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GENERALIZED NET FOR CONTROL AND OPTIMIZATION OF REAL PROCESSES THROUGH NEURAL NETWORKS, USING INTUITIONISTIC FUZZY ESTIMATIONS

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Abstract: We shall construct a Generalized Net (GN) that represents the functioning and the result of the work of real processes and simultaneously – the processes of their control and optimization on the basis of different suitable chosen neural networks solving concrete optimization procedures giving intuitionistic fuzzy estimations and using information generated by the GN.
Keywords: Control, Generalized net, Neural network, Optimization

1 Introduction

Generalized Nets (GNs, see [1]), are extensions of Petri Nets. Over the GNs a lot of operators are defined that change the structure or the behaviour of the GNs.

Here, basing on the idea for the sixth hierarchical operator, defined over GNs (see [2]), and the idea for using the GNs as tools for control and optimization (see [4, 10]), we discuss the possibility to use the GNs as tools for control and optimization of real processes on the basis of different suitable chosen neural networks solving concrete optimization procedures and using information generated in the GN. As we will note below, for each type of neural networks there is a GN that is universal for this type, i.e., it represents the way of functioning and the results of the work of each neural network from the given type, below we will use the GNs, universal for the different types of neural networks and will mark them by GNNs.

Here we shall use all notations from [1] and only will mention, following [2], that the sixth hierarchical operator changes a token of a given GN to a subnet (see Fig. 1).

A short review and a bibliography on GNs has been given in [11].

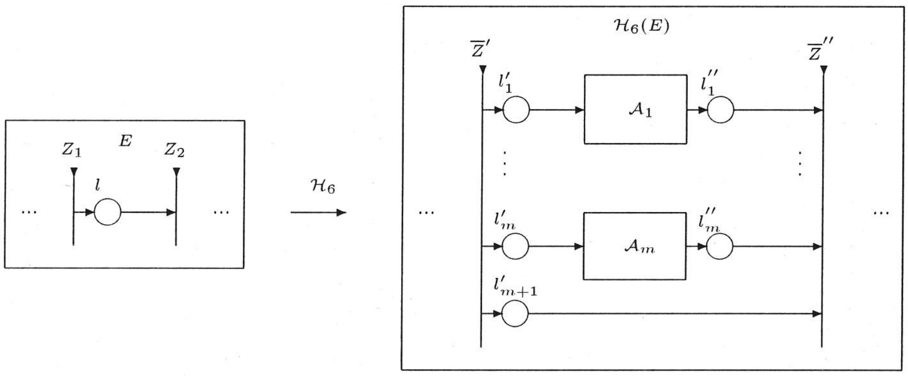

Fig. 1.

2 Generalized nets as a tool for control and optimization of real processes

Following [4] we will mention that the Petri nets and their extensions are primarily used for simulation of processes. The GNs-models are also used for simulation, but they are suitable for other applications as well. If a real-time environment is appropriately linked to a GN implementation (possibly also to databases, expert systems and other relevant software), GNs can be used for control of real processes flowing in this environment. The information from the environment enters the GN as initial or current tokens characteristics or as parameters for the transition condition predicates. The third application of the GNs is for optimization of the modelled processes. Up to now there are two GN-models of optimization procedures. In [1] a GN is constructed describing the process of transportational problem solving, while [3] discusses GN-models of traveling salesman-type problems. Practically, the process of solving of all other optimization problems can be described by GNs.

Below we shall construct a reduced GN from third type (Fig. 2) without local (i.e., for the transitions) temporal components, without transitions', places' and tokens' priorities and without places' and arcs' capacities. The tokens in this GN will keep all their history.

We shall describe the transition condition predicates and the tokens characteristics not fully formally for the sake of easier understanding of the formalism in use.

Some of the tokens below will obtain characteristics having Intuitionistic Fuzzy (IF) values (for intuitionistic fuzziness see [?]).

Initially, tokens $\alpha_1, ..., \alpha_m$ enter places $p_1, ..., p_m$, respectively, with initial characteristics corresponding to the parameters of a real process (of a set of parallelly flow real processes). At the same time moment tokens β and ν stay in places l_3 and n_0 with initial and current characteristics: *"criteria for choice of necessary GNNs"* and *"list of GNNs with corresponding IF-degrees of correctness that can solve respective optimization procedures"*.

In some time-moments tokens $\beta_1, \beta_2, ...$ can enter the GN through place l_1 with initial characteristics *"a new criterion for choice of necessary GNNs"*.

The later characteristic can have more complex form *"changes in the environment of the real processes; a new criterion for choice of necessary GNNs"*.

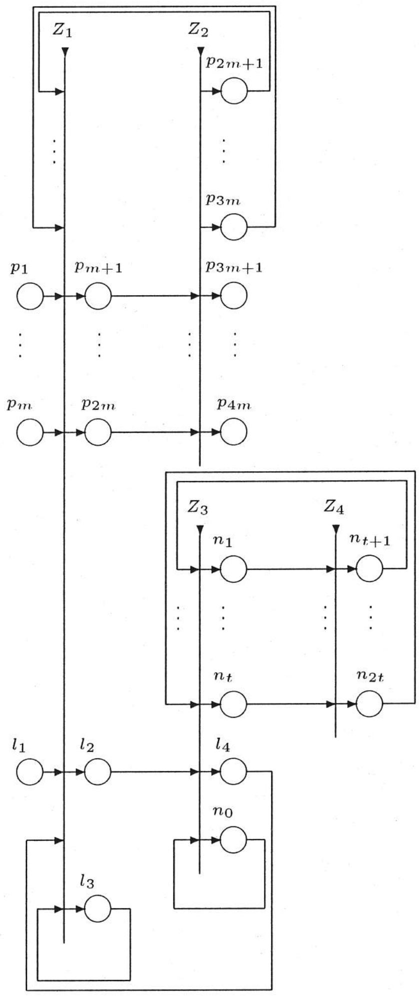

Fig. 2.

These tokens will enter place l_3 and will unite with token β that stays only there. By this way we interpret the process of actualization of the criteria that will be used in the global process.

$$Z_1 =< \{l_1, l_3, l_4, p_1, ..., p_m, p_{2m+1}, ..., p_{3m}\}, \{l_2, l_3, p_{m+1}, ..., p_{2m}\},$$

	l_2	l_3	p_{m+1}	...	p_{2m}
l_1	*false*	*true*	*false*	...	*false*
l_3	$W_{3,2}$	*true*	*false*	...	*false*
l_4	*false*	*true*	*false*	...	*false*
p_1	*false*	*false*	*true*	...	*false*
$\vdots$	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
p_m	*false*	*false*	*false*	...	*true*
p_{2m+1}	*false*	*false*	*true*	...	*false*
$\vdots$	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
p_{3m}	*false*	*false*	*false*	...	*true*

,

$$\wedge(\vee(l_1, l_3, l_4), \vee(p_1, ..., p_m, p_{2m+1}, ..., p_{3m})) >,$$

where

$W_{3,2}$ = "there is a necessity of solution of optimization problem(s) by GNNs".

Tokens $\alpha_1, ..., \alpha_m$ enter places $p_{m+1}, ..., p_{2m}$, respectively, with current characteristics corresponding to the current parameters of the real process(es).

When the truth-value of $W_{3,2}$ is *true*, token β will split to two tokens – the same token β, that will continue staying in place l_3, and a new token β^0 with a characteristic *"a list of necessary GNNs"* in place l_2.

Below, by $TIME$ we shall note the current time-moment.

$$Z_2 =< \{p_{m+1}, ..., p_{2m}\}, \{p_{2m+1}, ..., p_{4m}\},$$

$$\begin{array}{c|cccccc}
 & p_{2m+1} & \dots & p_{3m} & p_{3m+1} & \dots & p_{4m} \\
\hline
p_{m+1} & W_{m+1,2m+1} & \dots & false & W_{m+1,3m+1} & \dots & false \\
\vdots & \vdots & \dots & \vdots & \vdots & \dots & \vdots \\
p_{2m} & false & \dots & W_{2m,3m} & false & \dots & W_{2m,4m}
\end{array},$$

$$\vee(p_{m+1}, ..., p_{2m}) >,$$

where for $1 \leq i \leq m$:
$W_{m+i,2m+i} =$ "$TIME < T + t^*$",
$W_{m+i,3m+i} =$ "$TIME \geq T + t^*$",
where T is the initial time-moment and t^* stands for the duration of the GN-functioning.

Tokens $\alpha_1, ..., \alpha_m$ enter places $p_{2m+1}, ..., p_{3m}$, respectively, with current characteristics corresponding to the current parameters of the real process(es), calculated on the basis of the results of the optimization procedures through some GNNs and represented by the current β-characteristic, described below. The results of the functioning of these procedures are estimated by IF values.

Tokens $\alpha_1, ..., \alpha_m$ enter places $p_{3m+1}, ..., p_{4m}$, respectively, in the final time-moment with final characteristics describing the final parameters of the modelled process(es).

$$Z_3 =< \{l_2, n_0, n_{t+1}, ..., n_{2t}\}, \{l_4, n_0, n_1, ..., n_t\},$$

$$\begin{array}{c|ccccc}
 & l_4 & n_0 & n_1 & \dots & n_t \\
\hline
l_2 & false & true & false & \dots & false \\
n_0 & W_{0,l} & true & W_{0,1} & \dots & W_{0,t} \\
n_{t+1} & false & true & false & \dots & false \\
\vdots & \vdots & \vdots & \vdots & \dots & \vdots \\
n_{2t} & false & true & false & \dots & false
\end{array},$$

$$\vee(\wedge(l_2, n_0), \wedge(n_0, \vee(n_{t+1}, ..., n_{2t})) >,$$

where for $(i = 1, ..., t)$
$W_{0,l} =$"there is a final solution of the GNNs",
$W_{0,i} =$"there is a necessity of using of the i-th GNN".

Token β^0 enters place n_0 and unites with token ν that obtains characteristic *"list of the GNNs that must be used"*.

The number t of the GNNs is determined beforehand. Token ν splits to some (less or equal to t) tokens that enter some of the places $n_1, ..., n_q$ with respect to the GNNs that must work, and with characteristics (for $i = 1, ..., t$) *"initial data for the i-th GNN, p_i, q_i, τ_i"*, where p_i and q_i are the lower and higher boundaries of the interval of the solutions of the i-th GNN (obviously, $p_i \leq q_i$) and τ_i is the degree of correctness of the GNN.

If we would like to describe the process of GNNs (or, eventually, of the neural network working), then places $n_1, ..., n_t$ will be changed by the hierarchical operator H_6 to subnets.

For example, we can use the following list of GNNs.

Eleven Generalized Net models representing the way of functioning and optimization of different types of neural networks were constructed. The first one presents neural networks that are learned with teacher (supervised neural networks) [6, 7, 8, 9, 12, 14, 15].

In learning with teacher a result, which is known and gives self - regulated direction to the neural network has to be achieved. The weight coefficients are changed as to achieve the fixed by the teacher quantity. After its learning, the neural network is tested – only entry signals are submitted, without the signal which must be received. The concrete exit values are received at the network's exit.

Some types of NNs introducing the work of the feed forward were described by the GNs [12, 15]. In [7, 8, 9] GN-models are described that represent a neural networks learning algorithm "Backpropagation"; the GN-model from [14] presents an accelerating learning of the algorithm "Backpropagation" from [13].

The GN-models of the next type NN - self organizing map (SOM) were constructed in [5, 16]. The SOM is a subtype of artificial neural networks (unsupervised neural networks). It is trained using unsupervised learning to produce low dimensional representation of the training samples while preserving the topological properties of the input space. This makes SOM reasonable for visualizing low-dimensional views of high-dimensional data, akin to multidimensional scaling. Paper [11] contains repesentation of a GN-model of the work of the SOM. The GN-model in [5] describes the optimization of the SOM with time-limits.

The next GN-model reprezents the work of the Grossberg neural network [18]. Grossberg NN is also one of the type of unsupervized NN. This NN uses a model based on the human visual system.

The GN-model in [17] reprezents the work of the Learning Vector Quantization (LVQ).

The LVQ network uses both unsupervised and supervised learning for each classification. In LVQ network each neuron in first layer is assigned to a class, with several neurons often assigned to the same class. Each class then assigned to one neuron in the second layer.

When all processes of GNN-working have finished, token ν splits to two tokens - the same token ν and token β' that enters place l_4 with a characteristic *"final agregated IF-results of the work of the GNNs"*.

This final result can have one, some or all of the forms:

- "pessimistic form":

$$\langle \min_{1\leq i\leq t} \frac{\rho_i - 0.5\tau_i - P}{Q-P}, \max_{1\leq i\leq t} \frac{Q-\rho_i - 0.5\tau_i}{Q-P}\rangle;$$

- "optimistic form":

$$\langle \max_{1\leq i\leq t} \frac{\rho_i - 0.5\tau_i - P}{Q-P}, \min_{1\leq i\leq t} \frac{Q-\rho_i - 0.5\tau_i}{Q-P}\rangle;$$

- "average form":

$$\langle \frac{1}{t} \sum_{1\leq i\leq t} \frac{\rho_i - 0.5\tau_i - P}{Q-P}, \frac{1}{t} \sum_{1\leq i\leq t} \frac{Q-\rho_i - 0.5\tau_i}{Q-P}\rangle,$$

where

$$P = \min_{1\leq i\leq t} p_i,$$

$$Q = \max_{1 \le i \le t} q_i.$$

Obviously, the following inequalities are valid:

$$0 \le \min_{1 \le i \le t} \frac{\rho_i - 0.5\tau_i - P}{Q - P} + \max_{1 \le i \le t} \frac{Q - \rho_i - 0.5\tau_i}{Q - P} \le 1,$$

$$0 \le \max_{1 \le i \le t} \frac{\rho_i - 0.5\tau_i - P}{Q - P} + \min_{1 \le i \le t} \frac{Q - \rho_i - 0.5\tau_i}{Q - P} \le 1,$$

$$0 \le \frac{1}{t} \sum_{1 \le i \le t} \frac{\rho_i - 0.5\tau_i - P}{Q - P} + \frac{1}{t} \sum_{1 \le i \le t} \frac{Q - \rho_i - 0.5\tau_i}{Q - P} \le 1.$$

Hence the above estimations have IF-forms.

$$Z_4 =< \{n_1, ..., n_t\}, \{n_{t+1}, ..., n_{2t}\},$$

$$\begin{array}{c|ccc} & n_{t+1} & \dots & n_{2t} \\ \hline n_1 & W_{1,t+1} & \dots & false \\ \vdots & \vdots & \dots & \vdots \\ n_t & false & \dots & W_{t,2t} \end{array},$$

$$\vee(n_1, ..., n_t) >.$$

The tokens from place n_i enters place n_{t+i} with characteristic *"ρ_i – the result of work of the i-th GNN",* $(i = 1, ..., t)$, where $p_i \le \rho_i \le q_i$.

3 Conclusion

In [1, 4, 10] the authors have discussed the idea that in the framework of a given GN solutions can be obtained on the basis of different suitable chosen data bases, expert systems and optimization procedures, and the GN-results can influence the tokens transfer, tokens characteristics and/or the truth values of the transition condition predicates. In future, a GN, combining the four discussed types of subnets of a given GN, will be constructed.

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