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Artificial Neural Networks: Applications in Nanotechnology

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1. Introduction

Artificial neural networks (ANNs), as techniques that mimic the processing way of information in human brain have emerged as promising methods in dealing with non-linear and complex relations. The ability to learn, tolerance to data noises and capability to model incomplete data have made them unique analyzing approaches in many scientific procedures. When employing neural nets, once the network has been trained, new data in similar domain may be analyzed and predicted avoiding the time- and money- consuming experiments. Taking into account that to solve problems, ANNs may combine the data from literature and experiments, the potential of this approach can be easily estimated in nanoscience and nanotechnology.

Two types of training are commonly employed when using ANNs. While in unsupervised networks, the training procedure is not affected by the output(s) of the network; supervised networks attempt to modify the neurons weights so that the network output(s) becomes as close as possible to the desired output. As application in nanotechnology, supervised associating networks may be considered as alternatives to conventional response surface methodology (RSM). The unsupervised feature-extracting networks are alternatives to principal component analysis (PCA) and are able to map multidimensional data sets onto two-dimensional spaces. Therefore, ANNs not only have attracted the attention of many computer scientists, but also a huge number of successful applications of them is found in the literature, reporting problems solving in various areas of sciences, engineering and business.

Although increasing number of ANNs applications are now observed in diverse scientific fields, nanotechnologists do not generally appear to be interested or fully aware of the potentials of such approaches. Here we have described principles of the ANNs in dealing with certain properties of nano-materials. To present the '*state of the art*', available publications on nanotechnology and nanoscience which have used the advantages of ANNs have been evaluated. In this chapter, a brief description about importance of nanotechnology has been given. We then have summarized common applications of ANNs and tried to identify various areas in nanoscience and nanotechnology where the successful application of ANNs can be envisaged, followed by the areas of future developments.

2. Importance of nanotechnology

The lecture "There's Plenty of Room at the Bottom" by Richard R. Feynman in 1959 -that it is nowadays considered as one of the classic science talks in twentieth century- is now regarded as the basic idea for nanotechnology (Bhushan, 2004). In this lecture the potentials of nano-sized materials has been considered (Poole Jr. and Owens, 2003) and publishing Encyclopedia Brittanica on a pin head has been predicted (Balaz, 2008). The quote by the American visionary about nanotechnology is also amazing: "Just wait-the next century is going to be incredible. We are about to be able to build things that work on the smallest possible length scales, atom by atom. These little nano-things will revolutionize our industries and our lives" (Smalley, 1999). It is predicted that in near future, nanotechnology will play an important role in our economy and society, as is being observed in computers, cellular/molecular biology and many others fields. Nanotechnology is about to show its significant role in areas such as medicine, materials and manufacturing, energy, information technology, electronics, etc (Bhushan, 2004).

Nanotechnology in Oxford dictionary means: "the branch of technology that deals with dimensions and tolerances of less than 100 nanometers, especially the manipulation of individual atoms and molecules" (Oxford Online Dictionary, 2010). The National Science Foundation, defines nanotechnology as "research and technology development at the atomic, molecular or macromolecular levels, in the length scale of approximately 1–100 nanometer range, to provide a fundamental understanding of phenomena and materials at the nanoscale and to create and use structures, devices and systems that have novel properties and functions because of their small and/or intermediate size" (National Nanotechnology Initiative, 2004).

In order to realize the importance of nanotechnology, analysis of nanotechnology market is probably the first approach. In 2000, the market of microsystems was about 15 billion USD. Considering an annual increase rate of 10-20%, more than 100 billion USD is anticipated as the market size of microsystems for the end of 2010. In 2001, the nanosystems market was about 100 million USD, while the expected market for the integrated nanosystems is about 25 billion USD by the end of 2010. Such notable increase is thought to be due to the extensive impact they may have in their different applications. Certainly, the role of governments in supporting nano-related technologies should be considered, too (Bhushan, 2004). So far, a large variety of nano- devices and structures have been employed in areas such as sensors, actuators, and miniaturized systems and a large market is anticipated for nano/micro electromechanical machines (NEMS/MEMS) in the near future (Bhushan, 2004; Lyshevski, 2001). Development of NEMS and MEMS is necessary to the economy and society, since these electromechanical systems have shown important effects in medicine, manufacturing and fabrication, aerospace and avionics, information technologies, automotives, public safety, etc (Lyshevski, 2001). Bearing in mind the fact that many initiatives and governments have devoted considerable funds for research and development in nanotechnology, and will probably continue to do so, nanotechnology can still be regarded as "intact" area of research and development in both its science and technology aspects.

3. Classification of applications of ANNs

Reviewing the literature, several classes of applications may be identified for ANNs (Mehrotra et al., 1997; Gardner and Dorling, 1998; Kalogirou, 2001; Agatonovic-Kustrin and

Beresford, 2000; Manisha et al., 2008; Achanta et al., 1995). To avoid the common complications raised when attempting to distinguish between such classes, here we review the ANNs applications without scrutinizing the differences suggested for each application class.

ANNs may be used to *recognize* a specific output *pattern* when presenting an input sample (Mehrotra et al., 1997). Employing this ability, ANNs can effectively solve difficult problems such as recognition of sounds, images or videos. Interestingly, this task may be performed with no priori definition for the pattern. In this case, a completely new pattern is identified by the network.

Recognizing the laws underlying the system behavior is the most accurate way for *prediction*. However, finding these laws is not usually easy. Studying the variables together instead of investigating a single variable at a time (i.e. one-factor-at-a-time approach) is usually a suitable option to obtain better knowledge, thus taking better prediction. Perfect prediction is not possible, but reasonable prediction can be obtained by neural networks (Mehrotra et al., 1997; Weigend et al., 1990; Li et al., 1990).

Another application for the ANNs is what usually called as *function approximation*. Computational models are often some functions that map numerical inputs to numerical outputs (Mehrotra et al., 1997). Function approximation is described as constructing a function that with acceptable approximation generates similar outputs from input valuables. This process is done through learning based on available training data. Unlike most statistical techniques, which usually end up in a distinct equation, when using ANNs, mathematical function relating the outputs to the input variables may not be clear (Mehrotra et al., 1997). Tracking the behavior in a moving object can be regarded as a good example for function approximation. Herein one may approximate behavior of the object understudy as a function of time (Mehrotra et al., 1997).

When the goal of a problem is *optimization* of a function, ANNs may be employed as attractive option. For example when attempting to arrange the components on a circuit board to reach the minimum length for the wire while certain parts should be connected to certain others, we are optimizing the components structure. Problems in this category can also be dealt by ANNs (Mehrotra et al., 1997).

4. Application of ANNs in nanotechnology

In this section, we group the applications of ANNs in three classes: applications in nanomaterials, in nanomedicine, and in nanophysics.

4.1 Nanomaterials

The science and technology of nanomaterials consist of subfields which study or develop materials with nanoscale dimension having unique properties (Clarkson et al., 2004). The majority of nanotechnology works include preparation and characterization of nanomaterials.

The first report on application of ANNs in nanomaterials was in 2000 (Lee et al., 2000), where the sensitivity signals of an array was modelled using artificial neural network, and a gas recognition system was implemented for the classification and identification of explosive gases. The properties of multi-dimensional sensor signals obtained from the nine sensors were analyzed using PCA technique, and a gas pattern recognizer was implemented using a multi-layer neural network with an error back propagation (EBP) learning algorithm. As shown in Fig. 1, the network contained an input layer with nine nodes

receiving the data from the sensors on the sensor array, a hidden layer with eight neurons, and an output layer with nine nodes. The simulation and experimental results showed that the proposed gas recognition system is capable of identifying explosive gases.

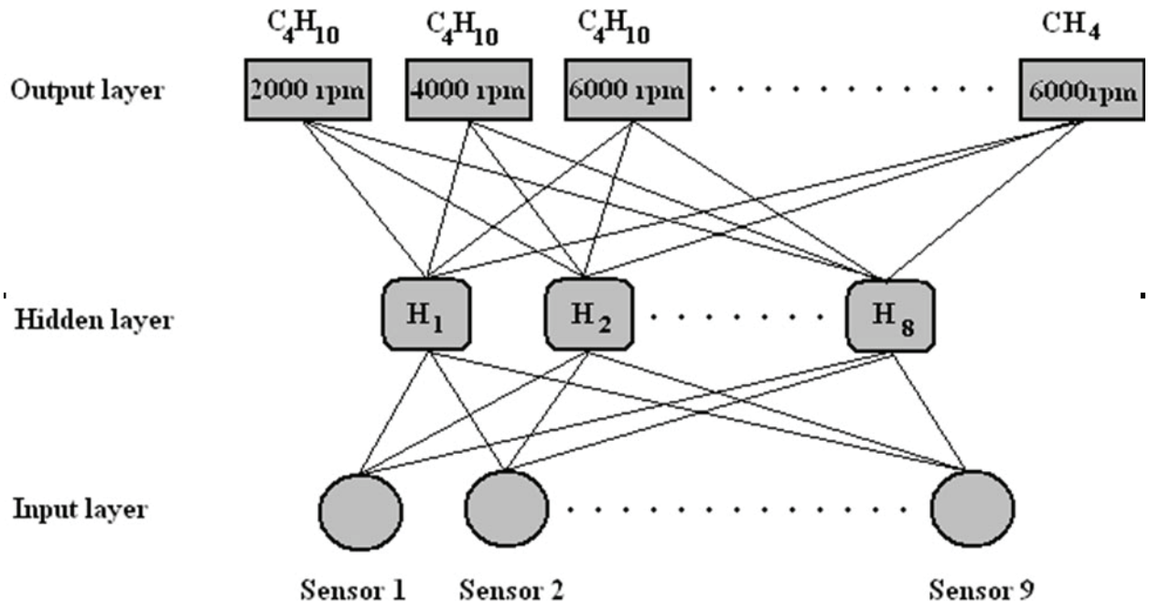


Fig. 1. Schematic of the multi-layer neural network structure for gas recognition system.

Lee et al. (Lee et al., 2001) (Lee et al., 2002) have published two papers on developing recognition systems which can classify and quantify the volatile organic compounds (VOCs). The gas pattern recognizer was implemented using a multi-layer Neural Network with an EBP learning algorithm. The neural network consisted of an input layer (which received data from the sensors on the sensor array), a hidden layer and an output layer. The overall network structure used in this study was similar to the one shown in Fig. 1. The work indicated that the proposed gas recognition system is effective in identifying VOCs.

A three-layer BP-ANNs model (five-input model) was developed to predict purity of $SrTiO_3$ nano-crystals (Qing-li and Quan-xi, 2006). The network used in this study included reaction time, reaction temperature, molar rate of $TiCl_4$ to HCl, NaOH concentration and $SrCl_2$ concentration as input variables and purity of $SrTiO_3$ as the output. It was found that the BP neural network is efficient for predicting the purity of perovskite-type $SrTiO_3$ nano-crystals.

In another study, finite element (FE) simulation and ANNs approach was used (Lee et al., 2007) to describe the elasto-plastic stress–strain behaviour in coated layers using nano-indentation tests. A single-bahaviour model, with one stress-strain behaviour and a layer-behaviour model with separate layers and substrates were used. The loading–unloading data (i.e., force displacement) with changes in yield strength and strain hardening exponents obtained from the FE simulations were employed as training data for the ANN, and the loading–unloading data from the indentation tests were used as the input data. The outputs of the ANNs were the yield strength and strain hardening exponent, which generated the same loading–unloading data as the indentation test did. The layer-behaviour model was shown to be satisfactorily accurate.

Combination of finite-element (FE) simulation and ANNs modelling is becoming an interesting tool in nanomaterials. A study by Haj-Ali (Haj-Ali et al., 2008) reported the use of ANNs models in dealing with nanohardness tests in a wide range of materials with nonlinear behavior. ANNs models were trained with separate FE simulations with nonlinear properties and different geometries. When generating the model, from load-displacement indentation response, only the monotonic loading part was utilized, which is a key difference from classical experiments which normally use the unloading portion. The experimental nanoindentation tests included a silicon substrate with and without a copper film in its nanocrystalline form. Comparing the results from the modelling with those available in the literature, the obtained model was suggested as very efficient with the ability to calibrate and predict the inelastic material properties for depths above 50 nm. The overall resisting force in the study was found to be a continuum response.

Optimal variables for preparation of sol-gel prepared colloids of titania were determined using ANNs in a report by Liau et al (Liau and Dai, 2008). In this work, the inputs are concentration of [NH_3], [H_2O], and reaction temperature; while the outputs are the titania particle size (PS) and particle size distribution (PSD). The relationship of the operating variables (inputs) and PS and PSD (outputs) can be built using the ANN approach. The built ANN model can then represent the input–output relation in the sol–gel processing system and predict PS and PSD in relation to operating conditions. The model was then used to optimize the operating variables in order to obtain desired particle size with narrow particle size distribution. The feasible optimal operating conditions can be determined to fabricate monodispered uniform TiO_2 particles for practical cases.

Preparation of composites of polyphenylene sulfide (PPS) filled with short carbon fibers (SCFs) and sub-micron particles of TiO_2 to study the tribological behaviour of the composite using ANNs has been reported by Jiang et al. (Jiang et al., 2008). The extrusion and injection-molding technique to prepare the particles followed by sliding wear tests to optimize the composition of PPS, suggested 15 vol.% SCF and 5 vol.% TiO_2 as the lowest specific wear rate. More optimal composition was estimated from the ANNs as 15 vol.% SCF and 6 vol.% T_iO_2 chosen input variables in neural network were material compositions (PPS matrix, short carbon fiber, nano-TiO_2 particles and lubricant contents) and testing conditions (sliding speed and applied pressure) while the output variables were specific wear rate and friction coefficient, as well as the range of the experimental values.

In 2009, Madadlou et al. (Madadlou et al., 2009) predicted micelles particle size. The following five variables were used as inputs to networks: pH value of casein solutions, frequency of ultrasonic bath (kHz), frequency of ultrasonic probe (kHz), acoustic power of sonication (W) and time of sonication (min). The output of system was particle size (nm) of re-assembled casein micelles. It was measured with a laser diffraction based particle size analyzer. The size of micelles differed from 203 to 431nm. A feed-forward network having one hidden layer was used in this study. Optimization was performed on number of hidden neurons, epochs and training runs as well as momentum coefficient and step size. They also stated that RSM can be successfully used in optimizing the topology of ANNs but RSM considered as a complicated and time-consuming task. Using this approach results in shortening the time required for optimization and providing the possibility of analyzing the influence of more variables on performance of networks.

Prediction of heat transfer in copper–water nanofluid by ANNs was reported in differentially heated square cavity (Santra et al., 2009). The nanofluid was taken as a non-

Newtonian fluid and the network was trained based on resilient-propagation (RPROP) algorithm. Input and output data were from a numerical simulation. Results of simulation and ANNs model were compared and was reported to be correct in the range of training data. Furthermore, taking into account the considerable longer times required for simulations, the RPROP based ANNs was suggested as competitive alternative in prediction of heat transfer.

In 2009, Shokuhfar et al. (Shokuhfar et al., 2009) studied the effect of different training approaches on the ANNs when dealing with Al_2TiO_5- based ceramics. Herein, addition of micron size talc led to satisfactory stabilizing behaviour. In addition, nano boehmite and colloidal silica managed to improve other physical properties. Subsequently, using BP-ANNs, the effect of temperature and additives percentages on the density of bulk was estimated. Levenberg–Marquardt algorithm was found to have the best estimation and the response surfaces between the variables (additives percentage and temperature) are presented. The model was then suggested to be used in optimizing the sintering process for the particles.

The effect of concentration of MnS on the nano-crystalline $Cd_{1-x}Mn_xS$ size ustilizing feed-forward multilayer perceptron was reported by Jajarmi et al (Jajarmi and Valipour, 2009). The reports pointes out that the generated ANNs model can be considered as applicable method in predicting of the size of nano-crystalline nickel coatings. The grain size of nano-crystalline nickel was also the subject of another study by Rashidi et al (Rashidi et al., 2009). In their study, operation conditions were used as the inputs variables and the grain size of coating was taken as the single output of the model. Good agreement was shown between the predictions of the model and the experimental data. Performing the sensitivity analysis on the model, it was indicated that the current density was the most important factor, while the temperature had the lowest impact on the grain size.

In 2009, Sarkar et al. (Sarkar et al., 2009) used ANNs as tools to study the diameter of electrospun nanofibers. The input variables in this study were concentration of the solution, electrical conductivity, flow rate, and strength of the electric field. The results of the computer model indicated satisfactory viability for the neural network to predict the diameter of the nanofibers. From this study, insights into employing ANNs models in investigating electrospinning processes is determined.

In a series of ANNs models in 2009, Ma et al. (Ma et al., 2009) using back-propagation technique, studied the correlations between processing factors (high-energy planetary ball milling) and the morphology of nanocomposite WC–18at.%MgO powders. Milling speed, diameter of ball and weight ratio of ball-to-powder was investigated on the crystallite and particle size as well as specific surface. The model was shown to be capable of predicting properties of the composite at different milling parameters. Optimization in processing parameters and ball milling conditions was also suggested as another ability of ANNs in such situations.

A report by Corni et al. (Corni et al., 2009) detailed the effect of deposition time and applied potential as well as their interactions on synthesis of nano-composite films of Al_2O_3–polyetheretherketone on stainless steel. The process was performed in non-aqueous colloidal suspensions using electrophoretic deposition. In their study, the numbers of hidden layers, neurons in each layer and epochs were optimized to improve the results from this approach. Furthermore, this work was complemented by the use of Monte Carlo simulation to better study the effect of deposition time and difference of applied potential on the deposition yield of deposition.

In studies by Haciismailoglu et al. and Kucuk et al. (Haciismailoglu et al., 2009; Kucuk et al., 2009), dynamic hysteresis models from measurements in wide frequency range (1–50 kHz) were developed using ANNs by delta-bar-delta learning. They showed computation of hysteresis loops in nano-crystalline cores by ANNs, using dynamic Preisach model to be fast, with no need to so much of computational efforts. Using geometrical dimensions of cores, peak magnetic induction and magnetizing frequency as input parameters, the ANNs was shown to have acceptable estimation capability. The model is fast, and allows the application of standard learning algorithms for the neural network.

In a study by Averett (Averett et al., 2010), ANNs examined the effect of stress ratio, maximum fatigue stress, unreformed modulus, cycles and residual strain from fatigue as input variables on residual strength behaviour and elastic modulus degradation in filaments. The results indicate that ANNs can be used to predict the residual strength and modulus degradation behavior of poly(ethylene terephthalate) and poly(ethylene terephthalate) fibers with vapor grown carbon nanofibers under different loading conditions. In their study, back propagation were used along with momentum and conjugate gradient algorithms. The multilayer perception network was trained to model the mechanical behaviour in single filaments after loading of fatigue.

Catalytic conversion of two substrates namely, ethyl acetate and toluene, using two nanostructures catalysts HZSM-5 and Co-ZSM-5 was investigated by Hosseini et al. (Hosseini et al., 2010). The ANNs model was based on experimental data from wet impregnation prepared catalysts. Good agreement was shown between the results from the model and those of experiments. This study in agreement with other reports shows that the nanostructure catalysts show higher activity than other catalysts because of having higher specific surface area. The model makes it possible to predict how much each variable affects on the conversion efficiency.

Baseri et al. (Baseri et al., 2010) estimated the effect of concentration of liquid phase and the ratio liquid/powder on the mechanical strength of cement as well as both initial and final setting times in hydroxyapatite (HA). They employed back propagation ANNs with variety of inputs. The comparison of the predicted values and the experimental data indicated that the developed model had a satisfactory performance in estimation of the setting times and the mechanical strength in HA bone cement. Also, it was concluded that the prediction accuracy of 3-outputs model is better than those of other 1-output models.

Detailing the dialysis process performance under as a function of different conditions in dialysis has also been reported using ANNs by Godini et al. (Godini et al., 2010). Charged micelles were transferred through neutral and charged membranes and the behaviour of the micelles was studied using ANNs. High interconnections of the parameters as well as problems associated with the available models in tracking the performance of the process made the ANNs as interesting approach to study this case. The mass transfer was analyzed in terms of its amounts and the mechanism in both membranes in different conditions. The report shows that the developed model can deal with the process when manipulating the parameters individually or simultaneously with adequate accuracy.

4.2 Nanomedicine

Nanomedicine has been defined as "medical application of nanotechnology". Nanomedicine includes use of nanomaterials in medical applications, nanoelectronic biosensors, and future

applications of molecular nanotechnology. The main problem in nanomedicine nowadays is the toxicity issues and environmental aspects of nanomaterials (Freitas Jr., 1999).
The factors controlling the nanoemulsion particle size was studied by our group in 2008 (A. Amani, et al., 2008). Oil in water nanoemulsion samples with different percentages of co-surfactant and drug, applying various amount and rate of applied energy were prepared and the particle size was measured. The generated ANNs model demonstrated the ability of ANNs in dealing with such systems. The model indicated that the total energy amount was the dominant factor in influencing the final particle size.
We also (Amani et al., 2010) identified the parameters affecting the stability of nanoemulsions, using ANNs. A nanoemulsion preparation of budesonide containing polysorbate 80, ethanol, medium chain triglycerides and saline solution was designed, and the particle size of samples with various compositions, prepared using different rates and amounts of applied ultrasonic energy, was measured 30 min and 30 days after preparation. Data modelling and assessing were carried out using ANNs. The derived predictive model was validated statistically and then used to determine the effect of different formulation and processing input variables on particle size growth of the nanoemulsion preparation as an indicator of the preparation stability. The results of this study indicated that the data can be satisfactorily modelled using ANNs, while showing a high degree of complexity between the dominant factors affecting the stability of the preparation. The total amount of applied energy and concentration of ethanol were found to be the dominant factors controlling the particle size growth.
In a microfluidic reactor when nanoprecipitating a hydrophobic drug, ANNs was employed to find out the relationships between input parameters and the size of prepared nanoparticles (Ali et al., 2009). In this study saturation levels of drug, flow rates for solvent and antisolvent, angles for the inlet of microreactors and internal diameters were investigated and rate of antisolvent was found to have dominant role on determining final particle size.

4.3 Nanophysics

The subject of nanophysics is physics of systems having some tens of atoms (Joachim and Plevert, 2009). Considerable number of reports has been mentioned the use of ANNs in nanophysics:
In 2006, Kucuk and Derebasi (Kucuk and Derebasi, 2006) using the data from toroidal wound cores developed a mathematical model for core losses. The improved model was used to optimize the parameters for ANNs. Geometrical parameters, frequency of magnetising, resistivity of the soft magnetic materials and magnetic induction were input parameters while power loss and correlation coefficients comprised the output neurons. The correlation coefficients for calculation of power loss can simply be estimated from the ANN and GA genetic algorithm within acceptable error limits. This means that the ANN and GA could help to assess the core performance before manufacture, thereby reduce the material wastage. Studying nanoscale complementary metal-oxide-semiconductor (CMOS) circuits, Djeffal et al. (Djeffal et al., 2007) used ANNs and showed very acceptable comparisons between the results from numerical models and those of ANNs where L, VDS, VGS, tsi, tox, and ID were channel length, drain source voltage, gate source voltage,silicon film thickness, gate oxide thickness and drain current, respectively. Each of these parameters was indexed with one neuron. The activation function used in this ANN structure was the sigmoid

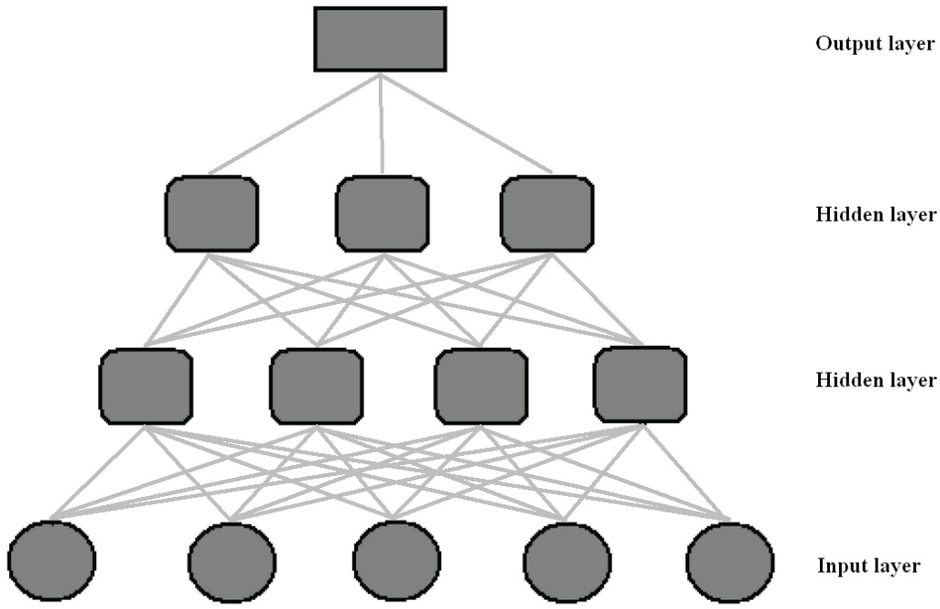


Fig. 2. Neural network consisting of two hidden layers.

function. It is important to denote that the number of input parameters of our ANN model can be extended for other parameters (temperature, band-to-band leakage current, and gate direct tunnelling current and ...). Is this work two hidden layer was used (Fig. 2) and the developed ANNs model indicated to be particularly appropriate as SPICE-like (simulation program with integrated circuit emphasis) tools for simulation of nanoscale CMOS circuits.

Three commercial membranes, based on nanofiltration techniques (ie. NF90, NF270, N30F) were utilized to treat solutions of three different salts in high concentrations (Al-Zoubi et al., 2007). Obtained data were modelled using ANNs and Spiegler–Kedem model. The model determined the reflection coefficients and the of the solute permeability at different levels of salinity. No more than 5% deviation was observed between the predictions by the ANNs and the experimental data. In total, the obtained results indicated that NF90 and NF270 hadhigh rejection at pressures above 5 bar for two salts (ie. Na_2SO_4, and $MgSO_4$), while the rejection for KCl was 30–89%. The third membrane produced lesser rejection for Na_2SO_4 and $MgSO_4$ salts with very low rejection for KCl.

In 2007, Farsi et al. (Farsi and Gobal, 2007) used a four-layer ANNs structure with two hidden to model the performance of a model capacitor. The output variables in this study were power and energy density and utilization to the intrinsic, synthetic and operating characteristics and the inputs included size of crystals (in range of 5-30 nm), lattice length and exchange current density of active material as well as employed cell current. The findings showed that results have a very good agreement with models, developed previously.

Incorporation into SPICE-like tools for simulation of nanoscale circuits has also been by Hayati et al. (Hayati et al., 2010), where ANNs modeled carbon nanotube metal–oxide-semiconductor field-effect transistors (CNT-MOSFETs). The ANNs model needed less computational time compared with other conventional models like non-equilibrium Green's function (NEGF) formalism with having similar accuracy. The ANN model was subsequently imported into HSPICE software as a subcircuit.

One of the most recent uses of ANNs in nanophysics is to generate explicit nonlinear empirical physical formulas (EPFs) in nonlinear electro-optical responses from doped nematic liquid crystals (NLCs) (Yildiz et al., 2010). Layered feed-forward neural network (LFNN) was used due to its ability in nonlinear function approximation. The obtained responses were successfully fitted to the model to predict the new response data. It was then concluded that generally, LFNN may be applied to construct different EPFs in various physical perturbation data such as thermal, molecular and optical conditions in doped NLCs.
ANNs have also been used to determine a relationship between diffuse reflectance spectra in near-infrared region and particle size. Back-propagation artificial neural network (BP-ANN) was utilized in by Khanmohammadi et al. (Khanmohammadi et al., 2010) to estimate the particle size from diffuse reflectance spectra. 44 nano TiO_2 samples were analyzed to validate the applicability of the new method in determining the particle size. It was shown that the BP-ANN caould successfully predict the size of nanoparticles.

5. Conclusion

The high number of reports of researches at nano-levels, manipulting and/or creating novel materials and processes has provided enormous applications in all aspects of human life. Nantechnology has shown its great potential in industrial processes, computers, pharmaceuticals and many other fields. Such a scientific breakthrough, as an inter-disciplinary tool has proved efficient in utilizing various sciecntific approaches such as physics, chemistry and medicine in dealing with a single problem. Surprisingly, the literature review on nanotechnology reports shows no large number. This chapter aims to highlight the need for increased understanding of applications of ANNs in nanotechnology so that these networks can be used even more efficiently in future applications. It should be clarified that here we have only focused on so far reported applications and undoubtedly much more uses can be suggested for ANNs dealing with nano-issues.
Models from ANNs are multifactorial models which can predict, classify, approximate function or recognise patterns in many disciplines. Theoretically, ANNs are able to estimate any function and if used properly, can be used effectively in any discipline, including nanotechnology. Outputs from ANNs models are generated from non-linear combinations of input variables and as shown in this chapter, such models can be effectively employed to deal with experimental data routinely observed in nanotechnology and to find rules governing a process from raw input data.
ANNs are now considered as easy-to-use, while reliable methodology, which is a new emerging technique in the new emerging science “nanotechnology”. To see more applications of ANNs in nanotechnology in future, we suggest that researchers in both academic and commercial areas of nanotechnology should be more familiarized with the idea of neural networks. Additionally, forming team groups of experimentalists with those working on neural networks and statistics needs to be promoted. We believe ANNs, as the tools with the ability to handle the nonlinear processes and avoiding the commonly observed noises in experimental data, are fascinating means of working with data observed by nanotechnologists.

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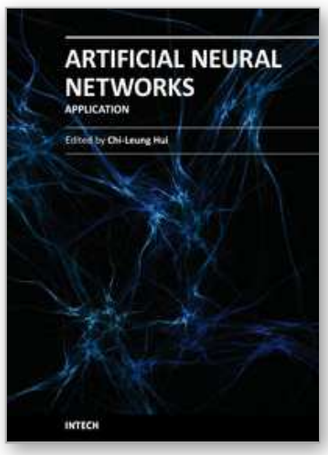
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This book covers 27 articles in the applications of artificial neural networks (ANN) in various disciplines which includes business, chemical technology, computing, engineering, environmental science, science and nanotechnology. They modeled the ANN with verification in different areas. They demonstrated that the ANN is very useful model and the ANN could be applied in problem solving and machine learning. This book is suitable for all professionals and scientists in understanding how ANN is applied in various areas.

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