# Toward a smarter electricity consumption

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# Context

## The Energy modelling initiative

The human activities cause strong pressures on the environment, including climate change, the degradation of air quality and reduction of biodiversity. One important contributor to these problems is the generation of electricity. For that reason, it has become necessary to improve the way electricity is generated and consumed (since both the production and demand are linked). The main strategies to reach that goal are to reduce the dependence on fossil fuels, increase the integration of renewable energy and enhance global energy efficiency. To that end, technologies are being developed, innovative management of power generation and demand are implemented, and energy models are improved to better represent these new realities in the design of energy policies.

***"Real-time modelling of electricity generation enable a better assessment of environmental impacts of electricity which leads the way to a new optimization of electricity consumption"***

In that context, the Energy modelling initiative (EMI) aims to identify experts and innovative energy models that could help in designing energy policies to mitigate climate change and global environmental degradation. Following the EMI call for projects our modelling approach on smart power consumption was selected. Its originality lies in the consideration for real-time changes in electricity generation and demand when assessing the emissions and environmental impacts due to electricity consumption. This approach opens the path to a new optimization of electricity consumption based on the real-time emissions intensity rather than only the real-time price of electricity.

More research is, however, needed to answer pending questions such as: how any consumers would comply with power consumption recommendations that would affect their daily habits? What would be the amount of electricity that could be displaced in time to reduce power generation emissions? How marginal power generators and their emissions would be affected by these changes in electricity consumption? How this modelling approach could be integrated into other energy models and what would be the benefits to do it?

# The Model

## Real-time energy modelling and smart consumption of electricity

### A. Model and type of results

The model is a methodological framework designed to (1) calculate electricity emissions based on temporally disaggregated power generation data *[defined as real-time emissions in this report]*, (2) provide real-time recommendations to electricity consumers and (3) assess the environmental benefits of enforcing such recommendations. Similarly to the TIMES model, regional data are necessary to design the model for a specific region. Practically, it can be applied to any region where temporally disaggregated power generation data *[defined as real-time power generation data in this report]* are available.

The model is made of three main interconnected modules as presented in Figure 1:

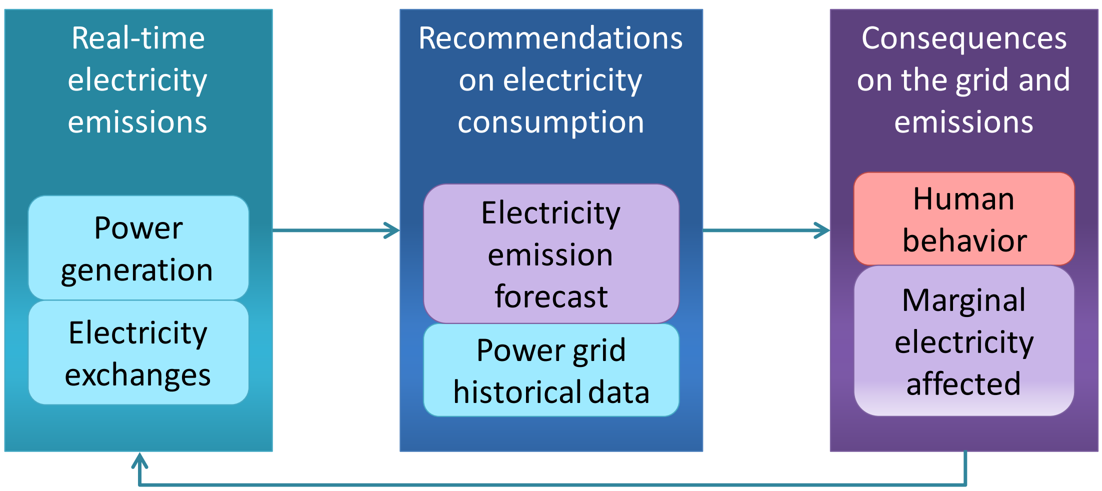


**Figure 1 – Structure of the electricity emission model**

The first element calculates the **real-time emissions of electricity** within a power grid. It uses the real-time information provided by the electricity operator (power generation and import/export of electricity) and the emission factor of each power generation technology. Environmental impacts due to these emissions can also be assessed for a large variety of indicators using a life cycle database such as the ecoinvent database and impact assessment methods such as Impact World+ or ReCiPe. In this report, the focus is made on greenhouse gas (GHG) emissions and climate change.

The second module provides **recommendations to electricity consumers** based on the **forecasted electricity emission intensity**. This emission forecast is based on grid mix predictions achieved with a machine learning model trained with power grid historical data.

The third module simulates the **effect of the recommendations on the consumers and their consequences on marginal power generation and emissions**. The compliance of the consumers with the recommendations is simulated with an agent-based model, while the marginal power generators are identified using the historical and real-time power grid data. Then, the emissions of the consumers and those saved by the recommendations are calculated using the first module.

The model is actually designed to assess the short term benefits of the smarter consumption of electricity but it is also aimed to assess the long term benefits in further developments.

### A.1 Technical description of the model

#### Module 1: Real-time electricity emissions

This module has been developed during several research projects to progressively include the concepts of global emissions, imported emissions and marginal emissions (Dandres et al., 2017; Maurice et al., 2014; Milovanoff et al., 2017; Walzberg et al., 2019a). The module calculates the emissions associated with the consumption of electricity (past or real-time) and the anticipated emissions due to a change in the future power demand. The emissions are calculated using eq. i and ii for a period *t* (1 second, 5 minutes, 1 hour or more).

$$Emissions = P(t) \times t \times EF(t) \quad \text{(i)}$$

Where:

- *P(t): power consumption during the time period t;*
- *EF(t): emission factor of the electricity during the time period t.*

$$EF\ (t) = \frac{\sum_i Gen_{Source(i)}(t) \times EF_{Source(i)}(t) + \sum_j Imp_{Reg(j)} \times EF_{Reg(j)}(t) - \sum_j Exp_{Reg(k)} \times EF_{Grid}(t)}{\sum_i Gen_{Source(i)}(t) + \sum_i Imp_{Reg(j)}(t) - \sum_i Exp_{Reg(k)}(t)} \quad \text{(ii)}$$

Where:

- *Gen* $_{Source(i)}$ *(t): power generation by the source i during the time period t;*
- *EF* $_{Source(i)}$ *(t): emission factor of the source i during the time period t;*
- *Imp* $_{Reg(j)}$ *(t): import of electricity from region j during the time period t;*

- $EF_{Reg(j)}(t)$: *emission factor of the region j during the time period t (see eq. iii below);*
- $Exp_{Reg(k)}(t)$: *export of electricity to region k during the time period t;*
- $EF_{Grid}(t)$: *emission factor of the power grid during the time period t:*

$$EF_{Grid}(t) = \frac{\sum_i Gen_{Source(i)}(t) \times EF_{Source(i)}(t)}{\sum_i Gen_{Source(i)}(t)} \quad \text{(iii)}$$

The emissions related to real-time or past electricity consumption are calculated based on all active power plants of the grid as well as the imported and exported electricity. Figure 2 summarizes the method.

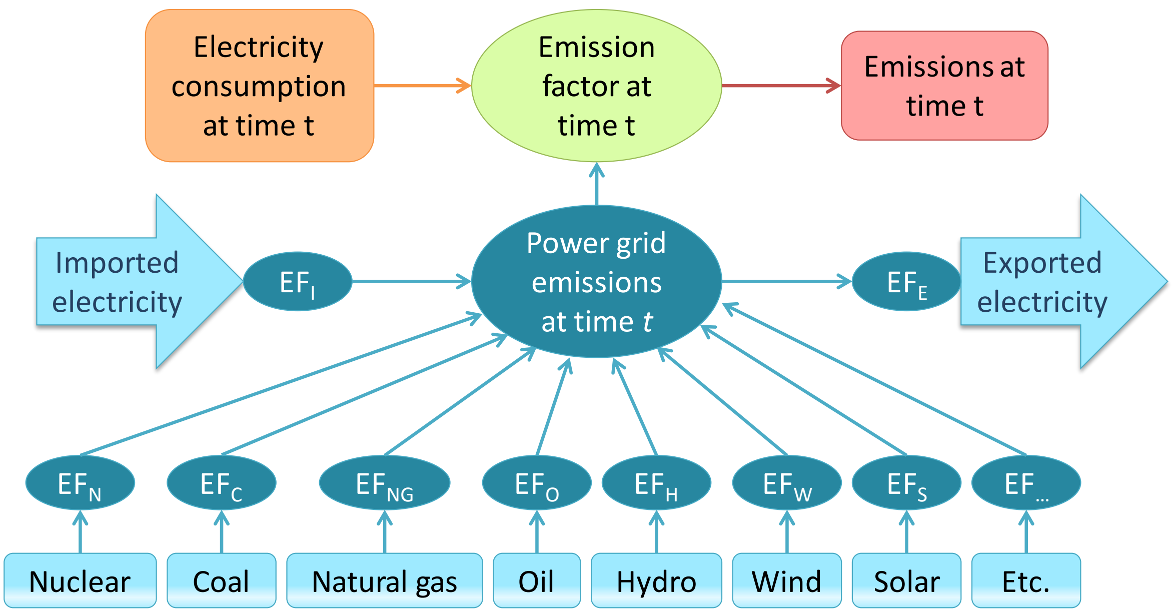


**Figure 2 – Calculation of real-time electricity emissions**

*Legend*: The emissions of each power generation technology are calculated using the electricity generated and the corresponding emission factor (bottom of the figure). Then, all emissions of local power generation are summed (center of the figure). Emissions from imported electricity are calculated using the emission factor of the exporting region and the amount of imported electricity (left part of the figure). The emissions from the exported electricity are calculated using the local power generation emission factor and the amount of exported electricity (right part of the figure). Imported emissions are added to local emissions while exported emissions are subtracted from them. The resulting total of emissions is then divided by the local power load (local power generation + electricity import – electricity export) to get the power grid emission factor (top of the figure). Finally, the emissions of consumed electricity are calculated using the electricity consumption and the power grid emission factor.

When it comes to calculate the marginal emissions related to a change in the future demand, only the power plants adapting their capacity to meet that change are considered. The identification of these so-called "marginal" power plants is, however, a complex task and there is no standardized method to do it (it is the purpose of another project with IEEE under the IEEE 1922.1 standard). Consequently, different results might be obtained depending on the chosen emission factor (global or marginal). The meaning of these results is however different and are therefore not equivalent. The calculation of the global electricity emission factors has been standardized in IEEE 1922.2 (Dandres et al., 2019)

In this model, the power plants are regrouped by technology (i.e. nuclear, natural gas, hydro, etc.) and the marginal technologies are identified every hour using the method presented in Dandres et al. (2017) to identify the local marginal technologies and improved in Walzberg et al. (2019a) to also include the marginal technologies located in interconnected networks. This method considers that all changes in non-intermittent power generation technologies would contribute, in proportion to their capacity changes, to fulfill a change in the power demand. Intermittent generators are excluded by default but could be considered depending on the perspective of the application of the method. Additionally, this method considers that the same marginal power generation technologies would be affected regardless the demand is increased or decreased.

### Module 2: Recommendations on electricity consumption

This module stands on the use of machine learning to predict the power grid emission factor in a region. It uses historical data to forecast the hourly emission factors for the next 24 hours. The method is summarized in Figure 3.

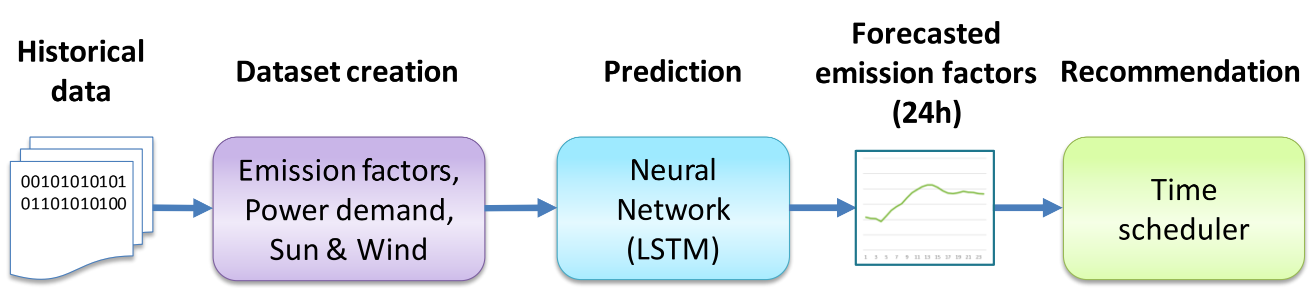


**Figure 3 – Recommendations on electricity consumption module**

The dataset used for the prediction is generated by the real-time electricity emission module and possibly completed with more data retrieved from the electric operator. Because machine learning needs a large dataset to train, it is required to calculate the hourly emission factors with at least 28 days of data. Since emission factors are usually comprised between 0 and 1, it is not necessary to normalize them. Depending on the share of intermittent renewable energy in the power grid, it might be necessary to complete the dataset with more data to reach a suitable level in predictions. Such data are the day ahead forecasts of the power demand and the intermittent renewable energy production. Once the dataset is ready, it is used to train a neural network that counts 3 layers of long short-term memory (LSTM) cells (see Figure 4). Several architectures were tested during the development of the module and the LSTM algorithm was chosen because of its better results due to its ability to select and keep past information of the time series. LSTM is a variant of the recurrent neural network (RNN) but differs from it because it can choose to update the cell state at each calculation sequence (each hour in our case).

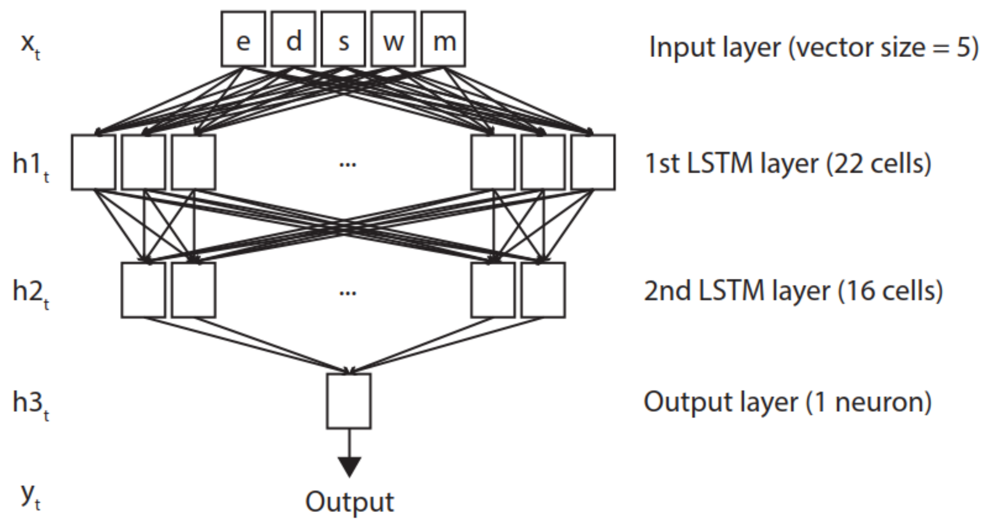


**Figure 4 – Architecture of the neural network**

*Legend*: the 5 elements of the X vector are the emission factor (e), the day ahead demand (d), the power generation from solar panels (s), the power generation from wind farms (w) and the mask (m). The mask is used to prevent the calculation of a prediction for the past hours (i.e., t < 1): it has a value of 1 for the past hours and 0 otherwise. X is processed by the three layers of the neural network (h1, h2 and h3) to generate 24 predictions (y, for 0 < t < 24). See Riekstin et al. (2018) for more details on the method.

Once the emission factors forecasts are obtained, the minimums are identified to provide recommendations. Practically, the recommendations depend on the type of consumers. For instance, for residential consumers, it would not be relevant to recommend launching washing machines and dryers at night due to noise issues and the need for a human intervention to empty the washing machine and fill the dryer. It could, however, be pertinent for loading the batteries of electric vehicles (assuming a timer can start loading the batteries at the right time). This means the consumer must be studied to understand his needs and flexibility to provide him with adapted recommendations on its electricity consumption.

It should be noted that the model is used in real-time and must be trained continuously to provide new predictions. Moreover, it is specific to the power grid on which it has been trained and should not be used for other power grids.

### Module 3: Consequences on power generation and emissions

Many reasons can explain why human beings won't follow recommendations involving a behavioural change. The purpose of this module is to evaluate to what extent the emissions can be reduced by real-time recommendations on electricity consumption provided to human beings. To that end, an agent-based model (ABM) is used to represent the acceptation of the consumers to comply with the recommendations. More than that, the ABM also evaluates the role of human interactions between consumers and uses it to enhance the adoption of the recommendations.

The ABM considers four types of electricity consumers that are defined according to their relation to energy: passive ratepayers, frugal goal seekers, energy epicures and energy stalwarts. Each of these energy consumers has a different probability to comply with a recommendation implying a behavioural change (e.e, a new schedule of electricity consumption, see Table 1).

**Table 1 – Type of energy consumer and compliance with behavioural recommendations**

| Type of energy consumer | Compliance with recommendations |
|---|---|
| Energy stalwarts | ++ |
| Frugal goal seekers | + |
| Passive ratepayers | - |
| Energy epicures | - - |

Each consumer may also be influenced by its neighbours through the share of information related to the demand-side management program. Such info can be the average compliance rate of participants, the avoided emissions by neighbours, the average electricity consumption, etc.

Figure 5 summarizes the structure of the agent-based model. The behavioural modelling of the consumer starts when he received a recommendation to adapt his electricity consumption. He may comply or not depending on his type of energy consumer (cf. Table 1). Then, through the share of information between consumers, each consumer compares himself to its neighbourhood. Through a set of probabilities, the model estimates the chance that a consumer that did not comply with a recommendation will still enforce it if (1) it has been enforced by its neighbours and (2) it is easy enough. Moreover, the model also considers the case where a consumer has complied with the recommendation and finally cancel it due to discouragement. For more detailed information on the model, see Walzberg et al. (2019b).

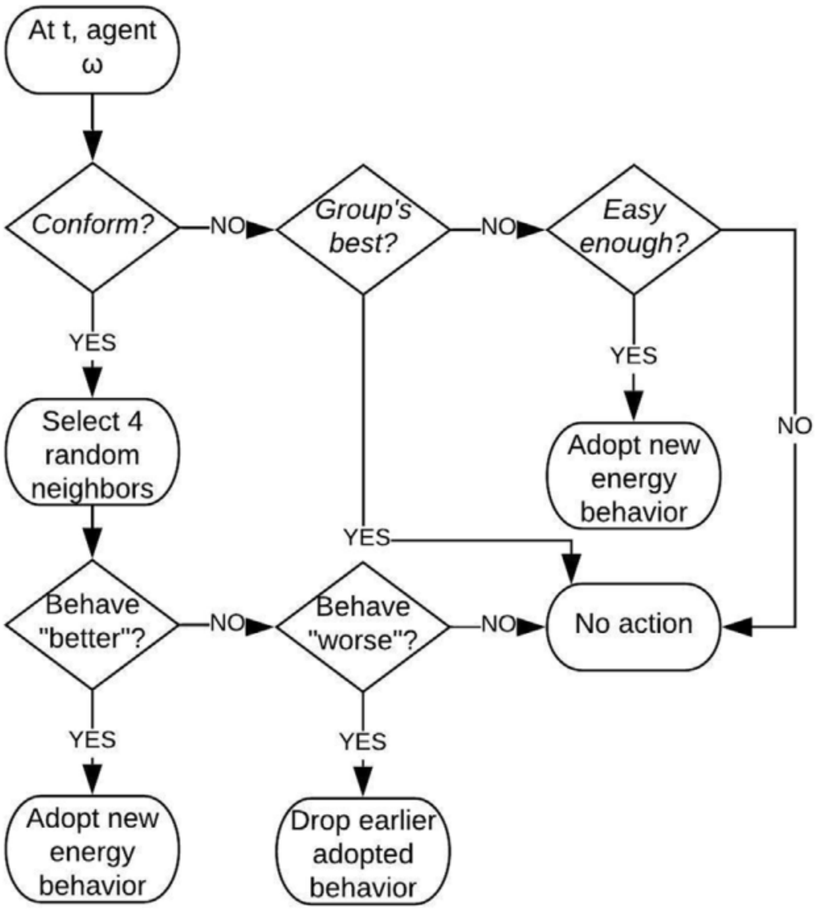


**Figure 5 – Structure of the agent-based model**

The emissions avoided by the measures are then calculated according to the adoption of the measures and the electricity emission factors corresponding to the time and region when and where the measures are applied. Considering only the fraction of the power consumption change at a time, the global and marginal emission factors are combined to calculate the GHG emissions avoided by the adoption of the measures:

$$E_m = \sum_t EF_{g,t} \times \min[P_t, P_{t-1}] + EF_{m,t} \times |P_t - P_{t-1}|$$

Where:

- $E_m$ is the avoided emissions over the studied period;

- *$EF_{g,t}$ and $EF_{m,t}$ the global and marginal emission factors at time t;*
- $P_t$ and $P_{t-1}$ are the power consumption at time t and the previous period of time;
- min[$A$,$B$] is the minimum between $A$ and $B$.

By combining different possible behaviours with their probability of occurrence among the population, the model provides a better representation of the reality than assuming, for instance, that 15% of the population will comply. Moreover, the agent-based model can explore different types of recommendations and information feedbacks to compare their effectiveness to increase compliance with the recommendations.

In theory, by modelling the entire population of an area the agent-based model could evaluate the global compliance with the electricity recommendations and estimate the reduction of the power demand and emissions. Practically, this module is, however, still at its early stage and has only been applied to a residential population living in smart houses. It is now required to model other segments of the population to be able to evaluate the effect of electricity consumption recommendations on the global power demand.

### A.2 Type of results

Given the three modules of the model, three types of results are generated:

- The **real-time electricity emission factors** that express the intensity of the power grid emissions at a specific time. Two types of emission factors are computed: the global emission factor representing the average emission rate of the power grid (of all power generators) and the marginal emission factor representing the emission rate of the power grid due to a change in the power demand (emission rate of the marginal generators). These emissions factors can be used in dynamic life cycle assessment, carbon footprint and any emission disclosure program. It is expected that the accuracy of the results of these methods would be increased as compared to the conventional methods that are based on annual average emission factors.
- The machine learning model that predicts the **emission intensity of the power grid electricity for the next twenty-four hours**. This tool can be used then to help the consumers to schedule their power demand and minimize their emissions. The tool is dynamic since it has to be trained constantly with new data (the last available power generation data).
- The **emissions avoided by the enforcement of a smarter consumption of electricity**. The model also generates knowledge on the factors influencing the acceptance of the

consumers to change their consumption behaviour. Such knowledge can be used when designing dynamic demand-side management programs.

## B. Model strengths and limits

The global strength of the model is to (1) provide a more accurate picture of the emissions due to electricity consumption, (2) help consumers to reduce their emissions and (3) generate useful knowledge to enhance the adoption of demand-side management programs. Nevertheless, the model can be improved and its strengths and limits differ for each module.

### *Module 1: Real-time electricity emission module*

The strength of this module is to provide a series of more accurate emission factors representing the emission intensity of electricity. These emission factors can then be used to calculate the emissions of an electricity consumer retrospectively (ex: annual emissions (i.e., scope 2 emissions in the GHG Protocol framework) of an enterprise) or to inform electricity consumers of the real-time rate of electricity emissions.

This module can be considered as very strong in theory but, practically, its strength depends on the data used to feed it. Thus, the input data are the limit of this model: inaccurate data decrease its strength.

The model uses two types of data:

1. The **power grid data** describing the real-time power generation and exchanges;
2. The **emission data** associated with the emissions of each power generation technology.

Ideally, the **power grid data** should correspond to the electricity produced by each power generation technology with a reasonable temporal granularity (e.g. hourly data). The power grid data should also include the exchange between the studied power grid and its interconnected electric networks.

The **emission data** should enable the calculation of the representative emission factors of the power generation technologies used in the power grid and the emissions due to the electricity imports. In this latter case, it means that the real-time power grid data of the interconnected electric networks are required if the electricity imports contribute significantly to the emissions of the studied power grid.

Considering that not all power grid operators provide real-time data, it often happens that the emission factor related to the electricity imported from an electric network has to be approximated using the annual average emission factor of that power grid (annual data are widely obtainable).

If the quality of the power grid and emission data is high, then the module provides a more accurate assessment of the emissions attributed to the consumption of electricity than conventional models.

The use of marginal emission factors to plan electricity consumption is an important feature of the model since a lot of "green electricity consumption plans" ignore the concept of marginal electricity. By identifying the marginal generators affected by changes in the demand, the module provides more representative assessments of the emissions that can be avoided by smart electricity consumption.

It should be noted, however, that there is some uncertainty on the marginal emission factors due to power grid operations. Indeed, marginal generators can be classed under different types depending on the temporal range they operate. Some are used in real-time (<5 min range) to meet changes in the power demand while others may fulfill the changes in the short term (10-30 min range) to free the real-time marginal generators. The modelling of the operation of these marginal generators is, however, difficult due to the lack of power grid historical data. Thus, the marginal emission factors calculated by the model are based on partial information regarding the operation of marginal generators. More representative marginal emission factors could be calculated with the availability of more detailed data. Another source of uncertainty on the marginal emission factors is the variation of the intermittent power generation. Indeed, some power plants have to adapt their capacity to absorb the changes in wind farms and solar panels generations to meet exactly the power demand. The method used to calculate the marginal emission factor includes these changes bringing some noise to the "real" marginal power mix that aims to identify the emissions associated with a change in the power demand (instead of a change in the production due to intermittent power changes). More research is actually being done on historical data to better understand the coupling of the controllable power plants with the intermittent power generators.

### Module 2: Recommendations on electricity consumption

The strength of the module is to provide information on the future intensity of electricity. Such information can be very useful to electricity consumers to schedule their activities and reduce the power grid emissions. This module uses the power grid data and emission factors calculated by the first module. Therefore, its robustness depends on that of the first module. Its strength is also dependent on the machine learning model performances. While the predictions of the global emission factors are good, improvements are necessary for the predictions of the marginal emission factors. For that reason, the second module is considered as semi-completed and needs further work. An important point regarding the use of the emission factors is that the use of the global emission factor aims to reduce the consumer emissions while the marginal emission factor aims to reduce the global emissions of the power grid. This subtility is important since minimizing its own emissions does not necessarily lead to the global minimization of emissions (Dandres et al., 2017).

**Global emission factors**: the predictions are generally good enough to help the consumers to reduce their own emissions but it is observed that when a sudden temperature change occurs between the training period (i.e. the past 28 days) and the predicted period (i.e. the next 24 hours), then the quality of the predictions are sometimes seriously affected. It can be explained by the influence of the temperature on the power demand. For instance, in winter, a sudden decrease in the temperature leads to a rapid increase in the use of heating systems that rises the global power demand. Similarly, in summer, a rise of the temperature is associated with the increasing use of air cooling systems that also increases the global power demand (symmetric effects can be observed with opposite temperature changes). In these situations, different power plants may be involved to meet the power demands of each period. Thus, the power mix of the training period and its emission rates may differ sensibly from those of the predicted period. These effects depend on the regions and the use of electric equipment to heat or cool the buildings. For that reason, the algorithm of the machine learning model is currently being improved by introducing meteorological data in its training. Moreover, due to the rapid development of machine learning techniques, new algorithms are also tested (Abdulnour et al., in preparation).

**Marginal emission factors:** the quality of the predictions is actually not suitable to help the consumers to reduce global emissions. While the global power mix changes slowly in time, the variations of the marginal power mix are greater and faster which results in more chaotic changes in the marginal emission factors. The prediction of marginal emissions is therefore still an area of research. Different approaches are being tested: predicting the marginal power mix or directly the marginal emissions. Using the power grid and emission data only (including forecasts provided by the electric operator) or also adding the prediction of the global emission factor. It is expected that the variations in the intermittent sources of energy impact the marginal power mix more than the global power mix. Thus, investigating the power mix changes due to changes in intermittent power generation could provide insightful information to predict the marginal power mix.

The strength of this module is to provide real-time information to the consumers so they can adapt their power demand to reduce global emissions. Moreover, instead of focusing on the global power mix, it aims to provide recommendations based on the power plants that would be truly impacted by a change in the demand. As demonstrated in Dandres et al. (2017) on the management of a cloud computing load dispatched between two data centers powered by different power grids, the consideration for the marginal electricity improves the usual way to minimize emissions and provides opportunities to additional emission reductions at the global level rather than just focusing on the data center level.

One important limitation of this module (for both the global and marginal emission factors) is that power grid data have to be collected continuously to feed the machine learning model that also has to be trained constantly.

### ***Module 3: Consequences on the power grid and emissions module***

This module stands on several hypothesis and data that are used to represent human behaviour. Moreover, the effective reduction of emissions is linked to the recommendations that are based on the predictions from the second module. Consequently, there are in theory two types of uncertainty that can affect the module results : (1) the uncertainty coming from the modelling of human behaviour and (2) the uncertainty due to wrong recommendations.

Unlike the second module, it is more complex to validate the modelling of the third module. Indeed, the predictions of the second module can easily be compared to the real emission factors. Comparing the predicted response of consumers to the real one would require access to power consumption data of people participating in a demand-side management program. Then, the results of the agent-based model could be compared to the real consumer response.

The main strength of the agent-based model is not the simulation results but its ability to identify the factors and drivers of human behaviours that lead to these results. Its main strength is its capacity to enhance the adhesion to demand-side management programs by proposing measures that will be more welcomed by the program participants. Another strength of the module is to take into account the effect of human interactions over time instead of considering each participant independently. One the one hand, it provides more realism to the simulations because such interactions happen and may influence the behaviour of each consumer. On the second hand, it enables the use of these interactions to enhance the adhesion of the population to the demand-side management program.

## C. How it compares with other models with similar objectives

To the best of the author’s knowledge, there is no model with similar objectives. Some methods or models may, however, have similar objectives of the model modules.

### *Module 1: real-time electricity emissions*

With the increasing availability of power grid data, methods and models have been developed to calculate real-time emissions of power generation (Gordon et al., 2009; Maurice et al., 2014; Roux et al., 2016; Tranberg et al., 2019). While Gordon was indeed a pioneer in studying the hourly variations of the factors in Ontario, our work (Maurice et al., 2014) was still among the firsts to propose a method to calculate it. IEEE 1922.2 (Dandres et al., 2019) is also the first initiative to standardize the calculation of a real-time electricity emission factor. Today, Internet websites https://www.electricitymap.org and https://www.watttime.org provide real-time emission factors for the regions where power grid data are available in real-time. Such information is commonly used by the information and communication technologies community to design algorithms that minimize data centre network emissions by processing the server load in the region where the emission rate is the lowest (Giacobbe et al., 2015; Li et al., 2016). These approaches neglect, however, the effect on the power grid of sudden increases in regional power demands. This is the reason why it is proposed to consider also the marginal emissions due to server load management within data centre networks (Dandres et al., 2017). The calculation of marginal electricity emissions has long been made in the context of life cycle assessment (LCA) (Mathiesen et al., 2009). But unlike the previous works in LCA, the method used in this model is based on historical data rather than market assumptions and it identifies a mix of marginal technologies rather than a single one. Furthermore, the method used in this model focused on different time scales than those documented in previous LCA models. The model provides marginal emission factors at a sharp temporal granularity rather than identifies the future power plants that will be added to the network in the coming years as done in previous LCA models.

The concept of marginal electricity remains actually still unknown by most of the people developing methods to reduce emissions related to electricity consumption. Thus, by providing marginal emission factors, the first module is, in the context of emission reductions by the consumers, ahead of other existing approaches.

### *Module 2: Recommendations on electricity consumption*

Machine learning is applied to a large variety of activities, including the electric sector, but at the time the second module was developed, only one study was found using machine learning to predict electricity emission factors (Wang et al., 2016). The authors followed a different approach to predict the emission of the PJM network (powering Mid-Atlantic US states). Instead of using the time series of electricity emissions they used the marginal price series of electricity. This approach seems to provide good results in networks were fossil power generation dominates. However, it does not seem to be successful in regions with significant contributions from renewable energy (because unlike fossil power, hydropower can generate marginal electricity at a very low cost). As reviewed by Rolnick *et al*. (2019)[1] new developments have been made in the field of power grids and machine learning but the method used in the model was not compared to them so far.

#### ***Module 3: Consequences on the power grid and emissions module***

This module has been released recently (October 2019) and the comparison with other models is too preliminary to be presented here.

### D. Its place in the energy landscape / modelling ecosystem

The purpose of the model is to provide real-time recommendations to electricity consumers to help them to reduce their emissions. Thus, it should be used to create and implement dynamic demand-side management programs. The consideration for marginal electricity and a better understanding of human behaviour would help to design more efficient measures: tackling the source of marginal emissions and increasing the chance that the behavioural measures are adopted by the participants of the demand-side management programs. It should be noted that it is an evolving model that needs to be updated in real-time with the power grid data (and possibly, in the long-term, with the trends in human behaviours).

The modules of the model could also be integrated into prospective energy models (TIMES and others) to take into account the effect of dynamic demand-side management programs in broader energy policies. It requires however that (1) the granularity of the prospective energy model is sharp enough to enable “real-time” recommendations to the electricity consumers.

Finally, the model has a huge potential for emission reductions with the emergence of the Internet of things and smart buildings. Indeed, assuming it will become possible to control each electric equipment, the smart programming of their usage could avoid a lot of emissions

[1] arXiv:1906.05433v2 [cs.CY] 5 Nov 2019

automatically without involving significant behavioural changes. For instance, it could become possible to program the loading of an electric vehicle by simply specifying the time when it has to be reloaded. Then, a smart controller would integrate the deadline constraint to find the best time to load the battery. In addition, the model could also share the electricity of the battery with the power grid to prevent the use of the most pollutant generators (while this effect could be negligible for one vehicle, it could become important for a fleet of electric vehicles).

## E. The state of development & evolution roadmap

The model is still under development but the modules are already able to provide concrete results.

### ***Module 1: real-time electricity emissions***

The calculation of the global emission factor is considered as completed (it has been standardized in IEEE 1922.2). The calculation of the marginal emission factor could be improved by dissociating the power plants that compensate for the fluctuations in intermittent power than the others that directly adapt their capacity to meets the change in the power demand.

### ***Module 2: Recommendations on electricity consumption***

The predictions of the global emission factors are most of the time good enough to help the electricity consumers to reduce their emissions but the predictions of the marginal emission factors need to be improved. Nevertheless, both prediction types could be improved by training the model with additional data (especially meteorological forecasts and information on coupling the intermittent and conventional generators) and testing new algorithms (data science is actually progressing very fast). The master student Lawrence Abdulnour (MILA) is currently improving the predictive algorithms by introducing an attention mechanism that weights the contribution of the training data depending on their feature (Abdulnour et al., in preparation). Preliminary results show that the mean absolute percentage error can be reduced by 3 % thanks to the attention mechanism added to the LSTM model.

### ***Module 3: Consequences on the power grid and emissions module***

The theory behind the module has been developed but it needs to be tested and validated in real cases. Unlike the two other modules, the application of this module to a specific population probably requires more effort to take into account the regional cultural specificities that influence human behaviour.

# Results

## A. Presentation and interpretation of the results

### *Module 1: real-time electricity emissions*

### Deployment: New England power grid

For the purpose of the explanation, the model has been deployed for the New England (NE) power grid (New England is located in the North-East of the USA). The NE power grid has a 20.8 GW installed capacity and relies mainly on nuclear and natural gas (see Figure 6).

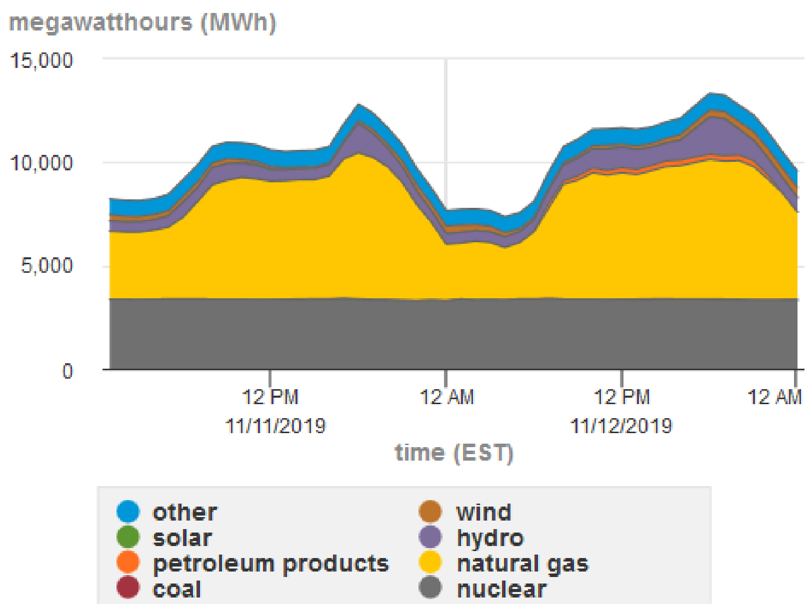


**Figure 6 – Hourly net generation by energy source in New England**
Source: U.S. EIA

It can be seen in Figure 6 that nuclear power plants have a steady production while natural gas power adjusts its capacity to meet the demand in real-time.

The NE power grid is interconnected with the New York (2000 MW), Quebec (2000 MW) and New Brunswick (1000 MW) power grids and usually imports electricity from the Canadian provinces.

Practically, the real-time emissions are calculated by multiplying the real-time power generation of each technology (data retrieved from the ISO-NE dashboard) with its corresponding emission factor (provided in Table 2).

**Table 2 – Emission factors for New England power plants**

| Technology | Emission factor | Unit |
|---|---|---|
| Coal power plant | 0.970 | $kgCO_2/kWh$ |
| Natural gas power plant | 0.417 | $kgCO_2/kWh$ |
| Oil power plant | 0.926 | $kgCO_2/kWh$ |

The emission factors were computed with the annual emission data of each NE power plant retrieved from the U.S. Energy Information Administration database (U.S. EIA). They include only the direct $CO_2$ emissions attributed to the combustion of fossil fuels. Therefore, nuclear and renewable power plants are associated with zero $CO_2$ emissions. More complete emission factors (i.e. life cycle emissions of power plants and non-$CO_2$ emissions) could be calculated with the ecoinvent database. $CO_2$ emissions from the biomass combustion are not accounted for here since the carbon was captured from the atmosphere during the biomass growth. It would, however, be pertinent to consider the timings of the carbon emissions and captures in the analysis of a bioenergy policy since these two phenomena do not occur at the same time and may affect the achievement of yearly GHG emission reduction targets.

The effects of imports and exports of electricity on the NE power grid emissions are also considered. When electricity is imported, emissions associated with its generation abroad (by New York or Canadian power plants) are added to the NE power grid emissions. When electricity is exported, emissions related to its generation (by NE power plants) are subtracted. Import and export data are also retrieved from the ISO-NE dashboard. Emissions are calculated by multiplying the amount of electricity imported/exported by the relevant regional emission factor that is calculated by summing the emissions of the local regional power plants and then by dividing them by the regional amount of electricity generated. It is implicitly assumed that imported electricity that is re-exported (a.k.a wheel-through) is not considered in that calculation. In other words, if New York is importing electricity from Pennsylvania (PJM power grid) at a given time and also exporting to New England at the same time, then it is assumed that the electricity exported to New England has been generated by the New York power plants and is not coming from Pennsylvania. This is a simplification of reality because wheel-through may actually occur but such transactions are very difficult to model due to the lack of public data to track them.

### Emission factors

The regional emission factors of New York power grid are calculated using the real-time power generation data provided by the NY-ISO dashboard. The emission factor of each generating technology has been calculated using the U.S. EIA database similarly to those of the NE power grid (see Table 4).

**Table 3 – Emission factors of the New York power plants**

| Technology | Emission factor | Unit |
|---|---|---|
| Natural gas power plant | 0.458 | $kgCO_2/kWh$ |
| Coal power plant | 1.042 | $kgCO_2/kWh$ |
| Oil power plant | 0.859 | $kgCO_2/kWh$ |
| Dual fuel power plant | 0.951 | $kgCO_2/kWh$ |

The regional emission factor for the Canadian province cannot be calculated in real-time due to the lack of real-time data for these regions. In the case of Quebec, electricity is mostly produced by hydroelectric dams and wind farms (99.8% of electricity is generated from renewable sources according to Hydro-Québec). Therefore, a null $CO_2$ emission factor is associated with the electricity imported from Quebec.

The New Brunswick power grid is supplied by a larger variety of energy sources than Quebec: nuclear, natural gas, oil, coal and renewable energy. Due to lack of real-time data, the New Brunswick emission factor was calculated with the annual power generation data provided in the last NB Power annual report by multiplying the amount of electricity generated by each generating technology with its corresponding emission factor (using NE emission factors as a proxy) and then by dividing the emissions by the total electricity generated in New Brunswick. The calculation leads to 0.250 $kgCO_2/kWh$. This example illustrates the difficulties that can be encountered when applying the model to a region where some real-time data are missing (data from the Canadian provinces in this case). It also shows the solutions to overcome these issues.

Practically, the $CO_2$ emissions of the NE power grid were calculated for each hour of 2018. Then, the NE emission factors were calculated by dividing these hourly emissions by the hourly power grid loads. Statistics results are provided in Table 4 for the local production and the power grid (including exchanges with other power grids).

**Table 4 – Emission factor statistics of the New England power grid**

| Hourly Emission factor | Local | Local + Import - Export | Unit |
|---|---|---|---|
| Average | 0.220 | 0.197 | $kgCO_2/kWh$ |
| Maximum | 0.492 | 0.439 | $kgCO_2/kWh$ |
| Minimum | 0.072 | 0.064 | $kgCO_2/kWh$ |
| Standard deviation | 0.057 | 0.053 | $kgCO_2/kWh$ |

It can be seen that the average New England emission factor is higher for local production. This is because New England generally imports electricity that is generated with low $CO_2$ emissions (especially from Quebec).

### Smart house emissions

The hourly emission factors are useful to calculate the $CO_2$ emissions of any electricity consumption. The use of hourly emission factors provides more accurate results for time-varying electricity consumption than using a yearly average as it is usually done in carbon footprint methods (ex: GHG Protocol).

For example, let's consider a house that would have the consumption profile represented in Figure 7. The power demand is low at night because the people sleep, then it rises in the morning when they prepare their breakfasts. Some of them go to work and have lunch off-site, while some others come back home to cook lunch. This explains why the demand is not as high as for breakfast. At the end of the afternoon, everybody comes back home and starts watching TV, doing laundry, preparing dinner, playing console games, etc. which result in an important increase in power demand. Finally, everybody goes to bed which reduces the power demand at night.

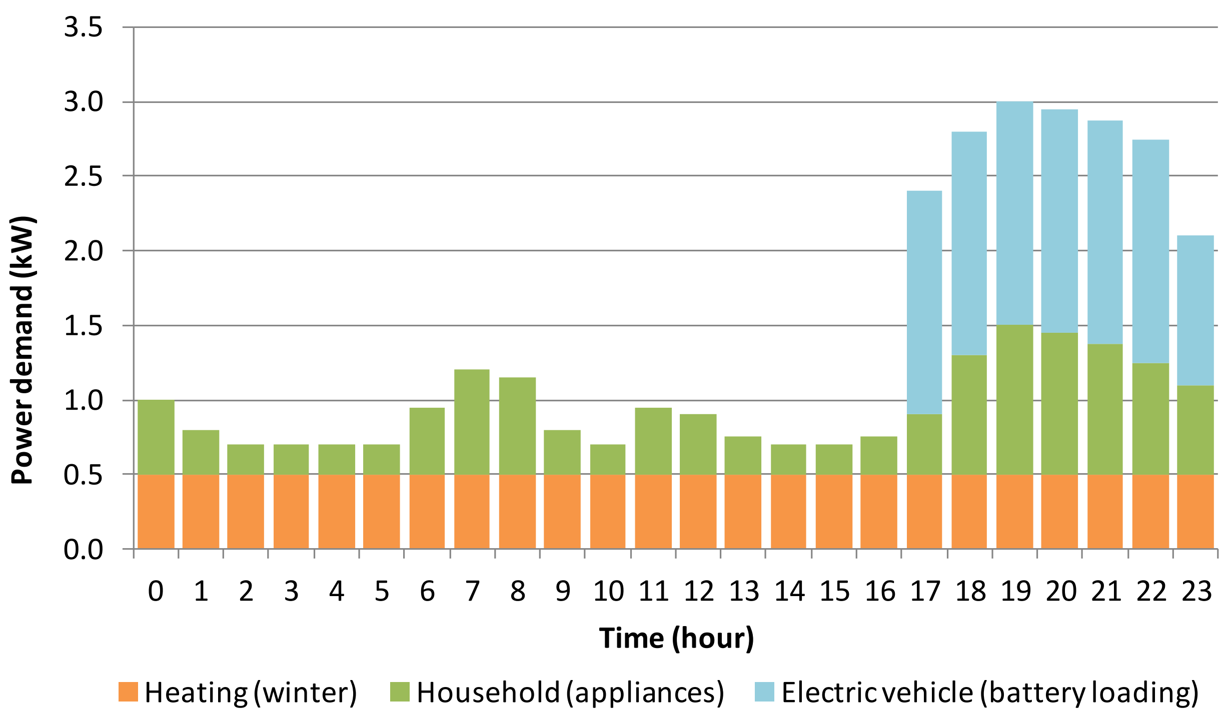


**Figure 7 – Hourly power demand of a household (example)**

Additionally to the house appliances, it is assumed an electric heating system is used from November to Mars (0.4 kW/h) and that an electric vehicle is plugged every day in the evening to reload its batteries (loading 10kWh using a 1.5 kW charger). Globally, with an annual consumption of 5840 kWh (excluding the electric vehicle) this household would be more efficient than the average one in Massachusetts[2] (7000 kWh).

If we apply the NE power grid model retrospectively to calculate the past household emissions, it is found that the use of the annual average emission factor would underestimate the household emissions by 6%. That underestimation is of 8% when focusing on electric vehicle emissions. Such errors in emission assessments may be significant sources of uncertainty when assessing the mitigation measure potentials which consequently may lead to non-optimized decisions. In the case of electric vehicles, the real GHG emissions reductions would be actually smaller than the one anticipated with the annual average emission factor.

### Other information

The model provides also a better knowledge of the emission intensity of household electricity consumption. For instance, loading the batteries of the electric vehicle emits 210 $gCO_2$/kWh while it is 190 $gCO_2$/kWh for the heating system. Combined with the volumes of electricity consumed and the flexibility of consumption, it enables the design of new energy efficiency policies. In this case, focusing on the battery loading would provide more emission reductions than targeting the electric heating system.

Finally, the model can help to follow the emissions over time. For instance, Figure 8 provides monthly household electricity emissions. It can be seen that these emissions may vary significantly for winter months despite the electricity consumption is very similar for each winter months (being different because of the number of days per month). It means that saving electricity in January would reduce more the emissions than saving it in December.

[2] https://providerpower.com/power-to-help/average-electric-bill-rates-consumption-massachusetts/

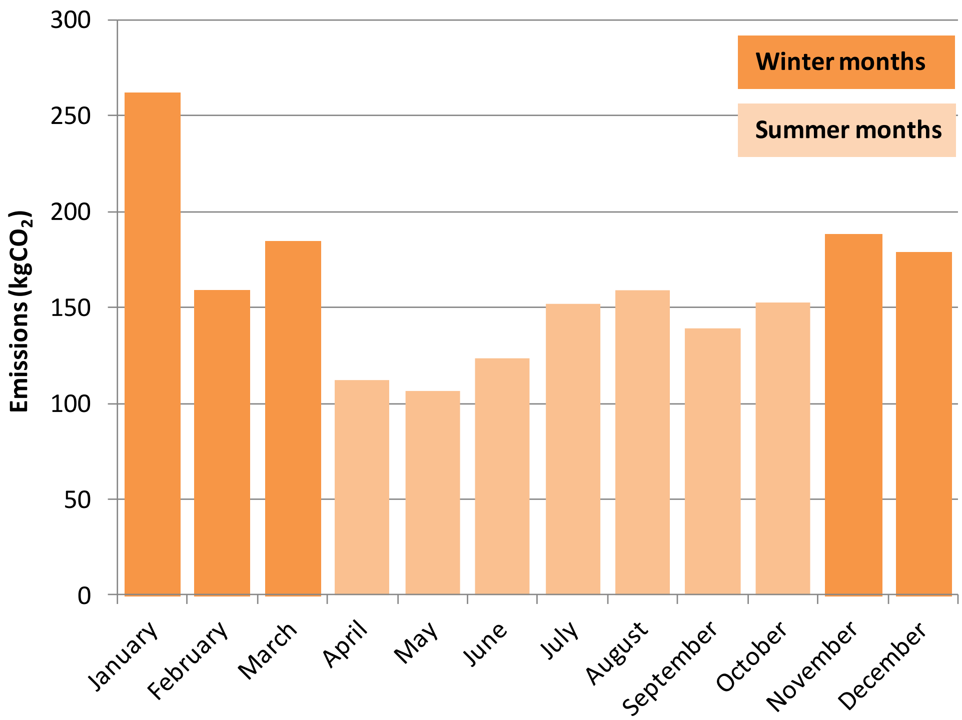


**Figure 8 – Household electricity GHG emissions per month**

## Global and marginal electricity emissions

In addition, the NE power grid model provides information on marginal electricity that can be used to optimize the electricity consumption of customers. One common mistake made by non-experts in power generation is to recommend the increase of power consumption at the time when the global electricity emission factor is the lowest to decrease their emissions. As illustrated below in the example, it is an oversimplification that can actually lead to an increase in global emissions.

Figure 9 represents the power generation in New England on June 15, 2018. It can be seen that nuclear power plants generate a steady amount of electricity regardless of the variation in power demand. Nuclear power plants emit no carbon emission during their operation. Thus, by contributing to 30 to 50 % of the power mix, they help to maintain a low global $CO_2$ emission factor (between 130 and 200 $gCO_2/kWh$, see Figure 11 hereafter).

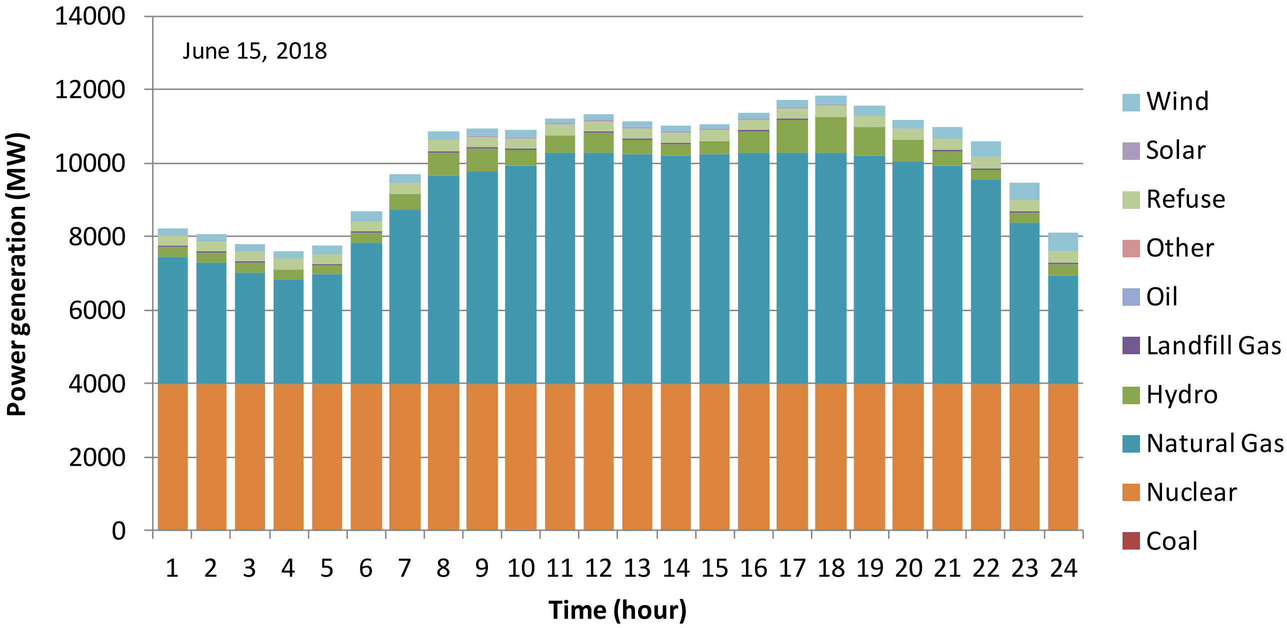


**Figure 9 – New England power generation on June 15, 2018**

Choosing the time when the emission factor is the lowest to minimize its GHG emissions assumes that all power plants will equally increase their capacity to face the additional demand. It is known, however, that nuclear plants won't increase their electricity production because of an increase in the power demand. Therefore, a different emission factor that only includes the power plants that adapt their generation capacity in response to a change in the demand must be used. This is the purpose of the marginal emission factor provided by the model.

Figure 10 identifies the changes in the capacity of each generating technology over the day. It shows that natural gas and hydropower contributions change the most during the day (natural gas in the early morning and night and hydro during the day). Figure 10 does not represent exactly the marginal electricity mix. Indeed, the marginal electricity is defined as the electricity generated by the generators that have adapted their power generation capacity to meet a change in the demand. However, Figure 10 also includes the power generation changes compensating for the intermittent generators.

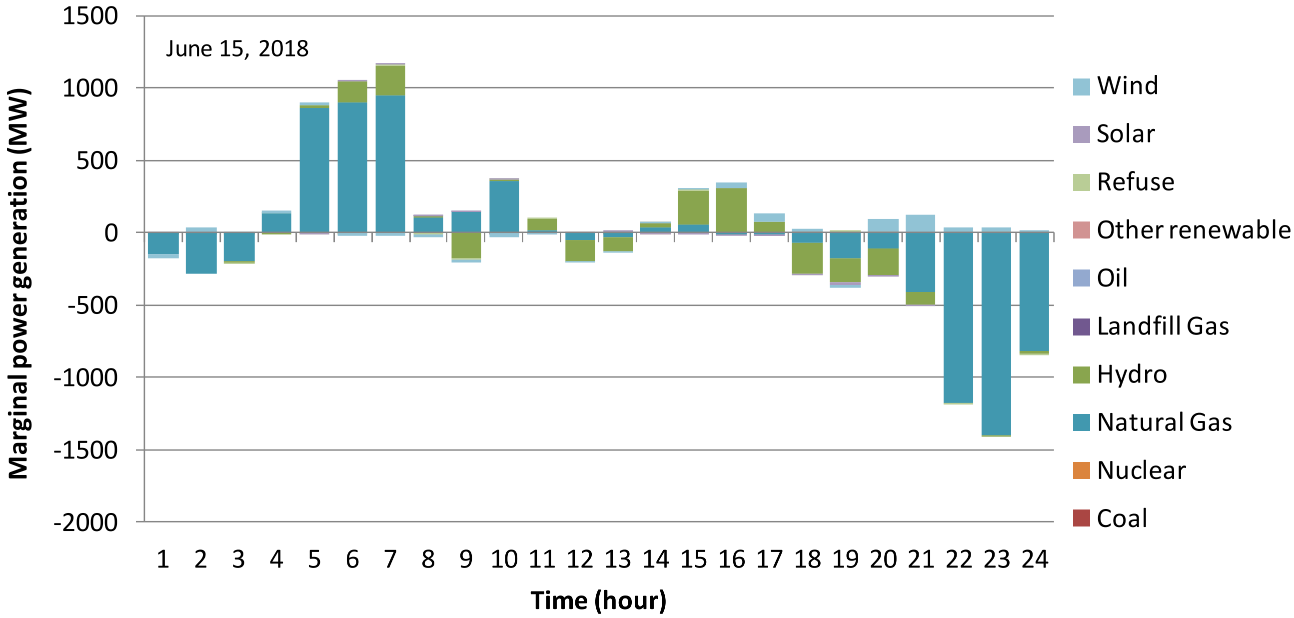


**Figure 10 – Changes in power generation in New England on June 15, 2018**

It can also be seen that some power plants increase their generation capacity at the same time than others reduce it. For instance, at 9 am hydropower is reduced (-180 MW) while it is increased from natural gas (+140 MW). In such a situation, it is unclear if an increase in the power demand would result in an increase in power generation from natural gas or a decrease in the reduction of hydropower. The approach developed in Dandres et al. (2017) (local marginal power generation) and then improved in Milovanoff et al. (2017) and Walzberg et al. (2019a) (adding global and marginal electricity imports and exports) solves that problem by considering all changes (with the exception of intermittent power) as possible contributors to marginal electricity.

Figure 11 compares the global and marginal emission factors for June 15, 2018, in New England. It shows that both emission factors do not have their minimum at the same time. While it is around 3-5 am for the global emission factor, it is around 4 pm for the marginal emission factor. More importantly, the two factors evolve in the opposite manner: the global emission factor is high during the day while at this time the marginal emission factor is low and inversely at night. This means for instance, that scheduling the consumption of 1 kWh at 3-5 am (minimum of the global emission factor) would, in fact, require the use of more emitting marginal generators. While an estimation based on the global emission factor would be 150 g$CO_2$, the usage of the marginal generators would, in reality, lead to 250 g$CO_2$, an emission increase of 67% in the emissions. This latter value should be seen as a maximum because a marginal demand becomes part of the global demand after a certain period of time. The length of that period is however unclear.

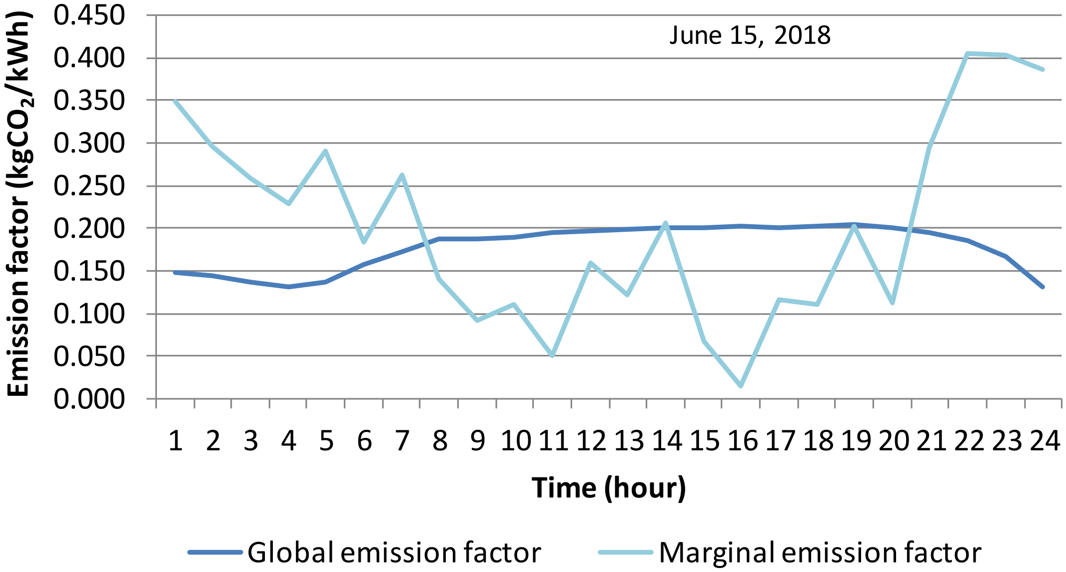


**Figure 11 – Average and marginal emission factors in New England on June 15, 2018**

In summary, the first module can generate two types of results. Average emission factors that are used to calculate the emissions due to the consumption of electricity (in the present or past) and marginal emission factors that are used to plan the electricity consumption in the future.

### Module 2: Recommendations on electricity consumption

The prediction module has been tested on several networks. Some results are presented here for the PJM network (Mid-Atlantic region in the US), France and Ontario. In each case, the LSTM model has been trained with the historical data of the power grid (cf. Table 5).

**Table 5 – Source of historical data of power grids**

| Power grid | Source of data |
|---|---|
| PJM interconnection | http://dataminer2.pjm.com/feed/gen_by_fuel |
| France | https://www.rte-france.com/fr/eco2mix/eco2mix-mix-energetique |
| Ontario | http://reports.ieso.ca/public/GenOutputbyFuelHourly/ |

The hourly electricity emissions factors for these power grids were calculated with the software Simapro (version 8) using the ecoinvent life cycle database (version 3). In the three cases, the predictions of the global emission factors were generally good enough to identify the time when the emission rates are the lowest and follow the hourly variations (see Figure 12, Figure 13 and Figure 14).

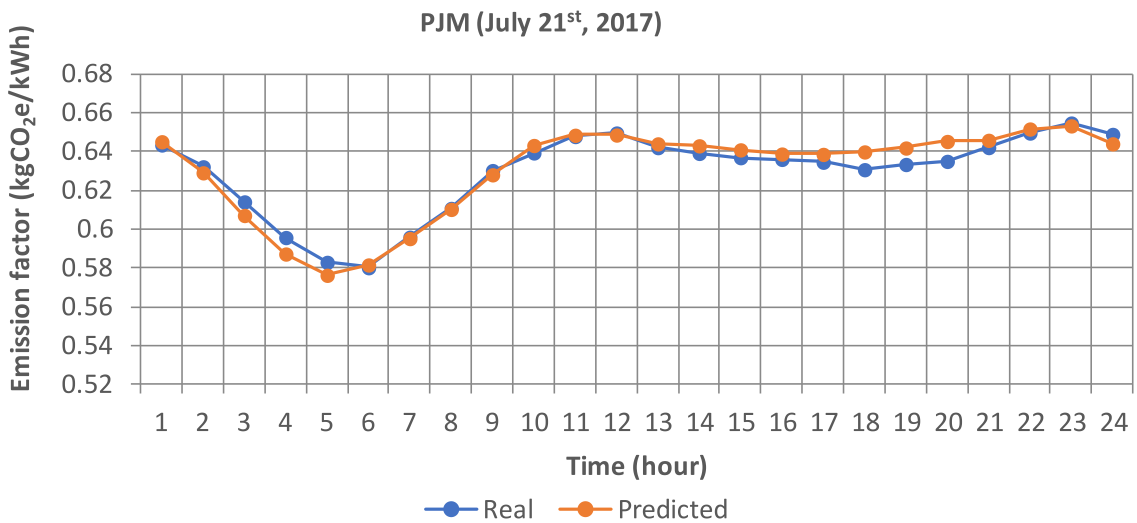


**Figure 12 – Example of a good prediction of the PJM emission factors**

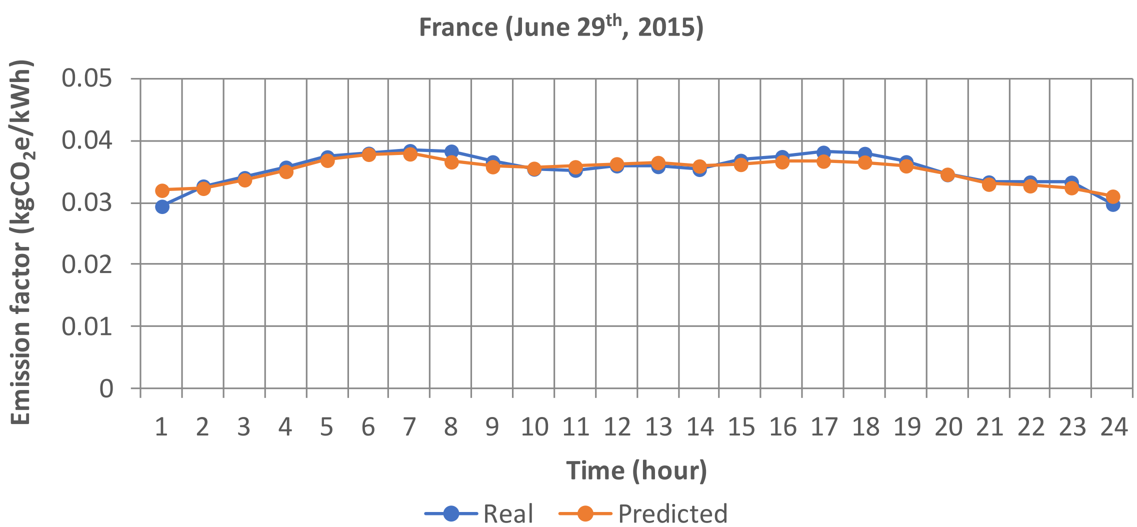


**Figure 13 - Example of a good prediction of the France emission factors**

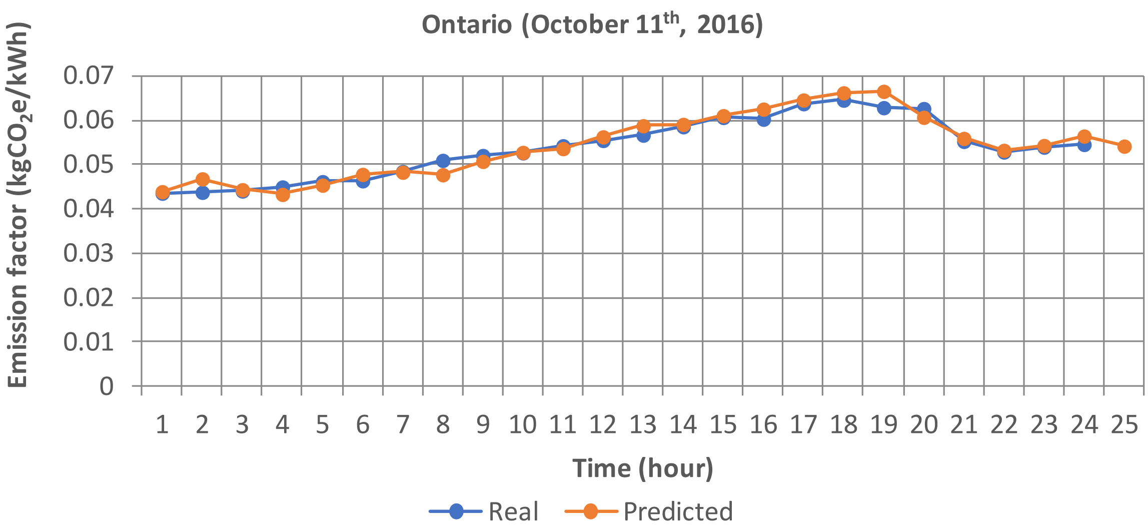


**Figure 14 – Example of a good prediction of the Ontario emission factors**

For some days, the predictions diverge from the reality generally due to sudden changes in the temperature (see Figure 15, Figure 16 and Figure 17). It is interesting to note that even if the predicted values are wrong in these cases, the shape of the curve is usually still valid.

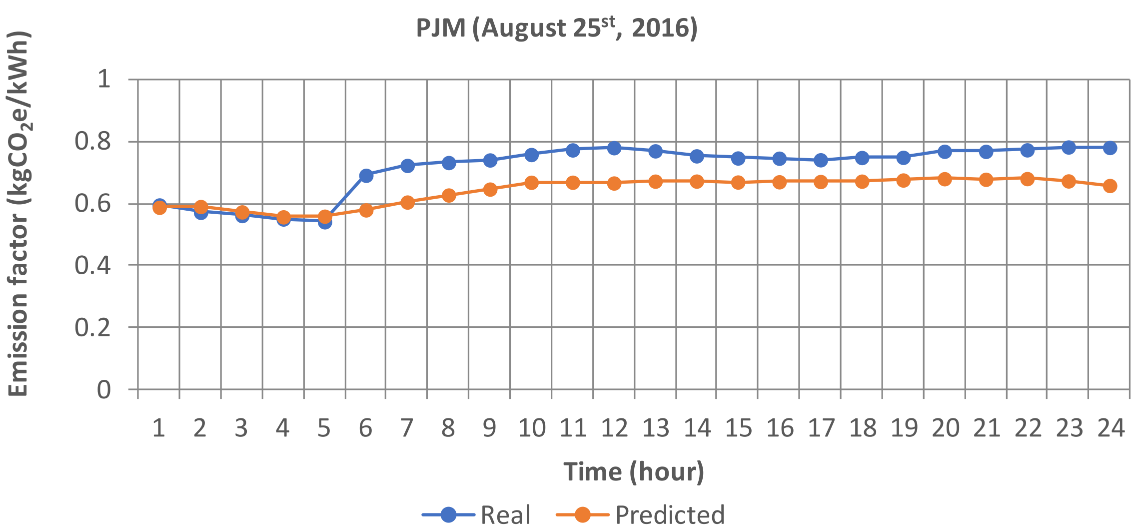


**Figure 15 – Example of a diverging prediction of the PJM emission factors**

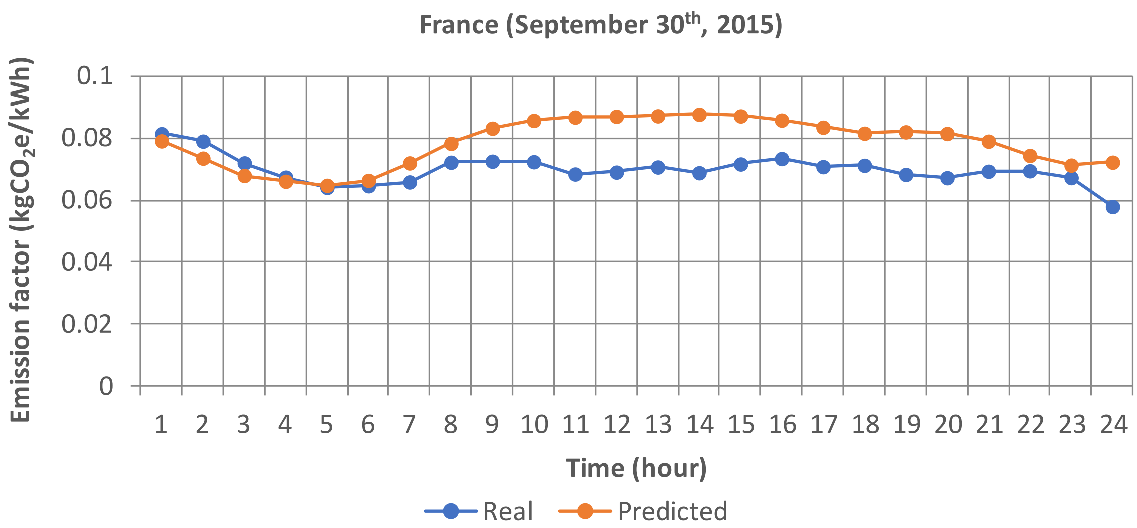


**Figure 16 – Example of a diverging prediction of the France emission factors**

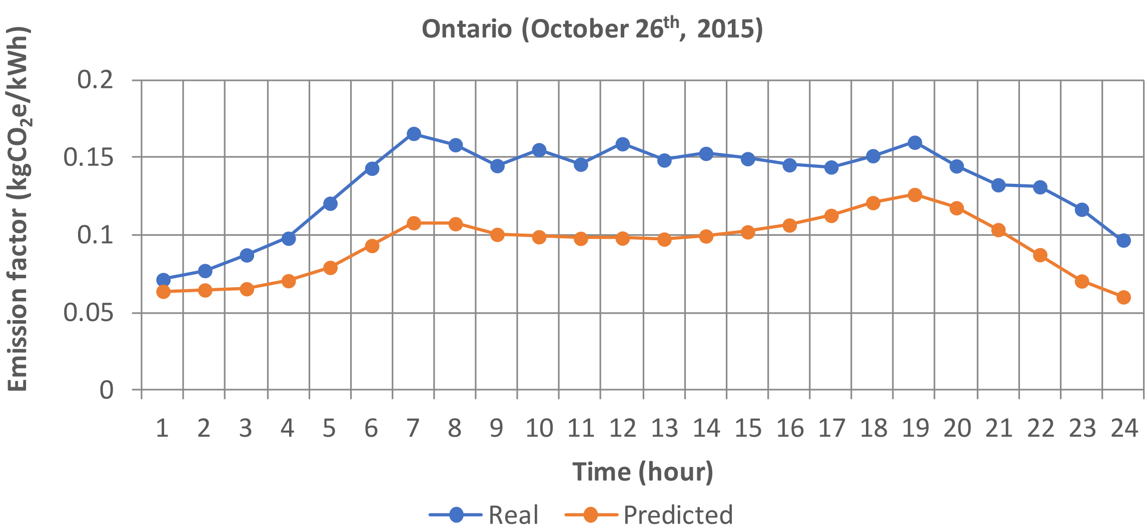


**Figure 17 – Example of a diverging prediction of the Ontario emission factors**

On average, the relative error of the prediction is 2% for PJM, 11 % for France and 12% for Ontario. The higher errors for France and Ontario are due to the more important contribution of intermittent sources of electricity (wind or solar) that are less foreseeable. Considering the PJM emission factors are around 5 times greater than the ones of France and Ontario, the absolute error on emission factors is similar for all regions.

The prediction of the emission factors enables the development of electricity consumption strategies to reduce GHG emissions. These strategies should be adapted to consumer profiles and the flexibility to change their habits. For instance, a strategy could focus on concentrating the power consumption when the emission factor is the lowest while another could simply aim to reduce the power consumption when the emission factor is the highest. Some strategies could focus on shifting the power demand while others could also aim to reduce the power demand.

The emerging Internet-of-things offers new possibilities to manage automatically electric industrial equipment and household appliances. This is, therefore, a great opportunity to integrate smart strategies in the design of connected objects.

### *Module 3: Consequences on the power grid and emissions module*

The best power consumption strategies may fail to reach their objectives if they are not effectively implemented. One source of failure is human behaviour, that is why it has to be considered in these strategy deployments.

The human behaviour model was tested in a virtual case study where people of 100 smart homes located in the region of Toronto (Ontario power grid) were receiving recommendations to minimize their GHG emissions over one year (April 2013 to March 2014). Two types of measures were recommended to the people: shifts and reductions of power consumption. It is assumed the people would not apply more than one measure at a time. Three scenarios were explored to evaluate the reductions of GHG emissions due to the enforcement of the measures:

- Scenario 1: recommendations on power shifts only;
- Scenario 2: recommendations on power reductions only;
- Scenario 3: recommendations on power shifts and reductions.

Each scenario was simulated 10 times with the agent-based model (a greater number of simulations would have led to more accurate results but considering the long time needed to run a single simulation, 10 simulations were judged sufficient for the purpose of the demonstration in this report).

Figure 18 presents the results of the simulation regarding the reduction in electricity and GHG emissions.

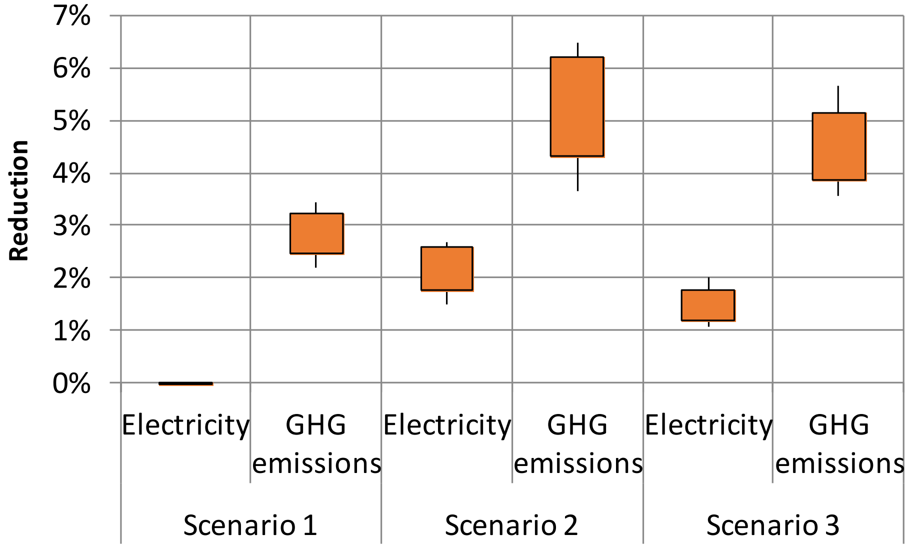


**Figure 18 – Reductions of power consumption and GHG emissions due to measures**

*Legend*: in each column, the reduction is presented as a range of values (the orange box) defined as the average reduction +/- the standard deviation. The minimum and maximum reductions observed during the simulations are also reported (the vertical black line). Scenario 1 includes recommendations on power shift only, scenario 2 includes recommendations on power reductions only and scenario 3 includes both types of recommendations.

It can be seen that despite there is no reduction in power consumption in scenario 1, shifting the power demand in time still enables a 3 % reduction in GHG emissions. In the second scenario, a decrease of 2 % in electricity consumption provides a 5.5 % reduction in GHG emissions. Finally, the GHG emission reductions of the third scenario are between the first and second scenario (it does not cumulate the reductions of the first two scenarios since only one measure can be adopted at a time). The third scenario, despite it offers more options to the consumers that could facilitate the adoption of the recommendations, does not enable more reductions in GHG emissions. Its reductions are however close to those of the second scenario.

# Discussion

## Place in the ecosystem

### A. Usage

#### *Concrete examples*

**From current or past studies**

The modules of the model have been used in various contexts to calculate the emissions due to electricity consumption, predict the best time to consume electricity, model the human behaviour in demand-side management programs. The module results are sometimes used in a broader model to generates other results ( e.g. Elzein et al. (2018) where the real-time emissions factors are used to operate energy storage systems in a smart grid context).

- Maurice et al. (2014): the GHG emissions of a cloud computing system powered by the Ontario electric utility are assessed hour by hour over a year. It is found that these emissions may vary significantly between hours, days, weeks, months and seasons. Moreover, the comparison with the emissions calculated using the annual emission factor reveals that using a static emission factor may be an important source of uncertainty on the GHG emission calculation.
- Vandromme et al. (2014): the authors calculate the GHG emissions of a videoconference system using real-time emission factors. They compare different computer server configurations (cloud vs non-cloud, and varying the number of CPU and size of RAM allocated to the videoconference service) to identify the one minimizing the GHG emissions of the service. It is also found that server virtualization enables a significant reduction in GHG emissions.
- Dandres et al. (2015): the GHG real-time emissions of several server configurations providing an instant messaging service are compared (cloud vs non-cloud, and varying the number of CPU and size of RAM allocated to the videoconference service). A compromise is found to reach a certain quality of services (involving more computer resources) without compromising the GHG emissions. The cloud configurations are always associated with the lowest emissions.

- Dandres et al. (2017): the server load of an online service (e.g., computing, picture or video editing, etc.) is dispatched along a data centre network to minimize its GHG emissions in real-time. The results show that the consideration for the consequences of sudden data centre power demand changes on the power grids (marginal electricity and related emissions) plays an important role when minimizing the GHG emissions of the data centre network.
- Milovanoff et al. (2017): the environmental performances of several demand-side management programs are compared in the French context. The use of real-time emission factors enables a deeper comprehension of the environmental impacts associated with the consumption of electricity (power generating technologies and electricity imports) depending on the time it is consumed. The results show the importance to take into account electricity imports and reveal that it is not possible in France to minimize simultaneously the GHG emissions of electricity and its impacts on the human health, the ecosystems and the natural resource depletion.
- Riekstin et al. (2017): the authors develop and train a machine learning model with power grids data to identify the best time of the day to use an appliance in the Quebec province. It is found that launching the dishwasher at the right time may save up to 25 % of its GHG emissions as compared to the worst time.
- Riekstin et al. (2018): the model proposed in the previous paper is improved and tested in other regions: US (PJM interconnection), Ontario and France. The predictions are then used to optimize the power consumption of a smart house and reduce its GHG emissions in real-time. It is found, in the Ontario case, that 30 $gCO_2e$ can be saved for each dishwasher cycle if it is started at the right time. In the case of an electric vehicle, reloading the batteries (7.8 kWh per day, in Ontario) at the proper time can save up to 310 $gCO_2e$ per day.
- Elzein et al. (2018): a dynamic model is developed to optimize the operations of an energy storage system deployed in one of the regional French power grids (Normandy). The environmental impacts of the power grid are calculated in real-time and an algorithm optimizes the time to unload the energy storage system (to prevent the use of the most polluting generators) and reload it (when the emission factor is the lowest). Several optimization strategies are compared (minimizing the production cost, the GHG emissions, the impact on the human health, ecosystems and natural resource depletion). Once again, it is found that not all objectives can be minimized simultaneously. The results also show that the use of real-time emission factors greatly

improves the accuracy of the emission assessment of the energy storage as compared to methods using static emission factors.

- Dandres et al. (2019): this paper presents the IEEE 1922.2 standard in which the electricity emission module has been standardized to calculate the emissions of information and communication technology systems. Nevertheless, this standard focuses on the calculation of the real-time electricity emission factors and can be used to assess the emissions attributed to any electricity consumption (i.e., using the global emission factor).
- Walzberg et al. (2019a): the authors assess the environmental impacts of household electricity consumption using global and marginal emission factors under different temporal granularity (hourly up to annually). They design a method combining global and marginal emission factors to properly assess the benefits obtained by real-time side demand programs. It is found that using a too gross temporal granularity may significantly increase the uncertainty of the results.
- Walzberg et al. (2019b): an agent-based model is developed to simulate the behaviour of electricity consumers regarding the adoption of a real-time demand-side management program. The authors found that the conformity of the consumers toward their neighbours is an important driver in the program adoption. The agent-based model is embedded in a dynamic life cycle assessment framework (using real-time emission factors) to automatically calculate the environmental benefits achieved by the program adoption.

### Possible future studies

Several types of studies could be conducted with the model and its modules.

First, studies could be made on the electricity consumers to evaluate the potential to reduce their GHG emissions using real-time recommendations reducing or shifting the power demand. These studies should be conducted on the residential, institutional, commercial, small and medium enterprises and industrial sectors. For each sector, the study should consider the flexibility in the power consumption and the synergy effects (if any) with other sectors. The GHG emission reduction potential should be investigated at the equipment level (or at least, group of similar equipment) since the flexibility in the power consumption may vary between equipment (ex: fridge and washing mashing have different flexibilities). Studies would focus on the actual GHG emission reduction potential but also explore prospective scenarios where habits and infrastructures could evolve to a more desirable situation (ex:

changing working times, enable electric vehicles to share their electric power with the power grid, etc.). Prospective studies should be conducted with the help of proper energy models such as E3MC/Energy2020, etc. The studies should determine if recommendations could be automated (using connected objects) or based on human behaviour. It is expected that with the upcoming 5G and Internet of things, the smart automation of power consumption would rise sensibly for all sectors. Nevertheless, it should not be assumed that all the connected objects will automatically comply with the power consumption recommendations. Indeed, they might be programmed with other objectives that might enter into conflict with the reduction of GHG emissions. For instance, enforcing the required quality of service of an online service may require some extra power consumption by the IT equipment involved.

This first set of studies would provide inputs for the second series of studies simulating the compliance of the connected objects and human beings regarding the smart power consumption recommendations. Behavioural models (agent-based and/or machine learning models) would be built for each type of electricity consumer and then their behaviour in response to the recommendations would be simulated. Behavioural models would be used in recursive simulations to identify the drivers facilitating the adoption of the recommendations and improve the format of the recommendations (media used, incentive type, nudge or not, etc.). Techno-economic studies would be conducted to evaluate the rebound effects potentially caused by saving electricity and emissions and defined measures that could counter them. Indeed, saving electricity could enable other usages of electricity that would then cancel the benefits of the recommendations. Similarly, the reduction in GHG emissions could be used as carbon offsets for other activities that would in the end not result in emission reductions. Once again, with the upcoming 5G era, it is anticipated that more data will be available to characterize the behaviour of people and connected objects. Such data would beneficiate to behavioural models.

The third type of exploratory study would analyze the transformation of the electricity sector under the assumption of global smart consumption of electricity (i.e., people and objects globally comply with the recommendations provided to them to mitigate their GHG emissions in real-time). Indeed, it is anticipated that the use of marginal generators would evolve significantly if all consumers would change their power consumption profile. The equilibrium should be found to prevent the creation of new peak hours that would require using pollutant power generators. This means that an interactive algorithm should be designed to manage the recommendations in real-time. That algorithm would constantly calculate the anticipated marginal emission factors based on the number of consumers willing to adapt their behaviour, the potential marginal generator, the forecasted power demand and meteorological conditions.

#### *How can it help at policy elaboration?*

In the short term, the model can greatly help in the development of demand-side management programs to reduce GHG emissions. Then, it can help to define more global energy policies by providing a new variable to influence the power demand and reduce GHG emissions. The model could then be used interactively with other energy models to study energy policy effects on the economy, the environment and the society. As suggested previously, the model could be used to investigate the environmental benefits of electric vehicle policies. The model would provide recommendations on the best time to reload batteries to minimize emissions and possibly share the electricity of batteries with the power grid (the electric vehicle would act as multiple small power generators) to reduce the use of the most polluting power generators. Moreover, the model would provide hints on the most efficient incentive to convince people to use/buy electric vehicles.

### B. POSSIBLE SYNERGY WITH OTHER MODELS

#### *i. How to go beyond current results (what's needed)?*

The model can be improved in several ways. **In the first module**, the calculation of the marginal electricity emissions could be refined by considering the different temporal ranges of the marginal generators used to adapt the production to the demand in real-time. It is seen that some power grids use different marginal generators to handle the changes in the power demand within 5 min, 10 min and 30 min. Integrating this temporal scale in module 1 would also improve the assessment of the environmental benefits of power consumption recommendations. Moreover, a deeper investigation of the power grid data could also help to identify the generators that compensate for the fluctuations of the intermittent power (and that are not directly affected by a change in the power demand).

**In the second module**, the machine learning model should be improved to enable better predictions of the marginal emission factors. This means probably that more data should be used to train the model (such as meteorological forecasts) but also possibly a different neural network architecture and algorithms could be envisaged. The machine learning model for global emission factors can also be improved with the development of new algorithm in data science.

**In the third module**, behavioural models should be developed for all types of electricity consumers. The main difficulty to achieve this task is the lack of behavioural data and the difficulty to validate the models. Nevertheless, more data are being generated by people (due to the increasing use rate of connected objects). Ideally, the model could be linked to a demand-side management program and data of each registered user could be used to improve the behaviour model in real-time. For that reason, 5G and the Internet of things represents an opportunity to drastically improve the behavioural model. Ethics and cybersecurity should, however, not be neglected when collecting and using people's data. A promising approach would be the combination of machine learning models to generate knowledge from behavioural raw data and agent-based models integrating that knowledge in the behavioural model. New causality links between strong adhesion to demand-side management programs and consumer characteristics could be identified by machine learning and then spread among the consumers through nudges.

#### *ii. Does it make use of common data sets?*

The model uses power grid data: historical power generation by technology, power demand and intermittent generation forecasts. With the future development of the model it is also anticipated to use meteorological forecast (probably: temperature, wind, sunshine and humidity) and people data (behavioural data regarding the adhesion to environmental measures).

#### *iii. Is it a standalone tool only?*

The model is standalone but can also be integrated into another energy model to improve some aspects of its modelling (calculate more accurate or predict electricity emission factors, simulate the people's behaviour). The integration would be especially relevant when the model uses temporally disaggregated data of power generation or consumption.

#### *iv. If not, has it soft or hard coupling?*

N/A

#### *v. Does it feed on other models output?*

The model could be fed by other models to evaluate the environmental benefits of energy policies that use temporally disaggregated data. For instance, an energy model could provide a future electricity mix from which our model would analyze the potential reductions of GHG emissions and propose recommendations to reach these reductions. The lack of knowledge regarding the existence of other models limits actually the evaluation of the possibility to use our model with other energy models. The energy sector has many facets represented by different models, but we have explored only a few of them so far. That is why it is important to keep meeting other energy experts and discuss possibilities offered by model combinations.

### *vi. Can it produce inputs for others?*

The model could produce inputs for other models. Accurate emission factors can be used to better model the emissions (direct or life cycle) and environmental impacts of power generation. The short term predictions of the emission factors might also be useful in an optimization context. Finally, any study involving behavioural effects would benefit from the agent-based model (behaviours are often modelled as scenarios but they usually fail to represent the reality).

# References

Dandres, T., Farrahi Moghaddam, R., Nguyen, K. K., Lemieux, Y., Samson, R., & Cheriet, M. (2017). Consideration of marginal electricity in real-time minimization of distributed data centre emissions. *Journal of Cleaner Production, 143*, 116-124. doi: http://dx.doi.org/10.1016/j.jclepro.2016.12.143

Dandres, T., Moghaddam, R. F., Nguyen, K., Lemieux, Y., Cheriet, M., & Samson, R. (2015). *Applications and challenges of life cycle assessment in the context of a green sustainable Telco cloud*. Paper presented at the EAI International Conference on Smart Sustainable City Technologies (S2CT), Toronto. https://link.springer.com/chapter/10.1007/978-3-319-33681-7_19

Dandres, T., Riekstin, A. C., & Cheriet, M. (2019, 18-19 June 2019). *Considering the temporal variability of power generation in the assessment of ICT emissions: presentation of the IEEE 1922.2 standard draft.* Paper presented at the 2019 IEEE Sustainability through ICT Summit (StICT).

Elzein, H., Dandres, T., Levasseur, A., & Samson, R. (2018). How can an optimized life cycle assessment method help evaluate the use phase of energy storage systems? *Journal of Cleaner Production*. doi: https://doi.org/10.1016/j.jclepro.2018.11.076

Giacobbe, M., Celesti, A., Fazio, M., Villari, M., & Puliafito, A. (2015). *Evaluating a cloud federation ecosystem to reduce carbon footprint by moving computational resources*. Paper presented at the 2015 IEEE Symposium on Computers and Communication, Larnaca, Cyprus. https://www.computer.org/csdl/proceedings/iscc/2015/7194/00/07405500-abs.html

Gordon, C., & Fung, A. (2009). HOURLY EMISSION FACTORS FROM THE ELECTRICITY GENERATION SECTOR – A TOOL FOR ANALYZING THE IMPACT OF RENEWABLE TECHNOLOGIES IN ONTARIO. *Transactions of the Canadian Society for Mechanical Engineering, 33*(1), 105-118. doi: 10.1139/tcsme-2009-0010

Li, X., Wang, R., Luan, Z., Liu, Y., & Qian, D. (2016). Coordinating workload balancing and power switching in renewable energy powered data center. *Frontiers of Computer Science, 10*(3), 574-587. doi: 10.1007/s11704-015-5018-9

Mathiesen, B. V., Münster, M., & Fruergaard, T. (2009). Uncertainties related to the identification of the marginal energy technology in consequential life cycle assessments. *Journal of Cleaner Production, 17*(15), 1331-1338. doi: DOI: 10.1016/j.jclepro.2009.04.009

Maurice, E., Dandres, T., Farrahi Moghaddam, R., Nguyen, K. K., Lemieux, Y., Cheriet, M., & Samson, R. (2014). *Modelling of Electricity Mix in Temporal Differentiated Life-Cycle-Assessment to Minimize Carbon Footprint of a Cloud Computing Service*. Paper presented at the ICT4S, Stockholm, Sweden. http://www.atlantis-press.com/php/download_paper.php?id=13453

Milovanoff, A., Dandres, T., Gaudreault, C., Cheriet, M., & Samson, R. (2017). Real-time environmental assessment of electricity use: a tool for sustainable demand-side management programs. *The International Journal of Life Cycle Assessment*. doi: 10.1007/s11367-017-1428-2

Riekstin, A. C., Hedjam, R., Dandres, T., & Cheriet, M. (2017). *Statistical-Based Method to Determine the Best Hour of the Day Regarding GHG Emissions for a Smart Home Appliance*. Paper presented at the 2017 IEEE Smart World Congress, San Francisco.

Riekstin, A. C., Langevin, A., Dandres, T., Gagnon, G., & Cheriet, M. (2018). Time Series-Based GHG Emissions Prediction for Smart Homes. *IEEE Transactions on Sustainable Computing*, 1-1. doi: 10.1109/TSUSC.2018.2886164

Roux, C., Schalbart, P., & Peuportier, B. (2016). Accounting for temporal variation of electricity production and consumption in the LCA of an energy-efficient house. *Journal of Cleaner Production, 113*, 532-540. doi: http://dx.doi.org/10.1016/j.jclepro.2015.11.052

Tranberg, B., Corradi, O., Lajoie, B., Gibon, T., Staffell, I., & Andresen, G. B. (2019). Real-time carbon accounting method for the European electricity markets. *Energy Strategy Reviews, 26*, 100367. doi: https://doi.org/10.1016/j.esr.2019.100367

Vandromme, N., Dandres, T., Maurice, E., Farrahi Moghaddam, R., Nguyen, K. K., Lemieux, Y., . . . Samson, R. (2014). *Life Cycle Assessment of Videoconferencing with Call Management Servers Relying on Virtualization*. Paper presented at the ICT4S, Stockholm, Sweden. http://www.atlantis-press.com/php/download_paper.php?id=13452

Walzberg, J., Dandres, T., Merveille, N., Cheriet, M., & Samson, R. (2019a). Accounting for fluctuating demand in the life cycle assessments of residential electricity consumption and demand-side management strategies. *Journal of Cleaner Production, 240*, 118251. doi: https://doi.org/10.1016/j.jclepro.2019.118251

Walzberg, J., Dandres, T., Merveille, N., Cheriet, M., & Samson, R. (2019b). Assessing behavioural change with agent-based life cycle assessment: Application to smart homes. *Renewable and Sustainable Energy Reviews, 111*, 365-376. doi: https://doi.org/10.1016/j.rser.2019.05.038

Wang, C., Wang, Y., Miller, C. J., & Jeremy, L. (2016, 17-21 July 2016). *Estimating hourly marginal emission in real time for PJM market area using a machine learning approach.* Paper presented at the 2016 IEEE Power and Energy Society General Meeting (PESGM).