Sustainable Production and Consumption 25 (2021) 162–172

Contents lists available at ScienceDirect

Sustainable Production and Consumption

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

Research article

Potential for using guest attendance forecasting in Swedish public catering to reduce overcatering

Christopher Malefors*, Ingrid Strid, Per-Anders Hansson, Mattias Eriksson

Department of Energy and Technology, Swedish University of Agricultural Science, Box 7032, Uppsala SE-75007, Sweden

A R T I C L E I N F O

Article history:
Received 25 May 2020
Revised 21 August 2020
Accepted 21 August 2020
Available online 26 August 2020

Keywords:
Food waste
School kitchens
Inventory model
Forecasting
Neural network approach
System optimization

A B S T R A C T

Food waste is a significant problem within public catering establishments, caused mainly by serving waste arising from overcatering. Overcatering means that public catering establishments rarely run out of food but surplus ends up as food waste. The challenge is to find a solution that minimizes food waste while ensuring that sufficient food can be provided. A key element in this balancing act is to forecast accurately the number of meals needed and cook that amount. This study examined conventional forecasting methods (last-value forecasting, moving-average models) and more complex models (prophet model, neural network model) and calculated associated margins for all models. The best-performing model for each catering establishment was then used to evaluate the optimal number of portions based on stochastic inventory theory. Data used in the forecasting models are number of portions registered at 21 schools in the period 2010–2019. The past year was used for testing the models against real observations. The current business as usual scenario results in a mean average percentage error of 20–40%, whereas the best forecasting case around 2–3%. Irrespective of forecasting method, meal planning needed some safety margin in place for days when demand exceeded the forecast level. Conventional forecasting methods were simple to use and provided the best results in seven cases, but the neural network model performed best for 11 out of 21 kitchens studied. Forecasting can be one option on the road to achieve a more sustainable public catering sector.

© 2020 The Authors. Published by Elsevier B.V. on behalf of Institution of Chemical Engineers.
This is an open access article under the CC BY license. (http://creativecommons.org/licenses/by/4.0/)

1. Introduction

The global population is estimated to reach 9.6 billion people around 2050 (United Nations, 2019). To accommodate this, a series of changes are needed to keep Earth within its planetary boundaries and achieve a safe operating space for humanity (Rockström et al., 2009). Sustainably feeding a growing population is a challenge that needs urgent attention, since agricultural production is a significant driver for transgression of several planetary boundaries and poses a threat to boundaries currently regarded as lying in the safe zone (Campbell et al., 2017). Acute interventions are needed at global scale to achieve a sustainable food system that can deliver on-point. One of many interventions to create a sustainable food system is to target the vast amounts of food that are currently destroyed, spoiled, or dumped for various reasons, and reduce the level of food waste by 75% by 2050 (Springmann et al., 2018). The Food and Agriculture Organization of the United Nations (FAO) suggests that more effort is needed to map the food waste situation and identify how food waste reduction on an overarching level can be achieved (FAO, 2019). On a global scale, the United Nations targets food waste within its sustainable development goal 12.3, which states that by 2030 food waste should be halved (United Nations, 2015). However, primary data and methods to battle food waste are lacking, and improvements are badly needed in most cases (Xue et al., 2017).

In Sweden, most food waste occurs at the consumer level (SEPA, 2020), and different efforts are needed to obtain a sustainable food system. On such effort is to reduce the high rate of overcatering within the Swedish hospitality sector (Katajajuuri et al., 2014; Storup et al., 2016). This sector is currently growing as more people obtain the economic means to eat out (Bezerra et al., 2012; Kant and Graubard, 2004; Lachat et al., 2011; Nielsen, 2002). It can thus be a future hotspot for waste generation, but with great potential for improvement since food at the end of the supply chain have accumulated more resources and overall prevention of food wasted throughout the life cycle is benefitial (Abeliotis et al., 2015).

Previous food waste studies of the hospitality sector all report that roughly 20% of food produced ends up as waste (Boschini et al., 2018; Byker et al., 2014; Camilleri-Fenech et al., 2020;

* Corresponding author.
E-mail address: christopher.malefors@slu.se (C. Malefors).

https://doi.org/10.1016/j.spc.2020.08.008
2352-5509/© 2020 The Authors. Published by Elsevier B.V. on behalf of Institution of Chemical Engineers. This is an open access article under the CC BY license. (http://creativecommons.org/licenses/by/4.0/)

Engström and Carlsson-Kanyama, 2004; Falasconi et al., 2015; Silvennoinen et al., 2015; Sonnino and McWilliam, 2011). Waste at serving accounts for approximately two-thirds of this waste (Eriksson et al., 2020; 2017; Malefors et al., 2019). Public catering is a significant actor in Sweden, since approximately half of all midday meals in the food service sector are served in the public sector (National Food Agency, 2019), by catering establishments in hospitals, preschools, schools, and elderly care units. School kitchens are the most significant actor in the public catering segment, with almost 1.3 million meals served to Swedish pupils every day throughout the school year. School meals are provided to the students free of charge, funded by taxes (Swedish Parliament, 2010). Similar approaches to school meals are used in Finland (Tikkanen and Urho, 2009) and Estonia (Ministry of Education and Research of the Republic of Estonia, 2019), but otherwise it is rather unique. Because the meals are free of charge, the setting in which school kitchens operate is also unique, since planning the number of meals to serve can be based on the number of students registered in the school. However, despite these optimal conditions, fluctuations in canteen guest numbers still occur. This is one of the risk factors in food waste (Steen et al., 2018), since kitchen staff do not get appropriate information regarding the number of guests in time. One way of avoiding overcatering is the use of forecasting techniques, which could help catering establishments in the hospitality sector, and especially school kitchens, get a good grasp of how many guests will turn up to a specific meal.

This knowledge is often embedded within kitchen staff with many of years of experience, but can be difficult to acquire for newcomers to the sector. Moreover, even experienced staff can still have problems with changes in expected numbers of customers. Accurate models and tools for forecasting numbers of guests would thus be helpful for experienced kitchen staff, and also for establishments within the hospitality sector with high staff turnover. However, this would require kitchen staff to act upon the information provided by forecasting models and tools, hopefully leading to less overcatering and less food waste. Previous studies have shown that kitchen staff and food service providers generally add an extra margin in meal production (Boschini et al., 2020; Steen et al., 2018), in order to avoid running out of food, a negative outcome in the eyes of the guests (Wang et al., 2017) and a source of shame for kitchen staff. The problem is therefore two-fold; there is little knowledge about how many guests will turn up to a specific meal, and the kitchen needs to prepare an acceptable margin of food to avoid shortages and loss of goodwill (van Donselaar and Broekmeulen, 2012) and have a backup ready in case of shortages.

The first decision that kitchens need to take is in ordering food for a set menu. The order is usually placed one to two weeks before the meal takes place. The second decision is on how much food to produce, which is normally done on the same day, or the day before, the meal is served. These decisions are usually taken by the responsible kitchen chef. One way of dealing with this supply and demand problem is to use tools from operational research for managing inventory and forecast the anticipated future based on historical data, in order to identify the optimal quantity to produce (Hillier and Lieberman, 2014). Scientific inventory methods, combined with various classical and new approaches to forecasting problems, such as neural network models, are currently attracting increasing attention. However, these techniques have not been examined in the context of public catering, to assess their potential contribution to a more sustainable food service sector. The problem of overcatering is multifaceted and can be broken down into three major areas in the public catering context. The first type is food-dependent, and refers to food left by guests on the plate or discarded by kitchen staff during food preparation due to taste or appearance. The second type is also food-dependent and relates to portion size. The third type of overcatering problem is food-independent and is defined by supply exceeding demand. This study focused on food-independent overcatering, which can be addressed by forecasting guest demand, bridging the gap between supply and demand in order to optimize this system.

The aim of the study was to evaluate and apply forecasting models to estimate the number of daily guests in Swedish school kitchens and, based on the estimates, identify the optimal number of portions for the kitchens to produce. Loss of goodwill and penalties for food waste, along with practical limitations, were also assessed in light of creating a more sustainable public catering sector.

2. Materials and methods

The work comprised four steps (Fig. 1): data collection; modeling number of guests using different forecasting models; model evaluation to select the best-performing model; and model application to determine the optimal number of portions school kitchens should produce, with a sensitivity analysis of the findings.

2.1. Data

The data used for the analysis comprised material from 21 public school kitchens in Sweden, which were selected as suitable test subjects for forecasting models because they were willing to share their data upon request and had data available for several years. Thus no random selection of units was performed. All of the selected kitchens serve meals to students ranging in age from 6 to 19 years, thus excluding preschool kitchens and elderly care units, which are other common public catering services provided by Swedish municipalities. The students are offered without cost,

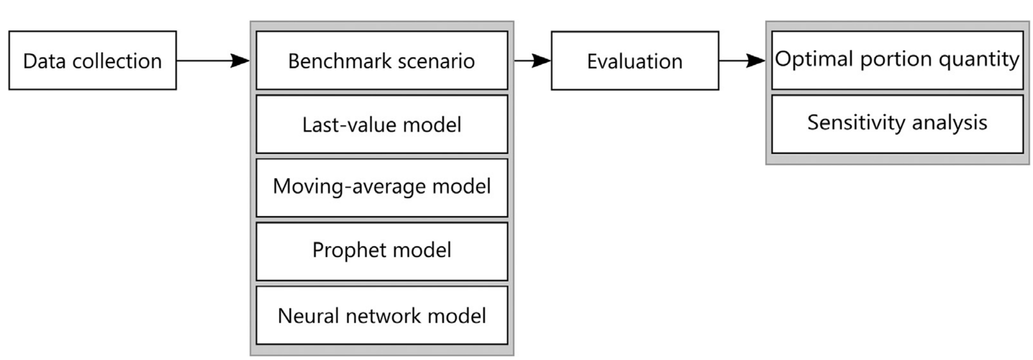

Fig. 1. Different steps of the present analysis, ranging from data collection to determining the optimal number of portions for school kitchens using the best-performing forecasting model.

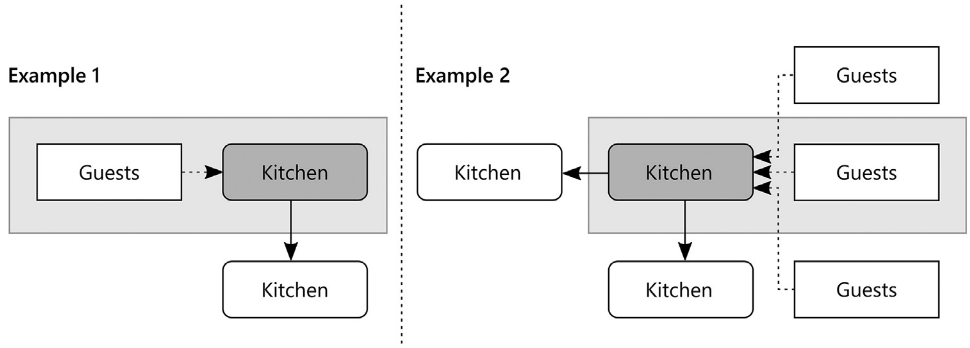

Fig. 2. Examples of different organizational situations within public catering establishments in Sweden. (Example 1) Straightforward case where a school has a kitchen and dining hall within the school facility, and also sends warm food to a satellite kitchen. (Example 2) Slightly more complex case where the school has a kitchen that also receives guests from other schools close by and produces food for several satellite kitchens.

Table 1
Characteristics of the 21 kitchens included in the study. Kitchens 10 and 13 are satellite kitchens, the others are production kitchens. Age denotes the age group of pupils normally served by the kitchen. Years of data states indicates number of years for which historical guest data were available. Amount of guests is number of students enrolled at the school in 2019/2020 (small = 50–200 guests, medium = 200–500, large = 500+.

Code	Age	Years of data	Amount of guests
1	6–9	10	Small
2	6–12	10	Small
3	6–12	10	Small
4	6–12	10	Small
5	6–12	10	Small
6	6–12	10	Small
7	6–12	10	Small
8	6–12	10	Small
9	6–12	10	Small
10	6–7	4	Small
11	10–12	5	Small
12	6–12	10	Small
13	6–12	10	Medium
14	6–12	10	Medium
15	13–15	10	Large
16	16–19	10	Medium
17	16–19	10	Medium
18	16–19	4	Large
19	16–19	4	Large
20	16–19	4	Large
21	16–19	4	Large

school meals every school day (Swedish Parliament, 2010), which in practice means that they do not bring any own lunch with them to the school. The most frequently served meal is lunch in the selected kitchens, although breakfast and snacks may also be served. Table 1 shows the characteristics of the studied kitchens and the target group that normally eats in the establishment, kitchen size in terms of number of guests enrolled in the school year 2019/2020 (categorized as small, medium, and large kitchens), and number of years for which data on guests were available. All of the kitchens operate under a budget set by the public catering organization and the average selling price for kitchens 1–17 to the school organization was 77 SEK/portion, with a purchasing cost for food items at around 22 SEK/portion. The actual values can differ slightly between kitchens, depending e.g., on demand for special diets, which are usually associated with higher ingredient prices, and thus purchasing costs. Kitchens 18–21 could not provide any economic data for the study.

Not all schools have a kitchen, which means that students need to walk some distance to get their lunch. Some of the kitchens are also responsible for preschools, whose children eat within the establishment, or provide cooked food for other schools. Fig. 2 shows some of the set-ups found within a public catering organization. In the straightforward case, guests eat within the same building as the kitchen, and the kitchen provides warm food to a satellite kitchen. In the more complicated case, the production kitchen provides food to several satellite kitchens and also has guests arriving from a number of places.

A school year in Sweden consists of at least 178 days between late August and early June (Swedish Parliament, 2011). The autumn term includes one week of holiday, usually at the end of October. A winter holiday of approximately 2–3 weeks covers Christmas and the new year. The spring term has one holiday week in mid-February and one week around Easter, plus scattered national holidays in May. Some schools remain open during the holidays and serve meals during this period to other establishments who are still open, such as preschools. The school kitchen typically offers students two lunch options, where one options usually consists of a main component like meat or fish with a supplementary component like potatoes, rice, pasta and vegetables or salad. The other option is usually a 'greener' version of the first option or soup. The menu follows a five- to seven-week cycle, where the heads of catering for the kitchens meet with public catering managers and set the menu together. Local adaptations are encouraged, and options can be shifted or removed depending on the local context and availability of seasonal and regional food items. In some cases the staff, such as teachers eat in the facility or the school kitchen get visitors which influence the number of portions to produce, however these meals are not for free as they are for the students.

2.2. Collection of data

Data on number of guests eating school meals were collected from 2010 to 2019 by the municipalities themselves, by counting plates after every lunch. One counting procedure involves drawing tally marks on the dishwasher for each full tray and then multiplying the total by the capacity of each tray (usually 18 plates). Another approach is to collect one plate from each full tray and all plates from the last incomplete tray, and calculate the total number of plates. In this study, it was assumed that one plate was equal to one portion, which is equivalent to one guest. However, this might not necessarily be accurate, since guests are allowed to re-fill their plate or take several plates. Plate data are thus an approximation of the number of guests served, since no point-of-sale data are available to extract information regarding guest flow as the meals are free of charge for the students. No significant changes were made in the way meals were served to the guest during the period for which data was obtained. Fig. 3 displays changes over time in

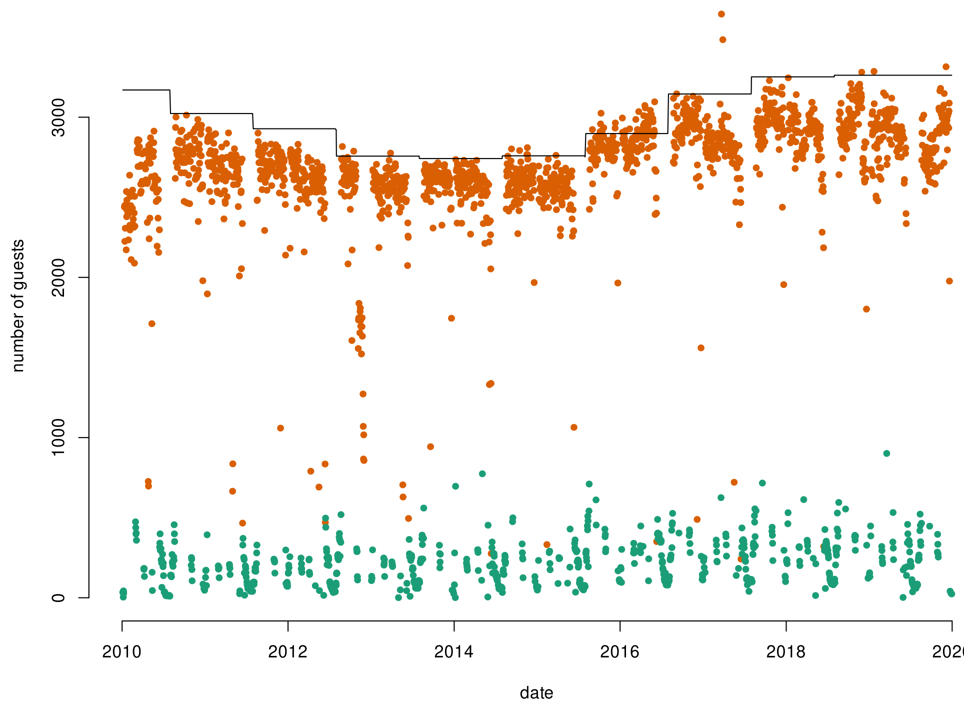

Fig. 3. Number of guests over time at school kitchens in a municipality (containing data from 15 schools who had a complete data set of 10 years) where ● indicates normal day and ● indicates holiday with less activity, where the schools provides meals to other establishments within the public catering organization. The line shows the number of students enrolled, and can be taken as the maximum of guests that need to be provided with food.

the number of guests in the school kitchens, with an indication of whether the day was a typical day or a holiday. The diagram also shows maximum number of enrolled students, which roughly indicates the carrying capacity of the municipality in terms of number of guests the kitchens should provide with food.

The following data were obtained during the period for all school lunches served within the municipality:

- Number of guests, taken as plate count per day for lunch.
- Dates for Holidays/breaks when less or no activity took place in the kitchens.
- Enrolled students per school and school year as of October (official numbers from the Swedish National Agency for Education 2019).

The number of guests in the form of counted plates acts as the basis for billing purposes that the public catering organization sends to other parts of the organization within the municipality, such as preschools, schools and elderly care units to get paid. Different municipalities apply different approaches, but most use some kind of guest indicator to determine the amount to charge internally, either by counting plates or by estimating the number of guests from a schedule or similar techniques. Since the municipalities use counted plates as an indicator of number of guests, the data can be seen as trustworthy. If the amount of plates is exceptionally large on one day for some reason, the ordering organization would react to this, since it is not keen on overpaying for meals.

2.3. Transformation and filtering of data

The data collected from the kitchens were transformed into a standardized format similar to that proposed by Eriksson et al. (2018). The focus was on forecasting typical days, so all holidays and extreme values defined as falling outside the interquartile range (Tukey, 1977) per school and school term were removed before entering the modeling step. This is because kitchens already have a good understanding of guest seasonality and when guests will be missing due to upcoming holidays, but struggle with the variability observed during normal weekdays. The intention was for the filter to remove known features (such as holidays and known study visits) from the dataset, in order to focus on the modeling aspects.

2.4. Identification, selection, and evaluation of forecasting models

Forecasts can be obtained using qualitative and quantitative techniques. This study focused only on quantitative approaches for statistical time series, i.e., a series of numerical values taken by a random variable over time. Forecasting in general involves analysis of past time-series data to estimate one or more future values of the time series. The forecast depends on a model of the behavior of the underlying time series (Hyndman and Athanasopoulos, 2018). Here, the focus was on capturing time series models that would be practically implementable by kitchen establishments, ranging from the most straightforward model (last-value forecasting) to more advanced approaches using neural networks. The intention was for the models to act as forecasting approaches that kitchen managers and chefs could implement. The performance of different models was compared to determine which model or combination of models would perform best under different circumstances. Since schools are obliged by law to provide food for all students (Swedish Parliament, 2010), all models were benchmarked against a reference scenario where food was prepared for all students enrolled, even if they did not turn up. In reality, the final number of portions prepared is adjusted somewhat based on kitchen staff's local knowledge of their guest situation, since not all students eat a school meal every day for various reasons, such as sickness, truancy (Ramberg et al., 2018) or because they choose to eat elsewhere, which is mainly done by older students. The best-performing model for each kitchen was then tested with different margins, to determine the number of days for which the model underestimated the number of portions. Finally, the optimal portion quantity was determined and sensitivity analysis of the quantity was performed.

2.4.1. Benchmark scenario

The benchmark scenario (all students enrolled are provided with food) was expressed as actual number of portions each day (A_t) relative to number of students enrolled for a defined time period:

$$Benchmark\ scenario = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{Enrolled\ students - A_t}{Enrolled\ students}\right| \tag{1}$$

This scenario shows the average level of deviance regarding number of portions per day from the number of students enrolled per school year. It is the scenario that the public catering organization is required by law to deliver, and assumes that all students entitled to a meal turn up. This can be viewed as a business-as-usual scenario and as the outcome if no manual corrections are made by kitchen staff in their daily work.

2.4.2. Last-value forecasting

The most basic forecasting model is last-value forecasting, also often called naïve forecasting, where forecasting procedure uses the value of the time series observed at time $t(x_t)$ as the forecast at time $t+1(F_{t+1})$ yielding:

$$F_{t+1} = x_t \tag{2}$$

This simplified technique, stripped of seasonal influences, was compared here with more sophisticated techniques. All available data that passed the filter were used for this model, but for fairer comparisons with models that require training, only the last year of available data were used for evaluation.

2.4.3. Moving-average model

The moving-average forecasting procedure averages the data only for the last n periods and uses this information as a basis for the forecast for the next period:

$$F_{t+1} = \sum_{i=t-n+1}^{t}\frac{x_i}{n} \tag{3}$$

A clear limitation of this approach is that the input gets equal weight, so older information that might no longer be representative is treated the same way as more recent observations. In this study, periods of 2 and 5 days were used to capture recent trends for a working week and make decisions for the coming period. Since moving-average forecasting is within the same family as last-value forecasting, all available data that passed the filter were used for this model. However, for fairer comparisons with models that need training, only the last year of available data were used for evaluation.

2.4.4. Prophet forecasting model

To assess more complicated features of the time series, the open-source prophet package (Taylor and Letham, 2017) was applied. The model considers time series forecasting as a curve-fitting exercise and does not consider temporal dependence structures in the underlying data. The technique uses a decomposable time series model and is based on three main components (trend, seasonality, and holidays), which are combined in the following equation:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{4}$$

where $g(t)$ is a trend function that models non-periodic changes in the values of the time series, $s(t)$ represents periodic changes, and $h(t)$ represents holiday effects which occur at potential irregularity over one or more days. The error term ϵ_t represents changes which are not accommodated by the model. The model needs training to perform forecasting. We used data for the period January 1, 2010 to December 31, 2018 (90% of all data points) as training data and data from 2019 as test data. For kitchens which had fewer years of historical data, the last available year was used as test data and the rest as training data. Number of plates and holiday data were used as input to the model for making predictions based on the data from the training period.

2.4.5. Neural network model

To monitor potential complex nonlinear relationships, a simple sequential neural network was tested, using the network as a framework for learning representation of the data. A sequential multi-layer network with one input layer, two hidden layers with 32 neurons each, and one output layer was selected. It was implemented with the help of the Keras API (Chollet et al., 2015). The same data as in the prophet model were used, with number of plates and holiday data as input, but with additional information about number of students enrolled for each school year. The model was trained with data for each school from January 1, 2010 to December 31, 2018, and evaluated against data for 2019. For the kitchens with fewer years of available data, the last year was used for testing and the rest of the data for training of the models. Training was aborted once the model performance stopped improving and Adam optimization was used in the compilation step of the models.

2.4.6. Forecasting errors and evaluation

There are multiple options for evaluating and assessing errors (Gooijer and Hyndman, 2006). In this study, mean absolute percentage error (MAPE) was selected for its interpretability. It is defined by:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{5}$$

where A_t is the actual value observed and F_t is the forecasted value. Since some of the models needed training to perform a forecast, all models were evaluated against the last year for which the schools had data, to make a fair evaluation. Thus in the case of last-value forecasting and the moving-average model, only the last year of available data that passed the filtering process was used for evaluation. Since kitchens operate under different conditions (Eriksson et al., 2018), all models needed to include some kind of margin to be of practical use. Knowledge of number of days on which a forecast will underperform, and by how much, could provide kitchens with additional information that is currently lacking (Steen et al., 2018). Therefore the actual demand in 2019 with different forecasting margins ($\alpha = 0 - 10, 15, 20, 25$ and 30%) was used to determine how many days the forecast was an underestimate, and by how much in terms of portions for the worst day observed. This was done by counting the amount of underestimation days and the magnitude of underestimation for different margins according to:

$$\sum_{i=1}^{n}[(y - \hat{y}_\alpha) > 0], \max_i(y - \hat{y}_\alpha) \tag{6}$$

The days with the largest magnitude of underestimation were categorized into three ranges: 1–9 portions, 10–29 portions, and 30+ portions, which was roughly equivalent to having 1, 1–3, and 3+ standard GN (Gastro norm) 1/1 containers of food as backup.

2.5. Optimal portion quantity

Since kitchen staff face uncertainties in guest numbers, they need to balance the risk of overcatering against the risk of shortages and, in the classical example Hadley (1963), find an optimal number, Q^*, of portions to produce. Using an inventory model that recognizes the stochastic nature of demand, x, with a probability distribution function and a cumulative distribution function, and where food is perishable, leads to this kind of optimization problem. The portions produced, Q, have a cost per portion, v, and are sold at p per portion. If $Q \geq x$, then $Q - x$ portions are left at the end of this single period system and can theoretically be salvaged for per-unit revenue, g, which could be potential biogas value, for instance. If $Q < x$, then $x - Q$ portions represent a "lost" sales cost or goodwill loss, B, per portion. The problem can be stated as follows:

$$\Pi(Q,x) = \begin{cases} px - vQ + g(Q - x) & \text{if } Q \geq x, \\ pQ - vQ - B(x - Q) & \text{if } Q < x. \end{cases} \tag{7}$$

where the goal is to maximize the total expected profits according to:

$$E[\Pi(Q)] = \int_0^Q [px - vQ + g(Q - x)]f(x)dx + \int_Q^\infty [pQ - vQ - B(x - Q)]f(x)dx \tag{8}$$

The optimal order quantity (Q^*) is set such that:

$$\Phi(Q^*) = \frac{p - v + B}{p - g + B} \tag{9}$$

In order for kitchens to reduce their overcatering, one key solution is to have spare stock that is ready for instant serving when food from the ordinary menu runs out, since school kitchens need to serve all the guests. Our model did not allow shortages, which were instead dealt with using spare stock that can meet demand. Assumptions for the model were therefore:

- The system is a one-period model with no set-up costs.
- Demand is given by the actual outcome and the forecast value, for which the distribution is known
- Portions are sold for a price p per portion and at a cost v per portion
- There exists an unlimited amount of portions in spare stock that can be served instantly if the ordinary planned food runs out. The cost of this spare stock of food is included in B
- When using the spare stock, a goodwill cost of B SEK/portion will arise, which in this case is the cost of avoiding loss of goodwill and preventing shortages occuring, through the use of the spare stock.
- When the spare stock is used, the exact amount can be produced to satisfy customers and no considerable waste occurs. Portions are still sold for the price p per portion.
- Ordinary food from the planned menu that is overcatered and becomes waste has a small but limited value as a commodity, used for instance for biogas production, but the value can be offset by the cost of transportation and handling (Eriksson and Strid, 2013). In our case it was denoted g, which is also known as a holding cost in the literature. The parameter g can also be seen as a parameter for a "waste penalty cost", which can be viewed as a fictive cost for handling or the associated share with throwing away food.

Fig. 4 illustrates the system today and our proposed approach, both of which are shown with a fictive demand distribution. The left-hand side reflects the condition today, a system where no shortages are allowed and production is always in-phase with the number of students enrolled at the school, even if they do not show up to eat lunch. Under these circumstances, the blue area displays the average overcatered amount, which today becomes waste. The right-hand side illustrates our proposed system, where shortages are allowed but dealt with, and the optimal number of portions to produce is known (in this case located at $x = 110$). When a shortage occurs in this system, food is taken from a spare stock, for instance a freezer, to serve all guests.

To find the optimal number of portions a kitchen should produce, the average economic data from kitchens that could provide such data were used ($p = 77$ SEK/portion and $v = 22$ SEK/portion), with the additional assumption that the loss of goodwill was 80 SEK per portion. This included the purchase cost of the food taken from the backup stock and the cost of supplying this to guests who might anticipate getting food from the ordinary menu. The optimal portion quantity was then compared against different values of goodwill in a sensitivity analysis, to get an understanding of how goodwill impacts the optimal quantity produced. The goodwill costs tested were 50, 80 (base case), 200, and 1000 SEK/portion. The parameter g was also explored in a sensitivity analysis as a "waste penalty cost", in order to asses how the optimal production quantity changed when a penalty was applied to the food waste generated. The values of g tested where, 1, 10 and 20 SEK/portion and the goodwill cost in that analysis was fixed at 80 SEK/portion.

3. Results

Overall, the neural network model performed best and was the model with the lowest MAPE score for 11 out of 21 kitchens. The moving-average model with a two-day window was the best-performing model for seven kitchens, the prophet model was the best-performing model for three kitchens. However, there was sometimes very little differences between the models, as indicated by the results in Table 2, where the moving average model with a five-day window was equally good as its moving average equivalent with a two-day window or the neural network model in two of the cases (Kitchen 3 and 8). The moving-average and neural network models consistently performed better than the benchmark scenario, and the last-value approach was better than the benchmark scenario in 18 of 21 cases. The prophet model performed better than the benchmark scenario in 14 of 21 cases.

A good model needed to achieve a balance, and not just produce a forecast. A key element in this was to have some associated margins in place, since the forecast for some days will underestimate guest demand and that for other days will overestimate demand. Table 3 shows how often the forecast was an underestimate, depending on the margin added to the forecast, and by how much, in terms of how many portions were missing in the worst case during the period. It is easier to throw away food than to cook new food, so a balance is needed to obtain a feasible margin that is acceptable and practical. At 0% there was no margin and, for the 2019 data, in the worst case the forecast underestimated actual demand on 105 days out of roughly 178 school days for kitchen 6, while in the best case it underestimated actual demand on 71 days out of 178 for satellite kitchen 13. The first observation where the forecast margin yielded 0 days of underestimation was for kitchen 14 at 5% margin. At 6% margin, one more kitchen (12) was on the safe side and kitchen 13 was close, having just one day of underestimation. On passing the threshold of observing 0 days of underestimation, the amount of portions underestimated also dropped to zero. At 10% margin, 10 of the kitchens had 0 days of underestimation. Larger units struggled and, even at 30% margin for the proposed forecast, five large kitchens did not have a single day of the school year without underestimation. They would need to have at least 10–29 portions or 30+ portions to meet the demand for the 1–5 days when they would be short of food.

A good margin is to some extent a trust issue, but can be optimal. To find an optimal solution to the supply and demand problem, Eq. (9) was used to determine the optimal production quantity for each kitchen shown in Table 4. The optimal production quantity has some margins in place, since $\Phi(Q^*)$ was 0.86, which exceeded the average value of 0.5, so in most cases there

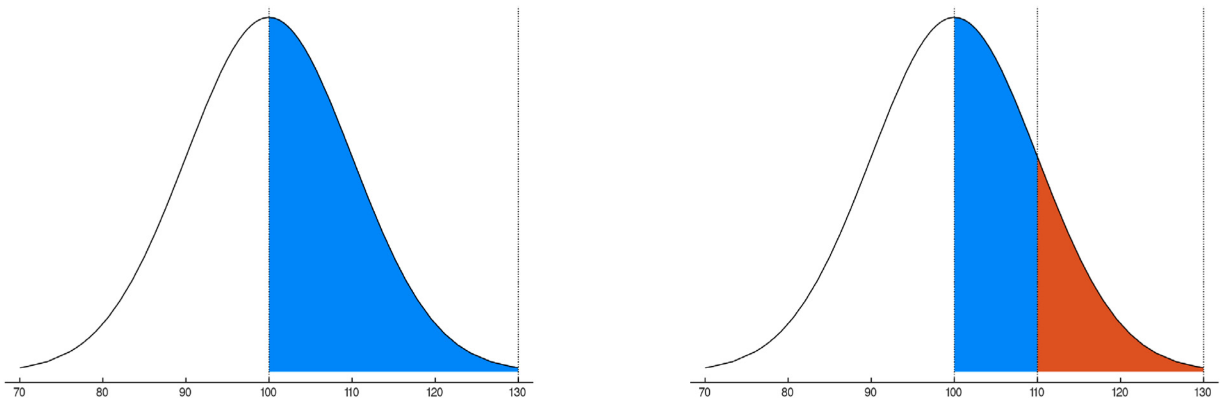

Fig. 4. Fictive distribution of demand to illustrate the problem of overcatering. (Left) The current situation, where the line at 100 is the average number of portions and the line at 130 indicates the level of service applied today. In this scenario there is no shortage of portions, and hence the area between 100 and 130 represents overcatering and associated waste generated on average. (Right) A proposed system where shortages are allowed and the optimal number of portions to produce is known, in this case located at $x = 110$. On average, this system will have some overcatering, but if food runs out guests are served food from a backup system, such as ready-to-eat food from a freezer. This is represented by the area between 110 and 130 which indicates the probability of such events.

Table 2
Mean absolute percentage error (MAPE, %) values obtained for the different models compared against the benchmark scenario (%). Unreasonable results are indicated by -. The best model for each kitchen is highlighted.

Code	Benchmark	Last-value	Moving-avg (2)	Moving-avg (5)	Prophet	Neural Network
14	3	9	**1.3**	1.4	–	1.5
12	3.2	2.8	**1.7**	1.8	5.2	1.8
13	3.7	2.3	2.2	2.1	5.9	**2**
5	5.8	2.9	2.3	2.3	11.9	**2.2**
2	6.5	7	6.1	5.1	8.7	**4.3**
7	6.9	2.4	**2.1**	2.2	3.9	2.3
10	6.9	3.9	**2.8**	3	4.1	3.1
3	7.8	3.9	**2.8**	**2.8**	7.5	3.2
9	7.9	3.3	3	3.1	10.4	**2.9**
8	8.8	2.9	2.6	**2.5**	26.9	**2.5**
1	11.1	8.8	5.4	4.7	10.9	**4.6**
21	13.8	14.7	11.4	10.3	9.4	**9**
4	13.9	4	**3.4**	3.6	12.9	3.7
11	20.4	16.3	14.3	12.2	**10.2**	10.5
15	21.1	10.1	8.6	7.7	9.4	**6.9**
16	24.6	15.8	13	11.2	13.2	**8.9**
18	24.6	15.1	13.8	13.2	**10.1**	10.4
17	30.7	12.6	9.4	8.7	28.6	**8.2**
6	32.8	3.1	**2.6**	2.7	4.4	2.7
19	42.9	13.8	12.6	11.4	**9.8**	10.3
20	45.4	14.6	12.1	11.3	11.9	**10.1**

Table 3
Added forecast margin (%), number of days on which the amended forecast underestimated actual demand for 2019, and the number of portions by which demand was exceeded, displayed in ranges of 1–9 portions (🔵), 10-29 portions (🟡) and 30+ portions (🟠).

Code	0%	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	15%	20%	25%	30%
3	81 🔵	80 🔵	46 🔵	37 🔵	28 🔵	16 🔵	9 🔵	5 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
1	79 🔵	78 🔵	64 🔵	50 🔵	37 🔵	20 🔵	16 🔵	10 🔵	6 🔵	5 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
4	92 🔵	88 🔵	59 🔵	46 🔵	27 🔵	19 🔵	12 🔵	6 🔵	3 🔵	2 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
6	105 🟡	85 🔵	71 🔵	47 🔵	28 🔵	17 🔵	7 🔵	2 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
12	87 🟡	63 🔵	43 🔵	24 🔵	9 🔵	2 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
14	81 🟡	44 🟡	19 🔵	7 🔵	5 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
10	87 🟡	64 🟡	40 🔵	24 🔵	15 🔵	11 🔵	7 🔵	6 🔵	2 🔵	1 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
7	86 🟡	71 🟡	56 🔵	28 🔵	15 🔵	7 🔵	4 🔵	3 🔵	2 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
5	81 🟡	63 🟡	42 🟡	26 🔵	13 🔵	8 🔵	6 🔵	4 🔵	1 🔵	1 🔵	1 🔵	0 🔵	0 🔵	0 🔵	0 🔵
13	71 🟡	40 🟡	25 🟡	11 🔵	4 🔵	2 🔵	1 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
2	89 🟡	88 🟡	72 🟡	53 🟡	37 🟡	27 🟡	18 🔵	13 🔵	10 🔵	6 🔵	4 🔵	1 🔵	0 🔵	0 🔵	0 🔵
8	100 🟡	89 🟡	64 🟡	46 🟡	28 🟡	20 🟡	10 🔵	3 🔵	2 🔵	1 🔵	0 🔵	0 🔵	0 🔵	0 🔵	0 🔵
9	100 🟡	81 🟡	63 🟡	37 🟡	26 🟡	20 🟡	8 🟡	6 🟡	3 🟡	2 🔵	1 🔵	0 🔵	0 🔵	0 🔵	0 🔵
17	82 🟠	78 🟠	77 🟠	65 🟠	57 🟠	51 🟠	40 🟠	35 🟠	32 🟠	27 🟠	24 🟠	10 🟡	5 🟡	0 🔵	0 🔵
16	89 🟠	81 🟠	77 🟠	68 🟠	61 🟠	59 🟠	48 🟠	47 🟠	45 🟠	40 🟠	37 🟠	24 🟡	13 🟡	3 🔵	2 🔵
15	90 🟠	81 🟠	74 🟠	65 🟠	58 🟠	48 🟠	44 🟠	38 🟠	35 🟠	31 🟠	22 🟠	9 🟠	2 🟠	1 🟡	0 🔵
21	84 🟠	80 🟠	72 🟠	65 🟠	55 🟠	49 🟠	42 🟠	36 🟠	33 🟠	31 🟠	27 🟠	11 🟠	5 🟠	2 🟡	0 🔵
11	90 🟠	86 🟠	81 🟠	76 🟠	72 🟠	70 🟠	64 🟠	56 🟠	48 🟠	46 🟠	44 🟠	18 🟠	12 🟠	5 🟠	1 🟡
18	89 🟠	84 🟠	81 🟠	77 🟠	72 🟠	66 🟠	63 🟠	57 🟠	48 🟠	41 🟠	40 🟠	25 🟠	14 🟠	8 🟠	2 🟠
19	79 🟠	76 🟠	69 🟠	61 🟠	58 🟠	53 🟠	46 🟠	44 🟠	41 🟠	38 🟠	35 🟠	21 🟠	13 🟠	5 🟠	2 🟠
20	83 🟠	77 🟠	67 🟠	64 🟠	62 🟠	56 🟠	53 🟠	50 🟠	46 🟠	43 🟠	43 🟠	28 🟠	15 🟠	8 🟠	5 🟠

Table 4
Optimal portion quantity Q^* and sensitivity analysis for goodwill costs and "waste penalty cost" for the different kitchens in the study according to Eq. (9), with selling price set to 77 SEK and purchase cost to 22 SEK. The optimum is based on an estimated goodwill cost of 80 SEK/portion, which gives $\Phi(Q^*) = 0.86$. Kitchens 18–21 are excluded because they could not provide any economic data.

	Optimum	Goodwill (SEK)			Wastepenalty cost (SEK)		
Code	Q^*	50	200	1000	1	10	20
1	**71**	70	74	78	71	70	69
2	**86**	85	89	94	86	85	84
3	**90**	89	91	95	89	89	88
4	**98**	97	100	105	98	97	96
5	**114**	114	116	118	114	114	113
6	**138**	137	139	144	138	137	136
7	**149**	149	151	154	149	148	147
8	**113**	112	114	117	113	112	112
9	**142**	141	144	149	142	141	140
10	**130**	129	132	136	130	129	128
11	**155**	152	165	180	156	150	146
12	**205**	204	206	210	205	204	203
13	**233**	232	235	240	233	231	231
14	**322**	322	325	331	322	321	320
15	**607**	600	626	658	609	596	587
16	**171**	169	177	194	171	168	165
17	**359**	353	371	396	358	351	344

was no shortage of food, but the food not eaten became waste. The optimal portion quantity was based on a goodwill cost of 80 SEK/portion.

To get an understanding of how the goodwill cost (which is difficult to quantify) affected the optimal portion quantity, a sensitivity analysis was performed (Table 4). Table 4 also shows the fictional "waste penalty cost" (g) which is the cost associated with throwing away food. Overall, lower goodwill cost pushed the optimal portion quantity closer to the expected average of portions. The same occured when a "waste penalty cost" was introduced, which for higher costs pushed the optimal portion quantity closer to the average. This is all in line with the underlying mechanics of equation 9. When comparing the different goodwill costs, the largest difference between the optimal portion quantity was found for kitchen 11, a fairly small kitchen serving guests aged 10–12 years, which for a goodwill cost of 1000 SEK/portion deviated by around 14% from the optimal order quantity at a goodwill cost of 80 SEK/portion (base case). The smallest difference was observed for kitchen 14, a medium-sized kitchen serving guests aged 6–12 years, which for a goodwill cost of 50 SEK/portion did not differ at all compared with the optimal portion quantity for the base case of a goodwill cost of 80 SEK/portion. On examining the "waste penalty cost", the largest deviation in optimal portion quantity was again observed for kitchen 11, for which for a "waste penalty cost" of 20 SEK/portion deviated by around 6% from the optimal portion quantity (Table 4). The second largest deviation was observed for kitchen 17, quite a large upper secondary school, which deviated by around 4% at a "waste penalty cost" of 20 SEK/portion. No difference regarding the optimal portion quantity was observed at a 'waste penalty cost' of 1 SEK/portion for kitchens 5–14 and 16, and the remaining kitchens had in absolute terms a difference of around one portion.

4. Discussion

By using quite simple forecasting techniques, it proved possible to predict quite accurately the number of school meals to produce. However, the outcome depends on the kitchen and the underlying guest patterns. Using simple methods appears tempting, but it is uncertain whether the forecasts they produce lead to the desired goal of reducing overcatering and food waste. Kitchens would need to be willing to change routines and to act upon the information provided by forecasting, an issue which would need to be tested in practice. This study sought to provide some answers on what forecasting strategy to use and in what way. Since kitchens are not all the same and there is no silver bullet solution that will work in all cases, strategies need to be developed individually to meet the different challenges that arise in different kitchens. Large kitchens with older students are more inclined to have a larger variability among the guests, making this scenario harder to forecast than for smaller kitchens who serve younger students, who usually don't walk away from the school meal. On the other hand larger kitchens might have the capacity and the resources to handle shortages better with a backup option. One obvious drawback of all forecasting strategies is that there needs to be reliable data on hand in order to make forecasts in the first place. When looking at plate data for some of periods included in the present analysis, it is clear that there were some uncertainties in the reported data for various reasons. For example, the same amount was reported for several days or there were missing data for some days. The data were collected using a self-reporting system, so there will always be some associated flaws. However, the same data are used for internal book-keeping, so the same kind of challenge will be transferred to the public catering management level. The first step before implementing any kind of forecasting system is to review organizational structures, since some public sector management falls within different municipal departments that operate under different budgets. This means in practice that the school management organization issues instructions to the public catering organization on how many portions to produce, but the number of portions may exceed the number of students enrolled at the school, which implies that the school organization adds some margin. Conversely, since the public catering organization gets paid by the school for how many portions they produce, the number of portions may in some cases be over-reported in order increase revenue to the organization. Last but not least, communication is a key element since no forecasting model can capture future disruptive events, including simple events such as study trips planned by the school, but not communicated to the kitchen. Even on normal days communications (or the lack of them) between the school organization and kitchen organization (WRAP, 2011) have the potential to play a major role for the kitchens ability to produce the right amount of food.

The neural network approach was the model that suited most kitchens best in the present analysis. While it was quite a simple model by neural network standards, it was still quite complex compared with the classical approaches, which could easily be implemented with no prior forecasting experience. The problem with all forecasting models is that they are uncertain and need to have some margins in place, or a backup plan ready so that kitchens can serve food to all students (who turn up), according to Swedish law. These margins can be quite large for small kitchens or for satellite kitchens that depend on an external production kitchen and therefore have problems storing backup food on-site for days when the forecast produces an underestimate. This is illustrated by the case of satellite kitchen 13, a medium-sized satellite kitchen that needed at least 7% margin on the forecast to be on 'the safe side'. To avoid excess food, satellite kitchens would need to have some kitchen equipment to store and serve backup stocks on days when demand exceeded supply, or have other means to supply all guests with food. For instance, kitchen 12 could implement the simple neural network with a 5% margin to be ready for two days per school year when the forecast underestimated the number of portions needed, and for those days have 1–9 portions on standby from the freezer. Smaller satellite kitchens appeared not to be as vulnerable and could manage well by implementing forecasting with some margin. This would be of special interest to preschools, which are often connected to a larger school where the kitchen is not far from the guests in reality. Smaller production kitchens did not suffer from the same kind of problems as satellite kitchens. They could benefit from reducing their production quantity stepwise or could implement a forecast with almost no margin at all, if they have some backup food, for instance saved from another day, ready for instant heating. Another aspect that needs to be considered is holidays, when most school kitchens serve fewer guests, and accurately forecast demand during such periods. One solution could be to use some kind of simple forecasting method or tune the neural network by training on holiday data alone. A further aspect that needs to be considered is how to forecast demand during extreme external events that cause a severe drop in guest numbers. In such cases, neural networks trained with data from several kitchens with similar characteristics (such as age of guests served) could potentially be very useful, if these kitchens can get access to historical data and some indication of how to model the anomalies in demand observed during extreme events.

In this study, economic data were used to find an optimal portion quantity in terms economic value, an approach that can be extended to encompass and optimize other aspects. Depending on the unit studied, the approach has potential to cover different kinds of values kitchens should optimize. This is also pointed out in a previous study by Schneider and Eriksson (2020), which showed that different types of products in supermarkets contribute differently to the share of food waste depending on the units applied in the analysis. For instance, a low mass of wasted meat can have a much larger share of environmental impact and cost. Applying this reasoning to the food service sector, it could be appropriate to allow higher margins on 'green' alternatives compared with more meat-heavy dishes. Thus kitchens experiencing large fluctuations in number of guests would greatly benefit from serving greener options, provided that backup stock is maintained and can properly serve all guests when food on the regular menu runs out. Waste that still occurs depending on the aspects selected for optimization can have som value depending on how it is handled and the waste management options available (Eriksson et al., 2015). However, prevention of waste has the highest priority according to various guidelines on managing food waste (USEPA, 2015; WRAP, 2014).

Estimating goodwill in economic terms is difficult, especially for a system that does not completely obey market rules. The same guests are very likely to come back to school catering establishments, since most do not have the option of eating elsewhere, so goodwill is different in this context. School kitchens could lower the number of portions produced in steps, inform guests that on some days the ordinary menu will run out and backup stock will be used to make up the shortfall, and explain why this was necessary. This could be a successful way of gaining acceptance for the change. In reality, the economic data for school kitchens may deviate, since some kitchens may have to serve more special diets, which are more expensive, and therefore influence the portion selling price and the purchasing cost of the ingredients. Overall, some kitchens make a financial loss and the portions they produce cost more than the revenue they bring in if all associated costs are taken into account. Kitchens that make a loss are 'subsidized' by other kitchens within the organization that make a profit. On an overarching level, the goal of the school catering organization is not to make a profit, but to break even, so the system is somewhat of an artificial economy. However, the approach used in this study to investigate goodwill costs and "waste penalty costs" yielded some interesting results suggesting that each kitchen has its own challenges and thus that individual measures will be needed for different kitchens. Overall, for some kitchens high goodwill cost will have a large impact on the optimal portion quantity related to the base case, pushing the optimal portion quantity closer to the current situation where the kitchens provide food for all enrolled students, whereas other kitchens will not be greatly affected. The same reasoning applies to the "waste penalty cost", which in most cases would need to be very high to push the optimal portion quantity closer towards the expected portion quantity average. Combining forecasting with a backup stock approach can lower overcatering. In the present analysis, the benchmark scenario suggested that kitchens could reduce MAPE from around 20–45% to as low as around 2–3% in the best case, even if some margins were added to the forecast. Today, kitchens do not seek to identify the optimal number of portions to produce and the system is optimized to produce close to 100% service level, due to fear of shortages. By stepwise adjusting the service level downwards, applying appropriate margins, knowing approximately how many times a shortage is likely to occur, and having a backup stock ready, fear of unknown shortages could be overcome.

It is difficult to assess the potential of forecasting if it were broadly introduced in all public catering establishments. However, as a result of forecasting in this study, the weighted average went down from around 16% in the benchmark scenario to, in the best case, 5% for the neural network model, an improvement of around 10 percentage units. If kitchens applied this best-case model combination in practice, they would need to have some margin in place, of around 5%, to be assured in their everyday work, which implies that today's level of overcatering food waste of around 20% would drop to 15%. Applying this improvement to the official Swedish food waste figures for public catering at the current level of 73,000 tons (SEPA, 2020) would lower the amount of food waste by around 18,250 tons. Introducing forecasting would not be free of charge, but the costs are difficult to estimate exactly. Assuming that the cost of introducing such a system is 10 MSEK and that the food thrown away is worth 20 SEK per kg, the potential saving would be roughly 350 MSEK annually for this prevention measure in the public catering sector alone. It is however doubtful if these savings can be observed since the money might be allocated to something else since municipalities have a broad range of responsibilities.

This study provide insights that can help school kitchens deal with an uncertain future or can at least provide them with a plan for trimming production based on forecasts, to address the problem of overcatering and thereby reduce food waste. The study was based on data from Swedish school kitchens, which is a specific case, however school catering is not something unique for Sweden and even if some of the settings might differ these have a lot in common with other cases where a frequent guest basis exist, such as workplace canteens, hospitals and hotels (Silvennoinen et al., 2015; Wang et al., 2017) where overcatering is a problem (Aamir et al., 2018). There is therefore a great potential for such food service actors to use concepts as forecasting put forward by this study and others (Ryu et al., 2003; Ryu and Sanchez, 2003; Sel et al., 2017) to reasonably balance supply and demand. If this is also combined with knowledge on how to deal with shortages by having a backup stock ready, this might be a useful combination of tools to minimize overcatering, prevent food waste, and achieve a more sustainable food system.

5. Conclusions

By using different forecasting approaches, in the best case guest demand in school catering establishments was predicted with a mean average percentage error of 2–3%. Even simple forecasting methods revealed potential to lower overcatering and address food waste levels. Our recommendation for kitchens is to start with a simple forecasting technique with some acceptable margins and be prepared to handle shortages if the margin is not adequate. Having some sort of forecast will always be better than the existing system, where kitchens prepare food for all enrolled students even if they show up or not. To lower food waste there is a need to reduce overcatering in public sector establishments and allow shortages, but to have backup stock ready for instant serving. By reducing the production rate stepwise, an optimal and feasible level of portion numbers can be achieved, with great potential to lower food waste. Satellite kitchens would benefit greatly from having some kitchen equipment, such as a freezer and oven, together with a forecast with some margin to properly handle fluctuating demand. However, all information on guest numbers provided to kitchens needs to be acted upon by kitchen staff in order to reduce overcatering. It is important to take the findings of this paper and test in reality in order to gain knowledge on how this can be a useful tool to reduce food waste, as technical aid might not always be used to their full potential.

Declaration of Competing Interest

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

Acknowledgments

This work was carried out in the project Adding Value in Resource Effective Food Systems (AVARE) supported by H2020 ERA-net Cofund on Sustainable Food Production and Consumption (SUSFOOD2) and by the Swedish Research Council for Sustainable Development (Formas), grant number FR-2018/0001. The authors would also like to thank the organizations and kitchens who provided data to the study.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.spc.2020.08.008.

References

Aamir, M., Ahmad, H., Javaid, Q., Hasan, S.M., 2018. Waste not, want not: a case study on food waste in restaurants of Lahore, Pakistan. J. Food Prod. Mark. 24 (5), 591–610. doi:10.1080/10454446.2018.1472695.

Abeliotis, K., Lasaridi, K., Costarelli, V., Chroni, C., 2015. The implications of food waste generation on climate change: the case of Greece. Sustain. Prod. Consum. 3, 8–14. doi:10.1016/j.spc.2015.06.006.

Bezerra, I.N., Curioni, C., Sichieri, R., 2012. Association between eating out of home and body weight. Nutr. Rev. 70 (2), 65–79. doi:10.1111/j.1753-4887.2011.00459.x.

Boschini, M., Falasconi, L., Cicatiello, C., Franco, S., 2020. Why the waste? A large-scale study on the causes of food waste at school canteens. J. Clean. Prod. 246, 118994. doi:10.1016/j.jclepro.2019.118994.

Boschini, M., Falasconi, L., Giordano, C., Alboni, F., 2018. Food waste in school canteens: a reference methodology for large-scale studies. J. Clean. Prod. 182, 1024–1032. doi:10.1016/j.jclepro.2018.02.040.

Byker, C.J., Farris, A.R., Marcenelle, M., Davis, G.C., Serrano, E.L., 2014. Food waste in a school nutrition program after implementation of new lunch program guidelines. J. Nutr. Educ. Behav. 46 (5), 406–411. doi:10.1016/j.jneb.2014.03.009.

Camilleri-Fenech, M., i Sola, J.O., Farreny, R., Durany, X.G., 2020. A snapshot of solid waste generation in the hospitality industry. The case of a five-star hotel on the island of Malta. Sustain. Prod. Consum. 21, 104–119. doi:10.1016/j.spc.2019.11.003.

Campbell, B.M., Beare, D.J., Bennett, E.M., Hall-Spencer, J.M., Ingram, J.S.I., Jaramillo, F., Ortiz, R., Ramankutty, N., Sayer, J.A., Shindell, D., 2017. Agriculture production as a major driver of the earth system exceeding planetary boundaries. Ecol. Soc. 22 (4). doi:10.5751/es-09595-220408.

Chollet, F., et al., 2015. Keras. https://keras.io.

van Donselaar, K.H., Broekmeulen, R.A., 2012. Approximations for the relative outdating of perishable products by combining stochastic modeling, simulation and regression modeling. Int. J. Prod. Econ. 140 (2), 660–669. doi:10.1016/j.ijpe.2012.02.023.

Engström, R., Carlsson-Kanyama, A., 2004. Food losses in food service institutions examples from sweden. Food Policy 29 (3), 203–213. doi:10.1016/j.foodpol.2004.03.004.

Eriksson, M., Malefors, C., Bergström, P., Eriksson, E., Osowski, C.P., 2020. Quantities and quantification methodologies of food waste in swedish hospitals. Sustainability 12 (8), 3116. doi:10.3390/su12083116.

Eriksson, M., Osowski, C.P., Malefors, C., Björkman, J., Eriksson, E., 2017. Quantification of food waste in public catering services—A case study from a Swedish municipality. Waste Manag. 61, 415–422. doi:10.1016/j.wasman.2017.01.035.

Eriksson, M., Persson Osowski, C., Björkman, J., Hansson, E., Malefors, C., Eriksson, E., Ghosh, R., 2018. The tree structure—A general framework for food waste quantification in food services. Resour. Conserv. Recycl. 130, 140–151. doi:10.1016/j.resconrec.2017.11.030.

Eriksson, M., Strid, I., 2013. Svinnreducerande Åtgärder i Butik : Effekter på Kvantitet, Ekonomi och Klimatpåverkan. Naturvårdsverket, Stockholm.

Eriksson, M., Strid, I., Hansson, P.-A., 2015. Carbon footprint of food waste management options in the waste hierarchy—A Swedish case study. J. Clean. Prod. 93, 115–125. doi:10.1016/j.jclepro.2015.01.026.

Falasconi, L., Vittuari, M., Politano, A., Segrè, A., 2015. Food waste in school catering: an Italian case study. Sustainability 7 (11), 14745–14760. doi:10.3390/su71114745.

FAO, 2019. The State of Food and Agriculture 2019: Moving Forward on Food Loss and Waste Reduction. Food and Agricultural Organization of the United Nations, Rome.

Gooijer, J.G.D., Hyndman, R.J., 2006. 25 years of time series forecasting. Int. J. Forecast. 22 (3), 443–473. doi:10.1016/j.ijforecast.2006.01.001.

Hadley, G., 1963. Analysis of Inventory Systems. Prentice-Hall, Englewood Cliffs, N.J.

Hillier, F.S., Lieberman, G.J., 2014. Introduction to Operations Research. McGraw-Hill Education Ltd, New York.

Hyndman, R.J., Athanasopoulos, G., 2018. Forecasting: Principles and Practice. OTexts.

Kant, A.K., Graubard, B.I., 2004. Eating out in america, 1987–2000: trends and nutritional correlates. Prev. Med. 38 (2), 243–249. doi:10.1016/j.ypmed.2003.10.004.

Katajajuuri, J.-M., Silvennoinen, K., Hartikainen, H., Heikkilä, L., Reinikainen, A., 2014. Food waste in the finnish food chain. J. Clean. Prod. 73, 322–329. doi:10.1016/j.jclepro.2013.12.057.

Lachat, C., Nago, E., Verstraeten, R., Roberfroid, D., Camp, J.V., Kolsteren, P., 2011. Eating out of home and its association with dietary intake: a systematic review of the evidence. Obes. Rev. 13 (4), 329–346. doi:10.1111/j.1467-789x.2011.00953.x.

Malefors, C., Callewaert, P., Hansson, P.-A., Hartikainen, H., Pietiläinen, O., Strid, I., Strotmann, C., Eriksson, M., 2019. Towards a baseline for food-waste quantification in the hospitality sector—quantities and data processing criteria. Sustainability 11 (13), 3541. doi:10.3390/su11133541.

Ministry of Education and Research of the Republic of Estonia, 2019. Pre-school, basic and secondary education | Estonian Ministry of Education and Research. https://www.hm.ee/en/activities/pre-school-basic-and-secondary-education.

National Food Agency, 2019. Fakta om offentliga måltider. https://www.livsmedelsverket.se/matvanor-halsa--miljo/maltider-i-vard-skola-och-omsorg/fakta-om-offentliga-maltider/.

Nielsen, S., 2002. Trends in food locations and sources among adolescents and young adults. Prev. Med. 35 (2), 107–113. doi:10.1006/pmed.2002.1037.

Ramberg, J., Låftman, S.B., Fransson, E., Modin, B., 2018. School effectiveness and truancy: a multilevel study of upper secondary schools in Stockholm. Int. J. Adolesc. Youth 24 (2), 185–198. doi:10.1080/02673843.2018.1503085.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E.F., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J., Nykvist, B., de Wit, C.A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P.K., Costanza, R., Svedin, U., Falkenmark, M., Karlberg, L., Corell, R.W., Fabry, V.J., Hansen, J., Walker, B., Liverman, D., Richardson, K., Crutzen, P., Foley, J.A., 2009. A safe operating space for humanity. Nature 461 (7263), 472–475. doi:10.1038/461472a.

Ryu, K., Jang, S.S., Sanchez, A., 2003. Forecasting methods and seasonal adjustment for a university foodservice operation. J. Foodserv. Bus. Res. 6 (2), 17–34. doi:10.1300/j369v06n02_03.

Ryu, K., Sanchez, A., 2003. The evaluation of forecasting methods at an institutional foodservice dining facility. J. Hosp. Financ. Manag. 11 (1), 27–45. doi:10.1080/10913211.2003.10653769.

Schneider, F., Eriksson, M., 2020. Routledge Handbook of Food Waste. Routledge, Abingdon, Oxon New York, NY.

Sel, Ç., Pınarbaşı, M., Soysal, M., Çimen, M., 2017. A green model for the catering industry under demand uncertainty. J. Clean. Prod. 167, 459–472. doi:10.1016/j.jclepro.2017.08.100.

SEPA, 2020. Matavfall i Sverige. Uppkomst Och Behandling 2018. Swedish Environmental Protection Agency.

Silvennoinen, K., Heikkilä, L., Katajajuuri, J.-M., Reinikainen, A., 2015. Food waste volume and origin: case studies in the finnish food service sector. Waste Manag. 46, 140–145. doi:10.1016/j.wasman.2015.09.010.

Sonnino, R., McWilliam, S., 2011. Food waste, catering practices and public procurement: a case study of hospital food systems in wales. Food Policy 36 (6), 823–829. doi:10.1016/j.foodpol.2011.09.003.

Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B.L., Lassaletta, L., de Vries, W., Vermeulen, S.J., Herrero, M., Carlson, K.M., Jonell, M., Troell, M., DeClerck, F., Gordon, L.J., Zurayk, R., Scarborough, P., Rayner, M., Loken, B., Fanzo, J., Godfray, H.C.J., Tilman, D., Rockström, J., Willett, W., 2018. Options for keeping the food system within environmental limits. Nature 562 (7728), 519–525. doi:10.1038/s41586-018-0594-0.

Steen, H., Malefors, C., Röös, E., Eriksson, M., 2018. Identification and modelling of risk factors for food waste generation in school and pre-school catering units. Waste Manag. 77, 172–184. doi:10.1016/j.wasman.2018.05.024.

Storup, K., Mattfolk, K., Voinea, D., Jakobsen, B., Bain, M., Reverté Casas, M., Oliveira, P., 2016. Combating Food Waste: An Opportunity for the EU to Improve the Resource-Efficiency of the Food Supply Chain. Vol. 34. doi:10.2865/8374.

Swedish National Agency for Education, 2019. Statistik. https://www.skolverket.se/skolutveckling/statistik.

Swedish Parliament, 2010. Svensk författningssamling. Skollag (School law) 800.

Swedish Parliament, 2011. Svensk författningssamling. Skolförordningen 185.

Taylor, S.J., Letham, B., 2017. Forecasting at scale. Peer J Prepr. 5, e3190v2. doi:10.7287/peerj.preprints.3190v2.

Tikkanen, I., Urho, U.-M., 2009. Free school meals, the plate model and food choices in finland. Br. Food J. 111 (2), 102–119. doi:10.1108/00070700910931940.

Tukey, J., 1977. Exploratory Data Analysis. Addison-Wesley Pub. Co, Reading, Mass.

United Nations, 2015. Transforming Our World: The 2030 Agenda for Sustainable Development.

United Nations, 2019. World Population Prospects 2019: Data Booklet (ST/ESA/SER.A/424). Department of Economic and Social Affairs, Population Division.

USEPA, 2015. Sustainable Management of Food. https://www.epa.gov/sustainable-management-food.

Wang, L.-e., Liu, G., Liu, X., Liu, Y., Gao, J., Zhou, B., Gao, S., Cheng, S., 2017. The weight of unfinished plate: a survey based characterization of restaurant food waste in chinese cities. Waste Manag. 66, 3–12. doi:10.1016/j.wasman.2017.04.007.

WRAP, 2011. Food Waste in Schools. Waste Resources Action Programme, Branbury.

WRAP, 2014. Why take action: Legal/policy case | WRAP UK. http://www.wrap.org.uk/content/why-take-action-legalpolicy-case.

Xue, L., Liu, G., Parfitt, J., Liu, X., Herpen, E.V., Stenmarck, Å., O'Connor, C., Östergren, K., Cheng, S., 2017. Missing food, missing data? A critical review of global food losses and food waste data. Environ. Sci. Technol. 51 (12), 6618–6633. doi:10.1021/acs.est.7b00401.