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Domestic hot water consumption prediction models suited for dwellings in central-southern parts of Chile

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ABSTRACT

Domestic hot water (DHW) consumption in dwellings can play a key role in the development of policies that are focused on energy poverty, and in improving energy efficiency, among other aspects. There is an important variability observed with DHW among different countries due to technical, sociological, climatic, and economic factors. Most studies that deal with DHW predictions are based on stochastic models, and only a few apply time series or statistical methods. In the case of Chile, the country is undergoing a policy development process, and there is little information about DHW consumption. As a result, it is fundamental to have DHW consumption prediction models that are focused on dwelling. For this reason, the study analysed the possibility of using time series models to make future estimations about monthly domestic hot water (DHW) consumption. To this end, consumption data obtained from 98 apartments between 2015 and 2021 were used, and 3 approaches were applied namely, exponential smoothing, basic structural model (BSM), and state-space model (SSM). The results showed that exponential smoothing and state-space methods allowed to obtain satisfactory results with regard to percentage error and confidence levels. Therefore, these models could be used to make future estimations of domestic hot water (DHW) consumption.

1. Introduction

Today, climate change and global warming are probably some of the greatest threats humanity is facing, and their cause is associated to high energy consumption and carbon dioxide (CO_2) emission levels [1]. The building sector represents a large part of energy consumption and CO_2 emissions in the world. According to the 2017 Global Status Report of the United Nations and the international energy agency (IEA) for 2016 [2], buildings represented 30% of the consumed energy, and 28% of CO_2 emitted at a global level. Therefore, improving energy efficiency in this sector is key to counteract environmental threats [3]. On the other hand, the residential sector comprises 73% of the consumed energy, and 61% of CO_2 emissions of the building sector, that is to say, the residential sector by itself consumes 22% of global energy, and is responsible for 17% of all CO_2 emissions in the world [2]. Thus, it is exigent that this sector mitigate this issue, at the earliest [4,5].

In most countries, the residential sector constitutes more than 25% of the country's total energy consumption [6], such that in many

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cases, it ranges between 11 and 27%, with values in Latin America ranging between 16 and 27% (See Table 1).

The total energy consumption of most homes is constituted by heating, domestic hot water (DHW), electric appliances, and lighting [34]. In the European Union, heating and DHW can constitute up to 79% of the final energy consumption of a home [35], while for the member countries of organisation for economic co-operation and development (OECD), this value is almost 69% [2]. However, DHW consumption has been underestimated and has remained constant [36], even though it represents a relevant part of the home's consumption [36]; following by heating [37]. In the United Kingdom, DHW consumption constitutes between 20 and 25% of residential consumption [27,28], in the European Union it is 14.8%, and in the United States, 19% [7]. For most Latin American countries, this value is above 17%, and above the average of OECD. However, it is possible to see that the percentage that DHW constitutes is very variable when compared to the total consumption of the home, reaching a minimum of 7% for Colombia, and a maximum of 44% for Sweden.

This variability observed in DHW consumption in the residential sector depends on technical and sociological factors [39]. The number of occupants, their age, climate, and economy, among other factors, have been detected as key [34,38,and40]]. In particular, the number of occupants is closely linked to DHW consumption, and it is more important than the climate factor [41]. Meyer and Tshimankinda [42] analysed dwellings in South Africa and concluded that dwellings with more occupants consume a lower amount of DHW, as these represent the low-income and/or developing population. This aspect was detected in another study conducted in Greece as well [43]. Likewise, Evarts and Swan [44] found that the highest consumption appears in 3-person dwellings, falling as the number of people increases. Merrigan [45] found that starting from a base of 2 people, for every additional person, the consumption increases linearly in 45 L/day, while Ahmed et al. [40] identified that the presence of children leads to higher DHW consumption. Aydinalp et al. [46] studied the reliability of a prediction model for DHW using consumption profiles and socio-economic factors.

Even so, personal and custom-related factors can have an impact, which means that DHW consumption is difficult to estimate [47]. For the same reason, consumption profiles are not the same in all countries [38], and they can also vary from dwelling to dwelling [40]. Two studies conducted in residential buildings in the Finnish cities of Tampere [40] and Helsinki [48], reported similar DHW consumption, with an average of 43 and 44 L/person/day, respectively. However, there is a high variation in the range of this consumption: the former from 20 to 70 L/person/day; and the latter, from 0 to 300 L/person/day.

Table 2 shows the variability in consumption in litres per person per day (L/person/day) found in research projects in different countries, with values ranging between 32.3 L/person/day (Greece) to 140 L/person/day (South Africa). In Chile, the DHW consumption value has not yet been determined accurately, and it is presented in the 2018 Final Report for Energy Use of Chilean Homes [18] in used energy format, where the value of litres per person is only expressed for water heaters and washing up (17.1 L/person/day). Other approaches could be the values used for thermal solar system calculations, such as the one used by López-Ochoa et al. [49], which is 30 L/person/day based on the regulations, or 40 L/person/day indicated by the Chilean Solar Power Association [50].

Due to the variability in DHW consumption among countries, its estimation is relevant from multiple perspectives [59]. Firstly, realistic hot water demand patterns are required both for public policy and quantification of compliance with energy consumption reduction goals and their projection. Secondly, they are needed to size the impact at a neighbourhood or housing unit level and plan investments as well as suggest improvements and optimization of DHW systems [60], and more recently, for their automation [61].

There are different methods to make predictions. In the energy consumption area, these have been studied in-depth, and paper reviews have compiled the most commonly used methods [62–64]. However, these methods have not been applied greatly to estimate future DHW consumption. Fuentes et al. [60] state that most studies that deal with DHW predictions are based on stochastic models

Table 1
Percentage of residential energy and DHW consumption for different countries.

Country	Residential sector energy consumption over country consumption (%)	Source	Energy consumption for domestic hot water over total energy consumption of the home (%)	Source
OECD	20.0	[2]	16.4	[2]
USA	21.1	[2]	19.0	[7]
Canada	13.1	[8]	19.3	[9]
Mexico	17.9	[10]	19.9	[10]
Spain	17.1	[11]	17.3	[12]
Australia	11.1	[13]	23.0	[14]
New Zealand	11.0	[15]	29.0	[15]
Germany	25.0	[16]	14.0	[16]
Chile	16.0	[17]	20.0	[18]
Uruguay	17.1	[19]	20.0	[20]
Argentina	27.0	[21]	17.0	[21]
Colombia	16.3	[22]	7.0	[22]
Portugal	17.7	[23]	23.5	[23]
France	27.5	[24]	30.7	[24]
European Union	26.1	[25]	14.8	[26]
United Kingdom	29.0	[27,28]	25.0–20.0	[27,28]
Finland	16.8	[29]	15.2	[30]
China	11.7	[31]	14.0	[32]
Sweden	15.0	[33]	44.0	[43]

Table 2
DHW consumptions per person in different countries.

Country	DHW consumption L/person/day	Study scope	Source
Switzerland	55.0	–	[51]
	33.0		[52]
Finland	43.0	182 apartments	[40]
	43.6	86 apartments	[48]
Germany	64.0	–	[51]
France	69.6	–	[51]
Spain	30.0	According to the technical guidelines	[53]
Portugal	40.0	–	[51]
Argentina	54.5	Calculated based on 3.3 persons/dwelling	[54]
Chile	17.1[a]	3500 surveys	[18]
Estonia	55.0	113 residential buildings	[55]
Denmark	41.0	National statistics	[56]
South Africa	80.0–140.0	National statistics	[57]
Greece	32.3	4 residential buildings	[43]
Latvia	39.3–44.7	4 residential buildings	[58]
Canada	94.0	–	[51]
United Kingdom	64.7	–	[14]
United States	40.0	–	[51]

[a] Only water heaters and washing up (does not include shower). Calculated from the average number of people per dwelling projected for 2020 by the INE (National Statistics Institute).

and few apply time series or statistical methodologies. Neural networks [46,65,and66]] are among those methods that have been used to predict DHW consumption. As for time-series models, Gelazanskas and Gamage [67] used a series of forecasting models, including exponential smoothing, seasonal autoregressive integrated moving average (SARIMA), seasonal decomposition, and a combination of them to make a 24-h prediction based on individual dwellings, showing that this type of method has the potential to be used to control DHW. Popescu and Serban [68] used time-series analysis to predict dynamic hot water consumption in district heating systems. Denis et al. [61] evaluated the energy savings that can be achieved by using predictions with time series, focusing on specific water heating devices, which are triggered at the exact time the users require hot water to avoid its loss. Finally, Horkai [69] uses time series to study the relationship between DHW consumption and outdoor temperature in Budapest. In his time series, the "decomposition model is able to estimate hot water consumption per apartment per day for a future month with 94% probability" [69]. However, these studies have mainly focused on generating water consumption predictions for their control, either for a water heating device (individual or district-based) or the housing unit, to seek an efficient production that minimizes energy use. Till date, no studies have been identified that make DHW consumption projections in dwellings to generate inputs to establish energy policies. Likewise, studies that have used time-series have been made in other climate and sociocultural contexts, mainly in the European countries and Canada, which is why it is not clear how these methods can be applied or adapted to a context like Chile.

It is important to note that Chile is setting parameters to define energy poverty policies [70], and for that reason, this study seeks to define average DHW consumption in homes, in order to contribute to energy poverty policies that fit the reality. In this sense, one of the most important aspects of energy policies is the estimation of future situations to reduce the vulnerability of families. Therefore,

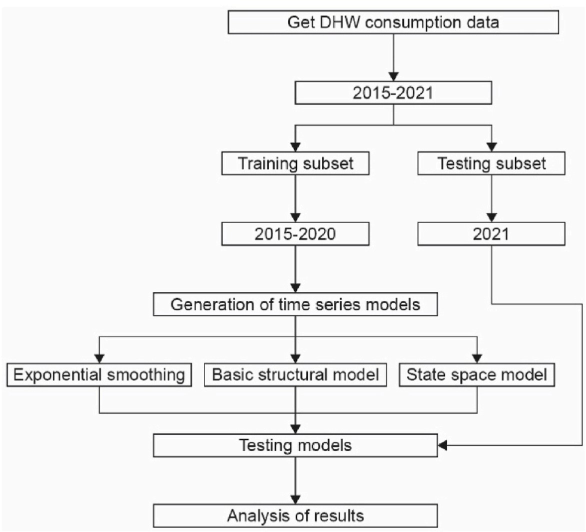

Fig. 1. Research flowchart.

characterising and predicting DHW use is key, not because efficient use and energy-saving measures can be implemented from this, or so that a design that is fit for hot water generation systems [60] can be put in place, but because this can contribute towards the implementation of policies to reduce the risk of energy poverty, especially in vulnerable residential contexts.

Based on the above, this study analysed the possibility of using time series to make future DHW consumption estimations, by not just integrating parameters of level, trend, and seasonality, but by also considering outdoor temperature as a critical factor for the estimations. The analysis included 3 different time series approaches using a DHW consumption database of Chilean dwellings obtained between 2015 and 2021.

2. Methodology

The methodological framework of this research comprised a series of steps to obtain predictive DHW consumption models in Chilean dwellings. For this, a monitoring process was made for a set of dwellings between 2015 and 2021. These measurements were made on a monthly basis and used to generate the training and testing sets (August 2020–May 2021). The training set was used to generate several time series models using 3 different approaches, while the testing data was used to validate the errors of the estimations. These steps are summarized in Fig. 1 and explained in the following subsections.

2.1. Case study and monitoring

A housing block with 98 apartments in the Bio-Bio Region, in Chile, was chosen as the case study (classified as Csb following the Koppen-Geiger classification, corresponding to a temperate climate with dry and mild summers), which had DHW being generated using a gas boiler and individual consumption meters. Considering the number of rooms, 3 different types of dwellings are distinguished among the 98 apartments, namely 1-bedroom dwellings (22 apartments) (Dw-B1), 2-bedroom dwellings (55 apartments) (Dw-B2), and 3-bedroom dwellings (21 apartments) (Dw-B3). An average occupation of 2 people was estimated in the Dw-B1 dwellings, 3 in Dw-B2, and 4 in Dw-B3. A weighted average was considered for the analysis with all the dwellings (Dw-AllB).

The monthly consumption of the dwellings was recorded for 6 years, from July 2015 to May 2021, covering all seasons. Fig. 2 shows the monthly values and monthly average of the DHW consumption values, both in L/day and L/person/day. This extensive collection period was considered to obtain representative results of the dwellings and to consider variability in consumption linked to outdoor temperature. The consumption records were taken monthly by the individual DHW meters of each apartment, which were Class B ISO 4064. Meanwhile, for DHW consumption estimations with regard to outdoor temperature, measurements were obtained from the Chilean National Air Quality Information System, using the meteorological station located at the coordinates UTM 673817 E 5927247 N.

2.2. Statistical treatment

Due to the length of the study period when data was collected, there were periods where different apartments did not have any consumption, or their consumption was abnormally low. For this reason, it was decided that the following adjustments were to be made to the original database: those apartments lacking more than 50% of the data, i.e., equal to zero litres per day, were eliminated, to reduce the number of apartments to 20 for Dw-B1, 45 for Dw-B2, and 21 for Dw-B3; and those apartments that had less than 50% of the data or were below 24 l/d/p were replaced by the monthly mean of each typology for the year and month when the data was missing. This replacement was done considering that consumption is related to the monthly mean temperature, and therefore, each month and year would have variations that affect DHW consumption. On the other hand, the 24 l/d/p value was established bearing in mind that according to the data previously collected in Chile, these indicate that the consumption from using just the water heater and washing up (without shower use) is 17.1 l/d/p. Considering this, and the fact that a water flow of 0.1 l/s for over 4 min generates a consumption of 24 l/d/p, this is an acceptable threshold to be considered as a minimum consumption, without it being exceeding the consumption seen in other countries (See Table 2), instead of the value used by López-Ochoa et al. [49], which is 30 l/d/p based on the regulations, or the value indicated by the Chilean Solar Power Association, which is 40 l/d/p [50].

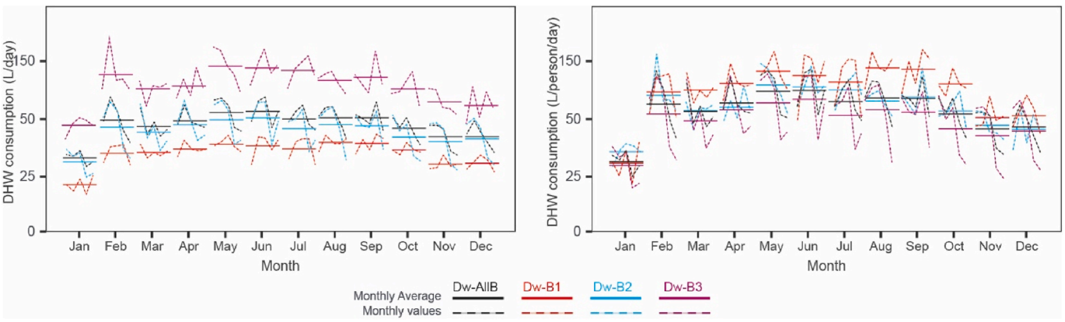

Fig. 2. Monthly values and monthly average of DHW consumption for the study period. The graph on the left shows the consumption in L/day, while the graph on the right shows it in L/person/day for the different types of dwellings: Dw-AllB (all dwellings), Dw-B1 (1-bedroom dwellings), Dw-B2 (2-bedroom dwellings), and Dw-B3 (3-bedroom dwellings).

2.3. Time series models

In this study, 3 different approaches were used for the time series, namely exponential smoothing, basic structural model (BSM), and state-space model (SSM).

2.3.1. Exponential smoothing

This is a relatively simple technique to use with time series. Exponential smoothing is a method where a prediction is continuously revised based on the most recent data. The method employs an iterative algorithm that in each time period (month or week), makes a forecast about the behaviour of the series based on duly weighted averages of previous data. In this sense, exponential smoothing assigns exponentially decreasing weights as the observation ages, that is to say, the oldest data is given less weight compared to the newest. Therefore, the most recent data has a higher weight in these predictions.

In this case, a triple exponential smoothing, which is also known as Holt-Winters, must be considered because it account for the components of level, trend, and seasonality defined by the following expressions:

$$
\begin{aligned}
&Level\ L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1}) \\
&Trend\ T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \\
&Seasonality\ S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \\
&\mathrm{Pr}ediction\ (Y\_t\ ) \hat{=} \big(L\_(t-1) + T\_(t-1)\ \big)\ S\_(t-s)
\end{aligned}
\tag{1}
$$

Where α and β are smoothing constants that are between zero and one, and “s” is the length of the seasonality or number of months or quarters in a year.

To successfully apply these equations, data of the variable being forecast from at least two previous periods must be available. This has been satisfied through a broad data collection period, which exceeds two periods. On the other hand, the values of α and β have been determined to minimise the mean absolute percentage error (MAPE).

2.3.2. Basic structural model

BSM is a local trend model with an additional seasonal component. In BSM, a time series comprises a stochastic local trend, a seasonal trend, and a remainder. BSM is defined as follows:

$$
\begin{aligned}
&y_t = \mu_t + \gamma_t + \varepsilon_t, \varepsilon_t\ N\big(0, \sigma_\varepsilon^2\big) \\
&\mu_{t+1} = \mu_t + v_t + \varepsilon_t, \varepsilon_t\ N\big(0, \sigma_\varepsilon^2\big) \\
&v_{t+1} = v_t + c_t, w_t\ N\big(0, \sigma_c^2\big) \\
&\gamma_{t+1} = -\gamma_t - \gamma_{t-1} - \ldots - \gamma_{t-11} + w_t, w_t\ N\big(0, \sigma_w^2\big)
\end{aligned}
\tag{2}
$$

Where μ_t *and* v_t represent the mean and slope of the series (Level), respectively, γ_t is the seasonal component (Season), all of which are modelled by stochastic processes. With $\alpha_t = (\mu_t v_t \gamma_t \gamma_{t-1} \cdots \gamma_{t-10})'$, the model used is as follows:

Where

$$
\begin{aligned}
&Z_t = \big(Z_{[\mu]}, Z_{[\gamma]}\big) \\
&T_t = diag\big(T_{[\mu]}, T_{[\gamma]}\big) \\
&R_t = diag\big(R_{[\mu]}, R_{[\gamma]}\big) \\
&G_t = diag\big(G_{[\mu]}, G_{[\gamma]}\big)
\end{aligned}
\tag{3}
$$

Where

$$
\begin{aligned}
&Z_{[\mu]} = (1, 0) \\
&Z_{[\gamma]} = (1, 0, \ldots, 0) \\
&T_{[\mu]} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \\
&T_{[\gamma]} = \\
&R_{[\mu]} = I_2 \\
&R_{[\gamma]} = (1, 0, 0, \ldots., 0)' \\
&G_{[\mu]} = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & \sigma_c^2 \end{pmatrix} \\
&G_{[\gamma]} = \sigma_w^2
\end{aligned}
$$

2.3.3. State-space for consumption and temperature

Since the formulation of exponential smoothing models that is defined above does not allow for the inclusion of explanatory variables, the state-space approach was considered in this study to explain hot water consumption in litres/day and client water consumption in litres/day person by the monthly mean temperature variable. The mean monthly temperature is equal to the sum of the mean daily temperatures by the number of days of the month, with the daily mean temperature being the mean value between the daily maximum and minimum temperatures.

The state-space approach of Durbin & Koopman (2012) is frequently used in time series analysis [71]. The general model can be written in the following manner:

$$y_t = Z_t\alpha_t + \varepsilon_t, \varepsilon_t\ N(0, H_t) \tag{4}$$

$$\alpha_{t+1} = T_t\alpha_t + R_t\eta_t, \eta_t\ N(0, Q_t) \tag{5}$$

Where "n" represents the length of the time series, and "α_t" is a vector of unobservable components of dimension "mx1", called the state vector. The matrix Z_t, T_t, and R_t are system matrices defined according to the model considered and, for this particular case, they are detailed below. The perturbations ε_t and η_t are assumed as independent, with normal distribution of zero mean and variances H_t and Q_t, respectively. For this research, it is considered that these variances are constant.

From the above, Eq. (4) is known as "equation of measurements or observations", and Eq. (5) is called "equation of state", and it represents the motion of components in the process over time. The idea is that conditional to observations, several components of the process can be estimated, such as level, trend, and seasonality, among others.

For this work, the model was expressed in the following manner:

$$y_t = \mu_t + \lambda x_t + \varepsilon_t, \varepsilon_t\ N\left(0, \sigma_\varepsilon^2\right)\quad \mu_t = \mu_{t-1} + \varepsilon_t, \varepsilon_t\ N\left(0, \sigma_\varepsilon^2\right) \tag{6}$$

Where y_t is the monthly hot water consumption, μ_t represents the mean (Level), λ represents the effect of changing the temperature by one degree over the hot water consumption.

It is important to note that on estimating a state-space model, it may be interesting to analyse some of its components in particular. In this case, the interest focuses on estimating the λ coefficient, which represents the effect of temperature over hot water consumption, in particular the variation in DHW consumption, if the temperature increases by one degree.

2.4. Approaches considered and model validation

The 3 approaches described in subsection 2.3 were used to generate the time series. However, the possibility of designing specific time series models for each housing typology was considered. Therefore, for the purpose of this study, a model was designed for each approach, which estimates the average consumption of all the dwellings (Dw-AllB), and specific models, which estimate the average consumption of each dwelling by the number of bedrooms, namely 1-bedroom dwellings (Dw-B1), 2-bedroom dwellings (Dw-B2), and

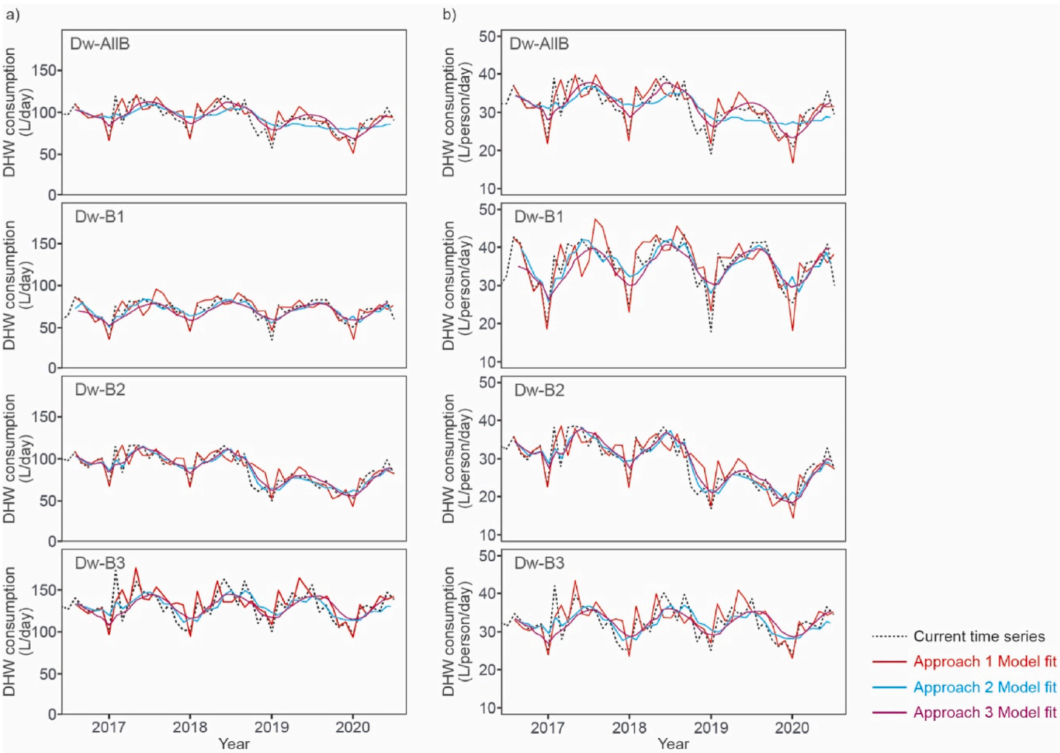

Fig. 3. DHW estimation level in a) L/day and b) L/person/day, with the 3 approaches and different dwelling typologies.

3-bedroom dwellings (Dw-B3). Likewise, the possibility of estimating two different output variables was considered due to the importance they have in the development of energy policies: DHW consumption expressed in L/day, and DHW consumption expressed in L/day/person. Therefore, the results of this study are based on the development of 24 different time series models obtained from the combination of 3 different approaches, with 4 different forms of case study and 2 output variables.

To analyse the errors of estimations, the mean absolute percentage error (MAPE) was used. MAPE is an indicator of the demand forecast performance that measures the size of the (absolute) error as percentages (Eq. (7)). The fact that it estimates a magnitude of the percentage error implies that this is an indicator that is frequently used by those making forecasts due to its easy interpretation [72, 73,and74]].

$$MAPE = \frac{\sum_{t=1}^{n} A_t - F_t \vee \overline{A_t}}{n} \cdot 100 \tag{7}$$

Where A_t represents the real value observed, F_t is the forecast, and n is the number of observations.

The evaluation and validation of the errors in estimations of the models were derived from the testing data (August 2020–May 2021), using the performance obtained with the test period.

3. Results and discussion

Firstly, the performance of these prediction models was analysed. To this end, the estimation levels of the time series were first analysed (Fig. 3), and MAPE values were obtained for each combination of the approach and output variable (Table 3). In the case of the time series in Fig. 3, the dashed line represents the original behaviour of the time series, while the solid lines are the adjustment of each model. In the case of consumption and temperature state-space models, the analysis focused on the estimation of λ coefficient as well (Table 4), which represents the effect of outdoor temperature on DHW consumption. Regarding the consumption estimations in L/day, it was seen how, for the combinations of all the dwellings, consumption fell by 0.20 L/day if the temperature increased by 1 °C. These values vary for different dwellings. Thus, while 1-bedroom dwellings have a similar reduction of 0.19 L/day, in the case of 2-bedroom dwellings, the fall is more significant, with −0.32 L/day. In the case of 3-bedroom dwellings, an increase of 0.04 L/day is seen for each 1° rise. As for the estimation of consumption in L/person/day, the trends were similar to those obtained in L/day; however, the scale of values varied. In this sense, for every 1 °C increase in temperature, the reduction values ranged between 0.08 and 0.09 L/person/day in all dwelling typologies, except in the 3-bedroom ones, which saw an increase of 0.01 L/person/day. These values allow us to see the DHW consumption variation trends against an increase in outdoor temperature. For a similar study in multi-apartment buildings in Budapest [69], a 1 °C rise in outdoor temperature resulted in around a 1 L decrease in domestic hot water (DHW) consumption per apartment, per day. Just like in our study [69], differences were also found in this value depending on the dwelling typology.

In any case, the analysis of the degree that fits the estimations obtained for the 3 time series approaches was made using variations of MAPE values. Thus, in the case of models designed for mean values of all dwellings (Dw-AllB), it could be seen how Approach 1 (exponential smoothing) and Approach 2 (BSM) obtained a higher value in two output variables, while in Approach 3 (consumption and temperature state-space), the MAPE value was lower. In any case, the MAPE values under these approach-output variable combinations were always lower than 10%, except for the L/day variable with Approach 2, which is why they could be considered as acceptable. It is worth stating that Approach 3 had a lower percentage of errors in the estimations, with values below 2.5%. Likewise, it was seen how the design models for the consumption prediction of different sized dwellings (1, 2, or 3 bedrooms) had MAPE values that were similar to those obtained in the joint models of all the dwellings. In this sense, the use of specific models for each housing typology did not imply an improvement in MAPE values since cases with MAPE increases, which range between 1.1 and 1.59%, and reductions, which range between 0.11 and 3.3%, were obtained. From the study conducted by Gelažanskas L and Gamage K [67], it was concluded that the best performance was obtained for a combination of STL/ETS and STL/ARIMA techniques.

Hence, the time series obtained error values that can be considered valid. In any case, these MAPE values are based on the errors obtained in the fit of the time series with training data, but they did not allow to evaluate reliability in the predictions of new data. For this reason, the estimations obtained by the model between August 2020 and May 2021 were analysed. Figs. 4 and 5 show the time series of estimations of each approach-output variable combination in L/day and L/person/day, respectively. Tables 5 and 6 represent the thresholds obtained for some confidence levels of 80 and 95% for each DHW consumption variable, respectively. As observed, the confidence levels for Approaches 1 and 2 have higher slack in comparison to Approach 3. In this sense, the consumption estimations in L/day of all the dwellings for a confidence of 80% obtained slack that ranged between 13 and 16.7 L/day in Approach 1, and between

Table 3
MAPE values obtained in the development of these models.

Type	MAPE (%)					
	Approach 1		Approach 2		Approach 3	
	L/day	L/person/day	L/day	L/person/day	L/day	L/person/day
Dw-AllB	8.30	8.19	9.97	10.2	2.41	2.47
Dw-B1	7.84	7.84	7.89	7.89	2.30	2.30
Dw-B2	9.40	9.40	6.90	6.90	3.99	3.99
Dw-B3	9.78	9.78	7.74	7.74	1.92	1.92

Table 4
λ values obtained in the state-space models for consumption and temperature (Approach 3).

Type	-value	
	L/day	L/person/day
Dw-AllB	−0.20	−0.08
Dw-B1	−0.19	−0.09
Dw-B2	−0.32	−0.11
Dw-B3	0.04	0.01

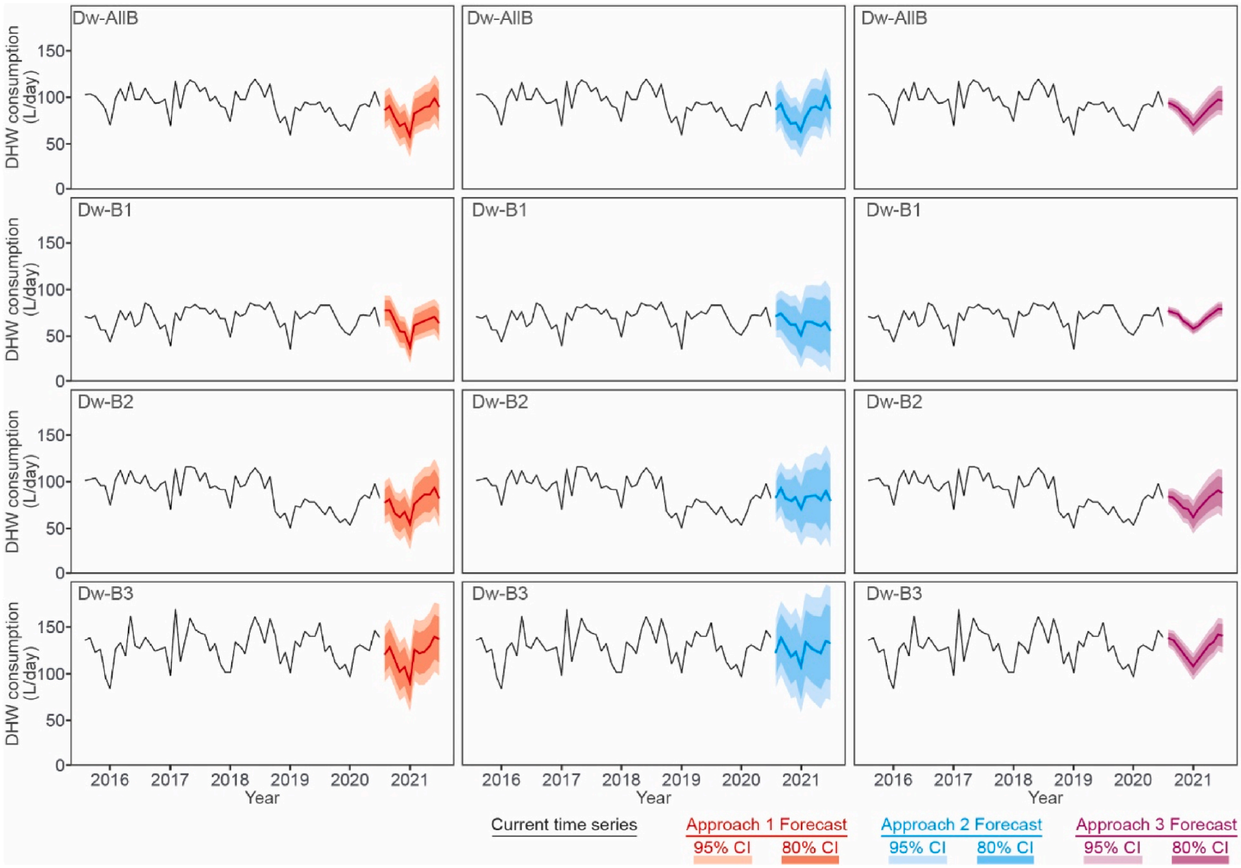

Fig. 4. DHW prediction in L/day with the 3 approaches and different housing layouts.

16.6 and 20.6 L/day in Approach 2. In the case of Approach 3, the values ranged between 3.6 and 10.3 L/day. Thus, the use of consumption and temperature state-space models allows to achieve a lower amplitude in the confidence levels, thus ensuring that a higher number of predictions fit the forecast value. Within the literature reviewed, few studies integrate outdoor temperature in the DHW consumption projection models. In the case of Horkai [69], its relevance is highlighted alongside how climate change may lead to a reduction in consumption, particularly in Budapest. Although this study did not make climate change projections, it did identify a similar trend, acknowledging that by increasing the temperature, the demand falls, but this was done to a lesser extent than compared to Budapest.

On the other hand, the use of specific models for each housing type derived the same behaviours in the slack trends, even though most of the cases obtained higher slack values with the specific housing models. In the case of 95% confidence, the slack values increased significantly in Approaches 1 and 2, with increases that ranged between 5.7 and 21 L/day, while in Approach 3, the increase ranged between 1.6 and 8.7 L/day. Even in the case of DHW consumption estimations in L/person/day, it was observed that Approaches 1 and 2 had a larger slack in the two confidence levels, while Approach 3 had a smaller one. In the literature, it has been identified that the prediction models lose accuracy when they are generated with less data; this is associated with discrimination on the basis of housing typologies or individual dwellings, which is why many studies have opted to make predictions by grouping housing units. According to Gelažanskas et al. [67], it is more difficult to reliably predict individual hot water usage compared to total usage.

Thus, to analyse the slacks of confidence levels, Approach 3 is the one that allows to obtain more accurate confidence intervals. In

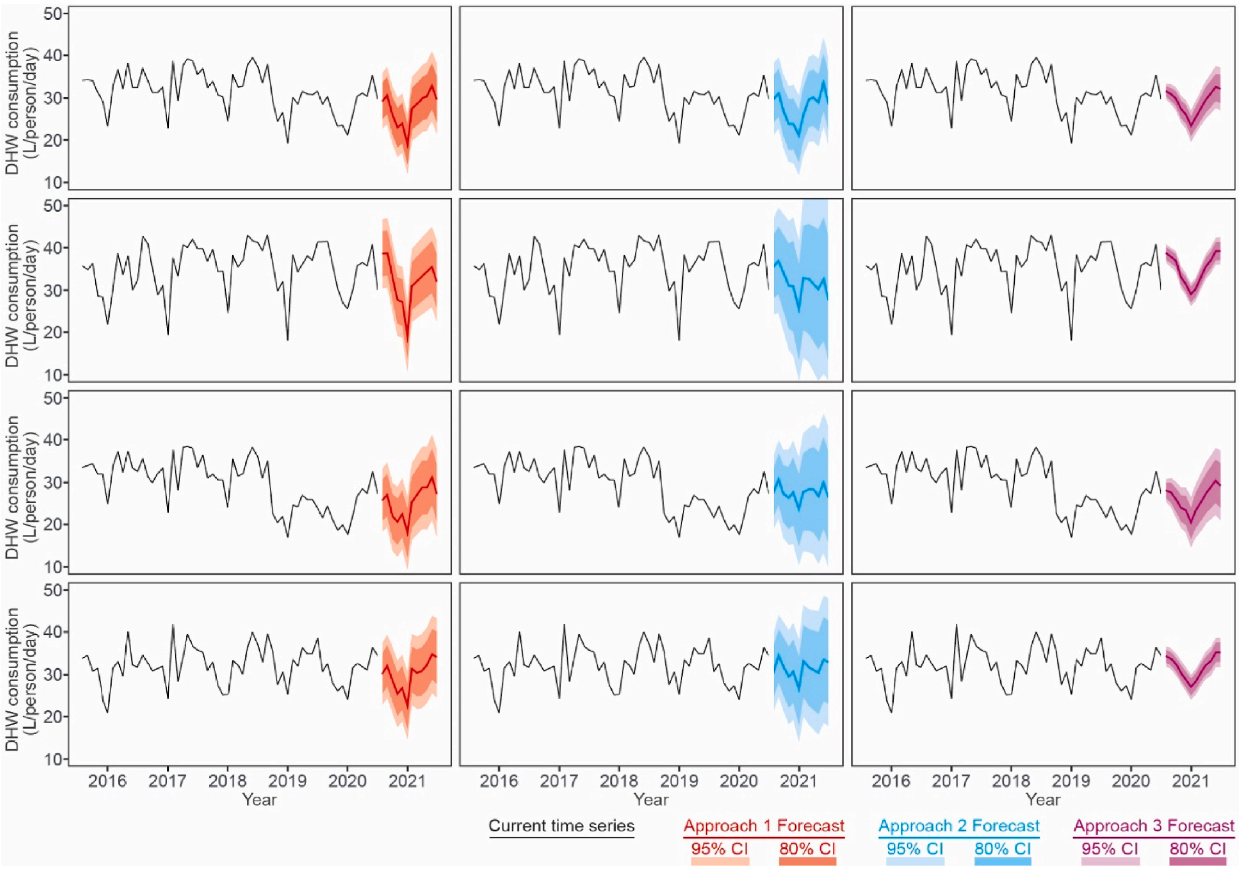

Fig. 5. DHW prediction in L/person/day with the 3 approaches and different housing layouts.

Table 5
Values associated to the confidence levels of estimations for consumption prediction in L/day.

Approach	Type	80% (L/day)			95% (L/day)		
		Average value	Minimum value	Maximum value	Average value	Minimum value	Maximum value
Approach 1	Dw-AllB	14.7	13.0	16.7	22.5	19.8	25.6
	Dw-B1	11.4	10.7	12.7	17.5	16.3	19.4
	Dw-B2	17.5	14.5	20.2	26.8	22.2	30.9
	Dw-B3	21.6	19.2	24.5	33.1	29.4	37.5
Approach 2	Dw-AllB	18.8	16.6	20.6	28.7	25.3	31.6
	Dw-B1	23.3	14.9	29.8	35.6	22.7	45.6
	Dw-B2	25.9	16.9	32.9	39.6	25.9	50.3
	Dw-B3	32.9	24.6	39.7	50.3	37.6	60.7
Approach 3	Dw-AllB	7.4	3.6	10.3	11.4	5.5	15.7
	Dw-B1	4.1	3.0	5.1	6.3	4.5	7.8
	Dw-B2	11.6	5.1	16.4	17.8	7.8	25.0
	Dw-B3	9.3	6.1	12.0	14.2	9.3	18.3

any case, the analysis was complemented with a comparison between the estimations of time series and real consumption values between August 2020 and May 2021. For this, the analysis was based on the MAPE value obtained in the predictions and percentage of correct data included within the confidence levels (Table 7). As observed, the estimations obtained with Approaches 1 and 2 had an error level that was close to the real data. Thus, the MAPE value ranged between −4.2 and 7.8% in the layouts of Approach 1, and between 2.7 and 23% in Approach 2, where the value of 23% was obtained only with the 2-bedroom dwellings. Approach 3 also obtained suitable values, with some MAPE values below 15%. The MAPE values of Approaches 1 and 3 are within the ranges found by Ristow et al. (2021) for the water demand forecasts at an urban scale [75]. However, the estimations were more suitable with Approach 1. This can also be seen with the number of results included within the degrees of confidence of the estimations. In this sense, the estimations of Approach 1 allowed to obtain 77.8 and 88.9% of the months estimated within the range of estimations, while

Table 6
Values associated to the confidence levels of estimations for consumption prediction in L/person/day.

Approach	Type	80% (L/person/day)			95% (L/person/day)		
		Average value	Minimum value	Maximum value	Average value	Minimum value	Maximum value
Approach 1	Dw-AllB	4.9	4.3	5.6	7.5	6.6	8.5
	Dw-B1	5.7	5.3	6.3	8.7	8.2	9.7
	Dw-B2	5.8	4.8	6.7	8.9	7.4	10.3
	Dw-B3	5.4	4.8	6.1	8.3	7.4	9.4
Approach 2	Dw-AllB	6.3	5.6	6.9	9.6	8.5	10.5
	Dw-B1	11.6	7.4	14.9	17.8	11.4	22.8
	Dw-B2	8.6	5.6	11.0	13.2	8.6	16.8
	Dw-B3	8.2	6.1	9.9	12.6	9.4	15.2
Approach 3	Dw-AllB	2.4	1.2	3.4	3.7	1.8	5.2
	Dw-B1	1.8	1.4	2.2	2.8	2.2	3.3
	Dw-B2	3.8	1.7	5.4	5.9	2.6	8.3
	Dw-B3	2.0	1.6	2.3	3.0	2.4	3.6

Table 7
Performance obtained with the period between August 2020 and May 2021.

Approach	Type	Output (L/days)			Output (L/person/day)		
		MAPE (%)	80% (%)	95% (%)	MAPE (%)	80% (%)	95% (%)
Approach 1	Dw-AllB	0.5	88.9	100.0	1.2	88.9	100.0
	Dw-B1	4.9	77.8	100.0	4.9	77.8	100.0
	Dw-B2	7.8	88.9	100.0	7.8	88.9	100.0
	Dw-B3	−4.2	77.8	100.0	−4.2	77.8	100.0
Approach 2	Dw-AllB	2.7	88.9	100.0	3.3	88.9	100.0
	Dw-B1	9.1	100.0	100.0	9.1	100.0	100.0
	Dw-B2	23.0	100.0	100.0	23.0	100.0	100.0
	Dw-B3	3.8	100.0	100.0	3.8	100.0	100.0
Approach 3	Dw-AllB	5.6	66.7	77.8	7.2	66.7	77.8
	Dw-B1	15.0	11.1	22.2	14.8	11.1	22.2
	Dw-B2	11.9	55.6	100.0	11.9	55.6	100.0
	Dw-B3	2.6	66.7	88.9	2.7	55.6	88.9

Approach 3 obtained between 11.1 and 66.7%. This smaller number of months within the acceptability ranges of Approach 3 was due to the tight tolerance level range. In contrast, Approach 1 obtains an appropriate balance between the MAPE value and percentage of months classified correctly. Therefore, the use of this approach, i.e., exponential smoothing, may be a suitable methodology to make estimations of DHW consumption time series in Chilean dwellings. Anyhow, the state-space model could also be considered as a useful methodology to make the estimations, but its calculation process is more complex compared to that of Approach 1.

Table 8
Optimal values for the parameters by approach.

		(l/day)			(l/day/person)		
Exponential smoothing.Approach 1		α_t	β_t	γ_t	α_t	β_t	γ_t
	Dw-AllB	0.2452	0	0.0001	0.1850	0	0.6152
	Dw-B1	0.1347	0	0.0001	0.0662	0	0.5151
	Dw-B2	0.3061	0	0.0005	0.2936	0	0.6353
	Dw-B3	0.0001	0	0.0001	0.1346	0	0.4850
Basic structural model.Approach 2		μ_t	β_t	γ_t	μ_t	β_t	γ_t
	Dw-AllB	74.02134	−0.53852565	11.5478812	24.53226	−0.19562744	3.46273118
	Dw-B1	56.71414	−0.70033564	2.45660611	28.35714	−0.35016293	1.2281604
	Dw-B2	63.85254	−0.47301566	7.9239585	21.28418	−0.15767188	2.6413198
	Dw-B3	116.0038	−0.68443077	17.729859	29.00098	−0.17111007	4.43237023
State-space for consumption by temperature.Approach 3		μ_t			μ_t		
	Dw-AllB	0.6941					
	Dw-B1	0.7099					
	Dw-B2	0.9048					
	Dw-B3	0.5001					

In the case of exponential smoothing, the α_t, β_t, and γ_t parameters, which are shown in Table 8, must be estimated. The proposed BSM and state-space models (SSM) consider variant parameters over time. Table 8 presents the final values of estimation of components considered in each formulation.

4. Conclusions

Domestic hot water (DHW) consumption in dwellings may play a really important role in establishing energy policies. For this reason, this study looked at 3 different time series methodologies to make future DHW consumption estimations, namely exponential smoothing, basic structural model (BSM), and state-space model (SSM). Using a DHW consumption database from July 2015 to May 2021, the following conclusions could be established:

- State-space models (SSM) showed the variations associated to DHW consumption and outdoor temperature. Generally speaking, DHW consumption tends to increase by 0.2 L/day and 0.08 L/person/day with an increase of 1 °C in most housing typologies.
- The fit of the models to the training database was satisfactory. In this sense, the results showed how MAPE values were below 10% in the 3 approaches. Thus, the 3 time series methods present suitable characteristics to obtain models adjusted to DHW consumption training datasets. In any case, this aspect could present slight variations if the extension of training database was different. With regard to this, the training data used corresponds to a time series with monthly values between July 2015 and July 2020.
- No differences were detected in the performance of estimations between the use of joint models for all dwellings and individual models for each housing typology, i.e., considering the number of bedrooms.
- The state-space model (SSM) obtained the lowest MAPE values in the training and a smaller slack in the confidence levels analysed (80 and 95%). However, future estimations obtained had a better fit with the exponential smoothing model, which also had some MAPE and slack values in the acceptable confidence levels. On the contrary, BSM did not obtain suitable results being the least suitable methodology to make DHW consumption estimations. Therefore, based on these results, exponential smoothing and state-space models are the most suitable approaches to make DHW estimations.
- Following the principle of statistical parsimony, which establishes that a model must be as simple as possible, it would be recommendable to use the simplest, i.e., exponential smoothing, as it is the easiest to implement, does not require independent variables, and delivers acceptable MAPE values.

The results of this study constitute a suitable methodology to predict the future situations of Chilean families and develop policies on energy matters. In this sense, high DHW consumption can lead to fuel poverty situations [76]. The availability of a predictive system like those developed through the time series in this study, could allow to define future situations. Thus, this research has direct implications for guiding the construction industry and policies to define and measure DHW consumption in Chile. Likewise, it is worth highlighting the international nature of the results.

Ultimately, the results of this study are of great interest for architects, engineers, policymakers, and governments. In addition to this, the methodologies designed here present a high degree of international application, as the datasets can be easily obtained by monitoring dwellings. Anyhow, in future steps for this research, some of the limitations detected should be addressed. Firstly, the estimations that were analysed in the study are from one year. The establishment of long-lasting energy policies may require making estimations for several years. The use of time series models to estimate DHW consumption in several periods has not been done in this study and should be addressed in future work. Secondly, the variable nature that DHW consumption may have between regions in a single year should be considered in future studies, to evaluate the limitations of time series-based predictive models.

Author Statement

Pérez-Fargallo, A.: Conceptualization, Methodology, Formal analysis, Investigation, Writing- Original draft preparation, Writing- Reviewing and Editing. Bienvenido-Huertas, D.: Visualization, Investigation, Validation, Writing- Original draft preparation. Contreras-Espinoza, S.: Visualization, Investigation, Validation, Writing- Reviewing and Editing. Marín-Restrepo, L.: Visualization, Investigation, Validation, Writing- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] P. Nejat, F. Jomehzadeh, M.M. Taheri, M. Gohari, M.Z. Muhd, A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries), Renew. Sustain. Energy Rev. 43 (2015) 843–862, https://doi.org/10.1016/j.rser.2014.11.066.
[2] Iea International Energy Agency, Energy efficiency indicators: overview, Paris, https://www.iea.org/reports/energy-efficiency-indicators-overview, 2020. (Accessed 8 August 2021).
[3] X. Cao, X. Dai, J. Liu, Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade, Energy Build. 128 (2016) 198–213, https://doi.org/10.1016/j.enbuild.2016.06.089.
[4] G. Trotta, J. Spangenberg, S. Lorek, Energy efficiency in the residential sector: identification of promising policy instruments and private initiatives among selected European countries, Energy Efficiency 11 (2018) 2111–2135, https://doi.org/10.1007/s12053-018-9739-0.
[5] M. del, P. Pablo-Romero, R. Pozo-Barajas, R. Yñiguez, Global changes in residential energy consumption, Energy Pol. 101 (2017) 342–352, https://doi.org/10.1016/j.enpol.2016.10.032.
[6] H.X.H. Bao, S.H. Li, Housing wealth and residential energy consumption, Energy Pol. 143 (2020) 111581, https://doi.org/10.1016/j.enpol.2020.111581.
[7] U.S. Energy Information Administration, Monthly Energy Review, 2020. October 2020.
[8] Canada Energy Regulator, Canada's Energy Future 2019, 2019.
[9] Natural Resources Canada, Residential End-Use Model, Ottawa, 2019.
[10] Comisión Económica para América Latina y el Caribe CEPAL, Informe nacional de monitoreo de la Eficiencia energética de México 2018, Ciudad de México, 2018.
[11] Instituto para la Diversificación y Ahorro de la Energía, Balance del Consumo de energía final 2018, 2020.
[12] Instituto para la Diversificación y Ahorro de la Energía, Consumo para usos y energías del sector residencial (2010-2018), 2020.
[13] Department of Industry and Science, Australian Energy Update 2015, 2015. Canberra.
[14] Department of Industry and Science, Residential Energy Baseline Study, 2015. Australia.
[15] Ministry of Bussiness Innovation and Employment, Energy in New Zealand 2019, 2019.
[16] E. Grealis, A. Musch, H. Rau, Energy Demand Challenges in Europe, Springer International Publishing, 2019, https://doi.org/10.1007/978-3-030-20339-9.
[17] Comisión Nacional de Energía, Balance energético, 2018, http://energiaabierta.cl/catalogo/balance-energetico/, 2019. (Accessed 8 August 2021).
[18] Corporación de Desarrollo Tecnológico, Informe final de usos de la Energía de los Hogares Chile 2018. https://energia.gob.cl/sites/default/files/documentos/informe_final_caracterizacion_residencial_2018.pdf, 2019.
[19] Ministerio de Industria Energía y Minería de Uruguay, Balance Energético, 2019, 2018.
[20] Ministerio de Industria Energía y Minería de Uruguay, Informe Nacional de Monitoreo de la Eficiencia Energética de la República Oriental del Uruguay, 2015.
[21] M. Gastiarena, A. Fazzini, R. Prieto, S. Gil, Gas versus electricidad:uso de la energía en el sector residencial, Petrotecnia, 2017, p. 10. https://www.academia.edu/34016037/Gas_versus_electricidad_uso_de_la_energía_en_el_sector_residencial?auto=download&campaign=weekly_digest.
[22] Departamento Nacional de Planeación - República de Colombia, Energy Demand Situation in Colombia, 2017.
[23] Instituto Nacional de Estatística Portugal, Inquérito ao consumo de energia no sector doméstico - 2010, 2011.
[24] Odyssee-MURE, France: energy profile. Energy efficiency trends and policies. http://www.speroforum.com/site/article.asp?idarticle=9839&t=France%3AEnergy profile, 2020.
[25] Eurostat, Energy statistics - an overview. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview, 2020. (Accessed 8 August 2021).
[26] Eurostat, Energy consumption in households. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_consumption_in_households, 2020. (Accessed 8 August 2021).
[27] T. Zhang, P.O. Siebers, U. Aickelin, A three-dimensional model of residential energy consumer archetypes for local energy policy design in the UK, Energy Pol. 47 (2012) 102–110, https://doi.org/10.1016/j.enpol.2012.04.027.
[28] V. Haines, K. Kyriakopoulou, C. Lawton, End-user engagement with domestic hot water heating systems: design implications for future thermal storage technologies, Energy Res. Social Sci. 49 (2019) 74–81, https://doi.org/10.1016/j.erss.2018.10.009.
[29] G. Trotta, Assessing energy efficiency improvements and related energy security and climate benefits in Finland: an ex-post multi-sectoral decomposition analysis, Energy Econ. 86 (2020) 104640, https://doi.org/10.1016/j.eneco.2019.104640.
[30] Statistics Finland, in: Energy Consumption in Households 2018 Energy Consumption in Households Fell Further, 2020, 2018.
[31] M. Gao, Q. Wang, L. Li, C. Liu, Comprehensive energy-saving method for sheet metal forming, Int. J. Adv. Manuf. Technol. 104 (2019) 2273–2285, https://doi.org/10.1007/s00170-019-04022-4.
[32] X. Zheng, C. Wei, P. Qin, J. Guo, Y. Yu, F. Song, Z. Chen, Characteristics of residential energy consumption in China: findings from a household survey, Energy Pol. 75 (2014) 126–135, https://doi.org/10.1016/j.enpol.2014.07.016.
[33] G. Savvidou, B. Nykvist, Heat demand in the Swedish residential building stock - pathways on demand reduction potential based on socio-technical analysis, Energy Pol. 144 (2020), https://doi.org/10.1016/j.enpol.2020.111679.
[34] L.G. Swan, V.I. Ugursal, I. Beausoleil-Morrison, Occupant related household energy consumption in Canada: estimation using a bottom-up neural-network technique, Energy Build. 43 (2011) 326–337, https://doi.org/10.1016/j.enbuild.2010.09.021.
[35] European Commission, Heating and cooling | energy. https://ec.europa.eu/energy/topics/energy-efficiency/heating-and-cooling_en, 2015. (Accessed 8 August 2021).
[36] M.Z. Pomianowski, H. Johra, A. Marszal-Pomianowska, C. Zhang, Sustainable and energy-efficient domestic hot water systems: a review, Renew. Sustain. Energy Rev. 128 (2020) 109900, https://doi.org/10.1016/j.rser.2020.109900.
[37] S. Edwards, I. Beausoleil-Morrison, A. Laperrière, Representative hot water drawn profiles at high temporal resolution for simulating the performance of solar thermal systems, Sol. Energy 111 (2015) 43–52, https://doi.org/10.1016/j.solener.2014.10.026.
[38] A. Ferrantelli, K. Ahmed, P. Pylsy, J. Kurnitski, Analytical modelling and prediction formulas for domestic hot water consumption in residential Finnish apartments, Energy Build. 143 (2017) 53–60, https://doi.org/10.1016/j.enbuild.2017.03.021.
[39] A. Chmielewska, M. Szulgowska-Zgrzywa, J. Danielewicz, Domestic hot water consumption in multi-apartment buildings, in: E3S Web of Conferences 17, 2017, https://doi.org/10.1051/e3sconf/20171700014.
[40] K. Ahmed, P. Pylsy, J. Kurnitski, Monthly domestic hot water profiles for energy calculation in Finnish apartment buildings, Energy Build. 97 (2015) 77–85, https://doi.org/10.1016/j.enbuild.2015.03.051.
[41] D.S. Parker, Research highlights from a large-scale residential monitoring study in a hot climate, Energy Build. 35 (2003) 863–876, https://doi.org/10.1016/S0378-7788(02)00244-X.
[42] J.P. Meyer, M. Tshimankinda, Domestic hot-water consumption in South African apartments, Energy 23 (1998) 61–66, https://doi.org/10.1016/S0360-5442(97)00069-8.
[43] K.T. Papakostas, N.E. Papageorgiou, B.A. Sotiropoulos, Residential hot water use patterns in Greece, Sol. Energy 54 (1995) 369–374, https://doi.org/10.1016/0038-092X(95)00014-I.
[44] J.C. Evarts, L.G. Swan, Domestic hot water consumption estimates for solar thermal system sizing, Energy Build. 58 (2013) 58–65, https://doi.org/10.1016/j.enbuild.2012.11.020.
[45] T.J. Merrigan, Residential hot water use in Florida and North Carolina, Build. Eng. 94 (1988). https://www.techstreet.com/standards/da-88-10-2-residential-hot-water-use-in-florida-and-north-carolina?product_id=1713203. (Accessed 9 August 2021).
[46] M. Aydinalp, V.I. Ugursal, A.S. Fung, Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks, Appl. Energy 79 (2004) 159–178, https://doi.org/10.1016/j.apenergy.2003.12.006.

[47] J. Rouleau, A.P. Ramallo-González, L. Gosselin, P. Blanchet, S. Natarajan, A unified probabilistic model for predicting occupancy, domestic hot water use and electricity use in residential buildings, Energy Build. 202 (2019), https://doi.org/10.1016/j.enbuild.2019.109375.

[48] K. Ahmed, P. Pylsy, J. Kurnitski, Hourly consumption profiles of domestic hot water for different occupant groups in dwellings, Sol. Energy 137 (2016) 516–530, https://doi.org/10.1016/j.solener.2016.08.033.

[49] L.M. López-Ochoa, K. Verichev, J. Las-Heras-Casas, M. Carpio, Solar domestic hot water regulation in the Latin American residential sector with the implementation of the Energy Performance of Buildings Directive: the case of Chile, Energy 188 (2019), https://doi.org/10.1016/j.energy.2019.115985.

[50] Asociación Chilena de Energía Solar, CAP.5 Cálculo de prestaciones energéticas, n.d.

[51] I. Knight, N. Kreutzer, M. Manning, M. Swinton, H. Ribberink, European and Canadian residential non-HVAC electric and DHW load profiles for use in simulating the performance of residential cogeneration systems, Annex 42 (2007).

[52] Boverket, Regelsamling För Byggande, BBR, 2011, 2012.

[53] Asociación Técnica Española de Climatización y Refrigeración (ATECYR), Guia Tecnica de agua caliente sanitaria central. www.idae.ec, 2010.

[54] L. Ianelli, S. Gil, Agua Caliente Sanitaria en Argentina ¿Cuáles son las opciones más convenientes?, 3, 2020, pp. 3–6. https://www.researchgate.net/publication/339508459_Agua_Caliente_Sanitaria_en_Argentina_Cuales_son_las_opciones_mas_convenientes.

[55] T.-A. Koiv, A. Toode, Heat energy and water consumption in apartment buildings, Proc. Est. Acad. Sci. 7 (2001) 235–241.

[56] B. Bøhm, F. Schrøder, N.C. Bergsøe, Varmt Brugsvand: Måling af forbrug og varmetab fra cirkulationsledninger, 2009.

[57] South African National Standards, Water Supply and Drainage for Buildings, 2012.

[58] K. Tumanova, A. Borodinecs, A. Geikins, The analysis of the hot water consumption and energy performance before and after renovation in multi-Apartment buildings, IOP Conf. Ser. Mater. Sci. Eng. (2017) 251, https://doi.org/10.1088/1757-899X/251/1/012058.

[59] R. Yao, K. Steemers, A method of formulating energy load profile for domestic buildings in the UK, Energy Build. 37 (2005) 663–671, https://doi.org/10.1016/j.enbuild.2004.09.007.

[60] E. Fuentes, L. Arce, J. Salom, A review of domestic hot water consumption profiles for application in systems and buildings energy performance analysis, Renew. Sustain. Energy Rev. 81 (2018) 1530–1547, https://doi.org/10.1016/j.rser.2017.05.229.

[61] Y. Denis, F. Suard, A. Lomet, D. Chèze, Saving energy by anticipating hot water production: identification of key points for an efficient statistical model integration, Artificial Intelligence for Engineering Design, Analysis and Manufacturing, AI EDAM (Artif. Intell. Eng. Des. Anal. Manuf.) 33 (2019) 138–147, https://doi.org/10.1017/S0890060419000143.

[62] C. Deb, F. Zhang, J. Yang, S.E. Lee, K.W. Shah, A review on time series forecasting techniques for building energy consumption, Renew. Sustain. Energy Rev. 74 (2017) 902–924, https://doi.org/10.1016/j.rser.2017.02.085.

[63] D. Mariano-Hernández, L. Hernández-Callejo, F.S. García, O. Duque-Perez, A.L. Zorita-Lamadrid, A review of energy consumption forecasting in smart buildings: methods, input variables, forecasting horizon and metrics, Appl. Sci. 10 (2020) 1–27, https://doi.org/10.3390/app10238323.

[64] N. Wei, C. Li, X. Peng, F. Zeng, X. Lu, Conventional models and artificial intelligence-based models for energy consumption forecasting: a review, J. Petrol. Sci. Eng. 181 (2019) 106187, https://doi.org/10.1016/j.petrol.2019.106187.

[65] C. Bennett, R.A. Stewart, C.D. Beal, ANN-based residential water end-use demand forecasting model, Expert Syst. Appl. 40 (2013) 1014–1023, https://doi.org/10.1016/j.eswa.2012.08.012.

[66] L.G. Maltais, L. Gosselin, Predictability analysis of domestic hot water consumption with neural networks: from single units to large residential buildings, Energy 229 (2021) 120658, https://doi.org/10.1016/j.energy.2021.120658.

[67] L. Gelažanskas, K.A.A. Gamage, Forecasting hot water consumption in residential houses, Energies 8 (2015) 12702–12717, https://doi.org/10.3390/en81112336.

[68] D. Popescu, E. Serban, Simulation of domestic hot-water consumption using time-series models, in: 6th IASME/WSEAS International Conference on HEAT TRANSFER, THERMAL ENGINEERING and ENVIRONMENT (HTE'08), 2008. https://www.researchgate.net/publication/267414381.

[69] A. Horkai, A statistical analysis of the relationship between domestic hot water consumption and mean outdoor temperature in Budapest, Idojaras 125 (2021) 53–82, https://doi.org/10.28974/idojaras.2021.1.3.

[70] Ministerio de Energía, Energía 2050. Política Energética de Chile, Santiago de Chile, 2017.

[71] J. Durbin, S.J. Koopman, Time Series Analysis by State Space Methods, Oxford university press, 2012.

[72] E. Arandia, A. Ba, B. Eck, S. McKenna, Tailoring seasonal time series models to forecast short-term water demand, J. Water Resour. Plann. Manag. 142 (2016) 4015067.

[73] M.A. Al-Zahrani, A. Abo-Monasar, Urban residential water demand prediction based on artificial neural networks and time series models, Water Resour. Manag. 29 (2015) 3651–3662.

[74] M. Yalçıntaş, M. Bulu, M. Küçükvar, H. Samadi, A framework for sustainable urban water management through demand and supply forecasting: the case of Istanbul, Sustainability 7 (2015) 11050–11067.

[75] D.C.M. Ristow, E. Henning, A. Kalbusch, C.E. Petersen, Models for forecasting water demand using time series analysis: a case study in Southern Brazil, J. Water, Sanit. Hyg. Dev. 11 (2021) 231–240, https://doi.org/10.2166/washdev.2021.208.

[76] H. Yoon, D. Sauri, E. Domene, The water-energy vulnerability in the Barcelona metropolitan area, Energy Build. 199 (2019) 176–189, https://doi.org/10.1016/j.enbuild.2019.06.039.