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Analyzing the Effects of the Dwelling Characteristics on the Space Heating Costs with Bayesian Networks

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Analyzing the Effects of the Dwelling Characteristics on the Space Heating Costs with Bayesian Networks

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ABSTRACT

Energy is one of the main concerns of humanity because energy resources are limited and costly. Hence, effective use of energy is important. In order to reduce the costs and to use the energy for space heating effectively, new building materials, techniques and insulations facilities are being developed. Therefore, it is important to know which factors affect the space heating costs. This study aims to introduce the use of Bayesian networks to analyze the effects of dwelling characteristics on the space heating costs. The Bayesian Network model shows that the space heating costs of the dwellings are mostly affected by the heating systems used. The second important factor appears to be the existence of external wall insulation. The third most important factor, however, is the building age. Additionally, dwellings on the ground floors and on the first floors appear to pay the highest space heating costs. On the other hand, dwelling type and facing direction seem not to have a considerable effect on the space heating costs.

Keywords: Space heating costs, house heating, energy-saving, Bayesian networks

1. Introduction

Dwellings use energy for various purposes such as space and water heating, cooking, lighting, running electrical appliances. According to Eurostat (2017) the main use of

energy in dwellings, which is 64% of the final energy consumption, is for space heating. Thus, space heating is the major cause of energy consumption in dwellings. Energy is costly. Thus, space heating cost is one of the important elements in the family budgets. In addition, it is reported that dwellings are the fourth largest source of CO_2 emissions in the EU and they produce 9.9% of the total emissions (Martinopoulos et al., 2016). Thus, finding ways to control or cut back on these costs are necessary to reduce energy consumption, to save natural resources and to reduce carbon emissions. The dwelling characteristics and building design have significant effects on the heating energy performance of the buildings (Kazanasmaz et al., 2014). In this study, the effects of the dwelling characteristics on the space heating costs are investigated by the introduced Rank Correlation Bayesian Network model.

In literature, there are various studies concerning heating cost and employing various methods. Rehdanz (2007) investigated the effects of the space heating costs, building characteristics and the socio-economic status of dwellings in Germany. As a result, it was understood that the heating costs of the homeowners are less than those of tenants are. Hassouneh et al. (2010) performed a study to investigate the influence of window types on the energy balance of the apartment type buildings in Amman, Jordan. Meier and Rehdanz (2010) used multiple linear regression analysis to investigate the factors determining the space heating costs in the United Kingdom. An important finding in the study is that, unlike in Germany, house owners have greater heating costs than tenants do. Zoric and Hrovatin (2010) investigated the effects of heating and dwelling types on the energy efficiency of the houses in Slovenia. It was observed that heating type directly affects energy efficiency. Nair et al. (2010) conducted a survey on house owners to reduce the energy use of individual detached houses in Switzerland. They concluded that energy-efficiency investments should supported. Laureti and Secondi (2012) investigated

different family groups, heating type, heating technologies, dwelling structural features and the effects of family socio-economic status on the heating costs in Italy. They showed that the space heating concept was not only influenced by the socio-economic characteristics of the families but also the external factors, which they cannot control. Kazanasmaz et al. (2014) examined the relations between architectural considerations and energy performances of the buildings in İzmir, Turkey and they made suggestions to predict the level of energy performances of the buildings in the early design phase. Ziemele et al. (2015) studied the economy of heat cost allocation in apartment buildings in Riga, Latvia and suggested a model to allocate the heating costs in each apartment fairly. Wessels (2015) stated that the energy consumption of the buildings built in the Netherlands before 1970 was very high and these buildings constituted approximately 12.5% of the buildings in the country. Therefore, he discussed ways of minimizing the energy consumption of these buildings. Longhi (2015) investigated the effects of changes in socio-economic conditions of dwelling members and building properties on energy costs. It was observed that socio-economic changes had little effect on energy costs, but dwelling size had a significant effect on energy costs. Schmitz and Madlener (2016) investigated the effects of socio-demographic variables such as age and gender on building types and technical characteristics in explaining the heating costs of houses. One of the important findings is that the heating cost rate of low-income dwellings is higher than the dwellings with high-income levels. Hill (2015 aimed to investigate the determinants of residential energy cost in Austria. It was concluded that energy costs are more affected by regional characteristics, dwelling characteristics, socio-economic factors, and income level. Risch and Salmon (2017) aimed to identify the main factors affecting the energy consumption of the dwellings in France. It was concluded that residential and climatic characteristics made the greatest impact on the energy

consumption in the houses. However, socio-demographic factors were observed to have a very low effect. Rose and Kragh (2017) studied the distribution of heating costs in multi-story apartment buildings in Denmark by suggesting a cost calculation method.

Research gap and motivation of the study

Recently machine learning techniques like Bayesian networks are becoming popular as the performance and capacity of the computers are increasing. Compared to other statistical estimation methods that work with additive models, Bayesian networks advantageous and robust especially in handling big data because they have no restrictive distributional or probabilistic assumptions. This study aims to introduce the use of Bayesian networks to analyze the effects of various characteristics of a dwelling unit on its space heating costs.

2. Materials and Methods

2.1 Bayesian networks

Bayesian networks are a branch of probabilistic graphs, which were introduced by Pearl (1985). A Bayesian network can be looked upon a graphical representation of conditional joint probability distributions of the variables that they involve. As well as representing a probability distribution, Bayesian networks also display the causal inference among these variables. A Bayesian network consists of two main components as graphical structure and probabilistic structure.

The graphical structure consists of nodes which represent the random variables and the edges which are directed arrows among the nodes. The nodes connected to each other by an edge are called adjacent and this connection indicates an association between the two

nodes. The lack of any edge between two nodes, on the other hand, indicates the absence of an association between them. When each pairs of nodes are adjacent, the graph is said to be a complete graph. An example of a Bayesian network is shown in Figure 1.

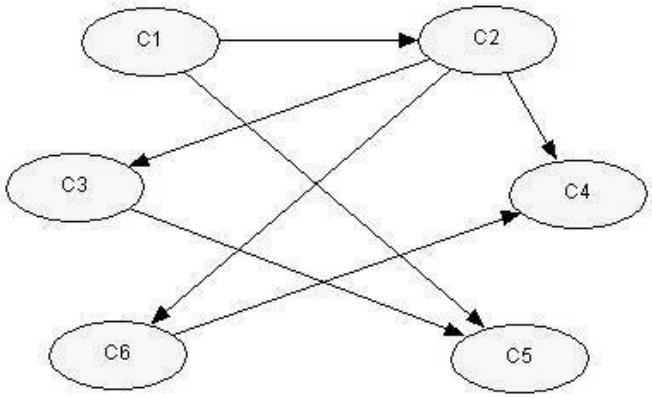

Figure 1. Example of Bayesian network

Figure 1 consists of 6 nodes named C1, C2, C3, C4, C5 and C6. A node from which an edge is directed is called a parent node while a node which an edge is directed to is called a child node. In Figure 1, for example, C1 is a parent node of C2 and C5, while C5 is a child node of C1 and C3. A path can be defined as the series of edges and the nodes connected by them. Bayesian networks have the Directed Acyclic Graph (DAG) structure in which no cycles are allowed on the paths. That is, it is impossible to return to any node by following the path of any edge directed from this node.

The graphical structure of the Bayesian networks consists of the Conditional Probability Tables (CPT) determined by the joint probability distribution of the nodes. Let the set of the nodes in a Bayesian network be $\mathrm{V} = (V_1, V_2, \dots, V_k)$. For a specific value of $V_i = v$ and a configuration u of the elements in $\mathrm{U} \subseteq \mathrm{V}|V_i$, the conditional probabilities are given as follows.

$$P(v_i|u) = \frac{P(v_i,u)}{P(u)} = \frac{\sum_{s\in S} P(v_i,u,s)}{\sum_{s\in S, v\in v_i} P(u,s,v)} \quad (1)$$

where s is a configuration of $S = \mathrm{V}|\{\mathrm{U}, V_i\}$, and s and v_i denote the sample spaces of S and V_i respectively. Moreover, the joint probability density function of V is as follows.

$$P(V_1, V_2, \dots, V_k) = \prod_{i=1}^{k} P(V_i|v) \quad (2)$$

There are two approaches to build the structure of a Bayesian network. In the first approach the structure is constructed manually based on an expert opinion. The number of nodes and edges and their directions are determined by the expert considering the causal relations among the nodes. Hence, in this kind of Bayesian networks, the edges among the nodes also imply a causal relation. The second approach is called structure learning. In the structural learning the Bayesian network is built directly from the data set by the help of various algorithms. In a Bayesian network built by any kind of structural learning algorithm, however, the edges do not need to imply a causal relationship; instead, they just indicate the presence of a dependency.

There are three kinds of structure learning algorithms in general: score-based algorithms, constraint-based algorithms and hybrid algorithms. Score-based algorithms firstly build some candidate network structures. Afterwards, they assign scores to these candidate networks using various scoring functions which measure the fit of the model to the data set. They finally select the network structure having the highest score. K2, Bayesian Dirichlet equivalent uniform (BDeu), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Log-Score can be given as some examples for these scoring functions. The calculation of Log-Score is as follows (Heckerman et al., 2000).

$$logscore(V_1, \dots, V_r) = \frac{\sum_{i=1}^{r} log_2 P(V_i|model)}{rk} \quad (3)$$

where, r is the number of cases and k is the number of nodes existing in the model. Greater Log-Score means better fit of the model to the data set. More detailed information about Bayesian networks can be found in Pearl (1988), Jensen and Nielsen (2007), Holmes and Jain (2008).

2.2. Data and model

The data was derived from 500 dwellings in Mugla province in Turkey. The data involves 10 variables as the nodes of the Bayesian network, which are space heating costs, building age, heating system, dwelling type, number of rooms, dwelling size, floor level, facing direction, external wall insulation, and double glazing. The list of these nodes and their definitions are given in Table1.

Table 1. The variables and their descriptions

Variable	Description	Levels
Space heating costs	The average amount of money (Turkish Lira-TL) paid for space heating in the dwellings per month	0-99 100-199 200-299 300-399 400 or over
Building age	The age of the building in years	0-9 10-19 20-29 30 or over

Heating system	The heating system used for space heating in the dwelling	Air conditioner or Electric Stove Coal Stove Central Heating or Boiler
Dwelling type	The type of the dwelling as a flat or a detached house	Flat Detached House
Number of rooms	The number of the bedrooms aside from 1 living room	1 Living Room 1 Living Room and 1 Bedroom 1 Living Room and 2 Bedrooms 1 Living Room and 3 Bedrooms 1 Living Room and 3 Bedrooms or more
Dwelling size	Size of the dwelling (m^2)	0-59 60-119 120-179 180 or over
Floor level	The level of the floor on which the dwelling is located	Basement Ground Floor First Floor Second Floor Third Floor Fourth Floor Fifth Floor or higher
Facing direction	The direction which the longest side of the dwelling faces to	East West North South

External wall insulation	Existence of external wall insulation at the dwelling	Available Not Available
Double glazing	Existence of double glazing at the dwelling	Available Not Available

To build a Bayesian network to analyze the effects of dwelling characteristics on space heating cost, three separate Bayesian networks were build based on PC, Greedy Thick Essential and Bayesian Search algorithms in GeNIe (2019) software. Table 2 shows these algorithms and their Log-Score values.

Table 2. Bayesian network algorithms employed and their Log-Score values

Algorithm	**Log-Score**
PC	-3886.80
Greedy Thick Thinning	-4238.46
Bayesian Search	-4371.47

Table 2 shows that the algorithm having the greatest Log-Score is the PC algorithm. Hence, in the model selection phase, the Bayesian network estimated by the PC algorithm was adopted. The Bayesian network, which was visualized in Netica (2019) software, is demonstrated in Figure 2.

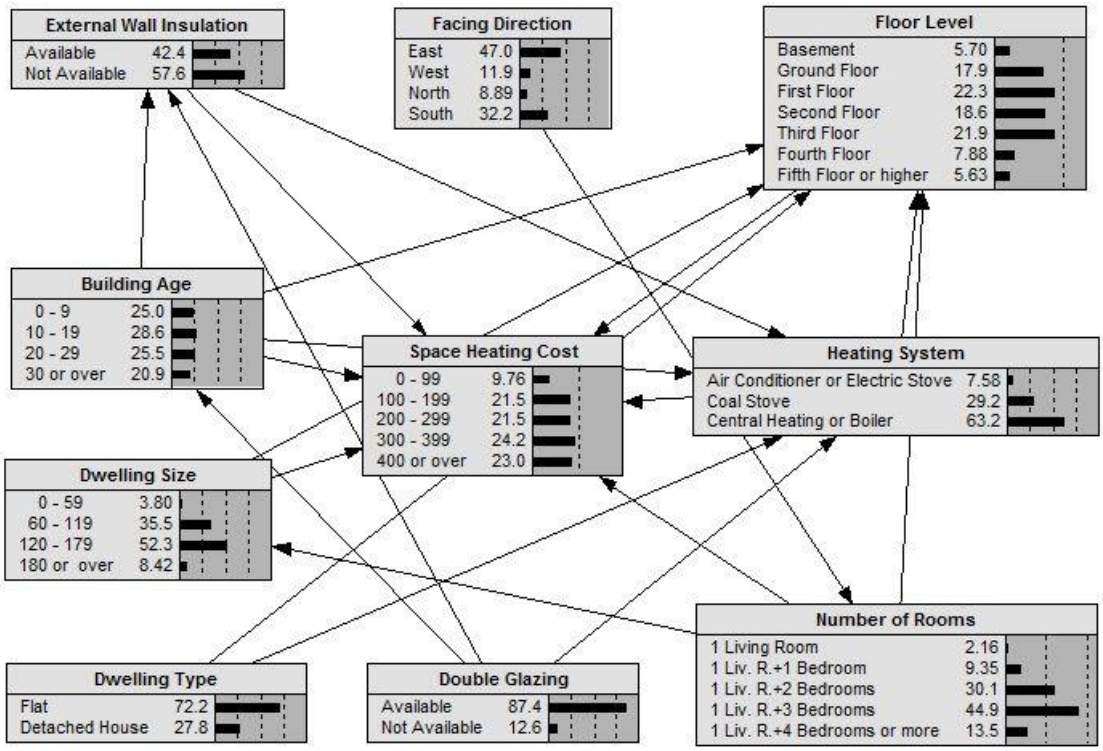

Figure 2. Bayesian network for the effects of dwelling characteristics on space heating costs estimated by PC algorithm

2.3. Model validation

In evaluating the model performance, Receiver Operating Characteristic (ROC) curves can be used to measure the model prediction performance (Hand, 1997). ROC curves are drawn by plotting the true positive rate (sensitivity) against the false positive rate (1-specificity). AUC scores can be defined as the amount of areas under the ROC curves. AUC scores range between 0 and 1. If the AUC score is 1, the prediction made by the model involves no error. Figure 3 shows the ROC curve and the corresponding AUC value to measure the estimation performance of the Bayesian network model for the space heating costs between 0-99 TL.

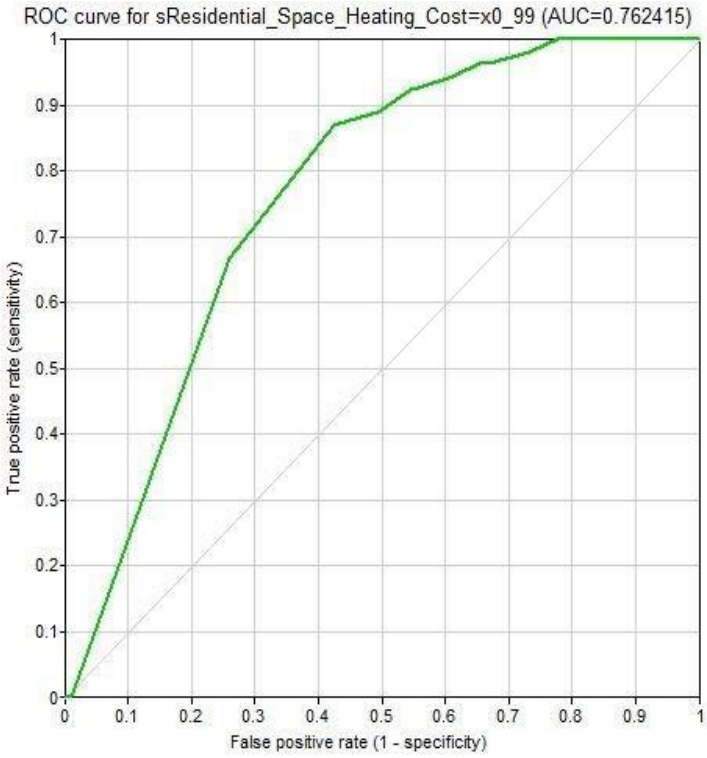

Figure 3. Correct estimation rate of the space heating costs between 0-99 TL

The AUC score in Figure 3 shows that the Bayesian network estimated the space heating costs, that are between 0-99 TL, successfully with a probability of 0.76. Figure 4 shows the ROC curve and the corresponding AUC value to measure the estimation performance of the Bayesian network model for the space heating costs between 100-199 TL.

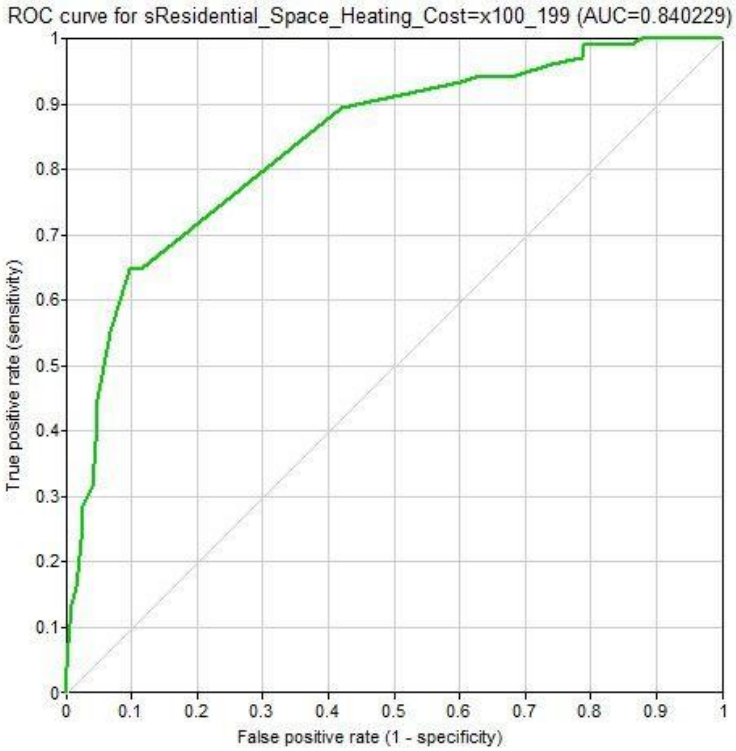

Figure 4. Correct estimation rate of the space heating costs between 100-199 TL

In Figure 4, the AUC score is 0.84. Hence, it is seen that the Bayesian network estimated the space heating costs, that are between 100-199 TL, successfully with a probability of 0.84. Figure 5 shows the ROC curve and the corresponding AUC value to measure the estimation performance of the Bayesian network model for the space heating costs between 200-299 TL.

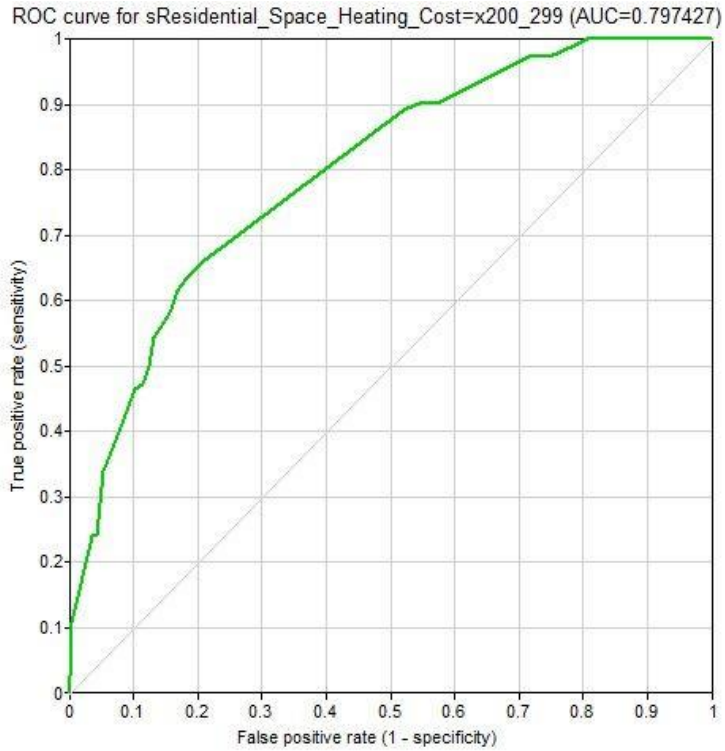

Figure 5. Correct estimation rate of the space heating costs between 200-299 TL

In Figure 5, the AUC score is 0.80. Thus it can be said that the Bayesian network estimated the space heating costs, that are between 200-299 TL, with an 0.80 probability of success. In order to measure the estimation performance of the Bayesian network model for the space heating costs between 300-399 TL, the ROC curve and the corresponding AUC value are demonstrated in Figure 6.

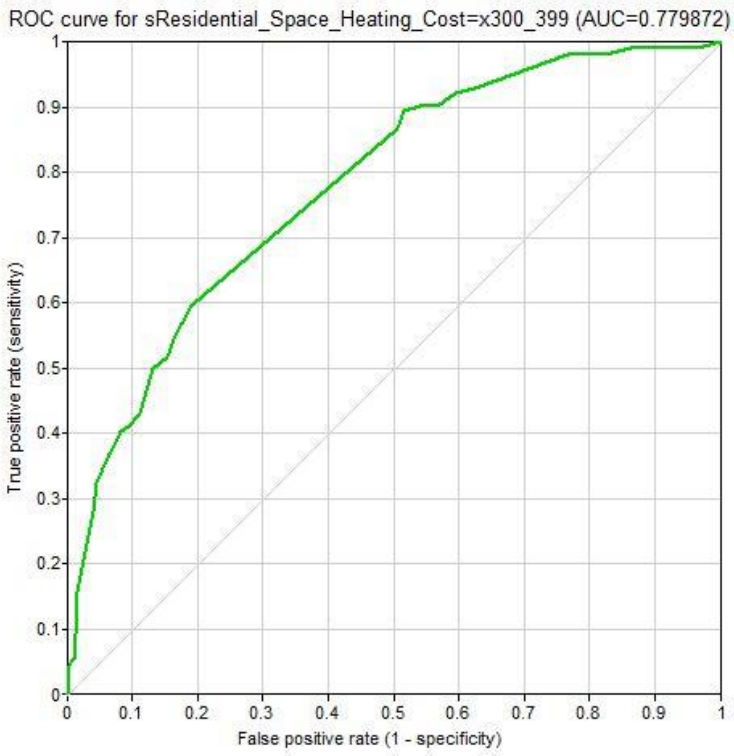

Figure 6. Correct estimation rate of the space heating costs between 300-399 TL

In Figure 6, the AUC value indicates that the probability of the correct estimation rate of the Bayesian network for the heating costs between 300-399 TL is 0.78. Finally, Figure 7 shows the ROC curve and the corresponding AUC value to measure the estimation performance of the Bayesian network model for the space heating costs that are 400 TL or over.

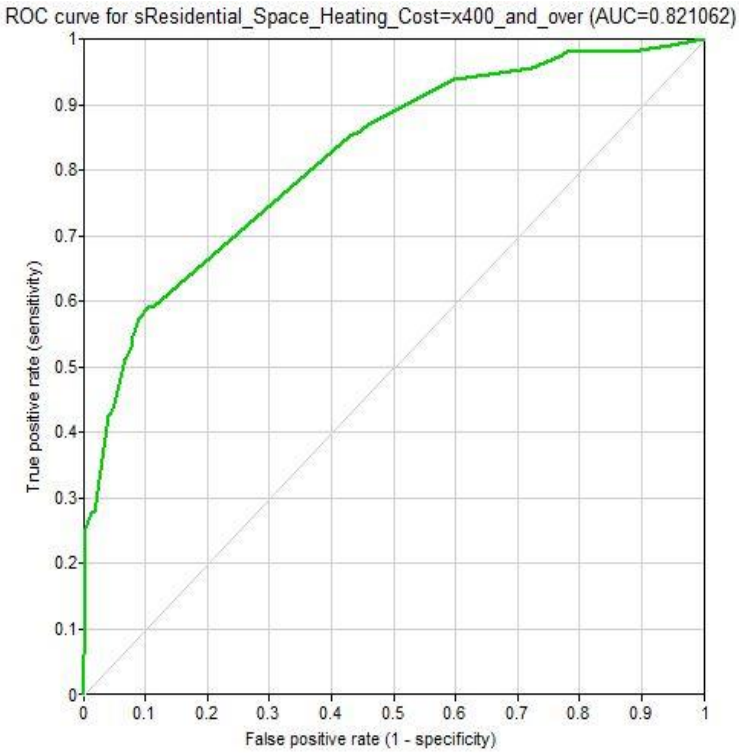

Figure 7. Correct estimation rate of the space heating costs between 400 TL or over

In Figure 7, the AUC score is 0.82. Thus, it can be concluded that the Bayesian network estimated the space heating costs that are 400 TL or over successfully with a probability of 0.82. In order to make a comparison easily, all the AUC scores calculated for dwelling space heating costs are given in Table 3 briefly.

Table 3. AUC scores of the space heating costs

Space Heating Cost (TL)	AUC Scores
0-99	0.76
100-199	0.84
200-299	0.80
300-399	0.78
400 or over	0.82

Table 3 shows that 0.76 is the the lowest AUC score that belongs to the space heating costs between 0-99 TL. This means that the heating costs in this interval were estimated with the least success rate. However the space heating costs that are 100-199 TL were estimated with the highest success rate of 0.84.

2.4. Sensitivity analysis

In order to see how much space heating cost is affected by the changes in the levels of other nodes, it is possible to perform a sensitivity analysis on the Bayesian network estimated. Entropy Reduction (ER) can be used as a measure of sensitivity in Bayesian networks. The calculation of ER is as follows (Marcot et al., 2006).

$$I = H(Q) - H(Q|F) = \sum_q \sum_f \frac{P(q,f) log_2[P(q,f)]}{P(q)P(f)} \quad (4)$$

Where $H(Q)$ is the entropy of the node Q without any evidence, $H(Q|F)$ is the entropy of the node Q conditional to an evidence belonging to the node F and q, f are the states of Q and F respectively. Table 4 shows the ER scores of the nodes on the output node space heating cost obtained in Netica (2019) software.

Table 4. Results of sensitivity analysis for space heating cost node

Node	Entropy Reduction
External wall insulation	0.09413
Building age	0.08910
Heating system	0.08788
Floor level	0.04801
Number of rooms	0.03377
Dwelling size	0.02781
Double glazing	0.01841
Dwelling type	0.00281

Facing direction	0.00130

According to the results of the sensitivity analysis given in Table 4, the space heating cost of the dwellings is affected mostly by the external wall insulation with a level of 0.09413 entropy value. The second most important factor appears to be the building age which has an entropy value of 0.08910. The third is the heating system of the dwelling whose entropy value is 0.08788. It is also seen that the facing direction of the dwelling seems to have the least effect on the space heating costs of the dwellings.

3. Results and Discussion

In Bayesian networks, it is possible to perform analyses and make estimations for any node by propagating the evidences through the network. For instance, for a flat type dwelling assumed to be facing to North, on the second floor, between 20-29 years old, heated by coal stove and between 120-179 m^2, and also assumed to have 1 living room and 3 bedrooms but not to have external wall insulation or double glazing, Figure 8 demonstrates the state of the Bayesian network when these evidences are propagated through the network.

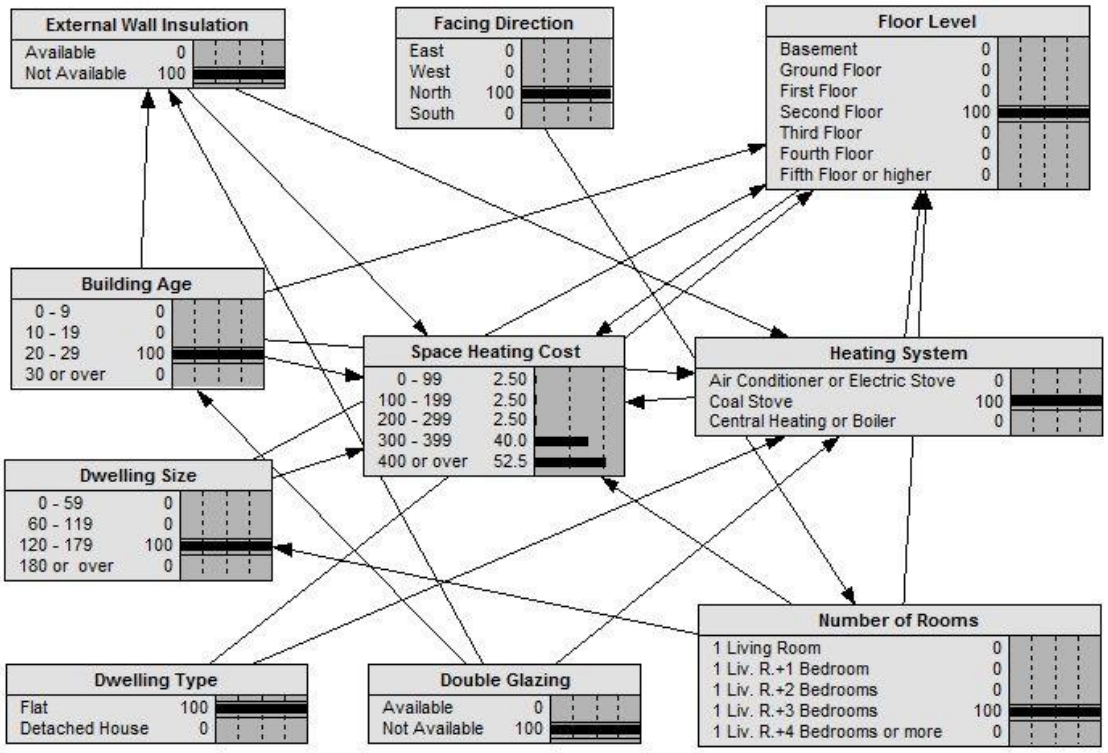

Figure 8. State of the estimated Bayesian network after propagation of the evidences

Figure 8 shows that the space heating cost of this dwelling is estimated to be 400 TL or over with the highest probability of 52.5% and between 300-399 TL with a probability of 40%.

Some analysis results and discussions provided by the estimated Bayesian network are given below.

As far as floor level is considered, the dwellings on the ground floors and the first floors seem to pay the highest space heating cost compared to the ones on the other floors. 30% of the dwellings on the ground floor and 34.3% of the dwellings on the first floor pay 400 TL or more per month. On the other hand, third and fourth floors seem to be paying less than the others. They pay 100-199 TL on the average with a proportion of 29.3% for the third floors and 27.5% for the fourth floors. This result is consistent with results given

by Ziemele et al. (2015) who report that the apartments located on the top and bottom floors of a building have more heat loss than the other floors. When floor level factor is considered along with building age, it is seen that the ground floors in new building pay 200-300 TL (38.3%) whereas in buildings that are aged 30 or over, the ground floors pay 400 TL or over (44.9%) just as the fifth or higher floors (27.6%). However using central heating or boiler in old buildings decreases the space heating costs of the ground floors to 300-399 TL interval (29.3%). Least space heating costs are paid by residents living on the third floors in new buildings as 100-199 TL (53.6%). If residents living on the third floors are living in old buildings and using coal stoves for heating, their space heating costs increase to 300-399 TL band with a probability of 36.2%

The size of the dwelling, as expected, increases the heating cost as it gets larger. The dwellings between 0-59 m^2 pay 100-199 TL with the highest probability of 26.4% and the ones between 60-119 m^2 pay 200-299 TL with the highest probability of 26.8%. However, when the size becomes greater than or equals to 120 m^2 the most popular cost immediately becomes 400 TL or more with a probability of 28%. This result is supported by the findings of Rehdanz (2007) stating that heating costs decrease with the size of the property in Germany. While residents living in a comparatively large dwellings, such as 120-179 m^2, that are located on the third floors pay 100-199 TL space heating costs (32.9%), the space heating costs increase to 400 TL or over if they are living on the the first floors.

In general, more than half of the dwellings having 3 bedrooms seem to pay the highest amount of cost 400 TL or more with a probability of 51.7%. The ones having 4 or more bedrooms also pay 400 TL or more with a probability of 38%. The dwellings having 1

bedroom and 2 bedrooms pay 300-399 TL with the highest probabilities of 26.2% and 33.4% respectively.

The average monthly space heating costs of the dwellings having external wall insulation appears to be 100-199 TL with the highest probability of 35.2%, while the ones which do not have external wall insulation pay 400 TL or more on the average with the highest probability of 31%. Thus, it can be concluded that the lack of external wall insulation almost doubles the space heating costs. Indeed, in the sensitivity analysis, external wall insulation appeared to be the most important factor affecting the monthly space heating costs. This result is supported by many other studies such as Alvarez et al. (2016) who showed that insulation reduces energy costs in low income housings in Mexico, Cheung et al. (2015) who suggest that as well as the presence of the external insulation, the thickness of the insulation is also significant to reduce the energy consumption of the high rise-apartments in Hong Kong.

Building age is another important factor affecting the space heating costs. In fact, older buildings seem to pay higher space heating costs compared to the newer ones. This result is consistent with the findings in United Nations (2018) stating that although new buildings are more expensive to build, they are more energy-efficient compared to the old ones. Kazanasmaz et al. (2014) also support this result by reporting that older buildings are less energy-efficient due to the lack of insulation in Izmir, Turkey. In addition, Rehdanz (2007) also suggests that old buildings are more expensive to heat in Germany. The average amount cost is 200-299 TL for the buildings 0-9 years old with the highest rate of 30.5%. However, for the buildings which are older than 30 years, the average rate of cost is 400 TL or over with the highest rate of 39.8%.

When the heating system used in the dwelling is considered, coal stoves appear to be the costliest one. Dwellings heated by coal stove spend 400 TL or more with the highest probability of 41.7%. Air conditioner and electric stoves also seem to be costly, since, 28% of the dwellings heated by these systems also pay 400 TL or more on the average. Central heating or boiler systems, however, are comparatively cheaper systems which lead to a cost 100-199 TL with the highest probability of 27.7%. These results are similar to the findings of Meier and Rehdanz (2010) in Great Britain. They state that space heating costs are highest if electricity is used while costs for gas are lowest. Rehdanz (2007) also found out that there is a strong effect of the kind of heating system on space heating costs in Germany.

Existence of the double glazing at the dwelling slightly changes the space heating costs. When it is available, the proportion of the costs is distributed almost equally among the second, third and fourth categories 100-199 TL, 200-299 TL, and 300-399 TL. However, when it is not available the most popular average monthly space heating costs increases to the category of 400 TL or more with a slight change in the highest probability which becomes 38.5%. Cheung et al. (2005) also supports this result by stating that the thermal insulation performances of external walls are more effective than those for windows, in their study in Hong Kong.

The study suggests that there is not a significant difference between the space heating costs of the detached houses and the flat type dwellings. In Great Britain, however, Meier and Rehdanz (2010) found out that tenants, who mainly live in flats, pay less heating costs than owners, who mostly live in detached houses. This difference can be explained by the energy efficiency of the flats compared to the houses. On the other hand, Rehdanz (2007) suggests that, in Germany, owners, who mostly live in houses, are likely to pay less space

heating costs than tenants, who mostly live in flats. This is because the owners are more careful about the energy efficiency and insulation conditions of their houses.

It seems that facing direction of the dwelling does not appear to have a considerable amount of direct effect on the space heating costs of the dwellings. A study by Hassouneh et al. (2010) in Amman, Jordan, however, suggest that facing directions of the buildings are important when combined with the suitable kind of window glasses at the appropriate direction to reduce the costs of heating and cooling of the apartment type buildings.

4. Conclusions

In conclusion, Bayesian networks are useful, practical, and efficient tools to analyze the multilateral relations among various variables simultaneously. Bayesian networks enable researchers not only to see the dependencies among the variables but also to observe the change in their values as the other variables in the network change. Space heating costs are affected by various factors. In this study, the effects of the dwelling characteristics such as building age, heating system, dwelling type, number of rooms, dwelling size, floor level, facing direction, existence of external wall insulation, and existence of double glazing on space heating costs were analyzed. In the analysis, both the amounts of costs these factors cause and their ranks of effect on the heating cost were provided. The most important advantage of Bayesian networks in search of such relations is that, unlike other analysis methods, Bayesian networks calculate the conditional probabilities taking into consideration both joint direct and indirect relations among all the variables existing in the network. Moreover, it is also possible to see the degree of the effects of the other variables on the target variable, which is space heating costs in this study, by performing a sensitivity analysis. The model can also be extended by adding other factor nodes that might affect the space heating costs into the network.

The study shows that the space heating cost of the dwellings in Mugla Province is affected mostly by the external wall insulation. In fact, the lack of external wall insulation almost doubles the space heating costs. Therefore it is strongly recommended to use external wall insulation in this area. The second most important factor is the building age and the third is the heating system. The older buildings seem to pay more space heating costs compared to the new ones. When the heating system is considered, coal stoves, air conditioners, and electric stoves appear to be the costliest heating systems. Hence, these systems should be replaced by central heating or boiler systems which are comparatively less costly. Moreover, the direction of the dwelling has the least effect on the space heating costs of the dwellings. Another finding is that existence of the double glazing at the dwelling slightly decreases the space heating costs. Additionally, the dwellings on the ground floors and the first floors appeared to pay the highest space heating cost. Therefore, dwellings on these floors need to be more effectively insulated. As the size of the dwelling increases the heating cost increases too. However, it was determined that there is not a significant difference between the space heating costs of the detached houses and the flat type dwellings existing in the study area**.**

Compliance with Ethical Standards:

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Ethical approval: This article does not contain any studies with human participants or animals performed by.

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