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Performance of Models Based on a Linear Regression and Neural Networks

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Abstract: In this paper the comparison of models based on a linear regression and neural networks is presented. The analyzed models are the generalized profile function models, GPFM. The GPFM provides approximations of the individual models (individual stem profile models) of the objects using only two basic measurements. The performances of the obtained GPFM, by using the linear regression relations and neural networks are compared by a test platform in MATLAB with a simple graphic user interface. It is shown that application of both linear regression and neural networks provides the efficient and robust generalized model with very good performances.

Keywords: Neural networks, Linear regression, Profile function, Generalized profile function models.

1 Introduction

This paper presents the comparison of the generalized profile function models based on linear regression and neural networks. The **generalized profile function models**, GPFM, provides approximations of individual models (individual stem profile models) of any object (spruce tree) in the region without detailed measurements on the every object. Development of the nonlinear generalized models, is given in [1 – 3] and linear in [4 – 6]. A derivation of the GPFM based on neural networks is described in [7 – 11]. For the purpose of comparison and testing of the both proposed approach, a test platform in MATLAB with a simple graphic user interface is created, [12].

Note that a region can contain thousands of individual objects with individual profile model. Since the complete (detailed) measurements on all objects are practically impossible, we shall try to find GPFM that enables obtaining any individual model only by using the basic measured values D and H, that is, the sets of values, data pairs, (1.3, D) and (H, 0), where D is the diameter of a tree at breast height, 1.3 m and H is the total height of a tree. Generally speaking, the values of data pairs (h, r) denote the tree radius r at the height h.

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The GPFM enables to obtain a hight accuracy of the computed volume of standing trees. This is very important for sustainable management of the observed ecological system.

2 Input Data

A total 42 objects, [13], are considered in this paper. On each object a total of 13 diameters are measured and 1092 data (546 data pairs) was used to generate and validate the models. The **Total** dataset was divided into two subsets: the **Basic** (model**)** and the **Validation** datasets, so that the Basic dataset contains the first half of the Total dataset.

The basic statistical properties of all three input datasets, average values, medians, standard deviation (SD), minimum and maximum values, are summarized in the **Table 1**.

Table 1
Summary statistics of the input datasets.

	D[cm] *H*[m]	Aver.	Med.	SD	Min.	Max.
Total Dataset	*D*	27.57	28.25	10.58	6.00	48.40
	H	24.28	24.77	7.86	5.65	36.15
Basic Dataset	*D*	31.66	28.60	6.52	21.70	47.00
	H	27.48	26.80	4.80	20.40	35.00
Validation Dataset	*D*	23.49	18.90	12.32	6.00	48.40
	H	21.08	19.80	9.07	5.65	36.15

Table 1 show that the Validation dataset contains the same minimum and maximum values of *D* and *H* as the Total dataset. The Basic dataset contains bigger trees, and the averages of D and *H* are the biggest. Note also that Hui and Gadow (1997) [1] and Korol and Gadow (2003) [2] use **only one** dataset.

3 Models Used

Two forms and types of stem profile models are reported in this paper:

(1) the model based on the modified Brink's function, MBF, Brink and Gadow 1986, [14], Riemer et al. 1995, [15] and

(2) the model based on neural networks, NN, [7 – 9, 11]. For every model tree (stem) the data-pairs (height-radius) were measured and the all available data were fitted by using the both methods.

3.1 Application of MBF

The application of MBF is very favorable in the process of conifer stem profiles modeling and other processes of this type. The canonical form of this function, [15] is:

$$r(h) = u + v\,\mathrm{e}^{-ph} - w\,\mathrm{e}^{qh}, \tag{1}$$

where:

$$u = \frac{i}{1-\mathrm{e}^{q(1.3-H)}} + \left(\frac{D}{2} - i\right)\left(1 - \frac{1}{1-\mathrm{e}^{p(1.3-H)}}\right), \tag{2}$$

$$v = \frac{\left(\frac{D}{2} - i\right)\mathrm{e}^{1.3p}}{1-\mathrm{e}^{p(1.3-H)}}, \tag{3}$$

$$w = \frac{i\,\mathrm{e}^{-qH}}{1-\mathrm{e}^{q(1.3-H)}}. \tag{4}$$

As we can see, *u, v* and *w* depend on the basic measured values *D* and *H* and the parameters *i, p* and *q.* The **original values** of these parameters can be determined by using a standard optimization procedure, in the **process of fitting** the measured stems. Standard optimization procedures can be applied using standard program packages such as Curve Expert (User defined models), Statgraphics Plus or SPSS for Windows. Note that the Levenberg-Marquardt algorithm is included in all of these program packages. At the end of this process, parameters *i, p* and *q* are to be obtained for all the observed individual stems.

The optimization procedure requires, besides the basic measured values *D* and *H*, minimum 3 new measured data-pairs, (*h, r*). The **original values** of the parameters *i, p* and *q* versus *D* and *H* are presented in Fig. 1a, 1b, 1c, 1d, 1d, 1e and 1f. In these figures, the intercept on *y* axis is *a*, *b* the slope of regression line, *S* standard error and *R* correlation coefficient.

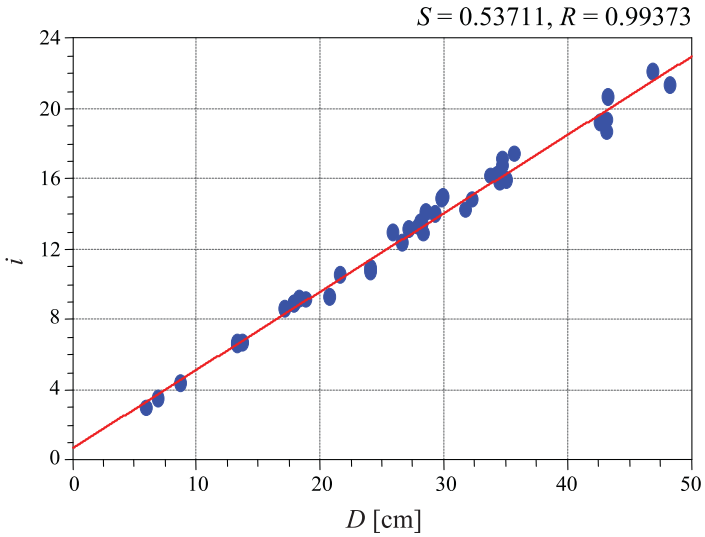

Fig. 1a – *The original values of the parameters i versus D* ($y = a + bx$, $a = 0.70187$, $b = 0.44560$).

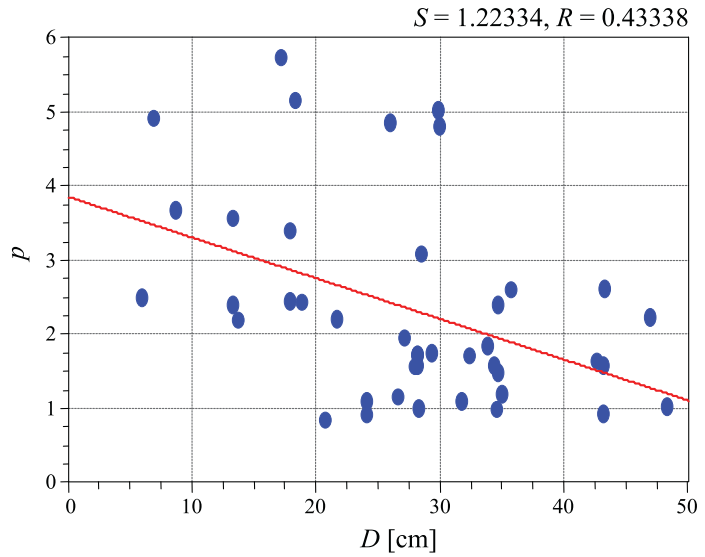

Fig. 1b – *The original values of the parameters p versus D* ($y = a + bx$, $a = 3.85462$, $b = -0.05493$).

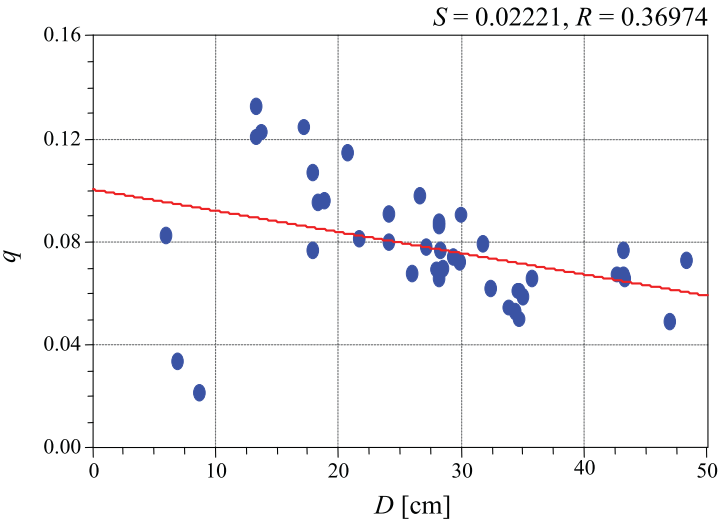

Fig. 1c – *The original values of the parameters q versus D* ($y = a + bx$, $a = 0.10040$, $b = -0.00083$).

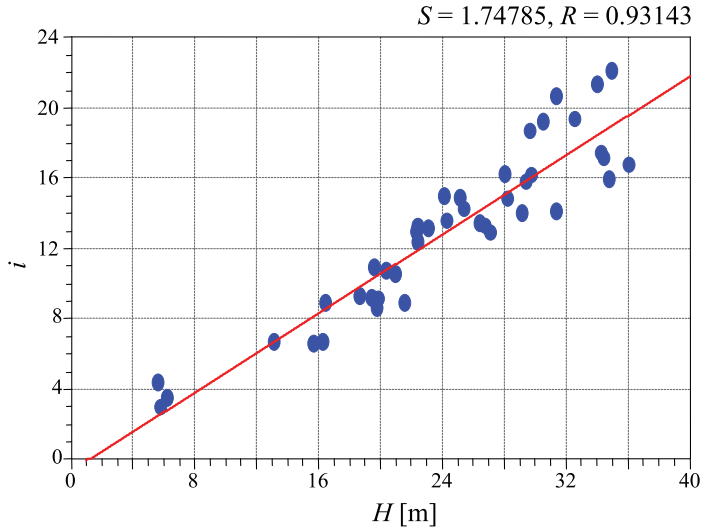

Fig. 1d – *The original values of the parameters i versus H* ($y = a + bx$, $a = -0.65502$, $b = 0.56183$).

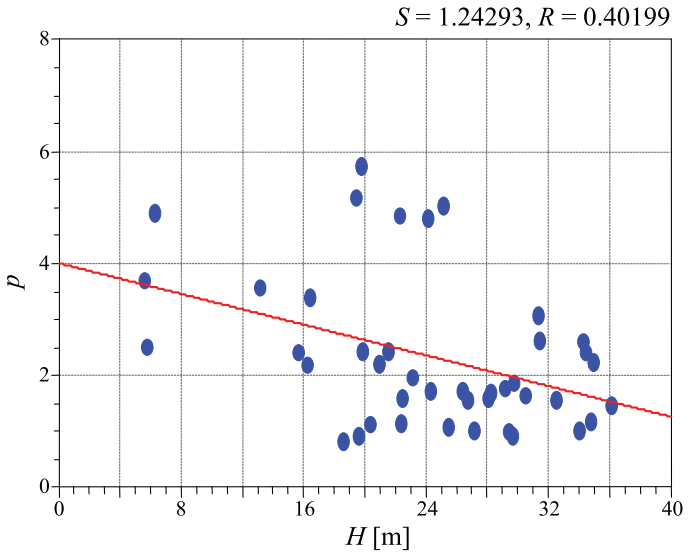

Fig. 1e – *The original values of the parameters p versus H* ($y = a + bx$; $a = 4.00437$, $b = -0.06853$).

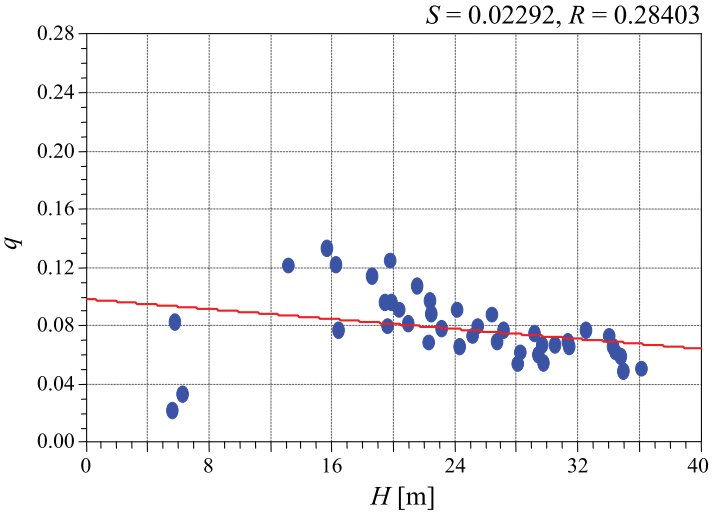

Fig. 1f – *The original values of the parameters q versus H* ($y = a + bx$; $a = 0.09835$, $b = -0.00085$).

3.2 Application of neural networks

Generally speaking a neural network is a machine like human brain with properties of learning capability and generalization. The basic property of this network is that it enables approximation of complicated nonlinear functions, [16]. A typical structure of a NN is three-layer feed forward NN. The commonly used activation functions of neural networks include linear functions for output (layer) neurons, logistic sigmoid functions for hidden (layers) neurons, and identity functions for input (layer) neurons, [17 – 19]. The number of hidden layers and neuron in each layer is problem depended complexity (Obvious problem complexity defines NNs complexity). The number of weights determines the learning ability. So it is very important to choose correct number that can train network correctly and not entrapped into over fitness for limited data. So we choose a topology that balances generalization and specialization [20].

In modeling many different biological process NN ensure smaller modeling error than classical methods [21]. In this study, a three layered feed forward NN with back propagation algorithm and with 2 *tansing* neurons in the hidden layer were used. The *tansig* neurons have logistic sigmoid tangent hyperbolic transfer function.

In this paper models with different heights increment but with same number of data pairs are used. For example, for the smallest (5.65 m) and for the largest (36.15 m) tree, the height increments of 5.65 mm and 36.15 mm are used respectively. In this way all models have 1001 data pairs. In process of developing of the generalized model, the normalized individual models are needed. Because of that all available individual models are normalized.

Normalization along x axis was done by using the total stem height H, and along y axis by using the stem radius measured at the ground level, $y(0)$. In other words, the normalized models show a plot of relative radiuses against relative heights.

The very common form (shape) of the normalized individual model is presented in Fig. 2 by the **dashed line**.

In the considered case, the presented **normalized** model corresponds to the 53-year-old spruce. In the same figure, the normalized individual models of the 103 and 12-year-old spruces are presented with solid and doted lines, respectively. The error of modeling, (i.e. the model variation from the measured data), of the first model, the 53-year-old spruce, is presented in Fig. 3.

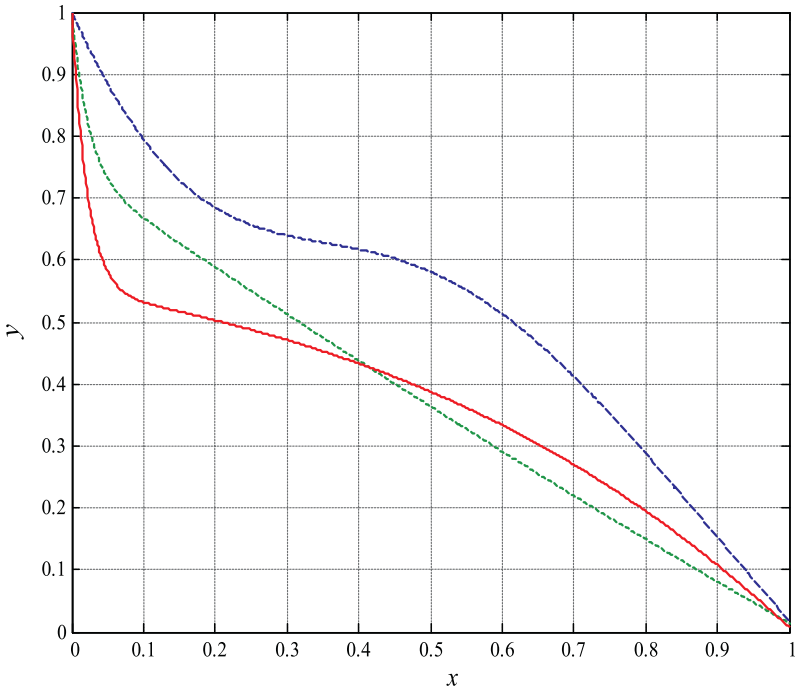

Fig. 2 – *Three characteristic normalized models.*

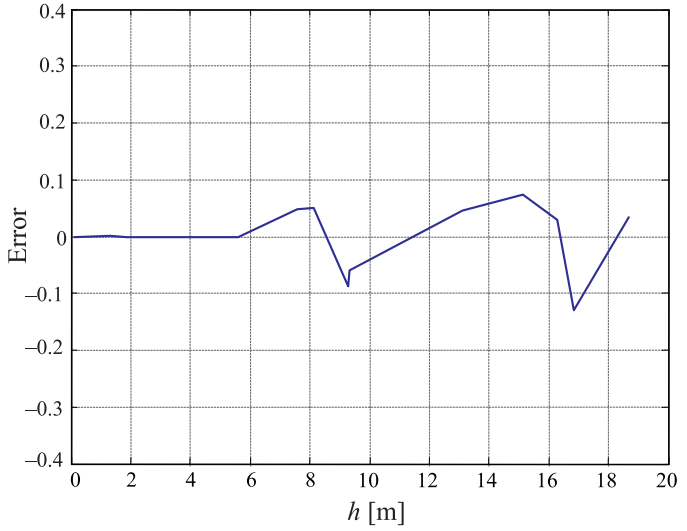

Fig. 3 – *Error of modeling normalized by D/2.*

4 Generalized Profile Function Model

In this section, we shall try to find GPFM that enables obtaining approximations of any individual model only by using the basic measured values *D* and *H*.

4.1 GPFM based on application of MBF

In the case of the application of MBF and linear regression, the aim is to find a set of appropriate regression relations in order to estimate the form parameters *i, p* and *q* at the regional level. In other words, the aim is to determine the form parameters *i, p* and *q* only using linear relation of *D* or *H,* or of *D* and *H*.

In Figs. 1a, 1b and 1c standard errors *S* are smaller than in Figs. 1d, 1e and 1f, respectively. In addition, regarding the same figures, correlation coefficients *R* are larger in Figs. 1a, 1b and 1c, than in Figs. 1d, 1e and 1f, respectively. Based on Fig. 1 and on values of standard error, *S* and correlation coefficient *R*, it can be concluded, that if only the simple linear regression is used, it is better to determine the parameters *i, p* and *q* using a linear function of *D* than of *H*. In this way, we get *Model 1*. Similar approach for the corresponding data set (156 objects) is given in [4].

Model 1.

$$i = 0.70187304 + 0.445596080D, \tag{5}$$

$$p = 3.85461520 - 0.054925113D, \tag{6}$$

$$q = 0.10039749 - 0.0008251098D. \tag{7}$$

Note that standard errors, *S*, for parameter *q*, in the cases when *q* is presented by linear functions of *D* or *H*, are very similar, Figs. 1c and 1f, 0.0222 and 0.0229, respectively. However, as *q* defines the performance of MBF in the upper part of the stem, i.e., from the inflection point to the top of the tree, it is logical to expect good result in the case when *q* is a function of *H*, also. Based on this fact, *Model 2* is defined by (5), (6) and (8).

Model 2.

$$q = 0.09835186 - 0.00085263342H. \tag{8}$$

Based on Figs. 1b and 1e, it can be concluded that there is very low correlation between *p* and *D* or *H*, *R* = 0.4334 and 0.4020 respectively. The correlation between *q* and *D* or *H* is even less, 0.3697 and 0.2840 respectively. It can be seen that there is a very large dispersion of points on Figs. 1b, 1c, 1e and 1f. Also, analysis show that in the cases of using polynomial functions of 2 and 3 degree, correlation coefficients will not be significantly larger. These facts serve as **the justification for applying linear functions** instead of

complex nonlinear functions, used in [1 – 3]. The similar example for a different dataset is given in [4]. It is shown in [6], by using 5 different models based on simple and multiple linear regressions that *Model 2* represents the best linear model for the studied region.

4.2 GPFM based on NN

In the case application NN, the generalized model is obtained as mean (average) value of all available **normalized** individually profile models. Computation of the mean normalized model based on the adequate (sufficient) dataset of normalized individual profile function models (as in Fig. 2) will produce the GPFM for the considered region. The GPFM will have a satisfactory accuracy if the used normalized individual profile function models are adequately selected. An adequate dataset should encompass a sufficient number of characteristic stands with model trees. In our case, the characteristic stand contains one or two model trees.

In Fig. 4 the dashed line represents the first generalized profile function model, GPFM 1, based on the first 21 analyzed trees, that is, on the Basic dataset. The dotted line represents the second generalized stem profile model, GPFM 2, based on the second set of 21 analyzed trees, that is, on the Validation dataset. The two models are very similar, so that it can be assumed that practically the model GPFM 1 was validated by the model GPFM 2. This means that 21 stems are sufficient to generate an acceptable generalized model.

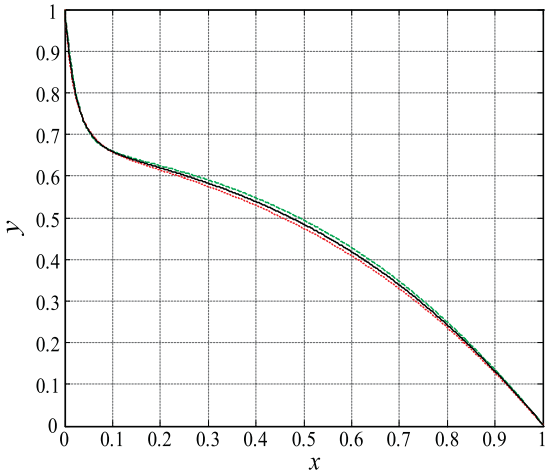

Fig. 4 – *Generalized profile function models*, GPFMs.

The solid line represents the generalized model, GPFM, based on all analyzed trees and we can say that a very convergent generalized model is

obtained. It can be concluded that the generalized model, GPFM, is the special normalized model which is presented in Fig. 4 or GPFM is in fact, GPFM table with 1001 corresponding data pairs.

The presented generalized model in Fig. 4 can be used for generating the approximate of any individually profile model. The renormalization is performed so that each individual (renormalized) model passes through the characteristic point (x_0,y_0), (x_0 *breast height* = 1.3 m, $y_0 = D/2$, *radius at breast height*) and the final point *(H,*0). The renormalization per x axis is performed with H, and per y axis with $y(0)$ where:

$$y(0) = (D/2) / [y\ (1.3/H)]. \tag{9}$$

The value $y(1.3/H)$ is obtained using the obtained generalized model, Fig. 4., or from the GPFM table.

5 Comparison of the Obtained Generalized Models

The accuracy and applicability of the presented generalized models will be assessed in this section. Accuracy of the generalized models will be tested by the regression analysis. Correlation coefficients and standard errors between the measured and estimated radiuses r and referent and estimated volumes will be computed.

5.1 Comparison of the estimated radiuses

The results of testing of accuracy of the estimated radiuses r in the case of applications GPFM based on neural networks, but with smaller data sets, with 6, 14 and 20 objects, are presented in [7 – 9, 11], also.

In this paper comparison of the obtained generalized models is based on Figs. 5, 6, 7 and 8.

A Comparison of measured and estimated *r*
(GPFM based on linear regression)

The comparison of the measured and estimated radiuses r for all h, in the case of applications and GPFM based on linear regression, *Model 2,* is presented in Fig. 5.

It can be seen in Fig. 5, that the deviation of the estimated r from measured r is too high. It is known that the biggest difference between the measured and estimated radiuses r occurs for the biggest radiuses because of irregularity the root swelling trees (The biggest difference occurs on the ground level). Because of that in numerous papers, the comparison of the radiuses is made only for heights above ground level bigger than 1 m, Korol and Gadow (2003) [2].

The comparison of the measured and estimated radiuses in the case of linear regression, only for $h > 1$ m, is presented in Fig. 6.

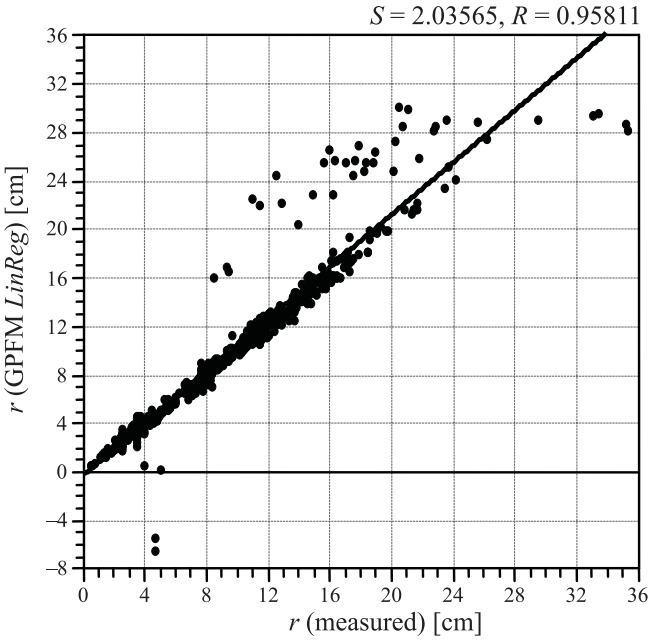

Fig. 5 –*Comparison of measured and estimated r for all h* (GPFM *based on linear regression*).

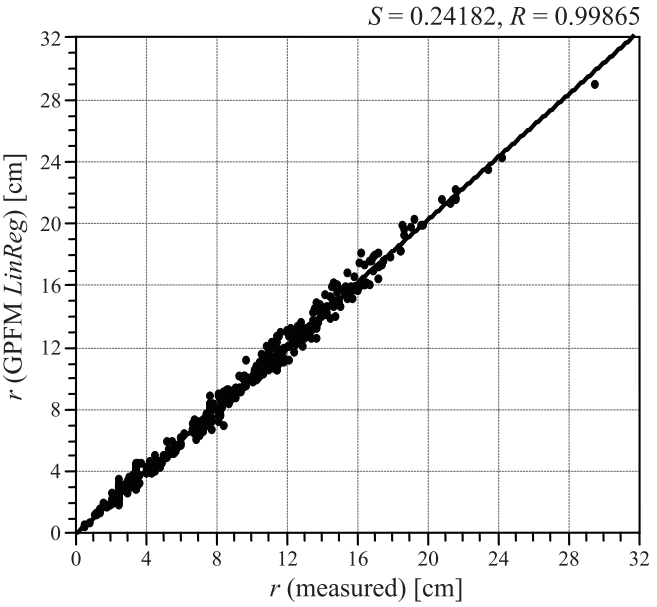

Fig. 6 – *Comparison of measured and estimated r only for h* > 1 m (GPFM *based on linear regression*).

Values of the statistics of data comparison by the regression analysis for all 4 figures (Figs. 5, 6, 7 and 8) are presented in **Table 2**. The first pair of results of the data comparison represents intercept on *y* axis and the slope of regression line. It is obvious that the ideal angle of the slope of regression line obtained by the comparison of the estimated and the measured data is 45°, and that it should start from the origin. In other words, the value of the parameter *b* should be near 1.0, and the value of parameter *a*, intercept on *y* axis, should be near 0. The second pair of the results refers to the standard error of the estimate *S*, and the correlation coefficient *R*. It can be seen in **Table 2** that the values of the intercept on ***y*** axis and standard error of the estimate, Fig. 5, are irregular and extreme height, –0.1998 and 2.0356.

It can be seen in Fig. 6 and **Table 2**, that the intercept on ***y*** axis, the slope of regression line, standard error of the estimate and the correlation coefficient are satisfactory.

B Comparison of measured and estimated *r* (GPFM based on NN)

In the case of applications of neural networks, comparison of the measured and estimated radiuses, of all *h*, is shown in Fig. 7.

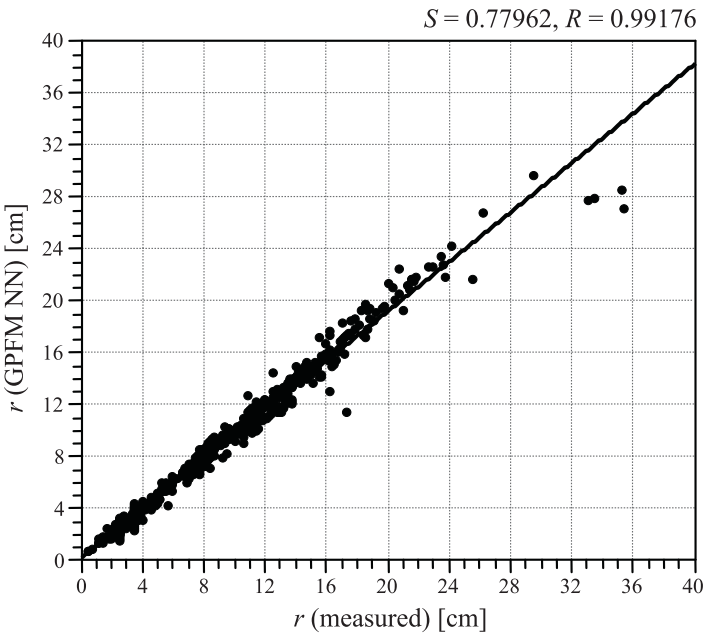

Fig. 7 – *Comparison of measured and estimated r for all h* (GPFM *based on* NN).

As we can see, Fig. 7, in the case of using GPFM based on neural networks, for all h, the intercept on y axis, the values of the slope of regression line, standard error of the estimate and the correlation coefficient are satisfactory, **Table 2**.

The comparison of the measured and estimated radiuses in the case of using GPFM based on neural networks, for h > 1m, is presented in Fig. 8.

Table 2
Values of the statistics of data comparison.

Statistics of the *r* comparison					
	Interc. *a*	Slope *b*	Std. Err. *S*	Corr. coeff. *R*	R^2 [%]
LR all data	−0.19985	1.07482	2.03565	0.95811	91.80
LR for h>1.m	0.00356	1.01326	0.24182	0.99865	99.74
NN all data	0.22339	0.95279	0.77962	0.99176	98.37
NN for h>1.m	0.04813	0.97498	0.48017	0.99594	99.18

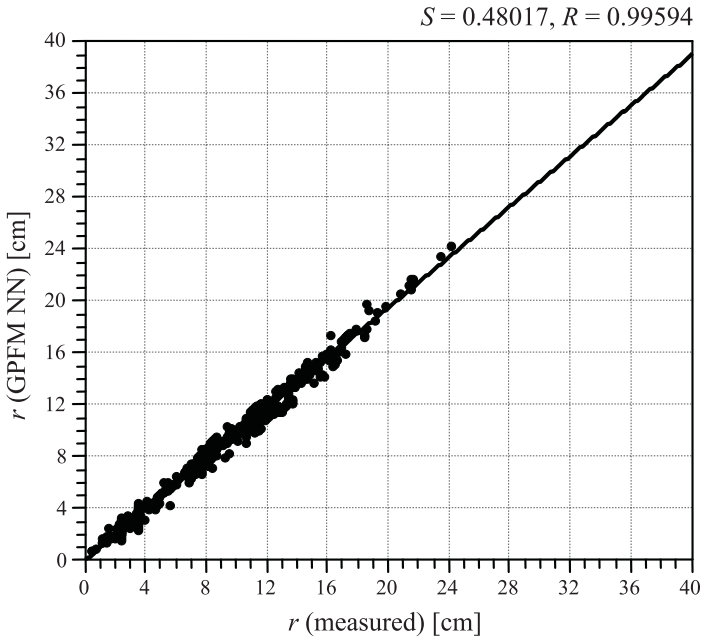

Fig. 8 – *Comparison of measured and estimated r only for h* > 1m (GPFM *based on* NN).

The slopes of regression lines in Figs. 6 and 8 are very close to 1, 1.0133 and 0.9750, **Table 2**. Also, the correlation coefficients are very similar, 0.9987 and 0.9959.

It is important to emphasize that in the case of applications GPFM based on neural networks, acceptable results are obtained practically for all radiuses.

5.2 Comparison of accuracy of the obtained GPFMs in volumes computing

The very important purpose of the generalised stem profile models is to estimate both the individual standing trees volumes (with an acceptable accuracy) and the total stand volume (as precisely as possible). Evidently that the estimate of volume of the individual trees should be unbiased.

A Comparison of referent and estimated *V* (GPFM based on linear regression)

Using the assumption that the stem is a symmetric geometrical figure which is formed by rotating the stem profile function around *h*-axis, it is possible to get an expression for stem volume computing. The volume can be calculated now using (10), that is, the definite integral [15], where the sub-integral function is the square of the stem profile function, equation 1.

$$V(h) = \pi \int_0^h (u + v\,\mathrm{e}^{-ph} - w\,\mathrm{e}^{qh})^2 \,\mathrm{d}\,h\,. \tag{10}$$

In the considered case, the square of the profile function is an integrable function, so that it is possible to determine an analytic expression for calculation of the stem volume [15, 22]. These references present explicit relations and also several examples of the calculated volumes.

Testing of the accuracy of the obtained GPFM is performed by comparing the obtained estimated volumes with the referent volumes. **The estimated volumes** represent the volumes based on GPFM, *V*(GPFM), and the the **reference** volumes are obtained for every stem individually, using MBF, that is, using the original values of *i*, *p* and *q* parameters, [15, 22], **Table 3**, *V*(MBF).

In **Table 4**. basic values of the statistics of the estimated volumes based on GPFM, are given.

The volumes will be compared by applying the regression analysis. The first pair of results of the volume comparison represents statistical performance in volume estimation. These are regression statistical parameters, standard error of the estimate, S_{VE} and the correlation coefficient R_{VE}. The second pair in the results contains the slope of the regression line and the intercept on *y* axis.

Evidently, the slope of the regression line obtained by comparing the estimated and the reference volumes, in the ideal case must have the angle of 45° and has to start from the origin. In other words, parameter *b* has to have value near 1.0 and parameter *a*, that is the intercept on *y* axis, has to have the value near 0.

Table 3
The basic values of the statistics of the calculated volumes based on MBF and original i, p and q parameters.

	V [m^3]	Aver.	Med.	SD	Min.	Max.
Total Data set	*MBF*	0.9464	0.7973	0.7774	0.0098	2.8930

Table 4
Values of the statistics of the estimated volumes.

	V [m^3]	Aver.	Med.	SD	Min.	Max.
Total Data set	GPFM *Lin. Reg.*	0.9839	0.8176	0.7991	0.0459	3.0444

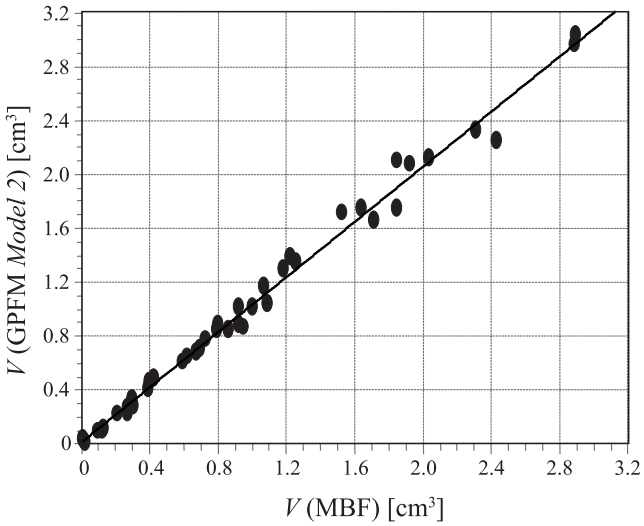

Fig. 9 – *Statistical performances in volume estimation* (GPFM *based on linear regression*), $a = 0.0156$, $b = 1.0222$.

B Comparison of referent and estimated *V* (GPFM based on NN)

When NNs are used for obtaining the individual profile function, stem volumes can simply be calculated by using the ***inner vector product*** instead of numerical integration. With the assumption that all the values of $r(h)$ define the ***row vector R***, the volume can simply be calculated by the equation:

$$V(NN) = \pi \boldsymbol{R} \cdot \boldsymbol{R}^T \cdot \Delta h\,, \tag{11}$$

where Δh is the height increment (5.65 – 36.15) mm. In the considered case, the row vector $\boldsymbol{R}$ contains 1001 values.

The basic statistical performance of the calculated volumes *V*(*NN*) based on (11) are presented in **Table 5**. Note that these values are very similar with values presented in **Table 3**.

Table 5

The basic values of the statistics of the calculated volumes.

	V [m^3]	Aver.	Med.	SD	Min.	Max.
Total Data set	NN	0.9473	0.7953	0.7755	0.0100	2.8905

Testing of the accuracy of the obtained GPFM is performed by comparing the obtained estimated volumes with the referent volumes. **The estimated volumes** represent the volumes based on GPFM, *V*(GPFM), and the **referent volumes** are in fact *V*(NN).

In **Table 6** values of the statistics of the estimated volumes based on GPFM, are given.

Table 6

Values of the statistics of the estimated volumes.

	V [m^3]	Aver.	Med.	SD	Min.	Max.
Total Data set	GPFM	0.8938	0.7764	0.7124	0.0105	2.7375

Testing of the efficiency of volume estimation can be performed by comparing the obtained estimated volumes with the referent volumes by the regression analysis. As in the case of radii comparison, in the ideal case it is necessary that four important regression parameters have already mentioned values.

Comparison of the estimated and referent volumes done by regression analyses for the total data set is illustrated by Fig. 10.

We can see in Fig. 10 that the volumes based on GPFM do not deviate much (except four points) from the referent volumes, S_{VE} = 0.0853 and R_{VE} = 0.9930, **Table 7**. It can be seen that the regression line starts approximately from the origin, as the translation along *y* axis is only 0.0326.

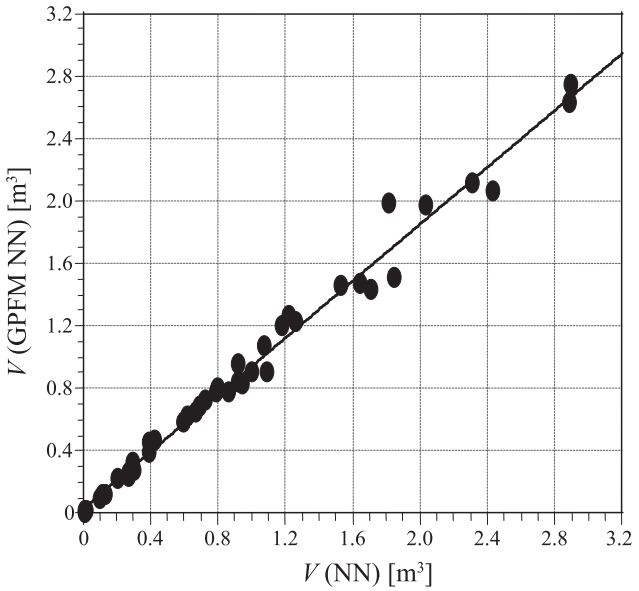

Fig. 10 – *Testing of volume estimation V*(GPFM) *versus V*(NN) (GPFM *based on* NN).

Table 7
Values of the statistics of volume estimation using GPFMs.

Statistics of the *V* comparison					
	Interc. *a*	Slope *b*	Std. Err. *S*	Corr. coeff. *R*	R^2 [%]
GPFM *Lin. Reg.*	0.0156	1.0222	0.0772	0.9954	99.08
GPFM NN	0.0326	0.9100	0.0853	0.9930	98.60

6 Conclusion

By comparing the measured and estimated radiuses, it is shown that the obtained generalized profile function models, based on linear regression and neural networks, can be very successfully used in the process of the approximation of the individual profile functions. The standard errors for h>1m in the case linear regression is smaller, 0.24182 compared with 0.48017, in the case of the application of neural networks, **Table 2**. However, the correlation coefficients between measured and estimated data in the case linear regression for h > 1m and neural networks for all h are very high, over 0.99 for both

GPFM. GPFM based on neural networks practically can be used for all h. Typical limits ($h > 1.0$ m) are not needed in this case. From this point of view the obtained generalized profile function model based on neural networks is better than the models based on linear or nonlinear regression.

Accuracy of estimated volumes obtained by using generalized profile function models, based on both linear regression and neural networks are satisfactory, **Table 7**. Results obtained by regression analyses presented in **Table 7** show inappreciable preference of GPFM based on linear regression regarding of volumes estimation.

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