10.48047/jocaaa.2024.33.08.78

Semiconductor Process Innovation: Leveraging Big Data for Real-Time Decision-Making

1.Botlagunta Preethish Nandan , SAP Delivery Analytics ,ORCID ID : 0009-0008-3617-8149

Abstract

Semiconductor manufacturing is evolving rapidly, driven by rising demand across the economy and the arrival of new production technologies. Over the past 30 years, the industry has steadily ramped up production capacity, and today is aggressively investing in new fans to stay ahead of the growing demand for semiconductors. Semiconductor manufacturing was traditionally a sequential process with expansive fabrication lines that could span more than a kilometre in length. Decision-making processes in these facilities were also sequential and treatment-based, with data transformed through the choice of a number of treatment functions on available signal spectra, and subsequently used for quarry-based decisions. Therefore, decision-making was performed off-line with delays of several seconds to minutes for individual machines. With the introduction of small-footprint and smaller-dimension chips, sensors are now being integrated into fabrication machines to monitor processes in-chip. That trend, in combination with new manufacturing technologies, has the potential to dramatically change the operating environment of semiconductor fabs, including the need for real-time data-driven decision-making (DDD) processes in hours or even minutes. This requires the development of real-time, on-line, data-driven monitoring and diagnostic methods, leveraging big data and AI-ML technologies.

In the big data age, rapid industrial development comes with concerns about data ownership and data privacy, and controlling data ownership and data privacy deals with data collection. In practice, data ownership and privacy concerns vary across industries: healthcare and finance industries are often at the forefront of data and privacy issues while manufacturing has continued to primarily rely on internal data storage. However, global data access is becoming a trend. In semiconductor manufacturing, with increasing computational capacity and integration complexity, the cost of privately storing tool and equipment data is rising, and external data access to IP and technology licensing has emerged as a possibility. In line with global data access, several companies and industry groups are building cloud-based data endpoints for semiconductor manufacturing equipment, which will allow access to previously private data at a wide range of time scales from real-time control to year-wide macro analysis. Global data access potentially unlocks new data-driven opportunities including prioritized global fab maintenance decision-making and real-time cross-fab monitoring for technology mismatch detection that are not achievable with local factory-centric data sets.

Keywords: Semiconductor Manufacturing,Process Innovation,Big Data Analytics,Real-Time Decision Making,Smart Manufacturing,Predictive Maintenance,Yield Optimization,Machine Learning,Data-Driven Engineering,Process Control,Industry 4.0,AI in Semiconductors,Advanced Process Control (APC),Data Integration,Digital Twin Technology.

1. Introduction

The semiconductor manufacturing process is multi-step and multi-tool, requiring highly customized equipment, processes, and materials. Tools include both batch and single wafer processes. The processes are initially established, then continuously monitored, and adjusted by on-site engineers. In an ideal scenario with adequate resources, there is domain knowledge to anticipate equipment malfunction, and with disciplined process monitoring and control, there are not many unexpected events. However, it has been challenging to handle emerging non-expert and unexpected events due to fast-paced technology development, increasing environmental complexity, and gradually reduced investment advantages.

Operation and monitoring of capital-intensive equipment is often regarded as an expert knowledge-based task. As such, monitoring is resource-intensive, with engineers outfitting process equipment with the necessary sensors and tools to monitor the process proactively. Despite intensive engineering care, the actual performance of the equipment depends largely upon the characteristics of its environment. Several events that are beyond human knowledge have occurred, including unforeseen external interference, upcoming equipment malfunction, and operator error. Detection of such non-explicit events is a challenge. Even in well-trained environments, operator error requires increased state awareness to provide state-related capabilities.

Often, engineers do not have the time to investigate each individual fault due to the scale of problems. Understanding how the equipment works is deemed to be the engineers' responsibility, and non-expert chips are alleviated by written or documented experiences. This is a lazy approach to learning. Not all sub-issues of past chips can be documented

10.48047/jocaaa.2024.33.08.78

or written down. Further, equipment operation is dynamic in nature. Old experience cannot be easily applied to newly emerging issues. Non-expert issues are thus difficult to identify and understand.

Widening the focus back to the individual chip, details of some neglect convert to beneficial features to assist human decision-making. Surprisingly, it is found that close examination of the spatio-temporal variation of the collected signals provides neat patterns of chip characterization. System variability, both noisiness and non-repeatability, is primarily observed from multiple perspectives.

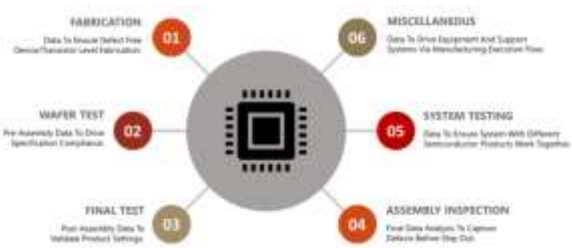

Fig 1: AI In Semiconductor Industry Innovations

1.1. Background And Significance

The semiconductor process industry is committed to continuously improving productivity and enhancing product quality. As the size of devices continues to shrink and device architecture becomes more sophisticated, the number of process steps per product has increased dramatically. This has led to longer lead times and greater challenges in maintaining process health. Moreover, the classical methods for process control and optimization are becoming limited and degrees of freedom for process adjustment are shrinking. A paradigm shift regarding process control is called for, i.e., one in which the role of big data and timely insights should be elevated to a first-class citizen.

The explosive growth of data and advancements in cloud computing have offered enormous opportunities for the process industry. Data with high volume, high velocity, high variety, and high veracity, or “big data”, is stored in various available databases. These data offer critical process insights ranging from time scales of minutes to months. Intelligent, cross-functional machines that leverage big data to convert these actionable insights into timely actions or decisions are envisioned. Machine-learning algorithms that can “learn” process knowledge, statistical tools with which to quantify the health state of machines, and APIs for real-time information sharing have all matured together to help realize this vision.

Such a cohesive framework, termed “data-driven decision-making (DDDM)”, will enable closed-loop or real-time decision-making. Such a framework is novel and critical for process innovation. Nevertheless, realizing this vision presents numerous challenges. The semiconductor process has, on average, 500 variables per tool or up to a million variables in a fab, including both controllable parameters and sensor data. Encompassing the full set of parameters may be unobtainable or unrealistic, calling for the development of a subset of core or critical variables with which to represent the system. Similar challenges exist with regard to process insights, which come in various forms of information.

Optimizing process control policies in the DDDM framework is also complicated by the presence of multiple objectives or competing goals. High product quality reduces defects at the expense of higher costs related to rework, which focuses on yield or capacity at the expense of quality. Process monitoring, fault detection and classification, fault tolerance, scheduling optimization, cost optimization, control optimization, equipment health monitoring or predictive maintenance, and so on are just some of the application areas in which co-optimization is needed.

Equ : 1 Yield Prediction Model

$$Y = e^{-\sum_{i=1}^{n} D_i \cdot \lambda_i}$$

Where:

- Y: Process yield
- D_i: Defect density in region i (real-time sensor data input)
- λ_i: Defect sensitivity factor for region i

2. Overview of Semiconductor Manufacturing

The semiconductor manufacturing process begins with sand being transformed into a splinter-sized silicon chip – the substrate on which chips are built – that undergoes a series of steps at various machines like photolithography stations, wet benches, and ion implanters, among others. The chips are then tested to ensure that they meet specifications and are packaged in multi-layered protective shells. The manufacturing of semiconductors has a few unique characteristics. First, the end product is the result of a long series of operations, often involving hundreds of steps. Reducing the cycle time of any one step may have little effect on the overall manufacturing cycle time. Moreover, in order to realize its potential, the tool completing an operation must be given sufficient work to keep it busy. The most

10.48047/jocaaa.2024.33.08.78

difficult problem in the semiconductor industry is the introduction of new designs while continuing to manufacture legacy designs. Each design creates a process requiring specific design rules that impact all other designs.

The common work element in the manufacturing of all types of chips is the coating, exposure, development, etching, doping, and passivation of a silicon wafer. Each of these operations is complicated by the need to introduce and remove chemicals, all of which can damage the expensive silicon wafer. A series of tools, each capable of handling one operation, has been developed by large companies; these tools are integrated into a line for 24/7 operation. Semiconductor manufacturing is expensive and must be monitored regularly. As the process becomes less stable, more opportunity exists for a defect to enter the final product. This can trigger wafer scrapping, which implies lost revenue in gaining that fabrication cycle again. Conversely, a series of expensive test masks, which define the patterns to be inserted on silicon, may suddenly go out of production. A macro-process indicating which job steps are being undertaken on which work-in-progress might be determined.

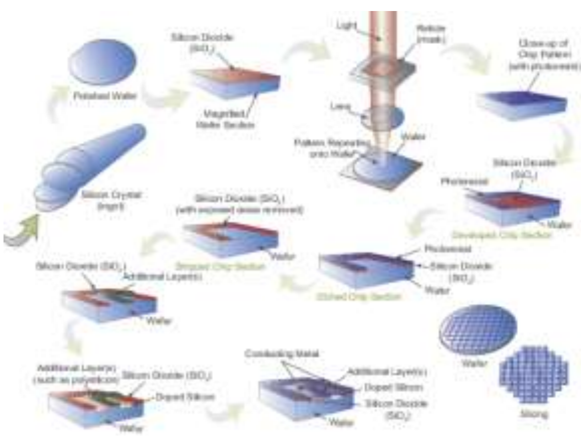

Fig 2: Semiconductor Manufacturing

3. The Role of Big Data in Semiconductor Processes

In the semiconductor industry, technology development to enable the observation and alteration of processes in real time opens new possibilities for further innovation in semiconductor process development and manufacturing. As a consequence of Moore's Law, semiconductor process innovation by further miniaturization to use the nanometer scale (nm) has been aimed at better performance, more functionality, and lower costs for a chip. The process steps consist of fabrication, characterization, and analysis to implement further technology nodes together with design architecture. These tasks are easier to implement when a process is mature, but they turn more difficult and labor-intensive with technological challenges shrinking further. In addition to modern instrumentation/system, major new technology is required for concept development, modeling, experimentation, and data analysis throughout the required high level of integration and miniaturization to innovate semiconductor processes. To achieve the intended targets, there are increasing demands for process innovation methods and their products. With the advancement of high-performance computing, new methods using large-scale optimization, simulation, and sensor data analysis are developed, which could deliver suboptimal performance-driven designs or models. By employing state-of-the-art deep-learning networks, methodologies and their products can be optimized to provide autonomous predictive development, which significantly enhance the viability of technological advancement. As a consequence of the maturity of semiconductors, semiconductor technology development on the research level tends to be down-scaled. However, this will limit resource investment on further technological advancement by non-competitive and increasing burdens with raising costs and enlarging problems. Consequently, a paradigm shift in the semiconductor industry to startup smaller firms for co-development and exchange intellectual properties is highly disputable. To this end, an alternative approach should be actively sought for feasible solutions.

4. Data Collection Techniques

Data collection techniques are capable of gathering critical information about the wafer follow status and manufacturing system. It is important to note that there is a significant difference between data that can capture characteristics at a higher level. Specifically, data streaming from equipment sensors can reflect lithography patterning attributes, process tool physical condition, operations strategies such as job scheduling, maintenance history, etc. All the collected data require pre-processing including denoising, visualization, storage, etc. New methods for semi-supervised, robust, and online pre-processing are required. They need to be continuously trained for good predictive performance in changing environments and would benefit from processed data sharing among different tools.

Lot information such as line input/output, processing history including product ID, job, and machine pairing info, etc. provides contextual information about the lot-to-lot variability of the manufacturing sequences and processes. Traditional techniques including clustering, Markov modeling, and random walk enable the extraction from the

10.48047/jocaaa.2024.33.08.78

base information and characterize the overall operations logics. They can be expanded to online unfavorable pattern detection. However, they usually regard the sequence data as discrete symbols, but the tools are equipped with advanced sensor measurement devices so that this information should also be included. New data-driven techniques that combine the base sequencing extraction and batch-wise off-follow status measurement feature extraction would provide more insightful and decisive instructions for dynamic process control.

A large number of methods, both physical-based and statistic-based, are available for the detailed process characterization using big data. Some place emphasis on similarity matching to classify the products into any defined failures. Others focus on regime identification to understand the change points of batch-type processes. Nevertheless, existing literature has to rely on either one of these two, while a universal framework that allows both measurements is critical for understanding the tool. Continuous data streams bring further challenges for the methodologies and require innovative real-time anomaly detection techniques.

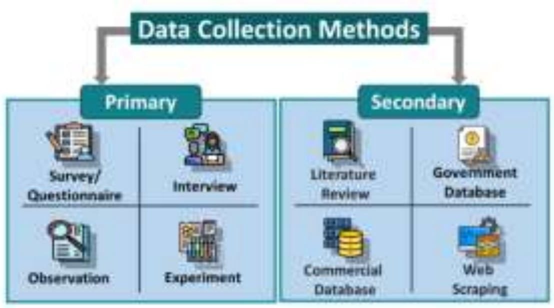

Fig 3: Data Collection Methods

4.1. Sensor Technologies

A large amount of data from sensors monitoring the wafer fabrication process is generated in semiconductor manufacturing factories. Monitoring data from sensors installed on manufacturing equipment is useful for fault prediction, performance degradation diagnosis, and semiconductor particle yield improvement. Sensors measuring the environmental state of the cleanroom are crucial for analysis and improvement of yield by predicting the wafer-related possibilities. Growing additional tests such as the rogue port test to splice leads, adding buffing to reduce scratches, and further manual inspection still does not prevent unaccounted losses, and dying from Fast-Interphases (FI) has begun to increase. Silicon test rejection lights off new starts, but care must be taken as this may hide the true yield. Twenty plus years ago, particle scattering, magnetically based, and other such low-cost systems were predicted to dominate thinly. Twenty models bidding on this understood that the best chance to find a true fail early, without a continuous enhanced sensor regime, would be to analyze the existing low-cost systems. These control various stages of wafer fabrication as related yield losses on a batch basis; while expensive, the alternative would be common fault-space measurement systems. Analytics can discover and extract key features from the present sensors, and explore modeling to see if the particle loading state (or fault) can be forecasted and how it is related to yield loss.

The wafer fabrication process in semiconductor manufacturing is a sophisticated and complex process. Sophisticated and expensive equipment is used to fabricate products following well-defined process operations, which are supplemented with lots of feedback controls. For example, optical inspection systems have been developed to detect particles and scratches on the wafer surface after the silicon photolithography process. Once a problem is detected, the wafer can be rerouted to a separate wafer cleaning process. However, although advanced sensing technologies are available and utilized, signals from the sensors exhibit lots of variation and are often of poor quality. Since the same sensor can indicate different indications for different batches and faulty wafers, it is extremely difficult to accurately diagnose and proactively respond to yield degradation patterns. Furthermore, unlike the well-defined outputs from the inspection systems, observing output quality data directly from the wafer fabrication process is virtually impossible. Therefore, there is a need for an effective data-driven soft sensing model capable of accurately inferring wafer fabrication quality information using data from affordable sensors.

Equ : 2 Feature Drift Detection (Using KL Divergence)

$$D_{KL}(P||Q) = \sum_{x \in X} P(x) \log \left(\frac{P(x)}{Q(x)} \right)$$

Where:

- $P(x)$: Historical distribution of feature x
- $Q(x)$: Real-time distribution from incoming data
- High D_{KL} indicates significant process drift

4.2. Data Acquisition Systems

The changes from centralized to distributed data processing offer new possibilities for real-time big data analytics implementation. Fully utilizing fog computing provides a clear separation of concerns in system design, enabling

10.48047/jocaaa.2024.33.08.78

multiple implementations of specific components. In this context, open-source means implementing normal big data analytics across multiple cloud distributed systems, directly accessible through the known interface. Chip-scale silicon waveguides with a cross-section of 500 nm × 220 nm are patterned in a silicon-on-insulator substrate. The designed waveguide is utilized with end-user applications. The eye diagram of 10 Gb/s data demonstrates an error-free operation over 20 km of standard single mode fiber. Through reformulating a centralization-based graph model, a set-cover-based spread model is obtained to extract an optimal subset of sensors for real-time processing. The controller's communication load is also reformed as network flow to capture the data-driven part in an ops-nodes-stripped sensor graph.

The extensive evaluations indicate the algorithm's efficiency in reducing communication load while sustaining event detection robustness. The proposed procedure allows real-time data acquisition and its visualization for parametric studies. The method is successfully applied to explore cases concerning surge subjects. Aspects of the related numerical demand levels and attained parallel efficiency are also analyzed. The advantage of the proposed modeling procedure lies in the capability of data acquisition visualization for parametric studies. Bayesian networks are promising for real-time prediction and decision-making after integrating with a distributed architecture. CPDs of nodes in the Bayesian networks should be updated over time, which describes a challenging study direction. Data acquired from a wide range of sensors are infused incrementally to carry out the long-term decision-making task.

5. Data Analysis Methods

In semiconductor manufacturing, process equipment generates data continuously and volumes grow quickly as technology nodes shrink. While there are great opportunities in Big Data, current statistics and modeling approaches in semiconductor manufacturing are not adequate for dealing with the increase in data volume, velocity, and complexity. Batch processes, in particular, present a grand challenge. Most large-volume applications in IC manufacturing use batch processes, from polysilicon deposition and epitaxial growth to etch and chemical vapor deposition (CVD), and general wearable and 3D-IC applications use batch processes for new process steps. Compared to individual wafer processing, batch processes generate a wealth of data from a large number of samples simultaneously and provide opportunities for comprehensive online process measurements with low overhead. However, handling the high-dimensional and temporal data representing multivariate processes remains a major challenge.

The semiconductor manufacturing operation is heavily governed by computer-based equipment, instruments, and control systems that constantly generate multiple types of time-stamped digital process signals. Amid the rapid growth of semiconductor volume and revenue, there has emerged an exponential increase in the number of installed process units and a second exponential increase in the system integration and interconnectivity of manufacturing machines and devices, resulting in the wide availability of large amounts of manufacturing data. These datasets include measured and derived, scalar and array, frame-based and time-synchronized signals, schemes, alarms, and events from literally thousands of sources. Automated sensors in semiconductor power equipment typically sample RTD temperature probes every five seconds, resulting in over 100 megabytes of measurement data every day.

Despite the huge potential benefits of such available data, statistical methods for process monitoring and modeling have not kept pace with increased data volume, dimensionality, and complexity. Conventional control methods based on straightforward statistics and a clear understanding of the underlying physics and chemistry are still widely used in the semiconductor industry. Statistical run-to-run control methods utilize a concise representation of multivariate measurements to adjust equipment work states for next runs despite disturbances. However, such statistical approaches have a limited ability to handle batch processes, with time-varying input factors, due to computational and methodological bottlenecks.

Fig 4: Data Analysis Techniques

5.1. Statistical Analysis

To guarantee effective and precise process monitoring, batch-type plasma etching tools must be better modeled. To accomplish this goal, substantial efforts are made to enhance arc detection methods and increase the accuracy of soft sensors. Using effective systematic approaches, the ability of softer sensors to predict etch rates during the monitoring of

10.48047/jocaaa.2024.33.08.78

these tools is enhanced. Furthermore, methods based on statistical process control are developed to flag monitoring qualities. Improvements in alarm decision trees adjust the hard sensors' sensitivity and specificity differently to change the trade-off between false alarms and uncaught excursions.

Improved process monitoring techniques are added to process modeling. The use of an improved design of experiment (DoE) procedure significantly increases the quality of obtained soft sensors. A method is introduced that enables better prediction of chamber-to-chamber (C2C) adjustments. This method produces simpler C2C models as a result of better and more high-quality data matching the underlying modeling assumptions.

Process normality is defined as a state in which the recorded monitor data does not display abnormal behavior. To guarantee process normality, the underlying batch model acquisition must be proper in the sense that under nominal settings, recorded monitor data follow the batch model perfectly. A review is presented of the methods used to model existing processes/workflows. These methods consist of classical state-based process modeling approaches, statistical process monitoring, and machine learning techniques. Newer work in the field of analog process monitoring is also discussed, focusing on the problem of creativity versus predictability.

5.2. Machine Learning Algorithms

The goal is to leverage big data analytics to help in critical parameters optimization in semiconductor processes, resulting in a smaller process window as well as a smaller cycle time to establish the process. Machine learning (ML) algorithms, due to their great generalization capability, ability to treat large databases, and good automation level, are utilized. Data selection using KMeans with the significant reduction of process data size that meets error tolerance/availability is performed. Two AI recipes based on shallow/decision tree-based models were proposed and compared with the performance and visualization. It is shown that the proposed ML-based thin oxide prediction can drastically reduce spontaneous degradation/testing time.

The most critical gate dielectric processes would be compatibility between performance/prevention, thin oxide process, that oxide thickness miniaturization could enlarge a set of electrical property parameter variation (off-current, on-current, sub-threshold, steepness, and breakdown voltage). This results in difficulties both in preventing spontaneous degradation and spillage increase in testing time. A statistical study shows the process optimization space, which is the major process window that gathers about 20% good devices. Outsiders result in poor properties, thereby alerting the problem. This shows optimization procedure iteration (Pi=0, 1) every 3s of time taken by 3-ML/GLM. This method could provide an efficient solution to automatically determine the critical locations to mask weak locations in other testings, optimize the process further, and facilitate the test-generation computing speed. Because the compact sequencing of the ML gives the probability distribution of previous test results, using retention time, history determination as variables helps model and characterize the matching devices uniquely.

The success of the physics-based ML model is in large part due to the complementarity of ML and physics. On the one hand, physics knowledge-based modeling provides a good initial structure for the ML approaches, and the explicit physics of compact modeling delivers interpretability of the ML model itself. In short, the decoding part, i.e. physics-based ML is a hierarchical network comprising a series of physics-based coarse-grained ML sub-models. On the other hand, the ML predictions are used to build up a hybrid model where simply cascade the IA model and physics-based model together through equivalent variable conversion or entirely replace/augment physics-model parameters by ML networks with physics constraints.

5.3. Predictive Analytics

Predictive analytics is a technology that has been increasingly highlighted in many industries due to the success stories of its applications. Predictive models are getting more and more effortless to create due to the abundance of collected data and improved computing power. However, predictive models only have the potential to create new applications if they are embedded in the operations' real-time execution loop or everyday practices. This represents a novel and larger challenge for many industries, including semiconductor manufacturing. The need for real-time decision-making support is specifically called out in the semiconductor manufacturing industry as the technical gap to close with other industries where predictive analytics is already applied.

One area of decision-making would be predictive maintenance for equipment health. The goal is to predict machine breakdowns and trigger actions to mitigate the chances for non-elective stoppages. It is an important domain for the semiconductor industry since maintenance actions for lithography machines, for example, are costly and time-consuming. If preventive maintenance can be done in a planned manner based on models of when machine breakdowns occur, it could lead to smoother and more efficient production. Another identified area of decision-making is the recommendation of the best decision options

10.48047/jocaaa.2024.33.08.78

and plan disruption detection and alerts after an unforeseen event that has affected the production.

The innovative aspect of the approach is in the semi-automated applications of predictive models with decision-making based on implemented criteria and thresholds. The latter change over time according to the context and take into account business goals. A different type of real-time decision-making would be to provide an alert after an event in production and early present the best actions and options. This should be done by single-objective optimization models that take the production plan and the event scenario as input data.

6. Real-Time Decision-Making Framework

Real-time decision-making of industrial processes can be modeled as a mathematical optimization problem such as Latin hypercubes sampling or other more advanced algorithms in precise execution time and casting maximization or minimization functions in accuracy based on prior knowledge. The benefits of fast camera based noncontact approaches exploiting temporal information from silhouette images were emphasized. As a prominent preventive approach, on-line prediction either with ring buffers in the online setting or over sliding windows in the more general case are options to continuously assess newly arrived data. However, interrelated samples over the time might lead to decision redundancy. Abstraction methods based on clustering and quantization have been developed to reduce computational load in modeling, estimation, and prediction. An online version adopted with the K-means and K-representatives search is proposed. Predictive quality monitoring methods assess the predictor generalization over future unseen processes ahead of execution. As an alternative to instantaneous monitoring, classical approaches provide retroactive assessment while some alternatives circumvent reference signals or fresh data and perform efficient direct monitoring based on judgment justifications using sampling or selections tailored for sensitivity functions, which resulted in a standard-level explainable AI provision for continuous operation monitoring. Business intelligence, intelligence data analysis, and process and scheduling optimization-related queries can be processed either as custom on-demand processes or pre-synthesized on updated data. User queries can also be submitted as criteria attributes, while the detection of infeasible data lack proper on-the-fly quality indexes, attributes, or triggers for sampling and streaming types might be beneficial for real-time scales. Queries can be mined from user executions or sampled to ensure generalization. Data indexing by attributes or types can significantly speed up filtering from massive data as sparsely searched exponentially-sized combinations might not be feasible even in small-time batches.More importantly, in the big data era, there are excessive amounts of irrelevant data which led to increased consumer perplexity. In order to produce good decisions in complex situations, decision support tools which can filter only the relevant data and reduce cognitive burden for decision makers in semiconductor industries are in urgent need. In order to reduce perplexity in capturing intelligence, problem-based single objective smart DSPs like WAFER/DIEs selection, Heuristic neighbor WAFERs searching and Info Novelties extraction/Dynamics prediction were developed. The approaches used in those DSPs can be generalized across industries.

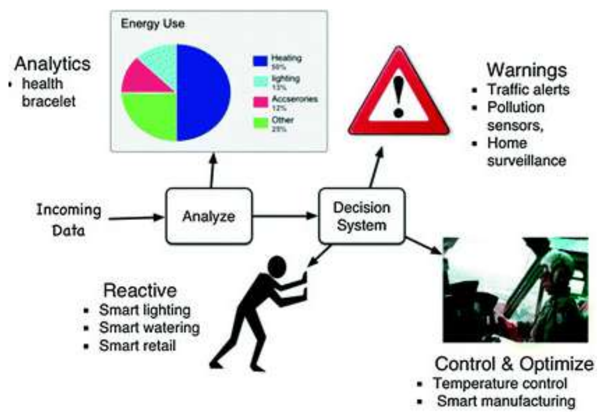

Fig 5: Real-time decision-making

6.1. Decision Support Systems

Big data decision support systems in semiconductor industries are to analyze all the data captured from machine and environmental sensors in the fab. Strong change agents like AI are needed to filter only the relevant data in order to accelerate the decision making process. Efficient integration of large amounts of diverse data offers better understanding of the manufacturing intelligence and improves overall performance and yield. Digitalization has become a prevalent trend across various industries in recent years. Advanced sensors and monitoring systems are now extensively used to capture large amounts of data in a variety of formats, including structured measurements, categorical indicators, and unstructured logs and images. It is generally accepted that the more data is available, the more insightful decisions can be made to automate and accelerate business processes. However, many organizations still fall short of extracting optimal insights from the data, and often face challenges like dimensionality, diversity, veracity, and variability in capturing, storing, and leveraging the data.

Big data decision support systems (DSS) are needed in semiconductor industries to analyze all the data captured

10.48047/jocaaa.2024.33.08.78

from machine and environmental sensors in the fab. For general purpose large semicon fab, CAD data and program selection can take time in the order of 5000 iterations, given a diverse number of equipment, product type and hundreds of pre-defined recipes, which is beyond the time limit of >1 hour imposed by rigorous OOD criteria. To reduce the number of CAD nodes, decisions made prior to casting lots are explored. Timely short-term decision aids will become more crucial when the number of critical lots increases exponentially. Strong change agents like AI and advanced data mining techniques are needed in digitization and artificial intelligence journeys.

6.2. Automated Control Systems

The big data collected via monitoring, prognostics, and diagnosis can be leveraged via tuning exhaustive rules to automate control systems that make decisions in real time in the semiconductor process. For a well-digitized semiconductor process, tons of data can be collected for monitoring, feature extraction, and modeling on each equipment. In a big data-driven method, a monitoring rule of thumb can be tuned and used to create indicators on important characteristics, diagnostics, or prognosis on usage state. In a contrary way, rules can be tuned to automatically control systems that make classic rules into more accurate smart ones. Usually, the rule of thumb discovery generalizes classical wisdom of operations, process engineers, across teams and sites. With automated sensor extraction to build the descriptive models, the already smart rules can be improved via execution forecasts compared with the optimal sequence. Semantic rules can be leveraged further for more complex decisions like changeover. Intelligent optimization knobs can be tuned with big data on how to use rules to adjust execution-systems. On tuning improvement, there are initial default parameters provided by the process engineer, who usually knows the limits for safety. The tuning is then built on parameterized fuzzy systems with sequential d-points sampling, or evolutionary algorithms that automatically sample new points based on historical results. Usually a few d-points leads to a few smarter knobs being accessible, though one may pursue searching for all smart knobs.

7. Case Studies in Process Optimization

Effective monitoring and modeling are crucial to enhance product quality and equipment performance, as well as to reduce manufacturing costs in semiconductor manufacturing. Plasma etching is a batch-type process commonly employed to fabricate semiconductor devices. While it is a critical step in the semiconductor fabrication process, the tools are also very expensive and numerous parameters have to be finely tuned to achieve the desired process results. Furthermore, the tools are often built with complex and nonlinear dynamics. Therefore, the monitoring and modeling of plasma etching tools remain very challenging research topics.

Dynamically identify the abnormal substrates in an operational plasma etcher with hidden Markov models. The run-to-run control strategy adjusts the recipe input values in between successive throughput lots by observing the process conditions of the current lot. The concerns on the return conditions of a batch-type process introduced by the lack of product-level measurements are addressed. A method is derived to dynamically adjust recipe input values to compensate for variations in product quality that do not reach the excursion limit, based on the underlying plant model. It is analytically shown that the return conditions can be guaranteed during steady-state operation in non-excursion risk cases. Moreover, conditions on the performance of the controller are derived to ensure this property. The concepts are illustrated with simulations based on first-principle models of a plasma etching process. A method to detect faults of end-point detection sensors in an etching process, which can ignore non-faulty substrate signatures and accommodate stochastic measurement noise.

A method is developed to foliate the differencing ocean faithful corrections of process average. Experimental results are conducted to demonstrate the method with a combustion system, and it is validated to be effective and efficient. Fault-tolerant control of linear systems subject to controller faults and external disturbances based on two fault diagnosis methods. In both methods of re-evaluating the parameters of the faulty controller and of estimating the uncertain linear controller, stability conditions for the resulting closed-loop systems are derived. A study of the design of unknown input observers for nonlinear systems, followed by a case study with an industrial plasma etcher.

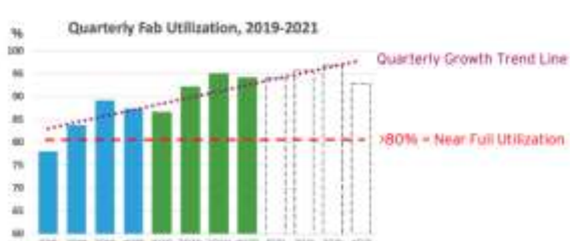

Fig 6: Semiconductor Industry

7.1. Wafer Fabrication

In addition to the differences in the product between semiconductor and traditional manufacturing, both the variability of product quality and the distinction in the

10.48047/jocaaa.2024.33.08.78

process flow characteristics have a significant effect on production control. Variations in the quality of a semiconductor wafer, which can cause electrical failure of the semiconductor circuit, arise from the fabrication processes to which the wafer is subjected in a wafer fabrication facility (Fab) . Such variations arise as well in traditional manufacturing, but much attention has not been given to it, as the design for manufacturing eliminates defects at a greater cost. Moreover, such machines often employ highly controlled process tooling and testing to assure the shape upon which reproduction is based, thus eliminating variability downstream. Therefore, product quality variation is more pronounced and more important in wafer fabrication to the manufacturer, equipment vendor, and end-user alike.

Whereas assembly, test, and front-end processes at the die level are concurrent and hence depend on wafer global workflow, the flow at the wafer level into fabrication is serial. Therefore, aside from a limited number of tools that can simultaneously process wafers at two different processing steps, there are no machines that process several wafers at the same time. However, the processing of a single wafer is spread out over time and space, with individual processing tools distributed around the plant, on which multiple chips at least two orders of magnitude smaller than the wafer are fabricated. Each processing step will be complex in itself, since they take a lot of time (min to hours), require high precision (sub-micron), and the input/output signals travel infinitely through measurement chains, thereby being subject to distortion. All wafers pass through the same sequence of steps and they pass through them separately one-by-one.

Equ : 3 Optimization of Process Parameters (Gradient Descent)

$$\theta_{t+1} = \theta_t - \alpha \nabla_\theta J(\theta_t)$$

Where:

- θ_t: Vector of process parameters at time t
- α: Learning rate (tuned using historical big data)
- $J(\theta_t)$: Cost function (e.g., inverse yield, defect rate)
- Used for adaptive process tuning in real-time

7.2. Yield Improvement

In the semiconductor industry, yield enhancement is one of the most important concerns as it directly affects the cost efficiency and the competitiveness in the market. As chips become more complex, the manufacturing is facing added challenges, and a multi-dimensional quest for yield enhancement has emerged as the most important and effective lever to reduce costs and increase financial returns. A one-percentage point increase in chip yield could drive net profit up to 10% or even more jump. Hence, the measurements to quickly adapt to the changes, enhance product yield, and optimize resource utilization are in perennial demand.

With the internalization of sensors and the gigantic advancement of IoT techniques, massive amounts of manufacturing data are being generated in various forms such as time sequences, tables, and images. To leverage this enormous resource, machine learning techniques have been increasingly used in smart manufacturing for enhancing yield related tasks such as analyzing the critical process steps that affect the die yield most, assisting the technician in troubleshooting and optimizing the process, detecting the potential cause of a data anomaly, identifying defect categories for automating the defect classification job, etc.

Despite the ardent efforts in yield enhancement in semiconductor manufacturing, the development and deployment of these strategic machine learning techniques in practice often require massive professional knowledge in mathematics and domain. Thus, those advanced techniques cannot be rapidly integrated and adapted to the tasks or phenomena changes such as design changes, fault happening, tool shift, and the emergence of new defect categories. This effectively restricts the fast feedback loop for current manufacturing intelligence approaches, leading to huge wasting of on-line value discovery. To reduce the sophisticated configuration burden for every task and every practitioner, efforts have been devoted to AutoML tools that automatically seek optimal models for a non-expert user.

8. Conclusion

The advent of Big Data provides an opportunity to move sensible regular analytical decision-making closer to real-time. Analogously, the continuously increasing understanding of data science opens a door for more complex analytical models. However, turning this new wealth into novel value-generating solutions is not trivial. The opportunities are at the intersection of new information technology and advanced modeling, algorithms that are tuned for the specific availability.

The additional dimension that Big Data mechanisms provide is necessarily some learning type—learning may include human adjustments and adaptations of algorithms considering a new context, replacing themselves with

10.48047/jocaaa.2024.33.08.78

incoming structural data, etc. Adaptable models can have a dimension of what to process and analyze the data now. Using experience or domain knowledge to appreciate that the obtainable data is more effective than another regarding using it for robust yield prediction. Involving scalable models for establishing cross-factor interactions from sparser machine learning insight into acquiring high-quality and calibrated input data also indicates added value.

The numerous dimensionalities and the countless weights of the approach reflect that this contribution urges more utmost attention from the research community, academia, and industry for the purpose of getting it right and of transferring knowledge from domains where recent data-involved solutions involve innovative approaches on small time scales due to simpler underlying principles or faster-governing bottlenecks. Tackling the most important challenge for some industrial domain is hence regarded as a crucial research necessity for society. In addition, continuing effort must be put into understanding the deceleration of progress and the enhanced scrutiny and evidential procedures combined with trust in technology and knowledge.

8.1. Future Trends

The emerging trend of Industry 4.0 describes a new industrial paradigm that leverages physical systems in smart factories and improves processes through data-based performance evaluation. The development of advanced manufacturing has enabled real-time analysis and more precise decisions based on data refined in the factory knowledge mining process. The demand for semiconductor chips and high complexity of IC designs drive innovations through new materials, advanced architectures, and fabricating processes. This increasing difficulty in chip production escalates the need for large amounts of data to characterize, monitor, and control complex chip fabrication processes. However, the lag of silicon wafer fabrication technologies compared to the fast-growing chip design technologies leads to the necessity of continuous improvement of fabrication sequences, parameters, and preventative maintenance. Despite the efforts in process improvement, there exist various issues caused by uncertainties in the prediction of each knowledge source, possibly leading to wrong implementation and missing opening-up opportunities.

The framework of the overall data value chain for data-driven decisions is divided into five layers: (1) data sources, (2) data acquisition, integration, & management, (3) data analysis, (4) decision making, & (5) acting upon decisions. Challenges along the value chain are outlined based on the predictive maintenance use case and mapped onto the layers of the data value chain. To explore the usability of data-driven solutions, a hierarchy of readiness levels has been proposed. In this context, the focus is on the lowest level - data sources. Several considerations for selecting data sources for greater usability are highlighted. Guidelines on how to increase the usability of the selected data sources are given, focusing on data preprocessing. Finally, an empirical illustration of the introduced considerations and guidance is given, focusing on several data sources from the manufacturing domain. Although some relatively easy-to-predict failures can be detected early today, the aim is to improve the models and cover a broader range of failure types.

9. References

[1] Challa, S. R., Malempati, M., Sriram, H. K., & Dodda, A. (2024). Leveraging Artificial Intelligence for Secure and Efficient Payment Systems: Transforming Financial Transactions, Regulatory Compliance, and Wealth Optimization. Leveraging Artificial Intelligence for Secure and Efficient Payment Systems: Transforming Financial Transactions, Regulatory Compliance, and Wealth Optimization (December 22, 2024).

[2] Revolutionizing Automotive Manufacturing with AI-Driven Data Engineering: Enhancing Production Efficiency through Advanced Data Analytics and Cloud Integration . (2024). MSW Management Journal, 34(2), 900-923.

[2] Pamisetty, A. (2024). Application of agentic artificial intelligence in autonomous decision making across food supply chains. European Data Science Journal (EDSJ) p-ISSN 3050-9572 en e-ISSN 3050-9580, 1(1).

[3] Paleti, S., Mashetty, S., Challa, S. R., ADUSUPALLI, B., & Singireddy, J. (2024). Intelligent Technologies for Modern Financial Ecosystems: Transforming Housing Finance, Risk Management, and Advisory Services Through Advanced Analytics and Secure Cloud Solutions. Risk Management, and Advisory Services Through Advanced Analytics and Secure Cloud Solutions (July 02, 2024).

[4] Chakilam, C. (2024). Leveraging AI, ML, and Big Data for Precision Patient Care in Modern Healthcare Systems. European Journal of

10.48047/jocaaa.2024.33.08.78

Analytics and Artificial Intelligence (EJAAI) p-ISSN 3050-9556 en e-ISSN 3050-9564, 1(1).

[5] Kummari, D. N. (2023). Energy Consumption Optimization in Smart Factories Using AI-Based Analytics: Evidence from Automotive Plants. Journal for Reattach Therapy and Development Diversities. https://doi.org/10.53555/jrtdd.v6i10s(2).3572

[6] Federated Edge Intelligence: Enabling Privacy-Preserving AI for Smart Cities and IoT Systems. (2024). MSW Management Journal, 34(2), 1175-1190.

[7] Koppolu, H. K. R. (2024). The Impact of Data Engineering on Service Quality in 5G-Enabled Cable and Media Networks. European Advanced Journal for Science & Engineering (EAJSE)-p-ISSN 3050-9696 en e-ISSN 3050-970X, 1(1).

[8] Sriram, H. K. (2024). A comparative study of identity theft protection frameworks enhanced by machine learning algorithms. Available at SSRN 5236625.

[9] Paleti, S., Singireddy, J., Dodda, A., Burugulla, J. K. R., & Challa, K. (2021). Innovative Financial Technologies: Strengthening Compliance, Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures. Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures (December 27, 2021).

[10] Singireddy, J. (2024). AI-Driven Payroll Systems: Ensuring Compliance and Reducing Human Error. American Data Science Journal for Advanced Computations (ADSJAC) ISSN: 3067-4166, 1(1).

[11] Chava, K. (2023). Integrating AI and Big Data in Healthcare: A Scalable Approach to Personalized Medicine. Journal of Survey in Fisheries Sciences. https://doi.org/10.53555/sfs.v10i3.3576

[12] Challa, K. (2024). Enhancing credit risk assessment using AI and big data in modern finance. American Data Science Journal for Advanced Computations (ADSJAC) ISSN: 3067-4166, 1(1).

[13] Pandiri, L. (2024). Integrating AI/ML Models for Cross-Domain Insurance Solutions: Auto, Home, and Life. American Journal of Analytics and Artificial Intelligence (ajaai) with ISSN 3067-283X, 1(1).

[14] Malempati, M. (2024). Leveraging cloud computing architectures to enhance scalability and security in modern financial services and payment infrastructure. European Advanced Journal for Science & Engineering (EAJSE)-p-ISSN 3050-9696 en e-ISSN 3050-970X, 1(1).

[15] Recharla, M. (2023). Next-Generation Medicines for Neurological and Neurodegenerative Disorders: From Discovery to Commercialization. Journal of Survey in Fisheries Sciences. https://doi.org/10.53555/sfs.v10i3.3564

[16] Kaulwar, P. K., Pamisetty, A., Mashetty, S., Adusupalli, B., & Pandiri, L. (2023). Harnessing Intelligent Systems and Secure Digital Infrastructure for Optimizing Housing Finance, Risk Mitigation, and Enterprise Supply Networks. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 372-402.

[17] Kalisetty, S., & Lakkarasu, P. (2024). Deep Learning Frameworks for Multi-Modal Data Fusion in Retail Supply Chains: Enhancing Forecast Accuracy and Agility. American Journal of Analytics and Artificial Intelligence (ajaai) with ISSN 3067-283X, 1(1).

[18] Chava, K., Chakilam, C., Suura, S. R., & Recharla, M. (2021). Advancing Healthcare Innovation in 2021: Integrating AI, Digital Health Technologies, and Precision Medicine for Improved Patient Outcomes. Global Journal of Medical Case Reports, 1(1), 29-41.

[19] Annapareddy, V. N., Preethish Nanan, B., Kommaragiri, V. B., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent

10.48047/jocaaa.2024.33.08.78

Manufacturing. Venkata Bhardwaj and Gadi, Anil Lokesh and Kalisetty, Srinivas, Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing (December 15, 2022).

[20] Meda, R. (2024). Enhancing Paint Formula Innovation Using Generative AI and Historical Data Analytics. American Advanced Journal for Emerging Disciplinaries (AAJED) ISSN: 3067-4190, 1(1).

[21] Sai Teja Nuka (2023) A Novel Hybrid Algorithm Combining Neural Networks And Genetic Programming For Cloud Resource Management. Frontiers in HealthInforma 6953-6971

[22] Suura, S. R. (2024). The role of neural networks in predicting genetic risks and enhancing preventive health strategies. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 2(1).

[23] Kannan, S. (2024). Revolutionizing Agricultural Efficiency: Leveraging AI Neural Networks and Generative AI for Precision Farming and Sustainable Resource Management. Available at SSRN 5203726.

[24] Transforming Customer Experience in Telecom: Agentic AI-Driven BSS Solutions for Hyper-Personalized Service Delivery. (2024). MSW Management Journal, 34(2), 1161-1174.

[25] Singireddy, S. (2024). Applying Deep Learning to Mobile Home and Flood Insurance Risk Evaluation. American Advanced Journal for Emerging Disciplinaries (AAJED) ISSN: 3067-4190, 1(1).

[26] Leveraging Deep Learning, Neural Networks, and Data Engineering for Intelligent Mortgage Loan Validation: A Data-Driven Approach to Automating Borrower Income, Employment, and Asset Verification. (2024). MSW Management Journal, 34(2), 924-945.

[27] Srinivas Kalyan Yellanki. (2024). Building Adaptive Networking Protocols with AI-Powered Anomaly Detection for Autonomous Infrastructure Management . Journal of Computational Analysis and Applications (JoCAAA), 33(08), 3116–3130. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/2423

[28] Transforming Customer Experience in Telecom: Agentic AI-Driven BSS Solutions for Hyper-Personalized Service Delivery. (2024). MSW Management Journal, 34(2), 1161-1174.

[29] Sriram, H. K., Challa, S. R., Challa, K., & ADUSUPALLI, B. (2024). Strategic Financial Growth: Strengthening Investment Management, Secure Transactions, and Risk Protection in the Digital Era. Secure Transactions, and Risk Protection in the Digital Era (November 10, 2024).

[30] Paleti, S. (2024). Neural Compliance: Designing AI-Driven Risk Protocols for Real-Time Governance in Digital Banking Systems. Available at SSRN 5233099.

[31] Sriram, H. K., Challa, S. R., Challa, K., & ADUSUPALLI, B. (2024). Strategic Financial Growth: Strengthening Investment Management, Secure Transactions, and Risk Protection in the Digital Era. Secure Transactions, and Risk Protection in the Digital Era (November 10, 2024).

[32] Pamisetty, V. (2023). Leveraging AI, Big Data, and Cloud Computing for Enhanced Tax Compliance, Fraud Detection, and Fiscal Impact Analysis in Government Financial Management. International Journal of Science and Research (IJSR), 12(12), 2216–2229. https://doi.org/10.21275/sr23122164932

[33] Komaragiri, V. B. Harnessing AI Neural Networks and Generative AI for the Evolution of Digital Inclusion: Transformative Approaches to Bridging the Global Connectivity Divide.

[34] Annapareddy, V. N. (2024). Leveraging Artificial Intelligence, Machine Learning, and Cloud-Based IT Integrations to Optimize Solar Power Systems and Renewable Energy Management. Machine Learning, and Cloud-Based IT Integrations to Optimize Solar Power Systems

10.48047/jocaaa.2024.33.08.78

and Renewable Energy Management (December 06, 2024).

[35] Pamisetty, A. (2024). Leveraging Big Data Engineering for Predictive Analytics in Wholesale Product Logistics. Available at SSRN 5231473.

[36] Dodda, A. (2024). Integrating Advanced and Agentic AI in Fintech: Transforming Payments and Credit Card Transactions. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 1(1).

[37] Gadi, A. L., Kannan, S., Nanan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87-100.

[38] Adusupalli, B., & Insurity-Lead, A. C. E. The Role of Internal Audit in Enhancing Corporate Governance: A Comparative Analysis of Risk Management and Compliance Strategies. Outcomes. Journal for ReAttach Therapy and Developmental Diversities, 6, 1921-1937.

[39] Suura, S. R., Chava, K., Recharla, M., & Chakilam, C. (2023). Evaluating Drug Efficacy and Patient Outcomes in Personalized Medicine: The Role of AI-Enhanced Neuroimaging and Digital Transformation in Biopharmaceutical Services. Journal for ReAttach Therapy and Developmental Diversities, 6, 1892-1904.

[40] Kummari, D. N. (2023). AI-Powered Demand Forecasting for Automotive Components: A Multi-Supplier Data Fusion Approach. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 1(1).

[41] Sheelam, G. K. (2024). Deep Learning-Based Protocol Stack Optimization in High-Density 5G Environments. European Advanced Journal for Science & Engineering (EAJSE)-p-ISSN 3050-9696 en e-ISSN 3050-970X, 1(1).

[42] AI-Powered Revenue Management and Monetization: A Data Engineering Framework for Scalable Billing Systems in the Digital Economy . (2024). MSW Management Journal, 34(2), 776-787.

[43] Sriram, H. K. (2023). The Role Of Cloud Computing And Big Data In Real-Time Payment Processing And Financial Fraud Detection. Available at SSRN 5236657.

[44] Paleti, S., Burugulla, J. K. R., Pandiri, L., Pamisetty, V., & Challa, K. (2022). Optimizing Digital Payment Ecosystems: Ai-Enabled Risk Management, Regulatory Compliance, And Innovation In Financial Services. Regulatory Compliance, And Innovation In Financial Services (June 15, 2022).

[45] Singireddy, J. (2024). AI-Enhanced Tax Preparation and Filing: Automating Complex Regulatory Compliance. European Data Science Journal (EDSJ) p-ISSN 3050-9572 en e-ISSN 3050-9580, 2(1).

[46] Karthik Chava. (2022). Harnessing Artificial Intelligence and Big Data for Transformative Healthcare Delivery. International Journal on Recent and Innovation Trends in Computing and Communication, 10(12), 502–520. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11583

[47] Challa, K. Dynamic Neural Network Architectures for Real-Time Fraud Detection in Digital Payment Systems Using Machine Learning and Generative AI.

[48] Lahari Pandiri. (2023). Specialty Insurance Analytics: AI Techniques for Niche Market Predictions. International Journal of Finance (IJFIN) - ABDC Journal Quality List, 36(6), 464-492.

[49] Recharla, M., & Chitta, S. AI-Enhanced Neuroimaging and Deep Learning-Based Early Diagnosis of Multiple Sclerosis and Alzheimer's.

[50] Malempati, M. (2023). A Data-Driven Framework For Real-Time Fraud Detection In

10.48047/jocaaa.2024.33.08.78

Financial Transactions Using Machine Learning And Big Data Analytics. Available at SSRN 5230220.

[51] Pandiri, L., Paleti, S., Kaulwar, P. K., Malempati, M., & Singireddy, J. (2023). Transforming Financial And Insurance Ecosystems Through Intelligent Automation, Secure Digital Infrastructure, And Advanced Risk Management Strategies. Educational Administration: Theory and Practice, 29 (4), 4777–4793.

[52] Lakkarasu, P. (2024). Advancing Explainable AI for AI-Driven Security and Compliance in Financial Transactions. Journal of Artificial Intelligence and Big Data Disciplines, 1(1), 86-96.

[53] Gadi, A. L., Kannan, S., Nanan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87-100.

[54] Meda, R. (2023). Developing AI-Powered Virtual Color Consultation Tools for Retail and Professional Customers. Journal for ReAttach Therapy and Developmental Diversities. https://doi.org/10.53555/jrtdd.v6i10s(2).3577

[55] Nuka, S. T., Annapareddy, V. N., Koppolu, H. K. R., & Kannan, S. (2021). Advancements in Smart Medical and Industrial Devices: Enhancing Efficiency and Connectivity with High-Speed Telecom Networks. Open Journal of Medical Sciences, 1(1), 55-72.

[55] Suura, S. R. Artificial Intelligence and Machine Learning in Genomic Medicine: Redefining the Future of Precision Diagnostics.

[56] Kannan, S., & Seenu, A. (2024). Advancing Sustainability Goals with AI Neural Networks: A Study on Machine Learning Integration for Resource Optimization and Environmental Impact Reduction. management, 32(2).

[57] Motamary, S. (2022). Enabling Zero-Touch Operations in Telecom: The Convergence of Agentic AI and Advanced DevOps for OSS/BSS Ecosystems. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3833

[58] Singireddy, S. (2024). Predictive Modeling for Auto Insurance Risk Assessment Using Machine Learning Algorithms. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 1(1).

[59] Mashetty, S. (2024). The role of US patents and trademarks in advancing mortgage financing technologies. European Advanced Journal for Science & Engineering (EAJSE)-p-ISSN 3050-9696 en e-ISSN 3050-970X, 1(1).

[60] Yellanki, S. K. (2024). Leveraging Deep Learning and Neural Networks for Real-Time Crop Monitoring in Smart Agricultural Systems. American Data Science Journal for Advanced Computations (ADSJAC) ISSN: 3067-4166, 1(1).

[61] Challa, S. R. (2024). Behavioral Finance in Financial Advisory Services: Analyzing Investor DecisionMaking and Risk Management in Wealth Accumulation. Available at SSRN 5135949.

[62] Paleti, S. (2023). Data-First Finance: Architecting Scalable Data Engineering Pipelines for AI-Powered Risk Intelligence in Banking. Available at SSRN 5221847.

[63] Pamisetty, V., Dodda, A., Singireddy, J., & Challa, K. (2022). Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies. Jeevani and Challa, Kishore, Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies (December 10, 2022).

[64] Komaragiri, V. B., Edward, A., & Surabhi, S. N. R. D. Enhancing Ethernet Log Interpretation And Visualization.

10.48047/jocaaa.2024.33.08.78

[65] Kannan, S., Annapareddy, V. N., Gadi, A. L., Kommaragiri, V. B., & Koppolu, H. K. R. (2023). AI-Driven Optimization of Renewable Energy Systems: Enhancing Grid Efficiency and Smart Mobility Through 5G and 6G Network Integration. Available at SSRN 5205158.

[66] Kommaragiri, V. B., Preethish Nanan, B., Annapareddy, V. N., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Venkata Narasareddy and Gadi, Anil Lokesh and Kalisetty, Srinivas.

[67] Pamisetty, V. (2022). Transforming Fiscal Impact Analysis with AI, Big Data, and Cloud Computing: A Framework for Modern Public Sector Finance. Big Data, and Cloud Computing: A Framework for Modern Public Sector Finance (November 30, 2022).

[68] Paleti, S. (2023). Trust Layers: AI-Augmented Multi-Layer Risk Compliance Engines for Next-Gen Banking Infrastructure. Available at SSRN 5221895.

[69] Rao Challa, S. (2023). Revolutionizing Wealth Management: The Role Of AI, Machine Learning, And Big Data In Personalized Financial Services. Educational Administration: Theory and Practice. https://doi.org/10.53555/kuey.v29i4.9966

[70] Machine Learning Applications in Retail Price Optimization: Balancing Profitability with Customer Engagement. (2024). MSW Management Journal, 34(2), 1132-1144.

[71] Someshwar Mashetty. (2024). Research insights into the intersection of mortgage analytics, community investment, and affordable housing policy. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 3377–3393. Retrieved from https://www.eudoxuspress.com/index.php/pub/article/view/2496

[72] Lakkarasu, P., Kaulwar, P. K., Dodda, A., Singireddy, S., & Burugulla, J. K. R. (2023). Innovative Computational Frameworks for Secure Financial Ecosystems: Integrating Intelligent Automation, Risk Analytics, and Digital Infrastructure. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 334-371.

[72] Implementing Infrastructure-as-Code for Telecom Networks: Challenges and Best Practices for Scalable Service Orchestration. (2021). International Journal of Engineering and Computer Science, 10(12), 25631-25650. https://doi.org/10.18535/ijecs.v10i12.4671

[73] Kannan, S. The Convergence of AI, Machine Learning, and Neural Networks in Precision Agriculture: Generative AI as a Catalyst for Future Food Systems.

[74] Suura, S. R. (2024). Agentic artificial intelligence systems for dynamic health management and real-time genomic data analysis. European Journal of Analytics and Artificial Intelligence (EJAAI) p-ISSN 3050-9556 en e-ISSN 3050-9564, 1(1).

[75] Meda, R. (2022). Integrating IoT and Big Data Analytics for Smart Paint Manufacturing Facilities. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3842

[76] Nandan, B. P., & Chitta, S. (2022). Advanced Optical Proximity Correction (OPC) Techniques in Computational Lithography: Addressing the Challenges of Pattern Fidelity and Edge Placement Error. Global Journal of Medical Case Reports, 2(1), 58-75.

[77] Lakkarasu, P. (2023). Designing Cloud-Native AI Infrastructure: A Framework for High-Performance, Fault-Tolerant, and Compliant Machine Learning Pipelines. Journal for ReAttach Therapy and Developmental Diversities. https://doi.org/10.53555/jrtdd.v6i10s(2).3566

[78] Kaulwar, P. K. (2022). Securing The Neural Ledger: Deep Learning Approaches For Fraud Detection And Data Integrity In Tax Advisory Systems. Migration Letters, 19, 1987-2008.

10.48047/jocaaa.2024.33.08.78

[79] Pandiri, L., Paleti, S., Kaulwar, P. K., Malempati, M., & Singireddy, J. (2023). Transforming Financial And Insurance Ecosystems Through Intelligent Automation, Secure Digital Infrastructure, And Advanced Risk MaRecharla, M., & Chitta, S. (2022). Cloud-Based Data Integration and Machine Learning Applications in Biopharmaceutical Supply Chain Optimization.nagement Strategies. Educational Administration: Theory and Practice, 29 (4), 4777–4793.

[80] Pandiri, L., Paleti, S., Kaulwar, P. K., Malempati, M., & Singireddy, J. (2023). Transforming Financial And Insurance Ecosystems Through Intelligent Automation, Secure Digital Infrastructure, And Advanced Risk Management Strategies. Educational Administration: Theory and Practice, 29 (4), 4777–4793.

[81] Challa, K. (2023). Optimizing Financial Forecasting Using Cloud Based Machine Learning Models. Journal for ReAttach Therapy and Developmental Diversities. https://doi.org/10.53555/jrtdd.v6i10s(2).3565

[82] Chava, K. (2020). Machine Learning in Modern Healthcare: Leveraging Big Data for Early Disease Detection and Patient Monitoring. International Journal of Science and Research (IJSR), 9(12), 1899–1910. https://doi.org/10.21275/sr201212164722

[83] Kalisetty, S., & Singireddy, J. (2023). Optimizing Tax Preparation and Filing Services: A Comparative Study of Traditional Methods and AI Augmented Tax Compliance Frameworks. Available at SSRN 5206185.

[84] Sriram, H. K. (2022). Integrating generative AI into financial reporting systems for automated insights and decision support. Available at SSRN 5232395.

[85] Koppolu, H. K. R. Deep Learning and Agentic AI for Automated Payment Fraud Detection: Enhancing Merchant Services Through Predictive Intelligence.

[86] Sheelam, G. K. (2023). Adaptive AI Workflows for Edge-to-Cloud Processing in Decentralized Mobile Infrastructure. Journal for Reattach Therapy and Development Diversities. https://doi.org/10.53555/jrtdd.v6i10s(2).3570ugh Predictive Intelligence.

[87] End-to-End Traceability and Defect Prediction in Automotive Production Using Blockchain and Machine Learning. (2022). International Journal of Engineering and Computer Science, 11(12), 25711-25732. https://doi.org/10.18535/ijecs.v11i12.4746

[88] Chakilam, C. (2022). Integrating Machine Learning and Big Data Analytics to Transform Patient Outcomes in Chronic Disease Management. Journal of Survey in Fisheries Sciences. https://doi.org/10.53555/sfs.v9i3.3568

[89] Pamisetty, A. (2024). Leveraging Big Data Engineering for Predictive Analytics in Wholesale Product Logistics. Available at SSRN 5231473.

[90] Gadi, A. L. (2022). Connected Financial Services in the Automotive Industry: AI-Powered Risk Assessment and Fraud Prevention. Journal of International Crisis and Risk Communication Research, 11-28.

[91] Dodda, A. (2023). AI Governance and Security in Fintech: Ensuring Trust in Generative and Agentic AI Systems. American Advanced Journal for Emerging Disciplinaries (AAJED) ISSN: 3067-4190, 1(1).

[92] Pamisetty, A. Optimizing National Food Service Supply Chains through Big Data Engineering and Cloud-Native Infrastructure.

[93] Challa, K. (2022). The Future of Cashless Economies Through Big Data Analytics in Payment Systems. International Journal of Scientific Research and Modern Technology, 60–70. https://doi.org/10.38124/ijsrmt.v1i12.467

[94] Pamisetty, A. (2023). Cloud-Driven Transformation Of Banking Supply Chain Analytics Using Big Data Frameworks. Available at SSRN 5237927.