

Benchmarking Energy Quantification Methods to Predict Heating Energy Performance of Residential Buildings in Germany

Simon Wenninger, Christian Wiethe

Business & Information Systems Engineering (2021)

Appendix (available online via <http://link.springer.com>)

A1 Hyperparameter tuning

Table A 1 Tuned hyperparameter set for the best-performing Artificial Neural Network from the nested cross-validation. The superscript * implies that after mutation no bound was applied

Hyperparameter	Number of layers	Neurons per layer	Dropout rate	Learning rate	Batch-size
Ranges	[1, 50]	[5, 200]	[0, 0.95]	$[10^{-7}, 10^0]$	$[2^2, 2^{10}]$
Tuned values	1	69	0	$10^{-2.64}$	2^2

Table A 2 Tuned hyperparameter set for the best-performing Extreme Gradient Boosting from the nested cross-validation. The superscript * implies that after mutation no bound was applied

Hyperparameter	Eta	Gamma	Maximum depth	Minimum child weight
Ranges	$[10^{-3}, 10^{-0.3}]$	[0, 5*]	[1, 10]	[0, 5*]
Tuned values	$10^{-1.18}$	2.38	4	3.38
Hyperparameter	Column-sample	Sub-sample	Alpha	Lambda
Ranges	[0.05, 1]	[0.05, 1]	[0, 5*]	[0, 5*]
Tuned values	0.80	0.65	3.20	6.83

Table A 3 Tuned hyperparameter set for the best-performing Random Forest from the nested cross-validation. The superscript * implies that after mutation no bound was applied

Hyperparameter	Minimum node size	Maximum number of leaves	Random elements	Number of trees
Ranges	$[2^0, 2^{7*}]$	$[2^{-3}, 2^{5*}]$	[1, 14]	$[2^4, 2^{10}]$
Tuned values	$2^{1.7}$	$2^{7.8}$	6	2^9

Table A 4 Tuned hyperparameter set for the best-performing Support Vector Regression from the nested cross-validation. The superscript * implies that after mutation no bound was applied

Hyperparameter	Cost	Epsilon	Gamma
Ranges	$[2^{-4}, 2^4]$	[0, 2]	$[2^{-6}, 2^{-3}]$
Tuned values	$2^{-0.72}$	0.86	$2^{-4.78}$

A2 Copula Structure

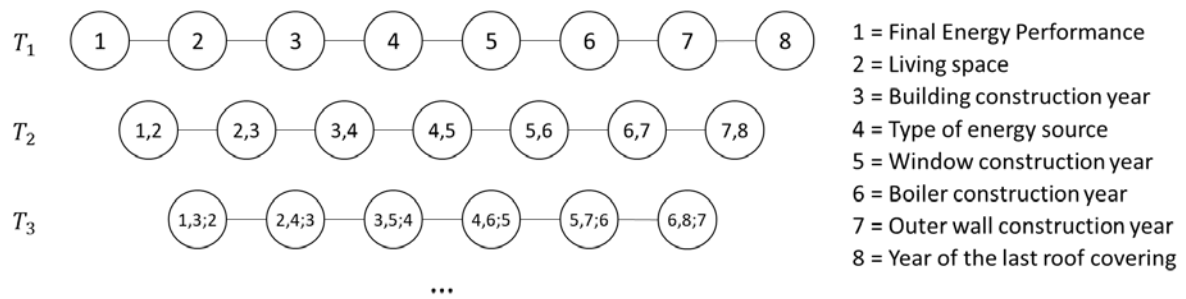


Figure A 1 Resulting D-vine copula structure.

The sequences indicate the trees, the higher-order trees follow analogously

A3 Supervised Machine Learning Reportcard

Table A 5 Supervised Machine Learning Reportcard for rigour documentation following the design by Kühl et al. (2020)

General Information	Problem statement	Predict Final Energy Performance of single- and two-family houses in Germany with multiple attributes/variables		
	Data gathering	The data originates from the nationwide “Modernisierungs-Kompass” (Modernization Compass) offered by the EN-OP Institute (enop.de) as well as from two German energy consultant companies (c.f. Section 4)		
	Sampling	No sampling of data (post-stratification for Performance Evaluation Measures)		
	Data quality	Generally high, partly missing or incorrect values		
	Data pre-processing methods	c.f. Section 4		
	Feature engineering and vectorizing	c.f. Section 4		
All	Performance evaluation measure for hyperparameter tuning	Stratified Coefficient of Variation, stratification according to German building stock		
	Parameters	c.f. Appendix A1		
ANN	Parameter optimization	Yes	Search space Search algorithm	c.f. Appendix A1 Genetic algorithms
	Data split	Nested cross-validation, 5 outer folds, 10 inner folds		
	Performance evaluation measure for training	Mean Squared Error		
	Performance measure increase between test and train (risk of overfitting)	1.86 % (stratified Coefficient of Variation)		
	Parameter optimization	No (no hyperparameter) Nonparametric bivariate building blocks, parsimonious forward selection, AIC as termination criterion		
Copula	Data split	10-fold cross-validation		
	Performance evaluation measure for training	Conditional loglikelihood		
	Performance measure increase between test and train (risk of overfitting)	0.13 % (stratified Coefficient of Variation)		
	Parameter optimization	Yes	Search space Search algorithm	c.f. Appendix A1 Genetic algorithms
XGB	Data split	Nested cross-validation, 5 outer folds, 10 inner folds		
	Performance evaluation measure for training	Mean Squared Error		
	Performance measure increase between test and train (risk of overfitting)	3.44 % (stratified Coefficient of Variation)		
	Parameter optimization	Yes	Search space Search algorithm	c.f. Appendix A1 Genetic algorithms
RF	Data split	Nested cross-validation, 5 outer folds, 10 inner folds		
	Performance evaluation measure for training	Mean Squared Error		
	Performance measure increase between test and train (risk of overfitting)	9.35 % (stratified Coefficient of Variation)		
	Parameter optimization	Yes	Search space Search algorithm	c.f. Appendix A1 Genetic algorithms
SVR	Data split	Nested cross-validation, 5 outer folds, 10 inner folds		
	Performance evaluation measure for training	Support Vector Regression objective function		
	Performance measure increase between test and train (risk of overfitting)	1.80 % (stratified Coefficient of Variation)		
	Parameter optimization	Yes	Search space Search algorithm	c.f. Appendix A1 Genetic algorithms

A4 Variable importance plot

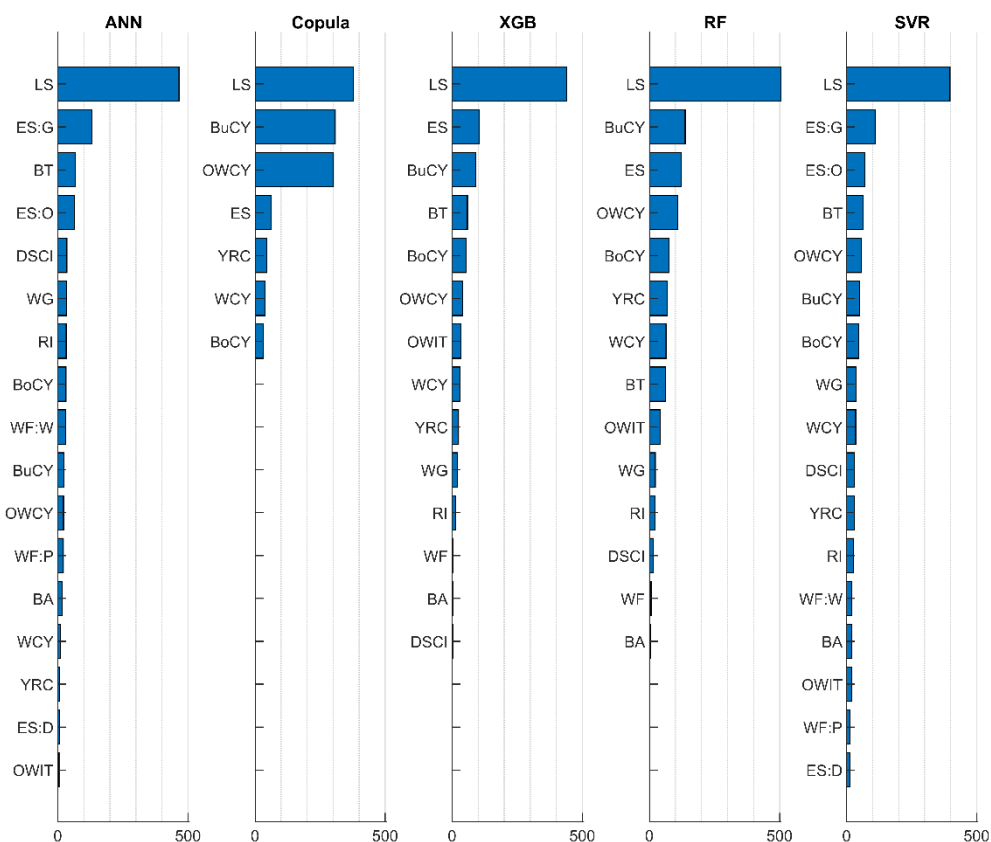


Figure A 2 Complete variable importance plot for the data-driven EQMs (for variable abbreviations see Table A 6)

Table A 6 Variable abbreviations for the variable importance plot in Figure A 2

Attributes	Key	Attributes	Key
Basement available	BA	Boiler construction year	BoCY
Building construction year	BuCY	Building type	BT
Double skin construction insulation	DSCI	Living space	LS
Material of window frame (Wood, plastic, aluminium)	WF: W/P	Outer wall construction year	OWCY
Outer wall insulation thickness	OWIT	Presence of double skin construction insulation	DSCI
Presence of roof insulation	RI	Type of energy source (Oil, gas, district heat, etc.)	ES: G/O/D
Type of window-glazing	WG	Window construction year	WCY
Year of the last roof covering	YRC		