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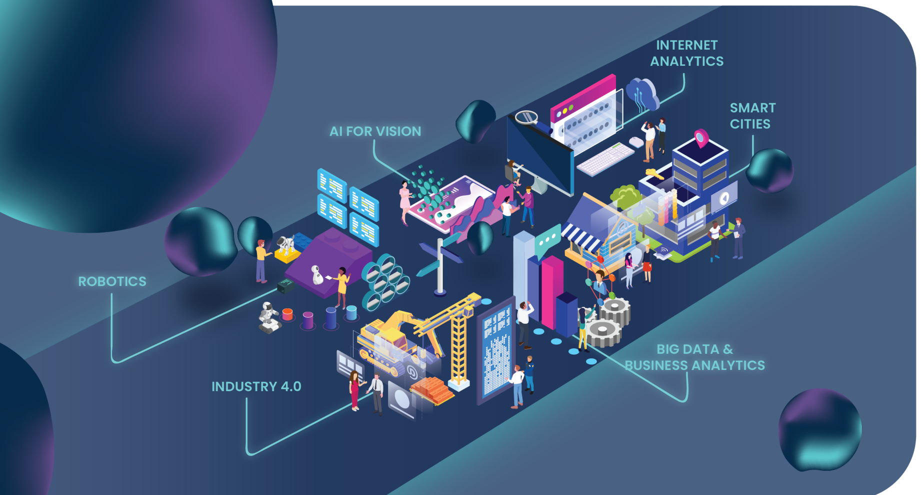

Design optimization of renewable energy systems for NEZBs based on deep residual learning

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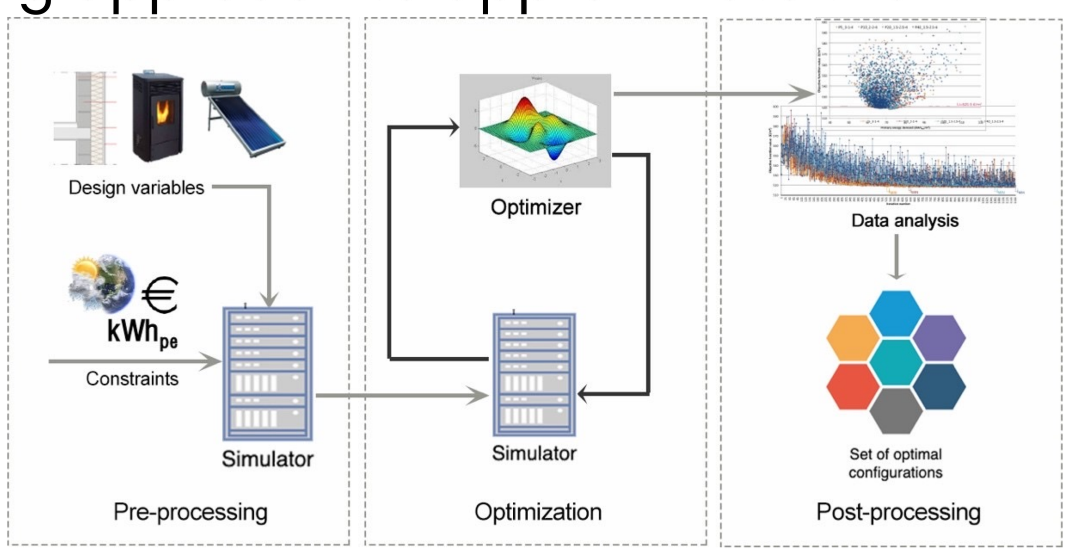
Motivation and background

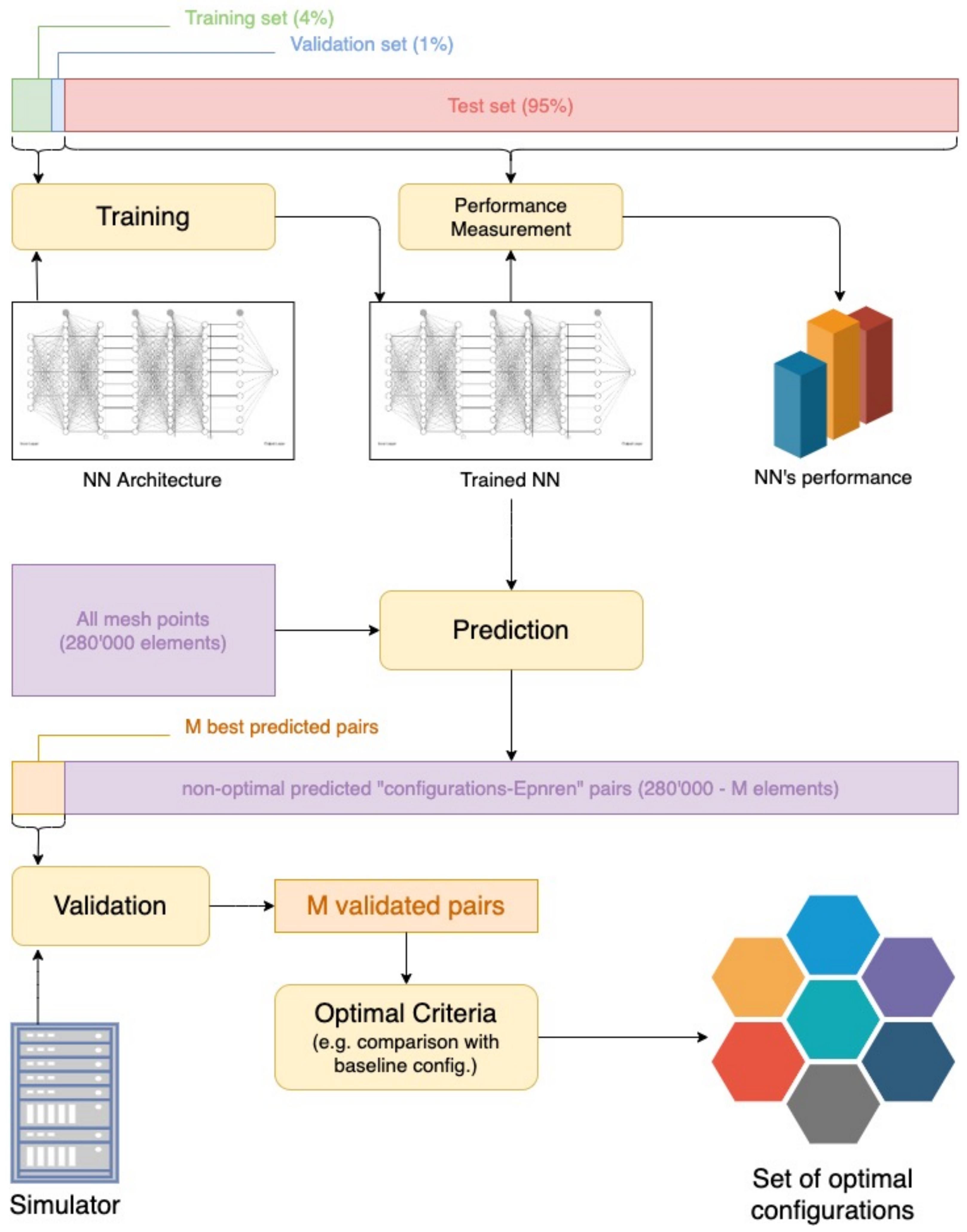
The design of renewable energy systems for Nearly Zero Energy Buildings (NZEBs) is a complex optimization problem. Simulation-based optimization has proved to be able to support the the search of an optimal design, but the computation burden of simulations is very high, leading to slow, or inaccurate, solutions. We propose a deep residual learning approach to approximate the simulator, and use the learned function to solve the optimization problem.



Proposed pipeline

Variable description	Name	Unit	Min	Max	Steps
Number of solar collectors (Approx. total area of the solar field)	N_coll	-(m^2)	35 (150)	70 (300)	7
Volume Ratio	HSt_ratio	l/m^2	40	110	7
Cold storage volume	CSt_vol	m^3	4	10	6
FlowRate_solar loop	FR_sol	kg/hr	8000	12000	4
FlowRate_Hot Water loop	FR_HW	kg/hr	8000	12000	4
FlowRate_Chilled Water loop	FR_ChW	kg/hr	8000	12000	4
FlowRate_Cold Water loop	FR_CW	kg/hr	11200	16800	4

The simulator is evaluated on a number **P** of configurations. These are used to train a deep residual neural network. Once the DNN approximates with good quality the simulator, the best **M** configurations of the disign space are selected for further analysis.

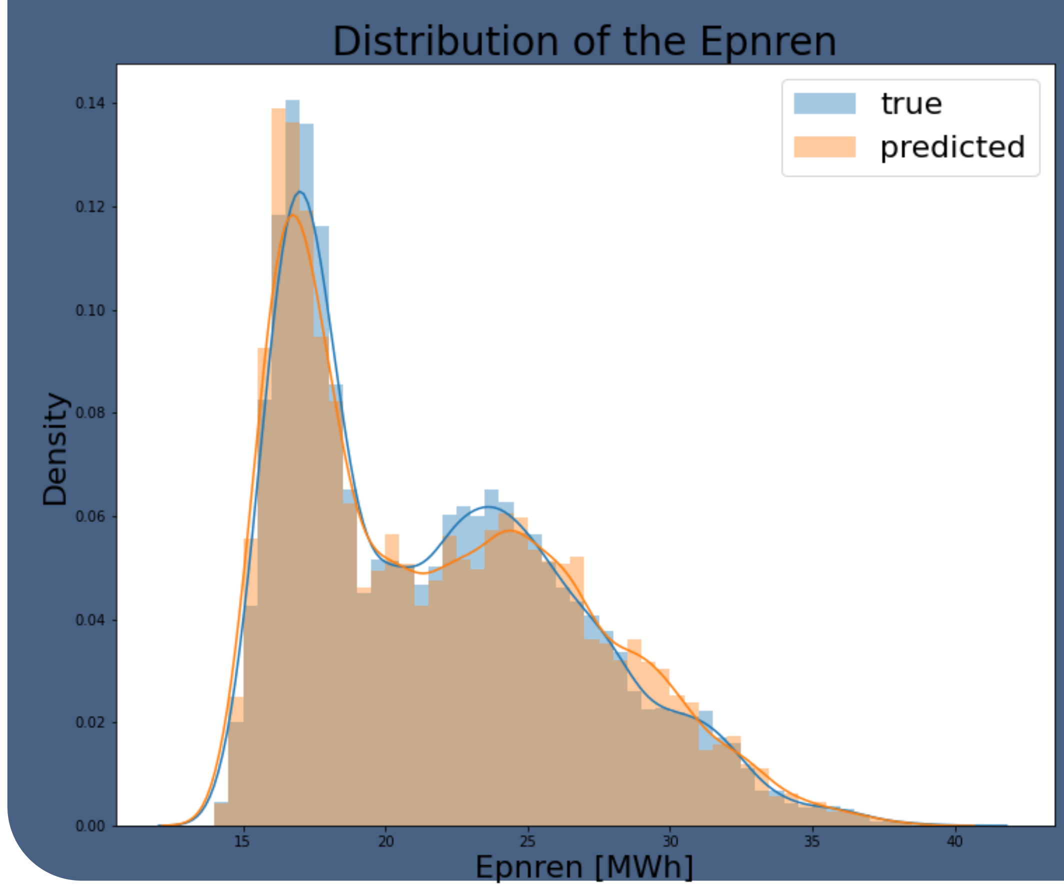


Approximation of the simulator

The proposed DNN achieves a good quality of prediction (r.e.~3%) using only the 0.4% of points of the design space for the training phase.

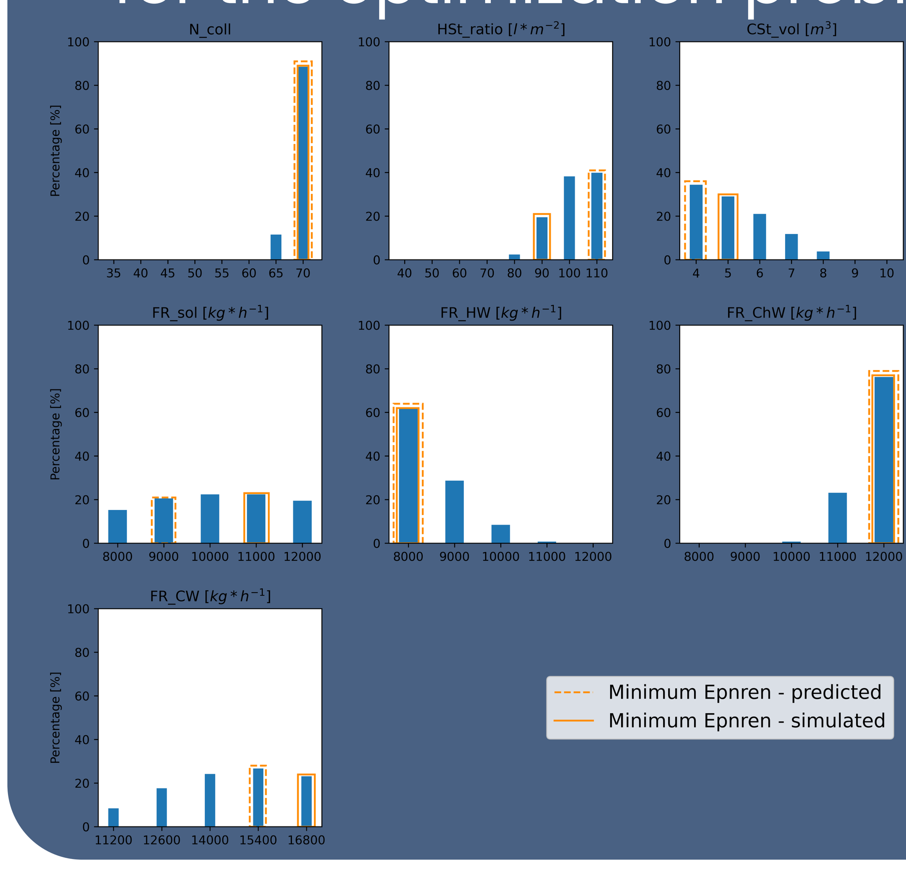
Statistics of errors on the test set for N.

	Relative Error	Absolute Error (MWh)
Mean value	3.30%	0.740
Standard deviation	5.38%	1.206
First quartile	0.79%	0.159
Median (second quartile)	1.81%	0.379
Third quartile	3.63%	0.813



Results of the optimization

It is possible to explore the entire design space and to analyze an arbitrary number of solutions for the optimization problem.



Statistics of errors on the M = 1′000 selected design alternatives for N.

	Relative Error	Absolute Error (MWh)
Mean value	1.86%	0.281
Standard deviation	1.26%	0.193
First quartile	0.84%	0.123
Median (second quartile)	1.71%	0.254
Third quartile	2.71%	0.410

Statistics of the differences between the Epnren values of the M = 1′000 selected design alternatives and the value 28.370 MWh (Epnren of the initial design).

	Epnren saving w.r.t. Initial design	
	Percentage	MWh
Mean value	−47.30%	−13.420
Standard deviation	0.96%	0.272
Minimum	−49.19%	−13.954
First quartile	−48.00%	−13.619
Median (second quartile)	−47.37%	−13.439
Third quartile	−46.63%	−13.225
Maximum	−44.76%	−12.698

Conclusions and future work

The proposed method based on deep residual learning can

- Obtain a good quality of prediction, compared with the simulator;
- Speed up the optimization problem and increase the accuracy of the optimization;
- Increase the quality of the exploration of the design space ;

Future work will be dedicated on different case studies of different levels of complexity, up to the case complete ZEB design problems.