Statistical Approaches to Forecasting Domestic Energy Consumption and Assessing Determinants: The Case of Nordic Countries

Samad Ranjbar Ardakani, Seyed Mohsen Hossein, and Alireza Aslani

ABSTRACT

The residential sector accounts for large share of total annual energy use in the Nordic countries due to the extremely cold climates and high household heating demand. Most domestic energy consumption in the Nordic countries is for space heating and providing hot water. The purpose of our study was to forecast the annual energy consumption of the Nordic residential sectors by 2020 as a function of socio-economic and environmental factors, and to offer a framework for the predictors in each country.

Our research models the domestic energy use in Nordic countries based on social, economic and environmental factors. Applying the multiple linear regression (MLR), multivariate adaptive regression splines (MARS), and the artificial neural network (ANN) analysis methodologies, three models have been generated for each country in the Nordic region. Using these models, we forecasted the Nordic countries domestic energy use by 2020 and assessed the causal links between energy consumption and the investigated predictors. The results showed that the ANN models have a superior capability of forecasting the domestic energy use and specifying the importance of predictors compared to the regression models. The models revealed that changes in population, unemployment rate, work force, urban population, and the amount of CO_2 emissions from the residential sectors can cause significant variations in Nordic domestic sector energy use.

INTRODUCTION

Europe's Nordic countries include Denmark, Finland, Norway, Iceland and Sweden. Due to social perspectives and the desire for secure energy supplies, renewable energy utilization has an important role in the development of energy policies. According to the International Energy Agency (IEA), the Nordic countries were responsible for 186.2 megatons of annual CO_2 emissions during the early 1990s which was reduced 17% by 2014. Despite European Union (EU) efforts to decrease the CO_2 emissions of the Nordic countries, their share has increased by 0.3%, due mainly to increased emissions by Norway and Iceland. After the EU established goals to reduce greenhouse gas emissions that contribute to global warming, the countries approved treaties and adopted the EU's domestic sector policies on sustainable development.

EU policies recognize that renewable energy and energy efficiency are key to lowering fossil fuel dependency and meeting their short-term and long-term goals [1-4]. As a consequence of these efforts, IEA and World Bank data shows that the share of CO_2 emissions from residential buildings and commercial and public services declined from 13.6% in 1990 to 4.2% in 2014. Though fossil fuel prices have declined in the recent years, the Nordic countries (except Iceland and Norway) have decreased emissions. The Nord Pool, the region's primary electricity market operator, facilitated regional de-carbonization. Renewable energy technologies (e.g., wind power in Denmark and hydropower in Norway and Sweden) provide abundant supplies of electricity for the Nord market. By balancing the market's generated power, the Nord Pool has simplified regional electricity accessibility. The Nordic countries, except Denmark, invested heavily in energy-intensive industries. Regardless, they have substantially increased their shares of electricity and biomass, reduced their shares of industrial and residential sector fossil fuel use during the past two decades, and enhanced their economic and energy security [5].

Denmark is one of the world's leaders in energy efficiency. Based on IEA reports, the country has decoupled gross domestic product (GDP) from energy consumption and CO_2 emissions [1]. Danish wind power has a key role in the Nordic electricity market. The country invested heavily in electrification due to dependency on renewables, particularly wind power. In 2015, Denmark's share of wind generated electricity was 42%—the world's highest [5]. Denmark consumed 538.8

PJ of energy in 2014, and the domestic sector was responsible for 31% of total final consumption (TFC) [6].

Mean building energy use per person rose by 0.2% per year between 1990 and 2014 in the Nordic countries. IEA experts explained the increase due to growth in the services sector. After approving the EU's Energy Performance of Buildings Directive (EPBD), the Nordic governments revised their energy consumption policies for buildings and developed new standards and requirements for their residential sectors [7].

Denmark's share of residential and commercial sector total CO_2 emissions declined from 12% in 1990 to 8% in 2014. During this period, the shares of renewables and wastes in residential energy consumption increased from 8.4% to 20.2%. Many Danish households are not simply power consumers, but also produce electricity using household windmills and solar panels [8]. Due to their climatic conditions, Denmark's building energy use has high demand for heating energy [9]. The Danish, Finnish, and Swedish governments provide energy system flexibility by using combined heat and power (CHP) systems with heat storage, a strategy adopted just after the 1973 oil crisis [10]. At that time, 90% of Denmark's energy demand was satisfied by imported fossil fuels despite the country having substantial North Sea oil and gas reserves. Using district heating and implementing energy efficiency measures allowed Denmark to become a net oil exporter [11].

Finland's total energy consumption in 2014 was 1,027.7 PJ. Finland has second highest per capita Nordic energy use after Iceland, which accounts for almost a quarter of the region's energy consumption. Among IEA countries, Finland consumes a median amount of energy [2]. Finland's industrial sector (particularly the energy-intensive pulp and paper industries) accounts for the largest share of its energy use. Finland's domestic energy sector was responsible for 20.6% of TFC in 2014 [12]. Between 1990 and 2014, Finnish building floor area increased 40%, energy use per m^2 increased by 127%, and the county's per capita total building final energy consumption increased by 60% [5]. Finland's residential sector share of total CO_2 emissions decreased from 12.2% in 1990 to 4% in 2014, while the share of renewables in its TCF increased 8%.

In an effort to comply with carbon-neutral district heating policies, a third of Finland's residential buildings were using district heating by 2012. The government also encouraged families to live in apartments rather than detached houses by pricing the cost of district heating for detached houses much higher than for apartments [13]. Compactly designed apartments and structures consume less heating energy since they have lower conductive heat transfer [14]. Finally, increasing urban density facilitates the utilization of district heating for residential buildings which enhances energy efficiency.

Iceland has the lowest population among the Nordic countries and the lowest total annual energy consumption. However, the country has the world's highest per capita electricity use due to its low population density, electricity use by its aluminum industry and its extremely cold climate. The total energy use of Iceland in 2014 was 114.6 PJ. The shares of its industrial and residential sectors were 51.4% and 13.7% respectively [15]. Geothermal energy is used to meet the county's high demand for space heating and electricity generation. Geothermal power plants generate more than a quarter of Iceland's electricity and supply almost two-thirds of its primary energy use. About 85% of Iceland's total primary energy supply in 2014 was from indigenous renewable resources [16]. Iceland does not belong to the Nord Pool due to the distances between Iceland and Norway or Denmark [17]. However, the Nord pool supported the Icelandic Electricity Grid (Landsnet) in establishing a market for electricity based on the use of the Elbas system and continuous trading [18].

The TFC of Norway in 2014 was 842.1 PJ, and the share of its residential sector energy use was 19.1% [19]. Due to energy-intensive industries and high building heating demand, the country has a high per capita electricity use second only to Iceland [20]. While Norway's government attempted to decrease the share of buildings in total CO_2 emissions by 6.3%, the share of renewables in the TCF was relatively constant from 1990 to 2013 and declined in 2014. In Norway, 81% of residential energy use in 2013 was from electricity. The share of district heating in Norwegian energy consumption in 2013 was only 2%. Lacking district heating availability, in 2012 the primary heating source for more than 70% of Norwegian households was electricity. There are large variations in housing energy composition in Norway. While only 5% of households living in Oslo used heat pumps in 2012, the corresponding value for Hedmark/Oppland was about 40% [21,22].

The total energy consumption of Sweden was 1,335 PJ in 2014 and the share of its residential sector was 20.8% [23]. The economy of Sweden relies heavily on energy-intensive industries, including steel manufacturing, pulp, paper, and heavy vehicle production. The country substantially decreased its industrial and residential sector fossil fuel usage while increasing the use of renewables such as biomass and solar thermal. The Swedish government has also invested heavily in the nuclear energy. The share of its domestic buildings in total CO_2 emissions declined by 14.7% between 1990 and 2014. The EU's present policy is to decrease the share of nuclear power for electricity generation in Nordic countries from 22% in 2013 to 6% by 2050, with Sweden developing low-carbon energy solutions other than nuclear power after 2030 [5]. A large part of final energy consumption in Sweden is used for space heating in buildings. In 2013, the energy use for space heating and hot water in residential buildings was 11% less than in 2000. This reduction was due to the improved energy efficiency of heating appliances, particularly heat pumps, and district heating energy intensity [24].

By 2014, over 21% of total energy consumption in the Nordic countries was consumed by the residential sectors. However, the domestic sector in the EU was responsible for 24% of TFC. Because of the high energy demand for space heating in the Nordic countries, the corresponding governments were partially successful in applying their domestic sector energy efficiency policies [5].

Assessing residential sector energy trends is more difficult when compared to sectors such as transportation and industry. The issues are mainly due to the variety of buildings with different characteristics, the variable behavior of building occupants, and the lack of comprehensive data sets to model domestic energy use [25]. Understanding the detailed characteristics of the domestic sector is essential to clarify the interrelated and complex features of end-use energy consumption in the Nordic countries. The purpose of our study was to forecast the annual energy consumption of the Nordic residential sector by 2020 as a function of socio-economic and environmental factors, and to provide a framework for specifying the importance of each country's predictors. Determining factors that influence residential energy consumption is essential for policy-makers to adopt the best ways to lower energy use and CO_2 emissions. Hence, we discuss the determinants of domestic energy use chosen in this study to model residential energy consumption. We next introduce statistical methodologies for modeling, including MLR, MARS concept and the ANN approach [26]. Based on these methods, we generated three models for each country and compared their potential for predicting energy use and understanding the importance of investigated predictors.

Determinants of Domestic Energy Consumption

Research shows the importance of assessing the factors that affect domestic sector energy use and evaluating their interactions [27,28]. Policy-makers have recognized many parameters influencing domestic end-use energy consumption, which are classified as socio-economic factors, dwelling factors and appliance factors. Jones et al. [29] in a comprehensive literature review introduced these factors (see Figure 1).

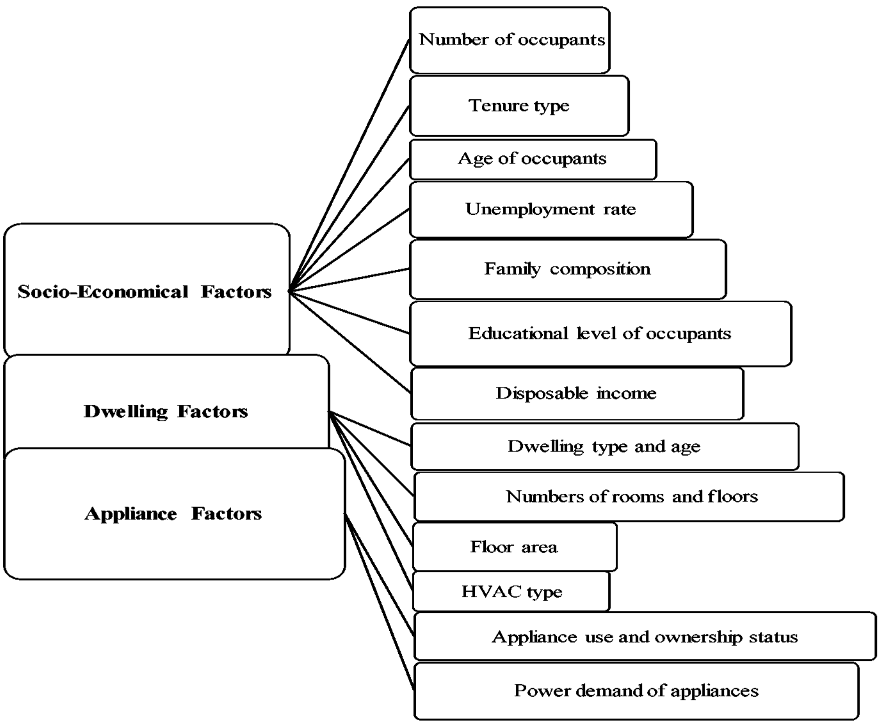

Figure 1. Determinants of residential sector energy use.

Previous studies revealed that there is a direct relationship between energy use, especially electricity use, and residential sector size [30-37]. The larger the population, the higher the energy consumption. Researchers showed that single occupancy dwellings in Ireland consume 19% less electricity weekly compared to two person households [36]. In another study, Zhou and Teng found that for every additional household member in China, electricity consumption increases by 8% [38].

In our study, we used the annual population of Nordic countries as a parameter demonstrating the size of the domestic sector. This choice was mainly due to the lack of reliable data on the actual number of residents in some of the investigated countries. Using annual dwelling stock data helped overcome this problem. The population of the Nordic countries has risen by 13% (about 3 million) since 1990. The Nordic Council reported that during this period the populations of Iceland and Norway increased by 28% and 21% respectively. Births overtaking deaths and immigration outstripping emigration are the main causes of population growth during the last two decades [39]. Table 1 contains the population of Nordic countries between 1990 and 2015.

Table 1. The population of Nordic countries between 1990 and 2015.
Source: Worldbank.org.

Country	Population 1990	Population 1995	Population 2000	Population 2005	Population 2010	Population 2015/16
Sweden	8,558,835	8,826,939	8,872,109	9,029,572	9,378,126	9,798,871
Denmark	5,140,939	5,233,373	5,339,616	5,419,432	5,547,683	5,676,002
Finland	4,986,431	5,107,790	5,176,209	5,246,096	5,363,352	5,482,013
Norway	4,241,473	4,359,184	4,490,967	4,623,291	4,889,252	5,195,921
Iceland	254,826	267,468	281,205	296,734	318,041	330,823

Another important social parameter influencing energy consumption is the age structure of the population. Some researchers claimed that this factor influences both the macro and micro level energy use, especially in the transportation and residential sectors [40-46]. Other studies evaluated the impact of age structure on total annual CO_2 emissions and residential sector shares [47-51]. These studies emphasized the importance of age structure as one of the determinants of energy consumption. We evaluated the impact of this parameter on the Nordic region's domestic sector end-use energy consumption. We considered that people of different ages have different disposable income levels and accordingly variable rates of energy consumption. Children and older persons use less energy in comparison to mature adults because of differences in their activities. The percentage of people aged between 15 and 64 was used as an age structure factor in our study. Table 2 shows this data from 1990 to 2015. It is important to understand the effects of this parameter on the Nordic residential energy use. The Nordic Council declared that the ratio of old to young people is increasing due to lower birth rates and longer life spans. Nordic countries have among the highest birth rates among European countries. Finland has the oldest age structure and the county's life expectancy has risen to 84 over the last two decades. Forecasts predict that more than 8% of the Nordic peoples will be over the age of 80 by 2040 [39].

Table 2. The share of population aged between 15 and 64 (work force).
Source: Worldbank.org.

Country	% of total labor force 1990	% of total labor force 1995	% of total labor force 2000	% of total labor force 2005	% of total labor force 2010	% of total labor force 2015/16
Sweden	64.3	63.7	64.3	65.3	65.3	62.8
Denmark	67.4	67.4	66.7	66.1	65.4	64.2
Finland	67.3	66.8	66.9	66.7	66.4	63.2
Norway	64.8	64.6	64.8	65.6	66.2	65.7
Iceland	64.4	64.3	65.1	66.2	66.9	66.0

Disposable income influences domestic energy consumption. Previous studies showed that disposable income directly impacts electricity consumption [33,35,36,52,53]. Leahy and Lyons found that Ireland's income elasticity compared to electricity consumption by appliances was 4% [36]. Though Nordic countries commonly use district heating systems in urban areas, the increase in disposable income may enhance the utilization of individual heating facilities in the domestic sector and increase the TFC. For Norway and Iceland, this likely results in wider use of electricity for heating [5]. Therefore, we used the annual growth rate of household disposable income as a determinant of residential energy consumption.

The level of urbanization is an important determinant of domestic energy usage, effectively influencing policies regarding socio-economic progress [43,54-58]. As people migrate from rural to urban areas, they engage in urban activities and work for the industrial, commercial or service sectors. This initially enhances industrial production and GDP, since the migrated people often require new infrastructure which increases development. This increases urban energy consumption and CO_2 emissions. Increasing energy use can create urban heat island (UHI) effects if offsetting energy efficiency measures are not implemented. Muye et al. showed that the migration of rural residents to urban areas in China increases emissions since use of biofuels, electricity, coal, and liquefied petroleum also increases [59]. People living Nordic countries use district heating and geothermal energy in urban areas which has a positive impact on the region's domestic energy use. We evaluated the impacts of the percentage of urban population on Nordic residential energy consumption. According to the Nordic Council, the population growth in the urban and suburban areas was greater than elsewhere. During the past two decades, many peripheral areas lost population to the cities increasing urbanization [39]. Table 3 provides urban population percentages for the Nordic countries from 1990 to 2015.

Among social factors, there is less study on the causes and effects of educational levels on residential energy consumption. Aixiang assessed the link between energy consumption, the number of technological scientists, the number of people studying in the tertiary education level, and the amount of the research and development (R&D)

Table 3.
Percentages of urban population in Nordic countries (1990 to 2015/16).
Source: Worldbank.org.

Country	% of urban population	% of urban population	% of urban population	% of urban population	% of urban population	% of urban population
	1990	1995	2000	2005	2010	2015/16
Sweden	83.1	83.8	84.0	84.3	85.1	85.8
Denmark	84.8	85.0	85.1	85.9	86.8	87.7
Finland	79.4	81.0	82.2	82.9	83.6	84.2
Norway	72.0	73.8	76.1	77.5	79.1	80.5
Iceland	90.8	91.6	92.4	93.0	93.6	94.1

funding in China [60]. The results indicated that improving energy efficiency in China's Jiangsu province highly depends on education levels and technology. Given the dramatic increase in the percentage of Nordic people with tertiary education, the study evaluates the impact on the residential energy consumption.

Along with the impressive improvement in educational levels and population increases over the last two decades, the domestic per capita energy use of the Nordic countries was relatively constant. This indicates the importance and effectiveness of educational development and spending in R&D in these countries. All of the Nordic countries, except Norway (investing 1.7%), invested more than the 2% EU average in R&D [61]. The Nordic Council estimated that 35% to 50% of Nordic people aged between 15 and 74 studied at the secondary education level and 22% to 34% at the tertiary educational level. Among the Nordic countries, Norway and Finland have the most population with tertiary education and Denmark has the least [62].

Resident employment status influences end-use energy consumption of households affecting the level of disposable income [29]. Unemployed people with low incomes lack potential to enhance their energy consumption. Studies on the relationships between energy consumption and rates of unemployment consistently report that there is no significant link between these two factors [63-65]. Nevertheless, we considered the parameter as one of our independent variables. One of the EU targets for labor is an employment rate of 75% for the working age group of 15 to 64 by 2020. It appears that the Nordic countries with the exception of Finland can partially meet this target [66]. Table 4 shows the unemployment rates between 1991 and 2014.

The last two determinants of domestic energy consumption considered in our study involved environmental issues. The link between energy use and the first parameter, CO_2 emissions, was investigated in previous studies which indicated that there is a direct relationship between them [56,67,68]. Table 5 shows the percentages of CO_2 emissions by the residential sector between 1990 and 2013. As the last parameter, this study analyses the link between the annual percentage of renewables and waste in household energy consumption to clarify how the enhancement of the parameter over the last two decades has influenced end-use energy consumption.

The work's inspiration comes from Fumo and Biswas, who used regression analysis to predict domestic sector energy use [69]. They

Table 4.
The unemployment rate in the Nordic countries (share of total labor forces).
Source: Worldbank.org.

Country	% unemployed 1991	% of unemployed 1995	% of unemployed 2000	% of unemployed 2005	% of unemployed 2010	% of unemployed 2014/16
Sweden	3.3	9.3	5.9	7.8	8.7	8.0
Denmark	9.1	7	4.5	4.8	7.5	6.6
Finland	6.5	15.3	9.7	8.4	8.4	8.6
Norway	5.4	4.9	3.4	4.6	3.6	3.4
Iceland	2.5	4.9	2.3	2.6	7.6	5.0

claimed that for bottom-up approaches to developing a model for domestic energy use, the statistical methods are more simple and useful in comparison to engineering approaches. Among the statistical methodologies, regression analysis showed a promising potential to model sector energy use. Using statistical approaches, we first predict domestic end-use by 2020, and then discuss the importance of the predictors for Nordic countries. The number of models and types of methods in our study vary. We compare the capabilities of traditional and advanced statistical methodologies to model residential sector energy demand in the Nordic countries mostly based on the social factors.

Methodology

The statistical approaches, including regression, conditional demand analysis, and neural network are capable of linking a response variable with one or more predictor variables. The response variable in this study is residential energy consumption in Nordic countries. All

Table 5.
Percentage of CO_2 emissions from the Nordic countries residential sector.
Source: Worldbank.org.

Country	% of residential CO2 emissions 1990	% of residential CO2 emissions 1995	% of residential CO2 emissions 2000	% of residential CO2 emissions 2005	% of residential CO2 emissions 2010	% of residential CO2 emissions 2013/16
Sweden	17.7	15.5	12.1	7.3	5.5	3.6
Denmark	12.4	10.2	9.4	9.2	8.4	8.3
Finland	12.2	10.9	6.4	6.1	4.6	4.4
Norway	9.0	5.9	4.7	4.1	3.7	3.0
Iceland	2.6	2.0	1.4	0.9	0.5	0.5

of the previously mentioned predictors are defined as continuous variables.

Using this model, we can estimate domestic sector energy use for the Nordic countries. We generated three models for each country based on the MLR analysis, MARS concept and the ANN approach [70,71]. Forecasting with these methods requires a prediction set, provided with another methodology. For this purpose, the additive Holt-Winter (HW) algorithm is used.

Additive Holt-Winter

The additive HW method is a version of the HW algorithm which is capable of forecasting historical data despite trendy behavior [72]. The series of formulas are:

$\hat{y}_{t+}h_{t=}l_{t+}h_{bt+}s_{t-m}+h_{m}+$

$_{lt=}\alpha(\gamma_{t-}s_{t-m})+(1-\alpha)\,(_{lt-1}+b_{t-1})$

$b_t=\beta^*\,(l_t-l_{t-1})+(1-\beta^*)b_{t-1}$

$s_{t=}\gamma(\gamma_{t-lt-1-}b_{t-1})+(1-\gamma)s_{t-m}$

The error correction equations are:

$_{lt}=_{lt-1+}b_{t-1+}\alpha e_t$

$b_t=b_{t-1}+\alpha\beta^*e_t$

$s_t=s_{t-m+}\gamma e_t$

$e_t=\gamma_t-(l_{t-1}+b_{t-1}+s_{t-m})=\gamma_t-\hat{y}_{t|t-1}$

Where l is level, b is trend, s is the seasonal component, α, β, and γ are smoothing parameters, m is the period of seasonality, e is error, and y is the observation [73].

Multiple Linear Regression

The multiple linear regression (MLR) methodology is one of the traditional modeling approaches capable of explaining the variations in a response variable using the change in predictors. The MLR models a dependent variable as a function of independent factors and estimates the regression coefficient for each predictor [70]. The regression coefficients represent the value at which the response variable changes when the independent variables change. The MLR model has the following form:

$\gamma=b_1x_1+b_2x_2+\ldots+b_nx_n+\mathrm{c}$

In this equation, b_i is the regression coefficient. The less the degree of variability of the residual values in relation to the overall variability, the greater the prediction accuracy model. This ratio is referred as the coefficient of determination, named R^2, and represents the capability of the model in fitting the input data as a function of the target variable. The importance value of determinants for the MLR is the t-statistic corresponding to the regression coefficient estimate of each independent variable [74].

Multivariate Adaptive Regression Spline

The nonparametric regression technique, MARS, is a form of the stepwise linear regression developed by Jerome Friedman in 1991 [75].

The model is much simpler in comparison to other approaches such as neural network and random forest. However, the MARS was derived from linear regression methodology; it can organize nonlinear links between the target and predictors. This methodology has been used by other researchers to predict building energy efficiency.

The MARS is popular for its flexible models and automatically adjusting the models to propose the most reasonable interaction between the response and dependents. It uses linear basis functions such as $(x\text{-}t)_+$ and $(t\text{-}x)\_$ in combination to propose the final equation as a polynomial function. The + sign means the MARS only considers the positive part of defined linear functions. Therefore,

$$(t\text{-}x)_- = \{x\text{-}t,\ \Lambda x<t\ \ 0,\ otherwise$$
$$(x\text{-}t)_+ = \{x\text{-}t,\ \Lambda x>t\ \ 0,\ otherwise$$

The variable t represents the knot location of predictor x. The general form of a MARS model is,

$$\gamma = f(\mathrm{x}) = \beta_o + \sum^1_{i=1} \beta_i\, h\,(x_i)$$

In this equation, $h_i(x)$ is a function from set C, containing the candidate reflected pairs function. β_i is the coefficient estimated with standard linear regression. MARS considers the values as weight representing the importance of the dependent variables. During forward stepwise, the MARS chooses those basis functions from set C which effectively reduces the residual error in each step. Then the methodology applies a backward procedure to prune the model by eliminating basis functions with the smallest increasing effect in the least squares. It uses a generalized cross validation (GCV) error function to evaluate the goodness of fit, considering the residual error and model complexity [74]. The formula for the GCV function is:

$$\mathrm{GCV} = [\sum^1_{i=1} (\gamma_i - f(x_i))^2] \div [1\text{-}\ (1+cd)/I]^{\ 2}$$

For this formula, I is the number of cases in the dataset, d is the degree of freedom, and c is the penalty factor for choosing the basis functions from set C. For all MARS models in our study, the degree of interaction is 6, the penalty is 3, and the threshold value is zero. To determine the variable importance, we computed the reduction in GCV for each dependent variable added to the model [74]. Then the reductions were summed for each corresponding continuous predictor to determine their importance. Using this methodology, the dependent variables not included in the pruned final model have a zero importance.

Artificial Neural Network

The artificial neural network (ANN) is a simple modeling approach often used by policy-makers. An ANN system comprises highly interconnected nodes called neurons [71]. For generated optimal networks, ANN tools effectively map patterns of input parameters onto the patterns of corresponding output variables by training the nodes and making them suitable for an alternative series of patterns. When the model is generated, the ANN applies the model to a new input pattern to forecast the proper output pattern. Among the various types, this study uses a feed forward ANN with a backward propagation learning algorithm for training the model. The formula is:

$$b_j = f\,(\sum^{1}{}_{i=1} w_{ij}\, \alpha_i - T_j)$$

For this formula, b_j is the output vector, a_i is the input vector, w_{ij} is the weighting between neurons i and j, T_j is the internal threshold, and f is a hyperbolic tangent transfer function. To improve the performance of the model, the ANN uses the following equations to adjust the threshold values and the weight factors [76].

$$T_j^{new} = T_j^{old} + \eta(\sum\delta_{pj}) + \alpha\Delta T_j^{old}$$
$$w_{ij}^{new} = w_{ij}^{old} + \eta(\sum\delta_{pj}O_{pi}) + \alpha\Delta w_{ij}^{old}$$

In these equations, η is the learning rate in the model, α is the momentum coefficient of the backward propagation learning algorithm, while ΔT and Δw are the previous change of threshold values and weight factors. O and p are the outputs and respective patterns. We normalized all of each pattern's data with values between -1 and 1, generated the initial weight factor with a random selection between -0.2 and 0.2, and set threshold values to zero.

Understanding the importance of variables using ANN is complicated compared to the previous approaches. One of the best solutions to this problem is to perform a sensitivity analysis of the model. We used the weight method sensitivity analysis, proposed by Garson, and applied by Montaño and Palmer to feed forward neural networks [77,78]. The formula for this methodology is:

$$Q_{ik} = [\sum^{L}{}_{j=1}((w_{ij} / \sum^{N}{}_{r=1} w_{rj}) v_{jk})] \div [\sum^{N}{}_{j=1}(\sum^{L}{}_{j=1}((w_{ij} / \sum^{N}{}_{r=1} w_{rj}) v_{jk}))]$$

In this equation, w_{ij} is the connection weight between the input neuron i and the hidden neuron j, and v_{jk} is the connection weight between the hidden neuron j and the output neuron k. Q_{ik} is the variable importance.

The overall performance of each model is measured using the coefficient of determination (R^2), calculated by:

$$R^2 = 1 - [\sum^{N}{}_{i\text{-}1}(\gamma_i - f(x_i)]^2 \div [\sum^{N}{}_{i\text{-}1}(\gamma_i - \bar{y})]^2$$

For this equation, f is the estimated function, y is the observations, and N is their quantity.

Denmark

Performing the forecasting model process, three models were generated for Denmark. The ANN model showed superior performance in comparison to the other regression methodologies. The R^2 of ANN, MARS, and MLR was 0.99, 0.8 and 0.61 respectively. Although the ANN model estimated that Denmark's residential energy use will experience a parabolic trend between 2015 and 2020, the regression models showed an approximately constant trend. However, there is a large difference between the estimated values. Considering that the final energy consumption of Denmark's domestic sector in 2014 was 165,630 Tj, the ANN model provides a more reasonable estimate of 2015 energy consumption. Figure 2 shows the forecasted trend of energy use between 2015 and 2020.

Research by Williams and Gomes indicated that predictors are highly affected by the type of model [74]. Figure 3 shows the weighted mean normalized importance of predictors. We used the R^2 of each model to determine the weighted mean of each predictor. The sensitivity analysis of Denmark's neural network model revealed that household disposable income, share of population aged 15 to 64, unemployment rate, and share of CO_2 emissions in total annual emissions have the greatest effects on energy consumption. For the MARS model, the

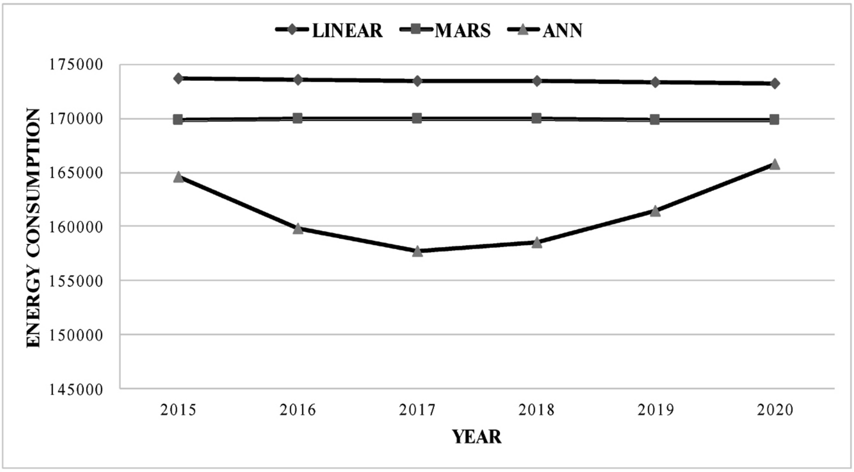

Figure 2. Forecasted trends for energy use (Tj) in Denmark's domestic sector.

population growth rate had the highest importance; the share of CO_2 emissions and the other significant predictors of ANN model ranked in the mid-range. The MLR model showed that the growth of population and household disposable income have the greatest effects on energy use. Hence, the three models agreed that the growth of disposable income, unemployment, population growth, and the percentage of people aged from 15 to 64, have significant effects on Denmark's residential energy use. An elasticity analysis indicted that household disposable income, gross enrollment ratio, and the percentage of the population aged from 15 to 64 are more effective in comparison to the other parameters (see Figure 4).

Finland

For Finland, all three models have an acceptable R^2. The coefficient of determination for the ANN, MARS, and MLR models was 0.99, 0.6 and 0.66 respectively. The difference between the R-value of the ANN model and the other two models is surprising. The 2014 energy consumption of Finland's domestic sector was 212,020 Tj. Among the models, the MLR had the most reasonable estimation for 2015, and the MARS model predicted the worst one. Based on the ANN and MLR forecasts, the energy use in the domestic sector will decline between 2015 and 2020. This considers that energy use declined between 1991 and 2014. However, the MARS estimated that the energy consumption

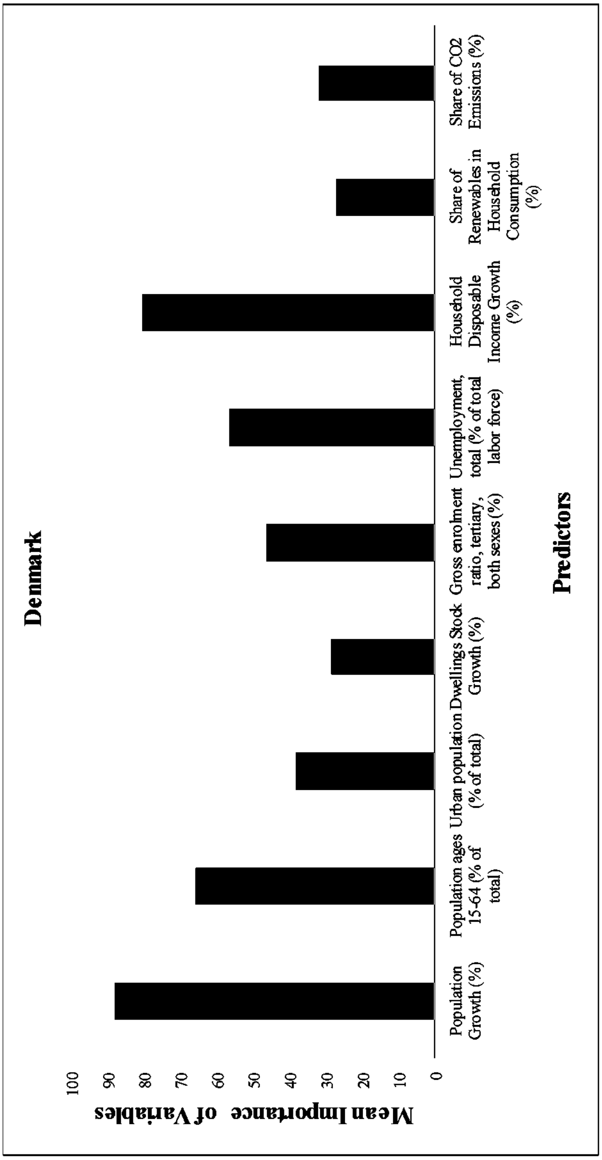

Figure 3. The mean weighted importance of predictors in Denmark's residential sector.

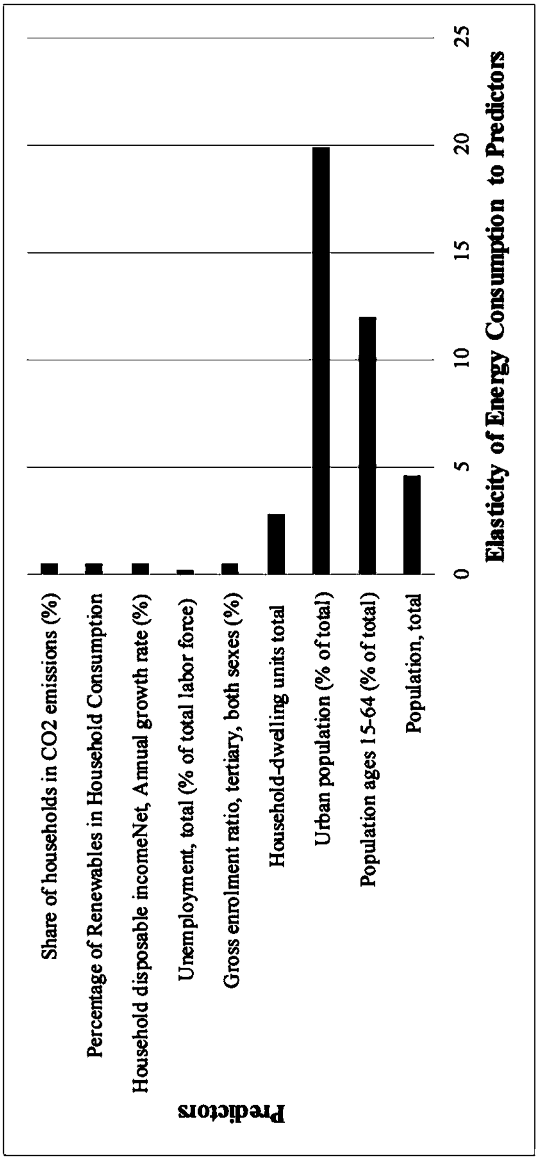

Figure 4. Results of the elasticity analysis for Denmark.

would increase slightly during this period. Hence, the MARS methodology was unable to efficiently forecast Finland's energy use. Figure 5 shows the estimated values for energy use between 2015 and 2020 for Finland's residential sector.

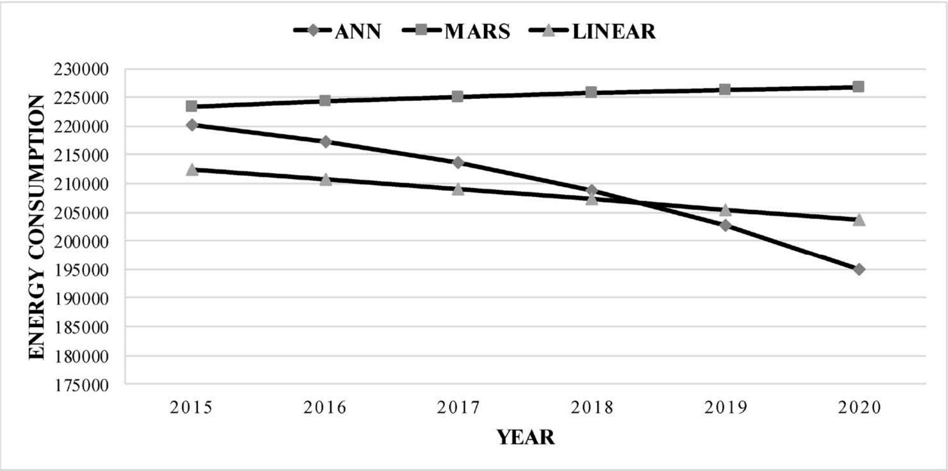

Figure 5. Forecasted trends for energy use (Tj) in Finland's domestic sector.

The MARS performed poorly in regard to determining predictor importance. The model revealed that changes in the share of renewables has the most effect on domestic sector energy consumption. The ANN and MLR models presented conclusive evidence that the parameter has an insignificant effect. The two models achieved a consensus on the effectiveness of the unemployment rate, the percentage of population aged 15 to 64, and population growth. The elasticity analysis also showed that urban population, age structure, and population growth have the most importance.

Finland's residential sector energy consumption fluctuated widely between 1991 and 2014. While energy use dropped 3.9% in 1993, it increased 3.6% in 1994. A similar situation also occurred in 2000 and 2001. Most economists believe that the global economic crisis in 2008 deeply affected Finland's economy in 2009 and 2010. During this period, Finland's residential energy use increased 15% while declining 12.5% in 2011. These fluctuations affected the performance of the regression models. Alternatively, the elasticity analysis results seem to contrast,

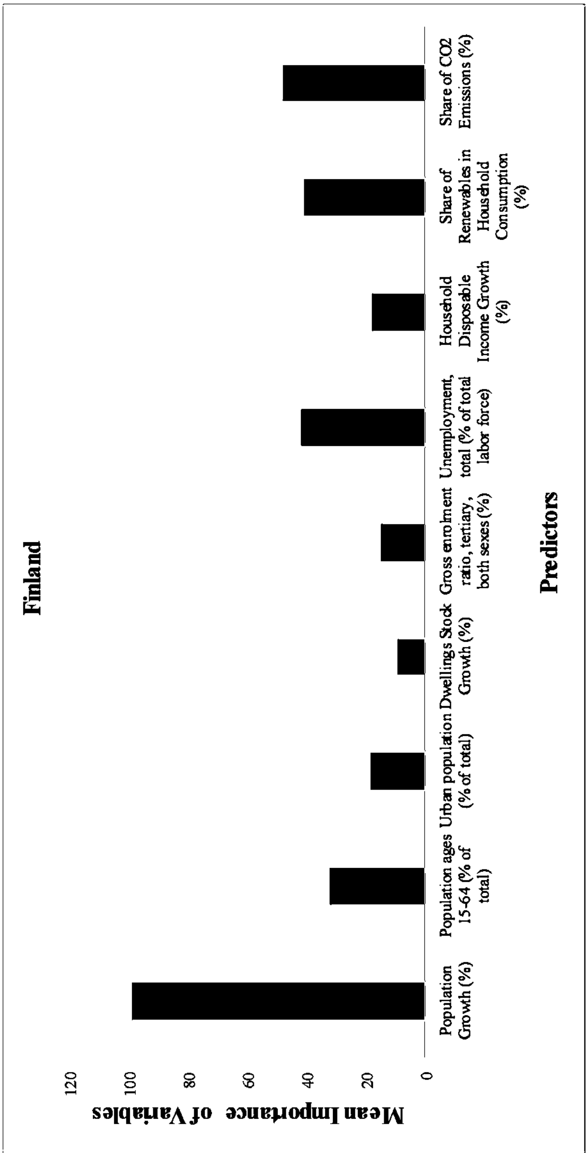

Figure 6. The mean weighted importance of predictors in Finland's residential sector.

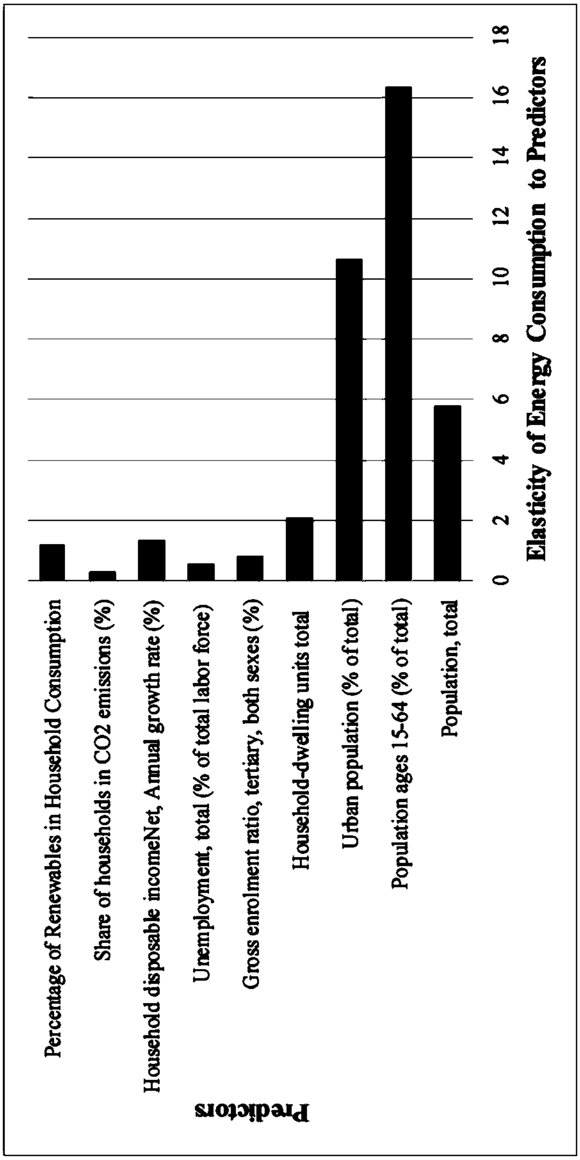

Figure 7. Results of the elasticity analysis for Finland.

since domestic energy use experienced sharp fluctuations, and some of the predictors changed gradually over the last two decades. The proportion of people aged 15 to 64, as the active people in Finland, has gradually declined between 1991 and 2014. At the same time, the total population and the urban population increased by 9.5% and 5.9% respectively. Consequently, the age structure in Finland positively effects energy consumption, and surprisingly, the growth of total population and urban population had a negative effect.

There is evidence that in some of the heavily urbanized countries (e.g., Ireland, Denmark and the UK), electricity usage from apartments and semi-detached houses is much less than for detached houses [36,79,80]. The transformation of Finland's social structure by urbanization between 1990 and 2015 created opportunities for people to live in more compact quarters such as apartments. During this period, the number of attached houses and blocks of flats increased by 248% and 34% respectively. With the country's low population density (17 inhabitants per km^2) and its high demand for space heating, greater urbanization combined with increased biomass usage in CHP systems substantially improved domestic sector energy efficiency. Figure 6 shows the weighted average importance of the dependent variables. Figure 7 shows the elasticity of energy use to the predictors for Finland's domestic sector.

Iceland

The three methodologies efficiently modeled the energy consumption in Iceland's residential sector. The ANN model and MARS model had R-values of 0.99, and the value for the MRL model was 0.96. While all three models had an equal estimation for energy use in 2015, the MARS model predicted an increasing trend for the following years, and the ANN and MLR models predicted a nearly constant distribution for energy use in the following years. The historical data showed that domestic energy use increased 46% between 1991 and 2014. Based on the MARS forecasting model, energy consumption increases 6.1% from 2015 to 2016. This difference between the forecasted values after 2017 occurred because the MARS model was mistaken in choosing the most suitable predictors. Figure 8 shows the forecasted domestic sector energy use in Iceland through 2020.

All of the models agreed on the effectiveness of the percentage of urban population and population aged 15 to 64. Figure 9 shows the av-

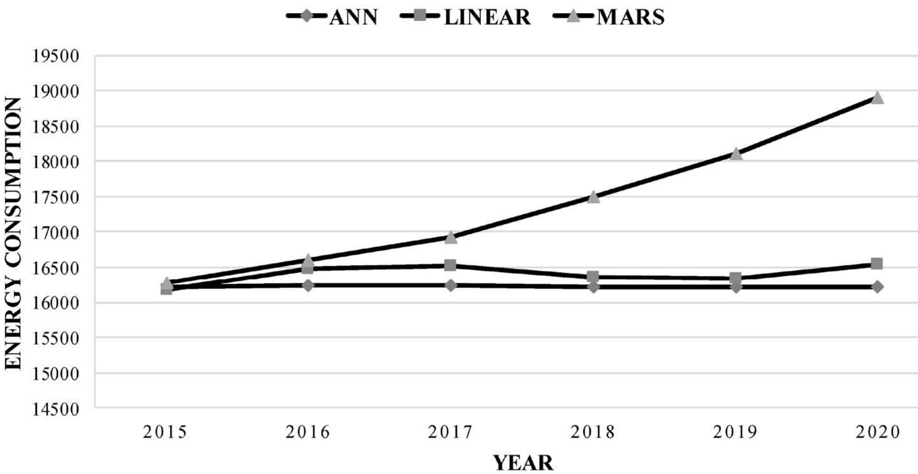

Figure 8. Forecasted trends for energy use (Tj) in Iceland's domestic sector.

erage normalized weighted importance of the dependent variables for Iceland.

The elasticity analysis (see Figure 10) shows that the gross enrollment ratio and unemployment rate are insignificant determinants of Iceland's domestic energy use; yet based on the MARS model the two parameters had the most importance. The MLR and ANN models indicated that the residential sector share of total CO_2 emissions and share of renewables in the final energy consumption were significant. However, the two parameters were not used in the MARS proposed model.

Sweden

Although the proposed variables efficiently modeled Sweden's residential energy use, the forecasted values for energy use by 2020 offer entirely different trends (see Figure 11). The R-value of the ANN, MARS, and MLR models was 0.99, 0.9 and 0.76 respectively. The ANN model forecasted declining energy use while the MLR model predicted no change for Sweden's residential end-use energy consumption between 2015 and 2020. The MARS model predicted a slightly increasing trend for this period.

There has been some fluctuation in level of Sweden's domestic energy consumption during the last two decades. The biggest changes occurred in 1996 and 2010, when unemployment rates were very high.

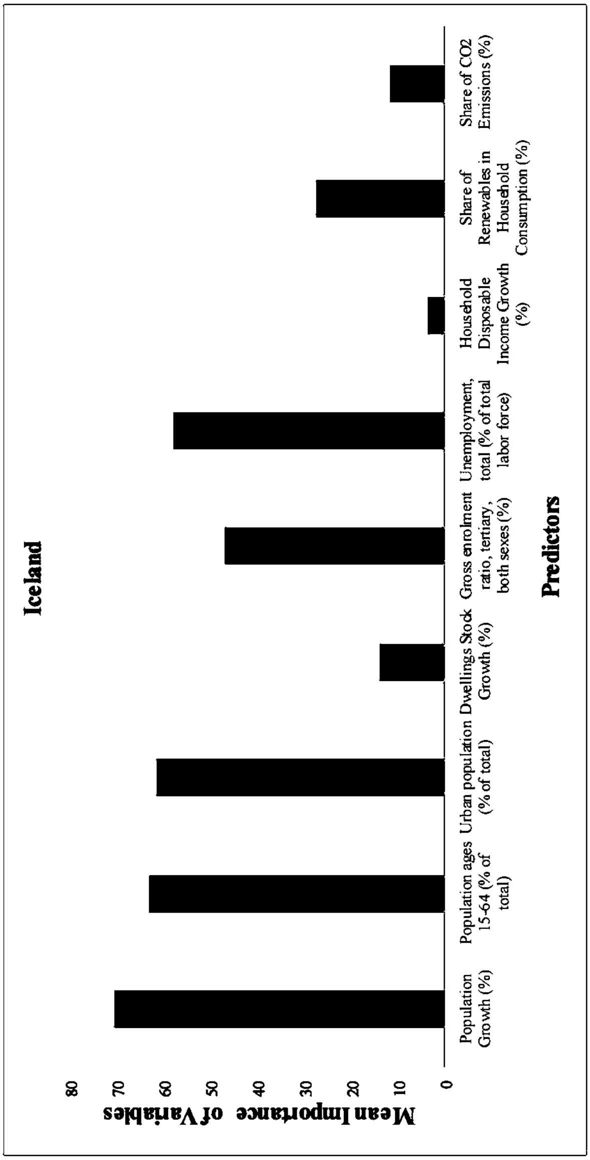

Figure 9. The mean weighted importance of predictors for Iceland's residential sector.

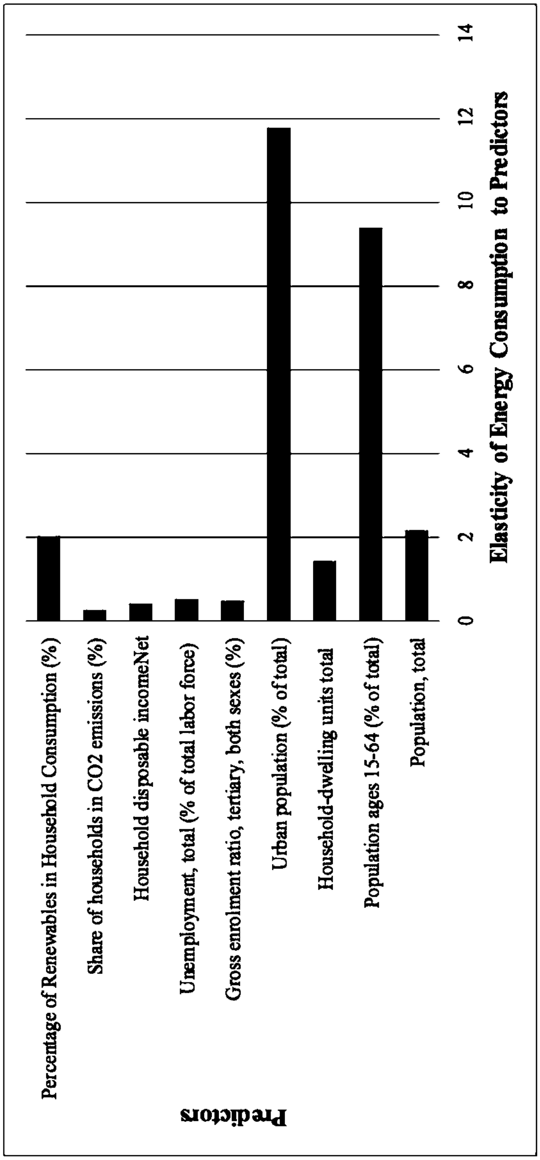

Figure 10. Results of the elasticity analysis for Iceland.

In places with high unemployment rates and poor weather conditions, people tend to spend more time indoors which increases energy use. Figure 12 shows the weighted normal importance of the predictors and Figure 13 shows the elasticity of energy use to those predictors. All three models, particularly the MARS, indicated the importance of unemployment as a determinant of energy consumption. Nonetheless, the sector set a record low for energy use in 2014, consuming 277,710 Tj, the least amount in the past two decades. Hence, the fluctuations in historical data adversely affected the models, and forecasted predictors with the AHW algorithm. This caused Sweden's forecasts to be incorrect. The ANN model predicted that Sweden's residential energy consumption would decline 61% by 2020, the MARS model forecasted that it would increase 20%, and the MLR forecasted that it will be constant. The models represent high *R*-squares, making judgments about their forecasting capabilities seemingly impossible. Regardless, the models achieved consensus on the effectiveness of some parameters—age structure, unemployment rate, dwelling stock and CO_2 emissions from residential buildings—and for the others there were differences between their magnitudes and ranks.

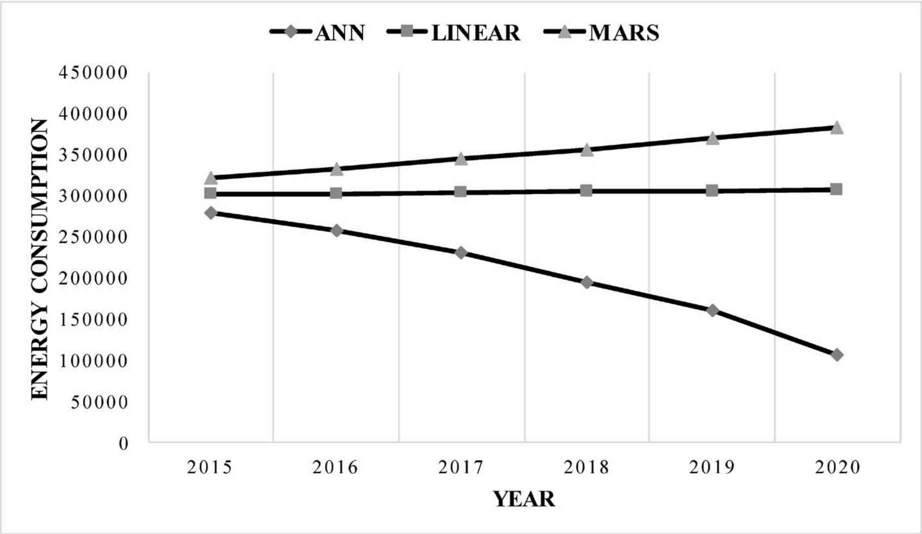

Figure 11. Forecasted trends for energy use (Tj) in Sweden's domestic sector.

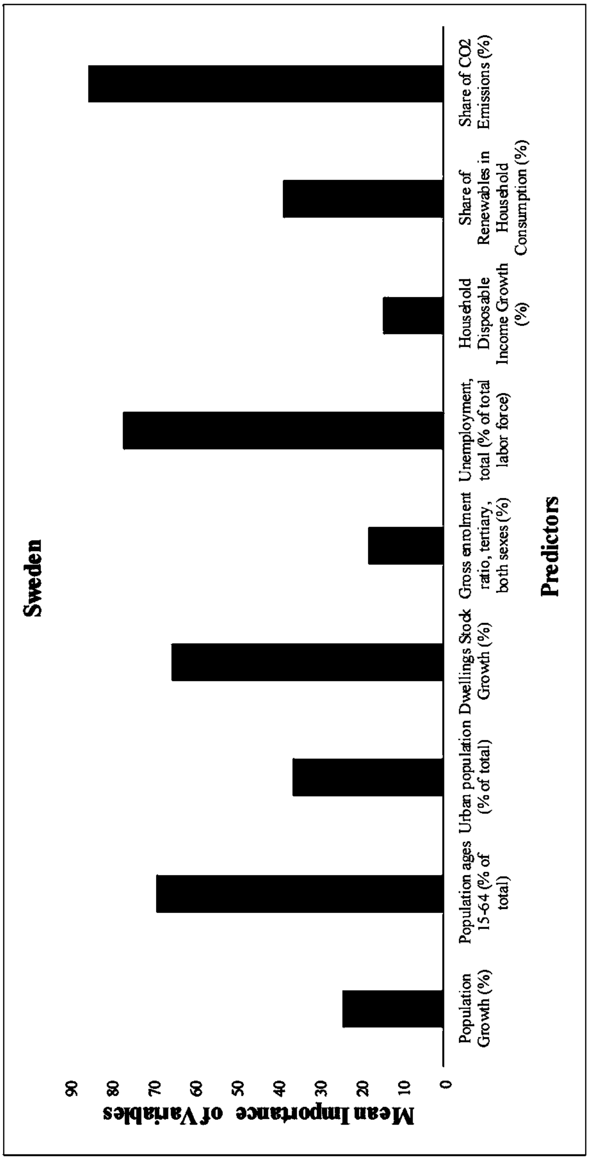

Figure 12. The mean weighted importance of predictors for Sweden's models.

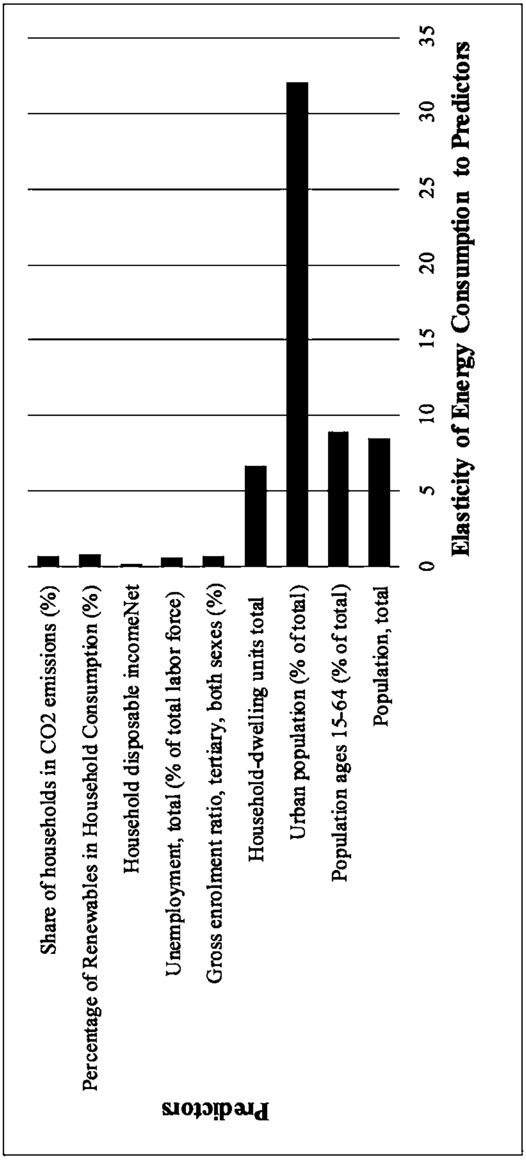

Figure 13. Results of the elasticity analysis for Sweden.

Norway

Similar to the previous models, the ANN model had the highest performance considering the R^2 while the MLR model had the lowest. The R-values for the ANN, MARS and MLR models were 0.91, 0.8 and 0.58 respectively. The final 2014 energy use of Norway's domestic sector was 160,606 Tj. Hence, the ANN model, followed by the MARS model provided the most reasonable estimate of 2015 energy use. Both forecasted similar slightly decreasing trends for energy consumption between 2015 and 2020. Figure 14 shows the estimated values of energy consumption in Norway's domestic sector. The historical data also show a downward trend in domestic sector per capita energy consumption. However, the total energy use of households increased slightly between 1991 and 2014, particularly after 2008. Despite the effects of the global economic crisis on energy consumption, the number of detached houses and farmhouses equipped with heat pumps increased by 18% between 2009 and 2014. The increase in the number of detached houses and farmhouses during this period adversely affected residential sector energy use. The Norway Statistics data show that residents living in these houses invested in heat pump technologies.

The proportion of the population living in Norway's urban areas increased 8% between 1991 and 2014. According to the ANN and MARS models, variations in urban population have the greatest impact on residential energy use (see Figure 15). The elasticity analysis revealed that small changes in the age structure, urban population, population

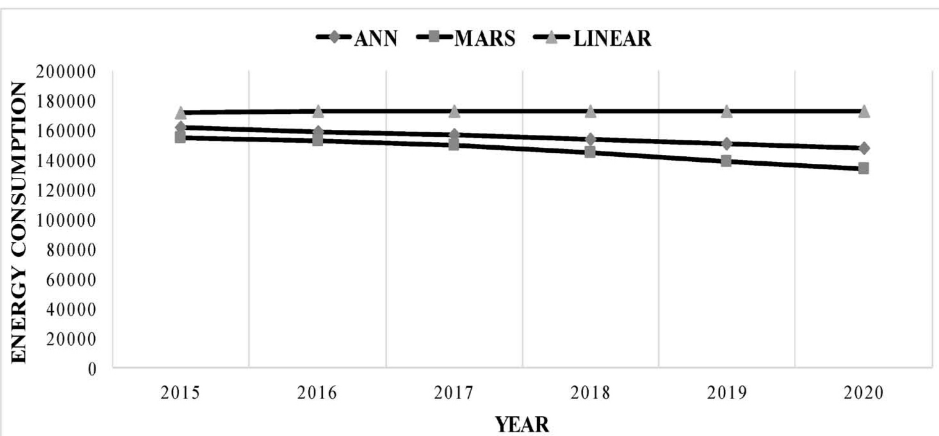

Figure 14. Forecasted trends for energy use (Tj) in Norway's domestic sector.

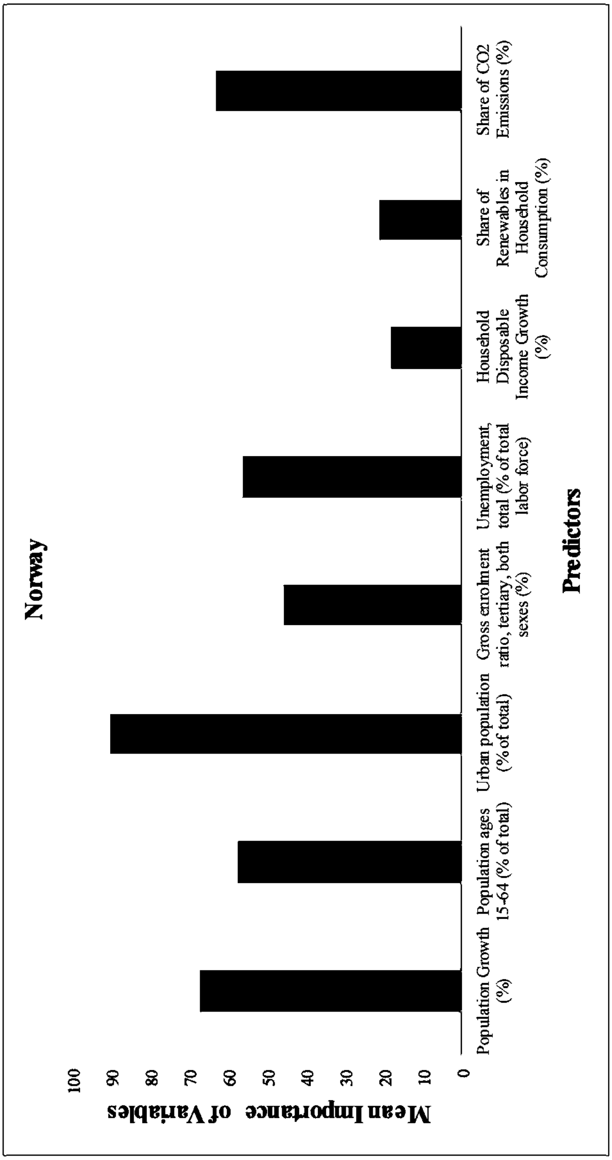

Figure 15. The mean weighted importance of predictors for Norway's models.

growth, gross enrollment ratio, and unemployment rates have considerable impacts on residential energy consumption. The elasticity values of energy consumption to the predictors are provided in Figure 16. These parameters are significant in the ANN and MARS models. The two methods efficiently modeled Norway's residential energy use and similarly forecasted energy consumption to 2020. Despite neglecting the share of renewables, the predictors have a close importance value in both models. Norway's models were generated using eight predictors, since valid data were unavailable for the growth rate of dwelling stocks.

Discussion

Three different methodologies were used to model the energy use of the Nordic domestic sectors. Among them, the ANN method efficiently modeled domestic energy use for all of the countries based on the investigated predictors. Forecasting energy use by 2020, the ANN and MLR models offered similar trends for all of the residential sectors, except for Sweden. While showing acceptable performance, the MARS model could not reasonably forecast residential sector energy use by 2020, except for Norway's domestic sector. The study indicated that the MARS is mainly suitable for high input dimensional problems. There is a big disadvantage to using these approaches for forecasting energy use. They require an additional method (i.e., the AHW) to forecast historical data for future years which affects forecasting precision. Precision forecasting needs to consider shorter interval data.

The main purpose of our study was to determine the effects of social and environmental factors on energy use. To this end, we conducted the forecasting analysis mainly to validate the results of models and evaluate their potential to model residential sector energy consumption. The models revealed that changes in some of the investigated factors (total population growth rate, unemployment rate, age structure, urban population, and the share of CO_2 emissions from the residential buildings) have significant effects on annual residential energy use. Over the past two decades the population of the Nordic countries increased by 13.3%. Most of this growth occurred in the urban areas. The governments further developed urban areas, enhancing dwelling stocks, especially apartments and attached houses. Since the Nordic countries commonly use CHP systems to meet their heating requirements, urban development policies effectively impact changes in residential sector energy use. Compact apartments and attached houses using CHP and

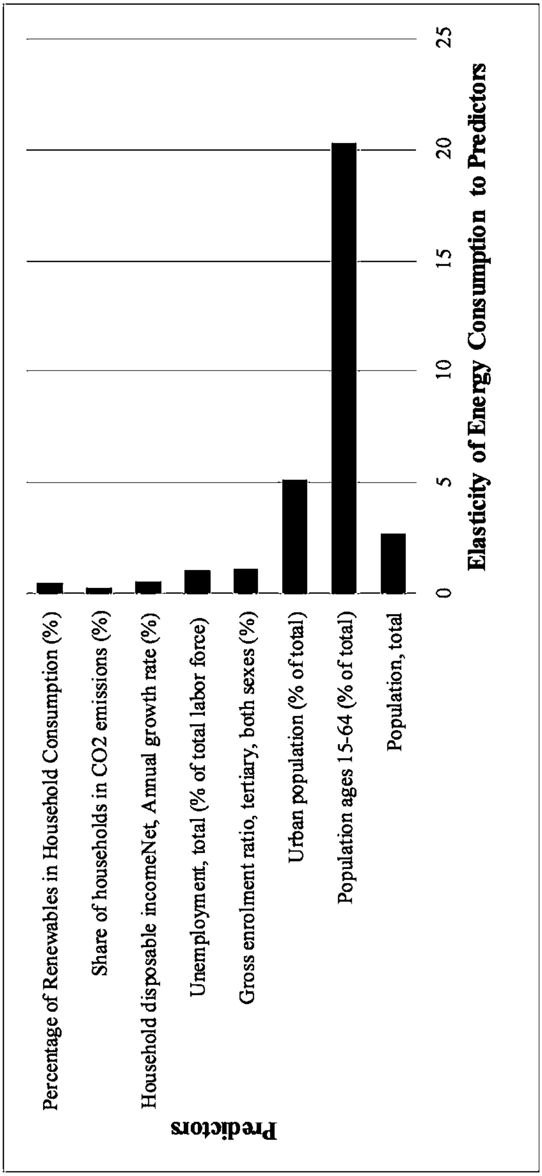

Figure 16. Results of the elasticity analysis for Norway.

geothermal systems are typically more energy efficient than detached houses.

In the past, the Nordic countries were heavily dependent on imported fossil fuels for their transportation systems and energy intensive industries. Their share of fossil fuels in residential end-use energy consumption was relatively high. This was a direct cause of energy supply problems faced by the countries after the oil crisis in 1973. Afterwards, they heavily invested in renewable energy technologies. Sweden and Denmark have established leadership roles in sustainable energy systems. According to the IEA in 2013, the share of renewables in the final energy consumption of Sweden was greater than 33%. Historical data offer the following for the period between 1991 and 2014:

- Denmark's residential sector relies heavily on solid biofuels and solar thermal energy; their shares have increased.
- Finland's domestic sector uses resources similar to Denmark. Since the Danes live in lower latitudes and have greater solar resources, they have 8.4 times as much solar thermal infrastructure.
- Swedish households also use primary solid biofuels, biogases and solar thermal.
- The share of renewables in the domestic sectors of Iceland and Norway have declined during this period. Iceland uses geothermal resources for primary energy which generated consistent power until 2013 and declined afterwards. Norway's domestic sector relies on renewable resources including solid biofuels and hydro-electricity for heating demand. Energy supply systems must rely on multiple resources to maintain resiliency. Norway and Iceland need new renewable resources to respond to their large residential sector energy demand.

Promoting policies for more compact cities with carbon-free energy systems supports the objectives of improved energy security, health, economic development and sustainability in Nordic countries. There are strong arguments to phase out nuclear power plants, particularly in Sweden. The overall mean weighted normalized importance of population growth and share of urban population indicate the importance of these relationships.

While past studies showed that unemployment rates are not significant, ours shows that this parameter effectively and indirectly influences residential energy consumption in some Nordic countries [63-65]. We also found a close relationship between energy use in residential energy consumption and age structures in Nordic countries. This means Nordic countries with young populations need to invest more in residential sector energy efficiency and renewable energy. The rapid growth of young populations affects unemployment rates by increasing the size of the labor force. The results showed that the other independent variables are less important in the proposed models. Table 6 provides a summary of the importance of variables in different categories.

CONCLUSIONS

This study forecasted domestic sector end-use energy consumption in Nordic countries by 2020, investigating the causal links among energy consumption, total population growth, urban population growth, age structure, education level, unemployment rate, dwelling stock, share of CO_2 emission, and the share of renewable energies in domestic sectors. Time variations of these parameters is mainly due to changes in the human development index (HDI), developing the economy and urban areas, and the level of investment in renewable and sustainable energies.

The three models offer good performance when considering their R^2, led by the ANN, followed by MARS, and finally the MLR model. Recently developed models like the ANN and MARS provided better performance than the traditional MLR. Although Fumo and Biswas [69] indicated on the performance of statistical approaches, our study revealed that by using these methods, it is difficult to obtain accurate predictions of Nordic domestic sector energy consumption because of the following reasons:

- The MLR approach only looks for the linear relationship between the dependent variable and predictors. Using quantile regression might provide a better solution for this problem in future studies.
- Another factor limiting the performance of the MLR is the assumption of the predictors being completely independent variables. While there are close relationships between most of the predictors in this study, the results also showed that using multilevel models like the ANN may enhance prediction accuracy.

Table 6. Importance of investigated predictors in different models and countries.

Countries		Population Growth (%)	Population ages 15-64 (% of total)	Urban population (% of total)	Dwellings Stock Growth (%)	Gross enrolment ratio, tertiary, both sexes (%)	Unemployment, total (% of total labor force)	Household Disposable Income Growth (%)	Share of Renewables in Household Consumption (%)	Share of CO_2 Emissions (%)
Denmark	ANN	69.4	93.1	49.4	25.3	37	86.4	100	56.3	72.2
	MARS	100	54.8	54.8	43.0	48.2	43.0	45.9	0	0
	MLR	100	40.6	0	14.2	58.2	33.7	96.2	20.3	13.4
	Mean	88.0	66.0	38.2	28.5	46.5	56.7	80.3	27.4	31.8
Finland	ANN	100	54.6	19.3	23.4	14.6	58.4	6.7	15.9	54.1
	MARS	99.7	0	0	0	4.0	4.0	0.65	100	2.0
	MLR	97.7	39.8	41.2	0	29.2	65.7	56.0	0.9	100
	Mean	99.3	31.8	18.4	9.1	14.8	41.5	17.6	41.0	48.2
Iceland	ANN	38.4	69.2	100	20.8	7.1	21.6	9.0	57.0	8.2
	MARS	85.0	85.0	24.9	0	100	85.0	0	0	0
	MLR	100	25.5	52.7	22.2	36.6	76.1	0	19.8	32.5
	Mean	70.7	63.2	61.6	14.0	47.0	57.9	3.51	27.5	11.8
Sweden	ANN	48.7	65.9	48.5	100	28.9	56.7	37.0	74.2	63.9
	MARS	0	60.9	36.0	21.0	0	100	0	15.4	98.9
	MLR	20.6	85.6	19.5	72.8	26.7	78.3	0	16.1	100
	Mean	24.5	69.4	36.5	65.5	18.3	77.4	14.46	38.6	85.5
Norway	ANN	91.9	26.7	100		67.1	70.3	34	17.3	51.9
	MARS	50.58	59.9	100		47.9	83.3	0	0	83.3
	MLR	52.2	100	62.8		10.6	0	19.3	54.1	54.1
	Mean	67.32	57.5	90.2		45.6	56.3	18.4	21.0	63.3
Overall Importance		69.4	58.3	49.2	24.5	35.3	60.4	25.5	29.1	48.8

- Though the MARS method makes no assumptions about the types of relationships between domestic energy use and predictors, this method (like the MLR) assumes no link between predictors in the corresponding model.
- The ANN method is a data-driven approach and needs no assumptions regarding the type and form of model. The methodology has disadvantages. Despite its impressive performance for prediction, it is difficult to interpret the generated model. The model is susceptible to over-training, which may cause instability in the obtained results. Accurate forecasting with the ANN requires a thorough understanding of the model. Using artificial intelligence networks is recommended for future studies.

Regardless of these drawbacks, our study revealed interesting information about the determinants of domestic energy use in Nordic countries. Despite the view of previous works about the effects of unemployment rates on domestic energy use, the sensitivity analysis showed that the parameter had a large effect on Nordic residential energy consumption between 1990 and 2014. The other important determinant is the share of residential sector CO_2 emissions. Except for Denmark, this factor has a key role in the models generated for Nordic countries. The other three major predictors are population growth, proportion of population in urban areas, and the share of people aged from 15 to 64 (work force). In most of the generated models, the work force parameter and the unemployment rates had similar normalized importance, led by the second, which demonstrates a close relationship between the two parameters.

The proportion of populations living in urban areas is a primary determinant of domestic energy use in Nordic countries. High regional heating demand and the use of district heating and geothermal energy enhances the importance of concentrating populations in Nordic countries. Using energy-efficient boilers in combination with inexpensive carbon-free energy in district heating systems has improved energy efficiency in the Nordic domestic sector during the last two decades.

The Nordic governments should heavily invest in residential infrastructure to accommodate an additional 3.9 million residents by 2050, plus further develop urban areas, district heating systems, and geothermal technologies to maintain or improve levels of energy. The issue raises an alarm for country's like Norway with little investment in district heating systems during the last two decades. Electricity is not the best future energy source for heating in Norway. A better option is for these countries to invest in small and medium CHP systems, especially in rural areas. Larger cities should enhance the capacity of large CHP and district heating systems, since these systems are more energy-efficient and environmentally friendly for Nordic climates.

Acknowledgements

The data and projections used in our study have been excerpted from authentic sources. The authors appreciate the assistance provided by following institutions:

International Energy Agency, www.iea.org.
The Worldbank group, www.Worldbank.org.
Danish Statistics Agency, www.statbank.dk.
Danish Energy Agency—Energistyrelsen, www.ens.dk.
Finnish Statistics Agency—Tilastokeskus, www.stat.fi.
Icelandic Statistics Agency, www.statice.is.
Norwegian Statistics Agency, www.ssb.no.
Swedish Statistics Agency, www.scb.se.
Nordic Council of Ministers and the Nordic Council, www.norden.org.

References

[1] Energy Policies of IEA Countries - Denmark (2011). Review. https://www.iea.org.
[2] Energy Policies of IEA Countries - Finland (2013). Review. https://www.iea.org.
[3] Energy Policies of IEA Countries - Norway (2011). Review. https://www.iea.org.
[4] Energy Policies of IEA Countries - Sweden (2013). Review. https://www.iea.org.
[5] Karlsson, K., Münster, M., Skytte, K., Pérez, C., Venturini, G. and Salvucci, R. (2016). Nordic energy technology perspectives.
[6] International Energy Agency (2014). Statistics IE. Balances, Denmark. https://www.iea.org.
[7] Railio, J. (2005). Energy Performance of Buildings Directive. Influences on European standardization and on ventilation and air-conditioning industry, update and follow-up. Page 3.
[8] Kitzing, L., Katz, J., Schröder, S., Morthorst, P. and Andersen, F. The residential electricity sector in Denmark: a description of current conditions. Working paper, Technical Univrsity of Denmark, Kgs. Lyngby. http://orbit.dtu.
[9] The Danish Energy Agency. Energy efficiency trends and policies in Denmark. www.odyssee-mure.eu.
[10] Barriers for flexibility in the district heating-electricity interface (2016). www.lsta.com.
[11] Whitehead, F. (2014). Lessons from Denmark: how district heating could improve energy security. The guardian.
[12] International Energy Agency (2014). Statistics IE. Balances, Finland. https://www.iea.org.

[13] Paiho, S. and Reda, F. (2016). Towards next generation district heating in Finland. *Renewable and Sustainable Energy Reviews*, 65, pages 915-24.
[14] Znouda, E., Ghrab-Morcos, N. and Hadj-Alouane A. (2007). Optimization of Mediterranean building design using genetic algorithms. *Energy and Buildings*, 39(2), pages 148-53.
[15] International Energy Agency (2014). Statistics IE. Balances. https://www.iea.org.
[16] National Energy Authority of Iceland (2016). Geothermal. http://www.nea.is/geothermal/.
[17] Mäntysaari, P. (2015). E.U. electricity trade law: the legal tools of electricity producers in the internal electricity market. Springer.
[18] Pool, N. (2007). Annual Report. www. nordpoolspot. com/about.
[19] International Energy Agency (2014). Statistics IE. Balances. Norway. https://www.iea.org.
[20] Gebremedhin, A. (2012). Introducing district heating in a Norwegian town-potential for reduced local and global emissions. *Applied Energy*, 95, pages 300-4.
[21] Statistics Norway (2012). Energy consumption in households. https://www.ssb.no/en/husenergi/.
[22] Eva Rosenberg Institute for Energy Technology (2015). Energy efficiency trends and policies in Norway. www.odyssee-mure.eu.
[23] International Energy Agency (2014). Statistics IE. Balances. Sweden. https://www.iea.org.
[24] International Energy Agency (2016). The IEA CHP and DHC Collaborative CHP/DHC Scorecard: Sweden. http://www.iea.org.
[25] Swan, L. and Ugursal, VI. (2009). Modeling of end-use energy consumption in the residential sector: a review of modeling techniques. *Renewable and Sustainable Energy Reviews*, 13(8), pages 1,819-35.
[26] Friedman, J. (1991). Multivariate adaptive regression splines. The annals of statistics. Pages 1-67.
[27] Lomas, K. (2010). *Carbon reduction in existing buildings: a transdisciplinary approach*. Taylor and Francis.
[28] Oreszczyn, T. and Lowe, R. (2010). Challenges for energy and buildings research: objectives, methods and funding mechanisms. *Building Research and Information*, 38(1), pages 107-22.
[29] Jones, R., Fuertes, A. and Lomas, K. (2015). The socio-economic, dwelling and appliance related factors affecting electricity consumption in domestic buildings. *Renewable and Sustainable Energy Reviews*, 43, pages 901-17.
[30] Bedir, M., Hasselaar, E. and Itard, L. (2013). Determinants of electricity consumption in Dutch dwellings. *Energy and Buildings*, 58, pages 94-207.
[31] Tso, G. and Yau, K. (2007). Predicting electricity energy consumption: a comparison of regression analysis, decision tree and neural networks. *Energy,* 32(9), pages 1,761-8.
[32] Wiesmann, D., Azevedo, I., Ferrão, P. and Fernández, J. (2011). Residential electricity consumption in Portugal: findings from top-down and bottom-up models. *Energy Policy*, 39(5), pages 2,772-9.
[33] Druckman, A. and Jackson, T. (2008). Household energy consumption in the UK: a highly geographically and socio-economically disaggregated model. *Energy Policy*, 36(8), pages 3,177-92.
[34] Kavousian, A., Rajagopal, R. and Fischer, M. (2013). Determinants of residential electricity consumption: using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior. *Energy*, 55, pages 184-94.

[35] Brounen, D., Kok, N. and Quigley, J. (2012). Residential energy use and conservation: economics and demographics. *European Economic Review*, 56(5), pages 31-45.
[36] Leahy, E. and Lyons, S. (2010). Energy use and appliance ownership in Ireland. *Energy Policy*, 38(8), pages 4,265-79.
[37] Tso, G. and Yau, K. (2003). A study of domestic energy usage patterns in Hong Kong. *Energy*, 28(15), pages 1,671-82.
[38] Zhou, S. and Teng, F. (2013). Estimation of urban residential electricity demand in China using household survey data. *Energy Policy*, 61, pages 394-402.
[39] The Nordic Council of Ministers. The population Nordic cooperation. http://www.norden.org.
[40] O'neill, B. and Chen, S. (2002). Demographic determinants of household energy use in the United States. *Population and Development Review*, 28, pages 53-88.
[41] Liddle, B. (2004). Demographic dynamics and per capita environmental impact: using panel regressions and household decompositions to examine population and transport. *Population and Environment*, 26(1), pages 23-39.
[42] Prskawetz, A., Leiwen, J. and O'Neill, B. (2004). Demographic composition and projections of car use in Austria. *Vienna Yearbook of Population Research*, pages 175-201.
[43] Liddle, B. (2004). Impact of population, age structure, and urbanization on carbon emissions/energy consumption: evidence from macro-level, cross-country analyses. *Population and Environment*, 35(3), pages 286-304.
[44] Jorgenson, A., Rice, J. and Clark, B. (2010). Cities, slums, and energy consumption in less developed countries, 1990 to 2005. *Organization and Environment*, 23(2), pages 189-204.
[45] York, R. (2007). Demographic trends and energy consumption in European Union Nations, 1960-2025. *Social Science Research*, 36(3), pages 855-72.
[46] York, R. editor (2007). Structural influences on energy production in south and east Asia, 1971-2002. Sociological Forum: Wiley Online Library.
[47] Okada, A. (2012). Is an increased elderly population related to decreased CO_2 emissions from road transportation? *Energy Policy*, 45, pages 286-92.
[48] Menz, T. and Welsch, H. (2012). Population aging and carbon emissions in OECD countries: accounting for life-cycle and cohort effects. *Energy Economics*, 34(3), pages 842-9.
[49] Martínez-Zarzoso, I. and Maruotti, A. (2011). The impact of urbanization on CO_2 emissions: evidence from developing countries. *Ecological Economics*, 70(7), pages 1,344-53.
[50] Liddle, B. and Lung, S. (2010). Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. *Population and Environment*, 31(5), pages 317-43.
[51] York, R. (2008). De-carbonization in former Soviet republics, 1992-2000: the ecological consequences of de-modernization. *Social Problems*, 55(3), pages 70-90.
[52] Blázquez, L., Boogen, N. and Filippini, M. (2013). Residential electricity demand in Spain: new empirical evidence using aggregate data. *Energy Economics*, 36, pages 648-57.
[53] Halvorsen, B. and Larsen, B. (2001). Norwegian residential electricity demand—a microeconomic assessment of the growth from 1976 to 1993. *Energy Policy*, 29(3), pages 227-36.
[54] Fan, J., Zhang, Y. and Wang, B. (2016). The impact of urbanization on residential energy consumption in China: an aggregated and disaggregated analysis. *Renewable and Sustainable Energy Reviews*.

[55] Sun, C., Ouyang, X., Cai, H., Luo, Z. and Li, A. (2014). Household pathway selection of energy consumption during urbanization process in China. *Energy Conversion and Management*, 84, pages 295-304.
[56] Ali, H., Law, S. and Zannah, T. (2016). Dynamic impact of urbanization, economic growth, energy consumption, and trade openness on CO_2 emissions in Nigeria. *Environmental Science and Pollution Research*, 23(12), pages 12,435-43.
[57] Yuan, B., Ren, S. and Chen, X. (2015). The effects of urbanization, consumption ratio and consumption structure on residential indirect CO_2 emissions in China: a regional comparative analysis. *Applied Energy*, 140, pages 94-106.
[58] Wang, Q., Zeng, Y. and Wu, B. (2016). Exploring the relationship between urbanization, energy consumption, and CO_2 emissions in different provinces of China. *Renewable and Sustainable Energy Reviews*, 54, pages 1,563-79.
[59] Ru, M., Tao, S., Smith, K., Shen, G., Shen, H. and Huang, Y. (2015). Direct energy consumption associated emissions by rural-to-urban migrants in Beijing. *Environmental Science and Technology*, 49(22), pages 13,708-15.
[60] Aixiang, T. (2011). Research on relationship between energy consumption quality and education, science and technology based on grey relation theory. *Energy Procedia*, pages 1,718-21.
[61] The Nordic Council of Ministers. Total research and development expenditure Nordic cooperation. http://www.norden.org.
[62] The Nordic Council of Ministers. Educational attainment at upper- and post-secondary level Nordic cooperation. http://www.norden.org.
[63] Yohanis, Y., Mondol, J., Wright, A. and Norton, B. (2008). Real-life energy use in the UK: how occupancy and dwelling characteristics affect domestic electricity use. *Energy and Buildings*, 40(6), pages 1,053-9.
[64] Cramer, J., Miller, N., Craig, P., Hacket, B., Dietz, T. and Vine, E. (1985). Social and engineering determinant and their equity implications in residential electricity use. *Energy*, 10(12), pages 1,283-91.
[65] Frederiks, E., Stenner, K. and Hobman, E. (2015). The socio-demographic and psychological predictors of residential energy consumption: a comprehensive review. *Energies*, 8(1), pages 573-609.
[66] The Nordic Council of Ministers. Denmark—per cent employed of the population between 15-64 Nordic cooperation. http://www.norden.org.
[67] Feng, Y., Chen, S. and Zhang, L. (2013). System dynamics modeling for urban energy consumption and CO_2 emissions: a case study of Beijing, China. *Ecological Modelling*, 252, pages 44-52.
[68] Hossain, M., Li, B., Chakraborty, S., Hossain, M. and Rahman, M. (2015). A comparative analysis on China's energy issues and CO_2 emissions in global perspectives. *Sustainable Energy*, 3(1), pages 1-8.
[69] Fumo, N. and Biswas, M. (2015). Regression analysis for prediction of residential energy consumption. *Renewable and Sustainable Energy Reviews*, 47, pages 332-43.
[70] Aiken, L., West, S. and Pitts, S. (2003). Multiple linear regression. Handbook of psychology.
[71] Wang, S. (2003). Artificial neural network. Interdisciplinary computing in java programming. Springer, pages 81-100.
[72] Bertolini, M., Bevilacqua, M. and Ciarapica, F., editors (2010). Re-engineering the forecasting phase using traditional and soft computing methods. Industrial Engineering and Engineering Management. 2010 IEEE International Conference. IEEE.
[73] Holt-Winters seasonal method. https://www.otexts.org.
[74] Williams, K. and Gomez, J. (2016). Predicting future monthly residential energy consumption using building characteristics and climate data: a statistical learning

approach. *Energy and Buildings*, 128, pages 1-11.
[75] Fridedman, J. (1991). Multivariate adaptive regression splines (with discussion). *Annual Statistics*, 19(1), pages 79-141.
[76] Jung, S. and Lee, S. (2006). In situ monitoring of cell concentration in a photobioreactor using image analysis: comparison of uniform light distribution model and artificial neural networks. *Biotechnology Progress*, 22(5), pages 1,443-50.
[77] Garson, D. (1991). Interpreting neural network connection weights.
[78] Montano, J., and Palmer, A. (2003). Numeric sensitivity analysis applied to feedforward neural networks. *Neural Computing and Applications*, 12(2), pages 119-25.
[79] Bartiaux, F. and Gram-Hanssen, K., editors (2005). Socio-political factors influencing household electricity consumption: a comparison between Denmark and Belgium. ECEEE summer study proceedings.
[80] Wyatt, P. (2013). A dwelling-level investigation into the physical and socioeconomic drivers of domestic energy consumption in England. *Energy Policy*, 60, pages 540-9.

ABOUT THE AUTHORS

Samad Ranjbar Ardakani—Department of Management, payamnoor university (Pnu), 19395-3697-Tehran, Iran. E-mail: samadrajnb@pnu.com.

Seyed Mohsen Hosseini—Renewable energy and environment department, Faculty of New Sciences and Technologies, University of Tehran, Tehran, Iran. E-mail: s.mohsen.hosseini@ut.ac.ir.

Alireza Aslani—Renewable energy and environment department, Faculty of New Sciences and Technology, University of Tehran, Iran. Corresponding author. E-mail: Alireza.aslani@ut.ac.ir.