A Review of Related Work on Machine Learning in Semiconductor Manufacturing and Assembly Lines

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ABSTRACT

This paper deals with applications of machine learning algorithms in manufacturing. Machine learning can be defined as a field of computer science that gives computers the ability to learn without explicitly developing the needed algorithms. Manufacturing is the production of merchandise by manual labour, machines and tools. The focus of this paper is on automatic production lines. The areas of interest of this paper are semiconductor manufacturing and production on assembly lines. The purpose of this paper is to review the relevant papers describing the applications of machine learning techniques in these fields of manufacturing thus creating a firm foundation for further research in the matter of machine learning in manufacturing.

CCS Concepts

•Computing methodologies → Machine learning; Supervised learning; Unsupervised learning; •Applied computing → Computer-aided manufacturing;

Keywords

machine learning, manufacturing, supervised, unsupervised, assembly line, semiconductor

1. INTRODUCTION

Machine learning applications have been present in manufacturing for the last two decades. Systems based on this technology are deployed with the goal to automate some of the tasks emerging from the dynamic field of industrial manufacturing. Some of the examples are expert systems for decision making support, systems for scheduling of concurrent production on assembly line, systems for predictive maintenance of machines used in production process as well as the manufacturing fault diagnoses systems.

In order to build a knowledge-based system that automates some of the tasks in manufacturing, detailed domain-expert knowledge has to be gathered. This step is crucial for any knowledge-based system as this expert knowledge is required for the system implementation. This step is also the most time-consuming and there is always the danger of invalid or incomplete knowledge transfer between the domain expert and the developers of the system. Machine learning techniques may decrease the development time of such systems and they often reveal knowledge that might be overlooked by those acquiring the domain-knowledge.

Machine learning can be defined as a field of study in computer science that enables the personal computers to automatically get more efficient at a given task through experience [37]. This field emerged from *pattern recognition* and *statistical inference*. A large portion of machine learning algorithms are classification algorithms. For the given training data set, defined as classified examples, the selected algorithm develops a model which is then used to classify new datasets. Many manufacturing problems belong to the class of classification problems where the industrial domain experts are requested to assign a class to an object or dataset according to the state of the parameters of that object.

Based on the experience made in this field, faults happen quite often in the process of production of any kind. Not being able to detect and correct those faults means increase of production costs and it could even be a reason for production delay or complete standstill. These reasons led to increased interest of industry for machine learning techniques as a most efficient way to develop an expert knowledge-based system. The investigation of published papers in this field of study showed that machine learning techniques are used in different branches of industry. Industry fields in focus of this paper are semiconductor manufacturing and automated assembly lines.

The goal of this paper is to show through several practical examples that the application of machine learning techniques on manufacturing problems can lead to increased productivity and decrease of production costs by early detection of production faults. The most of the publications reviewed and cited in this paper are up to 15 years old, not including the ones dealing with the theoretical concepts of machine learning. The ACM and IEEE libraries were searched for publications in the fields of interest for this paper.

One practical example of a challenge in semiconductor manufacturing is the thickness prediction of CVD (Chem-

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ical Vapour Deposition) on wafers. Using Virtual Metrology (VM) and Root Cause Analysis (RCA) (explained in detail in [39]) one can detect irregularities in CVD material thickness, thus predicting the wafers of lower quality. In semiconductor manufacturing, production is based on wafers where wafers are organized into lots (25 wafers = 1 lot). The goodness of the production process is assessed by measuring one or more parameters on the wafer (for CVD, it is the thickness of the deposited material). Such measurements are costly and time-consuming and the common practice is to do measurements only on a small portion of wafers belonging to the same lot, usually only on a single wafer. Thus, the information about the goodness of the non-assessed wafers across the lot is missing. This leads to difficulties in detecting drifts in production. One way around this problem is the Virtual Metrology approach. The production data, originating from fabrication machines from different stages of semiconductor manufacturing process (temperature, pressure, etc.) is used to estimate the goodness of physically non-assessed wafers. It provides at least an estimation of wafer quality.

2. INDUSTRIES OVERVIEW

The focus of this paper is on the application of machine learning methods in semiconductor manufacturing and assembly lines. This section provides rather short presentation of facts important for both of the named industry fields.

2.1 Semiconductors manufacturing

The semiconductor manufacturing industry is one of the most technologically advanced industries today and as such it is also one of the most cost-intensive industries. The $336 billion industry of semiconductors [46] provides enough opportunities for researches to apply new technologies with the goal to decrease the production costs. The pervasive nature of the semiconductor devices implies that they are widely used in every segment of our lives; such devices can be found in our mobile phones, personal computers, cars etc. With ever increasing time-to-market expectations, solving production problems and increasing yield in such a complex production process as it is in case of a semiconductor manufacturing, is getting more difficult. A range of production problems can be detected by means of statistical analysis [41] and design of experiments [6] which provides a solid ground for well-tuned manufacturing processes. When the occurring problems are caused by non-linear interactions of different process parameters in combination with ever increasing amounts of data produced in the process, solving these problems is getting tougher. In the milestone paper [13] the authors presented the future challenges for modeling and control in semiconductor manufacturing. Since the year 2000 significant research effort is invested in this area and advances made are mostly enabled by the application of machine learning and computational advances [39]. As already stated in the introductory part of this section, the semiconductor manufacturing is one of the most complex and technologically advanced manufacturing processes. The process typically consists of more than 500 steps. All those steps in semiconductor fabrication in fab are monitored thus generating immense amounts of data. In recent years, all the fabrication equipment is delivered with equipment/production sensors. Although the real-time monitoring of production is possible, the amount of generated data is so overwhelming that the timely detection of production faults is difficult to achieve. It is the *BigData* technology that enables the predictive maintenance in this case. The typical order of fabrication steps, as described in [30], [26] are: synthesizing of silicon wafers out of silicon material, fabrication of integrated circuits on newly synthesized silicon wafer, putting the integrated circuit into the package in order to produce ready to use product and testing. Figure 1 depicts some

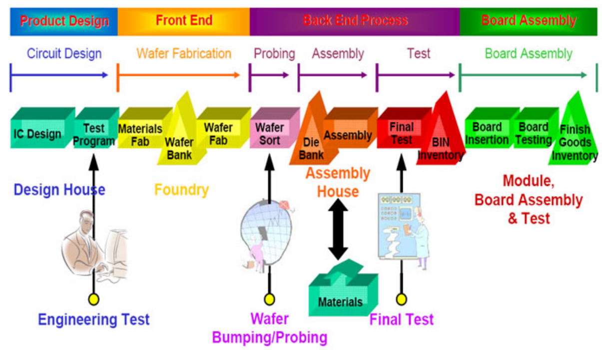

Figure 1: Simplified semiconductor fabrication process overview[2]

of the semiconductor fabrication steps. As the goal of this paper was not the completeness of the semiconductor fabrication methodology description, interested readers could find the additional and more detailed information on this topic in [26] and [34].

2.2 Assembly Line Process

The second field of manufacturing of interest for this paper is the automated assembly line. This kind of manufacturing process can consist of dozens of subsequent workstations. In-line measuring equipment and different types of sensors could be installed in assembly stations, thus being able to produce huge amount of useful data. One good example is the robotised car-body assembly line. One such example is published in [25]. Similar to semiconductor manufacturing, production faults can be introduced to the system virtually in every step of the assembly process. It is hard to diagnose and localize such faults if they are in non-liner relationship. Some of the solutions for this kind of problems, which can be solved by using machine learning algorithms, are reviewed in this paper.

3. MACHINE LEARNING (ML)

Machine learning provides methods that can generate solutions for complex problems. For some problems it is not feasible to specify the exact solution manually. Machine learning techniques can be seen as very useful tools for pattern discovery in large datasets. It is important to state the fact that there is no single ML technique or algorithm optimal for all the problems in manufacturing. Every single use case has to be analysed separately and according to the requirements of the problem an appropriate machine learning technique has to be applied. A machine learning algorithm has to fulfill several requirements in order to be applicable in

[2]The figure shown is taken from http://www.li-sion.com.tw/en/support.asp?pno=5, 16.08.2016

manufacturing. Some of the most important requirements stated in [32] are:

- being able to handle different types of data (numerical, textual, images etc.)
- being able to deal with noise and outliers in data
- real-time processing
- being able to deal with huge datasets and/or high-dimensional datasets

Machine learning techniques are usually classified in three main groups according to the *feedback signal* available to the learning system [38]:

- **supervised learning**: the algorithm is fed with labelled examples and this *knowledge* is used to learn and build a model. The generated model is used to solve the problem of the same type but this time for non-labelled data. Classification problems are the typical representative of supervised learning.
- **unsupervised learning**: the learning algorithm is fed with non-labelled data. The goal of such an algorithm is to discover patterns in non-labelled data and/or to extract features from the given unlabelled dataset. Clustering is a typical problem solved by unsupervised learning algorithms.
- **reinforcement learning**: a machine learning algorithm interacts with a dynamical environment while performing actions toward fulfilment of the goal without a *teacher's* evaluation if the performed actions are good or bad. A typical example for reinforcement learning is the *self-driving car*.

Only the first two classes are examined for this paper because no information about application of reinforcement learning in manufacturing was found. Further, some of the most common approaches in machine learning will be shortly discussed.

The most prominent machine learning discipline is **classification**. For a given vector of input parameters together with the target function, the learning algorithm builds a prediction model. By applying this model on future examples, predictions are made. Parameters of the input vector can be nominal or continuous attributes. If the target value of the input vector is not given, the expectation of the learning algorithm is to group/cluster the instances according to a predefined similarity/distance measure. This discipline of machine learning is called clustering.

Decision-tree induction is represented by several well known algorithms from the class of supervised learning.
Among them the most popular ones are **CART** (Classification and Regression Tree), **ID3** (Iterative Dichotomiser 3), **C4.5** and **C5.0**. Detailed review and theory behind these algorithms can be found in [5], [33]. By learning, algorithms of this family represent the knowledge in form of a decision-tree. Each node of such induced knowledge decision tree represents a test on an attribute in the dataset and each branch connected to that note is a possible outcome of the test. The leafs of the decision tree hold the class labels. When such an algorithm is applied on the training set, a decision tree is generated in top-down manner and the generated decision-tree can be translated in a sequence of IF-THEN rules. The advantages of this approach are: (i) algorithm is simple to understand and the results produced can be interpreted simply (ii) input data does not have to be preprocessed (iii) not restricted to numerical data (iv) good performance on both small and large datasets. There are special variations of decision-tree algorithms where, during the learning process, more than one decision tree is induced. The most popular algorithm of this kind is **RandomForest** [4].

The next group of algorithms are **Rule Induction** algorithms. There are many different rule induction algorithms in use today. Some of them are **CN** [7], **AQ** (Algorithm Quasi-optimal) [27], **RIPPER** (Repeated Incremental Pruning to Produce Error Reduction) [8], **SLIPPER** (Simple Learner with Iterative Pruning to Produce Error Reduction) [9] and **RULES** (RULe Extraction System) [31]. Contrary to decision-tree algorithms, rule induction algorithms directly generate a sequence of IF-THEN rules. The general mode of operation of these algorithms is to take one instance of data from the dataset at the time to induce a rule from it. After the rule is generated, the used data instance is removed from the dataset. This procedure repeats until all instances in the dataset are covered by at least one rule from the set of induced rules. A common name for both decision-tree induction and rule induction is **Inductive Learning**.

In contrast to inductive learning which has the idea to make a generalized model describing the training data, there is another approach to machine learning, called **Instance-Based Learning** [2]. By this kind of machine learning the actual data instances from the training dataset are stored in memory with the goal to describe the dataset. Typical representatives of instance-based learning are the **k-nearest-neighbor** [40] algorithm and **Support Vector Machine (SVM)** [10]. The main advantages of the instance-based learning algorithms are the ability to model complex targets and the fact that there is no loss of information caused by generalization of the training data. On the other hand, the costs at classification time can be high because of the fact that all the classification calculations are done at the time of arrival of instances to be classified.

Neural Networks are a robust, general purpose method for learning real and discrete valued targets. The robustness of this method implies that it is designed to successfully handle noisy input data. Because of this fact, neural networks are well suited for analysis of sensor signal data. Examples of such data are microphone or camera signals. The neural networks can be used in both supervised and unsupervised modes, supervised for classification and unsupervised for clustering. The best known classification algorithm is the **Back-Propagation** algorithm for **Multilayer Perceptron Networks**, the most popular type of neural networks. Interested readers find further information on this topic in [16]. As stated earlier, neural networks can additionally be used for clustering. One of the algorithms used for this purpose is the **Self-Organizing Map (SOM)** algorithm [22].

The next class of algorithms investigated in this work are based on the **Bayesian Approach**. Such algorithms exploit the probabilistic approach to model representations by using the Bayes theorem. There are different implementations of this approach varying between a simple Bayesian classifier [12] which learns just the class description, to the

Bayesian Networks [17] which learn the full joint probability distribution of the attributes and classes. **Naive Bayes** classification algorithm is really simple to implement and as such, it is often the algorithm of choice for text classification (email spam filter etc.). The data set being analysed is converted to frequency table and this intermediate table is than converted to probability table. If the assumption of independence of features holds, the algorithm converges quickly for even small training sets. Otherwise, if the features are correlated, this approach is probably not the best choice.

Unsupervised learning represents the second prominent machine learning discipline. The goal of the algorithms belonging to this group is to infer a function that is able to describe the hidden structure in non-labelled data. Since the input data is not labelled, there is no error feedback signal that can be used to evaluate the solution. Exactly the lack of error feedback signal differentiates the unsupervised from supervised learning. Clustering is a typical problem solved by unsupervised learning. Clustering can be defined as a grouping together of objects with the similar properties. An object is more similar to the other objects from the same group (cluster) than to the objects belonging to some other group. Usually, the object have more than one property, so, it can be thought of as a point in a high-dimensional space. The similarity of objects is defined as the distance between the points in space. Some of the distance measures used are: Euclidean, Cosine and Jaccard distance. Previously in this section, SOM was mentioned as a one of the clustering algorithms. Some of the other widely used clustering algorithms are **k-means** [20] and **hierarchical clustering** [3]. It is interesting to state that k-means algorithm has literally tens of variations adapted for different special case scenarios, thus making him one of the most widely used clustering algorithms.

4. APPLICATIONS OF MACHINE LEARNING IN MANUFACTURING

Semiconductor industry expansion began more than 30 years ago and since then significant effort is made in research, development and implementation of new technologies in order to make this technology what it is in the world today [29]. But ever increasing complexity of the semiconductor production process led to longer time periods needed to detect and localize equipment faults with hundreds or thousands possible production parameters involved. In the following text, some of the use cases of machine learning in semiconductor manufacturing will be presented.

Gardner and Bieker [15] describe the way Motorola engineers tackled the problem of inconsistent and unstable wafer yield. They presented three case studies demonstrating the usability of their proposed solution to this problem. The application of the self-organizing neural networks (Kohonen's self-organizing map) for clustering and rule induction in order to detect problems on wafer fabrication equipment installed in Motorola fabs was shown in detail. According to the study, they were able to localize production problems in three different use cases. They stated that the production problems could not be located with other methods for months. Possible outcome of not being able to solve the production issues was the loss of important customers. Fault detection and classification systems were widely deployed in recent years. Some of the examples are mentioned in [28], [1], [36]. Lee and colleges presented a fault detection system in [23]. The authors used the SVM model to perform the classification of the production data. They compared the experimental results with the results of back-propagation neural networks to validate the experimental results. The Pearson product-moment correlation was used to identify the influencing factors of production quality. In [45], Yu et al. describe a novel method of lithography hotspot detection. They used clustering to produce hotspot and non-hotspot clusters. The critical features were extracted from the produced clusters. Those features were used to train a SVM model. Similar experiments were carried out in [14], [11], [18]. Two more examples of application of self-organizing maps and support vector machines to identify the fabrication faults are presented in papers [21] and [24].

Another field of manufacturing where machine learning can be successfully deployed is the production on automatized assembly lines. As this case is of special importance for this paper, several papers from this field were reviewed. Contrary to the number of published papers in the field of machine learning in semiconductor manufacturing, there is only a limited number of papers published, which examine production on automatized assembly lines.

Wu et al. [44] developed a method for fault detection and localization by using support vector machines. They called the implemented system fuzzy fault system because it implements the detection of faults in a nonlinear fuzzy fault system with multi-dimensional input variables. The input and output variables are described as fuzzy numbers. By combining fuzzy theory and v-support vector classifier machines, they proposed a triangular fuzzy v-support vector regression machine (TF v-SVCM). In order to find the optimal parameters for this method, the particle swarm optimization method was used. By providing experimental results, the authors provided the evidence that the proposed solution is both feasible and effective in detecting the faults in car assembly line data. The same authors proposed another two similar approaches, [43], [42] for the same problem of fault detection in car assembly data. Those are modifications of the original approach, where, instead of using the v-SVC, the proposed methods use the Gaussian kernel and fuzzy wavelet kernel support vector classifier machine, respectively. In [35], Rodriguez et al. gave another example of a successful implementation of SVM in fault detection during the contact phase of the assembly process. The paper also deals with the correlation between the number of training examples with the overall system accuracy. Principal Component Analysis was used to decrease the number of examples needed to successfully train the classification system. Principal Component Analysis is defined as a statistical method used to transform the set of possibly correlated variables into the set of linearly uncorrelated variables called principal components [19]. The number of principal components is always less then or equal to the number of possibly correlated variables. Because of this fact, it belongs to the group of dimensionality reduction approaches.

The common contribution of all cited publications in this paper concerning the application of machine learning techniques in manufacturing is that the time needed to detect faults in production was decreased. In some cases it was crucial to use such techniques as otherwise the system faults could not be identified and localized.

5. CONCLUSION

By reviewing selected papers dealing with use-cases of machine learning applications in manufacturing, it is confirmed that machine learning techniques can be a very useful tool in manufacturing optimization. Although the reviewed papers only deal with machine learning applications in semiconductor manufacturing, assembly lines fault detection and concurrent task scheduling, it can be stated that machine learning can be successfully applied in many other manufacturing branches. The benefits of machine learning could be utilized for different purposes whether it is equipment/tool fault detection, root cause analysis or others. Its application significantly shortens the time needed to built almost any expert knowledge-based system, time needed to detect production or assembly faults thus giving more time to engineers to correct faults found. This is exactly the reason why machine learning could have such an economic impact on manufacturing. A lot of papers on this topic are published in recent years.

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7. REFERENCES

[1] T. Adamson, G. Moore, M. Passow, J. Wong, and Y. Xu. *Strategies for successfullz implementing fabwide FDC methodologies in semiconductor manufacturing.* AEC/APC Symposium XVIII, 2006.

[2] D. W. Aha, D. Kibler, and M. K. Albert. Instance-based learning algorithms. *Machine Learning*, 6(1):37–66, 1991.

[3] M.-F. Balcan, Y. Liang, and P. Gupta. Robust hierarchical clustering. *J. Mach. Learn. Res.*, 15(1):3831–3871, Jan. 2014.

[4] L. Breiman. Random forest. *Machine Learning*, 45:5 – 32, 2001.

[5] L. Breiman, J. Friedman, and R. O. Charles J. Stone. *Classification and Regression Trees.* Chapman and Hall/CRC, 1984.

[6] C.-F. Chien, K.-H. Chang, and W.-C. Wang. An empirical study of design-of-experiment data mining for yield-loss diagnosis for semiconductor manufacturing. *Journal of Intelligent Manufacturing*, 25(5):961–972, 2014.

[7] P. Clark and T. Niblett. The cn2 induction algorithm. *Machine Learning*, 3:261 – 283, 1989.

[8] W. W. Cohen. Fast effective rule induction. In *In Proceedings of the Twelfth International Conference on Machine Learning*, pages 115–123. Morgan Kaufmann, 1995.

[9] W. W. Cohen and Y. Singer. A simple, fast, and effective rule learner. In *Proceedings of the Sixteenth National Conference on Artificial Intelligence and the Eleventh Innovative Applications of Artificial Intelligence Conference Innovative Applications of Artificial Intelligence*, AAAI '99/IAAI '99, pages 335–342, Menlo Park, CA, USA, 1999. American Association for Artificial Intelligence.

[10] C. Cortes and V. Vapnik. Support-vector networks. *Machine Learning*, 20(3):273–297, 1995.

[11] D. Ding, J. A. Torres, and D. Z. Pan. High performance lithography hotspot detection with successively refined pattern identifications and machine learning. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, 30(11):1621–1634, Nov 2011.

[12] P. Domingos and M. Pazzani. Beyond independence: Conditions for the optimality of the simple bayesian classifier. In *Machine Learning*, pages 105–112. Morgan Kaufmann, 1996.

[13] T. F. Edgar, S. W. Butler, W. Campbell, C. Pfeiffer, C. Bode, S. B. Hwang, K. S. Balakrishnan, and J. Hahn. Survey automatic control in microelectronics manufacturing: Practices, challenges, and possibilities. *Journal Automatica (Journal of IFAC)*, 36:1567–1603, November 2000.

[14] J. R. Gao, B. Yu, D. Ding, and D. Z. Pan. Lithography hotspot detection and mitigation in nanometer vlsi. In *ASIC (ASICON), 2013 IEEE 10th International Conference on*, pages 1–4, Oct 2013.

[15] M. Gardner and J. Bieker. Data mining solves tough semiconductor manufacturing problems. In *Proc. 6th ACM SIGKDD Conference, Simoff*, pages 376–383, 2000.

[16] S. Haykin. *Neural Networks: A Comprehensive Foundation.* MacMillan Publishing Company, 1994.

[17] D. Heckerman. Bayesian networks for data mining. *Data Mining and Knowledge Discovery*, 1(1):79–119, 1997.

[18] N. Jia and E. Y. Lam. Machine learning for inverse lithography: using stochastic gradient descent for robust photomask synthesis. *Journal of Optics*, 12(4):045601, 2010.

[19] I. T. Jolliffe. *Principal component analysis.* Springer series in statistics. Springer, New York, Berlin, Heidelberg, 2002. Autre(s) tirage(s) : 2004.

[20] T. Kanungo, D. M. Mount, N. S. Netanyahu, C. D. Piatko, R. Silverman, and A. Y. Wu. An efficient k-means clustering algorithm: analysis and implementation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(7):881–892, Jul 2002.

[21] H. G. Kim, Y. S. Han, and J. H. Lee. Package yield enhancement using machine learning in semiconductor manufacturing. In *2015 IEEE Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, pages 316–320, Dec 2015.

[22] T. Kohonen. *Self-Organizing Maps.* Springer, 2001.

[23] C.-H. Lee, H.-C. Yang, S.-C. Cheng, and S.-W. Tsai. A hybrid big data analytics method for yield

improvement in semiconductor manufacturing. In *Proceedings of the ASE BigData & Social Informatics 2015*, ASE BD&SI '15, pages 9:1–9:4, New York, NY, USA, 2015. ACM.

[24] T.-S. Li and C.-L. Huang. Defect spatial pattern recognition using a hybrid som-svm approach in semiconductor manufacturing. *Expert Systems with Applications*, 36(1):374 – 385, 2009.

[25] J. M. Liu, S. T. Zhu, and H. M. Liu. A control system of the transferring robot in car assembly line. In *Information Technology Applications in Industry, Computer Engineering and Materials Science*, volume 756 of *Advanced Materials Research*, pages 303–306. Trans Tech Publications, 10 2013.

[26] G. S. May and C. J. Spanos. *Fundaments of Semiconductor Manufacturing and Process Control*. John Wiley and Sons Publishing, 2006.

[27] R. S. Michalski and K. A. Kaufman. The aq19 system for machine learning and pattern discovery: A general description and user's guide. *Reports of Machine Learning and Inference Laboratory, MLI 01-2, George Mason University Fairfax, VA 22030-4444*, 2001.

[28] T. Moore, B. Harner, G. Kestner, C. Baab, and J. Stanchfield. *Intel's fdc proliferation in 30mm hvm: Progress and lessons learned*. AEC/APC Symposium XVIII, 2006.

[29] P. R. Morris. *A History of the World Semiconductor Industry*. History of Technology. Institution of Engineering and Technology, 1990.

[30] S. Munirathinam and B. Ramadoss. Predictive models for equipment fault detection in the semiconductor manufacturing process. *IACSIT International Journal of Engineering and Technology*, 8, August 2016.

[31] D. T. Pham and A. A. Afify. Rules-6: a simple rule induction algorithm for supporting decision making. In *31st Annual Conference of IEEE Industrial Electronics Society, 2005. IECON 2005.*, pages 6 pp.–, Nov 2005.

[32] D. T. Pham and A. A. Afify. Machine-learning techniques and their applications in manufacturing. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, Mai 2005.

[33] J. Quinlan. Induction of decision trees. *Machine Learning*, 1:81 – 106, 1986.

[34] M. Quirk and J. Serda. *Semiconductor Manufacturing Technology*. Prentice Hall, 2000.

[35] A. Rodriguez, D. Bourne, M. Mason, G. F. Rossano, and J. Wang. Failure detection in assembly: Force signature analysis. In *2010 IEEE International Conference on Automation Science and Engineering*, pages 210–215, Aug 2010.

[36] A. Schirru, S. Pampuri, and G. DeNicolao. *Multilevel statistival process control of asynchronius multistream process in semiconductor manufacturing*. IEE Conference of Automation Science and Enginieering, 2010.

[37] P. Simon. *Too Big To Ignore: The Business Case for Big Data*. Wiley, 2013.

[38] P. N. Stuart Russell. *Artificial Intelligence: A Modern Approach*. Prentice Hall, 1995.

[39] G. A. Susto, S. Pampuri, A. Schirru, G. D. Nicolao, S. McLoone, and A. Beghi. Automatic control and machine learning for semiconductor manufacturing: Review and challenges. *The 10th European Workshop on Advanced Control and Diagnosis (ACD 2012)*, November 2012.

[40] Z. Voulgaris and G. D. Magoulas. Extensions of the k nearest neighbour methods for classification problems. In *Proceedings of the 26th IASTED International Conference on Artificial Intelligence and Applications*, AIA '08, pages 23–28, Anaheim, CA, USA, 2008. ACTA Press.

[41] W. H. Woodall. Controversies and contradictions in statistical process controlâĂİ (with discussion. *Journal of Quality Technology*, pages 341–378, 2000.

[42] Q. Wu, R. Law, and S. Wu. Fault diagnosis of car assembly line based on fuzzy wavelet kernel support vector classifier machine and modified genetic algorithm. *Expert Syst. Appl.*, 38(8):9096–9104, Aug. 2011.

[43] Q. Wu and Z. Ni. Car assembly line fault diagnosis based on triangular fuzzy gaussian support vector classifier machine and modified genetic algorithm. *Expert Systems with Applications*, 38(5):4734 – 4740, 2011.

[44] Q. Wu and Z. Ni. Car assembly line fault diagnosis based on triangular fuzzy support vector classifier machine and particle swarm optimization. *Expert Syst. Appl.*, 38(5):4727–4733, May 2011.

[45] Y. T. Yu, G.-H. Lin, I. H. R. Jiang, and C. Chiang. Machine-learning-based hotspot detection using topological classification and critical feature extraction. In *Design Automation Conference (DAC), 2013 50th ACM/EDAC/IEEE*, pages 1–6, May 2013.

[46] Y. Zhu and J. Xiong. Modern big data analytics for "old-fashioned" semiconductor industry applications. *ICCAD '15 Proceedings of the IEEE/ACM International Conference on Computer-Aided Design*, pages 776 – 780, 2015.