This document is downloaded from the
VTT's Research Information Portal
https://cris.vtt.fi

VTT Technical Research Centre of Finland

Decision Support Tool to Enable Real-Time Data-Driven Building Energy Retrofitting Design

Piira, Kalevi; Kantorovitch, Julia; Kannari, Lotta; Piippo, Jouko; Vu Hoang, Nam

Published in:
Energies

DOI:
10.3390/en15155408

Published: 17/07/2022

Document Version
Publisher's final version

License
CC BY

Link to publication

Please cite the original version:
Piira, K., Kantorovitch, J., Kannari, L., Piippo, J., & Vu Hoang, N. (2022). Decision Support Tool to Enable Real-Time Data-Driven Building Energy Retrofitting Design. *Energies*, *15*(15), [5408]. https://doi.org/10.3390/en15155408

VTT
http://www.vtt.fi
P.O. box 1000FI-02044 VTT
Finland

By using VTT's Research Information Portal you are bound by the following Terms & Conditions.

I have read and I understand the following statement:

This document is protected by copyright and other intellectual property rights, and duplication or sale of all or part of any of this document is not permitted, except duplication for research use or educational purposes in electronic or print form. You must obtain permission for any other use. Electronic or print copies may not be offered for sale.

Download date: 13. Oct. 2022

energies

Article

Decision Support Tool to Enable Real-Time Data-Driven Building Energy Retrofitting Design

Kalevi Piira, Julia Kantorovitch *, Lotta Kannari, Jouko Piippo and Nam Vu Hoang

VTT Technical Research Centre of Finland, 02150 Tekniikantie 21, 02150 Espoo, Finland; kalevi.piira@vtt.fi (K.P.); lotta.kannari@vtt.fi (L.K.); jouko.piippo@vtt.fi (J.P.); nam.vuhoang@vtt.fi (N.V.H.)
* Correspondence: julia.kantorovitch@vtt.fi

Abstract: The availability of near-real-time data on energy performance is opening new opportunities to optimize buildings' energy efficiency and flexibility capabilities and to support the decision-making and planning process of building retrofitting infrastructure investment. Existing tools can support retrofitting design and energy performance contracting. However, there are well-recognized shortcomings of these tools related to their usability, complexity, and ability to perform calculations based on the real-time energy performance of buildings. To address this gap, the advanced retrofitting decision support tool is developed and presented in this study. The strengths of our solution rely on easy usability, accuracy, and transparency of results. The automatic collection of real-time building energy consumption data gathered from the building management systems, combined with data analytics techniques, ensures ease of use and quickness of calculation. These results support step-by-step thinking for retrofitting design and hopefully enable a larger utilization rate for deep building retrofits.

Keywords: retrofitting design; energy-efficient buildings; decision support; IoT

check for updates

Citation: Piira, K.; Kantorovitch, J.; Kannari, L.; Piippo, J.; Vu Hoang, N. Decision Support Tool to Enable Real-Time Data-Driven Building Energy Retrofitting Design. *Energies* **2022**, *15*, 5408. https://doi.org/10.3390/en15155408

Academic Editors: Patrick Phelan and Jarek Kurnitski

Received: 9 June 2022
Accepted: 24 July 2022
Published: 26 July 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The energy transition of the EU building stock from being an energy waster to being highly energy efficient and an energy producer is a prerequisite for Europe's 2050 carbon neutrality [1]. Achieving these targets has called for the profound digitalization of the building sector, complemented with deep energy retrofitting actions. Catalyzed by carbon neutrality demands, digitalization driven by IoT technology, and recent data market and policy trends, energy data collection in the building industry has become more widespread. This wealth of big data and access to important pertinent information are opening new opportunities for buildings to become active players in the smart energy services market, as well as to be an evidence-based source of real information to support the decision-making and planning process of building infrastructure investment.

Several recent research survey articles have made an effort to assess the existing building energy modeling and performance tools from different points of view. In the studies by Maa et al. [2], Cetiner et al. [3], and Lee et al. [4], the focus was put on the sustainability of the design of retrofit actions, while others have focused on the suitability of early design phases (e.g., Schlueter et al. [5]) and the prediction of the energy performance of buildings (e.g., Foucquier et al. [6]). The evaluation tools for certain types of buildings, such as commercial buildings, were discussed by Leaman et al. [7], Lee et al. [4], and Hong et al. [8]. A number of reviews also compared the results of different tools through case studies (e.g., Srinivasan et al. [9]), and some studies have been dedicated to the specific geographical contexts, (e.g., Aste et al. [10] with the focus put on solar systems modeling in sub-Saharan African context). The evaluation tools specifically for zero energy buildings (ZEBs) have been extensively addressed in numerous studies such as Attia et al. [11], Deng et al. [12], Marszal et al. [13], and Santos-Herrero et al. [14]. Finally, the building-stock-based approaches to assess energy efficiency and optimize the retrofit investments were overviewed by Ruggeri et al. [15].

These studies have demonstrated that based on various criteria such as building's type, the initial data availability, respective performance indicators, desired accuracy, and the decision support needed, the specific tools need to be chosen.

Overall, the accurate estimation of the energy performance of buildings is a prerequisite to assessing the needs and outcome of building retrofit actions. One way to look at the existing tools is through used building energy assessment methods [16,17]. The methods can be based on physical models of the building and their components, or on the analysis of the statistical data acquired through measurements or other data collection means such as energy bills. There are also hybrid models that use the elements of both approaches.

The tools using statistical methods and leveraging only limited information about the building are convenient for a quick initial estimation. However, the accuracy of their output can be limited by the availability of good quality measurement data. The tools based on physical models provide very accurate results, as they require detailed knowledge about the building and its systems to perform the analysis of different aspects influencing the energy performance of buildings.

In European countries, such physical model-based tools as IDA-ICE [18] and EnergyPlus [19] are the tools that are widely used to calculate the energy performance (i.e., energy certificates) of buildings [16]. While these tools provide more accurate assessment results, they require professional skills for proper use. Furthermore, the use of the tools is typically time-consuming due to their complexity and the extensive input data needs [20]. The Home Energy Saver tool [21] addresses the need for simple tools to support non-specialized users in the audit process. The toolset supports modeling building, incorporating home-specific utilization and behavioral factors, as well as standardized asset modeling for the purposes of home energy rating. Still, baseline and energy efficiency-related calculations performed by the toolset are leveraging default parameters to model studied buildings.

Simultaneously, from a business point of view, a need for switching from light retrofits (savings of approx. 20%) to medium or deep retrofits (targeting over 50% energy savings) is needed [22]. To ensure larger retrofits with usually lower cost–benefit ratios, mindsets need to be shifted from thinking of retrofitting as one-off projects (at one single step) to step-by-step retrofitting [23]. By reducing investment risk, tools enabling retrofitting design and energy performance contracting based on continuous monitoring of building functions can enhance usage and transparency of step-by-step retrofitting thinking, thus enabling a larger utilization rate for deep building retrofitting. Various studies on the usability of retrofitting design tools have shown that there are no moderately easy-to-use simulation tools that are based on the calculations performed using real-time energy performance of a building and combine both cost-efficiency and energy-efficiency measures (e.g., Gonzalez Caceres et al. [24]). Multiple studies have also proven that barriers to energy performance contracting and efficient retrofitting include mistrust and lack of related information (e.g., JRC report [25]). A lack of transparency and easily understandable information is a significant barrier to the utilization of retrofitting design tools.

To address this gap, the advanced retrofitting decision support tool has been developed. The aim is to support users (facility managers, building owners, ESCOs) in the design and selection of the most appropriate building retrofitting actions. This is achieved by leveraging the real-time data coming from the actual operation of the building combined with occupants' behavior- and comfort profiles into iterative analytics and simulation loops to propose alternative retrofitting scenarios of selected buildings, thus helping respective users to enhance generic routines currently used in similar commercial products, which are based on the predicted energy performance of a building.

In the following, the paper is organized that the methods used to design and develop the retrofitting decision support is presented in Section 2. More specifically, the architecture, data analytics, and algorithms to enable the learning model of the studied building, as well as a technological stack used to deploy the solution, are discussed here. Section 3 is focused on the user interface that supports the user in the interaction with the tool. The tool evaluation results and gathered feedback are presented here also. The strengths of the developed solution compared with other existing tools are discussed in Section 4. Section 5 concludes this study by also outlining the aspects of future work.

2. Methodology

The retrofitting decision support tool utilizes real-time, automatically collected history data of building energy consumption, occupants' behavior, and comfort profiles. The latter aspects are taken in the tool data analytics inputs as occupants-related internal heat gains and related schedules and as set-point values for heating and cooling, respectively. The genetic algorithms are used to learn building parameters from aggregated measured data in order to construct a building energy performance digital twin model for its further AI-boosted analysis to support the recognition of building technical system malfunctions, inefficiencies, and optimization possibilities. At the same time, it provides the respective calculation of alternative retrofitting scenarios on the fly (indicating energy performance, carbon footprint, etc., measures before and after retrofitting, as well as indicating costs and payback). An intuitive visualization dashboard and clear definition of respective building key performance indicators (KPIs), as well as sufficient explanations, are utilized in retrofitting decision-making support to enhance usability. When needed, the prioritized pre-selected list of retrofitting actions can be further used for a more detailed analysis with the support of existing commercial simulation tools widely used in the industry, such as IDA-ICE. The overall methodology that has been used to research and develop the building components of the retrofitting decision support tool is presented in the following sections.

2.1. Retrofitting Tool Architecture

The building components of the retrofitting decision support tool are shown in Figure 1. The heart of the tool's backend comprises three components: the Fast Heating Cooling solver (Fast HC solver), database of retrofitting action and building stock default values, and Building Energy Baseline Model constructor (BEBM constructor).

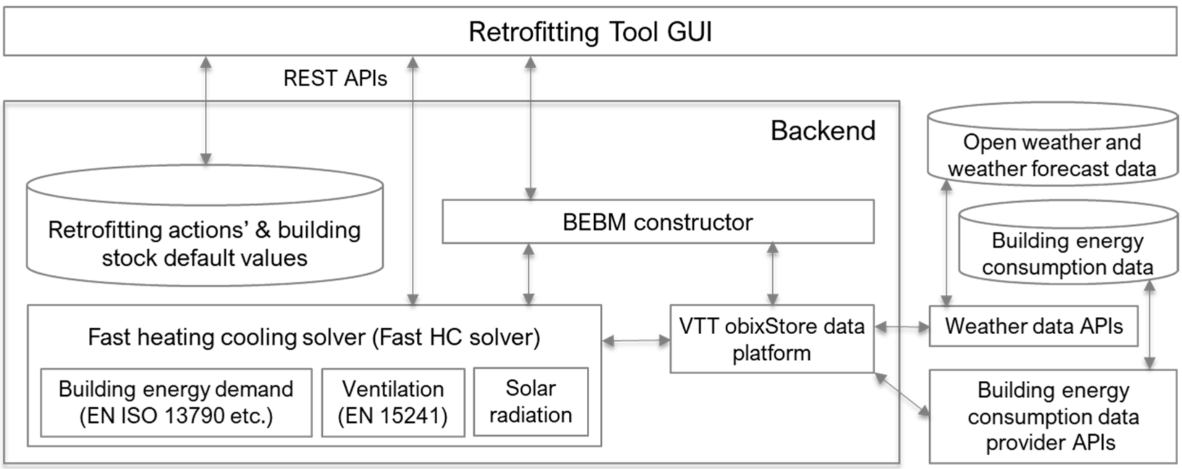

Figure 1. The retrofitting decision support tool architecture.

The Fast HC solver is a dynamic simulator that calculates buildings' energy consumption and thermal performance on an hourly basis [26]. Simulated consumptions are needed to be able to calculate the effects of different retrofitting actions and compare them to the baseline. It is based on EN ISO 13790:2008 (Energy performance of buildings: Calculation of energy use for space heating and cooling [27]) and EN 15241:2007 (Ventilation for buildings: calculation methods for energy losses due to ventilation and infiltration in buildings, [28]) standards as well as the models for estimating solar radiation.

The database includes various country-specific information such as default values for building stock (e.g., building type, construction year, etc.), typical schedules for different types of internal heat gains (e.g., appliances, lighting, occupant, ventilation, water, etc.), building technical systems info (e.g., energy efficiency (%), annual energy costs (€/m^2/a), used energy system fuel energy cost (€/kWh), fuel related CO_2 emissions (kg/kWh), yearly construction cost indexes, retrofitting actions classification for different categories (e.g., space heating, envelope insulation), equations for calculating retrofitting action related aid variables (e.g., new U-values for insulated envelope), retrofitting action investment unit cost (€/cost unit) and allowed min and max values for retrofitting parameters. This information is being systematically collected by VTT within a series of previous European and national research projects (e.g., EU NeZeR, SPHERE, RINNO, SYNERGY) and by utilizing the StatFin database, market information, and the national cost optimal calculation results. When retrofitting actions are selected, the database is used to calculate related costs and carbon footprints. The retrofitting cost calculation is based on the life-cycle costing method [29]. The investment costs and payback calculations and required data are based on the Finnish national cost optimal calculation results [30,31].

The BEBM constructor is a component that learns building parameters (i.e., construct digital twin) by measured building energy consumption and weather data. The learning model is based on genetic algorithms. The method estimates parameters by running the Fast HC solver with some initial parameters. It compares the simulated energy consumption with the measured one and manipulates the parameters and simulates again. Parameters with the best match with the real measurements are selected as the basis for the next manipulation round until the stopping criteria are reached (see details in the following Section 2.2).

Both Fast HC solver and parameter estimation utilize data stored in VTT obixStore data platform. The platform is based on the OASIS standard "Open Building Information Exchange" [32]. There is weather data in the platform collected from Finnish Meteorological Institute's (FMI) weather data API [33] as well as measured or simulated energy usage data for the building. Any necessary measured data regarding, for example, energy performance of the studied building, users' comfort profiles, weather information, etc., can be imported to the tool through the existing data providers such as ESCOs' platforms and other open data platforms. For the studies reported in this paper, the necessary building energy performance data is acquired from the Caverion platform [34] with the support of the SYNERGY open data platform and AI marketplace [35].

In case the measured building energy consumption data is not available, the web-based GUI allows users to import the default building parameters, otherwise, the parameters of the examined building are learned by the tool. The user is also supported with setting the retrofitting targets and the selection of retrofitting actions. The main outputs of the tool presented for the user are heating, hot water, cooling & electricity consumption for studied retrofitting actions. Additionally, payback time, investment costs, energy costs, and carbon footprint are calculated by reading all country-level background data (e.g., energy production/use carbon footprint, investments costs of the different king of building technical systems, installation-related unit work costs for different ages building, energy costs, etc.) that are available in the knowledge base.

2.2. BEBM Constructor (Algorithms for Learning Building Parameters)

To be able to reliably calculate the benefits of the possible renovation actions, the user needs to know the current state of the building. This baseline needs a lot of detailed information, e.g., the share of windows, building U-values, and ventilation parameters. Collecting this scattered information is time-consuming and using default parameters might cause incorrect results. BEBM constructor is developed to automate the harvesting of these parameters directly from the building measurements. It utilizes a genetic algorithm (GA) to find the parameter set that results in the best match between simulated and measured energy consumptions. This section describes the used algorithm in more detail.

GA is not a new method. As early as the beginning of the 1970s, John Holland developed the idea of genetic algorithms where the initial population can evolve through variations derived from the crossover between fittest individuals and through mutations [36]. These algorithms can be used, e.g., for optimization and search problems based on random heuristics.

The simulation engine used here has 84 parameters that can be selected for the BEBM constructor to find their correct values. These genes have been grouped into eight groups so that the end user can select which genes will be selected for the learning process. In other words, it is possible to select only one gene group or several grouped genes shown in Table 1. In addition, it is important that already known genes (gene groups) should be dropped out of the learning process. The main difference with the typical genetic algorithm-based approach is that genes used here include both integer and floating-point numbers, not only binary-based genes. The flow of the algorithm is shown in Figure 2.

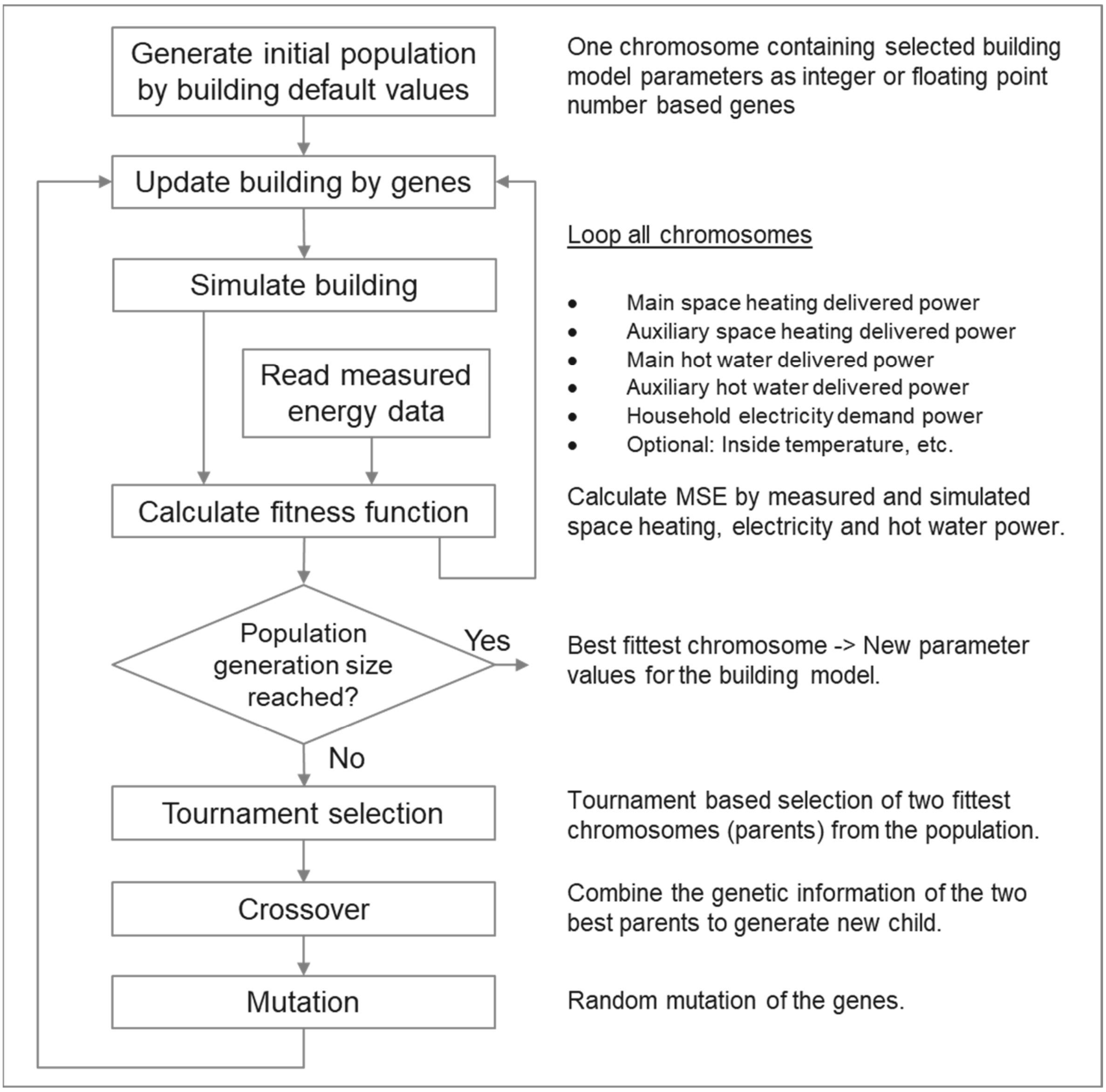

Figure 2. GA-based learning of building model parameters.

Table 1. Building model genes.

Chromosome-Related Gene Groups	Genes
Building	Total window area per total floor area, window area coefficient for south, movable solar shading reduction factor, horizontal shading angle, building heat capacity
Building envelope and ventilation	U-value for outside wall, U-value for upper floor, U-value for base floor, U-value for window, window type, building air tightness (n50), heat recovery efficiency for ventilation, ventilation preheating set value
Ventilation schedule	Ventilation-related workday, Saturday and Sunday schedules
Internal heat gains: appliances	Appliances related to internal heat gains and related workday, Saturday and Sunday schedules
Internal heat gains: Lighting	Lighting-related internal heat gains and related workday, Saturday, and Sunday schedules
Internal heat gains: Occupants	Occupants-related internal heat gains and related workday, Saturday and Sunday schedules
Water system	Total water consumption as liters per person per day, share of hot water in total water consumption
Hot water usage schedule	Hot water usage related workday, Saturday and Sunday schedules

The initial population (i.e., the first candidates for the simulation parameter sets) is generated based on the building default value database. This population is simulated with the Fast HC solver, and the quality of the results is resolved with the fitness function. The fitness function minimizes the MSE of selected measured and simulated variables, typically space heating, electricity, and domestic hot water heating power. Functions used here are [37]:

$$SE = ((P_{meas\_space\_heating} - P_{space\_heating})^2 + (P_{meas\_aux\_space\_heating} - P_{aux\_space\_heating})^2 + (P_{meas\_elec} - P_{elec})^2 + (P_{meas\_dhw} - P_{dhw})^2 + (P_{meas\_aux\_dhw} - P_{aux\_dhw})^2$$

$$MSE = \sum SE/n$$

where $P_{meas\ space\ heating}$ is measured and $P_{space\_heating}$ simulated space heating power of the primary heating system, $P_{meas\_aux\_space\_heating}$ is measured and $P_{aux\_space\_heating}$ simulated space heating power of possible secondary heating system, P_{meas_elec} measured and P_{elec} simulated electric power, P_{meas_dhw} measured and P_{dhw} simulated domestic hot water heating power from main heating system, $P_{meas\_aux\_dhw}$ measured and P_{aux_dhw} simulated hot water power delivered by a possible auxiliary heating system.

If the stopping criteria are reached, the parameters of the best simulation are assumed to represent the reference point for the building retrofitting actions. Criteria used here perform iterations until 400 generations (defined by GENERATION_SIZE parameter) are simulated. In case the criteria are not reached tournament selection, crossover, and mutation algorithms are used to create the next chromosome generation.

In tournament selection, the parent parameter sets (chromosomes) for the next generation are chosen from the population by randomly selecting n (usually 2) individuals to compete against each other. Those with the highest value of fitness function will be selected for the crossover. This type of parent selection preserves the variety of the genes for the next population [38].

In the crossover, the best two chromosomes are used as parents for the next parameter set (child chromosome) generation. Each child is generated by combining the genetic information of the parents [39]. For this work, the Apache Commons Math library crossover interface was implemented so that the floating-point number-based genes can also get a little bit lower or bigger values (multiplied by coefficient alfa) than the parents' values. For the integer genes, the crossover was changed so that these genes can also get integer values between the parents' values, not only parents' values.

Finally, the variation of the generation is broadened by introducing random mutations. This is done to prevent convergence to a local optima [40]. In our case, the mutation is done only for one gene in each chromosome.

After the BEBM constructor has found the final winning chromosome, this parameter set is delivered to the retrofitting tool GUI to be used for the simulation of the baseline.

Different GA parameters have a direct impact on the quality of the solution as well as keeping parameters' values "balanced" [40]. The next GA parameters have been used.

MUTATE_AT_THE_BEGINNIG: True
POPULATION_SIZE: 100

- i.e., the number of chromosomes in the generation. Big population size makes it possible to get away from the local optimum but increases the computation time [21,22].

ELITISM_RATE: 0.0

- ELITISM_RATE affects how many of the best chromosomes go to the next stage by avoiding the crossover and mutation operators. Prevents losing good solutions from the next generation [41].

CROSSOVER_RATE: 0.85

- CROSSOVER_RATE affects how many of the best chromosomes exchange genes.

TOURNAMENT_ARITY: 2

- TOURNAMENT_ARITY affects the chromosome selection process (2 chromosomes selected).

GENERATIONS_SIZE: 400

- GENERATIONS_SIZE defines the number of generations.

MUTATION_RATE: 0.5

- MUTATION_RATE defines what percentage (here 50%) of new chromosomes are subjected to mutation. Targets a single gene if gene mutation is allowed.

2.3. Validation of the Algorithm

The performance of the BEBM constructor is tested with simulated buildings, since with real buildings, it is hard to reliably harvest all the necessary building parameters. We have used the same Fast HC solver for simulating the measurements as the BEBM constructor uses for calculating the simulation results and given random values as a starting point for the parameter iteration. The resulted baseline parameters are compared to the ones used in the original simulations.

An example of the progress of the teaching process is shown in Figure 3. The upper part of the figure shows the difference between reference space heating energy consumption and related values using initial building values and the lower part of the figure describes the situation when stopping criteria are met.

The algorithm can find parameters resulting in simulations that fit the measurements well. Most of the identified parameters are close to the real ones. The average errors compared to the real ones are presented in Table 2.

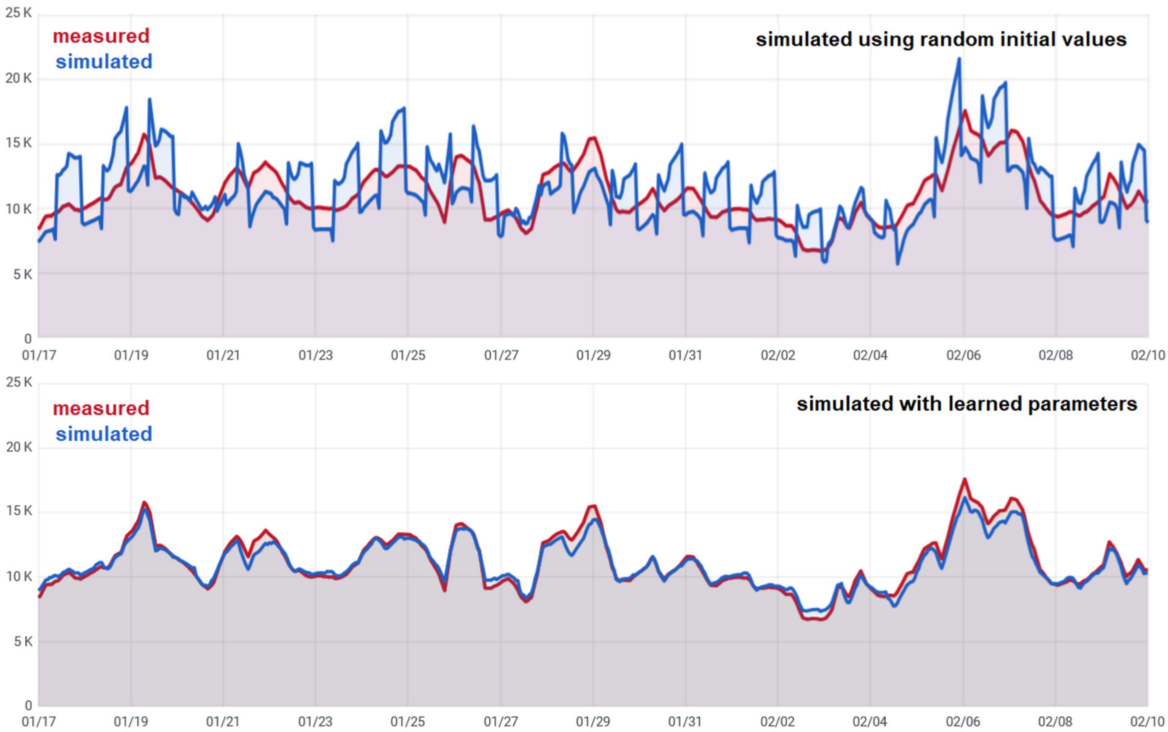

Figure 3. GA-based learning of building model (baseline parameters).

Table 2. The success of the identification method.

Genes	Average Error %
U-values	3.5
heat recovery efficiency of ventilation	2.7
air tightness n50 (air change rates at 50 Pa pressure difference)	5.8
windows parameters (area & share facing south)	4.9
heat capacity (one-hot encoded)	0.0
window type (one-hot encoded)	26.7
domestic hot water (consumption per person & share of hot water)	7.3

2.4. Technological Stack

In order to provide intended functionalities, the retrofitting decision support tool is built on the state-of-the art technologies and standards. More specifically, in the backend layer, (a) the open source based Apache Tomcat® [42] for running retrofitting tool's code and NodeJS [43] for running retrofitting tool's GUI code, (b) Angular JavaScript [44] for GUI implementation; in the data storage layers, (c) PostgreSQL [45] as the relational database for building energy and weather data storage and related default values for country-specific (e.g., Finland) building stock. The genetic algorithm-based learning of the simulation engine parameters has been programmed using Java programming language by utilizing Apache Commons Math library genetic algorithms [46].

3. The Retrofitting Decision Support Tool—Interaction with the User

From the user's point of view, the steps for using the retrofitting decision support tool via web GUI are visualized in Figure 4.

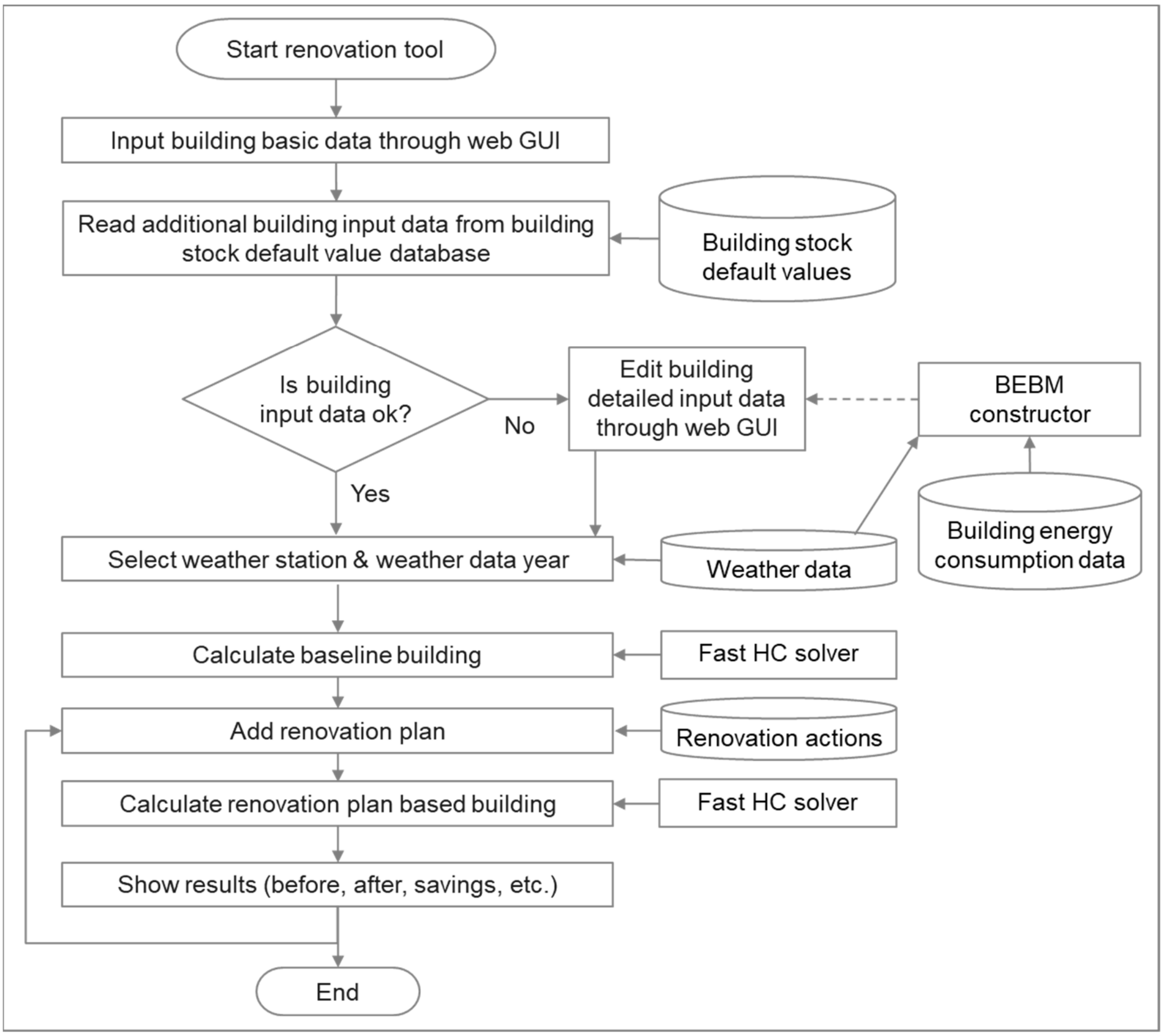

Figure 4. The steps for using the retrofitting tool via web GUI.

After starting the retrofitting tool GUI by a web browser, the user should give the basic information of the studied building (step 1). (Figure 5). This information is needed to query building baseline parameters from the building stock default value database. The basic information, such as building type, construction year, type of space heating, domestic hot water heating, and cooling systems, are provided by the user by the selections made from drop-down lists with the different options for each building parameter suggested by the tool. To facilitate the user work and to ease the respective definitions, the tool provides prefilled information about the typology of buildings, giving the default values of the building's characteristics.

In step 2, the user can edit the proposed building baseline parameters (Figure 6). At this point, adjusted baseline parameters calculated by the BEBM constructor can be used to update the initial baseline values.

After checking and optionally modifying building baseline parameters, the user must select a weather station and year of weather data to be used in the calculation (step 3).

In step 4, the user can add retrofitting plans for the examined building. The retrofitting plans may contain several retrofitting actions that are selected using a combo box. The available retrofitting actions include, for example, change of heating or cooling system and replacements with renewable technology (e.g., heat pumps), improving air tightness of building envelope, change of windows, or adding thermal insulation level of walls or floors. For each of these retrofitting plans, the tool lists alternative actions, as illustrated in Figure 7.

In the final step, the retrofitting tool calculates the baseline of building and retrofitting plans related building's energy performance. As a result, the tool presents the comparative values (heating energy consumption, cooling energy consumption, electricity consumption, carbon footprint, energy cost, investment, payback period) for the studied building as "before retrofitting", "after retrofitting", and achieved "savings by retrofitting", as presented in Figure 8.

The functionality and usefulness of the retrofitting decision support tool have been iteratively evaluated by two professional users (ESCOs, city decision makers) and one owner of a small private household during the design and development stage of the tool.

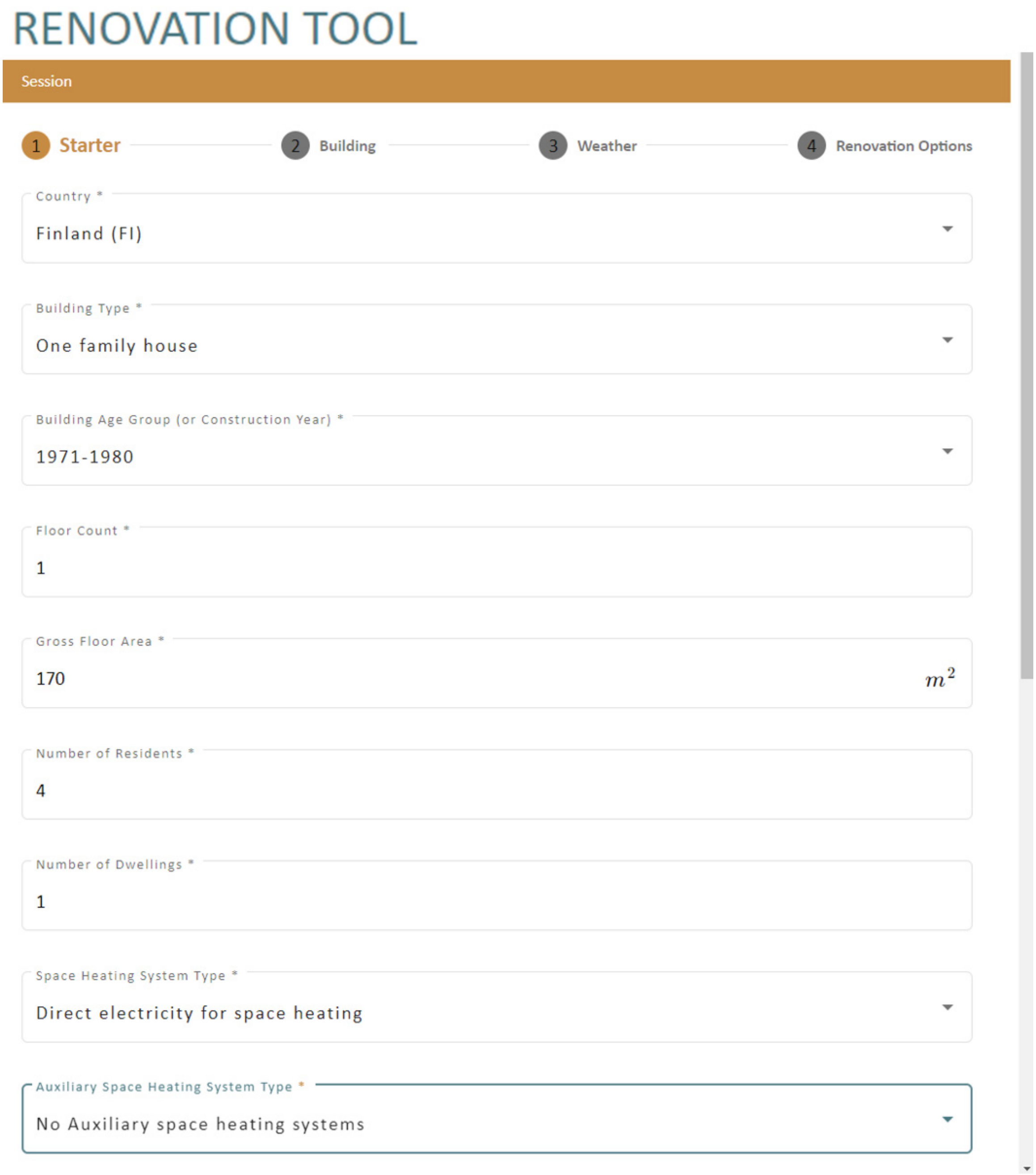

Figure 5. Retrofitting tool GUI, part of step 1.

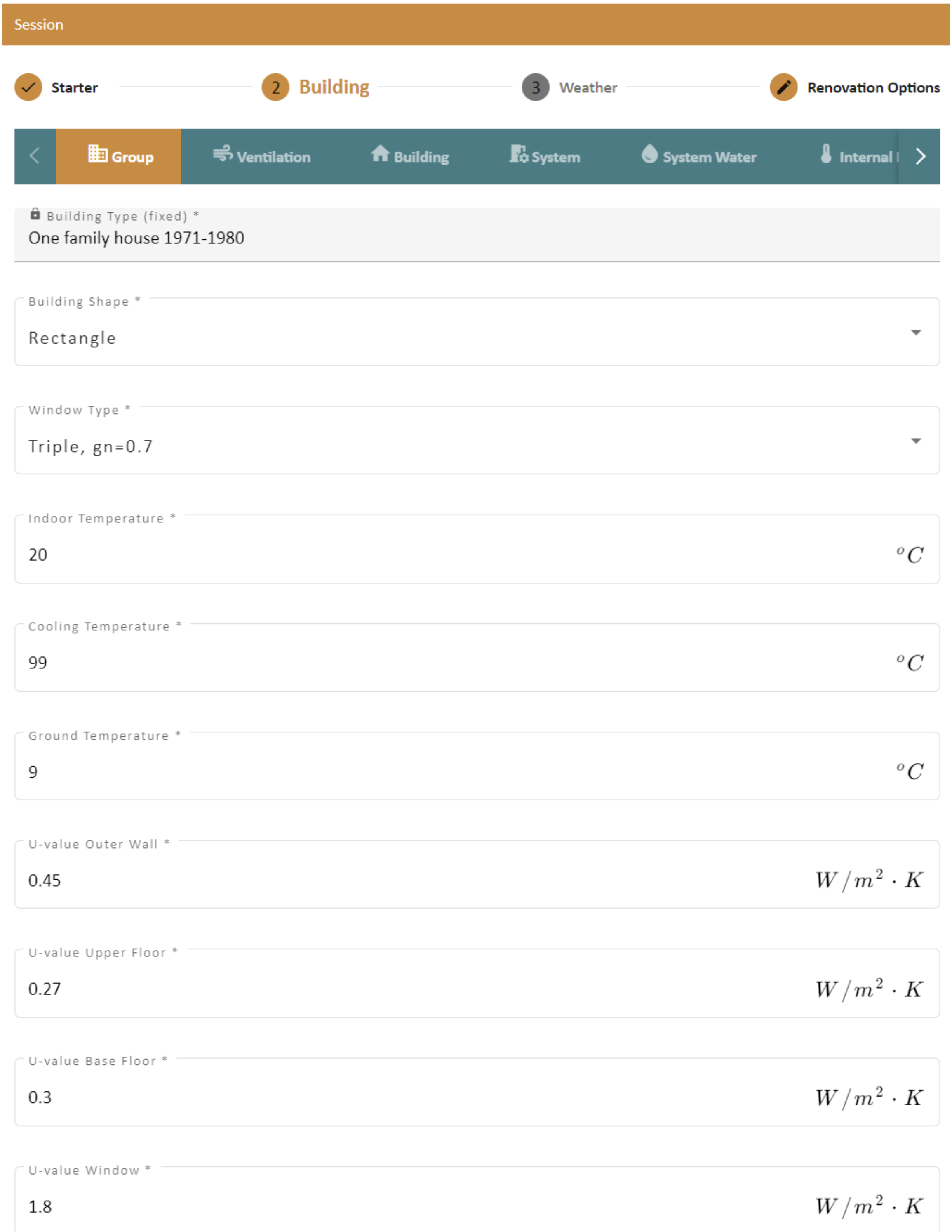

Figure 6. Retrofitting tool GUI: Step 2—Check (and modify) initial values for all building systems. Example of building group parameters.

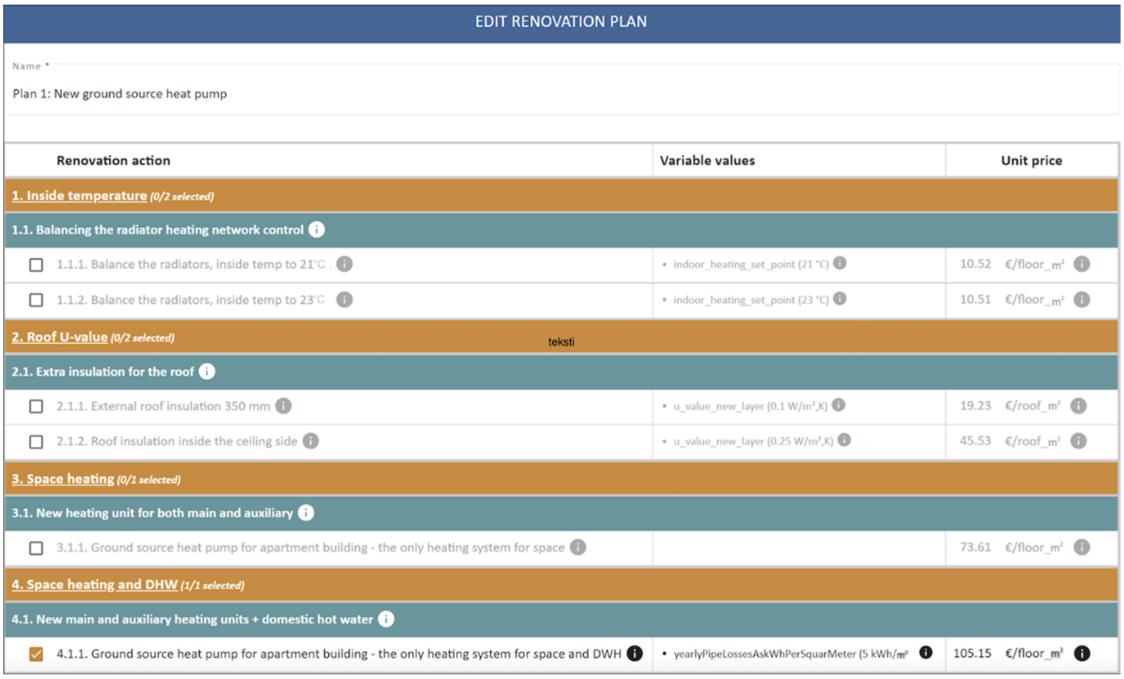

Figure 7. Retrofitting tool GUI: Step 4—Select/Edit retrofitting actions.

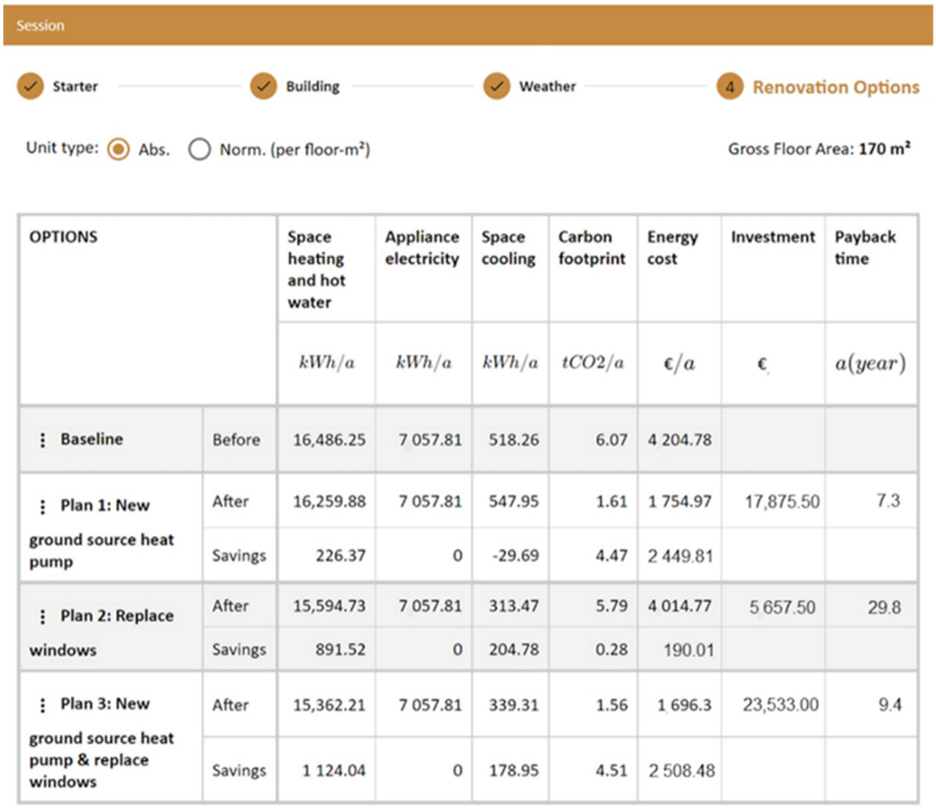

Figure 8. Retrofitting tool GUI: Results.

The evaluation has been organized by providing users with the link to the tool so that they could test various features offline. In addition, the evaluation form was given to fill out; it contained 10 questions. These questions were defined to assess the appropriateness of various functions of the tool and the easiness of the user interface to follow. Users have also been asked to rate the overall experience when testing various functions and encouraged to provide free-words feedback about the tool.

The overall experience has been assessed as 4/5. The tool was found as easy to use and learning it completely takes only a couple of runs. The user interface was easy to follow, simple, and logical when going between steps. Users did find the automatically suggested data prefilling at various steps of the tools appropriate and helping. On the usefulness of the tool, one user commented that the tool is great for early level assessment for the basic retrofitting actions and will help facility managers a lot to make early calculations and suggestions on what to retrofit. Additionally, the tool is helpful the most when one wants to quickly assess large building stocks for the easiest and most cost-effective retrofitting actions. Another use for the tool is residential single-family house owners that can quickly use the tool to assess the effectiveness of retrofitting actions. Other users (city representatives) commented that the tool could be useful for the cities' policymakers when they are looking for options for energy savings and emissions reduction. With this tool, it is possible to assess the impact of retrofit measures and make evidence-based decisions in terms of investments.

The evaluators have also provided some suggestions for improvements that have been taken in the iterative development process. They are related to the presentation of the results of applied retrofit measures, such as adding the costs for each of the retrofit measures and their effectiveness to be able to see which of the selected measurements would be most cost-effective immediately. At least in the minds of facility managers, the easiest and most cost-effective measurements are what interests them. In the current implementation of the tool, the results are calculated considering a combination of measures rather than presenting the influence of every measure. Some users have commented that they would like to see some sort of sensitivity analysis on, e.g., what retrofitting action has resulted in major savings in terms of costs and CO_2 emissions.

Moreover, the retrofitting tool has been compared with one of the commercial products —IDA-ICE, which is widely used by professionals. The subject of comparison was the amount of time required to produce an initial retrofitting plan for the studied building. The earlier research project with the objective to model and simulate 4-floor apartment building has been used as a reference for comparison.

It was estimated that for a user who has a previous experience with the IDA-ICE simulator, it takes roughly 1 work week (32 h) to model and simulate all necessary systems for a 4-floor apartment building. More specifically, it took 14 h to manually build the baseline case model for the simulator. Tuning the model so that the initially estimated energy consumption and measured consumption matched, consumed another 7 h. It took 3.5 h to build one retrofitting action (i.e., implementing exhaust air heat pump enhancement concept) and another 7 h to master the modeling of a heat pump system in the tool as it was a new model for the user. Exporting the results to Excel, including the calculation of annual energies, took an additional 0.5 h.

In contrast, with our solution, inserting input data about the studied building and retrofitting options with analysis takes only 10–30 min depending on the experience of the user. The only time-consuming steps are the collecting of missing input data from the energy certificate, which can be estimated as 1 h (if the energy certificate is provided) and learning the parameters with genetic algorithms (1 h of own time and 10 h of CPU time on a typical PC). It should be acknowledged, however, that the output of retrofit analysis from IDA-ICE provides a lot of detailed information that is not available from our retrofitting supporting tool. That is, our tool is intended for preliminary planning of renovation options, and once the renovation actions are selected, they can be further modeled in more detail with the IDA-ICE simulator.

4. Discussion

The definition (i.e., availability) of initial building energy performance baseline data is a well-known problem in energy performance assessment and design of building retrofitting. The existing simulation tools use predicted estimates for the energy performance that are gathered using building specs, energy performance certificates, and other respective technical documents. The mismatch between the predicted and measured energy performance of buildings is often referred to as the performance gap [47]. Many underlying causes for the performance gap are related to the use of unrealistic input parameters regarding facility management in building energy models [48]. Furthermore, the availability of the data concerning occupancy and user behavior may be problematic as well. Last, but not least, despite the number of available tools for the energy performance assessment, there is still a lack of tools that support an easy but accurate assessment of potential energy savings in building retrofitting.

The strengths of our solution rely on easy usability, building topology independence (residential, office, etc.), accuracy, and transparency of results. An open API enhances usability and the automatic collection of real-time building energy consumption data gathered from the building management systems. Combined with AI techniques that ensure ease of use and quickness of calculation results, the tool supports step-by-step thinking for retrofitting design and hopefully enables a larger utilization rate for deep building retrofits. Automatic pre-selection of retrofit targets aims to enhance the viability of pre-design and support the information-based selection of targets for deeper retrofitting design. Additionally, near-real-time data collection supports understanding how occupant behavior impacts technical system usability and retrofitting design.

Using the BEBM constructor is quite an easy way to identify the baseline for the retrofitting actions. In the studied case, the fit to the energy consumption measurements of the GA was rather good. However, currently, the method is only validated with simulated buildings, and testing with real measurement data is still required. Especially it should be investigated how the constructor handles the effects of real human behavior on energy usage. In addition, our fitness function concentrates on heating but does not take cooling or indoor temperature into account. This results in parameters having their biggest impact outside heating season are not as accurately found, e.g., window type, which is in our simulator separates from window U-value and affects mainly the window transmission coefficient, has remarkably worse result than the other parameters. Utilizing the method with buildings in warmer climates might require reevaluation of the fitness function. It is also possible that, in some cases, the BEBM constructor may find a parameter combination that results in a good level of MSE, but some parameters have wrong values since several genes affect in the same direction (e.g., cutting energy consumption). This may have an effect on the selected retrofitting action-related results.

The biggest challenge of the BEBM constructor is the used CPU time (several hours in a typical PC computer). This might cause a user to abandon this option and use suggested default values for the tool. On the other hand, finding the real parameter values of the building by manually looking through building drawings, finding properties of construction materials, and already implemented retrofitting takes more active time from the user than the automated method.

We have used a simulation time of 6 months for the BEBM constructor to utilize the possible variety of seasonal effects on genes. By shortening the simulation length, the execution time will be reduced. Finding an optimal simulation length would need further research. In addition, more advanced stopping criteria than a fixed number of generations could also result in a shorter execution time.

5. Conclusions

Overall, this paper proposes a novel tool that, by utilizing real-time automatically collected energy performance data of buildings (of various topologies) can effectively support decision-making in retrofitting design and planning. The initial feedback obtained from users indicated that the tool has great potential to support various stakeholders such as facility managers, city decision makers, and small residential house owners in the early level assessment of retrofitting actions efficiency.

To be able to reliably calculate the benefits of the possible retrofitting actions, the current state of the building should be known. Collecting this detailed scattered information about the studied building is time-consuming, and using default parameters might cause incorrect results. The developed tool allows automating the harvesting of these parameters directly from the building measurements. Hence, with this tool, it is possible to effectively validate the impact of retrofitting measures and make evidence-based decisions in terms of investments.

Although the results are promising, more research is still needed. For example, the usefulness of the tool can be improved by leveraging a multi-objective-based optimization approach for ranking selected retrofitting measures based on various measures such as energy savings, cost-efficiency, time, and many other parameters that are required to better support the business use cases in the retrofitting planning. The methods built towards shortening the simulation time to construct the baseline of the studied building based on measurement data still need some research.

Author Contributions: Conceptualization, K.P., J.K. and J.P.; methodology, L.K., J.P., K.P. and J.K.; software, J.P., N.V.H. and L.K.; evaluation and validation, L.K., K.P. and J.K.; writing—original draft preparation, J.K., K.P. and L.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research is done in the SYNERGY and BEYOND projects that were funded by the European Union's Horizon 2020 Research and Innovation program under Grant Agreements No. 872734 and No 957020, respectively.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The dataset used for the research is available for research purposes. Please contact Kalevi Piira (kalevi.piira@vtt.fi) to request access.

Acknowledgments: We would like to thank Aleksi Vuorenmaa (the development engineer at Caverion) for his assistance in providing us with the buildings' measurement data we needed to develop genetic algorithm-based analytics.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

1. European Climate Policies. Available online: https://ec.europa.eu/clima/policies/strategies/2050_en (accessed on 9 June 2022).
2. Ma, Z.; Cooper, P.; Daly, D.; Ledo, L. Existing building retrofits: Methodology and state-of-the-art. *Energy Build.* **2012**, *55*, 889–902. [CrossRef]
3. Cetiner, I.; Edis, E. An environmental and economic sustainability assessment method for the retrofitting of residential buildings. *Energy Build.* **2014**, *74*, 132–140. [CrossRef]
4. Lee, S.H.; Hong, T.; Piette, A.; Taylor-Lange, C. Energy retrofit analysis toolkits for commercial buildings: A review. *Energy* **2015**, *89*, 1087–1100. [CrossRef]
5. Schlueter, A.; Thesseling, F. Building information model based energy/exergy performance assessment in early design stages. *Autom. Constr.* **2009**, *18*, 153–163. [CrossRef]
6. Foucquier, A.; Robert, S.; Suard, F.; Stephan, L.; Jay, A. State of the art in building modelling and energy performances prediction: A review. *Renew. Sustain. Energy Rev.* **2013**, *23*, 272–288. [CrossRef]
7. Leaman, A.; Stevenson, F.; Bordass, B. Building evaluation: Practice and principles. *Build. Res. Inform.* **2010**, *38*, 564–577. [CrossRef]
8. Hong, T.; Piette, M.A.; Chen, Y.; Lee, S.H.; Taylor-Lange, S.C.; Zhang, R.; Sun, K.; Price, P. Commercial building energy saver: An energy retrofit analysis toolkit. *Appl. Energy* **2015**, *159*, 298–309. [CrossRef]
9. Srinivasan, R.S.; Ingwersen, W.; Trucco, C.; Ries, R.; Campbell, D. Comparison of energy-based indicators used in life cycle assessment tools for buildings. *Build. Environ.* **2014**, *79*, 138–151. [CrossRef]
10. Aste, N.; Adhikari, R.S.; Del Pero, C.; Leonforte, F. Development of an Interactive Building Energy Design Software Tool. In *Innovative Models for Sustainable Development in Emerging African Countries. Research for Development*; Aste, N., Della Torre, S., Talamo, C., Adhikari, R., Rossi, C., Eds.; Springer: Cham, Switzerland, 2020. [CrossRef]

11. Attia, S.; Hamdy, M.; O'Brien, W.; Carlucci, S. Assessing gaps and needs for integrating building performance optimization tools in net zero energy buildings design. *Energy Build.* **2013**, *60*, 110–124. [CrossRef]
12. Deng, S.; Wang, R.S.; Dai, Y.J. How to evaluate performance of net zero energy building—A literature research. *Energy* **2014**, *71*, 1–16. [CrossRef]
13. Marszal, A.J.; Heiselberg, P.; Bourrelle, J.S.; Musall, E.; Voss, K.; Sartori, I.; Napolitano, A. Zero Energy Building—A review of definitions and calculation methodologies. *Energy Build.* **2011**, *43*, 971–979. [CrossRef]
14. Santos-Herrero, M.; Lopez-Guede, J.M.; Flores-Abascal, I. Modelling, simulation and control tools for nZEB: A state-of-the-art review. *Renew. Sustain. Energy Rev.* **2021**, *142*, 110851. [CrossRef]
15. Ruggeri, A.G.; Gabrielli, L.; Scarpa, M. Energy Retrofit in European Building Portfolios: A Review of Five Key Aspects. *Sustainability* **2020**, *12*, 7465. [CrossRef]
16. Coakley, D.; Raftery, P.; Keane, M. A review of methods to match building energy simulation models to measured data. *Renew. Sustain. Energy Rev.* **2014**, *37*, 123–141. [CrossRef]
17. Fumo, N. A review on the basics of building energy estimation. *Renew. Sustain. Energy Rev.* **2014**, *31*, 53–60. [CrossRef]
18. IDA Indoor Climate and Energy Simulation Tool. Available online: https://www.equa.se/en/ida-ice (accessed on 9 June 2022).
19. EnergyPlus. Building Energy Simulation Tool. Available online: https://energyplus.net/ (accessed on 9 June 2022).
20. Häkkinen, T.; Ala-Juusela, M.; Shemeikka, J. Usability of energy performance assessment tools for different use purposes with the focus on refurbishment projects. *Energy Build.* **2016**, *127*, 217–228. [CrossRef]
21. Home Energy Saver. A Web Based Energy Analysis Tool for Consumers. Available online: https://homes.lbl.gov/home-energy-saver (accessed on 5 July 2022).
22. Comprehensive Study on Buildings Renovation. Available online: https://ec.europa.eu/energy/sites/ener/files/documents/1.final_report.pdf (accessed on 9 June 2022).
23. Maia, I.; Kranzl, L.; Müller, A. New step-by-step retrofitting model for delivering optimum timing. *Appl. Energy* **2021**, *290*, 116714. [CrossRef]
24. Gonzalez Caceres, A.; Diaz, M. Usability of the EPC Tools for the Profitability Calculation of a Retrofitting in a Residential Building. *Sustainability* **2018**, *10*, 3159. [CrossRef]
25. JRC Science for Policy Report. Available online: https://publications.jrc.ec.europa.eu/repository/bitstream/JRC106624/kjna28716enn.pdf (accessed on 9 June 2022).
26. Kannari, L.; Kiljander, J.; Piira, K.; Piippo, J.; Koponen, P. Building Heat Demand Forecasting by Training a Common Machine Learning Model with Physics-Based Simulator. *Forecasting* **2021**, *3*, 290–302. [CrossRef]
27. ISO 13790:2008. Energy Performance of Buildings: Calculation of Energy Use for Space Heating and Cooling. Available online: https://www.iso.org/standard/41974.html (accessed on 9 July 2022).
28. EN 15241:2007. Ventilation for Buildings: Calculation Methods for Energy Losses Due to Ventilation and Infiltration in Buildings. Available online: https://standards.iteh.ai/catalog/standards/cen/4138127b-0434-4265-95ef-4b075788e878/en-15241-2007 (accessed on 9 June 2022).
29. Life. ISO 15686-5. Buildings and Constructed Assets—Service-Life Planning—Part 5: Life-Cycle Costing. 2008. Available online: https://www.iso.org/standard/39843.html (accessed on 10 July 2022).
30. Saari, A.; Airaksinen, M.; Sirén, K.; Jokisalo, J.; Hasan, A.; Nissinen, K.; Vainio, T.; Möttönen, V.-H.; Pulakka, S.; Heljo, J.; et al. Energiatehokkuutta Koskevien Vähimmäisvaatimusten Kustannusoptimaalisten Tasojen Laskenta. Finland. 2013. Available online: https://cris.vtt.fi/en/publications/energiatehokkuutta-koskevien-v%C3%A4himm%C3%A4isvaatimusten-kustannusoptima (accessed on 9 July 2022).
31. Häkkinen, T.; Ruuska, A.; Vares, S.; Pulakka, S.; Kouhia, I.; Holopainen, R. *Methods and Concepts for Sustainable Renovation of Buildings*; VTT Technical Research Centre of Finland: Espoo, Finland, 2012.
32. OASIS Open Building Information Xchange. Available online: http://www.obix.org/ (accessed on 9 June 2022).
33. The Finnish Meteorological Institute Open Data. Available online: https://en.ilmatieteenlaitos.fi/open-data (accessed on 9 June 2022).
34. Caverion Building Performance Tools. Available online: https://www.caverion.com/ (accessed on 9 June 2022).
35. SYNERGY Big Data Platform and AI Marketplace. Available online: https://www.synergyh2020.eu/2021/12/16/synergy-the-big-data-platform-and-ai-marketplace/ (accessed on 9 June 2022).
36. Holland, J.H. Genetic Algorithms. *Sci. Am.* **1992**, *267*, 66–73. [CrossRef]
37. Sammut, C.; Webb, G.I. (Eds.) Mean Squared Error. In *Encyclopedia of Machine Learning*; Springer: Boston, MA, USA, 2022. [CrossRef]
38. Oladele, R.O.; Sadiku, J.S. Genetic algorithm performance with different selection methods in solving multi-objective network design problem. *Int. J. Comput.* **2013**, *70*, 5–9. [CrossRef]
39. Hassanat, A.; Almo-hammadi, K.; Alkafaween, E.; Abunawas, E.; Hammouri, A.; Prasath, V.B.S. Choosing Mutation and Crossover Ratios for Genetic Algorithms—A Review with a New Dynamic Approach. *Information* **2019**, *10*, 390. [CrossRef]
40. Katoch, S.; Chauhan, S.S.; Kumar, V. A review on genetic algorithm: Past, present, and future. *Multimed. Tools Appl.* **2021**, *80*, 8091–8126. [CrossRef]

41. Mirjalili, S.; Song Dong, J.; Sadiq, A.S.; Faris, H. Genetic Algorithm: Theory, Literature Review, and Application in Image Reconstruction. In *Nature-Inspired Optimizers. Studies in Computational Intelligence*; Mirjalili, S., Song Dong, J., Lewis, A., Eds.; Springer: Cham, Switzerland, 2020; Volume 811. [CrossRef]
42. Apache Tomcat Software. Available online: https://tomcat.apache.org/ (accessed on 9 June 2022).
43. Node.js Java Script Runtime Engine Software. Available online: https://nodejs.org/en/ (accessed on 9 June 2022).
44. Angular JS Framework. Available online: https://angularjs.org/ (accessed on 9 June 2022).
45. Open Source Rational Database. Available online: https://www.postgresql.org/ (accessed on 9 June 2022).
46. Apache Commons Math Library Genetic Algorithms. Available online: https://commons.apache.org/proper/commons-math/userguide/genetics.html (accessed on 9 June 2022).
47. De Wilde, P. The gap between predicted and measured energy performance of buildings: A framework for investigation. *Autom. Constr.* **2014**, *41*, 40–49. [CrossRef]
48. Li, X.; Wen, J. Review of building energy modeling for control and operation. *Renew. Sustain. Energy Rev.* **2014**, *37*, 517–537. [CrossRef]