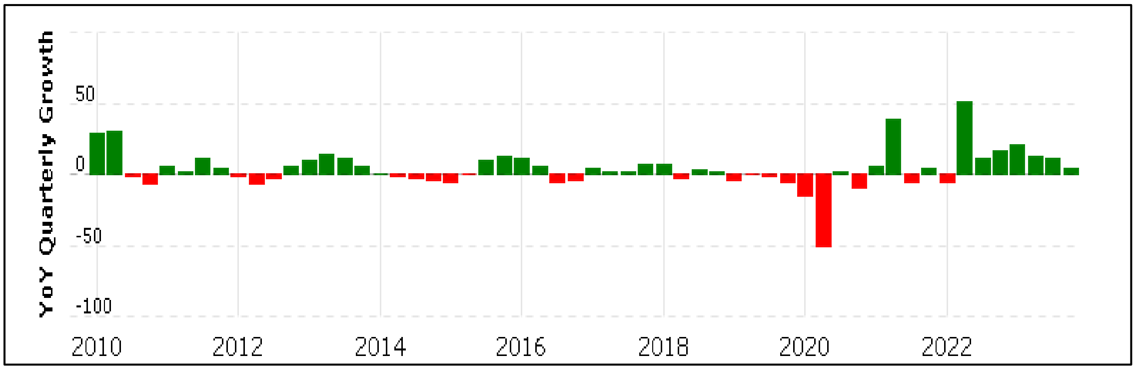


Figure 2 : YoY quarterly Growth of Ford (Macrotrends.net 2023)

This puts a lot of pressure on product development, manufacturing, quality, supply-chain, procurement, marketing, sales, service, and training throughout the vehicle development lifecycle. Year over year, it is becoming increasingly complex at the cost of optimal profitability while adding burdens on the company's ecosystem and sales. Figure 2 shows the year-over-year growth of the Ford Motor Company. "88% of its configurations sell fewer than 50 units each, and these configurations account only for 25% of its total sales." (Gauthier, 2020).

This led to a theory that complex product configurations are not optimally profitable. The product configuration's complexity incurs additional costs and time that are often not seen by the current accounting standards in the automotive industry.

As a result, this thesis attempts to measure the complexity of the product configurations across their lifecycle and the cost involved in defining, developing, implementing, and maintaining the product configurations.

1.2 Key Thesis Questions

For the automotive industry,

a. How are the car products getting complex with adding new configurable features or options?

b. How do we measure the product configuration complexity of an automobile?

c. How do we measure the cost of introducing a product variant?

1.3 Hypothesis

1) Understanding and identifying the product configuration complexity and its impact at each state of the automobile product lifecycle can help determine the realistic cost for implementing a new configuration in the vehicle product. This cost estimate can help auto manufacturers plan product offerings for optimal profitability.

2) Highly configurable products, specifically those with high manufacturing needs and diverse supply networks, disproportionally affect the designing, manufacturing, operations, product service, and training uncertainties and have a high long-term cost.

Chapter 2: Background Information

To understand product complexity, we must understand the definitions of the product, product system, and configuration and how configurations are created, implemented, and maintained throughout the product lifecycle. This section reviews the information necessary to build the complexity measurement model later.

2.1 What is a Product?

Definitions found in various standards and references:

1. A product is something that is, or has the potential to be, exchanged (Crawley et al. 2016).

2. A system considered from the point of view of a physical "system end product" (ANSI/EIA 2003) is made of system elements that may include hardware, software, infrastructure, and support services. The people and organizational aspects of the "whole system" of which the "product system" forms a part have to be considered in the design, but are provided by another organization. (INCOSE UK Chapter 2010)

3. An artifact that is produced, is quantifiable, and can be either an end item in itself or a component item (Project Management Institute 2008).

4. something (such as a service) that is marketed or sold as a commodity ("Definition of

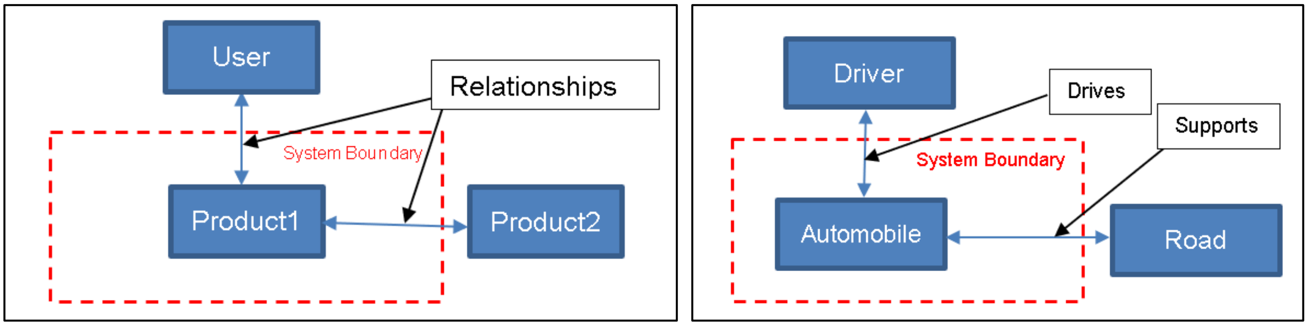
PRODUCT” 2024)

5. A product is an artifact that is created by some person or by some process such as a manufacturing process, software source code compilation and integration, building construction, creative writing process, or data processing (SEbok Guide 2023).

6. In manufacturing, products are purchased as raw materials and sold as finished goods (SEbok Guide 2023).

7. In general, a business product is defined as a thing produced by labor or effort, or the result of an act or a process. It stems from the verb produce, from the Latin prōdūce(re) (to) lead or bring forth. Since 1575, the word product has referred to anything produced, and since 1695, the word product has referred to a thing or things produced (Kotler and Kotler 1989).

For this thesis, the product is an automobile. The Automobile can be exchanged for money or another car, and it fits the definition of product as mentioned above in (1) by (Crawley et al. 2016). An automobile is made of system elements that may include hardware, software, infrastructure, and support services, which fits the INCOSE definition of the product. A car is purchased as raw materials and sold as finished goods (SEbok Guide 2023). An automobile is a manufactured product that involves many manufacturing and software processes. Figure 3 shows the schematic of a product. A User uses Product1 and interacts with another product, Product2. For example, an Automobile is a product used by the Driver (User) and interacts with the Road system.



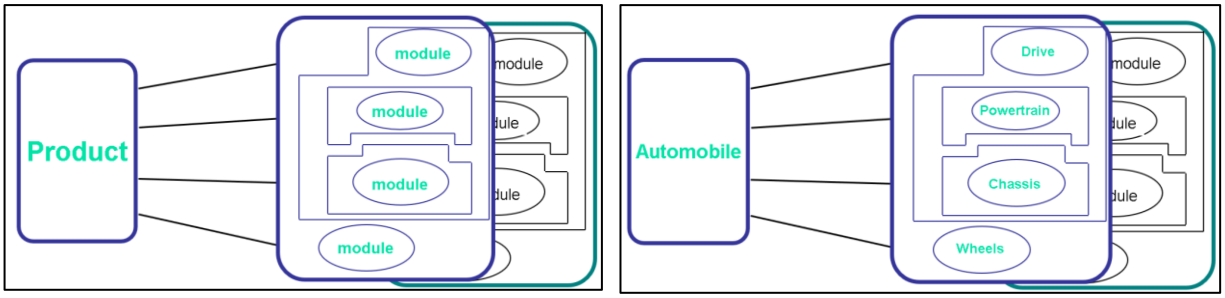
(a) (b)

Figure 3 : (a) Product Schematic, (b) An Automobile Product Schematic

2.1.1 Architecture of the Product

Product architecture comprises key elements of the product, how they relate to each other and their dependencies. For any given product, (Ulrich, Eppinger, and Yang 2020) have defined product architecture as the strategy by which function is mapped to form. There are two main categories of product architecture, integral and modular, which are defined by (a) the relationship between functions and components and (b) the interaction between components. An integral architecture implies complex mapping between components and functions and high incidental interaction between components.

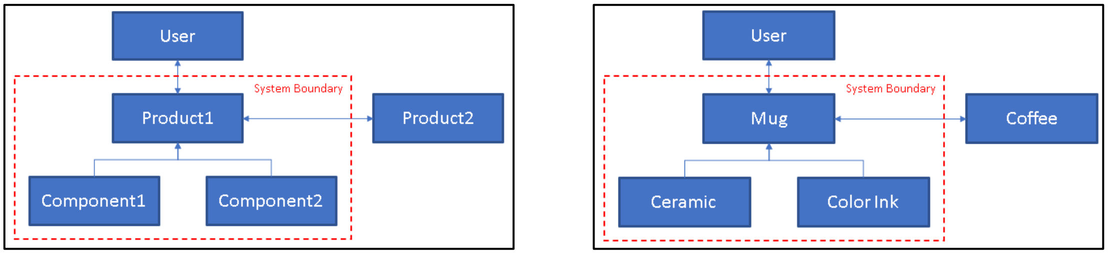
A scheme by which the functional elements of the product are arranged) or assigned) into physical building blocks (chunks) and by which the blocks interact (Ulrich, Eppinger, and Yang 2020), see Figure 4. The arrangement of functional elements into physical chunks which become the building blocks for the product or family of products (Ulrich, Eppinger, and Yang 2020).



(a) (b)

Figure 4: (a) Product Architecture (Ulrich et al., 2020) (b) An automobile Product architecture

2.1.2 Decomposition of the product



(a) (b)

Figure 5 : (a) Decomposition of the Product, (b) Coffee Mug decomposition to Level 1

The decomposition of a product, like shown in Figure 5, involves breaking down its complex structure into manageable components or subsystems, each serving a specific function or purpose. This disassembly process is integral to understanding the intricacies of the product and identifying opportunities for optimization and improvement. By deconstructing the product into its constituent parts, designers and engineers can analyze individual components in isolation, allowing for a detailed examination of their design, performance, and interaction with other elements. Furthermore, decomposition enables modularization, facilitating easier component maintenance, repair, and replacement. Through systematic decomposition, stakeholders gain deeper insights into the product's architecture and functionality, laying the groundwork for iterative refinement and innovation.

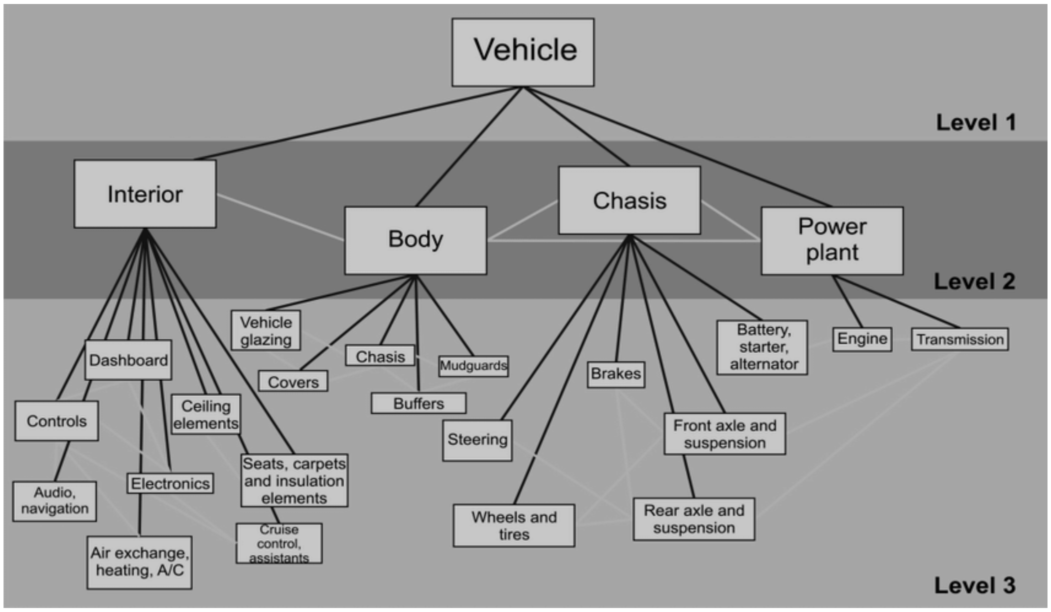


Figure 6: Vehicle decomposition (Zelinka et al., 2012)

A car comprises many components, each crucial in functionality, safety, and performance. At its core lies the powertrain, which consists of the engine or battery and motor, transmission, and drivetrain components responsible for generating and transmitting power to the wheels, see Figure 6. Surrounding this mechanical component are the chassis and body frame, providing structural integrity and support to the vehicle. Interconnected subsystems such as suspension, braking, and steering ensure road stability, control, and maneuverability. The electrical system consists of a network of wiring, sensors, and onboard computers for various functions such as engine management, lighting, and infotainment. Many safety features like airbags, seat belts, collision avoidance, lane-keep assistant, and spatial safety zones are designed to protect occupants in a collision. Additionally, numerous auxiliary components, including cooling, exhaust, and fuel systems, work together to facilitate efficient operation and enhance the driving experience. Collectively, these components form the intricate anatomy of a car.

2.2 What is Product Configuration?

“Functional and physical characteristics of existing or planned hardware, firmware, software, or a combination thereof as set forth in technical documentation and ultimately achieved in a product [IAQG 9100].”

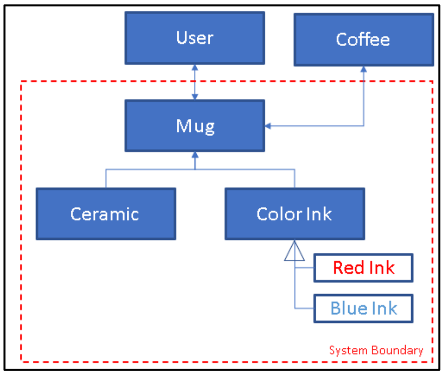


Figure 7:150% Bill of Material of a Coffee Mug

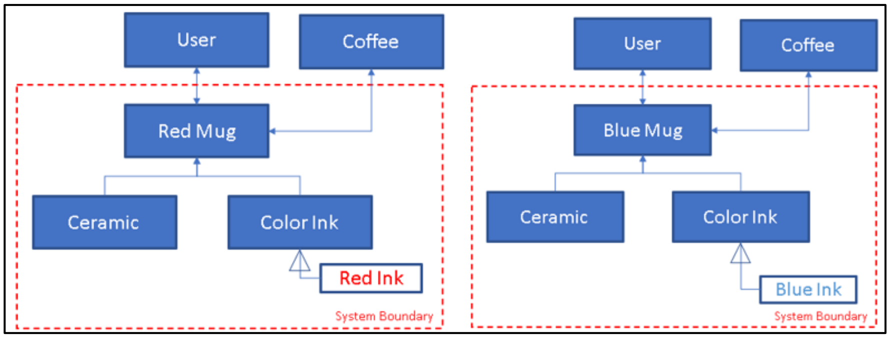


Figure 8: Coffee Mug configurations, two choices

Product Configuration is a fundamental aspect of product development and customization. Product Configuration refers to the approach of defining and selecting the specific features, options, and variations that comprise a product to meet customers' diverse needs and preferences. It examines various methodologies and approaches employed in Product Configuration, ranging from rule-based systems to advanced software solutions leveraging artificial intelligence and optimization algorithms.

In the example shown in Figure 7, the product is a Coffee Mug made of ceramic and Ink. The Ink has two options: Red and Blue Ink. The BOM contains all alternative parts; full overlays of parts are known as 150 % BOM. In the coffee mug example, the ‘color ink’ alternates are listed in the BOM. It is not helpful to build either a red or a blue mug.

An option must be chosen to get a precise BOM (also called a 100% BOM or resolved BOM), which can be used to make a finished product, as shown in Figure 8. For example in Table 1, red ink is selected to build a red coffee mug, and blue ink is omitted from the BOM. This table shows we can create tow unique builds that can be used to manufacture a finished coffee mug.

Table 1: Product Configurations combinations of a Coffee Mug

<table>
<tr><th>Configured BOM (150% BOM)</th><th>Configuration</th><th>Design Variant 1, Material Option</th><th>Design Variant 2, Color Ink Option</th><th>Resolved BOM (100%)</th></tr>
<tr><td>Mug
|-- Ceramic
|-- Color Ink
    |-- Red Ink
    |-- Blue Ink</td><td>Red</td><td>Ceramic</td><td>Red</td><td>RedMug.1
|-- Ceramic
|-- Red Ink</td></tr>
<tr><td></td><td>Blue</td><td>Ceramic</td><td>Blue</td><td>BlueMug.2
|-- Ceramic
|-- Blue Ink</td></tr>
</table>

For an automobile, it is even more complex. There are hundreds of options to choose from. Figure 11 shows the first level complexity for an F-150 truck configuration available to choose from. It has 14 variants with a total of 95 options to choose from. There are 287 billion unique builds of F-150 that can be made by selecting these options. However, the rule-based configuration reduces this number. Even after applying design, manufacturing, and marketing rules, the number of valid product configurations could easily be several hundred thousand in number.

2.2.1 Rule-based Configuration

Rule-based configuration is widely used in build-to-order automobiles. This method automates selecting product features and options based on predefined rules and constraints. In the rule-based configuration, logical rules are established to guide the selection process, considering factors such as customer requirements, marketing requirements, design and manufacturing compatibility constraints, and product dependencies. These rules govern the permissible combinations of features and options of a car. It ensures that only valid configurations are generated. These rules are defined by the domain experts and are applied during the configuration process to create customized product configurations efficiently.

There are many constraints added by the design, manufacturing, marketing, and regulations limitations. For example, the rear axle ration “3.73 Electronic Locking Axle Ratio” is only possible with a “3.5L PowerBoost® Full Hybrid V6 Engine” for the Platinum model. This is a design constraint. While the color choice “Shelter Green” is only available with the Raptor model of F-150. This is a Marketing constraint. The 8-foot box option is available only with the XL model, which could be a manufacturing constraint. An example of the regulation constraint is that only hybrid engines qualify for tax credits. Hundreds of such rules restrict certain combinations of the builds.

Table 2 shows that the top 15 automobile brands offer configurators to their customers to tailor their automobiles to the specifications they desire for personalization.

Table 2: Configurator used by top automakers worldwide

Automaker	Sold Autos in the Year 2024	Car Configurator / Build your own Car
Toyota	10307395	Available
VW	9239575	Available
Hyundai	7302451	Available
Stellantis	6392600	Available
GM	6188476	Available
Ford	4413545	Available
Honda	4188039	Available
Nissan	3374271	Available
BMW	2555341	Available
Changan	2553052	Available
Mercedes	2493177	Available
Renault	2235345	Available
Maruti Suzuki	2066219	Available
Tesla	1808581	Available
Geely	1686516	Available
Tata	954645	Available

2.2.2 Complexity in the Product Configuration

Complexity in product configuration grows from the intricate interplay of various variables, options, and constraints. The sheer volume of configurable features and their dependencies can lead to a combinatorial explosion, making it difficult to navigate and optimize configurations efficiently. Simply put, the complexity of the product configuration grows with the number of options available and its constraints.

In Figure 9, the Coffee Mug example continues by adding one more design variant, giving options for the choice of ceramics (Glass and clay), and adding a marketing variant by providing the type of users. Now, eight unique combinations are possible from these options available to build, as shown in Table 3.

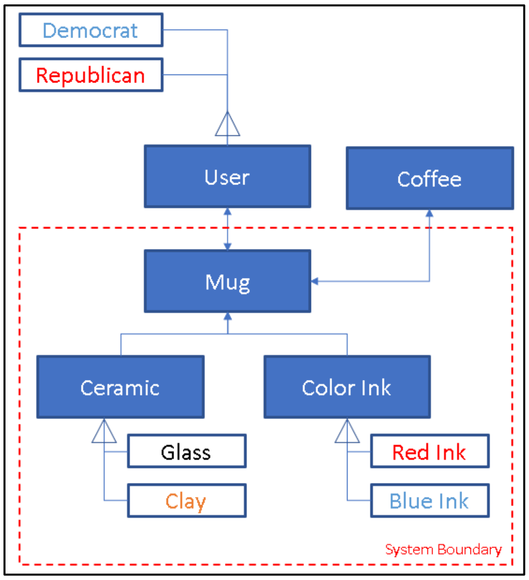


Figure 9: Coffee Mug Design & Marketing Variants

However, a marketing constraint was added. The user Republican must get only Red colored mugs. This is reflected in the marketing rule shown in Table 3, which checks whether the particular combination is valid.

Table 3: Coffee Mug configurations list with two design variants and one marketing variant

Configured BOM (150% BOM)	User	Design Variant 1, Material Option	Design Variant 2, Color Ink Option	Marketing Rule *If “User” = “Republican”, then, “Color Ink” = “Red”*	Resolved BOM (100%)
Mug |-- Ceramic |-- Glass |-- Clay |-- Color Ink |-- Red Ink	Republican	Glass	Red	True	RedMug.1 |-- Glass |-- Red Ink
	Republican	Clay	Red	True	RedMug.2 |-- Clay |-- Red Ink

|-- Blue Ink	Republican	Glass	Blue	False	Invalid Build
	Republican	Clay	Blue	False	Invalid Build
	Democrat	Glass	Red	True	RedMug.3 |-- Glass |-- Red Ink
	Democrat	Clay	Red	True	RedMug.4 |-- Clay |-- Red Ink
	Democrat	Glass	Blue	True	BlueMug.5 |-- Glass |-- Blue Ink
	Democrat	Clay	Blue	True	BlueMug.6 |-- Clay |-- Blue Ink

When more such requirements are added to the product, the product evolves. In Figure 10, the coffee mug has five different requirements are added. That can generate eighty-one unique builds of the coffee mugs. A third component is added to the bill of material: a thermal sleeve. This requirement comes from the user feedback. This thermal sleeve has three options: wool, cardboard, and leather. Wool and cardboard were chosen because of sustainability requirements. Manufacturing and regulatory requirements add two options for the glass material: toughened and recycled. The marketing team has added a new User: Independent user group. This resulted in doubling the bill of material from seven to fourteen. The node level components are increased from four to nine, as shown in Table 4.

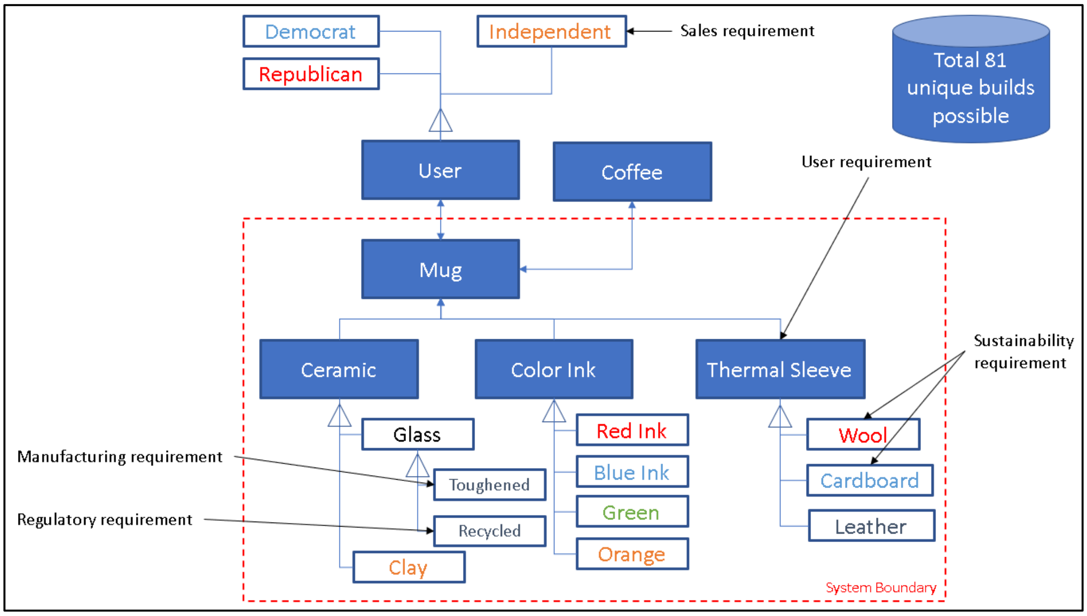


Figure 10: New requirements for the Coffee Mug manufacturing

Table 4: Increase in component options, increases the unique builds

Coffee Mug Model	150% BOM size	Node Items	Configurable components	Number of unique builds
Figure 4	3	2	0	1
Figure 5	5	3	1	2
Figure 6	7	4	2	6
Figure 4	15	10	3	81

Now, this gives a perspective of what it is like with the automobile configurations. An average automobile with a BOM size of over 30000 parts could have close to 100 configurable components. In the example shown for Ford's F-150 truck in Figure 11, there are over 15 variants with 98 configurable components available for consumers. The number of unique builds possible with this number is about 270 billion. These unique builds can be brought down with the design, manufacturing, and marketing constraints. However, the number of unique builds that result after applying all the constraints is estimated to be over two billion.

In a mass-production approach, every car assembled in the assembly line is the same. The instructions for installing different components remain the same. The sequence of installation also remains unchanged from car to car. This is not true for the mass-customization approach. Every car assembled on the assembly line could have a different component installed in a different sequence. This needs additional planning, monitoring, and control of the production line. This is just one example of how product configuration impacts the assembly line.

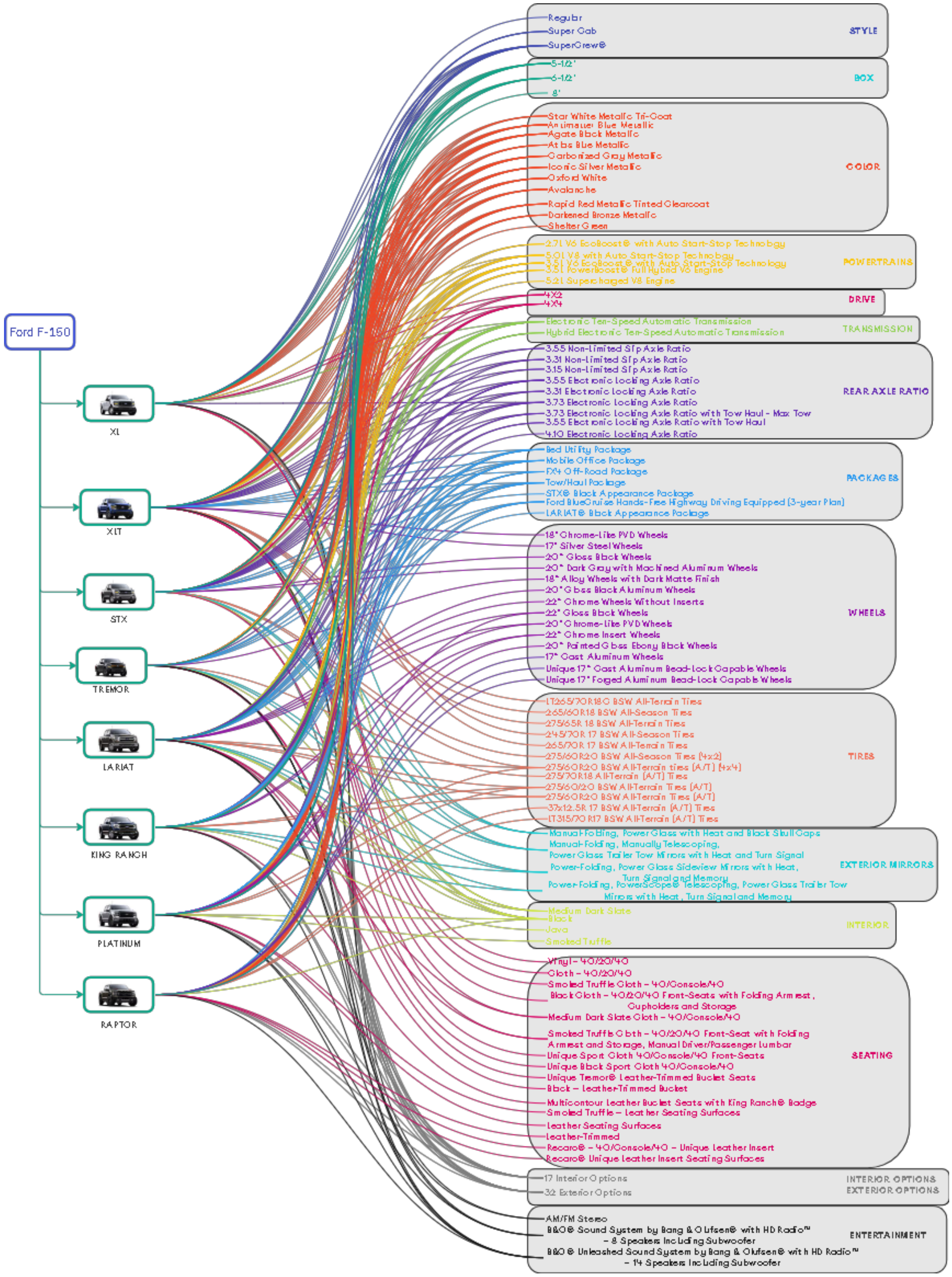


Figure 11 : Ford F-150® Build Options, data collected from ford.com (“Ford F-150® | Build & Price | Shop.Ford.Com” 2024)

2.3 Product Configuration – A multi-domain view

In product manufacturing, adopting a system of systems view involves recognizing the intricate interplay of subsystems that collectively contribute to creating a final product. Whether it's a consumer electronics device, a pharmaceutical drug, or a piece of machinery, each product comprises numerous subsystems, processes, and components that must operate harmoniously to achieve the desired outcome. This section emphasizes the holistic understanding needed to manage the complexity of modern manufacturing, where various elements such as supply chain logistics, production machinery, quality control systems, and workforce management interact dynamically. Engineers and managers must navigate these interconnected subsystems, considering factors like efficiency, reliability, and sustainability across the entire product manufacturing and the product service lifecycle.

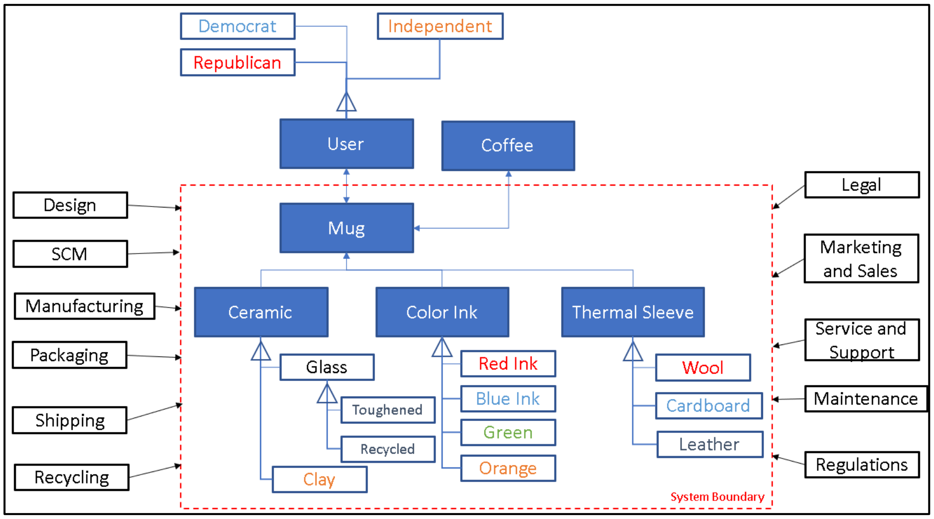


Figure 12: Domains related to the Coffee Mug product

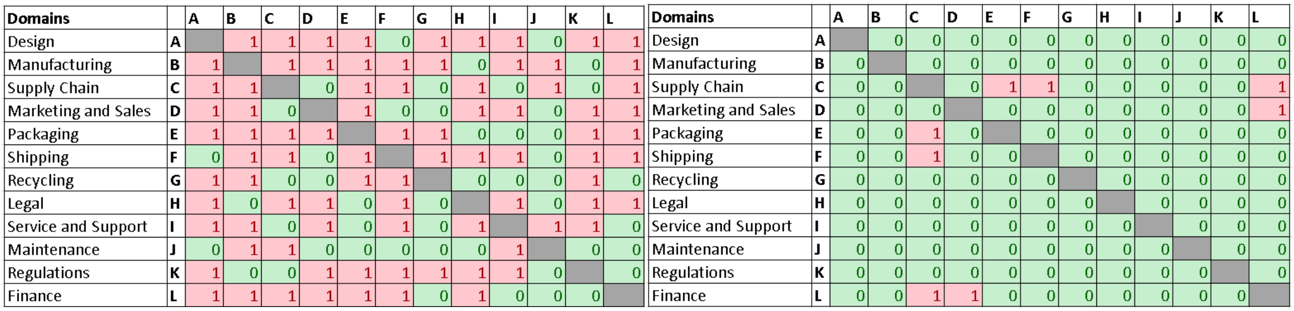
In Figure 12, the Coffee Mug example product shows that 11 different disciplines play a role in realizing the Coffee Mug as a product. Many of these disciplines work in parallel when a product is made. Many people, processes, and organizations work together to manufacture the right product. When the product changes, these disciplines must accommodate and adjust to these changes in synchronization with other disciplines. For example, when a 'Thermal Sleeve' was decided to be added, the design team conceptualized change and designed the sleeve to fit with the current mug design. Then, the prototypes are made to test and validate the new design. They work with the manufacturing domain to ensure the design change they anticipate is manufacturable. The manufacturing discipline works with the supply chain to ensure the availability of raw materials. In contrast, marketing and salespeople work with the design and manufacturing departments to meet customer needs. Similarly, other disciplines work simultaneously to get the product right.

Table 5: Domains affected by the addition of the new options to the Coffee Mug example

Domains	(a) New Thermal Sleeve (Cardboard)	(b) New Color (Green)
Design	Yes	No
Manufacturing	Yes	No
Supply Chain	Yes	Yes
Marketing and Sales	Yes	Yes
Packaging	Yes	No
Shipping	Yes	No
Recycling	Yes	No
Legal	Yes	No
Service and Support	Yes	No
Maintenance	Yes	No
Regulations	Yes	Yes
Finance	Yes	Yes

Table 5 shows two options added to the coffee mug product: (a) a Thermal Sleeve option, Cardboard, and (b) a new color, Green. Both of these options need different work or no work by various domains. The quick comparison shows that adding a new color option needs fewer domains involved to implement the change. However, adding a new Thermal Sleeve option impacts all the domains.

Figure 13 shows the DSM of interactions between different domains needed to implement the feature “Thermal Sleeve” or the Color option “Green.” The comparison shows fewer interactions between the domains necessary to introduce the color options, while the Sleeve option shows a busy interaction between the domains.



Domains		A	B	C	D	E	F	G	H	I	J	K	L
Design	**A**		1	1	1	1	0	1	1	1	0	1	1
Manufacturing	**B**	1		1	1	1	1	1	0	1	1	0	1
Supply Chain	**C**	1	1		0	1	1	0	1	0	1	0	1
Marketing and Sales	**D**	1	1	0		1	0	0	1	1	0	1	1
Packaging	**E**	1	1	1	1		1	1	0	0	0	1	1
Shipping	**F**	0	1	1	0	1		1	1	1	0	1	1
Recycling	**G**	1	1	0	0	1	1		0	0	0	1	0
Legal	**H**	1	0	1	1	0	1	0		1	0	1	1
Service and Support	**I**	1	1	0	1	0	1	0	1		1	1	0
Maintenance	**J**	0	1	1	0	0	0	0	0	1		0	0
Regulations	**K**	1	0	0	1	1	1	1	1	1	0		0
Finance	**L**	1	1	1	1	1	1	0	1	0	0	0	

(a) Thermal Sleeve (Cardboard)

Domains		A	B	C	D	E	F	G	H	I	J	K	L
Design	**A**		0	0	0	0	0	0	0	0	0	0	0
Manufacturing	**B**	0		0	0	0	0	0	0	0	0	0	0
Supply Chain	**C**	0	0		0	1	1	0	0	0	0	0	1
Marketing and Sales	**D**	0	0	0		0	0	0	0	0	0	0	1
Packaging	**E**	0	0	1	0		0	0	0	0	0	0	0
Shipping	**F**	0	0	1	0	0		0	0	0	0	0	0
Recycling	**G**	0	0	0	0	0	0		0	0	0	0	0
Legal	**H**	0	0	0	0	0	0	0		0	0	0	0
Service and Support	**I**	0	0	0	0	0	0	0	0		0	0	0
Maintenance	**J**	0	0	0	0	0	0	0	0	0		0	0
Regulations	**K**	0	0	0	0	0	0	0	0	0	0		0
Finance	**L**	0	0	1	1	0	0	0	0	0	0	0	

(b) Color (Green)

Figure 13: DSM of domain involved to implement feature or option in a Coffee Mug product

For the automobile industry, this multi-domain system is much more complex, diverse, and globally distributed. When a new feature is added to an automobile, the impact on each domain is much higher than in the coffee mug example. The interdisciplinary interactions between each domain demand highly coordinated efforts for optimal operations, low cost, and faster delivery.

2.4 Interim Conclusion on Complexity in Product Configurations

As industries evolve, so does the complexity of product configurations, and today's rapidly advancing technological landscape is making it more evident. With rising consumer demand for personalized products, companies are compelled to offer an ever-expanding array of options and features. This trend spans various sectors, from electronics and automobiles to software and consumer goods. As a result, the number of potential product configurations has skyrocketed, presenting significant challenges for manufacturers in design, production, and supply chain management. Moreover, technological advancements such as artificial-intelligence, 3D-Printing, and the Internet of Things (IoT) have further compounded this complexity by introducing new possibilities for customization and integration.

Additionally, globalization has introduced cultural and regulatory factors that influence product configurations, adding another layer of complexity to the mix. In response, companies invest in advanced digital technologies and data analytics to streamline product development and optimize supply chain operations. However, managing the growing complexity of product configurations remains daunting, requiring continuous innovation, collaboration, and strategic planning. As industries evolve, companies must adapt and embrace the complexities of modern product configurations to thrive in today's competitive marketplace.

The automobile industry has the most extensive landscape of product configuration complexity. Automakers are offering a vast array of customizable options and features. This proliferation of choices spans from engine types and transmission systems to interior amenities and exterior styling options, contributing to the exponential growth of product configurations. Additionally, technological advancements have empowered automakers to incorporate increasingly sophisticated electronic systems and connectivity features into their vehicles, further amplifying the complexity of product configurations. Moreover, regulatory requirements and safety standards continue to evolve, necessitating the integration of new technologies and features into automobile designs. Global market dynamics and competitive pressures compel automakers to innovate and differentiate their products continuously, introducing new variants and trim levels that cater to diverse consumer preferences. As a result, the automotive industry is witnessing a paradigm shift towards highly customizable and complex product configurations, posing significant challenges in design optimization, manufacturing efficiency, and supply chain management.

To navigate this complexity effectively, automakers need to know the real impact of any option or feature addition to the vehicle's entire lifecycle. This thesis will try to understand product configuration complexity in detail and compare different methods that use various theories to measure this complexity.

The next chapter reviews various literature on complexities associated with product configurations, how they are measured, and what methods are used to manage them.

Chapter 3: Literature Review

The literature research serves several areas of interest to this thesis. The study was performed to understand the terminology and latest research in the automobile industry's product configurations, mass customization, product complexity, and build-to-order strategies. In addition, emphasis was placed on understanding different methods used to manage Product Configuration complexities as enablers of mass customization and built-to-order strategies. Secondly, research was made to understand what types of complexities are present in automobile manufacturing and what methods are used to measure them.

Initially, it was thought to build a comprehensive model for measuring the product configuration complexity for an automobile. Unfortunately, it was not possible to comprehend the width and breadth of this topic to cover in this research. The literature research was re-focused on a comprehensive literature review to understand three topics: 1) methods used to manage product configurations, 2) type of complexities associated with the product configurations, and 3) methods to measure Product Configuration Complexity.

Table 6 summarizes the keywords used to perform research classified by area of interest.

Table 6: Summary of the keywords used to perform research

Concepts	Product Configurations concepts	Methods used to manage product configurations	Types of complexities associated with the Product configurations	Methods to measure Product Configuration Complexity

Keywords	Product Product Configurations Build to order BTO Mass customization Car configurations Product Variants	Configuration Management, Variant management, Bill of Material, Variability, Variant Options Management, Vehicle configuration rules, Design Automation, PLM, PDM, Car Configurator, Passenger car Modularization Modular Platform	Design complexity Structural complexity Car Manufacturing Product complexity Product line management Supply Chain Complexity	Graph Theory Suh's Theory Measuring product complexity Component count Graph Theory Complexity Analysis of an automobile Quantify complexity

3.1 Methods Used to manage the Product Configurations

3.1.1 Configuration Management (CM)

CM is a methodology that provides a technical and administrative framework for managing Configuration Items' development, manufacturing, and maintenance. It is an activity for establishing and maintaining a consistent record of the performance parameters of a product and its functional and physical characteristics compared to the product design and operational requirements (INCAS BULLETIN, 2019).

Configuration management is a management discipline applied over the product's life cycle to provide visibility into and control changes to performance and functional and physical characteristics (NASA 2024)

(1) CM can be thought of as a process for establishing and maintaining consistency of baselines, approving and controlling changes, and recording and reporting changes in the status of a system/product under development ("Systems Engineering for ITS - Configuration Management" 2024).

(2) Configuration management (CM) is the discipline of establishing and maintaining consistency of a product's functional and physical attributes throughout its life (("What Is Configuration Management and Why Is It Important?" 2024).

3.1.2 Configuration Management Process

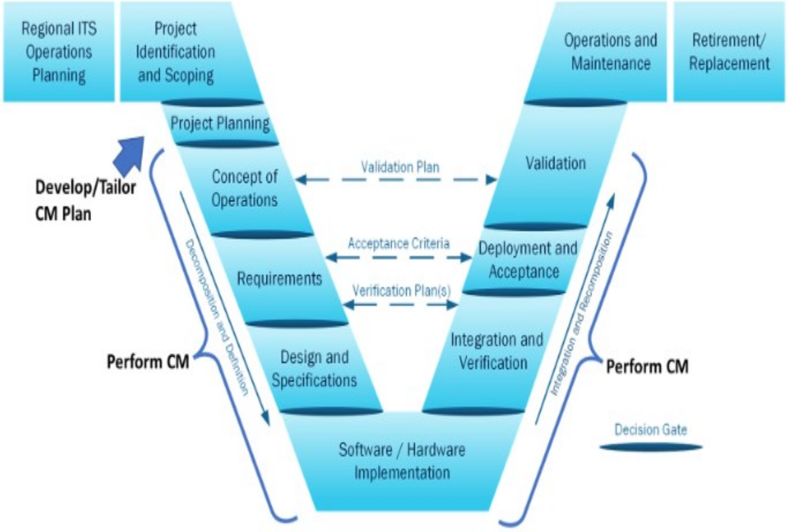


Figure 14: CM process review: Source AS9100

As defined by the Aerospace Standards AS9100 Store ("What Is Configuration Management?" 2024), "Configuration Management is the control of parts, oftentimes consisting of a complex set of subassemblies, of which, when combined, take a final form that is different from the individual parts. As a result, controlling the revisions of this final product entails controlling the revisions and status of each component to ensure that the final form meets the requirements. The process shown in Figure 14, must control product identity and traceability to requirements to guarantee that the documented information is consistent with the actual attributes of the products and services."

Configuration management is defined by ISO 10007 as "asking organizations to manage the components of a product. Breaking this down, configuration management consists mostly of two components – document control and product identification. Configuration Management is necessary when products are comprised of multiple parts (component parts) that come together to form a final product (master part)."

Figure 15 shows an electric car assembly (Dassault Systèmes, 2022) comprising about 19000 components. Components such as a battery, drivetrain, motor, wheel, transmission, seating, wheel, side mirrors, and steering assembly can be configured. For example, customers can choose Wheels between 19", 20", and 21" rim sizes. However, not every wheel size fits every car model. The Configuration Management helps define what variant is possible (for example, Wheel), what options that variant has (example, 19", 20", 21"), and which size of the wheel fits to which car model.

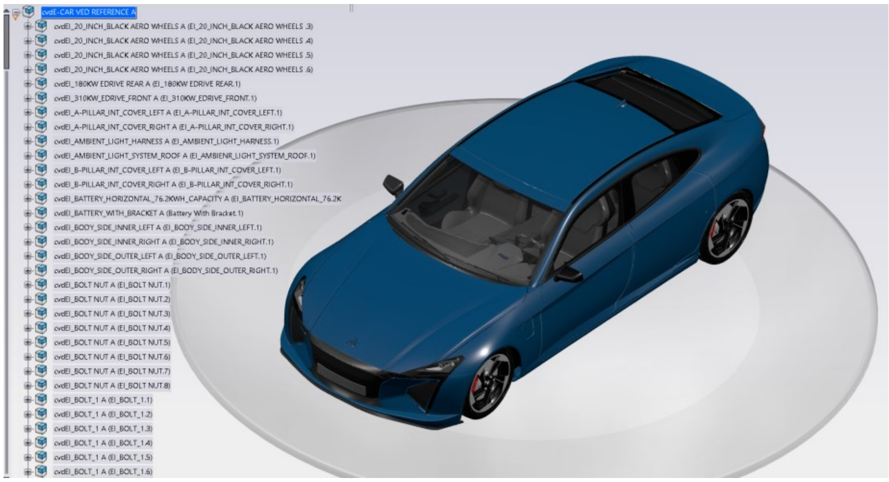


Figure 15:An electric car assembly seen in CATIA®3DExperience ® (Dassault Systèmes, 2022)

3.1.3 Model-based Variant Management

Variant management involves controlling and organizing different versions or variations of a product, system, or software. It aims to efficiently handle diverse configurations while ensuring consistency and quality across variants. For example, Ford's F-150® has eight models, each with many trims. Each model and its trims have specific features and options in it. Variant Management helps manage these relations between model and their features and options. Traditionally, the relationship between models and their features is defined later during the design phase. The car manufacturer often handles the top-level design and integration, and component designs are outsourced to suppliers. The car is a highly interconnected system, and defining variants and their features later in the design creates challenges in defining interfaces and during the integration phase. Model-based variant management allows for the modeling and description of variants in the early stages of systems development in the automotive industry. In model-based variant management, engineers use a modular and hybrid characteristics model to break them down into manageable chunks of features, from the early concept phase to production.

(Otten et al. 2019) provided an approach for variant management during the entire development lifecycle of E/E system architectures and the structure and composition of our proposed characteristics model. It presents a concept for model-based variant management for large Electric and Electronic systems. The author used a mix of a bottom-up approach for the formalized description and modeling variants and a top-down approach for the configuration support. It provides a hybrid characteristics model for the consistent and model-based description of variants. Implementing systems to manage and control the different product variants, including configuration management tools and software. Variant management is mainly driven by the production point of view. Managing variants within automotive development is based on the principle of product lines, where one common set of product artifacts is used to design different products (Reiser and Weber 2007).

This research used a modular and hybrid model to cope with product configuration complexities to handle different perspectives from early concept to development until the production stage. In this hybrid model, they have developed the tiers. “The first sub-model describes system-specific characteristics, the second sub-model focuses on the representation of the overall product structure, and the third sub-model describes common characteristics of the products.”

1. System-specific Characteristic: To express the specific functionality variability of the system, which is more related to the early concept stage.

2. Product Structure: Expressions of the variants with regard to the product structure, including special models and product lines.

3. Common Characteristics: Common variation throughout all abstraction levels of the system is specified in this level, shown in Figure 16:

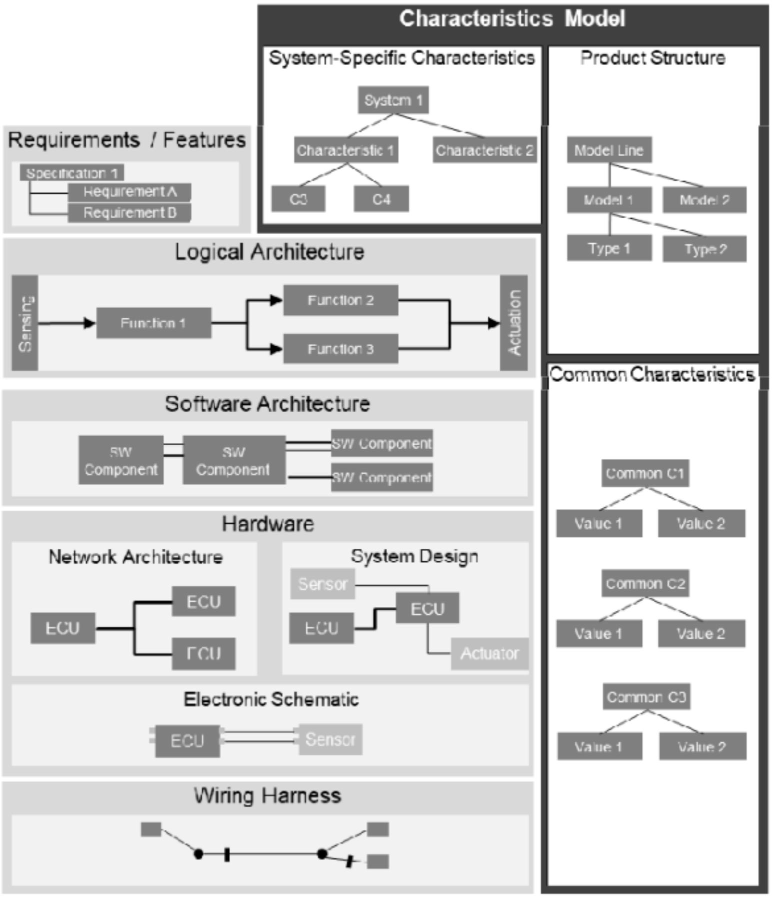


Figure 16: Hybrid characteristics model for variant management of E/E-Systems during concept and development (Otten et al. 2019)

This method provides early access to defining product variants during the conceptualization stage. However, the product is usually not matured at this stage, and the variability is unclear. This could be a good add-on variant management when a product is developed from another mature product.

3.1.4 Configuration Rules

Configuration rules and constraints govern the allowable combinations of product features and options to prevent infeasible or non-compliant configurations. Through the case study (Phelan et al. 2017), the authors identified that the OEM used a configuration management method that primarily represented the rule-based reasoning methods. In addition, many associated challenges are present, mainly the difficulty in making changes to the rule system and evaluating the changes.

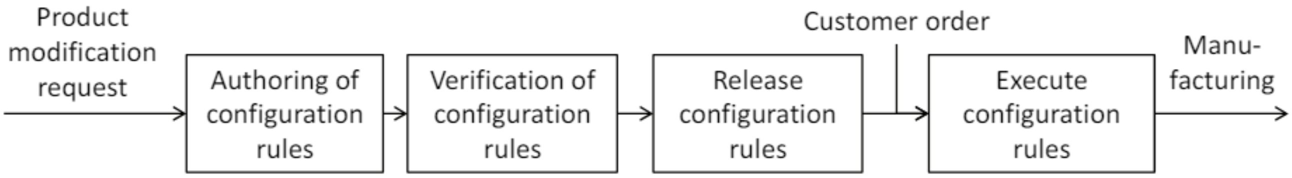


Figure 17: Schematic picture from the change of the vehicle configuration rules to the manufacturing of vehicles (Tidstam 2012)

Figure 17 shows how the configuration rules are introduced from the product modification request to a final vehicle build to the manufacturing.

3.1.5 Bill of Materials (BOM) management

Maintaining accurate and up-to-date BOMs that document the structure and composition of each vehicle configuration, including all components and their relationships, is extremely important to get the right vehicle built. (Chatras, Giard, and Sali 2015) It concludes that the context of strongly diversified mass production characterized by multiple combinatory restrictions required by this diversity as regards possible alternative components, such as Bill of Materials construction and use, pose daunting methodological problems. The BOM provides a hierarchical structure of all the sub-assemblies and components that makeup the vehicle. It also identifies the decisions to make or buy. There are associated drawings and references usually mentioned in the BOM. The BOM also consists of alternate and substitute components. To manufacture an automobile, an accurate BOM has to be built. Building this accurate BOM that only uses BOM management is complex. Every time a new configuration is created, a new BOM with the precise components will be needed. This is a daunting task. In the author's view, the detailed bills of materials for all potentially manufactured products make little sense due to the issue of finding the exact reference of an end product without the list of the relevant alternative components.

3.1.6 Standardization and Commonization Methods

This method establishes standard components, processes, and interfaces across vehicle programs to reduce the number of unique configurations and simplify manufacturing. (Antoniolli et al. 2017) found that the productivity and efficiency of both the workers and machines increased by 16% by standardizing the components and processes for the car air conditioning system for automotive manufacturers. It eliminated waste and generated value from the customer perspective by raining the OEE (Overall Equipment Effectiveness). ("Automotive News" 2008). This article suggests that Ford reduced the ordering complexity of the 2009 F-150 by more than 90 percent by maintaining various choices of features necessary to customers and standardizing packages of features across the F-150 trims.

3.1.7 Modularization Method

Modularization in auto design is designing products with interchangeable modules or components that can be easily assembled or replaced, allowing for greater flexibility and customization. A case study on the modularization of automotive product architecture (Kwak 2019) showed evidence of a higher degree of modularization in front-end, cockpit, and seat modules. However, they found that the body module has a lower degree of modularization.

This case study also showed many car makers modularized the design of passenger cars to achieve model diversification and reduction of cost and period in new product development at the same time

3.2 Types of complexities associated with the Product Configurations

3.2.1 Design complexity

Design complexity in car configurations arises from the need to accommodate a wide array of options, features, and customization preferences consumers' desire. Each configurable component, from engine types to interior packages, increases the complexity of the design process. Designers must ensure compatibility, functionality, and aesthetic appeal while keeping the interaction intact between variables. On top of its design, it must cover car trims with space constraints, weight distribution, and manufacturing feasibility.

The paper by (J. Liu, J. Jiang, and C. Liu 2012) highlights the challenges associated with managing design complexity within automotive configurators. The authors discuss how the increasing demand for customization options poses significant challenges regarding system architecture, user interface design, and computational efficiency. They also explore potential opportunities for overcoming these challenges, such as leveraging advanced algorithms and user-centered design principles. These insights resonate with the broader theme of product configuration complexity discussed in the thesis, highlighting the need for innovative approaches to measure the complexity for better decision making in the auto designs.

This research paper (M. B. Mortensen, H. Hauser, and D. A. Windt 2011) investigates the impact of product variety on design complexity in automotive configurations. The authors discuss how the proliferation of options and features can lead to increased design, manufacturing, and supply chain management complexity. They propose methods for effectively managing and optimizing product variety, including modular design principles and flexible manufacturing processes. These proposed methods need insights of complexity at multiple levels. Currently there is standard practice that can provide designer a bigger picture on the feature option complexity from its original requirement to manufacturing and ultimately maintenance state of the vehicle.

The literature review in (S. Bhosale and A. Joglekar 2014)provides a comprehensive overview of approaches and techniques for managing design complexity in automotive product development, specifically focusing on configuration management. The authors discuss various methods for modeling, analyzing, and optimizing design complexity, including modular design, parametric modeling, and simulation-based design.

(Fitch 2004) revealed that despite potential benefits to design, lifecycle mode are rarely used in design of complex products like automobile. It is because designing feature configurations require considerable information about the system being developed. The design forecasting method is applicable framework for performing detailed Design for X (DFX) analyses in complex design. Designers are responsible not only for the technical performance of the product but also, environmental performance, manufacturability, sourceability, and maintainability of the automobile. It needs a holistic perspective and current methodologies like lifecycle modeling still finds limited use during the design of complex products such as automobiles. The lack of data collection and modeling complexity are the primary reasons for this lack of use in different types of designs: variant design, adaptive design, originals design.

The takeaway from the design complexity in the auto industry is the designer must address design challenges with system architecture, user interface design, manufacturability and many other designs for x factors to effectively manage product configuration complexity. There is currently no metric that can provide designers a bigger picture on the impact of the design changes induced by the addition of feature options. There are researches and method that gives some forecasting ability in pockets to manage specific design complexity. This provides inputs to theory this thesis proposes that to manage product configuration complexity, designer must consider wider impact of their designs.

3.2.2 Structural complexity

The intricate interplay of varying configured components and subsystems manifests structural complexity in car configurations. The end product of a build-to-order car is composed of choices that can have less impact on the structure, for example, color choices. Still, options like transmission, powertrain, or advanced safety features and electronic systems can contribute to its overall complexity.

The paper by (A. Sheikh and A. Lindemann 2014) presents a systematic approach to modeling and managing structural complexity in the automotive industry. The authors discuss the importance of accurately capturing and quantifying design complexity and strategies for choosing the interfaces for reducing complexity. It also advocates modularization, standardization, and component reuse to manage structural complexity. (Lindemann, Maurer, and Braun 2008) in their book "Structural Complexity Management" described that the structural complexity exceeds boundaries of managing product variants alone, and many other disciplines and the aspects of the product design can be considered simultaneously. This book introduces an approach to complexity management that focuses on the connectivity in objects of product design, i.e., the constellations formed by existing linkages. Considered objects, for example product components or feature options, people or documents. Focusing on such constellations provides far-reaching possibilities for analysis. This thesis tries to cover a wider scope and impact of the product configuration complexities, just like mentioned by this author.

(Sinha 2014) mentions that the "structural complexity pertains to the underlying system architecture or, more generally, the enabling infrastructure." (Sinha and de Weck 2013) developed structural complexity in notional form, which is composed of three different subtypes of structural complexity: 1) Complexity due to components alone, C_1, 2) Complexity due to pair-wise component interactions, C_2, and 3) complexity due to topological formation, C_3. Figure 18 shows what comprises the overall metric calculating overall complexity, C.

Equation 1: Structural Complexity Metric (Sinha and de Weck 2013)

$$C = C_1 + C_2 * C_3$$

where,
C is the Structural Complexity,
C_1 Complexity due to components alone
C_2 Complexity due to pair-wise component interactions
C_3 Complexity due to topological formation

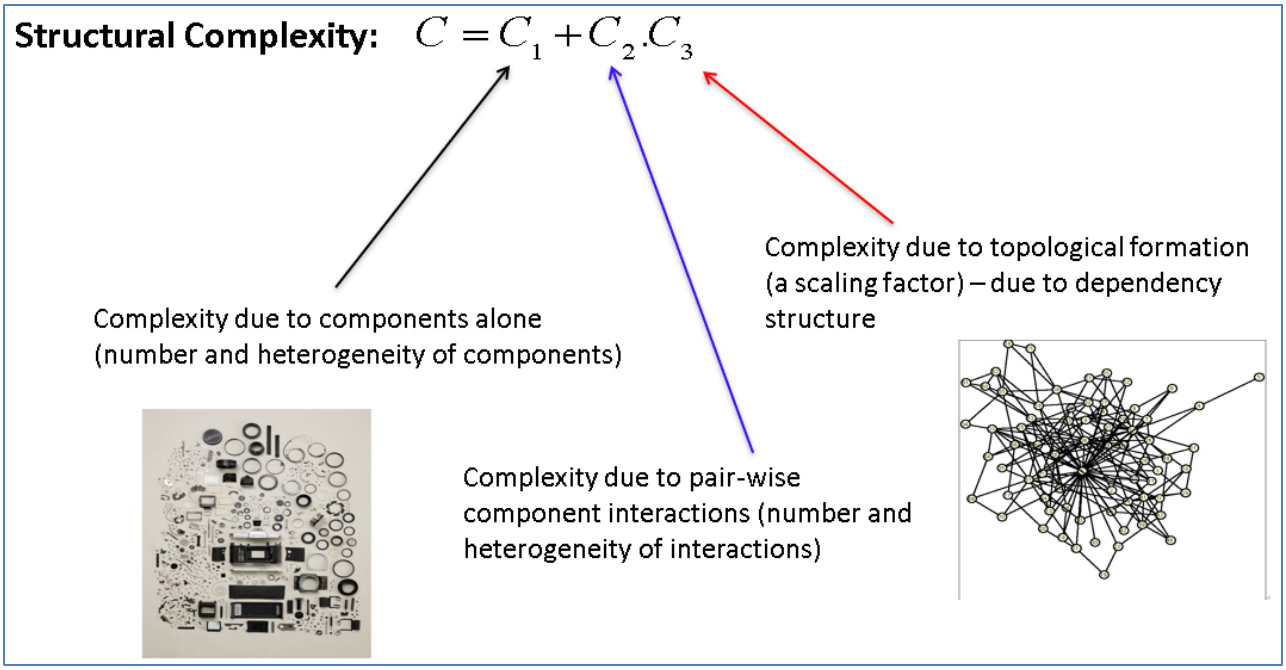


Figure 18: Structural Complexity Metric *(Sinha and de Weck 2013)*

The takeaway from the structural complexity in the auto industry is the understanding of how product variety impacts manufacturing. As the number of options and features increases, so does the complexity throughout the automotive production process. The structural complexity plays key roles in product configuration complexity. Structural complexity is reflected in to the design and manufacturing complexity. Hence, managing structural complexity manages the product configuration complexity.

3.2.3 Manufacturing Complexity

Manufacturing complexity stemming from build-to-order car configurations is a multifaceted challenge for automotive manufacturers. This customization increases complexity throughout the manufacturing process, as each vehicle must be uniquely assembled to meet the customer's specifications. Managing this complexity requires sophisticated production planning and scheduling systems to ensure efficient utilization of resources while accommodating the variability in orders of consumers in today's automotive market.

(Shehada 2014) showed that the build-to-order approach brings efficiency and lead time challenges to the automakers. The lead time for the car delivery is between 4 to 12 weeks. (García Sánchez, Vilasís Cardona, and Lerma Martín 2022) has suggested that production, inventory, and logistics should be adapted to the demand as long as companies continue working with the build-to-stock (BTS) strategy. In this framework, demand forecasting plays a relevant role.

(Efthymiou et al. 2012) analyses manufacturing complexity using five different methods and theories:

1) The chaos theory and non-linear dynamics theory - The presence of chaos in discrete manufacturing systems, in a strict theoretical sense, has not been solidly proven the stochastic behavior often observed in manufacturing cannot be identified by chaos theory.

2) The information theory approaches - Uses the Shannon entropy, However, a complexity value by this method by itself does not provide any contribution to the understanding of the manufacturing system.

3) Hybrid methods that attempt to address complexity by combining information theory approaches along with a coding system for machines and products. This method shares the

same limitation as information theory as it does not cover the entire manufacturing systems. However, the standardization in the manufacturing systems, a hybrid approaches may be more suitable to measure manufacturing complexity. The complexity of manufacturing systems could be measured using a structural complexity measure, based on the manufacturing systems'.

4) Methods that cannot be directly classified into one of the above categories that address physical domain complexity and range from computational mechanics up to fluid dynamic analogies. These methods include the fluid dynamic analogies, complexity cube, computational mechanics and Lempel Ziv complexity. They are still at an early development stage and do not provide any quantitative measurement of manufacturing complexity.

Manufacturers must adopt modular design principles and flexible manufacturing processes to effectively handle diverse product configurations while maintaining operational efficiency. Additionally, leveraging advanced algorithms and user-centered design principles can help streamline system architecture and user interface design, enhancing computational efficiency and user experience. Ultimately, addressing manufacturing complexity is crucial for automakers to optimize operations, minimize costs, and meet the growing demand for customization options in the automotive market. There are many methods and theories that are developed by the scholars to measure the complexity in the manufacturing systems. Most of these theories and methods provides a partial view of the manufacturing complexity. A hybrid methods can be considered promising, especially using structural complexity as a measure of manufacturing complexity for the product configurations.

3.2.4 Supply Chain and Organizational Complexity

(Beamon 1998) defines, “Supply chain management becomes more intricate, as manufacturers must coordinate the procurement of specific components and parts tailored to each configuration.” “A supply chain is a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer (Beamon, 1998)”. Supply chain management (SCM) involves the systemic and strategic coordination of these flows within and across companies in the supply chain with the aim of reducing costs, improving customer satisfaction, and gaining competitive advantage for both independent companies and the supply chain as a whole (Cooper and Ellram 1993). Managing complexities and risks is vital for every organization to survive in a competitive environment as they majorly influence supply chains (Gunasekaran, Subramanian, and Rahman 2015). “Organizational Complexity relates to the system development process and the organizational structure of the development team,” as defined by (Sinha 2014). Internal Supply Chain complexity is associated with material and information within the organization and covers aspects such as process, product, process, and organizational uncertainties. External supply chain complexity is related to material and information flows associated with other business partners (suppliers and customers). It involves drivers like globalization, technological innovation, high competition, and customer demand variety (P. Li 2011). Figure 19 shows structural and dynamic complexity as two umbrella classes that can cover most of the complexities that emerge within a supply chain, as identified by (Mehra et al. 2021)

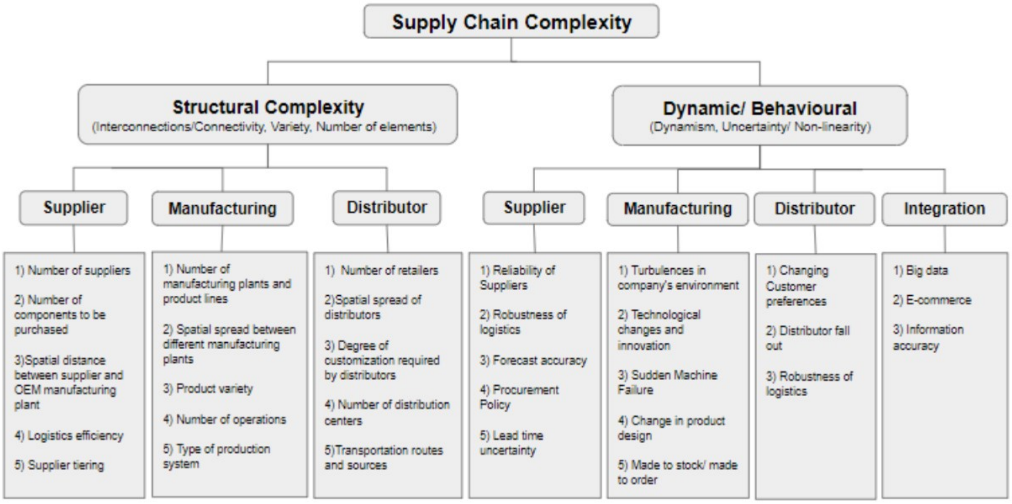


Figure 19: Hierarchy diagram for complexity sub-dimensions (Mehra et al. 2021)

According to an article by a European CEO (2011), complexity drivers can be classified into six overall categories: 1) External drivers (regulation, competition, economic turbulence, and other factors outside the business), 2) People (the everyday behaviors of employees and managers), 3) Process (the complexity of the business processes that are in use), 4) Strategic (the goals and decisions the board makes in terms of where to focus and how to win in a particular market), and 5) Organizational (how the business is structured, talent management and decision-making) and Products and services (their number, design and the structure of your portfolio).

(Felix Stracke, Rebentisch, and Mattern 2016) develops a framework to measure organizational complexity and thus make it visible and more easily controllable for project managers. This paper measures organizational complexity to enhance awareness, avoid excessively complex project organizations, and allow more precise assessments of a development project's cost and time. The automotive supply chain includes a multitude of Tier 1, 2, and Tier 3 suppliers or manufacturers with many assembly operations and dealerships. (Felix Stracke, Rebentisch, and Mattern 2016) defined that to calculate organizational complexity, one has to calculate complexity inside a group (intra-group complexity – group level) and between the groups (inter-group complexity – organizational level). They defined a new mathematical model based on (Sinha and de Weck 2013), which is expressed in Equation 2:

Equation 2: Organizational Complexity Metric (Felix Stracke, Rebentisch, and Mattern 2016)

$$C = C_{2G} * C_{3G} + C_{2O} * C_{3O}$$

where,
C is Organizational Complexity,
C_{2G}*C_{3G} quantities the complexity at the group level
C_{2O}*C_{3O} quantities the complexity at the organizational level

3.2.5 Functional Complexity

Functional complexity within product configurations is a critical area of inquiry, as it directly impacts design, manufacturing, and customer satisfaction. Three key papers shed light on different facets of this complexity and its implications for product development.

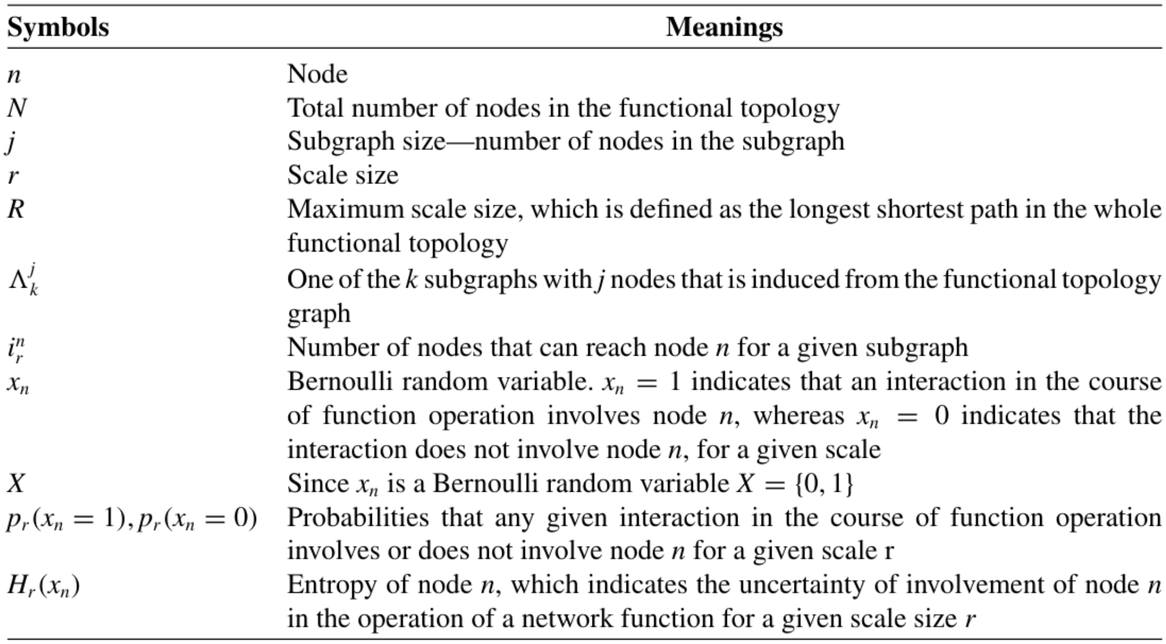
In their seminal paper, Smith et al. (2018) research into the relationship between functional complexity and product performance variability. Through an extensive literature review and empirical analysis, the authors highlight how the proliferation of customizable options and features contributes to increased complexity in product configurations. They argue that while offering a wide range of functions can enhance product differentiation and customer satisfaction, it also presents challenges in design optimization, manufacturing efficiency, and supply chain management. However, measuring functional complexity

Building upon this foundation, the second paper by Johnson and Lee (2019) explores the role of modularity in managing functional complexity in product configurations. Focusing on modular design principles, the authors investigate how modularity can facilitate the integration of diverse functions while maintaining flexibility and scalability. Their findings suggest that modular product architectures enable organizations to effectively manage functional complexity by standardizing interfaces, reducing dependencies, and enabling rapid customization.

(Dzaferagic et al. 2018) propose functional topologies to visualize and systematically study the relationships between system entities and have developed a metric C_F for the functional complexity (see Equation 3), which quantifies the variety of structural patterns and roles of nodes in the topology. This research studied the relationship between C_F and graph structures using the graph theory metrics in complex organizations. C_F is equal to zero for both a full mesh topology and a disconnected topology. They show that complexity is high for a structure with shorter average path length and higher average clustering coefficient. The graph theory metrics focus on individual aspects (e.g., clustering, connectivity, degree distribution) of the topology, whereas functional complexity quantifies the overall uncertainty of interactions between functional entities which emerge from the local interactions between them.

Equation 3: Functional Complexity by (Dzaferagic et al. 2018)

$$C_F = \frac{1}{R-1} \sum_{r=1}^{R-1} \sum_{j=1+r}^{N} \left| \langle I_r(\Lambda^j) \rangle - \frac{r+1-j}{r+1-N} I_r(\Lambda^N) \right|$$



Symbols	Meanings
n	Node
N	Total number of nodes in the functional topology
j	Subgraph size—number of nodes in the subgraph
r	Scale size
R	Maximum scale size, which is defined as the longest shortest path in the whole functional topology
Λ_k^j	One of the k subgraphs with j nodes that is induced from the functional topology graph
i_r^n	Number of nodes that can reach node n for a given subgraph
x_n	Bernoulli random variable. $x_n = 1$ indicates that an interaction in the course of function operation involves node n, whereas $x_n = 0$ indicates that the interaction does not involve node n, for a given scale
X	Since x_n is a Bernoulli random variable $X = \{0, 1\}$
$p_r(x_n = 1), p_r(x_n = 0)$	Probabilities that any given interaction in the course of function operation involves or does not involve node n for a given scale r
$H_r(x_n)$	Entropy of node n, which indicates the uncertainty of involvement of node n in the operation of a network function for a given scale size r

Lastly, the paper by Chen et al. (2020) offers a comparative analysis of functional complexity in different product development processes. Based on various industry case studies, the authors examine how functional complexity manifests in traditional waterfall, agile, and lean product development methodologies. Their research highlights each approach's unique challenges and opportunities, emphasizing the importance of aligning development processes with functional requirements to optimize performance and time-to-market.

Together, these papers provide valuable insights into the multifaceted nature of functional complexity in product configurations. The functional complexity is the less explored area in the research for many of the researchers. A few have used graph theory to measure the functional complexity.

3.3 Various Methods to Measure Product Configuration Complexity

3.3.1 Component Count:

Measuring production configuration complexity using the component count method involves quantifying the level of complexity based on the number of unique components or parts required for manufacturing a product. This method offers a straightforward approach to assessing complexity by analyzing the diversity and volume of elements involved in different configurations. (Börold et al. 2020) Used deep learning-based digital image processing method to count the number of objects in two different types of automobiles. By counting the number of unique parts needed for each product variant, see Equation 4, manufacturers can gain insights into the intricacy of their production processes and identify areas where complexity may arise. This method is mainly used for comparing different product configurations, allowing manufacturers to prioritize resources and streamline production workflows accordingly.

While this method provides a quantitative measure of complexity, it may not fully capture other factors, such as interdependencies between components or variations in assembly processes. Thus, it is often used with other complexity metrics to provide a more comprehensive understanding of production configuration complexity. The term "α coefficient" sometimes refers to component complexity. The alpha is the weighting factor that is applied to each component or class of components when summing them up to characterize the overall component complexity.

Equation 4: Component Count for the Product Configuration

Component Count per Product Configuration = Unique Config BOM Count per Product Configuration

3.3.2 Variability Analysis

Variability analysis analyzes the variations or options available within the product. This could involve different configurations, features, or options that customers can choose from. Variability analysis for build-to-order car configurations consists of evaluating the range and impact of customizable options and features offered to customers. In automotive manufacturing, build-to-order systems allow customers to personalize their vehicles according to individual preferences, resulting in diverse potential configurations. Variability analysis aims to systematically assess the implications of this customization on various aspects of the production process, including manufacturing lead times, supply chain logistics, and production costs. By analyzing the variability in customer preferences and order specifications, manufacturers can identify common patterns, trends, and outliers, enabling them to optimize production planning and resource allocation. Additionally, variability analysis helps manufacturers anticipate and mitigate potential bottlenecks or challenges associated with accommodating diverse configurations, enhancing overall production efficiency and customer satisfaction. By comprehensively understanding variability, manufacturers can tailor their operations to effectively meet the dynamic demands of build-to-order car configurations while maintaining quality and profitability.

(Marshall L. Fisher 1996) examines variability with two product mix variables: (1) the average level of option content on the cars produced that month and (2) the standard deviation in option content per car.

Equation 5: Options Variability Metric

Options Content = This variable equals the number of options on an average car from the list of options, n,
Option Variability = the standard deviation in the number of options per car.

3.3.3 Suh's Complexity Theory

This research (Blecker and Abdelkafi 2006) considers the product configurations from the perspective of Suh's theory (Suh 2005). Suh's theory of complexity, also known as the Axiomatic Design theory, provides a structured framework for designing complex systems. It emphasizes the importance of minimizing complexity by achieving independence between functional requirements and design parameters. (Blecker and Abdelkafi 2006) "Suh's theory abandons the idea of complexity as an absolute measure and defines it relative to what should be achieved or known." "Within this framework, complexity consists of time-dependent and time-independent complexities. Time-independent complexity can be divided into real and imaginary complexities, whereas time-dependent complexity may be divided into combinatorial and periodic complexities (Blecker and Abdelkafi 2006)".

(Blecker and Abdelkafi 2006) applied Suh's theory to the mass customization of automobile product configurations. They examined the complexities concerning its fundamental functional requirements, namely, the satisfaction of customer requirements, economic production, and fast delivery. These essential functions are achieved by three design parameters: product variety, the position of the decoupling point, and production flow, as shown in Figure 20. Their analysis of this design matrix has revealed that the mass customization system is a coupled system.

$$\begin{cases} \mathrm{FR}_1 = \text{Satisfy specific customer requirements} \\ \mathrm{FR}_2 = \text{Produce economically} \\ \mathrm{FR}_3 = \text{Deliver fast} \end{cases}$$

$$\begin{cases} \mathrm{DP}_1 = \text{Product variety} \\ \mathrm{DP}_2 = \text{Position of the decoupling point} \\ \mathrm{DP}_3 = \text{Production flow} \end{cases}$$

$$\Longrightarrow \quad \begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} A_{11} & A_{12} & 0 \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}$$

Figure 20: Functional requirements and design parameters of a mass customization system (Blecker and Abdelkafi 2006)

3.3.4 Cognitive Complexity Theory

(Ghosh et al. 2011) proposes a metric to measure the total cognitive complexity of the configuration model corresponding to a product configuration system, expressed as a UML class diagram. The author used Basic Control Structures (BCSs) for cognitive complexity, a functional complexity associated with designing and understanding the software system. They adopted the Cognitive Weights of BCSs from (Shao and Wang 2003) and used them to account for the impact of business rules on the configuration by cognitive weights, as shown in Table 7.

Table 7: Cognitive weights of BCSs for Business Rules

Category of BCS	**BCS**	**Cognitive Weight**
Assignment	Assignment (ASS)	1
Branch	If-Then-Else (I-TE) or implication	2
Iteration	Iteration	3
Embedded	User Function Call (UFC)	2
	Standard Function Call (SFC)	1

Table 8: Cognitive Weights of Attribute Datatypes

Datatype Category	**Attribute Domain**	**Cognitive Weight**
Primary	Integer, Float, Boolean	1
Derived	Named Domain	2
User-defined	Function, Class	3

The author used the weighted method, shown in Table 8 to calculate Cognitive Complexity (CC) as a sum of Business Rules Complexity (BRC) + Attribute Complexity (AC), as shown in the equation below – CC = AC + Sum of BRC in the Product configuration,

Equation 6: Cognitive Complexity Metric

$$CCi = AC + \sum_{k=1}^{p} BRC_{\mathrm{k}}$$

3.3.5 Hierarchical Structure Analysis:

Complexity metrics have been developed for “applications such as consumer products, software, trajectory selection, and assembly systems. Although existing complexity metrics were developed to reduce product design and development costs, their lack of simplicity in formulation and robustness has limited their applicability. This paper proposes a standard methodology for comparing and evaluating these metrics (Crespo-Varela et al. 2012).” It introduces dimensions of complexity that should be considered in developing product configuration complexity metrics. To this end, this paper introduces variables that integrate multiple facets of complexity into a single metric (Crespo-Varela et al. 2012) and evaluates the hierarchical structure of the product, including subassemblies, modules, and components. Complex hierarchical structures can increase configuration complexity. (Sinha and de Weck 2013), measure the Structural Complexity of the technical system in this form

Structural Complexity, also shown in Equation 1, $C = C_1 + C_2 * C_3$, where C_1 represents the sum of complexities of individual components alone, C_2 (local effect) is the number and complexity of each pair-wise interaction, C_3 (global effect) effect of architecture or the arrangement of the interfaces. The Schrodinger equation of organic molecular systems inspires this functional form of measuring structural complexity.

(Bashir and Thomson 1999) A metric was developed to quantify complexity by focusing on product functions and analyzing their hierarchical decomposition. This can be mathematically represented as:

Equation 7: Bashir and Thompson's Metric

$$PC = \sum_{j=1}^{l} Fjkj$$

where,
PC is the product complexity,
F j is the number of functions at level j,
l is the number of levels,
k j is the weight for level j, where k1 = 1, k2 = 2, etc.

3.3.6 Graph Theory:

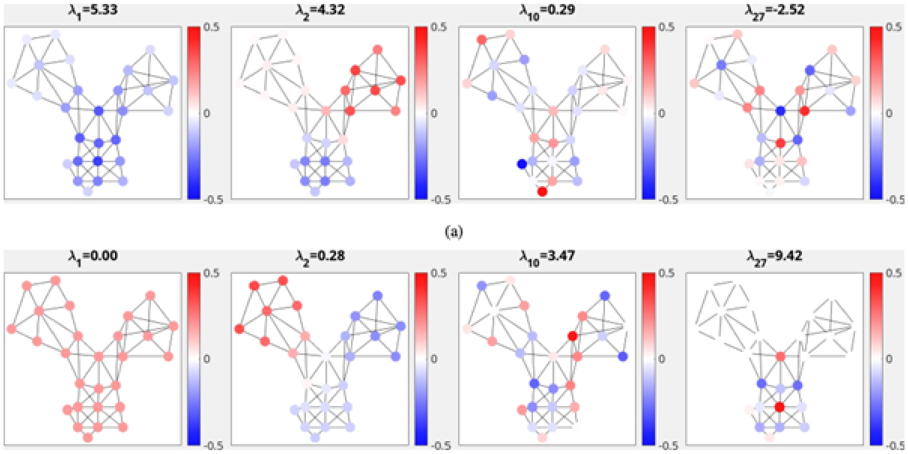
Represent the product as a graph where components are nodes and dependencies are edges. Analyze the graph to identify complexity metrics such as connectivity, centrality, and clustering coefficient. The book (X. Li, Shi, and Gutman 2012) explains the first definition of graph energy in the year 1978 as $E(G) = \sum_{i=1}^{n} |\lambda_i|$. (Sinha and de Weck 2014) uses generic graph theory as the “sum of absolute of eigenvalues of the graph adjacency matrix.” (Gutman and Furtula 2017) has surveyed over 600 research papers on graph energies and found 60+ flavors of graph energy metrics.

3.3.7 Graph Signal Processing (GSP) Metric

Graph theory has become a valuable tool for understanding and analyzing complex systems in various domains, including product development and manufacturing. While there is limited research on the use of graph signal processing (GSP) in this context, many studies explore the broader applicability of graph theory in characterizing and managing product complexity.

One relevant paper by (Smith, J, Johnson, M, and Chen, L. 2019) explores the application of graph theory in modeling and analyzing product structures and configurations. The authors propose a graph-based representation of product components and their interconnections, enabling the visualization and analysis of complex relationships within product architectures. Through case studies in the automotive and aerospace industries, they demonstrate how graph theory can facilitate the identification of critical components, dependencies, and bottlenecks, thereby informing design decisions and optimization strategies.

Per (Ortega et al. 2018), “There is a nice one-to-one correspondence between the ordered value of the frequency and the corresponding degree of variation or complexity of the time spectral component. In GSP, the frequencies are defined by the shift eigenvalues. We can order the graph frequencies by relating them to the complexity of the spectral component.” In Figure 21, 4 different frequencies correspond to the different eigenvalues ranging from lowest to highest frequency.



(a)

(b)

Figure 21: Example of elementary frequencies obtained from different algebraic representations of the same graph (a) Adjacency matrix, (b) Laplacian matrix

3.3.8 Other notable mentions

Analyze customer feedback and support data to identify common issues or challenges related to product configuration. This can provide insights into areas of complexity. For example, (Makumbe, Rebentisch, and Seering 2012) asked this question to about 80 companies: What makes module XYZ complex from a global product development point of view? This method gives a high-level idea of areas where product complexity is perceived. Another expert evaluation method seeks input from domain experts or experienced engineers to assess the product configuration's complexity qualitatively. Their insights can complement quantitative analyses to evaluate empirically the definition of complexity in terms of the number of parts, amount of interactions, technological novelty, etc.

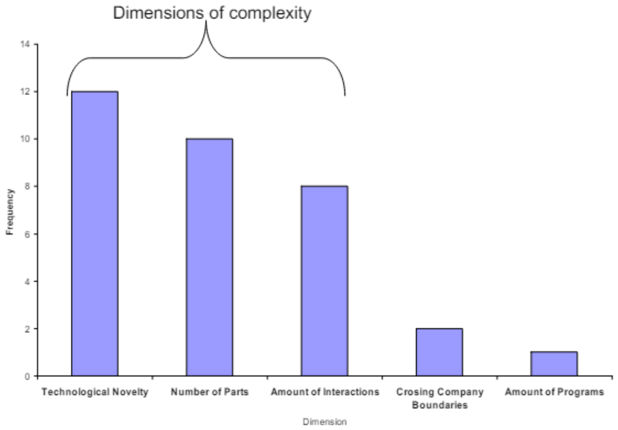
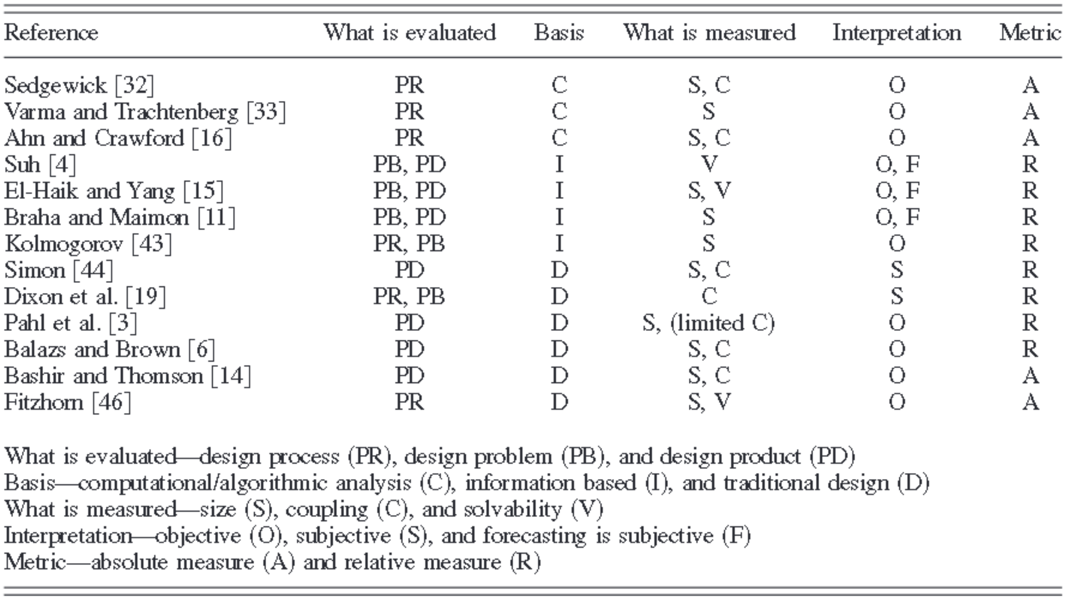


Figure 22: What makes module XYZ complex? (Makumbe, Rebentisch, and Seering 2012)

(Summers and Shah 2010) shows the comparison of different complexity metric in Table 9 and (Hennig, Topcu, and Szajnfarber 2021) has listed more than 68 complexity metrics on the graph theory alone as shown in Table 10.

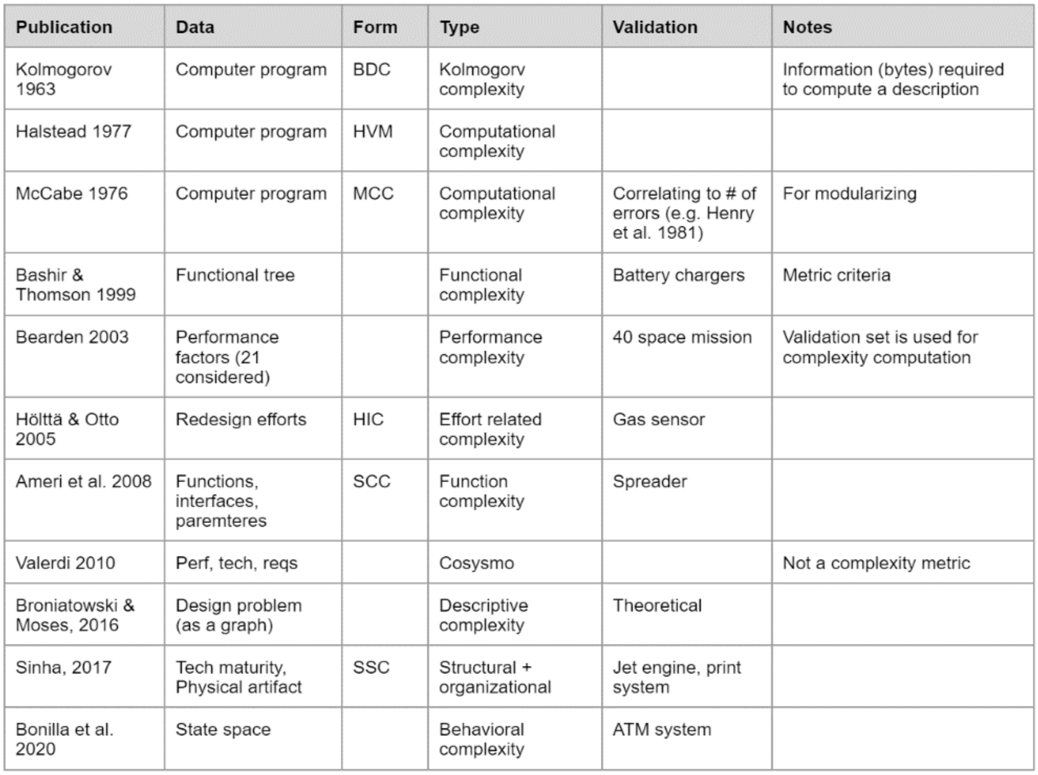
Table 9: Complexity measure comparison (adapted from (Summers and Shah 2010))



Reference	What is evaluated	Basis	What is measured	Interpretation	Metric
Sedgewick [32]	PR	C	S, C	O	A
Varma and Trachtenberg [33]	PR	C	S	O	A
Ahn and Crawford [16]	PR	C	S, C	O	A
Suh [4]	PB, PD	I	V	O, F	R
El-Haik and Yang [15]	PB, PD	I	S, V	O, F	R
Braha and Maimon [11]	PB, PD	I	S	O, F	R
Kolmogorov [43]	PR, PB	I	S	O	R
Simon [44]	PD	D	S, C	S	R
Dixon et al. [19]	PR, PB	D	C	S	R
Pahl et al. [3]	PD	D	S, (limited C)	O	R
Balazs and Brown [6]	PD	D	S, C	O	R
Bashir and Thomson [14]	PD	D	S, C	O	A
Fitzhorn [46]	PR	D	S, V	O	A

What is evaluated—design process (PR), design problem (PB), and design product (PD)
Basis—computational/algorithmic analysis (C), information based (I), and traditional design (D)
What is measured—size (S), coupling (C), and solvability (V)
Interpretation—objective (O), subjective (S), and forecasting is subjective (F)
Metric—absolute measure (A) and relative measure (R)

Table 10: More than 68 complexity metrics (adapted from (Hennig, Topcu, and Szajnfarber 2021))



Publication	Data	Form	Type	Validation	Notes
Kolmogorov 1963	Computer program	BDC	Kolmogorv complexity		Information (bytes) required to compute a description
Halstead 1977	Computer program	HVM	Computational complexity		
McCabe 1976	Computer program	MCC	Computational complexity	Correlating to # of errors (e.g. Henry et al. 1981)	For modularizing
Bashir & Thomson 1999	Functional tree		Functional complexity	Battery chargers	Metric criteria
Bearden 2003	Performance factors (21 considered)		Performance complexity	40 space mission	Validation set is used for complexity computation
Hölttä & Otto 2005	Redesign efforts	HIC	Effort related complexity	Gas sensor	
Ameri et al. 2008	Functions, interfaces, paremteres	SCC	Function complexity	Spreader	
Valerdi 2010	Perf, tech, reqs		Cosysmo		Not a complexity metric
Broniatowski & Moses, 2016	Design problem (as a graph)		Descriptive complexity	Theoretical	
Sinha, 2017	Tech maturity, Physical artifact	SSC	Structural + organizational	Jet engine, print system	
Bonilla et al. 2020	State space		Behavioral complexity	ATM system	

3.4 Summary of the Literature Review

This section describes the method followed for selecting, implementing, and validating the model development to measure the product Configuration Complexity. In this exercise, different types of complexities found in Chapter 3.3 related to product configurations are mapped with the various methods used to measure product configuration complexity from Chapter 3.3. And the relevant literature is mentioned in the cell with matching theory and complexity as shown in Table 11.

Table 11: Theories used to measure different complexities

Theory	**Functional Complexity**	**Design Complexity**	**Structural Complexity**	**Manufacturing Complexity**	**Supply Chain Complexity**	**Organizational Complexity**
Graph Theory	(Bashir and Thomson 1999)	(Sinha and de Weck 2014)	(Sinha and de Weck 2014)	(Modrak and Bednar 2016)	(Beamon 1998)	(Felix Stracke, Rebentisch, and Mattern 2016)
Variability Theory	(Forti, Ramos, and Muniz 2023)	(Marshall L. Fisher 1996)	(Marshall L. Fisher 1996)	(Marshall L. Fisher 1996)		
Component Count		(Börold et al. 2020)	(Börold et al. 2020)	(Börold et al. 2020)		
Axiomatic Design Theory	(Suh 2005)	(Suh 2005)	(Keating 2000)	(Efthymiou et al. 2012)		
Cognitive Complexity Theory	(Shao & Wang) 2003)		(Shao and Wang 2003)			

This literature review sheds light on multiple aspects of the product configuration complexity. Many scholars have attempted to define the complexity using many methods. The methods used to manage product configurations encompass various techniques to ensure consistency, traceability, and efficiency throughout the product lifecycle. (“Systems Engineering for ITS - Configuration Management” 2024) Configuration Management (CM) provides a framework for controlling changes and maintaining records of product characteristics. The configuration management process emphasizes controlling revisions of parts to guarantee that the final product meets the requirements. Model-based Variant Management facilitates early modeling and description of product variants, which is crucial in complex systems like automobiles (Otten et al. 2019). Configuration Rules govern allowable feature combinations, while Bill of Materials (BOM) Management ensures accurate documentation of product structures. Standardization and Commonization reduce complexity by establishing common components and processes, enhancing productivity. Modularization enhances flexibility and customization by designing products with interchangeable modules or components (Phelan et al. 2017). These methods collectively address challenges in managing product configurations, and ensuring quality and compliance while accommodating diverse customer needs (Chatras, Giard, and Sali 2015).

Per (S. Bhosale and A. Joglekar 2014) Design Complexity arises from accommodating various options, features, and customization preferences. Challenges include ensuring compatibility, functionality, and aesthetic appeal while managing space constraints, weight distribution, and manufacturing feasibility. Structural Complexity manifests through the intricate interplay of configured components and subsystems (Sinha and de Weck 2014). Challenges include accurately capturing and quantifying design complexity, managing interfaces, and reducing overall system complexity. (Shehada 2014) showed that the manufacturing Complexity stems from build-to-order car configurations, leading to unique assembly requirements for each vehicle. Challenges include efficient production planning, scheduling, and adapting to variability in orders.

Supply Chain and Organizational Complexity relate to coordinating the procurement of specific components and parts tailored to each configuration (Beamon 1998). Challenges include managing internal and external supply chain flows, organizational structure, and complexity drivers such as regulations, competition, and process complexities. Functional Complexity directly impacts design, manufacturing, and customer satisfaction. Challenges include managing various customizable options, optimizing design manufacturing efficiency, and aligning development processes with functional requirements (Gunasekaran, Subramanian, and Rahman 2015).

These complexities necessitate sophisticated management strategies, including modular design, standardization, flexible manufacturing processes, efficient supply chain coordination, and alignment of development processes with functional requirements. Researchers and practitioners explore various methodologies and frameworks to effectively address these complexities and enhance product quality, innovation, and competitiveness in dynamic market environments (P. Li 2011). (Felix Stracke, Rebentisch, and Mattern 2016) has shown that the organizational side has become excessively complex, and the required ability to control and manage it has not been achieved. Many development projects exceeded the cost and schedule due to rising organizational complexity. (Felix Stracke, Rebentisch, and Mattern 2016) develops “a framework to measure organizational complexity and thus make it visible and more easily controllable for project managers.”

There are various methods to measure product configuration complexity, offering insights into different dimensions and approaches:

Component Count quantifies complexity based on the number of unique components or parts required for manufacturing. It provides a straightforward measure for comparing different product configurations, allowing prioritization of resources and streamlining production workflows (Börold et al. 2020).

Variability Analysis analyzes variations or options available within the product to assess the implications on production processes. It helps identify patterns, trends, and outliers in customer preferences to optimize production planning and resource allocation. (Marshall L. Fisher 1996) examines variability with two product mix variables: (1) the average level of option content on the cars produced that month and (2) the standard deviation in option content per car. Research (Blecker and Abdelkafi 2006) considers the product configurations from the perspective of Suh's theory (Suh 2005), emphasizing independence between functional requirements and design parameters to minimize complexity. The author applies this theory to the mass customization of automobile product configurations, focusing on achieving fundamental functional requirements through design parameters.

Cognitive Complexity Theory: (Ghosh et al. 2011) propose a metric to measure cognitive complexity in configuration models, incorporating Basic Control Structures (BCSs) and business rules. Calculates Cognitive Complexity (CC) as a sum of Business Rules Complexity (BRC) and Attribute Complexity (AC) in the product configuration.

Hierarchical Structure Analysis: (Sinha and de Weck 2013) evaluates the hierarchical structure of the product, including subassemblies, modules, and components. Measures structural complexity based on the complexity of individual components, pair-wise interactions, and global architectural arrangements.

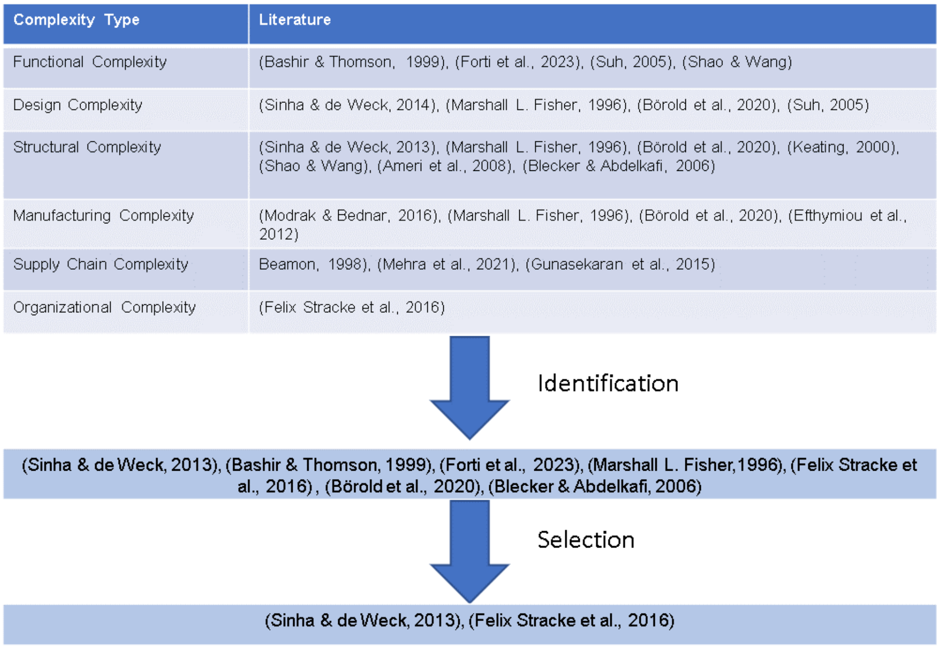
Graph Theory: Represents the product as a graph to analyze complexity metrics such as connectivity, centrality, and clustering coefficient. Utilizes graph signal processing (GSP) to model and analyze complex relationships within product architectures, facilitating design decisions and optimization strategies. There are many researchers (Smith, J, Johnson, M, and Chen, L. 2019), (Ortega et al. 2018), and (Sinha and de Weck 2013) use graph theory in their metrics to measure product complexity.

These methods offer diverse perspectives on measuring product configuration complexity, ranging from quantitative component counts to qualitative expert evaluations. By combining multiple metrics and approaches, manufacturers can comprehensively understand complexity and identify areas for improvement in product design, manufacturing, and supply chain management.

Chapter 4: Model

4.1 Complexity Metric Selection for the Analysis

This section explains the method for selecting the complexity metric for the analysis. The objective was to find a user-friendly method that can be easily used in the existing Product Configuration management tools, like PLM. The complexity metrics are narrowed down from the literature review and divided into complexity types to which each metric corresponds, as shown in Figure 23.



Complexity Type	Literature
Functional Complexity	(Bashir & Thomson, 1999), (Forti et al., 2023), (Suh, 2005), (Shao & Wang)
Design Complexity	(Sinha & de Weck, 2014), (Marshall L. Fisher, 1996), (Börold et al., 2020), (Suh, 2005)
Structural Complexity	(Sinha & de Weck, 2013), (Marshall L. Fisher, 1996), (Börold et al., 2020), (Keating, 2000), (Shao & Wang), (Ameri et al., 2008), (Blecker & Abdelkafi, 2006)
Manufacturing Complexity	(Modrak & Bednar, 2016), (Marshall L. Fisher, 1996), (Börold et al., 2020), (Efthymiou et al., 2012)
Supply Chain Complexity	Beamon, 1998), (Mehra et al., 2021), (Gunasekaran et al., 2015)
Organizational Complexity	(Felix Stracke et al., 2016)

(Sinha & de Weck, 2013), (Bashir & Thomson, 1999), (Forti et al., 2023), (Marshall L. Fisher,1996), (Felix Stracke et al., 2016) , (Börold et al., 2020), (Blecker & Abdelkafi, 2006)

(Sinha & de Weck, 2013), (Felix Stracke et al., 2016)

Figure 23: Filtering Process

4.1.1 Filtering of the metrics

Initially, fifteen metrics were reduced to ten by selecting only those researches that provide a formal mathematical formulation that could be useful in integrating with the configurator applications.

Rationale for the Initial Filtering of Metric: (Bashir and Thomson 1999) formulated functional complexity based on the number of functions and the depth of their functional trees (hierarchies). It can be used with an application that has functional decomposition used as a part of designing the product. While (Forti, Ramos, and Muniz 2023) use modular function deployment (MFD) and design structure matrix (DSM) to manage modularization because of their similar characteristics in commercial and academic software availability. (Shao and Wang 2003) used cognitive theory to measure complexity in the software. In a typical auto design, cognitive load is not captured; hence, this metric was omitted.

(Sinha and de Weck 2013) uses graph theory and have a simplified formula that calculates the individual component complexity, interactions, and topological complexity. This method is used by many scholars. (Felix Stracke, Rebentisch, and Mattern 2016) had the research focused on organizational complexity, which is based on (Sinha and de Weck 2013), and had a mathematical formulation to measure the organizational complexity. Product configurations have a defined structure, and Sinha's method is suitable to calculate the structural complexity of the product configuration.

(Marshall L. Fisher 1996) research is considered because it analyzes a similar problem of how product variety impacts plant productivity, and empirical evidence and simulation analysis were done over three years of data collected. (Börold et al. 2020) employs deep learning-based image processing for automated classification and counting of different components. This research was considered for its novice approach.

(Modrak and Bednar 2016) were eliminated due to the lack of simplicity in the mathematical formulation of the complexity metric. (Ameri et al. 2008) has developed a metric for products, and their metric is based on probability values. There is no numerical solution, so it was not considered for selection.

As a result of the first elimination, the second group of seven complexity metrics remained. These seven metrics are further studied based on their applicability to measure different complexities discussed in Chapter 3.2. Figure 23 shows the categorization of each research based on the type of complexities it is suitable for.

The second step in selecting the complexity metric was based on its applicability in measuring different complexities. (Sinha and de Weck 2013) method helps measure structural complexity as well as design complexity. It is also used in measuring organizational complexity by (Felix Stracke, Rebentisch, and Mattern 2016). The data needed for this metric, like component complexity pair-wise interaction between components, can be easily extracted from any configuration management tool.

(Marshall L. Fisher 1996) examines variability with two product mix variables, options content, and options variability, which is the core of the vehicle product configuration. However, it is not within the scope of calculating the variance of different options for the production configuration. It will be helpful for the marketing and sales domain, where calculating the variance of the option will help decide which feature option of the vehicle is popular vs which is least popular.

(Bashir and Thomson 1999) is more useful for functional complexity measurement. However, product configuration does vary much with functions and has more structural variety in it. Hence, Bashir's approach is not suitable for calculating product configuration complexity. (Forti, Ramos, and Muniz 2023) used MFD and DSM, which could be challenging to integrate with commercial configuration management tools due to their complexity.

Final Selection: (Sinha and de Weck 2013) and (Felix Stracke, Rebentisch, and Mattern 2016) metrics are selected for the thesis analysis. Together, this thesis provides coverage to measure the product configuration's complexity in various domains like design, manufacturing, and organizational management for the product configuration. These two researches stem from the same theories so there will be a common ground for most of the analysis in this thesis. Sinha's method provides a mathematical formulation that can be effectively implemented and integrated with commercial tools to calculate the product configuration complexity. The scaling up for the large data is easier with Sinha's approach of calculating structural complexity. Table 12 shows the final selection of the complexity metric for this thesis. The next section defines each equation and its applicability to measure the product configuration complexity.

Table 12: Final Selection of the Complexity Metric for the thesis model

Complexity Metric	Structural Complexity	Organizational Complexity
(Sinha and de Weck 2013)	Equation 1: Structural Complexity Metric (Sinha and de Weck 2013)	NA
(Felix Stracke, Rebentisch, and Mattern 2016)	NA	Equation 2: Organizational Complexity Metric (Felix Stracke, Rebentisch, and Mattern 2016)

4.2 Structural Complexity (SC) adopted from (Sinha and de Weck 2013):

The original equation developed by (Sinha and de Weck 2013) has three variables to measure the structural complexity; refer to Equation 8:

Equation 8: Sinha's Structural Complexity Metric

$$C = C_1 + C_2 * C_3$$

where,
C is the Structural Complexity,
C_1 Complexity due to components alone
C_2 Complexity due to pair-wise component interactions
C_3 Complexity due to topological formation

For this thesis, each variable is adopted to suit the product configuration components, as shown in Figure 24.

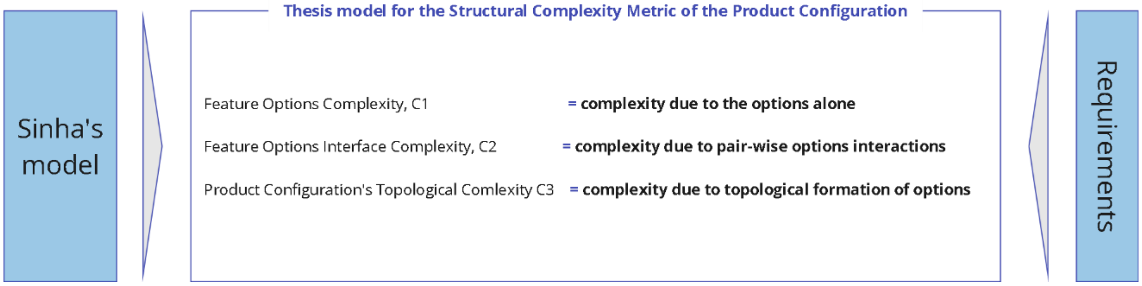


Figure 24: Structural Complexity Model of the Product Configuration, merged with Sinha's model

Equation 9: Thesis model equation for Structural Complexity Metric (Structure Module), adopted Eq. 6

$$C = C_1 + C_2 * C_3$$

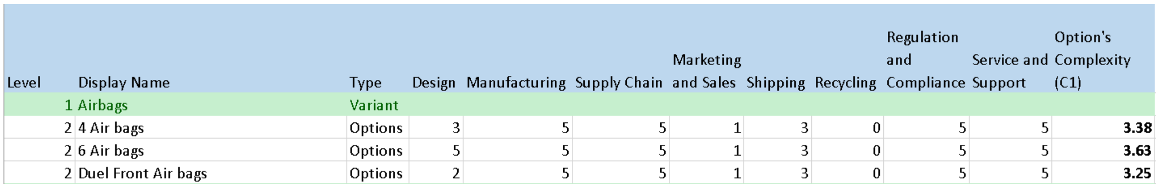
where,
C is the Structural Complexity,
C_1 Complexity due to options alone
C_2 Complexity due to pair-wise options interactions
C_3 Complexity due to the topological formation of the product configuration

The details on how to calculate C_1, C_2, and C_3 *are discussed in the following sections.*

4.2.1 C_1 (α coefficient), complexity due to the options alone

In the context of product configurations, individual feature options serve as components. Consequently, the complexity of each component (C_1, represented by the coefficient α) is calculated by assessing individual feature options. This metric is defined through a rating technique applied to each option available within a variant. Ratings are assigned on a scale from 1 to 5, with 5 denoting the highest complexity. For each option, complexity ratings are established within various domains. For instance, considering a hypothetical scenario, shown in Table 13, where an Airbag variant for a car offers three options (4 Airbags, 6 Airbags, and Dual Front Airbags), complexity ratings are assigned under each domain based on the perceived complexity of the option within that domain. While manufacturing and regulatory aspects may contribute to high complexity ratings, other domains, such as Recycling, may exhibit minimal complexity. It's important to emphasize that the provided ratings are hypothetical and should be validated through consultation with domain experts and subject matter specialists during implementation.

Table 13: Options complexity for each domain on a scale of 1 to 5 with notional data (5 being the most complex)



Level	Display Name	Type	Design	Manufacturing	Supply Chain	Marketing and Sales	Shipping	Recycling	Regulation and Compliance	Service and Support	Option's Complexity (C1)
1	Airbags	Variant									
2	4 Air bags	Options	3	5	5	1	3	0	5	5	**3.38**
2	6 Air bags	Options	5	5	5	1	3	0	5	5	**3.63**
2	Duel Front Air bags	Options	2	5	5	1	3	0	5	5	**3.25**

Equation 10: Options Complexity Equation

Options complexity, α = Average of all the domain-specific complexities

The final Product Configuration Options Complexity is a sum of all the option complexity, denoted by C_1

Equation 11: Product Configuration Options Complexity, C_1

$$C_1 = sum\ (\alpha)$$

4.2.2 C_2 (β coefficient), complexity due to pair-wise options interactions

This metric is defined using the interactions between the options. These options are assembled and connected on the product line or at the car dealer location. Some options are physically connected and exchange energy, information, force, or mass. This metric is calculated using the interface complexity defined by an Options DSM with a weighted interface method.

In Table 14, the interactions between the pair-wise options are captured. Four types of interactions are considered, and each has given a weight adopted from (Sinha and de Weck 2013). For example, the Battery is connected physically to the Battery Charger; it also exchanges energy and information, hence its weightage = 0.5+1.0+1.0 = 2.5. The interaction weights are shown in the top left cell of the table.

Table 14: DSM for the Option’s Interface Complexity of the Product Configuration

(Read column to row) Physical connection = 0.5 Information Flow = 1.0 Energy Flow = 1.0 Mass Flow = 1.0		Airbags	Battery Capacity	Battery Charger Type	Body Style	Camera	Drive System	Drive Train Types	Front Motor Power	Grade Type	Headlight & Tail Lamp Types	Infotainment System	Market Location	Rear Motor Power	Rear Seat Folding	Rear View Mirror	Roof Types	Seat Type	Side Mirror Types	Steering Wheel Type	Thermal Management	Wheel Sizes
Variant Name	**ID**	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**	**U**
Airbags	A	3.63	0	0	1.5	0	0	0	0	1.5	0	0	0	0	0	0	2.5	0	0	2.5	0	0
Battery Capacity	B	0	4.5	1.5	0.5	0	1.5	2	2.5	0.5	0	0	0	3.5	0	0	0	0	0	0	2.5	0
Battery Charger Type	C	0	2.5	3.88	0.5	0	0.5	1.5	2.5	0	0	0	0	2.5	0	0	0	0	0	0	1.5	0
Body Style	D	0.5	1.5	0.5	2.38	0.5	0.5	1.5	1.5	0	1.5	1.5	0	0.5	1.5	1.5	1.5	1.5	0.5	1.5	0	0.5
Camera	E	0	0	0	0.5	4.38	0	0	0	0	0	1.5	0	0	0	2.5	0	0	1.5	1.5	0	0
Drive System	F	0	0.5	1.5	1.5	0	2	1.5	1.5	3	0	2.5	0	2.5	0	0	0	0	0	0.5	0	0
Drive Train Types	G	0	1	1.5	1	0	2.5	1.5	2.5	0	0	1	0	1.5	0	0	0	0	0	0.5	0	0
Front Motor Power	H	0	2.5	1.5	0.5	0	1.5	2	4.5	0	0	2.5	0	1.5	0	0	0	0	0	0.5	0	0
Grade Type	I	0.5	0.5	0	0	0	1.5	0	0	2.25	0	0	1.5	0	0	0	1.5	0	0	0	0	0
Headlight & Tail Lamp Types	J	0	0	0	1.5	0	0	0	0	0	2.63	2	0	0	0	1.5	0	0	0	1.5	0	0
Infotainment System	K	0	0	0	1.5	2.5	1.5	2.5	2.5	0	1.5	4	0	2.5	0	2	2	1.5	1.5	2.5	2.5	1.5
Market Location	L	0	0	0	0	0	0	0	0	0.5	0	0	3	0	0	0	0	0	0	0	0	0
Rear Motor Power	M	0	2.5	2.5	1.5	0	1.5	1.5	1.5	0	0	2.5	0	4.25	0	0	0	0	0	1.5	0.5	0
Rear Seat Folding	N	0	0	0	1.5	0	0	0	0	0	0	0	0	0	3.38	0	0	1.5	0	0	0	0
Rear View Mirror	O	0	0	0	1.5	1.5	0	0	0	0	1.5	1.5	0	0	0	2.63	0	0	0	1.5	0	0
Roof Types	P	1	0	0	2.5	0	0	0	0	1.5	0	2.5	0	0	0	0	3.5	0	0	0	0	0
Seat Type	Q	0	0	0	2.5	0	0	0	0	0	0	2.5	0	0	1.5	0	0	3	0	0	0	0
Side Mirror Types	R	0	0	0	1.5	1.5	0	0	0	0	0	1.5	0	0	0	0	0	0	3.25	1.5	0.5	0
Steering Wheel Type	S	1.5	0	0	2.5	2.5	2	2.5	2	0	1.5	2.5	0	1.5	0	1.5	0	0	1.5	3.38	1.5	0
Thermal Management	T	0	1.5	2.5	0	0	0	0	0	0	0	1.5	0	0.5	0	0	0	0	1.5	2	3.5	0
Wheel Sizes	U	0	0	0	0.5	0	0	0	0	0	0	1.5	0	0	0	0	0	0	0	0	0	1.25

Here, the assumption is made that all the options under the same feature have the same interface complexity. In an earlier example of the Airbag options in (2), options (4 Airbags, 6 Airbags, and Dual Front Airbags) could have different interface complexity. The ‘6 Airbags’ will have more interfaces than the ‘Dual Front Air bags.’ The model assumes a typical interface complexity at a feature level for this exercise.

Equation 12: Options Interface Complexity, β Equation

Options Interface Complexity, β = *Sum of options pair-wise interactions weightage (by SME approximations for each interaction)*

The final Product Configuration Interface complexity, $C_{2,}$ is defined below:

Equation 13: Product Configuration Interface Complexity, C_2

$$C_2 = sum(\beta)$$

4.2.3 C3 (γ coefficient), complexity due to topological formation of options

For the product configuration, the topology is the same as the structural topology. This complexity is defined as the matrix or graph energy of the adjacency matrix of a network. The options represent the formal structure, and Options DSM captures its interaction structure. The adjacency matrix *A* ∈ Mnxn of a network is defined as follows, adopted from (Sinha and de Weck 2013):

Equation 14: Adjacency matrix A ∈ Mnxn of a network

$$A_{ij} = \begin{cases} 1 \ \forall \ [(\mathrm{i,j})|(\mathrm{i} \neq \mathrm{j}) \text{ and } (\mathrm{i,j}) \in \Lambda \\ 0 \text{ otherwise} \end{cases}$$

Where *A* represents the set of connected nodes. The diagonal elements of matrix *A* are zero. The corresponding matrix energy of the network is defined as the sum of singular values of the adjacency matrix (Sinha and de Weck 2013):

Equation 15: Matrix energy of the network

$$A(E) = \sum_{i=1}^{n} \sigma_i,$$
$$where\ \sigma_i\ represents\ i_{th}\ singular\ value$$

Once the matrix energy is calculated, the Options Topological Complexity, C_3, can be calculated with Equation 16, adopted from (Sinha and de Weck 2013):

Equation 16: Options Topological Complexity, C_3

$$C_3 = \frac{A(E)}{\gamma}$$

Where A(E) represents matrix energy and γ account for the number of options in a product configuration

For example, Table 15 shows the unitized form of DSM from Table 14. Wherever there is an interface between two options, the value of 1 is assumed, and for no interfaces, the value is 0. The value of γ is a normalization factor for a number of options (n) in the product configuration, i.e., 21 unique options would have γ = 1/21.

Table 15: DSM for the Topological Complexity of the Product Configuration

Variant Name	ID	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
Airbags	A		0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0
Battery Capacity	B	0		1	1	0	1	1	1	1	0	0	0	1	0	0	0	0	0	0	1	0
Battery Charger Type	C	0	1		1	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0	1	0
Body Style	D	1	1	1		1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	0	1
Camera	E	0	0	0	1		0	0	0	0	0	1	0	0	0	1	0	0	1	1	0	0
Drive System	F	0	1	1	1	0		1	1	1	0	1	0	1	0	0	0	0	0	1	0	0
Drive Train Types	G	0	1	1	1	0	1		1	0	0	1	0	1	0	0	0	0	0	1	0	0
Front Motor Power	H	0	1	1	1	0	1	1		0	0	1	0	1	0	0	0	0	0	1	0	0
Grade Type	I	1	1	0	0	0	1	0	0		0	0	1	0	0	0	1	0	0	0	0	0
Headlight & Tail Lamp Types	J	0	0	0	1	0	0	0	0	0		1	0	0	0	1	0	0	0	1	0	0
Infotainment System	K	0	0	0	1	1	1	1	1	0	1		0	1	0	1	1	1	1	1	1	1
Market Location	L	0	0	0	0	0	0	0	0	1	0	0		0	0	0	0	0	0	0	0	0
Rear Motor Power	M	0	1	1	1	0	1	1	1	0	0	1	0		0	0	0	0	0	1	1	0
Rear Seat Folding	N	0	0	0	1	0	0	0	0	0	0	0	0	0		0	0	1	0	0	0	0
Rear View Mirror	O	0	0	0	1	1	0	0	0	0	1	1	0	0	0		0	0	0	1	0	0
Roof Types	P	1	0	0	1	0	0	0	0	1	0	1	0	0	0	0		0	0	0	0	0
Seat Type	Q	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0		0	0	0	0
Side Mirror Types	R	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0		1	1	0
Steering Wheel Type	S	1	0	0	1	1	1	1	1	0	1	1	0	1	0	1	0	0	1		1	0
Thermal Management	T	0	1	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	1		0
Wheel Sizes	U	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	

This complexity provides the global effect by the effect of architecture arrangement or arrangement on the interfaces. Figure 25 shows how the topological complexity increases as we move towards more ‘distributed’ architectures.

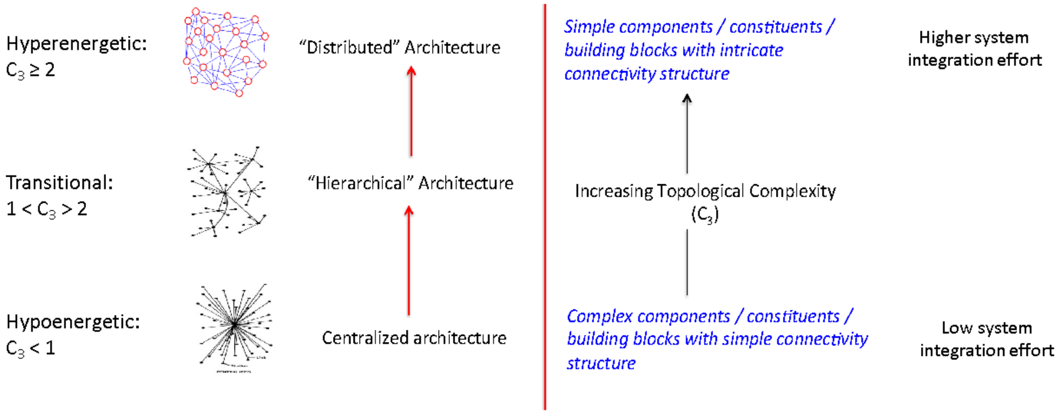


Figure 25: Topological Complexity: Interpretation

4.3 Organizational Complexity (OC) of the Product Configuration adopted from (Felix Stracke, Rebentisch, and Mattern 2016):

For this thesis model, the organizational complexity of the product configuration is measured as shown in Equation 17:

Equation 17: Organizational Complexity Metric (Felix Stracke, Rebentisch, and Mattern 2016) ((Organization Module)

$$C = C_{2G} * C_{3G} + C_{2O} * C_{3O}$$

where,
C is Organizational Complexity,
C_{2G}*C_{3G} interface complexity at the group (G) level
C_{2O}*C_{3O} the complexity at the organizational (O) level

This method is used to calculate organizational complexity with a few assumptions. The details of this complexity metric adoption for the product configuration organizational complexity are discussed in the following sections.

4.3.1 Organizational Interface Complexity, C_2

(Felix Stracke, Rebentisch, and Mattern 2016) measures the Organizational Interface Complexity, C_2 as a function of strength and importance, $S_{ij,}$ of the organization, and characteristics of each interaction, C_{ij}. The weighting vector assigns weights to each cluster in C_{ijG} and C_{ijO}. The total sum of weights equals 1.

Equation 18: Organizational Interaction Complexity, C_2, adopted from (Felix Stracke, Rebentisch, and Mattern 2016)

$$C_2 = \sum_{i=1}^{n}\sum_{j=1}^{n} s_{ij} * (\overrightarrow{w_{ij}} * \overrightarrow{c_{ij}})$$

where,
S_{ij} measures the strength of interaction using cluster interdependence at the group level,
C_{ij} is a function of the six interface characteristic clusters
$_{i,j}$ representing the interfaced organizational units
W_{ij} weighing vector to each cluster (total sum of weight equals 1)

1) Measurement of the $S_{ij,}$

(Felix Stracke, Rebentisch, and Mattern 2016) utilized the task interdependence to calculate the $S_{ij,}$– be captured by fraction of task that is dependent on input and the level of overlap (task percentage where data is exchanged). For this thesis model, to calculate the $S_{ij,}$value, the level of abstraction for the organization is shown below in the Figure 26 compared to the original method defined by the author.

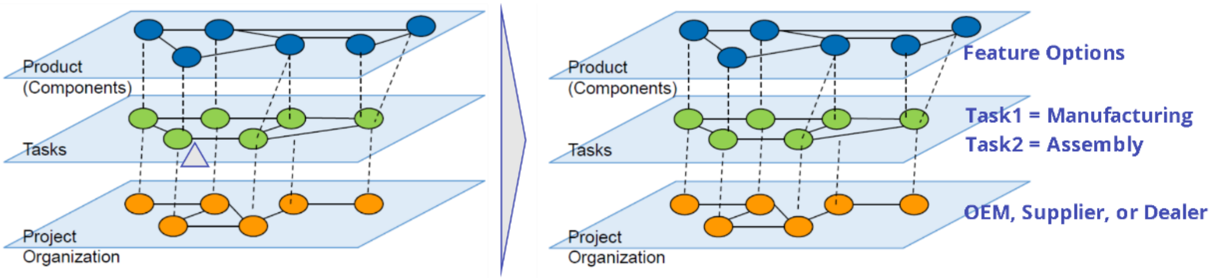
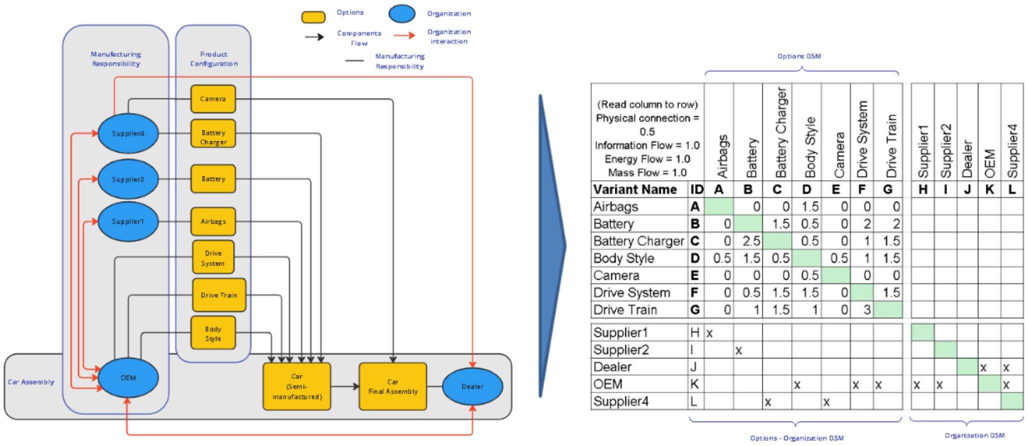


Figure 26: Level of abstraction in product configuration adopted from (Felix Stracke, Rebentisch, and Mattern 2016)

This model uses the Multi Domain Matrix (MDM) for two major tasks for the product configuration options: 1) Manufacturing and 2) Assembly. From the example of Figure 29, many feature options components move from Supplier to OEM/Dealer or OEM to Supplier/Dealer. For instance, if the battery moves from the supplier to the OEM, it must be installed on the car before it is shipped to the dealer. Meanwhile, the seat and side mirrors are moving from OEM to the dealer. There is also an interface between the Supplier and the Dealer to get the Wheel components to the Dealer site.

These interfaces between OEM, Supplier, and OEM are considered Organizational level interfaces shown in Figure 27.



(Read column to row) Physical connection = 0.5 Information Flow = 1.0 Energy Flow = 1.0 Mass Flow = 1.0		Airbags	Battery	Battery Charger	Body Style	Camera	Drive System	Drive Train	Supplier1	Supplier2	Dealer	OEM	Supplier4
Variant Name	**ID**	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**
Airbags	**A**		0	0	1.5	0	0	0					
Battery	**B**	0		1.5	0.5	0	2	2					
Battery Charger	**C**	0	2.5		0.5	0	1	1.5					
Body Style	**D**	0.5	1.5	0.5		0.5	1	1.5					
Camera	**E**	0	0	0	0.5		0	0					
Drive System	**F**	0	0.5	1.5	1.5	0		1.5					
Drive Train	**G**	0	1	1.5	1	0	3						
Supplier1	H	x											
Supplier2	I		x										
Dealer	J											x	x
OEM	K				x		x	x	x	x			x
Supplier4	L			x		x							

Figure 27: MDM of Interfaces between organization

2) Measurement of $C_{ij,}$

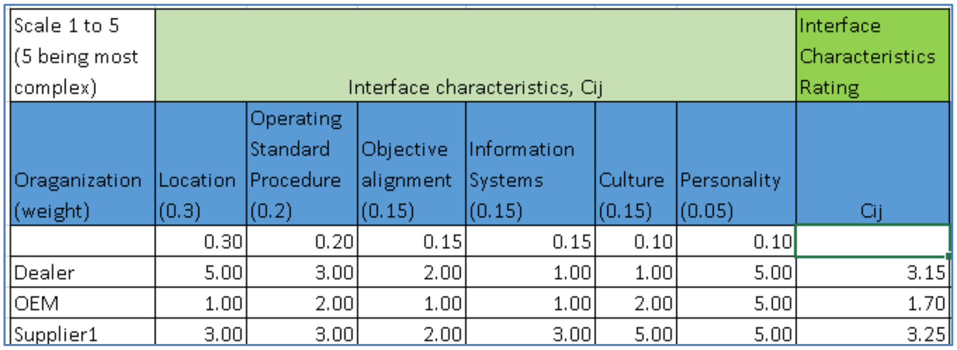
The original method by (Felix Stracke, Rebentisch, and Mattern 2016) uses the weighted sum method to assess $C_{ij,}$. This thesis model uses a simple rating method for each characteristic. Each organization is rated between 1 to 5 (5 being the most complex) for each characteristic as defined in Equation 19:

Equation 19: Function of six interface characteristics, Cij, adopted form (Felix Stracke, Rebentisch, and Mattern 2016)

$$\overrightarrow{c_{ijG}} = \begin{pmatrix} Location \\ Operating\ standard\ procedure \\ Objective\ alignment \\ Information\ systems \\ Culture \\ Personality \end{pmatrix} \qquad \overrightarrow{c_{ijO}} = \begin{pmatrix} Location \\ Operating\ standard\ procedure \\ Objective\ alignment \\ Information\ systems \\ Culture \end{pmatrix}$$

An example of weighted interface characteristic ratings is shown in Table 16. The $C_{ij,}$value is the average of all the ratings.

Table 16: Organizational Interface Characteristic Rating, Cij, sample data



Scale 1 to 5 (5 being most complex)	Interface characteristics, Cij						Interface Characteristics Rating
Oraganization (weight)	Location (0.3)	Operating Standard Procedure (0.2)	Objective alignment (0.15)	Information Systems (0.15)	Culture (0.15)	Personality (0.05)	Cij
	0.30	0.20	0.15	0.15	0.10	0.10	
Dealer	5.00	3.00	2.00	1.00	1.00	5.00	3.15
OEM	1.00	2.00	1.00	1.00	2.00	5.00	1.70
Supplier1	3.00	3.00	2.00	3.00	5.00	5.00	3.25

(Felix Stracke, Rebentisch, and Mattern 2016) defined the group and organization, as shown in Figure 28. As shown in the figure, this model considers three organizations involved in the product configurations, namely OEM, Suppliers, and Dealers.

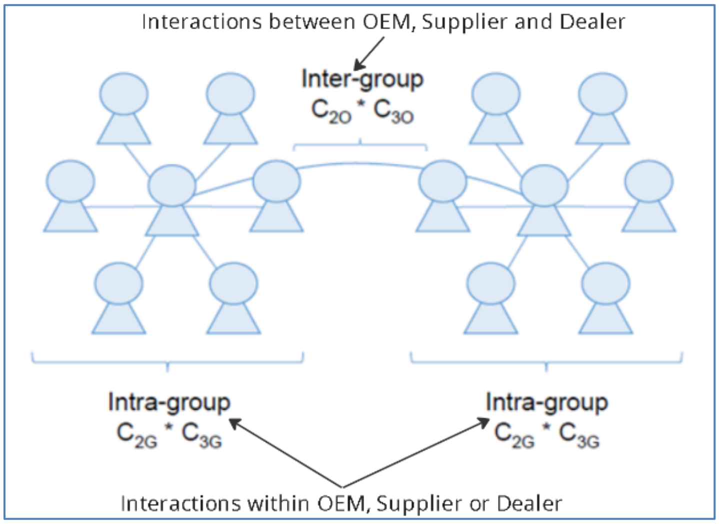


Figure 28: Intra-group and inter-group complexity, adopted from (Felix Stracke, Rebentisch, and Mattern 2016)

As defined by (Felix Stracke, Rebentisch, and Mattern 2016), Indicator *G,* in this case, marks the group level, while *O* indicates the organizational level—aggregation of complexity on both levels accounts for the overall organizational complexity.

To adopt this complexity at the group level for the product configuration, the interfaces between OEM, Supplier, and Dealer are captured in Figure 29. The interface complexity at the group (G) level (denoted by $C_{2G}*C_{3G}$) is considered the interface within the OEM. This is shown with the red arrow. It shows that the 'Steering Wheel' assembly is manufactured and assembled at the OEM factory.

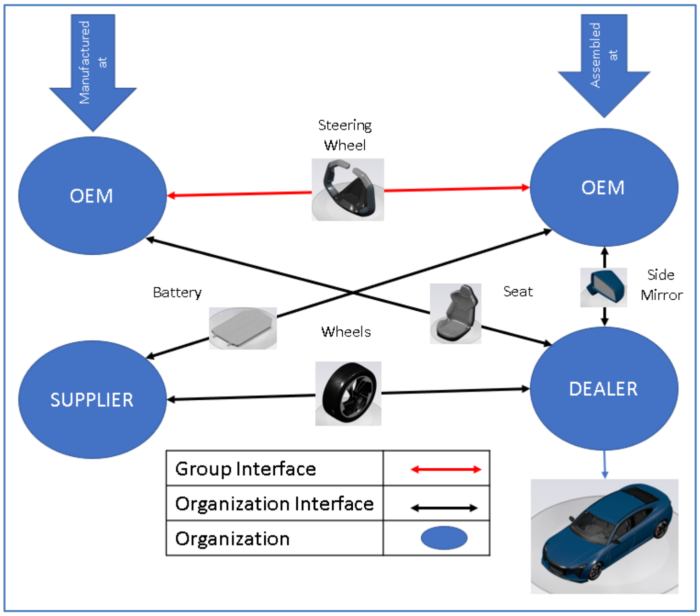


Figure 29: Organization interactions and options component flow until the final assembly: Images source: (Dassault Systèmes 2022)

4.3.2 Organizational Architecture Complexity, C_3

The organizational architecture complexity, C_3, is measured as defined in Chapter 5.2.3.

4.4 Hybrid Model to measure Product Configuration Complexity (PCC)

This thesis considers integrating two distinct complexities outlined in Chapters 4.2 and 4.3 to construct a hypothetical hybrid model for Product Configuration complexity. The hypothesis posits that Product Configuration complexity can be conceptualized as a function of two primary factors: (a) structural complexity, about the unique assembly requirements for each vehicle build, and (b) organizational complexity, which encompasses the logistical challenges associated with relocating and assembling numerous components across multiple locations. The proposed hybrid model aggregates these complexities into a singular indicator, providing a comprehensive understanding of Product Configuration complexity.

Equation 20: Product Configuration Complexity Equation

Product Configuration Complexity (PCC) = Structural Complexity (SC) + Organizational Complexity (OC)

4.5 Cost Model of the Product Configuration Complexity (PC_{cost})

The cost model for the Product Configuration is based on three different costs at each feature option level.

1) Transport Cost, TC = The cost associated with transferring options components from one organization to another organization (E.g., Supplier to OEM or OEM to Dealer).

2) Assembly Cost, AC = The cost associated with installing/assembling options components onto the vehicle

3) Quality Control (QC) Cost, QC = The cost associated with the additional QC required to certify the quality of individual options for individual product configuration

Table 17 shows a notional example of these costs. The options components are manufactured at various organizations (i.e., OEM, Supplier, or Dealer) and assembled at different locations (i.e., OEM or Dealer) to build the final automobile.

Table 17:Feature Options Cost Example

Product Configuration Options (i)	Manufactured at (Organization)	Assembled at (Organization)	Transport Cost ($) (TC)	Assembly Cost ($) (AC)	QC Cost ($) (QC)	Total Cost ($), τ_i = TC+AC+QC
Option1	OEM	OEM	$0	$125	$60	$185
Option2	OEM	Dealer	$100	$50	$25	$225
Option3	Supplier	OEM	$200	$75	$30	$305
Option4	Supplier	Dealer	$300	$100	$50	$450
Option5	Dealer	Dealer	$0	$30	$20	$50
Product Configuration Cost, PCcost = sum of (τ_i)						$1215

Equation 21: Options Cost Equation

$$\textit{Options Cost, } \tau_i = \textit{Transport Cost, TC} + \textit{Assembly Cost, AC} + \textit{QC Cost, QC}$$

Equation 22: Product Configuration Cost Equation (Cost Module)

$$\textit{Product Configuration Cost, PCCost} = \textit{sum of } (\tau_i)$$

The cost model presented in this study confines its analysis to specific components, including transport, assembly, and quality control costs associated with special product configuration orders. It is important to note that this model does not encompass other potential expenses such as tariffs, export-import duties, taxes, excise, or currency fluctuations. Notably, the unique nature of each product configuration poses a challenge in quality control sampling, warranting particular attention to the quality cost aspect.

4.6 Model Input, Process, and Output

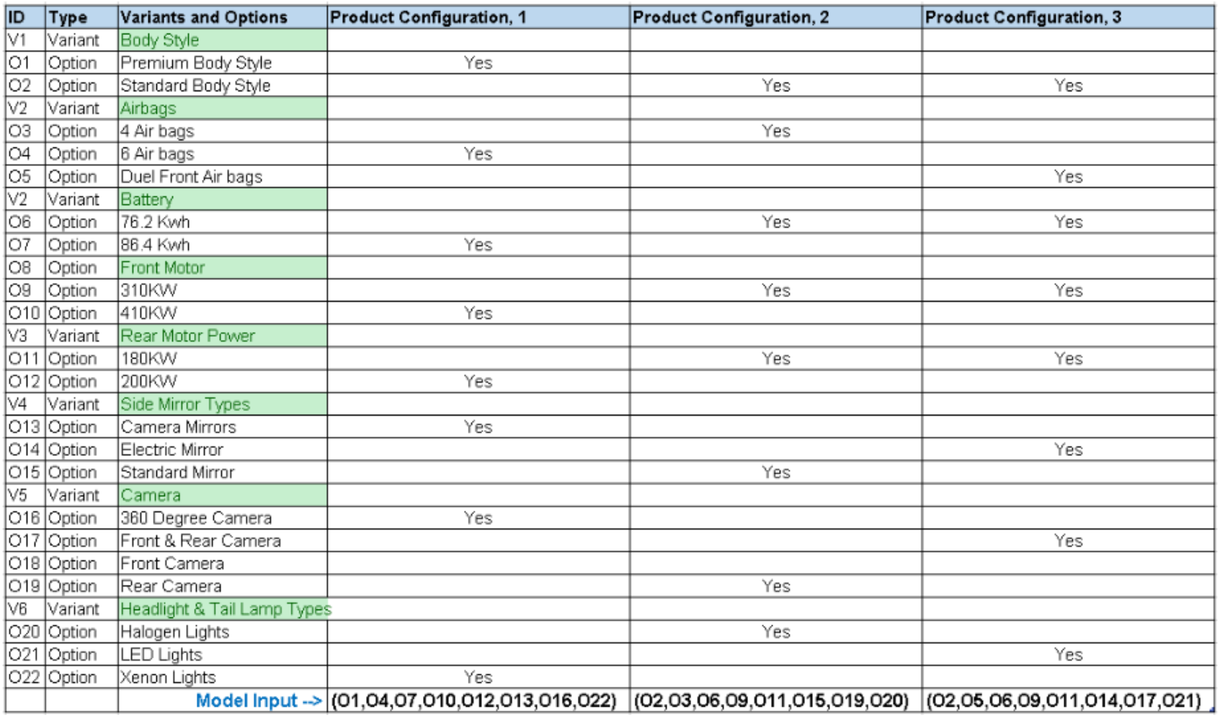
Input: This model takes input from the product configuration regarding the options list.

Equation 23: Model inputs

$$Model\ Input = [Feature\ Options\ List]$$

In Table 18, for example, three different Product configurations are created by selecting various options. Each configuration has a unique list of options. This list is defined with the options ID, which is used as input for the model.

Table 18: Model Input Example



ID	Type	Variants and Options	Product Configuration, 1	Product Configuration, 2	Product Configuration, 3
V1	Variant	Body Style			
O1	Option	Premium Body Style	Yes		
O2	Option	Standard Body Style		Yes	Yes
V2	Variant	Airbags			
O3	Option	4 Air bags		Yes	
O4	Option	6 Air bags	Yes		
O5	Option	Duel Front Air bags			Yes
V2	Variant	Battery			
O6	Option	76.2 Kwh		Yes	Yes
O7	Option	86.4 Kwh	Yes		
O8	Option	Front Motor			
O9	Option	310KW		Yes	Yes
O10	Option	410KW	Yes		
V3	Variant	Rear Motor Power			
O11	Option	180KW		Yes	Yes
O12	Option	200KW	Yes		
V4	Variant	Side Mirror Types			
O13	Option	Camera Mirrors	Yes		
O14	Option	Electric Mirror			Yes
O15	Option	Standard Mirror		Yes	
V5	Variant	Camera			
O16	Option	360 Degree Camera	Yes		
O17	Option	Front & Rear Camera			Yes
O18	Option	Front Camera			
O19	Option	Rear Camera		Yes	
V6	Variant	Headlight & Tail Lamp Types			
O20	Option	Halogen Lights		Yes	
O21	Option	LED Lights			Yes
O22	Option	Xenon Lights	Yes		
		Model Input -->	**(O1,O4,O7,O10,O12,O13,O16,O22)**	**(O2,O3,O6,O9,O11,O15,O19,O20)**	**(O2,O5,O6,O9,O11,O14,O17,O21)**

Process and Output: See Table 19

Table 19: Process and Modules and equations for the thesis model

Input	Measure	Module	Output	Interpretation
Product Configuration Options List	Structural Complexity, C	Structure Module = Equation 9	C is the Structural Complexity	A higher value indicates high complexity
			C_1 Complexity due to options alone	
			C_2 Complexity due to pair-wise options interactions	
			C_3 Complexity due to the topological formation of the product configuration	Referring to Figure 25, increasing topological complexity increases system integration efforts.

	Organizational Complexity, C_o	Organization Module = Equation 17	C_o is Organizational Complexity,	A higher value indicates high complexity
			C_{2G}*C_{3G} interface complexity at the group (G) level	A higher value indicates higher integration efforts within the organization
			C_{2O}*C_{3O} the complexity at the organizational (O) level	A higher value indicates higher integration efforts between organizations
	Overall Complexity, *PCC*	*PCC* = *C* + C_o	Product Configuration Complexity (PCC)	A higher value indicates higher overall complexity
	Product Configuration Cost, PC_{COST}	Cost Module = Equation 22	Product Configuration Cost in $	The cost involved in building the Product Configuration. Helpful in comparison between two Product Configurations.

4.7 Model Formulation

Equation 24: Model formulation

$$Input = [Options\ List] \rightarrow \begin{bmatrix} Structure\ Module \\ Organization\ Module \\ Cost\ Module \end{bmatrix} = Outout = \begin{bmatrix} Structural\ Complexity, SC \\ Oragnziational\ Complexity, OC \\ Porduct\ Configuration\ Complexity, PCC \\ Product\ Configuration\ Cost, PCcost \end{bmatrix}$$

Refer to chapters 4.2, 4.3, 4.4, and 4.5 for details about the structure, organization, and cost modules.

Equation 25: Thesis Model Equation

$$Input = \begin{bmatrix} O1 \\ O2 \\ Ox \\ On \end{bmatrix} = \begin{bmatrix} C = C_1 * C_2 * C_3 \\ C_O = C_{2G} * C_{3G} + C_{2O} * C_{3O} \\ PCcost = \text{sum of } (\boldsymbol{\tau}\mathbf{i}) \end{bmatrix} = \begin{bmatrix} Structural\ Complexity, SC \\ Oragnziational\ Complexity, OC \\ Porduct\ Configuration\ Complexity, PCC \\ Product\ Configuration\ Cost, PCcost \end{bmatrix}$$

Where, O_1,O_2,Ox..,O_n is the list options choices for the product configurations

C = Structural Complexity
C_O= Organizational Complexity
C_1 = Complexity due to options alone
C_2 = Complexity due to pair-wise options interactions
C_3 = Complexity due to the topological formation of the product configuration
$C_{2G}*C_{3G}$ = interface complexity at the group (G) level
$C_{2O}*C_{3O}$ = the complexity at the organizational (O) level

4.8 Model Application

The hybrid model integrates structural and organizational complexities, and the cost model offers valuable insights and practical applications for OEMs in managing product configuration complexity. Here is how the model can be applied:

1) **Cost Estimation:** The model could enable OEMs to estimate the total cost associated with different product configurations. By considering transport costs, assembly costs, and quality control costs for individual feature options, the model can be used to review the financial implications of each configuration. This allows OEMs to make informed pricing, profitability, and resource allocation decisions.

2) **Optimization of Organizational Interactions:** The organizational complexity component of the model focuses on the interactions between OEMs, suppliers, and dealers. The model can highlight areas where organizational interactions can be optimized for efficiency and cost-effectiveness by analyzing interface complexity at the group and organizational levels. For example, identifying opportunities to streamline supply chains, reduce lead times, or consolidate assembly processes helps with optimal profitability and operational performance.

3) **Complexity Management:** With insights from the structural and organizational

complexity metrics, OEMs can effectively develop strategies to manage and mitigate product configuration complexity. By identifying components or interactions that contribute disproportionately to complexity, OEMs could explore alternative design options, standardize processes, or simplify assembly procedures to reduce overall complexity. This proactive approach helps minimize production bottlenecks, enhance product quality, and improve customer satisfaction.

4) **Scenario Analysis and Decision Support:** The model facilitates scenario analysis by allowing OEMs to simulate different product configurations and evaluate their impact on cost, complexity, and operational efficiency. By exploring various "what-if" scenarios, OEMs could assess the trade-offs between complexity and cost, identify optimal configurations, and make data-driven decisions to maximize profitability and competitiveness in the market.

5) **Continuous Improvement:** The model is valuable for continuously improving and optimizing product configuration processes. By monitoring key metrics such as structural complexity, organizational interactions, and product configuration costs over time, OEMs can identify trends, patterns, and areas for improvement. This iterative approach enables OEMs to adapt to changing market conditions, customer preferences, and technological advancements while maintaining competitiveness and profitability.

Overall, the application of the hybrid model and cost model provides OEMs with actionable insights and decision support tools to effectively manage product configuration complexity, optimize organizational interactions, and drive continuous improvement in product development and manufacturing processes. By leveraging these insights, OEMs can enhance operational efficiency, reduce costs, and deliver high-quality products that meet customer expectations and market demands.

4.9 Model Risks and Uncertainties

1) **Data accuracy:** This model is developed using an academic understanding of many factors related to vehicle product configurations. The actual data must be validated before implementing this model. This model does not consider the risks and uncertainties associated with the product configurations.

2) **Data coverage:** Many options are composed of sub-assemblies or sub-components. For example, the Steering Assembly consists of many sub-components. The complexity within such options is not considered for this model. However, using the (Sinha and de Weck 2013) method, the complexity of such options can be calculated for the precise measure.

3) **Insufficient Interactions:** This model does not consider the operational interactions on the product line. Many interfaces and interactions with the tooling, fixtures, V&V, and sourcing are involved in integrating a feature option into the vehicle design. This model does not cover all the interactions to calculate the interface complexity.

4) **Model Complexity:** The complexity of the hybrid model integrating structural and organizational complexities could lead to challenges in implementation and understanding. There is a risk that the model may become too intricate for practical use

within existing Product Configuration Management tools, potentially requiring extensive training or specialized expertise to operate effectively.

5) **Validity of Complexity Metrics:** While the selected complexity metrics have been chosen based on their applicability and mathematical formulations, there is a risk that they may not fully capture all aspects of product configuration complexity. Specific nuances or dimensions of complexity may be overlooked or underestimated, leading to biased results and incomplete assessments.

6) **Subjectivity is Complexity Assessment:** Assigning complexity ratings to individual feature options involves subjective judgment, as reflected in the scale from 1 to 5 (Chapter 4.2.1). This subjectivity introduces uncertainties regarding the consistency and accuracy of complexity assessments, especially when different individuals or teams are involved in rating options across various domains.

7) **Data Availability and Quality:** The accuracy and reliability of the model output depend heavily on the availability and quality of input data, particularly regarding transport costs, assembly costs, and quality control costs associated with individual feature options. Incomplete or inaccurate data could lead to biased cost estimations and misinformed decision-making.

8) **Complexity in the Cost Model:** The cost model considers multiple factors, including transport costs, assembly costs, and quality control costs. However, overlooking other potential expenses, such as tariffs, taxes, or currency fluctuations, could significantly impact the overall cost estimation analysis.

9) **Implementation Challenges:** Integrating the model into existing Product Configuration Management tools, like PLM, may pose implementation challenges, including compatibility issues, data integration complexities, and user interface design considerations. Ensuring seamless integration and user adoption may require additional resources and expertise.

10) **Model Output Interpretation:** While the model outputs provide valuable insights into product configuration complexity and associated costs, there is a risk of misinterpreting or misusing the results. Users may struggle to accurately interpret the implications of complexity metrics and cost estimations, leading to suboptimal decision-making or inefficient resource allocation.

Chapter 5: Research Methodology

Until now, the thesis has introduced the topic and its significance, discussed the motivation behind this research, and proposed key thesis questions with the hypothesis in (Chapter 1.) In (Chapter 2) fundamental concepts related to the research are defined, such as "What is a Product?" and "What is Product Configuration?" Examine the complexity involved in product configuration, including rule-based configuration. In (Chapter 3), existing literature on methods used to manage product configurations and various types of complexities associated with product configurations, such as design, structural, manufacturing, supply chain, and functional complexities, are being reviewed. The literature review also explored different methods to measure product configuration complexity and compare complexity metrics.

This chapter briefly overviews the research methodology employed to investigate product configuration complexity. The study aims to advance understanding in this critical product development and management area by integrating diverse research approaches and analytical techniques.

5.1 Modeling Approach

The literature review in (Chapter 3: Literature Review, has provided a foundation and necessary information about the type of complexities associated with the product configuration, different methods to measure those complexities, and a variety of research that employ those methods and metrics that will be used to build a model that could measure the product configuration complexity. In (Chapter 4), a careful analysis has been performed to select complexity metrics for the analysis. The most suitable complexity (Structural and Organizational Complexity) is chosen to measure the product configuration complexities. Two metrics are based on two methodologies from research papers: 1) (Sinha and de Weck 2013) and (Felix Stracke, Rebentisch, and Mattern 2016), which are adopted to measure the product configuration complexities. The cost model is built upon the representative cost data in product configuration design, manufacturing, quality control, and transport. The new hybrid model has specific model inputs that can be gathered from the commercially used product configuration data curated for this thesis (see Chapter 5.2). The model formulation, process, outputs in terms of complexity metric, and the cost measure have been defined in (Chapter 4). There are various applications, associated risks, and uncertainties with this hybrid model being discussed in (Chapter 5.)

The goal of developing a product configuration complexity measurement model for this thesis is to be able to use the commercial product configuration data. For that, the model considers the practical approach and sees various complexity metrics and their use in using commercial data. The following section explains the details of the research data used in this thesis.

5.2 Research Data

5.2.1 Product Configuration Data

A commercial-level data set of car product structure, variant features, and options are used to test the thesis model. Partial data came from the (Dassault Systèmes 2022), where the sample electric car models and their configuration are created for commercial demonstration purposes. This data could produce 477 million different product configurations. There are 18 configuration rules used to establish design, manufacturing, and marketing constraints. These configuration rules are practically used in the industry. After applying these rules, the size of the valid product configurations is reduced to just 1320. It helps them to focus on the representative dataset and contains perpetual growth of product configuration data. Table 20 shows the details of the data used to test this model.

Table 20: Thesis test dataset

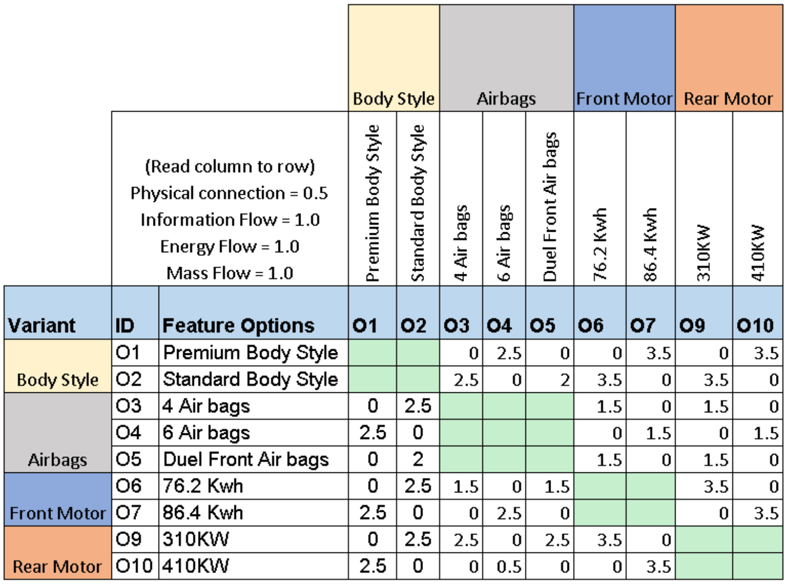
Description	Size (numbers)
Total 150% BOM Size	19752
Total Electric Car Models	8
Total Variant Features	21
Total Feature Options	60
Configuration Rules	18
Total Product Configurations	1320
Suppliers manufactured options	12
OEM manufactured options	9
Total Suppliers	17
Total Dealers	1
OEM Locations	1

1) Options Individual Complexity, C_1 – Each feature option is assigned a complexity on a scale of 1 to 5 (5 being the most complex), using the method defined in 4.2.1 C1 (α coefficient), complexity due to the options alone.

2) Options Interface Complexity, C_2 – This is an options interactions complexity, defined using the method discussed in (Chapter 4.2.) Using the DSM, all the 60 feature options have assigned interface weightage. The weights shown in Table 21, for the interfaces are representative created explicitly for the thesis using the commercial data, and a more sophisticated method can be used to capture accurate interface complexity (Sinha and

de Weck 2013) method.

Table 21:Example of interface complexity weightage assigned to the options pair.



			Body Style		Airbags			Front Motor		Rear Motor	
		(Read column to row) Physical connection = 0.5 Information Flow = 1.0 Energy Flow = 1.0 Mass Flow = 1.0	Premium Body Style	Standard Body Style	4 Air bags	6 Air bags	Duel Front Air bags	76.2 Kwh	86.4 Kwh	310KW	410KW
Variant	**ID**	**Feature Options**	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**	**O7**	**O9**	**O10**
Body Style	O1	Premium Body Style			0	2.5	0	0	3.5	0	3.5
	O2	Standard Body Style			2.5	0	2	3.5	0	3.5	0
Airbags	O3	4 Air bags	0	2.5				1.5	0	1.5	0
	O4	6 Air bags	2.5	0				0	1.5	0	1.5
	O5	Duel Front Air bags	0	2				1.5	0	1.5	0
Front Motor	O6	76.2 Kwh	0	2.5	1.5	0	1.5			3.5	0
	O7	86.4 Kwh	2.5	0	0	2.5	0			0	3.5
Rear Motor	O9	310KW	0	2.5	2.5	0	2.5	3.5	0		
	O10	410KW	2.5	0	0	0.5	0	0	3.5		

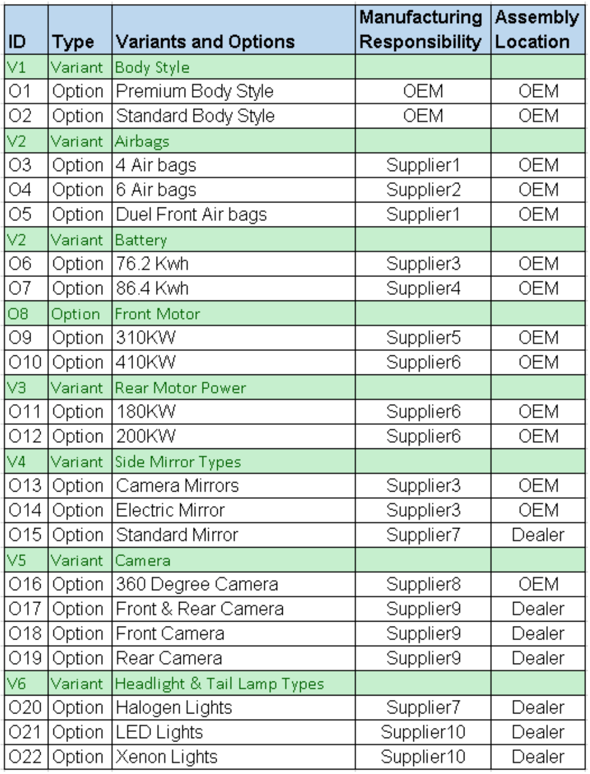
Assumptions: A couple of configuration rules are considered here when assigning interface weightage. For example, Table 21 shows zero interfaces between the Standard Body Style and the ‘6 Airbags’ option. The configuration rule defines that the ‘6 Airbags’ option is not available for the Standard trim. Hence, there will not be any interface between them. On the other hand, the ‘6 Airbags’ option is available with the Premium trim, and it carries 2.5 weight. These weights are assigned arbitrarily to demonstrate that the different options under the same feature may have different interface complexity from other options.

3) Options Topological Complexity, C3 – This is a topological complexity of the options, defined using the method discussed in (Chapter 4.2.3.) The tool (“Real Statistics Resource Pack | Real Statistics Using Excel” 2024) calculates the SVD.

5.2.2 Organizational data for the Product Configurations

Notional data for the organizational complexity analysis was generated by the author based on his experience working with OEMs in the auto industry. The data assigns a manufacturing responsibility to each feature option, assuming each option is manufactured and/or assembled by OEM, supplier, or dealer. Each option has a location of assembly associated with it. An example is shown in the Table 22:

Table 22: Manufacturing Responsibility and Assembly Location of the Feature Options



ID	Type	Variants and Options	Manufacturing Responsibility	Assembly Location
V1	Variant	Body Style		
O1	Option	Premium Body Style	OEM	OEM
O2	Option	Standard Body Style	OEM	OEM
V2	Variant	Airbags		
O3	Option	4 Air bags	Supplier1	OEM
O4	Option	6 Air bags	Supplier2	OEM
O5	Option	Duel Front Air bags	Supplier1	OEM
V2	Variant	Battery		
O6	Option	76.2 Kwh	Supplier3	OEM
O7	Option	86.4 Kwh	Supplier4	OEM
O8	Option	Front Motor		
O9	Option	310KW	Supplier5	OEM
O10	Option	410KW	Supplier6	OEM
V3	Variant	Rear Motor Power		
O11	Option	180KW	Supplier6	OEM
O12	Option	200KW	Supplier6	OEM
V4	Variant	Side Mirror Types		
O13	Option	Camera Mirrors	Supplier3	OEM
O14	Option	Electric Mirror	Supplier3	OEM
O15	Option	Standard Mirror	Supplier7	Dealer
V5	Variant	Camera		
O16	Option	360 Degree Camera	Supplier8	OEM
O17	Option	Front & Rear Camera	Supplier9	Dealer
O18	Option	Front Camera	Supplier9	Dealer
O19	Option	Rear Camera	Supplier9	Dealer
V6	Variant	Headlight & Tail Lamp Types		
O20	Option	Halogen Lights	Supplier7	Dealer
O21	Option	LED Lights	Supplier10	Dealer
O22	Option	Xenon Lights	Supplier10	Dealer

To mimic real-world scenarios, options are assigned with all possible combinations of manufacturing responsibility and assembly locations. These details are created assuming the components are made at one of the organizations, OEM, Supplier, or Dealer, and assembled at OEM or Dealer locations.

1) Each organization (OEM, Supplier, and Dealer) has been assigned a value of $S_{ij,}$ and $C_{ij,}$ for each option.

5.3 Analysis Strategy

This model analysis involves checking various scenarios for their usability. Four scenarios are used for the validation, chosen from the practical point of view, shown in Figure 30. The model provides meaningful insights about the product configurations using these scenarios.

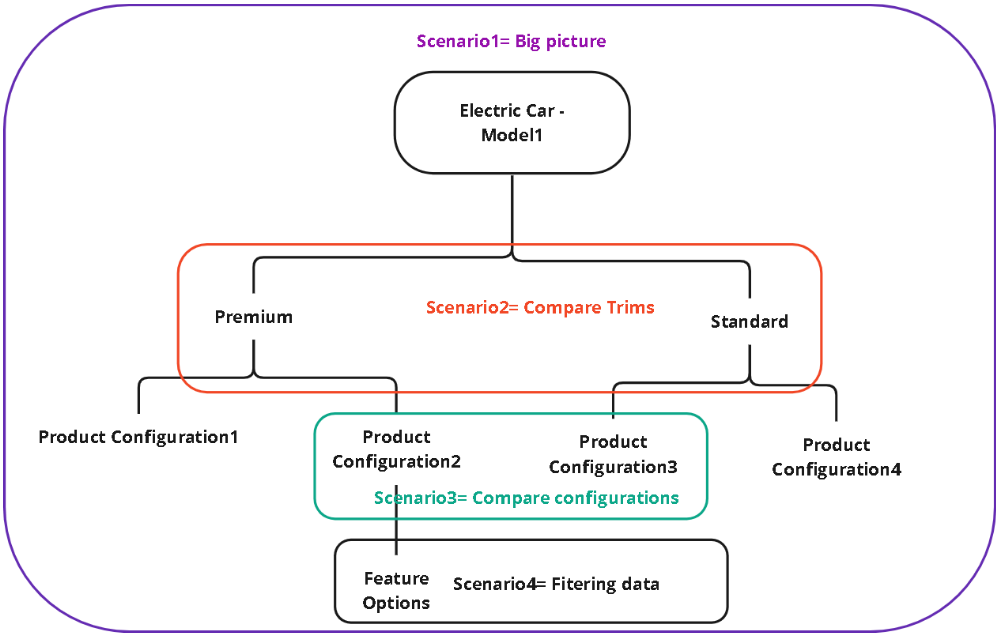


Figure 30: Model validation scenarios

Scenario 1: This scenario provides a holistic view of the complexity and cost distribution across all valid product configurations for an electric car model. Plotting structural and organizational complexities along with associated costs reveals the overall landscape of product configurations. The distinct clustering formation highlights the correlation between higher complexity and increased costs. This scenario is crucial as it helps identify patterns and outliers, facilitating strategic decision-making for managing and optimizing product configurations on a broad scale.

Scenario 2: This scenario focuses on comparing the cost and complexity between different trims of the same model. Zooming in on trim-specific details provides insights into the complexity and cost variations within a single model. The data shows how different trims, such as Standard and Premium, cluster together, with Premium trims typically being more complex and expensive. This scenario is important because it allows the thesis to evaluate the trade-offs between different trims, aiding in the selection of trims that balance customer preferences with manufacturing feasibility and cost-effectiveness.

Scenario 3: In this scenario, individual product configurations are compared, particularly useful for designers, manufacturing engineers, and factory planners. Examining specific configurations helps identify which configurations are more complex and costly. This targeted comparison can guide engineers in focusing their efforts on optimizing specific trims or configurations, enhancing design efficiency, and reducing unnecessary complexity.

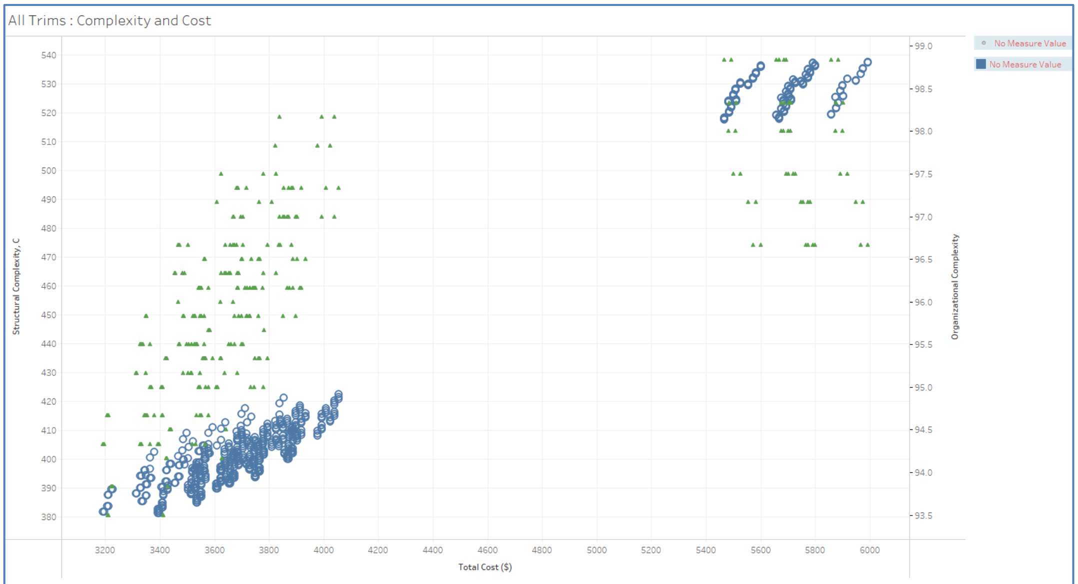
Scenario 4: This scenario explores the effects of removing specific feature options on product configurations' overall complexity and cost. It explores how simplifying configurations might reduce structural and organizational complexity and associated costs. This scenario is essential for the thesis to see if it can provide insights to balance feature offerings with cost efficiency, helping engineers make informed choices about which features to retain or eliminate to optimize product configurations.

Each scenario contributes to the thesis by demonstrating practical applications of the complexity model, providing empirical evidence to support decision-making in product design, manufacturing, and strategic planning within the automotive industry. A tool (“Business Intelligence and Analytics Software | Tableau” 2024) has been used to plot the graphs in (Chapter 6).

Chapter 6: Model Results

6.1 Scenario 1: Big Picture of All the Configurations' Complexity

In this scenario, all the valid product configurations for the electric car model are plotted with their respective structural and organizational complexities and the associated costs. This scenario gives a bigger picture of how a particular model's complexities and costs are distributed. Figure 31 shows a distinct clustering formation for structural and organizational complexities in this hypothetical situation. It also indicates that the higher the complexity, the higher its costs. A structural and organizational complexity has been calculated for all the 1320 product configurations, along with its associated cost. This dataset is then placed in a tradespace graph to see the complete picture. Cost on X-axis Vs Complexities on Y- axis, gives a complete tradespace of all the configurations in all the trims



Total Cost ($) vs. Structural Complexity, C and Organizational Complexity. For pane Structural Complexity, C: Color shows details about Measure Names. For pane Organizational Complexity: Size shows details about Measure Names. The data is filtered on Rear Seat Folding, Roof Types, Body Style, Market Location, Infotainment System, Steering Wheel Type and ID. The Rear Seat Folding filter keeps 60-40 Split Fold, Full Seat Fold and One By One Fold. The Roof Types filter keeps Carbon Fiber, Panoramic Roof, Sliding Sun Roof and Standard Roof (Hardtops). The Body Style filter keeps Premium Body Style and Standard Body Style. The Market Location filter keeps Africa, Asia Pacific, Europe, North America and United Kingdom. The Infotainment System filter keeps Advanced, Medium and Standard. The Steering Wheel Type filter keeps 3-spokes flat-bottom multi-function, 3-Spokes Multi-Function Leather and 4-Spokes. The ID filter keeps 1,320 of 1,320 members.

Figure 31: All Trims: Complexity Vs Cost

6.2 Scenario 2: Comparing Two or More Trims

This scenario compares two trims for their cost and complexity. This data can further zoom in to see trim-specific complexity and cost distribution. In this validation, two trims from the same model are compared; refer to Figure 32. All the valid product configurations for these trims are selected for comparison.

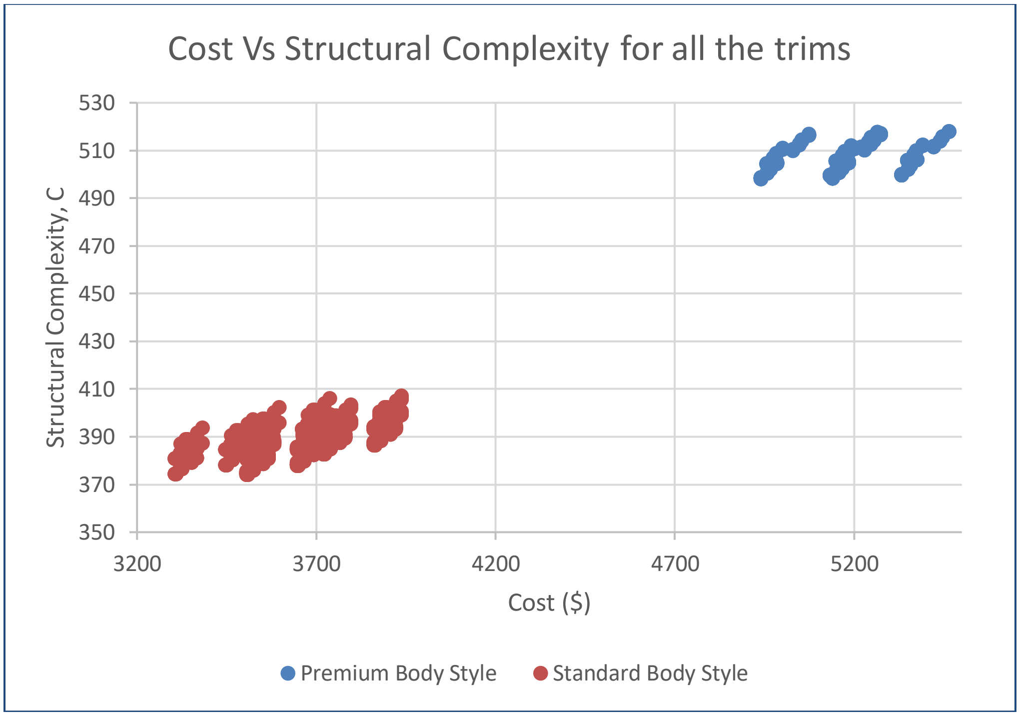
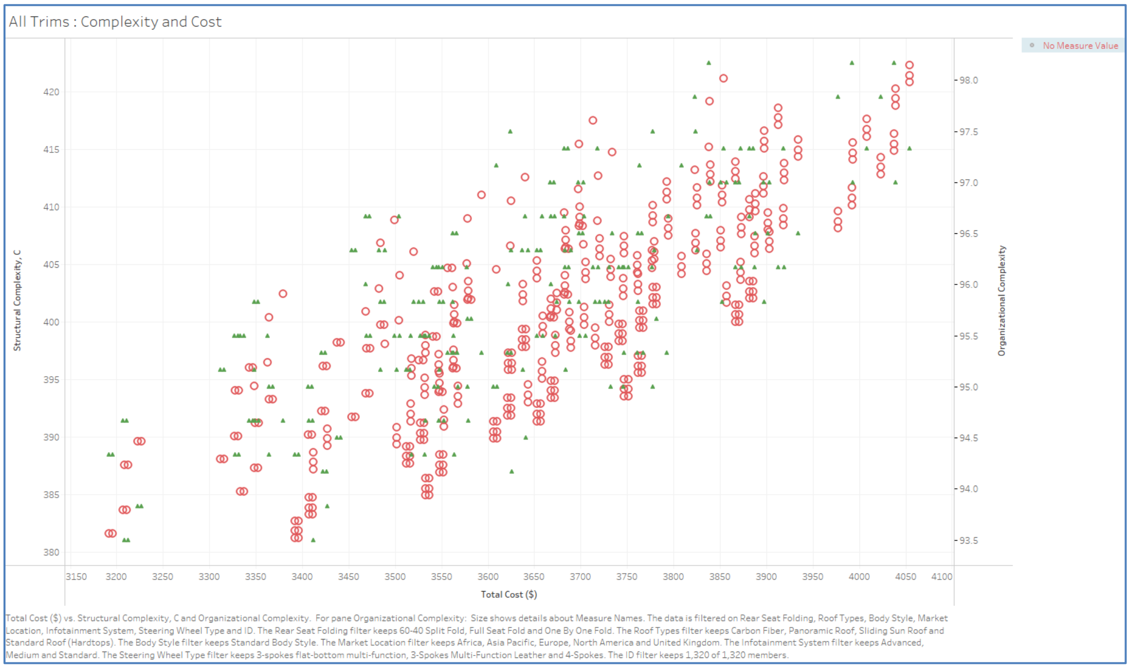


Figure 32: Cost vs. Structural Complexity, based on the trim

Figure 32 shows a cluster formation of two different trims. All the product configurations with Standard or Premium trim are clustered together. The Premium Body style is more complex and costlier than the Standard Body style trim.



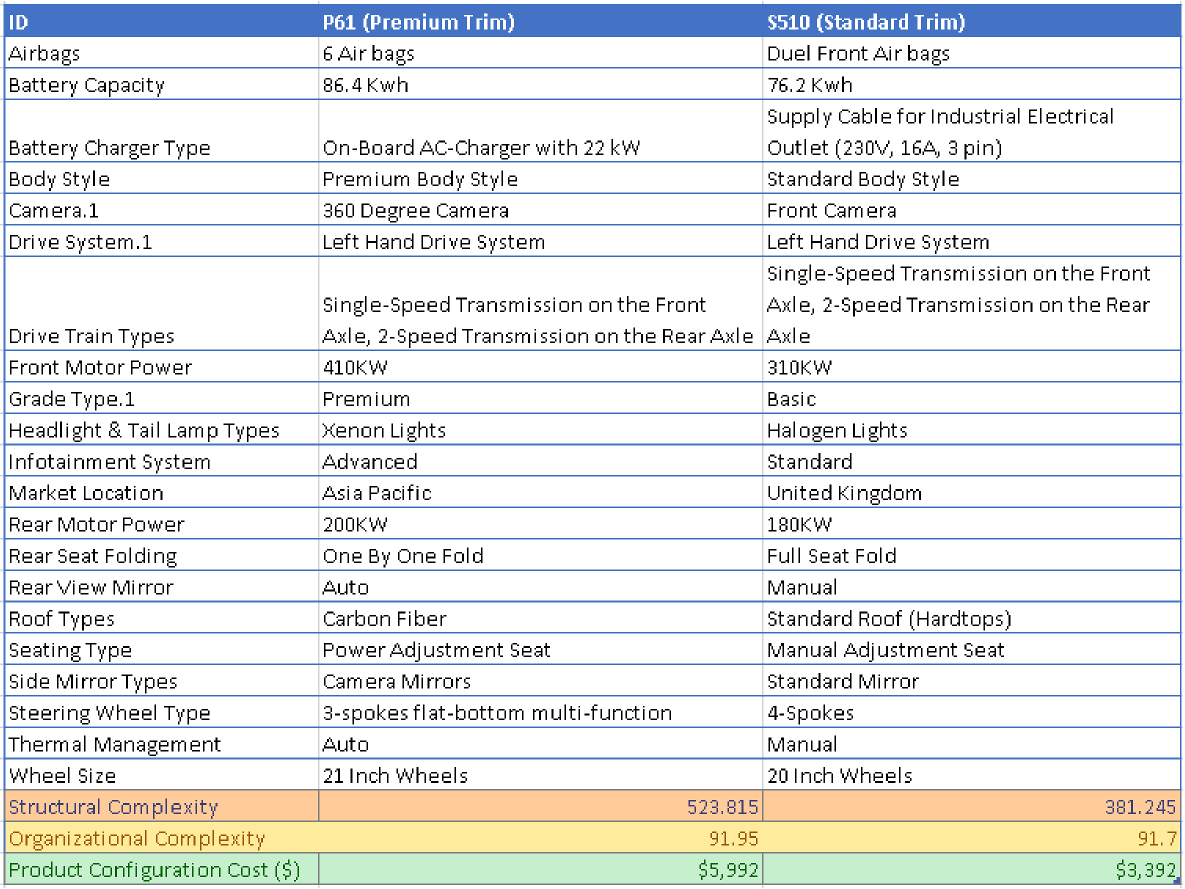
Total Cost ($) vs. Structural Complexity, C and Organizational Complexity. For pane Organizational Complexity: Size shows details about Measure Names. The data is filtered on Rear Seat Folding, Roof Types, Body Style, Market Location, Infotainment System, Steering Wheel Type and ID. The Rear Seat Folding filter keeps 60-40 Split Fold, Full Seat Fold and One By One Fold. The Roof Types filter keeps Carbon Fiber, Panoramic Roof, Sliding Sun Roof and Standard Roof (Hardtops). The Body Style filter keeps Standard Body Style. The Market Location filter keeps Africa, Asia Pacific, Europe, North America and United Kingdom. The Infotainment System filter keeps Advanced, Medium and Standard. The Steering Wheel Type filter keeps 3-spokes flat-bottom multi-function, 3-Spokes Multi-Function Leather and 4-Spokes. The ID filter keeps 1,320 of 1,320 members.

Figure 33: Standard Trim all configurations (Cost vs. Complexity)

In a similar view, in Figure 33, Standard trim-specific details are observed for all its valid product configurations.

6.3 Scenario 3: Comparing Two or More Product Configurations

This is especially useful and often used by designers, manufacturer engineers, and factory planners to compare two different configurations. In the example, Figure 34 shows the comparison of two product configurations. They both belong to different trims. The complexity and the cost indicator might help engineers focus on the specific trims for optimizations.

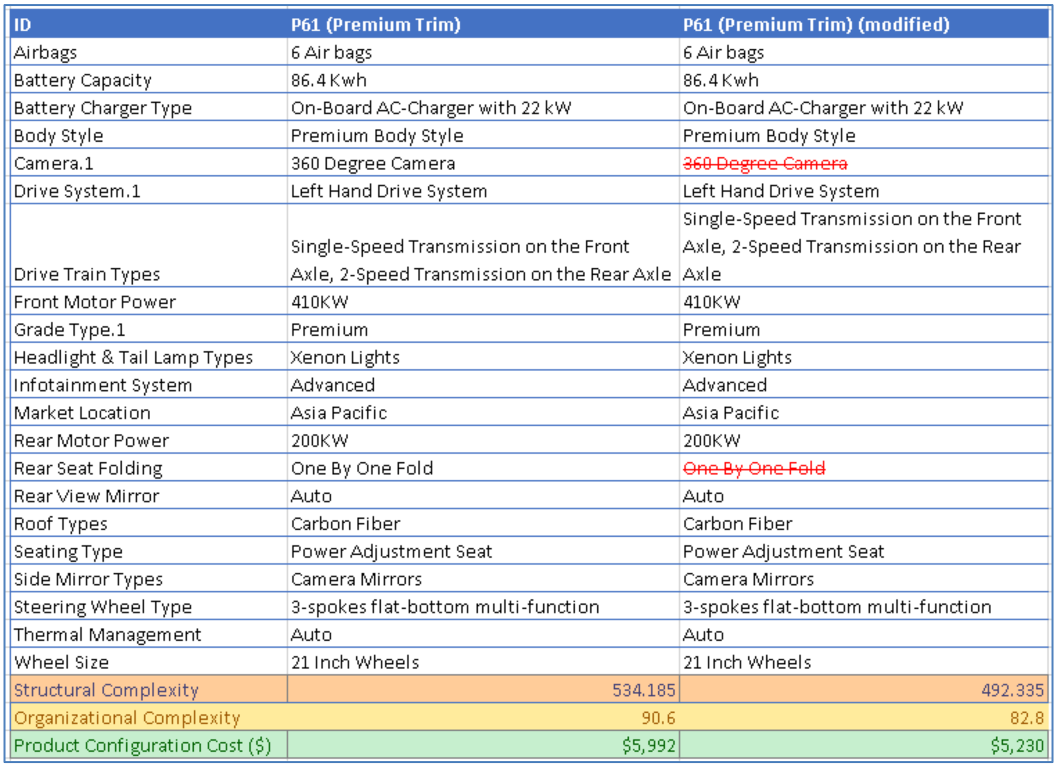


ID	P61 (Premium Trim)	S510 (Standard Trim)
Airbags	6 Air bags	Duel Front Air bags
Battery Capacity	86.4 Kwh	76.2 Kwh
Battery Charger Type	On-Board AC-Charger with 22 kW	Supply Cable for Industrial Electrical Outlet (230V, 16A, 3 pin)
Body Style	Premium Body Style	Standard Body Style
Camera.1	360 Degree Camera	Front Camera
Drive System.1	Left Hand Drive System	Left Hand Drive System
Drive Train Types	Single-Speed Transmission on the Front Axle, 2-Speed Transmission on the Rear Axle	Single-Speed Transmission on the Front Axle, 2-Speed Transmission on the Rear Axle
Front Motor Power	410KW	310KW
Grade Type.1	Premium	Basic
Headlight & Tail Lamp Types	Xenon Lights	Halogen Lights
Infotainment System	Advanced	Standard
Market Location	Asia Pacific	United Kingdom
Rear Motor Power	200KW	180KW
Rear Seat Folding	One By One Fold	Full Seat Fold
Rear View Mirror	Auto	Manual
Roof Types	Carbon Fiber	Standard Roof (Hardtops)
Seating Type	Power Adjustment Seat	Manual Adjustment Seat
Side Mirror Types	Camera Mirrors	Standard Mirror
Steering Wheel Type	3-spokes flat-bottom multi-function	4-Spokes
Thermal Management	Auto	Manual
Wheel Size	21 Inch Wheels	20 Inch Wheels
Structural Complexity	523.815	381.245
Organizational Complexity	91.95	91.7
Product Configuration Cost ($)	$5,992	$3,392

Figure 34: Comparison of two product configurations

6.4 Scenario 4: Impact of Product Configuration Alteration

This scenario allows us to validate the impact of removing an individual or set of feature options on the overall complexity and cost of the product configuration. In this scenario, two feature options, “360 Degree Camera” and “One by one Fold – Rear Seat Folding,” are removed form the product configuration to see the impact on the complexities and the cost. Table 23 shows a significant decrease in structural and organizational complexity; proportionately, the cost is also reduced.



ID	P61 (Premium Trim)	P61 (Premium Trim) (modified)
Airbags	6 Air bags	6 Air bags
Battery Capacity	86.4 Kwh	86.4 Kwh
Battery Charger Type	On-Board AC-Charger with 22 kW	On-Board AC-Charger with 22 kW
Body Style	Premium Body Style	Premium Body Style
Camera.1	360 Degree Camera	~~360 Degree Camera~~
Drive System.1	Left Hand Drive System	Left Hand Drive System
Drive Train Types	Single-Speed Transmission on the Front Axle, 2-Speed Transmission on the Rear Axle	Single-Speed Transmission on the Front Axle, 2-Speed Transmission on the Rear Axle
Front Motor Power	410KW	410KW
Grade Type.1	Premium	Premium
Headlight & Tail Lamp Types	Xenon Lights	Xenon Lights
Infotainment System	Advanced	Advanced
Market Location	Asia Pacific	Asia Pacific
Rear Motor Power	200KW	200KW
Rear Seat Folding	One By One Fold	~~One By One Fold~~
Rear View Mirror	Auto	Auto
Roof Types	Carbon Fiber	Carbon Fiber
Seating Type	Power Adjustment Seat	Power Adjustment Seat
Side Mirror Types	Camera Mirrors	Camera Mirrors
Steering Wheel Type	3-spokes flat-bottom multi-function	3-spokes flat-bottom multi-function
Thermal Management	Auto	Auto
Wheel Size	21 Inch Wheels	21 Inch Wheels
Structural Complexity	534.185	492.335
Organizational Complexity	90.6	82.8
Product Configuration Cost ($)	$5,992	$5,230

Table 23: Feature options impact on the cost and complexity measured by the model

This model worked with the representative real data and provided meaningful insights into the product configuration complexity and associated cost.

Chapter 7: Discussions

The data built for this thesis mimic the real-world data in size, structural, and organizational interactions. It does have a comprehensive and representative set of product configurations. We have seen the real-world example of the Ford-150 truck in Figure 11, which shows that real data does have over 100 options to choose from and can generate millions of product configurations. The data built for this thesis have over sixty options, which can create over 477 million different product configurations. This goes close to the empirical data to provide valid inputs to the complexity model developed by the thesis.

Utilizing sample data that closely resembles real-world automobile configurations offers numerous benefits within the context of the thesis. Firstly, it provides a practical foundation for validating the proposed model and methodologies. By analyzing data that reflects actual product configurations, the thesis can ensure the accuracy and reliability of their findings, thus enhancing the credibility of the thesis outcomes. Additionally, working with realistic sample data allows for a more comprehensive understanding of the complexities inherent in automotive configurations, enabling the thesis to identify key patterns, trends, comparisons, and challenges in the product configurations. Moreover, leveraging sample data that mimics real-world scenarios enables this thesis to derive actionable insights that can directly inform decision-making processes for automotive manufacturers, leading to improved product design, manufacturing efficiency, and overall operational performance.

The thesis data is comparable with the real-world data. However, using the real-world data with this model will further enhance and validate the usefulness of this hybrid complexity.

7.1 Limitations

1) This sample data uses a simplified organizational assignment to each option for the organizational complexity and does not consider multi-level and multi-organizational involvement of manufacturing feature option components. In the real world, sourcing, logistics, and inventory have complex organizational and geo-social structures. Many components can have more than one manufacturing responsibility and assembly location.

2) One limitation of the cost model employed in the thesis framework is its reliance on simplified cost structures and assumptions. While the model aims to estimate the costs associated with product configurations, it may not fully capture cost elements of a nuanced and dynamic nature across the entire product lifecycle. For instance, the model may overlook indirect costs, such as logistics, inventory, R&D investments, marketing expenses, or long-term warranty obligations, which can significantly impact the overall cost dynamics. Additionally, the model's cost estimations may be based on generalized assumptions rather than precise data points, potentially leading to inaccuracies in cost projections. As a result, the cost model's outputs should be interpreted cautiously, acknowledging the inherent limitations in its ability to provide comprehensive and precise cost assessments for automotive product configurations.

3) Additionally, conducting sensitivity analysis by varying input parameters and evaluating the model's response can help assess its robustness and identify potential areas for

improvement. Collaborating with industry experts, stakeholders, and end-users to gather feedback and insights on the model's performance and usability is also crucial for validation. By validating the model against diverse datasets and scenarios, OEMs can ensure that it accurately represents the complexities of product configuration processes and provides valuable insights for decision-making and optimization.

7.2 Observations from the model and analysis

1) Individual Options Complexity, C_1: Individual C_1 options complexity might help identify the design and manufacturing intricacies. This thesis considers each feature option as a component; however, each option is a system. This thesis model can measure the structural and organizational complexity of the option as a system. Hence, the interaction within each feature option can also provide meaningful insights and accurate input into the product configuration complexity model.

   Figure 35 shows how this might work. The individual seat option has its own structural and organizational complexity. This model can measure the seat option complexity, which feeds into the Product Configuration Complexity as individual option complexity.

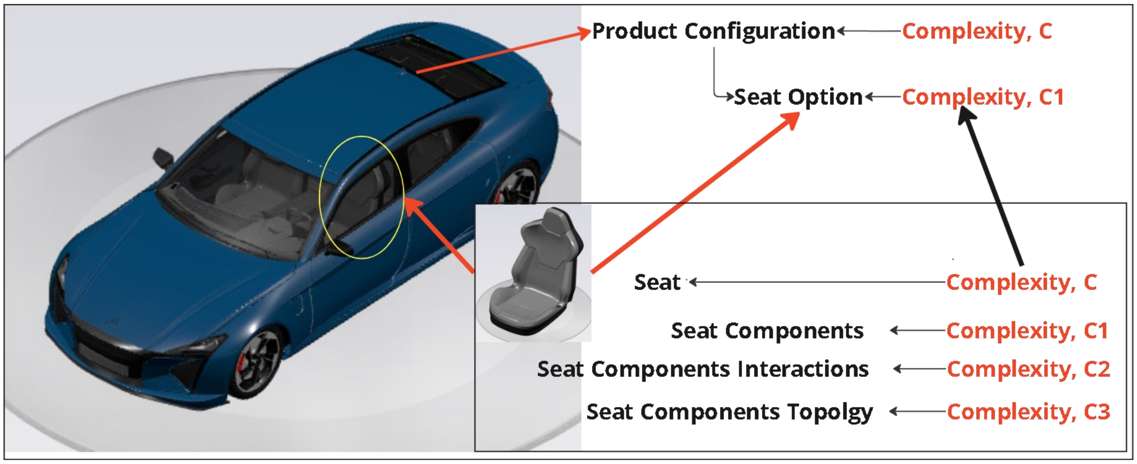
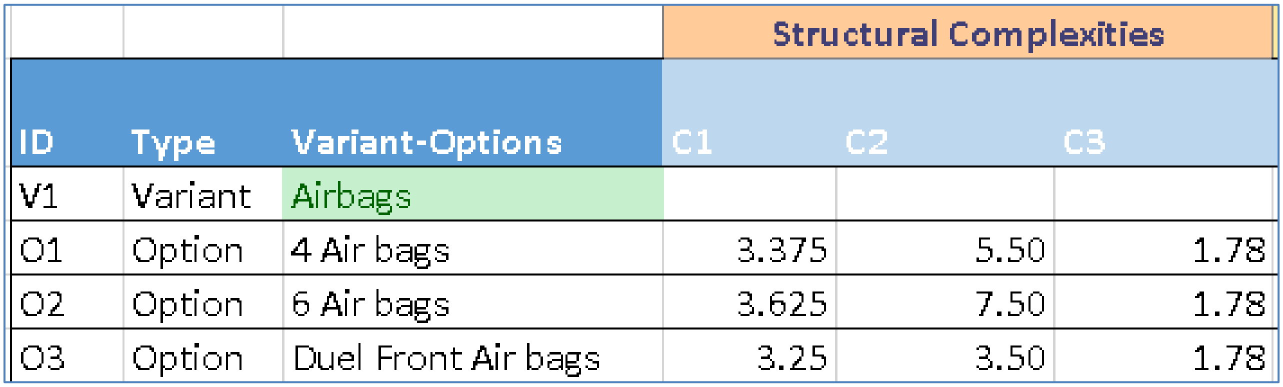


Figure 35: Options-specific complexity feeds into Product Configuration Complexity

Understanding the intricacies of individual feature options is crucial for engineering decision-making. This information can guide engineers in optimizing the design, improving manufacturing processes, and streamlining operations to enhance overall product configurability and performance.

2) Topological Complexity, C_3: When comparing two product configurations from the same model or trim, the topological complexity value for structural and organizational complexities came out the same. The reason is, for C_3 calculations it unitizes the interface complexity. For example, Table 24 shows that the 6 Airbags option has more interfaces than the 2 Airbags option, and both will have the same unitization value of 1. The SVD calculation for both options will always be the same. The C_3 will differ when there are unequal options from the same trim or different features from different car models.

Table 24: Same topological complexity across all the options



			Structural Complexities		
ID	Type	Variant-Options	C1	C2	C3
V1	Variant	Airbags			
O1	Option	4 Air bags	3.375	5.50	1.78
O2	Option	6 Air bags	3.625	7.50	1.78
O3	Option	Duel Front Air bags	3.25	3.50	1.78

The consistent topological complexity across different car configurations highlights the importance of interface management in engineering decisions. Understanding these nuances helps engineers identify critical interface points and optimize design strategies accordingly.

3) Cost Model: The thesis model utilizes a cost from limited domains. Many domains, like R&D, logistics, inventory, and sales, greatly influence the cost of the option offered. Many product lifecycle management tools provide an accurate cost of the component from R&D, manufacturing, operations, sourcing, inventory, sales, and marketing. Plugging that cost into the thesis model will give more accurate results to support the decision-making.

4) Key Commercial Decisions: OEM often has to decide on the commercial success of introducing any vehicle feature. It is essential to see if the complexity comes from the upward domains like requirement, functional, or design complexity or from lateral and downward domains like manufacturing, sales, sourcing inventory, support, and maintenance. This model may help justify introducing or pruning a feature option versus the benefits of increasing or decreasing sales or the cost of configuration vs. sales price.

Table 23 shows that the ‘360 Degree Camera’ and ‘ One by one Seat fold’ options cost only $762/car extra to introduce in the vehicle; if that option can be sold at a much higher price, maybe the complexity is justified.

5) Critical Technical Decisions: The structural complexity, in particular, is a helpful tool for designers to compare two options. A better option has less complexity, more functions, and less cost. The interface complexity of options will help identify the hotspot of the interactions. This will help R&D focus on specific areas where complexity is concentrated.

   Similarly, the organizational interactions to manage all the options will be helpful in manufacturing, procurement, and inventory control. This model may be helpful in factory planning and supply management decisions.

6) Key Benefits of Introducing Car Feature Options: New options offer numerous benefits for automakers and consumers. For automakers, it provides a competitive edge by allowing them to cater to diverse customer preferences and market demands. By offering a wide range of feature options, automakers can differentiate their products, enhance brand loyalty, and increase market share.

7.3 Additional potential applications

This model may help automakers to adapt quickly to changing trends and technological advancements, fostering innovation and product development. The meaningful insights the hybrid model provides will help introduce a feature option in the car. A few applications of this model are identified below:

1) Optimizing Product Configuration: The thesis model can be applied to optimize product configuration in the automotive industry by analyzing the complexities associated with different feature options. Design Engineers can use the model to identify the most efficient configurations that balance customer preferences, manufacturing feasibility, and cost considerations.

2) Supporting New Feature Introduction: Automakers can leverage the thesis model to assess the feasibility and impact of introducing new vehicle features. By evaluating the structural, organizational, and cost complexities associated with each feature option, engineers can make informed decisions about which features to include in future vehicle models. This application allows automakers to stay competitive by offering innovative features that meet customer demands while ensuring cost-effectiveness and manufacturability.

3) Enhancing Supply Chain Management: The organizational complexity can provide insights into the whole sourcing cycle of the feature options sourcing cycle. By analyzing the organizational complexities of different feature options, procurement managers can identify the potential bottlenecks and inefficiencies within the supply chain and compare different options to implement strategies to improve supplier collaboration and enhance overall supply chain resilience.

4) Informing Design Decisions: Engineers can use the thesis model to inform design

decisions during product development to all other domain engineers. By evaluating the structural complexity of different design options, engineers can identify areas for optimization and improvement and coordinate with multi-discipline optimization efforts.

5) Supporting Cost-Benefit Analysis: The thesis model can facilitate cost-benefit analysis for various engineering decisions in the automotive industry. By quantifying the complexities and costs associated with different feature options, engineers can compare the potential benefits against the associated costs. This application allows automakers to prioritize investments in features that offer the highest return on investment while minimizing risks and uncertainties.

Chapter 8: Conclusion and Future Work

8.1 Conclusion

This thesis comprehensively explores product configuration complexity in the automotive industry, aiming to develop a robust model for evaluating and managing this complexity. The in-depth literature review established a foundation of knowledge regarding the nature of product configurations, their associated complexities, and the methods used to measure and manage them.

Here are the key takeaways:

- The product configuration complexity in the auto industry proliferates with growing feature options, and with that grows many other complexities like design, manufacturing, and sourcing complexities in the vehicle's entire lifecycle. These complexities create challenges for automakers to optimize vehicle development. This thesis first lays a foundation for learning how product configurations get complex by adding new configurable features or options.

- No single metric can measure the complexity of the car configuration. Hence, this thesis attempted to develop a method that can measure product configuration complexity using a model that includes structural and organizational complexity.

- This research leverages insights from diverse domains such as design, manufacturing, configuration management, variant management, and many complexity measurement theories and research to build a hybrid model. Two complexities are chosen in this hybrid model: 1) the structural complexity, which reflects the functional and design complexity, and 2) the organizational complexity, which is often unseen but can cause significant challenges for automakers. These complexities are based on (Sinha and de Weck 2013) and (Felix Stracke, Rebentisch, and Mattern 2016) research. Their theories are employed here to measure the product configuration complexities.

- To measure the product configuration complexity, this thesis uses the hypothetical data used by the author that imitates the real-world electric car product structure and product configurations in size, structure, and organizational assignments. This representative dataset provides a structural complexity that can reach the real-life scenario. However, to gain confidence in this model, real-life product configuration data, cost, and organization assignments can be used to validate this hybrid model accurately.

- Measuring product configuration complexity has many practical applications in the auto industry, and it can help determine the realistic cost of implementing a new configuration in a vehicle. This cost estimate can help auto manufacturers plan product offerings for optimal profitability.

The model's application involved case studies and model validation exercises, wherein data was utilized to validate the accuracy and effectiveness of our approach. Validating this model with real-world data and scenarios will prove its usefulness. By comparing different product configurations and car trims, this thesis model demonstrated the model's utility in capturing the nuances of product configuration complexity and providing actionable insights for decision-making.

The thesis discussions highlighted several vital observations and considerations, including the importance of individual option complexity assessment, the uniformity of topological complexity values, and the implications of cost modeling and commercial and technical decision-making.

The thesis directly addresses the hypothesis by researching the complexities of product configuration throughout the automobile product lifecycle. Comprehensive research and analysis provide insights into the intricate interplay of factors affecting the cost implications of implementing new vehicle configurations. The thesis highlights the disproportionate impact of highly configurable products on areas in many domains. Through case studies, model validation, and discussions, the thesis provides crucial information on how understanding and identifying product configuration complexity can inform decision-making processes for auto manufacturers, enabling them to plan product offerings strategically to maximize profitability while managing and justifying costs associated with uncertainties in design, manufacturing, and operations.

In conclusion, this thesis contributes significantly to understanding and managing product configuration complexity in the automotive industry. The thesis has provided automakers with a valuable tool for optimizing product configurations, enhancing decision-making processes, and staying competitive in a rapidly evolving market landscape by developing a hybrid model that integrates structural and organizational complexities. The continued research and refinement of the model will be essential to address emerging challenges and capitalize on opportunities in the automotive sector.

8.2 Future Work

While the hybrid model integrates structural and organizational complexities with the cost model and presents a robust framework for analyzing and managing product configuration complexity, there are several avenues for future research and development to enhance its capabilities and applicability. Here are some potential areas for future work:

1) **Integration of Additional Complexity Metrics**: Expand the model to incorporate additional complexity metrics beyond structural and organizational complexities. For example, incorporating cognitive complexity metrics to assess the cognitive load associated with different product configurations and operations in each domain would be a helpful addition. The variability analysis might give more ideas about factory planning to manage the manufacturing complexity.

2) **Dynamic Modeling:** Develop dynamic modeling capabilities to account for the evolving nature of product configurations over time. This could involve incorporating real-time data feeds from production systems, supply chain networks, and customer feedback mechanisms to continuously update and refine the complexity and cost estimates for different configurations.

3) **Risk and uncertainties:** Incorporating risk and uncertainties to refine this hybrid model and cost model will enhance its ability to measure the complexity and cost of the product configuration accurately. By acknowledging and addressing potential risks and uncertainties, OEMs can mitigate adverse outcomes and improve the reliability of their car model.

4) **Sensitivity Analysis:** The factor considered in this thesis that impacts the product configuration complexity is limited, and its actual impact is not analyzed. Conducting the sensitivity analysis to evaluate each factor impacting the model and identify key variables or parameters can significantly influence the results. This would help understand the relative impact of different factors on complexity and cost, thereby guiding decision-making and resource allocation strategies more effectively.

5) **Optimization Algorithms:** This model can help identify optimal product configurations that balance complexity, cost, and other performance criteria. This could involve developing optimization algorithms to automatically generate and evaluate various configuration options, enabling OEMs to find the most cost-effective solutions for specific market segments or customer requirements.

6) **Validation and Calibration:** Validate and calibrate this model using real-world data and automotive and manufacturing industry case studies. This would involve comparing the model predictions with actual production data, customer feedback, and financial performance metrics to assess its accuracy and reliability in practical applications.

7) **User Interface and Visualization Tools:** Develop user-friendly interfaces and

visualization tools to facilitate model adoption and decision-making by OEMs and other stakeholders. This could include interactive dashboards, scenario analysis tools, and graphical representations of complexity and cost metrics to enhance accessibility and usability.

8) **Application to Other Industries:** Extend the application of the model to other industries beyond automotive manufacturing, such as aerospace, consumer electronics, and healthcare. This would involve customizing the model parameters and algorithms to address different industry sectors' unique characteristics and challenges, broadening their impact and relevance.

9) **Cost-benefit Analysis:** The emergence of the application of this model can be seen in improved efficiency, reduced costs, and enhanced decision-making capabilities for managing product configurations. This is the return on investment that OEMs quantify to see the impact of the decision made using this model. These decisions can lead to streamlined production processes, optimized supply chain logistics, and better resource allocation, resulting in cost savings and increased profitability.

By addressing these areas for future work, the hybrid and cost models can be further refined and optimized to provide actionable insights, decision support, and competitive advantages for OEMs in managing product configuration complexity and driving innovation in manufacturing processes.

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A: Appendix

A1: Configurator used by top automakers worldwide

Automaker	Sold Autos in the Year 2024	Car Configurator / Build Your Own Car
Toyota	10307395	Available
VW	9239575	Available
Hyundai	7302451	Available
Stellantis	6392600	Available
GM	6188476	Available
Ford	4413545	Available
Honda	4188039	Available
Nissan	3374271	Available
BMW	2555341	Available
Changan	2553052	Available
Mercedes	2493177	Available
Renault	2235345	Available
Maruti Suzuki	2066219	Available
Tesla	1808581	Available
Geely	1686516	Available
Tata	954645	Available