The Anticipatory Aspect in Neural Network Control

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Introduction

Humans tried always to construct machines which are capable to imitate their capabilities and their intellige-nce in order to facilitate their life and dominated the world. One of the privileged domains where they have to demonstrate important performances is in systems control.

The classic control system is based on transfer function mathematic description. This system reacts always exactly in the same way when the same input is present, giving the impression that it "looks" at the input for the first time. It is incapable to "memorize" and to "remember" its previous comportment. This behavior doesn't allow relating any kind of "intellige-nce" to the classic control system. For control purpo-ses it is obvious the necessity and usefulness of systems which are able to "remember" and react in ac-cordance with acquired experience from their past. In other words, control systems capable to anticipate, even weakly. Ability which allows to speak for a first order of intelligence in the system.

In this direction there are two main approaches:
1. the neural networks [1-3] and
2. the fuzzy logic [4] based control systems.

This paper discusses the neural network approach.

One of the recent Neural Network applications is in the control domain. Their approximation capabilities of Multilayer Perceptron (MLP) made them a popular choice for modeling nonlinear systems and for imple-menting general – purpose nonlinear controllers. For this purpose, different control algorithms and archite-ctures, with special capabilities, are implemented in solving the nonlinearity problems. In any Neural Net-work control algorithm, the essential difference from the classic control is based on the effect that a model of the plant, under control, is created, in order to describe, by prediction, its dynamic future behavior. This gives to the process control the knowledge of the system's expected comportment in possible inputs. This characteristic gives the system an "intelligence" dimension, as it arms with anticipation capabilities, rending it more efficient, with better performances.

Anticipation

From the philosophical point of view, there are different approaches for the term anticipation. The Greek philosophy, Stoicians and Epicurians, appoint as anticipation the relation between *universal and particular*, or in other terms, is the capacity of human mind to *posses and use abstract ideas, before the immediate perception of the object* and is referred to the possibility of extrapolating from universal to particular [12].

Robert Rosen [6], gives a definition more closely to the contemporary technical point of view. According to this definition: "*an anticipatory system is a system containing a predictive model of itself and/of its environment which allows it to change state at an instant in accord with the model's predictions pertaining to a later instant*". The formulation of this description is viewed with simplicity in
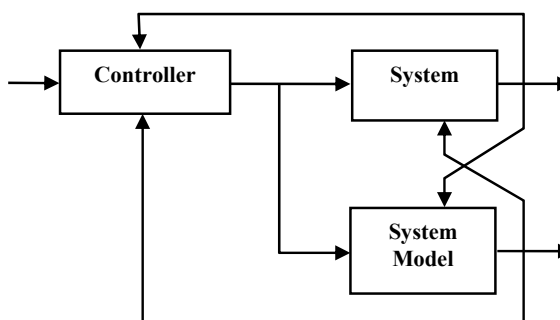

Fig. 1. The anticipatory system

Robert Rosen conjectures that adaptation and learning systems in biological processes are anticipatory systems and anticipation is the main difference between living and non-living systems. He states that the evolution of an anticipatory system *S(t)*, at each time step, is driven by the predictive model *M(t+1)* at a later time, and that the predictive model is not affected by the system. Thus, with this

statement, a finite difference equation system can be written as:

$$\Delta S / \Delta t = [S(t+\Delta t) - S(t)] / \Delta t = F[S(t), M(t+\Delta t)]; \quad (1)$$

$$\Delta M / \Delta t = [M(t+\Delta t) - M(t)] / \Delta t = G[M(t)]. \quad (2)$$

Daniel Dubois's interpretation of anticipatory system is quit different of that of Robert Rosen and wands model evolution to be a function of itself as well as of the system [7]. With Dubois interpretation the finite difference equation system becomes:

$$\Delta S / \Delta t = [S(t+\Delta t) - S(t)] / \Delta t = F[S(t), M(t+\Delta t)]; \quad (3)$$

$$\Delta M / \Delta t = [M(t+\Delta t) - M(t)] / \Delta t = G[S(t), M(t+\Delta t)]. (4)$$

Further more, Daniel Dubois makes a distinction between strong and weak anticipation. A weak anticipatory system computes its future states, as function of its states at past times, present time, and predicted –by model-future times, according to equation:

$$X(t+1) = F[\cdots, X(t-1), X(t-1), X(t), M(t+1), M(t+2), \cdots, p], \quad (5)$$

where p denotes a control parameter

A strong anticipatory system computes its next state, as function of its states at past times, present time, and even its states at future times, according to equation:

$$X(t+1) = F[\cdots, X(t-1), X(t-1), X(t), X(t+1), X(t+2), \cdots, p], \quad (6)$$

where: p denotes a control parameter

In strong anticipation those future states, are computed in using the equation itself, and the system becomes self-referential in computing its future states from itself and not from a model based prediction.

Following to this short description of anticipation, the three main Neural Network Control algorithms will be described.

Neural Network Predictive Control

The neural network predictive controller, as all other algorithms presented in this work, uses two steps to realize the control procedure:

1. In order to identify the plant behavior a neural network model of a nonlinear plant, to predict future plant response, is created.
2. In the control stage, the model is used to train the controller and the control input, that will optimize system performance over a specified future time horizon, is calculated [8]. In the plant identification phase the controller trains the neural network plant model in order to acquire the forward dynamics of the plant. For the training process the prediction error is used as input to the learning algorithm (Fig. 2).

The neural network plant model uses the plant previous inputs and outputs to predict future values of the plant response, over a specified time horizon, and these predictions are used, by a numerical optimization program, to determine the control signal that minimizes a performance criterion J over the specified horizon.

$$J = \sum_{j=N}^{N_2} (y_r(t+j) - y_m(t+j))^2 + p \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2, \quad (7)$$

where: N_1, N_2, N_u: define the horizons over which the tracking error and the control increments are evaluated; u' - the tentative control signal; y_r - the desired response; y_m - the model response; p - u' contribution on performance index.
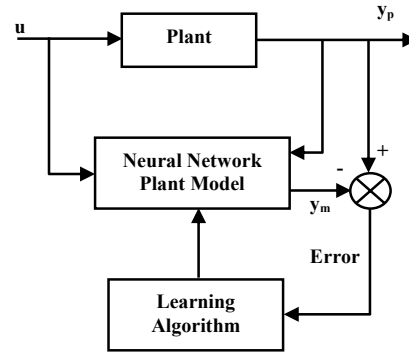

Fig. 2. System identification

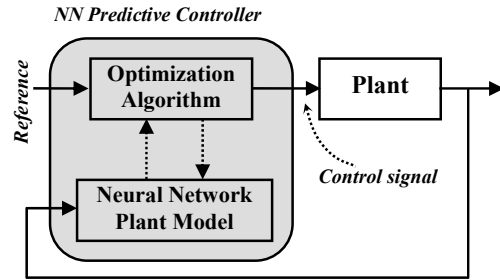The system block diagram becomes as in Fig. 3.

Fig. 3. NN Predictive Controller

NARMA L2 Control

The principal idea of NARMA-L2 (Nonlinear Autoregressive – Moving Average) controller is to transform nonlinear system dynamics into linear, by canceling the nonlinearities.

The model used for the plant implementation is described as:

$$y(k+d) = N[y(k), y(k-1), \cdots, y(k-n+1), u(k), u(k-1), \cdots u(k-n+1)], (8)$$

where $u(k), y(k)$ - the system input and output respectively.

The Neural Network training, during the identification phase, is realised in order to approximate the nonlinear function N.

If the system follows a desired reference trajectory y_r then the nonlinear controller must be of the form:

$$u(k) = G[y(k), y(k-1), \cdots, y(k-n+1), y_r(k+d), u(k-1), \cdots u(k-m+1)]. (9)$$

The Neural Network training (minimisation of Mean Square Error) is to create the G function of the controller [9].

The NARMA-L2 controller approximate model is in companion form [10]:

$$\hat{y}(k+d) = f[y(k), y(k-1), \cdots, y(k-n+1), u(k-1), \cdots u(k-m+1)] +$$

$$+ g[y(k), y(k-1), \cdots, y(k-n+1), u(k-1), \cdots u(k-m+1)]u(k). \quad (10)$$

where, the next controller input *u(k)* is not contained in the nonlinearity.

The resolving controller input has the form:

$$u(k) = \frac{y_r(k+d) - f[y(k), y(k-1), \cdots, y(k-n+1), u(k-1), \cdots u(k-m+1)]}{g[y(k), y(k-1), \cdots, y(k-n+1), u(k-1), \cdots u(k-n+1)]}. \quad (11)$$

For realisation problems of this equation (control input *u(t)* calculation is based on the same time output *y(k)*) is more realistic to use instead the following equations:

$$y(k+d) = f[y(k), y(k-1), \cdots, y(k-n+1), u(k), u(k-1), \cdots u(k-m+1)] +$$

$$+ g[y(k), \cdots, y(k-n+1), u(k), \cdots u(k-n+1)]u(k+1); \quad (12)$$

$$u(k+1) = \frac{y_r(k+d) - f[y(k), \cdots, y(k-n+1), u(k), \cdots u(k-n+1)]}{g[y(k), \cdots, y(k-n+1), u(k), \cdots u(k-n+1)]}. \quad (13)$$

where *d≥2*.

The NARMA-L2 controller, which realises this function, is shown in Fig. 4.
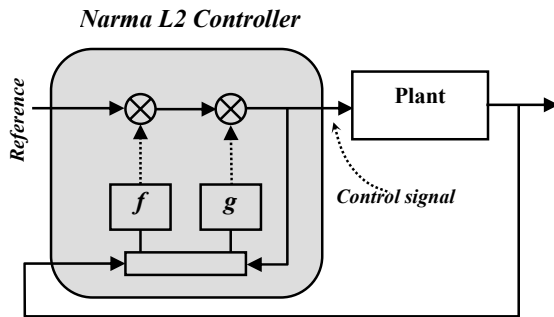
Narma L2 Controller

Fig. 4. NARMA-L2 controller

Model Reference Control

The Model Reference architecture requires, in addition of previous architectures, a separate neural network controller. The plant model identification takes place first and then the controller is trained, so that the plant output follows the reference model output. The block diagram of the all process is presented in Fig. 5.
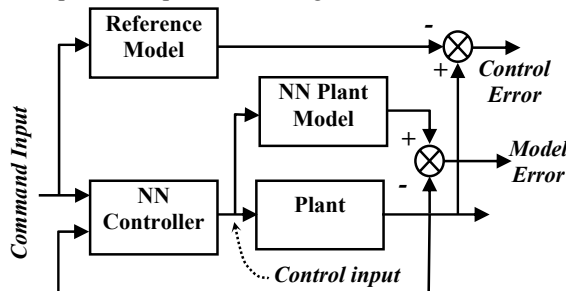

Fig. 5. Model Reference Control

Conclusions

The insertion of Neural Networks in classic control introduces the anticipatory aspect in control and dedicates a new, more efficient, approach in control systems, as it is shown from the typical system responses. This approach has a different logic and philosophy from classic control methods and renders the system more "intelligent". For more complex evolutionary dynamic systems, it constitutes a modern control tool strongly anticipatory, if the dialog possibility exists between plant and model, in order to update the last one about plant evolution. This autoanticipation aspect opens a new horizon in control engineering.

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G. Tsirigotis, D. Bandekas, D. Pogaridis, J. L. Lázaro. Prognozuojami neuroninių tinklų kontrolės būdai // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2005. – Nr. 2(58). – P. 10–13.

Prognozuojami būdai, kaip pagrindinės aukšto intelekto sistemų charakteristikos, įvedamos į kontrolės sistemą neuroninių tinklų kontroleriais, suteikia tai sistemai „intelektą", ir ji tampa pajėgi „atsiminti" ankstesnę elgseną bei vėliau panaudoti ją kontrolės algoritme tinkamam kontrolės signalui nustatyti. Neuroninių tinklų kontrolės prognozavimas yra pagrįstas daugiasluoksnio perceptrono prognozavimo galimybėmis. Toks perceptronas, naudojamas gamyklinio modelio konstrukcijoje, yra pagrindinis kontrolės proceso elementas. Išnagrinėti neuroninių tinklų prognozavimo būdai, pagrįsti kitokios struktūros kontroleriu, ir lyginami klasikinės ir neuroninių tinklų kontrolės rezultatai. Il. 5, bibl. 11 (anglų kalba; santraukos lietuvių, anglų ir rusų k.).

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The anticipatory aspect, essentially characteristic of high level intelligence systems, introduced in control systems by Neural Network controllers, gives an "intelligence" to the control system, as it becomes able to "remember" its past behaviour and use it afterwards in control algorithm in order to establish the appropriate control signal. Anticipation, in Neural Network control, is based in prediction capabilities of Multi Layer Perceptron, used in plant model construction, essential element of control process. In this work, the anticipatory aspect in Neural Network, different kind, controller's structure is examined, and comparison between classic and Neural Network control is made. Ill. 5, bibl. 11 (in English; summaries in Lithuanian, English and Russian).

Г. Тсириготис, Д. Бандекас, Д. Погаридис, Х.Л. Лазаро. Проблемы контроля нейронных сетей // Электроника и электротехника. – Каунас: Технология, 2005. – № 2(58). – С. 10–13.

Анализируются способы прогнозирования контроля нейронных сетей. Предлагается в систему контроля ввести «интеллектуальные характеристики», которые отражают основные параметры современных сетей. Главной задачей такого контроля является ввод высоких интеллектуальных свойств систем. В качестве основного элемента прогноза контроля используется многослойный перцептрон. Сравниваются результаты классического контроля и предлагаемого интеллектуального перцептрона при оценке качества нейронных сетей. Ил. 5, библ. 11 (на английском языке; рефераты на литовском, английском и русском яз.).