On the Approaches to Construction of Hybrid GMDH Algorithms

Olga Moroz, Volodymyr Stepashko

International Research and Training Center for Information Technologies and Systems of the NAS and MES of Ukraine
Address: 40, Glushkov Ave, Kyiv, 03680 GSP, Ukraine

stepashko@irtc.org.ua, moroz5olga@gmail.com

Abstract. *Recenly, methods of computational intelligence to solve training and structur optimization problems of many types of Artificial Neural Networks are widely used. The same can be said of the GMDH-type Neural Networks in still narrow sence. This paper presents a brief overview of the known cases of combining GMDH-type Neural Network with methods of other Artificial Intelligence paradigms.*

Keywords

Artificial Neural Networks, Group Method of Data Handling,
Hibridization, Evolutionary Computation, Genetic Algorithm,
Partical Swarm Optimization, Differential Evolution,
Group of Adaptive Model Evolution

1 Introduction

Among all paradigms of Artificial Intelligence (AI) we consider three basic ones such as Evolutionary Computation (EC), Swarm Intelligence (SI), Artificial Neural Networks (ANN). Methods of these paradigms have been used successfully in real-world applications, for example, data mining, combinatorial optimization, fault diagnosis, classification, pattern recognition, knowledge discovery, system identification, clustering, control, scheduling, predicting and time series approximation.

2 Some paradigms of AI

Evolutionary Computation or evolutionary algorithms (EAs) [1, 2] is a paradigm in the AI domain that aims at benefiting from collective phenomena in adaptive populations of problem solvers utilizing the iterative progress comprising growth, development, reproduction, selection, and survival as seen in a population. EAs are the most well known, classical and established algorithms among nature inspired algorithms based on the biological evolution in nature that is being responsible for the design of all living beings on Earth, and for the strategies they use to interact with each other. EAs employ this powerful design philosophy to find solutions of hard problems. EAs are non-deterministic or cost based optimization algorithms.

Usually grouped under the term EC or EAs, the domains of Genetic Algorithm (GA), Genetic Programming (GP), Differential Evolution (DE), Evolutionary Strategy (ES), Learning Classifier Systems (LCS), Estimation of Distribution Algorithms (EDA) and most recent Paddy Field Algorithm (PFA) are founded.

They all share a common conceptual base of simulating the evolution of individual structures and they differ in the way the problem is represented, processes of selection and the usage/implementation of reproduction operators. The processes depend on the perceived performance of the individual structures as defined by the problem.

Swarm Intelligence [3] is a collective behaviour of decentralized, self-organized systems, natural or artificial. The term swarm is used for an aggregation of animals such as fish schools, bird flocks and insect colonies such as ant, termites and bee colonies performing collective behaviour. The individual agents of a swarm behave without supervision and each of these agents has a stochastic behaviour due to her perception in

the neighbourhood. Local rules, without any relation to the global pattern, and interactions between self-organized agents lead to the emergence of collective intelligence called swarm intelligence.
SI can be described by considering five fundamental principles.

- *Proximity Principle*: the population should be able to carry out simple space and time computations.
- *Quality Principle*: the population should be able to respond to quality factors in the environment.
- *Diverse Response Principle*: the population should not commit its activity along excessively narrow channels.
- *Stability Principle*: the population should not change its mode of behavior every time the environment changes.
- *Adaptability Principle*: the population should be able to change its behavior mode when it is worth the computational price.

The most popular SI algorithms are Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony Optimization (ABC), Cuckoo Search (CS), Firefly Algorithm (FA), Intelligent Water Drops (IWD), Gravitational Search Algorithm (GSA) and Charged System search (CSS).

The field of Artificial Neural Networks is concerned with the investigation of computational models inspired by theories and observation of the structure and function of biological networks of neural cells in the brain. They are generally designed as models for addressing mathematical, computational, and engineering problems. As such, there is a lot of interdisciplinary research in mathematics, neurobiology and computer science based on ANNs [4].

ANNs are massively parallel interconnected networks of simple elements which are usually adaptive and their hierarchical organizations are intended to interact with the objects of the real world in the same way as biological nervous systems do. The basic components of a neural network are nodes that correspond to biological synapses. The weighted inputs to a neuron are accumulated and then passed on to an activation function that determines the nervous response. A positive weight represents an excitatory connection while a negative weight represents an inhibitory connection. In fact, the units were originally invented as an attempt to model biological neurons, hence the use of the term ANN.

There are many types of neural networks which fall into one of two categories:

- Feed-forward Networks where input is provided on one side of the network and the signals are propagated forward (in one direction) through the network structure to the other side where output signals are read. These networks may be comprised of one cell, one layer or multiple layers of neurons. Some examples include the Perceptron, Radial Basis Function Networks, and the multi-layer perceptron networks.
- Recurrent Networks where cycles in the network are permitted and the structure may be fully interconnected. Examples include the Hopfield Network and Bidirectional Associative Memory.

ANNs are generally used for function approximation-based problem domains and prized for their capabilities of generalization and tolerance to noise.

There are two main problems in ANN modeling such as ANN training parameters and Selection of an optimal topology, that have a great impact on their performance. The mathematical basis for the vast majority of training algorithms is to utilize gradient information to adjust the connection weights between nodes in the network. Its use implies drawbacks such as slow convergence (training) rates, neglected multiple extremum points, infinitesimally small step sizes (e.g. learning rates), costly computation, no guarantee that algorithm converges to an optimum point, entrapped in local minimum points, necessarily imply a least-mean-squared-error criterion, non-differentiability of many error function [5].

Also significant ANNs drawbacks are:

- the search space of possible topologies is infinitely large, complex, multimodal, and not necessarily differentiable
- there is little reason to expect that ANN can find a uniformly best algorithm for selecting the weights in a feedforward artificial neural network. At present, neural network design relies heavily on human experts who have sufficient knowledge about the different aspects of the network and the problem domain.
- as the complexity of the problem domain increases, manual design becomes more difficult and unmanageable.

Stochastic training algorithms can provide an attractive alternative by removing many of these drawbacks. Thus they are well suited for training in a wide variety of cases, and often perform better overall than the more traditional methods. While individual techniques from these AI paradigms have been applied successfully to solve real-world problems, the current trend is to develop hybrids of paradigms, since no one paradigm is superior to the others in all situations. In doing so, they respectively strength the components of the hybrid AI system and eliminate weaknesses of individual components.

In [6] Abraham A. and Grosan C. emphasize the need for hybrid evolutionary algorithms, illustrate the various possibilities for hybridization of an evolutionary algorithm and also present some of the generic hybrid evolutionary architectures that has evolved during the last couple of decades. A very comprehensive review of using EAs in the design of ANN can be found in [7].

3 GMDH-type neural network

The GMDH was developed by Ivakhnenko [8] as a multivariate analysis method for complex systems modelling and identification. In this way, GMDH was used to circumvent the difficulty of knowing a priori knowledge of mathematical model of the process being considered. Therefore, GMDH can be used to model complex systems without having specific knowledge of the systems.

The main idea of GMDH is to build an analytical function in a feedforward network based on a quadratic node transfer function whose coefficients are obtained using regression technique. Its structure is very similar to that of multilayer feedforward neural networks but the number of layers as well as the number of nodes is objectively defined by an external criterion in accordance with the incompleteness theorem. Multilayer algorithms do not perform an exhaustive search amongst all the candidate models but if the number of selected models in every layer is large enough, the optimum solution will never be lost. The most popular type of activation function is the second order polynomial but a number of alternative partial descriptions have been also tested.

GMDH is ideal for complex, unstructured systems where the investigator is only interested in obtaining a high-order input-output relationship. GMDH algorithm can be applied to given data set of a system where it tries to find relation between input data and output data without much interference/involvement of an investigator. Hence this can be treated as a good data mining tool where data is transformed into knowledge for decision making. The most pronounced feature of GMDH is that it can choose the really significant input variables among dozens of these, thus actually reducing the dimension of the solved problem.

In addition to ANN drawbacks GMDH has its own drawbacks. Anastasakis and Mort [9] have carried out a comprehensive study of the shortcomings of GMDH, the most problematic can be stated such as:

- ill-suited to solve complex problems with many inputs, almost equally important;
- using local methods to find optimal solutions;
- tends to create complex polynomials for relatively simple systems;
- tends to create highly complex networks (model) when it comes essentially nonlinear systems, limitations due to its overall structure (square polynomial of two variables);
- do not objectively evaluate coefficients by least squares;
- has a fixed structure and determined character search for a better model;
- do not effective in addressing the multi-task;

Recently, hybrid intelligent systems (HIS) are becoming popular due to their capabilities in handling many real world complex problems, involving imprecision, uncertainty and vagueness, high-dimensionality. However, the popularity of HIS is well known in the ANN domain but not well in the GMDH domain. Therefore, this paper aims to study the up-to-date Hybrid Self-Organizing Modeling Systems including ANN and GMDH based hybrid systems.

4 Some known hybrid GMDH-type algorithms

Hybrid of DE and GMDH. In [10, 11] the hybrid of DE [12] and GMDH systems have created and clearly showed that this structure is superior to the conventional GMDH approach. The architecture of model is not predefined but can be self-organized automatically during the design process. The hybrid DE and Singular Value Decomposition (SVD) is used for simultaneous parametric and structural design of GMDH networks used for modelling and prediction of various complex models. The DE-GMDH approach has been applied to the problem of developing predictive model for tool-wear in turning operations; the exchange rate problem; the Box-Jenkins gas furnace data, with experimental results clearly demonstrating that the proposed DE-GMDH-type network outperforms the existing models both in terms of better approximations capabilities as well as generalization abilities.

Hybrid of GP and GMDH. In [13, 14] GMDH-based approach to GP, which integrates a GP-based adaptive search of tree structures, and a local parameter tuning mechanism employing statistical search (i.e. a system identification technique) is presented. In traditional GP, recombination can cause frequent disruption of building blocks, or mutation can cause abrupt changes in the semantics. To overcome these difficulties, traditional GP with a local hill climbing search, using a parameter tuning procedure is supplemented. More precisely, the structural search of traditional GP with a multiple regression analysis method and establish adaptive program called "STROGANOFF' (i.e. STructured Representation On GAs for NOnlinear Function Fitting) is integrated. The fitness evaluation is based on a "Minimum Description Length (MDL)" criterion, which effectively controls the tree growth in GP. Its effectiveness by solving several system identification (numerical) problems and compare the performance of STROGANOFF with traditional GP and another standard technique (i.e. "radial basis functions") is demonstrated. The effectiveness of this numerical approach to GP is demonstrated by successful application to computational finances.

Hybrid of GA and GMDH. In [15-19] a hybrid of GA [20] and GMDH systems have created, which is superior to the conventional GMDH method. This paper presents a specific encoding scheme to genetically design GMDH-type neural networks based on using a hybrid GAs and SVD to design the coefficients as well as the connectivity configuration of GMDH-type neural networks used for modelling and prediction of various complex models in both single and multi-objective Pareto based optimization processes. Such generalization of network's topology provides near optimal networks in terms of hidden layers and/or number of neurons and their connectivity configuration, so that a polynomial expression for dependent variable of the process can be achieved consequently.

Hybrid of PSO and GMDH. Such algorithms have been proposed in [21, 22]. PSO is used to solve any optimizing problems whereas GMDH itself is a self-organizing modeling method which heuristically determines the optimum model of a given problem [23]. The reason for bringing the idea of hybridization was to overcome the existing shortcomings of traditional GMDH which is mainly of its combinatorial behavior of progressing through layers to find the optimum model of a given problem. Firstly, it makes the assumption that good approximation quality in the past guarantees the good approximation in the immediate future which is a greedy approach. GMDH only picks preallocated number of best solutions of the current layer to move to next layer. It ignores all other solutions which are unfit in early stages but might generate very fit solution in later stages. Hence choice of solution is always locally best. That means traditional GMDH has high chances of being trapped into local best solution. Secondly, the termination condition of traditional GMDH process depends on the quality of output value in layer by layer approach of nodes selection. It also uses a greedy approach that keeps track of local best solutions in the current layer. The iteration process is stopped as soon as new layer generates poorer solution than previous layer. GMDH tries to refine the model in each layer until the best estimation of the model that predicts the output with least error is obtained.

The principal approach of modeling of PSO-GMDH and traditional GMDH is more or less same. In PSO the whole population (of constant size) of swarm particles progresses iteratively until the optimum solution is found. Iterative process of PSO can be compared with layered approach of GMDH where swarm particles search for better position in each iteration as GMDH nodes look for better solution in each layer. The proposed hybrid PSO-GMDH uses a heuristic search process which makes it more attractive for efficiently searching for large and complex search spaces. It is likely that solution found by traditional GMDH is trapped into local minimum whereas PSO's domain of search space is infinitely large and it has its internal mechanism to avoid being trapped into local minimum. The tendency of PSO is that each particle keeps searching for better solution. Un-like traditional GMDH PSO doesn't stop the search process if the best solution of the next layer is not better than previous layer.

Group of Adaptive Model Evolution (GAME). P. Kordik [24] created the GAME as a hybrid GMDH-based self-organizing modeling system which uses neurons (units) with several possible types of transfer functions (linear, polynomial, sigmoid, harmonic perceptron network, etc.). The GAME is an original data mining method. It can generate models for classification, prediction, identification or regression purposes. It works with both continuous and discrete variables. The topology of GAME models adapts to the nature of a data set supplied. The GAME is highly resistant to irrelevant and redundant features, suitable for short and noisy data samples. The GAME engine further develops the MIA GMDH algorithm. A GAME model has more degrees of freedom (units with more inputs, interlayer connections, transfer functions etc.) than MIA GMDH models. GAME engine also use genetic search to optimize the topology of models and also the configuration and shapes of transfer functions within their units.

5 Conclusion

Hybridization of intelligent systems is a promising research field of modern AI related to the development of the next generation of intelligent systems. A fundamental stimulus to the investigations of Hybrid Intelligent Systems is the awareness amongst practitioners and in the academic communities that combined and integrated approaches will be necessary if the remaining tough problems in AI are to be solved.

One major conclusion resulting from the carried out studies in implementing hybrid AI paradigms and GMDH network is that population-based optimization techniques (GP, GA, DE, PSO, etc.) are all candidates of hybridization with GMDH. Further research activities include incorporating more design features to improve the modeling solutions and to realize more flexibility.

References

1. De Jong K. A. Evolutionary Computation: A Unified Approach. / The MIT Press Cambridge, 2006, P.267
2. Back T. Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic algorithms / Oxford University Press Oxford, 1996, P.319
3. Kennedy J., Eberhart R.S. Swarm Intelligence // Morgan Kaufmann Publishers Inc. San Francisco, 2001, P.512.
4. Haykin S. Neural Networks - A comprehensive foundation/ Pearson Education, 1999, P.823
5. Porto, V.W.: Evolutionary computation approaches to solving problems in neural computation. In: Back, T., Fogel, D.B., Michalewicz, Z. (eds.) Handbook of Evolutionary Computation Back, pp. D1.2:1–D1.2:6. Institute of Physics Publishing / Oxford University Press, New York (1997)
6. Abraham A., Grosan C. Engineering Evolutionary Intelligent Systems: Methodologies, Architectures and Reviews // Studies in Computational Intelligence (SCI) 82, 1–22 (2008)
7. Yao X.: Evolving artificial neural networks. Proceedings of IEEE 87(9), 1423–1447 (1999)
8. Ivakhnenko A.G.: Polynomial theory of complex systems.// IEEE Trans. on Systems, Man and Cybernetics SMC-1, 364–378 (1971)
9. Anastasakis L., Mort N. The Development of Self-Organization Technique. In: Modelling: A Review of The Group Method of Data Handling (GMDH), Research Report No. 813, Department of Automatic Control & Systems Engineering, The University of Sheffield, Mappin St, Sheffield, S1 3JD, United Kingdom (October 2001)
10. Onwubolu, G.C. Design of hybrid differential evolution and group method in data handling networks for modeling and prediction. Information Sciences 178, 3618–3634 (2008)
11. Onwubolu, G.C., Sharma, S., Intrusion Detection System using Hybrid Differential Evolution and Group Method of Data Handling Approach // The 2nd International Conference on Inductive Modelling (ICIM'2008), 2008, 255-262 pp.
12. Price K. V., Storn R. M., Lampinen J. A. Differential Evolution. A Practical Approach to Global Optimization / Springer-Verlag Berlin Heidelberg 2005, P.542
13. Iba H., de Garis H., Sato T. System Identification Approach to Genetic Programming/ In: Proc. of IEEEWorld Congress on Computational Intelligence, pp. 401–406. IEEE Press, Los Alamitos (1994)
14. Iba H., de Garis H. Extending Genetic Programming with Recombinative Guidance/ In: Angeline, P., Kinnear, K. (eds.) Advances in Genetic Programming 2. MIT Press, Cambridge, 1996, pp.69-88
15. Vasechkina E. F., Yarin V. D. Evolving polynomial neural network by means of genetic algorithm: some application examples/ J. Complexity International, Vol. 9, (2001), 729-744.
16. Sakaguchi A., Yamamoto T. A Study on System Identification Using GA and GMDM Network, IEEE 2003. (86) Arab Monetary Foundation, www.amf.org Industrial Electronics Society, 2003. IECON '03. The 29th Annual Conference of the IEEE (Vol.:3) 2387 - 2392
17. Nariman-Zadeh, N., Darvizeh, A., Ahmad-Zadeh, G.R.: Hybrid genetic design of GMDH-type neural networks using singular value decomposition for modeling and predicting of the explosive cutting process. In: Proc. Instn. Mech. Engrs., vol. 217, Part B, pp. 779–790 (2003)
18. Nariman-Zadeh, N., Darvizeh, A., Jamali, A., Moeini, A.: Evolutionary design of generalized polynomial neural networks for modelling and prediction of explosive forming process. Journal of Material Processing and Technology 164-165, 1561–1571 (2005)
19. Nariman-Zadeh N., Jamali A. Pareto genetic design of GMDH-type neural networks for nonlinear systems. /In: Proc. of the International Workshop on InductiVe Modelling, Drchal J, Koutnik J, (eds.). Czech Technical University: Prague, Czech Republic. p. 96-103. 2007
20. Goldberg, D.E.: Genetic algorithms in search, optimization, and machine learning. Addison-Wesley, Reading, 1989.
21. Voss M., Feng X. A New Methodology For Emergent System Identification Using Particle Swarm Optimization (PSO) And The Group Method Data Handling (GMDH) // GECCO 2002: Proceedings of the Genetic and Evolutionary Computation Conferen, pp. 1227-1232.
22. Onwubolu G.C., Sharma S., Dayal A., Bhartu D., Shankar A., Katafono K. Hybrid particle swarm optimization and group method of data handling for inductive modeling. In: Proceedings of International Conference on Inductive Modeling, Kyiv, Ukraine, September 15-19 (2008)
23. Kennedy J., Eberhart R. C. Particle Swarm Optimization// Proceedings of the IEEE International Conference on Neural Networks, Perth, Australia, pp. 1942-1948, 1995.
24. Kordik P. Fully Automated Knowledge Extraction using Group of Adaptive Models Evolution. PhD Thesis, Dept. of Comp. Sci. and Computers, FEE, CTU Prague, Czech Republic (September 2006) 303