Editorial
Artificial Neural Networks to Systems, Man, and Cybernetics: Characteristics, Structures, and Applications

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***Abstract*—The goal of this special issue is to present recent high-quality papers that deal with the applications of artificial neural networks (ANN's) to systems, man, and cybernetics (SMC). This special issue explores the state-of-the art in the applications of ANN to the SMC community. ANN's technology has reached a degree of maturity as evidenced by the increasing number of applications including the ones that have been reduced to practice. In this editorial, we present background and theoretical information related to ANN's, general characteristics, models, applications, and structures of ANN's.**

***Index Terms*—Applications of artificial neural networks, learning algorithms, models, structures.**

I. Introduction

ARTIFICIAL neural networks (ANN's) and neural engineering/computing in the wide sense are among today's most rapidly developing scientific disciplines. ANN's are parallel computational models that consist mainly of interconnected adaptive processing units. These networks are considered fine-grained parallel implementation of nonlinear dynamic and static systems. An ANN is an abstract simulation of real nervous system that contains a collection of processing units or processing elements (PE's) communicating with each other via axon connections. Such a model resembles the axons and dendrites of the nervous system. Because of its self-organizing and adaptive nature, the model provides a new parallel and distributed paradigm that has the potential to be more robust and user-friendly than traditional schemes [1]–[14].

The study of artificial neural networks is an attempt to simulate and understand biological processes in an intriguing manner. Today, we are witnessing the dawn of a new revolution in technology that will revamp the infrastructure of many approaches to solve cybernetics, information, and system engineering problems, among others. It is of interest to define alternative computational paradigms that attempt to mimic the brain's operation in several ways. Neural networks are an alternative approach to the traditional von Neumann programming schemes.

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Interest in neural networks has increased in recent days due partly to some significant breakthroughs in research in architecture, learning/training algorithms, and operational characteristics. Advances in computer hardware technology that made neural networks implementation faster and more efficient have also contributed to the progress in research and development in neural networks. Much of the drive has arisen because of the numerous successes achieved in demonstrating the ability of neural networks to deliver elegant and powerful solutions, especially in the fields of learning, pattern recognition, optimization, and classification, which have proved to be difficult and computationally intensive for traditional von Neumann computing schemes.

Due to its interdisciplinary nature, encompassing computing, biology, neuropsychology, physics, engineering, biomedicine, communications, pattern recognition and image processing, etc., the field of neural networks attracts a variety of researchers and developers from a broad range of backgrounds. Today, there are many different paradigms and applications of neural networks, reflecting research and development groups. ANN's are viable computational models for a wide variety of applications including pattern recognition, speech recognition and synthesis, image compression, adaptive interfaces between human and machines, clustering, forecasting and prediction, diagnosis, function approximation, nonlinear system modeling and control, optimization, routing in parallel computer systems and high-speed networks, and associative memory. The field of neural networks links a number of closely related areas that include parallel and distributed computing, connectionism, and neural computing. These areas are brought together with the common theme of attempting to exhibit the computing method which is witnessed in the study of biological neural systems [5]–[10].

II. Background

In artificial neural networks, the element that corresponds to a biological neuron is called a processing element (PE). A simple PE combines its input paths by adding up the weighted sum of all inputs. The output of a PE is the signal that is generated by applying the combined inputs to an appropriate transfer function (see Fig. 1). Learning takes place in the form of adjustment of weights connecting the inputs to the PE. There

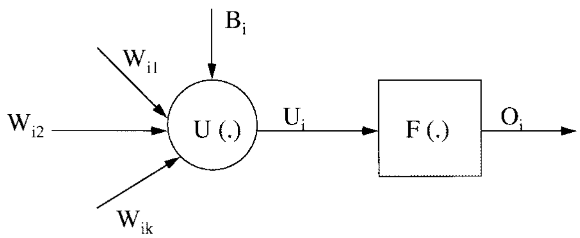

Fig. 1. A general neural model.

are various ways in which the PE's are interconnected in neural networks as groups called layer or slab, and also, there exists a variety of training (learning) rules that determine how, when, and by what magnitudes are the weights updated. For example, a typical backpropagation type of neural network element (see Fig. 2) transfers its inputs as follows:

$$O_k^{[s]} = f\left[\sum_j w_{kj}^{[s]}\, y_j^{[s-1]}\right] = f(\text{net}_k^{[s]}) \tag{1}$$

where

$y_j^{[s-1]}$ current output state of jth neuron in layer $s-1$;

$w_{kj}^{[s]}$ weight on connection joining the jth neuron in layer $(s-1)$ to kth neuron in layer s;

f activation/transfer function.

A suitable activation function can be chosen for each layer by trial-and-error method from among several commonly used functions such as TanH, Sigmoid, and linear. In (1), traditional sum is used to obtain $\text{net}_k^{[s]}$. However, several other variants of $\text{net}_k^{[s]}$ may be used and their relative effect on the neural network performance can be studied. A few of the general purpose summation functions are

$$\text{Maximum: net}_j = \max_i\,(w_{ji}y_i) \tag{2}$$

$$\text{Minimum: net}_j = \min_i\,(w_{ji}y_i) \tag{3}$$

$$\text{Majority: net}_j = \sum_i \text{sgn}\,(w_{ji}y_i) \tag{4}$$

$$\text{Product: net}_j = \sum_i w_{ji}y_i \tag{5}$$

$$\text{City-Block: net}_j = \prod_i\,[y_i - w_{ji}]. \tag{6}$$

The information propagates through ANN's in response to the input patterns. Differential error at each hidden layer is computed as follows:

$$\begin{aligned}\delta_j^{[s-1]} &= -\delta E/\delta(\text{net}_j^{[s-1]})\\ &= f_k'\,(\text{net}_j^{[s-1]})\cdot\Sigma(\delta_k^{[s]}w_{kj}^{[s]})\end{aligned} \tag{7}$$

and the corresponding delta weights are added to all the weights in the system.

$$w_{ji}^{[s-1]} = l\text{coef}\cdot\delta_j^{[s-1]}\cdot z_i^{[s-2]} + \text{momentum factor} \tag{8}$$

where $l$coef $=$ learning coefficient.

This is done for each (input, desired output) pair when delta-learning rule is in effect. However, the convergence speed for ANN's can be improved when other rules such as normalized-cumulative-delta (Norm-Cum), Delta-Bar-Delta (DBD), and Max-Prop. rules are used along with a suitable momentum factor [6], [7].

The direction of signal flow, types of training and activation function, values for learning parameters, number of neurons in each layer, etc., are a few of the current active research areas. The following design factors are important aspects to the characterization of ANN models [9], [10], [15].

1) supervised, unsupervised or reinforcement learning paradigms;
2) decision and approximation/optimization formulations;
3) ANN structures;
4) static and temporal pattern recognition;
5) activation functions
6) individual and mutual training strategies.

III. Characteristics and Models of ANN's

A fundamental feature of artificial neural networks is their adaptive nature, where learning by examples replaces programming in solving problems. This important feature makes such computational paradigms very appealing in the application domain where one has little or incomplete understanding of the problem to be solved, however, there exists some training data. The parallel and distributed architecture feature of ANN's allows for fast computation of solutions when these networks are implemented on parallel and/or distributed computer systems [16]–[18].

One aspect of ANN's is the use of simple processing elements which are essentially approximate models of the neurons in the brain. It is estimated that the brain contains over 100 billion (10^{11}) neurons of different types and 10^{14} synapses in the human nervous system. Recent studies in the brain have found that there are more than 1000 synapses on the input/output of each neuron. A neuron is the fundamental cellular unit of the nervous system and, in particular, the brain. The "artificial neuron" is the basic building block unit of any ANN. Each neuron can be regarded as a simple processing element that receives and combines signals from many other neurons through input structures called "Dendrites." For a combined input signal having values greater than a certain threshold, the firing of a neuron takes place resulting in an output signal that is transmitted along a cell component called "axon." The axon of a neuron splits up and connects to dendrites of other neurons through the "synapse." The strength of the signal transmitted across a synapse is called synaptic efficiency, which is modified as the brain learns [9], [16]–[18].

There are two types of ANN models.

1) The biological type which encompasses networks mimicking biological neural systems such as audio functions (cochlea) or early vision functions (retina). The main objective of the first type is to develop a synthetic element for verifying hypotheses related to biological systems. The ANN's are not used directly for data processing. For instance, research on biological type

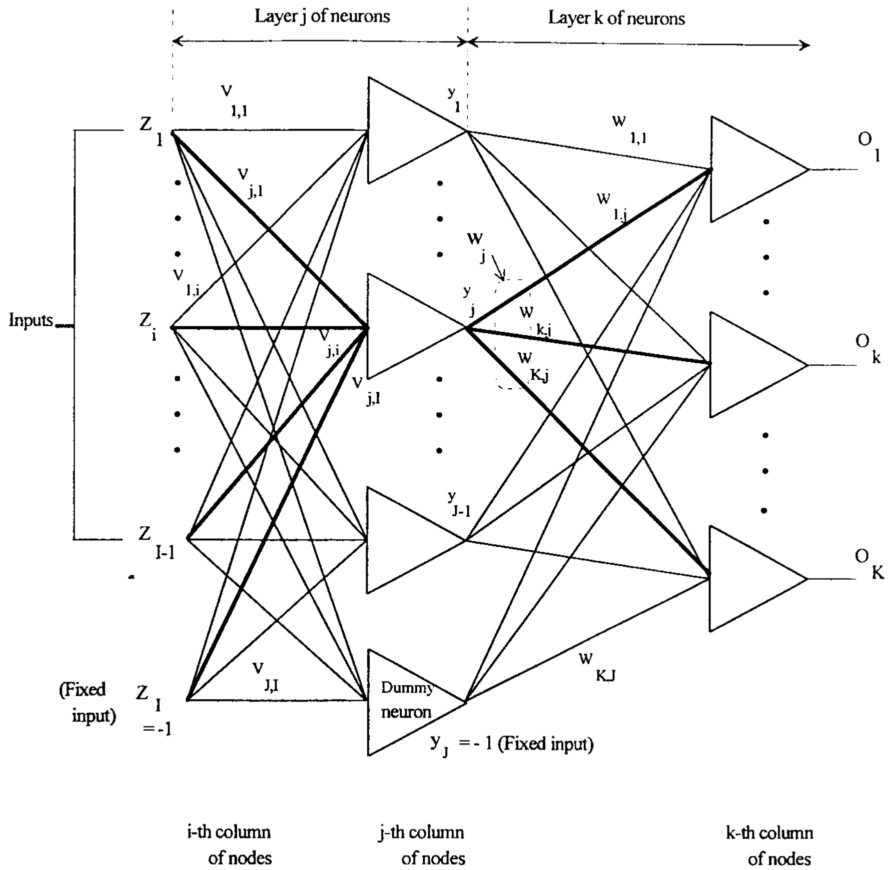

Fig. 2. Two-layered feedforward neural network.

vision neural networks has focused on functions such as motion field, edge detection, and binocular stereo vision [19]. In natural retina vision processing, edge information is extracted via lateral inhabitation between retinal neurons. Depth perception (stereopsis) is formed by comparing images from the two eyes in primates. Many of such biological processing examples have provided useful results for the development of ANN's. The structure of the cerebral cortex can be modeled by 3–6 layers of neurons. The neurons (PE's) and interconnection synapses constitute the major elements for information processing. Most neurons possess tree-like structures called "dendrites" that receive input signals from other neurons across synapses (junctions). Some neurons communicate with few nearby ones while others make contact with thousands. The branching extension that carries neurons output to the dendrites of other neurons is called the axon. A neuron sends its output to other neuron via its axon. The axon carries the data through a series of waves of current that depends on the neurons voltage potential. A neuron collects signals at its synapses by adding all excitatory and inhibitory influences acting upon it. The neuron fires and sends this message to other neurons via the outgoing synapses. The neuron function is often modeled as a threshold function, if the excitatory influence is dominant [17], [18].

2) The second type is the application-driven neuron which depends less on faithfulness to neurobiology. An application-driven ANN can be defined as an ANN architecture that comprises massively parallel adaptive PE's with an interconnection network. In these models the architecture is dictated by the application needs. Many of such ANN's are represented by the so-called connectionist models. In general, neurons and axons are mathematically modeled by activation and net functions, respectively (see Fig. 1). The selection of these functions depends in most cases on the applications of the ANN models. In other words, application-driven ANN models are only loosely tied to the biological realities. They are tightly associated with advanced and intelligent processing in recognition, optimization, and classification. Such models have the potential of offering a revolutionary technology for modern high-performance computer and information processing. The reasons for the strengths of application-driven ANN's can be enumerated as follows [9], [10].
   a) Parallel and distributed processing capability: they employ a large number of PE's that are interconnected together using an interconnection scheme that depends on the type of the paradigm.
   b) Adaptiveness and self-organization: they offer adaptive and robust processing capabilities by adopting

adaptive learning (training) and self-organization rules.

c) Fault-tolerance: this is a very attractive feature for many applications.

d) Nonlinear processing: this characteristics is very important as it enhances the networks approximation, noise immunity and classification capabilities.

Neural networks can be classified into different categories based on the selected criterion. Based on the learning (training) method (algorithm), we can divide neural networks into supervised, unsupervised, and reinforcement learning types. Supervised learning refers to the design of a classifier in the case that the underlying class of available samples is known. In supervised learning, each input pattern received from the environment is associated with a specific desired target pattern. The weights are usually synthesized gradually, and at each step of the learning process they are updated in order to minimize the error between the networks output and a corresponding desired target. In the unsupervised learning case, it is necessary to classify data into a number of groups without the aid of a training set. The goal here is to separate the given data into M classes. The idea is to optimize some criterion or performance metric/function defined in terms of the output activity of the units in the network. The weights and outputs in this case are usually expected to converge to representations that capture the statistical regularities of the input data. In order to accomplish this a clustering criterion is defined which assigns a numerical value to each possible assignment of samples to clusters. It is too costly in general to simply evaluate the criterion for each possible assignment, therefore, a method must be used to find an optimal assignment. The third class is the reinforcement training (learning) algorithm which is between supervised and unsupervised learning. Reinforcement learning involves updating the networks weights in response to an "evaluative" teacher who basically tells whether the answer is correct or incorrect. It involves rules that may be viewed as stochastic search mechanism that attempt to maximize the probability of positive external reinforcement for a given training set.

From the point view of estimation, we can classify artificial neural networks into estimating and nonestimating families. The estimating neural networks use the Parzen estimators for estimating the probability density function (PDF) for a given data set. The other family is made up of no-estimating neural networks which cannot estimate PDF automatically from the data set.

It is the author's expectation that in the future we will have open computing and processing systems where application-driven ANN's will play a great role along with traditional von Neumann and optical computing paradigms. A scheduler will decide where the task has to be scheduled. For example, if the task to be executed is an optimization or recognition task, then ANN-based platform/paradigm (neurocomputer) will be selected to execute it. If the task is a pure numerical computation such as matrix arithmetic then traditional von Neumann platform/paradigm will be used. For image processing and other similar tasks, optical computing platform/paradigm will be selected.

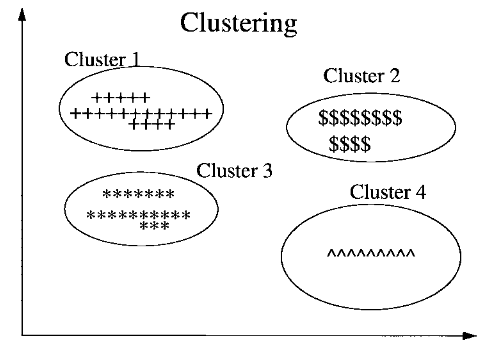

Fig. 3. A classification example.

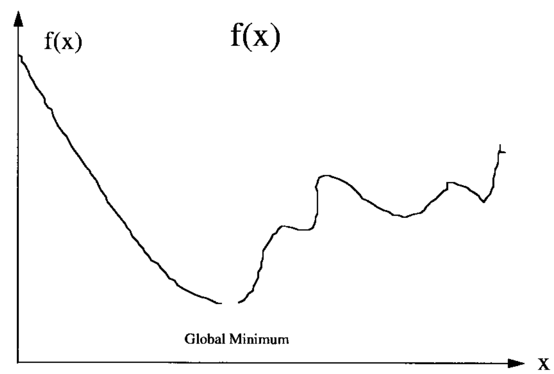

Fig. 4. Global minimum of the function $f(x)$.

IV. Application Categories

We can divide the application domain of ANN's into the following main categories: 1) classification, clustering, diagnosis and association; 2) optimization; 3) regression and/or generalization; and 4) pattern completion [1]–[10], [20]. A brief description of each category follows.

1) Category 1: Classification, clustering, diagnosis, and association: In this paradigm, input static patterns or temporal signals are to be recognized or classified. A classifier should be trained so that when a slightly distorted version of a stimulus is presented it can still be correctly recognized. The network should have a good noise immunity capability which is critical for some applications such as holographic and retrieval applications. An example is shown in Fig. 3.
2) Category 2: Optimization: ANN's are very appealing for solving optimization problems which involve finding a global minimum function (see Fig. 4). The determination of the synaptic weights is relatively easy once the energy function, $f(x)$, is found. The cost function is easy to find for some applications, however, in other applications, it has to be derived from a given cost criterion and some constraints related to the problem at hand. One of the main issues related to optimization problems is the possibility of obtaining a solution converging to a local minimum instead of a global minimum. Among the techniques that are proposed to tackle this problem are the simulated annealing and mean-field annealing [21]–[24].

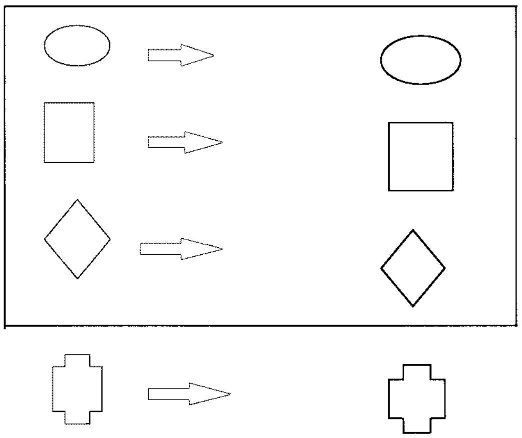

Fig. 5. A generalization example.

3) Category 3: Regression and generalization: Regression problem has been studied extensively. Linear and non-linear regression provide a smooth and robust curve fitting to training patterns. Usually, the system is trained based on the supervised training scheme using a large dataset. An ANN's is considered successful if it can closely approximate the teacher values for the trained data set and can provide smooth interpolations for the untrained data set. Generalization is used to yield a correct response to an input stimulus to which it has not been trained. The system must induce the salient feature of the input and detect the regularity. This regularity discovery is vital for many applications. It enables the system to function efficiently throughout the entire dataset (space), although it has been trained only by a limited portion of the entire data set (space). Fig. 5 shows an example. It is important to note that each ANN model tends to impose its own prejudice in how to generalize from a finite set training data. A good example that shows the difficulty with generalization is the parity-check problem where the backpropagation model consistently generalizes into a wrong result [22], [24].
4) Category 4: Pattern completion: In some classification problems, an implied task is the completion of information, that is, the recovery of original data given only partial information. We differentiate between static and temporal pattern completion problems. Markov models and time-delay dynamic networks are for temporal pattern completion while most traditional multilayer ANN's, Boltzmann machines, and Hopfield ANN's are for static pattern completion [10], [22].

V. Structure of ANN's

The major structural factors of ANN's are network size, connection structure, and all-classes-in-one network (ACON) versus one-class-in-one network (OCON) schemes.

In a feedforward multilayer ANN, there are one or more layers of hidden neuron (PE) units between the input and output neuron layers. The sizes of ANN's depend on the number of hidden neurons (PE's) per layer and the number of layers (slabs). The number of hidden PE's is directly related to the network capability. There is an optimum number of hidden PE's that must be properly determined in order to have the best performance. The number of layers is usually counted as the number of weight layers instead of neuron layers. There are one or more layers of hidden PE's between the input and output.

An ANN comprises of the neuron and weight building units/blocks. The behavior and performance of the ANN depends mainly on the interaction between these units/blocks. Layers are of three types: input, hidden and output layers. Two layers of neurons communicate using a weight connection network. We can identify four types of weight connections: feedforward, feedback, lateral, and time-delayed connections. In the feedforward type of connection, data from neurons of lower layer are propagated forward to neurons of upper layers via feedforward connection networks. In the feedback type, data are brought from neurons of upper layer back to neurons of lower layer. One excellent example on the lateral networks is the winner-takes-all-circuits, that serves the important role of selecting the winner. In the feature map example, by allowing PE's to interact via the lateral network, a certain topological ordering relationship can be preserved. Delayed elements can be included in the connections to provide temporal dynamic models. Such connections are more suitable for temporal pattern recognition.

There are two general plausible ANN structures: the ACON and the OCON. In the first approach, all classes are lumped into one large-size super network. In the OCON structure, a huge ANN is decomposed into many subnets in order to have subnets of small sizes where one subnet is devoted to one class only.

The ACON and OCON ANN's differ significantly in the size, and speed, that is the total number of synaptic weights and the training time. Let us assume that all subnets are of uniform size, say k. The number of hidden units of the ACON large ANN is denoted as K where $k \lll K$. The two structures, ACON and OCON, differ significantly in the size and speed, or in other words total number of synaptic weights and training time. Let n and N denote the input and output vector dimensions, respectively. The number of total synaptic weights for the ACON structure is equal to $(N+n)*K$. On the other hand, the total number of synaptic weights for the OCON structure is equal to $N*(n+1)*k \approx N*n*k$. When N is relatively small compared to n, the ACON structure could have compatible or less weight than the OCON structure. While if N is large, then OCON could have a major advantage in terms of network size. Moreover, OCON seems to perform better than ACON in training and recognition speed when the number of classes is large. Empirical studies have found that the convergence rate of ACON degrades drastically with respect to the size of the network due to the influence of conflicting signals from different teachers on the training process. By eliminating the inter-class connections, the OCON structure approach helps obviate such confusion. Each subnet in OCON type is specialized for distinguishing its own class from the alien patterns. Therefore, the number of hidden units k needed should be relatively small. Recent experimental results based on some speech and optical character recognition (OCR) have shown that 3–5 hidden neurons are all it needs for each subnet. The OCON structure may offer computational saving in the training stage and performance enhancement in the retrieving stage [9], [25].

VI. Scanning the Issue

In this special issue, we have accepted 11 regular papers and three correspondences out of 43 papers received from all over the world with representation from academia and industry. Each paper was refereed by at least three qualified reviewers according to the practice of this TRANSACTIONS. The accepted papers cover important SMC areas including estimation, associative memories, classification, diagnosis/analysis, pattern recognition, visualization, prediction and anticipation, diagnosis, and optimization.

Oommen, Altinel, and Aras present a method that applies the general philosophies of vector quantization (VQ) and discretized automata learning to estimate arbitrary distance functions. The proposed algorithms were tested on actual road-travel distances and they converged very quickly.

Shi *et al*. propose a general model for bidirectional associative memories that associate patterns between the X-space and the Y-space. Their model does not require the assumption that the interconnection weight from a neuron in the X-space to a neuron in the Y-space is the same as the one from the Y-space to the X-space. The effectiveness of their scheme was tested for recognition of noisy patterns and the performance in terms of storage capacity, attraction, and spurious memories was demonstrated by experimental results. Their results demonstrate that their general paradigm outperforms the most promising symmetrical bidirectional associative memory and the newly proposed asymmetrical bidirectional associative memory.

Pantazopoulos *et al*. present two neurofuzzy approaches to predict financial variables in a way that could be meaningful from an investment point of view. Their methods were tested with actual financial data and have shown a promise in decision making and planning.

Tang introduces a multiple competitive learning neural network fusion method for pattern recognition. Two distinct feature vectors are used along with gray-scale morphological granulometry and Fourier boundary descriptor, to show the efficacy of the classifier. His proposed algorithms were applied to 8000 underwater plankton images.

Lerner investigates the application of ANN's to automatic analysis of chromosome images. He analyzes this application from the point view of segmentation, feature description, selection, extraction and classification.

Murino proposes a new scheme for the design of structures of ANN's for pattern recognition. The method relies on subdividing the entire classification problem into smaller and simpler problems at different levels, each managed by appropriate components of complex neural network structures. He proposes three structures that are applied to surveillance systems aimed at monitoring a railway waiting room classifying potential dangerous situations. His approach shows better performance than classical statistical classification techniques.

Kusnadi *et al*. present a heuristic scheme to solve hierarchical graph layout problems. Their results show that this scheme is effective in replacing the constraint terms which otherwise are required in the formulation of the energy equation. In addition to guarantee a valid solution quickly, this scheme reduces the number of simulation parameters to adjust which provides flexibility in tuning the objective parameters.

Tsoukalas reviews the role of anticipation in intelligent systems and presents a new scheme for anticipatory control algorithms that use the predictive capability of ANN's in conjunction with the descriptive power of fuzzy if/then rules. His method is illustrated through the anticipatory control of a nuclear power plant. The results of the application to tracking control of reactor power indicate that the controller has excellent robustness and performance features.

Wang *et al*. apply fuzzy logic-inspired features to improve bacterial recognition through classifier fusion. A fuzzy logic rule-based system was used as a guide to find a good feature set for the recognition of Escherichia coli (E. coli) O157:H7. The fuzzy integral was utilized in the fusion of ANN's trained with different feature set to reach an almost perfect classification rate of E. coli O157:H7 PFGE patterns made available for the experiments.

Bolla *et al*. derive a neural network-based controller for the optimal allocation of bandwidth between two traffic types over a time division multiplexing link. The control is exerted through a randomized decision strategy that acts upon the acceptance of incoming connection requests of isochronous circuit-switched traffic, and minimizes a cost function accounting for connection refusal and packet loss rate.

Obaidat and Khalid propose a novel and adaptive cache replacement scheme based on an estimating type of ANN's where statistical prediction property of such ANN's is used to develop an ANN-based replacement policy which can effectively identify and eliminate inactive cache lines. Such an approach will provide larger free space for a cache to retain actively referenced lines. The proposed strategy can yield better cache performance as compared to the traditional schemes. Trace-driven simulation results have shown that with a probabilistic neural network, a significant improvement of 11% in the miss ratio can be achieved over the least-recently-used (LRU) scheme. The best-performing conventional near-optimal algorithm provided only 3.46% improvement over LRU for the same used benchmark suite.

Ornes and Sklansky demonstrate the visualization capabilities of the visual neural classifier using synaptic data. They also compare the visualization performance of Kohonen's self-organizing map. They demonstrate that visualization enables a designer to refine the classifier in order to achieve low error rates and enhances a user's ability to make classifier-assisted decision.

Lee and Tsai propose an improvement to an ANN proposed by Hussein and Kabuka [26] that can recognize features. They use the vigilance parameters and matching degrees to allow the combination of similar training patterns automatically in the same subnet. Networks obtained by their method can be smaller than those obtained by earlier work.

Finally, Al-Mulhem and Al-Maghrabi propose an efficient convex-elastic net algorithm to solve the Euclidean traveling salesman problem. Experimental results show that their algorithm outperforms many similar algorithms reported in the literature.

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