8-5-2019

Development of Smart Semiconductor Manufacturing: Operations Research and Data Science Perspectives

Marzieh Khakifirooz

Mahdi Fathi

Kan Wu

Recommended Citation

Khakifirooz, Marzieh, Mahdi Fathi, and Kan Wu. "Development of smart semiconductor manufacturing: operations research and data science perspectives." IEEE Access 7 (2019): 108419-108430. https://doi.org/10.1109/ACCESS.2019.2933167

IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received July 16, 2019, accepted July 29, 2019, date of publication August 5, 2019, date of current version August 20, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2933167

Development of Smart Semiconductor Manufacturing: Operations Research and Data Science Perspectives

MARZIEH KHAKIFIROOZ[1], (Member, IEEE), MAHDI FATHI[2], (Member, IEEE), AND KAN WU[3], (Member, IEEE)

[1]School of Science and Engineering, Tecnològico de Monterrey, Campus Santa Fe, Mexico City 01389, Mexico
[2]Department of Industrial and Systems Engineering, Mississippi State University, Starkville, MS 39762, USA
[3]Division of Systems and Engineering Management, Nanyang Technological University, Singapore 639798

Corresponding author: Marzieh Khakifirooz (mkhakifirooz@tec.mx)

ABSTRACT With advances in information and telecommunication technologies and data-enabled decision making, smart manufacturing can be an essential component of sustainable development. In the era of the smart world, semiconductor industry is one of the few global industries that are in a growth mode to smartness, due to worldwide demand. The important opportunities that can boost the cost reduction of productivity and improve quality in wafer fabrication are based on the simulations of actual environment in Cyber-Physical Space and integrate them with decentralized decision-making systems. However, this integration faced the industry with novel unique challenges. The stream of the data from sensors, robots, and Cyber-Physical Space can aid to make the manufacturing smart. Therefore, it would be an increased need for modeling, optimization, and simulation for the value delivery from manufacturing data. This paper aims to review the success story of smart manufacturing in semiconductor industry with the focus on data-enabled decision making and optimization applications based on operations research and data science perspective. In addition, we will discuss future research directions and new challenges for this industry.

INDEX TERMS Cloud computing, cyber-physical space, data science, Industry 4.0, Internet of Things, operations research, smart manufacturing, semiconductor industry.

I. INTRODUCTION

The importance of national manufacturing strategies such as *Advanced Manufacturing Partnership* and *Industry 4.0* have reemphasized the shifting standard of manufacturing and production system, which led to the fourth industrial generation.

The industrial revolution stream drives deployment of novel concepts for smart factories, new generation of monitoring and collaborating systems, or in general words, the smart manufacturing system. Smart manufacturing system is built upon the emerging advanced technologies including Cyber-Physical Space (CPS), Internet of Things (IoT), cloud and cognitive computing, big data analysis and information and communication technology [1]. The first step toward smart manufacturing is connectivity [2]. All the components in the industry must be connected to a single network which is being allowed by the CPS and IoT providing information interchange and connectivity to attain a flexible and self-adaptive production system.

On the other hands, as a part of the technology road-map for semiconductors driven by Moore's law system scaling [3], there are more and more challenges by the poverty of resources and emergence of information technology. Therefore, the seamless interaction of smart manufacturing components such as big-data, instant data, information technology (cloud, and multi-mode sensors), high-performance computing, mobile computing, and autonomous sensing and computing is necessary for driving ''More Moore'' (MM) technologies [4].

The paradigm of smart manufacturing and the semiconductor industry is a back-end loop design. Consider technologies enabling smart manufacturing can emerge the sensor technology, network communication, advanced in data analysis, and advanced in software and system as requirements for

The associate editor coordinating the review of this manuscript and approving it for publication was Rahul A. Trivedi.

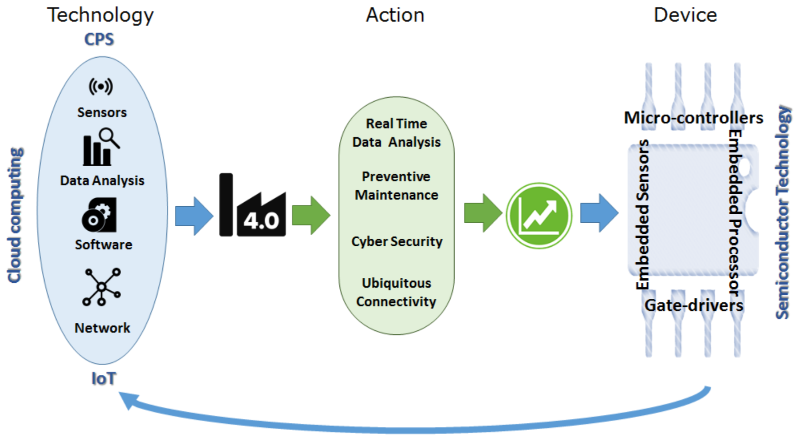


FIGURE 1. Relationship between smart manufacturing and semiconductor industry.

industrial development. Any evolution in the aforementioned components of smart manufacturing could affect directly on performance and quality enhancement, innovation, and smart production. Thereupon, intelligent semiconductor devices are vital solutions to this growth. In a back-end loop, this is the smart manufacturing technology which helps semiconductor industry to produce and perform smarter (see Fig. 1).

The operations control of manufacturing facilities of the semiconductor is known as a tough task and is envisaged as one of the most composite manufacturing environments. One solution to deal with these difficulties is to choose the manufacturing and process data to analyze and modeling processes to empower factories in order to intensify an enhanced knowledge of the challenges associated with the production process and to grow visions which can develop prevailing procedures. Hereupon, this is very important to have enough understanding of the prevailing position of research about decision making based data engineering technologies in the semiconductor industry and recognize fields for future research to maintain the further technologies for wafer manufacturing. Therefore, the contributions of this study can be summarized as 1) detect gaps in the existing works, 2) develop significant research ideas, 3) categorize existing research struggles and form a layout that can deliver different ideas related to the operations research and data science (OR&DS) area in smart wafer manufacturing.

To the best of our knowledge, there is no such a comprehensive study among the existing literature that has been covered all the aforementioned contributions of this study.

II. REVIEW METHOD

This paper provides a three-stage qualitative literature review method (identification, classification, and evaluation) [5] on the scientific progress of the fourth industrial revolution from the OR&DS perspective for semiconductor manufacturing. Most precisely, three research questions are given as follows:

1) *Identification*: what are the main challenges from the OR&DS points of view, enabling the industrial revolution in semiconductor manufacturing?
2) *Classification*: how are the OR&DS addressed the scientific and technological challenges in smart semiconductor manufacturing?
3) *Evaluation*: what are the managerial suggestions from the integrated information of reviewed papers to prevail the unseen and future challenges in the path forward to the implementation of smart semiconductor manufacturing?

The study applied a two-step screening procedure to select relevant studies. In the first place, the study carefully defined the scope of the literature review by selecting the studies which have used terms ‘‘semiconductor’’, ‘‘wafer,’’ ‘‘integrated circuit,’’ or ‘‘chip’’ in their title or indexed keywords. The study used the Scopus database as a search engine. The time-frame of review is narrowed by the milestone of national manufacturing strategies since 2011. From the search result, only literature reported in English and published in decision science field was included in the review process. In the second step, all cited literature are cross-checked using Google scholar search engine.

The study classified indexed keywords for further investigation. The indexed keywords of each article are classified in one group. The unrelated words to the OR&DS filed were removed, and a unique title is selected for all words with similar meaning. Then the decision support matrix is composed based on the classification result to illustrate the link among the keywords. Thereafter, the Mutually Exclusive-Collectively Exhaustive (MECE) method [6] was applied for feature extraction (select parent methods, and the most compatible technique with them). The steps of this classification procedure are summarized in Fig. 2. After data screening and key factor extraction, 47 keywords are selected by MECE method and classified into six families. The classification result is summarized in Table 1.

Selected literature varied in quality and quantity in different fields. To ensure that the search result was reliable, those studies that their methodology had high similarity with other studies were eliminated while considering the priority for recently published journal articles. The studies were

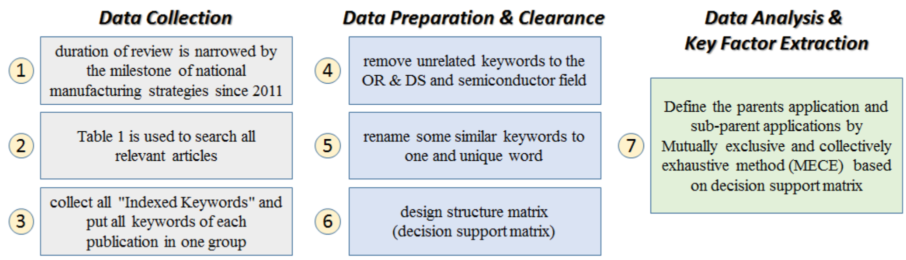


FIGURE 2. Key steps for classification the OR&DS indexed keywords.

TABLE 1. The MCME classification for OR&DS related keywords.

Parent Keywords	Family Member Keywords
Capacity Planning	Demand Forecasting & Delivery; Supply Chains; Customer Satisfaction; Enterprise Resource Planning; Resource Allocation & Facility Layout
Inventory Management	Flexible Manufacturing Systems; Scheduling & Rescheduling; Dispatching; Virtual Reality; Investment & Profitability; Work-In-Process; Random Process; Product Life Cycle; Cost Management; Maintenance; Cycle Time Reduction; Batch Processing; Risk Management
Sustainability	Assembly; Technology Transfer
Standardization	Re-engineering; Productivity; Reliability; Bench-marking; Operation Management; Human Resource Management; Just In Time Production; Machine Utilization; Product Test; Product Design; Data Reduction; System Diagnosis & Fault Detection; Quality Management; Environmental Management; Sales, Marketing & Financial Management; Product Line Design
Production Planning	Technology Management; Performance Measurement
Decision Support Systems & Decision Theory	Yield Management & Enhancement; Control & Monitoring (online/offline); Strategic Planning

evaluated and classified according to several methodological criteria in order to shortlist the qualify papers for further analysis of their main contribution as follows:

- Organize the **type of research** methods by Wieringa *et al.* [7] (including: validation, evaluation, solution, philosophical, opinion, experience)
- Classify the **areas of manufacturing** by Meziane *et al.* [8] (including quality management, design, process and planning, control, environment, health and safety, maintenance and diagnosis, scheduling, and virtual manufacturing)
- Categorize the **form of contribution** by keywording method [9] (including: architecture, framework, theory, methodology, model, platform, process, tool)
- Classify the **type of analytic** by Delen and Demirkan [10] (including: descriptive, predictive, and prescriptive)

III. ROAD-MAP OF OR&DS IN SEMICONDUCTOR

With regards to the information collected from the search process, this section explores how OR&DS influenced on semiconductor industry. The role of OR&DS in the smart semiconductor industry is reviewed by answering some additional research questions in this direction.

A. BY GROWING THE SMART MANUFACTURING, HOW OR&DS RELATED RESEARCH FOUND THEIR WAY INTO SEMICONDUCTOR MANUFACTURING INTELLIGENCE?

The historical review of the infrastructure of smart semiconductor manufacturing aligns with the fourth industrial revolution shows how decision-making process became mature in this industry by adapting the OR&DS tools. The summary shows that:

- **Before 2011**

Methods such as:

Data mining since the late 90s, AI since the late 80s, heuristic algorithm since the early 90s, Machine Learning since the late 80s, data development management since the late 80s, Fuzzy logic since the early 90s, optimization methods such as linear-programming since the early 90s, non linear-programming since 2000s and convex optimization since the early 90s, data visualization since the late 90s, game theory since the late 90s, queuing theory since 90s,

and concepts such as:

Advanced manufacturing since the late 80s, intelligence manufacturing since the early 90s, Enterprise Resource Planning (ERP) since the late 90s, Overall Equipment Efficiency (OEE) since the late 90s, Decision Support System (DSS) since 90s, virtual manufacturing since the early 90s, e-manufacturing since 2000s, and agent-based system since early 2000s

have been appearing in literature to discover the challenges in the semiconductor industry and moving forward to smart manufacturing. A summary of important research publications is presented in Table 2.

- **After 2011**:

Despite the needs for moving forward the intelligent production, the annual gathering and academic reports had a vital role in leading the semiconductor industry toward the smartness. Fig. 3 is summarized this progress.

B. WHAT KIND OF STUDIES IS BEING CARRIED OUT IN THE FIELD OF OR&DS IN SEMICONDUCTOR MANUFACTURING?

The main objective of this question is to focus on research in terms of the philosophical point of view along with practical

TABLE 2. Summary of most distinguished researches have been done before 2011.

Methods & Concepts	References
AI, Data mining & Machine Learning	[11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21]
Heuristic algorithm	[22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32],
Fuzzy logic	[33], [34], [35], [36]
Optimization	[37], [38], [39], [40], [41], [42], [43], [44]
Game theory	[45], [46], [44]
Advanced/ Intelligence manufacturing	[47], [33], [48] [49]
OEE	[50], [51], [52], [53], [54]

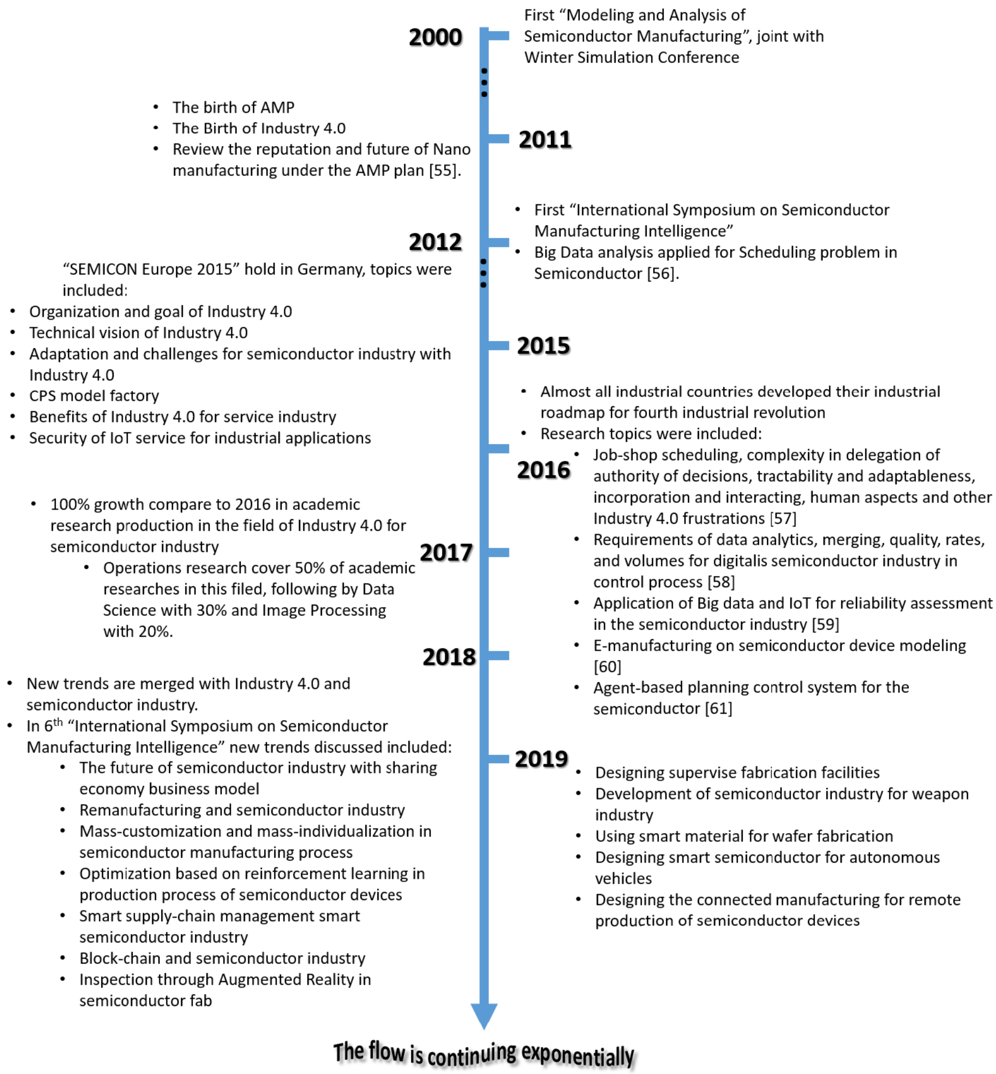


FIGURE 3. Road-map of the fourth industrial revolution for semiconductor manufacturing in the academic sector [55]–[61].

assessments. The classification result according to the definition of **areas of manufacturing** by Meziane *et al.* is depicted in Fig. 4. The result ratifies that there is an extensive gap in fitting the manufacturing design for intelligent layout. The intelligent layout design for manufacturing generally refers to system engineering design, sensor allocation problems, and design the software agent solutions merge with high-tech computing technology or service-oriented computing. There is also a lack of investigation on virtual manufacturing, simulation the physical environment, e-manufacturing, and AR. In addition, trends related to the environmental issues and health and safety such as green industry and re-manufacturing are demanding topics for smart manufacturing, which had less attention in semiconductor industry yet.

To determine the gap of the research for smart IC industry, we modified the classification by Meziane *et al.* for semiconductor manufacturing context. Fig. 5 illustrates the

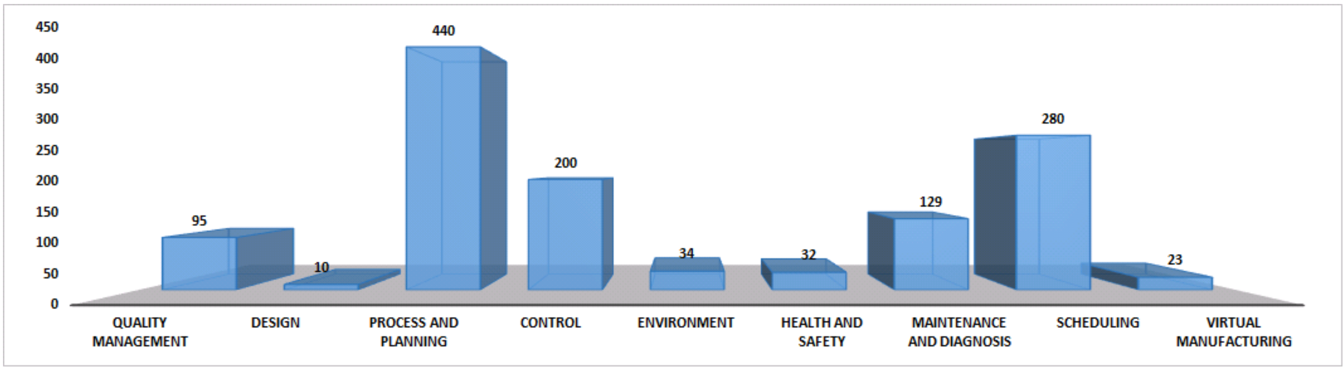


FIGURE 4. Class allotment of areas of manufacturing for smart semiconductor industry.

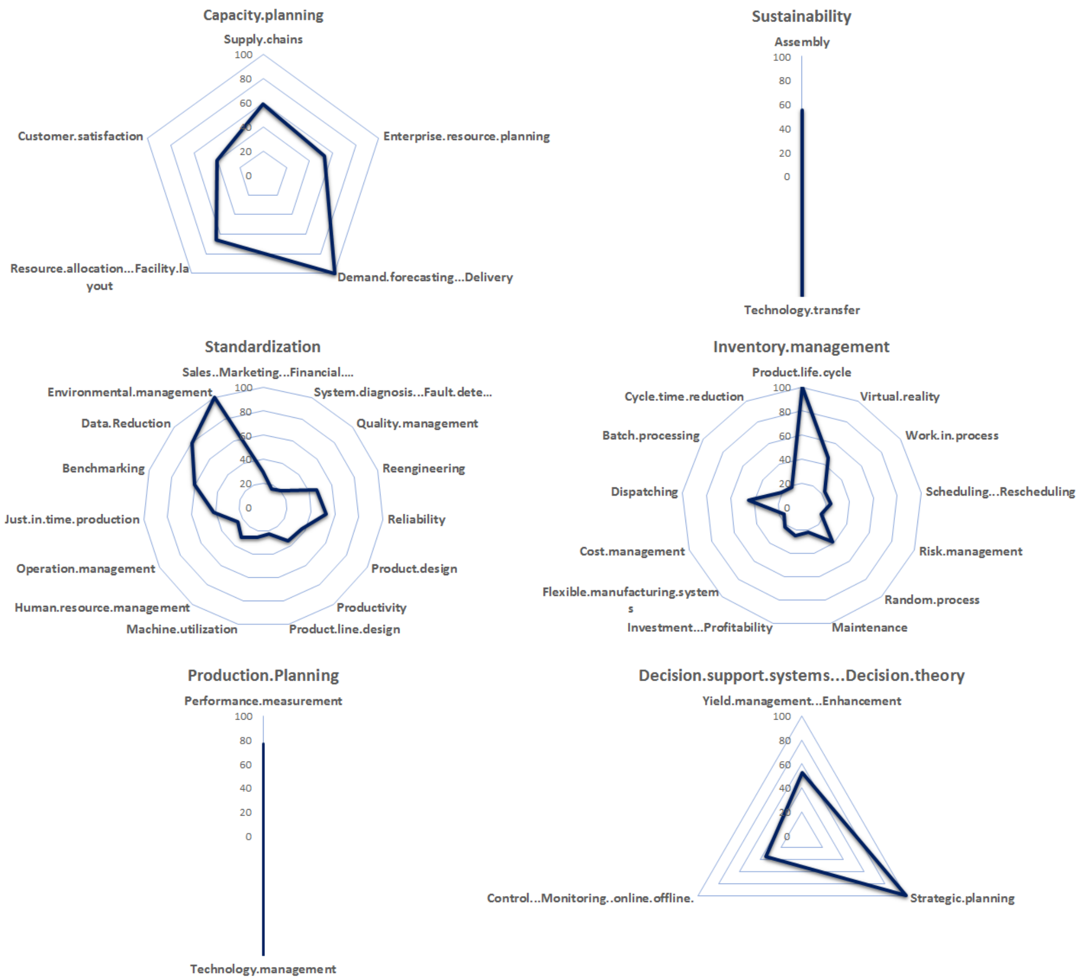


FIGURE 5. Contribution of most frequent topics among the literature since 2011 related to smart semiconductor industry based on classification in Table 3.

contributions of each class for the smart semiconductor industry. The scale of contribution defines such that the most relevant topic granted with the score of 100. Due to dependency among process steps in wafer fabrication, challenges are spread along the production process such that single solution cannot solve the problem. Therefore, the hybrid models are a ubiquitous solution in semiconductor-related literature to deal with an epidemic dimension of problems. The databases of most common techniques in Fig. 4 are used as the basis for Fig. 5. Fig. 5 demonstrates how the hybrid method is associated with each other. Following decisions could be extracted from Fig. 5:

1) CAPACITY PLANNING

- Enterprise resource planning is designed for increasing or decreasing capacity at the production facilities as well as planning when and whether to build new facilities.
- Demand forecasting highly related to customer requirements. The demands are unpredictable and can be lost if the manufacturer does not have enough capacity during a period of high demand.
- Capacity planning is a function of the hedge to meet the needs of the semiconductor capacity supplier and demander.
- In a semiconductor supply chain, the low demand variability and the high process flexibility are affected by capacity planning.

2) SUSTAINABILITY

- Design for sustainability includes full lifecycle concepts, design for assembly (and disassembly), design for extended life, and design for reuse/remanufacture/recycling [62].
- Performance measurement and technology alignment are tightly correlated because of dynamic and progressive shifts in deregulated markets.

3) STANDARDIZATION

- Standardization of environmental management systems is considered as a revolutionary force that will transform both the ways managers think about environmental functions and the relationship between manufacturing and environmental regulators (as evidence one can refer to ISO 14000 regulations).
- The relationship between standardization and data reduction could back to the data standardization for reducing variable variation, or can indicate to the influence of process standardization on reducing the number of unnecessary variables.
- Undoubtedly, similar to the other manufacturing process, semiconductor equipment quality can be improved through bench-marking, standardization, and automation [63].
- Just-in-time production (Kanban) is applicable for industries with less customization module and high standardization for producing products in small lots which are exactly matched with the nature of semiconductor device fabrications.
- Standardized processes can capture and institutionalize existing knowledge within organizational routines that help establish a common frame and working habits among employees [64].
- Standardization is a remedy for increasingly heterogeneous consumer needs, product and process complexities, plus reduction of scale economies. It can mitigate the effects of process complexity and product imperfection.
- standardization can enable the customization in product design [65].
- Lack of standardization causes system fault and error.
- There is a cyclical nature between standardization direction and customization direction such that the future of semiconductor devices is standardization in manufacturing but customized in the application.

4) INVENTORY MANAGEMENT

- According to the little's law [66] there is a cyclic relationship between the throughput, inventory (material inventory, WIP inventory, and finished product inventory) and cycle time, such that the high WIP is required for high throughput with low cycle time.
- Schedules can be used to manage the inventory requirements, and maintenance, where Flexible Manufacturing System consists of scheduling algorithm and involves the inventory information. A dispatching algorithm decides how to use factory resources upon the availability of resources. Therefore, manufacturers can manage the throughput, inventory, and consequently profitability, risk, and cost, all together.
- Visual simulation and the modeling process based on the virtual environment can facilitate the optimization of workshop layout (i.e., inventory management, scheduling, batch processing).

5) PRODUCTION PLANNING

- Performance measurement is the key to improving performance and is a prerequisite to improving production planning.
- The general policy of sustainable development mechanism is neglected essential details of how technology can be transferred successfully. Though technology can play an innovative role in improving sustainable manufacturing.

6) DECISION SUPPORT SYSTEM AND DECISION THEORY

- Supporting strategic decisions are more common in research development for semiconductor manufacturing. While the nature of strategic decisions is changing significantly from a single organization's strategies to internal layers of manufacturing.
- knowledge management for supporting process diagnosis and decision-making is required to approve by control and monitoring system as well as data acquisition.
- Yield management and enhancement normally are supported by DSS to epitomize the decision rules for expert engineers.

The classification study for the type of research method by Wieringa *et al.* [7] is illustrated in Fig. 6. Fig. 5 shows how the type of research is branched over topics, and Fig. 6 shows the contribution of each type of research based on philosophical points of view. For simplicity of comparison, according to the definition of "experience" in [7], and since this type of research has seldom happened in OR&DS filed,

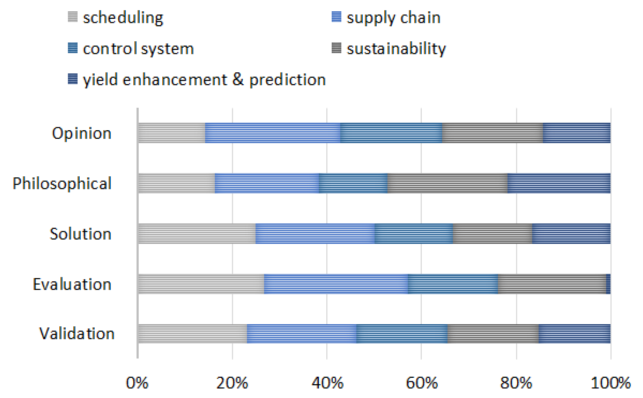


FIGURE 6. Partitioning the contribution of most common topic in smart semiconductor based on type of research.

we remove the experience from the list. Concluding from Fig. 5 and Fig. 6, digitizing the knowledge-based system has the lowest contribution among the other research topic in current statues which is required to have more inspection for advance development of smart semiconductor industry.

C. WHICH AREAS OF SEMICONDUCTOR MANUFACTURING ARE OR&DS TECHNIQUES BEING APPLIED IN?

The objective of this question is to highlight the types of inputs and outcomes. To categorize the literature according to the form of their contributions [9] we divided the attributes of contributions into two groups of variability based on outcomes and results (including architecture, framework, model, methodology), and variability on input information (including theory, platform, process, tool). In this category, the platform indicates the hardware or software components which enables the applications to execute, and the framework is the software solution for the problem. The process is the approach to reach that solution. The theory is the guideline or road-map for entering to the mathematical model. Subsequently, the tool addresses to the utilities for proposing the solution, and architecture is components which interact together to achieve the solution. Fig. 7 illustrates the 2D plot between each category. The result shows that there is a vacancy for research on integrating the mathematical model with software and hardware platforms. The theoretical approaches for developing the smart semiconductor industry plus the advantages of using high-tech computing technology provide more spaces for further investigation.

D. WHAT KIND OF ANALYTICAL ANALYSIS IS BEING USED IN THE AREA OF OR&DS IN SEMICONDUCTOR MANUFACTURING?

The objective of this question is to discuss the analytical approaches of OR&DS in the semiconductor industry. According to Delen *et al.* [10], the analytical analysis is classifying to descriptive, predictive, and prescriptive analysis where the descriptive analysis enables the business reporting,

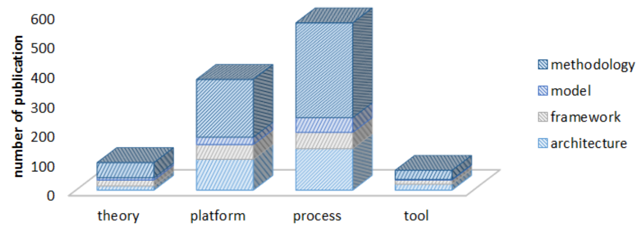


FIGURE 7. Class allotment of form of contribution methods applied in semiconductor industry.

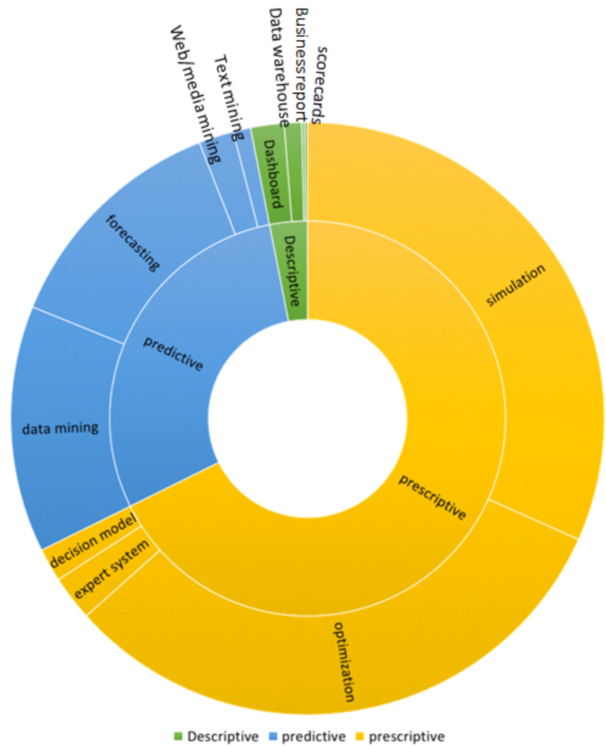


FIGURE 8. Type of analytical methods applied in semiconductor industry.

dashboards, data warehousing, and scorecards. Subsequently, the predictive analysis facilities data mining, forecasting, text mining, and Web or media mining and prescriptive analysis empower the expert systems, decision models, optimization, and simulation. Although we expect that the application of descriptive analysis and Web mining or text mining in semiconductor manufacturing is sporadic, we still considered all aspects of analytical analysis. The level of interest of each class of taxonomy presented in Fig. 8. Apparently, for developing smart semiconductor industry, the descriptive analysis will be an inevitable tool, basically for visualizing the production process from the event-driven process.

IV. MANAGEMENT SUGGESTION

Despite challenges mentioned in the preceding sections, in the following, some managerial suggestions are given for the development of smart semiconductor manufacturing environment.

1) DIGITALIZE KNOWLEDGE-BASED DSS

In a smart manufacturing environment, sharing expert domain knowledge at the manager-operator and operator-machine level is essential. Recommender systems and opinion mining can support real-time, data-based decision making. Machine/user relationship mining and clustering can increase the self-awareness, self-learning, and self-maintenance of production systems. Finally, Reciprocal Learning-Based DSS (RL-DSS) [67] can make repetitive decisions and reduce the human decision making a load. Routine decision tasks can be programmed, and learning algorithms can enhance performance. Then decision-makers can update their knowledge, and the improved system can help to create better decisions. Therefore, research opportunities in this domain include:

- Incorporating the behavior of human decision-makers into solutions.
- Automating decisions made by humans.
- Highlighting the interface of information systems with humans

2) INCORPORATE THE DYNAMICITY INTO THE SOLUTIONS

The dynamic nature of the semiconductor industry requires a dynamic solution. Dynamic characteristics are inherent features in all semiconductor devices and transistors. The dynamic behavior of semiconductor devices refers to the act when a device is connecting to a regulated source and rapid changes of voltage and current occur. On the other hand, to modeling the uncertainties concerning future characteristics of semiconductor technology, a long-term dynamic solution is required for endogenizing interactions between decision structure and uncertainties. Therefore to optimize the integrating the time horizon into one objective functions and to link different time steps in the model by various types of constraints, only dynamic constraints can solve the complexity of the problems. Research propositions include:

- Developing stochastic and dynamic versions of solutions and deterministic models [68].
- Anticipating the stochasticity in the models based on dynamic programming, robust optimization, and stochastic programming.

3) DESIGN SOFTWARE-BASED SOLUTION WITH USER-FRIENDLY INTERFACE

In this era of Industry 4.0, thanks to the integration of sensors and Edge Computing solutions that allow collection and access to online data, for customized development and implementations of smart manufacturing, a complete, code-less programming, and scalable wireless protocol software stack are required to help companies for real-time monitoring, predictive maintenance in less downtime, optimized industrial performances, and power conservation. The software is needed to be designed based on a user-friendly, modular architecture, and consist of development boards, debugging tools, and all other standard requirements. Research scopes include:

- Considering the role of high-tech computing techniques, including cloud computing techniques in decision-making and parallel computing on Graphics Processing Units (GPU).
- Knowing the restrictions of current packaged software for semiconductor management, process, and production.
- Proposing alternative software solutions including service-oriented computing and software agents for semiconductor planning and scheduling applications.
- Designing domain-specific solutions based on open-source software. The selection of an appropriate simulation tool is often crucial for the success of the project. General-purpose simulation tools often require much domain-specific customization. Therefore, domain-specific simulation tools, like Factory Explorer or AutoSched AP, are often a better choice for simulating wafer fabrication environment.
- Adapting the existing solution (i.e., SECS/GEM [69]) with IoT and cloud technologies and equipping them with more intelligent decision rules.

4) FORMING THE HYBRID CONFIGURATION OF OR&DS MODELS

OR techniques are primarily applied to the decision-making process. While there are many different ways to determine how to make decisions, the most mainstream OR techniques are focused on modeling decision problems in a mathematical programming framework. In these kinds of contexts, there is typically a set of decision variables, constraints over these variables, and an objective function dependent on decision variables that are subjected to minimize or maximize. DS, on the other hand, is mostly concerned with making inferences. DS typically starting with a big pile of data and the purpose is to infer something about data have not seen yet in the big pile. The most common related research purposes are 1) which solution yield the best results, 2) how the time-dependent models can be extended for the future, 3) how a big pile labeled data offer labels for new, unlabelled observations. Therefore, making a hybrid solution by a combination of OR&DS can fulfill all the needs for the trade-off between data analysis and decision-making process. Research domains include:

- Facilitating problems, and decision making based OR perspective by data mining techniques.
- Implementing "Manufacturing Execution System" (MES), "Enterprise Resource Planning" (ERP), and "Advanced Planning and Scheduling" (APS) for developing the integrated production planning and scheduling solutions. Integrating the APS with ERP and MES is a challenging issue to be considered.
- Decreasing the measurement uncertainty by merging the hybrid methodology with state of the art statistical inferences [70].

5) SIMULATION AND DATA-DRIVEN SOLUTIONS

As the scale and subsequently complexity of a production process grow, the characterization of the process model, which consists of physical elements becomes highly important. In particular, it is essential to employ a modeling approach that can handle specification of scalable physical models as size and complexity of data and system increases. Research opportunities include:

- Simulating physical environment in order to comprehend the connections in real setting circumstance and planning to find solution approaches in the risk-free environment.
- Visualizing production planning processes by the use of the event-driven process.
- Modeling and analyzing semiconductor challenges by utilization of various simulation paradigms (i.e., agent-based systems, hybrid models, reduced simulation models, systems dynamics).
- Supporting the different aspect of decision-making in the semiconductor by embedding the actual simulation methods in the existing and forthcoming information systems.

6) PROCESS INTEGRATION

As the costs of developing new product and restoring new technology increase, a detailed simulation model representing the production operations, tools matching, scheduling, and monitoring rules are needed for accurately planning the capacity of these facilities and regulations. The main challenge is a lengthy procedure of building, experimenting, and analyzing a sufficiently detailed model for a new design. The key to building accurate and computationally efficient models is to decide on the details representing the equipment capacity and advantage of applying high-tech technology. On the other hand, the impact of energy consumption on climate change and the rising cost of energy has become a challenging issue for the semiconductor manufacturing industry today. Regarding the new product design and use of new technology, designing and deploying green and sustainable manufacturing facilities is one of the key agenda from International Technology Road-map of Semiconductor (ITRS) for achieving the goals of ITRS, the product life-cycle information from recovery organizations needs to take into consideration to improve resource efficiency. Therefore, possible research scopes include:

- Integrating decisions made by the different elements in the system to avoid the ad hoc situation.
- Integrating the high-tech computing procedures to derive the computationally tractable models, and to discourse, the diverse uncertainties come across in the industry [71].
- Incorporating sustainability aspects into proposed solutions and deterministic models.
- Integrating the product lifetime into account for demand planning [72].

V. CONCLUSION AND FUTURE RESEARCH DIRECTION

As a conclusion and future research direction, we attempted to have a broader vision of the requirements for industrial development and intelligence manufacturing of semiconductor products. These requirements are barely indicated in literature with analytic context and are known as the new obligations for the next step toward smart manufacturing. Following we discuss some of the highlighted topics in this chain.

A. SEMICONDUCTOR SUPPLY CHAIN MANAGEMENT

Semiconductor SC is growing exponentially and contributing substantially to the global economy. This growth accompanies by continuous technology migration and minimizing cost for different applications in green energy, communication, computers, automotive, medical, and electronics industries. [73]. There are some survey papers for Semiconductor SC with the scope of needs, practices and integration issues such as 1) Research agenda framework for supply network integration (questionnaire-based) [74]; 2) Decision paradigms for SCM (questionnaire-based) [75]; 3) Successes and opportunities in modelling and integrating planning, scheduling, equipment configuration and fab capability assessment [76], [77]; 4) E-markets and SC collaboration [78], and 5) Strategic SC network design and SC simulation models [79], [80], [80].

According to [81] and [79], one future direction of semiconductor industry would be global SC simulation models based on a marketing-operations perspective which leads another research direction in the area of operations management such as production planning and demand fulfillment, inventory control, capacity and demand planning, and marketing and sales models. Moreover, positioning the ‘‘Order Penetration Points’’ (OPPs) in global semiconductor SC networks is another strategic competitive decision, especially for novel product architectures with new options which can be modeled with game theory (see [81], [82]).

B. SUSTAINABILITY AND RE-MANUFACTURING

Materials, products, and processes are becoming smarter, sustainable, energy-aware, and innovation-driven. Sustainability includes 1) Lower use of energy and materials, 2) Greater environmental friendliness [83], and 3) Circular economy and re-manufacturing [2]. Nowadays, the semiconductor industry has significantly and exponentially increased the rate of e-waste in daily life [84], [85]. There is a challenge for inventing efficient and pollution-free high-tech recycling technologies for e-waste, which help to enhance the comprehensive utilization of resources, and consequently, it will develop the cyclic economy. There is a critical future research direction on new recycling Electrostatic separation which is simple and optimize energy consumption without any wastewater discharge to recover the mixtures containing conductors (copper), semiconductors (extrinsic silicon), and nonconductors (woven glass-reinforced resin) in wafer fabrication process [86].

C. GREEN SMART SEMICONDUCTOR MANUFACTURING

Another future research stream would be data-driven decision making and optimization applications in integrated smart and green manufacturing. Some challenges in this area would be: 1) Business Model Challenge: manufacturers face threats from digital disruptors that are often quick to adapt traditional products and exploit new opportunities through the latest technology. 2) Data and Security Challenge: Smart manufacturing is heavily reliant on technology and data, which brings challenges of protecting data and ensuring security. Smart manufacturing systems and the generated data from that might also be targets for cyber attacks. 3) Operations Challenges: Manufacturers need to be agile and respond more quickly to update their technology. Connecting different systems to get an end-to-end picture of the manufacturing process, supply chain, and product usage are a further challenge [87].

Eventually, the fast-growing semiconductor manufacturing requires a Knowledge Management Systems (KMS) in order to support management DSS. This KMS will identify and analyze research trend gaps and organize a future research agenda for new product development [88].

ACKNOWLEDGMENT

Support from the Engineering and Sciences School at Tecnológico de Monterrey is acknowledged.

REFERENCES

[1] L. Wang and G. Wang, "Big data in cyber-physical systems, digital manufacturing and industry 4.0," *Int. J. Eng. Manuf.*, vol. 6, no. 4, pp. 1–8, 2016.
[2] A. Kusiak, "Smart manufacturing must embrace big data," *Nature*, vol. 544, no. 7648, pp. 23–25, 2017.
[3] R. R. Schaller, "Moore's law: Past, present and future," *IEEE Spectr.*, vol. 34, no. 6, pp. 52–59, Jun. 1997.
[4] M. M. Waldrop, "More than more," *Nature*, vol. 530, no. 7589, pp. 144–148, 2016.
[5] B. Esmaeilian, S. Behdad, and B. Wang, "The evolution and future of manufacturing: A review," *J. Manuf. Syst.*, vol. 39, pp. 79–100, Apr. 2016.
[6] C.-Y. Lee and B.-S. Chen, "Mutually-exclusive-and-collectively-exhaustive feature selection scheme," *Appl. Soft Comput.*, vol. 68, pp. 961–971, Jul. 2018.
[7] R. Wieringa, N. Maiden, N. Mead, and C. Rolland, "Requirements engineering paper classification and evaluation criteria: A proposal and a discussion," *Requir. Eng.*, vol. 11, no. 1, pp. 102–107, Mar. 2006.
[8] F. Meziane, S. Vadera, K. Kobbacy, and N. Proudlove, "Intelligent systems in manufacturing: Current developments and future prospects," *Integr. Manuf. Syst.*, vol. 11, no. 4, pp. 218–238, 2000.
[9] K. Petersen, R. Feldt, S. Mujtaba, and M. Mattsson, "Systematic mapping studies in software engineering," *Ease*, vol. 8, pp. 68–77, Jun. 2008.
[10] D. Delen and H. Demirkan, "Data, information and analytics as services," *Decis. Support Syst.*, vol. 55, no. 1, pp. 359–363, Apr. 2013.
[11] D. Khera, M. E. Zaghoul, L. W. Linholm, and C. L. Wilson, "A neural network approach for classifying test structure results," in *Proc. Int. Conf. Microelectron. Test Struct.*, Mar. 1989, pp. 201–204.
[12] M. H. Hansen and D. A. James, "A computing environment for spatial data analysis in the microelectronics industry," *Bell Labs Tech. J.*, vol. 2, no. 1, pp. 114–129, 1997.
[13] A. Famili, W.-M. Shen, R. Weber, and E. Simoudis, "Data preprocessing and intelligent data analysis," *Intell. Data Anal.*, vol. 1, no. 1, pp. 3–23, 1997.
[14] A. Kusiak, "Decomposition in data mining: An industrial case study," *IEEE Trans. Electron. Packag. Manuf.*, vol. 23, no. 4, pp. 345–353, Oct. 2000.
[15] M. Gardner and J. Bieker, "Data mining solves tough semiconductor manufacturing problems," in *Proc. 6th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2000, pp. 376–383.
[16] A. Kusiak, "Feature transformation methods in data mining," *IEEE Trans. Electron. Packag. Manuf.*, vol. 24, no. 3, pp. 214–221, Jul. 2001.
[17] D. Braha and A. Shmilovici, "Data mining for improving a cleaning process in the semiconductor industry," *IEEE Trans. Semicond. Manuf.*, vol. 15, no. 1, pp. 91–101, Feb. 2002.
[18] A. Kusiak, "Rough set theory: A data mining tool for semiconductor manufacturing," *IEEE Trans. Electron. Packag. Manuf.*, vol. 24, no. 1, pp. 44–50, Jan. 2001.
[19] P. Backus, M. Janakiram, S. Mowzoon, G. C. Runger, and A. Bhargava, "Factory cycle-time prediction with a data-mining approach," *IEEE Trans. Semicond. Manuf.*, vol. 19, no. 2, pp. 252–258, May 2006.
[20] C.-F. Chien, W.-C. Wang, and J.-C. Cheng, "Data mining for yield enhancement in semiconductor manufacturing and an empirical study," *Expert Syst. Appl.*, vol. 33, no. 1, pp. 192–198, Jul. 2007.
[21] S.-C. Hsu and C.-F. Chien, "Hybrid data mining approach for pattern extraction from wafer bin map to improve yield in semiconductor manufacturing," *Int. J. Prod. Econ.*, vol. 107, no. 1, pp. 88–103, May 2007.
[22] C. R. Glassey and W. W. Weng, "Dynamic batching heuristic for simultaneous processing," *IEEE Trans. Semicond. Manuf.*, vol. 4, no. 2, pp. 77–82, May 1991.
[23] C.-Y. Lee, R. Uzsoy, and L. A. Martin-Vega, "Efficient algorithms for scheduling semiconductor burn-in operations," *Oper. Res.*, vol. 40, no. 4, pp. 764–775, 1992.
[24] V. Chandru, C.-Y. Lee, and R. Uzsoy, "Minimizing total completion time on batch processing machines," *Int. J. Prod. Res.*, vol. 31, no. 9, pp. 2097–2121, 1993.
[25] D. S. Hochbaum and D. Landy, "Scheduling semiconductor burn-in operations to minimize total flowtime," *Oper. Res.*, vol. 45, no. 6, pp. 874–885, 1997.
[26] S. V. Mehta and R. Uzsoy, "Minimizing total tardiness on a batch processing machine with incompatible job families," *IIE Trans.*, vol. 30, no. 2, pp. 165–178, Feb. 1998.
[27] H. H. Xiong and M. C. Zhou, "Scheduling of semiconductor test facility via Petri nets and hybrid heuristic search," *IEEE Trans. Semicond. Manuf.*, vol. 11, no. 3, pp. 384–393, Aug. 1998.
[28] J. M. Swaminathan, "Tool capacity planning for semiconductor fabrication facilities under demand uncertainty," *Eur. J. Oper. Res.*, vol. 120, no. 3, pp. 545–558, Feb. 2000.
[29] S. J. Mason, J. W. Fowler, and W. M. Carlyle, "A modified shifting bottleneck heuristic for minimizing total weighted tardiness in complex job shops," *J. Scheduling*, vol. 5, no. 3, pp. 247–262, 2002.
[30] H. Balasubramanian and L. Mönch, J. Fowler, and M. Pfund, "Genetic algorithm based scheduling of parallel batch machines with incompatible job families to minimize total weighted tardiness," *Int. J. Prod. Res.*, vol. 42, no. 8, pp. 1621–1638, 2004.
[31] L. Mönch, H. Balasubramanian, J. W. Fowler, and M. E. Pfund, "Heuristic scheduling of jobs on parallel batch machines with incompatible job families and unequal ready times," *Comput. Oper. Res.*, vol. 32, no. 11, pp. 2731–2750, Nov. 2005.
[32] F. Pan and R. Nagi, "Robust supply chain design under uncertain demand in agile manufacturing," *Comput. Oper. Res.*, vol. 37, no. 4, pp. 668–683, Apr. 2010.
[33] S.-S. Chen, "Intelligent control of semiconductor manufacturing processes," in *Proc. IEEE Int. Conf. Fuzzy Syst.*, Mar. 1992, pp. 101–108.
[34] P.-C. Chang, J.-C. Hieh, and T. W. Liao, "Evolving fuzzy rules for due-date assignment problem in semiconductor manufacturing factory," *J. Intell. Manuf.*, vol. 16, nos. 4–5, pp. 549–557, Oct. 2005.
[35] K. M. Tay and C. P. Lim, "Fuzzy FMEA with a guided rules reduction system for prioritization of failures," *Int. J. Qual. Rel. Manage.*, vol. 23, no. 8, pp. 1047–1066, Oct. 2006.
[36] H.-Y. Kang and A. H. I. Lee, "Priority mix planning for semiconductor fabrication by fuzzy AHP ranking," *Expert Syst. Appl.*, vol. 32, no. 2, pp. 560–570, Feb. 2007.
[37] P. J. Gyugyi, Y. M. Cho, G. Franklin, and T. Kailath, "Convex optimization of wafer temperature trajectories for rapid thermal processing," in *Proc. IEEE Int. Conf. Control Appl.*, Sep. 1993, pp. 409–414.
[38] J. S. Kim and R. C. Leachman, "Decomposition method application to a large scale linear programming WIP projection model," *Eur. J. Oper. Res.*, vol. 74, no. 1, pp. 152–160, Apr. 1994.

[39] Y.-F. Hung and R. C. Leachman, "A production planning methodology for semiconductor manufacturing based on iterative simulation and linear programming calculations," *IEEE Trans. Semicond. Manuf.*, vol. 9, no. 2, pp. 257–269, May 1996.

[40] I. Chambouleyron, J. Martínez, A. Moretti, and M. Mulato, "Retrieval of optical constants and thickness of thin films from transmission spectra," *Appl. Opt.*, vol. 36, no. 31, pp. 8238–8247, 1997.

[41] S. Bermon and S. J. Hood, "Capacity optimization planning system (CAPS)," *Interfaces*, vol. 29, no. 5, pp. 31–50, 1999.

[42] S.-K. S. Fan, "Quality improvement of chemical-mechanical wafer planarization process in semiconductor manufacturing using a combined generalized linear modelling - non-linear programming approach," *Int. J. Prod. Res.*, vol. 38, no. 13, pp. 3011–3029, 2000.

[43] P. C. Chang and T. W. Liao, "Combining SOM and fuzzy rule base for flow time prediction in semiconductor manufacturing factory," *Appl. Soft Comput.*, vol. 6, no. 2, pp. 198–206, Jan. 2006.

[44] J. Asmundsson, R. L. Rardin, and R. Uzsoy, "Tractable nonlinear production planning models for semiconductor wafer fabrication facilities," *IEEE Trans. Semicond. Manuf.*, vol. 19, no. 1, pp. 95–111, Feb. 2006.

[45] A. Chatterjee, R. K. Nurani, S. Seshadri, and J. G. Shanthikumar, "Role of yield management in fabless-foundry partnerships," in *Proc. IEEE Int. Symp. Semiconductor Manuf. Conf.*, Oct. 1997, pp. P31–P34.

[46] S. Mallik and P. T. Harker, "Coordinating supply chains with competition: Capacity allocation in semiconductor manufacturing," *Eur. J. Oper. Res.*, vol. 159, no. 2, pp. 330–347, Dec. 2004.

[47] D. J. Miller and J. A. Fenimore, "The application of advanced manufacturing technology in semiconductor fabrication," in *Proc. 5th IEEE/CHMT Int. Electron. Manuf. Technol. Symp.*, Oct. 1988, pp. 201–205.

[48] N. W. Hatch and D. C. Mowery, "Process innovation and learning by doing in semiconductor manufacturing," *Manage. Sci.*, vol. 44, no. 11, pp. 1461–1477, 1998.

[49] J. F. Nijs, J. Szlufcik, J. Poortmans, S. Sivoththaman, and R. P. Mertens, "Advanced manufacturing concepts for crystalline silicon solar cells," *IEEE Trans. Electron Devices*, vol. 46, no. 10, pp. 1948–1969, Oct. 1999.

[50] R. C. Leachman, "Closed-loop measurement of equipment efficiency and equipment capacity," *IEEE Trans. Semicond. Manuf.*, vol. 10, no. 1, pp. 84–97, Feb. 1997.

[51] S. H. Huang, J. P. Dismukes, J. Shi, Q. Su, G. Wang, M. A. Razzak, and D. E. Robinson, "Manufacturing system modeling for productivity improvement," *J. Manuf. Syst.*, vol. 21, no. 4, pp. 249–259, 2002.

[52] R. Oechsner, M. Pfeffer, L. Pfitzner, H. Binder, and E. Müller, and T. Vonderstrass, "From overall equipment efficiency (OEE) to overall Fab effectiveness (OFE)," *Mater. Sci. Semicond. Process.*, vol. 5, nos. 4–5, pp. 333–339, 2002.

[53] J. H. Jacobs, L. F. P. Etman, E. J. J. V. Campen, and J. E. Rooda, "Characterization of operational time variability using effective process times," *IEEE Trans. Semicond. Manuf.*, vol. 16, no. 3, pp. 511–520, Aug. 2003.

[54] A. J. D. Ron and J. E. Rooda, "Equipment effectiveness: OEE revisited," *IEEE Trans. Semicond. Manuf.*, vol. 18, no. 1, pp. 190–196, Feb. 2005.

[55] J. Morse, "Advanced manufacturing partnership: Where does nanomanufacturing fit, and where should investments be made?" *NNN Newslett.*, vol. 4, no. 11, Jun. 2011.

[56] C.-Y. Hsu, C.-F. Chien, and P.-N. Chen, "Manufacturing intelligence for early warning of key equipment excursion for advanced equipment control in semiconductor manufacturing," *J. Chin. Inst. Ind. Eng.*, vol. 29, no. 5, pp. 303–313, 2012.

[57] K. Dequeant, P. Vialletelle, P. Lemaire, and M.-L. Espinouse, "A literature review on variability in semiconductor manufacturing: The next forward leap to Industry 4.0," in *Proc. Winter Simulation Conf.*, Dec. 2016, pp. 2598–2609.

[58] J. Moyne, J. Samantaray, and M. Armacost, "Big data capabilities applied to semiconductor manufacturing advanced process control," *IEEE Trans. Semicond. Manuf.*, vol. 29, no. 4, pp. 283–291, Nov. 2016.

[59] T. J. Tang, A. Chung, A. Zhao, R. Kang, M. Zhang, K. Chien, J. Yang, and J. Zhang, "An IoT inspired semiconductor Reliability test system integrated with data-mining applications," in *Proc. 2nd Int. Conf. Cloud Comput. Internet Things*, Oct. 2016, pp. 111–114.

[60] A. Weber, "The role of models in semiconductor smart manufacturing," in *Proc. e-Manuf. Design Collaboration Symp. (eMDC)*, Sep. 2016, pp. 1–3.

[61] R. Herding and L. Mönch, "Designing an ontology for agent-based planning and control tasks in semiconductor supply chains," in *Proc. Move Meaningful Internet Syst.* Cham, Switzerland: Springer, 2016, pp. 65–75.

[62] S. Paramanathan, C. Farrukh, R. Phaal, and D. Probert, "Implementing industrial sustainability: The research issues in technology management," *R&D Manage.*, vol. 34, no. 5, pp. 527–537, 2004.

[63] J. B. Silber, "Improving reuse of semiconductor equipment through benchmarking, standardization, and automation," Ph.D. dissertation, Dept. Civil Environ. Eng., Leaders Manuf. Program, Massachusetts Inst. Technol., Cambridge, MA, USA, 2006.

[64] M. M. Crossan, H. W. Lane, and R. E. White, "An organizational learning framework: From intuition to institution," *Acad. Manage. Rev.*, vol. 24, no. 3, pp. 522–537, 1999.

[65] J. M. Swaminathan, "Enabling customization using standardized operations," *California Manage. Rev.*, vol. 43, no. 3, pp. 125–135, 2001.

[66] J. D. C. Little and S. C. Graves, "Little's law," in *Building Intuition*. Boston, MA, USA: Springer, 2008, pp. 81–100.

[67] D. J. Power, M. Khakifirooz, M. Fathi, and P. M. Pardalos. (2018). *How Can Decision Support Aid Smart Manufacturing Initiatives?* http://dssresources.com

[68] M. Khakifirooz, C.-F. Chien, and M. Fathi, "Compensating misalignment using dynamic random-effect control system: A case of high-mixed wafer fabrication," *IEEE Trans. Automat. Sci. Eng.*, 2019.

[69] Y.-C. Fan and J.-Y. J. Chang, "Equipment communication architecture for smart manufacturing," in *Proc. IEEE Int. Conf. Smart Manuf., Ind. Logistics Eng. (SMILE)*, Feb. 2018, pp. 27–32.

[70] T. Paksoy, I. Karaoğlan, and H. Gökçen, P. M. Pardalos, and B. Torğul, "An experimental research on closed loop supply chain management with Internet of Things," *J. Econ. Bibliography*, vol. 3, no. 1S, pp. 1–20, 2016.

[71] C. Fang, X. Liu, P. M. Pardalos, and J. Pei, "Optimization for a three-stage production system in the Internet of Things: Procurement, production and product recovery, and acquisition," *Int. J. Adv. Manuf. Technol.*, vol. 83, nos. 5–8, pp. 689–710, 2016.

[72] X. Liu, J. Pei, L. Liu, H. Cheng, M. Zhou, and P. M. Pardalos, "Life cycle assessment in an IOT environment," in *Optimization and Management in Manufacturing Engineering*. Cham, Switzerland: Springer, 2017, pp. 209–246.

[73] C.-F. Chien and S. Dauzère-Pérès, H. Ehm, J. W. Fowler, Z. Jiang, S. Krishnaswamy, T.-E. Lee, L. Möench, and R. Uzsoy, "Modelling and analysis of semiconductor manufacturing in a shrinking world: Challenges and successes," *Eur. J. Ind. Eng.*, vol. 5, no. 3, pp. 254–271, 2011.

[74] T. Callarman, J. Fowler, E. Gel, M. Pfund, and D. Shunk, "Creating a research agenda framework for semiconductor supply network integration," in *Evolution of Supply Chain Management*. Boston, MA, USA: Springer, 2004, pp. 161–187.

[75] Y. Sun, A. Feller, D. Shunk, J. Fowler, T. Callarman, and B. Duarte, "Decision paradigms in the semiconductor supply chain: A survey and analysis," in *Proc. IEEE Int. Conf. Automat. Sci. Eng.*, Sep. 2007, pp. 106–110.

[76] K. Fordyce, R. J. Milne, C.-T. Wang, and H. Zisgen, "Modeling and integration of planning, scheduling, and equipment configuration in semiconductor manufacturing: Part I. Review of successes and opportunities," *Int. J. Ind. Eng., Theory, Appl. Pract.*, vol. 22, no. 5, pp. 575–600, 2015.

[77] K. Fordyce, R. J. Milne, C. T. Wang, and H. Zisgen, "Modelling and integration of planning, scheduling, and equipment configuration in semiconductor manufacturing part II. Fab capability assessment," *Int. J. Ind. Eng., Theory, Appl. Pract.*, vol. 22, no. 5, pp. 601–607, 2015.

[78] B. K. Bahinipati and S. G. Deshmukh, "E-markets and supply chain collaboration: A literature-based review of contributions with specific reference to the semiconductor industries," *Logistics Res.*, vol. 4, nos. 1–2, pp. 19–38, Mar. 2012.

[79] L. Mönch, R. Uzsoy, and J. W. Fowler, "A survey of semiconductor supply chain models part I: Semiconductor supply chains, strategic network design, and supply chain simulation," *Int. J. Prod. Res.*, vol. 56, no. 13, pp. 4524–4545, 2017.

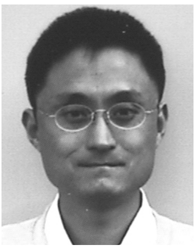
[80] R. Uzsoy, J. W. Fowler, and L. Mönch, "A survey of semiconductor supply chain models Part II: Demand planning, inventory management, and capacity planning," *Int. J. Prod. Res.*, vol. 56, no. 13, pp. 4546–4564, 2018.

[81] E. Teimoury and M. Fathi, "An integrated operations-marketing perspective for making decisions about order penetration point in multi-product supply chain: A queuing approach," *Int. J. Prod. Res.*, vol. 51, no. 18, pp. 5576–5596, 2013.

[82] E. Teimoury, M. Modarres, I. G. Khondabi, and M. Fathi, "A queuing approach for making decisions about order penetration point in multi-echelon supply chains," *Int. J. Adv. Manuf. Technol.*, vol. 63, nos. 1–4, pp. 359–371, 2012.
[83] P. Centobelli, R. Cerchione, and E. Esposito, "Environmental sustainability in the service industry of transportation and logistics service providers: Systematic literature review and research directions," *Transp. Res. D, Transp. Environ.*, vol. 53, pp. 454–470, Jun. 2017.
[84] M. Kwak, S. Behdad, Y. Zhao, H. Kim, and D. Thurston, "E-waste stream analysis and design implications," *J. Mech. Des.*, vol. 133, no. 10, 2011, Art. no. 101003.
[85] M. Sabbaghi, S. Behdad, and J. Zhuang, "Managing consumer behavior toward on-time return of the waste electrical and electronic equipment: A game theoretic approach," *Int. J. Prod. Econ.*, vol. 182, pp. 545–563, Dec. 2016.
[86] M. Xue, G. Yan, J. Li, and Z. Xu, "Electrostatic separation for recycling conductors, semiconductors, and nonconductors from electronic waste," *Environ. Sci. Technol.*, vol. 46, no. 19, pp. 10556–10563, 2012.
[87] P. M. Pardalos. (2017). *Smart/Green Manufacturing: Data Enabled Decision Making and Optimization Applications-Presentation*. [Online]. Available: http://www.ise.ufl.edu/cao/
[88] P. Centobelli, R. Cerchione, and E. Esposito, "Knowledge management in startups: Systematic literature review and future research agenda," *Sustainability*, vol. 9, no. 3, p. 361, 2017.

MARZIEH KHAKIFIROOZ received the M.S. degree in industrial statistics and the Ph.D. degree in industrial engineering and engineering management from National Tsing Hua University (NTHU), Hsinchu, Taiwan. She is currently an Assistant Professor with the School of Engineering, Tecnològico de Monterrey, Mexico. She has outstanding practical experience from her various global consultancies for high-tech industries. Her research interests include the application of optimization in smart manufacturing, Industry 4.0, decision making, and machine teaching. She is an Active Member of the System Dynamic Society and the Institute of Industrial and Systems Engineers (IISE).

MAHDI FATHI received the B.S. and M.S. degrees from the Department of Industrial Engineering, Amirkabir University of Technology (Tehran Polytechnic), in 2006 and 2008, respectively, and the Ph.D. degree from the Iran University of Science and Technology, Tehran, Iran, in 2013. He was a recipient of three postdoctoral fellowships. He was a Visiting Scholar with the Center for Applied Optimization, Department of Industrial and Systems Engineering, University of Florida (USA), and also with the Department of Electrical Engineering, National Tsing Hua University, Taiwan. He was with Optym as a Senior Systems Engineer and at A Model Of Reality, Inc., as a System Design Engineer in USA and several other companies in different industry sectors. He is currently a Postdoctoral Associate with the Department of Industrial and Systems Engineering, Mississippi State University. His research interests include queuing theory and its applications, stochastic process, optimization, artificial intelligent, uncertain quantification, smart manufacturing & Industry 4.0, reliability with their applications in health care, bio-medicine, agriculture, and energy. He is an active member of several societies and institutions and serves on the editorial board of several journals.



KAN WU received the B.S. degree from National Tsinghua University, Taiwan, the M.S. degree from the University of California at Berkeley, in 1996, and the Ph.D. degree in industrial and systems engineering from the Georgia Institute of Technology, in 2009. His Ph.D. dissertation received the third place for the IIE Pritsker Doctoral Dissertation Award, in 2010. He has over 10 years of experience in the semiconductor industry, from consultants to managers. He was the CTO and a Founding Team Member of a startup company in USA. He is currently an Assistant Professor with the Division of Systems and Engineering Management, Nanyang Technological University (NTU). His research interests include the performance evaluation of supply chains and manufacturing systems.