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Local weather prediction system for a heating plant using cognitive approaches

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ABSTRACT

Present-day requirements emphasize the need of saving energy. It relates mainly to industrial companies, where the minimization of energy consumption is one of their most important tasks they face. In our paper, we deal with the design of the so-called weather prediction system (WPS) for the needs of a heating plant. The primary task of such a WPS is timely predicting expected heat consumption to prepare the technology characterized by long delays in advance. Heat prediction depends primarily on weather so the crucial part of WPS is the weather, especially temperature, prediction. However, a prediction system needs a variety of further data, too. Therefore, WPS must be regarded as a complex system, including data collection, its processing, own prediction and eventual decision support. This paper gives the overview about existing data processing systems and prediction methods and then it describes a concrete design of a WPS with distributed data measuring points (stations), which are processed using a structure of neural networks based on multilayer perceptrons (MLP) with a combination of fuzzy logic. Based on real experiments we show that also such simple means as MLPs are able to solve complex problems. The paper contains a basic methodology for designing similar WPS, too.

1. Introduction

The pressure to companies with large energetic consumption as e.g. power and heating plants caused by steadily growing prices as well as environmental needs forces them to provide their services with minimal surplus of expended energy as really necessary. Such an approach requires a very accurate estimation of needed energy for safe securing their operation in advance. In other words, they need accurate prediction for planning not only energy supply but all other activities connected with this one as its purchase and preparing technology as well. More concretely, in the case of heat producers accurate weather and energy consumption prediction plays a key role in the production economy.

However, a *weather prediction system* (WPS) does not represent only weather prediction in this case but it is a group of tasks including data collection from various sources, their management, evaluation, own prediction and its interpretation as well as use for needs of planning and setting up technologies being used in the production process. All these parts create a process chain and are mutually influenced. Therefore, they cannot be considered separately. Besides these common features further tasks and means depend on specific needs of a given plant as its size, in our case used production and heat transportation technology where further influences play a certain role as geographic and climatic properties of the given area, of course population size but also such apparent details like life style of the population and structure of industry. We can see these aspects are in some way interconnected by weather situation but the heat production does not depend only on weather [1]. A more sophisticated WPS should also provide at least some direct proposals and advices for heat production and distribution prediction, which are the final required parts of information for the plant management.

In other words, the mentioned concept of a WPS points, in a more or less measure, at the need of mutual interconnection of the four aspects, namely computers, cognition, communication and control to fulfil given tasks of such a system.

With the aim to describe the sketched properties and design process of such a WPS the paper is organized as follows. Section 2 deals with the structure and its parts, which form a WPS from the functional point of view in general. Concurrently, it deals with a brief overview of methods used in weather prediction. This section is a state-of-art digest in this application area. In Section 3 a concrete WPS design for needs of a heating plant is discussed. Especially, its parts for data collection and heat power prediction are described in detail. Section 4 deals with experiments and their

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evaluation, which were done with real data. Finally, Section 5 summarizes main contributions and offers possibilities of further development.

2. WPS structure and weather forecast methods

A WPS can be divided at least into two functional parts – *Data Collection and Management* (DCM) system and *Own Prediction* (OP) system, see Fig. 1. The manner how data are collected influences methods used in the OP part, which is crucial for the quality of results, relating not only to their precision but also to versatility of their use. Therefore, requirements put on such a system are backpropagated from desired outputs through methods being able to acquire them and finally to the structure of the DCM system. There are several basic types of DCM and OP systems, which will be briefly mentioned and as a result of their comparisons we will draft a WPS proposed for a centralized heating plant in the city Košice located in the eastern part of Slovakia.

2.1. WPS structure

A DCM system consists of two, eventually up to four parts. The first part, *data collector*, is responsible for collecting data, which will be processed in the OP system. There can be diverse sources, formats as well as types of data. Principally, they can be obtained either from a centralized source like a weather forecast agency or a network of own measurement points (stations) distributed in a given area. Mainly in the latter case various tasks are performed from data transmission, through their pre-processing (e.g. normalization, correctness checks), transforming to a required data format up to including them to a database [2–5]. *Data evaluator* as the second part of DCM contains such operations as statistical evaluations, modelling uncertainties (e.g. probability, fuzzy) and data mining [6–9]. Its role is to prepare all data in a required form for the OP system. The third part, *results presentation*, is responsible for transforming all data, including also results from OP, to a suitable form for the user that can be the plant management or another information system. Here, we can mention works dealing with correct presentation of results about weather forecast for various humans [10]. *Decision supporter* is the last part of the DCM system, which relates to decision support tasks in the form of planning [11–14], warning [4,15,16] or some other advisory and control functions [17–19], which are final outputs of WPS. The last two parts of DCM are not mandatory and in simpler applications they can be merged with the data evaluator (marked in Fig. 1 as dashed blocks).

Weather forecast (prediction), as a core of the OP system, is a set of several variables such as temperature, humidity, precipitation, wind speed and power, cloudiness, eventually further special ones, which depend on the purpose we need for. Although these variables are of different physical nature they are mutually dependent. Often this fact enables us to utilize one method originally developed only for one variable but after necessary modifications also for others.

Basically, weather can be forecasted in two ways, either using the physical or mathematical one [20,21]. (In the latter case the notion prediction is more used.) In general, it can be stated that physical modelling, which is based on hydrodynamic atmospheric models, especially air mass movement modelling, using meteorological approaches, is advantageous for long-term predictions on a larger area (global scale forecasting). Mathematical modelling based on statistical evaluation of time series and their prediction is convenient mainly for short-term predictions on a local area (local scale predicting) [22]. Of course, it is not easy to unambiguously determine, which of these two cases should be used because many exceptions exist and we know mesoscale forecasting, too. Therefore, in many systems combinations of both approaches are designed [20,23,24].

Usually, weather agencies use physical air mass movement modelling with the *finite element method* to forecast weather for large areas like for a particular country or for the whole globe. The local time series prediction is usually focused to a single place on the map. Thus the accuracy evaluation for these two approaches is different, too. In the local time series prediction method the error is counted like in financial markets – the difference between predicted and real value over given time period. The physical air mass movement modelling does count the area on map, where the error is bigger than a given threshold, e.g. more than two degrees. In the first case the error can be measured in degrees of temperature, while in the second one it is in square kilometres.

2.2. Weather prediction methods

As for our purposes the local scale predicting is especially important we will deal mainly with methods used for mathematical approach. Originally, for weather prediction the conventional statistical methods based on building linear models were applied [25]. Their basic task is analysis of time series of measured variables. However, meteorological data lack for accuracy and often completeness, too. Data are affected by various kinds of uncertainty and perturbations. To solve this problem more sophisticated methods based on stochastic models were proposed

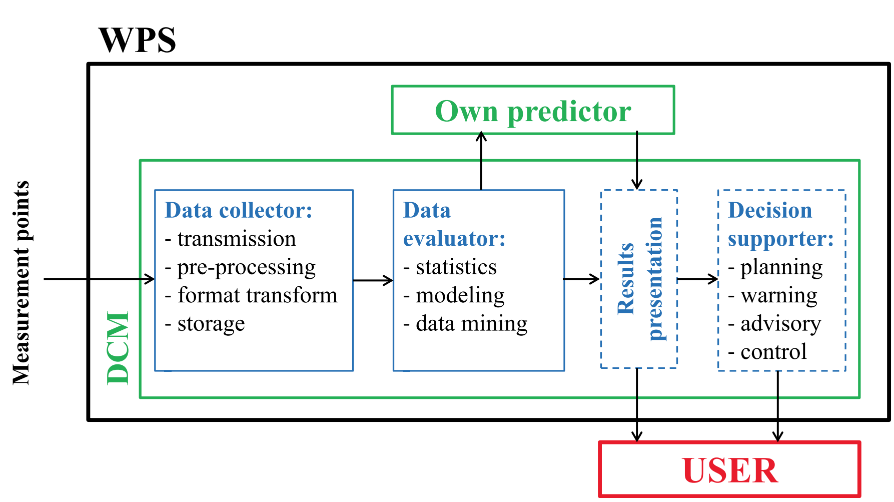

Fig. 1. Structure of a weather prediction system.

[26]. Besides, further means like *Kalman filter* [27] or *wavelet transform* [28] are added to these models to enhance their precision. There is still one other mathematical approach also related to the physical one, the so-called *ensemble forecasting*. In this case not only one deterministic forecast is calculated but a set (ensemble) of forecasts is modelled under slightly different initial conditions in parallel. So we obtain several alternatives with probabilities of their occurrence, which can be offered as they are or merged into one averaged forecast. In such a manner various uncertainties and possible perturbations are covered [29,30].

However, models based on 'conventional' statistical approaches need to be parameterized, which is not a simple task. At this point cognitive means, which mostly belong to the field of artificial intelligence, offer possibilities of automatic adjusting these parameters. Especially, *artificial neural networks* (NN) are advantageous for analyzing time series and we can find them in many papers dealing with prediction in general. Concerning weather prediction there have been proposed several prediction systems using various types of NNs, from simple *multilayer perceptrons* (MLP) [31,32], through more complicated types like *recurrent* NNs [33,34] up to hybrid combinations with other means of artificial intelligence as fuzzy logic for possibility of processing uncertain information, especially the well known architecture ANFIS [22], or evolutionary algorithms [35] for adjusting the parameters of NNs, e.g. NN with *particle swarm optimization* (PSO) [36] or NN with *migration algorithm* [37].

Further means from the area of cognition, as an element of machine learning, is the so-called *support vector machine* (SVM), whose role is to adjust parameters of the prediction model. As in the case of NNs also SVMs need a set of training data, which are used for regression analysis done by a selected SVM, whose outputs are the mentioned parameters [38]. Similarly, also SVMs can be combined with other means as e.g. PSO [39,40].

Finally, for the sake of completeness the hybridization of cognitive and conventional statistical methods should be mentioned, too. Either these approaches cooperate solving each one its own tasks or one approach helps in adjusting parameters of the other one. We can find mostly combinations of NNs with such means as Kalman filters, wavelets or *Markov chains* [41–43].

3. WPS implementation for the heating plant

Based on knowledge contained in the overview in Section 2 as well as experience with a weather prediction system for a heating plant for a city numbering the population of about 250,000 inhabitants we proposed basic modules of a WPS tailored for specific needs of this plant as well as several auxiliary modules (further modules are just in the stage of their implementation and testing). Based on notions explained in Section 2 we can define it as a local prediction system performing mainly temperature predictions, which utilizes measured data collected from own distributed measurement points (MP), further public data and forecasts from agencies. Besides, some specific technological data of the company are contained in the system, too. Therefore, it can be divided into two functional blocks: MP(s) and prediction system, which will be described in the following parts.

3.1. Design of a measurement point

There were two reasons why we choose the design of a distributed WPS utilizing also own measurements. Firstly, local prediction is more precise because global prediction is based on a larger region so it cannot consider local singularities. The geography of the city Košice is relatively complicated (some parts are in a basin open to south and some other parts are on hills, which belong to Carpathian mountains) and the consequences are sometimes in the form of significant temperature differences. Therefore, there is a necessity to consider needs for heat production of these city districts individually and not globally. In addition, a distributed WPS does not exclude a possibility to use also global weather forecast, where local prediction can help refining and extending agency weather forecast. Secondly, local prediction is very flexible so it can take into consideration also technology data and specific properties. Each plant has some special characteristics, which do not let to be included in a general concept so easily. Hence a kind of 'tailoring' for its needs is necessary. It relates to specific knowledge, experience and company customs, too.

The designed WPS enables to collect data from a network of MPs dispersed in the city area. At present, there are two MPs located in different parts of the city. MP consists of a weather station (in our case Vantage Pro2 [44]) and a control server. The weather station is capable to measure main weather parameters as air temperature, humidity, wind direction, air pressure, wind speed, rainfall and others. We can control it remotely by a private server, which is located usually up to several tens of meters from the weather station (e.g. in the closest building). This design enables doing contracts between the heating plant and private providers, owners of MPs, without any necessity to own all these stations. The private server is connected with a public server, which is located directly in the plant control centre, either by a WiFi or by a conventional wired connection. The public server is connected to Internet to receive measured data from MPs and forecasts from agencies as well as to offer the predicted information, see Fig. 2. There is also a possibility to locate the public server together with the MP but after creating a network of these points the first structure is preferred. From safety and data protection reasons the system is operated on Linux.

If we compare our design with Fig. 1 the private server works as a data collector besides the storage task, which is provided by a data management system, see Fig. 5. Of course, the private server controls and checks the function of the weather station, too. Further, the weather station can be observed by a supervisory camera giving visual information about the state of the station and hereby it minimizes the need to check it directly on the place. The public server communicates with the database and performs tasks of other three parts of WPS.

The presentation of WPS results can be summarized for the whole city or it can be addressed for each MP individually in the form of a web page, which is updated every 15 min. Fig. 3 shows the output web page for one MP (publicly available, see [45]), which contains identification name of a given MP, current weather situation (for comparison needs), current picture of the weather station (for transient checking) and scrollable graphs with predictions and input data. A more detailed information about the MP hardware and software construction can be found in [46].

3.2. Daily temperature profile and heat production prediction

One of our aims was to verify ability of NNs to solve complex prediction problems, where meteorological data are connected with a given technology as e.g. temperatures of heating boilers, temperature of returning water, etc. Although numbers of complex NNs types and auxiliary means as SVM, PSO, etc. exist (already mentioned in Section 2.2) they bring also new problems. The first of them is the necessity to adjust further parameters of these more sophisticated designs. It relates to both NNs and auxiliary means. In general, these parameters are more abstract than parameters of a simple MLP and the preparation of such systems can be more time consuming than adjusting the topology and learning parameter for backpropagation training.

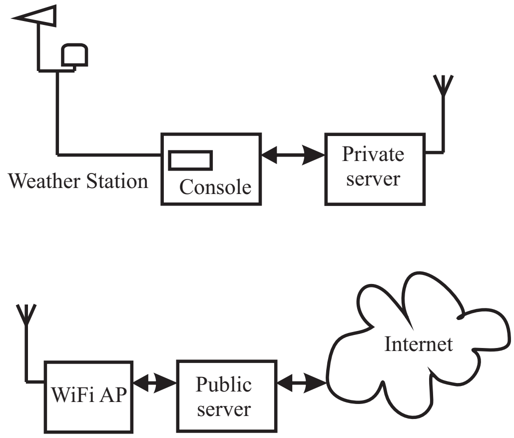

Fig. 2. Structure of a measurement point and its connection to the heating plant control centre.

The basic backpropagation procedure is simple. It was developed in the seventies and eighties by Werbos and Rumelhart (see a summary in [47]). It is a recursive gradient method for setting up weights for a neural network to minimize the training error J defined by:

$$J^p = \frac{1}{2}\sum_{i=1}^{N_0}(ev_i^p - x_i^p)^2, \tag{1}$$

where N_0 is the number of outputs, ev_i is the expected value of the ith output, and p is the pattern index from the training set. For every neuron we have:

$$x_i = f_i(\mathrm{in}_i) = f_i\left(\sum_{j=1}^{M} w_{ij}x_j + \theta_i\right), \tag{2}$$

where in_i is the input to ith neuron, f_i is its activation function, M is the number of its incoming connections, w_{ij} is the weight of connection from j to i and θ_i is the neuron bias. The *gradient-based minimization rule* for computation of weight changes is:

$$\Delta w_{ij} = -\gamma\frac{\partial J}{\partial w_{ij}} = -\gamma\frac{\partial J}{\partial \mathrm{in}_i}\frac{\partial \mathrm{in}_i}{\partial w_{ij}} = \gamma\delta_i x_j, \tag{3}$$

where γ is the so-called *learning rate* parameter and δ_i is a substitution variable called as *error signal*. To compute δ_i of the output units we get:

$$\delta_i = -\frac{\partial J}{\partial \mathrm{in}_i} = -\frac{\partial J}{\partial x_i}\frac{\partial x_i}{\mathrm{in}_i} = -\frac{\partial J}{\partial x_i}f'(\mathrm{in}_i) = (ev_i - x_i)f'(\mathrm{in}_i). \tag{4}$$

For the rest of neurons (not output ones) we must apply a chain rule for distributing the error signal recursively through the whole

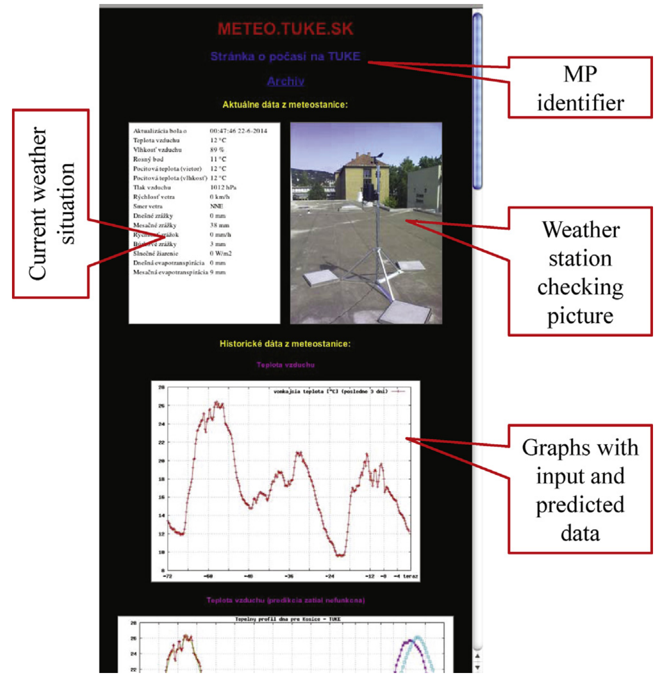

Fig. 3. Screenshot of the output www page describing a MP together with current weather situation and predicted variables.

network:

$$\begin{aligned}\delta_i &= -f'(\mathrm{in}_i)\sum_{h=1}^{N_h}\frac{\partial J}{\partial \mathrm{in}_h}\frac{\partial \mathrm{in}_h}{\partial x_i} = -f'(\mathrm{in}_i)\sum_{h=1}^{N_h}\frac{\partial J}{\partial \mathrm{in}_h}\frac{\partial}{\partial x_i}\sum_{l=1}^{N_l}w_{hl}x_l \\ &= -f'(\mathrm{in}_i)\sum_{h=1}^{N_h}\frac{\partial J}{\partial \mathrm{in}_h}w_{hi} = f'(\mathrm{in}_i)\sum_{h=1}^{N_h}\delta_h w_{hi},\end{aligned} \tag{5}$$

where N_h is the number of neurons with connections from the ith neuron and N_l is the number of neurons, which have connections to all N_h neurons (Fig. 4).

The rule (5) is the main recursive rule of the backpropagation learning describing the recursive backward propagation of the error signal from network outputs to inputs. Then we compute changes of weights from the error signal using the rule (3) and subsequently we change the weights.

Finally, the full algorithm is as follows:

1. Initialize random weights.
2. Enter inputs and compute outputs of the network.
3. Recursively compute δ_i.
4. Compute changes of weights Δw_{ij}.
5. Apply Δw_{ij}

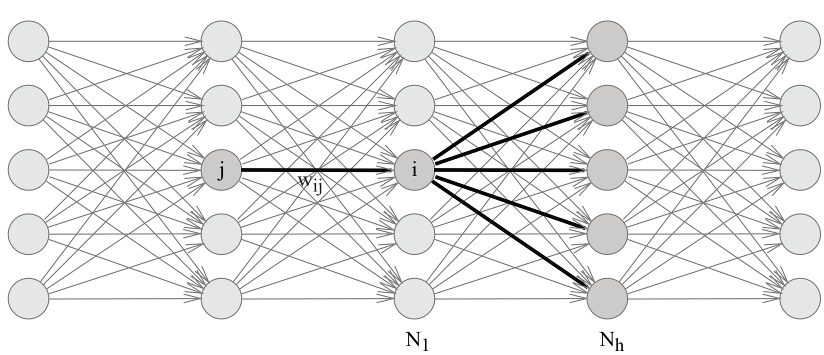

Fig. 4. Neural network structure with backpropagation learning.

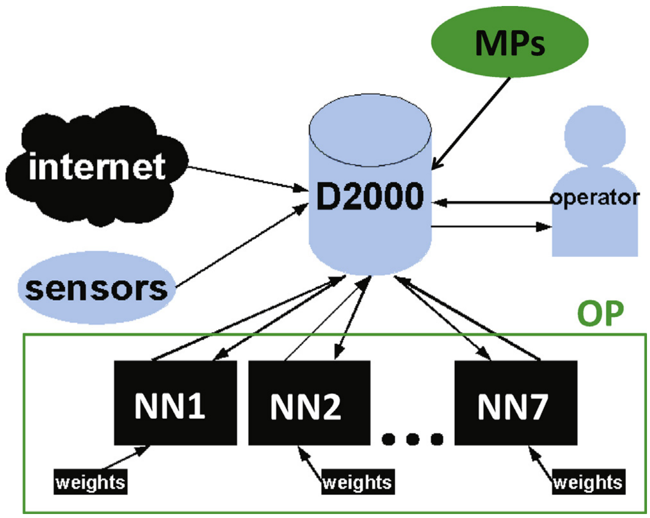

Fig. 5. Implementation of proposed WPS in the heating plant information infrastructure using the data management system IPESOFT D2000.

6. Repeat the process in points 1–5 until the error is not minimized.

There exist a lot of modifications of this basic backpropagation algorithm but for our prediction system this basic version was satisfactory.

Although it is necessary to design more or less intuitively (depending on designer's skills) several variants of MLPs and subsequently to do some experiments but it is not so much arduous as obviously supposed in the literature. Another problem is connected with the need to implement some particular properties of the plant technology in the prediction system. Thanks to the MLPs simplicity they enable building and analyzing a network of them quite easily, see Fig. 5. The problem can be in such a manner decomposed and each part solved partially whereas complex designs try to solve the whole problem in an all-in-one way. Therefore, we relied on skills and communication with the user, concretely with the control centre staff.

The database is an indispensable part of the prediction system because it stores all necessary data for prediction. As there are necessary further operations as handling and updating data, a data management system is needed. In our case it is the system IPESOFT D2000 [48]. It collects data from MPs, Internet and technology sensors as well as it stores outputs from the OP system. Of course, it also communicates with operators in the control centre and enables their access to WPS, see Fig. 5.

The OP system consists of seven MLPs, which are mutually chained, see Fig. 6. These MLPs are standard feedforward NNs with one hidden layer. They are trained by a momentum back-propagation algorithm using time windows. Five NNs predict temperature for various time intervals – 1 day, 1 week, 1 year – and two other NNs predict the amount of heat needed to be produced, which is computed by two variables, i.e. *steam power* and *total steam power*, which includes also production of hot water. The basic prediction step is for 15 min, i.e. all MPs, technology sensors as well as downloading operations of forecasts from agencies are performed in this interval.

Now we characterize tasks of individual NNs *NN1*–*NN7* (Fig. 6). *NN1* (Fig. 7) is doing basic temperature prediction for next 24 h, the so-called *daily temperature profile* (DTP) containing 96 values (24 h × 15 min intervals). It uses data of last 3 days from MPs and technology data. This prediction is important for immediate adjusting the technology to produce just required amount of heat

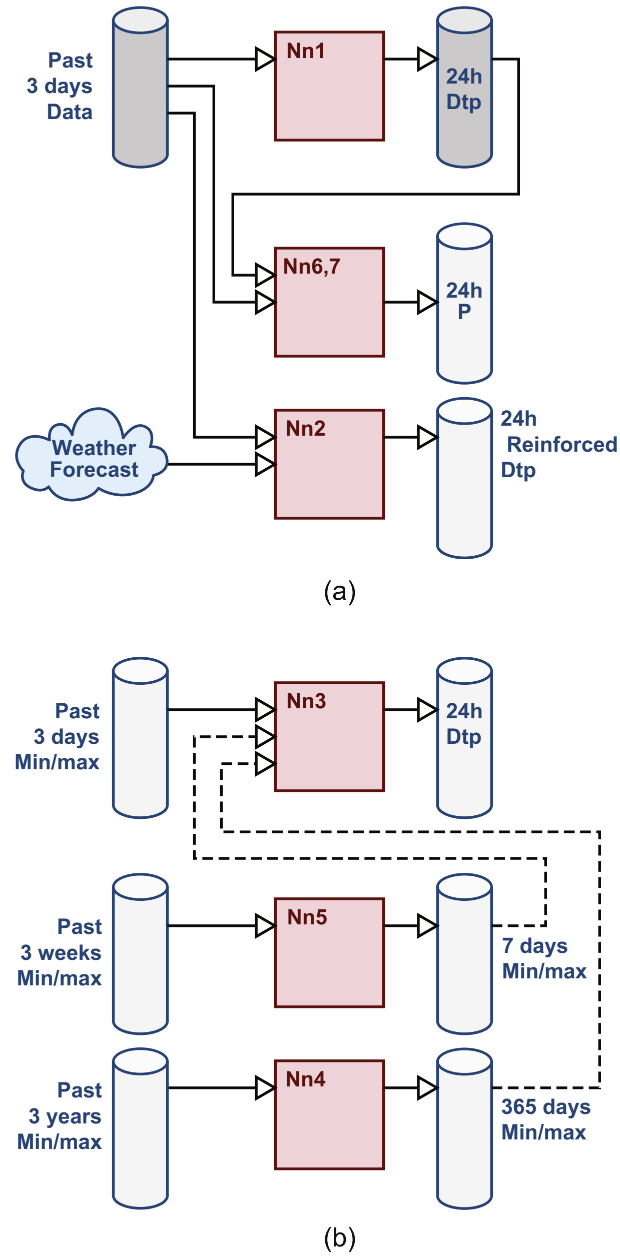

Fig. 6. A NNs structure of the OP system for temperature and heat prediction. The structure consists of two parts: (a) main predictions; (b) auxiliary predictions. Dashed connections are for optional extending 1-week and 1-year predictions to DTPs.

(neither less nor more). Other predictions are more auxiliary and serve as certain verification of DTP correctness.

NN2 utilizes the same data as *NN1* extended by data from weather forecast agencies. Nowadays data from three different agencies are collected, which are averaged. *NN2* should reinforce the forecasts from agencies and in future it should replace *NN1*.

NN3 plays a specific role. It is doing a simplified DTP prediction only from minimum and maximum temperatures of last 3 days. It takes into consideration also the day order (1–365) so the number of inputs has 9 values (3 day values × 3 days). Of course, the results are not so much precise than for *NN1* and *NN2*. It is used only as an interpolation mean for next two NNs.

NN4 is designed for a 1-year prediction of minimum and maximum temperatures (365 days × 2 temperatures, i.e. 730 values), which is based on weekly minimum and maximum temperatures of last 3 years. This prediction is from meteorological

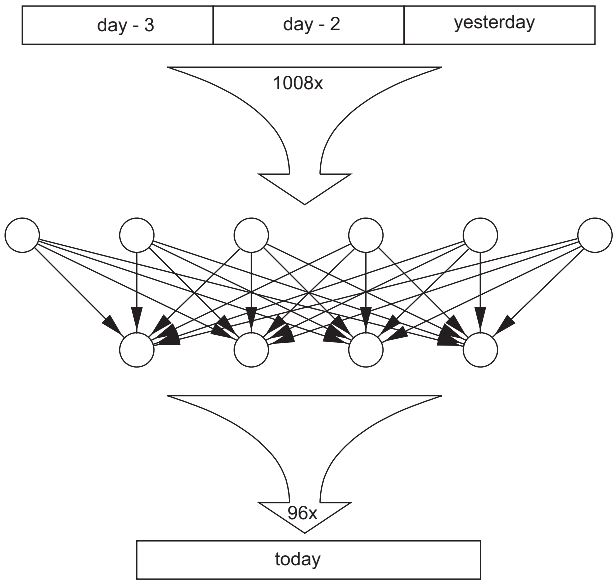

Fig. 7. Neural network predictor *NN1* works in the sliding window mode – last 3 days (3×24 h) are continuously fed into network and prediction for next 24 h is produced every 15 min. Neural network topology is $1008 \times 48 \times 96$, which means two layers of neurons: hidden layer with 48 neurons and output layer with 96 neurons. The 1008 inputs are just pointers to buffer with input data.

viewpoint a nonsense but from statistical point of view we can more or less rely on weather character of the previous period and deduce future weather to some extent. *NN4* can be combined by *NN3* and we will get DTPs for next year (refined 1-year prediction). The main function of such a long prediction is for planning purposes as doing contracts with coal and gas suppliers or maintenance.

NN5 is a compromise between *NN4* and *NN1* or *NN2*. It generates a 7-day prediction of minimum and maximum temperatures based on the same data types as *NN3* but from last 3 weeks (21 days $\times$ 3 day values as in *NN3* gives us 63 inputs and 14 outputs). It can be also combined with *NN3*.

Finally, the last two NNs predict the amount of heat for next 24 h in 15 min steps (96 outputs), i.e. *NN6* and *NN7* calculate total steam power and steam power variables, respectively. They utilize outputs from *NN1*, data from MPs and technology data. Based on Fig. 6, Table 1 summarizes basic parameters of designed NNs, which are MLPs with three layers (the first and third layer are the NN input and output, respectively). A more detailed information about the designed prediction system is in [49].

4. Experiments and their evaluation

The design of the OP system described in Section 3.2 was based on consultations with experienced operators of the heating plant. They recommended us variables, which should influence prediction results. After experiments with several proposals of various NNs topologies the best one was chosen.

For training and testing there were available 10-years data for most NNs. For training 4-years data and for testing remaining 6-years data were used. But we tried also other configurations and we do recommend to use 10 or more years of data for training. The mix of data sources we used for the heating plant system was defined by their operating environment and was composed from several sources inside and outside of the plant. But generally, for temperature prediction, meteorological data from the common meteorological station should be enough. We made available data from our station on the project page http://www.ai-cit.sk/WPS-HP [45].

We used linear and nonlinear time windows, where pattern sampling is dense for close past and then it is enlarged (1-h sampling for yesterday, 3-h sampling for the day before yesterday and 6-h sampling for the day before it). Motivation for this type of sampling is that experiments showed that most influencing data for tomorrow 24-h prediction are data from last 3–4 h of past. Further, after training we found the weights on links from temperature inputs were relatively high comparing to other inputs (which were also non-zero). Thus we think the temperature from past is more important for temperature prediction than humidity, wind or other weather variables.

We tried configurations with 2-days, 4-days, etc. long time windows on the input. We chose the 3-days long windows as the maximal length, which contributes any improvement to accuracy of the predictor with our size of training data (10 years). We had no problem with the number of inputs (1000 or 5000 inputs) as with our configuration of network (see Table 1). The learning times were sufficiently short so we had no motivation for further selecting inputs for the predictor. The backpropagation algorithm does it conveniently for us.

For each NN an evaluation was performed on data from 1 year and using a percentage modification of the *mean squared error* formula (MSE) the errors for training as well as testing data were computed, see Table 2. *NN1* confirmed our expectations of the best predictor. However, after designing a fuzzy controller for weighting forecasts from agencies we expect *NN2* will move to the first position. Besides, although expected results of other NNs are a little worse but not so much. We can use them as auxiliary predictors if *NN1* could not be used from any reason or for instance planning.

In Fig. 8 there are shown two comparative examples of real and predicted values and evaluations of all NNs are shown in Table 2. We consider these results as of good quality from two reasons. Firstly, we have only local data as an input of the predictor. As we have no information about coming storms, each sudden storm will make several degrees of error for a given day. Secondly, experts in the heating company considered these predictors as sufficient for their intended usage. However, these results are not the best possible ones and we proposed further improvement

Table 1
Summary of basic parameters of designed NNs *NN1*–*NN7*. Topology represents the number of neurons in the input–hidden–output layer. TD is for technology data and min/max for minimum and maximum temperature.

	Topology	Inputs	Outputs
NN1	1008–48–96	3 days (MP + TD)	Basic DTP
NN2	5616–192–96	3 days (MP + TD) + agencies	Reinforced DTP
NN3	9–200–96	3 days min/max	Simplified DTP
NN4	312–110–730	3 years min/max	1 year min/max
NN5	63–25–14	3 weeks min/max	1 week min/max
NN6	1104–48–96	3 days (MP + TD) + 1 day DTP	Total steam power
NN7	1032–48–96	3 days (MP + TD) + 1 day DTP	Steam power

Table 2
Percentage errors of *NN1*–*NN7* during 1 year computed on training and testing data after performing a given number of training cycles. Because of testing data lack *NN2* the testing was not performed. The 100 from 1458 training patterns means 100 randomly selected patterns from 4 years (4×365 days).

	Training data error [%]	Testing data error [%]	Number of cycles	Training patterns	Learning rate γ
NN1	4.1	11.4	600	100 from 1458	0.1
NN2	4.1	–	500	100 from 105	0.3
NN3	7.7	10.3	400	100 from 1458	0.1
NN4	10.2	13.1	300	3 from 10	0.1
NN5	12.8	12.9	300	4717	0.01
NN6	17.7	48.4	300	100 from 1458	0.2
NN7	10.5	24.1	300	100 from 1458	0.2

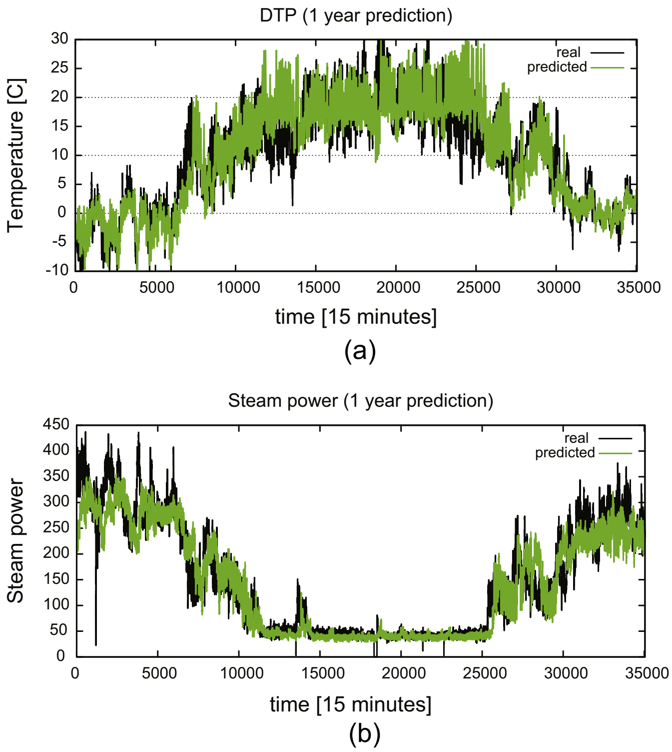

Fig. 8. Comparisons of real and predicted values during 1 year (about 35,000 patterns with 15 min sampling): (a) *NN1*; (b) *NN7*.

(network *NN2*) combining a statistical (based on neural networks) predictor with meteorological agency forecasts.

5. Conclusions

This paper describes the methodology and basic know-how for constructing a compact WPS for industrial needs. Our WPS design offers possibilities of its use not only for the heating plant company but thanks to its flexibility and openness it can be used also for other institutions and companies, e.g. for weather research, transportation and alert systems [50,51], etc. Of course, using web pages of individual MPs also the public can be informed about current local weather conditions.

From the viewpoint of the prediction method used we showed also a relatively complex problem can be solved with high quality and technological acceptance by simple MLPs with time windows if they are arranged in a proper NNs structure without a need to use complicated solutions. Even the heating plant management prefers the designed prediction based on NNs rather than standardized temperature modelling offered by agencies. However, it is necessary to state in consequence of climatic changes, which have been remarkable also in the city since last 15–20 years, physical weather modelling cannot be neglected but this system allows connecting both approaches, i.e. statistical and physical. Our own statistical approach serves as a refinement of forecasts based on physical modelling generated by weather forecast agencies.

The research in improving the prediction quality continues and as next steps we see including further weather variables, especially wind speed and cloudiness. Some initial experiments show promising improvement. Similarly, we try to apply further types of NNs, concretely recurrent NNs [52].

In our WPS fuzzy systems have a special position as auxiliary means for data handling and improving for further use by NNs. We have detected three significant tasks, which should be solved by means of uncertainty processing, namely: merging data from MPs to calculate averaged temperatures, merging forecasts from agencies to obtain an average global forecast and continuous connecting DTPs.

Especially the first two tasks are connected with experience and implicit knowledge of operators, which cannot be precisely expressed but rather by uncertain notions like small, big, slow, etc. in production rules, which are the most common human knowledge representation [53,54].

The first mentioned problem relates a fact that MPs have different ranges covering different areas concerning their requirements on heat (population, institutions, offices, etc.). For needs of merging data from MPs it is necessary to assign to individual MPs weights of importance, which are calculated using a fuzzy controller.

The second problem is of similar nature as the first one. For needs of NN2 (see Fig. 6) the information of global weather forecast is necessary, too. The forecasts are collected from three agencies. Their qualities differ to some extent and are not constant. For instance, during rains one agency produces better forecasts than another time. Now a design of a knowledge base is in preparation, which will reflect various relations between forecast qualities of these agencies with the ability of suspicious data detection [55].

The last mentioned problem corresponds to removing discontinuities, in other words filtering. As during prediction the time windows are used and they do not move continuously but frame by frame an effect of discontinuity happens. Its solving is a typical interpolation problem but instead of applying an artificial polynomial function we try to use real values from both DTPs. Also this problem is researched intensively now and first experiments show promising results.

However, the potential of fuzzy systems is considerably broader. They can be used for transforming the prediction results in a more comprehensive form for human perception [10,56], maybe later their personalization for a concrete user. Now we are experimenting with some adaptation approaches of knowledge bases for fuzzy systems [57,58].

As seen, the proposed WPS represents a case in point how the four aspects, i.e. computers, cognition, communication and control are mutually merged into one integral entity, where they create a networked prediction system for decision support (if not directly a control system) with use of some cognitive approaches in form of NNs and fuzzy systems being able to process the whole computation by means very close to human reasoning.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compind.2015.05.002.

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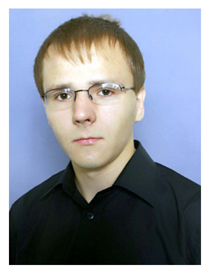

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