Chapter 9

Evolving Connectionist Systems for Adaptive Learning and Knowledge Discovery: A Review of Principles and Applications. From Neuro-fuzzy-, to Spiking-, Neurogenetic- and Quantum Inspired

Nikola Kirilov Kasabov
Auckland University of Technology
Auckland, New Zealand, nkasabov@aut.ac.nz;
https://academics.aut.ac.nz/nkasabov
George Moore Chair, University of Ulster,UK
Honorary Professor Teesside University UK and the University of Auckland NZ,

This chapter follows the development of a class of neural networks called evolving connectionist systems (ECOS). ECOS combine the adaptive/evolving learning ability of neural networks and the approximate reasoning and linguistically meaningful explanation features of symbolic representation, such as fuzzy rules. This review paper includes principles and applications of hybrid expert systems, evolving neuro-fuzzy systems, evolving spiking neural networks, neurogenetic systems, and quantum inspired systems, all discussed from the point of few of their adaptability and model interpretability. The chapter covers both methods and their numerous applications for data modelling, predictive systems, data mining, pattern recognition, across application areas of engineering, medicine and health, neuroinformatics, bioinformatics, adaptive robotics, etc.

9.1. Early Neuro-Fuzzy Hybrid Systems

The human brain uniquely combines low level neuronal learning in the neurons and the connections between them and higher level abstraction leading to knowledge discovery. This is the ultimate inspiration for the development of the evolving connectionist systems described in this paper.

In the past 50 years or so several seminal works in the areas of neural networks (Amari, 1967, 1990) and fuzzy systems (Zadeh, 1965, 1988) opened a new field of information science — the creation of new types of hybrid systems that combine the learning ability of neural networks, at a lower level of information processing, and the reasoning and explanation ability of fuzzy rule-based systems, at the higher level. Neural network (NN) models can learn from data and generalize on new data. Popular NN learning algorithm was the backpropagation learning for Multi-Layer Perceptrons (MLP), proposed independently by Rumelhart and Werbos. The backpropagation supervised learning algorithm is used to change the connection weights in a feedforward MLP network through propagating backwards the error between calculated output and the desired one. The algorithm brough many applications and is used also in the contemporary deep neural networks.

Other popular NN models are Hopfield pattern association model (Hopfield, 1995) and the Adaptive Resonance Theory (Carpenter and Grossberg, 1991).

Fuzzy logic, on the other hand, is a kind of symbolic knowledge representation. Combining the NN and fuzzy logic makes fuzzy rules to be learned from data and is a way to build more sophisticated application systems.

An exemplar system is shown in Figure 9.1 where, at a lower level, a neural network (NN) module predicts the level of a stock index and, at a higher level, a fuzzy reasoning module combines the predicted values with some macro-economic variables, using the following types of fuzzy rules (Kasabov, 1996).

$$\begin{aligned} &\textit{IF} < \textit{the predicted by the NN module stock value is increasing} > \\ &\textit{AND} < \textit{the economic situation is good} > \\ &\textit{THEN} < \textit{buy stock} > \end{aligned} \tag{1}$$

These fuzzy expert systems continued the development of the hybrid NN- rule-based expert systems that used crisp propositional and fuzzy rules (Hopfield, 1995; Izhikevich, 2004; Kasabov and Shishkov, 1993).

The integration of neural networks and fuzzy systems into expert systems attracted many researchers to join this theme. The low-level integration of fuzzy rules into a single neuron model and larger neural network structures, tightly coupling learning and fuzzy reasoning rules into connectionists structures, was initiated by Professor Takeshi Yamakawa and other Japanese scientists and promoted ata series of IIZUKA conferences in Japan (Yamakawa *et al.*, 1992; Zadeh, 1965). Many models of fuzzy neural networks were developed based on these principles (Furuhashi *et al.*, 1993; Lin and Lee, 1996; Kasabov, 1996; 1998; Kasabov *et al.*, 1997; Angelov, 2002; Angelov *et al.*, 2010)).

The early hybrid neuro-fuzzy research had a significant impact on the further development in the areas of neural networks and fuzzy systems, especially in their integration. One of the examples are the framework of evolving connectionist systems presented in the next section.

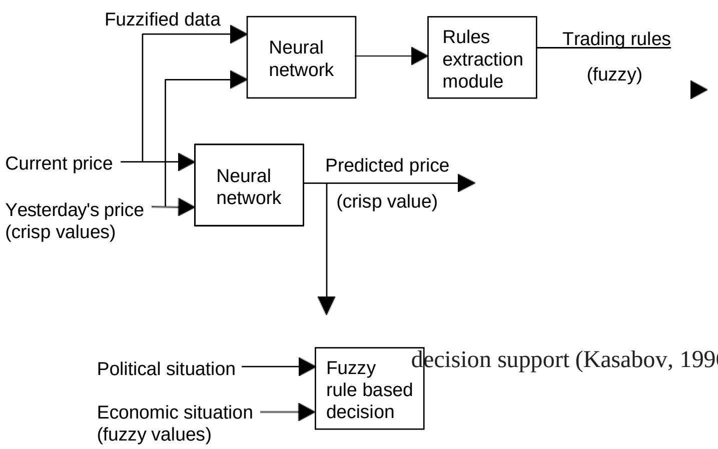


Figure 9.1: A hybrid NN-fuzzy rule-based expert system for financial decision support (Kasabov, 1996).

Decision
(buy/sell/hold
)(fuzzy &
crisp values)

9.2. Evolving Connectionist Systems (ECOS)

9.2.1 Principles of ECOS

In ECOS, insteadof training a fixed connectionist structure, the structure and its functionality are evolving from incoming data, often in an on-line, one-pass learning mode (Kasabov 2001; Kasabov and Song, 2002; Angelov, 2002; Kasabov, 2003).

ECOS are modular connectionist-based systems that evolve their structure and functionality in a continuous, self-organised, on-line, adaptive, interactive way from incoming information (Kasabov, 1998). They can process both data and knowledgein a supervised and/or unsupervised way. ECOS learn local models from data through clustering of the data and associating a local output function for each cluster represented in a connectionist structure. They can learn incrementally single data items or chunks of data and also incrementally change their input features (Kasabov, 2003, 2007). Elements of ECOS have been proposed as part of the classical NN models, such as SOM, RBF, FuzyARTMap, Growing neural gas, neuro- fuzzy systems, RAN (for a review see Kasabov, 2003). Other ECOS models, along with their applications, have been reported in (Watts, 2009; Futschik and Kasabov,2002).

The principle of ECOS is based on local learning — neurons are allocated as centers of data clusters and the system creates local models in these clusters. Fuzzy clustering, as a mean to create local knowledge-based systems, was stimulated by the pioneering work of Bezdek, Yager and Filev (Bezdek, 1987; Yager and Filev, 1994).

To summarize, the following are the main principles of ECOS as stated in Kasabov (1998):

(1) Fast learning from large amount of data, e.g., using 'one-pass' training, starting with little prior knowledge.
(2) Adaptation in a real time and in an on-line mode where new data is accommodated as it comes based on local learning.
(3) 'Open', evolving structure, where new input variables (relevant to the task), new outputs (e.g., classes), new connections and neurons are added/evolved 'on the fly'.
(4) Both data learning and knowledge representation is facilitated in a comprehensive and flexible way, e.g., supervised learning, unsupervised learning, evolving clustering, 'sleep' learning, forgetting/pruning, fuzzy rule insertion and extraction.
(5) Active interaction with other ECOSs and with the environment in a multi-modal fashion.
(6) Representing both space and time in their different scales, e.g., clusters of data, short- and long-term memory, age of data, forgetting, etc.
(7) System's self-evaluation in terms of behavior, global error and success and related knowledge representation.

In 1998, Walter Freeman, who attended the ICONIP conference, commented on the proposed ECOS concepts: "... Through the 'chemicals' and let the system grow...".

The development of ECOS, as a trend in neural networks and computational intelligence that started in 1998 (Kasabov, 1998) continued as many improved or new computational *methods* that use the ECOS principles have been developed along many *applications.*

9.2.2. Neuro-Fuzzy ECOS: EFuNN and DENFIS

Here we will briefly illustrate the concepts of ECOS on two implementations: EFuNN (Kasabov, 2001) and DENFIS (Kasabov and Song, 2002). Examples of EFuNN and DENFIS are shown in Figures 9.2 and 9.3 respectively. In ECOS, clusters of data are created based on similarity between data samples either in the input space (this is the case in some of the ECOS models, e.g., the dynamic neuro-fuzzy inference system DENFIS), or in both the input and output space (this is the case e.g., in the EFuNN models). Samples (examples) that have a distance to an existing node (cluster center, rule node) less than a certain threshold are allocated to the same cluster. Samples that do not fit into existing clusters form new clusters. Cluster centers are continuously adjusted according to new data samples, and new clusters are created incrementally. ECOS learn from data and automatically create or update a local fuzzy model/function, e.g.,

$$\textit{IF} < \textit{data is in a fuzzy cluster Ci} > \textit{THEN} < \textit{the model is Fi} > \tag{2}$$

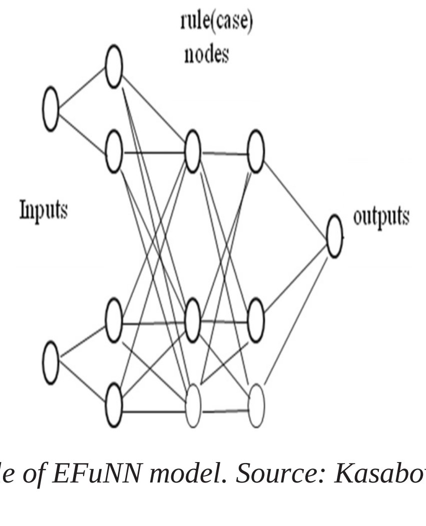


Figure 9.2: An example of EFuNN model. Source: Kasabov (2001).

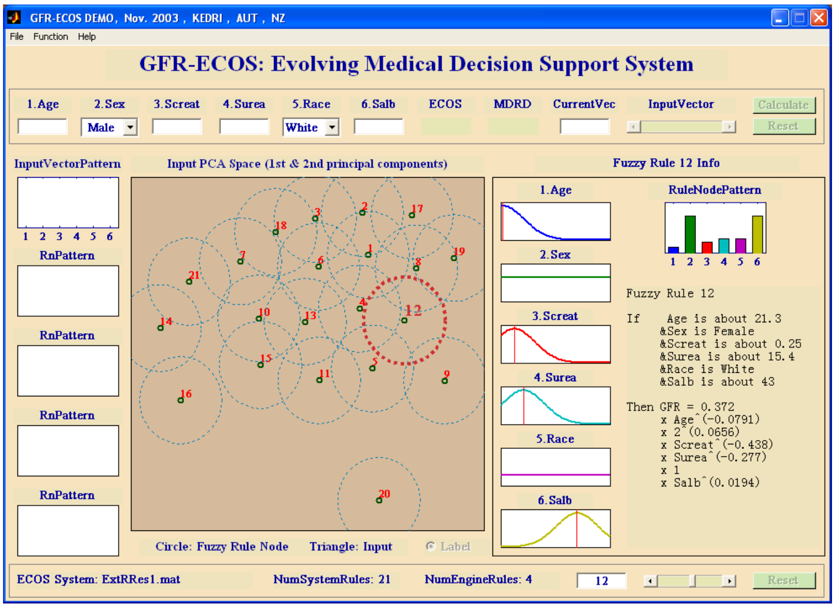


Figure 9.3: An example of DENFIS model. Source: Marshall et al., 2005; Kasabov (2002, 2003).

where Fi can be a fuzzy value, a logistic or linear regression function (Figure 9.3)or a NN model (Kasabov and Song, 2002, Kasabov, 2003)

A special development of ECOS is *transductive reasoning and personalised modelling*. Instead of building a set of local models (e.g., prototypes) to cover the whole problem space and then use these models to classify/predict any new input vector, in transductive modelling for every new input vector a new model iscreated based on selected nearest neighbor vectors from the available data (Vapnik, 1998). Such models are NFI and TWNFI (Song and Kasabov, 2006). In TWNFI for every new input vector the neighborhood of closest data vectors is optimized using both the distance between the new vector and the neighboring ones and the weighted importance of the input variables, so that the error of the model is minimized in the neighborhood area. A method for personalized modelling was introduced in (Kasabov and Hu, 2010).

9.2.3. Methods that Use Some ECOS Principles

Among other methods that use or have been inspired by the ECOS principles are:

— Evolving Self-organised Maps (ESOM) (Deng and Kasabov, 2003);
— Evolving Clustering Methods (ECM and ECMC) (Song and Kasabov, 2002);

— Incremental feature learning in ECOS (Ozawa *et al.*, 2010);
— On-line ECOS optimization (Minku and Ludemir, 2005; Chan *et al.*, 2004);
— Evolving Takagi–Sugeno fuzzy model based on switching to neighboring models (Angelov and Filev, 2004);
— Clustering and co-evolution to construct neural network ensembles (Minku and Ludermir, 2006);

Other methods that use or have been inspired by the ECOS principles are listed below (publications are available from www.ieeexplore.ieee.org; Google Scholar; Scopus). Some of the methods are referenced in the reference list and some of them are referenced here by the names of their authors:

- On-line ECOS optimisation, developed by Zeke Chan et al;
- Assessment of EFuNN accuracy for pattern recognition using data with different statistical distributions, developed by Ronei Marcos de Moraes et al;
- Recursive clustering based on a Gustafson–Kessel algorithm, by D Dovžan and I. Škrjanc;
- Using a map-based encoding to evolve plastic neural networks, by P Tonelli and J Mouret;
- Evolving Takagi–Sugeno fuzzy model based on switching to neighbouring models, by A Kalhor, BN Araabi and C Lucas;
- A soft computing based approach for modelling of chaotic time series, by J Vajpai and JB Arun;
- Uni-norm based evolving neural networks and approximation capabilities, by F Bordignon and F Gomide;
- Machine learning within an unbalanced distributed environment research notes, by HJ Prueller;
- FLEXFIS: a robust incremental learning approach for evolving Takagi–Sugeno fuzzy models, ED Lughofer;
- Evolving fuzzy classifiers using different model architectures, by P Angelov, E Lughofer, X Zhou (Angelov et al, 2010);
- RSPOP: Rough Set–Based Pseudo Outer-Product Fuzzy Rule Identification Algorithm, by KK Ang and C Quek;
- SOFMLS: online self-organizing fuzzy modified least-squares network, by J de Jesús Rubio;
- Finding features for real-time premature ventricular contraction detection using a fuzzy neural network system, by JS Lim;
- Evolving fuzzy rule-based classifiers, by P Angelov, X Zhou and F Klawonn;
- A novel generic Hebbian ordering-based fuzzy rule base reduction approach to Mamdani neuro-fuzzy system, by F Liu, C Quek and GS Ng;
- Implementation of fuzzy cognitive maps based on fuzzy neural network and application in prediction of time series, by H Song, C Miao, W Roel and Z Shen;
- Development of an adaptive neuro-fuzzy classifier using linguistic hedges, by B Cetisli.
- A meta-cognitive sequential learning algorithm for neuro-fuzzy inference system, by K Subramanian and S Suresh;
- Meta-cognitive RBF network and its projection based learning algorithm for classification problems, by GS Babu and S Suresh;
- SaFIN: A self-adaptive fuzzy inference network, by SW Tung, C Quek and C Guan;
- A sequential learning algorithm for meta-cognitive neuro-fuzzy inference system for classification problems, by S Suresh and K Subramanian;
- Architecture for development of adaptive on-line prediction models, by P Kadlec and B Gabrys;
- Clustering and co-evolution to construct neural network ensembles, by FL Minku and TB

Ludermir;
- Algorithms for real-time clustering and generation of rules from data, by D Filev and P Angelov;
- SAKM: Self-adaptive kernel machine - A kernel-based algorithm for online clustering, by H Amadou Boubacar, S Lecoeuche and S Maouche.
- A BCM theory of meta-plasticity for online self-reorganizing fuzzy-associative learning, by J Tan and C Quek;
- Evolutionary strategies and genetic algorithms for dynamic parameter optimization of evolving fuzzy neural networks, by FL Minku and TB Ludemir;
- Incremental leaning and model selection for radial basis function network through sleep learning, by K Yamauchi and J Hayami;
- Interval-based evolving modeling, by DF Leite, P Costa and F Gomide;
- Evolving granular classification neural networks, by DF Leite, P Costa and F Gomide;
- Stability analysis for an online evolving neuro-fuzzy recurrent network, by J de Jesus Rubio;
- A TSK fuzzy inference algorithm for online identification, by K Kim, EJ Whang, CW Park, E Kim and M Park;
- Design of experiments in neuro-fuzzy systems, by C Zanchettin, LL Minku and TB Ludermir;
- EFuNNs ensembles construction using a clustering method and a coevolutionary genetic algorithm, by FL Minku and TB Ludermir;
- eT2FIS: An evolving type-2 neural fuzzy inference system, by SW Tung, C Quek and C Guan;
- Designing radial basis function networks for classification using differential evolution, by B O'Hora, J Perera and A Brabazon;
- A meta-cognitive neuro-fuzzy inference system (McFIS) for sequential classification problems, by K Subramanian, S Sundaram and N Sundararajan;
- An evolving fuzzy neural network based on the mapping of similarities, by JAM Hernández and FG Castaeda;
- Incremental learning by heterogeneous bagging ensemble, by QL Zhao, YH Jiang and M Xu;
- Fuzzy associative conjuncted maps network, by H Goh, JH Lim and C Quek;
- EFuNN ensembles construction using CONE with multi-objective GA, by FL Minku and TB Ludermir;
- A framework for designing a fuzzy rule-based classifier, by J Guzaitis, A Verikas and A Gelzinis;
- Pruning with replacement and automatic distance metric detection in limited general regression neural networks, by K Yamauchi, 2009;
- Optimal incremental learning under covariate shift, by K Yamauchi;
- Online ensemble learning in the presence of concept drift, by LL Minku, 2011 (www.theses.bham.ac.uk)
- Design of linguistically interpretable fuzzy rule-based classifiers, by H Ishibuchi, Y Kaisho and Y Nojima;
- A compensatory neurofuzzy system with online constructing and parameter learning, by MF Han, CT Lin and JY Chang;
- Incremental learning and model selection under virtual concept drifting environments, by K Yamauchi;
- Active learning in nonstationary environments, by R Capo, KB Dyer and R Polikar;
- Real time knowledge acquisition based on unsupervised learning of evolving neural models, by G Vachkov;
- Flexible neuro-fuzzy systems, by L Rutkowski and K Cpalka;
- A self-adaptive neural fuzzy network with group-based symbiotic evolution and its prediction applications, by CJ Lin and YJ Xu;
- SOFMLS: online self-organizing fuzzy modified least-squares network, by J de Jesús

Rubio;
- A self-organizing fuzzy neural network based on a growing-and-pruning algorithm, by H Han and J Qiao;
- On-line elimination of local redundancies in evolving fuzzy systems, by E Lughofer, JL Bouchot and A Shaker;
- Backpropagation-Free Learning Method for Correlated Fuzzy Neural Networks, by Armin Salimi-Badr and Mohammad Mehdi Ebadzadeh;
- A projection-based split-and merge clustering algorithm, by Mingchang Cheng, Tiefeng Ma and Youbo Liu;
- Granular modelling, by Mohammad Tayyab, Bahari Belaton and Mohammed Anbar;
- Permutation entropy to detect synchronisation, by Zahra Shahriari and Michael Small;
- Evolving connectionist systems: Characterisation, simplification, formalisation, explanation and optimisation (MJ Watts, 2004, PhD Thesis; www.otago.ourarchive.ac.nz).

The above methods that manifest elements of ECOS have been applied in various applications , some of them listed in the next sub-section.

9.2.3. ECOS-Based Applications

Based on the ECOS concepts and methods, sustained engineering applications have been developed, some of them included in the list below and presented in (Kasabov, 2007) in detail:
- Discovery of diagnostic markers for early detection of bladder cancer, colorectal cancer and other types of cancer based on EFuNN (Pacific Edge Biotechnology Ltd, www.pebl.co.nz), (Futschik, Kasabov, 2002); (Futschik et al, 2002).
- Medical diagnosis of renal function evaluation using DENFIS (Marshall et al, 2005);
- Risk analysis and discovery of evolving economic clusters in Europe, by N Kasabov, L Erzegovesi, M Fedrizzi and A Beber;
- Adaptive robot control system based on ECOS (Huang et al, 2008);
- Personalised modelling systems (www.crunchouse.ai);
- Monthly electricity demand forecasting based on a weighted evolving fuzzy neural network approach, by PC Chang, CY Fan and JJ Lin;
- Decision making for cognitive radio equipment, by W Jouini, C Moy and J Palicot;
- An incremental learning structure using granular computing and model fusion with application to materials processing, by G Panoutsos and M Mahfouf;
- Evolving fuzzy systems for data streams, by RD Baruah and P Angelov;
- Handwritten digits classification, by GS Ng, S Erdogan, D Shi and A Wahab;
- On-line time series prediction system with EFuNN-T, by X Wang;
- Comparative analysis of the two fuzzy neural systems ANFIS and EFuNN for the classification of handwritten digits, by T Murali, N Sriskanthan and GS Ng;
- Online Identification of Evolving Takagi-Sugeno-Kang Fuzzy Models for Crane Systems, by RE Precup, HI Filip, MB Rădac, EM Petriu and S Preitl;
- Modelling ozone levels in an arid region-a dynamically evolving soft computing approach, by SM Rahman, AN Khondaker and RA Khan;
- A software agent framework to overcome malicious host threats and uncontrolled agent clones, by Sujitha, G. Annie and Amudha, T.;
- Comparing evaluation methods based on neural networks for a virtual reality simulator for medical training, by RM de Moraes and LS Machado;
- eFSM—A novel online neural-fuzzy semantic memory model, by WL Tung and C Quek;
- Stock trading using RSPOP: A novel rough set-based neuro-fuzzy approach, by KK Ang and C Quek;
- A stable online clustering fuzzy neural network for nonlinear system identification, by JJ

Rubio and J Pacheco;
- Evolving granular neural networks from fuzzy data streams, by D Leite, P Costa and F Gomide;
- Neural networks for QoS network management, by R del-Hoyo-Alonso and P Fernández-de-Alarcón;
- Adaptive on-line co-ordination of ubiquitous computing devices with multiple objectives and constraints, by E Tawil and H Hagras;
- Advances in classification of EEG signals via evolving fuzzy classifiers and dependent multiple HMMs, by C Xydeas, P Angelov, SY Chiao and M Reoullas;
- Online data-driven fuzzy clustering with applications to real-time robotic tracking, by PX Liu and MQH Meng;
- Evolving fuzzy systems for pricing fixed income options, by L Maciel, A Lemos, F Gomide and R Ballini;
- Combustion engine modelling using an evolving local model network, by C Hametner and S Jakubek;
- Intelligent information systems for online analysis and modelling of biological data, by MJ Middlemiss, (2001, PhD thesis, www.otago.ourarchive.ac.nz)
- Evolving neurocomputing systems for horticulture applications, by BJ Woodford;
- Neuro-fuzzy system for post-dialysis urea rebound prediction, by AT Azar, AH Kandil and KM Wahba;
- ARPOP: An Appetitive Reward-Based Pseudo-Outer-Product Neural Fuzzy Inference System Inspired From the Operant Conditioning of Feeding Behavior in Aplysia, by EY Cheu, C Quek and SK Ng, 2012;
- Artificial ventilation modeling using neuro-fuzzy hybrid system, by F Liu, GS Ng, C Quek and TF Loh;
- A data fusion method applied in an autonomous robot, by Y Qingmei and S Jianmin;
- Evolving fuzzy neural networks applied to odor recognition, by C Zanchettin and TB Ludermir;
- A reduced rule-based localist network for data comprehension, by RJ Oentaryo and M Pasquier;
- Faster self-organizing fuzzy neural network training and a hyperparameter analysis for a brain–computer interface, by D Coyle, G Prasad and TM McGinnity;
- Adaptive anomaly detection with evolving connectionist systems, by Y Liao, VR Vemuri and A Pasos;
- Creating evolving user behavior profiles automatically, by JA Iglesias, P Angelov and A Ledezma;
- Autonomous visual self-localization in completely unknown environment using evolving fuzzy rule-based classifier, by X Zhou and P Angelov;
-Online Training Evaluation in Virtual Reality Simulators Using Evolving Fuzzy Neural Networks, by LS Machado and RM Moraes;
- Predictive functional control based on an adaptive fuzzy model of a hybrid semi-batch reactor, by D Dovžan and I Škrjanc;
- An online adaptive condition-based maintenance method for mechanical systems, by F Wu, T Wang and J Lee;
- Driving profile modeling and recognition based on soft computing approach, by A Wahab, C Quek and CK Tan;
- Human action recognition using meta-cognitive neuro-fuzzy inference system, by K Subramanian and S Suresh;
- Hybrid neural systems for pattern recognition in artificial noses, by C Zanchettin and TB Ludermir;
- A novel brain-inspired neural cognitive approach to SARS thermal image analysis, by C Quek, W Irawan and Ng;
- Intrinsic and extrinsic implementation of a bio-inspired hardware system, by B Glackin, LP Maguire and TM McGinnity;

- Financial volatility trading using a self-organising neural-fuzzy semantic network and option straddle-based approach, by WL Tung and C Quek;
- A Bluetooth routing protocol using evolving fuzzy neural networks, by CJ Huang, WK Lai, SY Hsiao and HY Liu;
- QoS provisioning by EFuNNs-based handoff planning in cellular MPLS networks, by BS Ghahfarokhi and N Movahhedinia;
- Hybrid active learning for reducing the annotation effort of operators in classification systems, by E Lughofer;
- Classification of machine operations based on growing neural models and fuzzy decision, by G Vachkov;
- Computational intelligence tools for next generation quality of service management, by R del-Hoyo, B Martín-del-Brío and N Medrano;
- Solving the sales prediction problem with fuzzy evolving methods, by D Dovzan, V Logar and I Skrjanc;
- Predicting environmental extreme events in Algeria using DENFIS, by Heddam et al (Heddam et al, 2018);
- ICMPv6-Based DoS and DDoS Attacks Detection Using Machine Learning Techniques, Open Challenges, and Blockchain Applicability, by Mohammad Tayyab, Bahari Belaton and Mohammed Anbar;
- Prognostic of rolling elemn baring, by Murilo Osorio Camargos, Reinaldo Martinez Palhares, Iury Bessa and Luciana Balieiro Cosme;
- Estimating dissolved gas and tail-water in water dams, by Salim Heddam and Ozgur Kisi;
- The implementation of univariable scheme-based air temperature for solar radiation prediction: New development of dynamic evolving neural-fuzzy inference system model, by Ozgur Kisi, Salim Heddam and , Zaher Mundher Yaseend (Kisi et al, 1919);
- Multiple time series prediction (Widiputra et al, 2011).

While the ECOS methods presented above use predominantly McCulloch and Pitts model of a neuron, the further developed evolving spiking neural network (eSNN) architectures use a spiking neuron model applying the same or similar ECOS principles and applications.

9.3. Evolving Spiking Neural Networks (eSNN)

9.3.1. Main Principles, Methods and Examples of eSNN

A single biological neuron and the associated synapses is a complex information processing machine that involves short term information processing, long term

.

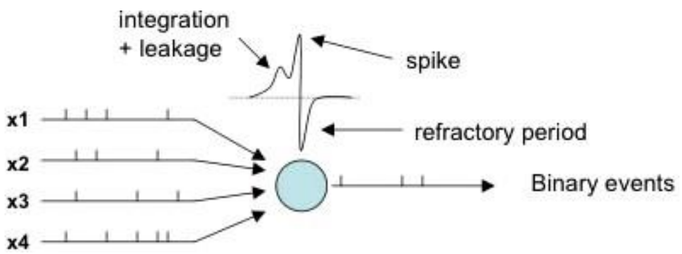


Figure 9.4: The structure of the LIFM of a spiking neuron

information storage, and evolutionary information stored as genes in the nucleus of the neuron. A spiking neuron model assumes input information represented as trains of spikes over time. When sufficient input information is accumulated in the membrane of the neuron, the neuron's post synaptic potential exceeds a threshold and the neuron emits a spike at its axon (Figure 9.4).

Some of the-state-of-the-art models of a spiking neuron include: early models by Hodgkin and Huxley (1952); more recent models by Maas, Gerstner, Kistler, Izhikevich and others, e.g., Spike Response Models (SRM); Integrate-and-Fire Model (IFM) (Figure 11.4); Izhikevich models; adaptive IFM; probabilistic IFM (for details, see: Hebb, 1949; Gerstner, 1995; Hopfield, 1995; Izhikevich, 2004; Kasabov, 2010).

Based on the ECOS principles, an evolving spiking neural network architecture (eSNN) was proposed (Kasabov, 2007; Wysoski *et al.*, 2010). It was initially designed as a visual pattern recognition system. The first eSNNs were based on the Thorpe's neural model (Thorpe and Delorme, 2001), in which the importance of early spikes (after the onset of a certain stimulus) is boosted, called rank-order coding and learning. Synaptic plasticity is employed by a fast supervised one-pass learning algorithm. Different eSNN models were developed, including:

— Reservoir-based eSNN for spatio- and spectro-temporal pattern recognition shown in Figure 9.5 (following the main principles from Verstraeten *et al.*, 2007);
— Dynamic eSNN (deSNN) (Kasabov *et al.*, 2013a) a model that uses both rank-order and time-based STDP learning (Song *et al.*, 2000) to account for spatio-temporal data;

and many more. For references, see (Schliebs and Kasabov, 2013).

Extracting fuzzy rules from an eSNN would make the eSNN not only efficient learning models, but also knowledge-based models. A method was proposed in (Soltic and Kasabov, 2010) and illustrated in Figures 9.6 and 9.7. Based on the connection weights (W) between the receptive field layer (L1) and the class output neuron layer (L2), the following fuzzy rules are extracted:

$$\text{IF (input variable } v \text{ is SMALL) THEN class } C_i; \quad \text{IF } (v \text{ is LARGE) THEN class } C_j \tag{3}$$

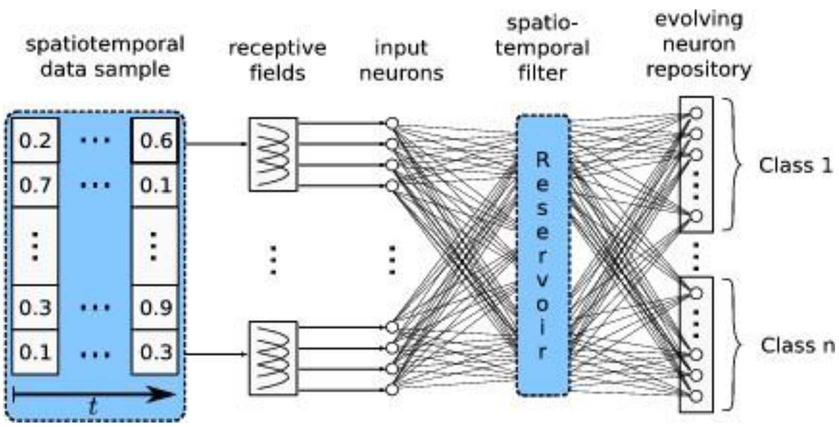
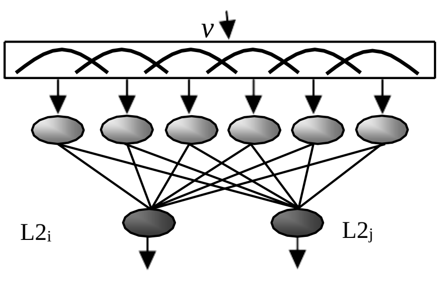


Figure 9.5: A reservoir-based eSNN for spatio-temporal pattern classification.



C_i C_j

Figure 9.6: A simplified structure of an eSNN for 2-class classification showing only one inputvariable using 6 receptive fields to convert the input values into spike trains.

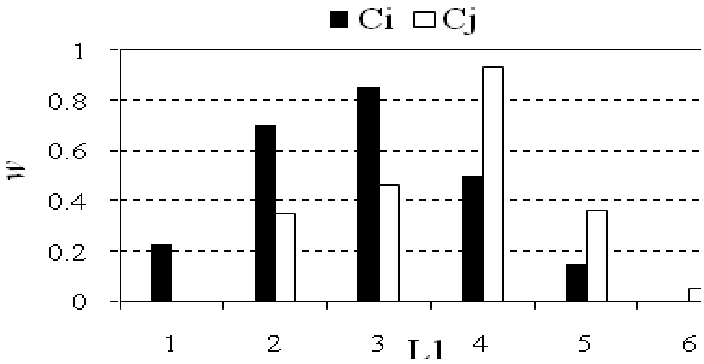


Figure 9.7: The connection weights of the connections to class Ci and Cj output neurons respectivelyare interpreted as fuzzy rules (equation 3).

9.4. Computational Neuro-Genetic Models (CNGM)

9.4.1. Main Principles

CNGM integrate principles of spiking neural networks and gene information processing. A neurogenetic model of a neuron is first proposed in (Kasabov, 2007) and studied in (Benuskova and Kasabov, 2007). It utilises information about how some proteins and genes affect the spiking activities of a neuron such as fast excitation, fast inhibition, slow excitation, and slow inhibition. An important part of the model is a dynamic gene/protein regulatory network (GRN) model of the dynamic interactions between genes/proteins over time that affect the spiking activity of the neuron — Figure 9.8.

New types of neuro-genetic fuzzy rules can be extracted from such CNGM in the form of:

IF < GRN is represented by a function F > AND < input is Small >
THEN < Class C > (4)

This type of CNGM is further developed into a comprehensive SNN framework called NeuCube for spatio/spectro temporal data modelling and analysis as presented in the next section.

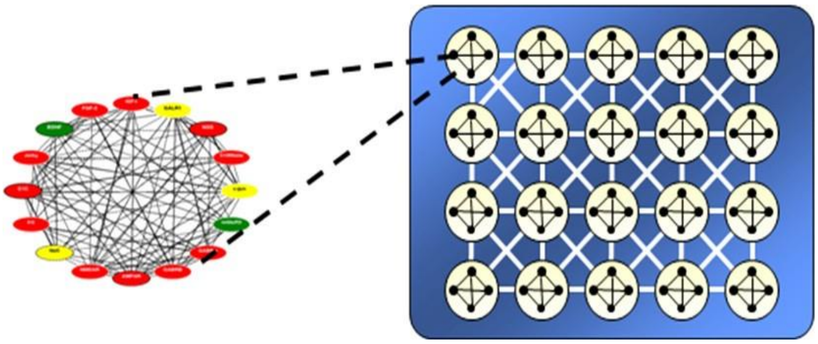


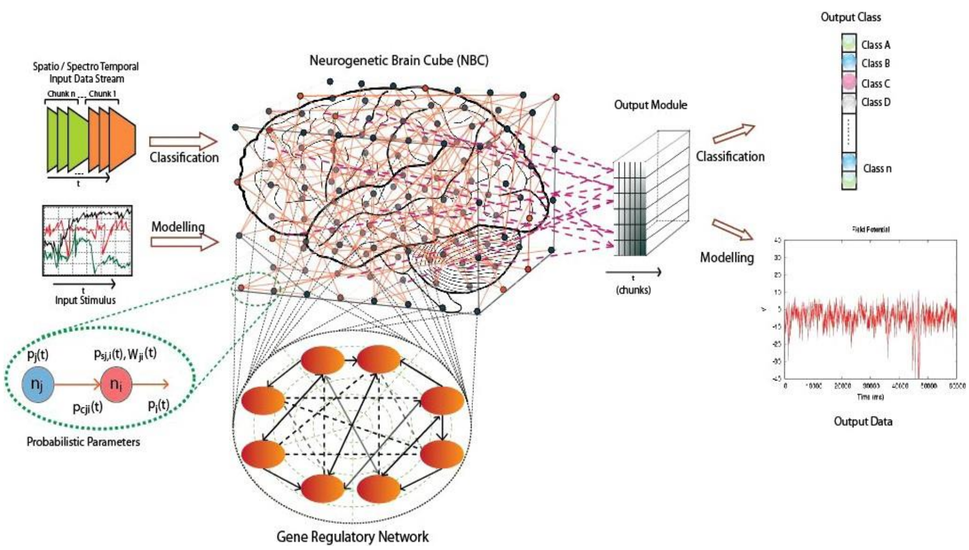
Figure 9.8 A schematic diagram of a CNGM framework, consisting of a GRN as part of a eSNN (Benuskova and Kasabov, 2007).

9.4.2. The NeuCube Architecture

The latest development of neurogenetic systems is NeuCube (Kasabov, 2014), initially designed for spatio-temporal brain data modelling, but then it is used for climate data modelling, stroke occurrence prediction and other applications (Kasabov, *et al.*, 2016).

The NeuCube framework is depicted in Figure 9.9. It consists of the following functional parts (modules):

— Input information encoding module;
— 3D SNN reservoir module (SNNr) for unsupervised learning;
— Output classification/regression module;
— Gene Regulatory Network Module.



.

Figure 9.9: A block diagram of the NeuCube architecture (from Kasabov, 2014)

Memory in the NeuCube architecture is represented as a combination of the three types of memory described below, which are mutually interacting:

— Short-term memory, represented as changes of the membrane level and temporary changes of synaptic efficacy;
— Long-term memory, represented as a stable establishment of synaptic efficacy — LTP and LTD;
— Genetic memory, represented as a genetic code.

In NeuCube similar activation patterns (called 'polychronous waves') can be generated in the SNNc with recurrent connections to represent short term memory. When using STDP learning, connection weights change to form LTP or LTD, which constitute long-term memory. Results of the use of the NeuCube suggest that the NeuCube architecture can be explored for learning long (spatio-) temporal patternsand to be used as associative memory. Once data is learned, the SNNc retains the connections as a long-term memory. Since the SNNc learns functional pathways of spiking activities represented as structural pathways of connections, when only a small initial part of input data is entered the SNNc will 'synfire' and 'chain-fire' *learned connection pathways* to reproduce *learned functional pathways*. Thus a NeuCube can be used as an *associative memory* and as a *predictive system*.

9.4.3. Applications of NeuCube

Current applications of the NeuCube include (see Kasabov et al, 2016; Kasabov, 2018):

• Brain data modelling and analysis, such as:
- Modelling EEG, fMRI, DTI data;
- Personalised brain data modelling (Doborjeh, M. et al, 2020);
- Sleep data modelling (
- Predicting brain re-wiring through mindfulness (Doborjeh, Z. et al, 2019)
- Emotion Recognition (Tan et al, 2020);

• Audio/Visual signals
- Speech, sound and music recognition;
- Video of moving object recognition

• Multisensory streaming data modelling
- Prediction of events from temporal climate data (stroke) (Kasabov et al, 2014);
- Hazardous environmental event prediction;
- Predicting risk of earthquakes (Kasabov et al, 2016);
- Predicting flooding in Malaysia by Muhaini Othman et al;
- Predicting pollution in London area (Maciag et al, 2019);
- Predicting extreme weather from satellite images;
- Predicting traffic flow (Lana et al, 2019);
- Odour recognition (Vanarse et al, 2020).

The above applications are only few of the current projects.

9.4.4. Neuromorphic Implementations

The different types of eSNN and neurogenetic systems, especially the NeuCube architecture, are suitable to be implemented as a neuromorphic hardware system for embedded applications. For this purpose, both digital (e.g., Furber, 2012) and analogue (e.g., Indiveri *et al.*, 2011) realizations can be used.

9.5. Quantum Inspired Optimisation of eSNN

eSNN have several parameters that need to be optimized for an optimal performance. Several successful methods have been proposed for this purpose, among them are: Quantum-inspired evolutionary algorithm, QiEA (Defoin-Platel *et al.*, 2009); and Quantum inspired particle swarm optimization method, QiPSO (Nuzly *et al.*, 2010).

Quantum inspired optimization methods use the principle of superposition of states to represent and optimize features (input variables) and parameters of the eSNN (Kasabov, 2007). Features and parameters are represented as qubits that are in a superposition of 1 (selected), with a probability α, and 0 (not selected) with a probability β. When the model output is calculated, the quantum bits 'collapse' in1 or 0.

9.6. Conclusion

This chapter presents briefly the methods of ECOS. ECOS facilitate adaptive learning and knowledge discovery from complex data. ECOS integrating principles are derived from neural networks, fuzzy systems, evolutionary computation, quantum computing and brain information processing. ECOS methods include:

- EFuNN and DENFIS;
- eSNN;
- deSNN;
- NeuCube;
- neurogenetic and
- quantum inspired.

ECOS applications are manifold, but perhaps most welcome they are in the environmental and health sciences, where the diagnostic phenomena are chaotic in nature and the data sets are massive and often incomplete. In the field of sustainability science, whether it is in analyzing issues related to sustainable resource utilization, countering global environmental issues, or the assurance of the continuity of life, (particularly human life) on earth, the speed of transformation is most rapid.

Massive data sets with the characteristics just described need to be analyzed, virtually in real time, for prognoses to be made and solutions to the issues sought at a heightened level of urgency. In this sense, evolving connectionist systems for adaptive learning and knowledge discovery can make a great contribution to the methodologies of intelligent evolving systems.

Acknowledgment

The work on this chapter is supported by the Knowledge Engineering and Discovery Research Institute (KEDRI, http://www.kedri.aut.ac.nz). Some of the methods,

techniques and applications are publicly available from: https://www.kedri.aut.ac.nz; https://www.theneucom.com; https://www.kedri.aut.ac.nz/neucube/; https://neucube.io.

As this is a review chapter, I would like to acknowledge the work of many authors who developed methods and applications of ECOS referring to the presented here material. I have not been able to reference all or even part of their work. Many of them have contributed greatly to the foundations of ECOS e.g.: S. Amari, T. Yamakawa, W. Freeman, J. Taylor, S. Grossberg, P. Angelov, D. Filev, J. Pratt,

I would like to acknowledge my students and collaborators who have worked with me on various ECOS related projects over the last 30 years or so, including: Lubica Benuskova, Michail Defoin-Platel, Enmei Tu, Zeng-Guang Hou and his students Nelson and James, Jie Yang and his students Lei Zhou and Chengie Gu, Giacomo Indiveri, Qun Song, Paul Pang, Israel Espinosa, Weiqi Yan. T. Ludemir, P. Pang, Lughofer M. Watts S. Ozawa, , B. Gabrys, Maryam Doborjeh, Neelava Sengupta, Zohre Doborjeh, Anne Wendt, Kaushalya Kumarasinghe, Akshay Gollolali, Clarence Tan, Vinita Kumar, Wei Cui, Vivienne Breen, Fahad Alvi, Reggio Hartono, Elisa Capecci, Nathan Scott, Norhanifah Murli, Muhaini Othman, Paul Davidson, Kshitij Dhoble, Nuttapod Nuntalid, Linda Liang, Haza Nuzly, Maggie Ma, Gary Chen, Harya Widiputra, Raphael Hu, Stefan Schliebs, Anju Verma, Peter Hwang, Snejana Soltic, Vishal Jain, Simei Wysoski, Liang Goh, Raphael Hu, Gary Chen. All of them worked on various modifications of ECOS methods, their implementations and applications.

I would like to acknowledge the editorof this volume Plamen Angelov for his incredible energy and efforts to put all these chapters together.

References

1. Amari S (1967) A theory of adaptive pattern classifiers. IEEE Transactions on Electronic Computers, 16: 299-307
2. Amari, S. 1990. Mathematical Foundations of Neurocomputing. Proc. IEEEE, 78, 1143-63.
3. Angelov, P. and Filev, D. (2004). An approach to on-line identification of evolving Takagi–Sugeno models. *IEEE Trans. Systems, Man and Cybernetics, Part B*, 34(1), pp. 484–498.
4. Angelov, P., D.Filev and N.Kasabov (eds) Evolving Intelligent Systems, IEEE Press and Wiley, 2010.
5. Benuskova, L, and N.Kasabov, Computational neuro-genetic modelling, Springer, New York, 2007.
6. Bezdek, J. ed. (1987) Analysis of Fuzzy Information, vols. 1,2,3, CRC Press, Boca Raton, Florida.
7. Carpenter, G. and S. Grossberg, Pattern recognition by self-organizing neural networks, MIT Press, 1991.
8. Chen, Y., J. Hu, N. Kasabov, Z. Hou and L.Cheng, NeuroCubeRehab: A Pilot Study for EEG Classification in Rehabilitation Practice Based on Spiking Neural Networks, Proc. ICONIP 2013, Springer LNCS, vol.8228, pp.70-77.
9. Defoin-Platel, M., S.Schliebs, N.Kasabov, Quantum-inspired Evolutionary Algorithm: A multi-model EDA, IEEE Trans. Evolutionary Computation, vol.13, No.6, Dec.2009, 1218-1232
10. Deng, D., N.Kasabov (2003) On-line pattern analysis by evolving self-organising maps, Neurocomputing, 51, 87-103.

11. Doborjeh, M., N. Kasabov, Z. Doborjeh, R. Enayatollahi, E. Tu, A. H. Gandomi, Personalised modelling with spiking neural networks integrating temporal and static information, Neural Networks, 119 (2019),162-177.
12. Doborjeh, Z., M. Doborjeh, T. Taylor, N. Kasabov, G. Y. Wang, R. Siegert, A. Sumich, Spiking Neural Network Modelling Approach Reveals How Mindfulness Training Rewires the Brain, Nature, Scientific Reports, (2019) 9: 6367, https://www.nature.com/articles/s41598-019-42863-x.
13. Doborjeh, Z., N. Kasabov, M. Doborjeh & A. Sumich, Modelling Peri-Perceptual Brain Processes in a Deep Learning Spiking Neural Network Architecture, Scientific REPORTS, Nature, | (2018) 8:8912 | DOI:10.1038/s41598-018-27169-8; https://www.nature.com/articles/s41598-018-27169-8
14. Furber, S. (2012). To Build a Brain, IEEE Spectrum, 49, 8, 39-41.
15. Furuhashi, T., Hasegawa, T., Horikawa S., Uchikawa, Y. (1993) An Adaptive Fuzzy Controller Using Fuzzy Neural Networks, in: Proceedings of Fifth IFSA World Congress, pp.769-772.
16. Futschik, M. and Kasabov, N. (2002) Fuzzy clustering in gene expression data analysis, Proc. of the World Congress of Computational Intelligence WCCI’2002, Hawaii, May, 2002, IEEE Press
17. Futschik, M., A. Jeffs, S. Pattison, N. Kasabov, M. Sullivan, A. Merrie and A. Reeve (2002), Gene expression profiling of metastatic and non-metastatic colorectal cancer cell-lines, Genome Letters, vol.1, No.1 (2002) 1-9.
18. Gerstner, W. (1995) Time structure of the activity of neural network models, Phys. Rev 51: 738-758.
19. Hebb, D. (1949). The Organization of Behavior. New York, John Wiley and Sons.
20. Heddam, S, Michael J. Watts, Larbi Houichi, Lakhdar Djemili and Abderrazek Sebbar, Evolving connectionist systems (ECoSs): a new approach for modelling daily reference evapotranspiration (ET0), Environ Monit Assess (2018) 190:216, https://doi.org/10.1007/s10661-018-6903-0
21. Hodgkin, A. L. and A. F. Huxley (1952) A quantitative description of membrane current and its application to conduction and excitation in nerve. Journal of Physiology, 117: 500-544.
22. Hopfield, J., Pattern recognition computation using action potential timing for stimulus representation. Nature, 376:33–36, 1995.
23. Huang, L. et al, (2008) Evolving connectionist system based role allocation for robotic soccer, Int. J. Advanced Robotic Systems, Vol. 5, Number 1, March 2008, 59-62.
24. Ibad Tasbiha, Said Jadid Abdulkadir and NorShakirah Aziz, Evolving spiking neural network: a comprehensive survey of its variants and their results, Journal of Theoretical and Applied Information Technology, 31st December 2020. Vol.98. No 24.
25. Indiveri, G., Linares-Barranco, B., Hamilton, T., Van Schaik, A., Etienne-Cummings, R., Delbruck, T., Liu, S., Dudek, P., Hafliger, P., Renaud, S. et al. (2011). Neuromorphic silicon neuron circuits. Frontiers in Neuroscience, 5.
26. Izhikevich, E. M. (2004) Which model to use for cortical spiking neurons? IEEE TNN, 15(5): 1063-1070.
27. Kasabov N (1998) Evolving Fuzzy Neural Networks - Algorithms, Applications and Biological Motivation. In: Yamakawa, T. and G.Matsumoto (eds) Methodologies for the conception, design and application of soft computing, World Scientific, pp 271 – 274
28. Kasabov N (2001) Evolving fuzzy neural networks for on-line supervised/unsupervised, knowledge–based learning. IEEE Trans. SMC/ B, Cybernetics 31(6): 902-918.
29. Kasabov N (2002) Evolving connectionist systems: Methods and Applications in Bioinformatics, Brain study and intelligent machines. Springer Verlag, London, New York, Heidelberg
30. Kasabov N, Kim J S, Watts M, Gray A (1997) FuNN/2- A Fuzzy Neural Network Architecture for adaptive learning and Knowledge Acquisition, Information Sciences - Applications, 101(3-4): 155-175

31. Kasabov N, Song Q (2002) DENFIS: Dynamic, evolving neural-fuzzy inference systems and its application for time-series prediction. IEEE Trans. on Fuzzy Systems, vol. 10:144 – 154
32. Kasabov, N. and Shishkov, S. A connectionist production system with partial match and its use for approximate reasoning. Connection Science 5(3/4): 275-305 (1993)
33. Kasabov, N. Connectionist fuzzy production systems. LNCS/AI, 847:114-128 (1994)
34. Kasabov, N. Foundations of Neural Networks, Fuzzy Systems and Knowledge Engineering. Cambridge, Massachussets, MIT Press (1996) 550p
35. Kasabov, N. Hybrid Connectionist Fuzzy Production Systems - Towards Building Comprehensive AI. Intelligent Automation and Soft Computing 1(4): 351-360 (1995)
36. Kasabov, N. Hybrid connectionist production systems. Journal of Systems Engineering 3(1): 15-21 (1993)
37. Kasabov, N. Incorporating neural networks into production systems and a practical approach towards the realisation of fuzzy expert systems. Computer Science and Informatics 21(2): 26-34 (1991)
38. Kasabov, N. NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks (2014), v.52,62-76, http://dx.doi.org/10.1016/j.neunet.2014.01.006
39. Kasabov, N., and Y. Hu (2010) Integrated optimisation method for personalised modelling and case study applications, Int. Journal of Funct. Informatics and Personalised Medicine, vol.3,No.3,236-256.
40. Kasabov, N., Dhoble, K., Nuntalid, N., & Indiveri, G. (2013). Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. Neural Networks, 41, 188-201.
41. Kasabov, N., Evolving connectionist systems: The knowledge engineering approach, Springer, 2007(first edition 2003).
42. Kasabov, N., Liang, L., Krishnamurthi, R., Feigin, V., Othman, M., Hou, Z.,. Parmar, P. (2013). Evolving Spiking Neural Networks for Personalised Modelling of Spatio-Temporal Data and Early Prediction of Events: A Case Study on Stroke. Neurocomputing, vol.134, 269-279, 2014, .
43. N. Kasabov, R. Schliebs and H. Kojima (2011), Probabilistic Computational Neurogenetic Framework: From Modelling Cognitive Systems to Alzheimer's Disease, IEEE Transactions of Autonomous Mental Development, 3, 4, 300-3011.
44. Kasabov, N. (ed) (2014) Springer Handbook of Bio-/ Neuroinformatics, Springer, 2014.
45. Kasabov, N. (2018) Time-space, spiking neural networks and brain-inspired artificial intelligence, Springer, 2018.
46. Kasabov, N., N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli, R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang (2016) Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube neuromorphic framework, Neural Networks, v.78, 1-14, 2016
47. Kisi, O. Salim Heddam and Zaher Mundher Yaseend (2019) The implementation of univariable scheme-based air temperature for solar radiation prediction: New development of dynamic evolving neural-fuzzy inference system model, Applied Energy, 241 (2019) 184-195.
48. Kumarasinghe, K., Kasabov, N. & Taylor, D. Brain-inspired spiking neural networks for decoding and understanding muscle activity and kinematics from electroencephalography signals during hand movements. Sci Rep 11, 2486 (2021). https://doi.org/10.1038/s41598-021-81805-4.
49. Kumarasinghe, K., N.Kasabov, D.Taylor, Deep Learning and Deep Knowledge Representation in Spiking Neural Networks for Brain-Computer Interfaces, Neural Networks, vol.121, Jan 2020, 169-185, doi: https://doi.org/10.1016/j.neunet.2019.08.029.
50. Laña I, Lobo JL, Capecci E, Del Ser J, Kasabov N, Adaptive long-term traffic state estimation with evolving spiking neural networks, Transportation Research Part C: Emerging Technologies 101:126-144, 2019, https://doi.org/10.1016/j.trc.2019.02.011

51. Lobo JL, Del Ser J, Bifet A, Kasabov N Spiking Neural Networks and online learning: An overview and perspectives, Neural Networks 121:88-100 2020, on-line publications 2019: https://www.sciencedirect.com/science/article/pii/S0893608019302655?via%3Dihub
52. Maciag, P.S., N. K. Kasabov, M. Kryszkiewicz, R. Bembenik, Air pollution prediction with clustering-based ensemble of evolving spiking neural networks and a case study on London area, Environmental Modelling and Software, Elsevier, vol.118, 262-280, 2019, https://www.sciencedirect.com/science/article/pii/S1364815218307448?dgcid=author.
53. Marshall, M.R. et al, (2005) Evolving Connectionist System versus Algebraic Formulae for Prediction of Renal Function from Serum Creatinine, Kidney International, vol. 6, 2005, 1944 – 1954.
54. Mohemmed, A., Schliebs, S., Matsuda, S., & Kasabov, N. (2013). Evolving Spike Pattern Association Neurons and Neural Networks, *Neurocomputing*, 107, 3-10.
55. Nuzly, H., Kasabov, N. & Shamsuddin, S. (2010). Probabilistic Evolving Spiking Neural Network Optimization Using Dynamic Quantum Inspired Particle Swarm Optimization, In LNCS, 6443, Springer.
56. Schliebs, S. and Kasabov, N., Evolving spiking neural networks: A Survey, Evolving Systems, 4 :97, 2013.
57. Schliebs S.et al, Integrated Feature and Parameter Optimization for Evolving Spiking Neural Networks: Exploring Heterogeneous Probabilistic Models, Neural Networks, 22, 623-632, 2009.
58. Schliebs, R. (2005), Basal forebrain cholinergic dysfunction in Alzheimer´s disease – interrelationship with β-amyloid, inflammation and neurotrophin signaling. Neurochemical Research, 30, 895-908.
59. Soltic, S. and Kasabov, N. (2010), “Knowledge extraction from evolving spiking neural networks with rank order population coding ,” *International Journal of Neural Systems*, 20:6, pp. 437-445.
60. Song, Q. and Kasabov, N. TWNFI- a transductive neuro-fuzzy inference system with weighted data normalisation for personalised modelling, Neural Networks, Vol.19, Issue 10, Dec. 2006, pp. 1591-1596
61. Song, S., K. Miller, L. Abbott et al., Competitive hebbian learning through spike-timing-dependent synaptic plasticity, Nature Neuroscience, vol. 3, pp. 919–926, 2000.
62. Tan, C., M.Sarlija, N.Kasabov, NeuroSense: Short-Term Emotion Recognition and Understanding Based on Statistical learning theory, John Wiley &SonSpiking Neural Network Modelling of Spatio-Temporal EEG Patterns, Neurocomputing, paper No.23238, 2021, https://authors.elsevier.com/sd/article/S0925-2312(20)32010-5.
63. Thorpe,S., Delorme, A., et al. (2001). Spike-based strategies for rapid processing. Neural Netw.,14(6-7),715-25.
64. Vanarse, A., Josafath Israel Espinosa-Ramos, Adam Osseiran, Alexander Rassau, Nikola Kasabov Application of a Brain-Inspired Spiking Neural Network Architecture to Odour Data Classification, Manuscript ID: Sensors-778506; 2020.
65. Vapnik, V., Statistical Learning Theory, John Wiley & Sons, NY, 1998.
66. Verstraeten, D., B. Schrauwen, M. D’Haene, and D. Stroobandt, An experimental unification of reservoir computing methods, Neural Networks, 20(3):391 – 403, 2007.
67. Watts, M. (2009) A Decade of Kasabov’s Evolving Connectionist Systems: A Review, IEEE Trans. Systems, Man and Cybernetics- Part C: Applications and Reviews, vol.39, no.3, 253-269.
68. Widiputra, H., Pears, R., & Kasabov, N. (2011). Multiple time-series prediction through multiple time-series relationships profiling and clustered recurring trends. Springer LNAI 6635 (PART 2), 161-172.
69. Wysoski, S., L. Benuskova, N. Kasabov, Evolving spiking neural networks for audiovisual information processing, Neural Networks, vol 23, 7, pp 819-835, 2010.
70. Yager R.R., Filev, D., Generation of fuzzy rules by mountain clustering, J. of Intell. and Fuzzy Syst., 2, 209-19, 1994

71. Yamakawa, T., E. Uchino, T. Miki and H.Kusanagi (1992) A Neo Fuzzy Neuron and Its Application to System Identification and Prediction of the System behaviour. Proceedings of the 2nd International Conference on Fuzzy Logic & Neural Networks, Iizuka, Japan, 477-483.
72. Zadeh L, (1965) Fuzzy Sets. Information and Control, vol.8, 338-353
73. Zadeh LA (1988) Fuzzy Logic. IEEE Computer 21: 83 – 93