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Accounting for fluctuating demand in the life cycle assessments of residential electricity consumption and demand-side management strategies

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ABSTRACT

The inclusion of temporal aspects in the environmental assessment of complex socio-technical systems is crucial. For power systems, such considerations allow computing the environmental impacts related to demand-side management strategies which could not be assessed with static data, such as temporal shifts of part of the demand from one period of the day to another. Several life cycle assessment (LCA) studies have included temporal aspects, but mostly regarding the system's production function. The consumption side of a socio-technical system, however, is also prone to fluctuate in time and its misrepresentation may lead to additional errors. In this study, the residential power demand of a set of Canadians' homes was modeled with a stochastic approach. Then, three different LCA approaches are compared: the use of an average or a marginal electricity mix and a combination of the two. The influence of the temporal granularity of data (yearly average or hourly data) on LCA results was also investigated. The case study of a simple demand-side management strategy illustrates the method. Results show that the assumption of a constant demand leads to errors regarding environmental impacts assessment, which may be as high as 136% depending on the period of the year assessed. Moreover, the wrong assumption regarding the nature of power demand leads to sub-optimal results for demand-side strategy: the use of an average electricity mix slightly increases greenhouse gas emissions, whereas applying a marginal mix decreases emissions by 10%.

1. Introduction

World scientists' recently reminded humankind of its lack of progress in the last 25 years toward solving environmental challenges (Rippple et al., 2017). The Sustainable Development Goals (SDGs) are a response to some of those challenges and aim at improving current and future generation lives and prospects (United Nations, 2017). Amongst them, SDG 12 seeks to ensure sustainable consumption and production patterns (United Nations, 2017). It is often difficult to assess the sustainability of a given activity because of the multiple and complex interactions to consider among economic, environmental, and social elements (Moon, 2017). However, understanding the complex interactions between human and natural systems is critical to creating sustainability solutions (Liu et al., 2015). In many instances, one may study sustainability questions adopting a socio-technical system view, where a social network of actors and a physical network of artifacts give form to a complex adaptative system (Van Dam et al., 2012).

Socio-technical systems are defined as systems in which the production and the use of technologies are distinguished but studied as a whole (Geels, 2012). Applying a socio-technical approach to study scenarios of low-carbon transitions allows understanding the dynamics of those transitions and going beyond the simple focus on technology fixes or behavior changes (Geels, 2012). In sum, this approach proposes to study the co-evolution of the production and the consumption sides of a system which changes. Examples of socio-technical systems studied in

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sustainability are cities (Deng et al., 2018; Williams, 2017), the agri-food system (Jedelhauser and Binder, 2018; Konefal, 2015), tourism (Lim et al., 2017), mining (Weiser et al., 2017), and transportation (Fallde and Eklund, 2015; Geels, 2012).

1.1. The power system as a complex socio-technical system

The electricity sector is also an example of socio-technical systems. It is made up of a network of technological artifacts (e.g., generation technologies such as wind farms or thermal power plants, transmission lines, etc.) and involves many interrelated actors (e.g., power suppliers, network operators, regulatory authorities, industrial and residential consumers, etc.) (Batten, 2009; Eisenberg et al., 2017; Van Dam et al., 2012). The power system co-evolves with the web of actors: the number of links in the network and their types change over time and affect both the technical and the social dimensions of the system (Van Dam et al., 2012). Indeed, the intertwined social and technical networks of the power system form a complex adaptative system: actors in the social network are responsible for the operation and development of the technical network which in turn affects the behavior of the actors (Van Dam et al., 2012).

Electricity and heat production was responsible for a quarter of global greenhouse gas emissions (GHG) in 2010 and thus fairly contribute to climate change (Intergovernmental Panel on Climate Change (IPCC), 2014). It is possible, however, to reduce the climate change impact of power systems, for instance, by decreasing the environmental impacts of electricity consumption (Dandres et al., 2017) or by increasing the share of renewables in the production mix (Milovanoff et al., 2018). Such strategies often lean on information and communication technologies (ICT) (Milovanoff et al., 2018).

ICT may be used to improve the environmental performance of human activities and technological processes. For example, teleconferencing and telecommuting reduce polluting emissions from transportation (Kitou and Horvath, 2006; Matsuno et al., 2007). Digitization is another example where ICT decrease media's environmental impacts (Reichart, 2002). At last, one promising application of ICT to lower power systems' environmental impact is the smart grid. By promoting demand-side management (DSM), the smart-grid could contribute to reducing the environmental impacts of power systems (Warren, 2014). DSM aims to better manage or reduce energy consumption on the demand side of the system to achieve objectives such as balancing supply and demand or facilitate the integration of renewables (Warren, 2014).

The residential sector represents around 30% of the total electricity use in OECD countries (Geng et al., 2017) and is responsible for 19% of global GHG emissions (Intergovernmental Panel on Climate Change (IPCC), 2014). Life cycle assessment (LCA) studies on the residential sector show that the operation phase is the main contributor of buildings' life cycle GHG emissions (mainly dues to space heating and cooling) (Geng et al., 2017). Moreover, the studies showed that those emissions were dependant on the sources and type of energy used in that phase (Geng et al., 2017). The application of LCA to study the use of electricity in the residential sector enables the investigation of different policy scenarios aiming at reducing its climate change impact. A study on retrofitting, for instance, compared the GHG emissions reduction of different heating system and building envelope scenarios in Canada (Pedinotti-Castelle et al., 2019). The authors showed that retrofitting generate environmental and economic benefits. Moreover, the export of saved electricity through retrofitting to neighboring regions help avoid power generation from natural gas, which brings about additional environmental benefits. Other examples include a study of the integration of renewables in a French house (Roux et al., 2016) or the choice of different building structures (Fouquet et al., 2015). The application of DSM strategies in the residential sector could also help reducing its climate change impact, for instance, via smart homes (Walzberg et al., 2017).

Concerning energy management, a smart home may be described as a combination of smart metering, smart appliances (or Internet of things), and home automation (Paetz et al., 2012). Those elements help the implementation of DSM strategies such as shifting demand from one period to another or energy conservation (Warren, 2014). Energy conservation avoids the use of energy and related GHG emissions in a rather straightforward way. Load shifting, however, does not intend to reduce energy consumption but instead aims to prevent the use of marginal electricity generation technologies such as coal plants (which cause more significant climate change impact) to meet the peak demand (Milovanoff et al., 2018). This DSM strategy makes the environmental assessment more difficult because it requires temporally disaggregated data of power systems. Otherwise, it is not possible to assess the consequences of the shifting load from one period to another (Walzberg et al., 2017).

1.2. Temporal aspects in life cycle assessment

An important, but often overlooked dimension when studying complex systems (such as power systems) is time (Van Dam et al., 2012; Weiser et al., 2017). Time plays a significant role in the environmental, social, and economic impact of human activities. Regarding socio-economic impact, time reconfigures social dynamics amongst stakeholders, which may change conclusions depending on the period assessed (Jones et al., 2017; Karami et al., 2017; Merveille, 2014). As to environmental impact, Levasseur et al. showed that consideration of time in LCA may also modify conclusions regarding the system assessed (Levasseur et al., 2010) and several works further developed their methodology particularly by proposing methods to generate dynamic life cycle inventories (LCI) (Beloin-Saint-Pierre et al., 2014; Cardellini et al., 2018).

LCA accounts for all matter and energy flows related to the entire life cycle of a product or a service (life cycle inventory or LCI), before calculating its related potential environmental impacts (life cycle impact assessment or LCIA) (Hellweg and i Canals, 2014). The methodology is applied to study two types of questions: 1) what are the potential environmental impacts of a product or service (ALCA) and 2) what are the environmental consequences of a change in demand of a product or service that underlies a decision-making process (CLCA) (Baustert and Benetto, 2017). For both ALCA and CLCA, products and services are assessed as to their capacity to fulfill a particular function, and therefore, a functional unit is defined before the assessment. ALCA models the physical flows between processes for the functional unit at a specific time. It is, therefore, a “snapshot” of the studied system [29]. In the case of CLCA, impacts of changes in demand of the functional unit, are computed. Thus, CLCA is not limited to the system's physical flows (Baustert and Benetto, 2017).

Since the 1960s, LCA underwent various developments in order to study more and more complex production and consumption systems (Bjørn et al., 2018; Hellweg and i Canals, 2014). Researchers developed different approaches regarding system boundaries, allocation methods, data aggregation levels, and time (Guinée et al., 2011). The consideration of temporal aspects is especially relevant to electricity infrastructure. Indeed, different generation technologies are used depending on the hour of the day and the season which leads to temporal variations in electricity environmental impacts (Dandres et al., 2017; Elzein et al., 2019; Milovanoff et al., 2018). Particularly in smart grids contexts which may favor shifting power demand in time. In LCA the inventory of elementary flows is, however, traditionally temporally aggregated to a given year.

Pehnt and later, Levasseur et al. first introduced the concept of dynamic LCA (Levasseur et al., 2010; Pehnt, 2006). Levasseur et al., notably, showed how to characterize a dynamic LCI with time-dependent characterization factors (Levasseur et al., 2010). However, the methodology does not clarify how to generate dynamic LCI data. Since then, significant steps were taken towards dynamic LCA and has led to numerous methodological development to include time in LCA (Beloin-Saint-Pierre et al., 2014; Cardellini et al., 2018; Dandres et al., 2017; Fauzi et al., 2019; Kono et al., 2017; Maier et al., 2017; Tiruta-Barna et al., 2016). One study, for instance, extended the enhanced structural path analysis method developed by Beloin-Saint-Pierre at al. to incorporate both spatial and temporal information in the LCI of wheat production in Cornwall, UK (Maier et al., 2017). While the authors found that emissions can be computed across space and time, they also highlighted that LCI databases are often not detailed enough to generate a comprehensive and realistic analysis.

Another study solved this issue by collecting high-resolution temporal data of electricity generation to calculate the dynamic LCI of electricity use in France (Milovanoff et al., 2018). According to their analysis, the lack of inclusion of detailed temporal information leads to underestimate or overestimate environmental impacts depending on the period considered. Moreover, their study emphasizes that variabilities of demand and production sources of power systems make the use of a dynamic LCI especially relevant. A similar study confirmed that the use of average rather than hourly emissions factors could lead to errors as high as 34% when assessing the emissions of electricity use in Germany (Kono et al., 2017). Moreover, the authors showed those errors were especially high during the weekend daytime and weekday nighttime, which was explained by higher or lower shares of renewables in the grid mix for these periods. Another study on French residential electricity consumption found that environmental impacts vary in line with the season (Roux et al., 2016). In winter, a higher share of coal and gas power plants in the grid leads to a higher climate change impact than in summer.

1.3. Problem statement and research objectives

For power systems, besides increasing the realism of the model, including dynamic aspects in the LCA allows assessing the environmental benefit of specific DSM strategies. For instance, strategies that shift part of the demand from one period to another (Milovanoff et al., 2018), or from one region to another (Dandres et al., 2017) may not be developed nor assessed with static data such as yearly average emission factors. As, power systems imply different generation technologies at different period of the day, month, and year, the use of LCA enables spotting potential environmental trade-offs (Turconi et al., 2013). Such trade-offs may emerge when DSM strategies are used within the smart grid. The shift of demand from a particular region or period to another may, indeed, reduce certain environmental impacts but deepen others depending on the technologies forming the grid mix in that period or region (Dandres et al., 2017; Milovanoff et al., 2018). Hence, temporal aspects must be considered in order to be able to evaluate the environmental consequences of the smart grid capacity to shift in time or space power demand. As the literature shows, many approaches have been developed to include temporal aspects in LCA; however, two main challenges remain.

First, not many studies have focused on the modeling of the demand side of the equation, i.e., the functional unit. Indeed, the use phase scenarios (which often define the functional unit) are often based on basic assumptions (di Sorrentino et al., 2016). Furthermore, the scenarios are usually static and do not account for changes in demand for a particular functional unit over time. Thus, better modeling of the use phase could increase the realism of the LCA and provide insight into how and why the demand for a given functional unit evolves (Walzberg et al., 2019). One LCA study on server's usage, for instance, simulated the hourly electricity demand of an average day and used an hourly electricity mix to compute the LCI (Dandres et al., 2016, 2017). Certain days of the year may, however, have a very different hourly profile than the assumed average (e.g., the day of the Super Bowl or the World Cup), which would result in errors in the assessment. This issue may be especially relevant if the atypical days of severs' usage coincide to atypical days of electricity generation environmental impacts. The challenge of adequately defining the functional unit was, thus, mentioned by the authors (Dandres et al., 2016). The error may remain small in the case of servers' usage; however, this may not be the case for residential electricity consumption. Indeed, the later highly fluctuate depending, for instance, on weather conditions.

Second, it is not always evident in the literature what type of LCA question is answered with a dynamic assessment. Some authors have used an attributional approach to build temporally disaggregated LCI (Milovanoff et al., 2018; Roux et al., 2016), while others applied a consequential view (Dandres et al., 2017). With regards to the minimization of servers' usage environmental impact, Dandres et al. show that using an attributional approach does not always allow an optimal reduction in environmental impact (Dandres et al., 2017). According to the authors, however, it is critical to reconcile those two approaches for policy implications. Thus, a solution for electricity systems could be "a hybrid method in which the allocation of the marginal and non-marginal emissions between all electricity consumers would depend on the steady and fluctuating parts of their power demands" (Dandres et al., 2017). In the case of DSM of residential electricity consumption, for instance, part of the demand is steady when compared to the business as usual (BaU) situation, and thus it should be assessed with an attributional approach. Another part of the demand, however, fluctuates (as compared to the BaU) due to the DSM strategy and should be assessed with a consequential approach. Hence, this article aims to:

- Demonstrate the relevance of taking into account the temporal variations of both the production and consumption sides in the case of the LCA of residential power demand,
- Propose an approach to assess the environmental impacts of the steady and fluctuating parts of residential power demand and apply it on a simple DSM case study.

2. Materials and method

In the environmental assessment of complex socio-technical systems such as power systems, it is necessary to realize that both the functional unit provided by the system in use and its production evolve (Fig. 1). In the case of residential electricity consumption, the use of electricity varies according to the time of the day (e.g., nighttime or daytime), the day of the week (weekend or weekday), or the month of the year (winter months or summer months). On the production side, variation in demand and the weather are some of the factors that affect the shares of the different production technologies used in the electricity mix. The following sub-sections present how temporal information was included on both the demand and production side of the assessment of residential electricity consumption. Next, a hybrid attributional-consequential approach to LCA is presented along with the case study.

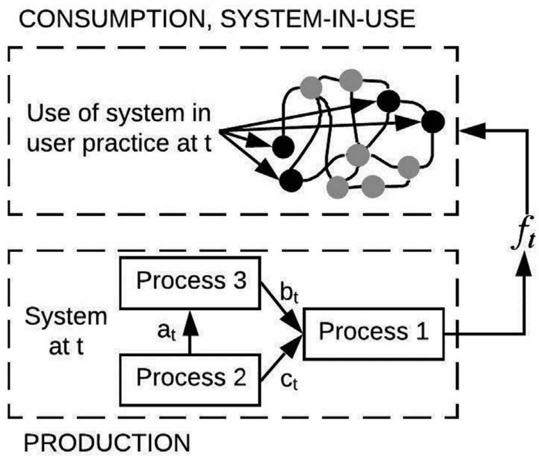

Fig. 1. Representation of a complex socio-technical system at time t. The production part of the system may be modeled with LCA while various modeling techniques may be used for the consumption part. In the figure, f_t designates the amount of a given functional unit used at t, a_t, b_t, and c_t designates the economic flows linking the technological processes of the product system.

2.1. A stochastic model of residential power demand

The starting point of the method is to define a set of households, each equipped with a set of appliances. For the case study, 10 Canadian households located in Toronto and 11 appliances (range, refrigerator, freezer, dishwasher, clothes washer and dryer, lighting, space heating, water heating, space cooling, and other small appliances) are modeled. The number of households was chosen to keep a low computation time. The choice and distribution of appliances, (i.e., the amount of each appliance in each household), follows National statistics (Natural Resources Canada, 2016). Statistical data are also used to establish yearly electricity consumption for each appliance (Table 1). Indeed, the comprehensive energy use database from Natural Resources Canada provides yearly electricity consumption for Ontario's residential sector, for each appliance and different years (Natural Resources Canada, 2016). From the database, information on Ontario's number of households and appliances per households may also be retrieved, allowing the determination of the values in Table 1. The studied period is one year from April 1, 2013, to March 30, 2014.

Then the stochastic model from (Paatero and Lund, 2006) (which was adapted in previous works (Walzberg et al., 2017, 2019)) is used to establish the power demand P_h at a particular hour h according to Equation (1).

Table 1
Appliance yearly electricity consumption (04/2013-04/2014).

Appliances	Yearly electricity consumption (kWh)
Stove & oven	646
Refrigerator	434
Freezer	333
Dishwasher	86
Clothes washer	60
Dryer	805
Lighting	1095
Space heating	19727
Water heating	6172
Space cooling	1171
Other appliances	94

$$P_h = \sum_j^m \sum_i^n (p_d(i,j,d) \times p_h(i,j,d,h) \times \delta_j) \quad (1)$$

where n and m designate the total number of households and electric appliances respectively. The probabilities p_d and p_h are the probabilities for a household i to use appliance j on the day d and hour h respectively. The probabilities p_d and p_h are taken from the literature (Walzberg et al., 2019). Finally, δ_j is the power demand for appliance j. To improve model realism, space heating and cooling daily electricity load (η_d and γ_d respectively) are correlated to the daily outside temperature through heating and cooling degree days (H_d and C_d respectively) (Equation (2) et 3):

$$\eta_d = \eta \times \frac{H_d}{\sum_d H_d} \quad (2)$$

$$\gamma_d = \gamma \times \frac{C_d}{\sum_d C_d} \quad (3)$$

with η and γ the yearly electricity consumption associated with the household space heating and cooling activities. Heating and cooling degree days H_d and C_d are determined from equations (4) and (5):

$$\begin{cases} H_d = T_b - T \text{ for } T \leq T_b \\ H_d = 0 \text{ for } T > T_b \end{cases} \quad (4)$$

$$\begin{cases} C_d = T_b - T \text{ for } T > T_b \\ C_d = 0 \text{ for } T \leq T_b \end{cases} \quad (5)$$

where T_b is the base temperature (in this study set to 18 °C), and T is the outside air temperature. Temperatures are taken from historical climate data, choosing Toronto's weather station (Government of Canada, 2016). The stochastic model is used to generate residential electricity consumption profiles with a time resolution of 1 h (Fig. 2). The Pearson correlation coefficient between the model's output data and historical power generation data is computed to

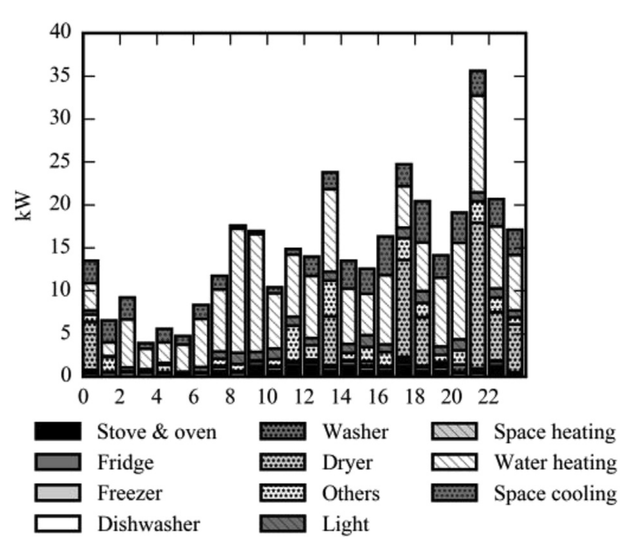

Fig. 2. Electricity load composition for 10 Canadian households (located in Toronto) on July 31, 2013.

validate the model (Independent Electricity System operator (IESO), 2015). A value of 0.7 was obtained, which indicates a high correlation. The differences between historical and model values could be explained by the fact that Ontario's data also include demand from the industrial sector as well as residential. This fact may explain why the correlation between the two sets of data is not higher.

2.2. Life cycle assessment including temporal aspects

The functional unit chosen for this LCA study is the *use of electric appliances, in kWh, by ten households living in Toronto from April 2013 to April 2014*. The specific period of 2013–2014 was chosen because of its greater variability in the grid mix composition (as compared to more recent periods) to highlight the potential errors made when the fluctuation in demand is not considered. The same methodology, however, could be applied to other datasets. The four endpoint impact categories of the Impact 2002 + methodology, (climate change, human health, ecosystem quality, and resource measured in kg CO_2 eq, DALY, PDF*m^{2}*yr, and MJ respectively), are used for the LCIA (Jolliet et al., 2003). The LCA is limited to the use of electricity to power households' appliances; the raw materials extraction, production, transport, and end-of-life of the appliances and the household's dwellings are therefore not included. The analysis is still relevant to the residential sector because the operational phase contributes to up to 90% of environmental burdens (Buyle et al., 2013).

2.3. Average hourly electricity mix

An hourly electricity mix is built to assess most accurately the household's hourly electricity consumption profiles. First, power generation data from each technology composing the grid mix as well as imports and exports are collected for each hour of the year from the operator which manages Ontario's power system (Independent Electricity System operator (IESO), 2015). Indeed, the IESO website provides information on electricity demand, supply as well as import and export on various temporal scales. The electricity mix is then modeled according to (6).

$$S = G + I - E \tag{6}$$

where S is the supply mix (which is used by households), G is Ontario's electricity production mix, I and E are respectively the imports from and exports to neighboring power systems (see Supplementary Materials S1).

Then, the ecoinvent database is used to set up the attributional LCI of the hourly electricity mix (also named *average hourly electricity mix* in the following) (Wernet et al., 2016). To that end, Ontario's electricity mix process from the ecoinvent database is used to set the correspondence between IESO technologies and the different ecoinvent processes (Table 2). Mostly regional processes are used. For Ontario's imports from Michigan and Minnesota, (representing less than 10% of overall imports), however, specific processes are not available in ecoinvent. For those imports, the process representing New York imports was thus chosen as a proxy.

2.4. Marginal hourly electricity mix

In a second approach, a consequential LCI of the hourly electricity mix is built (also named *marginal hourly electricity mix* in the following). First, the marginal sources of electricity are identified by determining the variations in generation per technology (including imports) between each hour of the hourly electricity mix, following the approach developed by (Dandres et al., 2017). Thus, the increase or decrease in power generation per technology and for each hour is obtained for Ontario's electricity mix. Second, once the marginal sources of electricity are identified, the ecoinvent database is used again to determine the hourly LCI. This approach supposes that marginal technologies contribute equally to the rises in power demand regardless of their increase or decrease in capacity (Dandres et al., 2017). Moreover, one limitation of Dandres et al. approach is that it does not consider electricity imports. Because utilities typically balance supply and demand with import and exports of electricity, the former may, however, be an important marginal source of electricity. Depending on the technologies used to produce electricity in the neighboring regions, this could affect the consequential LCI. Imports are therefore included for this study. Equation (7) summarizes how the different shares of the marginal hourly electricity mix are computed:

$$\alpha_{kt} = \frac{|g_{kt} - g_{kt-1}|}{\sum_{k} \left| g_{kt} - g_{kt-1} \right|} \tag{7}$$

where α_{kt} is the marginal share of the technology or import k between $t-1$ and t and g_{kt} and g_{kt-1} are the power generation of the technology or import k at t and $t-1$ respectively. An example of the determination of the average and marginal hourly electricity mix is provided in Supplementary materials S1.

2.5. Life cycle assessment approach for demand-side management strategies

2.5.1. Hybrid attributional-consequential approach

The marginal mix is meant to analyze environmental impacts due to changes in power demand, while the average mix is adapted to assess BaU electricity consumption (Dandres et al., 2017). In the case of DSM, it may be necessary to assess both the steady and the fluctuating part of residential electricity consumption to understand, for instance, where an untapped potential for better management exists. To that end, the average and marginal hourly electricity mixes may be used in combination. First, the marginal demand is identified by assessing the changes caused by the DSM strategy to the BaU residential electricity consumption. In a field study, for instance, this can be achieved by comparing data from before and after the introduction of the DSM program. In a prospective study such as this one, it entails the elaboration of detailed BaU and DSM scenarios. The constant part of the power demand is then assessed with the average mix, while changes are assessed with the marginal mix (Equation (8)).

$$s_t = \chi_t \varphi_t + \chi_t^* \varphi_t^* \tag{8}$$

where s_t is the environmental impact at t, χ_t, and χ_t^* are respectively the constant part and the change in power demand at t and φ_t and φ_t^* are the average and marginal mix impact factors at t respectively. An illustration of calculation for the climate change impact category is given in the Supplementary Materials S1.

2.5.2. Demand-side management case study

In the results section, this approach is applied to a simple DSM strategy: the shifting of households' dryers' loads up to 2 h later than usual. In a first scenario, statistical data are used to determine dryers' loads and elect usage hours according to the stochastic model. Due to the requirements in computational time, 30 days between April 2013 and April 2014 were selected for this part of the study (see Supplementary Materials S1). In a second scenario, the dryers' usage hours are set up as the average usage hour from the results of the stochastic model. This scenario allows studying the

Table 2
IESO generation technologies and related ecoinvent processes used for the LCA.

Technology in the IESO hourly data	Corresponding Ecoinvent 3.1 processes
Coal	electricity production, hard coal, CA-ON
	electricity production, lignite, CA-ON
	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014, CA-ON
Oil	electricity production, oil, CA-ON
Gas	heat and power co-generation, biogas, gas engine, CA-ON
	treatment of blast furnace gas, in power plant, CA-ON
	electricity production, natural gas, combined cycle power plant, CA-ON
	treatment of coal gas, in power plant, CA-ON
	heat and power co-generation, natural gas, conventional power plant, 100 MW electrical, CA-ON
	electricity production, natural gas, at conventional power plant, CA-ON
Nuclear	electricity production, nuclear, pressure water reactor, heavy water moderated, CA-ON
Hydro	electricity production, hydro, pumped storage, CA-ON
	electricity production, hydro, run-of-river, CA-ON
	electricity production, hydro, reservoir, non-alpine region, CA-ON
Wind	electricity production, wind, 1–3 MW turbine, onshore, CA-ON
	electricity production, wind, <1 MW turbine, onshore, CA-ON
	electricity production, wind, >3 MW turbine, onshore, CA-ON
Import New York	electricity, high voltage, import from NPCC, US only, CA-ON
Import Minnesota	electricity, high voltage, import from NPCC, US only, CA-ON
Import Michigan	electricity, high voltage, import from NPCC, US only, CA-ON
Import Manitoba	electricity, high voltage, import from CA-MB, CA-ON
Import Québec	electricity, high voltage, import from Quebec, CA-ON

effect of assuming a steady demand rather than using more detailed modeling of the use phase. For the 30 days and the ten households, the most likely dryers' usage hour is 6 p.m. and is therefore chosen for the average demand.

To be able to differentiate between the steady and the changing part of the residential electricity consumption, two situations are studied. First, in the BaU scenario, the daily usage hour of each household dryer is set up according to the stochastic model. In the DSM scenarios, this usage hour is shifted either 0, 1, or 2 h later depending on the objective of the DSM strategy (e.g., minimizing a chosen environmental impact or costs). The chosen objective is formulated as an integer linear programming problem of minimizing Equation (9):

$$f(\boldsymbol{x}) = \delta_d \boldsymbol{\mu}^{\boldsymbol{T}} x \tag{9}$$

In Equation (9), f is the objective function that needs to be optimized subject to the constraints (equation (10)–(13)). Furthermore, δ_d is the electricity consumption related to a single use of a dryer (which does not depend on the time of use). Still in equation (9), the unknown vector $\boldsymbol{x}$ is the concatenation of vectors $\boldsymbol{x}^{\boldsymbol{\omega}}$ for all households ω and $\boldsymbol{\mu}$ is the vector of hourly emissions factors for the day (thus $\boldsymbol{\mu}$ contains repeated values in order to have a similar size as vector $\boldsymbol{x}$). The optimization constraints are:

$$\sum_t x_t^\omega = \sum_t b_t^\omega, \ \forall \omega \tag{10}$$

$$\boldsymbol{\beta}^{\boldsymbol{T}} \left(\boldsymbol{x}^{\boldsymbol{\omega}} - \boldsymbol{b}^{\boldsymbol{\omega}}\right) \leq 2, \ \forall \omega \tag{11}$$

$$-\boldsymbol{\beta}^{\boldsymbol{T}} \left(\boldsymbol{x}^{\boldsymbol{\omega}} - \boldsymbol{b}^{\boldsymbol{\omega}}\right) \leq 0, \ \forall \omega \tag{12}$$

$$x_t^\omega, b_t^\omega \in \{0, \ 1\}, \ \forall \omega, t \tag{13}$$

In Equations (10)–(13), x_t^ω and b_t^ω are the t elements of vectors x^ω and b^ω. The first constraint of the integer linear programming problem (Equation (10)) ensures that the dryer is used the same number of times throughout the day (i.e., once) as the BaU scenario. Equations (11) and (12) constrain the shifting of dryer's load from none to a maximum of 2 h later than the BaU scenario. In equations (11) and (12), vectors $\boldsymbol{x}^{\boldsymbol{\omega}}$ and $\boldsymbol{b}^{\boldsymbol{\omega}}$ represent the optimized and BaU hourly usage of household ω's dryer, respectively. Both $\boldsymbol{x}^{\boldsymbol{\omega}}$ and $\boldsymbol{b}^{\boldsymbol{\omega}}$ contain twenty-three 0 and one 1, the latter representing the hour of the day when the dryer is used. The stochastic model set up the usage hour in $\boldsymbol{b}^{\boldsymbol{\omega}}$ unless when an average demand is assumed. In the equations, $\boldsymbol{\beta}$ is a vector containing terms of an arithmetic progression of common difference one which allows to set up the temporal constraints of the DSM scenarios.

This optimization problem could be applied to study the DSM of other appliances with some minor modifications to constraints to reflect each appliance specificity of use. A non-linear programming problem was also written and solved to assess the case where the DSM strategy's objective is to minimize daily variations in electricity consumption (Supplementary Materials S2). The integer programming problems are modeled with Pyomo and solved with Gurobi (Gurobi Optimization Inc, 2016; Hart et al., 2012).

3. Results and discussion

In this section, the relevance of temporally realistic scenarios is demonstrated for the case of the LCA of residential power demand. It shows that neglecting temporal aspects of the production and the consumption sides of socio-technical systems may both lead to errors in the assessment. Moreover, the importance of considering the proper LCA approach (consequential versus attributional) depending on use phase information is presented and illustrated with a DSM case study. The results are discussed in light of the literature.

3.1. Temporal aspects of production and consumption of electricity

First, the environmental impacts of yearly residential electricity consumption are computed with different simplifying assumptions regarding the temporal variability of the electricity mix and the power demand. Table 3 shows errors made in each of the four impact 2002 + endpoint categories when assuming a yearly average demand (805 kWh/day) or a yearly average mix (see Supplementary Materials S3) rather than using hourly power generation data. In the climate change impact category, the oversight of temporal aspect in electricity production and consumption both lead to similar low average errors (about 3%). Depending on the period of the year and the impact category, however,

Table 3
Errors due to two simplifying assumptions for each Impact 2002 + endpoint category and ten simulations of yearly residential electricity consumption.

	Climate change	Human health	Ecosystem quality	Resource
Errors due to the assumption of a yearly average demand (%)				
Average	−3.4	2.6	4.3	3.0
Standard deviation	<0.1	<0.1	<0.1	<0.1
Maximum overestimation	136.0	136.0	136.0	136.0
Maximum underestimation	66.7	66.7	66.7	66.7
Errors due to the assumption of a yearly average mix (%)				
Average	−2.7	2.8	4.3	2.9
Standard deviation	<0.1	<0.1	<0.1	<0.1
Maximum overestimation	150.3	42.0	36.5	29.2
Maximum underestimation	65.4	42.8	42.2	45.0

overestimation and underestimation may be higher. For instance, in the climate change impact category, error due to the yearly average mix assumption is 150.3% at 7 p.m. on August 18, 2013, and 66.7% at 9 p.m. on January 7, 2014, when assuming a constant demand. Moreover, when looking at July only, neglecting the temporal variability of power demand leads to an 8.6% underestimation of climate change impact and a 3.0% overestimation of impact in the resource endpoint category (see Supplementary Materials S3).

Although average errors may be similar, Fig. 3 shows how differently the simplifying assumptions affect households' electricity consumption environmental impact. While neglecting temporal aspects of electricity demand flattens out the curves of environmental impacts, discounting those aspects in the electricity mix underestimate or overestimate (depending on the period of the year) peaks of environmental impacts. The figure also explains why average errors are so low: the underestimation and overestimation of environmental impact throughout the year balance each other out. This result shows that for the Ontario power system, the simplifying assumptions may not cause significant errors if the period of the LCA is a whole year (less than 5%). This fact may, however, not be true if the period is a month, a week or a day, the latter being precisely the focus of certain DSM strategies such as load shifting. Thus, choosing to model an hourly electricity mix and demand rather than yearly average ones depends on the period assessed, the desired level of accuracy, and the variabilities of both electricity consumption and the mix emission factors. In this study,

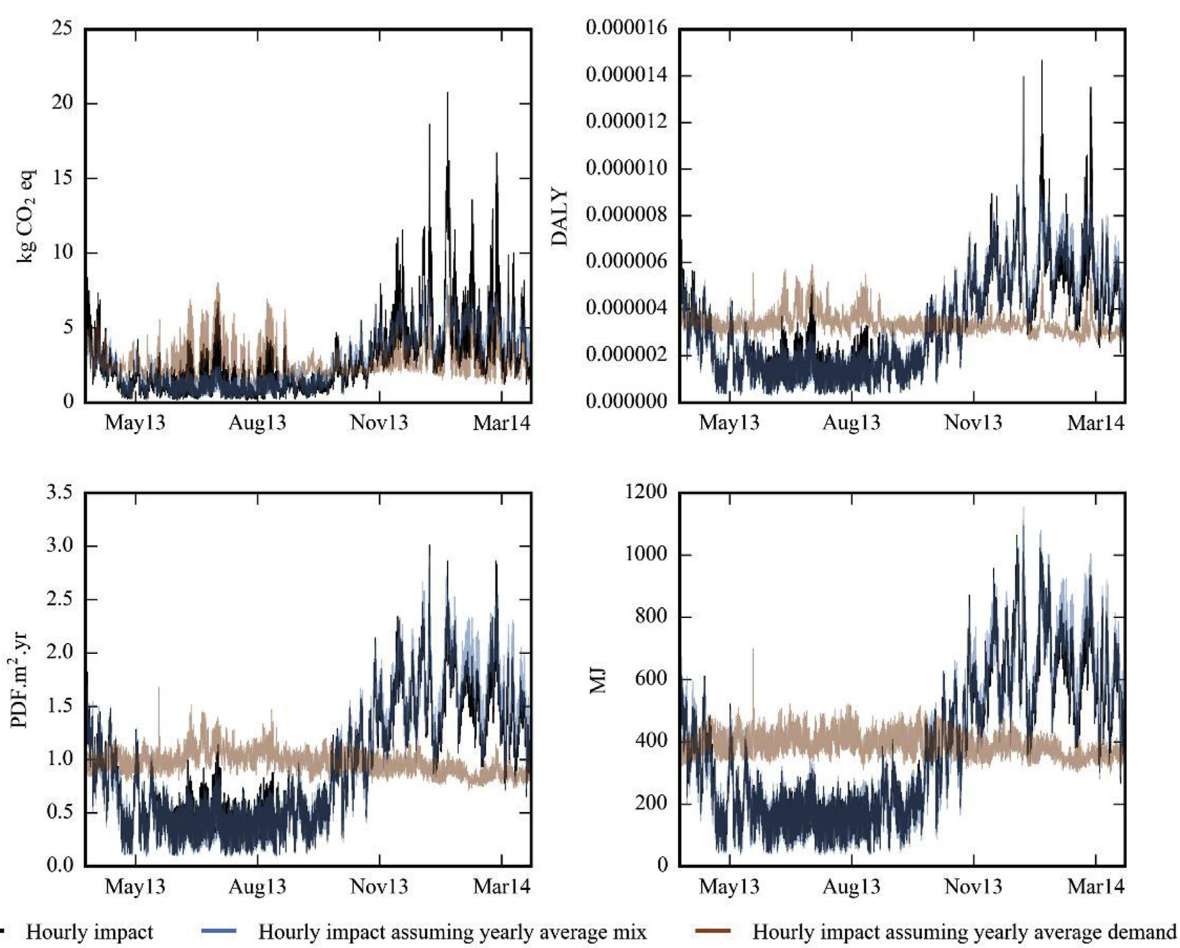

Fig. 3. Environmental impacts of the yearly electricity consumption of 10 households for each impact 2002 + endpoint categories under different assumptions.

for instance, if the period assessed is less than a year, the approach may be beneficial, but less so if the assessment spans several years (e.g., the building reference life). These conclusions also depend on the studied system and the electricity mix. A study on the German electricity mix found a similar conclusion regarding the use of annual rather than hourly emission factors (Kono et al., 2017). Another study in France showed, for instance, that the use of annual average mix rather than hourly data led to underestimations of impacts up to about 40% (Roux et al., 2016). Finally, another critical aspect to consider is the nature of power demand. Indeed, the power plants which meet fluctuation in demand are not necessarily the same as those meeting the overall demand (Milovanoff et al., 2018).

Hence, another possible source of errors, which involves the modeling of the production and consumption of electricity is related to the assumption made on the nature of the power demand. The DSM scenarios described above are next assessed with both an average and a marginal mix as well as a hybrid approach to explore the effects of these approaches to the LCA results.

3.2. Assumptions regarding the type of power demand and their effect in a DSM case-study

First, the impacts per kilowatt-hour of the hourly average and marginal electricity mixes were computed for the April 2013–April 2014 period (Supplementary Materials S3). Most of the year, the climate change impact per kilowatt-hour of the marginal electricity mix is higher than the average electricity mix, due to the higher contribution to the mix of coal generation and imports (Fig. 4). However, for the human health, ecosystem quality and resource

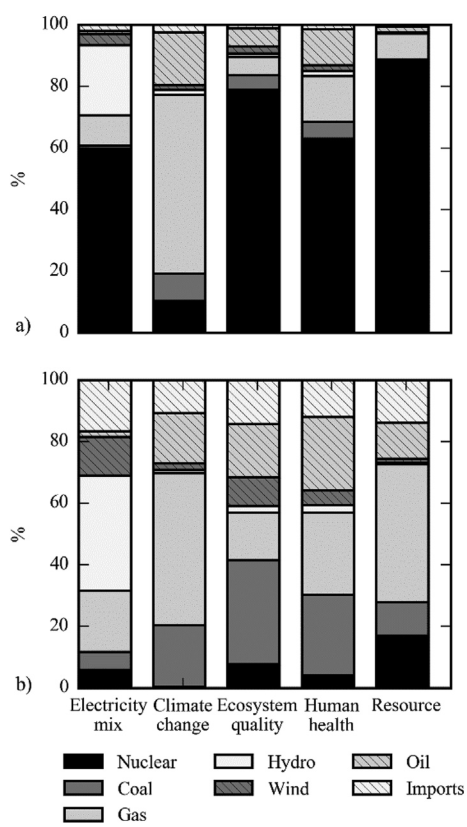

Fig. 4. Contribution of power generation technologies to yearly residential electricity consumption environmental impacts calculated with the a) average hourly electricity mix, b) marginal hourly electricity mix.

endpoint categories, the marginal mix impact per kilowatt-hour is most often lower than its average counterpart, this time due to the lower contribution of nuclear generation. The difference between the two approaches explains this result. The marginal mix represents the technologies that vary the most during the year: nuclear power plants, which are responsible for most of the mix impacts in the resource and ecosystem quality endpoints but produce electricity rather steadily, contribute less in average to the marginal than to the average electricity mix.

On the contrary, fossil fuels, responsible for most of the mix climate change impact, produce electricity in a more fluctuating fashion and thus contribute more in average to the marginal than to the average electricity mix (Fig. 4). Interestingly, in the marginal mix, imports' contribution increases by a factor ranging from 4 to more than 20 when compared to the average mix depending on endpoint category. It suggests that imports are often used to satisfy marginal demand and that they should be included in the LCA of power systems.

Moreover, for the April 2013–April 2014 period, the impact per kWh of the hourly marginal mix seems to vary more extensively than its average counterpart. For instance, in the climate change impact category, the impact per kilowatt-hour ranges of the average and marginal mix datasets are 0.21 kg CO_2 eq and 1.11 kg CO_2 eq, respectively. Standard deviations in this category are 0.03 kg CO_2 eq and 0.16 kg CO_2 eq for the average and marginal mix, respectively.

Then, the three modeling approaches were applied to the DSM scenarios in which marginal GHG emissions are minimized. This metric was chosen after looking at different metrics (see Supplementary Materials S3) and mix assumptions (see Fig. 6) because it allows a reasonable compromise with satisfactory impact reductions in all impact categories. Table 4 shows discrepancies when computing impacts with an average or a marginal mix rather than the hybrid approach. The table also reports errors due to a simplification of use phase modeling (i.e., when the dryers are always assumed to be used at 6 p.m.).

Results indicate that using the hourly average mix instead of the hybrid approach overestimate climate change impact by about 13% on average. For other impact categories, differences are below 6%. Discrepancies are more significant when using the hourly marginal mix, ranging from an average 62.5% underestimation in the resource category to a 184.0% overestimation in the climate change impact category. This difference in results between the use of the average and marginal mixes is explained by the fact that power demand is mainly steady in the dataset with average and maximum shares of marginal demand of 5.6% and 13.7% respectively. These results are in line with the literature (Collinge et al., 2018; Dandres et al., 2017; Roux et al., 2017; Smith and Hittinger, 2019). A similar study on lighting and air conditioning efficiency improvements in the United States showed that using an average rather than a marginal mix may underestimate by 50% or overestimate by 100% CO_2, SO_2, and NO_x emissions depending on the location of the household (Smith and Hittinger, 2019). Another study on two different types of buildings also showed that using a "static" attributional LCA rather than a dynamic consequential approach would underestimate by around 50% the buildings' climate change impacts (Collinge et al., 2018).

Assuming the dryers are always used at 6 p.m. (i.e., assumption of average demand) leads to underestimations ranging from 0.9% in the resource impact category to 6.4% in the climate change impact category on average. Depending on the period assessed, the error may be higher. For instance, on July 10, 2013, the error is 138.4% in the climate change impact category. Altogether, these results further show the relevance of modeling detailed production and consumption scenarios in the LCA of complex socio-technical

Table 4
Discrepancies due to three simplifying assumptions for each Impact 2002 + endpoint category and 30 simulations of the DSM strategy.

	Climate change	Human health	Ecosystem quality	Resource
Discrepancies due to the assumption of an hourly average mix (%)				
Average	12.7	5.8	4.8	1.1
Standard deviation	15.4	6.8	6.1	1.0
Maximum overestimation	67.0	23.9	23.6	4.1
Maximum underestimation	0.0	0.0	0.0	0.0
Discrepancies due to the assumption of an hourly marginal mix (%)				
Average	184.0	24.8	−11.5	−62.5
Standard deviation	118.9	54.0	44.5	10.0
Maximum overestimation	452.7	157.8	106.0	0.0
Maximum underestimation	0.0	41.3	64.7	78.0
Errors due to the assumption of an average demand (%)				
Average	−6.4	−3.5	−2.8	−0.9
Standard deviation	30.3	16.9	14.2	2.5
Maximum overestimation	53.7	21.5	18.4	2.3
Maximum underestimation	138.4	79.8	67.2	10.4

systems. They also demonstrate that when the power demand is mainly steady, a good approximation could be to use an hourly average mix. If the assessed demand differs significantly with the BaU situation, however, using an hourly marginal mix is a better compromise.

Fig. 5 details the origin of those discrepancies for one of the days assessed in the climate change impact category. The figure presents electricity load profiles depending on how the DSM strategy shifts households' dryers loads. As expected, when using a yearly average electricity mix, no shifting of dryers' load occurs (Fig. 5-b)). As a result, the GHG emissions avoided (when compared to the BaU scenario) from the DSM of dryers and computed with the hybrid approach are 0 kg CO_2 eq. In comparison, when the optimization decision is based on the hourly marginal electricity mix, dryers' loads are shifted throughout the day, for instance, from 1 p.m. to 3 p.m. (Fig. 5-a)). It results in 5.2 kg CO_2 eq avoided. Assuming an

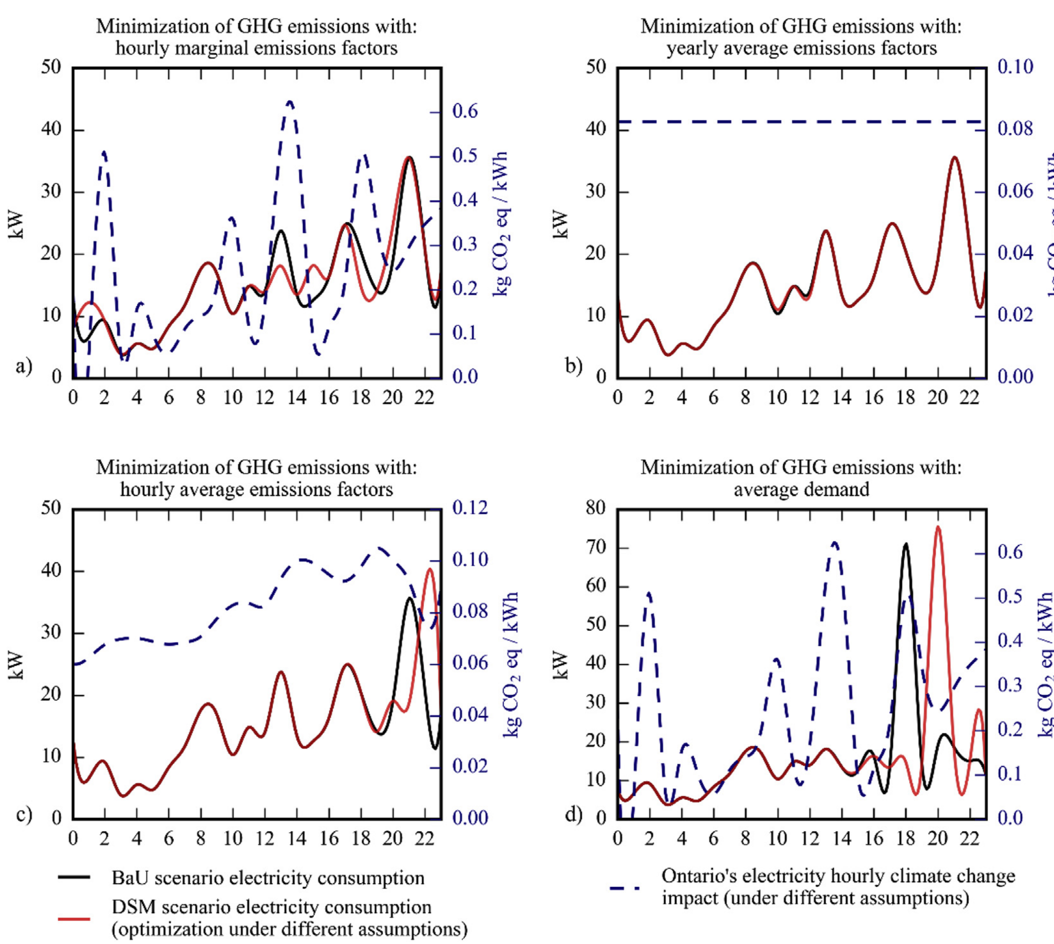

Fig. 5. Electricity consumption of 10 households on July 31st, 2013 for the BaU and DSM scenarios under different assumptions on the Ontario's electricity mix used for the minimization of climate change impact: a) hourly marginal emissions factors, b) yearly average emissions factors, c) hourly average emissions factors, and d) under the assumption of an average demand.

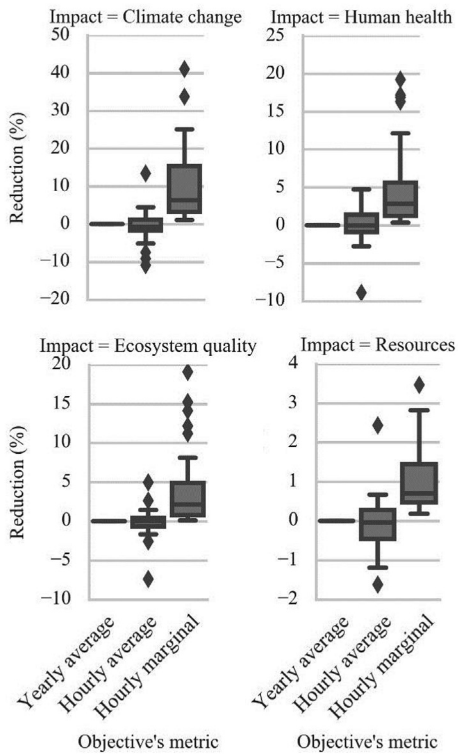

Fig. 6. DSM scenario minimization of environmental impact (optimization metrics are kg CO_2 eq, DALY, PDF.m^2.yr, and MJ for climate change, human health, ecosystem quality, and resource impact categories respectively) with different assumptions on Ontario's electricity mix.

average demand cause the ten households' dryers to shift their load from 6 p.m. to 8 p.m. (Fig. 5-d)). The simplifying assumption leads to overestimating avoided GHG emissions by 184.6% with 14.8 avoided kg CO_2 eq instead of 5.2 avoided kg CO_2 eq. Finally, an optimization decision made on the hourly average electricity mix causes the 8 p.m. and 9 p.m. dryers' load to be shifted to 10 p.m. (when GHG emissions factors are lower). The hourly marginal mix emissions factors are, however, the lowest at 8 p.m. during the 6pm–10pm period and thus the shift causes an increase of 0.9 kg CO_2 eq when the hybrid approach is applied to compute climate change impact. Overall the use of hourly marginal emissions factors for the load shifting causes a 17.1% reduction in GHG emissions (when compared to the BaU scenario) whereas employing hourly average emissions factors increases emissions by 2.9%.

3.3. Demand-side management results

As illustrated by Fig. 5, choosing the LCA approach most suited to the research question is crucial in the case of electricity systems and is a critical parameter to account for when making electricity consumption decisions. Indeed, as indicated above, a consequential approach might be better suited for decisions related to DSM as the power plants which would meet the variations in demand due to DSM are not necessarily the same as the power plants meeting the overall demand (Milovanoff et al., 2018). Thus, DSM optimization decisions should be made according to marginal emissions factors to avoid sub-optimal decisions.

Fig. 6 shows environmental impact reductions obtained with the DSM strategy when using the hourly average, hourly marginal, or yearly average electricity mixes to make the optimization decision. Environmental impacts are calculated with the hybrid approach, and the percentage reductions are obtained by comparing impacts from the optimized use of dryers and the BaU situation. The figure further demonstrates that using the hourly average electricity mix in the optimization decision may not always lead to climate change reductions. It is also true for the three other Impact 2002 + endpoint categories. Applying this electricity mix to the DSM strategy leads to slight average increases of 0.6% and 0.1% in the climate change and ecosystem quality impact categories and, in average, neither increases nor decreases impacts in the human health and resource endpoint categories. Finally, from the 30 simulations, the maximum reductions obtained with the hourly average mix are 13.4%, 4.7%, 5.0%, and 2.4% in the climate change, human health, ecosystem quality, and resource endpoint impact categories respectively.

The use of the hourly marginal mix gives very different results. First, as expected, none of the 30 days where the DSM is applied see an increase in environmental impact: by minimizing with marginal impact factors, environmental impacts are lower than for the BaU situation (Fig. 6). The DSM strategy allows reducing climate change, human health, ecosystem quality, and resource impacts by 9.9%, 5.1%, 4.2%, and 1.1% in average respectively. From the 30 simulations, the maximum reductions are 41.0%, 19.2%, 19.1%, and 3.5% respectively. Those results demonstrate, along with other work, the relevance of using marginal data when assessing a change in power demand (Collinge et al., 2018; Dandres et al., 2017; Elzein et al., 2019; Pedinotti-Castelle et al., 2019). A recent study showed, for instance, that the environmental benefits of decreasing electricity consumption (e.g., with retrofitting) depends on the marginal technology that is affected by the change (Pedinotti-Castelle et al., 2019). Moreover, the study highlighted the relevance of including exports of electricity. The present study also accounts for electricity exports. Furthermore, it uses hourly average and marginal mixes in combination to assess DSM strategies which shift in time part of residential power demand.

Finally, a sensitivity analysis on the number of appliances involved in the DSM strategy and the upper bound of the time constraint of the load shifting was conducted (Supplementary Materials S3). Adding new appliances results in merely adding up their average impact reduction. It is expected as all appliances shift their load to the same local minimum of the hourly marginal electricity mix impact factors (as constrained by the shifting period allowed) independently of each other. However, this behavior may not be the same if the objective of the DSM strategy is to minimize daily variations of power demand. Increasing the upper bound of the shifting period up to 4 h later than the BaU shows a different picture. Because an appliance may shift its load to a broader shifting period, the shift may reach a better local minimum than with a smaller shifting period, thereby increasing impact reductions. As the shifting period extends, however, more appliances may reach the daily minimum and thus, increasing the shifting period may not affect impact reductions anymore. This non-linear behavior implies that demand needs to be modeled in detail (e.g., by using a broad definition of the functional unit (Walzberg et al., 2019)) and that merely scaling up the results obtained for a particular case may not be sufficient to determine actual potential impacts.

3.4. Limitations and future work

This study demonstrates, along with other works, the limits of using yearly average rather than temporally disaggregated data in LCA. In the case of power systems, this leads to errors as it was previously shown (Collinge et al., 2018; Kono et al., 2017; Milovanoff et al., 2018; Roux et al., 2016). This study developed the analysis further, however, by showing that modeling more realistic demand scenarios by including temporal aspects is also relevant, as suggested by others (di Sorrentino et al., 2016; Sharp and Miller, 2016; Su et al., 2017; Walzberg et al., 2019). This consideration allows the assessment of complex socio-technical systems where both the production and the consumption functions co-evolve.

The study also illustrates the relevance of attributional and consequential approaches to LCA of power systems depending on the type of demand, particularly with regards to DSM strategies, as suggested by (Dandres et al., 2017). It is again relevant for the study of socio-technical systems of which some parts change: the changing demand on the consumption side is assessed with the identified marginal technologies of the production side. Similar studies highlighted the relevance of using marginal data, both in LCA and in power consumption decision (Collinge et al., 2018; Dandres et al., 2017; Elzein et al., 2019; Roux et al., 2017; Smith and Hittinger, 2019).

Roux et al., for instance, showed that the choice of the LCA approach changes the conclusion regarding the space heating option with the lowest carbon footprint (Roux et al., 2017). Likewise, in the DSM case study, the choice of the LCA approach changes the conclusion regarding the least emitting hour to choose for load shifting. The authors found somewhat similar discrepancies associated with the choice of the LCA approach: considering a yearly average electricity mix rather than an hourly one underestimate GHG emissions by about 20%, while using an hourly average mix rather than a marginal one underestimate GHG emissions by about 90% (Roux et al., 2017). The differences in results may be explained by the different system assessed (space heating system and load shifting of dryers) as well as the different countries of the studies (Canada and France). Collinge et al. also found comparable results: using a strictly hourly marginal mix rather than a hybrid approach overestimate impact by about 70% in the case of a LEED-certified building (Collinge et al., 2018). The differences in results from this study may be explained by a different geographical context as well as a different share of marginal demand. Finally, results from this study demonstrate, along with other work, that avoiding the use of marginal sources of electricity may bring environmental benefits (Pedinotti-Castelle et al., 2019). Thus, the choice of the LCA approach is crucial for policy implications to avoid sub-optimal decisions. The consideration for marginal emissions factors, for instance, is especially relevant for smart systems aiming at optimizing electricity consumption.

There are some limitations to this study, however. First, the temporal resolution of the stochastic model is rather low and, therefore, an appliance power demand at a particular hour may not reflect the reality of its power cycle accurately. Second, apart from clothes washers and dryers, no correlation in appliances use was accounted for. It is an obvious limitation as patterns of households' behaviors shape appliances' use (Micolier et al., 2019). Moreover, the DSM scenarios studied did not encompass all appliances and may have missed essential constraints such as the willingness for the occupants to comply with the DSM strategy. For instance, households may not be willing to shift certain appliances' load to specific periods of the day (e.g., late at night). The case study was also limited to 30 days and ten households. Those simplifying assumptions may affect the study's results, although not its general conclusions. Finally, as many DSM strategies involve variable tariffs, a rebound effect could occur and needs to be accounted for in the analysis (Walzberg et al., 2017).

Eventually, data obtained in real-time may avoid the need for modeling altogether. In the case of power systems, for instance, near real-time data from both production and consumption of electricity may be used for descriptive, predictive, and prescriptive environmental assessment (Riekstin et al., 2018). In other studies, real-time data in combination with life cycle assessment were used to compute environmental impacts of a grinding process (Filleti et al., 2017) and vehicles (Song et al., 2017). Some authors also proposed a framework to combine LCA and buildings' real-time data on occupancy behavior and construction technologies (Su et al., 2017). Thus, future work could study the advantage of using near real-time data in the LCA of complex socio-technical systems.

4. Conclusion

This article has shown that ignoring temporal aspects of both the production and consumption sides of complex socio-technical systems may lead to errors. In this study, climate change impact was underestimated or overestimated (depending on the period assessed) when a yearly average power demand was assumed rather than an hourly one. For instance, for the month of July, this assumption led to a 9% underestimation. Moreover, choosing the right LCA approach (attributional or consequential) is crucial when assessing a fluctuating demand. The different approaches may lead to discrepancies in the assessment and induce sub-optimal decisions. In a simple DSM case study, choosing an unsuited approach in the optimization algorithm led to an increase in climate change impact. The use of marginal emissions factors to shift in time households' dryer load allowed, however, a climate change impact reduction of about 10%. Thus, future DSM policies regarding load shifting should carefully choose the metric for optimization decisions. Designing such policies may entail, however, to be able to predict the emissions related to electricity consumption in near real time.

This study highlighted the need to account for temporal aspects in LCA, especially in the use phase of complex socio-technical systems. Further work also related to the use phase of power systems would be to study the potential for the rebound effect. In a broader perspective, the socio-technical approach entails to consider users of technology; in the case of DSM strategies this means considering aspects such as the “social optimum” in addition to the “technological optimum.”

Declarations of interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.118251.

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