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Chapter 7: Utilizing machine learning to optimize product lifecycle management from design to end-of-life

7.1. Introduction

Fulfilling customer needs through the right product, at the right moment, and at the right price is the main objective of product lifecycle management (PLM). PLM integrates information, processes, business systems, and people across an extended enterprise from the customers' perspective. This begins with the conceptualization of the product, continues through its design, manufacturing, distribution, purchase, support, and final disposal, and is supported by data and information storage and information technology. PLM brings together a company's functions and those of its suppliers, resellers, and customers to provide an integrated view of data, processes, and business systems. By uniting product data with business processes and systems throughout the organization and around the world, PLM enhances collaboration and enables organizations to capitalize on the synergies potential in product-related activities. The expected results are a shorter time-to-market, an improved product quality, reduced manufacturing costs, lower service and support costs, and a product line that better meets customers' needs (Kiritsis, 2011; Garcia & Freire, 2014; Liu et al., 2022).

Because PLM impacts the entire product lifecycle, all companies and organizations that affect the final product must be part of the collaborative team. This practice of breaking down the classical functional financial reporting from product conception to product sales creates the environment to visualize company opportunities for accelerated product development through innovation synergism. PLM rationalizes the development and management of product-related data that enable organizations to achieve their strategic objectives in costs, quality, and time. The PLM historical evolution has accumulated enormous amounts of data in this product-related repositories. Organizations are asking themselves how to take advantage of product-related data to improve PLM decisional processes (Younis et al., 2020; Yildizbasi, 2022).

7.1.1. Setting the Stage for Product Lifecycle Management

Product Lifecycle Management (PLM) has emerged, in the last decades, as a business strategy that manages the complete lifecycle of a product, from inception, through engineering design and manufacturing, to service and disposal. PLM integrates people, processes, business systems, and information to facilitate the effective and efficient management of products and associated data. The goal is to optimize performance, improve innovation, support collaboration, and manage for profit within a largely virtual enterprise structure in an accelerated time to market environment, with enhanced ability to deal with risk and uncertainty. PLM drives innovation onto the agenda of senior management and potential investors.

PLM also builds the knowledge infrastructure for innovation and by natural extension, competitive advantage. PLM has developed from an Engineering-centered perspective into a much broader multi-disciplinary concept that supports the entire Enterprise through the deployment of a knowledge-centric Approach, supported by Collaborative Enabling Technologies around a Products Developments and Service Ecosystem that extends out to Customers and Partners, supported by State-of-the-art Information Technology that services these activities, enabling dynamic Relationships and Transactions, all within the context of a defined Organizational Environment. Building on the Business and Technical Disclosure Concept, to embrace both the temporal and spatial aspects of the Product Lifecycle and Product Family, PLM is defined as the business view of a Product Family, the activities associated with developing and Commercializing Products within that Business and Technical context, the supporting Organizational Infrastructure all Businesses need to set up and maintain, and the tools and technologies to implement the required Processes to deliver Products that customers want. PLM allows companies to align their vision with product.

7.2. Overview of Product Lifecycle Management

Product Lifecycle Management (PLM), utilizing a technology and process focus, takes a broad look at the systems involved in the lifecycle of a company's products. PLM recognizes a continuum of product management activities beginning with product development, progressing through materials and manufacturing planning, project management, and supporting the customer, to managing the end of product life. PLM integrates people, processes, and technology and extends across technology and functional areas. PLM provides a system whereby both product-related information and product-related processes are available and useful to all employees and processes throughout the enterprise. To participate fully in the process of PLM, the company must dedicate itself to a rigorous system of data management, providing everyone with the necessary information and processes to make critical path decisions.

A primary goal of PLM is to facilitate a shared understanding of product-related concepts across functional areas to improve. Product-related knowledge includes design specifications, design and manufacturing process capabilities, internal budgets and financials, external market and customer requirements, manufacturing and materials-related capabilities, schedules, and tooling requirements. PLM involves the consideration and continuous management of a set of ideas, concepts, and details that result in sellable products. It covers activities that begin before product design starts and extend until after the product is no longer produced. Successful PLM depends on the integration of product-related knowledge developed by functional teams over a series of product development and production cycles.

PLM encompasses a broader scope than product development (PD) alone. PD is part of the overall PLM process. PLM can be viewed as a superset of PD covering many different activities and phases in a product's lifecycle. PLM focuses on managing a product's life and on making life easier for those who determine a product's life, "the product champions." They shepherd the product through design, production, and customer support while responding to changes in the marketplace.

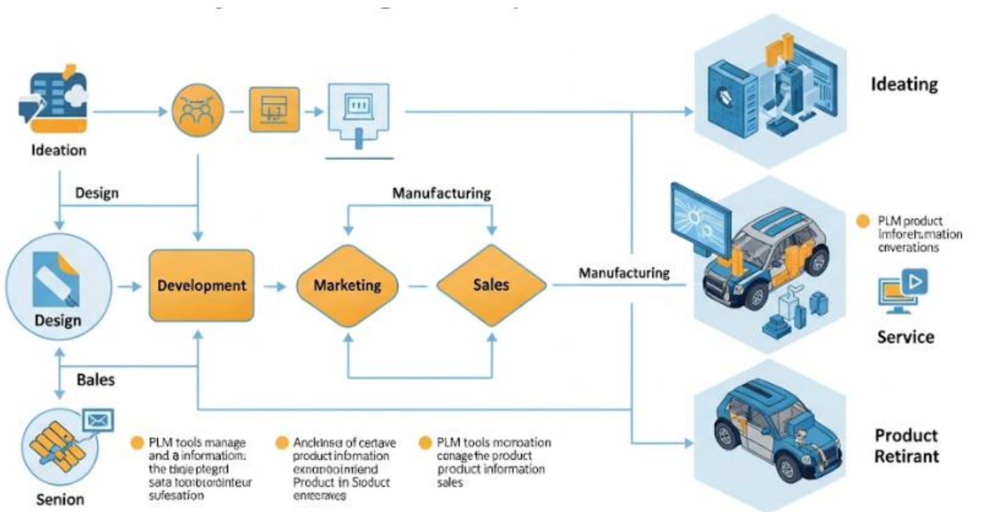

Fig 7 . 1 : Product Lifecycle Management

7.2.1. Definition and Importance

Various dynamic, non-linear, and interactive processes are involved in turning a conceptual idea for a product into a real, tangible, and marketable product. New products go through several transformations, and transition through various stages, from the inception of the idea to the sale of the product to the end customer and its subsequent support over its useful life, and finally to its disposal, or recycling after its useful life.

Each of these stages of the life of a product is filled with events that may have far-reaching implications in terms of the associated costs, the perceived customer value for the product, and the product's impact on society and the environment. The cumulative total of events associated with all the stages in the life of a typical product is termed the Product Lifecycle, which is a representation of the inevitable changes endured by a product during its life.

Proper and effective management of each stage of the product lifecycle is essential to meet product performance and profitability goals, and to optimize resource utilization, while keeping in mind the environmental and societal concerns associated with the product and its use. The importance of managing the product's choices and decisions across its lifecycle stems from the impact they can exert, and the potential they can create, for sustainable benefits. Effective decision-making can lead to enhanced performance, waste and cost minimization, better and greater market acceptance and competition, and societal benefit. From a functional standpoint, multiple departments making different and discrete decisions lead to poor integration of knowledge, expertise, and resources. Decisions made in one department impact decisions in other departments; therefore, coordination across departments at the organizational level is needed to manage the product lifecycle effectively. This was achieved through a product lifecycle management philosophy.

7.2.2. Stages of Product Lifecycle

This chapter addresses the stages of the product lifecycle. It is divided into two sections. In Section 2.2, we describe the generic stages of a product lifecycle, and Section 2.3 describes in detail the stages of a specific product lifecycle – managing the lifecycle of optical products. We take a generic approach to the product lifecycle. Different product categories or types will have product lifecycles of different lengths and some may have extra or fewer stages. However, the following sections can be considered the product lifecycle in outline. A typical product lifecycle consists of inception or development, introduction, growth, maturity, decline, and disposal. This is a simplification as different products will spend different amounts of time at each stage, may skip some stages altogether, and may be very cyclical, for example, high fashion items, art, or technology. Nevertheless, the underlying principle of the product lifecycle concept remains: products are born, live, and die and managing them at the various stages of their lifecycles can increase competitiveness and profitability.

The stages of the product lifecycle will affect both the PLC policies and strategy and the product position. The duration of each lifecycle stage is very important in determining the length of time that a product will be in the various stages, and what needs to be achieved. These factors, combined with the competitive environment, will affect the decisions and processes that need to be implemented at each stage. Focus on the product lifecycle concept is not new. The adoption of designers, marketers, and artists is very old, for instance, with respect to high fashion and technology both being very aware of the product lifecycle idea for a long time. However, it is only recently that industry has recognized the advantages and the need to manage product lifecycles with particular emphasis on the various stages of the cycle.

7.3. Machine Learning Fundamentals

Machine Learning (ML) is a branch of computer science and applied mathematics that studies algorithms and tasks that exhibit some form of intelligence from experience. An experience can be viewed as an overview of a specific application of the ML task, therefore defining the typical observations the algorithm will make during its operation, as well as any expected rewards for a given state or prediction. The term intelligent task is typically reserved to automatic, situation-specific strategies for tasks generally defined at a very high hierarchical level, such as perception, signaling, communication, and decision making. More specifically, a learning task is one that is performed by an agent that is able to acquire information about the world with the purpose of changing its behavior; it allows the agent to learn general rules from its observations, which will then allow it to predict and select the right action to take in any situations. Any technique that allows an agent to make better decisions based on prior iterations of that task can be considered a learning task. The mapping from experience to performance, which is at the center of the learning process, can be determined by different ways: supervised, semi-supervised, unsupervised, self-supervised, transfer, active, multi-task, inductive, or interactive learning. Through supervised learning, we can think of a practical way of associating a space of answers to a space of questions or contexts in which he answers in order to improve our chances of being right.

What may immediately appear as a technical detail, just an underlying formulation device in the sense that we could just as well describe a particular task in ML without necessarily pointing out the experienced mapping statistical nature, is in fact a very powerful principle. The large data and computational requirements of such pragmatic learning methods essentially drove the interest in ML in recent years. By exploiting the almost unknown joint distributions between the task categories and the input data, and the ease of representation by large combinatorial models, ML can be applied for predictive management to several tasks from many different domains. The basic idea is that when data and computational resources are available in large amounts, a more empirical approach should be taken, instead of relying on a small set of learned priors.

7.3.1. Introduction to Machine Learning

Machine learning is an essential research field in artificial intelligence that has significantly advanced in the past few decades. Machine learning comprises a variety of methods and algorithms inspired by the observation of how biological beings learn. It allows the use of computational models to learn from sampling, generalizing knowledge, and making predictions that are not instructed explicitly. The assisting components are sampling through data generation or laboratory measurements, generalization through model choice, and prediction through inference. In the current cloud-based era, a great quantity of data is produced every day by humans, machines, and research institutes, enabling the advancement of machine learning. Enabling algorithms, inspired by deep learning for neural networks, enabled the training of systems with hundreds of layers and trained for image classification and natural language processing. State-of-the-art models are available in open-source computer vision, NLP, and reinforcement learning platforms. These platforms allow one not only to access feasible pretrained systems but also, if the user possesses significant labeled validation data, to finetune them, thus adapting them to a task that relies on the labeled validation data. The combination of quantities of available data and state-of-the-art infrastructures enabled by the cloud is empowering society and becoming an enabling technology for breakthrough developments.

The name of the field of machine learning has recently become a label for all new methods allowing a computer to automatically extract patterns from data. These patterns allow the development of systems trained from data, rather than being explicitly programmed. The explicit programming approach is undoubtedly the most successful practice in computer science, which has generated almost all current successful computer-based decision-making applications. It has led, for example, to the computer-controlled molecules that we currently have in our pockets. However, some smart and stress-resilient humans enable the flight of massive machines that cross biosphere compartments by continuously making decisions based on a continuous flow of sensor data.

7.3.2. Types of Machine Learning

The field of machine learning is extensive and varied. Particularly, it can be tailored to tasks ranging from recommendations and predictions to knowledge extraction. Likewise, tasks in these areas can themselves vary greatly. This means that there are various dimensions or perspectives from which we can classify the machine learning field. Classical perspectives include type of supervision (for example supervised, unsupervised, semi-supervised, self-supervised, task-specific), the underlying algorithm used in training (such as neural networks, trees, ensemble, kernel-based), and the kind of task (for instance, classification, regression, or density estimation). Furthermore, these perspectives can themselves be further divided. In this chapter, we present the main types of machine learning.

In supervised learning, an explicit supervisory signal is provided for training, in the form of input-output pairs. This means that for every training input - be it an image, sound, text, or other type of information - the correct output is provided by some oracle. This supervision is also sometimes called external, because, at least in theory, it can be used to help improve the task, even if the task is far outside the capabilities of the students. There exist many types of supervisory signals – from the input being mapped to binary classes in classification, to real-valued scores in regression, or probability distributions in density estimation. There exist many types of tasks involving supervisory signals. For example, training a neural network to classify images of handwritten digits into one of 10 output classes (0 to 9), or estimating the function that relates the air temperature rate of change to a real-valued output which reflects the temperature at a 1km height in a region is termed supervised learning. In these tasks, the training dataset is composed of input images labelled with corresponding ground truth classes (the correct digits) in the case of image classification, or data collected over time containing both input and output variables in the case of system identification.

7.3.3. Key Algorithms in Machine Learning

Machine learning is extremely efficient in discovering and analyzing patterns in data. A number of algorithms have been developed across different ML types to realize the above capability. Some of the most common algorithms for computer vision/image processing are K-nearest neighbors, Convolutional Neural Nets, Random Forest, Support Vector Machines, and Decision Trees, Long Short Term Memory Networks, and Expectation-maximization Algorithm. Natural language processing has its own specific set of ML algorithms as well: Recurrent Neural Networks, and its specialized form, Long Short Term Memory Networks, Naïve Bayes, and Hidden Markov Model.

The above algorithms are representative of one or more of the major machine learning approaches: Predictive analytics, perceptron, convolutional neural network, restricted Boltzmann mask, hidden Markov model, support vector machine, K-means clustering, and expectation-maximization. Predictive analytics is the process of computationally extracting information from data sets and using it to predict future trends and behavior patterns. A practical application of predictive analytics is data mining. A perceptron may be a very simple model of a neuron, but it performs a binary classification task on a set of inputs, producing an output based on a threshold value. Convolutional neural networks are designed in particular for classification of images, and they have enabled huge strides in computer vision and practical applications: the classification of objects depicted in a photograph, and facial recognition. Restricted Boltzmann machines are stochastic neural networks that can learn a probability distribution over the set of inputs.

7.4. Integration of Machine Learning in Product Lifecycle Management

The adoption of PLM in industrial production environments is insufficient because of the high investment in the PLM digital backbone and the low perceived benefit on the company return. The PLM digital backbone consists of a PLM software suite provided by specialist vendors and the integration of this software suite in the IT landscape of the company, which often implies a connection to existing ERP and CAD systems. In the conservative field of industrial production, the investment in this digital backbone may seem bloated compared to the sum of point solutions that would solve very specific PLM use cases. Companies that do invest in a PLM solution point to the large range of visibility provided by PLM as the main benefit of interest. The earned visibility enables analysis and decision making on both PLM tasks and other related business processes, such as sourcing and production, that enable long-term company risk reduction and value creation. PLM Systems that comprise an IT and process integration digital backbone may contribute innovation cost reduction over market-orientation alone. The PLM digital backbone is of recursive design. PLM systems support use case workflows. Workflows enable structure and integration of the PLM process, documentation, temporary personnel, and the structure integration of all other company processes involved in the PLM task. The output of PLM workflows is valuable information, which contains data about materials properties, risks, and fabrication process cost and time. These data can be analyzed and reused to provide faster feedback to the PLM task decision-making.

Intelligent use of PLM digital backbone data for decision support and workflow automation is geared towards making the digital backbone profitable and occupying the space of data investment in intelligent enterprise architecture. Machine Learning research can thus reduce the perceived data economy of PLM systems and specializes their action towards the automation of dull and repetitive workflows. We assume that the investment in the digital backbone would be further incentivized, if this backbone were capable to support economic and risk management through decision making and automation of workflows for all company processes that contribute to the PLM task.

7.4.1. Role of Data in Machine Learning

Data is the most critical component required to implement machine learning into the modern product lifecycle management systems. Machine learning models take several different data types as input to implement a functional mapping of the data from inputs to outputs and build a model to identify various patterns hidden within the data. The models learn from the initial training data. These models are then validated with another testing dataset to monitor the model's functionality. The models are then used to predict the future data with the same input feature set. The overall objective of implementing machine learning is to take advantage of advanced computational capabilities and apply various machine learning algorithms onto various datasets and then extract useful prediction capabilities and functions for all. The traditional science of trial and error is replaced using various prediction algorithms. However, there are various considerations to be mindful of while using machine learning models.

For the model to generate maximal output accuracy, the input data should be in the format whose transformation resulted in the optimal prediction accuracy and correlation. In neural networks, the input data often should be normalized or scaled to eliminate the bias depending on other classifiers. In addition to enhancing the model performance, proper data pre-processing may help visualize the hidden patterns within the data. Training dataset and testing datasets are also considered important since they help the user analyze the model's accuracy on unseen data. If the model is trained with only a limited set of training data, functionality might reduce drastically on unseen data. On the other hand, appropriate data augmentation can help. However, as data augmentation increases the dimensions, the model can easily become misleadingly accurate. It becomes hard to monitor, especially in the case of neural networks or deep learning models, where the high predictive accuracy due to high dimensionality might mislead the user who is trying to explore the model's decision footprint.

7.4.2. Machine Learning Techniques for PLM

There are many types of algorithms for machine learning, with various strategies being employed in each of these for data representation, learning, and prediction. Each algorithm type has its own unique advantages and disadvantages, such that no one type of machine learning is most appropriate for general-purpose problem solving. Thus, various types of algorithms are often combined into one overall hybridized algorithm to leverage the advantages of each. Consequently, hybridized algorithms from different disciplines can contribute even better to solving some specific product lifecycle problem than the original stand-alone versions. This section begins with a brief description of and rationale for the utilization of some of the more important types of machine learning commonly utilized in PLM applications.

Experts have categorized machine learning applications in many different ways. Various machine learning tasks employed for PLM are classification, joint classification and regression, regression, ranking, time-series, association rule mining, structural, clustering or grouping, graph, and miscellaneous models that do not fit into the previous types. Most of the task types are primarily handled using either supervised learning or unsupervised learning. The selection of which machine learning algorithm to use will predominantly depend on the amount and quality of available data, the computational model, time, and energy limits, plus whether the task is supervised or unsupervised. These issues and constraints determine the success or failure of using machine learning techniques to solve specific PLM problems and must be taken into account in order to avoid some well-known pitfalls. The following subsections summarize common machine learning algorithms used for PLM. Some algorithms are much more prone to fail than others.

7.5. Design Phase Optimization

The design phase in PLM holds significant importance, as decisions made at this stage have profound effects on subsequent product phases. Given its impact on a variety of design objectives such as performance, manufacturability, assembly and service ease, recycling potential, and product costs, extensive research efforts have been dedicated to optimizing various aspects of the design phase. With the advent of advanced technologies and extensive user-generated data, the product design phase is being revolutionized with collaborative product platforms that promote active engagement by customers and designers alike. Such paradigm shifts in product design offer tremendous opportunities for organizations to develop data-driven design and design optimization approaches, which employ the latent potential of web data to maximize product acceptance and enhance design objectives.

The creation of innovative products requires multiple design choices in the design phase, including concept design, detailed design, design for manufacturability, design for assembly, design for reliability, design for service, and design for recycling. Conceptualization of unique product ideas that satisfy consumer needs can foster product acceptance and development. Despite the advancements in optimization methodologies and software, several organizations still rely on designers' knowledge and experience for addressing product design choices. Regardless of its advantages, such an approach suffers from subjectivity and may not address the different constraints associated with product design. Machine learning has provided data-driven approaches to the associated product design challenges across varying product phases.

Due to the unstructured nature of product development activity, ML applications in this area have focused primarily on aiding product development decisions, while leveraging the information cataloged in PLM and other related databases. The intent of ML is to directly provide information that makes it easier to make better decisions. Such data-driven approaches can be significantly helpful in product development decision areas, including product concept development, intuitive product design description, user-influenced product details, product design redesign, and product design validation.

7.5.1. Data-Driven Design Approaches

Products are traditionally designed based on expert knowledge and experience. In the past decades, this trial-and-error product design process has proven to be time- and cost-intensive, and presently, with the rapid increase in product complexity and diversity, on top of more volatile product market dynamics, expert-centric product design alone is not sufficient anymore. Unlike mechanical engineering, where closed-form equations and known design rules can capture the design behavior with a good level of accuracy, the design of complex multi-disciplinary products are often done through software simulation tools that capture the underlying physics behaviors in an accurate manner. Traditionally, the simulation-driven design process starts with some initial design variables being specified, and by following some iterative optimization procedures using the simulation tools, the most optimal or near-optimal product design is found. Though these optimization procedures reduce the time needed to search for the optimal design, they still don't capture the actual demand behind these design choices.

With the recent revolution of big data, optimization and machine learning, researchers have begun leveraging a data-centric approach to expedite critical design choices in the design and development phase. Specifically, design choices that can benefit from a data-driven approach typically satisfy two conditions: First, the design choice is among a small number of candidates and second, the correlation between the design choice and multiple business performance need to be explicitly established and substantiated. These methods have since been referred to as Data-Driven Design methods. Once these conditions are satisfied for a specific product design choice, Data-Driven Design methods provide a more accurate and cheaper surrogate for expert knowledge and expertise, allowing for better and faster design decisions. Leveraging data to guide the design of products across the entire product lifecycle is critical to optimizing activities from design to end-of-life. Moreover, the Data-Driven Design methods have the potential to be used across all activities.

7.5.2. Predictive Modeling for Design Choices

This section explores predictive modeling techniques that use data to analyze the limitations for possible design choices for a given product. A product design is most meaningful if it meets a specific purpose in order to satisfy a specific market segment. In order for the design to be successful, data about design attributes and market preferences must be obtained to predict how a set of design attributes resonate with consumers. The model accuracy can help establish the reliability of the predictions generated, which would consequently guide the product design decision.

Various forms of model algorithms can be utilized to predict consumer preferences over product attributes. The basic prediction methods such as Multiple Linear Regression and its extensions are commonly applied due to their interpretability in terms of refitting the model coefficients. Generalized Additive Models enables a semi-parametric functional improvement in model prediction. Specifically, GAM employs non-parametric functions on parts of the input space to yield better prediction as compared to MLR. Although MLR and GAM are useful in consumer market preference modeling, they are not scalable to higher dimensional input produced by interaction terms or high-dimensional functions.

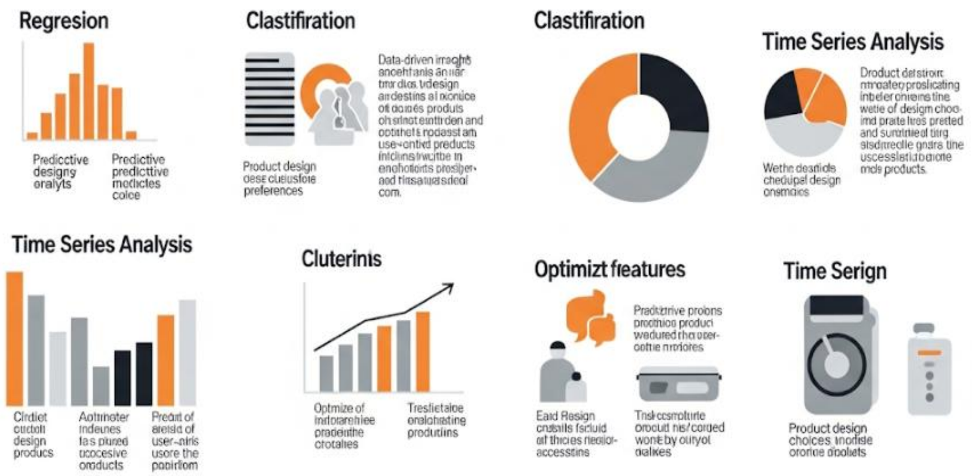

Fig 7 . 2 : Modeling Techniques for Product Design Choices

Machine Learning techniques can address many of the drawbacks of classical consumer preference modeling methods in performance scaling, accuracy, and automation capability. While MLR and GAM typically require an explicit formulation of the input to the function of interest, ML techniques alleviate this requirement in favor of improved prediction accuracy. Various regression methods fall under the ML category such as Classification Trees and Support Vector Regression, and Matrix-Completion model based on Singular Value Decomposition. Random Forest could achieve very high accuracy with high-dimensional input while offering good interpretability in identifying important input variables, but it is still prone to overfit in scenarios where sample size cannot keep up with the dimension of the input variable.

7.6. Manufacturing Process Enhancement

The Manufacturing process really connects designing activities with the product testing and validation steps since during this the product is fabricated, assembled when required, and delivered to customers. During this activity the product is transformed from its initial form into something tangible and valuable, but it is also worth noting that this step comprises a series of complex activities that could have a deep impact in product lifecycle costs. Manufacturing costs can correspond up to 75% of product cost and the product structure can have around 92% of impact at the manufacturing costs.

To add more complexity to the manufacturing process and resulting costs, products or their components can be subject to inspection and testing activities throughout the different stages of manufacturing until their shipment to customers, in order to prevent defective products from reaching the customer. Testing for defect detection is a crucial step in the product development process lineage and the cost of product's defective occurs at different phases of its lifecycle, including cost of exchanges, estimating recalling expenditures, the loss of brand reputation, and a decreasing return on investment in return on sales. Inspections for defect detection are indispensable due to the need of preventing defective products from entering the customer's premises.

Today, artificial intelligence is being used more broadly in a variety of ways to facilitate product production. Machine learning techniques have been investigated extensively to improve item quality by examining the data collected from the operational process. Focused on the application of distributed learning for detecting anomalous manufacturing or workpiece surface characteristic. The input data needed to train the learning algorithm is a set of photographs from the workpiece surface of acceptable quality. Further details are found in.

7.6.1. Quality Control through Machine Learning

Identifying product defects or their causes is critical to maintaining product quality, which is especially essential for products of high value, such as military hardware and automotive components. While product design and testing are crucial to enhancing product quality, manufacturing process control and defect scanning are the most critical quality assurance functions in modern industries. Traditionally, these tasks depend solely on human skills and intuition. However, recent advances in machine vision systems offer new ways to integrate machine intelligence capabilities into defect detection. Based on statistical and heuristic methods developed over the past several decades, computer vision algorithms today can solve challenging vision problems at almost human-level performance.

Still, the deployment of computer defect scanning systems is not focused solely on machine vision and traditional feature extraction methods. Often, old-school machine vision techniques, such as optical character recognition, are still used. Moreover, some companies have reported a reluctance to consider AI-assisted defect detection due to concerns about the black-box nature of ML methods as well as the additional costs that accompany AI-enhanced solutions. For those and other areas of quality assurance, ML is better suited for purposes that include solutions that detect anomalies in existing systems. Detecting defects is a well-defined computer vision problem. It has associated labeled images that are available for training supervised classifiers. Such classifiers must first be optimized for the specific images being scanned. Such ML classifiers have been trained under strict performance benchmarks and are easy to integrate into factory or assembly lines. Multiple commercial products exist that claim to enhance human performance with respect to defect detection. These systems achieve excellent performance in high-stakes environments, such as scanning for defects in semiconductor wafers. Such ML-enhanced solutions can be deployed on factory floor-mounted scanning systems, wearable goggles, and even mobile devices.

7.6.2. Supply Chain Optimization

Supply chain management is a crucial aspect of production chains for various industries. Many manufacturers consider their supply chain management as a strategic instrument to achieve a decisive competitive advantage in order to optimize logistics and apply advanced technologies. Applying machine learning into complex business operations in supply chain management adds a new level of transparency. Transparency provides more exact information for better understanding an enterprise's operations, which in return can open up new paths for optimization.

Artificial intelligence has made a great impact in logistics and supply chain optimization. Various fields of supply chain management have applied machine learning methodologies, like demand forecasting, scheduling, warehousing, predictive maintenance, inventory optimization, risk management, and last mile logistics. Several new developments are ahead of us; we cannot ignore the great ongoing work on optimization in company logistics and supply chain processes. From demand prediction for fashion as well as the prediction of demand from social media activities, up to hailstorm as well as rain prediction, new methodologies and concepts will enhance existing concepts. Adaptive heuristic or meta-heuristic optimization in the context of neural networks or reinforcement learning will drive intelligent autonomous concepts and systems to cope with complex problems in supply chain management. These systems and their components interact with each other in delivering goods and services needed at desired time at reasonable prices. AI will help to intelligently connect supply information flows and act on these signals. Machine Learning-based controllable and dynamic supply chain logistics will enable applications such as logistics route optimization, digital twins, self-controlling logistics networks, advance predictive analytics and data-driven insights, reinvent contract logistics, and reinvent last mile.

7.7. Sales and Marketing Strategies

Machine learning can play a crucial role in developing effective sales and marketing strategies to drive revenues at all stages of the product lifecycle from introduction to growth to maturity to end-of-life. It can help understand customer needs and behaviors in depth. Every potential customer segment may map to a different set of needs, and machine learning can help break down the mass of customers into distinct segments. That can in turn guide the type of marketing messages, campaigns, and channels that would be effective for each segment. With techniques like deep learning, customer attributes can be derived from visual, audio, and text information. Real-time learning techniques can refine the attributes, and therefore the segment definitions based on sentiment and brand perception analysis. Once needs are clearly defined, candidates for product or service solutions can be created or refined and tested by using generative design techniques.

Machine learning can also help focus product, service, and marketing offerings for particular customer segments based on sales trends, profitability analysis, and recommendations based on customer behaviors and preferences. In addition, it can also support product bundling and configuration. Lastly, machine learning can help track competitors' strategies and performance. By automatically extracting share price trends, and financial and organizational developments, insights on competitors' strategies can be derived, and alerts for significant events set up based on pre-defined thresholds.

Machine learning techniques can be applied to timed historical information to create accurate volume forecasts of product and service sales across total and market segments, across categories and parts, across channels, and globally and locally. For new products and services such as substitutes for legacy offerings, collaboration with other stakeholders in the lifecycle may be needed to develop forecast models. Those forecasts can then be automatically updated based on market conversations and commentary recovered using natural language processing techniques.

7.7.1. Customer Insights and Segmentation

Customer insights and segmentation are crucial in formulating effective marketing strategies. Traditional methods of customer segmentation rely on surveys and the analysis of internal data, which can be expensive and time-consuming, as they require detailed demographic data. Although these established techniques are still useful, the emergence of online customer data offers novel opportunities. This opens up new possibilities for customer insight generation as well as segmentation, as typical problems such as transaction non-disclosure or sample representativeness do not exist in this case. Customers are more likely to share their preferences and needs with firms on their websites, blogs, or social media sites and to include this information in their interactions with others. Furthermore, a multitude of clickstream data, where purchases are linked with the sequence of clicks that led to them, is available that can provide clues about customers' intents. From this data, researchers have proposed a number of innovative customer insight-generation and segmentation methods such as utilizing predictive analytics to identify preferences and needs or leveraging topic modeling to identify interests.

In applying these new methods in practice, companies need to acknowledge a number of factors that influence the likelihood of the successful implementation of advanced analytics techniques for customer insight generation and customer segmentation. External factors include data transparency, validity and credibility of online data, integration with offline data, customers' concerns, and data ownership; internal factors are managerial aptitude, internal expertise, and strategic intent. In particular, while both traditional and "new" customer segmentation techniques are helpful, organizations would benefit from using hybrid approaches. These approaches combine the strong points of both external and internal data sources while mitigating some of the drawbacks. The integration of these techniques requires thinking outside the box to make the best use of the available resources. After all, their marketing implementations and value lie in their ability to move from "talk" toward steering and managing a portfolio of services-based product offerings.

7.7.2. Demand Forecasting

Accurate forecasting in a supply chain is brought about by good demand planning and is fundamental to its performance. Generally, forecasting is the estimate of future events, whereas planning is the creation of detailed action proposals in qualitative and quantitative terms. The focus of supply chain forecasting is to predict demand as accurately as possible. Demand forecasting is part of the larger process of sales forecasting, which involves predicting market demand for products and services. Sales forecasting, however, is at a much more granular level, predicting requirement figures for each stock-keeping unit at specific locations for very short planning horizons. The sales and operations planning process attempts to integrate existing information and translate demand forecasts into more manageable terms that ease the tactical and operational planning and execution parts of the business.

To illustrate the importance of demand forecasting, an example based on a multi-stage supply chain for a non-perishable product made from saving-related components showed that a 10% forecast error in item demand in the first period, the heaviest demand period, would lead to: a 9% to 18% increase in production costs, depending on whether such irregular demand patterns are clustered on a specific period of time, or are evenly spread over time; a 9% to 15% decrease in service levels; a 10% to 13% increase in product cost; and a 114% to 154% increase in the time-related part of logistics costs. Both the service level as well as the total logistics costs were found to be much more sensitive to incorrect forecast assumptions than production costs.

7.8. Product Usage and Performance Monitoring

In the past, products were viewed as singular entities: once sold and delivered to customers, the manufacturer no longer interacted with it until it was at end of life and either disposed of or sent for recycling. Such products tended to be characterized as "black boxes"; that is, their internal mechanism was inaccessible to anyone but the manufacturers, and once sold, there was little or no information flow from the customer or the product back to the manufacturer. Product development and design activities, such as deciding on the materials and processes to be used, as well as the overall mechanisms and design principles employed to implement the function, were thus performed without fuller knowledge of the final product or how it would actually be used in practice, the performance metrics that would ultimately determine its success or failure among buyers, and social or other behaviors that affected production, display, and consumption. However, products are increasingly being designed and embedded with sensors that allow for real-time information exchange with the customer; advances in wireless communication and miniaturization technology have allowed products to become "smart," which has led to the rise of the Internet of Things. Products can now interact continuously and in real time with manufacturers, support organizations, and other products. Such developments are enabling enterprises to monitor and fine-tune the product during its use and to better understand customer preferences and patterns of use, which has led to more effective and efficient product servicing and enhancement.

The potential benefits of this digital transformation of products are substantial. Continuous monitoring of product use allows for the development of detailed timing, performance, and consumption profiles. In turn, these profiles can be used to better tailor or augment the product or service delivery, including fine-tuning or optimizing the schedules of energy, fuel, or other consumable resources to product initiation, allowing for better alignment of product provisioning with actual use. The use of sensors can also provide for predictive maintenance by the detection of signals and patterns associated with deterioration of performance, thereby mitigating risks associated with catastrophic failures.

7.8.1. Real-Time Data Analytics

Utilizing an enhanced telemetry of information received from the products will enable companies to fulfill the key objective of proactively monitoring and managing product usage and performance over the lifecycle. This requires the collection of data on product usage and performance from a variety of sources such as sensors, feedback from customers, suppliers, distribution and service channels, product test, etc. The data acquired will have to be properly analyzed in real-time, to drive fact-based decisions and trigger appropriate actions that would ensure the delivery of the promised product/service performance to customers throughout the expected usage duration. Moreover, the performance data from the actual product usage will have to be aggregated and related to product design characteristics and other contextual product lifecycle information that would help enhance design improvements.

The integration of artificial intelligence and machine learning techniques into the front-end of the tools used to analyze field product data will drive the realization of this enhanced capabilities for organizations. Such advanced capabilities in-skill the potential of discovering facts on the pseudo distribution of specific attributes across specific subgroups and the connection of attributes and subsequent performance of the product with other attributes previously unknown to impact performance. Speed and quality improvements in deciphering volumes of product usage data, such as computer vision enhancements integrated into the toolsets that take advantage of advanced neural networks will drive further progress. Enabling machine-empowered sophisticated analytics at user desktops will close the loop between making data available, analyzing it, and embedding the insights back into corporate processes. Putting advanced analytics to real-time use is a necessity for organizations challenged by the speed of digital competition.

7.8.2. Feedback Loops for Continuous Improvement

For example, lifetime assessments may vary tremendously due to a vast number of influential factors, e.g. container designs (size, volume, and the geometry of outer and inner surfaces), the materials selected and the performance of the production processes in terms of deviations from design specifications, the packaging and storage of products, the storage conditions (temperature, humidity, exposure to light, and physical stresses), and the handling of products until consumption. During product design, optimization and assessment processes can be applied to these innovative containers based on modeling, testing up to the final design confirmation, or a combination of these options. At lifetimes specified by the structure-function relationships, the cost of the product is in a balanced relationship with its probability of failure. However, these functions may be difficult to determine. Machine learning and other advanced data science analytics have the capability to extract latest lifetime performance information of product functions and their correlations with the factors discussed above from product performance data accumulated in large databases in order to adapt function-lifetime assessments crucially influencing cost and reliability. The product function-time correlation data base can be utilized for the real-time monitoring of the performance of products and to continuously modify and update function-lifetime assessments. In addition, machine learning methods can detect anomalies and relevant unknown correlated factors, raising the possibility of their consideration. Thus, the advanced analytics will constitute a powerful feedback loop from the post-marketing phase to the pre-production phase of the product life cycle.

7.9. End-of-Life Management

The last phase of the product lifecycle is the end-of-life (EOL). At that point, either the product becomes obsolete due to its reduced utility and/or support by the manufacturer or the product is pushed from the market by the arrival of new and more attractive versions of the product. During this phase, the decision about the product end-of-life should consider not only the economic costs, which are central in the other phases of the product lifecycle but also other non-economic aspects such as legislation and the customer's opinion. In the EOL phase, the product could either be recycled or disposed of, fulfilling the considerations of sustainability. The EOL strategy is especially important for complex products made of multiple materials. Once the product has reached the EOL, it might be that only the electric and electronic components should be discarded according to the level of degradation reached, leaving the hard structure still usable.

The actions to be undertaken during the EOL management are influenced not only by technical and economic factors but also by environmental and social concerns. Customers increasingly demand sustainable products, influencing the companies in fulfilling EOL activities. Eco-sustainability is becoming a requirement in many business sectors, prompting the emergence of large governmental regulation worldwide on EOL items. The cradle-to-cradle concept is trying to enhance the economic aspect by minimizing the amount of waste by reintroducing strategic materials into production processes, and stimulating companies to be more responsible by tracing the entire supply chain. According to the cradle-to-cradle concept, wasted materials would become nutrients, maintaining their utility until the end of life. The recycling can regenerate the resource, but only if the material is sent back into the right production process, ensuring that its properties are reusable. The new version of the product that goes into production with recycled materials is named “closed-loop”, as the EOL considerations are taken into account during the design phase along with re-design.

7.9.1. Sustainability Considerations

Sustainability considerations are placed high on the agenda due to growing global population, limited resources and climatic change. Therefore, products are not only designed according to cost-performance requirements but also with respect to sustainability aspects. Sustainability is a diverse term. Specifically, in the course of this work, the term sustainability is used with respect to product realization, in the concrete context realizing a product, such as design, production, or distribution. With respect to this context of application, sustainability refers to improving the product development and realization, e.g. design-for-sustainability and consequently, the product's lifecycle. This includes reduction of energy, material or water consumption, environmentally adverse material usage and respective emissions in each phase of the product's lifecycle.

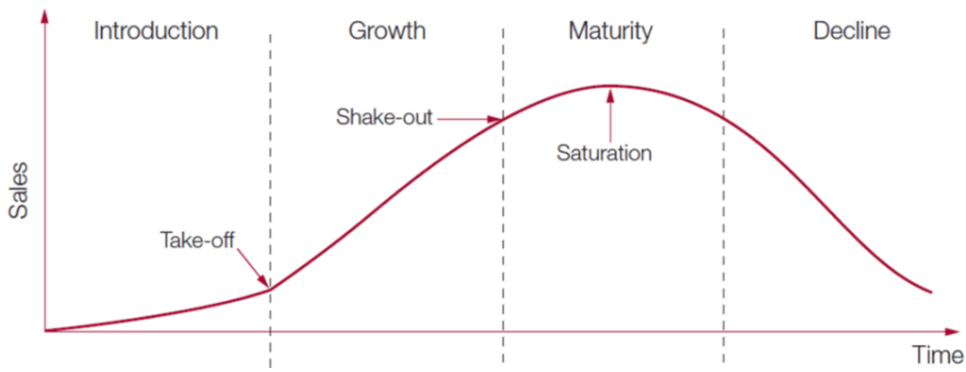

Fig 7 . 3 : Extend Product Market Presence

The need for creating products in a sustainable way is twofold: First of all, the innovations by developing tools and methods for engineers, product designers and decision makers. These innovations lead to improved sustainability measures in practical application within organizations, firms, and society. The second main need for creating products in a sustainable way is the readiness to adopt the innovations of tools and methods for engineers, which require organizational and cultural shifts, such as awareness of sustainability aspects, willingness to change product designs or business models, perform multi-criteria assessments of products. However, there is no actual planning and solving product lifecycle management tasks with respect to sustainable product performance impact, and consequences of product lifecycle stages on other product lifecycle stages, or other products in the product portfolio. In particular, sustainability aspects are often not taken into account, or they play a minor role.

7.9.2. Recycling and Disposal Strategies

Recycling and disposal of products at the end of life can have a significant impact on sustainable product design, management, and innovation. The environment is burdened with overregulation and no incentive to make products more recyclable, increase the cost involved for companies, and push them away from their core competencies. This is especially true for electronic products where the required methods to recycle and take materials from the product are delicate and time-consuming, specifically when there is an extensive use of toxic materials. Due to these issues, the infrastructure for recycling is lacking.

Increased prices for rare earth metals created higher scrap values, but yet many government regulations, taxes, and fees do not make it an appealing business. Companies should start considering not only the product costs but also the end product lifecycle costs associated with the reintegration of the used product back into the design process. The only very profitable product in the recycling chain is the bottom recycling of aluminum where it takes little financial investment to reintegrate it back into the supply chain as well as high demand.

The product design usually remains with the highest degree of freedom to achieve higher efficiency, create a more sustainable product, and influence the global footprint. Adding design functionality for less or no initial product complexity at the beginning of the lifecycle will be of best use to the end of life recycling strategies. The four main types of product design strategies are recycling and disposal, reuse, remanufacturing, and refurbishing. These functions help companies develop sustainable end of life recycling strategies and provide information on other available services at the end of the negative development product lifecycle.

7.10. Conclusion

Utilizing Machine Learning to Optimize Product Lifecycle Management from Design to End-of-Life concludes the exploration of a broad area of research that combines machine learning methodologies for optimizing several aspects of Product Lifecycle Management. The relationship between PLM and machine learning is reciprocal: on one hand, PLM provides large-scale and complex settings for application of machine learning optimization; on the other hand, machine learning is an enabler to optimize several complex PLM processes. To this end, we picked a few selected PLM domains and propose a handful of representative machine learning optimization methodologies for each, for direct contribution to the PLM area. Those domains include design optimization using predictive models, lifecycle data analytics and forecasting from historical data for PLM strategies support, and lifecycle simulation using machine learning for seeing the future of products and their ecosystems.

The complexity of the PLM optimization task, the fact that the PLM domain has a unique characteristic of cross-pollination of complex data and disparity of processes from component-level to the industrial ecosystem-level, and the rapid development of the efficiency and capability of machine learning algorithms, create risks but also tremendous opportunities for both the PLM and machine learning areas. While the research endeavors presented are a step towards further clarification of the potential contribution of machine learning, in terms of the development of machine learning-empowered algorithms that focus on artifacts and decision-making processes unique of the PLM domain, further work is needed for developing specific theory and methods for optimizing PLM using ML. Finally, research combining ML and PLM is important not only in advancing both areas, but also for addressing the tremendous challenges posed by the Fourth Industrial Revolution regarding the optimization of the design, production and delivery of products and services that are becoming more and more efficient and sustainable, based on process efficiency and reduction of waste.

7.10.1. Final Thoughts on Advancing PLM with Machine Learning

The overarching principle of the insights outlined in this book is that Machine Learning methods have the power to bring large benefits for Product Life Cycle Management teams and initiatives. PLM – from design to end-of-life – yields a large synthesis of activities, often with a multitude of tools and systems, either integrated into an information architecture or operating in silos. The volume of data created across these operations from different systems is large, and much of it is underexploited, leading to either missed opportunities or wasted efforts. Machine Learning can help unveil recommendations based on that data. Although these recommendations cannot supplant the judgment of long-term industry experts and the value of proximity to manufacturing issues, they can provide useful support to decision makers and workers in the breadth and depth of their tasks.

We have explored and presented insights from methods developed and applied in various domains: there is a vast number of unsolved problems in PLM, which would benefit from the application of ML approaches. Each domain tends to be tightly defined and specialized, but we advocate a diverse and interdisciplinary view on scientific developments, adoption and adaptation. We trust that the tools and domain-specific methods that have been presented will be useful both in academic and industry environments. For companies, the difficulty of PLM will require an exploration of solutions, many of which will require proprietary investments. The shared insights in the book may lower the risk threshold for companies wishing to utilize external parties to help solve their in-house challenges. Academic institutions can also contribute through closer collaboration with companies, in order to tightly coupling theoretical advances with practical developments.

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