On the Potential of Tertiary Espresso Machines to Provide Frequency Containment Reserves Services

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***Abstract*—The increase of renewables in the electricity mix is changing how power systems operate and adding new players to the energy markets. In a very short time, it is expected that aggregators can provide balancing services that leverage the flexibility of small and medium-sized consumers. This paper presents a study that assesses the potential of using professional espresso machines to provide Demand-Side Flexibility (DSF) services and, more concretely, Frequency Containment Reserves (FCR). The proposed methodology takes advantage of the coffee and steam boiler components of the coffee machine to identify opportunities to reduce the electricity demand, hence providing demand-side flexibility. The proposed methodology is evaluated using synthetic data generated from a dataset initially collected from an original professional espresso coffee machine during its daily operation. The results show that for a group of 100 coffee machines, the disposable power through the day would vary from 33 kW in the nighttime to 42 kW between 10 AM and 6 PM. The results also show that a minimum of 10 coffee machines are necessary to establish a non-zero disposable power and that after about 30 coffee machines are aggregated, the achievable disposable power becomes nearly linear.**

***Index Terms*—Demand-Side Flexibility, Frequency Containment Reserves, Tertiary Espresso Machines, Demand Prediction**

I. INTRODUCTION

The impact that climate change and global warming have on human existence occupies the attention of several scientists around the world. It is estimated that human activities have been responsible for the increase of global temperature by around 1○C degree above the pre-industrial level and are likely to cause further growth of global warming to 1.5○C within the next three decades [1]. To mitigate the adverse effects of global warming, the European Union (EU) prepared its climate policy. Among other measures, the EU emphasizes the importance of energy efficiency, setting an ambitious goal of 32.5% improvement up to 2030 [2].

To fulfill this commitment, various actions were taken, including introducing an eco-design and labeling policy, which supports low-energy solutions for a broad spectrum of industries and products. The EU eco-design and labeling policy, based on Directive 2009/125/EC [3], creates a framework for compulsory environmental requirements for 31 selected groups of products within the EU, including energy-using devices as well as other energy-related products.

The methodology for implementing the eco-design and labeling policy is described in the Eco-design Working Plan (EWP), currently, in version 2022-2024 [4]. The previous working plan study analyzed the tertiary hot beverage equipment, including espresso coffee machines. The evaluated products were free-standing hot vending machines, table-top full automatic machines, and porta-filter espresso machines. The estimated energy savings for the three products group was up to 11PJ per year in 2030. While these savings were below the pre-established threshold, the group was recommended to be included because Europe is the leading market, and half of the existing coffee machines are tertiary[1]. Furthermore, in many Member States, there has been an increase in coffee shops focusing on high-quality coffee [4].

However, one crucial aspect to consider is that these works focus mainly on the potential for reducing energy demand (e.g., setting power limits to appliances in off, standby, or networked mode [5]), leaving out relevant aspects such as the possibility of actively participating in electricity markets through the provision of Demand-Side Flexibility (DSF) services via an aggregator or an energy community as laid out in the recent reform of the European energy market design [6].

In this context, tertiary espresso machines offer an exciting opportunity to introduce a new player to the electricity market for two main reasons. First, they have two internal boilers to manage heating cycles that can be controlled without compromising the quality of the brewed coffees. For example, an injection of power into the grid from the perspective of a grid operator is achieved by the asset by reducing its power consumption in a given instant [7]. Second, the considerable availability of such devices represents a unique opportunity for independent aggregators that act on behalf of small consumers in the electricity markets. For example, in Europe alone, the stock of tertiary espresso machines is estimated to be above 1.5 million units [7], [8].

Against this background, this paper studies the potential of tertiary espresso machines to participate in DSF services, particularly Frequency Containment Reserve (FCR). To state more precisely, FCR was selected for three main reasons. First, the short duration of the service (in the order of a few minutes) [9] since it is more adequate to avoid drastic changes in the temperature of boilers. Second, the expectation of higher

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[1]https://www.grandviewresearch.com/industry-analysis/coffee-machine-market

profits for small players [10]. And finally, the recent efforts towards developing markets and establishing prequalification processes for such services [11].

To the best of our knowledge, this is the first work that addresses this topic. This contrasts with the case of domestic appliances, which have been studied in detail regarding their potential for providing DSF services, e.g., [12], [13].

This paper is organized as follows: Section II presents the background and related works. The dataset used in this work and the proposed methods are presented in Section III. The main results of this work are presented and discussed in Section IV. Finally, the conclusions, limitations, and future work directions are presented in Section V.

II. Background and Related Works

A. Balancing Services

Due to the physical characteristics of electricity transmission, i.e., a constant need for balance between consumption and production, it is relevant for the grid's security to provide a range of ancillary services. This includes the balancing services, which, based on EU guidelines on electricity balancing [14], consist of capacity and energy services that enable continuous maintenance of the system frequency within a predefined stability range.

The typical behavior of a commercial espresso machine consists of relatively significant power changes when extra heat is necessary to preserve the boiler's temperature or produce hot water and steam flow. Hence, espresso machines are more adequate for providing reserve services, as these services have a relatively short duration and require fast activation. There are currently four different types of reserves: 1) Frequency Containment Reserve (FCR), 2) Automatic Frequency Restoration Reserves (aFRR), 3) Manual Frequency Restoration Reserves (mFRR), and 4) Restoration Reserve (RR).

The above categorization is mainly based on their actual difference in the duration of delivery as well as the response time. Whenever the grid frequency has a drop or a spike, FCR is automatically activated (within a maximum 30-second period). Stabilizing the grid using FCR involves the cooperation of every Transmission System Operator (TSO) within the synchronous area. Next, after a few minutes, the frequency restoration process takes place. It includes automatic activation of Frequency Restoration Reserve (aFRR), whereas the launch of manual frequency restoration reserves (mFRR) depends on a direct request from the TSO. The purpose of FRR is to restore the nominal value of the grid frequency. The last step, which supports or replaces FRR, is activating the restoration reserve (RR). RR is usually switched on after 15 minutes, and participation in the service is not considered mandatory in the EU (however, the system should provide such a service).

The graphical representation of the reserve functionality is depicted in Fig. 1. According to the diagram, the general framework of load-frequency control consists of three main phases. Initially, after the frequency disturbance occurs, the joint action of FCR is activated for the whole synchronous area. The process starts almost immediately when a disproportion between production and electricity demand occurs. Consequently, the grid frequency is stabilized. If the FCR is insufficient, it is then replaced by FRR, restoring frequency to a given setpoint value. After that, RR supports or replaces the FRR for further grid stabilization.

In short, it can be concluded that coffee machines can be most suitable for FCR services mainly due to the much shorter duration of the service that will not drastically change the thermodynamic parameters of boilers. Consequently, the quality of the service (e.g., waiting time to reach the required temperatures) will be scarcely influenced, or, at least, the impact will be lower than in the case of FRR or RR [7].

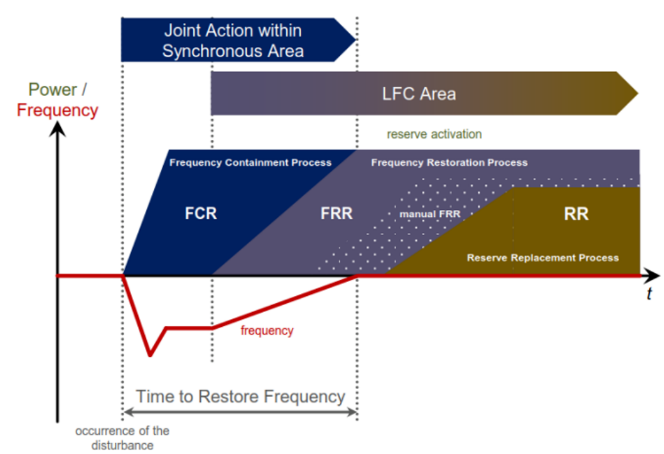


Fig. 1: Reserve activation structure as an answer for frequency drop (red line) - ENTSO-E [9].

B. DSF Potential of Individual Appliances

To the best of our knowledge, no published works have looked at espresso machines in the context of DSF. Instead, research on this topic gained traction at the domestic level (e.g., [15], [12], [16], [13]), with exciting preliminary results than can potentially be replicated to espresso machines and other commercial devices. In this regard, devices such as Air Conditioners (ACs), clothes washers and dryers, and water heaters receive the most attention due to their high energy consumption and technical feasibility since a thermostat controls them. Most data-driven models rely on fitting appliance consumption profiles to different flexibility scenarios, including the possibility of changing the power levels during the appliance operation and for deferring or anticipating the start of appliance usage [12], [16]. Other data-driven methods focus on identifying repeating inter-day and intra-day patterns for energy distribution and device operation, as the existence of peaks and off-peak periods for some devices shows the potential to shift their activation time [15], [13].

Finally, it is also relevant to refer to some works that look at espresso machines from different but complementary perspectives [8], [17], [18], [19], [20]. For example, [17] studied the potential energy savings for espresso machines and concluded that it is possible to reduce their energy demand between 10% and 40% depending on the type of machine. In [8], the authors estimated the stock size of tertiary espresso machines in Europe, reaching a number above 1.5

million units. Finally, in [19], the authors report on recent efforts to produce more sustainable coffee machines, focusing on designing components that can be easily disassembled, recycled, and re-manufactured.

Ultimately, while not directly related to DSF, these works are still very relevant to successfully implementing such services. For instance, the size of a stock is a clear indicator of the potential size of the markets in different countries. Likewise, having a standard design of the heating elements as proposed in [19] would bring enormous advantages concerning replication and standardization efforts.

C. Intermittent Demand Prediction

A vital characteristic of an espresso machine is the ability to deliver its products on demand despite extended periods of zero demand. An attempt to anticipate such erratic demand is ambitious and challenging because irregular demand arrivals are combined with different demand sizes [7]. The literature review shows that some solutions were discussed since this problem frequently occurs in several industries, primarily associated with stock control systems, for example, engineering spares kept at wholesale warehouses [21].

In this respect, J.D. Croston in [22] suggests decomposing the data into two independent series: the first associated with inter-demand intervals (IDI) and the second focused on the value of non-zero demand. Many other alternatives [23], [24], based on this method were later proposed, such as Syntetos-Boylan Approximation [25] or Teunter–Syntetos–Babai method [26]. They all, however, focus on estimating an average future demand. Nonetheless, a similar approach for data generation may be applied due to a similarity between coffee brewing behavior and stock control for intermittent demand. In particular, addressing coffee demand arrivals and sizes separately seems to be a reasonable concept.

However, before applying any direct technique, it is crucial to consider the possibility of temporal aggregation. This idea was successfully described and proven in [27]. According to this work, it is possible to decrease or even eliminate variance from demand arrivals by cutting down the frequency of the data.

Another relevant issue to discuss is the selection of proper distribution for the forecasting model. Numerous studies have investigated the goodness-of-fit of several parametric statistical distributions in intermittent demand. A lengthy discussion concerns the selection of a proper distribution for forecasting data. Considering the case of a discrete-time variable, a Bernoulli process can generate demands, whereas, for continuous time, the Poisson or Gamma distribution is used. Among others, a compound Poisson distribution has been discussed among operations research scientists [28], especially while applying it along with geometrical distribution for demand size. One may also follow the widely used normal distribution [22]. However, it would be somewhat unrealistic when applied to demand sizes. Interestingly, a normality assumption can be more reasonable in case of lead time demands due to the central limit theorem's impact on the summation of demands over a relatively long time horizon or when the coefficient of variation is low [29].

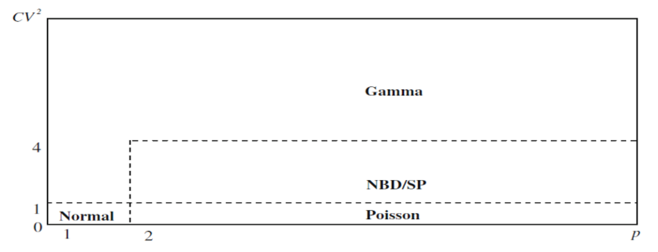


Fig. 2: Classification scheme for demand distributions, where p corresponds to IDI.

In this respect, Syntetos and Boylan [25] developed a demand distribution classification based on two parameters: the IDI and the squared coefficient of variation C_v^2. Their empirical study resulted in the scheme presented in Fig. 2. It can be observed that for low values of C_v^2 and IDI, a normal distribution is recommended. Low C_v^2 generally correspond to Poisson distribution, whereas Gamma is used for extreme cases. A negative binomial distribution seems to be a reasonable choice for other situations.

Another proposed qualification scheme divides data into qualifying and non-qualifying. The qualifying one will be considered when the variance is not smaller than the mean. Two distributions are recommended for them: NBD and Poisson. Similarly, based on IDI and C_v^2, four kinds of demand can be distinguished [30]: 1) Smooth – in which occurrence has very few no-demand values and demand itself has modest variation; 2) Intermittent – when there is plenty of no-demand data, but variation is not substantial; 3) Lumpy – with a very high variation of demand and high occurrence of no-demand data; and 4) Erratic – with very few no-demand arrivals and present high variability in demand size.

III. Dataset and Methods

The methodology to assess the potential of tertiary espresso machines for participating in FCR markets consists of three main steps: 1) investigate the patterns in coffee brewing within particular days and hours to find the timeslots for which disposable power for FCR services will be available; 2) generate new daily datasets including the timestamps of coffee brewing to simulate the aggregation of several espresso machines; and 3) for a given size of espresso machines aggregation estimate the disposable power. The espresso machine data used in this work and the three steps of the proposed methodology are described next.

A. Coffee Machine Dataset

This work uses data from a three-group coffee machine collected in a German café. This café is an independent, average-sized, urban-style café and bar serving hot and cold beverages, snacks, and drinks. It is open seven days per week from 8 AM to 11 PM except for weekends, with operating hours till 1-2 AM. The café owns two fully working espresso machines *La Marzocco Linea Classic model EE*. A tertiary espresso machine has five main elements: water boiler, coffee boiler, exterior, three brewing groups, and pump [31]. The first two are of particular interest due to their heat storage function. The steam boiler's central part is a stainless steel cylindrical tank with a minimum operating pressure of 1.5 bar. The effective volume and standard power rate are 11 liters and 3 kW, respectively. On the other hand, the coffee boiler has a much higher operating pressure equal to 9 bars and an effective volume of 5 liters. The suggested coffee-making temperature is 93.3°C and is maintained via PID controller with a dT of ±0.5°C [7].

The espresso machine was connected to a smart meter from March 2019 till March 2020. Due to technical reasons and the scope of this research, it was decided to consider three months from 1st October to 31st December 2019 as a reference period. The smart meter collects power values from each phase at 1Hz resolution and continuously transfers them to the central server. Due to some technical limitations of the smart meter, it was impossible to collect an error-free sample of data. As such, it was necessary to perform a data-cleaning step before proceeding with the remaining experiments. To this end, the percentage of missing values for each phase was calculated. The results were structured and presented in Fig. 3. It can be noticed that slightly more than 4% of the first phase values are missing, whereas this ratio equals 3.5% for the second and third phases. Furthermore, the right side of Fig. 3 shows how these missing values are correlated, i.e., it presents the percentage of all possible combinations of missing values within the dataset. 91% of all available data includes values for all the variables, whereas only 0.38% of the instances have missing values from all three phases.

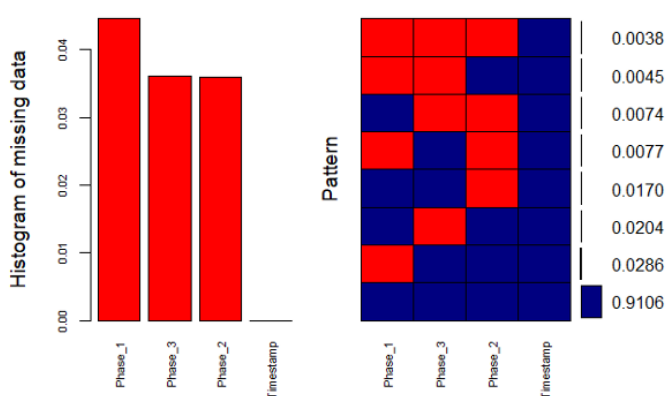


Fig. 3: Graphical presentation of missing values in a single day of data (5th October 2019).

It was decided that the missing values characterized by random occurrences would be replaced. Different methodologies were discussed; however, a simple approach of replacing NANs with the most recent non-NAN value before them was chosen. This approach reflects the behavior of the appliance's load because the particular elements of the heating cycle (such as the pump's operational time, steam, and coffee boiler heating phase) have a time length longer than one second.

B. Appliance Pattern Investigation

The first step is to analyze the impact of a particular hour and weekday on the appliance's load demand. This is especially important for markets where FCR services can be provided within small time intervals, i.e., different values can be contracted for different days, day periods, or even particular time blocks. On the other hand, for other sorts of markets, this approach might be beneficial to identify the bottleneck of the services.

An example plot of the espresso machine's three-phase power demand is presented in Fig. 4. The phase connection to the electrical elements is the following: Phase 1: steam boiler and coffee boiler, Phase 2: coffee boiler, and Phase 3: steam boiler and a pump. Periodical, rectangular high peaks reflect the power used for preserving heat in a steam boiler (colored red and yellow). In contrast, more flattered, uneven periodic rises show PID-controlled heating for a coffee boiler (colored black and red). Since no coffee is made at night, the pump's power consumption is not shown in the graph. In contrast, during the day, it is possible to observe several pump activations (around 300 W) when several coffees are brewed.

Due to the lack of additional indicators on coffee brewing, it is not feasible to identify the exact number of brewed coffee products. Therefore, it is assumed that it is possible to infer that a single coffee is produced when the pump works longer than 16 seconds. This value is slightly lower than 20 seconds, the usual minimum time for brewing one espresso [32]. However, it reflects the histogram of the pump's working time observed in the collected data and the exploratory data analysis.

It is important to stress that this assumption underestimates periods in which more than one coffee is brewed in short succession since even a more prolonged pump activation will account for a single coffee. However, for the sake of this research, the most relevant aspect is the identification of the periods in which coffee brewing started.

The interval for coffee counts is set to 10 minutes. Such generated load profiles will help identify the timeslots with similar power consumption. The timeslot with the lowest load value will be treated as an FCR bottleneck.

C. Data Generation

Based on data collected from October 1st 2019 to November 29th 2019 (60 days), it was decided to create a data generator to simulate a more significant number of espresso machines. The first step in following this approach was to establish a method to forecast the timestamps of brewing coffees.

In our specific dataset, there is some variation between IDI and CV2, depending on the level of aggregation and a particular day. However, most often, a squared coefficient of variation is lower than 1. On the other hand, as mentioned before, the IDI parameter can vary spectacularly, from values up to 200 (seconds resolution) to nearly 1 (aggregated data). Nonetheless, even aggregated data can obtain different values from 1 to 8 (between 20:00 and 21:00).

Considering this, selecting the most adequate distribution for a given dataset is challenging. However, based on Fig. 2,

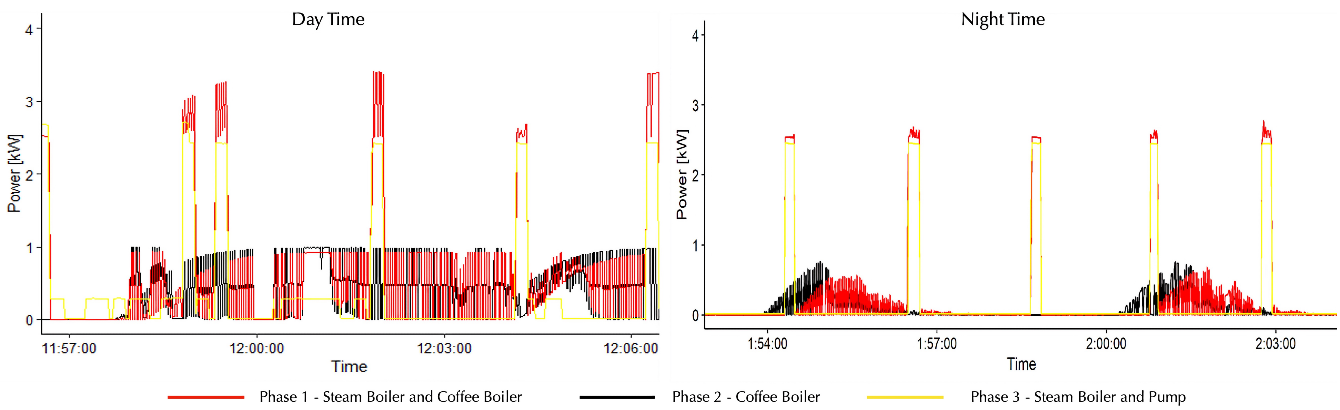


Fig. 4: Heating cycle of a coffee machine. Left: day time, right: night time.

one can suggest that NBD or Poisson distribution should be addressed, as the gamma distribution is too extreme and the normal one does not include the high IDI range. Although the Poisson distribution is very encouraging, it was decided to choose a negative binomial distribution for a few reasons. Firstly, the presented qualification scheme is based on empirical studies of stock-keeping units (SKU). Thus, a discrepancy between SKU and our dataset is probable. Consequently, a distribution suitable for a broader range of IDI and CV2 is needed. Secondly, the NBD for low values of CV2 can be less precise and provide more variety to our forecast. Consequently, it can mitigate the negative effect of building the prediction model on a single coffee machine. Following the above discussion, the same methodology will be followed to estimate intermittent demand as in [21]. The non-zero demands are forecasted using Bernoulli distribution and are described with the probability density function given by Eq. (1):

$$P(n) = \begin{cases} 1-p & \text{if n = 0} \\ p & \text{if n = 1} \end{cases} \tag{1}$$

where n is a possible outcome, equal to 1 with probability p (success) or 0 with probability $1-p$ (failure). It is a special case of binomial distribution with one number of trials. In our case, the probability p is equal to the inverse of the inter-demand interval:

$$p = \frac{1}{IDI} \tag{2}$$

This creates a binary vector B of a given length l, where one indicates that the demand is non-zero, and zero otherwise.

The size of the demand (number of coffees made when demand is non-zero) is calculated using the negative binomial distribution [28], [21] with given probability density function:

$$P(X=k) = \binom{k+r-1}{k} \times p^r(1-p)^k \tag{3}$$

where, k is the number of failures, r is equal to number of successes and p equals to probability of success, given by:

$$p = \frac{\mu}{C_v^2(1+\mu)^2} \tag{4}$$

where C_v^2 is the squared coefficient of variation.

The values generated with the negative binomial distribution are directly increased by 1 to avoid demands of zero and create a new vector C. Finally, the output is vector X_t:

$$X_t = B_c \times C_t, \quad t = 1, \dots, l \tag{5}$$

The final step is to bootstrap the values of IDI, C_v^2, and μ from the existing espresso machine data to generate the demand profiles of new coffee machines. To this end, a matrix with 60 x 3 dimensions is created, consisting of IDI, C_v^2, and μ for each of 60 days. The parameters C_v^2 and μ are assumed to follow a normal distribution from the collected data, which is reasonable due to their respective histograms. However, it was not possible to find a suitable proper distribution for IDI data. Hence, it was decided to generate new IDI values with a sampling method.

D. *Disposable Power Calculation*

The algorithm to calculate the disposal power from an aggregation of coffee machines takes four inputs: the number of coffee machines to aggregate, the level of accuracy representing the percentage of time for which a calculated disposable power is available, a database with the coffee boiler's power distributions that was built from the existing espresso coffee machine data, and the forecasted matrix of coffees with the assigned pumps' working time.

The algorithm is divided into two stages for each of the d coffee machines. The first focuses on the coffee boiler, whereas the second focuses on the steam boiler. It is assumed that the pump's consumption is negligible in comparison and is ignored in this analysis. Each stage is built on a night heating cycle, i.e., the cycle when coffees are not made. The on-duty time is when a coffee boiler is switched on, and the off-duty is when it is switched off.

In the case of a coffee boiler, the first step is to establish an initial start point. It is set to a random value with a range of average off-duty time +/- 10%. The length of the on-duty cycle is calculated respectively: 90-110% of the average value. Consequently, a $start_i$ and the $start_{i+1}$ are known for each cycle. Then, the pumps' operation times between both start points are summed, corresponding to the total pump's operating time between $start_i$ and $start_{i+1}$. Then, from a database of power distributions, a random one corresponding to a given pump's length is selected and copied in the middle of the cycle. In rare cases where the respective power distribution is missing, the algorithm automatically takes a distribution from the lower pump's operating time, increasing the pump's time of the next cycle. This might happen when a pump is constantly working for more than 200 seconds, i.e., when several coffees are brewed in quick succession.

The next step requires paying close attention to the steam boiler. First, power consumption due to heat loss through the tank walls will be considered. It corresponds to the steam boiler's night cycle. Thus, such a cycle will be projected based on five hours of night data. Similarly, as in the previous step, all time steps will be associated with mean values randomly adjusted with a 10% margin. It is beyond the scope of this analysis to model the connection between the steam boiler's power use and coffee production. Hence, for the sake of simplicity, it is assumed that 50% of coffees require steam. For randomly chosen 50% of coffee counts, we will adjust the projected steam boiler power to the pump's operation time. This correlation results from the average value of steam power per pump's time in previously discussed 20-minute intervals. Such value will be doubled to compensate for total energy loss from the assumption that only half of the coffees use the steam boiler. Furthermore, an adjustment is added to avoid overlapping between the on-duty cycle of the steam boiler (when it is simultaneously switched on due to the no-coffee cycle and because of coffee brewing) so that maximum power does not exceed 10 kW. An example of forecasted data for a single coffee machine is presented in Fig. 5 between 10 AM and 6 PM.

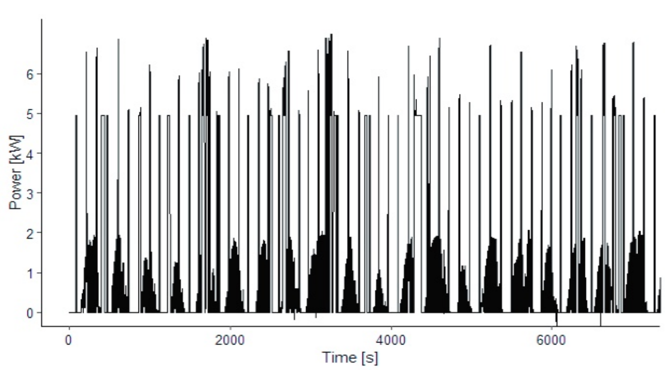


Fig. 5: Example of power demand generated based on data from 10 AM and 6 PM.

Finally, the power distributions from the coffee and steam boilers are combined and summed for the n synthetic espresso machines, resulting in a total power distribution. Subsequently, the estimated available disposable power is calculated by finding the maximum power that occurs at least 98% of the time. This is the disposable power for the n espresso machines.

IV. Results and Discussion

This section presents the results of applying the methodology to estimate the potential of tertiary espresso machines to provide FCR services. First, the data from the original espresso machine is presented in more detail. Then, the results are projected for up to 100 espresso machines to assess the amount of disposable power in function of the number of participating devices.

A. Load Profile of an Espressoo Machine Based on Particular Weekdays and Hours

This particular café operates throughout the week with various opening hours. Thus, it is relevant to investigate the impact of specific weekdays and hours on the load profile of a coffee machine. The analysis will help identify a bottleneck in the appliance's power consumption. Furthermore, for auxiliary service markets, which allow shorter time blocks for participants' bids, this will suggest a potential available power within particular time intervals. Two different approaches are presented to investigate the impact of time intervals for the load profile: the number of coffee brewed and the operation time of the pump.

In Fig. 6, a distribution of produced coffees is presented. The data is divided into separate weekdays such that any patterns within a week can be observed. Only the timeframe between 8 AM and 9 PM is depicted since no coffees are brewed at night. As observed, mornings and evenings are characterized by fluctuations because of switching the appliance on and off, respectively. The presented values of coffee brewed are obtained by calculating the averages for a particular weekday. In Fig. 6, a similarity between all the weekdays can be observed. Due to different opening hours, only Friday has a flat curve from around 8:00 AM to 10 AM. Apart from Friday, all weekdays have a morning increase in coffee production. It is, however, challenging to indicate the period with maximum values. Nonetheless, around 6 PM, the demand for drinks is decreasing.

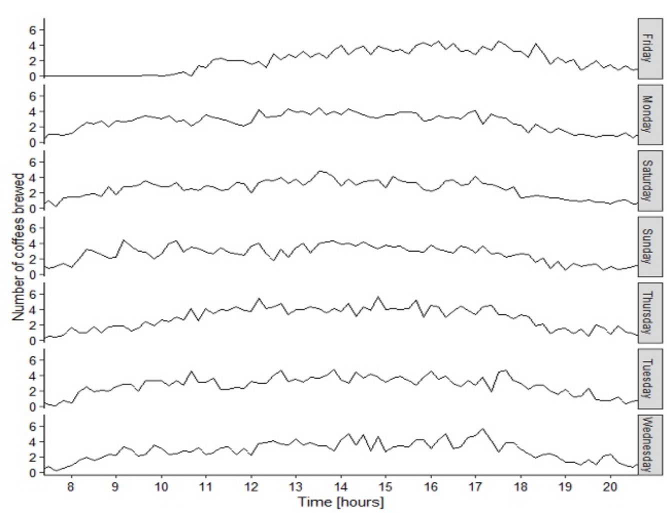


Fig. 6: Distribution of brewed coffees within weekdays and hours.

Ultimately, the appliance behavior can be divided into five stable periods:

1) Nighttime, when no coffees are brewed;
2) Morning time (8 AM to 10 AM), when a rapid increase in drinks production is observed;
3) Midday time (10 AM to 6 PM), when brewing coffees are on a stable level;
4) Evening time (6 PM to 8 PM), when demand is decreasing;
5) Closing time (8 PM to 9 PM), the last hour of normal operation in the café.

Since the disposable power for FCR services is directly correlated with coffee brewing, one may quickly identify which periods of the day demonstrate the most significant opportunities for balancing services. Interestingly, based on Fig. 6, it is very likely that for the majority of the time (10 AM to 6 PM), there is the highest achievable disposable power. On the other hand, the last operating hour (8 PM to 9 PM) can be associated with our bottleneck time.

B. Disposable Power for FCR Services Based on Quantity of Espresso Machines

A disposable power for FCR services was calculated for all the five time periods mentioned above. The function of power based on the number of coffees is presented Figs. 7 and 8. This projection was prepared for the horizon of 100 coffee machines in all cases. The Y-axis describes the power, whereas the X-axis depicts the number of aggregated appliances. The values presented in the graph are the averages of 100 different machine aggregations (with 100 repetitions). The confidence interval covered 95% of the results and was obtained by computing the standard deviation of the 100 repetitions.

Interestingly, the curve is similar in all the graphs, which can be divided into three parts. The initial, horizontal part of the curve describes the time needed to establish a non-zero power distribution within at least 98% of the forecasted 8-hour-long dataset. When this condition is met, the first increment in disposable power appears in the graph. Next, the curve turns into a more convex, polynomial shape. It can play a role in a transition to its third, most relevant regime. The curve becomes linear when the aggregation level is around 25-30 espresso machines. Following this assumption of linearity, estimating the achievable disposable power for any quantity of devices is possible. The disposable powers per 100 machines are presented in Table I.

TABLE I: Values of disposable power per 100 coffee machines in given day periods.

Day Period	Disposable Power (kW)
Night time	33,17
Morning time (8:00 – 10:00)	39.33
Midday time (10:00 – 18:00)	42.65
Evening time (18:00 – 20:00)	36.90
Closing time (20:00 – 21:00)	35.69

Based on the assumption of linearity, the function of disposable power per espresso machine will be described analytically. The curves will be considered linear from X=30

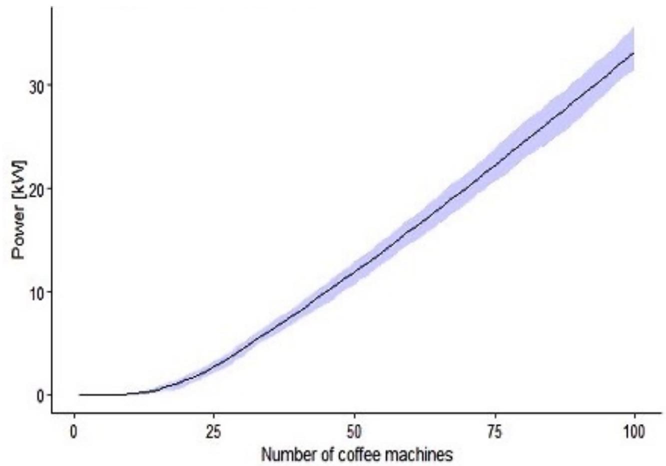


Fig. 7: Disposable power per number of aggregated coffee machines when no coffees are brewed.

onwards. Consequently, five functions are created and presented in Table II. Interestingly, the linear coefficient has a relatively small variance. Its difference between 'the worst-case scenario,' when no coffees are made, and midday time is only 0.13. Thus, one may point out that most energy is consumed for preserving the boilers in a ready-to-use state. This, on the one hand, emphasizes the importance of improving the energy efficiency of coffee machines. On the other hand, it also implicates relatively low dependence on providing FCR services on the behavior of coffee consumers.

TABLE II: Analytical forms of functions of FCR power in the different period.

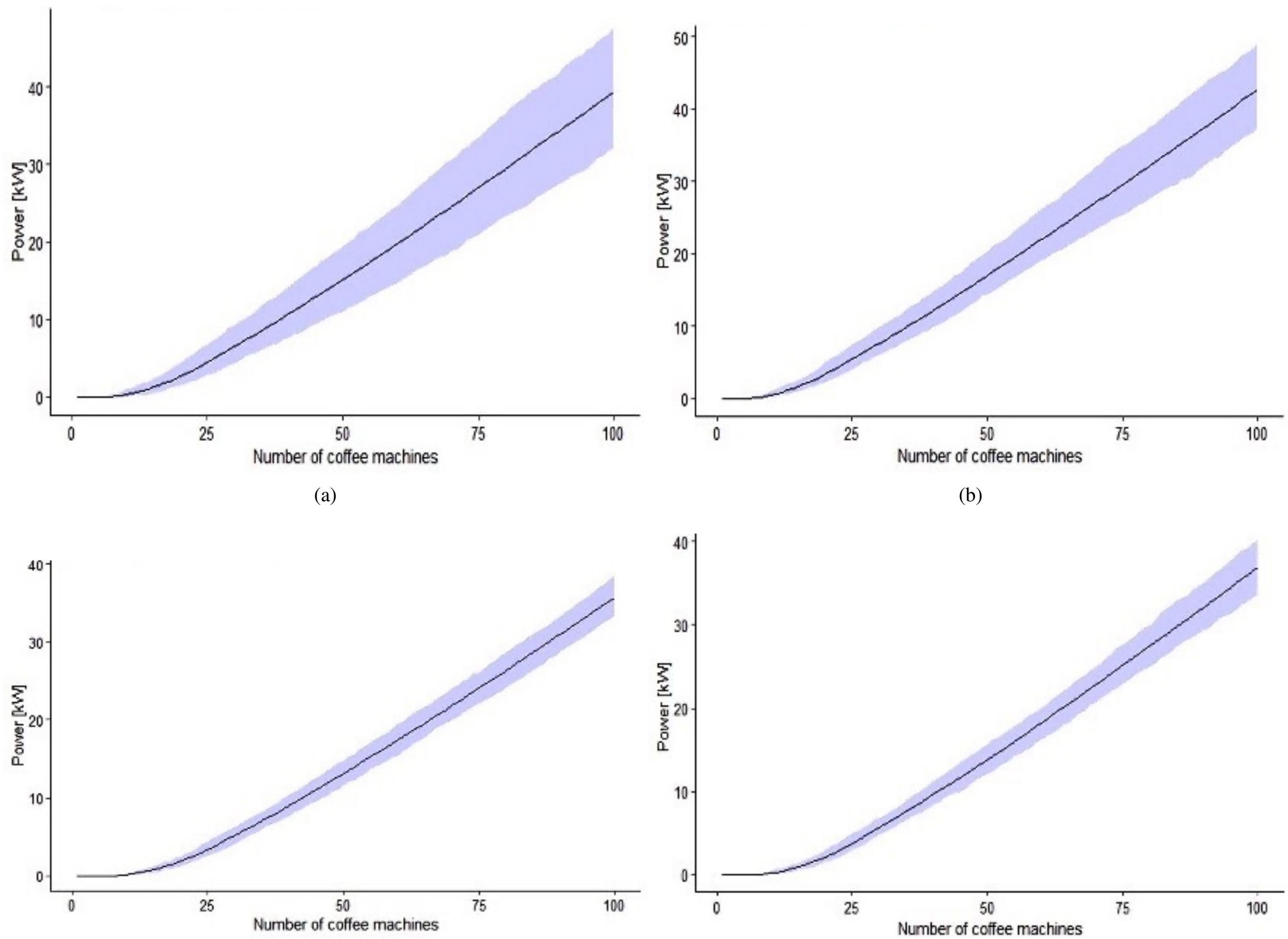
Day Period	Disposable Power (kW)
Night time	$F(x) = 0.41x - 7.82$
Morning time (8:00 – 10:00)	$F(x) = 0.47x - 7.54$
Midday time (10:00 – 18:00)	$F(x) = 0.50x - 7.38$
Evening time (18:00 – 20:00)	$F(x) = 0.45x - 7.67$
Closing time (20:00 – 21:00)	$F(x) = 0.43x - 6.78$

V. Conclusion

This paper presented a study to assess the potential of tertiary coffee machines to participate in FCR services. The methodology was tested using synthetic data generated from actual data collected from one coffee machine in Germany.

Overall, the results show that it is possible to participate in delivering FCR services provided enough espresso machines are aggregated. Ultimately, this can also be seen as an indicator of the potential for including other gastronomy appliances in the demand-side flexibility market, dominated mainly by larger industrial consumers or the aggregation of household appliances.

In fact, introducing clean energy sources in restaurants has already been identified as one of the pillars of sustainable restaurants [33], where the authors claim that restaurants should consider buying green energy or offsetting carbon emissions. In this sense, this claim aligns with the work proposed in this paper since providing FCR is an indirect way to increase renewable energy penetration.



(a) (b) (c) (d)

Fig. 8: Disposable power per number of aggregated coffee machines: (a) between 08:00 and 10:00; (b) between 10:00 and 18:00; (c) 18:00 and 20:00; (d) 20:00 and 21:00.

There are, however, some challenges and limitations that still need to be addressed in future work.

First and foremost, it is important to remark on the simplicity of the FCR estimation algorithm that relies on a set of assumptions derived from data observation. In this sense, in future iterations of this work, it would be important to include data-driven methods to automatically identify and classify the different transitions observed in the power demand data. One possible alternative would be the application of Non-Intrusive Load Monitoring (NILM) [34] to identify the moments when coffee is being brewed.

Second, it is assumed that the bottleneck of FCR services will be delivering power to the grid, i.e., power reduction of an espresso machine rather than receiving power from the grid. This, however, should be verified and discussed further. Likewise, the impact of delivering the balancing services on the thermodynamic state of steam and water and, consequently, on the product quality should be analyzed in future iterations of this work.

Another limitation is that the entire data analysis was based on the power consumption of a single espresso machine in a particular café in Germany. Consequently, the results may be biased toward the specific behavior of this particular coffee house.

Furthermore, future works should consider different approaches for the applied methodology. For example, it can be very relevant to examine other forecasting techniques, including the application of deep neural networks such as Long Short-Term Memory Networks (LSTM), as these are known to produce accurate forecasts in time-series data. More importantly, forthcoming studies could further develop and confirm these initial findings by increasing the scope of the available datasets to a more extensive and dispersed set of espresso machines and gastronomy points. In addition, the investigation of delivering FCR by drawing power from the grid and its impact on product quality should be conducted.

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REFERENCES

[1] Ipcc, "Global Warming of 1.5ºC: IPCC Special Report on impacts of global warming of 1.5ºC above pre-industrial levels in context of strengthening response to climate change, sustainable development, and efforts to eradicate poverty," Cambridge University Press, Tech. Rep., Jun. 2022.

[2] "Directive (EU) 2018/2002 of the European Parliament and of the Council of 11 December 2018 amending Directive 2012/27/EU on energy efficiency (Text with EEA relevance.)," Dec. 2018.

[3] "Directive 2009/125/EC of the European Parliament and of the Council of 21 October 2009 establishing a framework for the setting of ecodesign requirements for energy-related products (Text with EEA relevance)," Oct. 2009.

[4] "Communication from the Commission Ecodesign and Energy Labelling Working Plan 2022-2024 2022/C 182/01," 2022.

[5] "Commission Regulation (EU) 2023/826 of 17 April 2023 laying down ecodesign requirements for off mode, standby mode, and networked standby energy consumption of electrical and electronic household and office equipment pursuant to Directive 2009/125/EC of the European Parliament and of the Council and repealing Commission Regulations (EC) No 1275/2008 and (EC) No 107/2009 (Text with EEA relevance)."

[6] "Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU (recast) (Text with EEA relevance)Text with EEA relevance."

[7] M. J. Krutnik, "Energy Services for The Food Industry," MSc, Técnico Lisboa, University of Lisbon, Lisbon, Portugal, Nov. 2020. [Online]. Available: https://fenix.tecnico.ulisboa.pt/cursos/mege/dissertacao/1128253548922346

[8] BIO by Deloitte, Oeko-Institut and ERA Technology, "Preparatory Study to establish the Ecodesign Working Plan 2015-2017 implementing Directive 2009/125/EC – Task 3 Final Report."

[9] K. Romeo, "All TSOs' proposal for the determination of LFC blocks for the Synchronous Area Continental Europe in accordance with Article 141(2) of the Commission Regulation (EU) 2017/1485 of 2 August 2017 establishing a guideline on electricity transmission system operation," ENTSO-E, Tech. Rep., Jul. 2018.

[10] J. Figgener, B. Tepe, F. Rücker, I. Schoeneberger, C. Hecht, A. Jossen, and D. U. Sauer, "The influence of frequency containment reserve flexibilization on the economics of electric vehicle fleet operation," *Journal of Energy Storage*, vol. 53, p. 105138, 2022.

[11] A. Pedro, M. Krutnik, V. M. Yadack, L. Pereira, and H. Morais, "Opportunities and challenges for small-scale flexibility in European electricity markets," *Utilities Policy*, vol. 80, p. 101477, 2023.

[12] R. D'hulst, W. Labeeuw, B. Beusen, S. Claessens, G. Deconinck, and K. Vanthournout, "Demand response flexibility and flexibility potential of residential smart appliances: Experiences from large pilot test in Belgium," *Applied Energy*, vol. 155, pp. 79–90, Oct. 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261915007345

[13] M. Afzalan and F. Jazizadeh, "Residential loads flexibility potential for demand response using energy consumption patterns and user segments," *Applied Energy*, vol. 254, p. 113693, Nov. 2019. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261919313807

[14] "Commission Regulation (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing (Text with EEA relevance.)," Nov. 2017.

[15] B. Neupane, T. B. Pedersen, and B. Thiesson, "Towards Flexibility Detection in Device-Level Energy Consumption," in *Data Analytics for Renewable Energy Integration*, ser. Lecture Notes in Computer Science, W. L. Woon, Z. Aung, and S. Madnick, Eds. Springer International Publishing, 2014, no. 8817, pp. 1–16.

[16] Y. Ji and R. Rajagopal, "Demand and flexibility of residential appliances: An empirical analysis," in *2017 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, 2017, pp. 1020–1024.

[17] I. Rothwell and E. Bush, "Preliminairy Study on Tertiary Hot Beverage Equipment," Bush Energie GmbH, Felsberg, Germany, Tech. Rep. SI/402594-01, Jul. 2017.

[18] Eric Bush, Jürg Nipkow, Barbara Josephy, Susanne Heutling, and Rainer Griesshammer, "Strategies to Enhance Energy Efficiency of Coffee Machines," in *Proceedings of the 5th International Conference on Energy Efficiency in Domestic Appliances and Lighting - EEDAL'09*. JRC, 2009.

[19] C. Favi, M. Marconi, M. Rossi, and F. Cappelletti, "Product Eco-Design in the Era of Circular Economy: Experiences in the Design of Espresso Coffee Machines," in *Advances on Mechanics, Design Engineering and Manufacturing III*, L. Roucoules, M. Paredes, B. Eynard, P. Morer Camo, and C. Rizzi, Eds. Cham: Springer International Publishing, 2021, pp. 194–199.

[20] N. Gross and E. Bush, "Efficient Coffee Machines – European energy label for residential and commercial use," in *Proceeding of the 11th International Conference on Energy Efficiency in Domestic Appliances and Lighting (EEDAL'22)*. Publications Office of the European Union, 2022.

[21] F. Petropoulos, S. Makridakis, V. Assimakopoulos, and K. Nikolopoulos, "'Horses for Courses' in demand forecasting," *European Journal of Operational Research*, vol. 237, no. 1, pp. 152–163, Aug. 2014.

[22] J. D. Croston, "Forecasting and Stock Control for Intermittent Demands," *Operational Research Quarterly (1970-1977)*, vol. 23, no. 3, pp. 289–303, 1972.

[23] D. J. Waller, "Methods for intermittent demand forecasting," in *Methods for Intermittent Demand Forecasting*, 2015.

[24] F. Petropoulos, N. Kourentzes, and K. Nikolopoulos, "Another look at estimators for intermittent demand," *International Journal of Production Economics*, vol. 181, pp. 154–161, Nov. 2016.

[25] A. A. Syntetos and J. E. Boylan, "The accuracy of intermittent demand estimates," *International Journal of Forecasting*, vol. 21, no. 2, pp. 303–314, Apr. 2005.

[26] R. H. Teunter, A. A. Syntetos, and M. Zied Babai, "Intermittent demand: Linking forecasting to inventory obsolescence," *European Journal of Operational Research*, vol. 214, no. 3, pp. 606–615, Nov. 2011.

[27] K. Nikolopoulos, A. A. Syntetos, J. E. Boylan, F. Petropoulos, and V. Assimakopoulos, "An aggregate–disaggregate intermittent demand approach (ADIDA) to forecasting: An empirical proposition and analysis," *Journal of the Operational Research Society*, vol. 62, no. 3, pp. 544–554, Mar. 2011.

[28] A. A. Syntetos and J. E. Boylan, "Intermittent Demand: Estimation and Statistical Properties," in *Service Parts Management: Demand Forecasting and Inventory Control*, N. Altay and L. A. Litteral, Eds. London: Springer, 2011, pp. 1–30.

[29] A. Syntetos and J. Boylan, "Demand forecasting adjustments for service-level achievement," *IMA Journal of Management Mathematics*, vol. 19, no. 2, pp. 175–192, 2008.

[30] M. Macchi, L. Fumagalli, R. Pinto, and S. Cavalieri, "A Decision Making Framework for Managing Maintenance Spare Parts in Case of Lumpy Demand: Action Research in the Avionic Sector," in *Service Parts Management: Demand Forecasting and Inventory Control*, N. Altay and L. A. Litteral, Eds. London: Springer, 2011, pp. 171–202.

[31] La Marzocco, "La Marzocco linea pb Manual," 2014.

[32] Speciality Coffee Association of Europe, "SCAE CDS: AUTHORISED TRAINERS HANDBOOK," 2022.

[33] W. Legrand, P. Sloan, C. Simons-Kaufmann, and S. Fleischer, "A review of restaurant sustainable indicators," in *Advances in Hospitality and Leisure*, ser. Advances in Hospitality and Leisure, J. S. Chen, Ed. Emerald Group Publishing Limited, Jan. 2010, vol. 6, pp. 167–183.

[34] R. Jiao, C. Li, G. Xun, T. Zhang, B. B. Gupta, and G. Yan, "A Context-Aware Multi-Event Identification Method for Nonintrusive Load Monitoring," *IEEE Transactions on Consumer Electronics*, vol. 69, no. 2, pp. 194–204, 2023.

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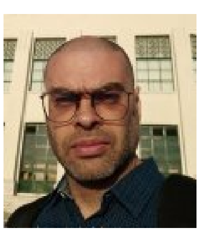

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