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THE IMPACT OF ENERGY-ECONOMICAL BEHAVIOR ON LONG-TERM ENERGETIC RETROFITTING ROADMAPS: A VINE COPULA QUANTILE REGRESSION APPROACH

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ABSTRACT

Energy efficiency is at the core of multiple national climate protection plans. Consequently, roadmaps for energy efficiency measures aim to undercut certain energy consumption limits for residential one- and two-family households. However, these roadmaps are often based only on physical building parameters, neglecting the impact of occupant behavior. In this paper, we apply vine copula quantile regression to derive residential household specific conclusions on optimal long-term energetic retrofitting roadmaps under consideration of energy-economical behavior of the occupants. Our analysis shows that these behavioral factors highly impact the recommendation of certain energetic retrofitting roadmaps. Compared to generic approaches this leads to average savings of 8.2% and up to 32.8% in exceptional circumstances. We conclude that future policy decisions on energy efficiency measures for residential buildings should consider behavioral factors to lever their effects.

Keywords: vine copula quantile regression, energy conservation in buildings, long-term energetic retrofitting roadmaps, energy-economical behavior

NOMENCLATURE

Abbreviations	
EEM	Energy Efficiency Measure
SHL	Specific Heat Load

1. INTRODUCTION

Despite ambitious international climate goals, the current investment volume of energy efficiency measures (EEMs) is not enough for the postulated low-carbon transition paths. With household space- and water heating accounting for a fifth of total energy consumption in Germany, this sector offers enormous potential to still reach these goals through energy efficiency improvements [1]. However, economically and ecologically sensible energy efficiency measures are often not implemented, which has coined the term energy efficiency gap [2]. This is partially due to the difference between estimated and realized energy bill savings, arising from imprecise predictions through the negligence of occupant behavior [3]. These uncertainties coupled with high risk aversion of decision makers lead to the rejection of EEMs [2]. Thus, models able to concisely predict energy bill savings potentially help to overcome the energy efficiency gap. However, since full refurbishment is often not feasible for financial reasons, we assume a stepwise approach in the form of roadmaps. We focus on space- and water heating, so EEM henceforth refers to energetic retrofitting.

The overall goal of this paper is to derive optimal long-term energetic retrofitting roadmaps by maximizing energy efficiency gains while explicitly accounting for energy-economical behavior. We elaborate on a method first introduced in [4] based on vine copula quantile regression to concisely predict energy bill savings after the implementation of EEMs. This approach enables analyzing different levels of energy-economical behavior as it provides full information on the distribution of energy consumption. At the same time, we implicitly include occupant behavior in the model fitting by relying on an extensive real-world data set of 25,000 German households.

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2. THEORETICAL BACKGROUND ON VINE COPULAE

A d-dimensional copula is a d-variate distribution function on $[0,1]^d$ with uniformly distributed marginals. For each d-dimensional random variable $X \sim F$ with marginal distribution functions F_i, $i = 1, \ldots, d$ exists a d-dimensional copula $\mathbb{C}$ equal to the joint distribution function [5]. The advantage of copulae is the ability to easily model multivariate data exhibiting complex patterns of dependence [6]. In higher dimensions, this is done using sequences of bivariate copulae, called vine copulae [6]. This work focuses on D-vines due to their flexibility and performance advantage when conditionally simulating a response variable $Y \sim F_Y$ for given predictor variables $X_i \sim F_i$. This can be mathematically expressed as

$$F^{-1}_{Y|X_1,\ldots,X_d}(\alpha|x_1, \ldots, x_d) = F_Y^{-1}\left(\mathbb{C}^{-1}_{V|U_1,\ldots,U_d}(\alpha|u_1, \ldots, u_d)\right), \quad (1)$$

where $V = F_Y(Y)$ and $U = F_X(X)$. Further, α and $\mathbb{C}^{-1}_{V|U_1,\ldots,U_d}$ are depicting the desired quantile and inverse of the conditional distribution function of V given $U_1, \ldots, U_d$, respectively [7]. Then, the left side of Equation (1) equals the value conditional on $x_1, \ldots, x_d$ at the α-quantile. Thus, this approach provides full information on the distribution of Y, mitigating the shortcomings of conventional point estimation methods. In [7,8] the authors compared D-vine copula quantile regression to competitor models finding that they, when correctly modelled and used, almost consistently outperform.

3. DATA PREPARATION AND MODEL FITTING

The used real-world data set comprises 25,000 German one- and two-family households with 74 variables depicting building characteristics, registered over the period from April 2007 to January 2014. Next to physical building components, it provides detailed information on regional affiliation, energy source, and technical variables, e.g., exhaust gas loss. Since a standardized measure for energy consumption is not directly included in the data set, we introduce the specific heat load (SHL), given in $\frac{W}{K \cdot m^2}$. The SHL enables meaningful comparisons by extracting influences from weather and living space based on the German V 4108-6 norm

$$Q = \frac{1}{1000} \cdot 24h \cdot SHL \cdot \mathcal{T} \cdot A_{living}, \quad (2)$$

where Q is the annual energy consumption in kWh, $\mathcal{T}$ the temperature influence, e.g., heating degree days, and A_{living} the living space. Next, we prepared the data by excluding contradicting, empty, or flawed entries, as well as variables lacking explanatory power for the SHL.

For model fitting, we prefer a variable selection analogous to [9] over a parsimonious forward selection algorithm by [8] based on Akaike information criterion and average coverage error. Thereby, we constructed groups of variables describing the same building component and chose only the strongest representants to avoid multicollinearity. The selected variables are building age, living space, energy type, presence of roof insulation, wall insulation thickness, window-glazing, exhaust gas loss, and presence of solar panels. This selection restricts to the compatible EEMs depicted in Table 1, which we use for the roadmap composition.

ID	Building component	Situation before EEM	Situation after EEM	Total costs
1	Heating system	Fan-assisted oil boiler, exhaust gas loss = 10%	Heat pump, exhaust gas loss = 0%	$662.91€ \cdot (A_{living})^{0.513}$
2	Roof insulation	None; U = 1.4	15 cm insulation; U=0.24	$192.62€ \cdot A_{roof}$
3	Solar panel installation	None	Two solar panels (~11m²)	$530.31€ \cdot (A_{living})^{0.501}$
4	Wall insulation	None; U = 1.4	15 cm insulation; U=0.24	$139.04€ \cdot A_{wall}$
5	Window replacement	Single glazing; U = 5.0	Triple thermal insulation glazing; U=0.7	$438€ \cdot A_{window}$

Table 1: EEMs compatible with our D-vine, costs based on [10]. U refers to the heat transition coefficient.

Building age and living space cannot be improved through EEMs, thus we ran several analyses with different fixed values (three living spaces and eight building ages). Moreover, we evaluated different quantiles of energy-economical behavior individually, namely 0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95, and 0.99, for a total of 216 analyses. Lower values refer to energy-conscious, higher values to energy-wasteful behavior.

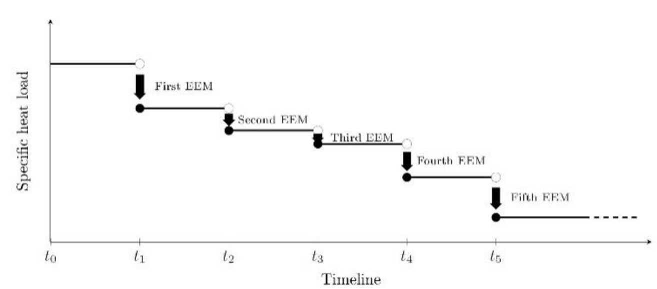

Figure 1:SHL process undergoing EEMs.

4. EMPIRICAL RESULTS AND DISCUSSION

When successively undergoing aforementioned EEMs, the SHL is lowered in each step, which equals a monotonically decreasing step function, as displayed in Figure 1. Then, for a given constellation of living space, building age, and energy-economical behavior, the specific roadmap was chosen which minimized the integral under the SHL process. Thereby, we differentiate between an absolute perspective, focusing on the SHL only, and a relative perspective, additionally accounting for the costs in Table 1. The aggregated results and most common paths for the absolute perspective are depicted in Table 2 and Figure 2, for the relative perspective in Table 3 and Figure 4.

ID	Step 1	Step 2	Step 3	Step 4	Step 5
Heating system	144	19	35	18	0
Roof insulation	0	12	52	138	14
Solar panel installation	13	106	69	22	6
Wall insulation	50	78	26	21	41
Window replacement	9	1	34	17	155

Table 2: Aggregated numbers of EEMs for each step in the absolute savings evaluation, added up for the 216 constellations. The numbers indicate how often the measures were implemented at each step.

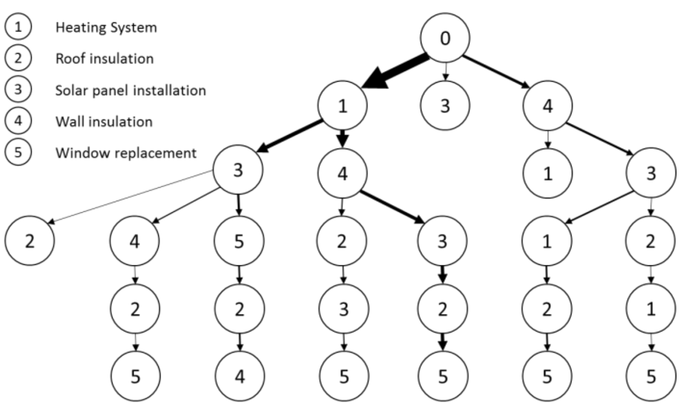

Figure 2: Most common paths in the absolute savings evaluation, "0" equals the initial, unrenovated state. Only branches with at least 10 occurrences are displayed. Thickness indicates frequency.

There is a more pronounced branch, starting with the heating system, as it exhibits the highest savings potential. Directly upgrading the heating system without prior insulations, however, is contrary to practice, as it might result in an oversized and thus inefficient system. Copulae are memoryless and can't reflect this issue correctly, thus caution is advised when interpreting the results.

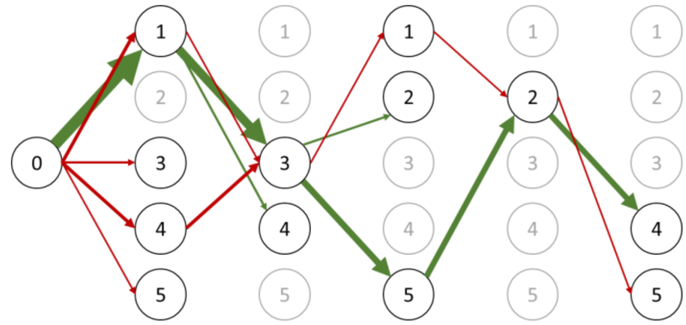

Figure 3: Most common paths for different levels of energy-economical behavior in the absolute savings evaluation. Green reflects energy-conscious households (1% and 5% quantiles) and red energy-wasteful households (95% and 99% quantiles). Only branches with at least 8 occurrences are displayed.[1] Thickness indicates frequency.

ID	Step 1	Step 2	Step 3	Step 4	Step 5
Heating system	130	77	2	6	1
Roof insulation	0	5	46	152	13
Solar panel installation	84	127	0	0	5
Wall insulation	2	7	135	32	40
Window replacement	0	0	33	26	157

Table 3: Aggregated numbers of EEMs for each step in the relative savings evaluation, added up for the 216 constellations. The numbers indicate how often the measures were implemented at each step.

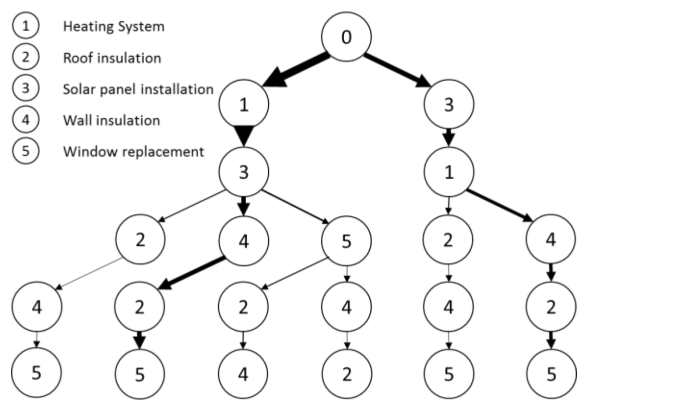

Figure 4: Most common paths in the relative savings evaluation, "0" equals the initial, unrenovated state. Only branches with at least 10 occurrences are displayed. Thickness indicates frequency.

So far, we considered all quantiles. However, when examining individual branches, we notice differences for varying energy-economical behavior. E.g., energy-wasteful households should more often prioritize insulation over heating systems and energy-conscious households should more often consider early window replacement. Figure 3 visualizes these results. The copula model indicates low influence from living space and building age compared to energy-economical behavior.

[1] We adjusted the thresholds for reasons of clarity and to convey the overall picture appropriately.

When accounting for the costs in Table 1, two paths become more pronounced, only further down the tree branches more strongly again. The aggregated results and most common paths are depicted in Table 3 and Figure 4. We find energy-economical behavior to highly effect these first two EEMs, as displayed in Figure 5.

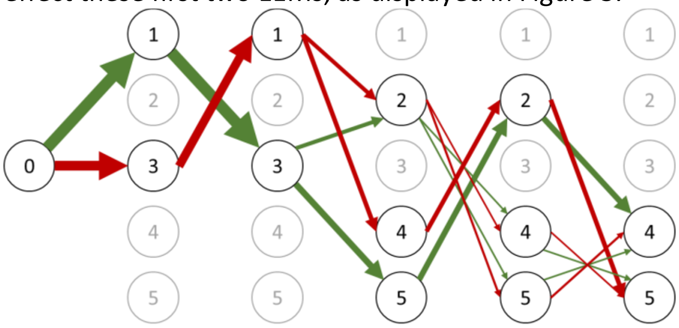

Figure 5: Most common paths for different levels of energy-economical behavior in the relative savings evaluation. Green reflects energy-conscious households (1% and 5% quantiles) and red energy-wasteful households (95% and 99% quantiles). Only branches with at least 8 occurrences are displayed. [1] Thickness indicates frequency.

To evaluate the economic benefit, we compared our model to a generic approach with no consideration of energy-economical behavior, i.e., which recommends the same roadmap to every household independent of the behavior. We settled for the roadmap recommended to the median household. Table 4 depicts the results.

	Absolute		Relative	
	Average	Peak	Average	Peak
1%-quantile	6.85%	32.86%	6.48%	28.17%
5%-quantile	5.37%	29.62%	4.87%	24.97%
95%-quantile	3.93%	16.73%	1.29%	15.96%
99%-quantile	9.48%	27.79%	5.64%	23.57%

Table 4. Average and peak savings per quantile when accounting for energy-economical behavior compared to a generic approach.

5. IMPLICATIONS AND CONCLUSION

In this paper, we applied D-vine copula quantile regression to an extensive real-world data set to derive optimal long-term energetic retrofitting roadmaps under consideration of energy-economical behavior. To the best of our knowledge, we are the first to investigate the interface of these domains. The conducted analysis has several practical and political implications. First, consideration of energy-economical behavior is crucial for decisions upon energetic retrofitting roadmaps. Second, the copula model considers the heating system to exhibit the highest savings potential. Since upgrading the heating system without prior insulation is contrary to practice, this advises retrofitting several building components simultaneously to receive the savings from the heating system earliest possible. Third, the overall inclusion of big data into energy consumption estimation should be considered and promoted, as engineering models currently do not reflect occupant behavior.

Our research, nonetheless, is beset with limitations. First, the memoryless property of our model does not allow for investigation of temporal interdependencies, which potentially explains the prioritization of the heating system. Second, the number of possible EEMs was limited due to the absence of further variables describing e.g., basement- and top floor insulation. Therefore, important EEMs were missing and a complete evaluation necessitates the cumbersome gathering of further data points. Third, the results are limited to German residential one- and two-family households, even though similar results are expected for other countries as well.

However, these limitations give rise to new research potential. One natural direction includes incorporating artificial intelligence into the copula approach to allow for temporal interdependencies. Also, a change in the underlying data set might be beneficial, relaxing the focus on one country only and considering further EEMs. In general, further research is necessary to holistically understand the impact of energy-economical behavior, as current research is scarce.

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