Chapter 11
Management Suggestions for Process Control of Semiconductor Manufacturing: An Operations Research and Data Science Perspective

Marzieh Khakifirooz, Mahdi Fathi, Chen Fu Chien and Panos M. Pardalos

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 promising significant opportunities to reduce cost, boost productivity, and improve quality in wafer manufacturing is based on the integration or combination of simulated replicas of actual equipment, Cyber-Physical Systems (CPS) and regionalized or decentralized decision-making into a smart factory. However, this integration also presents the industry with novel unique challenges. The stream of the data from sensors, robots, and CPS can aid to make the manufacturing smart. Therefore, it would be an increased need for modeling, optimization, and simulation to 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" (OR) and "Data Science" (DS) perspective. In addition, we will discuss future research directions and new challenges to this industry.

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11.1 Introduction

11.1.1 Industrial Revolution and "Industry 4.0"

The importance of national manufacturing strategies such as "Advanced Manufacturing Partnership" (AMP) of USA since 2011 [1], "Industry 4.0" of Germany since 2011 [2], "La Nouvelle France Industrielle" since 2013 [3], "Future of Manufacturing" of UK since 2013 [4], "Made in Sweden 2030" since 2013 [5], "Factories of the Future" of European Commission since 2014 [6], "Korea Manufacturing Innovation 3.0" since 2014 [7], "Industria Conectada 4.0" of Spain since 2014 [8], "Smart Industry" of Netherlands since 2014 [9], "Industry 4.1J" of Japan since 2015 [10], "Made in China 2025" since 2015 [11], "Fabbrica Intelligente" of Italy since 2015 [12], and "Innovation and Enterprise 2020 Plan" of Singapore since 2016 [13] have reemphasized the shifting standard of manufacturing and production system which led to the Fourth Industrial Revolution generation.

The industrial revolution stream drives the deployment of novel concepts for smart factories, new generation of monitoring and collaborating systems, or in general words the smart manufacturing system which it is built upon the CPS [14], "Internet of Things" (IoT) [15], and cloud and cognitive computing [16, 17]. The first step toward the smart manufacturing is the connectivity [18]. All the components in the industry must be connected to a single network, which is being allowed by the CPS and IoT which further confesses information interchange and alliance to attain a flexible and self-adaptive system of production. Moreover, by the integration of information and technologies, cloud and cognitive computing can facilitate the internet-based optimum interface and diagnostics, and can comprehend self-control system (self-learning, self-optimization, and self-awareness).

The fundamental concepts for designing smart manufacturing concerning the discipline and the precise distinction in their respective meaning and utilization are as follows [19]:

- Adaptation to human needs,
- Advance development of products and services,
- CPS,
- Corporate social responsibility,
- New systems in distribution and procurement,
- Self-organization,
- Smart factory.

The concepts mentioned above might experience several kinds of challenges and complications for smart manufacturing that may include technological, economical, social, political, and scientifical issues [20]. This paper aims to review the area of science and technology challenges and point out the industry which is one of the most capital-intensive and complex that is semiconductor manufacturing industry.

11.1.2 Semiconductor Industry and "Industry 4.0"

In this era as a part of the technology roadmap for semiconductors driven by Moore's law [21] system scaling, there is more and more challenges by the poverty of resources and emergence of information technology. While the goal of semiconductor industry possesses the ability to continue technology migration to maintain overall performance, it is practically challenging to secure this objective due to the demand for appropriate action, together with all the steps required for the design to marketing. Therefore, the seamless interaction of smart manufacturing components such as big data, instant data, information technology (cloud, and multimode sensors), high-performance computing, mobile computing, and autonomous sensing and computing is necessary for driving "More Moore" (MM) technologies [22].

The "International Technology Roadmap for Semiconductors" (ITRS) [23] identified several critical limitations faced by semiconductor industry in the near future, will involve most, if not all, system integration, heterogeneous integration, heterogeneous components, external system connectivity, and factory integration.

ITRS determined a 35–40% less die cost [24], as one of the technical and reliability requirements to sustain MM technology. To achieve this goal, ITRS identified process integration, as one of the essential functional elements and critical challenges to stimulate the need for research and development and to meet a sustainable level of MM technology. The ITRS metrology chapter has underlined that the primary drivers in dealing with process integration are smart automotive, green energy, mobile communication systems, big data, and medical and health technologies [25].

Process integration, in particular, is dealing with technology and requirements associated with several phenomena such as:

- Cross leveraging factory integration technologies, across boundaries to achieve economies of scale.
- Attaining financial development goals while margins are decreasing.
- Increasing global restrictions on environmental issues.
- Dealing with the growing complexity.
- Achieving factory requirements such as capability, cost, equipment reliability, and productivity.
- Meeting adaptability, scalability and extensibility requirements of a profitable pioneering factory.
- Post-conventional Semiconductor manufacturing uncertainty (i.e., manufacturing requirements for new devices, timing uncertainty to identify new devices).
- Constantly responding to ever fluctuating, intricate business demands.

This paper is an extended version of [26] and aims to provide a systematic literature review on the scientific progress of the fourth industrial revolution ("Industry 4.0"—the most pointed national smart manufacturing strategy) with the perspective of OR&DS for semiconductor manufacturing. Most precisely, three research questions are given below

1. What would be the main challenges in the OR&DS point of view, enabling the industrial revolution in semiconductor manufacturing?
2. How are the OR&DS addressed the science and technology challenges in smart manufacturing?
3. 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?

In Section 11.2, we identify the core challenges of wafer fabrication processes addressed in literature and the reviewing criteria are used for categorizing the findings and studies. In Section 11.3, we detail how these studies are considered the OR&DS fields into the intelligence semiconductor manufacturing, and how particular methods are distributed. Thereafter, from the gap in the literature, we propose some managerial suggestions in Section 11.4, for who are interested in walking into the field of semiconductor intelligence from the OR&DS perspective and in the domain of the "Industry 4.0". We conclude the paper in Section 11.5, by providing recommendations for further research and align our mindset for the next step.

11.2 Semiconductor Manufacturing Engineering

In semiconductor fabrication facilities (fabs), in order to fulfill the volatile demands of the high-mixed product, the related processes and electronic equipment are employed to produce Integrated Circuits (IC) with the help of a vast number of processing steps, batch processing models, sequence-dependent tool structures, the auxiliary resources [27] and recirculating flows. Therefore, this industry remains the most capital-intensive, for fully automated manufacturing systems [28]. The operations control of manufacturing facilities of semiconductor is known as 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 semiconductor industry and recognize fields for future research to maintain the further technologies for IC manufacturing. Therefore, this study aims to detect gaps in the existing works, develop significant research ideas, categorize existing research struggles and form a layout that will deliver different ideas related to the OR&DS area in smart IC manufacturing.

11.2.1 Challenges in Control of Semiconductor Manufacturing Process

Despite the sophisticated production process of wafer fabrication, the OR&DS techniques are using basically for the purpose of throughput enhancement and quality assurance. Regards the general application and intention of using OR&DS techniques, the main challenges in semiconductor manufacturing are categorized as follows:

- Photolithography process as the cutting-edge process and being bottleneck in the production process of semiconductor devices. The main challenge in the photolithography process is a misalignment between laser bean, wafer surface, and patterning mask, the error caused by this misalignment is called overlay error. Overlay error basically has a nonlinear relationship with overlay parameters and overlay parameters are not independent of each other.
- Large number of processing steps, batch tools, random equipment failures, re-entrant flows, sequence-dependent tool setups, and auxiliary resources for some process (i.e., photolithography process) are another source of challenges in semiconductor manufacturing process. Besides these facts, the semiconductor manufacturing equipment is extremely costly and to save the cost and time, the production schedule is mixed, or required to be patched. Dispatching the mixed schedule from equipment with auxiliary resources to cluster tools is one of the interesting topics which is required the state of the art of OR&DS techniques.
- Beside the dispatching, dynamic scheduling in semiconductor itself is a challenging topic. Scheduling system should design in a way such that consider the bottlenecks, reduce the length of production time or in another word the cycle time, maximize the throughput capacity and wafer capacity, and make a balance between the raw material inventory, wafer in process inventory, and finish product inventory.
- Run-to-run (R2R) control of semiconductor fabrication because of re-entrant flow of production process, required a flexible, accurate, stable, and fast optimization process. The main challenge is how to design the R2R control such that can deal with high-mixed dynamic scheduling plan of wafer fabrication. In addition, ITRS projected a roadmap for yield enhancement and error reduction which demanded a highly reliable control system.
- Delay for characteristics measurement from Metrology tools is unavoidable in semiconductor industry. This is a source of measurable and predictable uncertainties, however, make a challenge for process engineers to design a quality control system to deal with this source of uncertainty. Yet, there are several sources of unmeasurable uncertainties which in brief call noise. Dealing with noise is another challenge in semiconductor manufacturing environment.
- The final product in wafer fabrication is integrated circuit packaging for protecting the semiconductor device. The main challenge in this step is designing a packaging system which can protect the integrated circuit from

environmental changes like thermal effect and particle effect, or in general disturbance effect.
- Semiconductor manufacturing process is engaged with chemical processing. Most of the chemical processes are the source of uncertainties, they reduce the lifetime of fabrication equipment, are the source of particle, and change the balance in environmental factors. If the chemical process, doesn't react well for any reason, this will be affected on the quality of the wafer. One of the challenging processes which deal with chemical reaction is the etching process. The lifetime of etching tools is less than three days, and any uncertainty caused by quality reduction of etching tools affect on edge, depth, and length of the wafer, called critical dimension error.
- The automated material handling in semiconductor fabrication although brings a huge source of benefits to this industry, however, the dynamic scheduling system of wafer fabrication required a dynamic allocation system for material handling as well.

11.2.2 Review Method

The methodological review used in this study is the systematic review with the objective of history review, and status quo review [29]. In the first place, the duration of review is narrowed by the milestone of national manufacturing strategies since 2011. We abstracted how with development the national manufacturing strategies semiconductor industry is adapted to vision and evolution of the smart industry. From studies conducted after 2011, especially recent trends since 2017, most prevalent terms selected out of index terms of papers in the field of "smart semiconductor" or "semiconductor intelligence". The candidate search terms considered to be the most linked items to the scope of this paper are summarized in Table 11.1.

In this paper, the systematic review conducted based on several classification methods to categorize the review papers as follows:

- Organize the **type of research** methods by Wieringa et al. [30] (including: validation, evaluation, solution, philosophical, opinion, experience).
- classify the **areas of manufacturing** by Meziane et al. [31] (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 [32] (including: architecture, framework, theory, methodology, model, platform, process, tool).
- classify the **type of analytic** by Delen et al. [33] (including: descriptive, predictive, and prescriptive).

11.3 OR&DS Problems in Semiconductor

As mentioned previously in Section 11.1, the main challenges and threats engaged in semiconductor manufacturing and smart industry can be answered by OR&DS perspective solutions. Following this section, we provide OR&DS role in smart semiconductor industry by answering some additional research questions in this direction.

11.3.1 By Growing the "Industry 4.0", How OR&DS Related Research Found Their Way into Semiconductor Manufacturing Intelligence?

The milestone of smart manufacturing by national perspective plans started with AMP by the US government in 2011, which indicates the timeline of our roadmap design horizon based on OR&DS. The following is the historical review of the infrastructure of smart semiconductor manufacturing aligns with the Fourth Industrial Revolution.

- **before 2011**
  Methods such as
  - data mining [34–42], artificial intelligence [43], heuristic algorithm [44–46], machine learning [47, 48], data development management [49, 50], Fuzzy logic [51], neural network [52–54], linear programming [55], statistical analysis [56, 57], optimization method [58–62], and decision analysis [63–67]

Table 11.1 Main and candidate search terms

Major terms	Minor terms
Semiconductor manufacturing	High-tech industry, integrated circuit, wafer fabrication
Smart manufacturing	Advanced manufacturing, advanced robotics, agent-based system, augmented reality, CPS, Industry 4.0, integrated manufacturing, open manufacturing, smart manufacturing, virtual factory
Data science	Artificial intelligence, big data, classification, cloud computing, clustering, data architect, data-driven technology, data management, data mining, data visualization, deep learning, IoT, machine learning, predictive modeling, statistics
Operation research	Convex optimization, decision theory, dynamic programming, forecasting, game theory, graph theory, linear programming, mathematical programming, nonlinear programming, optimization, queueing theory, soft computing

and concepts such as

– advanced manufacturing [68], intelligence manufacturing [69], Enterprise Resource Planning (ERP) [70], Overall Equipment Efficiency (OEE) [71, 72], Decision Support System (DSS) [43, 73–77], risk management [78], virtual manufacturing [79, 80], e-manufacturing [81], electronics manufacturing service [82], research and development management [83, 84], digital management [85], and "industry as a whole" [86]

have been appearing in literature to discover the challenges in semiconductor industry and moving forward to the smart manufacturing.

- **2011**
  The birth of AMP.
  Morse [87] reviewed the reputation and future of nanomanufacturing under the AMP plan.
- **2012**
  The birth of "Industry 4.0".
  The first "International Symposium on Semiconductor Manufacturing Intelligence" (ISMI) launched in Hsinchu, Taiwan [88].
- **2013**
  The first US patent [89] cited the "Industry 4.0" into semiconductor industry.
  The earliest field in order of "Industry 4.0" was in the area of soft computing for scheduling dilemma in semiconductor manufacturing [90].
- **2014**
  Digitalization of "Industry 4.0" has been discussed at AKL congress.
  "Industry 4.0" is introduced as the Fourth Industrial Revolution [91].
- **2015**
  The "Industry 4.0" points of view appeared for the first time in the theoretical and analytical researched. This trend was published in the area of the discrete event [92] and scheduling.
  SEMICON Europa 2015 hold in Germany [93] with the primary context of "Industry 4.0" of semiconductor industry, and among all the highlighted trend in semiconductor intelligence discussed in the area of:

  – "*Organization and Goals of the* "*Industry 4.0*" *Platform*"
    Five frameworks are considered to undertake the organization and structure of the "Industry 4.0": (1) reference architecture, standardization, (2) innovation and research study, (3) safety of networked systems, (4) legitimate context, and (5) labor training.
  – "*Cyber-Physical-Production-Systems at the BTU Model Factory*"
    Address the need for fast and adaptive reconfigurable approaches in production planning, logistics and "Manufacturing Execution Control" (MES) for the "Industry 4.0" platform.
  – "*The Right Security for the IoT*"
    Data security, system integrity, Intellectual Property (IP) and product and service

quality were sanctioned as the requirement for fruitful application of "Industry 4.0".

- "*Technical Visions of "Industry 4.0"*"
  Explained in what ways semiconductor industry can sustain its role as the innovation driver in the area of manufacturing technologies and how it can grow from "Industry 4.0" initiative.
- "*Connecting things and services. How Industry 4.0 increases the benefit of automation at the Bosch 200mm-Waferfab*"
  Showed how modularity guarantees a modest role of high-tech automation in a current environment.
- "*Interface A: Candidate for "Industry 4.0"? Adoption and Challenges in Semiconductor Industry*"
  Introduced InterfaceA as an on-proprietary web technology-based interface which is equipped with data acquisition deliver a flexible interface among manufacturing tools and other IT resolutions and advances the limitation on data collection of the generic model for control of manufacturing equipment interface.

- **2016**
  Following that, most industrial countries have their road map for Fourth Industrial Revolution and digitized industry, researches focused more intensely on challenges and adversities emerged with semiconductor industry and smart manufacturing. Among all, some important researches are listed as follows:

  - Dequeant et al. [94]: a comprehensive review on variability in semiconductor manufacturing to meet the "Industry 4.0" obligations.
  - Waschneck et al. [95]: a comprehensive review of job-shop scheduling. A discussion on the complexity issue with regards to the delegation of authority of decisions, tractability and adaptableness, incorporation and interacting, human aspects, and other "Industry 4.0" frustrations.
  - Moyne et al. [96]: a discussion on the requirements of data analytics, merging, quality, rates, and volumes for digitalis semiconductor industry in control process.
  - Tang et al. [97]: a discussion on the application of big data and IoT for reliability assessment in semiconductor industry.
  - Weber [98]: an introduction to the e-manufacturing on semiconductor device modeling.
  - Herding and Mönch [99]: an introduction to agent-based planning control system for semiconductor.

- **2017**
  Researches have exponential growth with 100% improvement compared to 2016. Out of over 400 academic papers, the highest percentage of researches were in the field of OR (∼50%), following by DS (∼25%), roadmap and management field (∼12.5%) and image processing (∼12.5%) solutions.

- **2018**
The Sixth ISMI was held in February in Hsinchu, Taiwan and among all the highlighted trends in semiconductor intelligence discussed in the area of:

  – *The future of smart semiconductor manufacturing*
  The remanufacturing issue will be a new topic in wafer industry; the sharing economy will enter into semiconductor industry such that customers will design the products and semiconductor manufacturers may not be known only for IC products [100].
  – *Optimization of process tool operation for future semiconductor manufacturing*
  Chamber cleaning can meet the extreme in quality control while inducing the complexity. However, optimization with reinforcement learning can reduce the complexity [101].
  – *From smart machines to smart SCs: some missing pieces*
  The term "smart" doesn't indicate of using the ICT technology to take the faster decision. Smart means: better operations management decisions (more on-time delivery, better asset utilization, less inventory, lower costs, higher quality) and better systems design decisions (faster ramp, greater flexibility, higher adaptability) [102].
  – *Manufacturing and SC optimization with "Augmented Reality" (AR) technology and "Industry 4.0" concept*
  Discussion in a thriving industry and academic collaboration for the most extensive shipbuilder in the world by integrating an optimization method and innovative IT technology, AR. They developed an advanced SC and manufacturing solution named SCM-AR based on AR and Mixed Reality solutions in collaboration with Samsung Heavy Industries Co. [103].

11.3.2 What Kind of Studies Is Being Carried out in the Field of OR&DS in Semiconductor Manufacturing?

The main objective of the above inquiry is to focus on the sort of research is being carried out in OR&DS field in terms of philosophical point of view along with practical assessments. To investigate this question, as the foremost step, Table 11.1 is

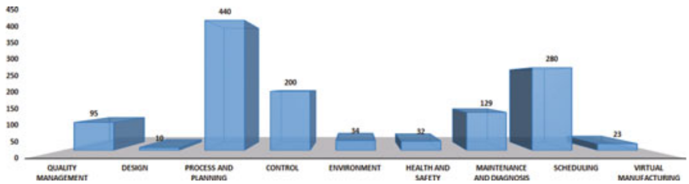


Fig. 11.1 Class allotment of **areas of manufacturing** for smart semiconductor industry

used to search all relevant articles since 2011. The articles (conference and journal papers), which were included at least one of the minor terms in semiconductor manufacturing and smart manufacturing and data science/operations research selected for the further analysis. We explored over 900 academic publications within this research. The classification result according to the definition of **areas of manufacturing** by Meziane et al. is depicted in Fig. 11.1. The result ratifies that there is an extensive gap in fitting the manufacturing design for intelligence layout. The intelligence 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 remanufacturing 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. with semiconductor manufacturing context. Some of the highlighted literature are cited as follows:

- OR
  - scheduling [104–109], production planing [110–112], job-shop scheduling [113], facility layout [114, 115], batch processing [115], bottleneck [116–118], dispatching [119–121], cycle time reduction [122–125], material handling [126], SC management [127, 128], inventory management [129, 130], demand forecasting [131, 132], capacity planing [133–138], lead time [139], supplier selection [140], purchase order [141], resource management [142, 143], pricing [144, 145], predictive maintenance [146], condition monitoring [147], operations planing and control [148–150], product quality [151], new product development [152, 153], industry development [154], user experience and interface [155–158], customer behavior[159], performance measurement [160], portfolio model [161], decision support system [162–164], large scale optimization [165], and sustainability [166].
- DS
  - Yield enhancement and prediction [167–172], WAT test [173], fault detection and classification [174–176], pattern extraction [177–179], root-cause detection [180], attribute decomposition [181], virtual metrology [182], rule-based system [183], and factor analysis [184].

Figure 11.2, illustrates the contributions of each topic in smart semiconductor industry. The scale of contribution defines such that the most relevant topic granted the smart semiconductor industry with the score of 100. Among all highlighted items, the yield enhancement and prediction, the scheduling problems, supply chain management, sustainability, and control system, are the major field of interest in articles since 2011. Due to dependency among process steps in wafer fabrication, challenges are spread along the production process such that single solution cannot clear up the

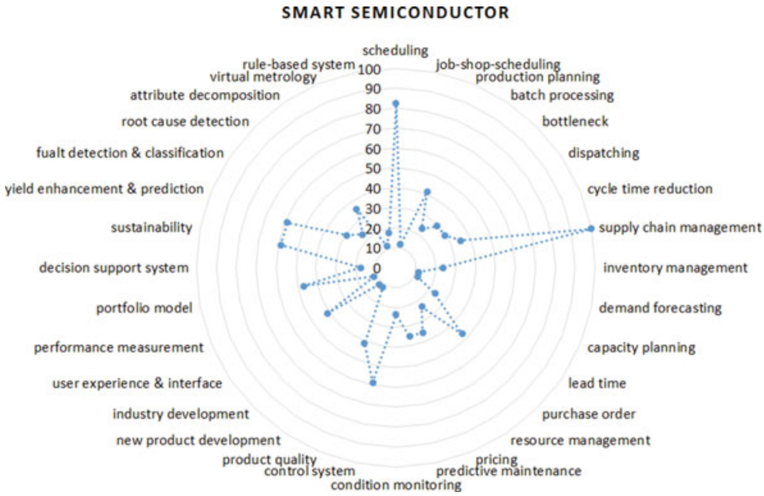


Fig. 11.2 Contribution of most frequent topics among the literature since 2011 related to smart semiconductor industry

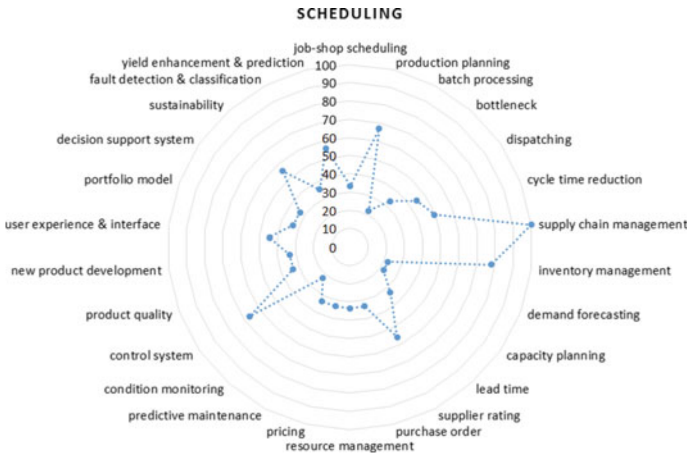


Fig. 11.3 Contribution of most frequent topics among the literature since 2011 related to scheduling in semiconductor industry

problem. Therefore, the hybrid models are a ubiquitous solution in semiconductor-related literature to deal with an epidemic dimension of problems. Figures 11.3, 11.4, 11.5, 11.6, and 11.7 demonstrate how the hybrid method is associated with each other where we only selected the most common techniques from Fig. 11.1. The results prove that the significant contribution is reminding among the most interesting topics, and there is an obligation for forming the hybrid configuration of OR&DS models for overcoming the dynamicity and measurement/unmeasurement uncertainty.

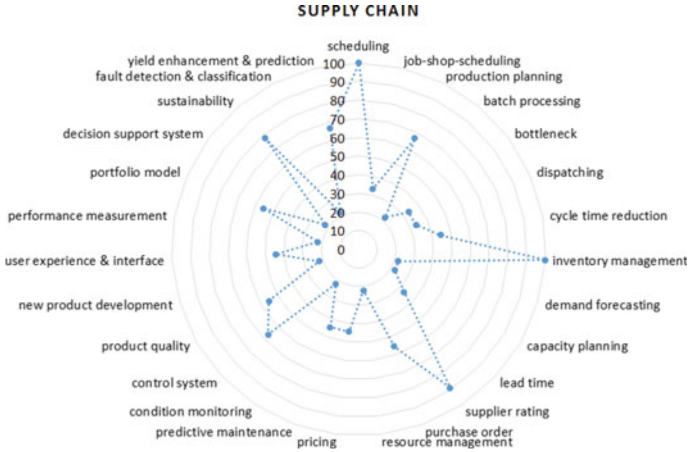


Fig. 11.4 Contribution of most frequent topics among the literature since 2011 related to supply chain in semiconductor industry

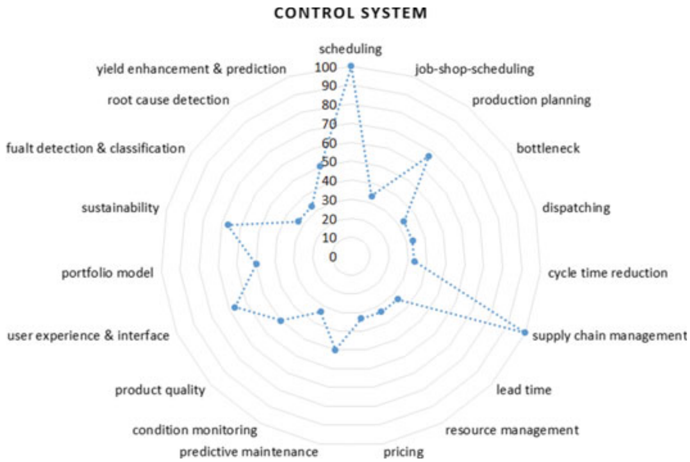


Fig. 11.5 Contribution of most frequent topics among the literature since 2011 related to control system in semiconductor industry

The classification study for the type of research method by Wieringa et al. [30] is illustrated in Fig. 11.8a, b. Figure 11.8a shows that how the type of research is branched over topics, and Fig. 11.8b 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 [30], and since this type of research his seldom happen in OR&DS field, we remove the experience from the list. Concluded from Figs. 11.3, 11.4, 11.5, 11.6, 11.7, and 11.8b, the decision support system and digitization the knowledge-based system have the lowest contribution among the other research topic

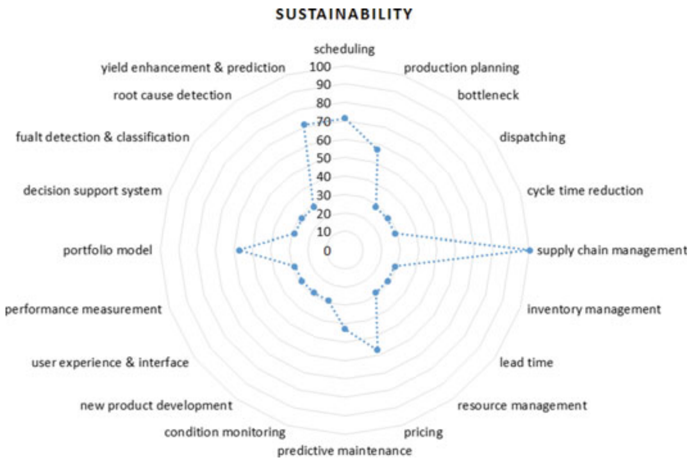


Fig. 11.6 Contribution of most frequent topics among the literature since 2011 related to sustainability in semiconductor industry

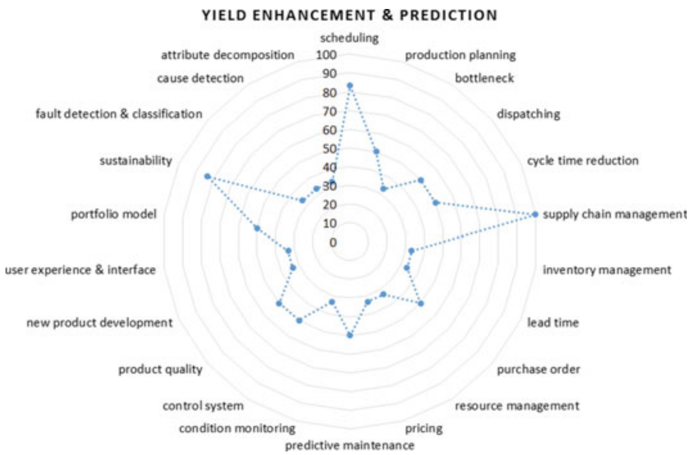
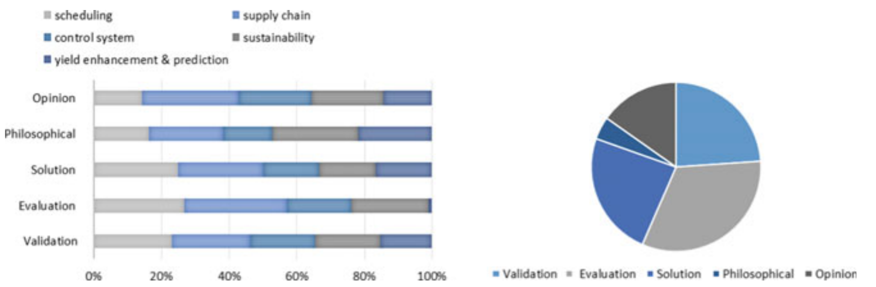


Fig. 11.7 Contribution of most frequent topics among the literature since 2011 related to yield enhancement and prediction in semiconductor industry

in current status which are required to have more inspection for advance development of smart semiconductor industry.



(a) Partitioning the contribution of most common topic in smart semiconductor based on **type of research**

(b) Class allotment of **type of research** for smart semiconductor industry

Fig. 11.8 Classification study

11.3.3 Which Areas of Semiconductor Manufacturing Are OR&DS Techniques Being Applied In?

The objective of the above inquiry is to highlight the types of inputs and outcomes from research struggles in the field of OR&DS. To categorize the literature according to the form of their contributions [32], we divided the attributes of contributions into two groups of variability on outcome and result (including architecture, framework, model, methodology), and variability on input information (including theory, platform, process, tool). In this category, platform indicates to the hardware or software components which enable the applications to execute while framework is the software solution for the problem. The process is the low-level processes to overcome the solution for problem and methodology is the approach to reach to that solution. The theory is the guideline or roadmap 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. Figure 11.9, illustrates the 2D plot between each category. The result shows that there is a vacancy for research on integration the mathematical model with software utilities, and hardware platforms. In addition, barely the mathematical solution has been used as the roadmap for decision makers which can be investigated in the future. The theoretical approaches for developing the smart semiconductor industry plus compatible utilities with high-tech computing technology have opportunely for further study.

11.3.4 What Kind of Analytical Analysis Is Being Used in the Area of OR&DS in Semiconductor Manufacturing?

The objective of the above inquiry is to discuss the analytics of OR&DS in the study carried out to smart technologies in semiconductor industry.

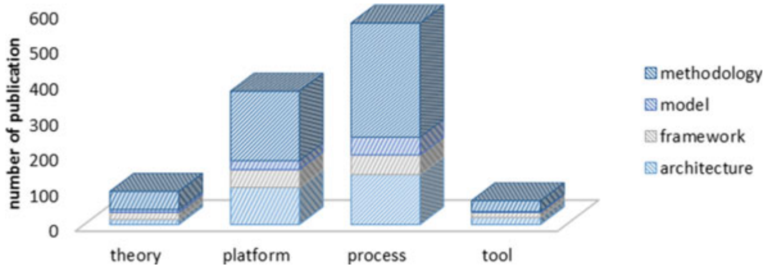


Fig. 11.9 Class allotment of **areas of manufacturing** for smart semiconductor industry

According to Delen et al. [33], the analytical analysis is classifying to descriptive, predictive, and prescriptive analysis where the descriptive analysis enables the business reporting, 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 by Fig. 11.10. Apparently, for advancement, the smartness into semiconductor industry, the descriptive analysis it will be an inevitable implement mainly for visualization the production process from the event-driven process.

To concentrate more deeply on analytical methods and their applications on the semiconductor industry, we come back to challenges discussed in Section 11.2 and review how analytic approaches applied to top challenges on control process of semiconductor products. Generally speaking, the popularity of techniques strongly depends on the popularity and severity of the challenges. The following are the details of applied methods for each challenge.

- **Photolithography process, overlay error**—challenges for compensating overlay error can be investigated through image processing [185, 186] (such as deep learning, and AI solutions [187]), optimal control algorithm design (such as linear and nonlinear programming and optimization [150, 188]), and learning-based algorithm (such as Markov decision process [189]) for enhancing the performance of robots and automated devices.
- **Scheduling and dispatching**-techniques in this field are not varied, more focuses are on optimization problems, however, the objective of optimizing models make a big emphasization on researches. The general optimization techniques appear in literature are meta-heuristic approaches or integer programming [104, 106–109, 113, 139, 190–194] in regards to the complexity and nature of problems. The minor challenges are addressed the batch data processing and dealt with this phenomena by simple techniques such as linear multivariate regression [195]. Recent trends utilized the integration of scheduling and dispatching control problems with other challenges in the production process such as advanced process control or

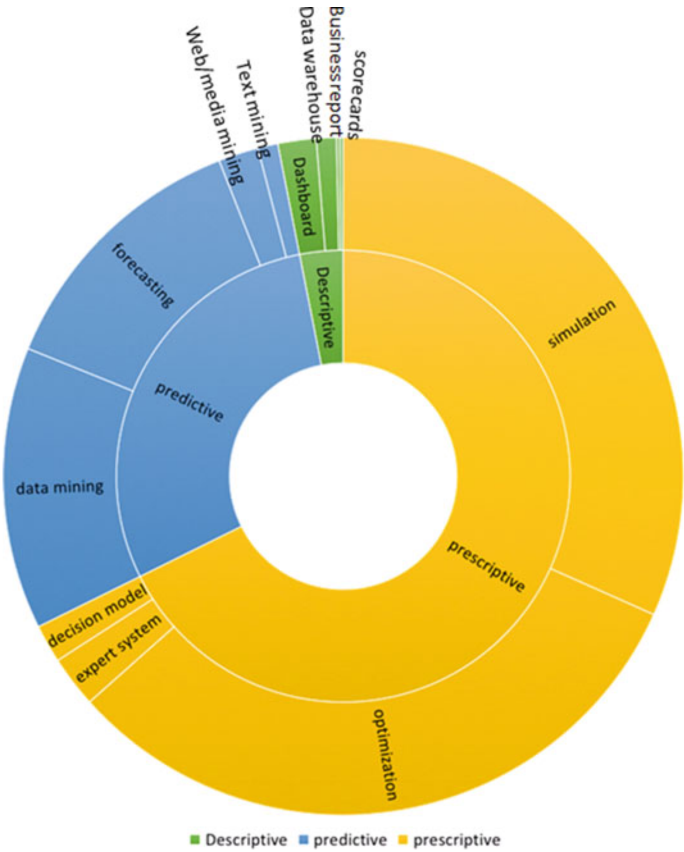


Fig. 11.10 Class allotment of **areas of manufacturing** for smart semiconductor industry

multi-agent-based system [196–198] and applied reinforcement learning for Heterogeneous sources [199–202] or AI models (e.g., neural network) [203] for the propose of clustering machine subgroups. If the challenges are related to queueing process, Markov processes also are alternative solutions in this field [204].

- **R2R control**—challenges for the R2R control in the semiconductor industry is divided into the design, optimization, application and process improvement. In the area of design, R2R controller could be designed for multi-input-multi-output (MIMO), multi-input-single-output (MISO) and single-input-single-output (SISO) systems, regards how is the dependency issue among the control variables [150, 168, 182, 205]. The most general structure of the R2R controller in the semiconductor industry is exponentially weighted moving average algorithm (EWMA) [206]. Consider the investigated problem and complexity of the control system, the EWMA is adjusted to double-EWMA (for multi-stage tasks) [207, 208] or threaded-EWMA (for the mixed process) [209]. In addition, smarter algorithms are intended to utilize optimal control design and replace it with traditional and popular EWMA techniques, recommended solutions are kernel-based algorithm [210], proportional–integral–derivative controller (PID) [150], learning-based algorithm [211], and game theoretical approaches (e.g., mini-max optimization) [171]. Trends in this field has potential to integrate with other techniques to deal with the different source of complexity in wafer fabrication process, such as clustering or principal component-based model for identifying the similar batch and design the decentralized R2R control for batch processing systems [212, 213]. The other major sources of challenges emerged with R2R control are addressing the improvement the control process through auxiliary resources, such as stability of control system under different sources of uncertainties and reach to steady-state control design [214–216], introduce new indexes for measuring controllability and reproducibility [211], enhance the precision of control parameters by automated or self-tuning algorithm [217], and emerge the control plant with metrology equipment [210, 218–220]. In addition, the R2R controller can assist with other phenomena rather than a control process, including, fault detection and root-cause identification and classification [221], change point detection, and yield enhancement [171]. Therefore, consider the application, the analytical approaches are specified (for details about model selection refers to other challenges). Other notable questions are how to deal with small size of data, how to derive error smoothly, how to design the R2R control system for dynamic system, and how to consider within process and between process R2R control models.

- **Disturbances and delay**—the main purpose of researches in this field is an investigation on the stability of other solution on the presence of any source of uncertainties. To do that, the first step is to simulate the unmeasurable uncertainties, the highlighted techniques are generally based on virtual metrology tools and can be classified on rule-based models such as fuzzy systems [222], or stochastic processes (e.g., Gaussian and non-Gaussian processes) [223]. In addition, plans for efficient and proper sampling can enhance the quality of data and reduce the noise [224]. Trends for root-cause detection and classification can help to find the source of uncertainties, the most approachable methods in this field are data mining approaches (e.g., principal component analysis, neural network or in general clustering or classification techniques) [225, 226]. In general words, challenges are tightened up with disturbance rejection models basically are related in control design and algorithm [227, 228].
- **Packaging**—since the quality of packaging strongly depends on thermal effects, major researches are addressed this challenges through the reliability and survival analysis such as degradation models or accelerated test [229]. In addition, before testing the reliability of packaging the thermal effects are predictable by thermal models based on Fourier series or Kalman filtering models [230]. To investigate the quality of packaging, few studies indicated this phenomenon by image processing [231, 232]. Furthermore, the packaging is almost the final production process in wafer fabrication, therefore has a strong correlation with yield testing result. Therefore, for the yield management purpose, one solution is to conduct the root-cause detection and classification based on the result from the packag-

ing process. Applicable methods in this step are clustering techniques with data mining approaches [40, 233–235].

- **Critical dimension**—although most approaches in this field are related to chemical and nanoengineering area, yet from the OR&DS perspective, the challenges for critical dimension enhancement are investigated by advanced process control and statistical quality control approaches [236, 237]. However, the recent advanced trends in this field are included the hybrid algorithm which could increase the performance of controller by adding optimization into process control [238, 239]. The more intelligent hybrid techniques are combined with the sequential learning or kernel-based learning such as support vector regression or other machine learning methods [167, 240, 241]. Some researches intended to produce virtual data by virtual metrology tools [242] to be able to have enough data as the basis requirements for applying traditional statistical inferences combined with learning techniques such as LASO and ridge regression [243, 244]. Other trends are investigated on root-cause identification for identifying the source of uncertainties and environmental protection through data mining approaches [171].
- **Scheduling for automated material handling**—scheduling challenges can be cover by two approaches, first, design an intelligent scheduling system basically through queueing theory and stochastic process [245], design the distributed network system by mathematical modeling languages such as Petri net [246–248], design the facility allocation by simulation optimization or design of experiment techniques such as Taguchi method [249, 250]. Second, find the optimal performance of dynamic multi-objective scheduling design through approaches such as heuristic optimization [143], sequencing optimization [251], and combinatorial optimization (e.g., Hungarian algorithm) [252]. The performance of the scheduling system could be measured in the field of quality control.

11.4 Management Suggestion

In semiconductor, managers need to overcome different challenges which are being mentioned in the above sections. Despite those challenges, in the following, we give certain future circumstances to "Industry 4.0" standpoints.

Digitalize knowledge-based decision support system

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

Incorporate the dynamicity into the solutions

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

Design software-based solution with user-friendly interface

- 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.

Forming the hybrid configuration of OR&DS models

- Facilitating planning 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.
- Decreasing the measurement uncertainty by merging the hybrid metrology with state-of-the- art statistical analyses [253].

Simulation and data-driven solutions

- Simulating the physical environment in order to comprehend the connections amid the real setting circumstance and planning to find solution approaches in the risk-free environment before applying them.
- 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 semiconductor by embedding the actual simulation methods in existing and forthcoming information systems.

Process integration

- 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 [254].
- Incorporating sustainability aspects into proposed solutions and deterministic models.
- Integrating the product lifetime into account for demand planning [255].

11.5 Conclusion and Future Research Direction

As a conclusion and future research direction, we attempted to have a broader vision on 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. In the following, we discuss some of the highlighted topics in this chain.

11.5.1 Supply Chain Management

Supply chain (SC) is growing exponentially and contributing substantially to the global economy. This growth is accompanied by continuous technology migration and minimizing cost for different applications in green energy, communication, computers, automotive, medical, and electronics industries [110]. There are some survey papers on SC in literature with the scope of needs, practices and integration issues in [256]; (1) Research agenda framework for supply network integration (questionnaire-based) in [257]; (2) Decision paradigms for SC management (questionnaire-based) in [258]; (3) Successes and opportunities in modeling and integrating planning, scheduling, equipment configuration and fab capability assessment in [259, 260]; (4) E-markets and SC collaboration in [261], and (5) Strategic SC network design and SC simulation models in [262–264].

According to [265] and [262], one future direction of semiconductor industry would be global SC simulation models based on a marketing operations perspective, which lead 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 [265, 266]).

11.5.2 Sustainability and Remanufacturing

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 [267], and (3) Circular economy and remanufacturing [18]. Nowadays, semiconductor industry has significantly and exponentially increased the rate of e-waste in daily life [268, 269]. 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 semiconductor [270].

11.5.3 Green Smart Semiconductor Manufacturing

Another future research stream would be data-driven decision-making and optimization applications in integrated Smart and Green Manufacturing. Some application challenges in this area would be: (1) Business Model Challenge: manufacturers face threats from digital disruptors that are often quicker 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 with it the challenges of protecting that data and ensuring it is secure. 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 [271].

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 [272].

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