Model for the Forecasting of the Fusion Temperature of Biomass Ashes

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Summary
Ash deposit is one of the most important problem in middle-big size power plant using biomasses as fuel. The growth of the quantities and the different typologies of biomasses increase seriously this problem. Ash deposit formation depend on their thermal behavior which depend fom their chemical composition. Using neural network analysis technique, in this document is reported the study of the relationship between concentrations of some typical element of inorganic part of biomasses and thermal behavior.

Key word: *Thermal Behavior, Model Prediction, Biomass, Neural network.*

Introduction

The energetic sector of biomasses pays always more attention to the possibility to recover agroindustrial residual materials for the production of thermal and electric energy. The high costs of the combustible fossils, the costs of disposal and the recent political environment stimulate the development of these activities. But the increase of the quantities and the different typologies of biomasses used in the systems based on the direct combustion has implied the increasing number of the problems related to the formation of agglomerations in furnace and to the deposit of ashes on the surfaces of thermal exchanger. The consequence is the decrease of the energetic efficiency, the difficulty to clean the inside parts in the plants, the corrosion phenomenon of the metallic walls and in the most serious cases the block of the production to allow the operations of maintenance. The low melting temperatures of the ashes of some materials represent the most important aspect at the base of these problems. This phenomenon is often associated to high concentrations of alkaline metals in the ashes of biomass, frequently noticed in the herbaceous plants generally richer in containing ashes in comparison to the woody materials. From the literature emerges how K, Na, S and Cl are the elements mostly monitored to follow these phenomena. In combustion, these elements can produce deposits of fused ashes on the grate of combustion and to form deposits in correspondence of the surfaces of thermal exchange. Currently the knowledge of the mechanisms of the deposits of ashes formation are not complete and they don't sometimes find technical comparisons. Considered the complexity of the phenomena in this document is proposed a project aimed to face the problem examining a high number of materials (80 samples) to underline the difference of thermal behavior of the ashes of combustion and chemical composition. The objective is to put in evidence the existence of relationships between chemical composition and ash melting temperature through mathematical elaborations based on the neural networks. The practical result is the obtainment of an algorithm of calculation able to develop forecasts regarding the thermal behavior of the ashes of a biomass.

Material and methods

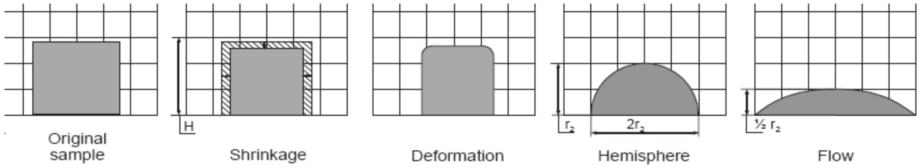
In this study 80 typologies of biomasses have been traced, spread and available in the Mediterranean area, potentially usable for energetic purposes in the existing power plants. All the samples have been characterized following the correspondent normative CEN of reference: the CEN/TS 15370 for the determination of the temperatures of fusion (of the fusion temperatures) and the CEN/TS 15290 for the determination of the content in chemical elements.

Table 1. Biomasses studied.

Woody biomasses	n.	Herbaceous biomasses	n.	Oleaginous biomasses	n.
Conifer chips	2	Corn straw	1	Sunflower cake	2
Wood chips	3	Barley straw	1	Brassica napus cake	1
Beech	1	Brassica napus straw	1	Olive residues	1
Spruce	1	Sorghum chips	2	Grape residues	3
Demolition wood	2	Rice hulls	1	Sunflower seed	1
Fruit stone	1	Tomato hulls	1	Biomass mix	n.
Olive stone	1	Grape hulls	1	Power plant mix	14
Poplar	4	Miscanthus straw	1	50% Spruce 50% Vine p.	1
Vine pruning	1	Amylaceous biomasses	n.	50% Vine p. 50% Corn g.	1
Fruit pruning	1	Oat grain	1	Ceneri pesanti	3
Olive pruning	1	Corn grain	5	Power plant bottom Ash	3
Wood residues	1	Barley grain	1	Other biomasses	n.
PKS	1	Wheat grain	3	Slaughter residues	2
Herbaceous biomasses	n.	Wheat bran	1	Citrus residues	1
Wheat straw	3	Rice grain	1	Coffe residues	1
Rice straw	1	Rice chaff	1	chickpea grain	1

The complete list of the used materials is proposed in table 1, where considered their heterogeneity, they have been divided in four typologies: woody (wooden) biomasses (BL), herbaceous biomasses (BE), starchy (amylaceous, farinaceous) biomasses (BA) and oleaginous (oily) biomasses (BO). Taking into account the different origins and typologies of the biomasses, it is considered that in their whole represents the big part of the potential complexity of the usable materials in the different energetic plants.
The ashes to be submitted to the melting analysis have been obtained departing from every biomass through complete incineration in furnace to 550°C as established from the CEN/TS 14775. According to the CEN/TS 15370, the phenomenon of ash melting of a sample includes four phases, to which refer the four defined characteristic temperatures. Particularly: shrinkage, deformation, hemisphere and flow (fig. 1). The melting temperature analysis has been carried out with the melting analyzer Sylab IF 2000 F, that allow to notice automatically the variation of physical state of a material, submitted to increasing gradient of temperature. Through an external optic system and a software of elaboration of the images it is possible to follow the course of the variation of the sample shape of ashes that in side view, proposes a prismatic profile.

Figure 1. Phases in the ash melting process (CEN/TS 15370).



The chemical analysis of the ashes carried out according to the normative CEN/TS 15290 require the digestion of the ash of biomass in a closed container, with the aid of an acids mixture. The solution is submitted therefore to a cycle of mineralization through microwaves mineralizator (Anton Paar - Multiwave 3000), which has been set with a program of mineralization suitable for the ashes of biomass. The product of the mineralization is diluted and submitted to analysis to spectrophotometer by the atomic emission to the plasma (PerkinElmer Optima 2100). The data received by the chemical analysis of the ashes regarding Al, Ca, Si, Na, K, P, Mg, Fe and Ti has been arranged in a database containing the results of the melting temperatures allowing to start the phase of statistic elaboration. Among the melting temperatures pointed out by the technical normative it was considered useful to set attention on the temperature of deformation (T_d). It is presumable that in correspondence of this temperature have begun the phenomena of slagging and fouling inside the combustion plants. Therefore, the model of forecast, object of this work, proposes to estimate the value of T_d in relationship of the above mentioned chemical elements composition. For the analysis of the data gained by the experimentation it was employed the software NeuroShell II that is based on algorithms developed with the technique of the neural networks. The neural networks are particularly suitable to resolve very complex mathematical models and characterized by an high background error of the data available. The software uses a part of the database data to develop one phase of phenomena learning process and another part as phase of self-control in which corrects and selects the algorithms of calculation. A third part of the database, finally, allows to calculate the value of R^2 on every developed algorithm. The precision of the developed model depends to the number and the quality of the data related to the analyzed process. The greater is the number of the available information for the software of calculation, the higher are the probabilities to obtain an algorithm able to make a good forecast. To verify the importance of these aspects were carried out different elaborations using a number of increasing input data. More in detail, three different algorithms were obtained beginning from the database respectively selecting from 30, 50 and 70 samples originating therefore three different starting databases: d_{b30}, d_{b50} e d_{b70}. The 10 lacking samples, that complete the experimental database, were used to verify the validity of the developed algorithms. The choice of these materials is based on a criterion of the representative of the biomasses. Particularly, the real values of T_d ashes of the 10 samples of biomasses were compared with the forecasted values of temperature of deformation (T_{df}) by the algorithms developed from the three database. The valuation of the three algorithms is based calculating the absolute middle error (E_{aa}) among the values of T_d and T_{df} of the 10 ashes of analyzed biomasses.

Results

In the table 2 are reported the values of descriptive statistic related to the chemical composition of the biomass ashes. It is possible to underline how in all the classes of the materials are predominant the presence of Ca, Mg, Si, P and K. Overall, a high variability of the chemical composition of the ashes is observed, particularly for the contents in potassium (0,9% - 29,4%), silicon (0,3% - 42,2%), phosphorus (0,2% - 48,3%), calcium (0,5% - 29,7%) and magnesium (0,2% - 41,2%). Considering the single classes of materials it is possible to underline that: the BL has the highest average value of Ca (11,0%); the BE distinguish itself for the highest average value of Si (20,8%); the BA and the BO distinguish themselves, on the contrary, for the highest average values of P and K, respectively 22,2% and 20,0% for the BA and 16,0% and 21,7% for the BO.

Table 2. Chemical ash composition.

Parameter	Al (%)	Ca (%)	Fe (%)	Mg (%)	Na (%)	P (%)	Si (%)	Ti (%)	K (%)
Wood biomasses									
Average	0,6	11	1,2	4,6	0,7	3,7	6,9	0,4	9,1
Min	0	4,5	0	0,3	0	0,2	0,3	0	0,9
Max	2,8	21,6	11,8	41,2	3,7	11,5	30,8	2,4	20,7
Herbaceous biomasses									
Average	0,3	6,6	0,4	1,1	0,9	3,1	20,8	0,1	13,6
Min	0	1,3	0	0,2	0,1	0,7	1	0	2,9
Max	1,1	16,5	2,2	2,6	3,7	8,7	42,2	0,6	26
Amylaceous biomasses									
Average	0,9	3,3	0,6	4,8	0,7	22,2	3,6	0,1	20
Min	0	0,5	0	0,3	0	0,8	0,3	0	12,2
Max	7	11,8	3,5	10,8	6,5	48,3	20,1	0,5	29,4
Oleaginous biomasses									
Average	0,3	7,1	0,4	1,8	0,3	16	3,5	0	21,7
Min	0	5,3	0	0,4	0,1	0,9	0,1	0	9,2
Max	1,1	9,2	1,1	7,8	1	35,3	20,8	0,1	27,9
Biomass mix									
Average	0,9	14,4	1,5	1,5	0,8	2,3	10,4	0,2	9,8
Min	0,1	6,8	0,4	0,6	0,3	0,9	1	0	5,8
Max	3,5	22,2	2	5,1	3,5	6,6	21,5	0,7	15,3
Other biomasses									
Average	1,2	13,1	2,5	2,7	1,3	10,5	4	0,1	10,3
Min	0	2,5	0	0,3	0,1	0,7	0,2	0	2,9
Max	4,6	29,8	15,5	8,8	5,2	35,6	16,6	0,3	22,5

In the table 3 are reported the values of descriptive statistic related to the T_d of the 80 samples of ashes. In general, it points out that the T_d of the ashes vary from 642°C to 1489°C. The lowest T_d are found in the starchy materials, while the higher values of T_d are characteristic of the woody materials. In the table 4 are shown the results of the differences among the T_d and T_{df} real values obtained with the three algorithms defined in the materials and methods. The values show as the algorithm obtained by the db_{70} give a lower E_{aa} in comparison to the db_{50} and to the db_{30}. The value of E_{aa} goes from 123°C, by the algorithm obtained with the db_{30} , up to 65°C by the algorithm obtained with the db_{70} (figure 2). In this last case the algorithm is characterized by a value of R^2 equal to 91,8%. It is still important to notice how passing from the algorithm of the db_{30} to that of the db_{70} a reduction of the negative errors is obtained.

Table 3. Ash deformation temperature (°C).

Parameter	Woody biomasses	Herbaceous biomasses	Amylaceous biomasses	Oleaginous biomasses	Biomass mix	Other biomasses
Average	1342	1024	838	1133	1285	1282
Min	1050	837	642	951	1192	753
Max	1489	1419	1300	1310	1466	1494

These errors result more dangerous when put a biomass in a class of higher T_d in comparison to that real class loosing the possibility to foresee phenomena of slagging and fouling.

Table 4. Forecast results obtained with Neuroshell.

		Neuroshell temperature error (°C)		
Samples	T_d (°C)	d_{b30}	d_{b50}	d_{bt70}
Conifer chips	1426	+68	+18	+18
Woody chips	1309	+173	+65	+113
Corn grain	774	+75	+102	+22
Wheat grain	760	+29	+110	+52
Rice straw	1003	+142	+84	-101
Wheat straw	962	+37	-12	-126
Sunflower cake	1155	+41	+107	-56
Olive residues	1182	+312	+262	-74
Power plant mix 1	1339	+113	+86	-85
Power plant mix 2	1239	+237	+172	+4
Min (absolute value)		29	12	4
Max (absolute value)		312	262	126

Discussion

Although a big variability of the ashes composition of biomasses exists above all in relationship to these elements that commonly are correlated with the phenomena of deposits in the combustion plants, some classes of homogeneous materials for typology and thermal behavior seem to show a similar chemical composition. This aspect is supported by the results of the study obtained by the neural networks able to return interesting algorithms for forecasting on the materials' thermal behavior beginning from the chemical composition.
The average error of about 60°C between the T_d and the T_{df}, further improvable increasing the number of available data , opens the way to an interesting practically perspective of the method. Such value represents, for the present technological level of the systems, a threshold of tolerance reasonably contained to the reach a correct management of the combustion plant. On the base of these presuppositions, the application of the forecast model proposed could be very interesting for the management of the combustible supplies especially in those middle-sized plants. In these contexts could be implemented a standard of biomasses quality used for the formulation of the mixtures also considering the chemical factors involved in the thermal behavior of their inorganic fraction.

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