Calgary's municipal buildings' energy consumption analysis and forecast

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Summary

CO_2 emissions are the leading cause of Global Warming, and countries worldwide are working to reduce their domestic emissions. Canada is set to zero-net emissions by 2050 and acts on different fronts. Although the emissions per capita are declining, the absolute emissions of the country are still increasing over the years. As part of the country's efforts, the Government of Calgary has set the same goal. We analyzed the Calgary corporate buildings data, which contains energy consumption from different municipal facilities. We pointed out that the overall electricity consumption in the city is declining, while natural gas consumption seems to be following an opposite trend. As a decision-making tool, forecasting models can predict what will be the future energy consumption. However, for that, complete data is required, containing the energy consumption of each building and structural information about the same. We forecasted global electricity and natural gas consumption using three different models: SARIMA + XGBoost, Facebook Prophet, and MARS. The first one showed to behave better with the seasonality and outliers, predicting a steady reduction of electricity consumption for the next three years, while the natural gas consumption will continue at the same level if no action is taken. Lastly, we did the impact analysis of the reduction of electricity consumption of the Calgary streetlights since 2016, due to an effort of the Government of Calgary to change the light bulbs to more energy-efficient ones and estimated that the savings are feeding the equivalent of more than 5000 houses in Alberta.

Introduction

Global warming is strictly correlated with Greenhouse Gas Emissions, and countries need to take action to reduce such waste released into the atmosphere. According to the Emissions Gap Report 2021 (UNEP and UNEP-DTU, 2021) from the United Nations Environmental Programme (UNEP), if all the countries continue their current climate commitments, global temperature will rise at least 2.7^oC by the end of the century. To achieve the 1.5^oC goal of the Paris Agreement, CO_2 emissions need to be cut in half in the next eight years, a reduction in 28 gigatons of CO_2 ($GtCO_2$) equivalent in annual emissions. To reach a 2^oC target, a drop of 13 $GtCO_2$ in annual emissions is needed by 2030. Buis (2019) shows that at 1.5^oC warming, around 14% of Earth's population will be regularly exposed to severe heatwaves, and this number jumps to 37% if warming is at 2^oC. Adding this to other catastrophic effects such as droughts, wildfires, decrease in the availability of drinkable water, increase in extreme precipitations in some areas (Western Canada included), impacts on biodiversity and ecosystems, and ocean impacts (sea-level rise, marine ecosystems, acidity, and oxygen levels), we need to take actions on different levels to mitigate global warming effects.

Canada has committed to reducing GHG emissions by 40-45% below 2005 levels by 2030 and reaching net-zero emissions by 2050 (Canada, 2020a). For this goal, the Government of Canada is investing on different fronts: improving energy efficiency in homes and buildings, changing to electric transportation by 2040, taxing emissions and improving the energy efficiency of the industrial structures, reducing oil and gas methane emissions to 40-45% by 2025, investing on renewable energy generation, and methane and CO_2 capture. Macquet et al. (2019) and Lawton et al. (2019) show the possibility and importance of injecting captured CO_2 into old oil and gas reservoirs, and this technology can be implemented to any "stationary" GHG emitter, such as industrial complexes. However, more is still required, and we need to be clear about where to focus.

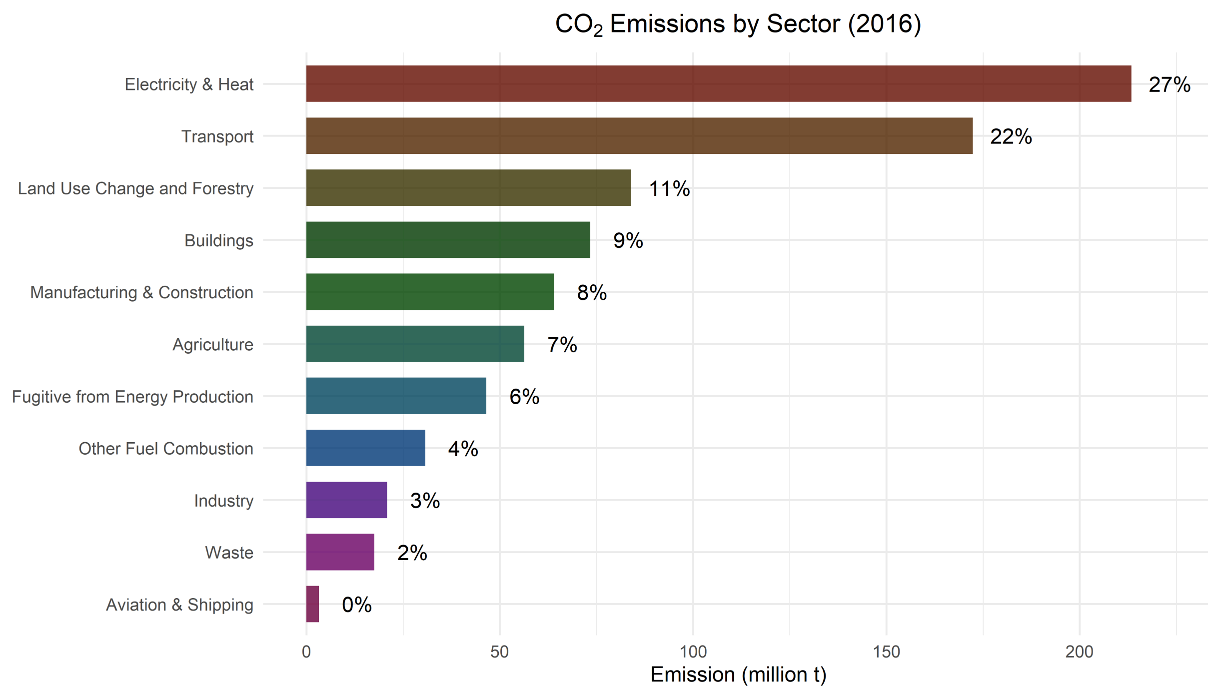

FIG. 1. Canada's CO_2 emissions by sector in 2016.

Our World in Data (Ritchie and Roser, 2020) gathered different datasets, including worldwide GHG emissions. Figure 1 shows how the CO_2 emission is distributed into Canada's economic sectors in 2016: Electricity & Heat and Transportation are the two largest emitters in Canada, and the first one is the focus of this project. Electricity and heat need an optimization effort: how can we maintain the same output and reduce energy consumption? One action would be improving buildings' heat efficiency and understanding the construction characteristics and how to optimize electricity usage. Part of the decisions lies in consumption forecasting. Bourdeau et al. (2019) and Wei et al. (2019) make a compilation of conventional (such as ARIMA and MARS) and machine learning (gradient boosting, deep learning) models for energy consumption forecasting. Somu et al. (2021) use a combination of clustering and deep learning algorithms to forecast the energy consumption of a four-store building in Bombay, India. Robinson et al. (2017) use commercial buildings characteristics to feed a gradient boosting model to predict energy consumption. Andelkovic and Bajatovic (2020) include historical weather information to predict gas consumption in Serbia, while Vinagre et al. (2015) uses external data, such as temperature and solar radiation, to guide a neural network model. Yu (2018) proposes a two-step approach that uses buildings engineering estimators and demand to come with a corrected consumption prediction. Kumar and Jain (2010) focus on Markov-based methods to predict energy consumption from different sources in India.

In this project, we will use data from Calgary's municipal buildings' historical energy consumption to understand the energy consumption of different structures and how Calgary's efforts to reduce GHG emissions are represented in the data. We try different algorithms to forecast future consumption using historical energy consumption from other sources. We also use a multivariate adaptive regression splines (MARS) model (Friedman, 1991) to study the impact analysis of the change of light bulbs of street lighting from 2016.

Calgary Municipal Buildings' Energy Consumption and Forecasting

Raymond (2018) gathered information on monthly energy consumption and generation (in kWh) over time (from 2014) of Calgary's municipal buildings. The data contains columns that allow the table to be divided into different categories for the data analysis: type of energy, type of business (offices, roads and transit, waste, etc.), facility name, year, and month. By grouping the data over different classes, we can summarize the data in different ways. However, it only contains the consumption and no information of the building itself, and such data can be essential to understand and forecast future energy usage. Furthermore, it is a relatively complex and rich dataset, so we can analyze it more globally and refine it to more local observations.

Guarido et al. (2021) presented a deep analysis of the energy consumption of Calgary's municipal buildings, showing the connection between the consumption with the yearly seasons, with higher consumption during the Winter (due to heating and shorter days). The analysis was done for each type of energy present in the data (electricity, natural gas, district energy, solar power, and solar thermal). In a quick observation, electricity consumption follows a reduction trend. In contrast, natural gas consumption seems to happen (the exception is 2020, but it is a unique year due to the COVID pandemic).

Forecasting future energy usage is essential for governments to make decisions and plan how to reduce CO_2 emissions. As we are missing specific buildings characteristics information, forecasting will be done more globally for electricity and natural gas consumption. Therefore, modelling was done with models that use historical data to predict future values. The models of choice are the Facebook Prophet (Taylor and Letham, 2017), the multivariate adaptive regression splines, or MARS (Friedman, 1991), and the SARIMA (Cowpertwait and Metcalfe, 2009) combined with the XGBoost algorithm (Chen and Guestrin, 2016). The XGBoost implements a gradient boosting (Hastie et al., 2001) solution. First, to evaluate the forecasting results, they are applied on a period of the data containing actual consumption measures. Still, they are not used for modelling, and lately, the models are trained on the complete data to predict future consumption.

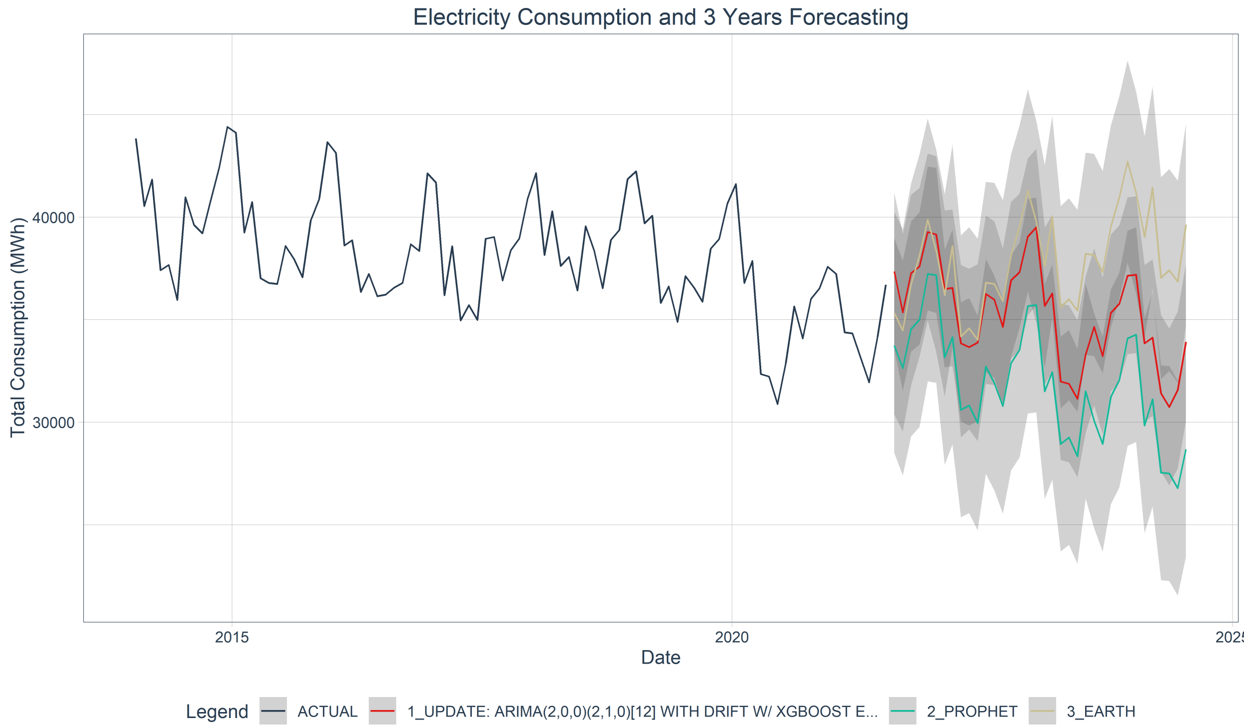

FIG. 2. Forecast of electricity consumption by Calgary's municipal buildings (black) using SARIMA + XGBoost (red), Facebook Prophet (green) and MARS (yellow).

Figure 2 shows the three years forecasting of electricity consumption. It is interesting how they diverge from each other by following different trends. The SARIMA + XGBoost (red) tracks the global descending direction of the data and was less affected by the 2020 and 2021 COVID pandemic years, while the Prophet (green) follows a more recent trend (as the model calculates localized trends) and is heavily impacted by 2020 and 2021. MARS (yellow) is a model that also estimates a regression model for different data ranges using *basis functions* and predicts an increasing electricity consumption, probably because it is following the 2020-2021 trend.

Guarido et al. (2021) forecasted natural gas consumption for the next three years, and the three models showed to be close to each other. Therefore, the trends are neither increasing nor decreasing, implying the same level of natural gas consumption for the next three years.

One exciting example of how the electricity consumption in Calgary's municipal buildings decreases is *street lighting*. Its consumption declined from 2016 to 2019 (Figure 3). According to Raymond (2018), this is due to the decision of the Government of Calgary to change the lamp bulbs of the streetlights to more energy-efficient ones. To calculate how much energy was saved, we calculated the consumption forecasting from 2016 to 2021 by training a model with data from 2014 to 2015.

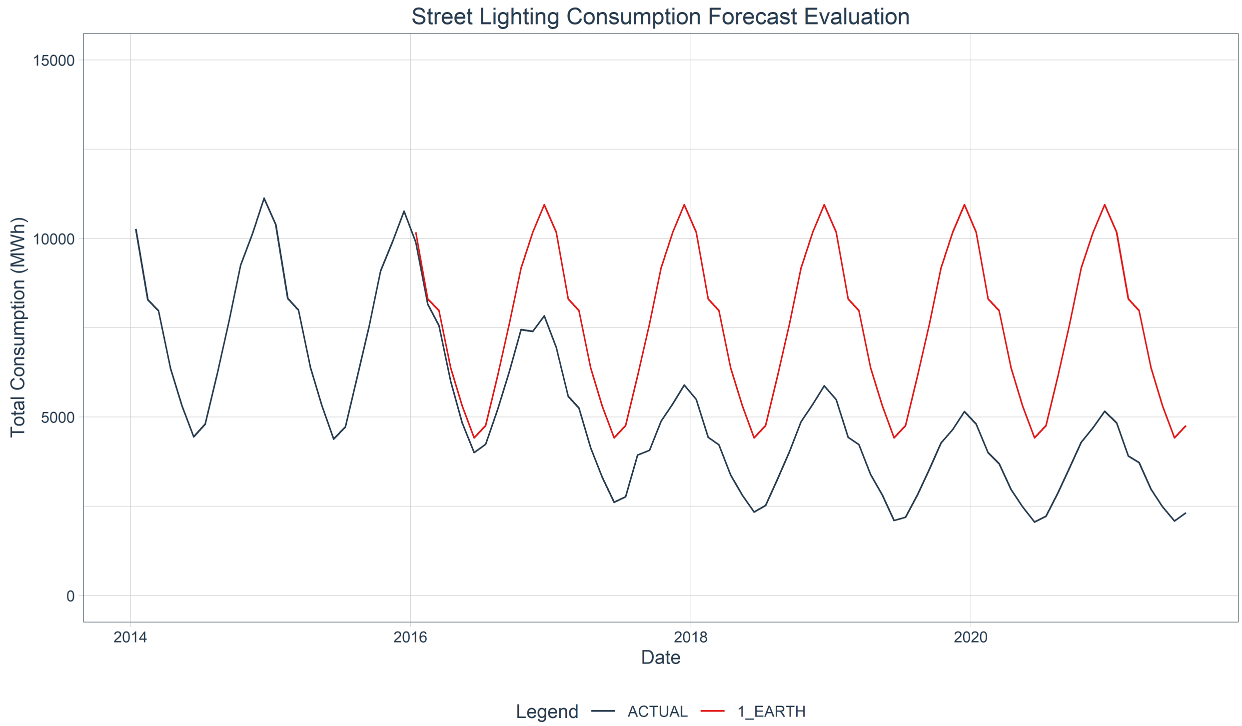

FIG. 3. Impact analysis of Calgary's street lighting reduction of electricity consumption.

As only two complete cycles (2 years) are used for training, the SARIMA + XGBoost and Prophet were not able to capture the seasonality of the data. However, MARS showed to be stable and could do such forecasting with a small amount of data. For example, figure 3 shows in red the calculated electricity consumption of the streetlights if the bulbs were not changed. **From January 2016 to September 2021, the savings on electricity consumption was about 212 GWh**. An average house in Alberta uses around 7200 kWh per year, and the savings on streetlight consumption could feed more than 5000 houses from 2016 to 2021.

Conclusions

CO2 emissions are pointed to as the leading cause of Global Warming, and countries worldwide are working to reduce their domestic emissions. Canada is set to zero-net emissions by 2050 and is acting on different fronts. Although the emissions per capita are declining, the absolute emissions of the country are still increasing over the years. As part of the country's efforts, the Government of Calgary has set the same goal.

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