Industrial & Systems Engineering Graduate Program (PPGEPS), Pontifical Catholic University of Parana (PUCPR)– Models to Support Decision Making

18th Brazilian Congress of Thermal Sciences and Engineering (ENCIT)

PREDICTION OF RESIDENTIAL BUILDINGS EFFICIENCY BASED ON DIFFERENTIAL EVOLUTION OPTIMIZATION AND RANDOM FOREST MODEL (ENC-2020-0397)

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Agenda

- Introduction
- Dataset
- Methodology
- Results
- Conclusion

Introduction

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- In the Brazilian context, residential buildings demanding 51% of the produced energy.;

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- The prediction of heating (HL) and cooling (CL) loads of residential buildings plays a key role, once the heating, ventilation, and air conditioning system are drivers of energy demand (Wang et al. 2018)

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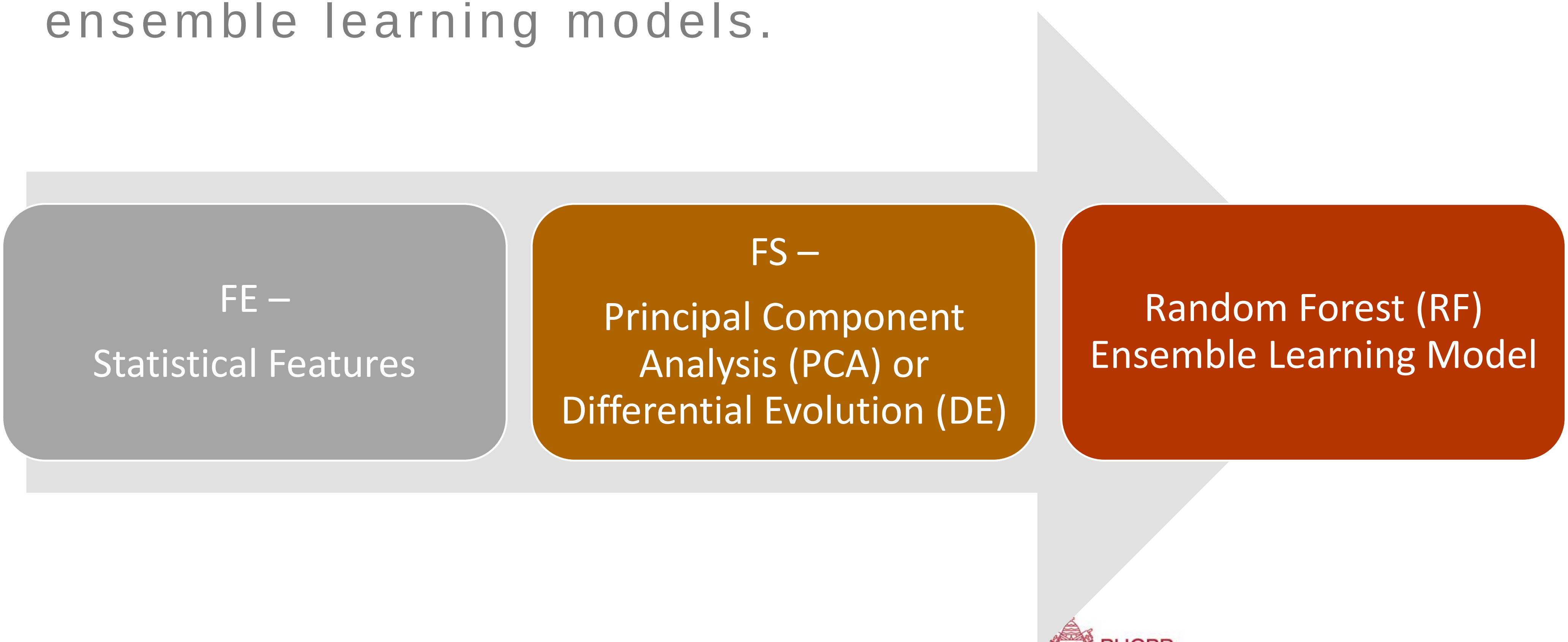
- Associates feature engineering (FE), features selection (FS) and ensemble learning model allows to develop an accurate predictive system;

Objective

- Evaluates the predictive performance of the predictive system by combining FE, FS, and ensemble learning models.



Comparison of different approaches to perform FS (using DE) and dimensional reduction (PCA) coupled with ensemble learning model (RF)

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Development of an integrated and accurate framework which employs FE, FS and ensemble learning models to predict HL and CL of residential buildings.

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Contributions

Dataset

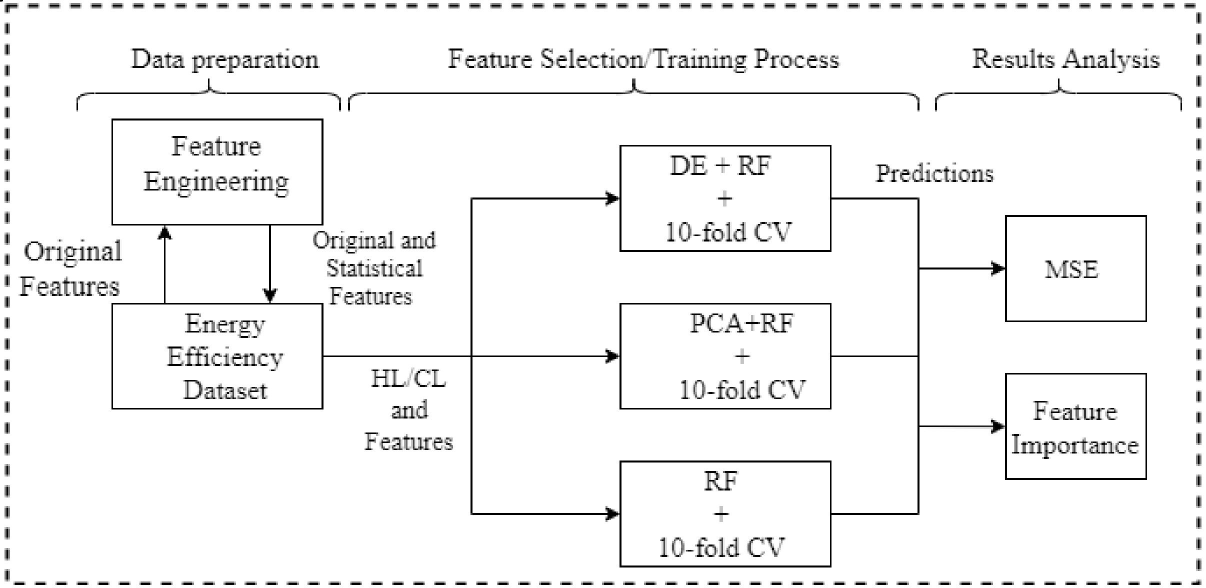
- Dataset adopted in this paper was proposed by **Tsanas and Xifara (2012);**
- 12 different building shapes (taking the elementary cube - 3.5×3.5×3.5) **simulated in Ecotect.**
- **Two outputs (Y) and eight inputs (X);**

Table 1: Description and statistical indicators of the input (**X**) and output (**Y**) variables

Variable	Description	Statistical Indicator				
		Minimum	Median	Average	Maximum	Std
X_1	Relative Compactness	0.62	0.75	0.76	0.98	0.10578
X_2	Surface Area	514.5	673.75	671.71	808.50	88.08612
X_3	Wall Area	245	318.5	318.5	416.50	43.62648
X_4	Roof Area	110.25	183.75	176.60	220.50	45.16595
X_5	Overall Height	3.5	5.25	5.25	7	1.75114
X_6	Orientation	2	3.5	3.5	5	1.11876
X_7	Glazing Area	0	0.25	0.2344	0.4	0.13322
X_8	Glazing Area Distribution	0	3	2.8125	5	1.55096
Y_1	Heating Load	6.01	18.95	22.3072	43.1	10.09020
Y_2	Cooling Load	10.9	22.08	24.5878	48.03	9.51331

Methodology

- **The FE** is used to obtain **statistical features** based on the **inputs** of the system;
- The **RF** is combined with **DE** algorithm for **FS**;
- The **RF** is combined with **PCA;**
- The **MSE** (mean squared error) is computed;



Results

Table 2: Results of the ensemble learning models in terms of MSE (30 runs) in the prediction of the HL and CL.

	Output					
Indicator	HL			CL		
	PCA–RF	DE–RF	RF	PCA–RF	DE–RF	RF
Minimum	0.5016	**0.2201**	0.2510	2.8294	**2.4948**	2.9671
Median	0.5911	**0.2352**	0.2675	3.1833	**2.8521**	3.2089
Average	0.6128	**0.2365**	0.2675	3.1490	**2.8426**	3.2166
Maximum	0.8146	**0.2566**	0.2945	3.5681	**3.1132**	3.5126

Results

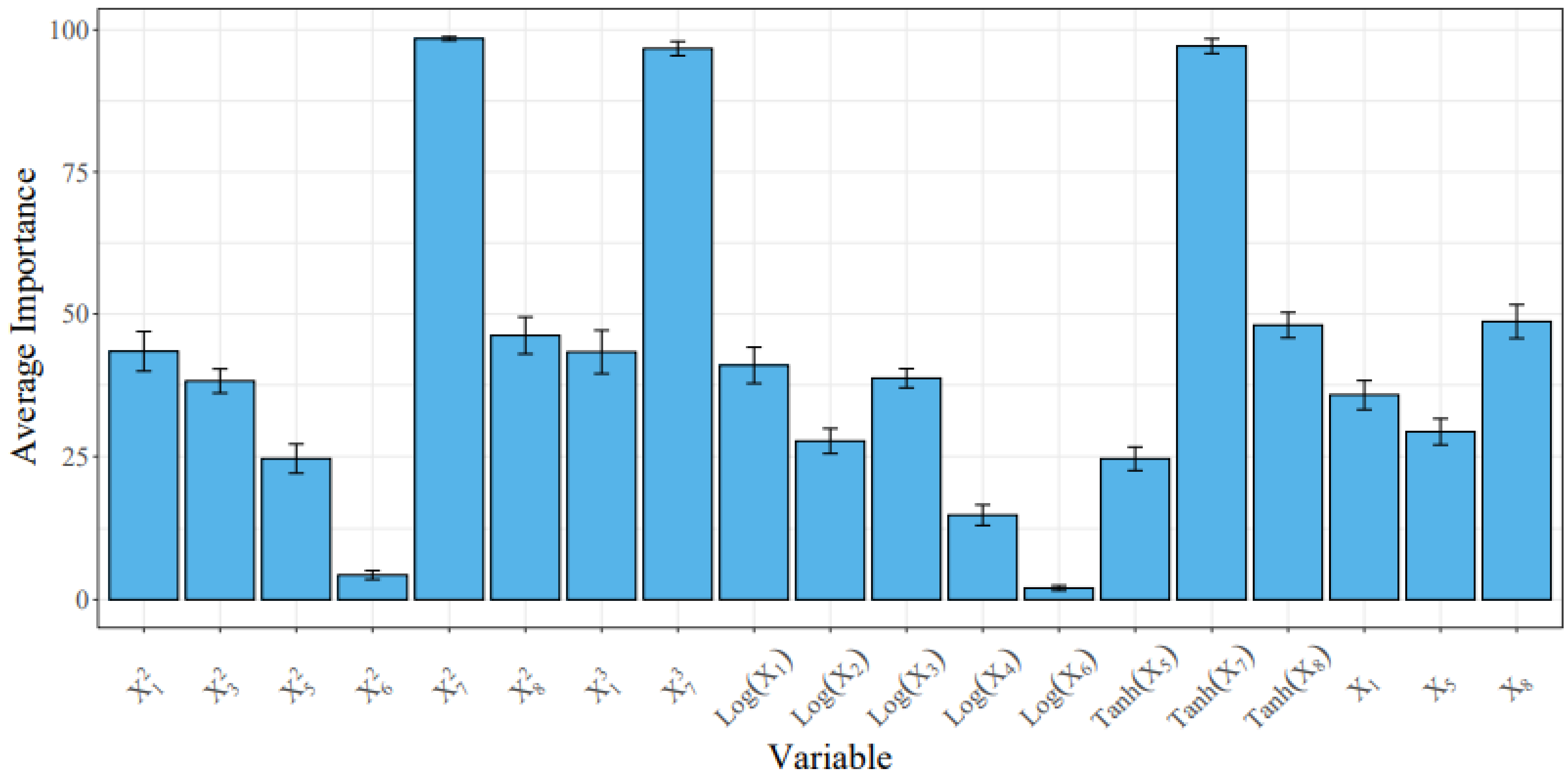


Figure 2: Feature Importance for HL

Results

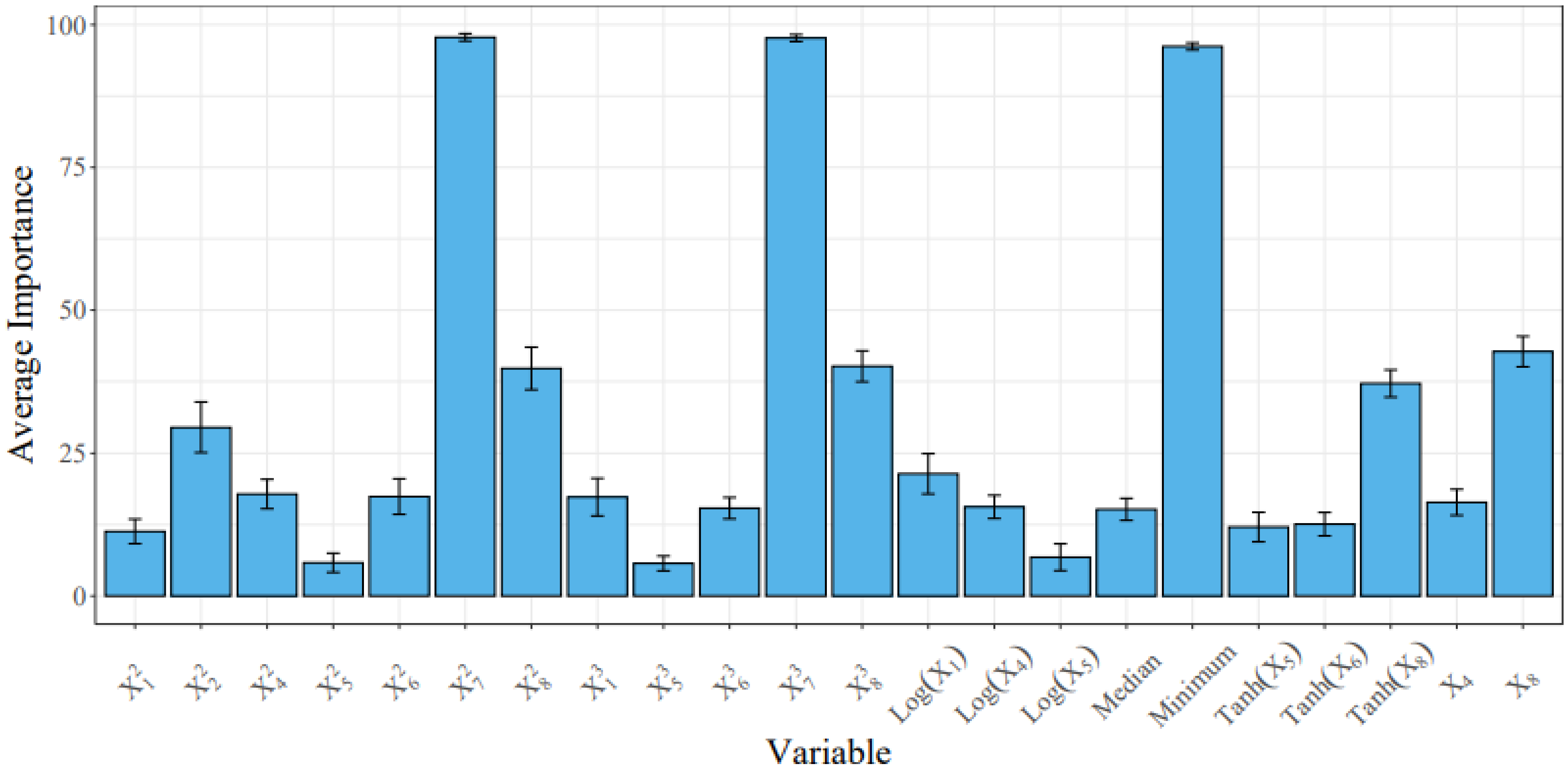
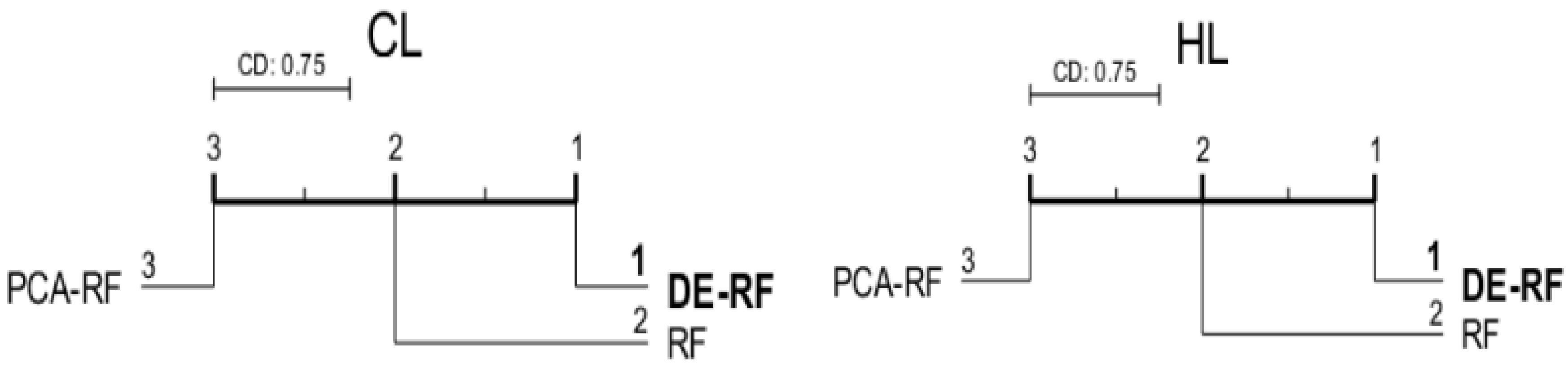


Figure 3: Feature Importance for CL

Results



(a) CL variable

(b) HL variable

Figure 4: Resulting critical differences (CD) plots for different evaluated models.

Results

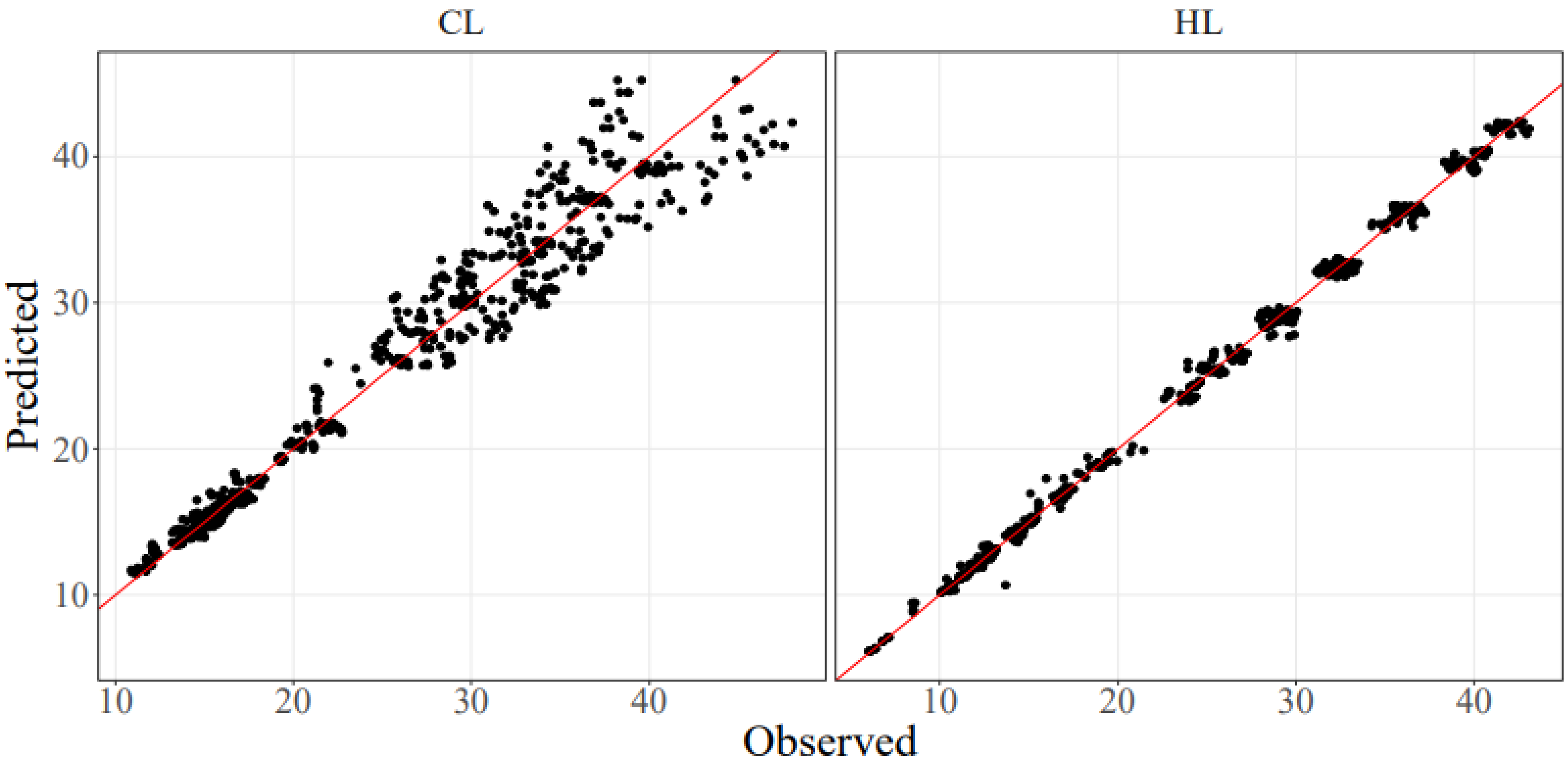


Figure 5: Observed versus Predicted values for CL (left) and HL (right) variables

Conclusion

- An ensemble model was evaluated to predicted CL and HL of residential buildings;
- The DE-RF model outperforms PCA-RF and RF models in terms of MSE;
- As future research is suggested to integrate stacking ensemble learning and other optimization algorithms to predict CL and HL in residential buildings.

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CAPES

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Thank you!

Any questions?