ENERGY OPTIMIZATION OF AN EXISTING BUILDING BASED ON A NEURAL NETWORK AND A GENETIC ALGORITHM

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ABSTRACT

When it comes to the refurbishment of existing buildings there are different objectives; for instance, the reduction of energy consumption, global warming potential (GWP) or costs. To find the optimal solution can be very challenging. Thus, the application of a building simulation model combined with a multi-objective optimization (MOO) might be useful. However, a drawback of a numerical optimization is the computational effort. In this paper we show that the replacement of the detailed building simulation model with a neural network can reduce the computational effort for a optimization analysis. Furthermore we conclude that it could be necessary to give special attention to the errors of the meta model on the boundaries of the range of validity.

In a first step, a detailed building model of an existing single-family house was developed. Based on the simulation results of this detailed model a neural network was created. A genetic algorithm was used to fulfil a multi-objective optimization for the building parameters of different retrofit measures to optimize thermal comfort, global warming potential (GWP) and costs.

INTRODUCTION

Climate mitigation is one of the major challenges of our society. In Europe, the building stock is responsible for 40% of all energy consumption and 36% of total CO2 emissions (EU-Council, 2010). Therefore, the refurbishment of existing buildings is a first priority measure when it comes to handle against climate change. Building energy simulation (BES) is one method to evaluate the impact of different renovation measures. To handle several objectives, for instance energy demand and costs, the BES can be combined with a multi-objective optimization (MOO).

The combination of BES and numerical optimization is widely used (Nguyen et al., 2014; Machairas et al., 2014; Evins, 2013). For a MOO the genetic algorithm is one of the most used techniques in the building community (Evins, 2013; Eisenhower et al., 2012). A genetic algorithm (GA) is a stochastic search technique based on natural biological evolution. One advantage to common methods like gradient based optimization is the population of solutions compared to a descent along a gradient. This reduces the likelihood of converges to a local minima. Examples of the use of MOO with a GA are (Wright et al., 2002). They used a MOO with a genetic algorithm to find the trade-offs between the thermal comfort and the energy cost of a single zone model. (Hamdy et al., 2011) optimized the carbon dioxide emissions and the costs for a two story house.

A drawback of MOO with a detailed building model is the computational effort. One opportunity for reducing the simulation time is to replace the building model with a meta model (Eisenhower et al., 2012; Nguyen et al., 2014). For instance, (Magnier and Haghighat, 2010) and (Asadi et al., 2014) are using a neural network and a genetic algorithm for a multi-objective optimization.

The current analysis shows a MOO for a building retrofit by replacing the detailed building model with a neural network. A genetic algorithm is used for the optimization. Therefore the refurbishment of a building shell from a single family home will be optimized under consideration of the objectives costs (Net Present Value - NPV), global warming potential and thermal comfort.

METHODOLOGY

In this paper the following approach was carried out:

- Definition of a case study and preparation of a detailed building model of a single-family home.
- Data collection from this detailed building model for the learning and testing of a meta model. The collection was executed with a Monte Carlo study combined with a sobol sampling of the defined building parameters.
- Development of a meta model based on the sampling data from the building model.
- Optimization of refurbishment measures with a genetic algorithm.

Case Study

The case study in this paper is taken from a project which analyses the influence of climate change on refurbishment in the residential sector. Three different districts of two cities are investigated. The used single-family home (SFH) represents a typical building of one of these three districts. The building is located in Munich, Germany, and has the following main parameters:

Tabelle 1: Building parameters

Parameter	**Value**	**Unit**
A/V (area to volume ratio)	0.85	$\frac{m^2}{m^3}$
Ū-value (mean U-Value)	1.18	$\frac{W}{m^2K}$
A_{win} (total window area)	15.23	m^2
NIA (net internal area)	130	m^2
U-value external wall	1.47	$\frac{W}{m^2K}$
U-value roof	1.10	$\frac{W}{m^2K}$
U-value floor	1.10	$\frac{W}{m^2K}$
U-value window	3.50	$\frac{W}{m^2K}$
SHGC - window	0.70	-

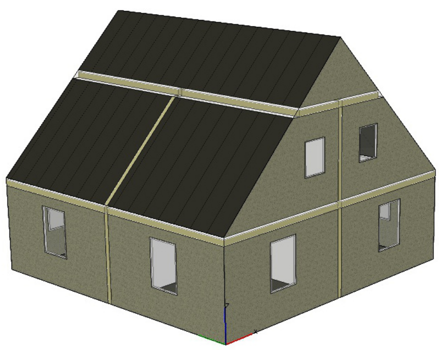

Abbildung 1: 3D model of the building

The detailed building model was developed in the software IDA ICE (Sahlin et al., 2004). The climate data is taken from the regional climate model (REMO) (Jacob et al., 2008) and focuses on the region of Munich. The simulation results of the analysis with IDA ICE provide the learning and testing data for the meta model.

Meta Model

A simple feed-forward neural network was used to construct the surrogate model. Neural networks are part of non-linear regression methods. They offer the opportunity to reproduce linear and non-linear relations between input and output variables inspired by theories about how the brain works (Kuhn and Johnson, 2013). The structure of a neural network is based on layers (Figure 2). The first layer represents the input variables, the last layer contains the output variables and the layers between are hidden layers. In each layer are neurons. The neurons are connected with weights, which are updated in the fitting process by a training algorithm until the output has a sufficient quality (Endisch, 2009). In this study the neural networks are built with the "*nnet*" package (Venables and Ripley, 2002) provided in the statistical software R (R Core Team, 2014).

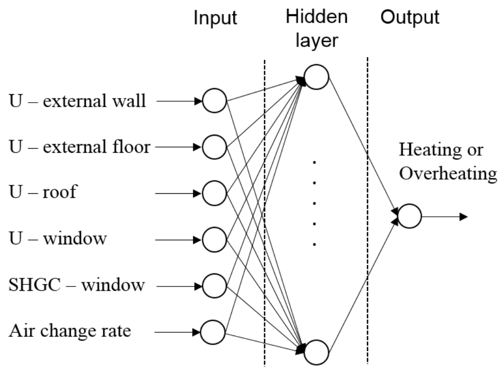

Abbildung 2: Schematic structure of the used neural network

Two neuronal networks are developed to replace the detailed building model: one with the output annual heating demand (q_{heat} $[kWh/a]$) of the whole building and the other with overheating degree hours $[Kh/a]$ of a critical zone. There are six input parameters representing the building (Figure 2). These parameters are necessary to analyse the energy efficiency of the building envelope. There is one hidden layer and the amount of neurons will be identified by a parametric study later on. The sample size for learning and testing is varied to analyse the influence on the model quality. Therefore a sample size of 1000, 10000 and 30000 was chosen. The sample data was split in 50 % for learning and 50 % for testing of the meta model.

The coefficient of variation (CV - RMSE) based on the root mean squared error (RMSE) was utilized as the performance metric in the analysis to compare the quality of the neural network during the calibration process.

$$CV = \frac{RMSE}{\bar{y}} * 100 \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (2)$$

While y_i is the observed value from the building model, $\hat{y}_i$ is the predicted value of the meta model; $\bar{y}$ is the mean of the observed values and n is the total number of observations.

Optimization

The used genetic algorithm was build up in (R Core Team, 2014) and has the following pseudocode more details in (Maderspacher, 2013):

Algorithm 1: Genetic Algorithm

Input: size α of population, number δ of generations

generate α feasible solutions randomly
save them in the population Pop
for i = *1 to* δ **do**
  splitting population $nc = \alpha/5$
  for j = *1 to* nc **do**
    $Pop_1 \leftarrow$ elitism select the first nc solutions(Pop)
  for j = *1 to* nc **do**
    $Pop_1 \leftarrow$ generate randomly solutions
  for j = *1 to* nc **do**
    $Pop_1 \leftarrow$ bit-flip mutation(Pop)
  for j = *1 to* nc **do**
    $Pop_1 \leftarrow$ one-point crossover(Pop)
  for j = *1 to* nc **do**
    $Pop_1 \leftarrow$ two-point crossover(Pop)
  $Pop \leftarrow$ Sorting(EvaluateFitness(Pop_1))
return Pop

The objective thermal comfort is represented with overheating degree hours (ODH) from (DIN4108-2, 2013). The ODH will not be directly optimized, they are used as a constraint for the heating demand. This is realized with a penalty function which adds additional heating demand if the ODH gets higher than 1200 $[Kh/a]$.

$$f(x) = \alpha * \left(\left(\frac{x - 1200}{max(x) - 1200} \right) * 10 \right) \qquad (3)$$

While x is the heating demand and α is the factor for weighting the penalty, the constant 1200 stands for the benchmark of the ODH in $[Kh/a]$ based on (DIN4108-2, 2013). In this study, α is defined by 100.000 to ensure that the optimal solutions always fulfil the rules and regulations.

To determine the costs of a retrofit measure, only the additional costs which relate to energy reduction are considered (BMVBS, 2012). Costs which are based on common renovation, for example the rent for a scaffolding are not included. The net present value (NPV) approach is used to asses the cost benefit of a refurbishment measure. For all measures a life cycle of 30 years is defined, the rate of return by 4 % and the increase of the energy prices by 5 %. The objective function for optimizing the global warming potential (GWP) and NPV is defined as:

$$f(x) = w_1 * -f_{NPV}(x) + w_2 * f_{GWP}(x) \qquad (4)$$

The function of GWP is based on the simulation results of heating demand combined with the penalty function for the ODH and a factor for the global warming potential. To turn the objective function into a minimization problem the function of the NPV gets a negative sign. Because the optimal solution of the NPV would be typically a maximization. Both functions are normalized to vary between 0.0 and 1.0. The factors w_1 and w_2 can be used for weighting the different objectives. In this study both factors are set to 0.5.

RESULTS AND DISCUSSION

Calibration of the neural network (NN)

In a first step, the number of neurons in the hidden layer were analysed for two objectives: heating demand (q_{heat}) and overheating degree hours (ODH). Therefore, the amount of samples for learning and testing of the neural network are varied. The coefficient of variance (CV) represents the model quality. If the value of the CV gets smaller the quality of the model increase.

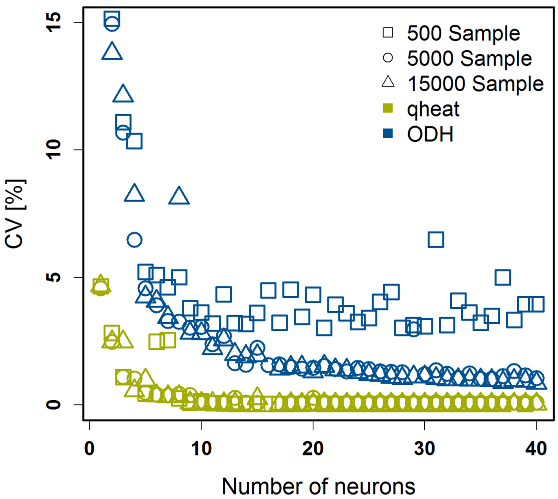

Abbildung 3: Variation of the number of hidden neurons and the influence on the CV for the objectives q_{heat} and ODH depending on the sample size

Figure 3 points out that the NN with the objective q_{heat} provides a better model quality with less samples compared to the objective ODH. Both models show a reliable quality with sample size of 5000 for learning. In a next step, a cross validation of both meta models was fulfilled. Figure 4 represents the cross validation of the objective q_{heat} with the predicted values on the y - axis and the results of the detailed building model on the x - axis. The NN has a suitable quality independent from the sample size.

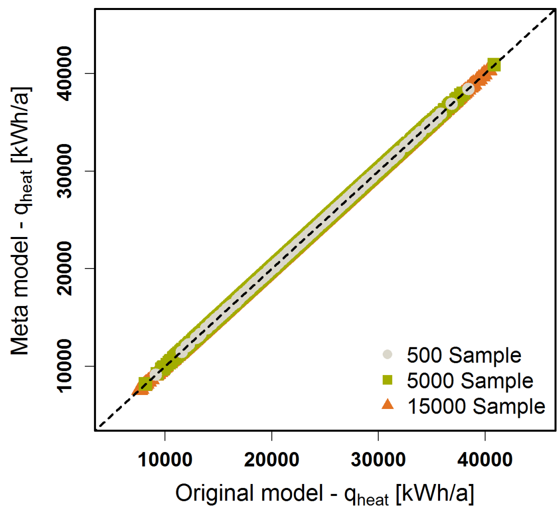

Abbildung 4: Cross validation of the NN-q_{heat}

An interesting point to note is the extension on the upper and lower limit of the range depending on the amount of samples. The neural network with 500 samples for learning has a minima q$_{heat}$ of 9156 $[kWh/a]$ and the one with 15000 samples for learning of 7587 $[kWh/a]$. This is caused by a more exhaustive description of the design space with a higher amount of samples. This is a very important fact, if a meta model is used for optimization. For example, if the objective q$_{heat}$ should be minimized without constraints the search of the optimization algorithm will definitely end on the lower limit of the surrogate model. Therefore, it is important to represent the limits of objective accurately.

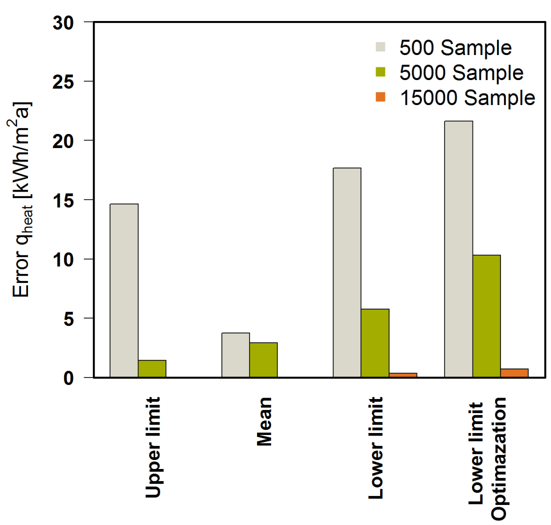

Abbildung 5: Absolute error on the upper and lower limit of the NN-q_{heat}

Figure 5 shows the absolute error of q$_{heat}$ on the upper and lower limit of the NN depending on the sample size. The fourth group of bars are results of a optimization of q$_{heat}$ without constrains. Figure 5 points out the necessity of analysing the upper and lower limit of the meta model which is used for optimization. If only the coefficient of variance and the results of the cross validation were taken into account for the model quality, it seems a sample size of 500 for learning would be enough.

The cross validation of the objective ODH in Figure 6 shows an appropriate model quality. An extension of the range depending on the sample size can be observed as well. A sample size of 15000 for learning also represents an accurate model quality on the upper and lower limit of the surrogate model (see Figure 7). Table 2 summarises the results of the parametric study for both objectives. All three criteria, RMSE, CV and the coefficient of determination R^2 of the cross validation indicate a resilient model quality. But based on the analysis of the error on upper and lower limit of the model (Figure 5 and 7) a sample size of 15000 for learning is chosen for further work.

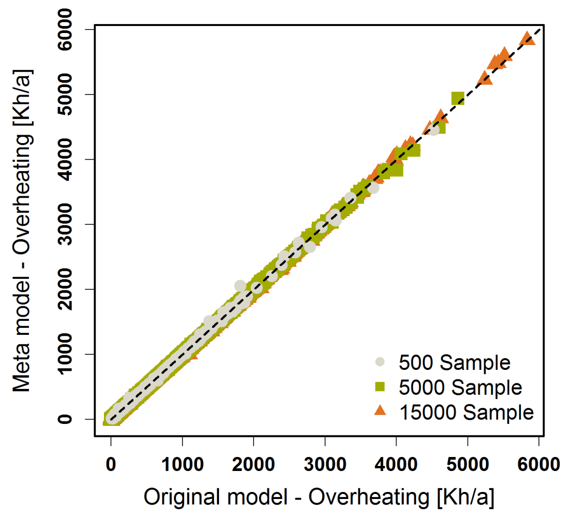

Abbildung 6: Cross validation of the NN-ODH

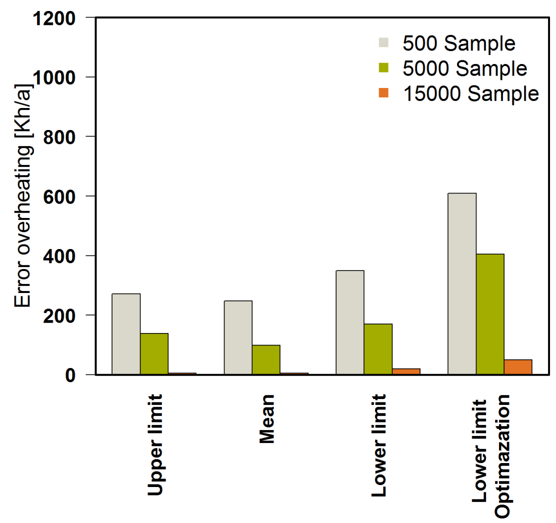

Abbildung 7: Absolute error on the upper and lower limit of the NN-ODH

Tabelle 2: Results of the parametric study

Samples	Neurons	RMSE	CV	R^2
500 q_{heat}	11	18.65	0.12%	0.999
500 ODH	21	20.20	3.01%	0.988
5000 q_{heat}	36	6.54	0.03%	0.999
5000 ODH	35	6.78	1.01%	0.998
15000 q_{heat}	36	6.17	0.02%	0.999
15000 ODH	40	5.67	0.84%	0.999

Calibration of the genetic algorithm (GA)

For a efficient performance of a genetic algorithm, it is necessary to carry out a parametric study. To evaluate the performance of the optimization algorithm it can be useful to define a number of optimization runs and look how much of the solutions find an optimum[1]. With the help of a cumulative distribution function it is possible to illustrate whether there is an optimum and how many solutions can find it. In Figure 8 it seems there is an optimum at around 6000 $[kWh/a]$. The solutions of the optimization with 500 runs (beige colour) do not reach the minimal energy demand of 5911 $[kWh/a]$. At the optimization with 5000 runs (green colour) around 5 % (0.05 on the y-axis) of the solutions show the optimum. With 25000 runs (orange colour) around 70 % (0.7 on the y-axis) of the optimization results can find the minimal q_{heat}.

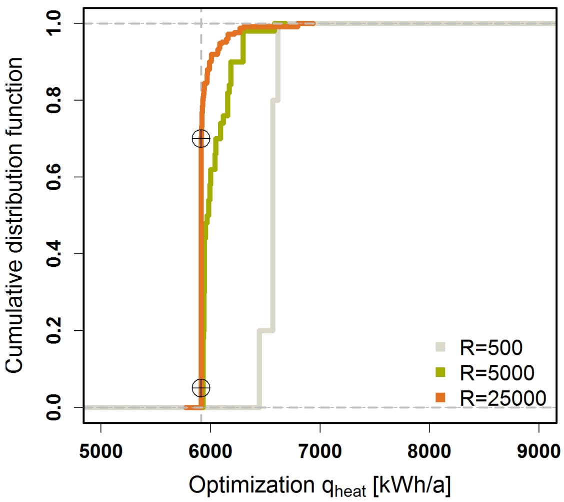

Abbildung 8: Cumulative distribution function of all optimization results depending on the number of runs

For the further investigation a maximum iteration of 25000 runs with 250 generations and population size of 100 was chosen. Detailed information about the parametric study of the GA can be found in (Maderspacher, 2013).

Optimization of heating demand (q_{heat}) and thermal comfort (ODH)

In a first step, the heating demand q_{heat} should be optimized with an improvement of the building envelope. If the renovation just considers the objective q_{heat} there could be problems during summer with overheating of critical rooms. Figure 9 shows the trade-off between ODH $[Kh/a]$ and q_{heat} $[kWh/a]$. There is a pareto frontier between these two objectives. A pareto optimal solution indicates that it is not possible to improve, based on the objective function, variable x without deteriorate variable y. In this case, if q_{heat} will be reduced, the overheating degree hours are increasing.

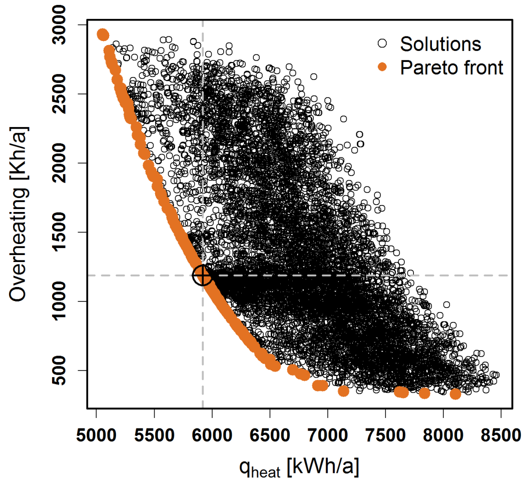

Abbildung 9: Solutions for the optimization of q_{heat} with a highlighted Pareto-optimal front

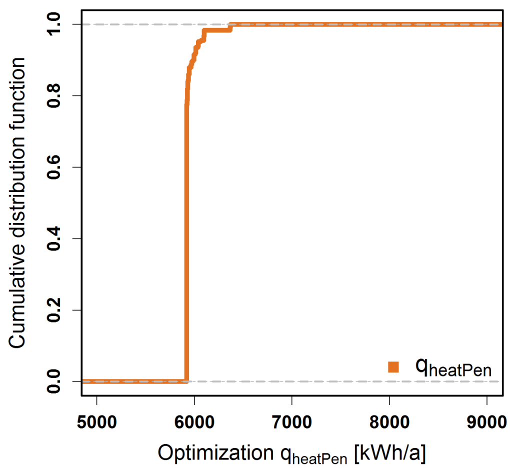

Abbildung 10: Cumulative distribution function of all optimization results from the objective q_{heat} (25000 runs).

In this case study, the objective thermal comfort will be considered further as a constrained for q_{heat}, realized by a penalty function (Eq. (3)). This is to ensure that all optimal solutions fulfill the benchmark of 1200

[1] A genetic algorithm contributes to the class of metaheuristics. This class of algorithms cannot guarantee to find an global optimum.

$[Kh/a]$ based on (DIN4108-2, 2013). Figure 10 illustrates the optimization results for q_{heat} combined with the penalty function (Eq. (3)). By comparing the optimum of 5911 $[kWh/a]$ in Figure 10 with Figure 9 the value of the ODH stands at 1193 $[Kh/a]$.

Table 3 shows the results and boundaries of the building parameters for the optimization of q_{heat}. The upper limit (Max) for the optimization parameters is based on the representative building of the case study. The lower limit (Min) is based on the passive house requirements. The benchmarks for the German rules and regulations for renovation are shown in (EnEV). The solutions for the optimization of q_{heat} (Opt) without a penalty for thermal comfort are as expected. The U-values are on the lower limit and the solar heat gain coefficient (SHGC) is on the upper limit of the optimization range. The results with the integrated penalty (Opt_{Pen}) are slightly different for the SHGC, which respects the benchmark for the overheating degree hours.

Tabelle 3: Boundaries and results of the building parameters for the optimization of q_{heat} and $q_{heatPen}$

	U - Wall	**U - Roof**	**U - Floor**	**U - Wind.**	**SHGC**
Max	1.47	1.10	1.10	3.5	0.7
Min	0.15	0.15	0.15	0.8	0.3
EnEV	0.24	0.24	0.3	1.3	-
Opt	0.15	0.15	0.15	0.8	0.7
Opt_{Pen}	0.15	0.15	0.15	0.8	0.45

Optimization of the net present value (NPV)

Another important objective for an optimal retrofit are costs. In this case study the net present value approach is chosen to compare the cost benefits of different renovation measures (see Section Optimization). Figure 11 represents the dependencies of the U-value and the NPV of different insulation measures based on the single family home of the case study. The diagram points out that for all measures the optimum of the NPV is not the minimum U-value. This indicates that the objectives minimizing q_{heat} and maximizing NPV have a trade-off. Based on the NPV, insulating the floor is not cost effective because the NPV never gets positive. The most profitable measure seems to be insulating the external wall.

Figure 12 and table 4 represent the results of the optimization of the net present value. There is an optimum of the NPV at 49128 $[EUR]$ in Figure 12. A comparison of the optimal building parameters (Opt_{Pen}) at table 3 and 4 show differences. The U-values for the insulation of the external wall, floor and roof for the objective NPV do not move to the lower limit of the range. This means, for a cost efficient renovation it is not necessary to save as much energy as possible. So there is a clear trade-off between minimizing energy consumption and maximizing the net present value.

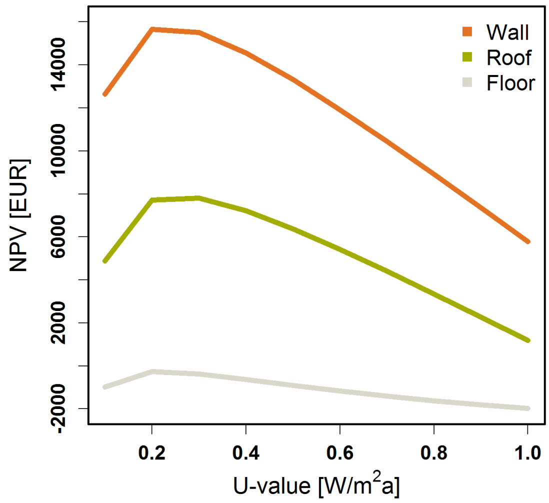

Abbildung 11: Net present value depending on the U-value of different renovation measures

Tabelle 4: Boundaries and results of the building parameters for the optimization of NPV

	U - Wall	**U - Roof**	**U - Floor**	**U - Wind.**	**SHGC**
Max	1.47	1.10	1.10	3.5	0.7
Min	0.15	0.15	0.15	0.8	0.3
EnEV	0.24	0.24	0.3	1.3	-
Opt_{Pen}	0.21	0.20	0.46	0.8	0.5

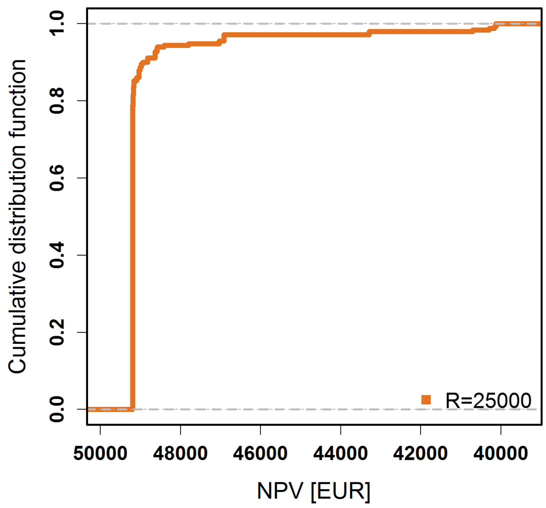

Abbildung 12: Cumulative distribution function of all optimization results from the objective NPV (25000 runs).

Multi-objective optimization of global warming potential (GWP) and net present value (NPV)

The results from the previous analysis demonstrate a trade-off between minimizing the heating demand q_{heat} (respectively the global warming potential (GWP)) and maximizing the cost benefits represented by the net present value. Thus a multi-objective optimization could be useful. Because in the case of two objectives with a trade-off the MOO provides results in form of a pareto frontier. Based on these pareto-optimal solutions a decision maker can chose an appropriate combination of retrofit measures. It is also possible to set different weights for the objectives (see Section Optimization) to affect the results of the MOO.

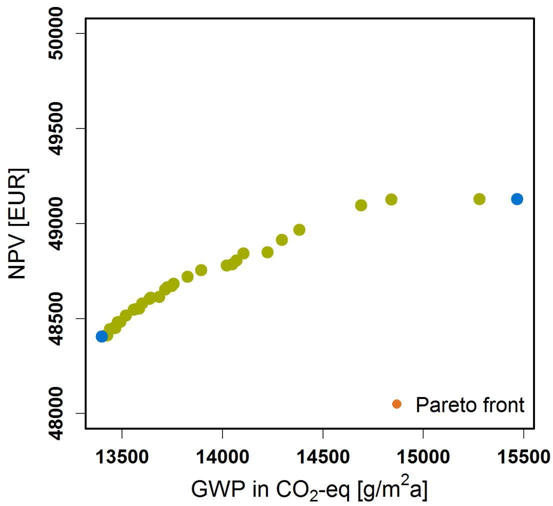

Abbildung 13: Pareto-optimal solutions of the Multi-objective optimization of GWP and NPV

Tabelle 5: Results of the building parameters for the MOO of NPV and GWP

	U - Wall	**U - Roof**	**U - Floor**	**U - Wind.**	**SHGC**
PO max	0.21	0.20	0.46	0.8	0.5
PO min	0.15	0.15	0.15	0.8	0.45

Figure 13 illustrates the pareto-optimal solutions for the objectives NPV and GWP. These results are based on balanced weights of both objectives (see Section Optimization). Table 5 shows an optimal setting of building parameters of the minimum and maximum solution of the pareto frontier (blue dots in Figure 13). These solutions are similar to the Opt_{Pen} building parameters of table 3 and 4.

Computational effort

To apply a MOO with a neural network instead of a detailed building model additional effort is necessary. Because at first a building model has to be developed[2] to provide a database for the learning and testing of a neural network. For the presented case study it took around 36 hours to provide the sampling data of 30.000 simulations of the detailed building model on a Intel Xeon CPU E5-2687W v3 3.10 GHz workstation with 20 threads. This is possible by parallelising the Monte Carlo process. Additional three days for training and validation of the neural network were needed.

Table 6 illustrates a comparison of the computational time for a detailed building model and a neural network of the case study. The building model requires 86 seconds for one simulation compared to 0.02 seconds needed by the neural network. For the optimization with the genetic algorithm the abort criterion was 25000 simulations. The neural network takes 79 seconds for an optimization process. Instead, the detailed building model takes more than three weeks for an optimization with 25000 runs. To analyse different refurbishment strategies, for example different interest rates of the NPV, a lot of optimizations are necessary. If a detailed building model is used for this analysis, the computational effort is not practical. This is specially the case because a numerical optimization process with a common BES tool is hard to parallelise. Therefore the additional effort for developing a neural network could be neglected.

Tabelle 6: Comparison of the computational effort of a detailed building model and a neural network

Model	**Simulation runs**	**Computational effort [s]**
Building model	1	86
Neural network	1	0.02
Building model	25000	21.5×10^5
Neural network	25000	79

CONCLUSION

In this paper, the advantage of a multi-objective optimization for a building retrofit and the capability of a neural network to replace a detailed building model was discussed. A refurbishment of a building envelope was optimized. In a first step, the trade-off between thermal comfort and heating demand was carried out. The second step illustrates the differences between maximizing the cost benefit and minimizing the glo-

[2]It is possible to use other sources for data to develop a meta model for instance measured data of a building.

bal warming potential. Based on the exemplary results of the case study, the benefits of the MOO to find solutions by combining different objectives were presented.

The neural network demonstrates the ability to replace a detailed building model for a multi-objective optimization. But as shown, it is necessary (behind the standard validation processes like cross validation and evaluating the CV) to analyse the upper and lower limits of the meta model carefully. Because during an optimization it is possible to reach the boarders of the valid area of the surrogate model. The neural network also demonstrates advantages in the computational effort for the optimization. For an MOO with 25000 simulations on a single core only 79 seconds are needed. For the same optimization a detailed building model requires 24 days. For the case study additional work of 5 days is necessary to develop the neural network. But once the surrogate model is developed it can be used for a wide range of analyses, e.g. optimizations with different rates of interest for the NPV or different weights for the objectives NPV and global warming potential.

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