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Application of a Model Based on Rough Set Theory (RST) to Estimate the Energy Efficiency of Public Buildings

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Abstract: The study was carried out on a group of 85 public buildings, which differed in type of use, construction technology and heating systems. From the collected data, a set of qualitative and quantitative variables characterizing them in terms of heat demand was extracted. In this paper, the authors undertook to test the suitability of a model based on rough set theory (RST), which allows the analysis of imprecise, general and uncertain data. To obtain input data for the RST model in quantitative form, the authors used an alternative approach, which is a method based on the thermal properties of buildings. The quality of the predictive model was evaluated based on the following indicators, such as the coefficient of determination (R^2), the mean bias error (MBE), the coefficient of variance of the root mean square error (CV RMSE) and the mean absolute percentage error (MAPE), which are accepted as statistical calibration standards by ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers). A quality-acceptable predictive model must meet the calibration conditions: MBE $\pm 5\%$, CV RMSE < 15% and $R^2 > 0.75$. For the analyzed RST model, the following values of evaluation indicators were obtained: MBE = -1.1%, CV RMSE = 11.8% and $R^2 = 0.91$. The evaluation results obtained gave rise to the conclusion that the method used, which is based on a limited amount of data describing buildings, gives good results in estimating the unit rate of energy demand for heating.

Keywords: energy characteristics of buildings; energy consumption; rough set theory; model based on thermal characteristics; public buildings

Citation: Piotrowska-Woroniak, J.; Szul, T. Application of a Model Based on Rough Set Theory (RST) to Estimate the Energy Efficiency of Public Buildings. *Energies* **2022**, *15*, 8793. https://doi.org/10.3390/en15238793

Academic Editor: Álvaro Gutiérrez

Received: 3 November 2022
Accepted: 20 November 2022
Published: 22 November 2022

1. Introduction

The energy performance of a building is a set of data to estimate the total energy demand of a specific building, guaranteeing its intended use [1]. This definition applies to all types of buildings for which energy consumption must be estimated. Energy performance calculations for buildings can be carried out using various methods, which can be divided into engineering calculations [2–10], statistical models, data-driven models [11–28] and hybrid models [29,30]. Analysis of the literature has shown that the most commonly used methods are statistical and artificial intelligence models based on neural networks, fuzzy logic and rough set theory. These models mainly focus on estimating energy consumption and thermal comfort in simulated or existing energy-efficient buildings very often equipped with renewable energy sources (e.g., heat pumps, photovoltaic panels and ceramic solar panels) [31–33] or passive and multifamily residential buildings [22,28,34,35]. The authors noted that there is a lack of accurate studies of actual buildings in the literature [11,34], for which it is difficult to obtain reliable and accurate data without technical documentation or taking an inventory of the building. The papers [20,22,25,28] presented the usefulness of methods for estimating energy in multifamily residential buildings made with large-plate technology using models using artificial neural networks [22], Takagi–Sugeno fuzzy modeling [28], or models based on rough set theory [20,25]. The models used in the indicated works used input data in quantitative (continuous) form, such as partition area, floor area, heated volume, shape coefficient of buildings, heat transfer coefficients and heating system power demand, among others. The input parameters, i.e., the heat transfer coefficient U [W/m^{2}K], or the A/V$_e$ (the ratio surface to volume) ratio for the indicated models were obtained from engineering calculations, which were then used in modeling heat consumption in buildings. The obtained forecasting results for the indicated methods in multifamily residential buildings are summarized in Table 1, where the indicators for evaluating the quality of the models are compared.

Table 1. Comparison of model quality assessment indicators.

Models	Index			
	MAPE [%]	MBE [%]	CV RMSE [%]	R2
BORUTA algorithm and RST [20]	9 ÷ 11	2.4 ÷ 5	5.5 ÷ 6	0.8 ÷ 0.85
ANN [22]	23 ÷ 29	4 ÷ 13	14 ÷ 24	0.6 ÷ 0.8
MARS [22]	17 ÷ 35	4 ÷ 14	15 ÷ 37	0.3 ÷ 0.8
SRT [22]	16 ÷ 27	5 ÷ 12	14 ÷ 28	0.4 ÷ 0.8
RST [25]	14 ÷ 18	−16 ÷ 2	18 ÷ 32	–
Takagi–Sugeno [28]	12 ÷ 25	−4 ÷ 12	7 ÷ 29	0.7 ÷ 0.9

For the studied group of objects, the best results were obtained for the method based on rough set theory using the BORUTA type data selection algorithm, where, for example, the mean bias error (MBE) was 2.4 ÷ 5%, while for the Takagi–Sugeno fuzzy model it was −4 ÷ 12%. For accuracy, the quality of the models was tested on a group of multifamily residential buildings characterized by similar parameters, both in terms of construction (large plate buildings), or type and use, as well as heating system (district heating network and district heating substations). In this paper, the authors undertook to test the usefulness of the chosen model, which is a model based on rough set theory (RST), in buildings other than multifamily residential buildings. Rough set theory was developed for the analysis of imprecise, general and uncertain data. An attempt was made to evaluate the suitability of this model for estimating energy performance in public buildings. According to the regulations [36], a public building is understood to be a building intended for, among other things, public administration, culture, education, health care, social and welfare, collective residence, banking service, commerce and postal services. An office building and a social building are also considered public buildings. The aforementioned buildings differ in their function, use and type of construction, as well as in the heating systems used. In the case of real buildings, when there are difficulties in obtaining reliable and accurate technical data describing building characteristics, operation and energy consumption for heating purposes, wishing to shorten tedious and time-consuming engineering calculations, other solutions should be sought to estimate energy consumption in this type of building. Therefore, it is advisable to test new methods based on a small amount of general data, which are present both in quantitative form (for example, the characteristic dimensions of the building, shape coefficient of buildings, power requirements for heating and seasonal energy consumption) and qualitative form (for example, the type of building, the type of construction, the method of use and the type of heating system). To obtain input data for the model based on rough set theory (RST) in quantitative form, the authors wanted to use an alternative approach, which is a method based on the thermal properties of buildings [37,38]. So far, this method has been used to estimate the power demand for heating buildings that do not have complete building documentation. Importantly, only one variable describing the building is needed to determine it, which is the heated volume [6]. It should be noted that, according to the literature review, the approach of combining the thermal model with the rough set theory has not been used in energy assessment of buildings before, so it is a novelty in this type of research.

To assess the quality of the adopted predictive model, such indicators as R^2, MBE, CV RMSE and MAPE were used, which were adopted as statistical calibration standards accepted by ASHRAE [39,40]. This will help answer the question of whether the method used, which is based on rough set theory, is suitable for estimating energy demand for heating public buildings and what accuracy/quality of prediction can be achieved.

2. Materials and Methods

2.1. Subject of the Research

The study was conducted in public buildings located in northeastern Poland, in a temperate continental climate (Dfb) [41], in the area of the IV and V climatic zones [42], for which the design outdoor temperature is in the range of −22 to −24 °C. According to ASHARE 169-2021 standards, the area is located in thermal climate zone 6A [43]. The number of degree-days in a standard HDD heating zone ranges from 4076 to 5032 °C·d [44]. According to the Central Statistical Office [45], there are about 57,000 public buildings in Poland. On this basis, a minimum sample size of 81 objects (for a confidence level of α = 0.95 and a maximum error of 10%) was determined in which to conduct research. The research was carried out in 85 public buildings such as schools, care and educational institutions, public administration buildings including offices, buildings used for cultural purposes and collective residences. These buildings have been designated as P1 to P85, where P stands for public building and 1-85 stands for the number of the test object. These buildings were constructed in three technologies, which can be defined as traditional masonry, made in large-block technology (for example, "Żerań Brick") and in prefabricated system large-panel. Between 2016 and 2021, these buildings underwent thermal modernization, consisting of thermal improvements to the building envelope of the building body and the modernization of heating systems. The supply of heat for heating was carried out by means of central heating systems, where different types of heat sources were used, such as district heating substation, gas boiler room, oil boiler room, solid fuel boiler room and heat pumps. For the purposes of the study, information on energy audits carried out with the participation of the author [46] was collected, describing the buildings tested, such as heated volume (V_e), heated surface (A_f) and shape coefficient of buildings (A/V_e), as well as the amount of annual energy consumption for heating ($Q_{H,f}$), converted to standard season conditions. Since some of the data describing the buildings are in qualitative form, it was decided to present them as follows:

Type of building: 1—schools, 2—care and educational institutions, 3—public administration buildings, 4—buildings used for cultural purposes, 5—collective residence;

Construction technology: 1—traditional masonry, 2—large-block (for example, "Żerań Brick"), 3—prefabricated system (large panels);

Heating system: 1—district heating substation, 2—gas boiler room, 3—oil boiler room, 4—solid fuel boiler room, 5—heat pumps.

The basic parameters describing the surveyed public buildings are summarized in Table 2.

Table 2. Basic parameters of the surveyed buildings.

Object	Parameters Describing Public Buildings						
	Type of Building	Construction Technology	Heating System	Heated Volume of Building V_e [m^3]	Heated Surface of the Building A_f [m^2]	Shape Coefficient of Buildings A/V_e [m^{-1}]	Annual Energy Consumption for Heating $Q_{H,f}$ [MWh]
P1	5	2	1	10,430	3676	0.46	485.3
P2	1	3	1	14,473	4317	0.44	297.9
P3	1	1	2	1578	506	0.61	44.1
P4	1	1	1	15,161	4220	0.52	1118.3
P5	1	1	5	3131	775	0.62	33.4
P6	1	1	3	7542	2384	0.56	293.3
P7	4	1	2	938	304	0.87	10.1
P8	3	3	2	16,743	4220	0.33	130.9

Table 2. *Cont.*

Object	Parameters Describing Public Buildings						
	Type of Building	Construction Technology	Heating System	Heated Volume of Building V_e [m^3]	Heated Surface of the Building A_f [m^2]	Shape Coefficient of Buildings A/V_e [m^{-1}]	Annual Energy Consumption for Heating $Q_{H,f}$ [MWh]
P9	5	1	3	9638	3542	0.29	439.3
P10	1	1	2	3601	1059	0.63	116.5
P11	4	1	4	445	167	0.88	16.1
P12	1	1	4	4000	1000	0.54	245
P13	1	1	4	8081	2005	0.52	74.2
P14	4	1	4	905	306	0.61	34.9
P15	1	1	1	26,110	4364	0.17	349.2
P16	2	2	1	6337	2400	0.56	115.2
P17	1	3	1	18,093	3242	0.35	337.2
P18	1	1	5	8441	2129	0.51	70.3
P19	1	1	5	5927	1535	0.42	67.6
P20	3	1	3	2776	974	0.48	60.4
P21	1	3	4	21,288	6437	0.48	759.6
P22	1	1	1	2721	664	0.45	35.2
P23	3	2	1	3765	1202	0.44	123.9
P24	3	1	4	581	161	0.66	13.7
P25	4	1	2	2158	907	0.92	74.4
P26	3	1	4	3275	919	0.41	51.5
P27	1	1	4	1733	585	0.89	72.6
P28	4	1	4	1509	531	0.72	11.7
P29	2	2	1	5825	1937	0.71	230.6
P30	1	1	1	1063	319	0.75	49.2
P31	1	1	4	1816	516	0.73	111
P32	1	1	5	7061	2005	0.39	78.2
P33	1	1	5	7249	2129	0.52	68.2
P34	3	1	4	3275	919	0.41	52.4
P35	3	1	3	2376	675	0.93	43.2
P36	1	1	4	2023	770	0.37	110.9
P37	1	1	3	3024	975	0.74	117
P38	1	1	2	2880	1059	0.63	119.7
P39	1	3	3	14,057	4194	0.29	520.1
P40	3	1	1	2143	693	0.82	69.3
P41	1	2	2	12,364	2197	0.43	162.6
P42	1	1	4	16,876	4729	0.41	250.7
P43	3	1	1	1630	556	0.75	26.7
P44	1	1	2	6754	1731	0.54	290.9
P45	1	1	1	1561	404	0.65	57
P46	1	1	1	6486	3056	0.58	168.1
P47	1	1	3	2805	883	0.79	31.8
P48	4	1	4	1131	306	0.61	34.9
P49	5	1	2	27,879	7268	0.35	850.4
P50	3	2	3	3228	974	0.48	60.4
P51	3	2	1	22,768	6532	0.45	300.5

Table 2. *Cont.*

Object	Parameters Describing Public Buildings						
	Type of Building	**Construction Technology**	**Heating System**	**Heated Volume of Building V_e [m^3]**	**Heated Surface of the Building A_f [m^2]**	**Shape Coefficient of Buildings A/V_e [m^{-1}]**	**Annual Energy Consumption for Heating $Q_{H,f}$ [MWh]**
P52	3	2	1	4707	1202	0.44	123.9
P53	1	2	4	21,095	4729	0.41	250.7
P54	3	1	3	3633	781	0.49	97.7
P55	1	1	3	11,756	1790	0.33	363.4
P56	5	1	1	7556	2281	0.74	225.9
P57	3	1	1	2143	693	0.82	69.3
P58	1	1	3	3024	975	0.74	117
P59	1	3	4	2762	914	0.54	125.3
P60	1	1	1	7918	2048	0.52	129.1
P61	1	1	4	2271	516	0.73	111
P62	1	1	4	2529	770	0.57	110.9
P63	1	1	2	2500	677	0.58	58.9
P64	4	1	5	1137	407	0.72	11.9
P65	1	1	5	32,476	9644	0.22	356.9
P66	1	1	1	16,399	5395	0.42	1494.5
P67	2	3	4	12,699	3344	0.51	441.5
P68	1	2	4	12,184	2848	0.43	370.3
P69	1	1	5	1467	465	0.86	15.4
P70	5	1	1	7651	2670	0.39	275.1
P71	1	2	1	19,544	5545	0.28	476.9
P72	1	1	2	2903	907	0.54	66.3
P73	3	1	4	2689	765	0.49	29.1
P74	1	1	2	1339	475	0.43	50.9
P75	5	1	5	6018	2030	0.61	99.5
P76	1	1	1	6331	2064	0.48	229.2
P77	3	3	1	11,560	3456	0.38	134.8
P78	1	1	3	2191	695	0.6	77.9
P79	1	3	4	18,247	3527	0.38	328.1
P80	1	1	4	8086	2308	0.47	196.2
P81	1	1	1	28,807	8610	0.39	809.4
P82	1	2	2	3420	836	0.46	59.4
P83	1	1	4	4304	1414	0.54	189.5
P84	1	1	3	9638	3542	0.29	170.1
P85	1	1	1	989	277	0.77	42.2

The analyzed group of buildings is characterized by an average value of heated surface of 2094 m^2 and heated volume, the average value of which is 7525 m^3. The coefficient of variation for these parameters is 94–98%, which indicates a very high diversity in the studied buildings. Annual energy consumption for heating ranges from 10 to 1494 MWh, with an average value of 199.9 MWh. Therefore, to be able to compare the facilities with each other, it was necessary to calculate the value of the unit energy consumption index. This indicator is the final energy demand index for heating *FE*, expressed in kWh·m^{-2}·year^{-1}, which was calculated according to Equation (1):

$$FE = \frac{Q_{H,f}}{A_f} \quad (1)$$

where *FE* is the "index of final energy demand for heating", [kWh·m^{-2}·year^{-1}]; $Q_{H,f}$ "the final energy demand for the heating season", [kWh]; and A_f the surface of temperature-controlled rooms, [m^2].

The energy performance *FE* of the studied group of public buildings is shown in Figure 1.

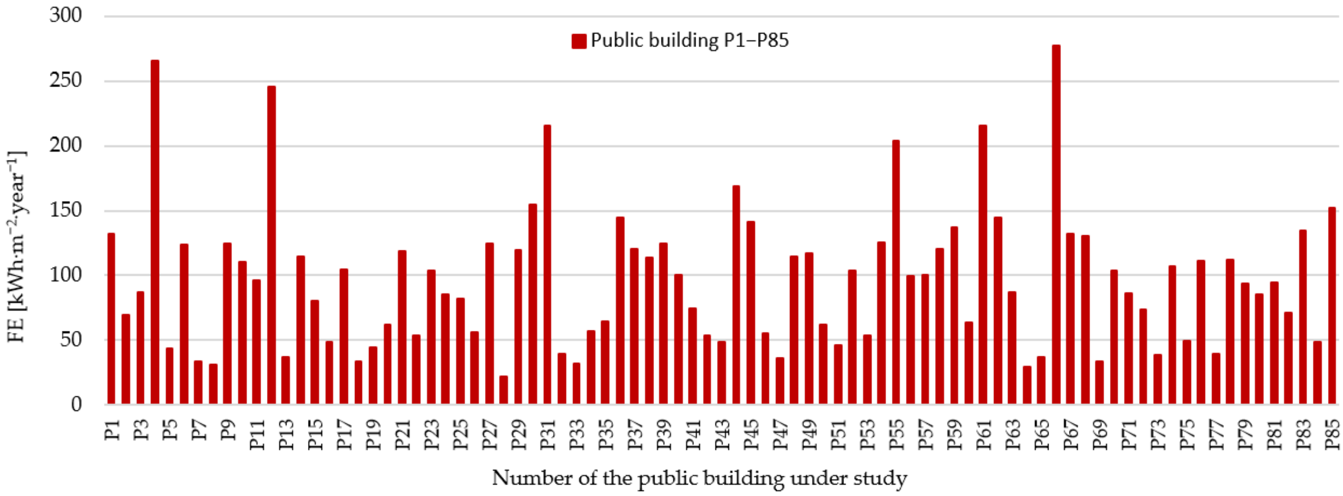

Figure 1. Comparison of the final energy demand index for heating for the studied group of public buildings.

The value of the indicator of final energy demand for heating *FE* varies from 22 to 277 kWh·m^{-2}·year^{-1}, with an average value of 96.5 kWh·m^{-2}·year^{-1}. The lowest value of the indicator was characterized by buildings heated by heat pumps, for which the average value of the *FE* indicator is 37 kWh·m^{-2}·year^{-1}; the most energy is consumed by buildings with a heating system where the heat source is solid fuel boilers. The average value of the indicator for these facilities is 110 kWh·m^{-2}·year^{-1}. An important parameter considered in the thermal calculation of a building is the design heat load (power demand for heating) expressed in kW. Calculation of the design heat load in accordance with the standard [43] requires the collection of detailed data regarding the materials used in the building partitions, the area through which heat loss occurs and the ventilated volume. Gathering such data requires checking technical documentation, and in the absence of such documentation, taking an inventory of the building, which requires time-consuming measurements of the building. The data collected from the audits in quantitative form (Table 2) characterizing the surveyed public buildings are very general. These data do not contain detailed information about the building envelope, the area fields through which heat losses occur or the values of ventilation air flows and thus do not allow engineering calculations to be made to determine the design heat load of the buildings. Therefore, the authors decided to use the relationship that was used in the works [37,38] in estimating the power demand for heating buildings, which was called "thermal characteristics". This quantity was determined empirically on the basis of statistical data [6,37]. For buildings whose heated volume is greater than 1000 m^3, this relationship can be written in the form of Equation (2):

$$\varnothing_h = 0.064 \cdot \sqrt[6]{V_e^5} \cdot s \quad (2)$$

where $\varnothing_h$ —is the approximate power requirement for heating the building, [kW];
V_e —heated volume of the building calculated according to external dimensions, [m^3];
s —correction factor depending on the outdoor design temperature, [−]; its value is respectively: 0.9 for −16 °C; 0.95 for −18 °C; 1.0 for −20 °C; 1.05 for −22 °C and 1.1 dla −24 °C [47].

The presented relationship was used to calculate the value of approximate power demand for heating the analyzed public buildings. To calculate this value, the data in Table 1 on heated volume of building were used. The results of the calculations for individual buildings are shown in Figure 2.

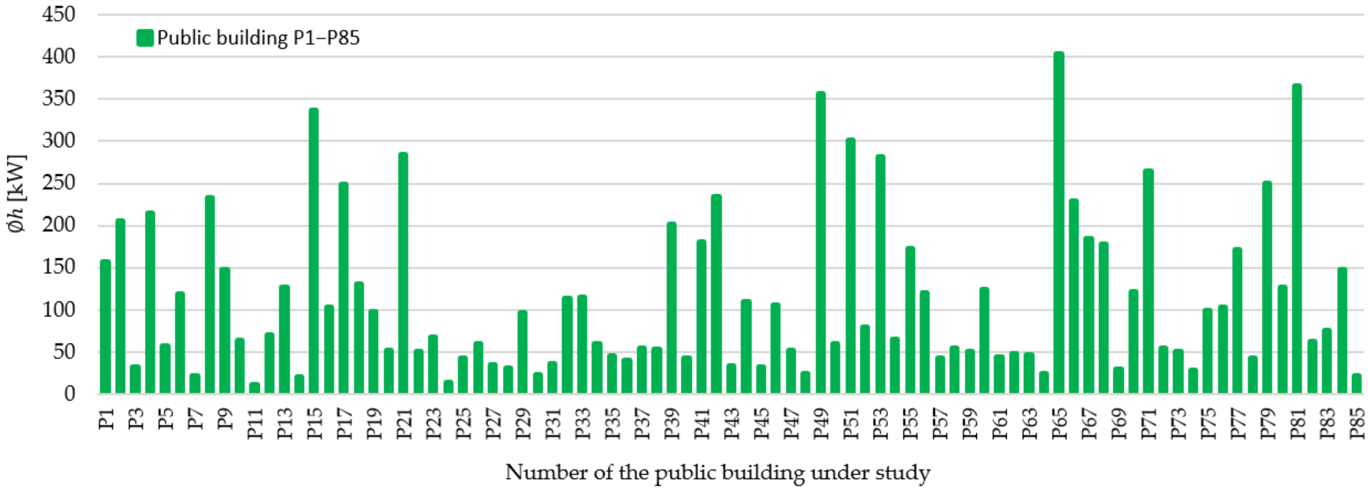

Figure 2. Compilation of values of approximate power demand $\varnothing_h$ for heating the studied group of public buildings.

The power demand for heating buildings calculated based on thermal characteristics ranges from 11 to 404 kW, with an average value of 112 kW.

2.2. Calculation Method for Energy Demand for Heating a Building

The values of the *FE* index [kWh·m^{-2}·year^{-1}]—energy demand for heating and $\varnothing_h$ [kW]—approximate power demand for heating, calculated from Equations (1) and (2), which are presented in Figures 1 and 2, and entered as the set of features characterizing the tested objects. They replaced the heated volume V_e and the heated surface A_f because these parameters (V_e and A_f) were used to calculate these indicators. Features that describe buildings are in qualitative form, such as the type of building, construction technology and heating system. Quantitative parameters include the final energy demand index for heating *FE* (Figure 1), the approximate power demand for heating the building (Figure 2) and the shape coefficient of buildings A/V_e (Table 2). The developed database of public buildings was randomly divided into two subsets in a ratio of 80/20. This created a training set (information system) containing 68 objects and a test set consisting of 17 objects.

The objects within the training set are presented in the form of a decision table (Table 3), where the characteristics of the buildings (conditional attributes) are denoted by symbols C_1–C_5 and the index of final energy demand for heating, which is a decision attribute, is denoted by the symbol D. Table 3 contains selected sample objects (from a subset of 68 buildings) included in the information system and how they are described.

Table 3. Information system (decision table).

Object Number	Condition Attributes					Decision Attribute
	C_1	C_2	C_3	C_4	C_5	D
1	5	2	1	157	0.45	132
2	1	3	1	206	0.44	69
30	1	1	3	55	0.74	120
68	1	1	5	30	0.85	33

For the aforementioned attributes, domains were determined according to the following assumptions:

C_1—type of building (1—schools, 2—care and educational institutions, 3—public administration buildings, 4—buildings used for cultural purposes, 5—collective residence);
C_2—construction technology (1—traditional masonry, 2—large-block, 3—prefabricated system);
C_3—heating system (1—district heating substation, 2—gas boiler room, 3—oil boiler room, 4—solid fuel boiler room, 5—heat pumps);
C_4—the approximate power requirement for heating the building, [kW];
C_5—shape coefficient of buildings, [m^{-1}];
D— index of final energy demand for heating, [$kWh{\cdot}m^{-2}{\cdot}year^{-1}$].

The groups of variables presented in Table 3, which are conditional attributes, were used to build a model for predicting final energy demand for heating buildings based on rough set theory (RST) [48]. This is a tool used to describe imprecise, uncertain knowledge and to model decision-making systems [49]. The attributes describing the buildings under study are characterized by a variety of ways of encoding the given features, which occur in both qualitative and quantitative forms. In this case, the integration of the valued tolerance relation (VTR) proves helpful [50]. The introduction of the valued tolerance relationship (VTR) into the rough set theory (RST) has made it possible to determine the upper and lower approximations of the set with different degrees of indistinguishability relations [51]. This makes it possible to compare two sets of data and obtain a result in the range from 0 to 1, the level of indistinguishability. This range is a membership function derived from the assumptions of fuzzy set theory. The closer the score is to 1, the more similar (indistinguishable) the objects are in terms of the analyzed characteristic, and the closer to 0, the more distinguishable they are [50–52]. In the prediction model used, decisions are made based on the following relationship: if certain conditions are met, a certain decision is made (according to Boolean inference). For example, for object 1 (Table 3): if (C_1 = 5) and (C_2 = 2) and (C_3 = 1) and (C_4 = 157) and (C_5 = 0.45) then (D = 132).

The presented method does not impose complex rules for controlling the considered features and the results of analysis. Only two main coefficients are used to control the importance of the conditional features in relation to the decision feature and the decision rules created: quality and accuracy of approximation—easy to apply and interpret. The general course of model construction using rough set theory (RST) is shown in Figure 3. A detailed description of the predictive model based on quantitative and qualitative variables is presented in the papers [51,52].

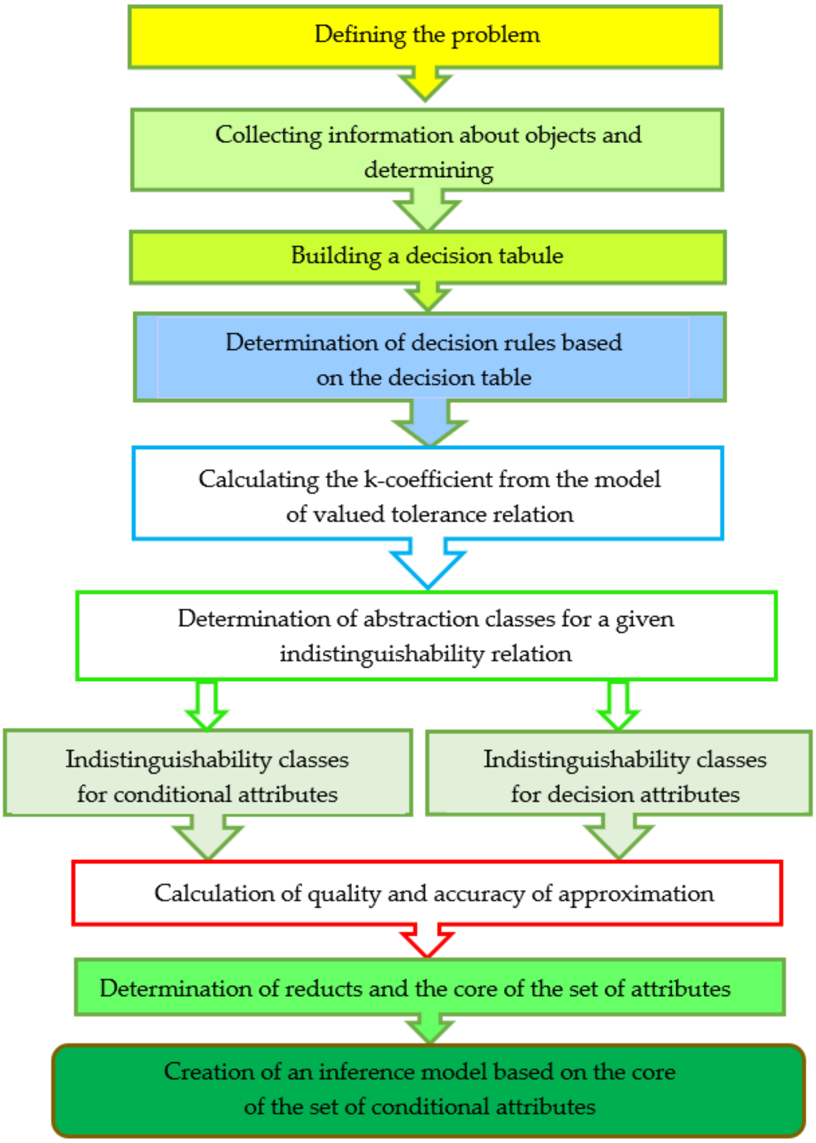

Figure 3. Scheme for building an inference model based on the core of a set of conditional attributes using rough set theory (RST).

3. Results and Discussion

Once the representative decision rules were selected (Figure 3), it was possible to proceed to determine the index of final energy demand for heating FE. The buildings in the test set were used for this purpose. For the set of 17 public buildings constituting the test objects (selected randomly from a set of 85 buildings labeled P1 to P85 in Table 2), the conditional attributes C_1–C_5 were assumed; then, with the application of the valued tolerance relation VTR, the decision rule membership levels were determined, so that the appropriate value of the FE indicator could be selected. The results obtained are summarized in Figure 4, where the values of heating demand indicators determined from the predictive model (RST) are compared with each other with actual values.

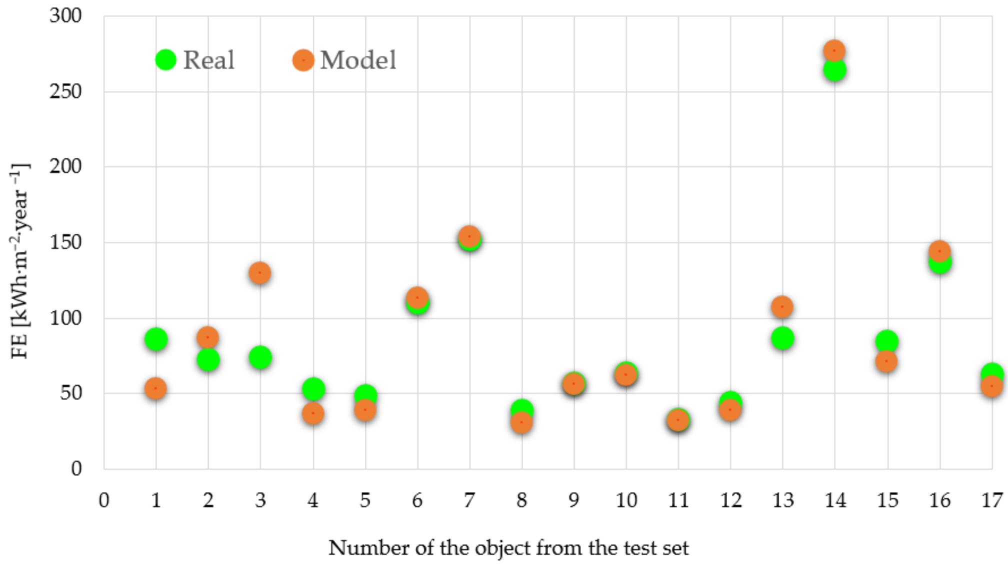

Figure 4. Comparison of the values of the FE heating demand index determined from the RST model with actual values.

Analyzing the results shown in Figure 4, it can be concluded that the model calculations differ from the actual data in the range of 1 to 56 kWh·m^{-2}·year^{-1}, with a mean value of 12.5 kWh·m^{-2}·year^{-1}. The confidence interval for the studied group of facilities ranges from 5.4 to 19.6 kWh·m^{-2}·year^{-1}.

Assessment metrics were calculated using Equations (3)–(6) [39]:

$$R^2 = \left(\frac{n_g \cdot \sum_{m=1}^{n_g} y_i \cdot y_i^P - \sum_{m=1}^{n_g} y_i \cdot \sum_{m=1}^{n_g} y_i^P}{\sqrt{\left(n_g \cdot \sum_{m=1}^{n_g} y_i^2 - \left(\sum_{m=1}^{n_g} y_i \right)^2 \right) \cdot \left(n_g \cdot \sum_{m=1}^{n_g} y_i^{P\,2} - \left(\sum_{m=1}^{n_g} y_i^P \right)^2 \right)}} \right)^2 \tag{3}$$

$$MBE = \frac{\sum_{m=1}^{n_g} \left(y_i - y_i^P \right)}{\sum_{m=1}^{n_g} y_i} \cdot 100\% \; m = 1, 2, 3 \ldots, n_g \tag{4}$$

$$CV\ RMSE = \frac{\sqrt{\sum_{m=1}^{n_g} \frac{\left(y_i - y_i^P \right)^2}{y_i}}}{\frac{1}{n_g} \sum_{m=1}^{n_g} y_i} \cdot 100\% \; m = 1, 2, 3 \ldots, n_g \tag{5}$$

$$MAPE = \frac{1}{n_g} \sum_{m=1}^{n_g} \left| \frac{y_i - y_i^P}{y_i} \right| \cdot 100\% \; m = 1, 2, 3 \ldots, n_g \tag{6}$$

where "y_i—is the actual value (quantity) in the facility i, and y_i^P—is the forecast value (quantity) in the facility i. The difference between y_i and y_i^P is divided by the actual value y_i and m is the index of number of test object; n_g is the number of objects (m = 1, 2, 3, . . . , n_g)".

According to ASHRAE Guideline [40] criteria, for the model to be considered well-calibrated, the value of the evaluation indices should not exceed:

- *MBE* index ± 5%,
- *CV RMSE* index 15%.

However, the value of the coefficient of determination should be $R^2 \geq 0.75$.

The results shown in Table 4 indicate that the model for estimating energy demand for building heating has acceptable quality, despite the use of a limited set of variables. According to the adopted methodology, acceptable models were considered those for which R^2 was above 0.75, MBE was within ±5% and CV RMSE was below 15%. The obtained error values give reason to conclude that, in the absence of building documentation, the approximation method gives good results in estimating energy demand for heating public buildings. These results are comparable to previous studies conducted on multifamily residential buildings, where similar and ASHRAE-acceptable indicator values were obtained for two models such as the Takagi–Sugeno fuzzy model [28] and the RST model using the BORUTA algorithm for quantitative feature selection [20].

Table 4. Model quality characteristics.

Assessment Indicator	Results
R^2	0.91
MBE (%)	−1.1
CV RMSE (%)	11.8
MAPE (%)	17

4. Conclusions

On the basis of a group of 85 public utility buildings subject to thermal modernization, differing in the type of use, construction technology and heating systems, a set of qualitative and quantitative variables characterizing buildings in terms of heat demand was distinguished. These variables were used to assess the usefulness of the model using the rough set theory (RST) for the prediction of heat demand for heating. The obtained prediction results allowed for the formulation of the following conclusions:

- Model calculations differ from actual data by an average of 12.5 kWh·m^{-2}·$year^{-1}$, with the confidence interval for the study group of sites ranging from 5.4 to 19.6 kWh·m^{-2}·$year^{-1}$;
- For the analyzed model, the values of the evaluation indicators proposed by ASHRAE are as follows: MBE = −1.1%, CV RMSE = 11.8% and R^2 = 0.91. One can express confidence that the method presented in this article gives good results in estimating the unit energy demand rate for heating;
- The presented tool can be used to quickly analyze energy consumption in the case of incomplete data or lack of building documentation for existing public buildings, which are characterized by a wide variation in terms of volume and heated area;
- The presented method can be used to check the correctness/accuracy of engineering calculations for determining the design heat load of buildings and the energy performance of public buildings that have undergone thermal improvements.

Author Contributions: Conceptualization J.P.-W. and T.S., data curation J.P.-W. and T.S.; investigation T.S., methodology T.S., project administration T.S. and J.P.-W., supervision J.P.-W. and T.S.; writing—original draft J.P.-W. and T.S.; writing—reviewing and editing J.P.-W. and T.S., funding J.P.-W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was performed within the framework of grants of the Bialystok University of Technology (WZ/WBiIS/4/2020).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: Thanks to the National Energy Conservation Agency in Bialystok, especially to W. Sarosiek, for providing data from Energy Audits performed in 2016–2019.

Conflicts of Interest: The authors declare no conflict of interest.

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