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The Estimation of Thin Film Properties by Neural Network

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Abstract: This paper presents a method based on neural network (NN) for estimating the properties of semiconductor thin film. Through the effective learning process, NN is able to catch the relationship between input and output pairs bypassing the complicated statistical steps such as model hypothesis, identification, estimation of model parameters, and verification. Such an estimator then can be developed to be a smart mechanism which can help the technician to set the relevant control parameters in the manufacturing process of thin film. In this research, the thickness and refractive index (RI) of thin film were estimated by the well learned NN model. From the studied results shown, the properties of thin film indeed could be estimated in advance according to the relevant control parameters in the manufacturing process. That also means the estimator we developed could be built and fulfilled its function.

Keywords: Neural Network, Thin Film, Manufacturing Process

1. Introduction

In recent twenty years, the high-tech skills have been developed widely and vitally in various electronic appliances, such as photoelectric, semiconductor and biomedical chips. The electronic industry has become the focus of economic development for many countries. Besides, due to the fast improvement of manufacturing technique, more and more electronic products are requested to be small and exquisite. Their function is requested to be more powerful either.

It is well-known that thin film is an important and indispensable part for many electronic products. Taking the wafer manufacturing as an example, the filming process plays an important and key role in the wafer front-end manufacturing step. Figure 1 shows the flowchart of wafer manufacturing process [1]. Thus, if the relevant manufacturing parameters of filming process could be set quickly and accurately, not only the efficiency of working machine can be greatly improved, but also the time and frequency of machine test can be reduced effectively.
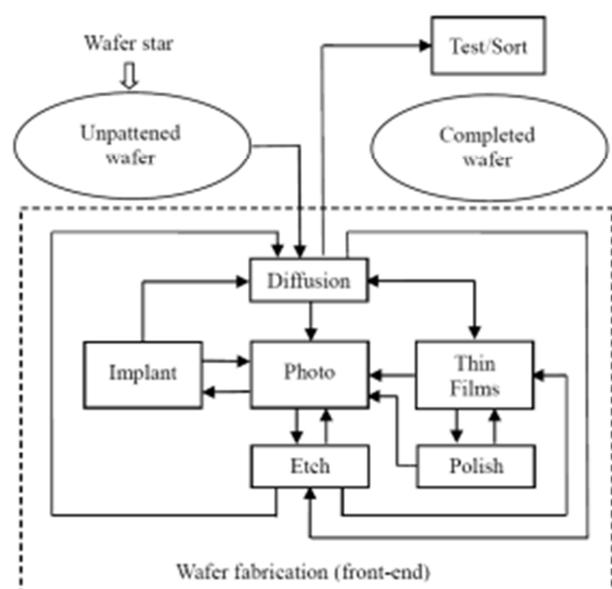

Figure 1. The manufacturing process of wafer.

Generally, Chemical Vapor Deposition (CVD) is the popular method used in the field of thin film manufacturing process. In CVD process, many complicated and nonlinear chemical and physical reactions are hardly analyzed. The phenomena of particle drift and variation are happened very often in the filming process either. Undoubtedly, these uncontrolled factors will affect the quality of filming process very seriously. Thus, how to set the adequate manufacturing parameters for improving the yield rate and reducing the times of machine test has become the most important work in the thin film manufacturing process. Unfortunately, trial-and-error is still the common method taken by the technicians in many companies. As we know, the number of failed manufacturing process and the defective product could be possibly raised, if the manufacturing parameters were determined by the technician based on personal experience only. Thus, several studies about the optimal thin film manufacturing have been proposed [2-5].

Recently, due to the fast development of artificial intelligent techniques, some studies about the optimal control of film manufacturing process were reported. For instance, the genetic algorithm (GA) had been used for searching the optimal parameters of physical vapor deposition manufacturing control process [4]. Hsieh, Tong, Cui and Hwang et al. proposed the film's control and estimation by using NN techniques [5-14].

Since the powerful learning and modeling capabilities, NN has been widely used in different applications, such as the signal processing and control [15-19]. Basically, through the well learning, NN could generate an efficient mapping between input and output pairs bypassing the complicated statistical steps. The well-trained NN model then can be used for the specific work.

In this research, an artificial intelligent (AI) system based on NN model for the estimation of film properties is studied. Its aim is that according to the estimation information provided, the junior technician with no full experience is able to make a good setting work for the manufacturing parameters in the filming process. Thus, such an AI system can not only help the technician to do the work of film manufacturing very efficiently and easily, but also reduce the rate of defective products and then save the production cost.

2. Neural Network

NN technique is the main tool used for constructing the estimator of film properties. As previous descriptions, the relationship between input and output pairs is expected to be obtained through the well learning of NN.

The NN structure commonly known as multi-layered feed-forward network is used in this study. The supervised NN with error back-propagation (BP) learning algorithm is taken for NN's training [15-17]. An example of a three-layered feed-forward NN architecture as shown in Figure 2 is the model of selected topology. Each layer is connected to a layer above it in a feed-forward manner, which means no feed-back from the same layer or a layer above. All connections have a multiplying weight associated with them. Training is equivalent to find the proper weights for all connections such that a desired output is generated for a given input set. Once the neural network is well trained, the proper input information could be inferred in accordance with an expected output. In other words, the useful information can be found for helping the technician to do the well control in the manufacturing process.
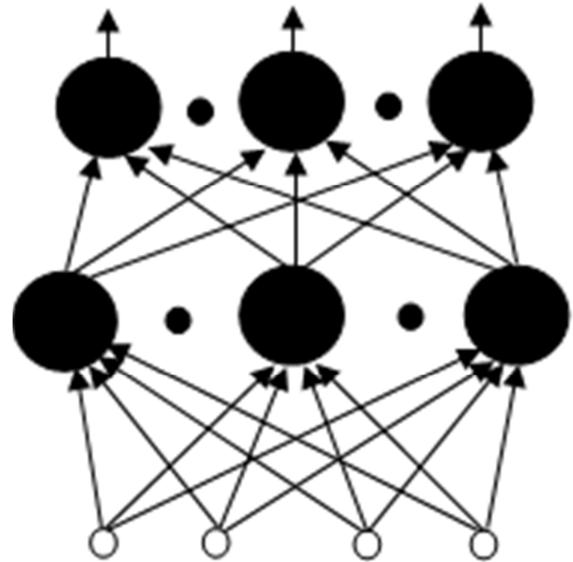

Figure 2. *A three-layered feed-forward NN architecture.*

In this study, the error back-propagation (BP) learning algorithm is used for NN's training. The major steps of BP learning rule algorithm is briefly summarized as follows [15-17].

1st step: Initialize all weights (ω_{ij}) to the small random values firstly.

2nd step: Present an input pattern with the corresponding desired outputs and then calculate the outputs.

3rd step: Find the error term for all nodes.

4th step: Adjust weights by

$$\omega_{ij}(n+1) = \omega_{ij}(n) + \alpha \delta_j X_i + \zeta(\omega_{ij}(n) - \omega_{ij}(n-1)) \qquad (1)$$

where n+1, n and n-1 are the next, present, and previous iteration numbers, respectively. δ_j is the error of node *j* and X_i is the ith input of node *j*. α is the learning rate, the step size in the gradient search algorithm. ζ is the momentum and its value is between 0 and 1.

5th step: Present another input pattern and go back to 2nd step.

3. Experiments

In our study, the thin film data manufactured by using two recipes, LDRXX and TEOSXX, were collected and simulated. Table 1 and Table 2 present the examples of two collected data sets. The numbers of LDRXX and TEOSXX data sets are 102 and 89, respectively.

Table 1. *The examples of data manufactured by using recipe LDRXX.*

Manufacturing Parameters							
DT	cSHDist	TEOS factor	TEOS (mgm)	HE (sccm)	O₂ (sccm)	HFRF (pre)	LFRF (pre)
25.5	420	0.9736	800	9000	8000	196	50.4
25.5	420	0.9736	800	9000	8000	196	51.4
26.5	420	0.9736	800	9000	8000	196	50.4
26.5	420	0.9736	800	9000	8000	196	51.4
26.5	420	1.0453	800	9000	8000	194	51.2
26.5	420	1.0453	800	9000	8000	193	50.4
25.5	420	1.0253	800	9000	8000	194	31.2
25.5	420	1.0253	800	9000	8000	164	51.2
27.5	420	0.9936	800	9000	8000	196	50.4
27.5	420	0.9936	800	9000	8000	216	50.4
Thin Film Properties							
Thickness				RI			
443				1.4590			
433				1.4590			
455				1.4619			
443				1.4627			
457				1.4609			
429				1.4624			
419				1.4816			
416				1.4821			
436				1.4820			
443				1.4804			

Table 2. *The examples of data manufactured by using recipe TEOSXX.*

Manufacturing Parameters							
DT	cSHDist	TEOS factor	TEOS (mgm)	HE (sccm)	O₂ (sccm)	HFRF (pre)	LFRF (pre)
38.0	310	1.0386	5250	4000	4200	797	209
38.0	310	1.0386	5250	4000	4200	798	209
38.0	310	1.0236	5250	4000	4200	793	209
38.0	310	1.0236	5250	4000	4200	795	210
38.0	310	1.0036	5250	4000	4200	763	199
38.0	310	1.0036	5250	4000	4200	765	200
38.0	310	1.0236	5250	4000	4200	765	200
38.0	310	1.0236	5250	4000	4200	795	200
38.0	310	1.0236	5250	4000	4200	780	200
38.0	310	1.0236	5250	4000	4200	765	200
Thin Film Properties							
Thickness				RI			
4983				1.4584			
4988				1.4587			
4814				1.4628			
4830				1.4628			
4885				1.4634			
4903				1.4633			
4832				1.4636			
4836				1.4629			
4839				1.4632			
4682				1.4629			

The values of thickness and RI of thin film are expected to be estimated by the well-trained NN model. In order to fairly demonstrate the effectiveness of NN model in the estimation of thin film properties, three same size data sets, i.e. LDR-1a, LDR-1b, and LDR-1c, are randomly reorganized from data

LDRXX. Similarly, three same size data sets, TEOS-1a, TEOS-1b and TEOS-1c, are randomly reorganized from data TEOSXX. In the simulations of data LDR-1a, LDR-1b and LDR-1c, 70 sets were used for NN's training and 32 sets were used for testing. For data TEOS-1a, TEOS-1b and TEOS-1c, 59 sets were used for NN's training and 30 sets were used for testing.

For all data sets, the size of NN in thickness estimation is 4-10-1. The inputs are DT, TEOS factor, HFRF, LFRF. In RI estimation, the size of NN is 5-10-1. The inputs are DT, TEOS factor, HFRF, LFRF and thickness. The mean absolute error (MAE) and mean absolute percentage error (MAPE) are used as the estimated measurements.

$$MAE = \frac{\sum_{i=1}^{N} | y_i - \hat{y}_i |}{N} \tag{2}$$

$$MAPE = \frac{\sum_{i=1}^{N} | y_i - \hat{y}_i / y_i |}{N} \times 100\% \tag{3}$$

Where, y_i and $\hat{y}_i$ are actual and estimated values. N is the total number of estimation data.

In order to observe the distribution behaviors of all training and test data sets, the simple statistical analysis was done. For example, Table 3 lists the information of mean value, variance and standard deviation for the whole LDR-1a data, LDR-1a 70 training data and 32 LDR-1a test data. Similarly, Table 4 and Table 5 list the statistics of data LDR-1b and LDR-1c, respectively. Table 6 lists the estimation errors of LDRXX data series performed by NN. For TEOSXX data, Table 7, Table 8 and Table 9 list the statistics of data TEOS-1a, TEOS-1b and TEOS-1c, respectively. Table 10 presents the estimation errors of TEOSXX data series performed by NN.

Table 3. *The distribution behaviors of data LDR-1a.*

Total Data (LDR-1a)		
Statistics	Thickness	RI
Mean	483.39215	1.47009
Var.	862.65673	0.000068761
Std.	29.37102	0.00829221
Training Data (LDR-1a)		
Statistics	Thickness	RI
Mean	477.87142	1.47021
Var.	1090.7511	0.000073625
Std.	33.02652	0.00858049
Test Data (LDR-1a)		
Statistics	Thickness	RI
Mean	495.46875	1.4698187
Var.	163.41835	0.000060046
Std.	12.78352	0.0077489

(Var.: Variance, Std.: Standard Deviation)

Table 4. *The distribution behaviors of data LDR-1b.*

Total Data (LDR-1b)		
Statistics	Thickness	RI
Mean	483.39215	1.47009
Var.	862.65673	0.000068761
Std.	29.37102	0.00829221
Training Data (LDR-1b)		
Statistics	Thickness	RI
Mean	479.58572	1.4696674
Var.	1126.9996	0.000074579
Std.	33.570816	0.00863592
Test Data (LDR-1b)		
Statistics	Thickness	RI
Mean	491.71875	1.4710001
Var.	197.82158	0.000056770
Std.	14.064906	0.00753455

(Var.: Variance, Std.: Standard Deviation)

Table 5. *The distribution behaviors of data LDR-1c.*

Total Data (LDR-1c)		
Statistics	Thickness	RI
Mean	483.39215	1.47009
Var.	862.65673	0.000068761
Std.	29.37102	0.00829221
Training Data (LDR-1c)		
Statistics	Thickness	RI
Mean	481.62857	1.4718357
Var.	800.9036	0.0000731506
Std.	28.300241	0.00855281
Test Data (LDR-1c)		
Statistics	Thickness	RI
Mean	487.25	1.4662563
Var.	1005.5484	0.0000391548
Std.	31.710382	0.00625738

(Var.: Variance, Std.: Standard Deviation)

Table 6. *The statistics of estimations for data LDRXX.*

Statistics	LDR-1a			
	Thickness		**RI**	
	Training	**Test**	**Training**	**Test**
MAE	6.3079	7.3324	0.001173	0.003112
MAPE	1.3182%	1.4888%	0.0799%	0.2112%
	LDR-1b			
Statistics	Thickness		RI	
	Training	Test	Training	Test
MAE	6.2145	6.8923	0.001089	0.003557
MAPE	1.3011%	1.4027%	0.0751%	0.2328%
	LDR-1c			
Statistics	Thickness		RI	
	Training	Test	Training	Test
MAE	6.8258	7.8785	0.001208	0.003345
MAPE	1.4255%	1.5989%	0.0832%	0.2275%

Table 7. *The distribution behaviors of data TEOS-1a.*

Total Data (TEOS-1a)		
Statistics	Thickness	RI
Mean	4967.382	1.4596821
Var.	6752.8295	0.00000177311
Std	82.175605	0.00133158
Training Data (TEOS-1a)		
Statistics	Thickness	RI
Mean	4942.0	1.4597865
Var.	8020.3105	0.00000241364
Std	89.55618	0.00155359
Test Data (TEOS-1a)		
Statistics	Thickness	RI
Mean	5017.3	1.4594768
Var.	562.2862	0.00000048738
Std	23.71257	0.000698123

(Var.: Variance, Std.: Standard Deviation)

Table 8. *The distribution behaviors of data TEOS-1b.*

Total Data (TEOS-1b)		
Statistics	Thickness	RI
Mean	4967.382	1.4596821
Var.	6752.8295	0.00000177311
Std	82.175605	0.00133158
Training Data (TEOS-1b)		
Statistics	Thickness	RI
Mean	4945.085	1.45999
Var.	7853.424	0.00000210681
Std	88.619544	0.00145149
Test Data (TEOS-1b)		
Statistics	Thickness	RI
Mean	5011.2333	1.4590766
Var.	1783.7709	0.000000594971
Std	42.23471	0.00077134

(Var.: Variance, Std.: Standard Deviation)

**Table 9.** *The distribution behaviors of data TEOS-1c.*

Total Data (TEOS-1c)		
Statistics	Thickness	RI
Mean	4967.382	1.4596821
Var.	6752.8295	0.00000177311
Std	82.175605	0.00133158
Training Data (TEOS-1c)		
Statistics	Thickness	RI
Mean	4983.356	1.4593307
Var.	4049.8537	0.00000110908
Std	63.638462	0.00105313
Test Data (TEOS-1c)		
Statistics	Thickness	RI
Mean	4935.967	1.4603734
Var.	10851.551	0.00000241653
Std	104.17078	0.00155452

(Var.: Variance, Std.: Standard Deviation)

Table 10. *The statistics of estimations for data TEOS-xx.*

Statistics	TEOS-1a			
	Thickness		**RI**	
	Training	**Test**	**Training**	**Test**
MAE	39.8665	16.2448	0.00059	0.00032
MAPE	0.812%	0.3243%	0.040%	0.022%
Statistics	TEOS-1b			
	Thickness		RI	
	Training	Test	Training	Test
MAE	41.2543	17.5334	0.00052	0.00027
MAPE	0.852%	0.3394%	0.0387%	0.0251%
Statistics	TEOS-1c			
	Thickness		RI	
	Training	Test	Training	Test
MAE	32.5743	19.225	0.00064	0.00032
MAPE	0.823%	0.0351%	0.0414%	0.0257%

The examples of superposition plot for thickness estimation are shown in Figure 3 and Figure 4. Figure 3 shows the example of NN's training result and Figure 4 shows the example of NN's testing results. In figures, the solid line stands the actual thickness values and the dotted line stands NN's estimated values.
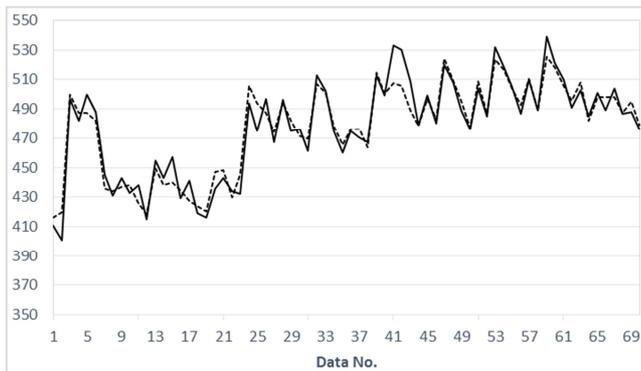
Figure 3. *The superposition plot of thickness for NN's training.*
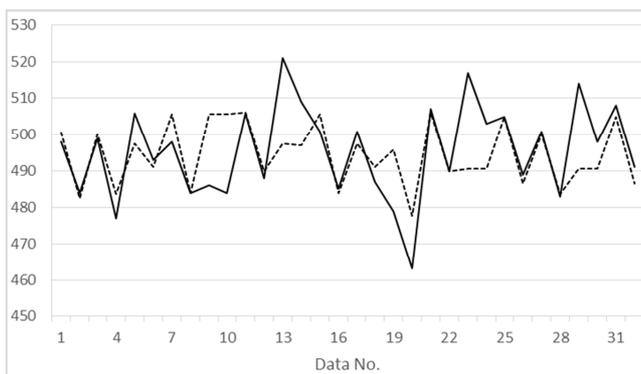
Figure 4. *The superposition plot of thickness for NN's test.*

Similarly, the examples of superposition plot for RI estimation are shown in Figure 5 and Figure 6. Figure 5 shows the example of NN's training result and Figure 6 shows the example of NN's testing result. Same as above figures, the solid line stands the actual thickness values and the dotted line stands NN's estimated values.
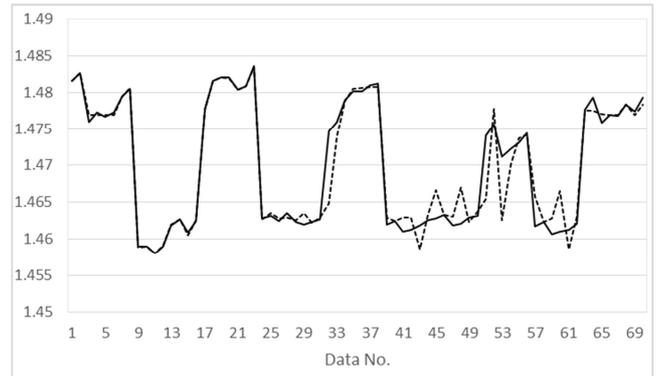
Figure 5. *The superposition plot of RI for NN's training.*
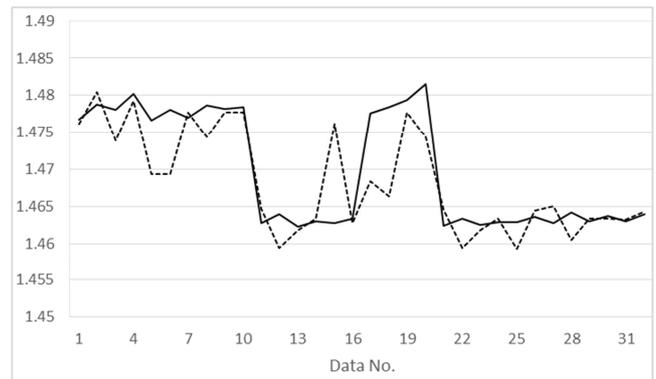
Figure 6. *The superposition plot of RI for NN's test.*

4. Results & Discussion

It is known that many unknown factors will affect the properties of thin film in its real manufacturing process. These unknown factors are usually uncontrolled and can be treated as the disturbances. Besides, different manufacturing machines have different physical characteristics. All these conditions might make the films have different properties even they are filmed under the same manufacturing parameters. In our study, we tried to use NN technique to catch the relationships among the film's properties and the relevant manufacturing parameters so that the film's properties could be estimated in advance. From the simulation results shown, the relationships between the film's properties and the manufacturing parameters indeed can be obtained by a well-trained NN model. For both thickness and RI estimations, the plots show that the trends of film's properties still can be estimated by NN.

5. Conclusion

In this research, the estimation for the properties of semiconductor's thin film based on NN technique was studied. From the study results shown, we conclude that NN model indeed has the ability to estimate the properties of thin film if NN was well-trained. In other words, these well-trained NN estimators could provide the important information to the technician for setting the proper manufacturing parameters in the filming process. The

technician is able to make the whole filming process more effective and successful. However, in this research, only a few manufacturing parameters were collected. We do believe that the estimation accuracy for the film's property could be improved greatly if more relevant manufacturing parameters can be considered and collected.

Acknowledgements

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