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A NOVEL METHOD GUIDING IC MANUFACTURING R&D DIRECTION: PERSPECTIVE FROM KNOWLEDGE INTEGRATION INNOVATION

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Abstract. *Integrated circuit (IC) manufacturing involves complex processes and may require months to complete. Thousands of messages will be generated during each process, and most messages can easily be identified and analyzed. However, ambiguous information remains as a kind of tacit knowledge that is one of the most essential issues of R&D management. Integrated innovation is an application of scientific/technological creative solutions to complex processes. This research uses a case study of a semiconductor company in Hsinchu Science Park in northern Taiwan. Traditional methods only yield the results inferred from explicit knowledge, and omit the results based on tacit knowledge. The integrated method can be designated as a clear direction for the R&D which uses the multivariate statistical analysis as virtual sensors. By involving Hotelling T2, and the principal component analysis (PCA), to generate specific results corresponding to the core of the high density plasma chemical vapor deposition (HDP CVD) equipment or process, eliminate inaccurate information using the experience rating in a 12-inch fab. This provides an approach that can guide the R&D engineers and illuminate the entire process. In sum, both process stabilization and cost savings are the major advantages of virtual sensors.*

Keywords: Integrated innovation method, R&D management, Virtual sensors, Knowledge management, Multivariate statistical analysis, IC manufacturing

1. **Introduction.** Knowledge is the key to a competitive advantage as a potential tool (Okatan [36]). Innovation capacity has become increasingly important for a firm's survival (Catherine et al. [8]; Niu and Hsin [35]). For the high-tech industry, innovation is represented by the excellent product development and the process efficiency improvement which exceeds those of their/its rivals. The R&D department plays a core role in promoting innovation and development (Adams and Lamont [1]; Cardinal et al. [7]; Cho et al. [10]; Halawi et al. [19]). Innovation is considered a force with the primary progress, prosperity and the management innovation application can result in the long-term competitive advantages (Crossan and Apaydin [12]; Hitt et al. [22]; Volberda et al. [47]). Furthermore, the knowledge-based approaches to innovation have emphasized the role of knowledge integration (Martín-de Castro [32]; Hurnonen et al. [24]).

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In a knowledge-based society, the processes by which knowledge is created, acquired, communicated, and applied must be effectively managed (Szulanski [44]; Martín-de Castro [32]). One of the results of knowledge management is innovation, which includes new products, new technologies, new markets, new materials, and new combinations (Alaei et al. [2]; Hurnonen et al. [24]), and the higher value for innovations that come from the new knowledge combinations (Hitt et al. [22]; Lahiri [28]; Penner-Hahn and Shaver [37]; Singh [42]; Wang et al. [48]). Knowledge management capabilities and knowledge innovation are the most important parts for improving business performances (Joaquín et al. [25]; Lin and Chang [30]; Okatan [36]). Knowledge integration innovation is more emphasized nowadays, especially in R&D.

Knowledge capital is often considered to be more important than financial and physical capital. In this paper, knowledge management is defined as the access to expertise, knowledge, and expertise that provides new capabilities, enables better performance, encourages development and innovation, and boosts customer value (Gloet and Terziovski [17]). Knowledge management is also a set of processes and usage systems that seek to alter the pattern of organizational knowledge processing and value (Scarbrough [40]; MilenaLopes et al. [33]). The awareness of the R&D engineers involved in a project determines its success (Gassmann and Zedtwitz [15]; Ritala et al. [39]). Indeed, knowledge management is the most important portion of R&D management in IC manufacturing.

Tacit knowledge is a type of information, best described as "we can know more than we can tell" (Polanyi [38]). Tacit knowledge is an important starter in the innovation process and it has a significant impact on the application for the innovation process. It is hard to capture from minds (Okatan [36]), as it is deeply rooted in an individual's actions and experiences (Polanyi [38]). Cardinal et al. [7] indicated that, in situations where a great deal of tacit knowledge is used for innovation, collaboration between cross-functional teams is essential. Unfortunately, the knowledge in these "recipes" is not necessarily codified, but often stays within the innovation and operational teams' routines and skills. Knowledge management can assist in the access and codification of such tacit knowledge. An engineer's experience and talent is a valuable tacit knowledge for an R&D department. Hence, systematizing practical experience for storage and access can bridge the gap between the experts and novices in an R&D department. Knowledge management can play a major role in facilitating collaboration, which, in turn, can assist in the sharing of the tacit knowledge (Coad and Rao [11]; Martín-de Castro [32]).

The fact that knowledge is not available in an explicit format makes the knowledge sharing and the application in the innovation process difficult, especially in the integrated circuit (IC) manufacturing industry, as this manufacturing process involves many complex messages. Most of the process's parameters can be observed by physical sensors, but to obtain the best parameter combination, some are tweaked by the R&D engineers using their accumulated experience. It is difficult to make this tacit knowledge concrete, which is one of the most important issues for the R&D management in the IC manufacturing process. Through usage of a database compiling of an engineer's expertise, tacit knowledge can be codified to make it explicit and more readily available for future innovations. Therefore, one of the motivations of this study is to realize tacit knowledge from engineering experts.

R&D is defined as discovering new knowledge regarding products, processes or services, etc., and then applying that knowledge to create (or improve) new (or existing) products, processes, and services, that fill the market needs. It is difficult to evaluate the R&D performance, as it is a complex construct (Lin and Chen [29]). Many studies on the R&D project success factors have reported a set of factors leading to the success of these projects based on personal experiences (Balachandra and Brockhoff [5]; Holzmann [23]).

Therefore, one of the principal determinants of the R&D project's success is the mode of knowledge involved (tacit/explicit) (Cavusgil et al. [9]; Gassmann and Zedtwitz [15]; Gloet and Terziovski [17]; Kirianaki et al. [27]), and knowledge management dynamic capabilities act as an important role for the innovation performance (Alegre et al. [4]).

The IC manufacturing industry plays an important role in the national economy of Taiwan (Niu [34]), and the IC manufacturing process involves complex systems and complex science (Gen et al. [16]). The manufacturing process may take months and involves hundreds of processes including diffusion, lithography, thin film deposition, and etching, performed on hundreds of machines, including implanters, chemical vapor deposition (CVDs), physical vapor deposition (PVDs), furnaces, steppers, and wet benches, and is measured by sensors or metrologies. Within each process, the parameters of control are the key factors of the yield rate. The duty of an IC manufacturing R&D is to optimize the process parameters. Therefore, the second motivation of this study is to explore the tacit knowledge from the manufacturing process.

Deposition of coatings by plasma enhanced chemical vapor deposition is the most complex of all plasma surface treatment techniques (Dhar [13]). The module development of the plasma enhanced chemical vapor deposition (PECVD) process includes several kinds of process parameters, such as the RF power, total pressure inside the reactor, flow rates of gases involved, substrate temperatures, type of electrodes used, and reactor type or geometry (gases, flow rate, vacuum percentage, electric and magnetic field intensity). Most of these process parameters have corresponding physical (direct or indirect) sensors which monitor their real-time value. After the reaction of all the parameters (molecular formula) in the PECVD chamber, the plasma forms and decomposes into a state of high density ions and molecules. During this complex interaction of physics and chemistry in the chamber, direct physical sensors can only detect the specific states inside the chamber and much of the process remains a black box. To acquire more detailed information, indirect physical sensors such as a residual gas analyzer (RGA), an optical emitter sensor (OES), or a voltage and ampere prober (VIProber) are employed. Thousands of individual pieces of information related to the optical spectrum, voltage and ampere distribution, and the density of the magnetic field are acquired. This mass of information exceeds the ability of an engineer to handle, and much of it is neglected.

Applying the multivariate statistical analysis as a virtual sensor can generate specific results about the core of the equipment or process, and eliminate inaccurate information using experience ratings. This approach can therefore be an efficient method for identifying productive directions for the R&D projects. However, there is lack of awareness of the innovation potential of modern methods for the R&D processes in many companies (Kirianaki et al. [27]). Thus, this paper explores the practices of the PECVD processes, focusing on the requirements, formation, applications, and extensions of the virtual sensors. The aim, therefore, is to describe the essentials of the virtual sensors for guiding the R&D direction, and to enhance the capability of the R&D processes in the semiconductor industry.

2. **R&D Management.**

Innovation is the creation of new knowledge and new ideas for achieving business changes. Herkema [21] defined innovation as a knowledge process aimed at creating new knowledge geared towards the development of commercial and viable solutions. Innovation is a process in which existing knowledge is used and new knowledge is collected, shared, and integrated (Martín-de Castro [32]). Therefore, knowledge is the main driving force behind innovation (Yang et al. [50]; Hurnonen et al. [24]), and fulfils a myriad of functions in the innovation realm. R&D management plays a key role in the development of the dynamic capabilities, which a firm's capabilities can integrate, build,

and reconfigure internal and external competitiveness (Teirlinck and Spithoven [45]).

In the development of IC manufacturing process, the most important procedure occurs in the vacuum chambers. Physical (direct or indirect) sensors are peer-to-peer sensors in the chambers, but this equipment cannot extract information on the complex interactions. During the process, there is no physical sensor that can output and explain the results of real-time states in the reaction chambers. Physical sensors merely provide basic information which only correlates to a part of the process results. They cannot always determine the root causes or determine the useful directions. Thus, the vacuum chambers function is as a black box in which engineers cannot easily predict and observe the manufacturing process. Traditionally, engineers have relied on their experience accumulation to overcome problems, but many issues remain unsolved. Because of ambiguous knowledge, the results cannot be explained. Indeed, tunnel vision is typical in the R&D process, and one cause is incomplete information. For the R&D engineers, this groping in the dark reduces their competitiveness and increases the costs of the R&D activity.

Virtual sensors can build a model in the vacuum chamber, as they are product property predictors and process fault predictors. Through the explication of the R&D engineers' tacit knowledge, they can complement the R&D management.

2.1. **Process environment.** ICs are devices used in most computers and electronic devices. Often known as a semiconductor or microchip, they have replaced traditional vacuum tubes and multi-transistor configurations. As their core operating system has shrunk to a mere chip, electronics have become smaller as well.

The IC manufacturing process begins with the extraction and purification of the silicon. Once it has been purified, heated, blended with boron and phosphorous, and stabilized, it is sliced into very thin layers and polished to create a smooth surface. Each layer is exposed to oxygen at a high temperature, which creates an oxide film on the surface. The silicon is then spun at a high speed to transform the oxide coating into a photo-sensitive material. A lithograph or photo of the desired circuit configuration is then transferred onto the surface of the IC using a projection lens, in a process known as photolithography. Once the circuit pattern has been transferred to the silicon, it is exposed to a gaseous blend that dissolves the oxide and photosensitive coatings. By removing these coatings, the image is transferred or etched onto the silicon. The IC is then connected to a lead frame using fine gold threads. The entire microchip is then encapsulated into a specific casing so that it can be fitted into an electronic device.

The process module is very complex, and there are four important roles in the whole process: IC design house, wafer factory, IC foundry, and the factory of testing and package (Figure 1). An IC design house means a company of electronics engineering, encompassing the particular logic and circuit design techniques. ICs consist of miniaturized electronic components built into an electrical network on a monolithic semiconductor substrate by photolithography. A wafer factory is a company which produces the silicon wafers. The silicon manufacturing process consists of crystal growth, wafer slicing, wafer polishing, wafer cleaning, epitaxial deposition, and metrology, etc. They are also differentiated by product or process type and diameter, 150mm, 200mm, and 300mm, etc. An IC foundry is a semiconductor fabrication plant (fab) which produces the electronic devices such as integrated circuits. A factory of testing and package means a company which provides the independent semiconductor manufacturing service in assembly and test. It develops and offers a turnkey solution covering the IC packaging, design and production of the interconnect materials, front-end engineering test, wafer probing, and the final test.

The four process modules in IC manufacturing are photolithography, diffusion, etching, and thin film deposition (Figure 1). Photolithography is a semiconductor process utilized

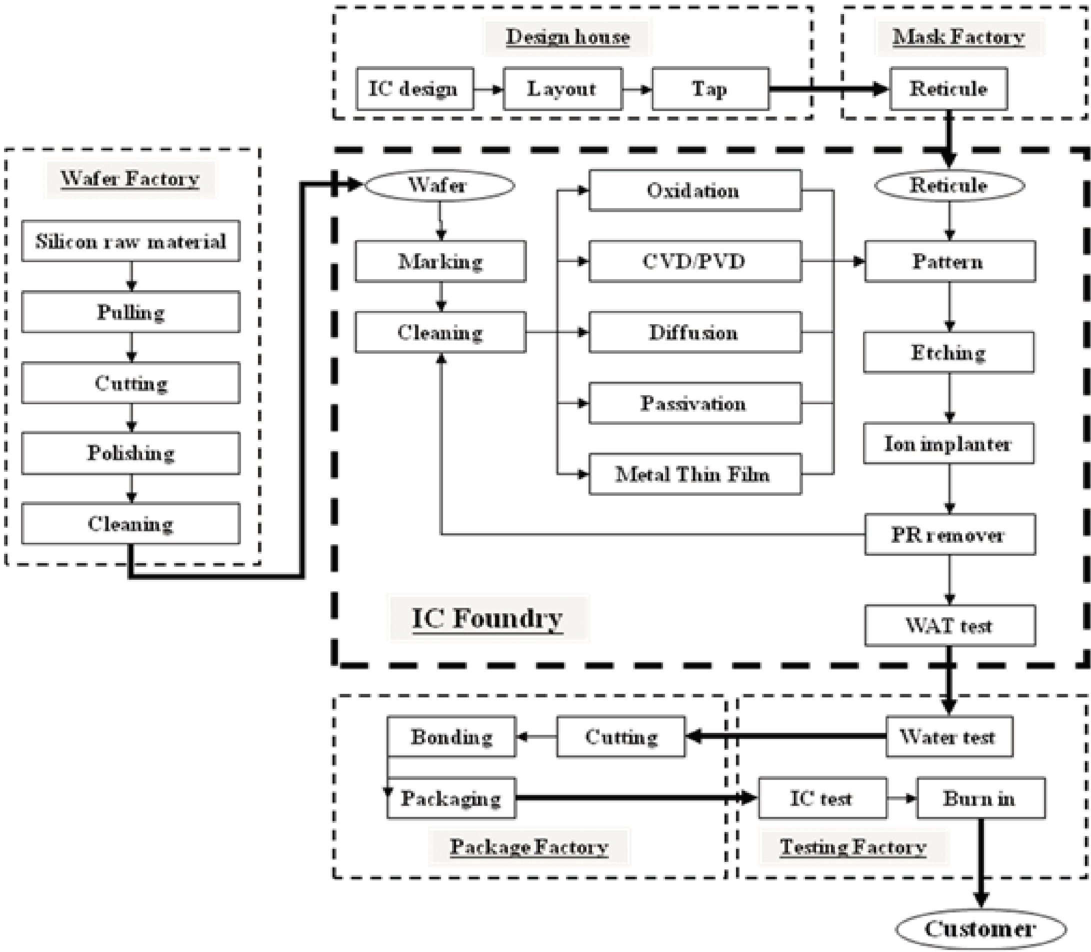

Figure 1. The flow of IC manufacturing process in this industry (the main process in a scope of boldface dotted line)

in the IC devices' fabrication to the wafer pattern on a substrate. It uses UV light to transfer a geometric pattern from a photomask to a light-sensitive chemical (photoresist, PR) on the substrate. Diffusion is a semiconductor process that involves the activities of atoms through a solid state, and is driven by a concentration gradient. Etching is employed in the semiconductor process to remove the layers from the surface of a wafer. Every wafer undergoes many etching steps in the whole manufacturing process. Thin film is used in the semiconductor process that involves a series of different chemical or physical procedures. Generally, the techniques are for using liquid or gas chemicals with evaporation methods, and the sputtering process or combinations.

The process module is very complex and difficult to summarize simply. This explores the CVD and PVD in thin film process modules as they are both processes for applying thin film. CVD is a process of applying a thin film to a substrate using a controlled chemical reaction, while PVD is the evaporation and sputtering processes of physically applying a thin metal film to a wafer.

CVD is a process of forming a film on a substrate, typically, by generating vapors from the liquid or solid precursors and delivering those vapors to the surface of a heated substrate where the vapors react to form a film. Systems for chemical vapor deposition are employed in the semiconductor fabrication, where CVD is employed to form thin films of semiconductors, dielectrics, and metal layers. Three types of vapor delivery systems commonly used for performing CVD include bubbler based systems, liquid mass flow

control systems, and direct liquid injection systems. The plasma assisted CVD is high-density plasma CVD (HDP CVD), a method of deposition which became widely accepted in advanced wafer fabs in the mid-1990s. As its name suggests, the plasma in HDP CVD is a high-density mixture of gases at low pressure, which is directed toward the surface of the wafer in the reaction chamber. The advantage is that it can deposit films to fill gaps with high aspect ratios over a range of deposition temperatures of 300°C to 400°C. The HDP CVD was initially developed for interlayer dielectric (ILD) applications, but it is also employed for deposition in ILD-1, shallow trench isolation, etch-stop layers, and the deposition of low-κ dielectrics.

The HDP CVD process involves a chemical reaction between two or more gas precursors. In the deposition of oxide ILD, oxygen (or ozone) is frequently used with a silicon-containing gas, such as silane (SiH4) or TEOS, along with argon. A source excites the gas mixture with RF or microwave power (2.45GHz), and directs the plasma ions into a dense region above the wafer surface to generate the high-density plasma. Indeed, oxidation of the Si (LOCOS) is the standard technology for providing electrically isolating active devices in ICs. As the demand for smaller geometry and higher circuit density increases, even more stringent requirements are being placed upon the isolation performance, and problems with LOCOS are beginning to surface. To overcome these limitations, the IC manufacturers have pursued an alternative process called shallow trench isolation (STI) as a substitute for LOCOS for isolating devices (Fazan and Mathews [14]). STI allows for higher chip density, thus, increasing the efficiency of usage of the Si wafers. A typical STI process involves etching a trench pattern through a nitride and thin pad oxide layers and into the silicon. Subsequently, a CVD oxide is laid over the entire wafer, filling the trench area and overlaying the nitride-protective active region. Chemical mechanical polishing (CMP) is then used to planarize the topography obtained by the preceding deposition processes, stopping on the nitride layer. The remaining nitride is subsequently removed by wet chemistry or reactive ion etching (RIE).

In general, the thin film process module involves PVD, CVD, and planarization. Physical and chemical reactions take place during this process, including absorption, surface migration, nucleation, and desorption. Chemically reactive plasma discharges are often used to modify the surface properties of the materials. Processing by plasma-assisted techniques is being increasingly used in various areas of production and manufacturing as diverse as the automotive, aerospace, biomedical, and microelectronics industries (Figure 2).

The plasma, sustained in a mixture of gas, vapors, vacuum, or electric and magnetic fields, contains a multitude of different neutral and charged particles. A large number of process parameters have to be controlled in plasma deposition, such as power, total pressure inside the reactor, the flow rates of the gases involved, substrate temperatures, type of electrodes used, and the reactor type or geometry. These controlled parameters are often interdependent and interact mutually in determining the material properties and deposition rates (Figures 3 and 4). Plasma can induce chemical reactions that may be considered advantageous because it allows the formation of new materials. However, it makes studying the parameters of the reaction control and reproducibility of composition difficult.

In this process, the R&D engineers can only acquire the information from the direct and indirect physical sensors. This information includes both explicit and tacit knowledge, and it involves correlation to process the results. Traditional methods only yield results which are inferred from the explicit knowledge, and omit the proportion related to the tacit knowledge. The cost of physically visiting each sensor to reprogram it is prohibitive

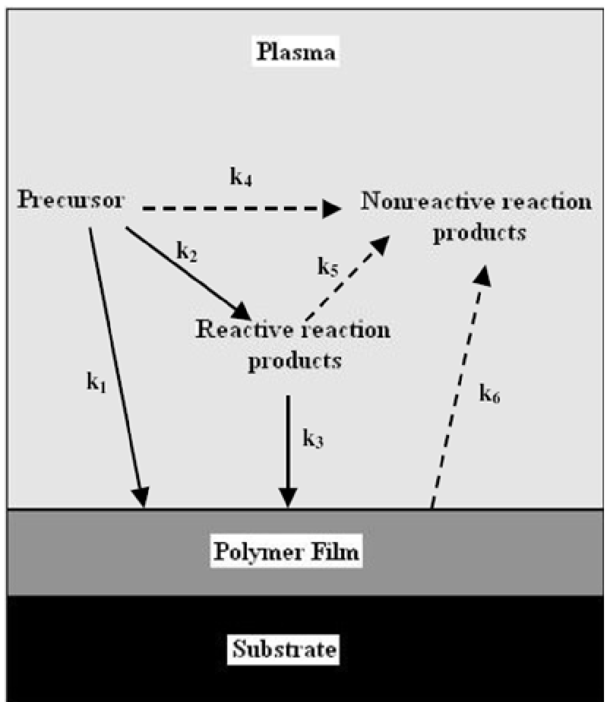

Figure 2. Different reactions during plasma polymerization (k_1-k_6 are the rates of the different reaction schemes)

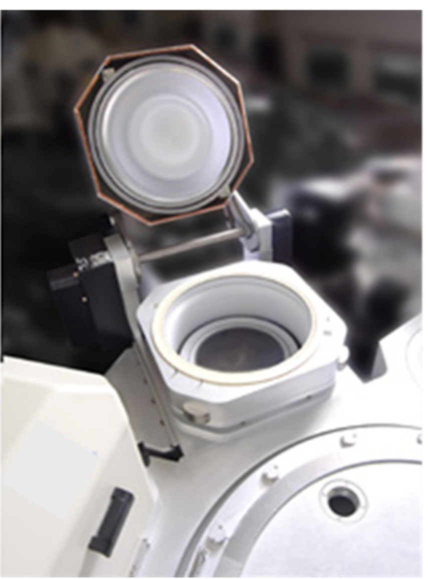

Figure 3. A PVCVE processing chamber for semiconductor equipment

(Kabadayi et al. [26]). Moreover, the technology of the physical sensor cannot send sufficient messages.

This paper addresses this challenge through the introduction of virtual sensors. We regard the most important message as hiding in the tacit knowledge. Virtual sensors provide a way to guide the R&D engineers and to bring to light the essence of the production process.

2.2. **Advantages of virtual sensors.** Virtual sensors can be the product property predictors and process the fault predictors, which operate rapidly and at a minimal cost. They

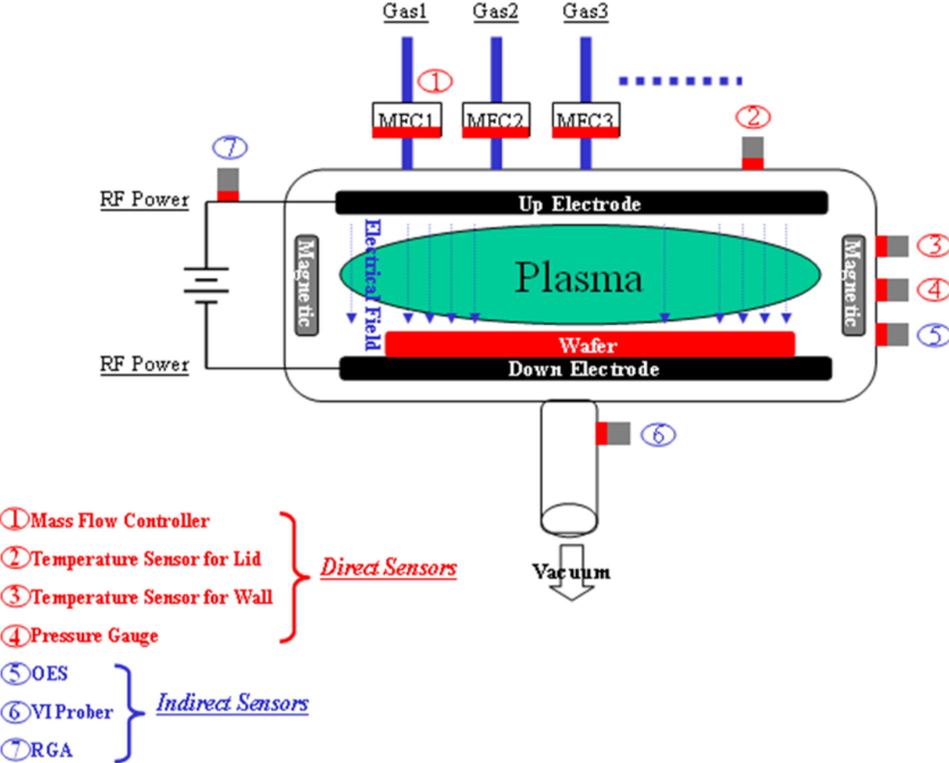

Figure 4. PECVD chamber

can easily distinguish the key performance factors and demonstrate comprehensive results. Accurate torque measurement is difficult to acquire in the general environment, but can be obtained on a dynamometer in the laboratory (Hanzevack et al. [20]; Srivastava et al. [43]; Thalmann [46]). A virtual sensor estimates the product properties or process conditions using the mathematical models, sometimes in conjunction with the physical sensors. These mathematical models use the physical sensor readings to calculate the estimated property or condition. The concept of virtual sensors applies to the entire chain of analytical steps leading up to the prediction of the reaction. Yang et al. [49] also contended that a multivariate statistical analysis can monitor and further control the processes to reduce production variation. The main advantage of using a virtual sensor is that the users can obtain reliable estimated measurements which were not previously available (Hanzevack et al. [20]).

A virtual sensor can bridge the gap between the explicit and tacit knowledge. It can be applied to classify the faults and predict the process results. A network of virtual sensors, each receiving filtered data from parts of the process, and can model the states of the processing equipment and thereby act as a part of the equipment. Each virtual sensor can provide an outcome which represents an estimated value for the overall result of the specific equipment states. A rule-based logic system is used to receive and process the signals provided by the plurality of equipment sensors, and the output signals provided by the virtual sensors, to monitor the processing equipment or to detect and classify faults within the processing equipment. The power of virtual sensors lies in the fact that the physical sensors used may be heterogeneous (in the case of our example, gas or vapor, vacuum or electrical), and the virtual sensor can combine these different types of data to compute an abstract measurement (Albertos and Goodwin [3]; Kabadayi et al. [26]; Thalmann [46]).

The major R&D work in a semiconductor manufacturer is the process development and the parameter optimization. The purpose is to enhance the quality and increase the yield rate of the ICs during the process. R&D engineers work with hundreds of parameters in the process. A great deal of money, instruments, and time are invested in the data acquisition processes. Bottlenecks generally exist in the area of tacit knowledge due to the complex chemical and physical reactions which cannot be abstracted during the production process (Table 1).

Table 1. Description of the process transaction

	Input (Controllable)	Process	Output (Process Results)
Location	Peripheral	Chamber	Wafer
Parameter	Gas flow Temperature Power Pressure electrodes RF power geometry	Chemical & Physical reaction **Plasma**	Deposition rate Uniformity Film stress Electrical characteristics Film thickness
Sensor	Direct	Indirect	**Metrology tool**
Knowledge Type (without virtual sensors)	Explicit	Tacit Virtual Sensor	Explicit **Incomplete Information**
Knowledge Type	Explicit	Explicit	Explicit **Complete Information**

In this study, the PECVD process states cannot be completely extracted by the physical sensors (direct & indirect sensors). Most of these sensors provide analog or digital signals of physical characteristics such as pressure, temperature, gas flow rate, electric current, electric voltage, and magnetic force. The key to the process improvement is to realize the hidden messages in the complex reactions of the physical and chemical characteristics. Applying multivariate statistical analysis as a virtual sensor is an effective and economical way to explore the functions of monitoring and fault detection/classification in the semiconductor equipment.

3. **Methodology.** The principal components analysis (PCA) is a technique for simplifying the multidimensional data sets for analysis. It is also a technique for forming new variables which are linear composites of the original variables. The maximum number of new variables that can be formed is equal to the number of original variables, and they are uncorrelated among themselves (Sharma [41]). Otherwise, the PCA can be used for the dimensionality reduction in a data set by retaining those characteristics that contribute most to its variance, by keeping the lower-order principal components, and ignoring the higher-order ones. Such low-order components often contain the "most important" aspects of the data.

To determine the principal component in forming the PC-space which archives the observations in the vacuum chamber, the next step is to limit the boundary. The Hotelling

T2 control chart is employed as a tool for detecting and classifying the faults by summarizing all the process variables and all the model dimensions, and indicating how far from the center (target) of the process they are along the principal component model hyper plane. We refer to this as a virtual sensor because it estimates the unmeasured complex chemical and physical reactions. In this paper, we use virtual sensors to generate an estimate of the real-time tool state variable parameters (SVIDs) during the processing of the wafer.

In this experiment, if the tool parameters as a function of time are considered as a data matrix X, then this data matrix can be modeled using the PCA as

$$X = 1 * \overline{X} + T * P' + E$$

where $\overline{X}$ is the average matrix; T is the score matrix, P' is the loading matrix, and E is the residual matrix.

The principal component scores $(t_1, t_2, t_3, \ldots)$ are columns of the score matrix T. The residual matrix E can be used to calculate the distance to the model in X space (DModX). The residual standard deviation (RSD) of an observation in the X space is proportional to the observed distance to the hyper plane of the PC model in the X space. The observed distances to the PC model in the X space (DModX) are presented as linear plots. A DModX that exceeds the critical DModX reveals that the observation may be an outlier in the X space. Normally, such distances are determined after all the components have been extracted.

The distance to the model (DModX) of an observation in a worksheet which is part of the model is

$$s_i = \sqrt{\frac{\sum e_{ik}^2}{(K - A)}} \times v$$

where v is a correction factor, (which is the function of the number of observations and the number of components), and slightly exceeds the unity. This correction factor takes account of the fact that the DModX is expected to be slightly smaller than the actual value for an observation in part of the training set because it has affected the model.

The normalized distance to the model is the observed absolute DModX divided by the pooled RSD of the model s_0.

$$s_0 = \sqrt{\frac{\sum\sum e_{ij}^2}{(N - A - A_0) \times (K - A)}}$$

where $A_0 = 1$ if the model is centered at zero; otherwise $(s_i/s_0)2$ has an approximate F distribution from which the probability of membership to the model can be determined. The distance to the model in the X space (row RSD), after A components (the selected dimension), for the observations is used to fit the model. If you select component 0, it is the standard deviation of the observations with scaling and centering as specified in the worksheet (without row means subtracted). That is, it is the distance to the origin of the scaled coordinate system.

In complex tool state monitoring, the Hotelling T2 control chart is employed as a tool for detecting and classifying faults. It summarizes all the process variables and all the model dimensions, indicating how far from the center (target) of the process are along the principal component model hyper plane.

Hotelling T2 for observation i, based on A components is,

$$T_i^2 = \sum_{a=1}^{A} \frac{t_{i_a}^2}{s_{t_a}^2}$$

where $s_{t_a}^2$ is the variance of t_a according to the class model

$$T_i^2 \times N(N-A)/A\left(N^2-1\right) \sim F_\alpha(A, N-A)$$

where N is number of observations in the model training set, and A is the number of components in the model or the selected number of components.

Therefore, if

$$T_i^2 > A\left(N^2-1\right)/N(N-A) \times F_\alpha \quad (p = 0.05)$$

then observation i lies outside the 95% confidence region of the model.

The confidence region of a two-dimensional score plot of dimension a and b is an ellipse with axis

$$\left[s_{t_a \text{ or } t_b}^2 \times F_\alpha(2, N-2) \times 2\left(N^2-1\right)/N(N-2)\right]^{1/2}$$

At zero significance level, the confidence region becomes infinite and is not shown on the plot.

Traditionally, the FDC is regarded as a two-step process in manufacturing. Recently, Goodlin et al. [18] proposed a simultaneous fault detection and classification technique that uses the fault vector approach to minimize the time to find, classify, and correct faults. The method reveals that different faults occur with different vector units in the space, and so provide a means of concurrently detecting and classifying the faults. This study examines an approach to simultaneous FDC that combines the PCA method, *Hotelling* T^2, and the *DModX* control chart to detect the designed faults of gas flow and RF parameters and classify the faults using the PCA vector space on the HDP CVD equipment. Therefore, we chose this task to demonstrate the usefulness of the virtual sensors in this paper.

4. **Case Study.**

4.1. **Experimental environment.**

An application runs with the support of the virtual sensor abstraction. In this section, we first describe how a developer defines the application's data requests using the virtual sensors. Then detail how the programs dynamically interact with data from the virtual sensors.

This research investigated the shallow trench isolation (STI) CVD process, performed on the commercially available Applied Material 300mm HDP CVD tool. The purpose of this process is to deposit a USG stack using the high-density SiH4/Ar plasma. The process is composed of a series of 17 steps (Yang et al. [49]). The first three steps stabilize the wafer load and the pressure. Step 4 is a brief plasma ignition step. Steps 5 to 8 cause the gas to flow and heat the chamber. Steps 9 to 11 are the main steps for depositing the STI layer. Steps 12 to 17 shut off the gases, cool the chamber, shut off the RF, and unload the wafer. The process chemistry is identical from steps 9 to 11. This work focuses only on the main deposition steps, which are the key to the whole process. All the analyzed data is based on steps 9 to 11.

A data collection module was installed in an HDP CVD tool to collect the SVIDs during the processing of the wafer, and 45 parameters were used in the collection plan. The sampling rate of the collection was set to 1Hz. In the CVD process, the expression of many parameters is measured and it becomes impossible to make a visual inspection in such a large multi-dimensional matrix. As a data-reduction technique, the principal component analysis is employed to reduce the dimensionality of the parameters and yield the most important data, while simultaneously filtering out noise in the CVD process. The data, although clumped around several central points in that hyperspace, will generally tend towards one direction. If one were to draw a solid line that best describes that

direction, then that line is the first principle component (PC1). The captured data can be plotted in terms of this axis, forming a PC vector space.

4.2. **Design of experiment (DoE).** The data on 100 normal wafers were collected as golden wafer data to build the boundary of the virtual sensor (Figure 5). Five wafers (Nos. 101∼105) were picked and designed to study the effects of the gas flow, pressure, voltage, and temperature variation. The factors of the DoE are generated from the critical parameters of the process and hardware. The gases of argon and helium are the main components of the plasma. The parameters of presses, E-chuck voltage, and CNT Dome temperature dominate the plasma environment. We set a 3% deviation for those parameters to acquire the variation during the main deposition (Table 2). Figure 3 plots the PCA scores of the first two principal components (t_1, t_2), where the oval-shape is the boundary of the virtual sensor. The cycled wafers represent the gas flow, pressure, voltage, and temperature of the DoE wafers. These wafers are the strong outliers, at a 95% confidence level (Figures 6-10). This indicates that the five parameters may have stronger correlations with the other parameters, and thus, impact the process results. This demonstrates the feasibility of the virtual sensor and shows its ability to extract the tacit knowledge.

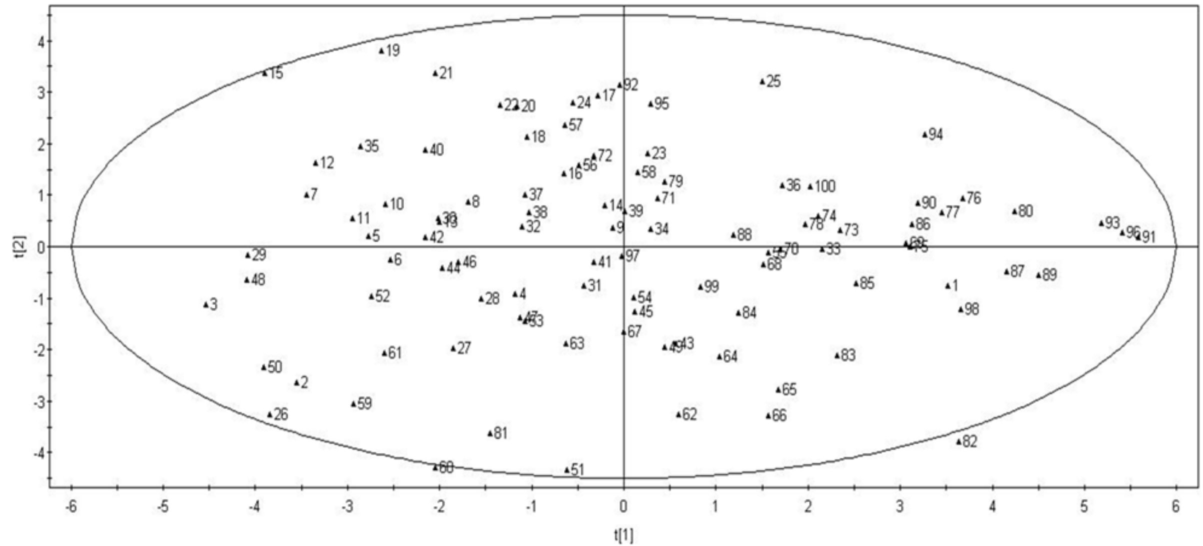

Figure 5. Golden wafer of the virtual sensor boundary

Table 2. Controlled information in the design of the experiment

Wafer No.	101	102	103	104	105
Parameters	Pressure	$Ar_{(Top)}$	E-Chuck$_{(Volt)}$	CNT Dome$_{(Temp)}$	$He_{(Side)}$
Setting	+3%	+3%	+3%	+3%	+3%

5. **Implications for the R&D Management and the Conclusions.** In this research, we have described the virtual sensors that allow the measurements of the abstract data types. Virtual sensors abstract a set of physical sensors and the operations that are performed on them, providing a new way of extracting data from the heterogeneous virtual sensors (Baroncini et al. [6]). This summary has been provided to allow the R&D managers and executives with a rapid appreciation of the content of this article.

This study addresses some advantages of the virtual sensor for the R&D management, as follows:

- To understand the root causes of the process problems
- To predict the process results before the physical instrument measurement results
- To predict the properties during the processing which cannot be measured online (in-situ)
- To obtain the process results faster, and make the corrections sooner to avoid any process problems
- To decrease the number of physical sensors used in the process to reduce the costs.

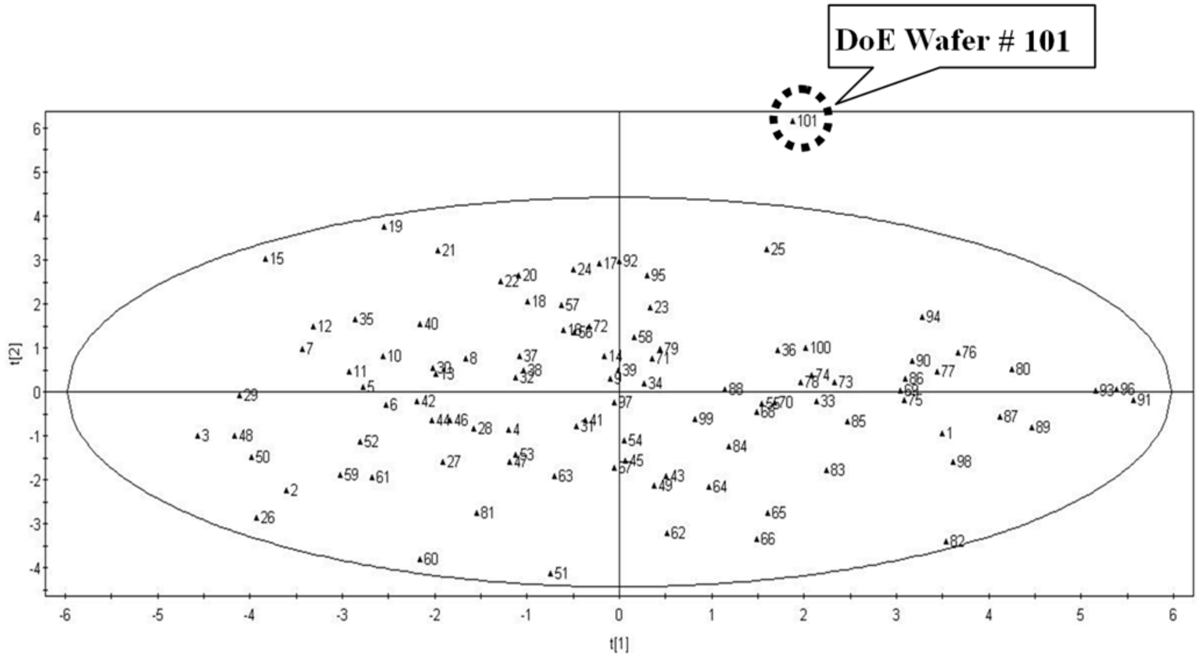

FIGURE 6. Wafer No. 101 parameter and impact process results

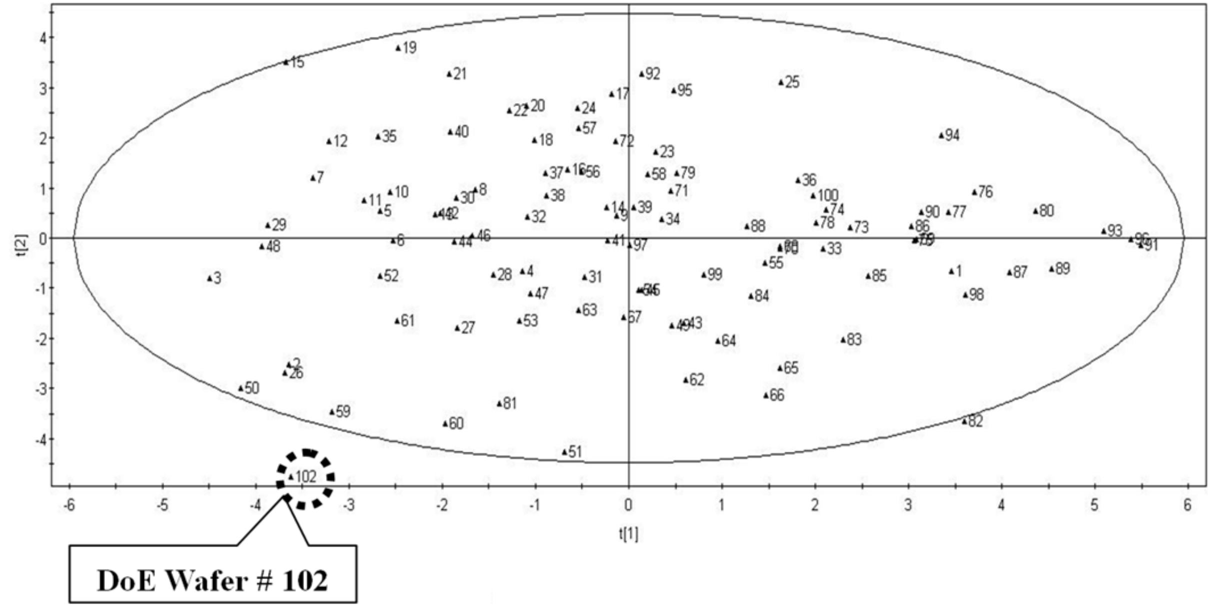

FIGURE 7. Wafer No. 102 parameter and impact process results

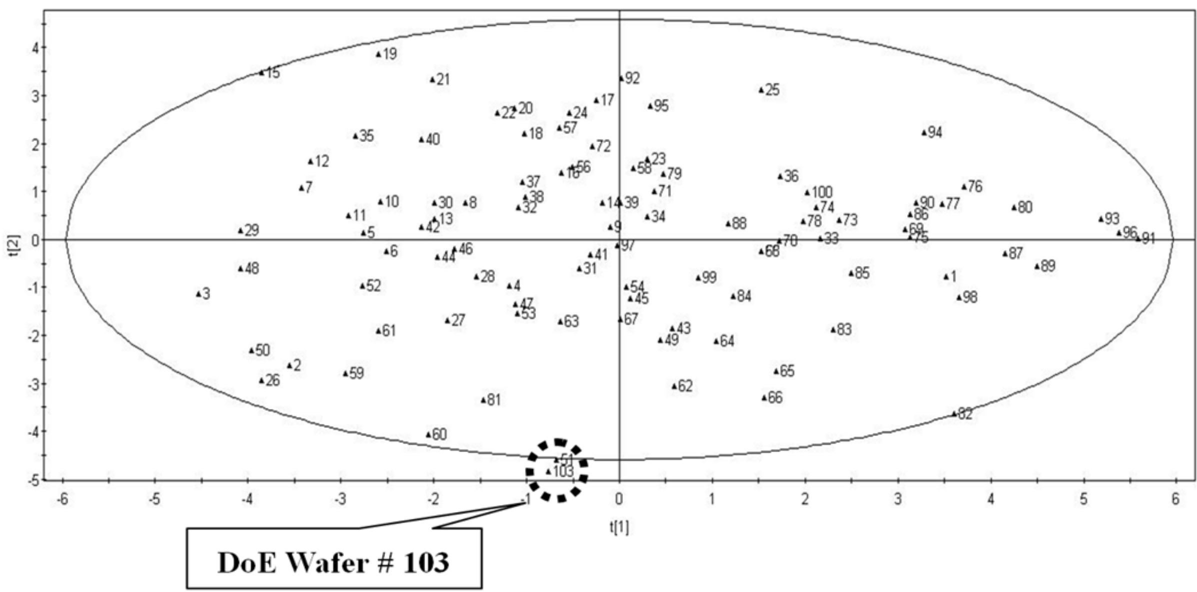

Figure 8. Wafer No. 103 parameter and impact process results

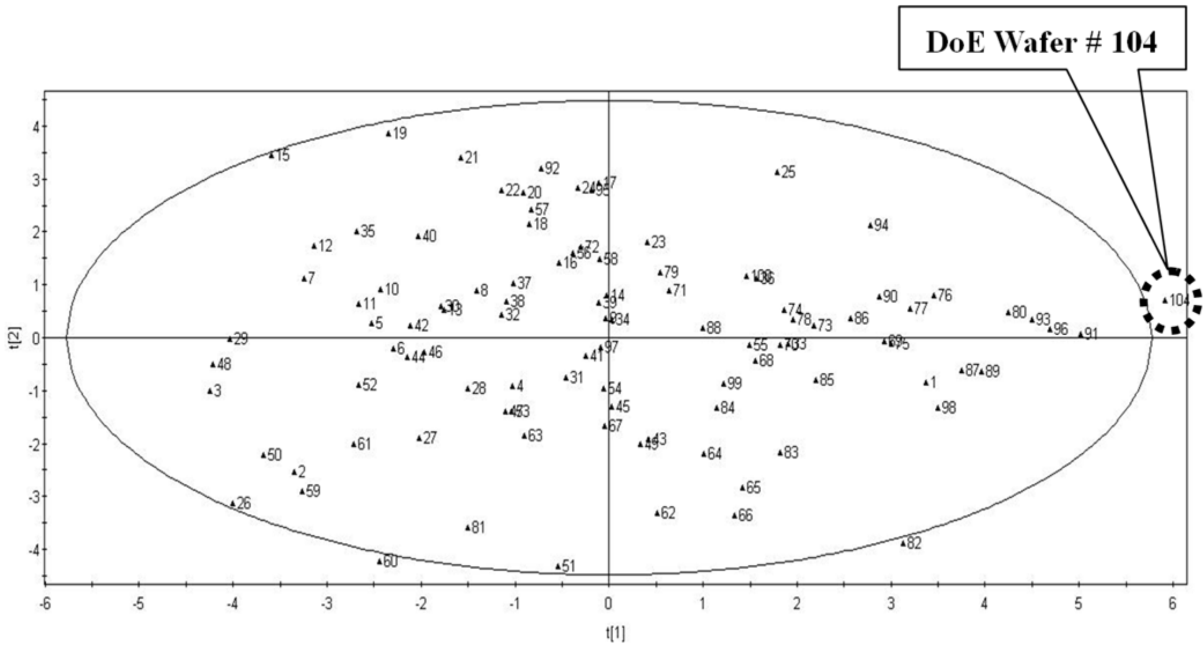

Figure 9. Wafer No. 104 parameter and impact process results

This application supports R&D, and is an essential activity in its development. Given the clear benefits of virtual sensors, they can also be applied in other fields and industries. The applications and categories of the virtual sensors depend on the input of the different data segments or parameter types. In this study, the data of the physical sensors employed can be applied as a predictor or an analyzer for the semiconductor equipment. Fault detection and classification (FDC) is a typical application of the virtual sensors to find faults and address its attribution. They provide clear and exact information for the engineers.

During the processing, the plasma status can be treated as a black box in a chamber. It is hard to apply real-time metrology to understanding the dynamic status of

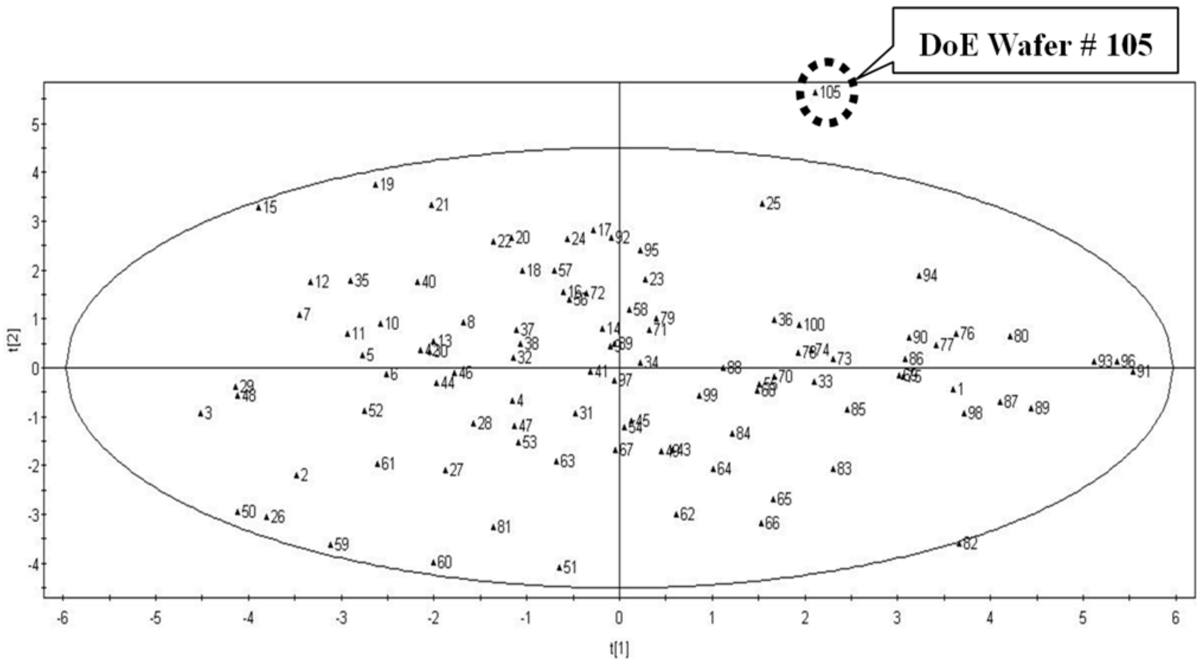

Figure 10. Wafer No. 105 parameter and impact process results

the plasma. In contrast, the virtual sensors know the real-time information for determining the deviate parameters (dimension-reduction) and classify in attribution terms (attribute-classification) to contribute a concise result. This helps the R&D engineers to clearly understand the details of the whole process and helps to develop the optimal process recipes.

Fault diagnosis and prediction of the semiconductor equipment are more difficult than that of the other traditional equipment due to their more complex structure. However, virtual sensors can execute a tool health report within an assigned period of time. Evaluating the optimum equipment maintenance within the process cycle enables the best usage of the periodic maintenance time (PM). Further, virtual sensors can be employed in the chamber matching to decrease the variation across the same type of chambers, enhance the abilities of the real-time correlation and feedback, feed forward the compensation from station to station, and also increase the robust design of the production line.

In sum, the process stabilization and cost saving are the main advantages of the virtual sensors. Moreover, this research demonstrates that applying virtual sensors can guide the direction of the R&D. This shows potential for usage in other manufacturing applications. Virtual sensors can also offer a way to tailor a generic sensing environment to specific applications. This will be especially necessary as sensors become more widespread for general purposes.

6. **Suggestion and Future Research.** This research may be a useful and relevant resource for an R&D process analysis. It involves the design of the high performance and highly efficient digital smart sensors and data acquisition systems. However, the golden model is the measuring standard of the virtual sensors. A poor model results from a floating measurement foundation. The sensitivity and stabilization of the virtual sensors depends on whether the golden model is robust enough. Proper data selection and input parameters are critical factors in the establishment of a golden model. This task relies on the experience of the senior engineers to prevent "garbage in, garbage out". The effects of environmental disturbances always exist within the chamber. This also affects the

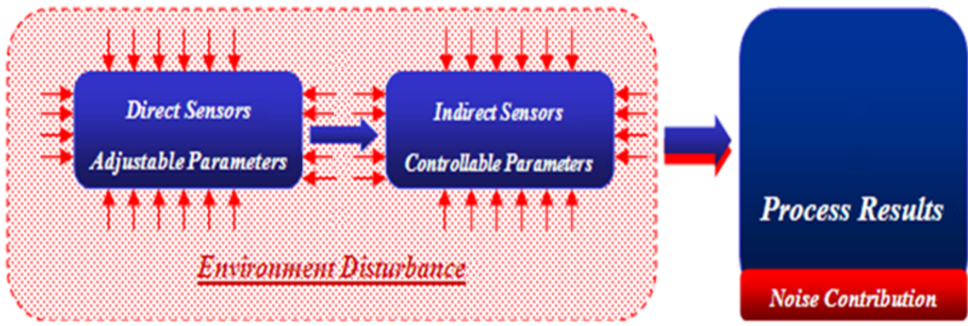

FIGURE 11. Environmental disturbances

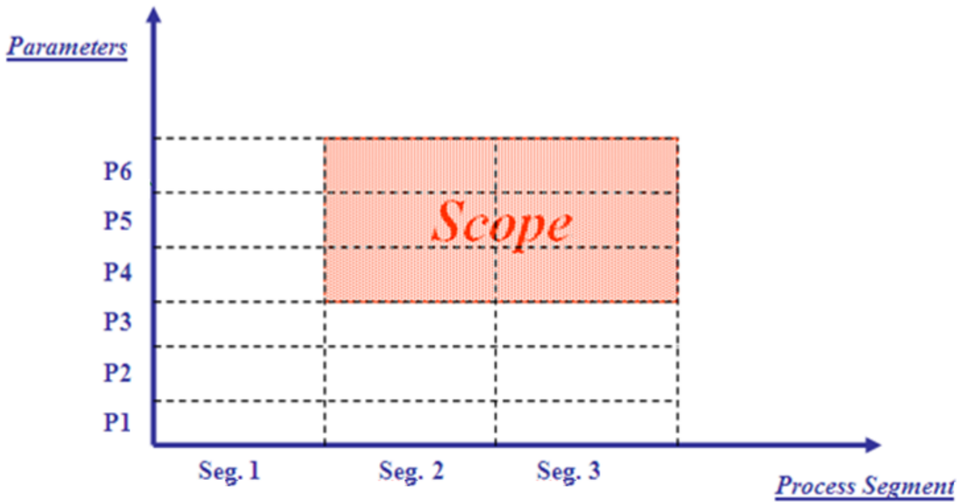

FIGURE 12. Scope confinement

manufacturing process and is not always reflected by the physical sensors. This means that part of the information is lost and cannot be usefully interpreted. In this case, the experience of the engineers is the only way to solving these problems (Figure 11).

In practice, most parameters will be thrown into the model and will result in a data jam. Furthermore, interactions within the parameters cannot be easily identified. The characteristics of the independent variables become ambiguous and affect the accuracy of the model. The resulting virtual sensors will be difficult to control and apply. It is therefore recommended that the scope and application be defined and confined before using a virtual sensor. The purpose of virtual sensors becomes clearer as the scope of the objectives narrow (Figure 12). The process segment axis identifies which process segments are selected for specific application. The parameter axis shows which parameters appear in the selected process segments. This can make the model more concise and thereby enhance its reliability, and the validity of the analysis results.

REFERENCES

[1] G. L. Adams and B. T. Lamont, Knowledge management systems and developing sustainable competitive advantage, *Journal of Knowledge Management*, vol.7, no.2, pp.142-154, 2003.

[2] A. Alaei, J. Shafass, A. Ariana and T. S. Maghvan, The role of knowledge management in created organizational innovation, *Journal of Basic and Applied Scientific*, vol.2, no.2, pp.1136-1141, 2012.

[3] P. Albertos and G. C. Goodwin, Virtual sensors for control application, *Annual Reviews in Control*, vol.26, no.1, pp.101-112, 2002.

[4] M. M. Alegre, M. H. Knowles, R. A. Robison and K. L. O'Nell, Mechanics behind breast cancer prevention – Focus on obesity, exercise and dietary fat, *Asian Pacific Journal of Cancer Preview*, vol.14, no.4, pp.2207-2212, 2013.

[5] R. Balachandra and K. L. Brockhoff, Are R&D project termination factors universal?, *Research Technology Management*, vol.38, no.4, pp.31-36, 1995.

[6] M. Baroncini, P. Placidi, G. C. Cardinali and A. Scorzoni, A simple interface circuit for micromachined gas sensors, *Sensors and Actuators A: Physical*, vol.109, no.1, pp.131-136, 2003.

[7] L. B. Cardinal, T. M. Allessandri and S. F. Turner, Knowledge codifiability, resources, and science based innovation, *Journal of Knowledge Management*, vol.5, no.2, pp.195-204, 2001.

[8] W. Catherine, L. K. Kilelu and L. Cees, Unraveling the role of innovation platforms in supporting coevolution of innovation: Contributions and tensions in a smallholder dairy development programmed, *Agricultural Systems*, vol.118, pp.65-77, 2013.

[9] S. T. Cavusgil, R. J. Calantone and Y. Zhao, Tacit knowledge transfer and firm innovation capability, *Journal of Business & Industrial Marketing*, vol.18, no.1, pp.6-21, 2003.

[10] S. P. Cho, S. Y. Park, G. S. Park, W. K. Lee and W. H. Song, Comparative analysis on the performance evaluation of national R&D projects, *Asian Journal of Technology Innovation*, vol.17, no.1, pp.121-142, 2009.

[11] A. Coad and R. Rao, Innovation and firm growth in high-tech sectors: A quantile regression approach, *Research Policy*, vol.37, no.4, pp.633-648, 2008.

[12] M. M. Crossan and M. Apaydin, A multi-dimensional framework of organizational innovation: A systematic review of the literature, *Journal of Management Studies*, vol.47, no.6, pp.1154-1191, 2010.

[13] R. Dhar, *Plasma Enhanced Metal Organic Chemical Vapor Deposition (PEMOCVD) of Catalytic Coatings for Fuel Cell Reformers*, Master Thesis, Washington State University, 2003.

[14] P. C. Fazan and V. K. Mathews, A highly manufacturable trench isolation process for deep submicron DRAMs, *Proc. of IEEE International Electron Devices Meeting (IEDM)*, Washington, New York, pp.57-60, 1993.

[15] O. Gassmann and M. Zedtwitz, Trends and determinants of managing virtual R&D teams, *R&D Management*, vol.33, no.3, pp.243-262, 2003.

[16] M. Gen, W. Zhang, L. Lin and Y. S. Yun, Recent advances in hybrid evolutionary algorithms for multiobjective manufacturing scheduling, *Computers & Industrial Engineering*, vol.112, pp.616-633, 2017.

[17] M. Gloet and M. Terziovski, Exploring the relationship between knowledge management practices and innovation performance, *Journal of Manufacturing Technology Management*, vol.15, no.5, pp.402-409, 2004.

[18] B. E. Goodlin, D. S. Boning, H. H. Sawin and B. M. Wise, Simultaneous fault detection and classification for semiconductor manufacturing tools, *The 201st Meeting of the Electrochemical Society, International Symposium on Plasma Processing XIV*, Philadelphia, PA, 2002.

[19] L. A. Halawi, R. V. McCarthy and J. E. Aronson, Knowledge management and the competitive strategy of the firm, *The Learning Organization*, vol.13, no.4, pp.384-397, 2006.

[20] E. L. Hanzevack, T. W. Long, C. M. Atkinson and M. L. Traver, Virtual sensors for spark ignition engines using neural networks, *Proc. of the American Control Conference*, Albuquerque, NM, 1997.

[21] S. Herkema, A complex adaptive perspective on learning within innovation projects, *The Learning Organization*, vol.10, no.6, pp.340-346, 2003.

[22] M. A. Hitt, R. E. Hoskisson and H. Kim, International diversification: Effects on innovation and firm performance in product-diversified firms, *Academy of Management Journal*, vol.40, pp.767-798, 1997.

[23] R. T. Holzmann, To stop or not: The big research decision, *Chemical Technology*, vol.2, no.2, pp.81-89, 1972.

[24] S. Hurnonen, P. Ritala and H. K. Ellonen, The role of knowledge-integration in service innovation project, *International Journal of Innovation Management*, vol.20, no.1, pp.1-27, 2016.

[25] A. Joaquín, K. Sengupta and R. Lapiedra, Knowledge management and innovation performance in a high-tech SMEs industry, *International Small Business Journal*, vol.31, no.4, pp.454-470, 2013.

[26] S. Kabadayi, A. Pridgen and C. Julien, Virtual sensors: Abstracting data from physical sensors, *Proc. of the 2006 International Symposium on World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, Buffalo, NY, pp.587-592, 2006.

[27] N. V. Kirianaki, S. Y. Yurish, N. O. Shpak and V. P. Deynega, *Data Acquisition and Signal Processing for Smart Sensors*, Wiley, New York, 2002.

[28] N. Lahiri, Geographic distrubtion of R&D activity: How does it affect innovation quality?, *The Academy of Management Journal*, vol.53, pp.1194-1209, 2010.

[29] B. W. Lin and J. S. Chen, Corporate technology portfolios and R&D performance measures: A study of technology intensive firms, *R&D Management*, vol.35, no.2, pp.157-170, 2005.

[30] C. W. Lin and H. C. Chang, Motives of transfer pricing strategies – Systemic analysis, *Industrial Management & Data Systems*, vol.110, no.8, pp.1215-1233, 2010.

[31] M. du Plessis, The role of knowledge management in innovation, *Journal of Knowledge Management*, vol.11, no.4, pp.20-29, 2007.

[32] G. Martín-de Castro, Knowledge management and innovation in knowledge-based and high-tech industrial markets: The role of openness and absorptive capacity, *Industrial Marketing Management*, vol.47, pp.143-146, 2015.

[33] C. MilenaLopes, A. Scavarda, L. F. Hofmeister, A. M. T. Thomé and G. L. R. Vaccaro, An analysis of the interplay between organizational sustainability, knowledge management, and open innovation, *Journal of Cleaner Production*, vol.142, pp.476-488, 2017.

[34] H. J. Niu, The career commitment of contingent employees: Evidence of on-site engineers in semiconductor industry, *International Management Review*, vol.7, no.2, pp.44-51, 2011.

[35] H. J. Niu and M. C. Hsin, The development of innovation and entrepreneurship: A literature review, *Journal of Innovation and Management*, vol.8, no.4, pp.33-62, 2011.

[36] K. Okatan, Managing knowledge for innovation and intra networking: A case study, *Procedia-Social and Behavioral Science*, vol.62, no.24, pp.59-63, 2012.

[37] J. Penner-Hahn and J. M. Shaver, Does international research and development increase patent output? An analysis of Japanese pharmaceutical firms, *Strategic Management Journal*, vol.26, pp.121-140, 2005.

[38] M. Polanyi, *The Tacit Dimension*, Anchor Books, Garden City, NY, 1967.

[39] P. Ritala, H. Eelko, A. Almpanopoulou and P. Wijbenga, Tensions in R&D networks: Implications for knowledge search and integration, *Technological Forecasting and Social Change*, vol.120, pp.311-322, 2017.

[40] H. Scarbrough, Knowledge management, HRM and the innovation process, *International Journal of Manpower*, vol.24, no.5, pp.501-516, 2006.

[41] R. P. Sharma, Chemical interactions and compromised immune system, *Fundamental and Applied Toxicology*, vol.4, no.3, pp.345-351, 1984.

[42] J. Singh, Distributed R&D, cross-regional knowledge integration and quality of innovative output, *Research Policy*, vol.37, pp.77-96, 2008.

[43] A. N. Srivastava, N. C. Oza and J. Stroeve, Virtual sensors: Using data mining techniques to efficiently estimate remote sensing spectra, *IEEE Trans. Genoscience and Remote Sensing*, vol.43, no.3, pp.590-600, 2005.

[44] G. Szulanski, The process of knowledge transfer: A diachronic analysis of stickiness, *Organizational Behavior & Human Decision Processes*, vol.82, no.1, pp.9-27, 2000.

[45] P. Teirlinck and A. Spithoven, Formal R&D management and strategic decision making in small firms in knowledge-intensive business services, *R&D Management*, vol.43, pp.37-51, 2013.

[46] D. Thalmann, Virtual sensors: A key tool for the artificial life of virtual actors, *Proc. of Pacific Graphics*, Seoul, Korea, pp.22-40, 1995.

[47] H. W. Volberda, F. A. J. van Den Bosch and C. V. Heij, Management innovation: Management as fertile ground for innovation, *European Management Review*, vol.10, pp.1-15, 2013.

[48] C. Wang, L. Chen and S. Chang, International diversification and the market value of new product introduction, *Journal of International Management*, vol.17, pp.333-347, 2011.

[49] C. Yang, C. J. Chang, H. J. Niu and H. C. Wu, Increasing detectability in semiconductor foundry by multivariate statistical process control, *Total Quality Management & Business Excellence*, vol.9, no.5, pp.429-440, 2008.

[50] C. Yang, Y. D. Wang and H. J. Niu, Does industry matter in attributing organizational learning to its performance?: Evidence from the Taiwanese economy, *Asia Pacific Business Review*, vol.13, no.4, pp.547-563, 2007.