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Radial Basis Function Neural NetworkModelForOptimizingThermal Annealing Process Operating Condition

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Abstract. Optimum thermal annealing process operating condition for nanostructured porous silicon (nPSi) by using radial basis function neural network (RBFNN) was proposed. The nanostructured porous silicon (nPSi) layer samples prepared by electrochemical etching process (EC) of p-type silicon wafers under different operatingconditions, such as varyingetchingtime (Et), annealing temperature (AT), and annealing time (At). The electrical properties of nPSi show an enhancement with thermal treatment.Simulation result shows that the proposed model can be used in the experimental results in this operating condition with acceptable small error. This model can be used in nanotechnology based photonic devices and gas sensors.

Introduction

Nowadays the conceptual design operation process using simulation and modeling makes it possible to do an essential assessment before systems are built without the need of expensive experiments, through commissioning and operation. The porous silicon fabrication process is the most important role in the production of electric material in all fields of industry. Therefore the device includes porous silicon are based on relatively well known and simple transduction principle which can be used in sensor, detector and photonic device for biomedical, chemical and environmental applications [1]. Many researchers focus on intelligence services to provide high production modeling for an important issue in all the fields of industry to analyze the relationship between diverse species and their most appropriate preparation process. The room temperature cathode-luminescence and photoluminescence of swift ion irradiated porous silicon zinc oxide nano-composites and evolutes the broad and flat emission band from 1.5 to 3.5 eV were reported by Yogesh Kumar et al. [2]. The relationship between experimental process and neural network models such as a generalized linear model, projection pursuit and cluster analysis were studied by Sarle's [3]. Brosse et al. [4] used back propagation for the prediction of fishing abundance in lakes for good fishing zones as well as for increasing the competitiveness of the fleet [5]. Among many different structures of the ANN (artificial neural network) such as the multi-layer preparation which is the most popular one [6-7], however, the training processes often settle in undesirable local minima of error surface or converge too slowly. Therefore, Radial Basis Function (RBF) neural network with triple-layer feed-forward neural network structure which has strong nonlinear mapping ability including fast convergence and global optimization is put forward byDong to predict the silicon content in blast furnace hot metal [8].

This research investigates the possible application of the neural network to model the porous silicon fabrication processes. Here in this work, ANN model can be improved simply by providing additional training data accurately in a shorter time to reduce the cost of experimental work for any practical application.Worth to mention that it can be used for nanotechnology based photonic devices and also nanotechnology based gas sensors [9].

Experimental Set Up

A brief description of the experimental setup and the procedure adopted for obtaining the experimental data on the porous silicon process with different operating variables is given. The Radial Basis Function Network (RBFN) prediction model hasthree input parameters such as Et, AT, and At and the output parameter Eg. The Matlab software tools used to learn the proposed model.

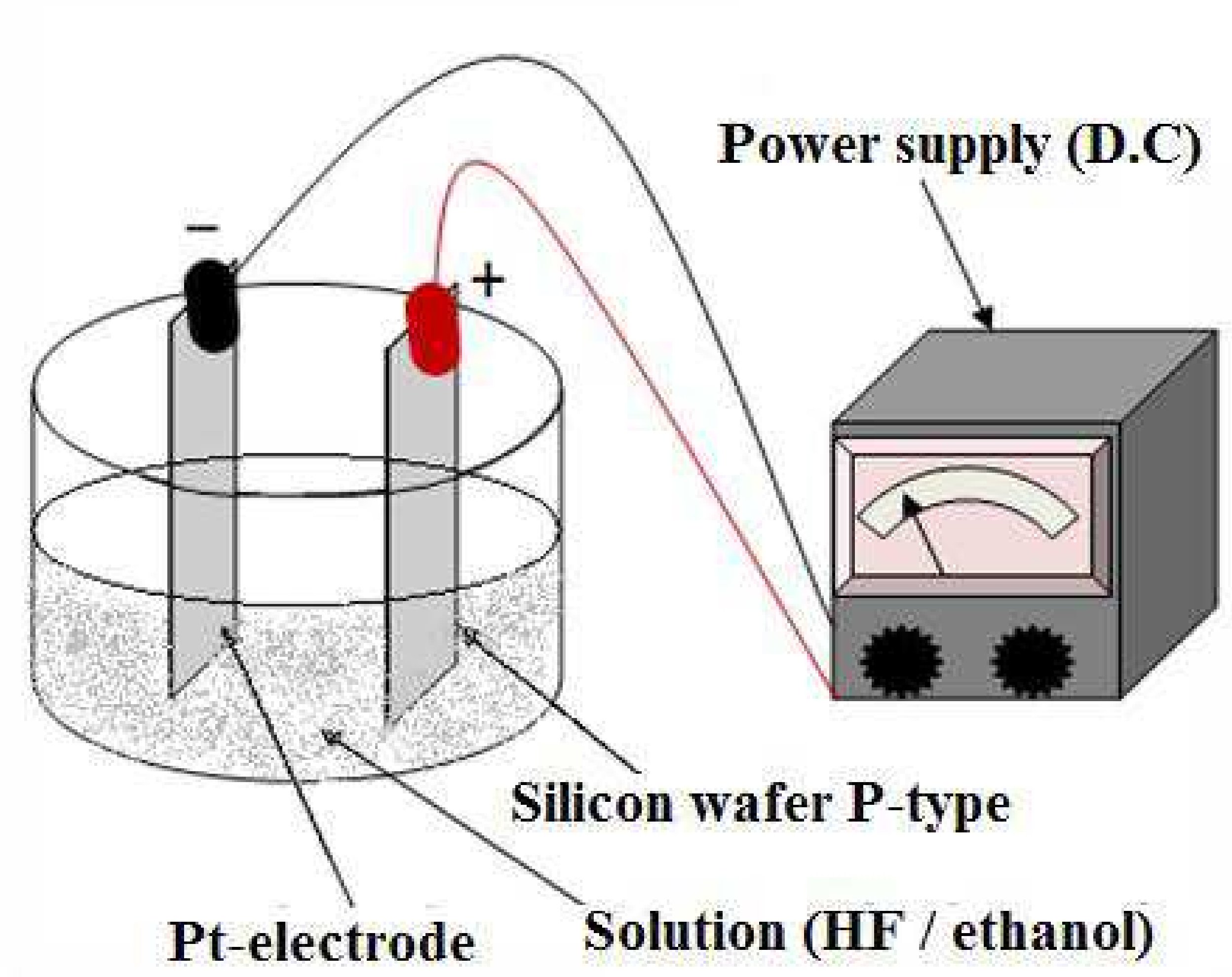


Fig. 1. The electrochemical etching system.

The simple set-up of the EC etching process is shown in Fig. 1. The electro-chemically etched area for all samples has been of 1 cm^2area. The porous silicon was etched in ethanol /HF (Hydrofluroic acid) mixture. Ethanol was added to the HF solution in order to improve the wettability of the acid and to allow for the F ions diffusion into the pores [10].The ethanol concentration for the etching was about 23.5%. The sample has been mounted in a teflon cell.The electrical circuit was completed by putting platinum electrode as a cathode in parallel to achieve the homogeneous nPSi layers [11-13].

Fig. 2 shows the thermal annealing system consist of the single tungsten halogen lamp (OSRAM 64575) with a power of 1000 *Watt* based on ceramic base. A parabolic reflector like half circuit has been used to increase the heating efficiency. Quartz tube with a 3 cm diameter has been closed from one side to prevent air from leaking. The annealing treatment has been occurring at vacuum pressure 10^{-3} *Torr*. The mirror-line surface which was etched has been put directly above the tungsten halogen lamp.The other side of the thermo-couple was connected by a temperature reader.

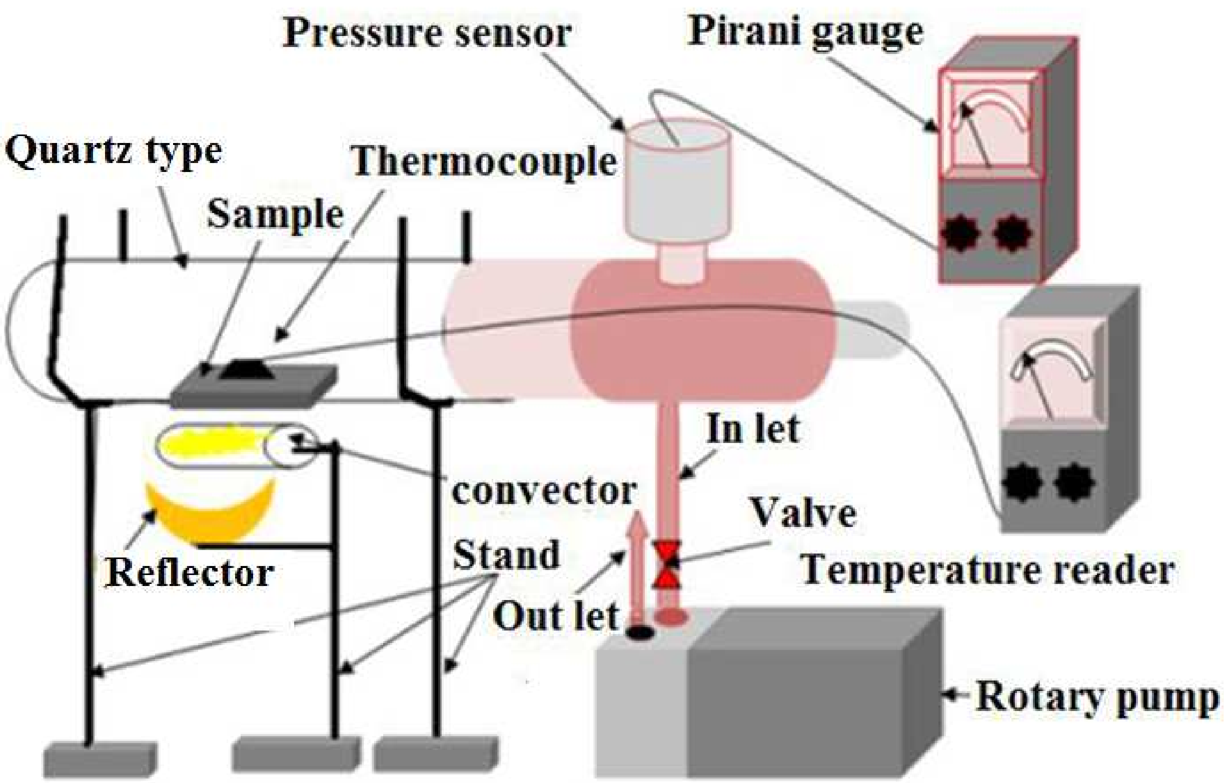


Fig. 2. Thermal annealing system set-up.

Results and Discussion

To measure the electrical properties and other related parameters, an ohmic contact with this layer was a necessary to be established [14]. Aluminum with a high purity (99.999%) was used to obtain Al thick layer electrodes. Thermal evaporation was achieved using a vacuum evaporation system (BLAZER BNEPVN 063 H), at a vacuum pressure 10^{-3}*Torr*. From the examples, ANN can handle continuous as well as discrete data and have good generalization capability as with fuzzy expert systems. An ANN is a computational model of the brain. They assume that the computation is distributed over several simple units called neurons, which are interconnected and operate in parallel thus known as parallel distributed processing systems or connection systems. Implicit knowledge is built into a neural network by training it. Several types of ANN structures and training algorithms have been proposed.

The basic form of RBF architecture involves entirely three different layers. The input layers are made up of source nodes while the second layer is a hidden layer of high enough dimension which senses a different purpose from that in a multilayer perception. The output layer supplies the response of the network to the activation patterns applied to the input layer. The tram formation from the input layer to hide is nonlinear whereas the transformation from the hidden from the unit to the output layer is linear.

Generally, it would be more reasonable and beneficial if hyper-ellipsoidal units be adopted to the RBFNN. The output of an EBF network can be defined as:

$$y_j(\mathbf{x}) = \sum_{i=1}^{l} w_{ji} h_i(\mathbf{x}), \quad j = 1,2,\cdots,m \tag{1}$$

$$h_i(\mathbf{x}) = \exp\left\{-\frac{D_i(\mathbf{x})}{\alpha_i^2}\right\}, \quad i = 1,2,\cdots,l \tag{2}$$

Where x is the input vector,α_i is the shape parameter controlling the spread of the ith basis function. $D_i(x)$ is the distance between the input vector and the ith center of thehyper-ellipsoid unit.

Proposed RBFNN Model. For effective prediction of the energy gap, the selection of proper inputs and outputs of ANN, the structure of the network and training of it using appropriate data should be done with utmost care. In the present study, inputs are selected as etching time (Et), annealing temperature (AT), and annealing time (At). The ANN outputs have been termed as one output node representing the Energy gap (Eg) as shown in Fig. 3.

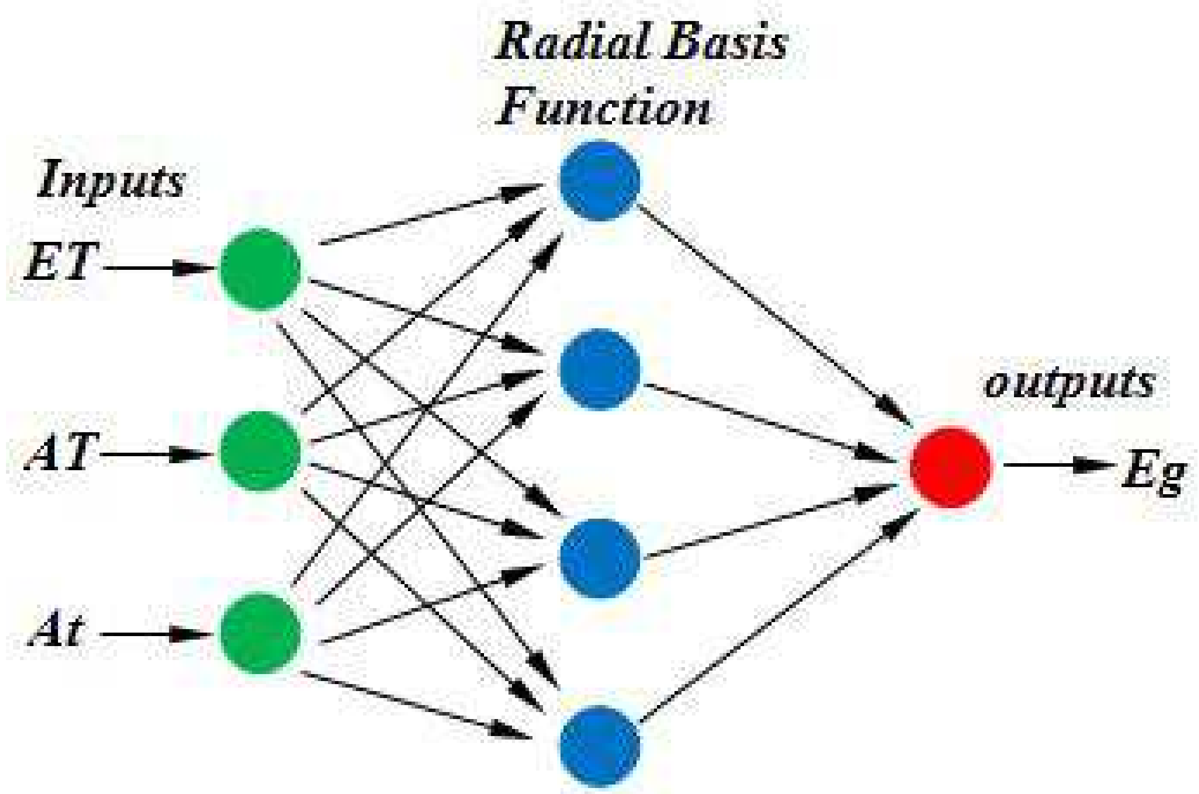
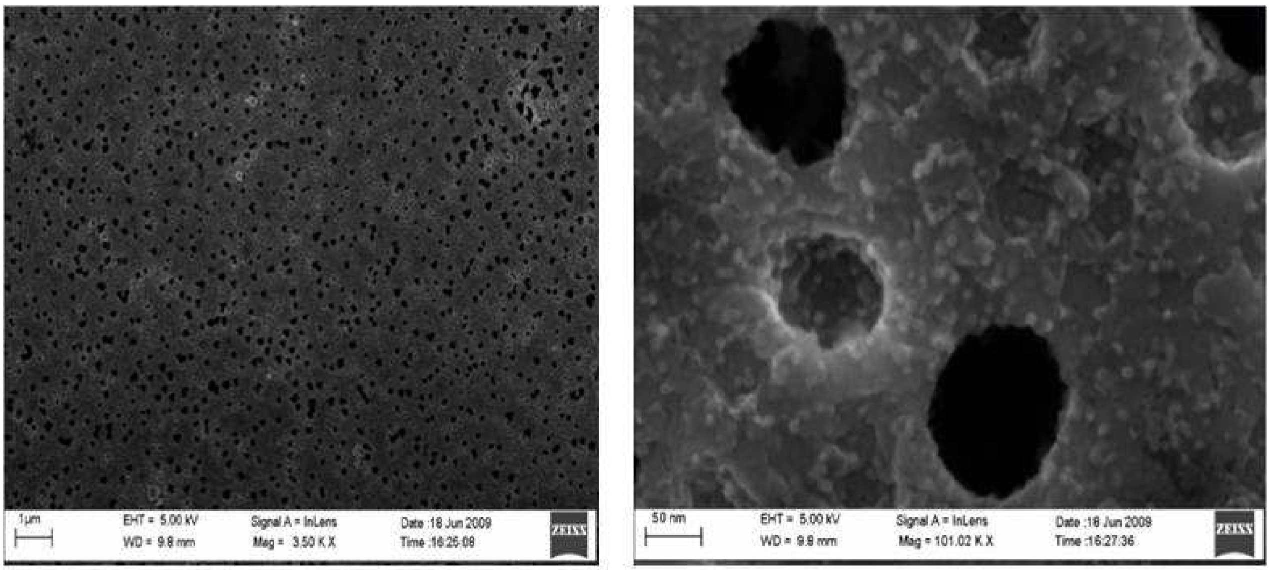


Fig. 3. RBFNN model for Thermal Annealing Process.

In this work, the structural properties of nPSi layer surface morphology, pore width, pore shape, thickness of walls between pores, and layer thickness have been studied by using high resolution scanning electron microscopy (Field Emission Scanning Electron Microscope, FESEM.4) as shown in figure 4a and figure 4b. The sample was prepared by 30 minutes etching time and annealed by rapid thermal annealing process at 700 ^{o}C using 15 seconds annealing time. Fig. 4a represents the FESEM images of the resolution size 1μm whereas figure 4b shows the FESEM images of the high resolution size of 50 *nm*. In addition, the Photoluminescence measurements (PL) were produced by using CW 325 nm, 400 mW He-Cd laser (Liconix 3205N) and the measurements were carried out using CCD-equipped spectrometer (Acton 300). The wavelength of the laser was in the range 450 - 900 *nm*, and the incident angle was 45 *degrees*. The spectrometer was placed normal to the sample surface. Figure 5 represents the photoluminescence spectrum of nPSi sample prepared by 30 minutes etching time and rapid thermal annealing temperature (a) at 500 ^{o}C and (b) at 600 ^{o}C by using 15 seconds annealing time.



(a) (b)

Fig. 4. Shows the FESEM images for the sample, having resolution size 1µm (a) and 50nm size (b) prepared by the 30 minutesetching time, and annealed by rapid thermal annealing process at 700 ° C by using 15 seconds annealing time.

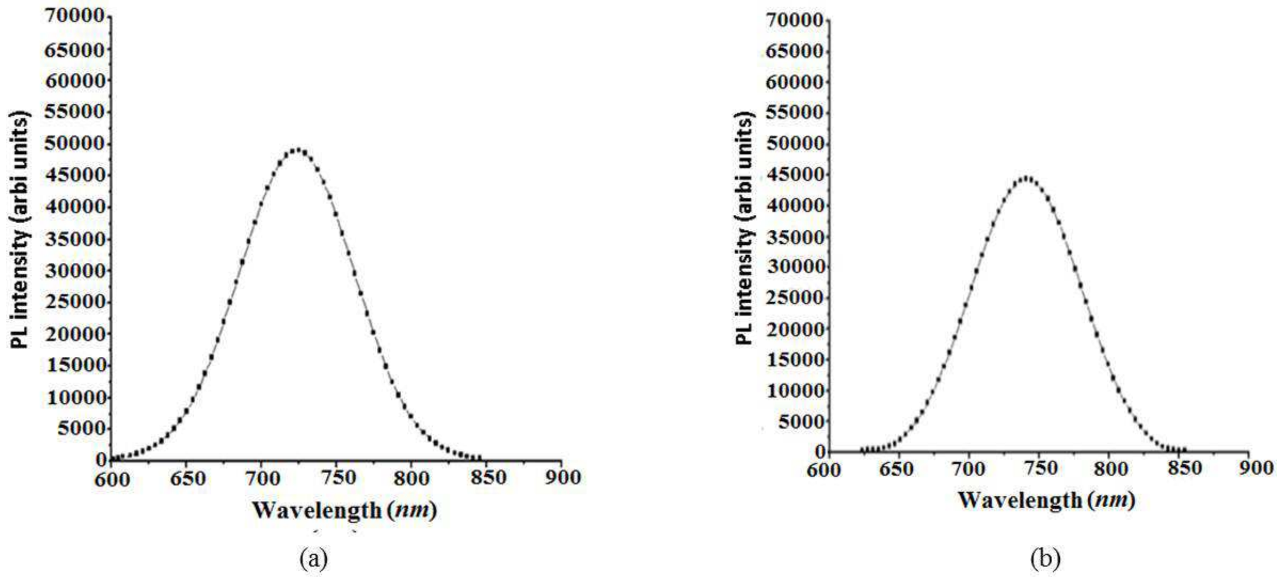


Fig. 5. Photoluminescence spectrum of nPSi samples prepared by etching time 30 min and RTA temperature (a) at 500 °C, (b) 600 °C and 15 secondsannealing time.

To train ANN models with experimental results, network architecture was required; first the entire training data file was randomly divided into training and testing data sets. Table 1, 90% of the data includes 72 patterns, were used to train the different network architectures where remaining 8 patterns were used for tests to verify the prediction ability of each trained ANN model. Since RBFNNs learn relations and approximate function mapping limited by the extent of the training data, the best use of the trained RBFNN models can be achieved in interpolation.

Table 1. Sample of two sets of experimental data for training RBFNN.

AT °C	***Energy gap (Eg). Ve***						**At *(sec.)***
300	2.131	2.110	1.966	1.910	1.891	1.840	10
400	2.142	2.116	1.968	1.920	1.886	1.837	10
500	2.165	2.119	1.970	1.935	1.880	1.830	10
600	2.174	2.120	1.972	1.946	1.872	1.827	10
700	2.183	2.126	1.990	1.957	1.855	1.820	10
800	2.188	2.128	1.997	1.960	1.845	1.816	10
300	1.787	1.749	1.695	1.649	1.591	1.549	15
400	1.783	1.740	1.689	1.641	1.580	1.543	15
500	1.772	1.730	1.680	1.632	1.572	1.531	15
600	1.768	1.722	1.671	1.621	1.569	1.520	15
700	1.761	1.713	1.660	1.612	1.561	1.512	15
800	1.752	1.702	1.651	1.603	1.552	1.508	15
Et (min)	10	20	30	40	50	60	

From the analysis of the results in Table 2, it is observed that the accuracy of the RBFNN method was slightly superior when compared to the experimental result based on Maximum Error (ME) and mean absolute error (MAE).

Table 2. Testing of RBFNN model.

Et (min.)	AT °C	At (sec)	Experimental Eg (eV)	RBFNN Eg.	Error
10	600	10	2.174	2.1252	0.0488
20	600	10	2.12	2.1798	-0.0598
30	500	10	1.97	2.0201	-0.0501
40	600	10	1.946	1.9798	-0.0338
10	500	15	1.772	1.7458	-0.0338
20	700	15	1.713	1.7377	-0.0247
30	800	15	1.651	1.6929	-0.0419
40	600	15	1.621	1.6805	-0.0595
10	600	20	1.55	1.5264	0.0236
20	700	20	1.53	1.5382	-0.0082
30	600	20	1.509	1.5732	-0.0642
40	700	20	1.489	1.4482	0.0408
				ME	0.0488
				MAE	0.052433

Conclusion

In conclusion, the application of Artificial intelligence in Modeling and simulation of complex engineering systems makes possible to reduce the need of expensive experiments through commissioning and operation. In this paper, radial basis function neural network (RBFNN) was used formodeling the thermal annealing process to predict the energy gap for nPSi. The experimental data for 144 samples has been used for training and testing. After trying many RBFNN structures acceptable small error tothe proposed model to mitigate the experimental results at this operating condition.This means with a short time and same algorithm can be used to optimize many experiments operating conditions.

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