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SOME ENGINEERING APPLICATIONS OF ANN IN CAD

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Abstract

A theory of the Computer Aided Design systems (CAD) has been one of the main targets of our research for many years. Generally CAD software is used for algorithmic tasks: calculations (e.g. optimisation or simulation), storage and searching for data in databases and edition of drawings and texts. However, many tasks are unsupported. Recently, a feasibility of Artificial Intelligence (AI) to improve CAD systems, especially Artificial Neural Networks (ANN), has been widely considered.

This paper presents application of ANN: for calculation and selection of pneumatic control valve in optimisation of pneumatic driving system and in optimisation of seat suspension system. It is argued that the proposed technique is better than any other commercial method, since in both the optimisation of pneumatic driving system and the optimisation of seat suspension system the optimisation process was many times shorter providing equally valuable optimisation task solutions.

In conclusion, it is postulated that ANNs give an opportunity to create improved CAD systems.

Keywords
artificial neural networks, Computer Aided Design, pneumatics.

Introduction

Computer Aided Design (CAD) is an intensely developed research and market area. An application of CAD software can improve quality and reliability of any project. It can accelerate a design process and help to solve it.

At present a computer is used for algorithmic tasks [1]. In CAD software one can recognise following algorithmic tasks: calculations (e.g. optimisation or simulation), storage and searching for data in databases and edition of drawings and texts. Recently Expert Systems (ES) utilised to decision problems have been created. However, many tasks are not aided et al. There are many reasons for this fact:

1. all heuristic (intuitive) activities, such as assessment of the design conception, selection of the criteria for optimisation or looking for new conceptions can be hardly supported because of their non-algorithmic character. Expert systems based on the theory of Fuzzy Sets (FS) and on languages of logic (e.g. PROLOG) could possibly offer solutions to these problems;
2. solutions to many algorithmic tasks are based on complicated mathematical models (e.g. set of non-linear partially differential equations). Usage of these models is too time-consuming and even a very fast computer cannot assure a cooperation between the designer and the CAD system;
3. there are substantial resources of information gathered from experiments or from previous design processes. There exists a problem of storing them in computer databases and reusing them.

A design process should be supported in all phases and on all levels, especially in the earliest ones, which role is the most significant.

For a few years a feasibility of Artificial Neural Networks (ANN) to improve CAD systems has been widely discussed. Some of such ANN applications are presented in this paper.

Calculation and selection of a pneumatic control valve

Traditional methods of calculation and selection of pneumatic control valves pose a problem of low accuracy and difficulty of computer implementation [2, 3].

Most of the methods use nomograms and tables. Their results are of various types: a manifold orifice diameter, a volume flow rate of air at standard conditions, a flow factor K_V (VID/VDE 2173), a sonic conductance C and a critical pressure ratio b (ISO 6358). They do not always describe a flow characteristic of a valve and cannot always be found in the catalogues. It has been also proven that the nomograms and the tables cannot be easily approximated with a use of the flow theory. Additionally, there are significant discrepancies between the results obtained by using various methods. A precise method, based on the Gerc model [4], however, is impractical because of its complexity.

Hence, one can conclude that a new method for calculations and selection of control valves is needed. This method should, by definition, be easy to apply in CAD systems. Moreover, it should also describe a flow characteristic of a valve, taking into consideration all the important parameters which have an influence on selection of a valve. Finally, this new method must prove that it is valid in a broad selection of parameters' values.

Using of an artificial neural network technique can be one of the possible solutions [5, 6].

The basic objective of ANN was an approximation of relations among the control valve parameters, the cylinder parameters and the specifications for the basic system (the cylinder with the valve). Having analysed real calculations and selection methods, as well as the vendor's catalogues, some variables were proposed; these were: cylinder diameter, piston diameter, force load on the piston, mass of moving elements, stroke of the piston, supplying pressure, time of a stroke as the input signals to the ANN and coefficient of the gas mass flow rate, supplying orifice diameter, time delay of the valve as output signals from the ANN.

The feed-forward ANN structure (the multi-layer perceptron) with Levenberg-Marquardt learning algorithm was selected [5]. The selection of the structure of ANN and the learning algorithm is described in detail in [6].

A learning data set was created by the computer simulation, based on E.W. Gerc model. The model is described in detail in [4]. The mathematical model was implemented in the MatLab/Simulink package environment. Input data do not cover all ranges, but only the possible and existing ones. Finally, the learning set of 4350 vectors was obtained.

Because of data type in the learning set a learning strategy similar to that known from learning of neurocontrollers was applied. Firstly, the relation from the data set was discovered by the first ANN; next the reverse relation was discovered by the second one (Fig. 1). The learning process was completed after 1000 epochs.

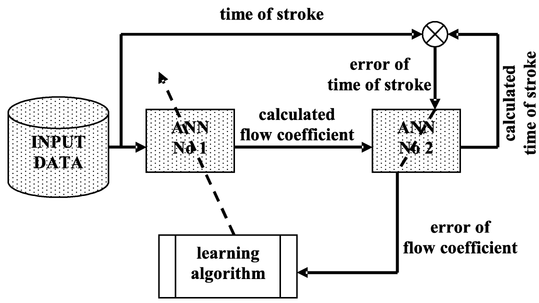

Fig. 1. Scheme of learning process.

Some tests were completed to determine the quality of the ANN, especially its capability of generalisation. The mean square errors for the test data set and for the learning data set were nearly the same: $1.93 \cdot 10^{-4}$ and $1.90 \cdot 10^{-4}$ (the precise results can be found in [5, 6]).

Percentage vectors fractions in the training and in the testing sets were computed, where the relative value of the error exceeded 1, 3, 5 and 10% (Table 1).

Table 1
Percent participation of vectors giving different relative error after 1000 epochs

Error limit	Learning set	Testing set
1%	35.0%	40%
3%	4.7%	5%
5%	0.8%	0%
10%	0.02% (1 vector)	0%

The preliminary results are very encouraging. Assuming that the mathematical model error does not exceed 3%, and the computing error of the ANN does not exceed 3%, it is strongly believed that even now at the current development stage, the proposed technique is better than any commercial method of calculation and selection of pneumatic control valve.

As opposed to the classical methods, this technique considers substantial parameters and requirements of the basic subsystem. Furthermore, it takes into consideration the distribution of the velocity, and not merely the average value of the that. What is more, it does not require any additional calculations to determine the real time of displacement.

Optimisation of pneumatic driving system

A general description of the thermodynamic phenomena in pneumatics requires an application the thermodynamic laws of changeable quantity of medium and leads to complicated non-linear differential models (it can be the set of 6 differential equations for a single pneumatic cylinder). These models (equations) are impossible to be solved analytically. A numerical integration with a use of digital computer is the only practical solution. A lack of fast computer models, which do not require a time consuming numerical integration, are the main reasons for popularity of optimisation in design of pneumatic driving systems.

Various criteria can be introduced for optimisation of pneumatic driving systems. The most important and the most popular ones are: absolute and relative energy consumption (to be minimised), working medium consumption (to be minimised), total time of single cycle action (to be minimised), costs of system creation (to be minimised), cost of system exploitation (to be minimised), durability and reliability (to be maximised), number of devices in the system (to be minimised).

A master criterion (target function) of optimisation (polioptimisation) can be combination of all or selected from criteria above. A selection of criteria determinates a set of mathematical models, which can be applied to solve an optimisation task.

Many decision variables which could be deployed in the process of optimisation of PDS can be pointed out. These variables relate to: the pneumatic cylinder (cylinder diameter, piston rod diameter, piston stroke, manifold orifice diameter), the pneumatic control valve (manifold orifice diameter, time of action, flow properties), the supply installation (supply pressure, diameters and lengths of pipes), the other pneumatic devices of the supply installation (flow properties) and the control system (type of control system and its describing variables).

A set of decision variables in a given optimisation task is determined by the selected criteria and constrains. It is also important that the majority of decision variables has a discrete and limited character (e.g. cylinder diameter).

Constrains in optimisation of PDS are an effect of: technological process requirements (minimum loaded force, maximum velocity), available financial means and future costs (maximal costs of creation and exploitation of the system, a time of creation), working conditions (e.g. parameters of existing supply installation – supply pressure, installation capacity) and ranges of validity of applying models.

A description of criteria and constrains ends the definition of an optimisation task.

In the first phase of the research an optimisation task was formulated [7] in order to find the value of parameters of a basic subsystem (a pneumatic cylinder with a supply control valve) and to minimise the following two criteria:

1. consumption of a pneumatic energy (product of cylinder chambers volume and supplying pressure),
2. total time of single cycle action,

with constrains:

1. maximum velocity of a piston,
2. minimum working load,
3. maximum supplying pressure.

During optimisation process calculations of values of all criteria and all constrains are required in each step. Application of a differential model, proposed by Gerc [4], is needed to solve such task but integration of the model is very time-consuming.

There is a possibility of applying other types of models to calculate the time of action and the maximum velocity. Tentative experiments have been performed.

A fast, specialised and parametric model of pneumatic cylinder was created by means of neural network technique. The task of this model was to calculate a time of piston action on a base of: pneumatic cylinder parameters, supply control valve parameters, supply installation parameters and requirements imposed by designer to pneumatic system.

The feed-forward artificial neural network structure was used, with the Levenberg-Marquardt method as a learning algorithm.

A learning set was created by computer simulation based on the model by Gerc. More than 4500 vectors of data were obtained [5].

The learning process was conducted by 700 epochs. Next, various tests were completed in order to determine the quality of the neural model. The maximum absolute error of calculated time in seconds was very satisfactory but the relative error was not (Fig. 2). It forced us to change the learning strategy. The learning set was transformed by a simple non-linear function and the learning process was repeated. The absolute error became a little bit worse but the relative error improved significantly (Fig. 3, 4 and 5).

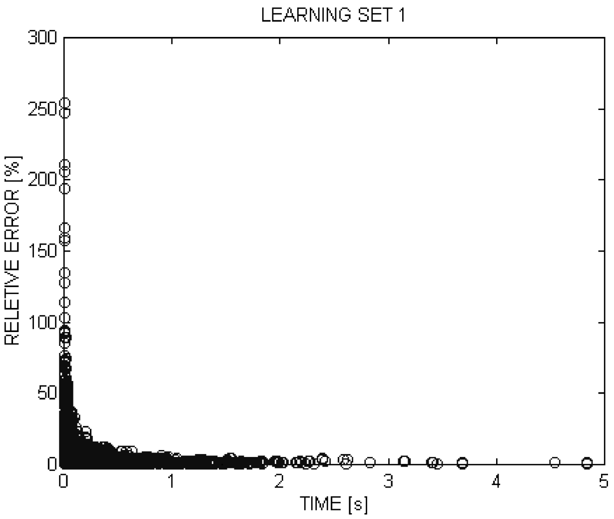

Fig. 2. Relative error v time value for the learning set 1.

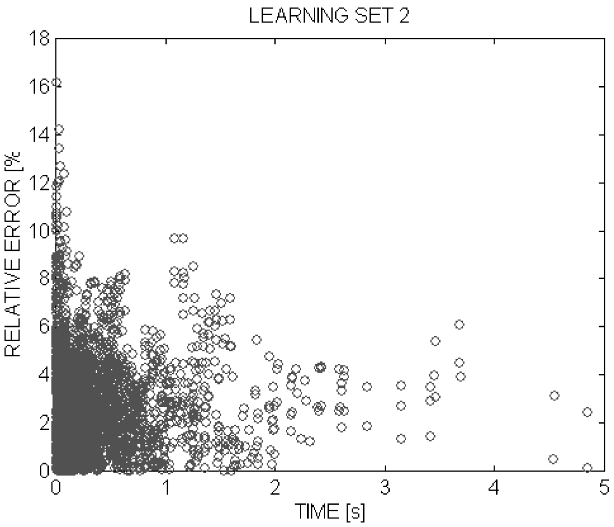

Fig. 3. Relative error v time value for the learning set 2.

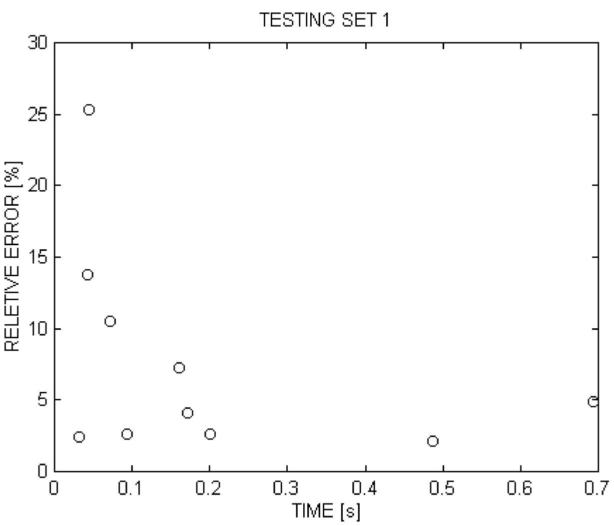

Fig. 4. Relative error v time value for the test set 1.

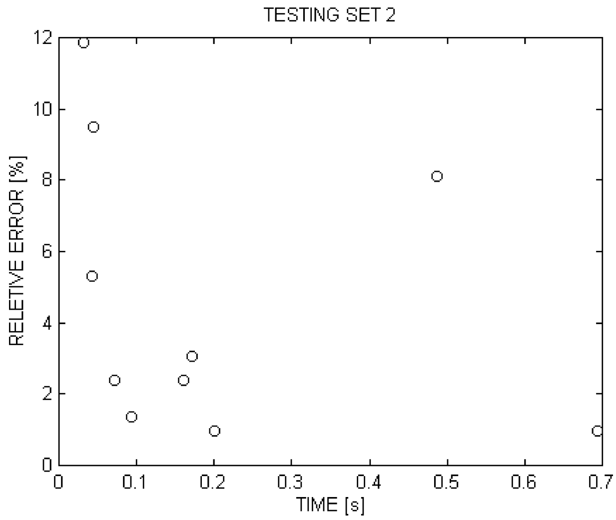

Fig. 5. Relative error v time value for the test set 2 (fast cylinders only).

The obtained specialised neural model of a pneumatic cylinder had a sufficient precision for typical pneumatic systems (the precise results can be found in [7]).

Tentative optimisation calculation utilising neural model proved advantages of this approach. A total time of optimisation calculations was many times shorter even for small systems (it means systems with low number of cylinders) than the time of the ones with differential models.

Optimisation of seat suspension system

The considered seat suspension system consists of a shear-guidance mechanism, a pneumatic spring and a hydraulic shock-absorber. The pneumatic spring is modified by means of an additional, non-deformable air reservoir; hence its characteristic stiffness can be modified. Furthermore, an extra damping force is introduced in the suspension system by throttling of the air-flow between the additional air reservoir and the pneumatic spring. Modifying the circular orifice inside the shock-absorber enables one to change the damping characteristics of the relative velocity domain. The non-linear shaping of the pneumatic spring and of hydraulic shock-absorber forces is desirable to obtain the best vibro-isolation properties of the suspension system. In order to enable adjusting the force characteristics of passive suspension, two criteria are defined: effective acceleration of isolated body (criterion k_1) and maximum relative displacement of suspension system (criterion k_2).

The effective acceleration on the seat should approach zero to protect isolated body from harmful vibrations; the maximum relative displacement of seat suspension should approach zero as well, in order to limit the suspension travel. These criteria are in opposition to each other. It means that an improvement in one criterion requires a degradation of the other.

Each criterion can be presented as a function of five independent decision variables:

x_1 – a volume of the additional air reservoir,
x_2 – an effective air-flow air between the additional reservoir and the pneumatic spring,
x_3 – a radius of the shear guidance mechanism,
x_4 – a diameter of orifice in the shock-absorber's piston,
x_5 – a length of orifice in the shock-absorber's piston.

A precise mathematical description of the plant as well as some experimental results are presented in [8–11].

During the preliminary research the optimisation is conducted separately for each criterion.

Having taken into consideration the object's degree of complexity and the theoretical basics of approximation, as well as having carried out several test runs it has been decided that:

1. two neural models should be created – one for each criterion,
2. a feed-forward neural network should be utilised (multi-layer perceptron) with five inputs (for x_1 to x_5 variables), one output (criterion K_1 value or criterion K_2 value) and one hidden layer with 17 and 27 neurones, respectively,
3. the back-propagation learning algorithm based on the Levenberg- Marquardt optimisation method seems to be the most suitable.

The learning process of the first network (criterion K_1) has been stopped after 1000 epochs with the maximal relative error (MAE) of 3.41% and the mean relative error (MRE) of 0.241%. Trials involving the test set have resulted in the maximal relative error of 1,52% and the mean relative error of 0.248%.

The learning process of the second network (criterion K_2) has been stopped after 2000 epochs with the maximal relative error of 9.70% and the mean relative error of 0.587%. Trials involving the test set have resulted in the maximal relative error of 4.88% and the mean relative error of 0.547%.

The obtained neural models have been regarded as capable of substituting the differential models in optimisation of the seat suspension system.

The optimisation process was conducted ten times for each criterion and each model – it amounted to a total of forty optimisation runs. The initial values of the decision variables were randomly selected from a set of defined ranges. The MatLab Simulink environment was used in all calculations. A constant step method was applied for an integration of the differential model because of the specific requirements of the first calculation criterion (K_1).

A comparison of optimisation results for the differential and neural models is presented in Table 2 (for the K_1 criterion) and Table 3 (for the K_2 one).

Precise analysis of the results can be found in [12]. Generally, all of the obtained results are consistent with the theory of seat suspension systems, other studies and experimental results. The obtained results indicate, that the neural models are much faster than the differential ones, providing equally valuable optimisation task solutions.

Table 2
Optimisation results for criterion K_1: x_1 to x_5 – optimal values of the decision variables for the differential model (DEM) and the neural model (ANN), the criterion value and the time of calculation

$x_1 \cdot 10^3$		$x_2 \cdot 10^5$		$x_3 \cdot 10$		$x_4 \cdot 10^3$		$x_5 \cdot 10^2$		$K_1 \cdot 10$		Time [s]		$\frac{T_{DEM}}{T_{ANN}}$
DEM	ANN	DEM	ANN	DEM	ANN	DEM	ANN	DEM	ANN	DEM	ANN	DEM	ANN	
8.83	8.33	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.86	7.23	7.31	667	1.34	498
8.83	9.03	1.00	1.00	1.30	1.29	3.00	3.00	1.00	1.83	7.23	7.32	847	1.28	662
8.83	8.32	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.86	7.23	7.31	608	0.983	619
8.83	8.32	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.86	7.23	7.31	615	0.952	646
8.83	8.33	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.86	7.23	7.31	616	0.936	658
8.83	8.31	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.86	7.23	7.31	572	0.873	655
8.83	8.32	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.86	7.23	7.31	1240	1.06	1170
8.82	8.32	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.86	7.23	7.31	900	0.921	977
8.83	8.33	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.86	7.23	7.31	817	1.56	524
8.82	8.32	1.00	1.00	1.30	1.26	3.00	3.00	1.00	1.85	7.23	7.31	532	0.951	559

Table 3
Optimisation results for criterion K_2: x_1 to x_5 – optimal values of the decision variables for the differential model (DEM) and the neural model (ANN), the criterion value and the time of calculation

$x_1 \cdot 10^4$		$x_2 \cdot 10^7$		$x_3 \cdot 10^2$		$x_4 \cdot 10^3$		$x_5 \cdot 10$		K_2		Time [s]		$\frac{T_{DEM}}{T_{ANN}}$
DEM	ANN	DEM	ANN	DEM	ANN	DEM	ANN	DEM	ANN	DEM	ANN	DEM	ANN	
1.00	1.00	58.30	52.70	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	576	1.030	559
1.00	1.00	23.30	80.80	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	612	0.437	1400
1.00	1.00	1.23	53.50	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	812	0.811	1001
1.00	1.00	90.00	75.80	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	373	0.936	399
96.20	1.00	1.00	72.90	12.80	5.00	1.50	1.50	1.30	1.30	2.12	2.24	416	0.920	452
1.00	1.00	8.28	79.30	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	440	0.640	688
1.00	1.00	6.41	39.10	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	914	0.671	1362
1.00	1.00	1.63	67.20	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	1040	0.686	1516
1.00	1.00	43.40	82.00	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	888	0.484	1835
1.00	1.00	1.33	75.10	5.00	5.00	1.50	1.50	1.30	1.30	2.24	2.24	662	1.090	607

Conclusions

Some applications of Artificial Neural Networks to improve CAD system have been presented in this paper. These are real-life engineering application. It can be concluded that the use of ANNs in CAD seems to be a good approach. Especially, application of neural models for substitution of the differential models gives very good results. For example in optimisation the neural models are much faster than the differential ones, providing equally valuable optimisation task solutions.

Although the presented examples mostly originate from Pneumatic Driving Systems the advantages of ANN should be the same in other areas of engineering activity.

Generally, it seems that artificial intelligence gives opportunity to create improved next generation of CAD systems.

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