Resources, Conservation & Recycling 160 (2020) 104845

Contents lists available at ScienceDirect

Resources, Conservation & Recycling

journal homepage: www.elsevier.com/locate/resconrec

Full length article

The On-Site Energy Demand of Meats Consumed in Restaurants

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ARTICLE INFO

Keywords:
Life cycle assessment
Life cycle inventory
Restaurant
Food away from home
Building energy modeling
Diet change

ABSTRACT

The environmental burden and resource intensity of the modern global food system have obtained increased recognition worldwide. Past studies focused primarily on the pre-consumption stages of food life cycle, while food service at the use stage has rarely been addressed due to a lack of understanding in how energy use in restaurants is associated with food items. In this study, we present a novel three-stage approach that quantifies food-item-level energy demand in restaurant service scenarios, which includes an energy-to-food stage, a cooking energy usage stage and a building energy simulation stage. Common restaurant-served meat products in the U.S. (beef, pork, and poultry) prepared using an oven, a griller, and a broiler in a restaurant kitchen were selected as case studies. The results show that the on-site energy demand of these meat products ranges from ~10 to 25 MJ/kg, which is comparable to the energy demand in the food production stage. Heating/cooling, cooking, and the water systems are the main sources of energy demand. This study is the first to quantify the energy demand of individual food items in restaurants and can complement existing food life cycle studies. The results can help improve the understanding of the environmental consequences of dietary change.

1. Introduction

The environmental impact of the global food system, with both intensive and extensive agricultural practices to support an ever-larger and richer population, has become a main driver of global environmental degradation (Tilman and Clark, 2014, Poore and Nemecek, 2018). Restaurants provide an avenue for customers to make "informed food choices" by granting them exposure to food environmental impact information via eco-labels or coded-menus, thus reducing food-related environmental impacts via transitioning toward diets containing less meat (Camilleri et al., 2019).

The environmental impact information of a product is usually evaluated based on life cycle assessment (LCA), as in several eco-labeling frameworks (e.g., the PAS 2050 (BSI 2008), the GHG Protocol (GHG Protocal and Carbon Trust Team 2013), and the International Organization for Standardization (ISO) 14067 (ISO 2018)). LCA is a systematic approach that considers the entire life cycle of products from resource extraction to end-of-life management, as well as their wide range of environmental impacts from resource use, climate change, water pollution, to human health (Finnveden et al., 2009, Yang and Heijungs, 2018). LCA is commonly used to determine and promote products, materials, technologies, and lifestyles that are more environmentally friendly, and it plays an increasingly important role in sustainability science and policy (Yang, 2016, Guinée and Heijungs, 2017, Guinee et al., 2011). Currently, however, only a limited number of LCA studies have incorporated restaurant on-site energy demand into meals' life cycles, although improving the on-site energy efficiency of restaurant operation has traditionally been regarded as a main practice to achieve the so-called "Green Restaurant" (Hu et al., 2010, Baldwin et al., 2011). Restaurants can encourage a larger amount of meat consumption (Saksena et al., 2018, Yuan et al., 2018) and are among the most energy-intensive types of commercial buildings (ENERGY INFORMATION ADMINISTRATION 2008). Neglecting the embodied environmental impact of each food item or building energy demand could eventually provide biased information to the customers.

One of the main challenges of incorporating energy demand in the use stage of the LCAs of restaurant meals is the lack of data availability. This challenge has mainly been addressed by two approaches. The most common approach is to exclude the energy contribution of the restaurant use stage from the system boundary and focus primarily on the food pre-consumption stages (i.e., production, processing, and distribution) (Saarinen et al., 2012, Pulkkinen et al., 2016, Benvenuti et al., 2016, Chen et al., 2016, Schaubroeck et al., 2018). The other approach is to simplify the use stage in the restaurant scenario to a household meal-serving scenario by considering only the portion of energy consumption from refrigeration and cooking, and by calculating

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https://doi.org/10.1016/j.resconrec.2020.104845
Received 3 December 2019; Received in revised form 18 February 2020; Accepted 23 March 2020
Available online 22 May 2020

Nomenclature

e_s	Characterized yearly-averaged on-site energy demand (MJ/kg)
E_A	Annual energy consumption for serving the target food item (MJ)
N_A	Annual number of meals
M	Mass of the target food item (kg)
e_{food}	Energy-to-food (MJ/kg)
E_{sens}	Combined sensible heat for cooking (MJ)
E_{melt}	Latent heat of fusion required for melting fat/water (MJ)
E_{evap}	Energy required for water vaporization (MJ)
M_0	Mass of raw food (kg)
$M_{0,\ n}$	Initial mass of food component n (kg)
W_{loss}	Water loss (kg)
C_p	Specific heat (MJ/kg · C)
T_f	Final Temperature (· C)
T_i	Initial Temperature (· C)
H_f	Heat of Fusion (MJ/kg)
H_v	Heat of vaporization (MJ/kg)
$E_{img,\ i}$	Hourly energy input to the imaginary appliance (Watt-hours)
E_0	Hourly energy input in idling scenario (Watt-hours)
E_H	Hourly energy input in heavy load cooking scenario (Watt-hours)
$R_{p,\ H}$	Production rate at heavy load scenario (kg)
$r_{p,\ i}$	Cooking demand in the i_{th} hour (kg)
U	Response factor of a cooking appliance
β	Ratio of the energy-to-food of a standard food item to the target food item
e^*_{food}	Energy-to-food for preparing a standard food item (MJ/kg)
E_p	Energy for preheating the cooking appliance (Watt-hours)
N_i	Hourly number of meals of the restaurant
N_D	Daily number of meals
C	Installed capacity of the restaurant
O_i.	Hourly occupancy of the area of the dining zone of the restaurant (%)
$\dot{q}$	Heat gain (MJ/hr.)
$\dot{q}_{rad,i}$	Hourly amount of radiant heat gain (MJ/hr.)
$\dot{q}_{lat,i}$	Hourly amount of latent heat gain (MJ/hr.)
P	Rated energy input rate (W)
F_u	Usage factor (%)
F_r	Fraction radiant (%)
F_l	Fraction latent (%)
prt	(Subscript) Stand for prototype model
img	(Subscript) Stand for imaginary appliance
rad	(Subscript) Stand for pure radiant appliance
lat	(Subscript) Stand for pure latent appliance
kit	(Subscript) Kitchen zone
$elec$	(Subscript) electrical equipment in the kitchen zone
F_{EH}	Fraction of the exhaust hood energy consumption
V_a	Minimum exhaust flow rate for a single island canopy hood (L/s per linear meter)
L	Length of the typical appliance in meters
V_t	Total predefined ventilation requirement
F_C	Fraction of kitchen cooling load
$\dot{q}_{t,kit}$	Total heat gain of the kitchen zone
η	Allocation factor
Y	Yield Rate
M_{meal}	Average mass of full restaurant served meals in the U.S. (kg)
E_A	Annual energy consumption (MJ)
E_{EH}	Annual energy consumption by the exhaust hood (MJ)
E_{share}	Energy consumption shared by the target food item and the rest of the meal (MJ)
E_H	Annual energy usage by heating (MJ)
E_L	Annual energy usage by lighting (MJ)
E_F	Annual energy usage by fan (MJ)
E_P	Annual energy usage by pump (MJ)
E_W	Annual energy usage by lighting (MJ)
E_R	Annual energy usage by refrigeration (MJ)
$E_{C,\ tot}$	Annual energy usage by cooling (MJ)
$E_{C,\ kit}$	Annual energy usage by cooling in the kitchen zone (MJ)

the amount of cooking energy demand based on household cooking models (Sonesson et al., 2003) or simplified cooking energy demand data sources (Hager and Morawicki, 2013, Kanyama, 2001) (e.g., studies by Ribal et al. (Ribal et al., 2016), Calderon et al. (Calderón et al., 2018),Mistretta et al. (Mistretta et al., 2019), and de Laurentiis et al. (de Laurentiis et al., 2018)). On the other hand, the studies that consider the energy consumption patterns in a restaurant scenario obtain the averaged energy demand per meal by monitoring the total energy consumption and the total food consumption during a period of time (Cerutti et al., 2018, Jungbluth et al., 2016). This method yields aggregated data for the averaged meals, so the data cannot be feasibly adapted to represent individual foods in the other studies. By incorporating all of a restaurant's energy consumption sectors, the results of the energy monitoring approach showed that the use stage accounts for about 40% of the GHG emissions from the production stage, while the use stage generally accounts for less than 10% for studies using household cooking models. Thus, the development of a generalized model that predicts the on-site energy demand for individual restaurant food items could facilitate the incorporation of the use stage and significantly mitigate uncertainty in environmental impact predictions.

The wider application of smart metering systems make the data representing restaurant energy consumption patterns increasingly available, especially when more advanced approaches are introduced into this area (e.g., the non-intrusive load monitoring (NILM) (Kim et al., 2017) method and machine learning models (Robinson et al., 2017, Rahman and Smith, 2017)). The key remaining challenge to achieve the calculation of food-item level energy demand is to determine the physical linkage between serving a single food item and the overall building energy usage. There are several issues to consider when addressing this challenge. First, the energy consumption patterns of the cooking appliances in restaurants are more complex than the household cooking scenario. In household cooking, the energy usage is mainly dependent on the recipe, the appliance type, and the cooking behavior (Hager and Morawicki, 2013). In additional to these factors, in a restaurant, the weekly and seasonal variation of customer volume, the composition of the menu, and operational parameters such as the weight of food cooked at a time and the hours of operation can all affect energy usage (Smith et al., 2001). Second, energy consumption in restaurants is highly aggregated. Although there are many energy end users, only the refrigeration systems, the interior equipment (e.g., gas cooking appliances), and water systems (used for sanitation and cleaning) are directly related to foods, which, however, usually deal with multiple food items simultaneously. Other energy end users are not food-related but instead maintain and improve the indoor environmental quality (IEQ) (e.g., maintaining the thermal and indoor air quality via the heating, ventilation, and air conditioning system (HVAC)). Furthermore, energy consumption in restaurants is highly variable, both temporally and geographically. For example, although the cooling load from a specific cooking process mainly depends on the appliance type and energy input rate, the extra energy required from the HVAC system to remove it depends on external climate conditions. As a result, the cooling load in each restaurant for a typical cooking process varies daily (morning/evening and midday) and seasonally (summer and winter). The cooling load also varies across regions due to differences in solar irradiation, temperature, and humidity.

In this study, we introduce a novel three-stage approach for quantifying the on-site energy demand associated with serving a food item as a portion of a meal in a sit-down single-use restaurant. We demonstrate this approach with common meat products, with the functional unit defined as a kind of meat of a certain weight and prepared by a typical cooking method (e.g., the 50 g grilled hamburger patty in a hamburger meal). Meat products were chosen since (1) they are often order-and-preparation foods (i.e. cooked to order) as opposed to being cooked in bulk, and (2) meats are generally known to have a higher environmental impact (Poore and Nemecek, 2018, Clark et al., 2019). The results of this study can complement LCA studies focused on pre-consumption stages and help to determine the full life-cycle impacts of meals served in restaurants, thus improving estimates of the environmental consequences of dietary changes and other interventions (e.g., eco-labels and social media apps) on food consumption.

2. Materials and Methods

2.1. Overview

The system boundary includes all the energy usage categories within the restaurant. The system input is the gas/electricity energy usage, and the products are meals being served by the restaurant. To address the above issues and to enable the disaggregation of energy demand to the target food item, we consider a hypothetical restaurant serving scenario containing two assumptions. First, the sole purpose of the restaurant is to serve meals. Second, the target food within the functional unit is prepared solely by a gas-fueled “imaginary appliance”, and this appliance is not used for any other purposes. The selection of a gas-fueled appliance is based on data indicating that the majority of cooking appliances in U.S. restaurants use gas as their energy source (Zhang et al., 2010). The first assumption suggests that the overall energy consumption can be allocated to either the target food item or the other meals. The characterized yearly-averaged on-site energy demand for serving the target food item, e_s, in MJ/kg, can therefore be defined as

$$e_s = \frac{\widetilde{E_A}}{N_m M} \tag{1}$$

where $\widetilde{E_A}$ is the portion of annual energy consumption in the restaurant that can be attributed to the target food item in MJ, N_m is the annual number of meals served in the restaurant containing the target food item, and M is the serving mass of the target food item in kilograms. Since e_s is defined on a per mass basis, then Eq. (1a) can be rewritten as

$$e_s = \frac{E_A}{N_A M} \tag{2}$$

where E_A is the energy consumption attributed to the target food item in the hypothetical scenario where *all* customers order a meal containing the food item, and N_A is the total annual number of meals served in the restaurant. This approach to modeling the hypothetical scenario allows for a feasible calculation of e_s since predictions of E_A and N_A are simpler than those for $\widetilde{E_A}$ and N_m. While the instantaneous energy demand can be also obtained under the hypothetical food consumption scenario, we examine the annual energy consumption to incorporate the temporal variations within a year, which include the daily variation of number of customers, the weekday/weekend variation in restaurant operation, and the seasonal variation of weather and solar irradiation.

The three-stage framework to obtain e_s includes determining the energy-to-food, calculating the energy input to the appliance, and acquiring the facility energy consumption via whole building energy modeling (BEM) (Fig. 1). Energy-to-food includes the portion of energy that is used to raise the temperature of the food item to its target cooking temperature (i.e. sensible heat) and the portion of energy corresponding to water evaporation and fat melting (i.e. latent heat). The energy-to-food of the target food item along with the number of customers determines the cooking load of the cooking appliance. Thus, the target food item is quantifiably related to the energy input of the cooking appliance. This energy input from this cooking appliance eventually converts to heat, which can be divided into four fractions: latent fraction (F_l), radiant fraction (F_r), convected fraction (F_{conv}) and lost fraction (F_{lost}) (U.S. Department of Energy (DoE) 2010). For a cooking appliance that is under an exhaust hood, the radiant fraction acts as a zone load of the HVAC system. The total energy demand of the HVAC system is then calculated as a part of BEM. BEM simulates energy consumption in buildings based on their location, construction, heat gain sources, and the setup of HVAC, water, lighting, pump and refrigeration systems. BEM enables the disaggregation of energy usage by metering all the energy end use groups as well as their load sources. Furthermore, BEM addresses geographical and temporal variations because of its flexibility of adopting various geographical- and temporal- specific models.

This three-stage framework connects the individual food item to the whole building energy consumption, enabling an allocation process that determines the target food item's energy as

$$E_A = E_A^* + \eta E_{share} \tag{3}$$

where E_A^* is the part of restaurant energy consumption in MJ that can be physically attributed to the target food item, and E_{share} is the part that shared by the whole meal and can be only allocated by a predefined allocation factor η.

2.2. Estimating the Energy Demand for a Typical Food Item: A Three-Stage Framework

2.2.1. Determination of Energy-to-Food

The energy-to-food, e_{food} in MJ/kg, for a specific food item is affected by the food item's uncooked water and fat content, cooking losses, thermal properties, and the cooking method and is calculated as

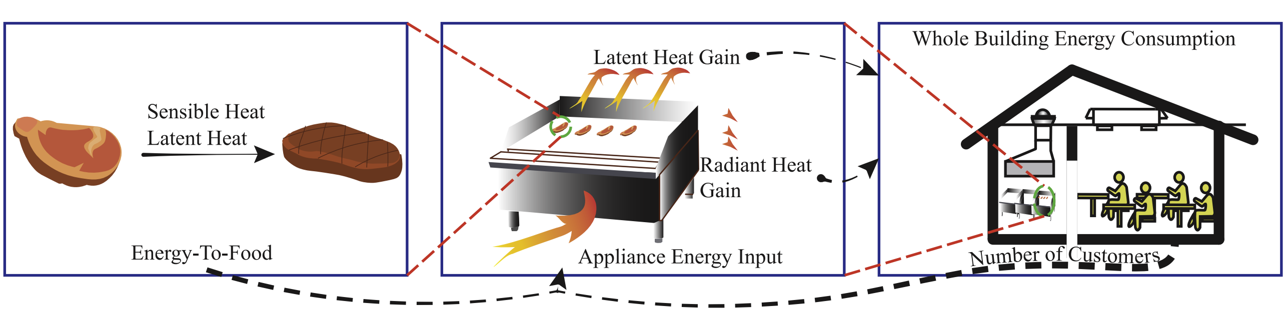

Figure 1. The three-stage framework for the determination of energy demand for meats serving in a restaurant. The heating of individual food items via cooking appliances is physically connected to the whole building energy consumption by acting as a cooling load on the building HVAC system.

$$e_{food} = \frac{E_{sens} + E_{melt} + E_{evap}}{M_0} \quad (3)$$

where M_0 is the mass of the raw food item. The combined sensible heat of each of the component n (ice, fat, water, and solid) in MJ is

$$E_{sens} = \sum_n M_{0,n} C_{p,n} (T_f - T_i) \quad (4)$$

where $M_{0,\ n}$, $C_{p,\ n}$ are the initial mass in kilograms and the specific heat in MJ/kg K of component n, respectively; and T_i and T_f are the initial and final bulk temperatures of the food item, respectively. The energy required for melting fat/water is

$$E_{melt} = \sum_n M_{0,n} H_{f,n} \quad (5)$$

where H_f is the latent heat of fusion in MJ/kg. Finally,

$$E_{evap,W} = W_{loss} H_v \quad (6)$$

is the energy required for water vaporization, where W_{loss} and H_v are the water loss in kg and the latent heat of vaporization of water in MJ/kg, respectively.

2.2.2. Cooking Appliance Energy Input

The cooking energy input is appliance-dependent and can be modeled based on three parameters: its energy performance in the heavy load scenario, its energy usage in the idling scenario, and its responses to cooking demand. This study addresses cooking energy input on an hourly variation basis to be consistent with BEM in that the smallest time interval for all activities is an hour.

The energy usage by thermostat-controlled appliances (e.g., griddles and ovens) can be modeled by the two-mode model, which assumes that the energy input of an appliance during operation is linearly related to its cooking demand (Horton and Caron, 1994). The model is characterized by the idling scenario (with energy input E_0 for zero cooking demand) and the heavy load scenario (with energy input E_H for cooking demand $R_{p,\ H}$) as

$$E_{img,i} = E_0 + \frac{E_H - E_0}{R_{p,H}} r_{p,i} \quad (7)$$

where $E_{img,\ i}$ is the energy input, in Watt-hours, to the imaginary cooking appliance in hour i of restaurant operational time; and $r_{p,\ i}$ is the cooking demand, in kg, during hour i. The slope $((E_H - E_0)/R_{p,H})$ indicates the rate of response of the appliance to the cooking demand. The mass-based cooking demand can be converted to an energy-to-food-based demand, and Eq. 7 can be reinterpreted as

$$E_{img,i} = E_0 + U \cdot \beta \cdot e_{food} \cdot r_{p,i} \quad (8)$$

where U is the response factor of the appliance and is defined as

$$U = \frac{E_H - E_0}{R_{p,H} \cdot e^*_{Food}} \quad (9)$$

where e^*_{food} is the energy-to-food of a standard food item, and β is the ratio of the energy-to-food of a standard food item to the target food item:

$$\beta = \frac{e^*_{food}}{e_{food}} \quad (10)$$

The standard food item is the typical food item that has been used to test the cooking appliances according to ASTM standard test methods (Bell et al., 2002).

The energy consumption of an appliance without thermostat control (e.g., a broiler) involves cooking in a heavy load scenario (at E_H) or in an idling state (at E_0), so the energy input is determined by the required time for cooking as

$$E_{img,i} = \frac{r_{p,i}}{\beta R_{p,H}} E_H + \left(1 - \frac{r_{p,i}}{\beta R_{p,H}}\right) E_0 \quad (11)$$

where the $r_{p,\ i}/\beta R_{p,\ H}$ term represents the fraction of time required for the appliance in hour i to be set to the heavy load scenario.

It is assumed that each of the imaginary cooking appliances needs to be preheated during the first restaurant operational hour. The required energy for preheating the imaginary appliance, E_p, in Watt-hours, is added to the corresponding time:

$$E_{img,1} = E_p + E_{img}(r_{p,1}) \quad (12)$$

2.2.3. Building Energy Modeling

The commercial prototype building models developed by the U.S. Department of Energy (DoE) are used for energy modeling based on both model availability and representativeness (U.S. Department of Energy (DoE) 2019). This set of models provides a wide range of temporal and geographical coverage (Deru et al., 2011). The models were run using the open-source BEM software EnergyPlus (Crawley et al., 2001).

The BEM stage includes two steps. The first step is to estimate the hourly energy input rate of the cooking appliance, $E_{img,\ i}$, based on Eqs. 7-12. The hourly production rate of the cooking appliance, $r_{p,\ i}$, is determined by the number of meals per hour that are served in the restaurant, N_i, as

$$r_{p,i} = N_i \cdot M_0 \quad (13)$$

N_i depends on various factors such as the fraction of occupied seats, the hours of operation, and the table turnover rate. Data representing the number of meals is rare due to its proprietary nature, which is a main reason that the 2018 CBECS survey (U.S. Energy Information Administration 2018) dropped their question on the annual number of meals. The installed capacity of the daily number of meals, C, and the fractional occupancy of the dining zone, O_i, of the prototype models (Deru et al., 2011) are first used for the estimation of the daily number of meals, N_D, and then a sensitivity assessment is conducted.

N_D is calculated as a fraction of the installed capacity since real occupancy is lower than 100%:

$$N_D = C \cdot \sum_{i=1}^{n} \frac{O_i}{100\%} \quad (14)$$

where n is the total operational hours of the restaurant. N_D is then allocated to each opening hour as

$$N_i = N_D \cdot \frac{O_i}{\Sigma O_i} \quad (15)$$

The goal of the second step is to disaggregate the energy usage of the imaginary appliance from the other gas appliances without changing the total heat gains from the original single gas equipment in the prototype BEM models. This involves the division of the gas equipment in the prototype model into three gas appliances: the imaginary appliance, a pure radiant gas appliance, and a pure latent gas appliance and the characterization of the new defined appliances with their rated energy input rate, P in MJ/hr., their hourly usage factor, F_u, and their heat gain fractions, F_r, F_l, and F_{lost}. The usage factor of an appliance is the ratio of the appliance's energy input rate to its rated energy input rate. The parameters for the new appliances are calculated based on the heat gain balance between the prototype model and the new model, which is interpreted as

$$\dot{q}_{r,prt,i} = P_{prt} \cdot F_{u,prt,i} \cdot F_{r,prt} = P_{img} F_{u,img,i} F_{r,img} + P_{rad} \cdot F_{u,rad,i} \cdot F_{r,rad} \quad (16)$$

$$\dot{q}_{l,prt,i} = P_{prt,i} \cdot F_{u,prt,i} \cdot F_{l,prt} = P_{lat} \cdot F_{u,lat,i} \cdot F_{l,lat} \quad (17)$$

where $\dot{q}_{r,prt,i}$ and $\dot{q}_{lat,prt,i}$ are the hourly radiant heat gain and hourly latent heat gain from the prototype gas equipment, MJ/hr, respectively; P_{prt}, P_{img}, P_{rad} and P_{lat} represent the rated energy input rate of the prototype gas equipment, cooking appliance, the pure radiant equipment and the pure latent equipment in MJ/hr., respectively; $F_{u,\ prt,\ i}$, $F_{u,\ img,\ i}$, $F_{u,\ rad,\ i}$ and $F_{u,\ lat,\ i}$ are the hourly usage factor of the corresponding appliances, respectively; and $F_{r,\ Prt}$, $F_{r,\ Rad}$, $F_{r,\ img}$, $F_{l,\ rt}$ and $F_{l,\ Lat}$ are the radiant heat gain factor and latent heat gain factors for the corresponding appliances.

Among the parameters in Eqs. 16-17, P_{prt}, $F_{u,prt}$, $F_{r,\ prt}$and $F_{l,\ prt}$are defined in the prototype restaurant model, and P_{img} depends on the selected appliance. $F_{r,\ img}$and $F_{l,\ img}$ can be obtained from the ASHRAE RP-1362[44]. Furthermore, since the definition of P_{lat}, P_{rad}, $F_{r,\ rad}$ and $F_{l,\ lat}$ won't affect the energy consumption attributed to the target food item as long as the overall heat gains are equivalent to the prototype model, these factors are defined for convenience as

$$P_{lat} = P_{rad} = P_{prt} \tag{18}$$

$$F_{r,rad} = F_{r,prt} \tag{19}$$

$$F_{l,lat} = F_{l,prt} \tag{20}$$

The usage factors $F_{u,\ rad,\ i}$ and $F_{u,\ lat,\ i}$ are then calculated using Eqs. 16-17. The BEM model is thereby completed by revising the original model file and by replacing the prototype gas equipment with the new appliances.

2.2.4. Allocation

We followed the hierarchy of avoiding or solving allocation tasks in the ISO 14044 (The International Standards Organisation 2006) for the allocation of energy consumption of end users other than cooking (i.e. $E_{A,\ img}$), which can be directly obtained from BEM results.

First, the exhaust fan usage and the cooling in the kitchen zone can be divided into subprocesses, and then the energy usage can be allocated by the corresponding load from each of the subprocesses. The exhaust hood is assumed to run at full flow and is used for both the imaginary appliance and other gas appliances. Thus, the fraction of the exhaust hood energy consumption by the imaginary appliance, $F_{EH,\ img}$, can be calculated based on the ventilation requirement for the imaginary appliance as

$$F_{EH,img} = \frac{V_a L}{V_t} \tag{21}$$

where V_a is the typical minimum exhaust flow rate required by the appliance in L/s per linear meter, L is the characteristic length of the appliance in meters, and V_t is the total predefined ventilation requirement in the prototype model as 1888 L/s.

The cooling energy consumption in the kitchen can be divided into three parts: the removal of heat gains from the imaginary appliance, the removal of heat gains from the cooking activity of the rest of the meal, and the removal of heat gains from other sources (e.g., people, lights, window, infiltration, and surface). The fractions of cooling load by the corresponding appliances are defined as

$$F_{C,img} = \frac{\dot{q}_{img}}{\dot{q}_{t,kit}} \tag{22}$$

$$F_{C,rad} = \frac{\dot{q}_{rad}}{\dot{q}_{t,kit}} \tag{23}$$

$$F_{C,lat} = \frac{\dot{q}_{lat}}{\dot{q}_{t,kit}} \tag{24}$$

$$F_{C,elec} = \frac{\dot{q}_{elec}}{\dot{q}_{t,kit}} \tag{25}$$

where $F_{C,\ img}$, $F_{C,\ rad}$, $F_{C,\ lat}$, $F_{C,\ elec}$ are the fractions of kitchen cooling load that can be allocated to the imaginary appliance, the pure radiant appliance, the pure latent appliance, and the kitchen electric appliance, respectively; $\dot{q}_{img}$, $\dot{q}_{rad}$, $\dot{q}_{lat}$, $\dot{q}_{elec}$ are the heat gains from the imaginary appliance, the pure radiant appliance, the pure latent appliance and the kitchen electric appliance at the cooling peak hour, respectively; and $\dot{q}_{t,kit}$ is the total heat gain of the kitchen zone at the cooling peak hour. The selection of peak cooling hour heat gain rather than the annual heat gain is to ensure that heat gains are part of the cooling load that must be removed from the kitchen zone (United States Department of Energy 2018).

Second, the remaining energy consumption is shared by the target food item and the rest of the meal. We choose a mass-based allocation factor for allocation, which is the fraction of the mass of the target food item of the whole meal, as:

$$\eta = \frac{M}{M_{meal}} \tag{26}$$

where M_{meal} is the mass of the total meal.

The E_A^* and E_{share} in Eq. 2 can then be updated as

$$E_A^* = E_{A,img} + F_{EH,img}E_{EH} + F_{C,img}E_{C,kit} \tag{27}$$

$$E_{share} = E_H + E_L + E_F + E_P + E_W + E_R + E_{C,tot} - E_{C,kit}(F_{C,img} + F_{C,rad} + F_{C,lat} + F_{C,elec}) \tag{28}$$

where $E_{A,\ img}$, E_{EH} and $E_{C,\ kit}$ are the annual energy usage by the imaginary appliance, by the exhaust hood and by the kitchen zone cooling, respectively; E_H, E_L, E_F, E_P, E_W, E_R and $E_{C,\ tot}$ are the annual energy usage by heating, lighting, fans, pumps, water system, refrigeration and cooling in MJ, respectively. The $E_{C,kit}(F_{C,img} + F_{C,rad} + F_{C,lat} + F_{C,elec})$ term is the part of kitchen zone energy consumption that has already been specified to either the target food item or the rest of meal, so the contribution is removed from the shared energy consumption.

2.3. Case Studies and Sensitivity Analysis

85 food item types were selected as the target food items in this study (Table S1). The cooking losses data were obtained from the USDA Table of Cooking Yields for Meat and Poultry (USDA 2014), and only food items that have been tested with grilling, broiling, roasting or baking were selected as target food items since, unlike some other cooking processes, no extra water was added during the testing process. All food items are assumed to have an initial temperature, T_i, of 4°C and cooked to a known final temperature, T_f, during testing. All food items have a serving mass M of 340 g, which is a typical regular serving size for meat products in a full service restaurant (Condrasky et al., 2007). The mass of the meal, M_{meal}, is 741 g (Roberts et al., 2018). The raw material weight, M_0, is food-item dependent and is determined according to the USDA Table of Cooking Yields for Meat and Poultry (USDA 2014) as

$$M_0 = \frac{M}{Y} \tag{29}$$

where Y is the yield rate of the food item. All moisture losses are assumed to stem from evaporation. The thermal properties of water, fat, and solids are obtained from the ASHRAE Handbook of Refrigeration (Faith et al., 2005), and the composition of the food items is obtained from FoodData Central (USDA Agricultural Research Service 2020). The mass of initial ice is zero for the case studies since T_i is above 0°C.

Three typical gas-fueled cooking appliances have been selected: a griddle for grilling, a broiler for broiling, and an oven for baking and roasting (Table S2). The properties of all the appliances are collected from publicly-available reports by the Food Service Technology Center (FSTC 2020).

The ranges of energy demand and geographical variations were examined using case studies conducted with models based on the ASHRAE 90.1-2016 standard in all climate regions, which totals 1,445 case studies. The temporal variations of energy demand due to variations of the ASHRAE 90.1 standards were examined using case studies with models following ASHRAE 90.1 -2004, -2007, -2010, -2013 and -2016 for a restaurant in New York (Climate Region 4A) and with the 30 food items with the lowest cooking yield, totaling 150 case studies.

A sensitivity analysis was performed with a typical food item served in New York with ASHRAE 90.1-2016 for three estimated factors in this study: the serving mass of the target food item M, the daily number of meals of the restaurant N_D, and the allocation factor η.

3. Results and Discussion

3.1. Case Study Results

Results of the case studies could be obtained through the Data Availability section in Supplementary Information. The range of on-site energy demand for serving food items in the case studies is 9.56 MJ/kg to 24.9 MJ/kg (Fig. 2a). This result indicates that, for the selected food items, the on-site energy demand in their restaurant serving stage is generally comparable to the cumulative energy demand in their production stage, which have mean values of 67.9 MJ/kg and 28.6 MJ/kg for beef and pork, respectively, and lower values for poultry products (Heller et al., 2018). The outliers in Fig. 2a represents foods prepared in Fairbanks, Alaska, where larger amounts of heating and water energy consumption are required.

The amount of on-site energy demand for the selected products is affected by their cooking method (Fig. 2). The foods prepared by a broiler have the highest mean on-site energy demand among the three types of appliances since a broiler is not thermostat controlled and has the highest idling energy consumption rate. On the contrary, cooking with an oven demands the least amount of on-site energy due to its low idling energy consumption, low response factor, and low radiant factor. In a real cooking situation, the energy demand may be even more distinctive among the appliances since appliances in restaurants can be primarily in an idling status (Swierczyna et al., 2009).

The cooking yield of the food item has more impact than its energy-to-food value on its on-site energy demand (Fig. 2b and Fig. 2c), so further analysis focused on foods with the same cooking yield. For a specified location, the annual energy usage by the restaurant's support systems is identical for all foods. When the cooking yield is high, the requirement of raw mass will be lower (Eq. 29), so a lower production rate and a lower cooking intensity are required (Eq. 8, Eq. 9 and Eq. 13). On the other hand, the influence of energy-to-food is less significant. No trend can be identified between the energy-to-food and the on-site energy demand for the oven scenario and the griller scenario (Fig. 2b) since only a mean of 15.6% of cooking energy is consumed by the energy-to-food. Most of the cooking energy is instead consumed by idling cooking appliances. Furthermore, though energy-to-food is directly related to the cooking energy consumption (Eq. 8 and Eq. 11), its small value (0.51 ± 0.12 MJ/kg) results in no significant effect on the cooking intensity of the cooking appliance. This result is consistent with the observations in Smith et al. (Smith et al., 2001), which showed that in real cooking scenarios, the cooking usage factors of the griddle and oven are only 6% and 10% higher than they are in idling conditions, respectively.

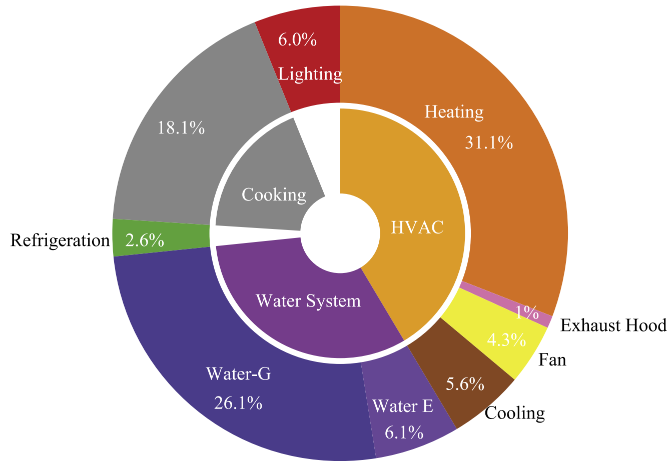

Figure 3. Disaggregation of on-site energy demand for "Pork, fresh, loin, leg cap steak, boneless, separable lean and fat" (NDB 10956) with prototype model of ASHRAE 90.1-2016 New York

Using building energy modeling (BEM) in this study identifies the contribution of energy consumption from each of the energy usage subcategories, addressing the geographical and temporal variations of foodservice energy demand. The dominant energy demand categories for restaurant food service are the HVAC system, water system, and cooking, which together account for more than 90% of total energy usage (Fig. 3). Cooking and refrigeration combined generally contribute to less than 25% of the total energy demand. The result is consistent with the ENERGY STAR estimate that refrigeration accounts for only 6% of total energy consumption (Energy Star 2010). The water system in total accounts to more than 30% of energy demand, with a main contribution from the gas-fired water heater. The results indicate that the simplification of restaurant cooking scenario to a household cooking scenario, which includes only cooking and refrigeration may significantly underestimate the energy demand of the use stage. Additionally, the geographical specific energy demand data can be easily

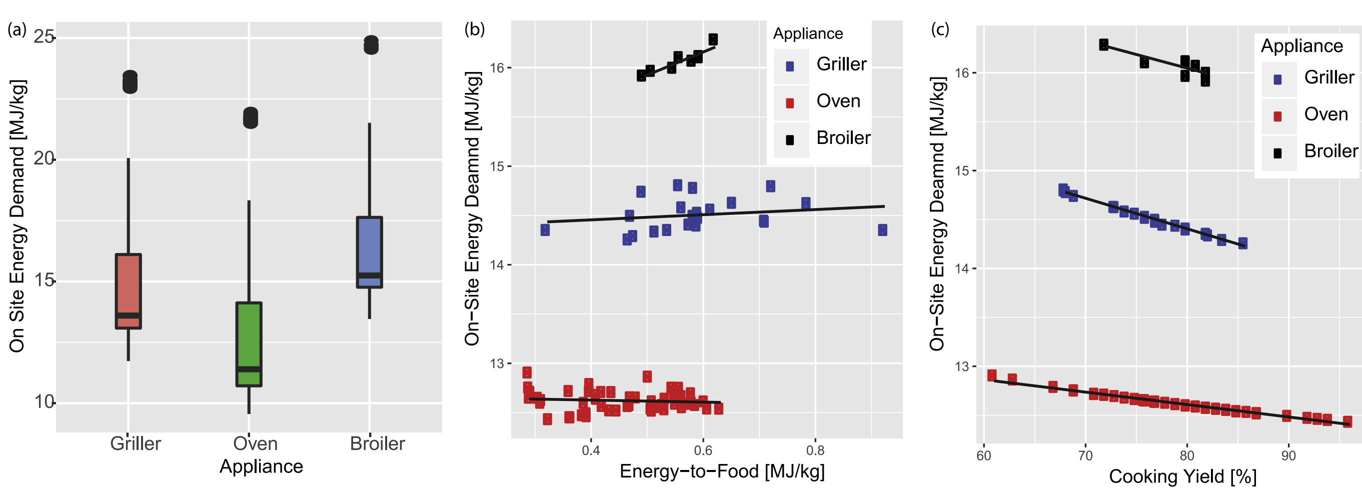

Figure 2. (a)The on-site energy demand distribution for the 85 types of food with ASHRAE Standard 90.1-2016 prototype model; (b) the relationship between the on-site energy demand and energy-to-food; (c) the relationship between the on-site energy demand and cooking yield for all the food items (model used for both (b) and (c) is the ASHRAE Standard 90.1-2016 prototype model of Climate Region 4)

translated to environmental impact result using regionalized emission factors of electricity or natural gas (e.g., from eco-invent (February, 2012) or e-Grid (U.S. Environmental Protection Agency, 2014)).

The geographical variation of serving a typical food item is primarily from the variation of energy consumption by the HVAC system (Fig. 4a). For example, the food item “Pork, fresh, spareribs, separable lean and fat, baked” (NDB 10940) has a heating energy demand ranging from 0.01 MJ/kg to 12.60 MJ/kg, and cooling energy consumption varying from 0.08 MJ/kg to 2.91 MJ/kg, while the internal activities level is the same for all climate regions. This result is due to restaurant models having varying thermal criteria and climate-related heat gains and heat losses in different climate zones, which are reflected in the BEM.

The temporal variations due to ASHRAE Standard 90.1 are also revealed by BEM (Fig. 4b). A drop is seen between 2007 and 2010, which reflects the effort to achieve ASHRAE's goal of 30% energy savings with 90.1-2010 (Thornton et al., 2011). This result may have, however, underestimated the temporal variations. Building energy modeling is designed for simulating the energy consumption in new or renovated buildings, so other factors that could dramatically impact the energy efficiency of a restaurant have not been taken into consideration. For example, poor maintenance has been found to contribute to 45% of extra electricity usage in restaurants (Mudie et al., 2016). Finally, it should be noted that the temporal variations in foodservice between weekdays and weekends have been addressed here by using different schedules for the appliances.

3.2. Results of Sensitivity Analysis

The disaggregation of energy demand shows that the portion allocated to the exhaust fan and the kitchen cooling load is a small (5%). The corresponding terms in Eq. 27 were dropped to analyze the results of sensitivity analysis. For hour i of restaurant operation, the energy demand is approximated as two parts (i.e. the cooking and shared parts):

$$e_{s,i} \approx \frac{E_{img,i}}{MN_i} + \frac{\eta E_{share,i}}{MN_i} = e_{s,img,i}+e_{s,\ share,i} \tag{30}$$

The sensitivity analysis is achieved by inserting Eqs. 8-10 and Eq. 12 into Eq. 30 for thermostat-controlled appliances, or by inserting Eqs. 9-12 into Eq. 30 for non-thermostat controlled appliances. The energy demand for cooking in the case study can be calculated as

$$e_{s,img,i} = \frac{E_0}{MN_i} + \frac{U\beta e_{food}}{Y} \tag{31a}$$

for thermostat-controlled appliances, or

$$e_{s,img,i} = \frac{E_0}{MN_i} - \frac{E_0}{Y\beta R_{P,H}} + \frac{E_H}{Y\beta R_{P,H}} \tag{31b}$$

for non-thermostat controlled appliances. In addition,

$$e_{s,share,i} = \frac{E_{share,i}}{N_i M_{meal}} \tag{32}$$

For the sensitivity assessment on the serving mass M of the target food item, E_o/MN_i is the only variable term for Eqs. 31-32. Thus, increasing the serving mass, M, decreases the cooking energy demand, while the shared energy consumption stays constant (Fig. 5a). For the sensitivity assessment on the allocation factor η, changes of η do not affect the amount of cooking energy, $e_{s,\ img,\ i}$, but increase the shared portion linearly (Fig. 5b). While in examining the variation of occupancy, increasing N_i decreases both the cooking and the shared part energy demand (Fig. 5c).

The results of the sensitivity analysis show that the energy demand is dependent on both the total served mass and the allocation strategy since the three-stage model and the functional unit are mass-based. The mass-based allocation method reveals the underlying physical relationship, so variations within the sensitivity analysis are explained with consistency. Other available allocation methods may not have such an advantage. For example, the energy content in kcal could also be used as a basis for allocation, which, however, may lead to a large variation among food products in the case studies since the energy content varies about a factor of three (from 1.13 kcal/g to 3.73 kcal/g) (Table S1). This large variation can be explained by the food component but can hardly be related to the energy demand of food item. In this manner, an energy-content-based allocation factor may underestimate the fraction of energy consumption to cooked food items but overestimate the energy demand for industrial-processed food items with high energy content. The study by Wu and Sturm (Wu and Sturm, 2014) shows that the averaged energy content for restaurant served entrées, appetizers, sides, salads, drinks, and desserts are 674 kcal, 813 kcal, 260 kcal, 496 kcal, 419 kcal, and 429 kcal. The preparation of entrées is

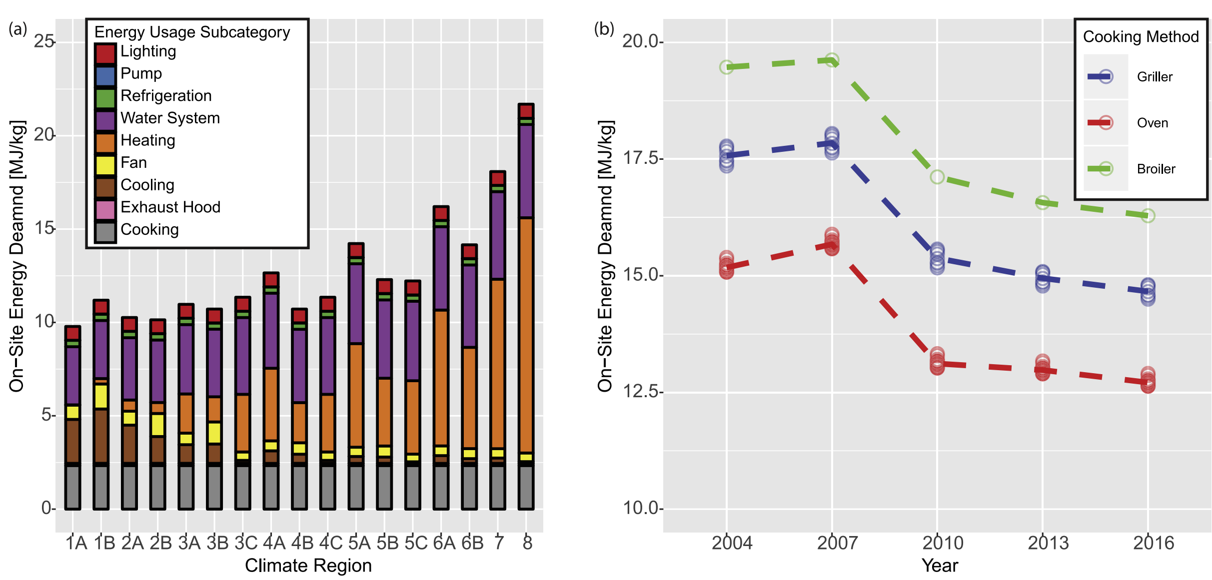

Figure 4. (a) The geographical variation of on-site energy demand (food item: “Pork, fresh, shoulder breast, boneless, separable lean and fat” (NDB 10940); model set: ASHRAE 90.1-2016); (b) Temporal variation of on-site energy demand represented by 30 food items with the lowest yield rate (model: ASHRAE 90.1-2016 in Climate Region 4)

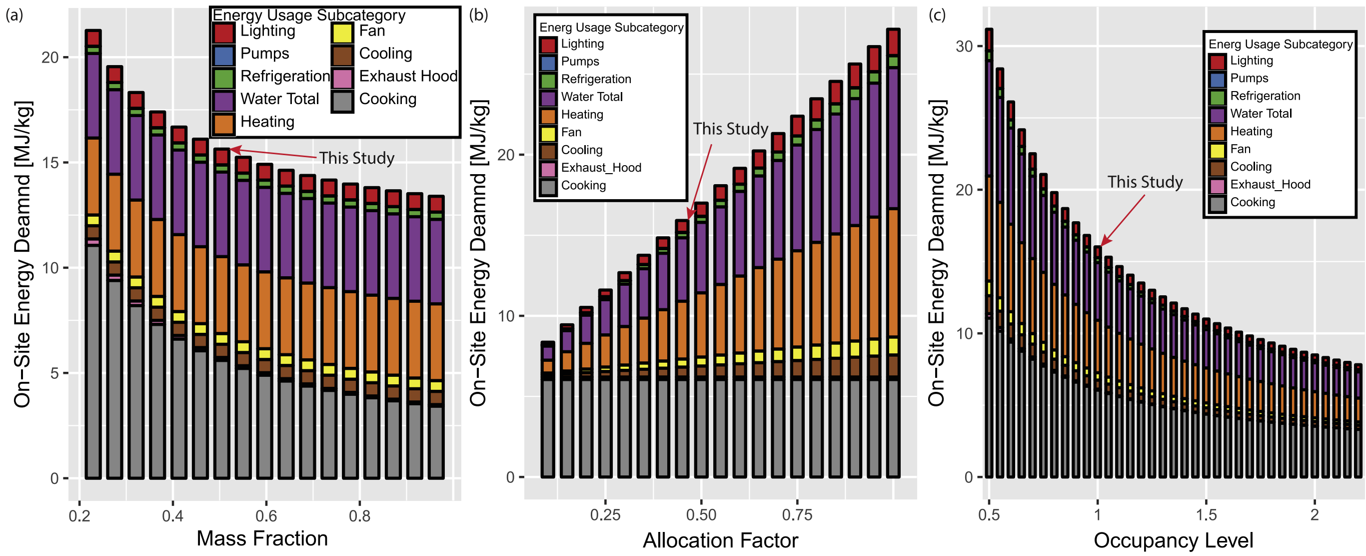

Figure 5. Results of sensitivity analysis on (a) the serving mass as a fraction of the total meal, (b) the allocation factor, and (c) the occupancy level as a factor of the occupancy in the current study of the restaurant (1 represents current study) (represented by food item "Beef, chuck, shoulder clod, top blade, steak, separable lean and fat, trimmed to 0" fat, all grades" (NDB 23060) with prototype model is ASHRAE Standard 90.1 -2016 New York)

usually related to cooking but accounts for only a small portion of energy demand in an energy-content-based strategy.

4. Conclusions, Limitations and Recommendations

In this study, we examined the on-site energy demand for serving meat products in restaurants and proposed a model that disaggregates the energy demand data at a food-item-level that represents real energy consumption patterns in restaurants. We developed a toolbox based on the proposed model, which enables the estimation of temporal-specific and regionalized data. Our results show that the energy demand of the use stage of meat products can be comparable to their production stage due to the contributions from the HVAC system and the water system. Our results could potentially act as important data sources for future LCA studies aiming at eco-labeling, thus facilitating diet change through customer intervention.

Our model is based on experimental studies of the cooking appliances' performance by the Food Service Technology Center (FSTC 2020), tests on the cooking yield by the USDA (USDA 2014), as well as numerical models of full-service restaurants by the DoE (U.S. Department of Energy (DoE) 2019). The following limitations should be acknowledged when using our results as secondary data in an LCA study:

1 The restaurant models in this study are hypothetical buildings that operate ideally to meet the minimum requirements of ASHRAE standards.
2 The appliances' properties represent the performance of typical models (Table S2). The results may vary by the appliance maker/model.
3 The typical cooking procedure is to heat the raw material from 4˚C to an inner temperature of about 68˚C to 71˚C. The cooking procedure details for each of the meat types, including the exact cooking temperature, the preheating temperature, and yield measurement can be found in the USDA's Table of Cooking Yield (Showell et al., 2012).

These limitations bring about recommendations for future studies. First, the toolbox in the Supplementary Information needs further development. Currently, the toolbox has only been developed for acquiring results for case studies. If the main framework of the three-stage model is maintained, then more features can be added in the future. For example, users may want to specify a few parameters using their own data, such as cooking losses, the parameters of cooking appliances, and allocation factors. Furthermore, only three cooking methods have been incorporated due to the availability of cooking yield data, and including other cooking methods requires more complex heat transfer models. For example, braising meat products requires adding extra water (and a corresponding additional energy input) to the food product, and insufficient data exist for this process. The energy demand for such cooking methods could be achieved in future studies by developing new appliance energy consumption models and by experimental collection of energy-to-food data and cooking yield data.

In this study, we considered only one pattern of food service (order-and-preparation), which allows for the calculation of cooking demand based on the variation of the number of customers. It is thus recommended to develop models for products prepared in bulk and served throughout a restaurant's operation (e.g., bread). Additionally, the sensitivity analysis results reveal the energy demand's high dependence on estimated parameters (i.e. the allocation factor and the occupancy level). A confidence interval for the results could not be quantified in the current study due to a lack of data to determine the variance of the estimated parameters. In future studies, the uncertainty may be mitigated by incorporating more sophisticated models for each of the modeling stages. For example, the current energy-to-food model may be replaced by a heat and mass transfer model (Zhang et al., 2015, Pan et al., 2000). More detailed BEM models can also be developed to address the problems within the current models. One identified problem is that the radiant fraction of the prototype gas equipment is only 0.2, while the radiant fraction for the imaginary appliance can be up to 0.4, which may force the radiant factor for the pure radiant appliance to be less than 0 to maintain the radiant heat gain balance per Eq. 16. All factors in the current study were constrained to be between 0 and 1 in the toolbox in the Supplementary Information to address this problem in completing the calculation.

Finally, future studies can aid life cycle assessment by collecting experimental data on building energy consumption and meal service for the calibration of numerical models. The results of our current model cannot be calibrated by currently-available household-cooking models, which lack of a consideration of the real restaurant operation scenario (e.g., cooking appliance's idling status, preheating frequencies, and the energy demand of systems despite of the cooking activities).

Credit Statement

Tao Dai: Conceptualization, Methodology, Software, Original draft preparation, Visualization

Yi Yang: Writing-Reviewing and Editing

Aaron Wemhoff: Supervision, Writing-Reviewing and Editing, Funding acquisition, Project administration

Declaration of Competing Interests

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

Acknowledgments

This material is based on work supported by the US Environmental Protection Agency under the Source Reduction Assistance grant program. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the Environmental Protection Agency. Yi Yang acknowledges funding from the US National Science Foundation (CBET-1639342).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2020.104845.

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