Integrated Product-Process Design: Conceptual Framework for Data Driven Manufacturing Resource Selection

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Declaration

I certify that this research work titled "*Integrated Product-Process Design: Conceptual Framework for Data Driven Manufacturing*" is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources, has been properly acknowledged / referred.

Signature of Student

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Copyright Statement

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I am thankful to Allah (SWT), who has guided me throughout this work at every step. Indeed, I could not have done anything without my creator's help and guidance. Whosoever helped me throughout my thesis, whether my parents or any other individual, was Allah's will, so indeed, none be worthy of praise but Allah (SWT).

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Dedicated to my mother and father, whose tremendous support and affection led me to this wonderful accomplishment

Abstract

With the extensive development of new technologies and the application of information in the manufacturing industry, immense volumes of distinct data are being generated and collected daily. However, this data is largely unusable as its not meticulously cleaned and processed. The effective utilization of such complex data is the cornerstone of data analytics, as successful analysis leads to useful, relevant, and actionable knowledge, which in the long run can prove to be revolutionary for any field and open new avenues. Although the application of data analytics in areas such as sales & marketing, healthcare, cybersecurity, and climate change is largely prevalent, the implementation of data analysis and its tools for efficient product & process design is an unexplored opportunity with large volumes of data generated by major stakeholders throughout the manufacturing and product-process design activity remaining underutilized. This thesis, therefore, defines a novel conceptual framework that applies data analysis to integrated product-process design (IPPD) for weighted data driven IPPD that amalgamates data generated from multiple streams. Primarily from the user perspective, supply chain network, current & upcoming technological processes, and competitor process and product designs, will be utilized. The proposed framework can be further used to create new products better aligned with customer requirements, enhance the overall quality of the product, improve production efficiency through new technological advancements, support the supply chain network, and give the applicant industry a competitive advantage against its competitors.

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CHAPTER 1: INTRODUCTION

The research work in this dissertation has been presented in two parts. First part is deliberating upon the need for a data driven manufacturing resource selection framework followed by a detailed explanation of the proposed framework. The second part includes the application of aforementioned conceptual framework on a case study.

1.1 Background, Scope and Motivation

Extensive research and development in new disruptive technologies and the advent of data as a resource has led to its greater use in almost every industry. The application of this nascent resource has led to a gold rush of the digital age with enterprises all over the world scrambling to acquire, store and utilize this new wealth. Although many industries have adapted to the age of data science and have been able to successfully capitalize on the implementation data for multiple purposes however, the proper utilization of Big Data in the field of manufacturing, especially product-process design, has not been fully realized. Massive amounts of data are generated by manufacturing processes, users, and the distribution networks. Proper analyses of the arising data from these areas could lead to a more consumer relevant product, produced by highly optimized manufacturing processes and distributed through an efficient supply chain

Heuristics and data analysis techniques depend on the requirements of the problem in question. These techniques are effective in solving problems of manufacturing processes, achieve automation, and identify patterns [1,2]. However, they are rarely used due to lack of research on overall master data and data analysis solutions which describe the actual options for presenting analysis results and their effective use in the actual production environment. Various conceptual models have been developed as tools to facilitate the introduction of data analysis in manufacturing systems. For instance, Lechevalier et al. [3] proposed a domain-specific framework for predictive analytics' applications in production. O'Donovan et al. [4] further suggested a set of data and system requirements for implementing equipment maintenance applications and information system model in an industrial environment to provide a scalable big data pipeline for the integration, processing and analysis of industrial plant data. Dutta and Bose [5] proposed the concept, planning and implementation framework of company big data projects. Moreover, Zhang et al. [6] suggested a general framework for big data analysis to make better decisions in product lifecycle management and cleaner production. Zhang et al. [7] also proposed a big data-based product lifecycle management framework to solve challenges such as the lack of reliable data and valuable information that can be used to support optimized business management decisions. Further, Tao et al. [8] proposed a data-driven intelligent manufacturing framework, which consisted of four modules: manufacturing module, data controller module, real-time monitoring module and troubleshooting module. Jun et al. [9] also provided a cloud-based big data analysis platform for the manufacturing industry. In addition to models that focus on the manufacturing fields, analytical reference decision making model data called CRISP-DM have also been used [10]. The data analysis system can be subdivided according to the hierarchical structure proposed in [11] and [12]. The hierarchical structure includes three levels viz. a viz. infrastructure layer, IT layer, and application layer. Another example of a reference architecture is a technology independent reference architecture, proposed by Pääkkönen and Pakkala [13]. The architecture is based on the analysis of different implementations of big data analysis systems that aim to promote the architectural design and selection of technical or business solutions in the development of data analysis systems. Moreover, concepts, characteristics, and uses of big data of Product Lifecycle Management (PLM) were developed by Lei et al. [14].

With data driven intelligent manufacturing frameworks proposed by various researchers along with decision making solutions for manufacturing as discussed above, it is imperative to discuss Integrated Product Process Design (IPPD) as well that works on the integration of product and process parameters in the design phase for effective material and manufacturing process selection [15]. Since material and manufacturing process selection is a crucial decision in the Design for Manufacturing (DFM), Lidong and Cheryl [16,17] studied cyber-attacks in disruptive technologies such as additive manufacturing (AM) and concluded that big data analytics is a valuable tool for maintaining network security by controlling and monitoring each process such as observation of physical parameters like molten pool temperature. Furthermore, Zaman et al. [18,19] defined an integrated design-oriented framework for resource selection in AM along with the showcase of an IPPD system based on multi criteria decision making. Both the frameworks aided in effective material and process selection by considering both the designer as well as the manufacturer's perspectives.

Consequently, it is evident from the literature review above that a great extent of research has been conducted on the application of big data analysis in manufacturing with a common feature being the use of basic concepts, such as identifying new potentially useful data sources and innovatively using data to improve the observational performance of the system with the help of decision-making methods. Also, this data comes from the Internet and sensor networks in the workplace installed in areas of design, manufacturing, and other related departments.

Moreover, researchers have proposed IPPD frameworks to extract data for material and process selection but seldom utilize concepts such as big data analytics for effective resource selection. To address the above deficiency, this research defines a new conceptual framework that would, with relevance to IPPD, help in the selection of relevant data streams for utilization in the IPPD process and through targeted analysis, define key performance indices from data streams that would define how the framework would impact the overall process. Secondly, processed data sets would also be identified that can be utilized in different IPPD stages for optimum results. Thirdly, application of weights to the data sets would assist in manipulating a certain stream of data depending on its relevance and necessity to the IPPD process. Last but not least, the framework would assist in the recollection of data from the process such that it can be reutilized thereby making the overall process reiterative leading to continuous product process design improvement in the long run.

CHAPTER 2: LITERATURE REVIEW

An incredible degree of work has been done in large information investigation in manufacturing. Showing a beginning revenue of scientists. The examination and use of enormous information investigation in the assembling business can be predominantly isolated into research on the presentation of general models of huge information examination in the assembling business, the business status survey and the advancement of arrangements, ideas, and Special applications for innovative work arrangement. A typical subject of these examinations is the fundamental thought of ideas, for example, recognizing new, possibly valuable information sources, coordinating information, and creatively utilizing information to work on the observational presentation of the framework. The information utilized in such activities and the information utilized for improving information examination arrangements come from the assembling climate and different spots, for example, from the Internet, sensor networks in the work environment and on public occasions. Keen information assortment and examination procedures rely upon the prerequisites for speed and mechanization.

These strategies are typically powerful in settling issues in complex cycles, in which non-unimportant models with numerous boundaries portray interaction states [1]. Shrewd investigation techniques can accomplish mechanization and recognition. Learning has accomplished exceptional outcomes in this field [2]. Be that as it may, by and by, these strategies are seldom utilized. The explanation is the absence of examination on generally ace information investigation arrangements, which portray the real choices for introducing investigation results and their genuine use in the real creation climate, and at last, give an adequate degree of safety. Numerous calculated models have been created as devices to work with the presentation of information investigation in assembling frameworks.

Lechevalier, Narayanan, and Rachuri [3] proposed an explicit space system for prescient investigation underway. The principle commitment of O'Donovan et al. [4] is a bunch of information and framework necessities for executing hardware upkeep applications in a modern climate, just as a data framework model. It gives a versatile enormous information pipeline and accommodates the joining, handling, and investigation of modern plant information Fault resilience. Dutta and Bose [5] proposed arranging and executing the structure of large organization information projects. Zhang et al. [6] proposed an overall system for huge information examination to settle on better choices in item lifecycle the board and cleaner creation dependent on huge information. Zhang et al. [7] proposed a major information-based item lifecycle in the board structure to settle difficulties, for example, the absence of reliable information and important data that can be utilized to help improve business executives' choices. Tao et al. [7] proposed an information-driven keen assembling system comprising four modules: producing module, information regulator module, ongoing checking module and investigating module.

Jun, Lee, and Kim [7] displayed a major information investigation stage for the assembling business. Bringing extensive information investigation into the assembling framework, notwithstanding models that emphasize the assembling field, other broader reference models and ideas from different fields, and generally have scientific reference model information called Fresh DM [8], KDD (Fayyad, Piatetsky-Shapiro and Smyth 1996) and SEMMA (created by SAS Institute) can be in every way utilized.

The worth chain illustrates a benchmark engineering for an information investigation arrangement [9] [10]. In the worth chain idea, a run-of-the-mill enormous information examination framework dependent on framework

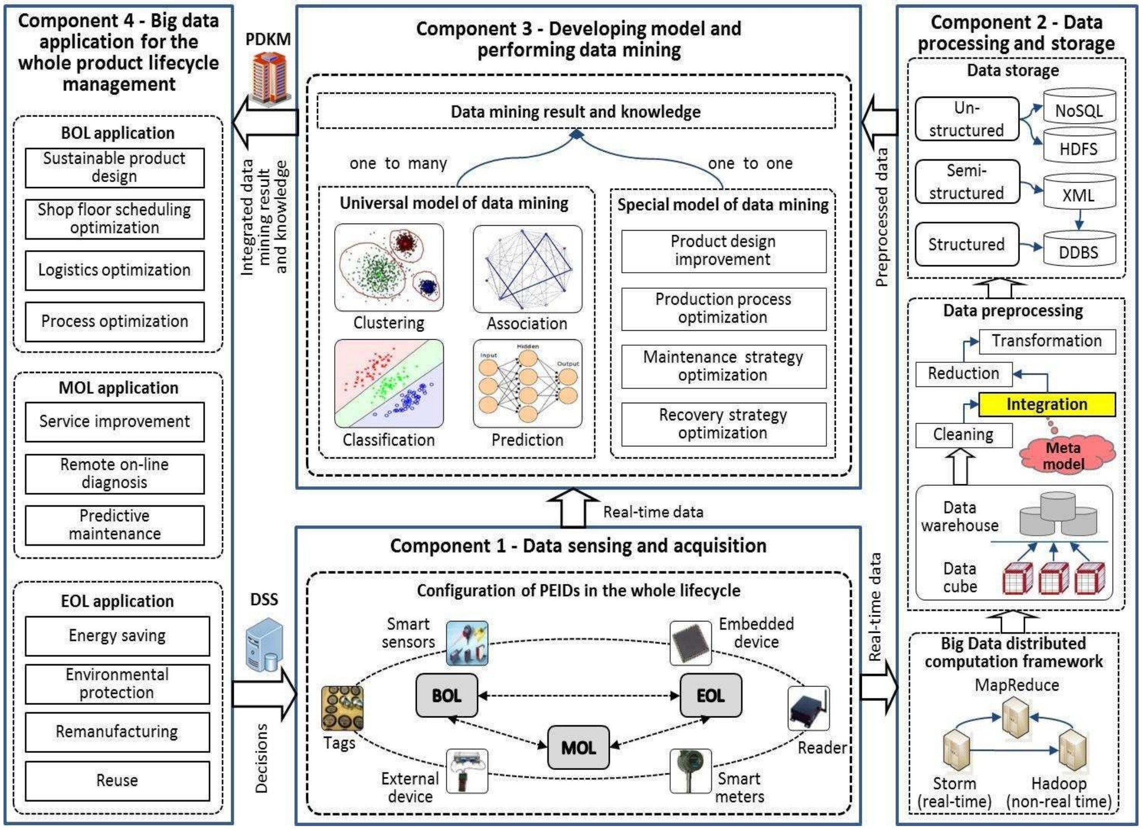


Figure 2.1: The designed framework for Big Data driven product lifecycle management by Zhang [6]

designing strategies is partitioned into four phases: (1) information age, (2) information securing, (3) information stockpiling and (4) information investigation. Because of utilizing this reference design when fostering an information examination arrangement, each stage characterizes the fundamental apparatuses, suitable techniques, and information stream inside and between stages. The proposed progressive construction can partition the information investigation framework [11]. The progressive design incorporates three levels: (1) the foundation layer, (2) the IT layer, and (3) the application layer. One more illustration of a reference design is innovation-free reference engineering, proposed by Pääkkönen and Pakkala [12]. The reference design depends on the investigation of various executions of large information examination frameworks. It intends to advance the building plan and determine specialized or business arrangements to improve information investigation frameworks.

Ideas, attributes and potential employments of enormous information of PLM were created by Lei et al. [13]. BDA significantly affects all areas of assembling. Today, it has viably advanced its execution in the AM field. As added substance producing is an arising innovation, it is still in the planning stage. All created nations work in AM. AM and BDA show their relationship with one another, and there is sufficient work to be done in such a manner. Lidong and Cheryl Ann [14] contemplated digital assaults in cutting-edge assembling. They added substance producing and inferred that BDA is a significant apparatus for keeping up with network security by controlling and observing each cycle. For AM, he proposed three central issues for further developing the checking framework and assault discovery techniques, to be specific, further developing programming control, further developing cycle observing, and further developing interaction checking through the roundabout perception of actual boundaries like liquid pool temperature from machine boundaries (like lasers). Power, assault. They are bound to be found [15]. while Jun et al. [16] set up an actual digital framework based on RFID on the assembling shop floor.

Zhang et al. discussed upon cyber physical system based self-organizing intelligent shop floor and a big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. [17] [18]

Wang et al. [19] demonstrated a capability index for repercussions incurred due to low quality, addressing a practical challenge of asymmetric tolerances in the quality characteristics. Wang et al. propose a data-driven supplier selection model using a Taguchi capability index with dissimilar/asymmetric tolerances. To construct fuzzy membership functions, mathematical programming utilizes confidence intervals. Gao et al. [20] demonstrate a decision tree-based predictive model for the inspection and maintenance of a culvert. Gao explains that the current State Department of Transportation utilizes archaic and outdated for the planning of culvert inspection, based solely on the size and its experimental condition. Therefore, the Synthetic Minority Over Sampling technique is utilized to predict the conditions of the given sample size of 12,400 culverts. The given system achieved 80% and 75% accuracy for the training and testing set, respectively.

He et al. [21] exhibited a clever information-digging structure for item plans. The exhibited system grandstands a unique way to deal with increment the flexibility of the item family and basically increment the precision, effectiveness and by an extensive insight of item the board. A CBA classifier is used to suggest an ideal setup plot. Ng et al. [22] Showcase their nitty-gritty writing audit on Intelligent computerization, exhibiting how theoretical ideas can be essentially used considering future viewpoints. The audit centres around versatile direction (DM), artificial brainpower (AI) and mechanical technology process mechanization (RPA) and through the blend of these to accomplish ideal functional effectiveness, choice quality and framework dependability. The audit endeavors to grandstand ongoing examination interests and applications, further developing how in future streamlined execution can be accomplished.

Shi et al. [23] showed an upgraded client prerequisite arrangement for item configuration utilizing colossal information and a further developed Kano model. The framework displayed how client audits (CR) are gathered by the utility of an engaged creeping strategy, after which item survey remarks are coordinated with applicable CRs for various levelled semantic likeness techniques. Finally, the CRS are arranged effectively and precisely to direct a more engaged item plan by technique for Curve development among CRs and capacity execution. Chen et al. [24] introduced an adaptable multi-process between waiter cooperative plan blend in an Internet circulated asset climate to assistant planners in planning an appropriated plan asset model and using an info yield stream model and calculation-based flexible multi-process bury waiter choice framework. An application on the 3-DOF wave power framework is displayed to approve results.

Jing et al. [25] presented a choice framework for a short set-based span esteemed intuitionistic fluffy (IVIFS) theoretical plan for thought with a different client inclination appropriation. The framework distinguished a specific interest by tracking its establishments in authentic information to shape an extraordinary inclination; the intuitionistic fluffy set is shown to help a choice framework that, under vulnerability, can use a harsh set to preprocess the intuitionistic fluffy set to frame IVIFS.

Shu et al. [26] present a Data-driven transport administration plan for a more maintainable last mile transportation framework. It features an exploration-based way to deal with user information to configure transport administration with improved and upgrade proficiency and accommodation of activity for last mile requests. Via an improved grouping calculation, directing and booking the bus administration is tended to.

A contextual investigation is examined to exhibit the helpful utilization of the interaction and confirm its presence.

Zhou et al. [27] present a novel information diagram-based streamlining approach for asset allotment in discrete assembling studios. The paper presents a choice framework dependent on an information diagram structure that is generally associated with coordination in designing information for a machining studio climate. It exhibits a three-stage strategy for defining an up-and-comer arrangement using a machining studio information to give pertinent information backing the development and assessment of the competitor administration pool.

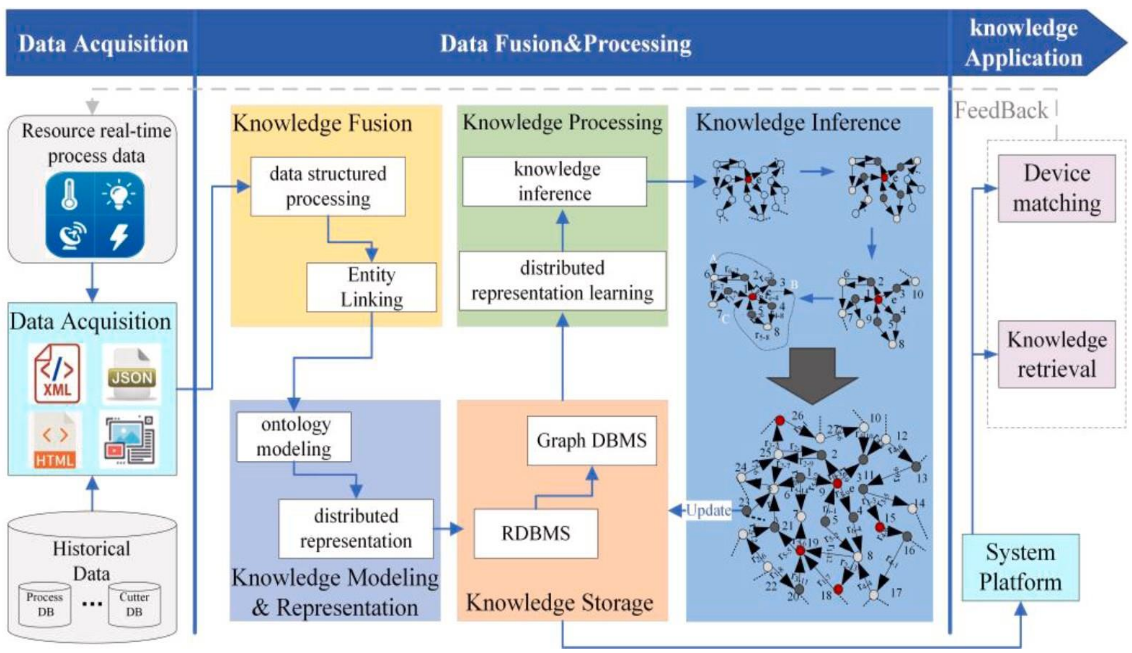


Figure 2.2: The framework for construction by Zhou [27]

As assembling is not any more developing actual items, changes in buyer requests, financial aspects of creation, and nature of items are probably the main choices in the assembling business which are made during designing plan [28]. It has been featured that the manufacturability of any part straightforwardly affects the expense (70–80%). Therefore, an originator ought to cook for it in the beginning phases of the plan and along these lines give a simple stage to continue as far as assembling and prompts decreased expenses of get together and plan operations [29]. The resulting acknowledgement has prompted the interest in simultaneous designing (CE), which incorporates the item advancement process with the members that settle on upstream choices to think about downstream and outer necessities [30] [31].

The simultaneous plan works under the idea of incorporating plan and assembling, yet additionally gives an "advancement" process that will cook for all plan compromises connected with item execution, i.e. usefulness, use, and backing. It is vital to comprehend that the opportunity to change the plan is greatly diminished as the plan develops from the primer level to full-scale creation [32]. Hence, it is essential to have the privilege to change the item improvement process in the planning stage to diminish creation costs, time for item advancement, and imperfections particularly connected with quality.

The thought explained above is an undertaking toward the blend of thing limits and cycle plan limits. The decision of material and collecting processes (i.e., appropriate gathering development) is associated with the past point of view. At the same time, the last choice worries the Design for Manufacturing (DFM), made by Stoll in 1988 to simultaneously consider the arrangement destinations and restrictions somewhat creating and is, for the most part, executed considering a particular collecting process. DFM is a piece of Design Theory and Methodology (DTM) systems. Here, the arrangement speculation interfaces with how to exhibit and plan while the arrangement system explains the arrangement communication model melding terrifically significant subtleties [33]. A huge route depending upon DFM is, along these lines, the selection of materials and collecting processes.

Likely, more than 80,000 materials exist in the world. Subject matter experts and associations are on a consistent post for deciding the "best compromise" for planning materials and gathering cycles to satisfy the customer needs and practical conclusions. An impressive part of the "standard materials" which have served the collecting region for so long are being replaced by "new materials" due to reliable assortments in the arrangement targets like execution, size, weight, and topography smoothing out [34] [35].

Moreover, goals (which can either be limited or cycle express or both) ought to be addressed in the arrangement stage to achieve the critical result. The trial-and-error approach, or what was used before, was used every so often to pick the material and related gathering process. This system cannot be followed today because the surges of collecting propel similarly as the spaces of utilization are effectively changing daily. Additionally, generally, there are three surges of gathering progressions: added substance, standard (joins subtractive), and cross variety. The degree of this paper is on the underlying two. ASTM portrays added substance creating (AM) as the "strategy associated with joining materials to make objects from 3D model data normally layer upon layer, rather than subtractive collecting headways, for instance, standard machining" [36].

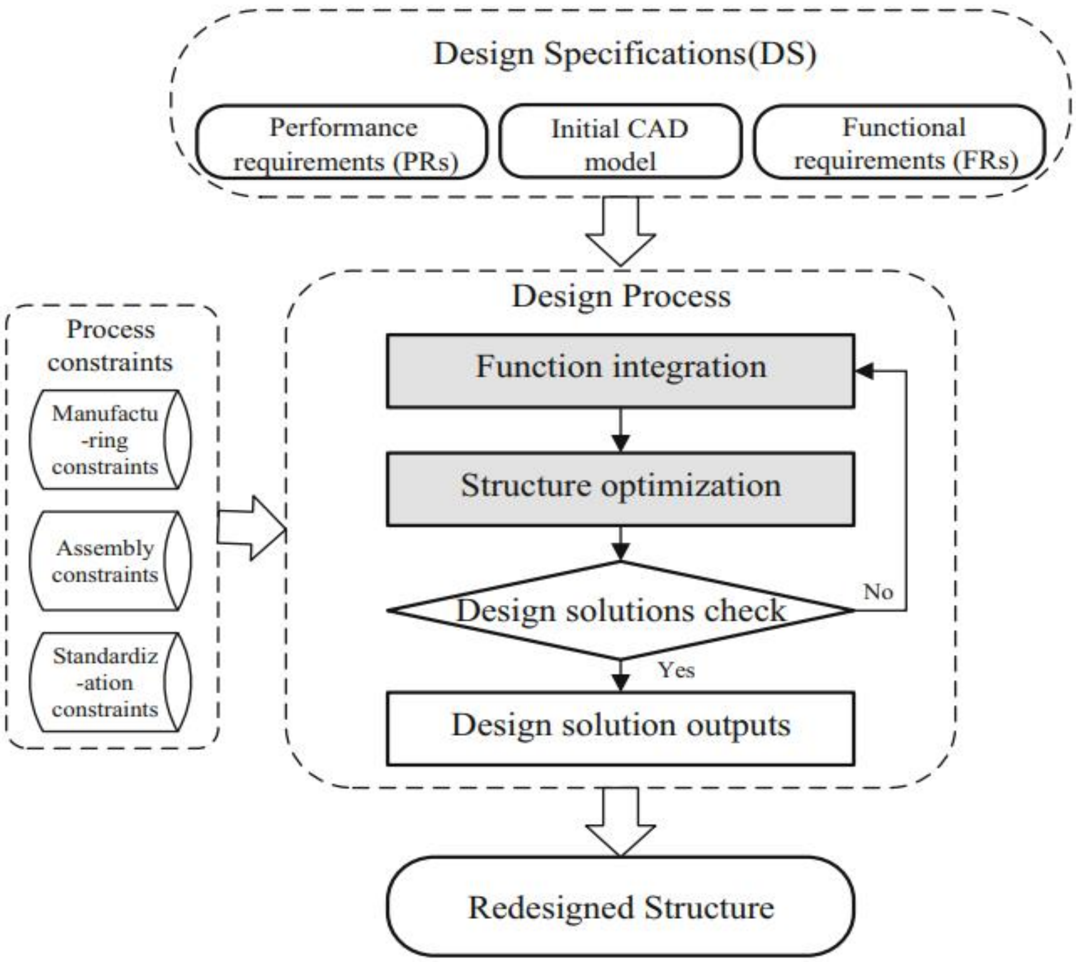


Figure 2.3: Proposed AM-enabled design method by Yang [33]

DFM runs well cover the Traditional Manufacturing (TM) processes recorded as a hard copy were to have a good arrangement, the components altogether addressed consolidate encouraging a deliberate arrangement, using standard parts, arranging the parts to such an extent that they have various uses, avoiding disconnected fasten, restricting social affair headings, staying aware of uniform divider thickness, and avoiding sharp corners [37].

A critical number of these components and collecting necessities are diminished concerning combination manufacturing (HM) and shockingly vanished in the more significant part concerning AM, which can make bits of any multifaceted numerical nature without TM helps, for instance, tooling [38].

Consequently, AM might significantly change how various things are made and appropriated. This similarly suggests that AM may genuinely transform into an "inconvenient" advancement. To comprehend how risky, it can become, it is significant to focus on the connection settings of TM [39]. Distinctive investigations recorded as a hard copy have worked on procedures to refine normal DFM with AM just as HM plan rules [40].

For example, plan rules similar to numerical likely results and cost, for instance, rethinking the whole assembling toward composed free construction setup, using as negligible regular substance as possible to work on the arrangement toward most raised strength and least weight, using sabotages and void developments, and arranging the best condition of the part according to the helpfulness, have taken the Design for Additive Manufacturing (DFAM) to an incomprehensible level [41].

Everything considered for both AM and TM parts, Cotteleer et al. [42] and Sharon [43] isolated them into seven locales: avionics, motor vehicles, clinical benefits, client things/devices and insightful associations, current applications, plan, and government/military. These applications have extraordinary "traditional" handiness documents and loads concerning various arrangement goals like cost, material strength, and energy usage. For example, the customer devices industry zeros in on lessened cost than material strength. However, execution and material strength have more conspicuous importance for the plane business than cost.

With various surges of cycles, vast spaces of use, and a high propensity toward the possibility of CE, the possibility of the right resource of development and the related materials and collecting processes [referred to as the resource decision (RS) issue from now on] transforms into an interdisciplinary effort. The picked material and collecting association should satisfy necessities connecting with a thing's lifecycle by thinking about components, for instance, plan planning, displaying, constancy, gathering, feel, and quality.

For example, Giachetti [44] depicted some material and cycle decision credits for the RS issue. He picked Mechanical or natural properties as the material credit fundamental for material decision. In contrast, he picked numerical, imaginative, and creation properties for the gathering framework decision as they are associated with commonsense requirements. Like this, it is clear from focusing on the decision measures that the RS issue requires input from various corners like current planning, material science and planning, and mechanical planning [45]. This also suggests that the RS issue will incorporate a couple of conflicting targets and will either lie in the window of multi-objective improvement (MOO) or multi-principles autonomous course (MCDM), or both [46]. Wright [47] depicted the cycle stream in a thing headway process by highlighting the critical objectives and considerations techniques are restricted [48].

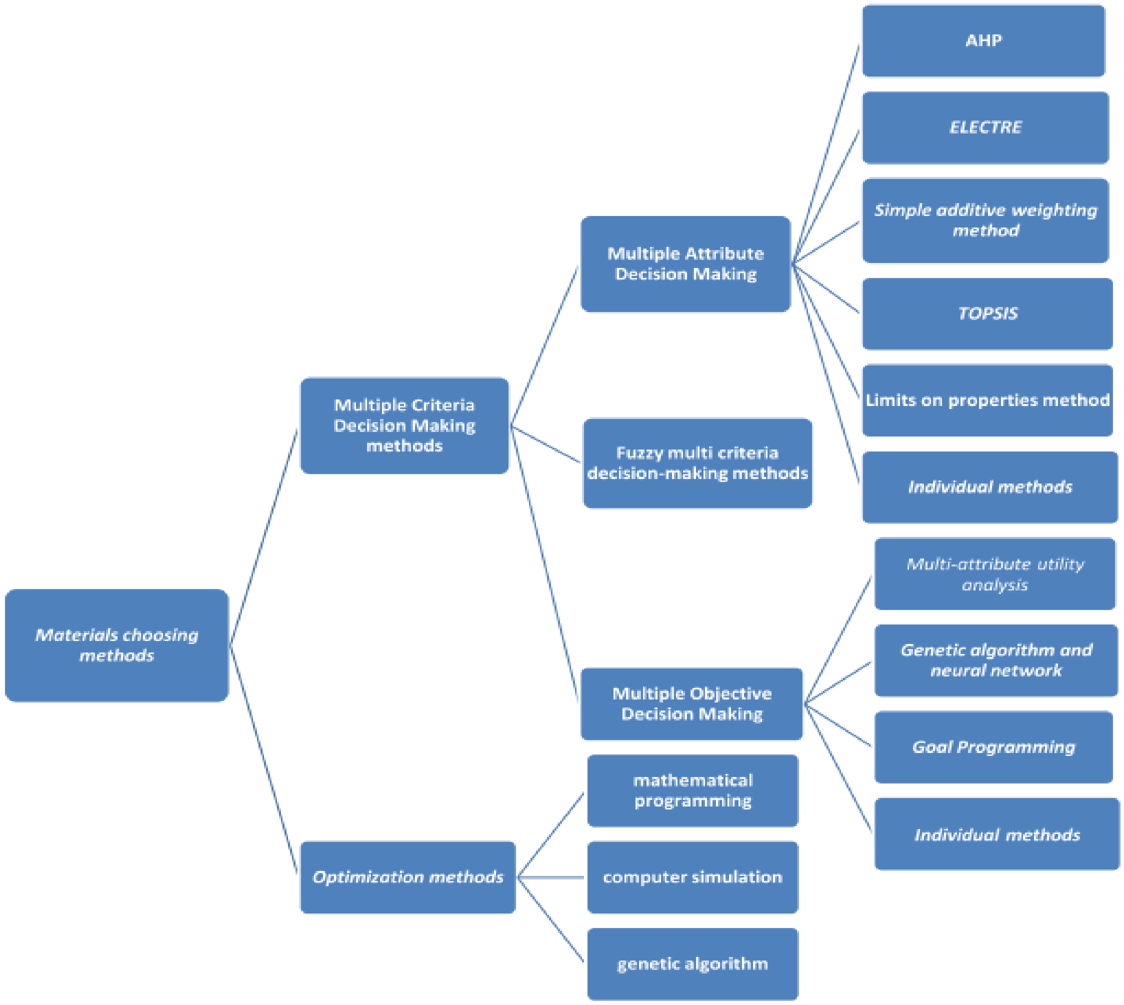


Figure 2.4: Classification of material choosing methods by Jahan [45]

In any case, this technique has for a long while been basically and with the movement of time and with new emerging development principles, for instance, cloud collecting and AM; associations and individuals are on a consistent undertaking to fulfil the targets of TQCSEK (i.e., fastest an optimal chance to-promote, best type, lowest cost, best help, cleanest environment, and high data) [49]. This similarly infers that the bolts on the lower side are fundamental to thing definition, while the bolts on the upper side are critical for process plan definition. Farag [50] re-underlined the arrangement stage by contemplating three components in arranging a section, creating processes, material properties, and limit and client essentials. The ideal arrangement is a trade-off between many conflicting conditions, for instance, monetary factors, practical necessities, prosperity concerns, and regular impact.

Since the beginning of Additive Manufacturing (AM) as Stereolithography (SLA) by 3D structures in 1987, AM has taken up an essential and stunning collect yearly advancement speed of 26.2% to accomplish a market worth of $5.165 billion each 2015 [51]. Diminished thing improvement cycles, extended and fixed up rules on acceptability, growing revenue for redid and adjusted things, redesigned part-multifaceted nature, reduced lead times and collecting cost, extended throughput levels, and the introduction of new game plans are a piece of the many market factors that have helped the connected advancement of AM to convey complex parts in tiny to medium assessed bunches [52] [53].

Likewise, the sum and collection of End-of-Life (EoL) things have mentioned the AM creation systems to be arranged possibly with the ultimate objective that the monetary and regular impacts are diminished [54]. This, moreover, consolidates the prerequisite for post-taking care of issues, for instance, departure of powder, support plans, stages and cleaning, as the surface quality would confine the utilization of the part conveyed [55].

Consequently, the current colossal field of taking care of advances and opponents in the hardware space of AM has all been tracked down, seeking after arranged goals to simultaneously design a thing, select a compromised material and pick a sensible creation process. This thought further goes under the area of Concurrent Engineering (CE) and Integrated Design (ID) which help in not simply diminishing thing progression time, plan patch up, and cost, yet moreover in additional creating exchanges between different components of the total thing improvement cycle by making upstream decisions to cook for downstream and outside necessities [56] [57].

As CE/ID is an undertaking towards the compromise of things and collaboration plan limits, the assurance of the 'best compromise' of materials and gathering processes from a pool of more than 80,000 materials to not simply satisfy the customer needs and pragmatic points of interest yet furthermore address the cycle express objectives, is a mind-boggling task inside itself. A couple of examiners have moreover implied applied cycle needs to assess the manufacturability and cost of determining arrangement in the early bits of the arrangement stages [58].

Nevertheless, since AM can work possibly goals free, it has invited new heights of plan opportunity by offering further developed complexities to the extent of shape, multi-scale plans, materials and value [59]. It can gather parts in a solo action without wasting much raw substance [60]. Moreover, this idea acclimates to CE requirements, which helps in extended productivity and quality of things [61]. Furthermore, the standard progressive stream or "Course model" is replaced in such a case with a "facilitated improvement technique", which follows an iterative framework cyclically by using free heading and extraordinary systems [62]. Concerning TM, a composed thing process plan (IPPD) was explained by Tichkiewitch and Veron [63] concerning a collaboration chain of delivering machining. Thibault et al. [64] elaborate on an expert structure and assembling advancement for process coordination in the delivering region. They made the thing cycle necessities by describing process plan outlines.

Furthermore, Skander et al. [65] proposed a data blend procedure which fused collecting limits in the thing definition stage by utilizing skin and skeleton features for the arrangement part. Earlier, Roucoules and Skander [66] had given a method for managing examination and mixing in the headway process. For examination, they pondered DFM and collected process assurance while creating prerequisites for the mix was considered. Plus, Bernard et al. [67] used the possibility of a "reference" by utilizing a data-based planning method for managing coordinated money-related principles in arrangement and creation decisions for a projected part. In any case, for the setting of AM in IPPD, there are relatively few assessments.

Klahn et al. [68] suggested two arrangement strategies for AM: "manufacturing driven arrangement approach" and "limit driven arrangement technique." The past framework can be used to mass adjust a part by keeping a customary arrangement and sticking to design rules of other gathering advancements, while the keep going framework chipped away at the limit of a thing as done by Klahn et al. [69] for a clinical contraption that was used in shockwave treatment

As the quantity of actual capacities and the related imperatives increment, more exertion is contributed by the calculations to look through the arrangement space, i.e., seriously registering time is needed for assembly. In addition, as a result, is a bunch of practical choices and not a solitary arrangement, the RS issue is all the more differently tended to in writing by the MCDM techniques where leaders recognize the most favored arrangement either by positioning or screening or both [70]

MADM issue implies the assurance of an optimal advancement resource from something like two plausible collecting processes/get-together of gathering processes dependent on no less than two credits [71]. As RS incorporates various characteristics' and necessities' evaluation, it can rely upon MADM systems. Cushioned MCDM, in light of everything, was made by Zadeh in 1965 to address questionable, ill-defined, and ambiguous issues in etymological terms like extraordinary, sensible, best, poor, etc. [72]. Maleque and Dyuti [73] used this procedure to pick the ideal material for the usage of a falling bicycle diagram. Ashby's "materials and cooperation assurance graphs" have also been used with phenomenal achievement by the Cambridge Engineering Selector (CES) for early screening of materials and cycles.

Ashby [74] proposed a nonexclusive material decision approach: plan essentials' understanding, screening of materials with the help of necessities, situating materials using the limit targets, and using support information with the help of material and cycle decision charts. "Case-based reasoning (CBR)" was used by two or three makers, but it bases on the recommended strategies of the past connecting with a case which may potentially be evident. For example, CBR was used by Berman et al. [75] for material decisions in petro science by using ARAMIS and AIR/CAIR assurance strategies. "Material Selection Programs" were used by specific makers to find suitable materials [76] [77]. These undertakings/gadgets assist the buyer with showing the necessities and engineering in starting periods of material assurance.

For instance, Kesteren et al. [78] involved three gadgets for the selection of materials viz. a viz. picture instrument, test device, and question gadget. Such undertakings/instruments are incredible for screening yet cannot perform assessments and are, by and large, used as informational indexes. RS issues regularly use such informational collections, yet they have their shortcomings. As a matter of first importance, very few RS structures have the collecting framework; glancing through the limit and utilization of these systems on complex thing enhancements can be a mind-boggling endeavor. Moreover, the data covered in these gadgets may not be sufficient. At last, KBSs were used for screening purposes which rely upon artificial thinking and search in an informational Index of information. Ipek et al. [79] dealt with the reasonability of things for the occasion of vehicle region by proposing a KBS to pick appropriate materials. Zha [80] further elaborates on soft KBS in concurrent arrangement to the extent of total creation cost. It can have many levels as required and can suitably manage impartial and enthusiastic qualities by getting relative heaps of the models [81].

Gupta et al. [82] managed AHP in the plausible gathering by exploring sensible collecting rehearses, for instance, process plan, eco plan, and lean practices, for making electrical sheets. Desai et al. [83] elaborate AHP connected with DFM to give superior versatility to join various principles for decision-making for RS issues. Likewise, Armillotta [84] used an adaptable AHP decision model to pick the proper AM process from many choices for models created utilizing a picked characterization (applied model, particular model, sand anticipating, hypothesis anticipating, and plastic frivolity). The credits included speedy structure, incredible precision, low material cost, etc. The fundamental burden AHP passes on is that all qualities should be independent [85].

In addition, "Strategy of Ranking Preferences by Similarity to Ideal Solution (TOPSIS)" was made to pick the best elective given a set number of models. Milani and Shanian [86] involved TOPSIS to peruse the material assurance for gears. Chakladar and Chakraborty [87] proposed a united TOPSIS-AHP method for managing select the most fitting groundbreaking machining process (ultrasonic machining, grinding plane machining, laser point of support melting, etc.) for a concerned material and shape incorporating a blend ELECTRE, one more MADM procedure, has been used by various makers for RS issues, with a more significant focus on the material decision.

For example, Shanian and Savadogo [88] involved ELECTRE IV for bipolar polymer material decision. At the same time, ELECTRE III was used by Shanian et al. for picking material in a get-together pondering weighting weakness. At long last, Jahan et al. [90] detailed a design considering the "weighting methodology" in evaluating the material decision. They further fostered the MADM situating procedures by giving a calculated method for managing enthusiastic, objective, and associated loads. Here, enthusiastic burdens rely upon an expert evaluation and best practices, objective burdens are obtained from the data that had some considerable familiarity with the issue, and related burdens are a blend of dynamic and objective burdens.

CHAPTER 3: METHODOLOGY

3.1 Data Driven Integrated Product-Process Design Framework for Manufacturing Resource Selection

The Data Driven Integrated Product-Process Design Framework proposed in this thesis follows a step-by-step procedure for Manufacturing Resource Selection (MRS), i.e., material and manufacturing process selection. The framework is impacted by data in the domains of functionality, economic, sustainability, product design, Data Driven Necessity (DDN). It further follows two major steps: screening and ranking with the former screening the material process alternatives, and the later ranking them for effective decision-making. The framework also considers user-designer requirements, cost, functional/technical data, and environment as part of the decision design criterion. Figure 3.1 shows the decision tree of the proposed framework with respect to MRS. The framework shows an interaction with a database that comprises of all relevant datasets necessary for data analysis for both, Product Necessity (PN) and Product-Process-Material-Machine (PPMM). A breakout of the Database and its individual storages containing data necessary for PN and PPMM is shown in figure 3.3 and explained in subsequent sections. The conceptual design-decision space, in context of IPPD, is considered the key stage of design process where the designer explores the fundamental scientific principles, constraints, and associated relations. The conceptual design decision space is shown in figure 3.2 The text to follow will explore avenues of decision making in each of the design stages.

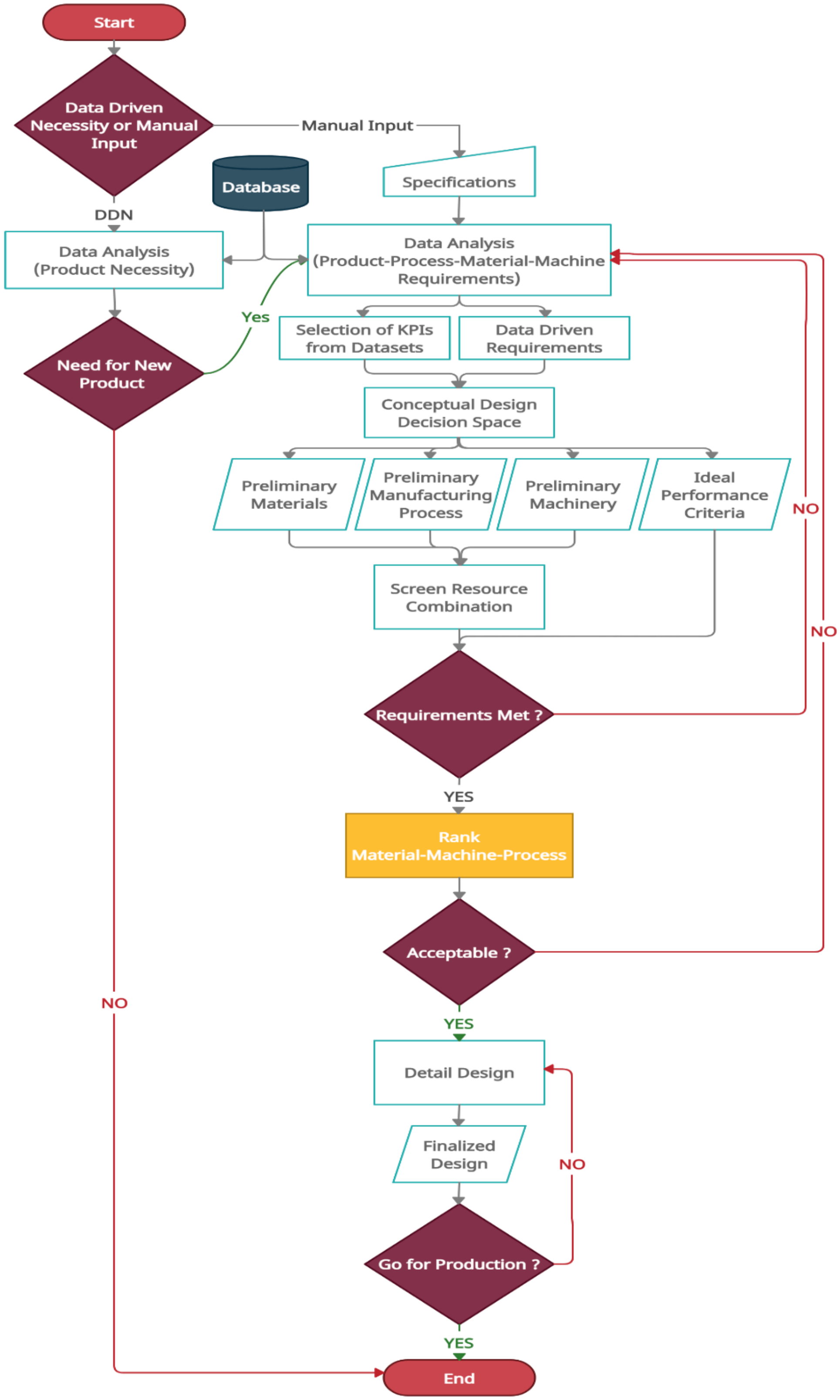


Figure 3.1: Proposed Framework

3.2 Proposed Framework

The proposed framework showcases a multistage decision system that encompasses all aspects of the design criterion in a simplistic yet complete manner. In the first stage, a decision regarding the process to be carried forward using Data Driven Necessity (DDN) or 'Manual Input' of specification required is taken. In essence either the user defines whether the necessity of new product should be generated using data analysis or it is preordained that a new product is required, and the specifications of the product are manually input into the Product-Process-Material Machine data analysis (DA PPMM) process for MRS. If DDN is selected as the modus operandi, the next process i.e., Data Analysis Product Necessity (DAPN) is carried out. The data sets present inside the database help in the determination whether a new product is required and in generating feasibility with respect to an enterprises capability to develop and manufacture said product. However as mentioned earlier, if the designer has pre-determined that a new product is required, the designer will then manually input the specifications of the required product as per their understanding into the DA PPMM process.

The next phase DA PPMM facilitates the designer in correct MRS with respect to materials, processes and machines required to carry out said processes. Furthermore, the process helps in determination of KPIs necessary for decision taking and performance measurement in the conceptual design decision phase and data driven requirements of the product. Following these two data analyses phases the framework then continues with the Conceptual Design-Design Space process, in which the product's design, performance, selected materials, manufacturing processes and machine are analyzed and a preliminary combination of MRS is decided upon based on a multitude of factors, necessary for a complete, efficient, and optimized design. Data regarding the products ideal performance is also generated during this phase which helps in the confirmation of the combination selected. Following this major process, the resources are screened for discrepancies and feasibility issues and a decision is given regarding the applicability of the RS in conjunction with the product's ideal performance criteria. The selected manufacturing resources are then ranked and a decision regarding it acceptability is taken from the design team. If in case the ranked PPMM combination is not acceptable the defined logic shall return the process to the DA PPMM. However, if the ranked combination is acceptable, the framework moves toward the detailed design phase during which a complete design of the product, bill of material and process plans are generated. After which the finalized design is outputted and rechecked regarding acceptability for production. This decision phase is iterative as shown, such that the detailed design can be improved upon if found unacceptable. As shown in the framework, the decision system is heavily impacted and influenced by two major data analysis phases i.e., PN and PPMM. Which in turn are directly influenced by datasets present inside the combined database. A detailed explanation of the datasets comprising the database is elaborated upon in the next section, with a pictorial reference for better understanding given in Fig. 2. As earlier discussed, Fig. 1. showcases the decision tree of the proposed framework with respect to MRS. A detailed explanation of each step is given in paragraphs below.

3.2.1 Decision 1; Data Driven Necessity or Manual Input

The first step of the decision tree deals with the argument regarding, whether the designer wants to go forward with Data Driven Necessity analysis or do they want to manually input specifications of the product into the next process block. This decision is based on completely on the designer's discretion. The designer may take this decision based on factors other than technical and functional data available to them. For example, Executive level decisions regarding specific requirements of the product, specific issues with the previous product development that need to be addressed in this iteration etc. It is important to note that DDN has its own dataset by which it derives the actual necessity of the product development.

3.2.2 Data Driven Necessity

Data Driven Necessity process block deals with the data analysis regarding whether the development of a new product is necessary. This process block is back by a relevant dataset in the database, i.e., DDN Data. This database deals with studies regarding current product market relevance, latest manufacturing technologies, economic feasibility studies, effectivity and performance of the current product and user reviews of the current product. An important as per to note here is that it is not necessary the studies be limited to only those mentioned above, rather it is completely up to the discretion of the designer to include or exclude studies, which they deem are necessary for the optimal DDN analysis. It is very important to note here that the studies need not be extremely complicated, rather they can be dealt with a logic gate concept in mind. That is, if for example users are not satisfied with the current product, then there is necessity for a new product. The studies do not need to go into detail regarding how much satisfaction is present within the end user. However, the feedback from these studies can and will be carried forward for consideration in the DA PPMM phase. A few suggested studies are detailed in Composition of the Database section.

3.2.3 Manual Input

The manual input of specification of product design is a process that is usually done by the designer. The designer needs to spend a lot of time on this process which affects the performance, user experience and designer experience. The manual input of specification of product design is an important part in the design process. It can be tedious and time consuming for designers, but it is necessary to provide accurate information about the product they are designing. In the case of the proposed framework, the manual input phase is present to address the situation if the development of the product has been deemed necessary by factors other than the DA PN, for example executive level decision. This input can also be used in the case that the requirements generated by the DA PN are aberrant and need to be manually overridden to create a streamlined product. An important aspect to note about the manual input phase is that it needs to be used to input actual technical specification of the product, including but not limited to, dimensions, performance, efficiency etc. This specification will then be carried into DA PPMM phase for generation of the preliminary PPMM combination through the data analysis of the specification and the manufacturing resources to successfully manufacture the product on a large scale.

3.2.4 Data Analysis Product-Process-Material-Machine

After the designer has manually input the specification or they have been generated by the DA PN phase, the requirements will need to be aligned with the optimal PPMM combination. In this regard the DA PPMM will call upon Economic, Functional, Sustainability, Current and Future Product Data and the temporary data generated from the DDN or MMDI phases. A detailed explanation of all the data blocks is explained later in the composition of database section. This process deals with the translating the specifications and requirements of the user and designer to into KPIs from individual datasets and technical requirements for manufacturing of the part. That is, if the part needs to be strong/hard and endure forces, then this process will translate these specifications into a set of KPIs, for example tensile strength, and data driven requirements for machining that level of tensile strength. It is important to note that each dataset will generate a separate datasheet of KPIs and technical requirements, examples of these are given in the composition of the database section. These datasheets will then be amalgamated for consideration during the Conceptual Design Decision Space. A step-by-step example of this process is given in the case study chapter, for better understanding. The generated data from the Data Analysis PPMM is directed into the CDDS for decision making. It is in CDDS that all the DA PN and DA PPMM related data is amalgamated and reviewed from all aspects of the product design. The data present in datasets relevant to the analysis are highlighted in the composition of database section. It is here that material and process are selected in cognizance with each, consequently the equipment needed to machine the material with the relevant process. This is done by keeping the product specifications in cognizance with process-material and machine combination. A final review of the combination is done in CDDS phase is which is detailed below.

3.2.5 Conceptual Decision Design Space

Fig. 3 highlights a conceptual decision-design space developed by the author. Once the set of requirements are generated, the information is routed to the conceptual design decision space. Decision-making in the development of products necessitates collaboration between multiple teams, the details outputted must be arranged and managed in a way that all parties achieve their goals. With reference to figure 3.2 multiple factors affect all stages of the product-process development.

Starting with DA PPMM, which amalgamates concerns from a multitude data sets present in the database since, the DA PPMM determines progress and effectivity of product design, its manufacturing process plan (MPP) and resources associated with MPP.

DA PN/DDN on the other hand specifically only deals with DDN data, comprising of studies that affect determination of the necessity of the product as already elaborated upon earlier. Furthermore, user requirements also play a key role in the decision space as, data present in this data set affect all stages of the framework since the RS is majorly if not completely dependent on data arising from the end user.

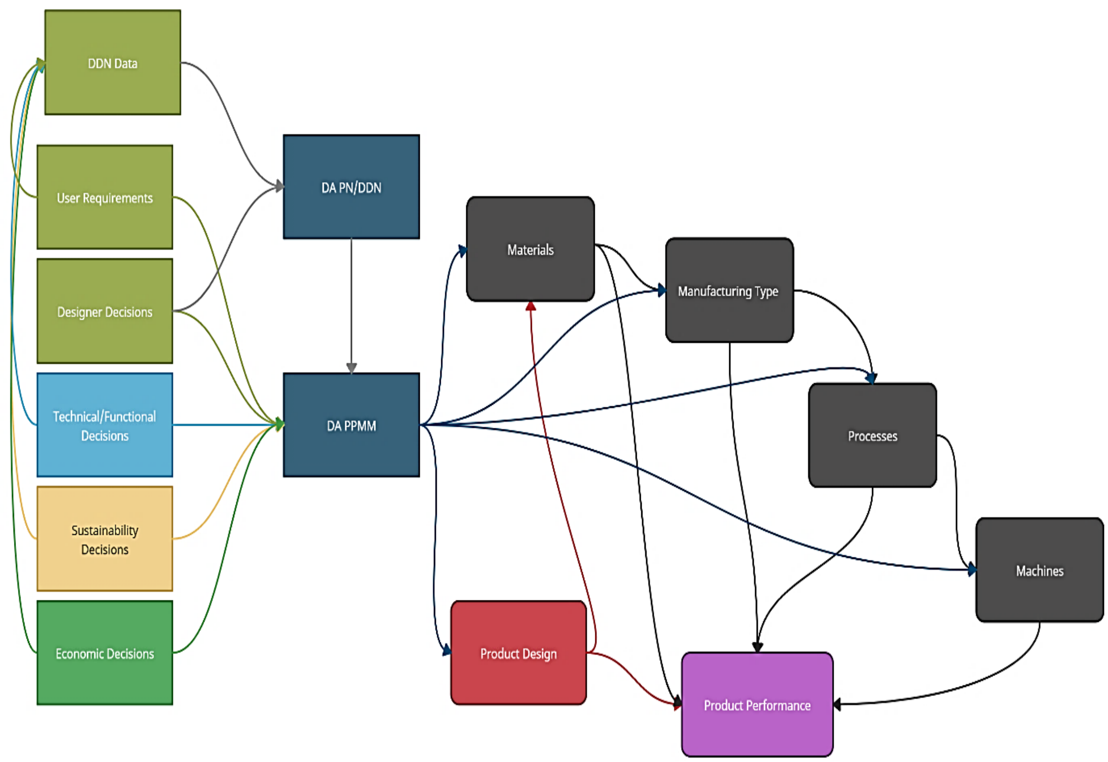


Figure 3.2: Conceptual Design Decision Space

The relationship between datasets and processes are highlighted in the figure below. It is important to note that, it is here that preliminary process-material-machine combination and ideal performance criteria is generated. This is done by step by step for each node. i.e., Processes are selected while keeping in mind the user requirements, designer decisions, functional decisions, sustainability, and economic requirements. In this manner each combination is rationally and step by step made and verified. Therefore, the result is a preliminary combination of process-material and machinery that can fulfill the requirements of the product. A detailed example of the decision taken for each node is given in the case study chapter.

3.2.5.1 Screening and Ranking

The preliminary combination of process, material, machinery i.e. the MRS is screened and ranked with respect to the requirements and the ideal performance criteria. The MRS is reviewed such that the combination does not contain any aberrant data and that the selected combination can successfully manufacture the product, as per the ideal performance criteria generated by the DA PPMM phase. This process is critical in ratifying the selection and that after this process is completed the framework moves toward the actual detail design of the product and consequently towards the production phase.

3.2.5.2 Detailed and Finalized Drawing

After the MRS combination is deemed acceptable, framework moves forward with the designing of the product i.e. all detailed drawings are finalized and the framework moves towards the production phase. This is the last process in the framework and after which the product can be mass produced, as per the requirements of the project. In the production phase, all the finalized drawings are converted into detailed engineering specifications, which will be followed when manufacturing the product. The design phase will be repeated several times as the product evolves.

3.2.6 Composition of Database

A breakout view of the database, the individual storages and the documents contained within those storages are shown in figure 3.1. The database provides input to both DA PPMM and PN. To elaborate, storages related to economic, functionality, sustainability and product data are linked directly to DA PPMM for optimal MRS. However, product data also serves DA PN, for DDN study. The database also contains Design for Manufacturing (DFM) guidelines and multiple-criteria decision-making (MCDM) tools to aid in design and optimized decision making in both DA PN and PPMM. Individual storages and their containing documents are further elaborated on as follows:

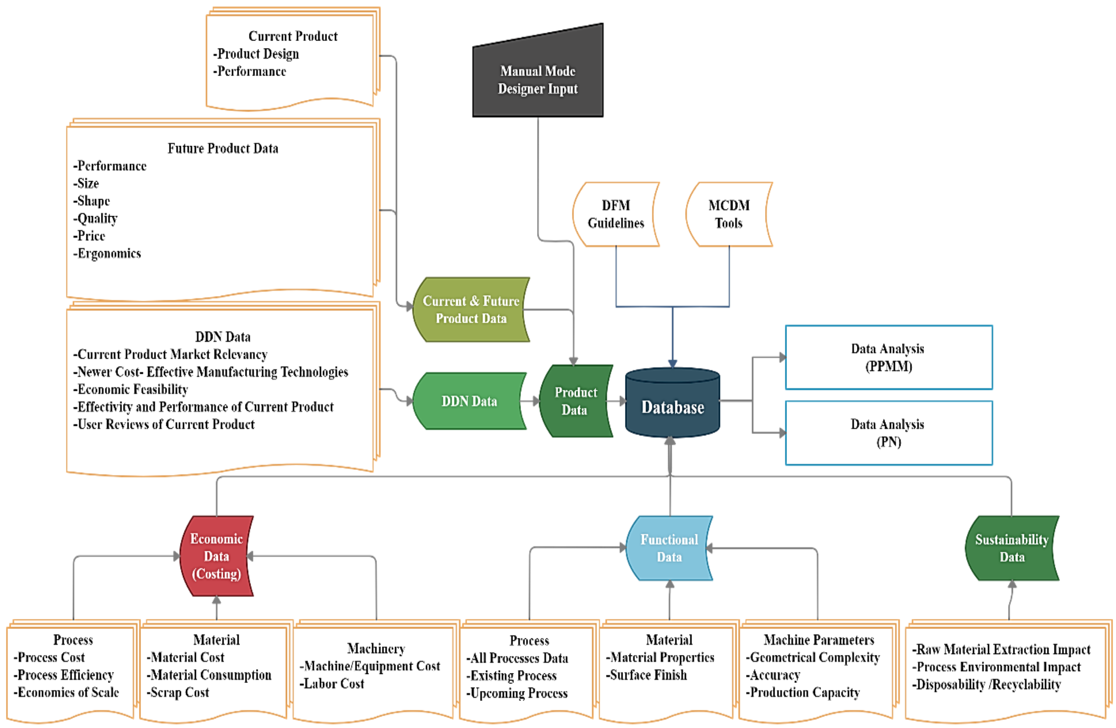


Figure 3.3: Database Design

3.2.7 Economic Data (Costing)

Documents contained within this storage relate to the process, material and machinery, and the cost associated with each of them. To further expound:

3.2.7.1 Process

Documents related to process with reference to economic data contained cost models regarding types of processes related to all major manufacturing type. Furthermore, data regarding process waste and its economic impact and data regarding output vs. average cost for all processes is present in the storage for development of specific cost models in cognizance with the product design. This dataset contains information related to individual processes and their costs, which are dependent on the volumes of production, the material and machinery utilized. The aforementioned data is correlated with Material and Machinery datasets present in the Economic Data. An Important decision factor here is, if the material for the part is fixed then, the process ability of the material will be taken into account for selection of type of process available. An example of the data is given in the table below

Table 3.1 Process Data Sample Table

Process Type	Average Cost/Piece	Average Overall Efficiency
Casting		
Forming		
Machining		
Additive Manufacturing		

After selection of process type from Table 3.1, we may proceed to secondary process selection. If for example Forming is selected as the process type, we will proceed to given in the table below

Table 3.2 Process Data Sample Table (Detailed)

Forming Type	Volume	Cost/Operation
Pressing		
Extrusion		
Forging		
Rolling		

3.2.7.2 Material

A complete set of documents that highlights cost of all types of common, special materials and alloys/composites that used in all manufacturing types. The document also displays the material wastage in cognizance with process data to represent the average material wastage for specific Processes to aid in selection of materials that reduce overall waste and loss of economy. Based off the already selected process type we may proceed to selection of materials applicable to the given process type. An important thing to note here is that both processes and materials may be selected in cognizance with each other. An example is given in the table below.

Table 3.3 Material Data Sample Table

Casting Type	Material Cost	Scrap Cost
Steel		
Aluminum		
Copper		
Titanium		

3.2.7.3 Machine

These documents present the cost of all mainstream and specialized manufacturing equipment for all manufacturing type. It also contains the labor cost associated with operation of said machinery. This data in cognizance with materials and process data will help in optimized selection of manufacturing equipment necessary for specified production type e.g., mass production or job shop level.

Table 3.4 Machinery Data Sample Table

Machine	Machine Cost	Labor Cost
Manual Press		
Mechanical		
Hydraulic Press		
Pneumatic Press		

3.2.8 Functional Data

Documents contained within this storage relate to the process, material and machinery, and the technical details associated with each of them. Specific documents are elaborated as follows:

3.2.8.1 Process

Data contained within these documents highlights technical data regarding all processes of all major manufacturing types, also current processes being employed for production of an existing product, if any. The last section of the document deals with research and development data i.e., upcoming processes. The document contains past knowledge of existing processes, current process employed and upcoming/future technologies. This is done to help in selection of best process type for the product at DA PPMM phase. As aforementioned, this dataset contains data related to existing processes and upcoming processes. So that the selection of processes in done in cognizance with the material and machinery. An example of this will be given in the case study.

3.2.8.2 Material

The document represents a dataset showcasing all material properties necessary for optimal RS in relation to process selected. Furthermore, data regarding surface finishes are also present within this document so that, selected material satisfies all user and designer requirements with respect to aesthetics and ergonomics. Furthermore, this dataset contains data related to detailed material properties. These details will help the designer in selecting the best possible material for the product. In continuation of above examples, Table 3-5 present sample data for sheet metal materials.

Table 3.5 Material Detailed Data Sample

Cold Rolled Low Carbon Reduced Steel						
Material Name	Yield Strength	Ultimate Tensile Stength (MPa)	Elongation %	Hardness	Density (gm/cm^3)	Youngs Modulus (GPa)
CR1/0390	340	390 MIN	~25	75	7.87	200
CR1/0440	390	440 MIN	~22	80	7.87	200
CR2/D	240	370	~31	65	7.87	200
CR3/DD	220	350	~35	57	7.87	200
CR4/EDD	210	350	~37	50	7.87	200

3.2.8.3 Machine Parameters

The document displays data regarding all machinery related to all major manufacturing types. Specifically, volume, accuracy and geometrical complexity that can be effectively managed by selected machine. This data in relation to selected process and material will aid in accurate selection of machinery equipment necessary for selected production type. Furthermore, it contains relevant data regarding machining capability with respect to geometrical complexity, accuracy and production capacity of the machinery. Such that, machinery selected in cognizance with the cost of investment from costing data is ratified with respect to the actual requirements of the part. The main aim of this dataset is to find the optimal balance between the cost and capability. An important aspect to note here is that this dataset is used in the DA PPMM phase in connection with the Economic Data to achieve aforementioned goal of optimal machinery selection.

3.2.9 Sustainability Data

These documents contain studies regarding; environment impact related to extraction of materials, the reusability of the product post lifecycle completion and a complete study of disposability and recyclability of materials. This dataset is crucial for maintaining operations within standards set by Sustainable Development Goals (SDGs) and would help the enterprise move toward carbon neutrality and eco-friendly MRS. The SDGs are a set of 17 goals that the United Nations has set for the world to achieve by 2030. These goals are aimed at ending poverty, fighting inequality and injustice, and tackling climate change. The SDGs have been broken down into 169 targets that need to be achieved to meet the goals. One of these targets is to ensure sustainable production and consumption patterns. This dataset is crucial for maintaining operations within standards set by SDGs.

The environmental sustainability data can be collected from a variety of sources, including product design, materials used in manufacturing, and disposability. With this data, we can better understand how our decisions affect the environment and make eco-friendlier choices. The data includes information about the materials and resources used in production, their recyclability, and their lifecycle. This data can be used to identify opportunities for reducing environmental impact, improving sustainability and will be helpful in product development as it helps companies create products that are eco-friendly by using the least amount of material possible while still meeting the needs of consumers. In this regard, review of product development with respect to sustainability is key and will result in future proof products that are not only reliable but ecofriendly. Thus, this dataset investigates sustainability data related to the processes and materials that are commonly used for manufacturing. A keen review of this during the selection of process material and machinery would result in the optimal selection of MRS which is closely aligned with the SDGs. A few suggested studies linked with the SDGs are:

1. Raw Material Extraction Impact
2. Process Environmental Impact
3. Disposability and Recyclability of Product

The above-mentioned studies will deal with the complete lifecycle of the product and therefore are very important. As the results of these studies may result in change of Material, Process or Machinery. The scope and applicability of these studies is dependent on the designer's requirements and may be neglected if the material and processes are fixed for the product.

3.2.10 Product Data

This storage comprises of a) DDN Studies b) Current and Future Product Data and space for manual entry of specifications/requirements of the new product. To elaborate:

3.2.10.1 DDN

These documents contain studies related to; relevancy of the existing product in the market, user reviews of the existing product, performance of the existing product and most importantly the economic feasibility study that would aid in deciding whether the enterprise can start and sustaining the new product lifecycle. These studies will aid in the DA PN phase and in conjunction with MCDM tools, help in developing a feasibility study that would help the designer in deciding if there is a data driven product necessity. A detailed explanation of a few suggested studies is given as follows:

3.2.10.2 Economic Feasibility

This study deals with the financial investment strength of the company or organization which seeks to develop a new product. The economic feasibility of product development is a key element in the decision-making process. The financial investment required for product development can be divided into three categories:

1) Initial Investment - The initial investment is the cost that needs to be invested at the beginning of the project.

2) Ongoing Investment - The ongoing investment is the cost that needs to be invested throughout the product development cycle.

3) Total Investment - The total investment is calculated by adding up all the initial and ongoing investments.

These three categories are crucial for determining whether a particular product will be economically feasible. Based on this understanding it is important to note that this study will help determining the optimal Man-Material-Machine combination. As it commonly understood that the investment strength and flexibility of the company often determines the result of the product development. Product Development is a process that requires a lot of investment. It is important to know the economic feasibility of the product before it is launched into the market. The financial investment of the Product Development can be broken down into four parts:

1) Research and Development (R&D)
2) Designing and Testing
3) Manufacturing
4) Marketing and Sales

As can be clearly understood from the above demarcation of investments, Research and Development and Designing and Testing investment is sub part of the Initial Investment while Manufacturing and Marketing are part of the Ongoing Investment. An important aspect to note here is that the process of DDN enable cross functional teams that can investigate each aspect of the above investment segments. That is, marketing and sales specialist may investigate last aspect of ongoing investment, while designers and manufacturing/industrial engineers may investigate the R&D and manufacturing line development of the new product.

3.2.10.3 Latest Cost-Effective Manufacturing Technologies

Manufacturing is becoming significantly more efficient and affordable thanks to the newest cost-effective manufacturing technologies. The latest and cutting edge of manufacturing technologies that are cost-effective are sought by businesses to lower costs and boost productivity. Based on these reasons it is one of the suggested studies that is included in the DDN analysis. An in depth review of the latest progress in cost effective manufacturing technologies would help the designer in primarily, deciding if the new product development is necessary and secondly, help in designing the product as well. The main aim of the review is to figure out if conventional technology would be used for the manufacturing or if there are newer technologies available which reduce the cost when compared to existing technologies. This in connection with the earlier suggested study of economic feasibility would be very important with respect to the financial planning of the product and its development.

3.2.10.4 Effectivity and Performance of the Current Product; Based on User and Designer Experience

The effectiveness of the current product is based on user experience and designer experience. There are many factors that affect the performance of a product, such as design, usability, and function. All these factors are important to the performance of a product. In this regard it is important to take feedback from not only the user but also the designer, such that the next iteration of the product is much more refined and is more closely aligned with the requirements of the end users. As part of DDN, it is required that information from end users be considered, in such a way that the data received is with respect to their satisfaction of the current product in use and that whether a new iteration or version of the product is necessary. If this is the case, then it would become necessary to develop a new product.

3.2.10.5 Current and Future Product

The documents contain data regarding all performance criteria and design of the existing product in production. The dataset al.so contains the future specifications of a new product as determined by user wants and reviews of existing product family

3.2.10.6 Manual Mode

This inputs mode directly inputs the specifications and requirements of a new product as decided by the design team per the assumed understanding of the user's demand and the design team's unique element of design which would aid in development of a unique aesthetic design. The manual input of specification of product design is a process that is usually done by the designer. The designer needs to spend a lot of time on this process which affects the performance, user experience and designer experience. The manual input of specification of product design is an important part in the design process. It can be tedious and time consuming for designers, but it is necessary to provide accurate information about the product they are designing. In the case of the proposed framework, the manual input phase is present to address the situation if the development of the product has been deemed necessary by factors other than the DA PN, for example executive level decision. Properly inputting technical details about the product at this phase is important.

An important aspect to note about the manual input phase is that it needs to be used to input actual technical specification of the product, including but not limited to, dimensions, performance, efficiency etc. This specification will then be carried into DA PPMM phase for generation of the preliminary PPMM combination through the data analysis of the specification and the manufacturing resources to successfully manufacture a product on a large scale.

3.2.11 DFM and MCDM

Design for Manufacturing is the process of designing products with an emphasis on how they will be manufactured. The goal is to create a product that can be easily and efficiently manufactured at an affordable cost. Multiple-Criteria Decision Analysis Tools are tools that help users make better decisions with the help of data analysis. They are used to evaluate alternatives and rank them based on their merits, which can then be used to make a decision. DFM and MCDM have been used in various industries to make decisions such as product design and development, production planning and control, quality management, supply chain management. DFM is an important part of the product development process. It helps companies to make more informed decisions about their design and production process, and it can help reduce costs. This dataset discusses the use of MCDM tools in DFM and how these tools and guidelines are integrated into CDDS for the decision-making process. These storages contain data regarding Design for Manufacturing (DFM) and multiple-criteria decision analysis tools (MCDM) that would impact the decision making and design development within DA PPMM and PN. The addition of these guidelines helps in the optimal operation and decision making within CDDS as well.

CHAPTER 4: CASE STUDY

4.1 Application of Framework on an Automotive Product Development Project

The automotive industry is a highly competitive market, and manufacturers are constantly looking for ways to reduce costs and enhance quality. The application of data analysis has given rise to new opportunities in design, production, and cost savings. Data analytics are applied to all aspects of the automotive industry, including, but not limited to, research and development for designing new products and parts, customer satisfaction with product quality and design, market research, logistics and supply chain management.

As discussed in the previous chapter, the application of Data Driven Integrated Product Process Design will result in optimal selection of Manufacturing Resources. In regard to this, the case study chapter deals with the application of the proposed framework on an automotive part. The motivation behind this case study is to examine how data analytics in connection with IPPD can be applied to enhance decision-making process in manufacturing and to validate the framework on a real-world product development project. Therefore, we will examine the step-by-step application of the framework and then discuss the output in the form of manufacturing resources in the results chapter.

The part in question for this case study is a complex sheet metal part for a hatchback vehicle from a global car manufacturer. The part has been selected for localization i.e., indigenous manufacturing for cost saving against labor and freight factors. In regard to this, some elements of the product development are aided by the International OEM for e.g. drawings, CAD designs and set of quality standards. However, other than the aforementioned resources, the product development is free to develop and manufacture the part as necessary, as long as the dimensions and quality standards provided by the OEM are met. Due to this influx of data early in the framework life cycle, the generation of MRS is streamlined and optimal. The details and parameters of quality of the part will be defined step by step with the application of the framework. The application section of this chapter will elaborate upon each process in consummate manner.

4.2 Application of Framework

As mentioned above in the introduction section, the part in question is a complex, load bearing and safety related sheet metal component for vehicle which needs to be developed locally. In the part is developed through a technical agreement, therefore, the drawing, CAD designs and set of quality standards are provided by the international OEM. Based on the last, during the application of this framework, some processes will be skipped, as the data being generated by these processes has already been provided by the OEM. The processes skipped will be mentioned and the data that has been received in lieu will be highlighted. The environment selected for this case study in Microsoft Excel as it provides ease of mathematical calculation and data analysis. The framework application can be done in different environments as well however, for this case study we will use MS Excel.

4.2.1 Decision 1; Data Driven Necessity/Manual Input

In the first step we will investigate the question of whether the process should follow Data Driven Necessity (DDN) or Manual input, i.e., should the designer manually input the specification/ requirements of the part. As mentioned in earlier section, the part is developed through a technical agreement, therefore, the drawing, CAD designs and set of quality standards are provided by the international OEM. Therefore, we take the decision of manually inputting the specifications of the part.

4.2.2 Manual Mode Designer Input

The design related data provided by the OEM is inputted in this step. The provided relates to:

AA. Part Design/Dimensions

BB. Material Specifications

CC. Subcomponent/Purchased Parts Specification

BB and CC are shown here for reference as follows:

Table 4.1 BB Material Specifications

S.No	Part Name (a)	Part Dimensions (b)					Material Specs (c)	Qty
1	Rear Seat Support Main	300	x	1360	x	0.65	SPCD 270 (t=0.65)	1
2	Rear Seat Support Reinforcement LH	360	x	125	x	1.2	SPFC590P (t=1.2)	1
3	Rear Seat Support Reinforcement RH	360	x	125	x	1.2	SPFC590P (t=1.2)	1

Table 4.2 CC Material Specifications

S.No	Part Name (a)	Part Dimensions (b)	Material Specs (c)	Qty
1	Projection Nut Weld	M10x1.2	Std	4

Furthermore, part design is also inputted into the MMDI phase.

4.2.3 DA Product (OEM Data)

As mentioned in project initialization phase i.e. MMDI, specification related to design and material details have already been provided by international technical partner through technical agreement (TA). That is, the DA Product phase may be skipped since design of the product has been provided. Therefore, we may move towards DA Process as per the material specification provided.

4.2.4 DA Process (Functional and Costing)

As per data given in MMDI Table 4.1, We see that the material specification has been provided, therefore we may move from there and work towards process selection that is appropriate and applicable to the material selected. For sake of ease, we will combine process selection through functional data and costing. Table 4.3 shows functional data taken from selected processes for the part in question while Table 4.4 shows data from the costing database. Manufacturing of part through machining seems viable due to dimensional accuracy, operational efficiency, and multiple cost factors. Also, since the cost of tooling for machining is low (cost does not include machinery, only the tools applicable for machining the part) when compared to forming. However, since this is a mass manufacturing project, average part manufacturing rate per hour is a critical factor to note. Nexus to last, forming may be selected for further data analysis.

Table 4.3 Process Data Analysis

Process Type	Capability to Process Material (CRC270 &590Process Type	Avg Pc/Hr	Dim. Acc.	Op. Eff.	Surf. Finish	Tolerance	Wastage
Forming	✓	30	95%	90%	↑	High	Medium
Machining	✓	<1	99%	99%	↑↑	Very High	High
Casting	✕	-	-	-	-	-	-
Additive Manufacturing	✕	-	-	-	-	-	-

Table 4.4 Process Costing Data Analysis

Process Type	Cost for Tooling (PKR) (A)	Maintenance Cost (PKR) (B)	Other Cost (PKR) (C)	Volume (V)	Cost/Piece (A+B+C)/V
Forming	11,300,000	3,600,000	2,160,000	100,000	118
Machining	10,000,000	1,800,000	1,080,000		59
Casting	-	-	-		-
Additive Manufacturing	-	-	-		-

As per the data shown above, it is decided that forming is the most feasible manufacturing process. Based off the DA Machine/Tooling analysis that is done alter in this chapter, we may calculate the cost of the part, based oof the tooling and volume.

Table 4.5 Forming Costing Analysis

Forming Type	Cost for Tooling in PKR (A)	No. of Dies	Cost/Piece in PKR (A/V)
Blanking	3,000,000	2	30
Forming	2,850,000	3	28.5
Trimming	4,500,000	2	45
Restrike Bending	700,000	1	7
Piercing	250,000	1	2.5
Total (Tooling only)	11,300,000	9	113

Nexus to above analysis-based decision, the total associated costs of this process, as per the design requirements of the part are given in the below table. The breakup of cost of tooling is given in the above section.

Table 4.6 Forming Total Tooling Cost Analysis

Cost Type	Value (PKR) (B)	Cost/Piece B/V
Tooling Cost	6,000,000	113
Maintenance Cost	3,600,000	36
Other Costs	2,160,000	22
Total Cost	11,760,000	170

As per the combined analysis of process functional and costing data done in DA Process, we see that forming is the best possible manufacturing process with high manufacturing speed, dimensional accuracy, and other functional factors. Furthermore, as per the costing analysis it is derived from the data that even though machining cost (tooling only) seems viable in comparison to forming however, when seen in cognizance with the functional data, it is noted that due to the requirement of mass manufacturing, forming is best option. Therefore, considering the high manufacturing speed requirement, forming is selected as the manufacturing process. This decision will lead into DA Machinery selection.

4.2.5 DA Material (Functional and Costing)

This section looks into the selection of material based on functional and costing data. As has been mentioned in the MMDI section, the OEM has already provided material specifications required for the part. Therefore, we may skip this section, as the material type has already been specified and the cost of the material associated is now dependent on the sourcing. Which is not in the scope of this framework. However, for the sake of continuation of the framework, latest quote from existing material source is taken and show in below table.

Table 4.7 Material Data Weight and Cost Analysis

Material Spec	Blank Size	Consumption		Price (Rs/KG)	Total Cost (Rs/KG)	Source
		Weight in KG (With Wastage)	Finished Weight			
(a)	(b)	(d)	(c)	(e)	(f = d x e)	
SPCD 270 (t=0.65)	292 x 1360 x 0.7	2.03	2.25	215.00	435.66	Local
SPFC590P (t=1.2)	365 x 125 x 1.2	0.43		324.50	139.47	Imported
SPFC590P (t=1.2)	365 x 125 x 1.2	0.43		324.50	139.47	Imported

4.2.6 DA Machine

This section investigates the selection of machinery based off data analysis of part requirements. As decided in the DA Process, the part will be manufactured by forming process. Furthermore, there will eleven distinct operations that need to be done before the part can completed. Therefore, for optimal speed of manufacturing all processes need to run in parallel. i.e., eleven presses need to select for the complete manufacturing process. Keeping this important variable in mind we may perform our analysis. An important aspect to note is that, forming process is dependent on machinery and tooling therefore, this analysis will delve deeper and select press tools, i.e. Dies and machinery needed to operate the aforementioned dies. In this regard the DA Machine section is divided into Tooling functional and costing analysis and Machinery functional and costing analysis

4.2.7 DA Machinery/Tooling Functional and Costing Analysis

This section investigates the analysis of functional data for tooling selection. Based of DA Process, we understand that the process needed for manufacturing this part is forming. Therefore, we need to conduct our analysis based off this output from DA Process Phase. As mentioned in the above section, we need to select tooling for processing the material before we select the machinery. In this regard, a calculator for quick and easy deductions of tooling has been made in our environment.

Based off the design inputted in the MMDI phase, a questionnaire system helps the designer in calculating approximate no of dies needed to form the part. The output of the questionnaire is given below.

S/No	P/No	P/Name	Grade		Blanking	Piercing	Forming	Drawing	Bending	Restriking	Total No of Dies
1	-	Rear Seat Support Main	SPCD	270	1	2	2	0	0	0	9
	Data	Value									
	Blanking Required	1									
	No Of Holes on Same axis	1									
	No of Holes on Tilted Axis	1									
	No of non-uniform holes	0									
	Forming Process	2									
	Drawing Process	0									
	No of bends	0									
	Restriking Required	0									
S/No	P/No	P/Name	Grade		Blanking	Piercing	Forming	Drawing	Bending	Restriking	
2	-	Rear Seat Support Reinfs	SPFC	590	1	1	1	0	1	1	
	Data	Value									
	Blanking Required	1									
	No Of Holes on Same axis	1									
	No of Holes on Tilted Axis	0									
	No of non-uniform holes	0									
	Forming Process	1									
	Drawing Process	0									
	No of bends	1									
	Restriking Required	1									

Figure 4.1: Forming Questionnaire System

Based off this system we see that we will require a total of 9 dies. However, for further analysis of the dies required, another datasheet for analysis has been made. This datasheet investigates the exact calculation of dies based off the blank output generated from forming suite.

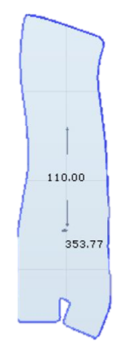
The output of the data sheet correlates the results of the questionnaire and proves the need for 9 dies for complete manufacturing of the part. The output of the data sheet is show below.

Rear Seat Support Main							Blank Picture
Material Cost Breakdown							
S/No	P/No	P/Name	Grade		Thickness	Standard	
1	-	Rear Seat Support Main	SPCD	270	0.65		

Item	Length	Width	Reference Data	
Calculated Blank Size	1342	279	Material Rate	215
Actual Blank Size	1372	309	Scrap Rate	100
Calculated Volume	243371.70		Density	0.00000785
Actual Volume	275566.2		Dwg Weight	3.1
Input Weight	5.1		Dim. Round Off	30
Calculated Weight	754452.3		Scrap Calculator	
RM Cost	1088.55374		Scrap Weight	Percentage
Scrap Cost	126.58		1.265760167	25
Material Cost	961.98			

Labour -Tooling Breakdown						Sheet Calculation									
S/No	Process	Process Time	Labour Rate	Labour Costing	Tooling Costing	Sheet Size		No. of Blanks	Sheet Size		No. of Blanks	L	W	T	Input Weight
1	Blank	0.50	2	1	PKR 2,500,000	1220	2440	0	2440	1220	3	1220	2440	0.65	5.06
2	Forming	0.50	2	1	PKR 950,000	1270	2250		2250	1270					
3	Forming	0.50	2	1	PKR 1,000,000	W	L		L	W					
4	Trimming	0.50	2	1	PKR 2,250,000	0.89	7.90		1.78	3.95					
5	Trimming	0.50	2	1	PKR 2,250,000										
				Total Labour Cost	Total Tooling Cost										
				5	8,950,000										

Rear Seat Support Reinfs x 2							Blank Picture
Material Cost Breakdown							
S/No	P/No	P/Name	Grade		Thickness	Standard	
2	-	Rear Seat Support Reinfs x 2	SPFC	590	1.2		



Item	Length	Width	Reference Data	
Calculated Blank Size	354	110	Material Rate	215
Actual Blank Size	384	140	Scrap Rate	100
Calculated Volume	46728.00		Density	0.00000785
Actual Volume	64512		Dwg Weight	3.1
Input Weight	0.5		Dim. Round Off	30
Calculated Weight	144856.8		Scrap Calculator	
RM Cost	118.213981		Scrap Weight	Percentage
Scrap Cost	13.75		0.137458118	25
Material Cost	104.47			

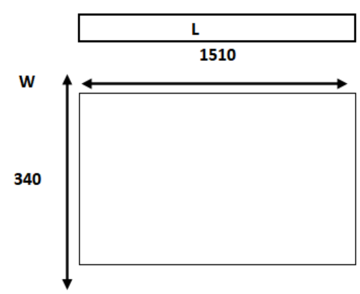
Labour -Tooling Breakdown						Sheet Calculation									
S/No	Process	Process Time	Labour Rate	Labour Costing	Tooling Costing	Sheet Size		No. of Blanks	Sheet Size		No. of Blanks	L	W	T	Input Weight
1	Blank	0.50	2	1	PKR 500,000	1220	2440	51	2440	1220	48	1220	2440	1.20	0.55
2	Forming	0.50	2	1	PKR 900,000	1270	2250		2250	1270					
3	Re Strike	0.50	2	1	PKR 700,000	W	L		L	W					
4	Piercing	0.50	2	1	PKR 250,000	3.18	17.43		6.35	8.71					
				Total Labour Cost	Total Tooling Cost										
				4	2,350,000										

Figure 4.2: Forming Blank Calculator

This data sheet helps in the analysis of the blank and guides in the calculation of number of dies. This datasheet utilizes the length and width of the blank along with the density of sheet metal for formulation of no of dies needed, calculated no of blanks that can be extracted from the standard sheet metal size of 1220 x 2440mm, calculation of scrap and overall material cost per part. Based off this data sheet we see that no of dies needed is in total 9. Other data is also show which will help in the following sections.

For calculation of the die cost, we must calculate the amount of force needed to form the part and punch standard size holes into it. This is important because, based off the force calculation the size of the die needed to withstand the forces involved. In this regard another datasheet for force calculation has been formulated for this application. The output of the datasheet is given below.

S/No	P/No			Part Name			Grade		Thickness		
1	-			Rear Seat Support Main			SPCD	270	0.65		
Die Clearance Calculator				Blanking/Forming Force				Punching Force			
Part Length	1372	Die Length	1510	K	0.8	Press Required		Perimeter	34.54	Press Required	
Part Width	309	Die Width	340	L	3700	519	Actual	Thickness	0.65	76	Actual
Thickness	0.65	Die Thickness	480	t	0.65	571	Safety	Shear Strength	0.3447	84	Safety
				Ts	270	600	RoundOff			100	RoundOff



S/No	P/No			Part Name			Grade		Thickness		
1	-			Rear Seat Support Reinfs x 2			SPFC	590	1.2		
Die Clearance Calculator				Blanking/Forming Force				Punching Force			
Part Length	384	Die Length	430	K	0.8	Press Required		Perimeter	34.54	Press Required	
Part Width	140	Die Width	160	L	1180	306	Actual	Thickness	1.2	140	Actual
Thickness	1.2	Die Thickness	320	t	1.2	382	Safety	Shear Strength	0.3447	154	Safety
				Ts	270	400	RoundOff			200	RoundOff

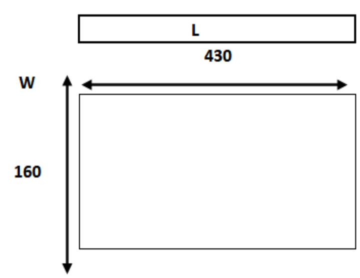


Figure 4.3: Die Size Calculator

As can be seen from the output, this analysis tells us the size of the dies needed based off the Blanking Force. The formula of the Blanking Force is given below

$$Blanking\ Force = K\ x\ Forming\ Circumference\ x\ Thickness\ x\ Tensile\ Strength \qquad (3.1)$$

Where K is the Shear Resistance but since it is difficult to know shear resistance, it is substituted by a value equal to 80% of the Tensile Strength [91]. This equation gives us the tonnage of the press needed to blank the sheet metal. This tonnage is then multiplied by 0.8 to give the thickness of the die needed to withstand the forces involved. The sheet also shows the tonnage required for punching holes in the sheet metal. This calculation is given by the formula:

$$Punching\ Force = Hole\ Perimeter\ x\ \ Thickness\ x\ \ Shear\ Strength\ Co\ Efficient \qquad (3.2)$$

Based off these two tonnages we may calculate the cost of the dies. We will also select the machinery based off these tonnage calculations as, the machinery required must be able to press the part with equivalent force. For calculation of the die material, a separate analysis sheet has been generated. The output of this sheet will help us in the cost calculation of the dies.

This data sheet tells us the cost of the dies based off the volume and density of the material best selected for each individual die. This results in total cost of dies being generated through this analysis. Furthermore, for the calculation of the machinery required, As the cost of machinery is largely dependent on the sourcing of the machinery, i.e., Korea, China, Taiwan etc. Therefore, a function of the machinery cost has been generated. For example, the machinery required for the Rear Seat Support is defined as 2a+2b, since two 600-Ton Presses and two 200-Ton Presses are needed. In connection with the last, the total sum of the machinery cost and the calculated die cost is given as follows.

$$2(A + X + Y) + 3(B) \tag{3.3}$$

4.2.8 Decision 2, 3, 4 Requirements/Acceptability/Production

Based off the study done post analysis, it is decided that the part is Go for Production. Therefore, Decisions 2 through 4 are greenlighted. The output of all phases is shown in the next chapter with actual pictures of Manufacturing Resources selected.

CHAPTER 5: RESULTS

5.1 Manufacturing Resource Combination

After application of the novel framework, an optimized manufacturing resource combination was generated, as per the output of all data analysis phases. This manufacturing resource selection was then applied to manufacture the product. The result of the product development is shown below. Furthermore, the combined result of all the stages data analysis phases is also given. The complete MRS that has been output is shown in figure 5.1. The generated MRS given below shows the number of presses and dies needed and the cost associated with the aforementioned tooling.

Part Name	Rear Seat Support Main						
Machinery Cost Calculation							
No of Operations	Min Tonnage	Max Tonnage	Min Cost of Machinery	Max Cost of Machinery	Total Cost Of Machinery	Weight	
5	200	600	A	B	2a+3b	1800	
Die Cost Calculator							
S. No	Operation Name	Material	Material Rate	Material Cost	Misc Cost	Cost of Die	Tonnage Required
1	Blanking	D2	1000	1,800,000	700,000	2,500,000	200Ton
2	Forming 1	FC500	300	600,000	350,000	950,000	600Ton
3	Forming 2	FC500	300	600,000	400,000	1,000,000	600Ton
4	Trimming + Piercing 1	D2/SKD11	1000	1,800,000	450,000	2,250,000	200Ton
5	Trimming + Piercing 1	D2/SKD11	1000	1,800,000	450,000	2,250,000	200Ton
Total Cost				6,600,000	2,350,000	8,950,000	
Part Name	Rear Seat Support Reinfs x 2						
Machinery Cost Calculation							
No of Operations	Min Tonnage	Max Tonnage	Min Cost of Machinery	Max Cost of Machinery	Total Cost Of Machinery	Weight	
4	200	400	X	Y	2x+2y	170	
Die Cost Calculator							
S. No	Operation Name	Material	Material Rate	Material Cost	Misc Cost	Cost of Die	Tonnage Required
1	Blanking	D2	1000	300,000	200,000	500,000	200Ton
2	Forming	FC500	300	500,000	400,000	900,000	400Ton
3	Restrike & Bending	High Carbon	600	500,000	200,000	700,000	400Ton
4	Piercing 1	D2/SKD11	1000	170,000	80,000	250,000	200Ton
Total Cost				1,470,000	880,000	2,350,000	

Figure 5.1: Complete MRS with Costing

After the application of the framework the tooling was designed and manufactured. The tooling was developed over the course 5 months and the corresponding development plan is shown in figure 5.3. As can be seen from the development schedule, project face delays in the last phase of die development. This was due to economic restriction on import of tooling and machinery. However, after the economic restrictions were lifted, the tools needed to process the dies was received after which the dies were completed. The part was successfully manufactured as per the generated MRS combination given by the framework. The manufactured tooling is shown below.

Figure 5.2: An overview of the dies after processing

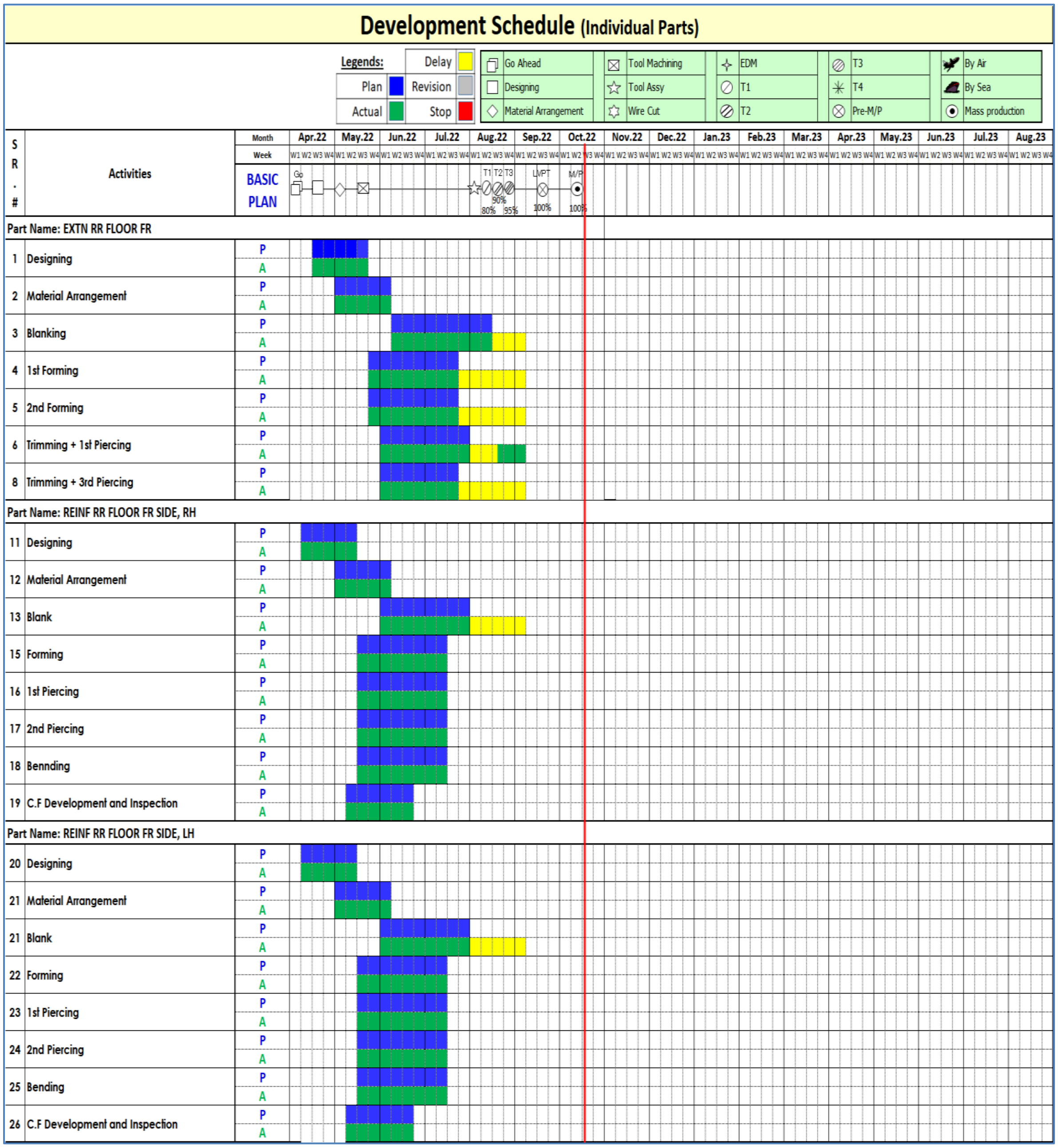


Figure 5.3: Development Plan

As show in the development plan, the first off tool sample was produced in the month of September. The produced part had some dimensional inaccuracies, which is common with 1st samples of sheet metal parts. The dies were later on improved so that the dimensional and fitment accuracy of the part could be enhanced. The improved and final part is shown below.

Figure 5.4. Developed Part

5.2 Future Work

Suggested future work of this framework is the addition of AI for data collection and automated actualization of Framework. This would enable faster, relevant, and accurate data collection. Furthermore, AI actualized framework would result in much better results of MRS. In future, the designer would be able to enter the basic parameters of the product that is required, and AI coupled with the suggested framework would enable the designer to get a completely new product, relevant to the requirements of the designer, with a complete MRS. This would enable a much faster product development cycle.

CONCLUSION

Application of data analytics in areas such as sales & marketing and cybersecurity is prevalent however, the implementation of data analysis for product & process design is an unexplored opportunity with large volumes of data generated throughout the manufacturing process. This thesis proposes a novel conceptual framework that applies data analysis to integrated product-process design (IPPD). The proposed framework can be used to new products aligned with customer requirements, enhance the overall quality, improve production efficiency, support the supply chain network, and give applicant industry a competitive advantage against its competitors. The proposed framework was validated through product development of an automotive part in case study the chapter. It was observed that through the application of the functional and costing data analysis during various stages of the case study, decision based on technical results were taken which resulted in a highly optimized manufacturing resource selection.

In future, addition of AI for data collection and automated actualization of framework would enable faster, relevant, and accurate data collection. The designer would be able to enter the basic parameters of the product that is required, and AI coupled with the suggested framework would enable the designer to get a new product, relevant to the requirements of the designer, with a complete MRS. This could prove revolutionary, as product development through artificial intelligence powered by big data would generate products much better aligned with consumer needs and the corresponding manufacturing resource selection would be highly optimized.

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