Optimal Operation of the Peat Drying Process in Steam Tube Dryers

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Abstract

Ukraine is an energy-dependent country and directing its efforts into economical use of its own energy resources. One relevant available energy source is peat briquette. During its production it is necessary not only to improve the quality of briquettes, but also to reduce the total expenses of energy required for their production, particularly in the drying process. For this, a mathematical model of peat drying is developed using the GMDH (Group Method of Data Handle). Next, with measured disturbances, optimal input variables for the drying process are found using mathematical optimization and ANN (artificial neural network). To avoid fast changing of the operational conditions while avoiding over drying or under drying of the peat, the operational conditions are classified into a number of classes. Finally, an iterative procedure for changing the input parameters from the past values to new values is introduced to ensure improved quality and energy efficiency.
Keywords: Group Method of Data Handling, peat drying, energy efficient process, regimes map, steam tube dryer

1 Introduction

A high increase in the price for Russian gas and further reducing of its consumption in the Ukrainian energy sector requires Ukraine to find other energy resources. One of the solutions is to use peat briquettes instead of gas because the price of 1 GJ net energy produced from peat briquette is less than half the price of that of gas.

Some of the advantages of using peat briquettes over other fuels in Ukraine are (Hnyeushev, 2008):

1. high calorific value, 16-18 MJ/kg,
2. environmentally safe fuel during combustion,
3. considerable reserves of peat in Ukraine,
4. after peat extraction, the bogs can be re-cultivated and transferred to the domestic uses.

One of the most important processes of peat briquettes production that determines its quality and is the most energy-intensive on the peat plant, is the process of drying peat. There is a lack of information and mathematical description associated with drying peat in steam tube dryers. Precise description of factors such as adjustment of fuel and air ratio during combustion and many significant perturbations that affect the process, are not readily available. This will lead to the production of poor quality peat, increases the cost of drying the peat and may give rise to emergency situations during the peat production.

For the development of methods for improving the operation of the drying process in the steam tube dryers, several investigations as described in (Korol' and Lishtvan, 2008) have been performed. Mathematical description, simulation and optimization of the production of peat briquettes and the drying process can be found in (Bohatov, 1976; Naumovich, 1984; Gatih and Genshaft, 1980). Research into the modelling and control of a rotary dryer have been carried out by (Yliniemi, 1999; Forsman and Slätteke, 2002; Slätteke and Åström, 2005).

A mathematical model of a physical system can be used for identification of the system, forecasting, and for optimization and control. For complex systems, various methods can be used for system identification and they have been studied actively in recent years. Among them the identification method known as Group Method of Data Handling (GMDH) — developed by A.I. Ivakhnenko, is well known (Ivakhnenko, 1970). The conceptual basis for the structure of the GMDH is based on heuristic self-organization, and the resulting polynomial equation obtained from its identification procedures is dependent on the Kolmogorov-Gabor polynomial. The development of the algorithm of GMDH that provide robust linear and nonlinear polynomial regression models can be found in (Aksyonova and Tetko, 2003). An inductive method that permits the choice of a model with least error and least bias and self-organizing data mining has been studied by (Ivakhnenko and Rogov, 2005).

In Section 2, the peat drying process, its basic conditions and disadvantages in the Ukrainian briquette plants

is described. Basic physical and mechanical properties of peat, the operational conditions of the drying process that affect the quality of dry peat, and the indicators for energy consumption are described. The feasibility of using the Group Method of Data Handling for creating a mathematical model of drying peat and the use of neural networks for determining the optimal input variables of the peat drying is shown with a brief description of the basic of GMDH.
In section 3, the development of a mathematical model of the peat drying process by using the experimental data obtained from the industrial plant is discussed. The implementation of the model and the selection of structure and parameters of the neural network that allows to find the best energy saving parameters of the drying process is described. This forms the main feature of classifying and recognizing the industrial situations that is described in section 4.
In section 5 the procedure of finding the optimal operational value for varying measurements is discussed. In section 6 and 7 discussions and conclusions of the approaches used for optimal operation of the drying process are given, respectively.

2 System description

Optimum drying regimes provide the most effective operations of dryers that satisfy modern requirements: quality of produced products, the minimum cost price (thermal and electrical energy consumption) and fire safety. The process of peat drying should be carried out with the aim of reducing costs for heat and electricity. The cost of electricity consist of the cost for electricity consumption by the electric drive of drum dryers, the electric drive of blowers (which determines the amount of air that passes through the dryer), and the electric drive of bootable units of dryer (auger and boot sleeves). Thermal energy is consumed as a heat carrier (saturated vapor) to heat the peat inside the dryer. As for the quality of peat, characteristics such as bulk density of peat and its temperature should be considered.
The main purpose of drying the peat is to produce dried peat with necessary moisture regardless of the fluctuations in the moisture content of the peat that enters into the dryer. According to various investigations the quality of peat depends on the duration and conditions of drying, temperature, primary moisture variation, average moisture content and the maximum particle size of the peat (Kulakovskyi and Rosen, 2013a).
A functional block diagram describing the process of drying the peat in the steam tube dryer is shown in Figure 1.

Variables Y_1, $Y_2, \ldots, Y_8$ are the outputs of the system which should be optimized and controlled. The input variables that are manipulated to obtain the desired outputs are denoted by $X_1, X_2, \ldots, X_4$. The disturbances that act on the system are represented by F_1, $F_2, \ldots, F_8$. The description of the inputs, outputs and the disturbances are presented

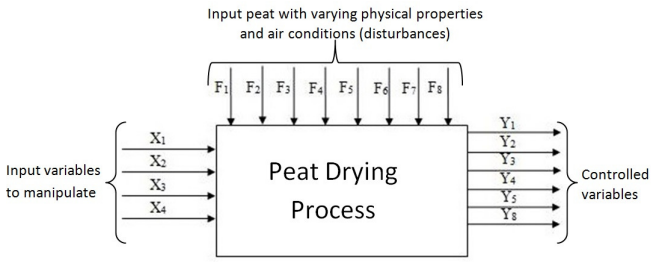

Figure 1. Functional description of peat drying process.

in Table 1. When the values of F_1, $F_2, \ldots, F_8$ change, the outputs variables Y_1, Y_2,...,Y_8 will also change. To adjust the outputs to the desired values (quality and energy consumption), optimal values of inputs X_1, $X_2, \ldots, X_4$ should be calculated and used.

Table 1. Description of variables and parameters in the peat drying process.

Var.	Description	Unit
X_1	auger rotational speed	rev/min
X_2	drum rotation speed	rev/min
X_3	steam temperature	$^\circ C$
X_4	fan flow rate	m^3/h
F_1	peat moisture	$\%$
F_2	peat bulk density	kg/m^3
F_3	peat ash content	$\%$
F_4	peat temperature	$^\circ C$
F_5	air temperature	$^\circ C$
F_6	peat flowability	$^\circ$
F_7	peat fractional composition	mm
F_8	peat moisture variation	$\%$
Y_1	dried peat moisture content	$\%$
Y_2	dried peat moisture variation	$\%$
Y_3	dried peat temperature	$^\circ C$
Y_4	electrical energy consumption	kWt
Y_5	drying agent exit temperature	$^\circ C$
Y_8	thermal energy consumption	$kJ{\cdot}h{\cdot}10^3$

Operation of the peat drying process with steam tube dryer is carried out according to a regimes map. Regimes map is a diagram of input variables and certain disturbances according for which the operator must set necessary regime of drying. A feature of the regimes map is that it helps to achieve the necessary moisture content and temperature of the dried peat in the drying process using input variables whose values depend on the characteristics of peat arriving at the plant. However, the operational regimes are not necessarily energy efficient, because the expediency of the adjustment of the drying process for a certain operational regime is not substantiated according to the influences due to disturbances in which the energy consumption for the drying would otherwise have been minimal (Hnyeushev, 2008). When using the regimes, there are often situations when briquettes are produced

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with degraded quality. This is mainly due to the fact that the peat drying process in plants is continuous and a piece of peat remains in the drum dryer for about 15 minutes (from the moment it enters into the drum until the moment it is leaves to the conveyor that takes away the dried peat to the press). In every 25-40 minutes (depending on the workload of trolleys, screw speed, the time required to prepare peat at preparatory department etc.) a new trolley with peat to be dried enters into the dryer. The physical properties of these new peat can differ significantly from the peat in the previous trolleys. It is too complicated to determine the exact moment when the peat from the new trolley enters into the dryer: the time of incoming peat with different properties can only be determined approximately. In addition, when a new trolley with peat having different physical properties is charged into the dryer, the peat from previous trolley content may still be inside the dryer. If the input variables are quickly modified based on the regime maps for the new incoming peat trolley, the peat from the previous trolley (which is still inside the dryer) may be over/under dried and the quality of the peat may be poor (defective products).

In order to develop optimal operating regimes it is necessary to:

1. Collect information of peat drying regimes used in a real plant.
2. Develop a mathematical model of the drying process.
3. Optimize the values of the input variables for energy efficient performance and for necessary quality of dried peat.
4. Develop a procedure for implementing the optimal operational conditions for the peat drying process.

Getting accurate information for the construction of a mathematical model of peat drying is possible after planning and conducting the experiments of a peat drying process in a real dryer. During the investigation of a peat drying process with steam tube dryer, it was found that there are some features that can rise the playback error of some output functions. So at first, it is necessary to resolve the problem of features selection. For every model it is necessary to include input variables and parameters that have influence on the output variables. This allows to filter separate features and reduce the overall error of the model (because each feature has a measurement error and we find a model of optimal complexity in which the error is minimal). This task can easily be solved by Group Method of Data Handling. GMDH possesses an advantage when there is no (or almost no) *a priori* information about the structure and distribution of model parameters and when experimental data is extremely small (even when the number of the model parameters are smaller than the number of observations). (Ivakhnenko and Yurachkovskij).

The idea is to construct a model of optimal complexity based only on data, i.e. by knowing only simple input-output relations of the system; GMDH will construct a self-organizing model (a higher-order polynomial of the input variables).

The GMDH approach for the construction of a mathematical model can be useful because (Ivakhnenko, 1970):

1. The optimal complexity of the model structure that is adequate to the level of noise in the data can be found. For real problems, with noisy or insufficient data, a simplified optimal model is more accurate.
2. It guarantees that the most accurate or unbiased models will be found, i.e. the method does not miss the best solution during exhaustive search (in the given class of functions).
3. Any non-linear functions or features, which can influence to the output variable can be used.
4. The method gets information directly from data and minimizes the influence of apriori assumptions about the model outputs.

Among the most well-known parametric algorithms are the combinatorial (COMBI) algorithm and the multiple iterative algorithm (MIA). The idea of all GMDH-type algorithms is to gradually generate complicated models and selecting a set of models that show a higher forecasting accuracy using data outside of the training set. These data outside of the training set are usually denoted a validation or testing set, and the top-ranked model is claimed to be optimally-complex.

The main idea of the COMBI algorithm is not miss any of the possible models (Ivakhnenko, 1971). Therefore, at each connection level, the COMBI algorithm:

1. covers all models;
2. conducts the selection of the best combinations of the variables.

The basic ideas of MIA is (Cheberkus and Ivakhnenko, 1980) to:

1. reduce the number of models considered in each row of the selection;
2. reduce the number of rows, and thus to accelerate the access to the best level of connection.

Therefore, for each row (in the MIA algorithm):

1. a fixed number of best transformation of a signals (each transformation of a signal is considered as a signal) is selected;
2. every combination of best variables creates a new signal in the transition to the next level.

For carrying out the identification it is possible to use an intelligent technology based on artificial immune systems (de Castro and Zuben, 1999), which allows to select the parameters of the mathematical model in accordance with the real signals. This approach is of particular relevance if the model has a large number of parameters.

According to Table 1, there are 15 design parameters in the model of the peat drying process and it is necessary to calculate 4 values of optimal input variables. For this reason development and installation of on-line optimization codes in programmable logic controllers (PLCs) for determining the optimal values of the input variables of the peat drying process will be more difficult than the hardware im-

plementation of neural networks in neurochips and neurosignal processors. Therefore, it is more appropriate to create a selection (data) for optimizing parameters and variables of the model under certain industrial operational situations for training, testing and construction of a neural network. For capturing the dynamics of the drying peat process, the most expedient action is to use a multilayer perceptron as a high-performance model after learning. A model with good extrapolation possibilities that allows to build functions of any complexity and is in sensitive to an increase in the number of input actions, is important for building a multivariate model (Yurachkovskij and Zaentsev, 1987). A multilayer perceptron model that is trained by experimental data allows to realize "input-output" characteristics of the system. This means that when new values of perturbations appear in the drying process, the perceptron model allows to calculate the optimal control actions.

There are cases when input variables are found to change by a large value. For example, let us consider that the temperature of the steam should be increased from 100°C to 130°C according to optimal value of X_3. This is done by burning an increased amount of peat for producing steam in the boilers. A significant amount of time is needed for changing the temperature (moving to the necessary operating conditions). It will be quite difficult to control the required amount of the peat needed for combustion in the boiler and the temperature of the drying agent (steam).

To overcome major inconvenience in the operation of the drying process caused primarily by the inertia of the process, it is advisable to carry out a classification and recognition of industrial situations. It means that for a certain set of values of the disturbances acting on the system, a range of values of control actions or input variables for which the energy consumption is lowest and the quality of dried peat is satisfactory, is selected. This facilitates the task of adjusting the drying process, reduces the possibility of a quick change of the values of input variables in the process of drying and increases the intervals where the peat gets dried with the required quality.

3 Modeling of peat dryer

In order to develop mathematical dependencies of the changes in the target or output variables Y_j due to changes in the input variables X_i, active experiments were conducted. For conducting experiments, it is first necessary to plan the experiment.

For planning the experiment, regime maps of steam tube dryers are used. The experiments were carried out in the peat plant "Soyne" in Ukraine, where the inputs variables were changed in a well planned manner within the allowed range of the operation conditions. An increase in the moisture content of the incoming peat necessitates an increased temperature of the steam in the dryer or a reduced speed of the feeder (auger) (drying speed) or, in rare cases, reducing the fan flow rate. The input variable X_3 interacts with X_2. If the feeding rate of the peat in the dryer is increased, then with a constant temperature of the steam, the time that the peat stays in the dryer should be increased. However, with a constant drying time, the temperature of the heat carrier should be increased (Kulakovskyi and Rosen, 2013b).

The input variable X_4 in the peat plant is practically not regulated (although it is a possible by using the electric drive present in the plant). The range within which employees can (in accordance with "Exploitation instructions") change the fan flow rate varies from 1370 to 1400 rev/min. This is due to the fact that in the existing regime maps this variable is ignored.

A plan of the active industrial experiments is shown in Table 2, where (-1) indicates the minimum, (+1) the maximum, and (0) indicates the average value of the input variables for certain values of the disturbances acting on the process.

Table 2. Plan of active experiments of drying in steam tube peat dryer.

Experiment	Input variables		
	X_1	X_2	X_3
1	0	0	0
2	+1	0	+1
3	+1	-1	0
4	-1	0	-1
5	-1	+1	0
6	0	+1	-1
7	0	-1	+1

Two series of industrial experiments using the plan of active experiments of drying with steam tube peat dryer (Table 2) were conducted. Results of the experiments are shown in Table 3.

It is necessary to relate the outputs Y_j to the inputs X_i. One possible way to model this relationship is to postulate an empirical model of type

$$Y_j^m = \sum_{k=1}^{N} \beta_{jk}\phi_k(X_1,\ldots,X_4;F_1,\ldots,F_8), \tag{1}$$

where β_{jk} is an unknown parameter (constant) while $\phi_k(\cdot)$ is a chosen set of basis functions. In the simplest case, N=12 and $k \in \{1,\ldots,4\}$: ϕ_k=X_k, or ϕ_k=F_{k-4} —in other words, a linear model in the manipulatable inputs X_j and disturbances F_j.

The error of the model on the training set is the sum of the errors of the individual training vectors, root-mean-square error (RMS).

$$E = \sum_{j=0}^{m} (Y_j - d_j)^2, \tag{2}$$

where Y_j – output variable of learning vector; d_j – the corresponding target output value system.

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Table 3. Experimental data set.

No.	F_1 [%]	F_2 $[kg/m^3]$	F_3 [%]	F_4 [°C]	F_5 [°C]	F_6 [°]	F_7 [mm]	F_8 [%]	X_1 $[\frac{rev}{min}]$	X_2 $[\frac{rev}{min}]$	X_3 [°C]	X_4 $[m^3/h]$	Y_1 [%]	Y_2 [%]	Y_3 [°C]	Y_4 [kWt]	Y_5 [°C]	Y_8 [kJ]
1	43.6	417	23	24.7	28	41.1	1.49	3.5	3.81	9.63	27.6	128	14.7	5	72.6	67.3	96.7	15685
2	42.6	385	22	26.6	28.5	41.4	1.58	5.82	3.76	9.58	27.58	129	17.9	7.2	70.4	66.61	102.8	16600
3	41.9	377	16.9	24.7	27	42.9	1.58	4.39	3.72	9.5	27.62	123	15.8	5.1	59.4	66.82	97.2	20500
4	41.4	341	17.1	27.6	27	42	1.74	3.49	3.7	9.4	27.8	124	14.7	8.5	57.2	67.17	94.8	19920
5	40.9	305	16.8	28	26	43.8	1.66	2.53	3.71	9.32	27.8	119	14	4.2	55	66.68	93.7	22010
6	41.2	333	16.1	26.1	26	43.7	1.54	2.66	3.73	9.33	27.84	126	14.6	3.1	58.9	66.93	96	20800
7	45.4	358	15.5	26.6	26	43.9	1.61	1.95	3.77	9.3	27.84	112	16.1	4.6	55	66.83	88.5	22600
8	44.9	367	15.3	24.7	25	43.5	1.45	2.69	3.77	9.1	28.16	118	17.6	6.1	57.2	68.89	91.5	21435
9	45.2	369	15.7	26.1	25	43.3	1.44	2.52	3.7	10.1	28.02	117	16.4	4.8	60.5	73.82	91	19835
10	45	399	15.9	27.1	25.5	41.4	1.52	2.12	4.1	10	28	124	16.3	4.9	63.8	75.03	96.5	20390
11	45.1	407	16	28	26	40.5	1.6	1.67	4.03	10.1	27.9	128	17.1	5.1	63.3	73.27	100	28015
12	42.9	425	15.9	26.6	26	39	1.54	2.09	3.2	8.7	27.94	130	16.6	2.9	61.6	65.37	103.1	16930
13	47.1	376	18	28	25.5	43.4	1.55	4.19	4.3	10	27.82	132	19.8	6.2	63.8	71.29	102.5	15585
14	43.5	372	17.1	26.4	26.2	42.3	1.56	3.01	3.8	9.4	27.53	119	17.6	6.1	60.1	68.45	98.7	15105

Table 4. Values of Root-mean-square (RMS) error of objective functions.

learning algorithm	Objective function					
	Y_1	Y_2	Y_3	Y_4	Y_5	Y_8
COMBI	0.053298	0.057419	0.062413	0.054312	0.038591	0.065312
MIA	0.013399	0.019476	0.044706	0.043124	0.036048	0.048965

The value of the root-mean square error of the peat drying process for outputs using COMBI and MIA algorithms are shown in Table 4. As an example, the models for calculating the output Y_8 (thermal energy consumption) created with MIA and COMBI algorithms are presented in Figure 2 and Figure 3 respectively.

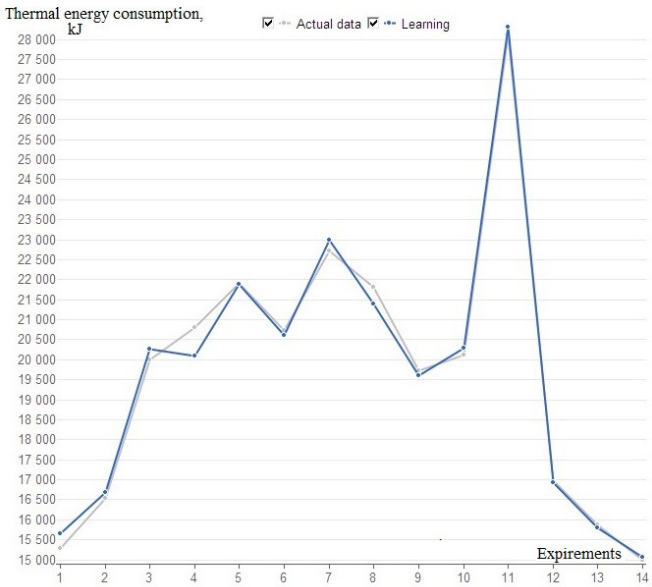

Figure 2. Graph of comparison of experimental data and model prediction of heat consumption (Y_8) using MIA GMDH algorithm.

From the plots of these figures and values of RMS error in Table 4 it can be concluded that the model constructed using GMDH with combinatorial algorithm has much higher RMS error than with MIA GMDH algorithm. The execution time of the COMBI algorithm is more than 3 times larger than that of the MIA algorithm because at each stage the best models that satisfy the necessary criteria are selected.

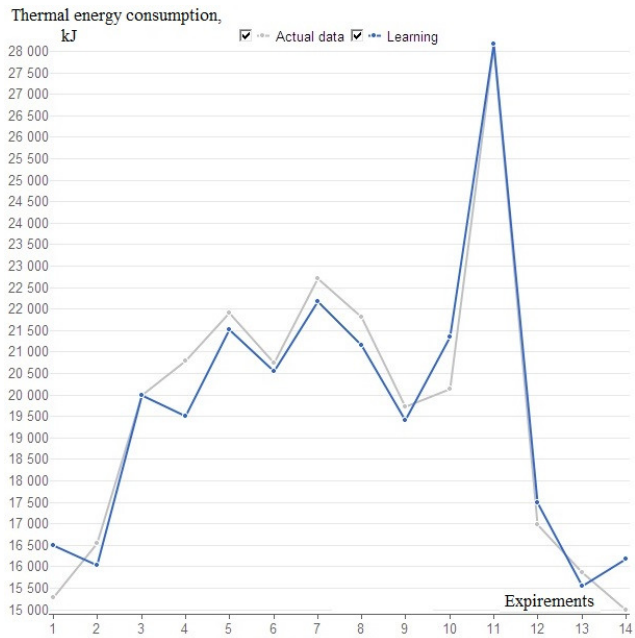

Figure 3. Graph of comparison of experimental data and model prediction of heat consumption (Y_8) using COMBI GMDH algorithm.

The main purpose of the work in this paper is to reduce the energy consumption for drying peat and to produce dried peat of required quality from the steam tube dryer. In other words, we consider two output functions to be minimized — consumption of heat and electricity. To solve the problem of the multi criteria which has two objective functions, the concessions method is applied (Gavrilov and Podinovskij, 1975). In order to minimize the energy consumption for the drying process, it is necessary to determine the amount of heat (in kJ) required for drying the peat at various physical properties. For this the required pressure and temperature of the saturated vapour (source of heat) should be determined. The minimum required values of the heat energy consumption for a series of experiments can be denoted by the symbol Z_k.

According to the factor analysis conducted in (Altuhov and Kulakovskyi, 2014) and the technical documentation of the peat briquette plant "Soyne":

1. the moisture content of dried peat (Y_1) should not exceed 20%,
2. differences in moisture content of the dried peat samples (Y_2) less than 6%,
3. temperature of the drying agent at the exit of the dryer (Y_5) should not exceed 120°C,
4. steam temperature (X_3) should not exceed 150°C,
5. temperature of dried peat (Y_3) should be in the range 30°C to 90°C,
6. speed of feeder/auger (X_1) — between 3 and 7 rev/min,
7. the frequency of rotation of the drum dryers (X_2) should be between 5 and 12 rev/min,
8. the air flow through the dryer (X_4) should not be more than $40 \cdot 10^3\ m^3/h$.

So, the conditions for minimizing the energy consumption of drying process in the peat steam dryer to obtain required qualitative characteristics of the dried peat and to maintain the safety of the briquettes production, the following objective function with constraints is considered. The models were obtained by using the GMDH method:

minimize

$$\begin{aligned} Y_4 = -315.781 - 0,2288F_1 + 0.0193F_2 \\ +1.004F_7 - 0,0624F_8 + 0.4966X_1 \\ +0,7834X_2 + 11.4723X_4 \end{aligned} \tag{3}$$

subject to

$$\begin{aligned} 0.6146F_1 - 0.4517F3 + 0.6422F_4 + 0.4832F_5 \\ -0.2333F_6 - 10.26F_7 + 1.186F_8 \\ +1.57X_1 - 1.693X_2 \leq 20 \end{aligned} \tag{4}$$

$$\begin{aligned} 64,21 + 1.571F_1 - 0.1532F_2 - 2.137F_4 - 3.06F_7 \\ +17.09F_8 + 1,084F_{12} + 1.124X_1 \\ +1.679X_2 + 2.356X_4 \leq 6 \end{aligned} \tag{5}$$

$$\begin{aligned} 30 \leq 608,2 + 1.235F_1 - 0.1552F_2 + 2.823F_5 \\ -4.354F_7 - 59.09F_8 + 7.84X_1 - 13.29X_4 \leq 80 \end{aligned} \tag{6}$$

$$\begin{aligned} -1,148F_1 - 0.1294F_2 + 1.961F_4 - 1.502F_5 \\ +1.074F_6 + 1.78F_8 - 1.782X_2 + 0.4177X_3 \leq 120 \end{aligned} \tag{7}$$

$$-364.4F_4 - 1022F_6 + 4107X_1 - 105X_3 + 2417X_4 = Z_k \tag{8}$$

$$3 \leq X_1 \leq 7 \tag{9}$$

$$5 \leq X_2 \leq 12 \tag{10}$$

$$X_3 \leq 150 \tag{11}$$

$$X_4 \leq 40 \tag{12}$$

It is not always advisable to adjust the plant operation for maximum productivity because the production volumes for a certain period is dictated by market conditions, in particular the demand for products. The most effective way of regulating the productivity of a dryer is by regulating the amount of peat that fills the tube (speed of auger rotation), i.e. input variable X_1. In addition, it is clear that the lowest electrical consumption will be during the minimum loading of the dryer and consequently during its lowest productivity. Therefore, in order to simplify further calculations and for considering the model's requirements, the possible values of the productivity must be divided into some levels of the auger rotational speed. For the "Soyne" peat plant where industrial experiments were carried out, it was divided into 3 levels — X_{1min}=2.5 rev/min, $X_{1average}$=3.5 rev/min, X_{1max}=4.5 rev/min.

Let the optimal input values be denoted by X_k^*, where $k \in \{1,2,3,4\}$ denotes the k^{-th} variables which corresponds to the optimal output value Y^{m*}_4. With the known values of F_k it is possible to find inputs X_k^*, where now $k \in \{2,3,4\}$, such that the output Y_4 is minimized. For every new values of the disturbances $F_1,\ldots,F_8$, the optimization code must be re-run (e.g. using the simplex method) and new optimal value X_2^*, X_3^*, X_4^* should be calculated.

Because of a limited number of experiments, there are few data for getting good prediction models for calculating X^{m*}_j. So synthetic data are created and used. Some of the disturbances F_k are correlated with each other. It is possible to find new values of the correlated disturbances using the Monte Carlo method (Vojtishek, 1999). From correlation analysis, it was found that parameter F_2 correlates with F_6, F_3 with F_5, F_3 with F_8 and F_7 with F_4 with a correlation coefficient of more than 50%. Some random numbers were used to compute the independent disturbances F_1, F_2, F_3, F_7 while the remaining disturbances were computed by using the correlation models and the Monte Carlo method.

By using an algorithm for searching the random values for the two factors, 86 observations were generated. In addition to 14 data series obtained from the experiments, a dataset of 100 inputs and 100 outputs for building a neural network was obtained.

The model that relates $F_1,\ldots,F_8$ to optimal values of input variables X_k^* where $k \in \{2,3,4\}$ could have a

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structure as,

$$X^{m*}_j = \sum_{k=1}^{N} \gamma_{jk} \varphi_k(F_1, \ldots, F_8), \quad (13)$$

where γ_{jk} — is an unknown parameter (constant) and φ_k is the basis function, e.g. artificial neural network (ANN). For ANN, it is necessary to select and formulate a learning procedure of the neural networks. Input vectors for the neural network are the values of the eight disturbances F_{1i}, F_{2i}, F_{3i}, F_{4i}, F_{5i}, F_{6i}, F_{7i}, F_{8i}, and outputs of the ANN are the optimal values of the input variables X^*_{2i}, X^*_{3i}, X^*_{4i}, where i — denotes the number of samples (experiment and synthetic data).

The required number of hidden neurons and the activation function of hidden and output neurons were optimized by using automated strategies for creating neural network model in the Statistica Neural Network (Borovikov, 2008) package.

Using ANN, the three best models with the lowest Root mean square (RMS) error of the input variables were created (Table 5). According to Table 5, the network MLP 8-4-3 has the lowest training and test errors compared to other two neural networks. MLP 8-8-3 has the best training performance and MLP 8-15-3 has the best test performance and the smallest training and test errors.

Since the network MLP 8-15-3 has negligible amount of residuals and a good results on training performance this network is chosen.

4 Classification and recognition of industrial regimes

Using the experimental data, extended with synthetic data, we use a classification algorithm and classify the data into a number N_r of operational regimes. The production of dried peat is split into different classes with respect to the consumption of electrical energy in the process of drying peat under certain disturbances. A total of four classes are formed. Each class is formed by assigning a maximum, minimum and an average value of Y^*_4 to the class. For each class there is a given range of the values of the input variables X^*_2, X^*_3, X^*_4, when X^*_k — is fixed to a known value as presented in Table 6.

To solve the problem of classifying the operational regimes, the training samples ($F_{1i}, \ldots, F_{8i}$, X^*_{2i}, X^*_{3i}, X^*_{4i}; Y_{4i}) for i=1,2,...,N are needed to calculate unknown function $f(F_1, \ldots, F_8, X_2, ..., X_4)$, if $f(F_{1i}, \ldots, F_{8i}, X^*_{2i}, X^*_{3i}, X^*_{4i})$=$Y_{4i}$ ε K=1,2,...,k. The data set $F_{1i}, \ldots, F_{8i}$, X^*_{2i}, X^*_{3i}, X^*_{4i} is divided into K=4 classes, such that the kth class represents the situation with input disturbances for which $f(F_{1i}, \ldots, F_{8i}, X^*_{2i}, X^*_{3i}, X^*_{4i})$=$K$. Then using discriminant analysis, new operating regimes can be recognized and assigned to the appropriate class. The aim of discriminant analysis is to develop methods for solving problems of recognition (discrimination) of new objects by comparing the magnitude of their attributes with those clusters that are already created. Such a comparison allows us to classify new objects (situations) and include them in one group (class). The equation for canonical discriminant function can be written as (Mueller and Cozad, 1988):

Table 6. Classification of industrial regimes for X_1=2.5.

Value	X_2	X_3	X_4	Y_4	Class
minimum	7.42	119.00	26.1	43.54	1
maximum	9.3	139.00	26.65	49.67	1
average	8.19	126.00	26.4	47.08	1
minimum	8.31	113.67	26.6	50.05	2
maximum	9.5	127.67	26.83	52.94	2
average	8.89	119.21	26.73	51.77	2
minimum	8.97	104.67	26.82	53.1	3
maximum	9.8	133.26	26.94	54.17	3
average	9.16	118.3	26.89	53.73	3
minimum	9.10	95.55	27.02	55.01	4
maximum	9.70	118.43	27.60	60.30	4
average	9.43	107.65	27.26	57.64	4

$$S_{km}=u_0+u_1X_{2km}+u_2X_{3km}+...+u_{11}F_{8km}, \quad (14)$$

where, S_{km} is the value (score) on the canonical discriminant function for case m in group k; X_{ikm} is the value of input variable X_i for case m in group k, F_{ikm} is the value of disturbances F_i for case m in group k and u_i are coefficients which produce the desired characteristics of the function.

Using the Mahalanobis distance (Jouan-Rimbaud and Maesschalck, 2000) for classification, a measure of the difference between two random vectors (X_i, X_{i+1}) with equal distributions is calculated as,

$$d(X_i, X_{i+1})=\sqrt{(X_i-X_{i+1})S^{-1}(X_i-X_{i+1})^T}), \quad (15)$$

with the probability that the sample belongs to data that is needed.

The Mahalanobis distance is the smallest distance for the class function to which the regimes belongs.

Since each sample is calculated using *a priori* knowledge of the model variables, the probabilities are called posterior probabilities. Also, the accuracy of classification of industrial regimes is assessed using a classification matrix that indicates the percentage of classification accuracy of the regime to the required class.

As an example, the classification matrix that indicates the accuracy of classifying the production regime to the required class in the steam tube dryer for X_1=2.5 is shown in Table 7. P_1, P_2, P_3, P_4 are the amount of data set that belongs to class $K \in \{1,2,3,4\}$. The results of the discriminant analysis of the peat drying regimes in the steam tube dryer showed that the data set which corresponds to a certain class, accurately belongs to a specific operational regime. The values of the coefficients for the classification

Table 5. The results of constructing the best neural networks for finding optimal parameters X_2, X_3, X_4 when X_1=2.5 using Statistica Neural Network package.

	Net. name	Training performance	Test performance	Validation performance	Training error	Test error	Validation error	Hidden activation	Output activation
1	MLP-8-4-3	0.6702	0.0337	0.82123	5.8844	1.85121	2.0113	Logistic	Logistic
2	MLP 8-8-3	0.9924	0.2589	0.84325	0.2769	6.38024	3.7267	Exponent.	Tanh
3	MLP 8-15-3	0.9899	0.3994	0.85092	0.1908	0.18109	4.0310	Logistic	Identity

Table 7. The classification matrix for indicating the accuracy of classifying the regimes for X_1=2.5.

Class	percent	P_1=7	P_2=9	P_3=42	P_4=42
1	100	7	0	0	0
1	100	0	9	0	0
3	97.619	0	0	41	1
4	100	0	0	0	42
Total	99	7	9	41	43

functions obtained from the results of discriminant analysis are presented in Table 8. The classification's functions

Table 8. Values of the coefficients u_i5 for X_1=2.5 obtained from the discriminant analysis.

Coeff.	P_1=7	P_2=9	P_3=42	P_4=42
u_0	-87196	-88996	-89339	-89273
u_1	3837.273	3676.194	3609.626	3607.79
u_2	349.0444	334.67	328.4349	328.0761
u_3	1640.103	1816.024	1877.824	1885.447
u_4	-682.357	-590.207	-573.424	-576.659
u_5	70.75283	66.05498	65.16128	65.2285
u_6	-347.997	-435.43	-440.25	-434.504
u_7	83.16267	130.5181	133.0582	128.128
u_8	530.0742	723.6801	733.9228	720.617
u_9	1302.379	1200.007	1187.654	1190.253
u_{10}	-3403.97	-5044.25	-5121.24	-5005.24
u_{11}	-664.441	-592.096	-578.54	-580.824

allow with sufficient accuracy to classify a sample to the required class.

5 Optimal operation of peat dryer

After classifying and recognizing industrial regimes it is necessary to develop an algorithm for operating the drying process of peat and to create a procedure for selecting input variables belonging to the relevant class. This is necessary to find a data set X^{**}_k which is the optimal value for a given value of disturbance F_k that would correspond to a certain class $\{X^{**}_k; F_k\}\ \varepsilon\ k_n$, where $n \in \{1,\ldots,4\}$. The algorithm for optimal operation of the peat drying process in steam tube dryers given below:

1 Before starting the dryer, the physical properties of peat are defined (N=1, where N is the number of measurement perturbations; F_{1i}, F_{2i}, F_{3i}, F_{4i}, F_{5i}, F_{6i}, F_{7i}, F_{8i}, i — is the number of iteration of the algorithm for setting the optimal values of industrial regime parameters). Then the operator sets the required value of productivity by using the given value of input variable X_{1i}. Next, new optimal values X^*_{2i}, X^*_{3i}, X^*_{4i} will be calculated using the neural network. These values must be set on the drying system. The nearest discriminant function which approximates the given industrial regime and therefore the class situation K^*_i, is defined by using discriminant analysis.

2 For the next measurements, N=2 (F_{1i+1}, F_{2i+1}, F_{3i+1}, F_{4i+1}, F_{5i+1}, F_{6i+1}, F_{7i+1}, F_{8i+1}), the optimum energy-efficient value of input variables (X^*_{2i}, X^*_{3i}, X^*_{4i}) are determined by using the neural network. After this, the class of production situation is determined using discriminant analysis. If the new class K^*_{i+1} lies in the same class as before (K^*_i), then no changes in the drying regime should be done. Thus the peat drying process is continues with values X_{2i}, X_{3i}, X_{4i}. If the new class K_{i+1} does not lie in the same class as before, then it is necessary to find new optimal values for the input variables. These values should belong to an appropriately defined new class of industrial regime.

3 At first, the value of X_{4i+1} must be set. This value should belong to a required class. Much of the electrical energy needed by the peat drying process is consumed by the fan. So we set the value of X_{4i+1}, which is closest to the area of the required class K^*_{i+1} ($X_{4,i+1} \in K^*_{i+1}$).

4 Change of value for X_{4i+1} leads to a change in the specific consumption of dry air ℓ. So it is necessary to determine a reasonable value of specific heat energy required to heat the drying agent due to change in the specific consumption of dry air ℓ. The specific consumption of heat for heating the drying agent (q_2,

kJ/kg of evaporated moisture) from the initial Θ_1 temperature to the final Θ_2 is written as,

$$q_2 = l \cdot c_{d.a} \cdot (\Theta_2 - \Theta_1), \tag{16}$$

where $c_{d.a}$ is a specific heat capacity of the drying agent; ℓ is specific consumption of dry air required to evaporate 1 kg of water.
According to equation (16), it is necessary to define specific consumption of heat for heating the drying agent from the initial to the final temperature. Then according to equation (17) minimum acceptable values of specific consumption of heat for evaporation (q). Specific consumption of heat, which is removed from the peat (Hnyeushev, 2008), is written as

$$q = q_1 + q_2 + q_3 + q_4, \tag{17}$$

where q_1 is specific consumption of heat for evaporation of peat; q_3 is specific consumption of heat for heating the drying agent; q_4 is specific consumption of heat losses to the environment.

For calculating the minimum value of q for the peat drying process, it is necessary to know the variables F_5, F_4, F_3, F_1, X_4, Y_1, Y_3, Y_5. The values of disturbances are measured for each trolley. Variable X_4 has value corresponding to X_{4i+1}. The values of Y_1 is set to the maximal allowable; Y_5, Y_3 are minimally-acceptable levels of the requirements for the production of dried peat by the minimum value of q for the process of drying peat. The values must be such that they allow to obtain the dried peat with required quality and require fire safety of drying with a minimum value of q for the process of drying peat.

So for determining the minimum available value of specific consumption of heat per of water, which is removed from the peat ($q_{\min}$), the values F_{1i+1}, F_{3i+1}, F_{4i+1}, F_{5i+1}, X_{4i+1}, $Y_{1\max}$=20%, $Y_{3\min}$=30°C, $Y_{5\min}$=90°C are used. The minimum value of steam consumption (Y_8) for the industrial regime (F_{1i+1}, F_{2i+1}, F_{3i+1}, F_{4i+1}, F_{5i+1}, F_{6i+1}, F_{7i+1}, F_{8i+1}, X_{2i}, X_{3i}, X_{4i+1}) is found by the formula Q=q·W (where W is the dryer productivity on evaporated moisture kg/h).

5 From a mathematical model of heat consumption obtained using GMDH, the value of X_3 can be found as

$$\begin{aligned} X_3 = -3.47048F_4 - 9.73333F_6 + 39.11429X_1 \\ +23.01905X_4 - 0.00952Y_8 \end{aligned} \tag{18}$$

So the optimal value of X_3 can be determined from the function of disturbances F_4, F_6, X_4, Y_8 that is determined previously (F_{4+1}, F_{6+1}, X_{4i+1}, Y_8).

6 The nearest discriminant function which approximates the given industrial regime (F_{1i+1}, F_{2i+1}, F_{3i+1}, F_{4i+1}, F_{5i+1}, F_{6i+1}, F_{7i+1}, F_{8i+1}, X_{2i}, X_{3i+1}, X_{4i+1}) is set. Then a new class of the industrial regime K_{i+2} is defined. The class K_{i+2} must be compared with K^*_{i+1}. The value X_{2i}, X_{3i+1}, X_{4i+1} must be set if class K_{i+2} corresponds to the class K^*_{i+1}. If not, the value of X_2 must be changed.

The value of input variable X_2 can be found by a mathematical relation X_2=$f(F_k;X^*_3,X^*_4)$ as,

$$\begin{aligned} X_2 = 18.0457 + 0.58F_3 + 0.1455F_4 \\ +0.1438F_8 - 0.1011X_3 \end{aligned} \tag{19}$$

This function was found using algorithm MIA of GMDH. Thus, the new value X_{i+2} can be found.

7 Next, for industrial regime $\{F_{1i+1}$, F_{2i+1}, F_{3i+1}, F_{4i+1}, F_{5i+1}, F_{6i+1}, F_{7i+1}, F_{8i+1}, X_{2i+1}, X_{3i+1}, $X_{4i+1}\}$ the new meaning of class K_{i+2} is determined. If new class K_{i+2} meets the required class K^*_{i+1}, then the value of the input variables are the following: X_{2i+1}, X_{3i+1} and X_{4i+1}. If not, the algorithm of searching the energy-efficient values of input variables should be continued.

8 Then new value X_{4i+1} must be found. The change of value will be carried out with the relevant step from the average value of the necessary class (see Table 6). The change of the value of X_4 must not be very large. So it is possible to choose a small step, e.g. $\pm$0.001.

9 Further, according to steps 4–8, the necessary values X^{**}_2, X^{**}_3, X^{**}_4, that would meet the desired class K^*_{i+1} are determined.

This searching algorithm will smoothly change the operating condition of drying peat. The algorithm allows to obtain the dried peat in a certain acceptable range, it meats the fire safety of the drying process, and the process will take place in energy-saving drying regimes.

6 Discussion

The use of GMDH allows to solve the problem of features selection of the mathematical model. In particular, only 7 input parameters out of 12 that describe the peat drying process were included into the electrical energy consumption function. The linear model of drying peat was created using experimental data. In this model, an objective function for minimizing energy consumption of the drying process and fulfilling quality requirements of dried peat and fire safety was chosen. Then, optimization of the value of input variables was carried out. After that, the structure of neural networks were found. The training of neural networks was completed with the best quality of reproduction the data on training and testing samples of drying peat process models by optimal energy saving control variables. In this model the values of disturbance influences were considered as inputs, and optimal

energy efficient values of input variables were obtained as outputs. For neural networks, exponential basis function was chosen and for hidden layers, logistics functions were chosen. The classification of industrial regimes and discriminant analysis were conducted. Regimes were classified with respect to minimum electric energy consumption. So classification was carried out in situations with optimum energy saving regimes. Also for every class, the boundaries of adjustment of each input variables were determined. A discriminant function was found from the experimental and synthetic data. The discriminant function allowed to determine the required class situation of energy consumption with high accuracy. An iterative algorithm for searching the values of input variables with the least change was developed. Each of these values will belong to the appropriate class of industrial regime. Adjustment of the value of input variables according to the class of necessary regime allowed to reduce the impact of sudden changes in the conditions of the process of peat drying in the dryer. This reduces the probability of obtaining dried peat that does not satisfied the quality requirements. The procedure of finding and setting values of input variables allowed to move smoothly from one class of industrial regime to another. For further improvement it is necessary to develop a control system. Input variables of drying process in this system should be obtained by using the operation procedure of peat drying process. Thus, system may be represented as two procedures — procedure for adjustment of the heat energy consumption (consisting of airflow adjustment (X_4) and expenses of drying agent (X_3)), and procedure for adjustment of the drum rotational speed (X_2).

7 Conclusions

An optimal procedure for the operation of a drying peat process was developed. This procedure consist of defining the class of industrial regimes that depends on energy consumption, and selection of necessary values of input variables corresponding to a given class. The operation procedure allows to reduce the consumption of energy for 9% for production 1 ton of briquettes compare with operation according to the regime's map , and to obtain the required quality of dried peat. For further improvement it is necessary to develop an automatic control system to facilitate the implementation of operation of the drying process.

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