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PREDICTION MODEL OF PUBLIC HOUSES' HEATING SYSTEMS: A COMPARISON OF SUPPORT VECTOR MACHINE METHOD AND RANDOM FOREST METHOD

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Abstract. *Data analysis and predicting play an important role in managing heat-supplying systems. Applying the models of predicting the systems' parameters is possible for qualitative management, accepting appropriate decisions relating control that will be aimed at increasing energy efficiency and decreasing the amount of the consumed power source, diagnosing and defining non-typical processes in the functioning of the systems. The article deals with comparing two methods of ma-chine learning: random forest (RF) and support vector machine (SVM) for predicting the temperature of the heat-carrying agent in the heating system based on the data of electronic weather-dependent controller. The authors use the following parameters to compare the models: accuracy, source cost and the opportunity to interpret the results and non-obvious interrelations. The time spent for defining the optimal hyperparameters and conducting the SVM model training is deter-mined to exceed significantly the data of the RF parameter despite the close meanings of the root mean square error (RMSE). The change from 15-min data to once-a-minute ones is done to improve the RF model accuracy. RMSE of the RF model on the test data equals 0.41°C. The article studies the importance of the contribution of variables to the prediction accuracy.*

Keywords: building heat supply, random forest, support vector machine

MODEL PROGNOZOWANIA SYSTEMÓW GRZEWCZYCH BUDYNKÓW UŻYTECZNOŚCI PUBLICZNEJ: PORÓWNANIE METODY SUPPORT VECTOR MACHINE I RANDOM FOREST

Streszczenie. Analiza danych i prognozowanie odgrywają ważną rolę w zarządzaniu systemami zaopatrzenia w ciepło. Wykorzystanie modeli do przewidywania parametrów systemu jest możliwe do zarządzania jakością, podejmowania odpowiednich decyzji sterujących, które będą miały na celu poprawę efektywności energetycznej i zmniejszenie ilości zużywanego źródła energii elektrycznej, diagnozowania i wykrywania nietypowych procesów w funkcjonowaniu systemu. W artykule porównano dwie metody uczenia maszynowego: Random Forest (RF) i Support Vector Machine (SVM) do przewidywania temperatury czynnika grzewczego w systemie grzewczym na podstawie danych elektronicznego regulatora pogodowego. Do porównania modeli autorzy wykorzystują następujące parametry: dokładność, koszt początkowy oraz możliwość interpretacji wyników i nieoczywistych zależności. Ustalono, że czas poświęcony na wyznaczenie optymalnych hiperparametrów i wytrenowanie modelu SVM znacznie przekracza dane parametru RF, pomimo zbliżonych wartości błędu średniokwadratowego (RMSE). Zmiana z danych 15-minutowych na dane raz na minutę została dokonana w celu poprawy dokładności modelu RF. RMSE modelu RF z danych testowych wynosi 0,41°C. W pracy zbadano znaczenie wkładu zmiennych w dokładność prognozy.

Słowa kluczowe: zaopatrzenie w ciepło budynku, random forest, metoda wektorów wspierających

Introduction

Nowadays economic challenges require searching for solving the issues of energy saving and energy efficiency. The efficiency of the actions aimed at saving the energy source are usually insufficient due to the lack of the complex approach to the issues of managing energy saving and energy efficiency, insufficiency of financing. It causes a significant improvement for the existing and developing information and technical decisions in the energy management [22, 23, 28]. Most of such decisions are based on monitoring and parameterizing the system by an energy manager that allows receiving and saving significant data. The intellectual data processing is known to play more and more important role in the issues of the optimal complex system management. Thus, the predicting models of the parameters of energy consuming systems allow the energy managers at different levels accepting substantiated decisions relating energy management based on the history data about the takes decisions and the received result, analyzing the factors influencing the energy efficiency and noting non-typical values of the system parameters that can be caused by technical breaks or inefficient managerial decisions.

1. Related work

Active implementation of the decisions relating to the automated monitoring and controlling the heating system allows not only controlling the amount of the consumed energy source but also saving large amounts of information on the system functioning, the amount of the consumed source itself and decisions concerning the system management accepted by an energy manager. Various methods of machine learning are widely spread due to the dramatic development of the artificial intelligent in the tasks of managing energy consumption [22, 23, 28].

In the research [24] the authors study the opportunity to predict the energy consumption in the central heating system with the help of Elman network with the use of the genetic algorithm that allows determining the shares in the models.

The comparison of the results received when using the neural networks and the random forest method in the task of predicting the amount of the used energy source observes the higher accuracy is achieved when using the first method [3]. The research6 compares the accuracy of the models of neural nets for predicting heat supply of a range of the building of the budget field and determines that the model of NARX type gives the most accurate results with the simplest design. The authors [10] develop the method of determining energy efficiency of the building with the use of multi-parameter regression based on the data of the municipal service bills and weather websites. SVM method is becoming more common for solving the practical tasks. The article [9] shows the results of modelling and studying the efficiency of the geo-thermal system with the use of SVM method that allows simplifying the modelling process. The authors have conducted a range of researches to determine the optimal parameters for regularization and the kernel parameters. In [8] uses the same method to predict the energy consumption in several buildings in Singapore: uses the data of the external temperature, solar radiation and relative humidity as the input parameters. In the researches [2] and [1] the comparison of the SVM, RF, Extra Trees and regression trees models determines that the stated models have comparative accuracy, different learning time and can be used for predicting solar energy received from the geothermal system. Moreover, RF and Extra Trees can be additionally applied as a tool for decreasing the dimension

of the input data. The issues of managing the heat supplying systems and the implementing the received results into the work of energy man-agers are not fully covered in spite of the number of researches that use machine learning methods for solving the practical tasks in the energy field [3, 24].

The article presents the research on the following aspects:

- comparing SVM and RF methods for predicting the temperature of the heat-carrying agent in the heating system based on the data of electronic controller since a lot of researches focus on neural nets [10, 21];
- using the ensemble RF method to analyze the importance of the contribution of variables into the prediction accuracy. The conducted analysis allows understanding the data and the interrelations between the parameters better [8, 9].

2. Machine learning methods

This part presents two algorithms: RF and SVM used for predicting the temperature of the heat-carrying agent in the heating system based on the data of electronic weather-dependent controller.

The SVM (method of data analysis that is applied for the tasks of classification and regression) is chosen as one of the methods of machine learning to create a predicting model of the heat-carrying agent temperature in the heating system [26]. It is based on the SRM principle that minimizes the upper error boundary that includes the sum of the learning error and the confidence interval instead of minimizing the learning error (empirical risk minimization) [1, 2].

Let us consider that we describe the objects with n-dimensional vectors where X – space of the objects, Y – target output: $X = R^n$, $Y = R$.

SVM of the linear separated data finds the linear function that approximate the output vector Y the best, the function ε – sensitivity that does not consider deviations $a(x_i)$ from y_i less than ε as errors.

The function is the following [7, 26]:

$$a(x) = w \cdot x + b \tag{1}$$

The method is used with different kernel functions to solve the problems of linear non-separability. This is the transfer from the initial space of the feature descriptions of the objects X to a new space H with the help of some transformations $\psi : X \to H$. If the space H has a comparatively high dimensionality, one can hope the sampling to appear linearly separable.

If we consider the vectors $\psi(x_i)$ and not the vectors x_i to be the feature descriptions of the objects, the SVM development is conducted as before. The expression (1) becomes the following [6, 20]:

$$a(x) = w \cdot \psi(x) + b \tag{2}$$

Minimization (2) is equal to a task of the quadratic programming with linear limitation of the types of inequalities. The dual task depending only on the dual variables appears hereby; only the objects of control should be left in the sample; the result is expressed through the scalar product of the objects and not through objects them-selves; kernels can be used.

Let introduce additional variables ξ_i^+ and ξ_i^- which meaning equal the lose on the increased and decreased answer $a(x_i)$ according to the meaning ε.

In this case, the minimization task (2) can be rewritten into the equivalent form as a task of the quadratic programming with linear limitations-inequalities relating to variables w_i, b, ξ_i^+, ξ_i^-

$$\begin{cases} \frac{1}{2}\langle w, w\rangle + C\sum_{i=1}^{l}\left(\xi_i^+ + \xi_i^-\right) \to \min\limits_{w,b,\xi^+,\xi^-} \\ y_i - \varepsilon - \xi_i^- \le w \cdot \psi(x_i) + b \le y_i + \varepsilon + \xi_i^+, \ i = 1,\ldots,l \\ \xi_i^- \ge 0, \ \xi_i^+ \ge 0, \ i = 1,\ldots,l \end{cases} \tag{3}$$

The positive constant C is a control parameter of the method and allows finding the compromise between the minimization of the separating hyperplane and the summary error [25, 29, 30].

The Lagrangian is expressed through dual variables λ_i^+, λ_i^-, $i = 1,\ldots,l$, and the scalar products $\langle x_i, x_j \rangle$ are replaces by the kernel $K(x_i, x_j)$:

$$\begin{cases} L(\lambda^+, \lambda^-) = -\varepsilon\sum_{i=1}^{l}\left(\lambda_i^- + \lambda_i^+\right) + \sum_{i=1}^{l}\left(\lambda_i^- - \lambda_i^+\right) y_i + \\ -\frac{1}{2}\sum_{i,j=1}^{l}\left(\lambda_i^- - \lambda_i^+\right)\left(\lambda_j^- - \lambda_j^+\right) K(x_i, x_j) \to \max\limits_{\lambda^-,\lambda^+} \\ 0 \le \lambda_i^+ \le C, \ 0 \le \lambda_i^- \le C, \ i = 1,\ldots,l \\ \sum_{i=1}^{l}\left(\lambda_i^- - \lambda_i^+\right) = 0 \end{cases} \tag{4}$$

Only the range of coefficients λ_i^+, λ_i^-, $i = 1,\ldots,l$ will differ from zero, and the data relating to them are the support vectors [11, 27].

The regression equation is expressed through the dual variables:

$$a(x) = \sum_{i=1}^{l}\left(\lambda_i^- - \lambda_i^+\right) K(x_i, x_j) + b \tag{5}$$

There are several control parameters in this method: accuracy parameter ε, constant C and parameters relating to the chosen kernel type. All the parameters are interdependent. The constant C controls the smoothness and flatness of the approximation function: the bigger one C leads to the bigger error fine and makes the learning machine bulky; the smaller one C, in the contrary, leads to the excessive error "transfer" that worsens the algorithm accuracy. The parameter ε influences the smoothness and the number of control vectors [12, 13, 14].

RF is the algorithm of machine learning that lies in the use of the bagging method on the set of the decision trees with the use of the method of random subspaces and can solve the tasks of classification and regression [13].

CART (classification and regression tree) is based on decreasing the level of heterogeneity – the task of classification or the chosen error level of assessing prediction – the task of regression on each node of the tree.

The characteristics of the trees of RF lie in their development without the padding function – the usage of the full depth: since we consider the average result of the set of trees, there is no need in adjusting each of them that is a deviation from the standard CART algorithm [12, 18].

Training of separate trees in RF takes place independent of each other, on different subset which parts can be repeated due to the use of the bagging method in the algorithm.

Bagging (from bootstrap aggregation) is one of the first and the simplest types of ensembles based on the statistic bootstrap method. Leo Breiman developed it in 1994. The method lies in the equal selection of N objects from the sample with returning: an object is selected from the sample (we consider each object with probability 1/N) though every time from all output N objects. Approximately 37% of samples are out of the bootstrap sampling and are not used.

The probability of the object getting into the sample (i.e. it is taken N times):

$$\left(1-\frac{1}{N}\right)^{N} \approx 1-\frac{1}{e} \approx 63\% \tag{6}$$

The bagging lies in training the regressors or classifiers on the samples that are generated by the bootstrap and creating the summing regressor or classifier that average the results of all the algorithms in the regression tasks and in the case of classification – on the voting results [5, 19].

Bagging allows decreasing the dispersion of the taught classifier by decreasing the value of the error difference when training the model on different data sets or, in other words, prevents overfitting. The efficiency of bagging is achieved due to the basic algorithms being taught on different samples and having compensating errors because of the diversity; rejections and absent values can't get to a part of samples that makes the RF algorithm resistant to them.

If there are missed values of predictors for the full observation when developing the model with the RF method, the prediction for the case is based on the previous node of the corresponding tree [4, 16].

The method of random subspaces allows decreasing the level of correlation be-tween the trees and avoiding overfitting. When building each of the stated number of trees in RF while creating nodes the selection of the feature used for the basis of separation is done only from the randomly chosen features from the sets of all data features. The basis algorithms are taught on different subset of the feature description [15, 17].

It is worth noting that the absence of the need in the usage of a separate set of data for validation is an advantage of the algorithm: since a part of data does not get into the bootstrap sample (approximately 37%), the mean squared error and the percentage of the described dispersion is calculated with the help of an out-of-bag error.

3. Materials and methods

To build a prediction model, the authors gather a set of data with 15-min interval from the monitoring and control automated system (MCAS) of multi-storey building during the period of October 13, 2017 – February 12, 2018 that include 32 parameters: Date – date, Time – time, Tout – outer temperature, Tin – inner temperature, Tin_yst – setting 1 of inner temperature for mode 1, Tin_yst_max – influence on the setting of inner temperature, , Tin_yst1 – setting of the inner temperature for mode 0, Tv – temperature of the heat-carrying agent when powering the heating system, Tvmin – setting of the minimal temperature Tv, Tvmax – setting of the maximal temperature Tv, Tv_yst – setting of the heat-carrying agent temperature when powering the heating system, Tv_tg – heat-carrying agent temperature when powering the heating system on the temperature diagram, S – diagram pitch, P – diagram shift, T1_tg – heat-carrying agent temperature when powering the house on the temperature diagram, Tret – heat-carrying agent temperature in the reverse heating system piping, Tret_tg – heat-carrying agent temperature in the reverse heating system piping on the temperature diagram, Tam – the combined temperature of the outer air, Tad – smooth value of the outer temperature, etc.

The following measurements are used to assess the efficiency of the developed models on the study and test samples: root mean square error (RMSE), mean absolute error (MAE) and determination coefficient (R^2):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)^2}{N}} \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - y_i\right| \tag{8}$$

$$R^2 = 1-\frac{\sum_{i=1}^{N}\left(y_i-\hat{y}_i\right)^2}{\sum_{i=1}^{N}\left(y_i-\bar{y}_i\right)^2} \tag{9}$$

where y_i – actual value, $\hat{y}_i$ – predicted value, N – number of values.

Root mean square error (RMSE) is used as a primary evaluation metric. Described dispersion is calculated with the help of an out-of-bag error [14].

Table 1. Value ranges of some predictors

No	Variable	Minimum, °C	Maximum, °C
1	Tout	-14.2031	15.1250
2	Tin	13.0000	19.9531
3	Tin_yst	12.0000	22.1094
4	Tin_yst_max	0.5000	0.5000
5	Tin_yst1	16.1250	20.1094
6	Tv	21.6562	67.1875
7	Tvmin	8.0000	45.0000
8	Tvmax	40.0000	80.0000
9	Tv_yst	0.0000	58.0000
10	Tv_tg	51.0000	66.0000
11	Tret	21.8437	140.0000
12	Tret_tg	46.0000	58.0000
13	Tam	-12.5781	14.7656
14	Tad	-10.6562	14.6719

4. Results and discussion

Hyperparameters of SVM model significantly influence the prediction accuracy and reliability. The number of parameters that require adjusting depend, first, on the choice of the kernel functions. Researches relating to the subject area often use the RBF (radial basis function) kernel to solve regression tasks, since it allows expressing non-linearly the sample in the high space and has a smaller number of hyperparameters for adjustment comparing to the polynomial kernel: kernel coefficient (γ), the "C" – constant of the regularization term in the Lagrange formulation (*C*), accuracy parameter (ε). The kernel coefficient equals $1/K$ as a default, where K – number of input variables. Thus, in this case $\gamma = 1/31 = 0.032$.

Since there in not a distinct method for determining the optimal adjustments of the model parameters, the adjustment of hyperparameters is the next stage. Grid search is a traditional ways of optimizing hyperparameters. It is an exhausting search through the manually determined subset of the hyperparameter space of the algorithm. The search algorithm should be guided by a metrics of efficiency that is usually measured by cross-validation in the training set. Since the hyperparameters being optimized are built in the Cartesian space and are checked in pairs when cross-validating, the algorithms suffers from the excessive dimension that leads to a significant increase of the execution time.

When cross-validating the train set of data is divided into k subsets of the same size. Each subset k is used as a set of data for checking while other subsets k-1 are used as a set of data for trainings. This research deals with the 10-times checks for choosing the optimal hyperparameters. Model parameters received after the grid search are given in Fig. 1.

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Parameter tuning of 'svm':

- sampling method: 10-fold cross validation

- best parameters:
 epsilon cost
     0.2  128

- best performance: 1.596522
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Fig. 1. Model parameters received after the grid search

RF method usually requires correction of the two main hyperparameters that influence maximally the adequacy and the result of the model: Number of trees (M) and minimal

number of variables used for splitting (n_{min}). Parameter M is a total number of the trees in the forest and relates to the efficiency of the calculation that creates the need in choosing such number of trees, which allows balancing the performance time and the prediction accuracy. 100 trees are chosen for our research, since the increase of the number do not result in the significant increase of the accuracy with the increase of the performance time. The typical value of the number of variables used for splitting (n_{min}) in the regression task is $p/3$, where p – number of input variables, in this research n_{min} – 10. The depth of trees is not limited in this work; the trees are developed in the full depth.

The table gives RMSE, R2 and MAE on the study and test samples for predicting Tv. The value of RMSE model of SVM is 0.95. Despite the accepted error level, time spent on the model adjustment and SVM sensitivity to the missing values, the complexity of the interpretations of the data contribution make the method too resource-consuming that, in its turn, causes the need in using more optimal method for predicting the heat-carrying agent temperature when powering the heating system.

Since random forest is used for the regression task, it is necessary to consider that the model will predict the value Tv adequately if the input values are within the range of the values of predictors (Table 1) used for the model training (train set).

The data are divided into two sets (train – 70% and test – 30%) before the model development. One set of 15-min data is used for modelling in both models.

The diagram of the comparison of the actual values of the heat-carrying agent temperature when powering the heating system and the values predicted by models with the additionally stated temperature of the outer air is given in Fig. 2.

In spite of the smaller error when using SVM method (table 2), RF algorithm is chosen for further research due to the opportunities of the result interpretation and non-obvious interrelations. The model training is decided to be conducted on every-minute data during the same period to increase the model accuracy (table 3).

Table 2. Results of prediction models performed by RF and SVM

Model	Train			Test		
	RMSE, °C	MAE, °C	R^2, %	RMSE, °C	MAE, °C	R^2, %
SVM	0.92	0.32	97.52	1.13	0.43	97.3
RF	1.1	0.39	97.49	1.19	0.42	97.13

Table 3. results of prediction model performed by RF (every-minute data)

Set	RMSE, °C	MAE, °C	R^2, %	Max. error, °C
Train	0.44	0.08	99.61	15.1
Test	0.41	0.075	99.65	14.95

There is a decrease of the RMSE value and the increase of the percentage of the describes dispersion on the approbation data. Thus, RF temperature model can be considered acceptable for the use aimed at predicting parameters of the heat-consuming system. Despite a big value of the maximal error, the authors note that the number of the predicted data on the approbation sample with the absolute value of error that higher than 5 degrees is 56 from 54,255 values.

The diagram of the comparison of the actual values of the heat-carrying agent temperature when powering the heating system and the values predicted by models with the additionally stated temperature of the outer air is given in Fig. 3.

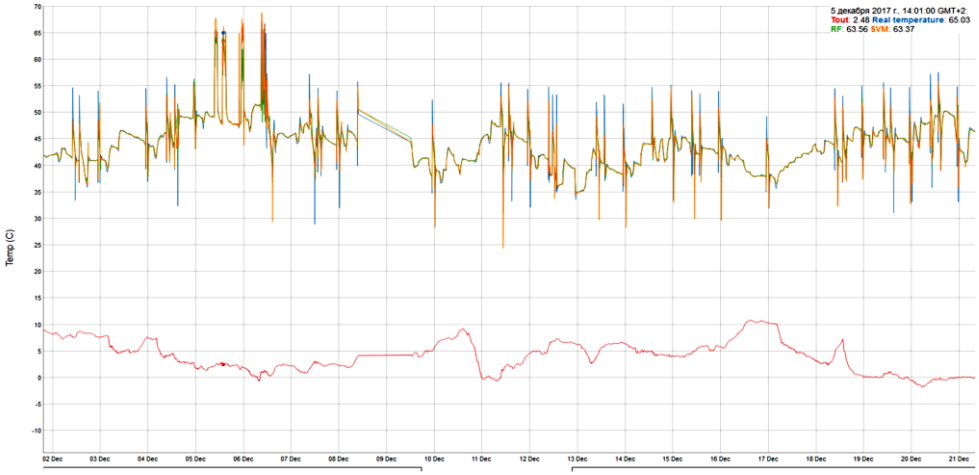

Fig. 2. The curve of the temperature estimated with the random forest and the SVM on the testing set

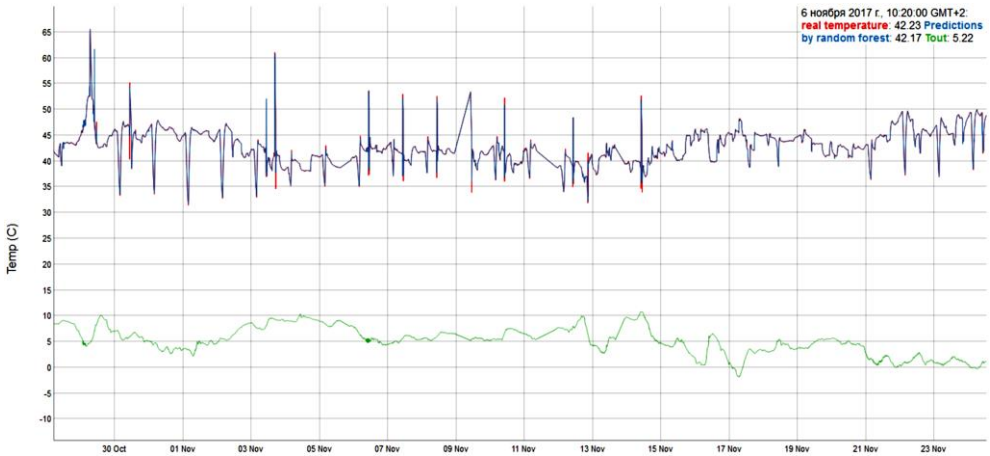

Fig. 3. The curve of the temperature estimated with the random forest on the testing set

The comparison of the result of the RF end model and the actual data is given on table 4. Mean value measuring the middle tendency in the set of data proves that the data predicted by the model are similar to the actual data. The standard deviation is the indicator of dispersing the values comparing to the values of the actual data is determined that SVM has almost similar standard deviation like actual data. The median of values received with the help of RF corresponds to the values received on the actual data. Minimal and maximal values allow dividing the data discharge. RF has a maximal value that is bigger than the actual data value. The kurtosis and skewness reflect the form of the data distribution. Skewness is a measurement of the data set symmetry. Kurtosis is the value describing the form of the distribution tail area and not the sharpness or the filling of the distribution [11, 30].

Table 4. Comparison of the statistical measures

Factor/Variable	Actual TV	RF
Mean	43.5	43.5
Median	43.8	43.8
Standard deviation	7.05	7.03
Kurtosis	3.14	3.16
Skewness	-1.26	-1.28
Range	45.56	45.14
Minimum	21.66	21.67
Maximum	67.22	66.81

The distribution of the mean minimal depth of each tree is studied to determine the importance of parameters: the depth of the node which splits on this variable and is the closest to the root of the tree (Fig. 4) and the complex measurement of the importance of variables (Fig. 5).

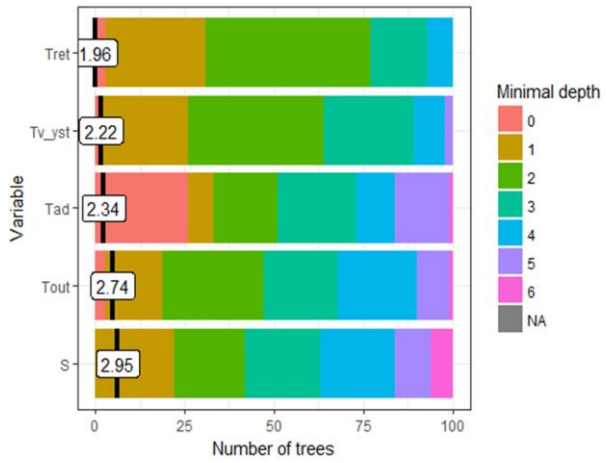

Fig. 4. The distribution of mean minimal depth

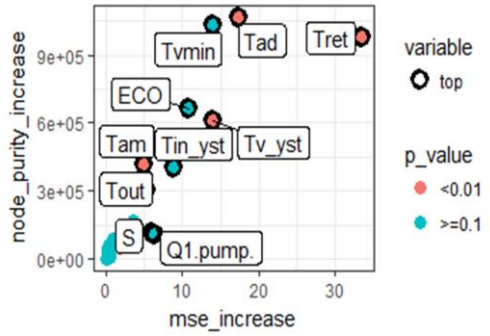

Fig. 5. The complex measurement of the importance of variables

Ordering variables on their mean minimal depth is quite accurate, thought considering the distribution of the minimal depth, the authors state that the predictor Tad should be assessed higher since it is the variable that is used more often for the first split at the root.

The values of the average increase of the mean square error [15] after the random replacement of the variable value (mse_increase) and increase of the mean node purity (node_purity_increase) which is the sum of square errors (SSE) are chosen as measurement of the complex (Fig. 5). P-values based on the binominal distribution of the node number that are split on the variable are used additionally. If the variable is important, it is used for splitting more often comparing to the random choice.

Although Tar and Tret are similar in the increase of the node purity and p-value based on the binominal distribution, the second one influences the prediction error more. It is worth noting that despite the high values of the chosen measurements on the variable Tvmin, the test based on the binominal distribution proves that the theoretical number of nodes where the variable is used for splitting exceeds the actual number, thus, the variable is seldom used for splitting and influences the prediction insignificantly.

5. Conclusions

The use of MCAS allows collecting a significant number of data relating to the system parameters and decisions accepted by the energy manager in addition to the decrease of the level of the consumed heating energy. It causes the opportunity for studying the issues of the efficient usage of energy sources with the help of the analysis of historic data and the support of the taken decisions. The article deals with comparing the methods of machine learning that allows applying the historic data instead of the complex mathematical apparatus to describe the building heat balance: RF and SVM are accuracy, source cost and the opportunity to interpret the results and non-obvious interrelations. RF algorithm is chosen for further research.

The authors develop the model of the heat-carrying agent temperature when powering the heating system based on the data on the parameters of the electronic weather-dependent controller with the help of RF algorithm. The values of the heat-carrying agent temperature in the reverse piping of the heating system and the smooth value of the outer temperature influence the value of the mean square error, besides these variables are often used to split the trees at the root that proves their significance. RMSE of the RF model on the test data equals 0.41°C. Maximal error is 14.96°C.

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