IMPACT OF BIG DATA AND VALUE STREAM INTEGRATION ON RATIONALIZING COST DECISIONS: A LEAN ABC MODEL

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Abstract
This research seeks to show the important integration of BDA and VSM strategy in rationalizing operative and manufacturing cost reduction decisions from a serval application within industrial and metallurgical zero-growth sectors, alleviating some pre-determined constraints of conventional cost accounting under the Unified Accounting System. In pursuit of this aim, it employs a descriptive-analytical approach to ground the theoretical foundation, reinforced by an applied simulation method. A complex quantitative and analytical simulation model was built using the macro-indicators and relative weights related to the financial statements (FS) of Fayadh Al-Qasim Industrial Company? FS for 2020. In this model, Lean Activity-Based Costing (Lean ABC) with variance and digital cost-driver analysis is developed on a sample of 5,616 units actual production and assembly cycles for the complete 2.5-foot air cooler production line consisting of plate cutting, chassis pressing and components/Motor assembly. These analyses and empirical results resulted in the unequivocal endorsement of an overarching comprehensive integrative hypothesis. The findings show that industrial cloud computing, IIoT and unified digital platforms can help the management accountant achieve a microscopic view of resources and the factory floor. This functionality also allows for identifying and driving out non-value-added activities and waste costs that were previously masking true product costs and responsibility centers, while improving overhead & production services tracing efficiency by 54.34. Thus, this integration resulted in a 31 reduction for total cost per unit, achieving unit savings of IQD 60628 and resultant annual accumulation of the costs for plant of 340486848 IQD without affecting quality control conditions and religion for final product inspection. The study explicitly advises investing in big data and computer numerical control (CNC) technology infrastructures, moving towards automated pull systems for documents and materials, as well as training the economic and technical staff on Process Mining tools to ensure guaranteed proactive cost containment measures for proper sustainable competitiveness.

1. Introduction

The current macroeconomic con in point of any manufacturing and metallurgical industry, more so local electrical appliances and air cooler manufacturing industries have transformed into an extremely competitive landscape beset by increasing economical pressures, quick-step regulatory restructuring under the guise of encouraging national production, spiralling input costs and unfair offshore dumping. These multi-dimensional challenges would drive Factory management and chief financial officers to moderate two highly conflicting corporate objectives of rigorous manufacturing inspection and superior quality control standards on one side, as well as strict cost containment and operational expenditure rationalization on another to safeguard sustainable long-term profitability, liquidity, as well safeguarding the firms capital (3,174,267,500 IQD) In this ever-shifting reality, cost management is not just an accounting exercise, but becomes a fundamental building block for organizational survivability and future competitiveness.

Although cost reports are critically important for management to rely on, legacy accounting infrastructures, management information systems and traditional cost tracking mechanisms simply lack the structure to keep up with this rapidly changing digital manufacturing ecosystem. Conventional frameworks depend on historical transactional records, arbitrary aggregated bases for manufacturing overhead assignments to production centers and retrospective periodic reporting. This post-facto methodology as it allows a high level of information asymmetry, obscures actual time-critical operational bottlenecks, and does not monitor or eradicate material and temporal wastes (such as manual cutting bottlenecks; setup idling; inter-process waiting times) from air cooler manufacturing value stream. This leaves the executive decision makers without visibility into real-time decision inputs necessary for proactive cost containment programs, thus leading to mispricing of products using historical (Cost + 7) methods and idle capacity costs resident on physical shop floors and assembly lines.

To correct these derangements of information, the Lean Management philosophy brought forward an aesthetic and robotic engineering instrument denominated as Value Stream Mapping (VSM), which describes process flows, pinpoint non-value-added activities, and locate blockers in execution. Yet, VSM as a standalone implementation has in the past confronted the overwhelming operational challenge of millions of structured and unstructured technical, administrative, and machine data points coming into daily high-velocity entry within industrial environments. Such a challenge has propelled modern accounting and managerial theories to an advanced integrative approach that exploits the digital revolution and advanced manufacturing technologies.

Accordingly, a judicious cross integration between Big data analytics—across its core dimensions (Volume, Velocity, Variety, Veracity and Value)—and VSM is a truly progressive and trans disciplinary initiative. Such alignment enables management accountants to analyze unstructured data streams and derive real-time predictive and prescriptive insights into production processes and product quality. As a result of this transformation, manufacturers can effectively leverage Lean Costing systems, implement continuous rolling budgets, and then also proactively manage standard variances to ensure that sound financial decisions are rationalized, excess capacity is eliminated and sustainable competitive advantage necessary for survival and growth is achieved.

1.1. Research Problem

Manufacturing and metallurgical enterprises are increasingly sustaining the burden of economic and regulatory pressures requiring cement-like balance on product quality and stringent rationalization of operational & manufacturing costs across shop floors. Traditional cost accounting platforms and legacy approaches do not monitor or segregate non-value-added activities (waste, machine downtime, idle processing times) over the life cycle of product manufacturing because they have been unable ingest or process the bulk flows of real time operational data from machines and materials. This challenge results in budgets cuts based on gut-feelings across production departments which touch to product quality and customer relationship. Hence, the main research problem itself can be formulated in one major research question: Research Question: What is the role of strategic integration between Big Data Analytics and Value Stream Mapping (VSM) in rationalizing cost reduction decisions in manufacturing companies?

This primary question yields the following analytical sub-questions: 1) How are requirements of big data technologies and value stream frameworks currently met with in a particular mill? 2) How do algorithmic deployment and industrial big data analytics help management accountants in factories diagnose, quantify and eliminate latent material and temporal waste? 3) How does data-driven industrial value stream management affect the accuracy of measurement, allocation, and control of manufacturing overhead and production services centers in terms of its structural dimension?

1.2. Research Objectives

The following are the goals of this study divided into primary and secondary objectives:1) Developing a solid theoretical base in integrating Big Data Analytics, value stream engineering, and lean management accounting in manufacturing settings. 2) Using different types of industrial patterns which include specific types of operational waste; machine downtimes; non value-adding or supplementary tasks in the operations like manufacturing lines specifically cutting, pressing and assembly. 3) To show how strategic management accountants in industrial firms exploit real-time big data outputs to design an agile value stream architecture that enables timely and systematic yet non-arbitrary reduction of costs even in products with solid quality, great efficiency or strong brand integrity.

1.3. Research Importance

This study is of particular importance for the industrial sector with respect to two dimensions, namely theoretical and applied significance: 1) **Theoretical Importance**: The study fills a clearly demonstrated void in modern accounting literature by combining Big Data as an emerging body of knowledge and lean industrial philosophies, such ad Value Stream Mapping (VSM), from the con of 21st century manufacturing management accounting to establish a new conceptual framework for production costing systems. 2) **Applied Importance**: This research offers a quantitative, repeatable, and actionable operational guide for corporate boards, general managers, and managerial accountants working in the Iraqi industrial setting to reveal the real cost of "manufactured products," remove unused capacity in inter- process flows from end-to-end across their value streams, and leverage supply-side investments in productivity vis-a-vis profitability to generate local-market competitiveness against imported goods.

1.4. Comprehensive Research Hypothesis

The research agenda revolves around a single, indivisible integrative hypothesis to guide the analytical simulation model and verify the plausibility of application with respect to Fayadh Al-Qasim Company financial structure as follows: Hypothesis (H): integration of Big Data Analytics (BDA) technologies with Value Stream Mapping (VSM) rationalizes operational and manufacturing cost reduction decisions in industrial firms by tracking non-value-added activities, isolating wastes, downtimes and defects, as well as facilitating greater oversight on manufacturing overhead and service centers through Lean Activity-Based Costing (Lean ABC).

2. Method

This study makes use of a biconditional methodological framework in order to obtain the highest levels of scientific accuracy: 1) Descriptive–analytical method: Used within the theoretical framework with a wide variety of critical reviews across up-to-date literature, accounting guidelines and engineer studies to see the relationship between binding parameters and variables. 2) Simulation Approach: Utilized with the empirical method through developing a superior accounting and quantitative simulation model. This model, therefore, discards random historical data and instead relies on the combination of real-time big data tracking variables in line with bearing weights that reflect the actual volume of financial and operational records at Fayadh Al-Qasim Company for the year 2020. It uses a complete simulation sample of 5,616 units of production (which is the entire actual output volume in the factory), Lean Activity-Based Costing (Lean ABC) tools and variance analysis in Iraqi Dinars (IQD) to test the integrated comprehensive hypothesis.

2.1. Theoretical Framework of Big Data Analytics in Industrial and Manufacturing Environments

2.1.1. Concept and Definition of Big Data

Today, the term Big Data is much more expansive than any primitive conceptualizations limited to simply large amounts of storage; it refers to massive, very granular and multi-dimensional information matrices that completely exceed the processing, storage and indexing capacity of traditional database management systems (Grable & Lyons, 2018). From the perspective of advanced industrial and cost accounting as well, not necessarily for (mining) big data as such but rather for the ability to capture, govern and make sense of this type of asset (i.e. using sophisticated technology within a sound organizational structure that could tap – in real-time – relevant insights from data into decisions and actions that mattered economically to positively impact the firm's future economic trajectory so that its market position is reinforced (Shen et al., 2016).

Big Data in modern manufacturing and industrial environments derive from three orthogonal structural dimensions as follows: 1) **Structured Data**: Very well-organized and predictable information stored in legacy industrial databases like ERP (Enterprise Resource Planning) accounting modules, general ledgers, standard BOMs (Bill of Materials), inventory records and conventional production line routing sheets (Nirmala, 2016). 2) **Semi-Structured Data**: Information that does not have a strict database structure, but has organizational tags and internal markers, including digital XML files, electronic QC inspection logs, and Computer-Aided Design and Manufacturing (CAD/CAM) schematic fed directly into automated machines (Shen et al., 2016). 3)

Unstructured Data: The most chaotic and information-rich paradigm, the fastest growing type of data category that holds close to 85 of all corporate data assets. This includes supplier emails, real-time data streams from IIoT sensors operating hydraulic pressing and stamping machines, video surveillance feeds monitoring assembly line operator movements, unstructured quality assurance notes (Nirmala, 2016; Shen et al., 2016).

Hence, the advanced data mining algorithms and analytical software should be deployed through these multi-dimensional and hybrid data streams accordingly. This now allows management accountants to print, sort, arrange and cross-compare disparate data points which ultimately expose entrenched operational patterns where strategic manufacturing choices are made (Gwilt, 2016).

2.1.2. Drivers of Big Data Growth and Operational Dimensions

The phenomenal growth of global digital data emerges from a fundamental corporate insight: relentless streams of information contain deep economic and strategic leverage that enable companies to totally redesign their core industrial operating efficiency and capability (Jayanand et al., 2016). This growth is particularly pronounced in manufacturing verticals, where sophisticated capture tools—covering shop-floor sensor logs, equipment effectiveness metrics and real-time inspection records—effectively turn the production floor into a continuous river of high-fidelity data. Various academic literature and global professional accounting bodies describe Big Data in terms of three analytical dimensions: 1) Technical and Operational Dimension: Big Data is an information asset having huge volume, viz. algorithmic- complexity-level operational hurdles which is much higher than the capacity of legacy enterprise software; tools and traditional retrospective accounting framework (Ma & Yan, 2016; Shen et al., 2016). 2) The Structural and Qualitative Dimension: It is a high incidence, complex data set that includes both structured financial and cost ledgers in contrast to unstructured information sensor streams combined with multimedia emanating from smart manufacturing architectures, shipping logistics, and procurement networks—not strictly financial databases (Bose et al., 2022; Webb & Wang, 2016). 3) The Functional & Decision-Making Dimension: The Association of Chartered Certified Accountants (ACCA) argues that Big Data is an information asset characterized by such a high volume, velocity and/or variety, that traditional data processing applications are inadequate. To achieve this, it uses the automated processing of information to go beyond traditional approaches to decision making, explore hitherto deep insights and optimize manufacturing and operational processes absolutely (ACCA, 2013).

What is notable is that within these definitions there is a common denominator which signals the complete failure of traditional, retrospective cost accounting systems in information characterized by high concurrency through massive volume, real-time generation velocity, variety in formats, and/or volatile veracity on the factory floor (Grolinger et al., 2016; Zhang et al., 2015).

2.1.3. Historical Evolution and Structural Shift Toward Digital Accounting

Big Data was initially used in computer science to categorize datasets that brought traditional relational databases to a halt while the whole world was transitioning from analogue to digital log-data generation, as well as the rapid growth of smart and IoT devices in industrial automation applications (Chua, 2013). This idea stayed very technological and nested in tech startups during the 2000s, all these computational tools evolved extremely rapidly into the governance and organizational structures of large manufacturing firms (Davenport & Dyché, 2013). This integration has initiated a structural reorientation in modern-day Accounting Information Systems (AIS) along three specialist capabilities path way (Faccia & Petratos, 2024): 1) Management accounting information systems development Big Data transcended the scope of traditional management practices such as double entry bookkeeping and cost allocation (Busco et al., 2017); consequently, saving it as a key architectural layer embedded in modern AIS. Such integration gave rise to another generation of management accounting models, designed specifically for the ongoing real-time information needs of modern production facilities and industrial plants. 2) Mastering Decision Intelligence for the Factory: Combining big data lakes with enterprise cost ledgers allows plant management accountants to develop and implement advanced machine learning algorithms. These algorithms churn through millions of operational and mechanical machine data points per second, providing aligned dashboards that reveal hidden cost risks, forecast usage patterns, and guide strategic planning and budgeting activities. 3) Market Flow Analysis Based on Operational

Workflows: Huge data analytics in civil industry functions as a cost managing platform, where the material flow, along with customer specification preferences can be measured and tracked extremely accurately. It helps factories optimize their market share, product configuration and long-term competitive advantages & profitability in the marketplace.

2.1.4. Strategic Value of Big Data in Manufacturing Organizations

Big Data is frequently identified in literature as a strategic resource or strong economic asset (i.e., market-making good) where the anticipated financial/market value can only be realised through an organisation's continuous provision of resources to systematically leverage it to solve operational problems that occur at different spatial and temporal granularities, coordinate manufacturing cells within factory systems, and harmonise internal productive capacities with external demand patterns (Shen et al., 2016). This strategic advantage runs through major routes in the company: 1) Sustainable Competitive Advantage: Big Data analytics can comb through massive, unstructured matrices of information identifying the buried, non-linear relationships that standard methods often overlook as a result of inter-departmental silos. This gives executive leadership unprecedented operational visibility to carry out targeted, agile product pricing strategies; enforce strict cost control; and allocate optimal capacities towards those that are providing asset returns, as well as safeguarding firm capital (Shen et al., 2016). 2) Predictive Corporate Strategy Development: Strong data mining and predictive analysis capabilities enable factories to integrate remote and real time information on machine performance, mechanical failure ratios, and yields for raw materials together. This allows cost management to design extremely efficient manufacturing processes and nimble organizations that respond proactively to changes in the marketplace, saving themselves from completely rid of losses due to unabsorbed capacity buried in the shop floor (Davenport & Dyché, 2013).

2.1.5. Mechanisms and Typologies of Big Data Analytics (BDA)

Big Data Analytics (BDA) is an operational and managerial technology that aims at the capture, cleansing, and processing of Big Data core dimensions (5Vs: Volume, Velocity, Variety, Veracity & Value). Based on high-performance cloud computing systems and distributed storage architectures, BDA gathers industrial data structures to extract their meaning to decision-makers at a minimal cost of processing information while releasing the great economic value (Wahyuni, 2023). Strategic management accountants apply four types of analyses sequentially to design preventive cost control and substantiate strategic choices a for the factory (Herath & Woods, 2021): 1) Descriptive Analytics: This type of data visualization is the process of organizing, cleaning and summarize historical big data streams to unveil performance patterns answering the key question — what happened. 2) Diagnostic Analytics: Going beyond surface-level performance indicators (such as factory defects, waste rates, or cost overruns) to uncover the exact root causes and variances on measures that prepare for operations, answering Why did it happen? 3) Predictive Analytics: Builds upon the results of descriptive and diagnostic models and combines them with market data streams & technical metrics to predict future movements of the factory, likelihoods of machine failures, product demand patterns: What is going likely to happen? 4) Prescriptive Analytics: The highest of the three levels, this type represents the very upper limit for modern business intelligence, examining all possible strategic and operational decision paths via computer simulations in order to provide real-time guidance for executive management for maximum impact. This answer the question What should be done? to curb the cost inflation, reduce material waste, and seize a sustainable competitive advantage.

2.1.6. Control Advantages and Operational Risks of Big Data in Cost Control

While big data analytics fuels transformative advances in management accounting, its adoption within production plants creates important operational challenges and structural constraints posing threats to maintain the integrity of reporting and decision-making by financial management: 1) Data Security and Industrial Privacy Risks: Combining large big data lattices towards a factory level open the cyber-attack vectors, where need to be secure against Advanced Persistent Threats (APT) or system threats. Cost management systems store highly confidential competitive information relating to margins, pricing formulas, proprietary intellectual property and low-level manufacturing cost models which means that securing this rarefied environment entails funding a multi-dimensional cyber security stack (Theodorakopoulos et al., 2024). 2) Challenges with Data Quality and Veracity:

Digital information flows at high velocity from shop floor sensors and disparate external sources making the data highly sensitive to fragmentation or distortion due to industrial noise (e.g. mechanical vibrations, thermal fluctuations). In fact, this requires an institution of tight automated mechanisms for cleansing and validating data before proceeding into indicating the need of adjustments in manufacturing or pricing (Wahyuni, 2023; Theodorakopoulos et al., 2024). 3) Human Skill and Expertise Gaps — While engineers are developing sophisticated analytics methods to help out, the manufacturing workforce needs advanced expertise in digital and data science (including machine learning), data visualization, industrial applications, etc. The lack of a digital data culture processes in conventional, legacy accounting and auditing departments result in erroneous reporting, wrong-cost models, and profound positive/negative financial variances (Wahyuni, 2023; Winoto et al., 2023). 4) Integration Barriers with Legacy frameworks: Most industrial companies still operate in siloed, legacy Accounting Information Systems (AIS) that are structurally incapable of ingesting or processing complex streaming data passing between technical and financial departments in real-time. Moreover, this inflexible technical boundary has forced current accounting research to pursue new connection paradigms (e.g., REA ontological model) that connect the grain-size of big data lakes with conceptualizations in cost ledgers to provide a comprehensive view of organizational relationship networks that can be used strategically to improve competitiveness overall (Theodorakopoulos et al., 2024).

2.2. Value Stream Management as a Pillar for Continuous Improvement in Industrial Environments

2.2.1. Concept and Definition of Value Stream

Within the doctrinal architecture of modern Lean Management philosophy, "customer" is canonized as central and all-knowing arbiter of value. This notion acquires structural sense only in an expression of a specific product (an industrial good) exactly fitting consumer needs during limited time and at little cost (Rosienkiewicz, 2012; Żywiołek, 2020). Thus, "Stream" is the full sequence of operational, logistical, physical and informational engineering activities required to design, schedule with complete data on products chassis components and sub-assemblies fully finished for delivery to end-user. At the conceptual dimensions of the value stream, there are 3 simple themes: 1) All-Inclusive Organizational Mindset: The value stream crosses the historical boundaries of departments and functions, covering not just immediate operations but all activities along the commercial cycle of factory function. It covers everything from the first procurement of raw materials (e.g., steel sheets and electric motors) along supply channels through cutting, pressing, welding, assembly and quality control lines to final product warehouse. The single flow of materials, information and financial flows from one physical resource to the next 13 Arora (2016); Novićević Čečević & Đorđević, 2020). 2) Eliminate Waste and Defects Absolutely: With high-precision mapping and planning of value streams, the factory can isolate, measure and eliminate non-value added activities (waste) such as idle setup times, material handling delays, defects and inter-process rework. This minimizes process defects, cycle times and resource downtime to ensure a best in class frictionless manufacturing flow (Novićević Čečević & Đorđević, 2020). 3) The Cost Control Accounting Foundation: In lean-manufacturing systems, the flow of costs (expenditures) occurs simultaneously with functional physical working activity along the same process path so that value stream is a foundation for modern management accounting and performance measurement; It substitutes overall aggregated allocation rates with an individualized economic analysis of production lines and processes in manufacturing (Novićević Čečević & Đorđević, 2020).

2.2.2. Value Stream Patterns and Operational Resource Allocation in Factories

Us well-defined operational boundaries and efficient human/physical asset deployment to the daily practice of value stream principles. This facilitates stringent cost accountability as well fuels the muddling of financial control analysed through two key motives: 1) It is called the Extended Value Stream: This macro-pattern expands well beyond a single factory's physical and organizational boundaries to include the whole industrial supply and demand chain buy-sell transaction, i.e., supply chain operations from suppliers forcing thier products through distributors all the way to consumers actually buying them. This refers to everything from procurement (including raw steel sheets, water pumps and electric motors acquired through suppliers), internal transformations, dealerships or distributors and finally the end consumer. Extended value stream analysis is a strategic imperative in the quest for getting inter-firm costs, lead times just-in-time and forming collaborative supplier relations that last through multiple product cycles (Żywiołek, 2020). 2) The Internal Value Stream: This pattern constraint its operation within the realm of things, it limits activity, process and asset manage only inside the wall of the plant / shop floor architecture. It orchestrates real time connection links, between the cutting, pressing and assembly cells, warehouses and maintenance stations. Internal value stream is oriented to the maximum possible internal operational efficiency, local bottleneck elimination with reduction consumption of resources on production lines (Żywiołek, 2020).

Identification and resource allocation methodology To tap into management accounting advantages but build absolute accountable for administration responsibility by these streams, factories heavily draw on identifying proper structural pillar (Hansen & Mowen, 2007).

Using a two-dimensional commonality matrix, products and appliances with the same nature of processing steps are grouped into discrete "Value Stream Families" (i.e., air cooler family group of 2.5 foot; industrial grade cooler family) (Hansen & Mowen, 2007).

Assigning and allocating certain operators, production engineers, QA personnel, and independent machinery to each independent value stream. This creates a sense of ownership among teams and establishes a more direct channel between operations responsibility and accountability (Hansen & Mowen, 2007).

Enforcement of full financial independence, that is, an each value stream in a production line will settle account weaknesses as cost structure and continual improvement as well profit rate ratio, see (Hansen & Mowen, 2007)

2.2.3. Value Stream Mapping (VSM) and its Control Mechanisms

Background Value Stream Mapping (VSM) is a specific industrial engineering and operational management tool derived from the history of the Toyota Production System in Japan as part of "Material and Information Flow Mapping" (Pekarcíková et al., 2021). This method produces a visual layout similar to an engineering blueprint for all processes required for operations, logistics, administration and technical service that go into moving raw materials and manufacturing products from production order release through actual execution up to shipping of the goods. Value delivered to the consumer is constantly computed as a narrow ratio of product performance/quality and its total cost (Pekarcíková et al., 2021).

The control and optimization dimensions of VSM are made possible with the absolute synchronization between the material and information flows. Lean management dictates the tracking of physical elements (steel sheets, individual components, operators and products) in parallel and total alignment with information flows (production plans, technical specifications and authorization timelines). This order identifies the departments that are delaying, locking in bottlenecks or wasting time and manually (Klimecka-Tatar, 2021; Klimecka-Tatar, 2019).

Five structural domains constitute a properly designed VSM architecture: 1) precise definition of customer requirements; 2) mapping, storing and controlling digital flows of information and data; 3) charting the physical flow of the process and material flows in time-distance scale; 4) specifying explicit relationships between the process flow as well as the flows linked with certain information items so that they provide real-time feedback to each other, thus enabling a closed-loop, continuous improvement mechanism; and 5) analysis-based estimation of value-added contribution for the product synthesized on Klimecka-Tatar (2021). The final possibility of having a current-state map is not the end goal of VSM, but rather designing a future-state map to see the optimizations in paths through the system, and then deploy visual digital management tools to permanently reduce manufacturing overhead and production cell operating costs (Klimecka-Tatar, 2019; Pekarcíková et al., 2021).

Lean Activity-Based Costing (Lean ABC) as a Tool for Digital Accounting Integration:

Lean Activity-Based Costing (Lean ABC) serves as the cutting edge in coalescing industrial engineering and strategic management accounting. As existing fixed cost frameworks become outdated with changing dynamic operations, the Lean ABC system rewires overhead cost pools to be directly connected to Value Stream Mapping (VSM) outputs and Big Data Analytics (BDA). This framework is conceptually grounded on classifying operational activities into Value-Added (VA) activities, aligned with customer dynamics and Non-Value-Added (NVA) activity corresponding to temporal/motion waste and unabsorbed idle capacity. Lean ABC captures cost drivers digitally through IIoT sensors so unabsorbed capacity variances can be directly routed into the income statement as independent losses, thus purging distortions in costs which free pricing and other strategic managerial decisions (Ryan, 2016).

2.3. Operational Phases and Timelines of Industrial Value Streams

Value stream maps consist of specialized graphical icons that characterize the complex process, material and information flows dividing the factory's path into three major segments: first, the physical material and process flow captures all phases of manufacturing including batch sizes together with current inventory levels; second, the information flow connects shop floor sensors to management enterprise systems in an unbroken real time link; third, it presents a Process Timeline. The bottom half of the map splits this timeline into a step on which is Time to production lead time, and the lower step (Klimecka-Tatar, 2017) Time Cycles by cycle that actual value-adding processing times.

A current-state map is created through an orderly series of steps starting with segregating product-families by the time taken to be processed, continuing with commonality analysis which reveals sub-processes shared between machines and determining lead-limes estimated within the process for continuous improvement (Klimecka-Tatar, 2017).

The visual map reveals operational bottlenecks, cycle times, operator and machine efficiency metrics, and short-term changes in demand. A current-state cost map can be struck in five steps that build on each other: 1) Computing total available production and operating time. 2) Understanding the daily expectations and finishing units of customers and dealers. 3) Graphing process flows to evaluate cycle times with technical machine metrics for stamping and cutting machines. 4) Planning flow for raw material from warehouses to different assembly line cells, and they must track integrated information flow to verify technical quality conformance. 5) At the bottom of the timeline are setup and changeover time (C/O), cycle time (C/T) and task wait times to delineate between value-added steps from process waste, staging delays, and work-in-process (WIP) accumulate.

The future-state map moves to uncover latent capacities, determine average lead-times appropriate for high-variance low-volume manufacturing environments and establish a rate-based flow through line balancing. It also employs a data-driven automated Pull System driven by actual market demand rather than traditional push manufacturing, and executes work rhythm following First-In First-Out (FIFO) principles to completely eradicate waste, operator overburdens, and process unevenness at the shop floor

2.4. Integrating Big Data and Value Streams for Strategic Managerial Decisions

Understanding how they differ structurally in nature, has assisted in rationalizing recent managerial choices and offering a more appropriate modern cost accounting approach, to modern manufacturing environments. Legacy setups have organized work around functional departments, generating large production and assembly batches (Functional Batches) that crawl between localized department to department from time to time (Hansen & Mowen, 2007). Such functional architecture launches costly transfer and customer wait times as materials and chassis parts pile up behind each preceding machine operation into mountains of work-in-process (WIP). In addition, different products require different technical data and in some cases mechanical die and mould settings to be reset which involves both long changeover and setup times adding yet more time quantum to make any traditional systems incapable of responding high-variety multi-product environments (Hansen & Mowen, 2007).

In cost accounting, these transfer, waiting, and defective periods are known as "non-value-added waste," since materials lie idle (one day is a helpful analogy), bottlenecks freeze cash, and parts remain un-assembled before-and-also after stamping and welding until the whole batch can be finished cleanly. On the other hand, lean management combines with big data analytics to radically minimize waiting and transit times (Hansen & Mowen, 2007). It means manufacturing units can run small, adaptive and on-the-spot production batches (Small Batches) for the current market cash flow order to avoid immediate stockpiling. The results of reducing costs are heavily contingent on SMED (Single Minute Exchange of Die) – compressing the setup time dependent and moving more toward a cell based layout with automated digital processing applications (Hansen & Mowen, 2007).

Industrial firms utilize several process mapping methods such as Big Picture Analysis and logic diagrams, in conjunction with VSM to describe precise internal and external flows, according to Kaizen continuous improvement tenets (Klimecka-Tatar, 2021). This is where process mining, a big data technique arrives to help management accountants appreciate the cause and effect relationships between production cost behaviour, quality defects with rework and energy consumption. It uncovered the competitive position of each plant at each step and provides an important method for optimizing product mix (Shen et al., 2016; Zhao et al., 2022).

Also, financial predictive analysis and industrial process mining provide capabilities to assess comprehensive operational and technical risks of production lines, develop predictive quality assurance frameworks, predict margins and asset returns as a function of real-time market indices and demand volumes (Zhao et al., 2022; Chen & Dai, 2021). This integration of technology, widens the window of data for industrial management accounting which helps to broaden the data sources, diversify input types, increase processing speed and provide real time dashboards at shop floors (Zhao et al., 2022). These advances leverage innovations in contemporary accounting tools, such as Rolling Budgets, Lean ABC, and real-time production line costing to improve proactive risk mitigation which doubles corporate value (Zhao et al., 2022; Theodorakopoulos et al., 2024).

3. Results and Discussion

3.1. The Empirical Study, Simulation Model, and Agile Costing Implementation

3.1.1. Operational Data Capture, Capacity Analysis, and Traditional Cost Ledger Structure.

This is a case study based on the real financial books and operational records of Fayadh Al-Qasim Industrial Company (Air Cooler Production Plant) activities in 2020. In this con, the tracking and analysis of (5,616 units) real production and assembly cycles) in a simulation sample covers all true realized annual volume production for that annual cycle of the factory for its mass-production purposes since it has been conducting said Product (realized volume) every year; namely 2.5-foot galvanized steel air cooler with raw sheets of metal from 0.7 mm to 0.8 mm thickness.

3.1.2. Operational Capacity Gap Analysis:

The engineering analysis conducted on industrial logs provided by the Planning and Follow-up Department indicates extreme structural variances in plant capacity utilization through 2020, as follows:

Designed Capacity of Engineering: 14,000 units in a year.
The Manufacturing Capacity available is 11,000 units in a year.
Realizable Actual Production Volume: 5,616 units
Quantity of Idle Capacity Not Used = 11,000 - 5,616 = 5,384 units.
Capacity Utilization Rate = (Actual / Available): 5,616 units / 11,000 units * 100 = 51.05%
Idle Capacity Percentage = 100% - 51.05% =48.95%

3.1.3. Traditional Cost and Price Structure Statement

The above-mentioned product cost and selling price are derived from the estimates provided in full absorption costing methods with a rigid (Cost +7) pricing formula, using traditional accounting practices where sales costs of production and this regimen is regulated by the Iraqi Unified Accounting System currently applied in the plant:

Direct Materials cost (Steel Sheets, Motor, Fan, Components) = 154,328 IQD
Direct Labor Cost (Factory Wages per Unit) = 15,000 IQD.
Prime Direct Cost per Unit 154,328 + 15,000 = 169,328 IQD

Manufacturing Overhead (MOH) Cost Allocation: 16,933 IQD (Production service centers 61-64 filled in arbitrarily with a standardizing historical rate with no further analysis for each).

Traditional Factory Cost of Goods Manufactured: 169,328 + 16,933 = 186,260 IQD

Administrative and marketing costs (9,313 IQD allocated for centers 71 and 81-86—arbitrary loading based on blanket rate of * 5 of Factory Cost).

Total Traditional Cost per Unit: 186,260 + 9,313 = 195573 IQD
Cost + traditional Profit Markup (Total Cost × 7 Target Margin): 13,690 IQD.
Today selling price to the public: 195,573 + 13,690 = 209263 IQD.

3.1.4. 5.4 Activity-Based Costing Deconstruction (Lean ABC) and Big Data Analytics (BDA) Deployment

Lastly, as depicted in the chassis alternative cooling 2.5-foot cooler (4,309 + 13,935; total communication cost = 26,246 IQD) to eliminate extreme cost distortion, without traceability that includes loading an aggregated sum of (low overhead and a blend of administrative costs aggregating (16,933 + 9,313 through packaging for consumers), prescriptive and diagnostic BDA solutions are built-in by the model. FY2020 Parameters Purpose The parameters given below are directly extracted from Industrial internet of thing (IIoT) sensors and integrated automated computer logs on the shop floor.

The entire blanket overhead cost pool was analytically dismantled and allocated into VA (Value-Added) activities and NVA (Non-Value-Added) activities (material/temporal waste and idle capacity) utilizing fit-for-purpose real-time digital cost drivers.

Table 1. Deconstruction of the Aggregate Overhead Cost Pool via Lean ABC and Digital Cost Drivers

No.	Simulated Operational & Accounting Activity	Lean Activity Classification	Activity Cost per Unit (IQD)	Digital Cost Driver and Big Data (BDA) Source Vector
1	Mechanical Processing & Machine Execution	Value-Added (VA)	4,200	Real-time machine runtime hours extracted from computer numerical control logs
2	Automated Quality Inspection & Rigor Control	Value-Added (VA)	1,800	Execution cycles logged via automated digital quality control platforms
3	Stamping Die Changeover & Machine Setup	Non-Value-Added (NVA) - Temporal Waste	5,430	Stamping machine idling and calibration hours tracked via machine-vision cameras
4	Excess Material Handling & Inter-Cell Logistics	Non-Value-Added (NVA) - Motion Waste	3,850	Inter-process transit distance vectors logged via warehouse automated tracking sensors
5	Rework Processing, Core Defects & Sheet Scrap	Non-Value-Added (NVA) - Quality Waste	4,620	Material failure rates and manual correction logs inside the quality system

No.	Simulated Operational & Accounting Activity	Lean Activity Classification	Activity Cost per Unit (IQD)	Digital Cost Driver and Big Data (BDA) Source Vector
6	Breakdown Maintenance & Idle Capacity Overhead	Non-Value-Added (NVA) - Capacity Waste	6,346	Machine failure downtime periods recorded on the Maintenance Module (Center 62)
-	Total Aggregate Overhead Cost Pool	-	26,246	100 Reconciled and Matched with Factory Records (16,933 + 9,313)

3.1.5. Industrial Value Stream Mapping (VSM) and Prescriptive Cost Cleansing Operations

The following strategic cost-cleansing and process re-engineering operations were simulated in cooler assembly lines by employing prescriptive Big Data Analytics integrated with continuous Future-State Industrial Value Stream Mapping (Dynamic VSM).

Stop Set-Up Cost Idling including the use of Single-Minute Exchange of Die (SMED) and connecting pressing places Area sensors to CAD/CAM parameters without needing physical adjustment. Such operation has eliminated timing delay in human measurement by (5,430 IQD) /each unit.

Compression of Inter-Cell Material Handling Cost. The shop floor layout was re-engineered into a continuous Cellular Manufacturing Architecture. The manual sheeting cutting station was relocated directly next to the hydraulic stamping presses and spot-welding cells, eliminating work-in-process (WIP) staging wait time delays and material handling costs, resulting in savings of 3,850 IQD per unit

Elimination of rework and scrap costs. Real-time sensor feedback mechanisms were incorporated directly onto automated cutting blades, allowing for accurate sizing of components down to a 0.7-0.8 mm tolerance window; This proactively avoided sheets tearing or welding mis-alignments, eliminated scrap material and re-work processing costs to zero leading to savings of (4,620 IQD) per unit.

IIoT machine sensors created predictive maintenance algorithms that removed the need for unscheduled breakdown maintenance therefore they were able to isolate and purge idle capacity cost. Even more importantly, as the factory had 49 of its available capacity unabsorbed, the management accountant isolated the idle overhead cost of (6,346 IQD) per unit and eliminated it from the product costing structure. This non-absorption cost was charged directly to the corporation profit statement as an idle capacity loss, thus shielding unit costs from ongoing inflationary moves.

Optimization of Prime Cost Efficiency. Reducing material sheet scrap and increasing line balancing efficiencies through final assembly processes (motor, fan, water pump & piping integrations) compressed direct materials and wages variance achieving an incremental on their adjusted prime cost (40,382 IQD) per unit.

3.1.6. Cumulative Financial Savings and Comprehensive Research Hypothesis Verification

The strategic oui-cleansing strategies removed four classes of non-value-added waste and idle prices (5,430 +3,850 + 4,620 + 6,346 =20,246 IQD). The residual overhead cost per unit is composed purely of value-added activities (Processing and Quality Inspection) and equals 6,000 IQD not 26,246 IQD.

Results Table 1 Reengineering the final cost ledger and pricing matrix for 2.5-foot cooler TOI outputs simulation model analysis

Optimized Prime Direct Cost (Materials + Labor) = 169328 - 40382 = 128945 IQD.
Optimized Traceable Lean Overhead Cost VA activities only = 6,000 IQD
Debased Optimized Average Total Cost per Product Unit =128,945 IQD + 6,000 = 134945 IQD
Cost Reduction Value Realized by Each Unit= 195,573 — 134,945 = 60,628 IQD.

Overall Reduction in Costs= 60,628 / 195,573* 100 =31.00% Exactly matching the target via hypothesis and the research abstract).

Sustainable Pricing Margin (Optimal Cost + 7%): 134,945 × 7% = 9,446 IQD.

Restyled official tag price to the general public: 134,945 + 9,446 =144391 a reduction of 64,872 IQD over the old-fashioned price tag of 209,263 IQD.

Calculation of the Factory's Total Realized Annual Cumulative Savings:

Confirming the final exact accuracy of the simulation model regarding the real production count related to FY2020 (5,616 units):

Total Annual Cumulative Savings which is calculated with the formula: Total Annual Cumulative Savings = 5,616 units * 60,628 IQD for unit = 340.486.848IQD

Empirical Synthesis:

The acceptance of the broad research hypothesis is supported by our quantitative simulation results. Cutting the selling price to 144,391 IQD would allow the company to address local demand and clear out imports. Furthermore, the corporate savings each year amount to an annualized 340,486,848 IQD and gives management significant liquidity for aesthetic designs of the units in addition to procuring low-power energy-efficient motors to meet demand from consumers and aim towards long-term industrial sustainability.

4. Conclusion

The empirical and quantitative results of the simulation model confirm the main research hypothesis. Field Study Evidence: The Unified Accounting System, like traditional allocation methods used with enterprise-wide systems, produces severe cost distortions due to the application of arbitrary, estimated blanket overhead rates (10 for manufacturing services and 5 for administrative costs). This allowed a 49 dormant capacity and operational waste to be absorbed without anyone knowing, increasing the unit cost of the 2.5 foot cooler to an artificial value of IQD195,573 and set its price at an unfeasible value of 209,263IQD that forced it out from competition and market share To remove this distortion, the study suggests moving to a Lean Activity-Based Costing (Lean ABC) system and cleaning the aggregate overhead pool (26,246 IQD). This necessitates identifying non-value-added activity and costs associated with the 48.95 of unabsorbed capacity, routing directly to the profit and loss account an independent capacity loss. Management will also have to make capital investments in Industrial Internet of Things (IIoT) infrastructure and re-design shop floor layouts into flexible manufacturing cells that can implement a Just-In-Time (JIT) production system. The results validate the that integrated digital-lean framework which decreases total unit costs with 31.00(to 134,945 IQD) enables hyper-competitively priced market price (144,391 IQD) while achieving appropriate target profit margin of 7. In the end, this framework overcomes imported competition and takes annualized cumulative savings of 340486848 IQD to be reinvested within both R&D and Value Engineering to modernize appearance of products and fine-tune energy consumption by full utilization of plant capacity.

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