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Review

Hybrid expert systems: A survey of current approaches and applications

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ABSTRACT

This paper is a statistical analysis of hybrid expert system approaches and their applications but more specifically connectionist and neuro-fuzzy system oriented articles are considered. The current survey of hybrid expert systems is based on the classification of articles from 1988 to 2010. Present analysis includes 91 articles from related academic journals, conference proceedings and literature reviews. Our results show an increase in the number of recent publications which is an indication of gaining popularity on the part of hybrid expert systems. This increase in the articles is mainly in neuro-fuzzy and rough neural expert systems' areas. We also observe that many new industrial applications are developed using hybrid expert systems recently.

1. Introduction

This paper surveys several journal articles, conference papers, books and literature reviews on the construction of the hybrid expert systems and classifies them according to the structure of the system, the algorithms utilized, the domain for which the hybrid expert system has been built, and the tools used for building/implementation. Meanwhile, it demonstrates the annual publication rate as an indicator of the hybrid expert system usage trend. We also analyze the related articles to determine the most dominant journals from an annual publication rate perspective.

The establishment of conventional expert systems by simulating the reasoning model of experts and the associated knowledge acquisition process is a challenging task. On the other hand, the construction of neural network depends on the existence of the examples and this feature of neural networks offers an advantage during the construction phase. Nevertheless, the insufficient explanation abilities perform neural networks as incomprehensible in contrast to conventional expert systems. Therefore, hybrid expert systems are introduced as a remedy which combines conventional symbolic rules and hybrid models which is the integration of symbolic and connectionist representation (Hatzilygeroudis & Prentzas, 2001). Although, the connectionist inference systems offer better solution for unexpected inputs, the symbolic inference systems and the hybrid systems are preferred for more complex tasks (Browne & Sun, 2001). The old hybrid intelligent systems usually integrate two intelligent technologies, namely, either neural networks and symbolic rules or neural networks and fuzzy systems. However, recent applications tend towards the hybrid integration containing two or more intelligent technologies (Hatzilygeroudis & Prentzas, 2004).

Liao (2003) offers a literature review on knowledge based systems and applications which contains a review from 1995 to 2002, Liao (2005) provides expert system methodologies and applications review from 1995 to 2004. Our present review is similar to those methodologies, but on a more specific subject of hybrid expert systems. To the best of our knowledge, it is the first study which provides a detailed review on different perspectives of hybrid expert system and connectionist expert system approaches. Six research questions are posed together with their motivations in Table 1. The suggested questions center around system structure approaches, algorithms, applications, building/implementation tools regarding hybrid expert systems and the percentage of articles published, and their respective journals.

This paper is organized as follows: First, we give an overview of our classification approach in Section 2. Section 3 gives our analysis in detail. Section 4 is a discussion on the analysis results and the future trends and Section 5 concludes the paper.

2. Review process

2.1. Inclusion criteria

The papers in our review include research on applications and knowledge management technologies, expert system methodologies, symbolic rule generation systems, hybrid expert systems, connectionist expert systems, neuro-fuzzy expert systems, rough set and rough neural expert systems.

The literature survey and subject descriptive papers which are mentioned in the introduction part are excluded. The included

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Table 1
Research questions.

Research question	Main motivation
1. What kind of approaches is used for hybrid expert system structure?	Identify the types of hybrid expert system structures, trends and opportunities
2. What kind of applications is available for a particular hybrid expert system approach?	Identify the types of hybrid expert system application categories for each approach, trends and opportunities
3. What are the mostly used algorithms in hybrid expert systems?	Identify the types of hybrid expert system algorithms for each approach, trends and opportunities
4. What are the mostly used building/implementation tools in hybrid expert systems?	Identify the types of hybrid expert system building/implementation tools for each approach, trends and opportunities
5. What are the dominant hybrid expert system journals?	Identify the most important hybrid expert system journals
6. What is the percentage of articles published annually?	Identify the publication rate on a yearly basis

papers are examined with respect to their publication years, system structures, application categories, algorithms, and building/implementation tools used. The evaluated papers for this review consist of 70 academic journals and 16 conference proceedings. The publication years of review papers are between year 1988 and 2010. The number of published papers per year is depicted in Fig. 1.

2.2. Classification of papers

The connectionist expert system approaches and the hybrid expert system papers can be categorized according to system structures such as neural network based expert systems, neuro-fuzzy expert systems and rough neural expert systems and several other criteria such as algorithms, application categories and building/implementation tools. We classify the papers according to the properties and categories in Table 2.

2.2.1. System structure approaches

As opposed to classical expert systems, connectionist expert systems realize automatic acquisition of knowledge out of a set of examples by employing usually feedforward trained neural networks. The reasoning capabilities of classical expert systems can be enhanced with the ability of generalization, the handling of incomplete cases and the construction of hybrid expert system structure either by neural network based expert systems, neuro-fuzzy expert systems or rough neural expert systems. The integrated technologies of neural networks and expert systems have made major advances since the landmark paper on connectionist expert systems by Gallant (1988). Saito and Nakano (1990) RN method produces rules that are in DNF (Disjunctive Normal Form). An approach that combines neural networks and symbolic learning is KBANN (Knowledge-Based Artificial Neural Networks) (Towell, Shavlik, & Noordewier, 1990). The algorithm initializes a neural network topology and weights using a set of approximately correct propositional rules. Compared with conventional networks KBANN provides a way to use problem-specific knowledge during learning. Reggia, Peng, and Tuhrim (1993) propose a connectionist model for diagnostic inference based on constraint optimization over a causal network. The Knowledge-Based Conceptual Neural Networks (KBCNN) model (Fu, 1993) and the RuleNet (McMillan, Mozer, & Smolensky, 1992) are two examples of this approach. KBCNN revises and learns knowledge on the basis of the network translated from the rule base that encodes the initial domain knowledge. When the network performance gets stuck during training, new hidden cells are added to different layers in order to generate new rules. Leao, Guazzelli, and Mendonca (1994) describes HYCONES II, which is a tool to enable the construction of hybrid connectionist expert systems to solve classification problems.

Other studies are due to Beckenkamp, Feldens, and Pree (1998) which is a hybrid (neural/symbolic) model called the Combinatorial Neural Model (CNM) that has been used in areas such as expert system development and data mining. Taha and Ghosh (1999) focus on the symbolic interpretation of artificial neural networks and hybrid intelligent systems. This structure consists of knowledge representation, implementing the connectionist model, network training, and rule extraction procedures. Also, Hudli, Palakal, and Zoran (1991), Chen and Chen (1992), Setiono, Baesens, and Mues (2008), Diederich and Barakat (2004), Nunez, Angulo, and Catala (2006), Wang and Lin (2010), Barreto and de Azevedo (1993), Karabatak and Ince (2009), Kai and Hui-ping (2009), Srinivasan, Eswaran, and Sriraam (2007), Prentzas, Hatzilygeroudis, and Koutsojannis (2001), Rao, Chen, and Chan (1994), Pan, Lian, Hu, and Ni (2005), Xu, Wu, and An (2003), Al-Mutawa and Moon (1993), Bhogal, Seviora, and Elmasry (1991), Vilhelm et al. (2000), Lin, Horng, and Lin (2009), Quah, Tan, Teh, and Shen (1993), Orsier, Iordanova, Giacometti, and Vila (1994), Gavrilov (2008) propose neural network based expert systems. Moreover, Chen, Chen, and Kuo (2010), Hengjie, Chunyan, Zhiqi, Yuan, and Lee (2009), Brasil, Rojas, Azevedo, and Almeida (2006), Zhang,

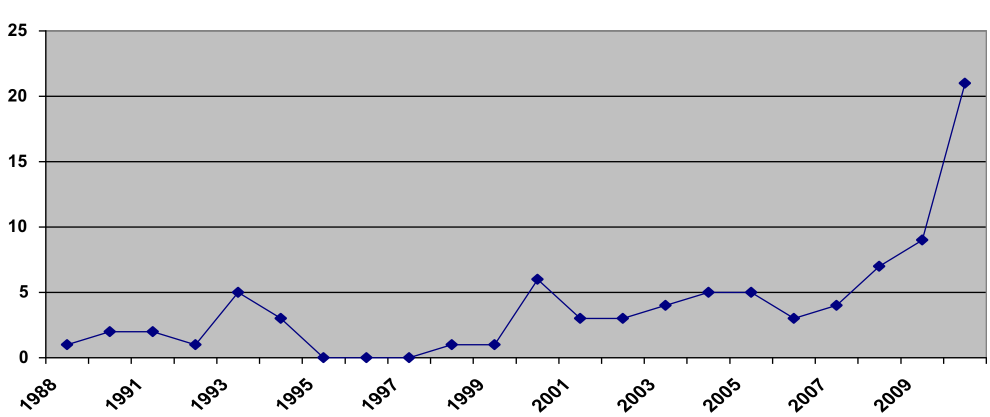

Fig. 1. Number of papers per year.

Table 2
Classification of papers.

Property	Categories
Year	Years between 1988 and 2010
System structure approaches	Neural network based expert systems Neuro-fuzzy expert systems Rough neural expert systems
Algorithms	Rule extraction based algorithms: Backward and forward chaining with NN General rule-extraction algorithms BP based learning Algorithms: The genetic-BP learning algorithm SOFAR & SOFM with genetic-BP algorithm Rough set algorithms: Rough set with NN Fuzzy type algorithms: TSK type fuzzy rule based system The fuzzy cognitive maps The interval type-2 FNN with BP Other types of algorithms: Re-Rx recursive algorithm on FFNN with C4.5 Hybrid rule-extraction from SVM with C5 RBF learning technique with SVM Hybrid learning algorithm Minimal realization learning algorithm
Application categories	Medical Education Finance Fault diagnosis Industrial applications, other 2...
Building/implementation tools	Additional programs Additional shells Additional interfaces, databases, block sets

Chen, and Li (2005), Ouyang, Lee, and Lee (2005), Wang and Chen (2008), Lee, Cho, and Kim (2007), Shapiro (2002), Sakthivel, Sugumaran, and Nair (2010), Hong, Wang, Wang, and Chien (2000), Paul and Kumar (2002), Reddy and Mohanta (2008), Tsang, Yeung, Lee, Huang, and Wang (2004), Heiss et al. (2002), Farquad, Ravi, and Raju (2010), Banakar and Azeem (2008), Esfahanipour and Aghamiri (2010), Hsu, Lin, and Cheng (2010), Song, Miao, Roel, and Shen (2010), Castro et al.(2009), Lu, Ong, and Chia (2000), Long and Wang (2009), Zarandi and Ahmadpour (2009), Radulović & Ranković, 2010, Moreno, Demetrio, & Ovalle, 2007, Wang and Elhag (2008), Dimitriou, Tsekeris, and Stathopoulos (2008), Haidar, Mohamed, Hussain, and Jaalam (2010), Üstündag, Kilinç, & Cevikcan, 2010, Ata and Kocyiğit (2010), Cheng, Tsai, and Sudjono (2010), Sargolzaei and Kianifar (2010), Giaquinto, Fornarelli, Brunetti, and Acciani (2009), Tsipouras, Voglis, and Fotiadis (2007), Kurnaz, Cetin, and Kaynak (2010), Baracskai and Dörfler (2003) describe neuro-fuzzy expert systems. Many intelligent hybrid systems are developed by using the rough set theory which is described by Pawlak in 1982 and the concept of rough set consists of approximation of a set by a pair of sets called lower and upper approximations of the set (Yahia, Mahmod, Sulaiman, & Ahmad, 2000). In the same way, Cheng, Chen, and Lin (2010), Dong et al.(2010), Jiang, Sui, and Cao (2010), Lingras (2001), Hu, Yu, and Guo (2010), Liu, Tuo, and Liu (2004), Wang, Ding, Zhou, and Zhang (2005), Pal, Dasgupta, and Mitra (2004), Swiniarski and Skowron (2003), Fan, Tseng, Chern, and Huang (2009), Bae, Yeh, Chi, and Hsu (2010), An and Tong (2005), Pai, Lyu, and Wang (2010), Ahn, Cho, and Kim (2000), Wang (2003), Tay and Shen (2002), Shen, Tay, Qu, and Shen (2000), Hou, Lian, Yao, and Yuan (2006), Swiniarski (2001), Witlox and Tindemans (2004) propose rough neural expert systems.

2.2.2. Algorithms

Algorithms utilized in the articles considered play an important role in the performance of the systems. Some of the frequently used algorithms for hybrid expert system construction are described next. Hudli et al. (1991) propose two reasoning procedures, backward and forward chaining of expert systems have been implemented using the neural network formalism. Chen and Chen (1992) describe connectionist expert systems for fault diagnosis using the well-known backpropagation-learning algorithm. Yahia et al. (2000) describe two learning methods of knowledge acquisition process, the first method using the rough sets as a mathematical representation, and the second method is the application of neural networks. These methods are integrated to produce new hybrid architecture of expert systems, which is referred to as the rough neural expert systems. Hong et al. (2000) offers a new algorithm for the problem of producing a set of maximally general fuzzy rules for training examples from quantitative data. Lingras (2001) suggests a rough set model for genetic encoding with unsupervised learning. Rough sets are employed to extract learning rules from an expert. Genetic algorithms are also used to develop rough sets in this model. Shapiro (2002) represents a hybrid model with the integration of neural networks (NNs), fuzzy logic (FL) and genetic algorithms to increase the performance rather than to use each one separately in insurance-related applications. Paul and Kumar (2002) propose a new subsethood-product fuzzy neural inference system (SuPFuNIS). Rule based knowledge is converted to network architecture and Gaussian fuzzy sets are used to connect the network. The supervised gradient descent and the subsethood-based method for rule generation on the trained network are used. This model is applied on Mackey–Glass time series prediction, Hepatitis medical diagnosis and function approximation benchmark problems. Heiss et al. (2002) represent an ANFIS based neuro-fuzzy classifier with a pruning algorithm and this model is used for the classification of sleep-waking states-stages in Childs with the sleep pattern detection system. The rules for sleep-stage NREM-I, the training process, pruning and definition of rules and parameters for the fuzzy classification system are determined. Swiniarski and Skowron (2003) propose applications of rough set methods for feature selection in pattern recognition and represent numerical results of face and mammogram recognition experiments using neural network with feature selection based on principal components analysis (PCA) and rough set methods. Diederich and Barakat (2004) define hybrid rule-extraction from artificial neural networks such as support vector machines which produces decision trees and rule sets by C5 method and applies this in medical diagnosis field. Liu, Tuo, and Liu (2004) represent a new rough neural network model. This model is trained by Levenberg–Marquart algorithm and applied to classifiy remote sensing images. Pal, Dasgupta, and Mitra (2004) define a rough self-organizing map (RSOM) with fuzzy discretization of feature space the quality of clusters and learning time are evaluated through experiments over the conventional SOM. Tsang et al. (2004) propose solutions to solve the nonoptimization and time-consumption problems for fuzzy production rules (FPRs). The solution contains enhancing local and global weights and developing an enhanced learning algorithm. Ouyang et al. (2005) describe a neuro-fuzzy network technique to extract fuzzy rules from a given set of input–output data for system modeling problems. Fuzzy clusters are generated incrementally from the training dataset and similar clusters are combined dynamically together through input-similarity, output-similarity and output-variance tests. Each cluster corresponds to a fuzzy IF–THEN rule and the obtained rules can be defined by a fuzzy neural network with a hybrid learning algorithm which combines a recursive singular value decomposition based least squares estimator and the gradient descent method.

Zhang et al. (2005) propose a new reconstruction way of BP neural network frame with genetic algorithm. The fault diagnosis expert system on sewage treatment plant is developed. Wang, Ding, Zhou, and Zhang (2005) improve a new relevance feedback algorithm-ARFRS. This algorithm uses the integration of rough set theory and neural network to represent the image retrieval performance. Nunez et al. (2006) presents the form of rule based learning systems with support vector machines (SVM) for symbolic interpretation of data. Radial Basis Function Neural Networks (RBFNN) learning techniques are applied to use support vectors from a learned SVM with Radial Basis Function (RBF) learning technique for the rule extraction. Brasil et al. (2006) suggest a hybrid module of the IACVIRTUAL meta-environment is represented and basically the Hybrid Expert System (HES) approach is formed by the Neural Networks Based Expert System (NNES) and the Rule-Based Expert System (RBES). Learning and optimization of the RBES are performed over the genetic-backpropagation based learning algorithm (GENBACK). Lee et al. (2007) define the fuzzy neural network (FNN) usually provides a theoretical basis for the fuzzy approximate reasoning (FAR) and single-staged fuzzy reasoning mechanisms. A new multi-staged FAR which is SOFAR (self-organizing FAR) is constructed and this can generate appropriate fuzzy rules with integrating self-organizing feature map (SOFM) and backpropagation parameters. Setiono et al. (2008) propose a recursive algorithm for extracting classification rules from feedforward neural networks and this rule extraction algorithm Re-RX is trained on data sets by applying the C4.5 decision tree method. Wang and Chen (2008) offer a Hammerstein recurrent neuro-fuzzy network with an online minimal realization learning algorithm for non-linear dynamic applications to determine the difficulty of network stability analysis. Reddy and Mohanta (2008) represent an intelligent algorithm based on wavelet MRA with neuro-fuzzy approaches for the determination of transmission-line faults. The ANFIS approach with Monte Carlo simulation is used for the statistical performance evaluation.

Banakar and Azeem (2008) describe two types of artificial neural networks by using features of wavelets and sigmodial activation functions. The neuro-fuzzy model is constructed with the results of summation wavelet neuro-fuzzy and multiplication wavelet neuro-fuzzy models. Fan, Tseng, Chern, and Huang (2009) present an incremental rule-extraction algorithm which is based on the unnecessary re-computing rule sets from the beginning and the produced approach updates rule sets by partially modifying the original rule sets which increases the database efficiency. Hengjie et al. (2009) offer a fuzzy neural network based on mutual subsethood (MSBFNN) and its fuzzy rule identification algorithms in order to solve difficult and time-consuming fuzzy rule derivation problem. Simulations on classification, regression and time series prediction fields are performed to represent the application of the MSBFNN. The backpropagation algorithm and linear transformation are performed in the parameter identification phase. Castro, Castillo, Melin, and Díaz (2009) implement the three interval type-2 fuzzy neural network (IT2FNN) architectures with hybrid learning algorithm techniques (gradient descent backpropagation and gradient descent with adaptive learning rate backpropagation) models for solving uncertainty of real life problems. In this study, a non-linear identification problem for control systems, comparative analysis of learning architectures IT2FNN and ANFIS, a non-linear Mackey–Glass chaotic time series prediction problem are investigated. Wang and Lin (2010) propose a model which integrates a neural network with case-based reasoning (CBR) and a rule-based system (RBS) to prevent causes of notebook computer breakdown. This model contains three phases: data extracting, group indexing and knowledge creation. The data extraction phase uses a self-organizing map (SOM) and a revised learning vector quantization network method to reduce isomorphic data to similarity characteristic-based clustering. The group indexing phase constructs a clustering index prediction model based on a backpropagation network (BPN) and genetic algorithm (GA). The knowledge creation phase uses CBR and RBS to create a notebook computer breakdown case selection model to determine the breakdown cause. Esfahanipour and Aghamiri (2010) offer a neuro-fuzzy inference system with a Takagi–Sugeno–Kang (TSK) type Fuzzy Rule Based System which is used for stock price prediction. Fuzzy C-Mean clustering is applied for identifying number of rules. Initial membership function of the premise part is defined as Gaussian function. TSK parameters are adjusted by Adaptive Nero-Fuzzy Inference System (ANFIS). Hsu et al. (2010) propose a TSK-type neuro-fuzzy system with multi groups cooperation based symbiotic evolution method (TNFS-MGCSE). The TNFS-MGCSE is developed from symbiotic evolution and the symbiotic evolution is different from traditional GAs (genetic algorithms) that each chromosome in symbiotic evolution represents a rule of fuzzy model. It is used to evaluate by numerical examples such as Mackey–Glass chaotic time series and sunspot number forecasting. Chen et al. (2010) offer a prediction model for the critical spare parts (CSP) requirement for machine operation. The backpropagation neural network (BPN) and moving fuzzy neuron network (MFNN) is used to construct the model and also the accuracy is compared with other prediction models such as gray prediction method, backpropagation neural network (BPN) and fuzzy neuron network (FNN). Song et al. (2010) suggest a fuzzy neural network to enhance the learning ability of the fuzzy cognitive maps (FCMs). The concept of mutual subsethood is used to interpret the causalities in FCMs. Farquad et al. (2010) propose a new hybrid approach for extracting rules from Support Vector Regression (SVR). Determination of the reduced training set in the form of support vectors using SVR and training the machine leaning techniques such as Classification and Regression Tree (CART), Adaptive Network based Fuzzy Inference System (ANFIS) and Dynamic Evolving Fuzzy Inference System (DENFIS) using the reduced training set are phases of hybrid model. The Root Mean Squared Error (RMSE) method is used to evaluate the efficiency of these techniques. Cheng et al. (2010) offer a technical analysis on the investment strategy and this study is based on the rough set theory and artificial neural networks inference system. It contains probabilistic neural network classification model, rough set classification model and hybrid classification model combining probabilistic neural network, rough sets and C4.5 decision tree method. Yeh et al. (2010) propose a prediction of business failure model to increase accuracy with the integration of rough set theory (RST) and support vector machines (SVM) technique. The data envelopment analysis (DEA) is applied as a tool to evaluate the input/output efficiency in this model. The performance of this model is evaluated by the comparison of backpropagation neural networks (BPN) approach with the hybrid approach (RST–BPN). Dong, Xiang, Wang, Liu, and Qu (2010) implement the rule-based structure–activity relationship (SAR) models with a rough set algorithm. The performance of the rough set method is evaluated by the decision tree learners, neural networks, support vector classifiers, LogitBoost approaches and the build-in approaches. (Sakthivel et al. (2010) offer a vibration based fault diagnosis of mono-block centrifugal pump model. The fuzzy classifier of this model is constructed with decision tree and rough set rules and tested using test data. The classification accuracy is obtained by the decision tree-fuzzy hybrid system and the classification process is performed by PCA, C4.5 decision tree algorithm and rough set methods. Jiang, Sui, and Cao (2010) represent a specific data mining problem – outlier detection and IE (information entropy)-based outliers in rough sets. In this study, the application of information entropy model for the measurement of uncertainty in rough sets and an algorithm for the effectiveness of IE-based method are developed. Hu, Yu, and Guo (2010) propose a model to extract fuzzy preference relations from samples characterized by numerical criteria. Fuzzy preference relations are used to build a fuzzy rough set model. The attribute dependency of the Pawlak's rough set model is generalized and algorithms for attribute dependency are developed. Bae, Yeh, Chung, and Liu (2010) propose new evolutionary algorithms which are referred as Intelligent Dynamic Swarm (IDS) and Particle Swarm Optimization (PSO). It is an alternative algorithm over Genetic Algorithms (GA) in optimization for feature selection in the field of data mining.

2.2.3. Application categories

Hybrid expert systems have found many applications in various domains such as medical, military, education etc. Barreto and de Azevedo (1993) use neural networks as associative memories to build a connectionist expert system for aiding medical diagnosis. Their system suggests obtaining more clinical data if the data available is insufficient to reach a conclusion. Al-Mutawa and Moon (1993) suggests the use of connectionist expert systems for process drift control in lithographic printing. Rao et al. (1994) propose a connectionist expert system for power distribution system fault diagnosis. Yahia et al. (2000) develop new hybrid architecture of expert systems called a rough neural expert system which is based on the connectionist neural networks and the reduction of rough set analysis. This system is applied on the field of medical diagnosis with an example of hepatitis diseases. Ahn et al. (2000) define a hybrid intelligent system estimating the failure of firms based on the past financial performance data with the combination of rough set approach and neural networks. Shen et al. (2000) propose a new method which is based on rough set theory to diagnose the fault for a multi-cylinder diesel engine. Lu et al. (2000) represent a hybrid neuro-fuzzy approach for developing the diagnostic acute myocardial infarction (AMI) of the 12-lead electrocardiogram (ECG). Swiniarski (2001) demonstrates numerical results of face recognition experiments on the learning vector quantization neural network with the principal components analysis and rough sets. Prentzas et al. (2001) offer a Web based Intelligent Tutoring System (ITS) for teaching high school teachers how to use new technologies. Tay and Shen (2002) propose a rough set model which is applied on the business failure and financial prediction. Wang (2003) defines a fuzzy rough set system to predict a particular stock price at any given time. Xu et al. (2003) implement the framework of the missile fault diagnosis expert system which is combined with a neural network structure. An and Tong (2005) implement a rough neural expert system which combines rough set theory and neural networks and is illustrated with a real example of diagnosis of coronary artery disease. Pan et al. (2005) represent an integrated neural network and expert system structure for intrusion detection. The expert system is used to develop the detection rate for known attacks and the BP network is applied to detect the unknown intrusions. Hou et al. (2006) presents a new method integrating rough set theory and an artificial neural network (ANN) on data-fusion technique to predict air-conditioning load. Srinivasan et al. (2007) represent a neural-network-based automated epileptic electroencephalogram (EEG) Elman and probabilistic neural networks detection system that uses approximate entropy (ApEn) as the input feature with Elman and probabilistic neural networks in the diagnosis of epilepsy. Moreno et al. (2007) present modeling of intelligent software agents for information gathering, estimating and recommendation to support the Colombian trading agent in buying electricity. Wang and Elhag (2008) offer an adaptive neuro-fuzzy system (ANFIS) which is used for bridge risks and the ANFIS has better modeling for bridge risks analysis than artificial neural networks and multiple regression analysis. Dimitriou et al. (2008) define an adaptive hybrid fuzzy rule-based system approach for the modeling and estimation of traffic flow in urban arterial networks. Karabatak and Ince (2009) describe an automatic diagnosis system for detecting breast cancer based on association rules and neural network. The association rules are used for reducing the dimension of breast cancer database and neural network is used for intelligent classification. Zarandi and Ahmadpour (2009) implement a fuzzy multi-agent system which is developed for electric arc furnace steel making processes. Each process of electric arc furnace steel making is assigned to be an agent and an adaptive neuro-fuzzy inference system is used to produce agents' knowledge bases. Long and Wang (2009) offer an integrated aircraft fuel fault diagnostic expert system which is based on the expert system and fuzzy artificial neural network theories. Giaquinto et al. (2009) define a neuro-fuzzy model to perform information derived from an automatic optical system which constitutes from three supervised neural networks and two fuzzy rule-based modules. Kai and Hui-ping (2009) define a pathology expert system on ANN which performs pathological diagnosis of unconventionality cells. Radulović et al., 2010 define the integration of both feedforward neural network and adaptive network-based fuzzy inference system (ANFIS) to evaluate electric and magnetic fields on power transmission lines. Haidar et al. (2010) define an intelligent artificial technique for vulnerability assessment of Malaysian power system. The feature extraction method and the generalized regression neural network is used to estimate vulnerability of a power system by applying the neuro-fuzzy technique. Üstündag et al. (2010) represent a systematic framework for the economic analysis for radio frequency identification (RFID) technology investment with a fuzzy rule-based system and Monte-Carlo simulation method. Ata and Kocyiğit (2010) suggest an adaptive neuro-fuzzy inference system (ANFIS) model to estimate the tip speed ratio (TSR) and the power factor of a wind turbine. Cheng et al. (2010) propose a fuzzy hybrid neural network (EFHNN) to enhance project cash flow management. Sargolzaei and Kianifar (2010) present an ANFIS for dynamic modeling of wind turbine Savonius rotor. Pai et al. (2010) propose an improved rough set theory model which performs linear discriminant process to analyze the academic achievements of junior high school students in Taiwan.

2.2.4. Building/implementation tools

Building/Implementation tools can be defined as additional programs, editors or shells used in the papers considered and can be categorized depending on the application and system architectures. Bhogal et al. (1991) describe a connectionist architecture, CAPS, for enhancing the performance of existing OPS5 programs by implementing them on connectionist networks. The system translates an existing OPS5 program into an interconnected and fully trained neural network. The translation program resolves the dynamic variable binding problems normally associated with connectionist architectures by using local representations that reduce the number of interconnections within the network. Thus CAPS eliminates the learning/training phase in creating a network. Quah et al. (1993) present a shell for developing connectionist expert systems, aimed at preserving the semantic structure of the classical expert system rules whilst incorporating the learning capability of neural networks. The shell represents each rule as a network element that is then dynamically linked up to form the rule-tree during the inferencing process. During the mid-1980s Matrix Controlled Inference Engine (MACIE) was developed by Gallant. MACIE generated a multi-layer perceptron that serves as the knowledge base for a connectionist expert system (Gallant, 1993). Orsier et al. (1994) define a hybrid system that is focused on the weaknesses of symbolic systems corresponding to the strong points of connectionist systems applied to expertise modeling. Then it presents the SYNHESYS shell which is composed of logic module (LM) and a connectionist module (CM). CM-knowledge

Table 3
Most important hybrid expert system journals.

Rank	Journal	Number	Proportion (%)	Cumulative proportion (%)
1.	Expert Systems with Applications	27	38.60	38.60
2.	Computers in Industry	3	4.29	42.90
3.	Information Sciences	3	4.29	47.20
4.	IEEE Transactions on Systems, Man, and Cybernetics – Part B: Cybernetics	3	4.29	51.50
5.	Journal of the American Medical Informatics Association	3	4.29	55.80
6.	IEEE Transactions on Neural Networks	2	2.86	58.70
7.	Neural Processing Letters	2	2.86	61.60
8.	IEEE Transactions on Fuzzy Systems	2	2.86	64.50

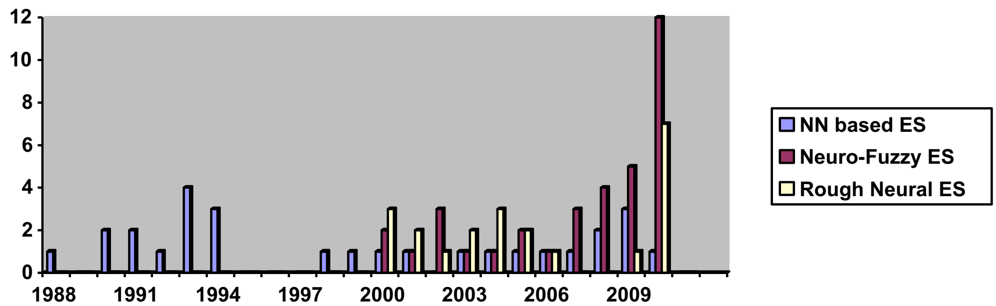

Fig. 2. Number of system structure approaches papers per year in review.

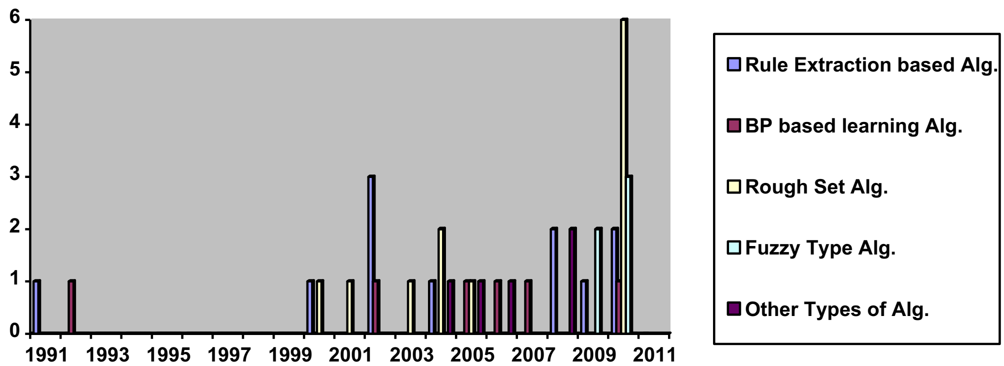

Fig. 3. Number of system algorithm papers per year in review.

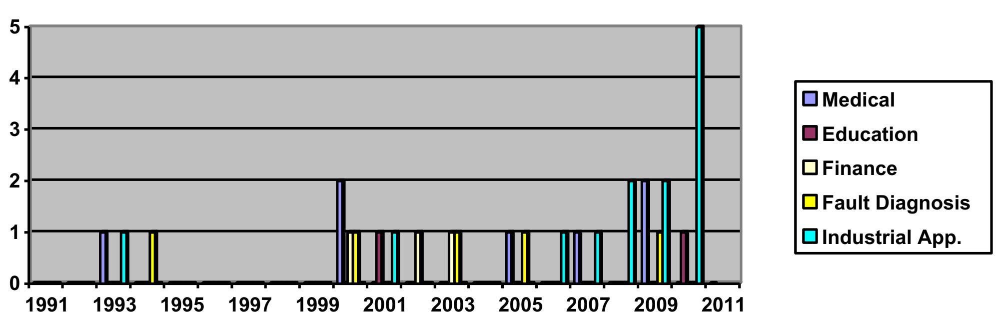

Fig. 4. Number of application categories papers per year in review.

extraction module is used for a medical application in the Electromyography. Vilhelm et al. (2000) define basic medical diagnosis applications which are intelligent alarms, intelligent monitoring, and diagnosis support. Building a complete medical diagnosis support tool requires the use of these models and the basic problem is communication between these various systems and the complexity of the composite result. A unified symbolic connectionist representation scheme is used to integrate these knowledge representation models in a single model. Baracskai and Dörfler (2003) demonstrate automated fuzzy-clustering using triangular and trapezoidal fuzzy-sets and an expert system shell used for clustering. Witlox and Tindemans (2004) propose a rough set approach in activity-based travel modeling and the Belgian travel diary survey. ROSETTA software is used to produce this model.

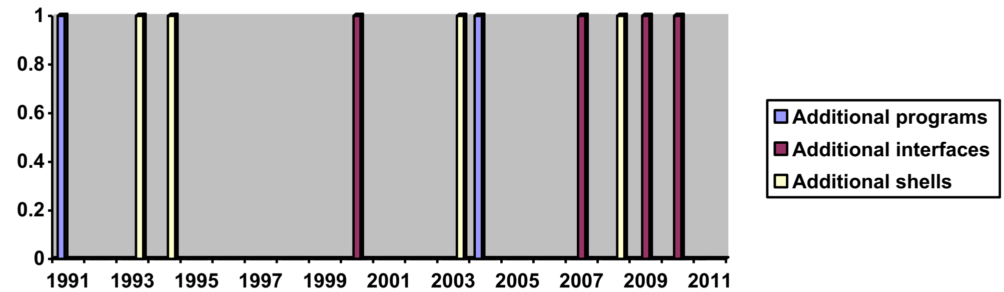

Fig. 5. Number of building/implementation tools papers per year in review.

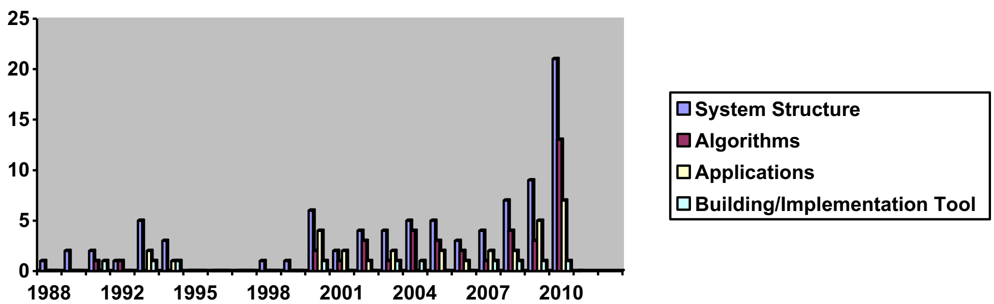

Fig. 6. Distribution rate of papers depends on evaluation criterias per year.

Tsipouras et al. (2007) propose a new method for the automated development of fuzzy expert systems. The developed model is tested by applying cardiovascular diseases' problems such as automated arrhythmic and ischemic beat classification. The initial set of rules is determined by expert cardiologists and the MIT-BIH arrhythmia database and the European ST-T database are used to optimize the fuzzy expert system for these problems. Gavrilov (2008) defines hybrid intelligent systems which are based on neural networks and rule based techniques and also application of hybrid expert systems on the shell ESWin. Lin et al. (2009) present a neural network with the micro-chip processor technology and an expert system which is called as the Integrated Car Repairing Tools is developed. Kurnaz et al. (2010) propose an ANFIS (adaptive neuro-fuzzy inference system) with autonomous flight controller for UAVs (unmanned aerial vehicles). MATLAB's standard configuration, the Aerosim Aeronautical Simulation Block Set, the Aerosonde UAV model, Gear open source flight simulator and gauges block set are used to implement this system.

3. Results

Seventy journal papers and 16 conference proceedings, excluding the survey articles, have been evaluated in this review. Publication years of papers are between 1988 and 2010. We present our results in the following subsections based on the research questions given in Table 1. Fig. 1 shows the publication year versus the number of papers published in that year for papers considered in this review.

3.1. Relevant hybrid expert system journals

We use hybrid expert system papers from 37 different journals. Journals with two or more papers on hybrid expert systems are displayed in Table 3, together with the corresponding number and proportions of papers. Proportions and cumulative proportions have been calculated by considering only the number of journal papers in review. Eight journals shown in Table 3 include 64.50% of all review papers.

3.2. Evaluation on system structure approaches

Fig. 2 represents the publication year versus the number of system structure approaches related papers used in the review.

3.3. Evaluation on algorithms

Fig. 3 represents the publication year versus system algorithm related papers used in the review.

3.4. Evaluation on application categories

Fig. 4 represents the publication year versus application categories related papers used in the review.

3.5. Evaluation on building/implementation tools

Fig. 5 represents the publication year versus building/implementation tools related papers used in the review.

3.6. Distribution rate of papers

In Fig. 6, the distribution rate of evaluation criteria papers are demonstrated which depends on system structure approaches, algorithms, applications and building/implementation tools and we examined 86 papers regarding to their publication date.

4. Conclusions

This paper surveys several recent publications around the intersection of neural networks, expert systems domains and specifically concentrates on recent trends in hybrid expert system development. The review papers are evaluated with respect to Hybrid Expert System structure approaches, algorithms, application categories and building/implementation tools. Section 3 summarizes our results in one table and six charts. Our results show an increase in the recent number of publications which is an indication of gaining popularity on the part of hybrid expert systems. This increase has been mainly in neuro-fuzzy and rough neural expert systems. Our results show a decrease in the number of publications which are solely on neural network based expert systems. This implies that the hybrid expert systems with symbolic interpretation and intelligent neural networks are more widely used in hybrid systems. This conclusion is consistent with the high rate of utilization of rough set and fuzzy type algorithms as depicted in Fig. 3. Many different applications have emerged for hybrid expert systems but the main increase is in industrial applications which are at the same time an indication of the capabilities of hybrid expert systems in solving applied problems. Our study reveals that more attention has been given to the building/implementation tools of hybrid expert systems which show an increase in the number of stand alone intelligent systems. Fig. 6 shows a growth in the number of system structure and algorithm related publications. This increase can be related to the emergence of new applications which require improvements in the algorithms and the system structures. Finally, we observe that unlike in the past most of the current hybrid expert system articles have appeared in particular journals, especially in Expert Systems with Applications where most of the articles are published.

Appendix A. List of included journals

Advances in Engineering Software
Advances in Neural Information Processing Systems
Applied Energy
Applied Intelligence
Applied Soft Computing
Artificial Intelligence
Artificial Intelligence in Medicine
Communications of the ACM
Computers and Artificial İntelligence
Computers & Education
Computers in Cardiology
Computers in Industry
Electric Power Systems Research
Engineering Applications of Artificial Intelligence
European Journal of Operational Research
Expert Systems with Applications
IEEE Engineering in Medicine and Biology
IEEE Transactions on Biomedical Engineering
IEEE Transactions on Fuzzy Systems
IEEE Transactions on Industrial Informatics
IEEE Transactions on Information Technology in Biomedicine
IEEE Transactions on Knowledge and Data Engineering
IEEE Transactions on Neural Networks
IEEE Transactions on Systems, Man, and Cybernetics – Part B: Cybernetics
Information Sciences
Insurance: Mathematics and Economics
International Journal of Applied Mathematics and Computer Sciences
International Journal of Computational Cognition
International Journal of Computational Intelligence Research
Journal of Advanced Computational Intelligence and Intelligent Informatics
Journal of Intelligent Information Systems
Journal of the American Medical Informatics Association
Mechanical Systems and Signal Processing
Neural Processing Letters
Neurocomputing
Pattern Recognition Letters
Transportation Research Part C

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