COMBINING SIMULATION AND ARTIFICIAL NEURAL NETWORKS: AN OVERVIEW

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Abstract

Artificial Neural Networks (ANNs) attempt to mimic the massively parallel and distributed processing of the human brain. They are generally used for learning or optimization purposes. Simulation models are frequently utilized to evaluate given possible configurations or organizations of complex systems. Combining ANNs and simulation allows a variety of complex decision problems to be addressed, where intelligent and simulation types of knowledge are used. Although many researchers have studied particular benefits of such a combination, no global analysis of the related literature seems to have been published. We propose to analyze the different publications involving simulation and ANNs. Through the relative literature study, several general types of approaches are pointed out and characterized. Typical approaches include learning from simulation experiments and the inclusion of intelligent modules in models. The concrete application of these combined utilizations is mentioned in a variety of areas, ranging from production to ecology or economics. These approaches are discussed and further research directions are suggested.

Keywords: Simulation, Artificial Neural Networks, Metamodel, Decision Support.

Presenting Author's biography

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1 Introduction

Artificial Intelligence (AI) methodologies have greatly inspired simulation approaches in the beginning of the nineties. After a declining interest, simulation and AI seem to benefit again from more interest from the research community. In fact, the design of complex decision support systems (DSS) can greatly benefit from the combination of several methods, which can play an important role in problem solving. Among the needed functions of those methods, evaluating a system could be done through simulation, especially when the system to evaluate is complex. Moreover, those decision supports tools can also need AI methods in order to be able to take decisions when needed. DSS may have to learn, to extract knowledge, sometimes to optimize in order to provide an efficient aid. Therefore, there are logical complementarities and a great potential to combine simulation and AI methods to build decision supports tools. Among the major AI approaches, ANNs are able to predict behaviors, to help to take decision, to learn, to model and, also for a specific type of ANNs, to optimize. Because of these capacities, many researchers have combined simulation with ANNs in various problems areas and with different objectives. Unfortunately, to our knowledge, it seems that no publication has reported any analysis of the issues related to combining simulation and ANNs.

The article is organized as follows. First, we will recall the main features of general ANNs. Then, we will describe the types of approaches that we have identified, which combine simulation and ANNs. A brief discussion of the papers illustrating each approach will be proposed. With respect to these published works, we will conclude and proposed some research directions related to the combination of simulation and ANN for decision supports issues.

2 Introductory background about Artificial Neural Networks

An ANN is an information processing method that is inspired by the biological nervous systems. ANN mimics the ability of biological neural systems in performing complex decision-making tasks without prior programming [1, 2, 3].

The general aim of ANN is to produce from a certain number of input values, pertinent output values.

ANNs are made up of neurons (figure 1); each neuron is connected with one or more other neurons by a set of connecting links called synapses. The input signal (input value or signal coming from the subsequent neuron) transmitted to a synapse j connected to a neuron i is multiplied by a synaptic weight w_{ij}. An adder sums the input signals received by the respective synapses of a neuron, and an activation function limits the permissible amplitude range of the output signal to some finite values, ANNs support a wide range of activation functions (e.g. sigmoid function, hyperbolic function …). The different ways to connect those neurons provide different types of ANNs.

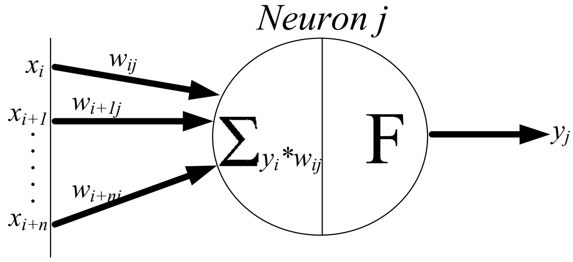

Fig.1 A neuron

ANNs are trained to produce the accurate input–output relationships [1, 2, 3]. Using a learning algorithm, the parameters are tuned to adjust the synaptic weights. Based on the user's objective and the available knowledge on the problem, the employed learning procedure can be either 'supervised' or 'unsupervised'.

In supervised learning, the network is trained using a set of existing input-output vector pairs (training set), training sets can be based on simulation results or on values obtained on real systems.

For each example of the training set, the network receives an input vector and produces an actual output vector. After each trial, the network compares the actual with the given output vector. It corrects any difference by slightly adjusting all the ANN weights until the produced output vector is similar enough to the given output, or the network cannot improve its performance any further.

In unsupervised learning, the network is trained using input vectors only. The network automatically constructs new output vector's elements when the similarity measured between the novel pattern and the most similar output vector's elements is too small to be incorporated.

There are many types of ANNs, the most well known are multilayer perceptions, which are generally supervised–trained with the error back-propagation algorithm [4].

Another popular class of networks is the self-organizing map, or Kohonen network [5]. A Kohonen network consists of two fully connected-unit layers. The output layer is generally ordered in a one-dimensional array or a two-dimensional matrix of units. The objective of this network is to build a map where units of an area are activated when inputs with similar characteristics are presented.

Radial basis function (RBF) networks are a particular class of multilayer networks [1], where learning is usually carried out in two steps: learning in the hidden layer (usually by an unsupervised method such as K-means clustering) followed by the output layer (a supervised method such as least squares estimation).

Among the other popular networks, there are adaptive resonance theory (ART) networks and their derivates (ART1, ART2, fuzzy ART, etc.) [6] and Hopfield models [7].

Dreyfus et al. [3], consider ANNs as non-linear statistical methods. Nevertheless, a large amount of data is required to overcome the existing non-linearity in the data structure. These ANNs are recognized for their robustness and their ability to handle imprecise and fuzzy information [8].

ANNs have been applied for decision support in many different fields (medicine, economics, robotic control, signal processing, computer vision…) during the two last decades [9, 2, 10]. Contrarily to ANNs, simulation models do have the capability to learn, to optimize or to decide. Therefore, combining both approaches can be quite useful when designing decision support systems. Several types of combinations are distinguished in the next sections.

3 Artificial Neural Networks and simulation for metamodeling

3.1 Principles

We first recall the definition of a metamodel [11]. Let Xj denote factors influencing the output of the real world system (j=1, 2, …, s), and let Y denote the system response, the relationship between the response variable Y and the inputs Xj of the system can be represented as following

$$Y=f1(X1, X2,…, Xs) \quad (1)$$

A simulation model is then an abstraction of the real system, in which we consider only a selected subset of the input variables {Xj/j=1, 2, ..., r} where r is significantly smaller than the unknown s. The response of the simulation Y' is then defined as a function f_2 that can be represented as

$$Y'=f2(X1, X2, …, Xr, v) \quad (2)$$

where v represent a random vector which representing the effect of the excluded inputs.

A metamodel is now a further abstraction, in which we select a subset of the simulation input variables {Xj/j=1, 2, ..., m; m≤r} and describe the system as

$$Y''= f3(X1, X2, …, Xm)+\varepsilon \quad (3)$$

where ε denote a fitting error, which has expected value of zero.

Simulation is a widely accepted tool in systems design and analysis of existing or proposed complex systems. Unfortunately, it is potentially expensive in terms of computer time, and should new ranges of conditions require evaluation, experiments must be repeated in full [12]. This is one of the reasons why it can be interesting to use metamodels instead of simulation models. Metamodels are often generated by the regression methods. ANN metamodels are introduced in [13] and discussed in [14].

Hurrion and Birgil [15] argue that metamodels developed using an ANN can produce more accurate responses than regression metamodels.

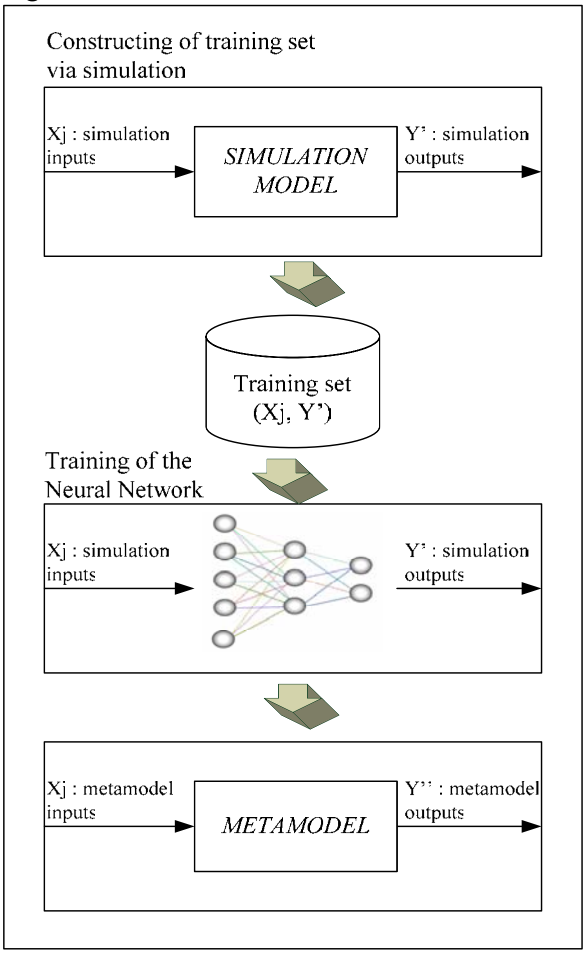

Fig. 2 Development of a ANN metamodel

Figure 2 summarizes the methodology for generating an ANN metamodel. In fact, we construct the simulation model, we collect data and then we train the ANN from these results. Then we use the ANN directly to evaluate new inputs.

An overview of published research on simulation metamodels for production applications can be found in [16]. At that time, Yu and Popplewell concluded that increasing number of published case studies in 1990's indicates that the techniques were matured from theoretical investigation to practical application.

Several others researches investigate method local issues for developing ANNs metamodels [17, 18, 19, 20].

3.2 Related Applications

Pierreval and Huntsinger [13] investigate the potential of ANNs as metamodels using a job shop model (discrete event worldview) and a coffee percolator (continuous worldview).

Latter, Fonseca and Navaresse [21] also proposed a feed forward multi-layered ANN metamodel as a possible alternative to the traditional job shop simulation models. Their ANN metamodel was able to estimate the manufacturing lead times for orders, simultaneously processed in a four-machine job shop.

Kilmer, Smith and Shuman [22] used input-output training pairs generated from an inventory simulation model to train two ANNs, one estimating mean total cost and the other estimating the variance of total cost. They used estimates of the mean and the variance of the cost produced by the ANN to predict confidence intervals for the inventory cost.

Wang and Yih [23] used ANN metamodel to measure the performance of control strategies for automated storage and retrieval systems (AS/RS). Then, regarding to those evaluations, they select the most efficient one.

Chan and Spedding [24] developed an ANN metamodel of an assembly system of optoelectronic products and they used this metamodel and a response surface approach to predict the system performance. Then a grid search method is connected to the metamodel to find optimum six-sigma configuration of the assembly process.

ANN metamodels are utilized in very specific domains; for example, Kwak et al. [25] proposed a metamodel-based method using ANN and simulation to solve the multi-variables problem of injection molding process. High-precision injection molding techniques are required for the fabrication of plastic optical lens. In this study, the ANN metamodel predicts the thickness reduction and the volumetric distortion rate in injection molding conditions.

In economics, Badiru and Sieger [26] used an ANN as a simulation metamodel in the financial analysis of risky projects. The developed metamodel can estimate the performance of potential future projects without re-running a time-consuming simulation.

In ecology, Pineros et al. [27] developed two metamodels: one based on multidimensional kriging, and another based on an ANN. On the presented case study, which concerns a nitrate leaching model, multidimensional kriging metamodel, they obtained better results than ANN metamodel. Nevertheless, as the results are very close, the authors concluded that it could not be generalized. Aussem and Hill [28] proposed an ANN metamodel to anticipate the propagation of the green alga *Caulerpa taxifolia* in the north-western Mediterranean Sea. The method provides reliable predictions of the covered surfaces, a couple of years in advance.

In military field, Kilmer [29] proposed to use an ANN metamodel for combat situations. This evaluation method is used to help analyzing practices. This author has developed similar approaches for medical problems. Kilmer et al. [30] developed an ANN metamodel of a discrete event stochastic simulation of a hospital emergency; they estimate the mean and the variance of patient time in the emergency department.

In civil aviation, Cassandras et al. [31] developed two ANNs metamodels. One for a tactical electronic reconnaissance problem; it describes the flight of a reconnaissance aircraft carrying a bearing angle measuring sensor over a radar field in order to detect ground-based radar sites. The other one represents an aircraft refueling and maintenance system as a component of a typical Air Tasking order.

ANN metamodeling was used in an optimization process to evaluate (faster than a simulation model) solutions proposed by the optimization methods. Hurrion [32] has used an ANN metamodel into a combinatorial search program, with a comparison test to find the optimum number of kanbans in a manufacturing system. Later, Hurrion and Birgil [15] carried out a comparison between two forms of experimental design methods for the development of regression and ANNs simulation metamodels. The results suggest that ANNs metamodels outperform conventional regression metamodels, especially when data sets based on randomized simulation experimental designs are used to produce the metamodels rather than data sets from similar sized full factorial experimental designs.

Wang et al. [33] have developed a hybrid knowledge discovery model, using a combination of a decision tree and an ANN metamodel in order to determine an appropriate dispatching rule using production data with noise information, and to predict its performance.

Wang [34] developed a hybrid genetic algorithm–neural network strategy for simulation optimization problems. The good approximation performance of ANN metamodel and the potential effectiveness of genetic algorithms are combined in view of searching for optimal designs.

4 Including Simulation and Artificial Neural Networks in a Decision Support Tool

4.1 Principles

Both ANN and a simulation model are embedded in a decision aid system. Most papers that we have classified in this category describe methods where simulation interacts all along a decision aid process or optimization process with an ANN. Figure 3 shows the general principles of simulation combined with ANN for decision aid system.

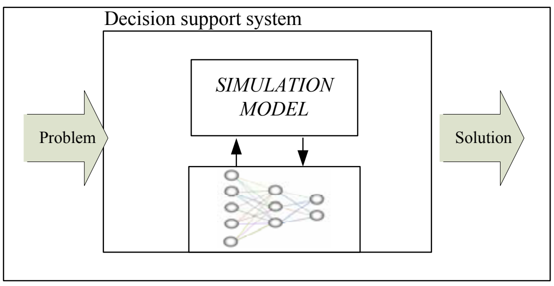

Fig.3 Artificial Neural Network and simulation for Decision aid system

We will see in the following how the combination is carried out depending on the context. The main aim is to better support and/or to automate the decision.

4.2 Related applications

Rovithakis et al. [35] address a problem of real time scheduling in the control of flexible manufacturing systems. They consider their problem as a control regulation problem that can be handled using a dynamic neural network. They prove that their network is efficient through simulation experiments.

Paternina-Arboleda and Das [36] developed a multi-agent reinforcement learning approach to obtain dynamic control policies for stochastic lot scheduling problem. In this study, ANNs, which seems to be considered as intelligent agents, choose dynamically the product type to be processed on each machine of the model according to the level of each product type stock. ANNs were trained using simulated data, based on a reinforcement learning algorithm.

Shiue and Guh [37] proposed a hybrid Genetic Algorithm-ANN approach. The GA evolves an optimal subset of system attributes, and simultaneously determines an optimal ANN topology and its learning parameters (according to various performance measures), whereas each ANN determined, according to the output of the GA, was trained by simulation data to evaluate the fitness of a given subset of system attributes. A discrete event simulation model is used to generate training examples for each constructed ANN.

Mouelhi and Pierreval [38] proposed a neural network approach to select dynamically in real time the dispatching rules. Based on the current system state and the workshop operating conditions the ANN make new decision about which rule to select each time a resource becomes available.

5 Simulation and external Artificial Neural Networks

In the following approaches, the general aim is still to develop decision aid or optimization system based on the combination of simulation and ANNs. Nevertheless, here, the ANN is not embedded in simulation. In those cases, we have qualified the ANN of external.

5.1 Principles

The general principle of those approaches is to construct a data base with the inputs and associated simulated outputs. Then the data base is modified depending on the final aim of the approach. This modified base, in which the inputs and outputs are not the same as in the simulation model, is used to train an ANN. The ANN will finally be exploited to take "good" decisions automatically. Figure 4 describes this methodology.

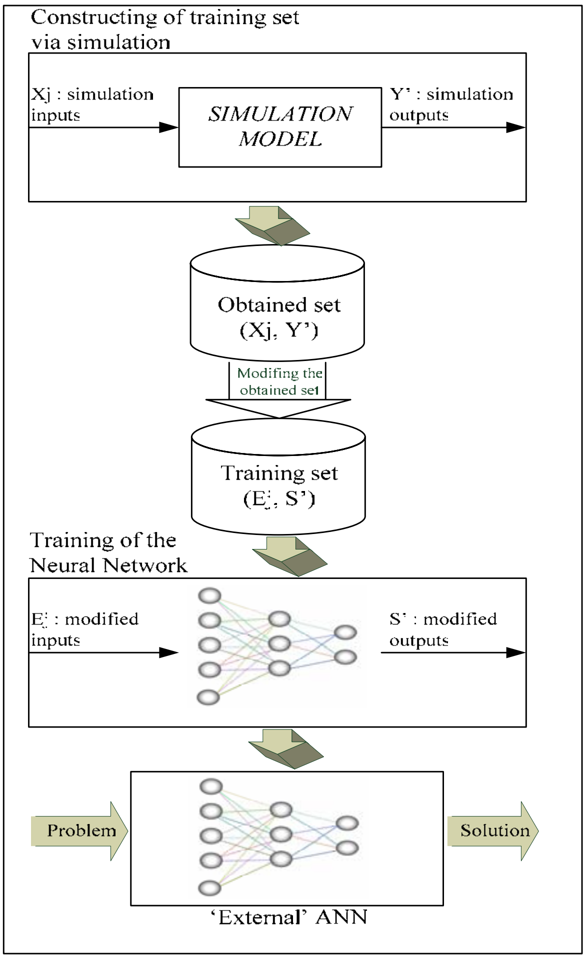

Fig.4 External Artificial Neural Network for Decision Support System

5.2 Related applications

Pierreval [38] developed a simulation model to evaluate dispatching rules according to different system states. Then, he created, from those simulated data, a training set which determines, for each system state, the adequate combination of dispatching rules.

Finally and based on this last training set, he trained the ANN to determine the best combinations of dispatching rules.

Madey et al. [39] developed a simulation model of a continuous improvement system in manufacturing (i.e. manufacturing workstation in GPSS). Giving the material property, the feed speed and the feed pressure of the machine, the simulation model measures the performances of the workstation. Then, based on the analysis of the simulation results, the authors developed an ANN to change the machine pressure and speed giving the model status.

Mollaghasemi et al. [40] demonstrated that ANN could be used in conjunction with simulation models to provide a decision support system for designing semiconductor manufacturing plant. In the study, ANN metamodel was developed to answer inverse questions (i.e., to estimate the inputs that are required to obtain specific outputs). In fact, for a given set of desired performance measures, i.e. cycle time, work-in-progress, and utilization of three different testers, the ANN suggests a suitable design of scheduling rules, and the number of each type of tester needed to achieve management's goal.

6 Artificial Neural Network as a modeling tool

6.1 General principle

From a general point of view, Fishwick [12] compares ANN approaches with traditional modeling approaches in simulation.. ANN can be used to model a part of a system that has to be simulated. For example it can be used when, in the simulation model, there is a human behavior or a complex reasoning to represent. Then the ANN could be trained either through real or simulated data. It becomes a part of the simulation model as a module to represent a particular way to take decision or to model a particular process. The Fig. 5 presents this use of ANN as modeling tool in simulation.

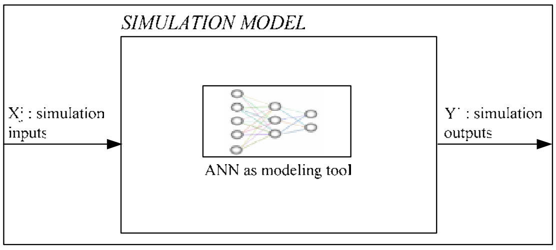

Fig.5 Artificial Neural Network as a modeling tool in simulation model

6.2 Related applications

Fishwick [12] compared ANN models with traditional modelling approaches, i.e. linear regression and response surface methods, and at that time concluded that the former is inadequate to represent system characteristics.

Song et al. [41] developed a simulation model for project planning in industrial fabrication. In their simulation, the processing times of manual operations are modeled and estimated through an ANN.

Antony et al. [42] developed a simulation model for granular systems where they integrated an ANN to model the micro-macroscopic characteristics of the system.

7 Artificial Neural Network and Visual Interactive Simulation

7.1 General principle

In Visual Interactive Simulation (VIS), a human user can directly interact or modify the simulation model with visual tools. One possible benefit to combine VIS and ANN is to study and analyze the human behavior during the simulation experiments. Then, those observations can be used to train an ANN. The ANN is then able to reproduce, or to predict the behavior of the human operator. It could have several applications from the automatic formalization of expert rules to intelligent help on some simulator for example. The figure 6 illustrates the main principle of those approaches.

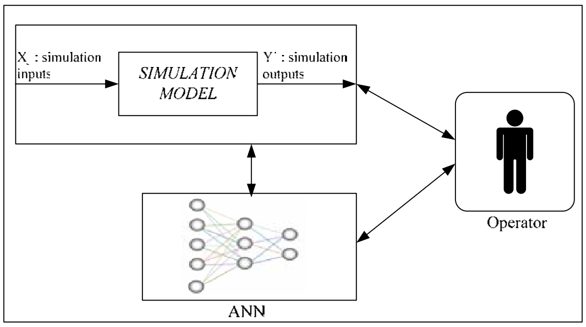

Fig.6 Artificial Neural Network and Visual Interactive Simulation

7.2 Related applications

In his early study on ANNs, Hurrion [43] developed an ANN in interaction within a visual interactive simulation model (VIS) of a coal depot. He suggested that an ANN combined with a VIS model can be used as a decision support tool. All results obtained from the simulation are exploited by the ANN. After a suitable period of training the quality of results obtained from the ANN matches those obtained by running the original VIS.

Hurrion [44] showed that using an ANN can be further employed as a Visual Interactive Meta Simulation technique to analyze the VIS model.

Alifantis and Robinson [45] developed an ANN decision maker for job shop scheduling problem. First, they proposed a visual interactive simulation of a job shop model. Second, by collecting the human decisions through the Visual Interactive Simulation, they used those data to train the ANN. Then, the ANN is exploited to provide decision support.

8 Conclusion and research directions

ANNs and simulation have been used together for several purposes. Most published papers are concerned with ANN metamodels, which have been addressed both from a methodological and a practical point of view, in various application area. The main objective is to save computing time through avoiding running long-time simulation model each time it is needed.

We have highlighted that ANNs can be used for several other purposes. They can represent certain parts of simulation models for which the dynamic behavior is too complicated to be directly modeled using usual simulation tools and can be more conveniently predicted through an ANN. Some works have pointed out the capacities to take intelligent decisions in the simulation through the ANN.

An important benefit of ANNS is their capacity to learn from simulation results, which can be very useful for decision support purposes. Several authors have demonstrated that choices between candidate strategies, in a decision making context, can be made by an ANN that has learnt through simulation. The training of a ANN can also be made by a VIS (visual interactive simulation), which can help to capture human reasoning strategies in context dependant complex situations, where expert knowledge would be very difficult to obtain and formalize.

Such possibilities offer a very interesting potential in several application areas where intelligent decision support tools are contemplated (manufacturing systems, military systems, etc.). Combining ANNS and simulation can allow achieving a real expertise in fields where it is difficult to obtain and formalize. Therefore these types of combinations represent particular methodologies for knowledge acquisition.

However, few concrete applications have used these principles yet so that interesting possibilities remain to explore in various application areas. As a matter of fact, although real problems have been addressed in medicine, ecology and military problems, with obtain good results (mainly ANNs metamodels), a lot of published works deal with academic problems, especially in production systems.

Several research directions can be highlighted from this literature analysis. The use of unsupervised learning approach would need to be better studied.

How to build a training set, especially for online decision making purposes remains an open research issue. This question is paused

in many learning approaches. The capacity of ANNs to optimize seems to be little investigated. This could be somehow surprising, regarding the number of works in of simulation optimization and the capabilities of ANNS in optimizing.
Knowledge extraction modules connected to VIS also represent interesting ways for learning to control complex systems.

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