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Forecasting time-varying arrivals: Impact of direct response advertising on call center performance

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ABSTRACT

This study investigates manpower planning and the performance of a national call center for scheduling car repairs and responding to road interventions. We model the impact of advertising on the required capacity and develop a forecasting model for incoming calls, where the impact of direct-response advertising is considered. With the estimation results, we forecast the number of incoming calls to the call center. Next, the forecasts are input into the capacity planning simulation module to directly simulate a service process at the highly disaggregated level. This simulation mimics the service level requirements and queue behavior and shows that the call center is operating at a high level of efficiency and performance. We illustrate that advertising may cause a temporary overload of the system and increase the number of abandoned calls, which is suboptimal for call center performance.

1. Introduction

Call centers, where customers' questions, needs, and requests are addressed, are essential systems, especially for large organizations (Buist et al., 2008). For companies that organize their businesses by collecting their orders via call centers, there is a crucial link between their call centers' effectiveness and their marketing activity. To meet the targeted service level, managers have to employ an appropriate number of skilled staff for the appropriate amount of time in call centers. The scheduling of an available pool of agents based on detailed short-term forecasts is a fundamental challenge for call center managers. As peak call moments can have short duration, the call center's staffing is not always sufficiently flexible to accommodate this demand. Therefore, modeling instability in call center arrivals and calculating staff requirements are crucial issues in call center management (Aktekin and Soyer, 2008; Chassioti and Worthington, 2004).

In practice, it can be challenging to provide the desired service level in the call center at peak call moments. Arrival rates may vary due to the hour of the day, day of the week, and month of the year and may vary across ad campaigns. (Testik, Cochran & Runger, 2004). In this study, we analyze the effectiveness of the operations of a specific call center, and we indicate routes to improvement. Our approach can be considered prototypical for companies in similar industries. Our analysis aims to investigate the extent that the results from the advertising/call relationship can be utilized in the capacity or manpower planning of the call center. The key research issue is the extent that the call center capacity can handle increased calls due to advertising. We investigate whether advertising affects the efficiency of the call center.

The outline of the paper is shown in Fig. 1. First, we develop a forecasting model for the incoming calls to the call center. Second, we construct a capacity planning model by discrete event simulation, where the forecasts feed the simulation. Last, we analyze the service level requirements and queue behavior in terms of waiting times, abandoned calls, and idle time.

The operation of the call center relates to queuing theory. For simpler, stable queuing systems, analytical tools can be employed. In our case, the average number of servers or agents varies from 1 to 48 or more each day. Moreover, a complex dynamic process characterizes the number of incoming calls. Therefore, we resort to a simulation of the system rather than to analytical methods.

In our study, two measures of the call center activity are of interest to the company. The first measure addresses relevant calls. These calls

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pertain to the business; refer to Kiygi-Calli et al. (2012) for more details. The second measure pertains to all incoming calls, which may be related to information requests or orders. This second measure is more relevant for the call center's operation, while the first measure more related to the actual conversion of calls to sales. We use a discrete event simulation that directly models the process, which allows integration of the forecasting system and the call center simulation. Our paper is an empirically relevant study for characterizing call center operations and performance.

The remainder of the paper is organized as follows: Section 1 describes the call center operation and the objectives that management wants to achieve in terms of effectiveness. In Section 2, we briefly review and discuss the literature related to our topic. Sections 3 and 4 explain the data and modeling of the incoming calls, followed by a discussion of the model results in Section 5. Section 6 contains the simulation model, and Section 7 discusses the simulation results. In Section 8, we discuss the conclusions.

2. Literature review

Many companies communicate with their customers via internally managed or outsourced call centers. In these centers, traditional telephone service is enhanced by additional customer contact channels, for instance, by interactive voice response (IVR) (Koole and Mandelbaum, 2002).

The random variation in incoming calls of the call center is a significant feature when assessing call center performance (Betts et al., 2000). According to the need of the call center manager, the call center data might be stored in real time or aggregated over time to measure the performance of the call center. Aldor-Noiman et al. (2009) use an arrival count model that is based on a mixed Poisson process approach. They propose a forecasting model to forecast the system load and implement a staffing rule and conclude that for the majority of any day, their forecasting model performs very well. Gao et al. (2019) propose a framework where process improvement and staffing optimization are integrated to enhance the call center performance. They develop four models and compare them using simulation. Gao et al. (2019) fill the critical gap in optimization studies for managed care organizations (MCOs).

Additionally, Brown et al. (2005) analyze a unique record of call center operations. They decompose the process into three components: arrivals, customer patience, and service time. This article is important, both theoretically and empirically, to characterize call center operations and performance.

One of the main issues in call center management is determining the staffing level to accomplish the desired service level (Aldor-Noiman et al., 2009). To determine the required number of agents for a given period, forecasting the system workload is necessary. In the literature, various statistical forecasting models, such as linear mixed models and autoregressive distributed lag (ADL) models, are used to determine the arrival rate of incoming calls (Kiygi-Calli et al., 2012; 2017). In the evaluation of the call center performance, typical service level metrics are the waiting times for callers, the number of abandoned calls due to excessive waiting times and the amount of time that the call center operators are idle, which means that there is excess capacity (Aksin et al., 2007). Accordingly, the main instrument for managing the call center is the number of agents and their working schedules concerning the incoming call volume. A balance must be obtained between excess capacity (idle time of operators) and experience in handling calls. Conceptually, call centers are single queue first-in-first-out, multiserver queuing systems, which are often investigated in operations research studies (Hillier and Lieberman, 2005).

The other critical issue in call center management is minimizing the staffing cost of the call center. Kolesar and Green (1998) apply a queuing theory approach in call center capacity management. They conclude that to achieve a high service level in call center operation, managers assign more staff than necessary, which is costly for companies. The disadvantages of queuing models may be that they tend to be time-consuming, complicated, simplifying, and unreliable (Buist et al., 2008; Grossman, Jr., 1999). On the other hand, simulation methods are robust and widely utilized for modeling dynamic systems in the literature (Buist et al., 2008; Grossman, Jr., 1999). Bapat and Pruitte (1998) discuss how call centers might maximize their investment using a simulation method. In Avramidis et al. (2010), the objective is to minimize the agents' total costs. Cezik and L'Ecuyer (2008) and Atlason et al. (2004) optimized staffing and scheduling problems and use an iterative cutting plane method, which relies on the service level function. This function is concave in the number of servers for minimizing staffing costs in the call center.

Modeling of the call center needs to be performed based on a detailed analysis of the operational data. The peaks in incoming calls need to be understood, and the factors that explain the number of incoming calls should be considered for different call centers (Soyer and Tarimcilar, 2007). Chassioti and Worthington (2004) propose a discrete event model and provide evidence of some essential insights in queue management. According to Chassioti and Worthington (2004), high traffic density is not disastrous if it only occurs for short periods. Testik, Cochran & Runger (2004) propose an online feed-forward server

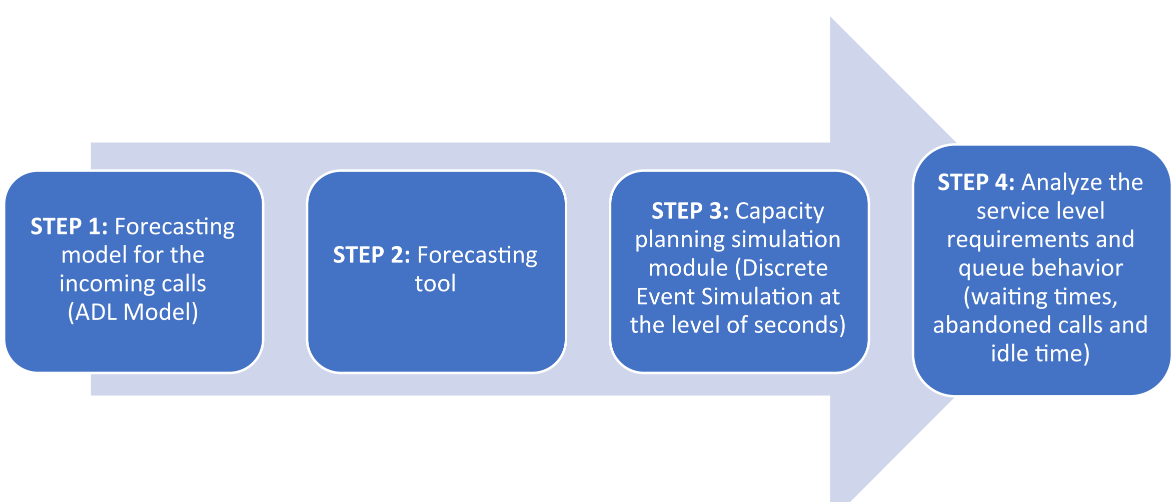


Fig. 1. Study plan of the paper.

controller that will compensate for unforeseen changes in arrival rates. According to their study, in slowly changing systems, the queue application can be analyzed as a constant Poisson arrival and service process. However, this method may not be realistic for other systems (Testik, Cochran & Runger, 2004).

Aksin et al. (2007) conducted a survey study on call center operations management and reviewed recent call center literature. They conclude that forecasting models have an important role in operations and are a critical input for resource acquisition. Therefore, companies should consider their marketing activities to forecast incoming calls to the call center. Furthermore, companies need to develop a balance between operations and marketing activities (Kotler, 1991). The marketing department, which establishes marketing policies, plans advertising schedules of a company. Operations should be arranged so that they do not cause conflicts due to inconsistent objectives (Eliashberg and Steinberg, 1993). Aksin et al. (2007) examine the interactions between call center operations and marketing activities. They make suggestions for integrating cross-selling activities in call center activities and improving the relationship between customer satisfaction and call center operations. Antipov & Meade (2002) propose a dynamic model that considers the multiplicative calendar effects and advertising response; their model addresses a system that is stimulated by advertisements. Their study constructs a forecasting tool for call frequency (Antipov & Meade, 2002).

Our study investigates the impact of the call volume and operational efficiency, where the call volume is affected by direct response commercials employed by an advertising company. First, we investigate the impact of direct response commercials on incoming calls at the national call center as moderated by different media (radio and TV channels) and broadcasting times. We use an autoregressive-distributed lag model, where the dependent variable is the total number of incoming calls aggregated at 15-minute intervals. Using the estimation results, we construct a simulation tool based on a weekly media plan. This tool computes the baseline forecasts (without advertising) and the forecasts generated by a media plan that relies on average gross rating points (GRPs) by the channel and time slot, which is a quarter of an hour. GRPs measure the audience size and are calculated as the reach times the average frequency (Govoni, 2004).

Next, we construct a discrete event simulation system to simulate the call center operating system. In the simulation, we link the forecasts to capacity planning, which requires a disaggregation from the forecasting time intervals (a quarter of an hour) to the interval with seconds. We use an arrival-inhomogeneous Poisson process in the simulation system.

Caramia et al. (2003a and 2003b) discuss the extremely dynamic behaviors of call centers. Caramia et al. (2003a and 2003b) propose two approaches to simulate the call center system. First, they utilize a process-oriented discrete-time simulation and discuss the critical aspects as customers abandon. Second, they develop a system dynamics simulation in which they generate a feedback loop. Caramia et al. (2003a and 2003b) show that the higher values of abandoned calls are attributable to the reinforcing feedback loops, which are connected with the low quality of the service that introduces the system to uncontrollable behavior. Their simulation length is 30 min, and they suggest extending the simulation length for future research. In our study, we develop the call forecasting model and estimate the number of incoming calls for active and inactive weeks. Our simulation length is one week, which is very long compared with previous studies. On the other hand, Armenia et al. (2006) apply a system dynamic approach and use the model to compare the different policies of skill-based routing (SBR). Their paper shows how a simulation model can be a useful tool for service system managers. They also show how dynamic SBR can improve the performance of the call center by optimizing staff management. Armenia et al. (2006) also propose a simulation length of 30 min and suggest extending the simulation length for future research.

The simulation gives incoming call arrival rates at each moment of the planning week (Brown et al., 2005). Discrete event simulation systems are driven by events in a time listing of events and the byproducts from this chronology (Allen, 2011). Cassandras and Lafortune (2009) and Wainer (2017) discussed these simulation systems in depth, among others. Robinson (2001) defines discrete event simulation as “hard” OR, works on a case study and develops a discrete event simulation to argue that “soft” (practical) problems that should be included in the proposed methodology for discrete event simulation. On the other hand, Lehaney (1996) introduces the idea of mixed-mode modeling, which involves both practical aspects (’soft’) and technical (’hard’) aspects and considers both necessary. Our paper proposes a framework in which the forecasting system and call center simulation tool are integrated to evaluate the call center performance, considering the impact of direct-response advertising. Our research shows the impact of marketing efforts on call center performance, and therefore, this paper fills a significant gap in the literature.

3. Data

We analyze the data related to a national call center, which collects all requests from consumers. The company broadcasts direct-response radio and TV commercials on national channels. In the first part of our study, we measure the impact of direct-response commercials on the number of incoming calls. The call center operates on a 24/7 basis, and the number of incoming calls is recorded in real time (seconds). Service centers are located in two different regions: Flanders (Dutch-speaking part of Belgium) and Wallonia (French-speaking part of Belgium). Although the media plans and communication channels are different in each region, a single telephone number is used. Agents, who are all bilingual, handle incoming calls irrespective of the customers’ language choices. Calls arrive at the central office via two channels. There are 800 incoming calls, which are directed to the call center number advertised in commercials or on the company website. There are also calls redirected from regional service centers.

The data cover the period from June 28, 2008 to December 16, 2009. The data are provided to us in 15-minute intervals, which yields 51,552 observations. Incoming calls are registered as Dutch or French calls according to the language choices of the customers. In addition, there are also undefined calls, that is, calls for which no language registration is available. Approximately 28% of the total calls are undefined. We treat them as a third region. Fig. 2 shows the generation of incoming calls by region. There are 3358 recorded radio commercials, spread over 14 radio stations broadcast between 6 AM and 8 PM, and 3100 TV commercials broadcast on 9 TV stations between 11 AM and midnight. The flow chart of the call center process is sketched in Fig. 3. In the data, service times are given, and incoming calls are defined as handled by agents or abandoned by the caller.

The maximum seat capacity of the call center is 61, and the total number of potentially available agents is 67. During the night hours, only one agent handles incoming calls. During the peak hours, the number of agents can reach 48. In the interactive voice response (IVR) system, customers are asked to choose a language, either Dutch or French. After the language choice, customers are asked to choose the type of service. The type of service can be either repair or replacement. Customers who are requesting replacement might ask detailed questions and need more information. Therefore, the duration of this type of call is longer than the average duration for repair calls. To answer the replacement calls, agents needed to receive specialized training. There is also an outsourced call center that operates between 8 AM and 8 PM on weekdays. Calls related to repairs are automatically redirected to this external call center during the mentioned hours. Customers whose waiting times are longer than 1 min are also redirected to the external call center. The call center’s target service level is handling 80% of the calls with a 12-second waiting time limit.

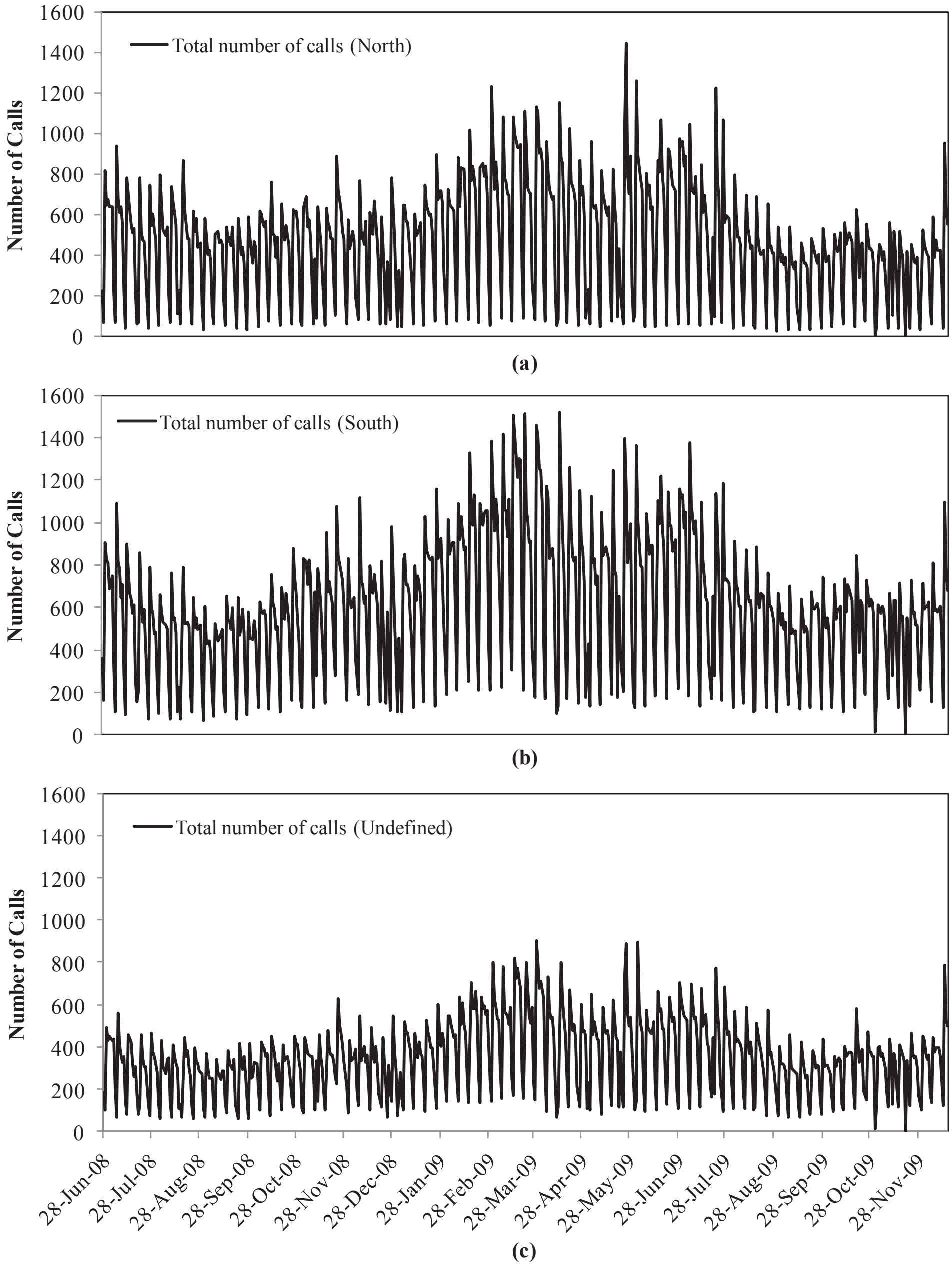


Fig. 2. Calls generation (daily).

4. Calls forecasting model

The call center operates according to a single queue/multiserver principle, and the total number of incoming calls is used as a dependent variable in our model. We compare the various models of interest by considering their forecast accuracy. Our study follows the modeling exercises of Chandy et al. (2001), Tellis et al. (2000), Tellis and Franses (2006), and Kiygi-Calli et al. (2012 and 2017), which generally recommend analysis at the most detailed level possible because aggregation removes useful information and may not produce better forecasts. Kiygi-Calli et al. (2012) employ a linear mixed model (LMM) for similar data, but we do not adopt the LMM model here for the following reasons:

a) The observation period is shorter and provides less information about individual time slots.
b) We use fifteen-minute intervals rather than hourly data, as the purpose in the current paper is to perform detailed forecasting of the call center dynamics rather than to assess the impact of advertising.
c) The increased frequency leads to fewer advertising spots per slot (and more slots without advertising), which limits the potential of LMM models.
d) While the LMM model is a powerful vehicle to allow for heterogeneity of advertising effects across channels, timeslots, and spot characteristics, it is not always superior in forecasting (Kiygi-Calli et al., 2017).

Therefore, for each of the three regions (Dutch-speaking, French-speaking, and undefined), we estimate a forecasting function based on an autoregressive distributed lag (ADL) model. This model is utilized for each region to forecast the number of calls over a planning horizon of one week. We consider the essential conclusions obtained from the

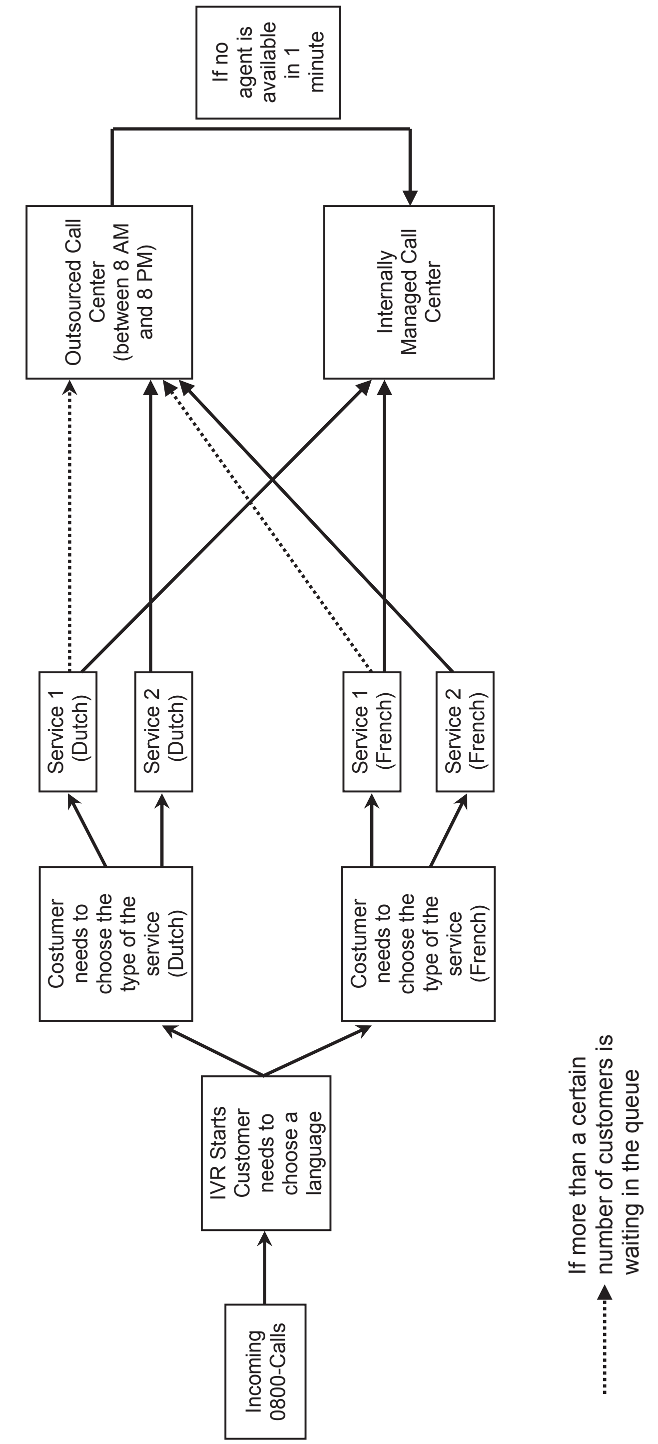


Fig. 3. Overview of the call center process (service 1: replacement calls, service 2: repair calls).

hourly LMM models and adapt them to the ADL model. These conclusions are listed as follows:

a. Advertising effects are not very heterogeneous. For forecasting, the overall GRP levels for radio and TV are adequate as predictors.
b. The autoregressive structure shows a goniometric pattern throughout the day.

These considerations lead to a model formulation, which is similar to the LMM model but imposes more homogeneity on the advertising effects. The most crucial difference is that we do not include any random effects, which makes the model easier to handle.

We determine the most useful lag structures for the autoregressive (AR) terms and GRP effects via Almon lags based on the significance and pattern of the estimates for increasing lags. In the first step, the AR process is modeled as an Almon lag of order (10, 10), which is equivalent to 10 lags without restrictions on the lag coefficients. The values of the AR coefficients obtained in this way are presented in Fig. 4. It is clearly observed that the values of the AR coefficients decrease with the order of the lags. Because the pattern changes at lag 7 and the lags with higher degrees are insignificant, the AR order is set to 7, which produces AR effects for lags up to 7 quarter-hour intervals. From a visual inspection (refer to Fig. 4), it can also be concluded that the AR term follows a quadratic reaction pattern. Thus, we conclude that Almon lags of order 7 and degree 2 provide a reasonable representation of the structure of the AR term for the model. In addition to the intraday AR effects, the daily and weekly AR terms are also deemed significant.

Fig. 5 displays the pattern of radio GRP coefficients of order 6 and degree 6. The radio GRP effects are significant to 4 quarter-hour intervals and the second degree. From these radio GRPs, we define the distributed lag (DL) pattern by using Almon lags of order 4 and degree 2 (4, 2).

The radio and TV GRP effects display a homogeneous pattern, as discussed in Kiygi-Calli et al. (2012). Therefore, we do not model these effects as heterogeneous. The data show intraday, weekly, and yearly cycles in the call pattern. The yearly cycle (seasonality) is approximated well by a goniometric wave. We expose this wave into the model as a sine and a cosine function of time with a one-year periodicity.

The final model specification is given by

$$Y_{R,t} = \&\mu + \left(\lambda_1 + \theta_1 \mathrm{Sin}\left(\frac{2\pi qd}{96}\right) + \theta_2 \mathrm{Cos}\left(\frac{2\pi qd}{96}\right)\right) Y_{R,t-1} + \left(\lambda_2 + \theta_3 \mathrm{Sin}\left(\frac{2\pi qd}{96}\right)\right.$$

$$\left. + \theta_4 \mathrm{Cos}\left(\frac{2\pi qd}{96}\right)\right) Y_{R,t-2}{}^{AR\text{terms}} + \left(\lambda_3 + \theta_5 \mathrm{Sin}\left(\frac{2\pi qd}{96}\right)\right.$$

$$\left. + \theta_6 \mathrm{Cos}\left(\frac{2\pi qd}{96}\right)\right) Y_{R,t-3} + \lambda_4 Y_{R,t-4} + \lambda_5 Y_{R,t-5}{}^{AR\text{terms}}$$

$$+ \lambda_6 Y_{R,t-6} + \lambda_7 Y_{R,t-7} + \overbrace{\lambda_{96}}^{AR\ \ terms} Y_{R,t-96} + \lambda_{672} Y_{R,t-672}$$

$$+ \overbrace{\delta^s\, sin\left(\frac{2\pi t}{672 \times 52}\right) + \delta^c cos\left(\frac{2\pi t}{672 \times 52}\right)}^{\text{seasonality}} + \overbrace{\beta_1\, Tr}^{\text{trend}} + \overbrace{\beta_2\, B_t + \beta_3 B_{t-96} + \beta_4 B_{t+96}}^{\text{holiday}}$$

$$+ \overbrace{\phi^0\, R_{R,t} + \phi^1 R_{R,t-1} + \phi^2 R_{R,t-2} + \phi^3 R_{R,t-3} + \phi^4 R_{R,t-4} + \phi^5 R_{R,t-5}}^{\text{Radio}}$$

$$+ \overbrace{\phi^6\, R_{R,t-6} + \phi^7 R_{R,t-7} + \sum_{23}^{hd=1} \phi^d_{hd} D_{t,hd} RD_{d-1,R,t}}^{\text{Radio}}$$

$$+ \overbrace{\gamma^0\, TV_{R,t} + \gamma^1 TV_{R,t-1} + \sum_{23}^{hd=1} \gamma^d_{hd} D_{t,hd} TVD_{d-1,R,t}}^{TV} + \sum_{95} q = 1 \varphi_q D_{t,q}$$

$$+ \sum_{6}^{d=1} \varphi_d D_{t,d}{}^{\text{day and week cycle}} + \varepsilon_t \tag{1}$$

where

Subscript R refers to the region (Dutch speaking, French speaking or undetermined),

$Y_{R,t} = \log(\ \text{Calls}\ _{R,t} + 1)$

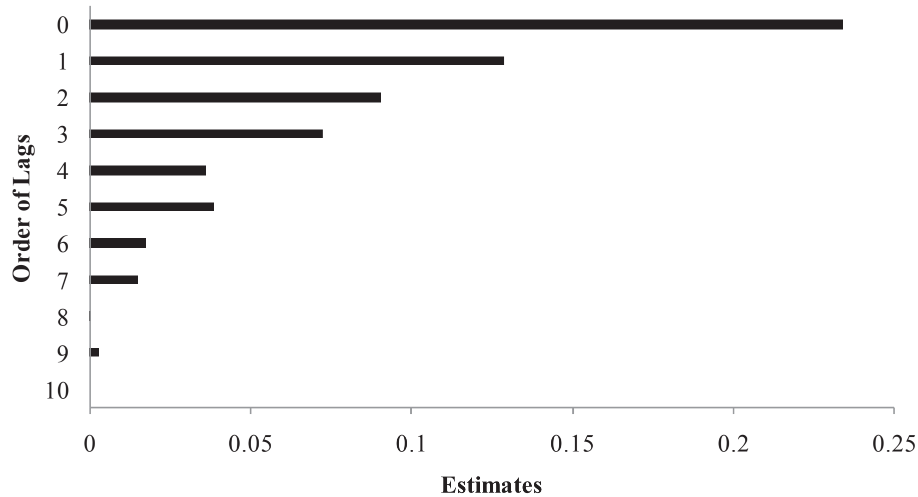


Fig. 4. Almon lag estimates of the autoregressive term.

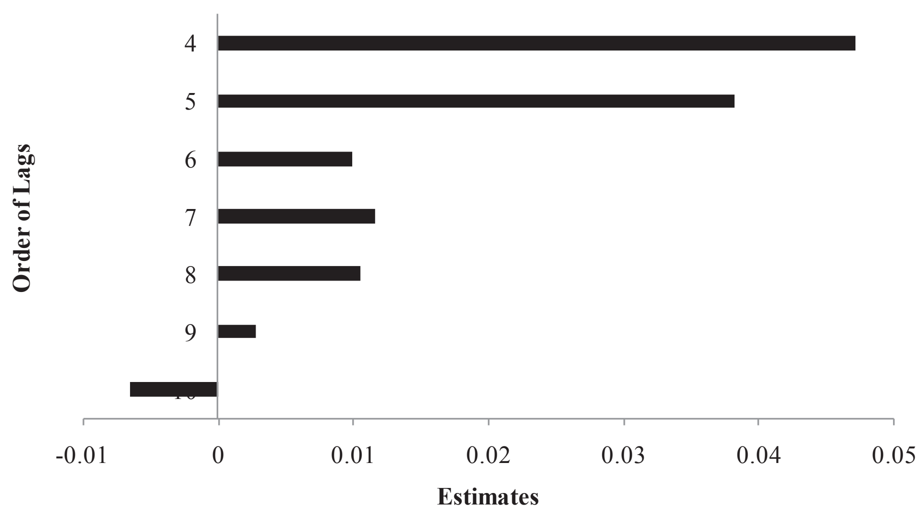


Fig. 5. Almon lag estimates of the radio GRPs.

$\mathrm{Sin}\left(\frac{2\pi t}{672\times 52}\right), \mathrm{Cos}\left(\frac{2\pi t}{672\times 52}\right)$ are the harmonic or goniometric regressors, which capture the intrayear seasonality in the data,

$$R_{R,t} = \log\left(\mathrm{RadioGRP}_{R,t} + 1\right)$$

$$TV_{R,t} = \log\left(TVGRP_{R,t} + 1\right)$$

$qd = 1\ldots,96$ denotes the qd'th quarter hour of the day. $\mathrm{Sin}\left(\frac{2\pi qd}{96}\right)$, $\mathrm{Cos}\left(\frac{2\pi qd}{96}\right)$ are the harmonic or goniometric regressors, which capture the intraday seasonality in the data,

$Tr_t$is a trend defined as $\frac{t}{672x52}$,

$B_t$is a dummy variable for bank holidays.

Advertising terms: $RD_{d-1,R,t}$ and $TVD_{d-1,R,t}$ denote the log of the total amount of radio GRPs and TV GRPs during the previous day; $D_{t,hd}$ is a dummy variable for hour *hd* of a day; $D_{t,q}$ is a dummy variable for quarter *q* in the week; and $D_{t,d}$ is a dummy variable for day *d* in the week.

In the model, calls and GRPs are expressed as natural logarithms after augmentation with 1. Kiygi-Calli et al. (2017) show that a natural logarithmic transformation is preferable for low levels of aggregation. The first three autoregressive terms exhibit goniometric behavior, which is also reported in Kiygi-Calli et al. (2012).

5. Results of the forecasting model

Table 1 shows the parameter estimates of model (1). The regions are Belgium-North (Region 1), Belgium-South (Region 2), and Undefined Calls (Region 3). The estimation results of the three regions present similarities in terms of the significant lag orders. We observe a highly significant goniometric wave for the autoregressive (AR) effects according to the estimation results. The first three lags of the AR terms show a pronounced and highly significant goniometric pattern, which are specified as waves with a periodicity of one day. Fig. 6 presents the waves of first-, second-, and third-order goniometric AR terms by a quarter of an hour for one week for the first region. In addition to these AR terms, the total AR term, which is the sum of the goniometric, daily, and weekly AR terms, is also shown in Fig. 6. The total autoregressive term has a peak of 1 at 11 AM and a low of 0.5 at 11 PM each day for region 1.

The one-day-lagged (AR (96)) terms have an effect of 0.025, 0.020, and 0.017 for the three regions. Furthermore, the one-week-lagged (AR (672)) terms are highly significant, with estimates of 0.101, 0.086, and 0.087 for the three regions.

Highly significant yearly seasonality is also observed for the three

Table 1
Estimation results of Eq. (1).

Eq. (1)		Estimate			Eq. (1)		Estimate		
Parameter name	Parameter	Region 1	Region 2	Region 3	Parameter name	Parameter	Region 1	Region 2	Region 3
Intercept	μ	−0.011 (0.019)	0.078 (0.021)	0.034 (0.020)	Current Radio GRP	ϕ^0	0.049 (0.006)	0.044 (0.007)	0.016 (0.005)
First-order lag	λ_1	0.217 (0.004)	0.230 (0.004)	0.171 (0.004)	1 qhr lag	ϕ^1	0.030 (0.004)	0.032 (0.004)	0.015 (0.004)
	θ_1	0.034 (0.005)	0.038 (0.005)	0.048 (0.005)	2 qhr lag	ϕ^2	0.017 (0.004)	0.022 (0.004)	0.013 (0.003)
	θ_2	−0.111 (0.006)	−0.091 (0.005)	−0.085 (0.006)	3 qhr lag	ϕ^3	0.010 (0.004)	0.015 (0.004)	0.012 (0.002)
Second-order lag	λ_2	0.152 (0.002)	0.156 (0.002)	0.129 (0.002)	4 qhr lag	ϕ^4	0.009 (0.006)	0.011 (0.004)	0.011 (0.002)
	θ_3	0.012 (0.002)	0.017 (0.002)	0.019 (0.002)	5 qhr lag	ϕ^5	0	0.010 (0.007)	0.009 (0.003)
	θ_4	−0.081 (0.003)	−0.074 (0.002)	−0.074 (0.003)	6 qhr lag	ϕ^6	0	0	0.008 (0.004)
Third-order lag	λ_3	0.100 (0.002)	0.099 (0.002)	0.095 (0.002)	7 qhr lag	ϕ^7	0	0	0.007 (0.005)
	θ_5	−0.010 (0.005)	−0.004 (0.005)	−0.010 (0.005)	1 day lag		Hourly Effect	Hourly Effect	0.002 (0.002)
	θ_6	−0.052 (0.006)	−0.057 (0.005)	−0.063 (0.006)	Current TV GRP	γ^0	0.084 (0.010)	0.060 (0.008)	0.026 (0.011)
Fourth-order lag	λ_4	0.063 (0.002)	0.058 (0.002)	0.069 (0.002)	1 qhr lag	γ^1	0.041 (0.010)	0	0
Fifth-order lag	λ_5	0.039 (0.002)	0.034 (0.002)	0.052 (0.002)	1 day lag		Hourly Effect	Hourly Effect	0.007 (0.001)
Sixth-order lag	λ_6	0.029 (0.002)	0.027 (0.002)	0.042 (0.002)	Seasonality	δ^s	−0.022 (0.003)	−0.030 (0.003)	−0.028 (0.003)
Seventh-order lag	λ_7	0.033 (0.004)	0.036 (0.004)	0.041 (0.004)		δ^c	0.010 (0.003)	0.003 (0.003)	0.001 (0.003)
One-day lag	λ_{96}	0.025 (0.003)	0.020 (0.004)	0.017 (0.004)	Trend	β_1	−0.009 (0.004)	0	0
One-week lag	λ_{672}	0.101 (0.004)	0.086 (0.004)	0.087 (0.004)	Holiday	β_2	−0.118 (0.011)	−0.106 (0.012)	−0.099 (0.011)

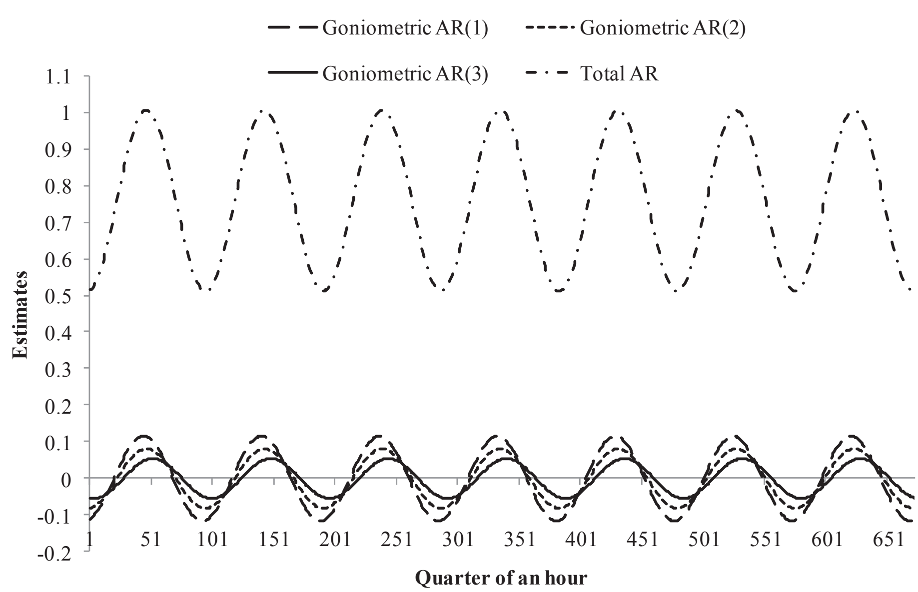


Fig. 6. Goniometric AR terms for a week (Region 1).

regions. Fig. 2 suggests that there is a goniometric yearly cycle in the three regions. In the first region (Dutch-speaking), we observe a negative trend with a value of 0.009. During bank holidays, the number of incoming calls decreases by approximately 10–12% for each region.

We observe highly significant and positive advertising effects for the three regions during the current time slot for radio and TV. The results of the lagged radio effects are given in Table 1. Radio GRPs' effects are significant for lags up to 7 quarter–hour intervals. For the first region, a quarter of an hour lag of TV GRPs is also significant with a value of 0.041. The effects of the radio GRPs and TV GRPs of the previous day were also significant.

The coefficients of determination (R^2) for the forecasting models are 0.88 for Region 1, 0.86 for Region 2 and 0.82 for Region 3. Higher orders of lags usually increase the R^2. However, this case is not observed in our final model results, which indicates that the R^2 values are quite stable.

We check the normative validity and predictive validity of our model. The proposed high-frequency data model in Eq. (1) includes parameters that provide the proper interpretation in terms of decay rates, the short-run effects of advertising, and as we have shown, accurate forecasts in 15-minute intervals. We tried several different forms for the model given in Eq. (1), but the current versions were the best in terms of the in-sample fit. In terms of the predictive validity, we compared the various models of interest by considering their forecast accuracies. The in-sample root mean square errors (RMSEs) for the logarithms of calls are 0.398, 0.447, and 0.423 for the three regions. The white noise tests (Bartlett's Kolmogorov-Smirnov statistic) are 0.014, 0.015, and 0.013, with p-values equal to 0.0002 or less than 0.0001. Minimal autocorrelation exists in the residuals of the model. The

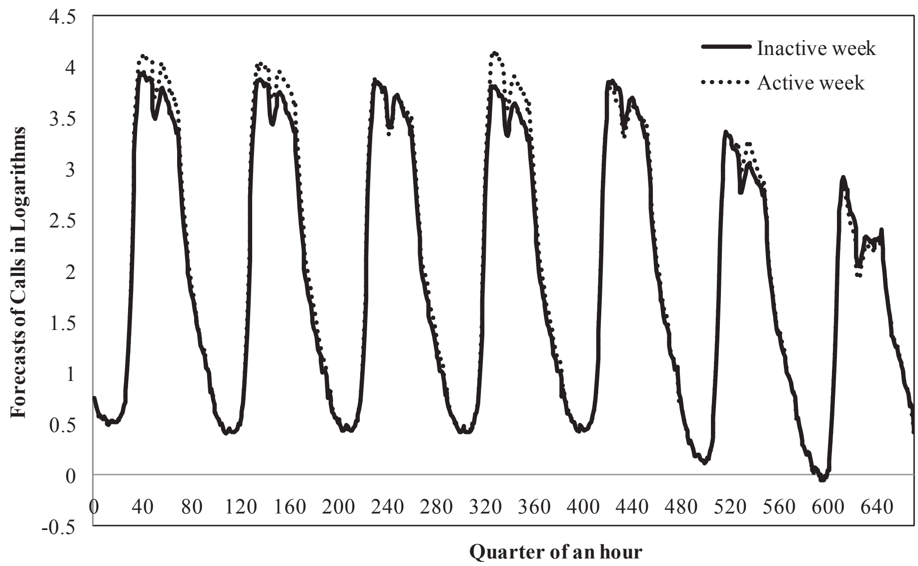


Fig. 7. Comparison of forecasts for active and inactive weeks.

maximum value of autocorrelation in the residuals is 0.015. Autocorrelations of this magnitude, however, will not substantially affect the results.

Fig. 7 shows the model forecasts for the benchmark call levels for an inactive week (without any advertising broadcasted) and the week-ahead forecasts for the week with a media plan, which is referred to as an active week. An active week is typically preceded by a week without ads. The difference between the benchmark call level and the week-ahead forecast gives the impact of the commercials. We use a real media plan for generating week-ahead forecasts, which is planned for a week by the company. The model can be employed to investigate the impact on the next week. Our focus is to investigate the impact during the active week.

6. Simulation

In the second part of this study, we evaluate the company's call center performance when direct-response commercials are broadcast. The call centers are dynamic systems that can only be modeled by simulation. To simulate the manpower planning system in seconds, we generate a discrete event simulation system. The simulation system is explained in Section 6.2 in detail. In the simulation, we link the week-ahead forecast of the forecasting model, which was previously discussed, with the call center capacity planning system. Therefore, the total of the three regions' simulated forecast calls is one of the inputs of the simulation system. We evaluate the simulation results using the manpower planning policy of the company during the inactive and active weeks. An active week means that the company broadcasts direct-response commercials spread throughout the week at irregularly spaced intervals. In contrast, an inactive week means that there is no advertising broadcasted during the entire week.

Table 2
Covariance matrix of the three forecast models.

Covariance matrix	Residuals (Region 1)	Residuals (Region 2)	Residuals (Region 3)
Residuals (Region 1)	0.16	0.02	0.02
Residuals (Region 2)	0.02	0.20	0.02
Residuals (Region 3)	0.02	0.02	0.18

6.1. *Simulation development model*

In the simulation process, there are two inputs: arrivals and manpower. We use the calculated total forecast as the arrival of the call center simulation. To calculate the total forecasted calls, we consider the forecasting error from the model, which was previously explained. First, we calculate the residual correlation using the Pearson correlation coefficient for the three regions. The statistics show that the residuals of the estimates are significantly correlated ($p < .0001$). Table 2 gives the covariance matrix of the residuals of the three forecasting models. As the residuals are correlated, the sum of the residuals' variances is calculated as

$$V = u^{'}E\left(e_R^{'}e_R\right)u$$

where $\widehat{e}_R$ is the matrix of residuals by region, u is the sum vector that is equal to {1, 1, 1}, and V is the covariance matrix of the residuals for three regions. We calculate the total variance as 0.65, which entails that we consider the forecasting error of the arrivals as a normal distribution with a mean of zero and a variance of 0.65. To calculate the total forecast, we draw a random disturbance from the normal distribution (0, 0.65) and add the backtransformed random disturbance to the simulated forecast calls. Subsequently, we use the calculated total forecast as an input of the call center simulation.

For the inactive week, we forecast the benchmark call level for one week without advertising broadcasted. For the active week, we forecast the incoming calls according to a typical media plan.

Our econometric model leads to high demands in terms of the horizon (a week), time unit, and complexity of the call process (lags up to seven quarter–hour intervals, completed by day, and week lags). The call center complexity is quite high (from 1 to 48 agents during a day cycle). In the forecasting model that was previously discussed, total calls are recorded in 15-minute intervals rather in hour intervals, as discussed in Kiygi-Calli et al. (2012). We consider the media plans and reach the GRPs of the advertisements. The inputs into this forecasting system are:

a. Last week calls. It is assumed that last week's calls are available before the planning week. If they are not available, the forecasting process can be based on the expected call levels for the last week, which is derived from the econometric models for the North, South, and undetermined regions.

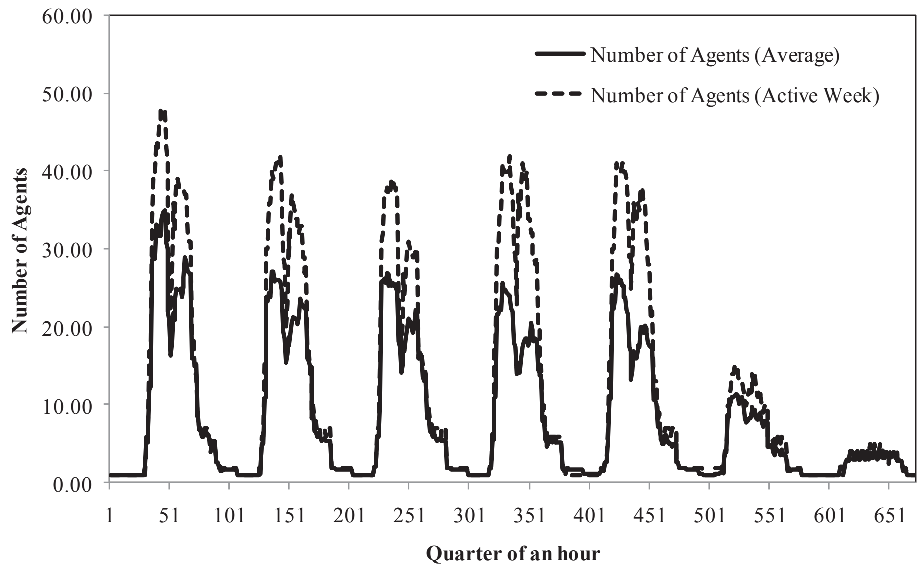


Fig. 8. Comparison number of agents for active and inactive weeks.

b. Media plan for the planning week.

The forecasting process results are imported into the simulation with the manpower schedule for the planning week. Fig. 8 represents the average number of agents for nonholidays and the number of agents in active advertising weeks. From the figure, we can conclude that the company changes its capacity planning policy, that is, the number of agents is increased in active weeks.

In the active week, the available manpower is the average number of agents observed during each week's 15-minute interval. In the inactive week, the manpower is modeled as the average manpower in the overall weeks without advertising by 15-minute intervals. These averages are computed, again excluding holidays.

During inactive weeks, the average number of agents in the call center changes from 1 during the night to 35 during peak hours. For active weeks, the manpower at peak times increases to 48 agents. Accordingly, the call center complexity is quite high (from 1 to 48 agents during a day cycle) in addition to the complexity of the call process.

In the simulation, incoming calls enter a queue. Customers may terminate the call before an agent responds to the call. These calls are referred to as abandoned Calls. Fig. 9 shows the relationship between the number of abandoned calls and the average number of incoming calls per agent by a quarter of a week. From this graph, we can conclude that there is a threshold at the ratio of 1.5 incoming calls per agent. When this ratio is less than 1.5, 12% of the incoming calls are abandoned. When the ratio exceeds 1.5, the abandoned call function changes. The function of abandoned calls (abandoned call function) is defined as

$$\begin{aligned} AC_t &= \left(0.068 + \left(0.045^*(\text{Calls}/\text{A})_t\right)\right)^* \text{ Calls}_t && \text{if } (\text{Calls}/A)_t >= 1.5 \\ &= 0.117^* \text{ Calls}_t && \text{if } (\text{Calls}/A)_t < 1.5 \end{aligned} \tag{2}$$

As discussed in the data section, the external call center operates between 8 AM and 8 PM. Between these hours, the incoming calls that are related to repair services that are directed to the external call center. The repair calls to the external call center comprise 7% of the incoming calls during daytime operations.

During daytime operations, customers who wait more than 90 s are

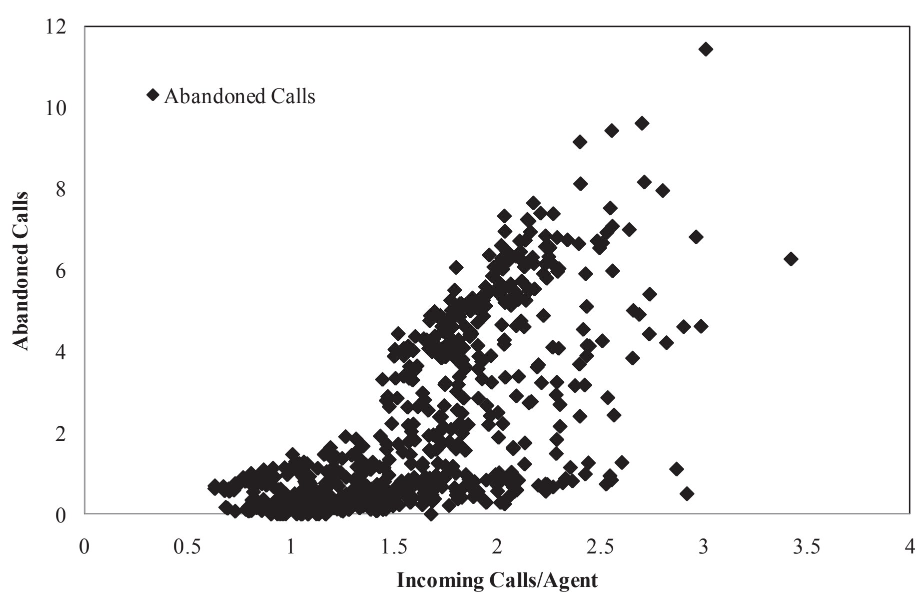


Fig. 9. Abandoned calls versus incoming calls per agent.

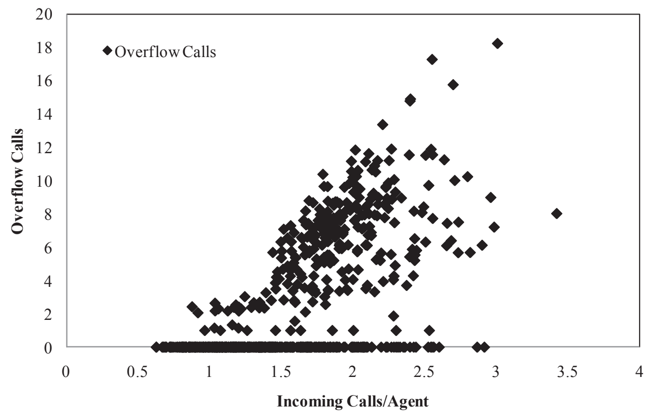


Fig. 10. Overflow calls versus incoming calls per agent.

redirected to the external call center. From the data, 5.5% of the total calls overflow with an average waiting time of 196 s. Fig. 10 shows the relationship between the incoming calls per agent and the redirected overflows between 8 AM and 8 PM. From the figure, we can conclude that there is a threshold at the incoming calls per manpower ratio of 1.5. During the daytime, when this ratio is less than 1.5, approximately 1% of the incoming calls are redirected to the external call center. If the ratio is greater than 1.5, we define an overflow function to identify it in the simulation. The function of overflow calls (overflow function) is given by

$$
\begin{aligned}
OC_t &= \big(0.047 + \big(0.007^*(\mathrm{Calls}/A)_t\big) \\
&\quad + \big(0.012^*(\mathrm{Calls}/A)_{t-1}\big) \\
&\quad + \big(0.011^*(\mathrm{Calls}/A)_{t-2}\big)^*\mathrm{Calls}_t \qquad \mathrm{if}(\mathrm{Calls}/A)_t >= 1.5 \\
&= 0.008^*\mathrm{Calls}_t \qquad \mathrm{if}(\mathrm{Calls}/A)_t < 1.5
\end{aligned}
\tag{3}
$$

Service time is the duration of the conversation between the customer and the agent. Subtracting abandoned, overflow, and redirected calls from the total incoming calls gives the net incoming calls that are effectively processed by the internal call center. The number of calls that agents can handle is linked to the available capacity. The waiting time is the amount of time spent in the queue.

6.2. Discrete event simulation

The managerial objectives are stated as follows: Eighty percent of customers should have a waiting time less than 12 s. Standard mathematical software, such as Mathematica, MATLAB, and Maple, straightforwardly allows for a discrete event simulation. We can use the sparse nature of the process by only tracking the calls at the relevant interarrival times, and simulating the system is more efficient by an order of magnitude and more flexible for addressing a varying number of agents.

The simulation algorithm is described as follows:

- Compute the week-ahead call process as previously described.
- Simulate the process at the per second level for a week.
- For each second, the number of calls is drawn from a Poisson distribution, with the mean arrival rate per second $\lambda_s$obtained by a linear interpolation between
  $\lambda_{qd}/(60^*15)$ and $\lambda_{qd+1}/(60^*15)$, where λ_{qd} is the number of calls obtained from the forecasts during the relevant 15-minute interval. This step involves a simulation of received calls, which yields approximately 200 calls more than the average total calls for a week in the data set. This result is consistent with expectations, as the observed average slightly decreases during holidays.
- For all arrivals generated at a particular second, we perform the following process:
  i. Each arrival is equipped with a random service time, drawn from the service time distribution (refer to Fig. 11), and a random patience, which tells the system after a specific timeframe that a call will be abandoned without service, drawn from the abandoned calls distribution (refer to Fig. 12). Figs. 11 and 12 show the distributions of the service times and the durations of the abandoned calls in the raw data. The service duration is defined as a lognormal distribution with a mean of 221 (exponential of 5.4) seconds and a standard deviation of 2.12 (exponential of 0.75) seconds when there is only one server in the system. We define the duration of an abandoned call as the patience of the customer. Fig. 12 shows that there is a threshold at 5.47 (exponential of 1.7) seconds for patience. Between 5.47 (exponential of 1.7) and 148 (exponential of 5) seconds, the percentage of patience was approximately uniform. The mean of patience is 31.2 (exponential of 3.44) seconds with a standard deviation of 2.56 (exponential of 0.94) seconds. The average service time observed is 3.68 min, which is employed in the discrete event simulation. Agents perform some administrative tasks between calls, but we do not have specific information about these tasks. The discrete event simulation does not consider the time spent between calls.
  ii. Determine the available number of agents at a specific point in time and read the earliest time that an agent will be available.

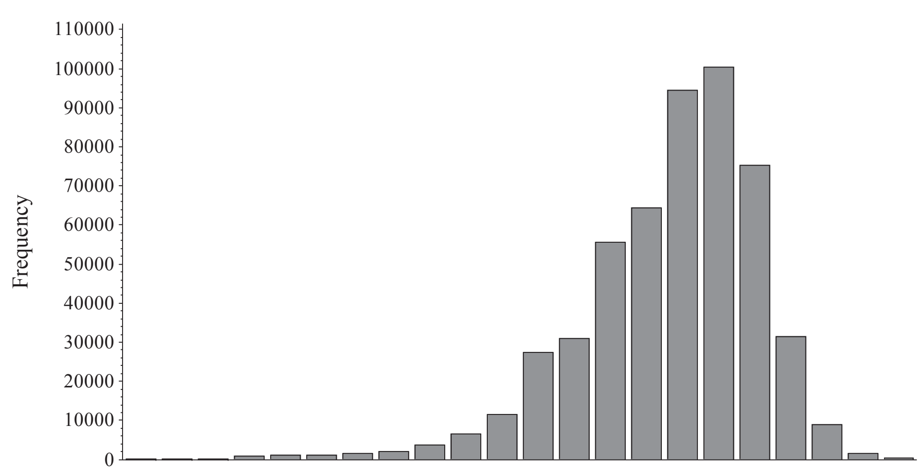


Fig. 11. Distribution of service time in logarithm of seconds [histogram of log (service time)].

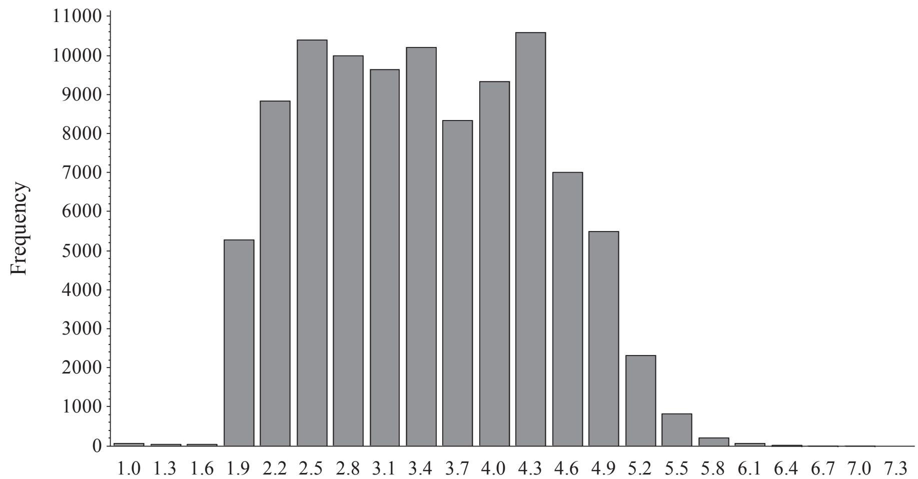


Fig. 12. Distribution of abandoned call duration in logarithm of seconds [histogram of log (abandoned call duration)]

iii. Calculate the necessary waiting time compared to patience. If patience is longer than the waiting time, update the time that the earliest available agent will be free again.
iv. Update the following metrics: total arrivals, abandoned, waiting times, processing time, redirected calls to the external call center, overflows, and idle capacity in the system.

- Compute the overall results: number of calls processed, and waiting time distribution.

7. Results of the simulation

The week-ahead forecasts are computed for inactive and active weeks, and the waiting times of the customers are evaluated for both weeks. Table 3 gives the percentage of the waiting times for the active and inactive weeks. For the active week, the percentage of the waiting times less than 5 s is 74.87%. The percentage of waiting times less than 12 s is 81.45%, and the percentage of waiting times less than 20 s is 100%.

In contrast, for the inactive week, the percentage of waiting times less than 5 s is 82.24%, the percentage of waiting times less than 12 s is 87.38%, and the percentage of waiting times less than 20 s is 100%.

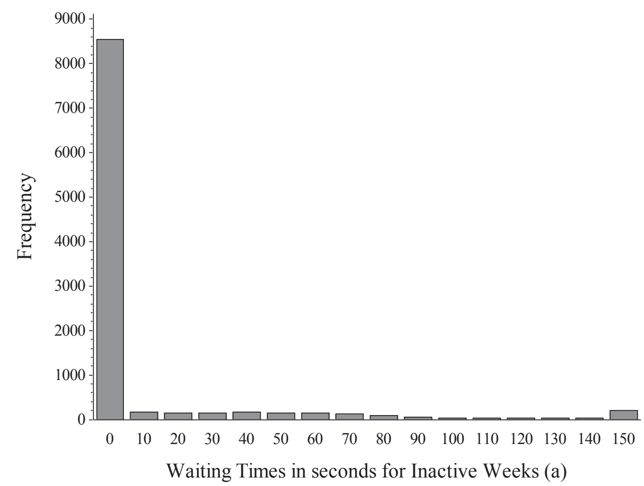
Fig. 13 (a) and (b) show a histogram of the waiting times, which reveals that the waiting times in the active weeks (refer to Fig. 13 (b)) are slightly longer than the waiting times in the inactive weeks (refer to Fig. 13 (a)). We discover that 4.12% of the callers leave the system within 10 s in the active weeks. On the other hand, in the inactive weeks, the percentage of calls that leave the system within 10 s decreases to 3.06.

Because the waiting times are less than 60 s, there are no overflows to the external call center. Table 4 presents the percentage of abandoned calls. For the active week, we found that the abandoned calls comprised 16% of the total calls and that 54.5% of the abandoned calls occurred between 6 AM and 12 AM. On the other hand, for the inactive week, the percentage of abandoned calls was 11% of the total calls, while 49% of the abandoned calls occurred between 6 AM and 12 AM.

We also calculate the idle capacity of the system. On average, the idle capacity is 44% of the total capacity and 57% of the total capacity in the inactive weeks and active weeks, respectively. Fig. 14 shows the idle capacity in minutes. The idle capacity of an active week is higher than

Table 3
Percentage of the waiting time comparison.

Waiting times	<5 s	<12 s	<20 s
Active week	74.87%	81.45%	100%
Inactive week	82.24%	87.38%	100%



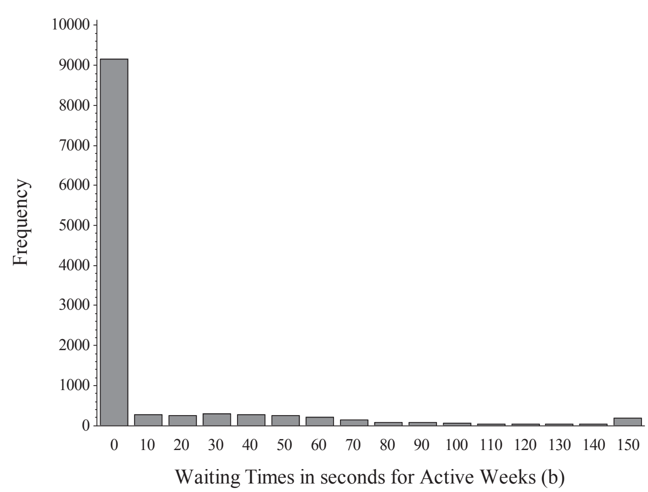


Fig. 13. Waiting times in seconds (discrete event simulation) for inactive (a) and active (b) weeks.

Table 4
Percentage of the abandoned calls comparison.

Abandoned calls	Active week	Inactive week
% of the abandoned calls in total	16%	11%
% of the abandoned calls in total (between 6 AM and 6 PM)	14.6%	9.7%
% of the abandoned calls between 6 AM and 12 AM in total abandoned calls	54.5%	49.2%

the idle capacity of an inactive week.

Fig. 15 (a) and (b) show the number of people waiting in the queue for inactive and active weeks, which was obtained from the discrete event simulation. The queue increases during active weeks, which generates more abandoned calls. Since advertising effectiveness is measured using (relevant) incoming calls that are answered, this increase in abandoned calls is a potential threat to advertising effectiveness.

8. Conclusions

In the first part of this study, we constructed a forecasting model for incoming calls, considering the impact of direct response commercials. We employed an ADL model and found a highly significant intraday pattern for the first three lags of the autoregressive terms. The forecasts from this model were utilized as inputs for evaluating the manpower planning of the call center. The stated call center objectives are quite ambitious, that is, for 80 percent of the incoming calls, the waiting times should be less than 12 s. We found that this objective is not fully realized.

With the discrete event simulation, we perform an evaluation. The inputs of the simulation are arrivals and manpower. The discrete event simulation uses random service times and patience based on the available data. The waiting times that are applied in the discrete simulation are based on the recorded duration. The ad hoc discrete event simulation efficiently addresses the issues and allows us to assess the system performance in detail. The discrete event simulation results show that the idle capacity in the active week is higher than that in the inactive week. In addition, we find that the waiting times are also higher in the active week. This tradeoff shows the difficulty of balancing excess capacity and waiting times.

The firm anticipates the increase in calls well during active weeks, as witnessed by the ratio of incoming calls per agent. The simulation shows an increase in queue size, waiting times, and abandoned calls in active weeks. On the positive side, our simulations indicate that the adjustments in manpower between active weeks and inactive weeks have caused an improved (on average, six calls/agent in an hour) ratio of calls to agents. On the downside, the system is inherently less manageable for active weeks, as indicated by a simultaneous increase in idle capacity and waiting times.

The system operates near the performance levels stated in the managerial objectives, even when the efficiency of the system is lower during active weeks. Our study shows that advertising has a detrimental effect on peak calls, which leads to higher waiting times and abandoned calls. According to managerial feedback, manpower planning is less flexible during the weekend. The simulation also shows that a considerable amount of the increased manpower capacity causes an increase in idle time.

8.1. Managerial implications

To determine the extent that the evaluation developed here can be implemented as a capacity planning tool, some further issues should be resolved.

a) Manpower planning

Is the manpower planning a closed loop? (that is, can it be adjusted on the spot based on the number of calls arriving or waiting time) or is it an open loop as assumed in our simulation (with predefined capacities for each time slot for a week)?

b) Data

Ideally, some additional data should be estimated or measured. One item would be a distinction between the waiting time for the calls and the service time for the calls. In our study, we obtain the total time that a customer spends in the system.

c) Validity checks

The primary point is to obtain a grip on realistic service times. The microsimulation is too optimistic in terms of waiting times and is too

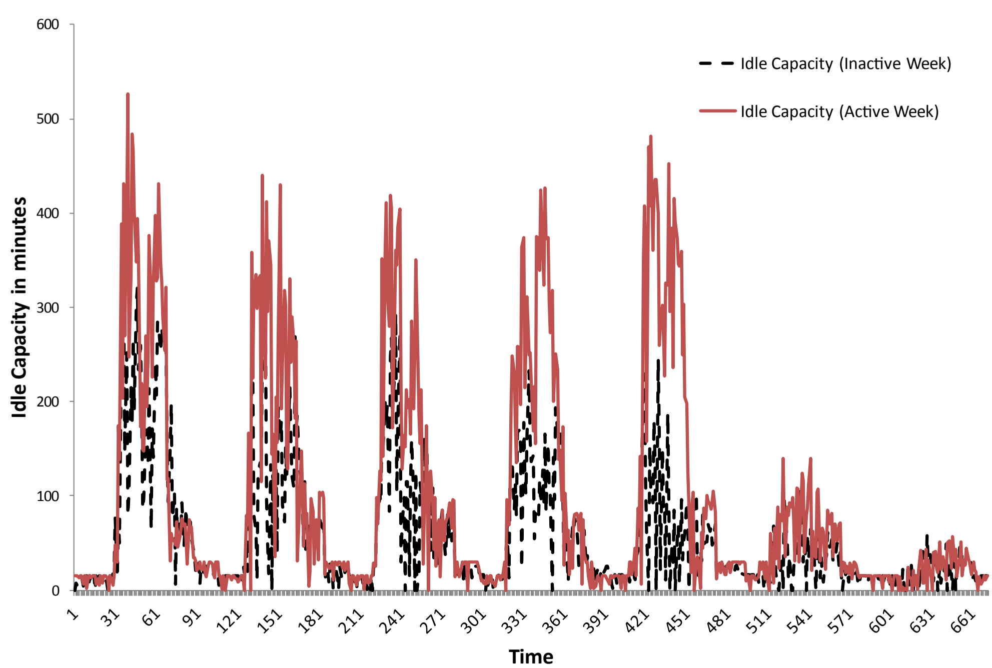


Fig. 14. Idle capacity in minutes for inactive and active weeks.

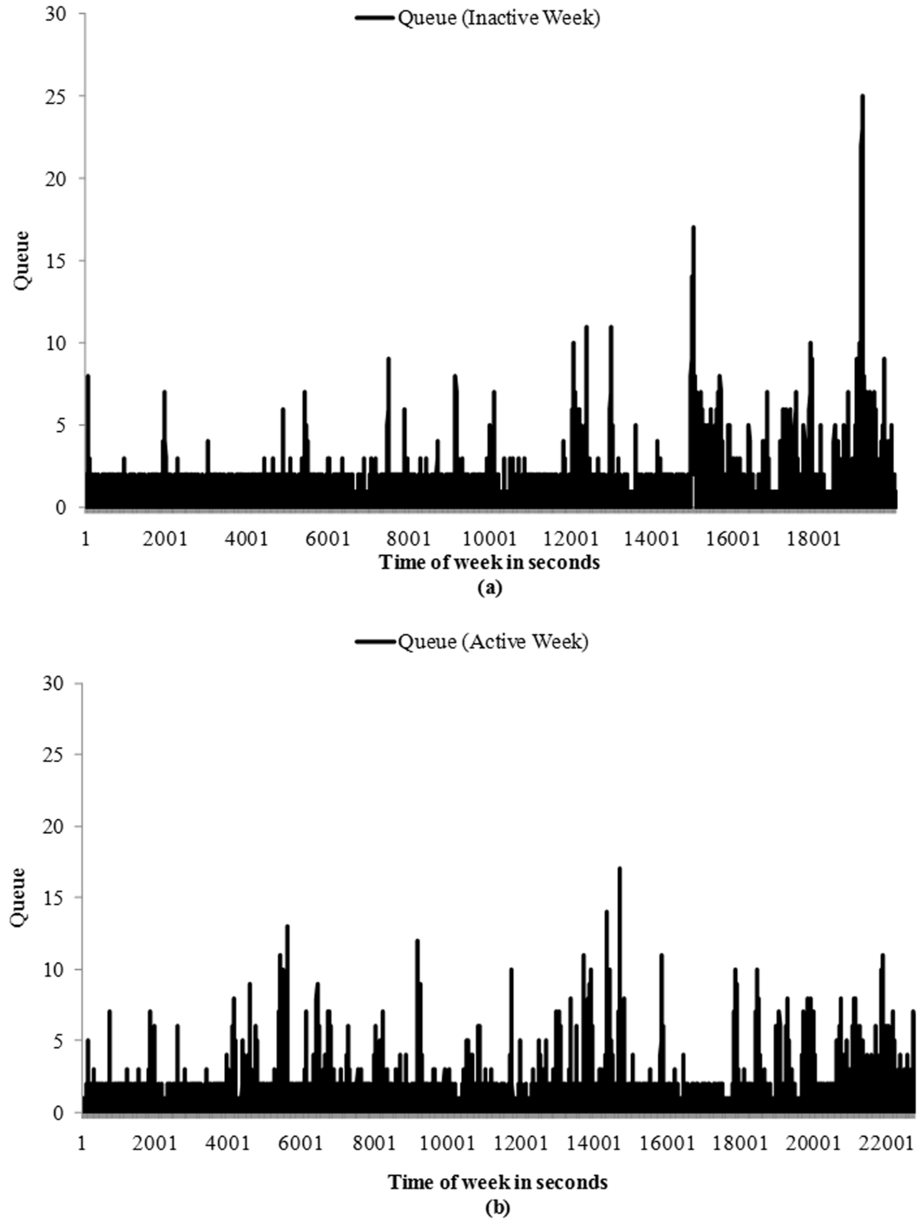


Fig. 15. Queue size for inactive (a) and active (b) weeks.

positive concerning the system performance, mainly because a better understanding of the administrative time that is needed between handling calls is required.

d) Service strategy

From a managerial point of view, the task is to reduce the call center demands to the minimum extent possible. This task is attempted by presenting the internet platform and the call center side by side in the advertisements. However, the call center remains crucial because the advertiser relies on impulse calling behaviors from the target customers.

The main contributions of our study are presented as follows: In this paper, we demonstrated the importance of the link between marketing activities and operational management. There is a gap in the call center literature, including models for long-term forecasting, personnel planning for comprehensive multiskill call centers, and resource acquisition planning for increasingly complex networks of service providers. The forecasting model developed in this study shows that the autoregressive (AR) and distributed lag (DL) structures are consistent with the AR and DL results obtained in the hourly models discussed in Kiygi-Calli et al. (2012). In the calls forecasting model, the number of incoming calls is employed as a dependent variable (Kiygi-Calli et al., 2012). We applied the novel methodology to analyze high-frequency advertising and call data by addressing the subtle seasonal cycles while accounting for the moderating variables, such as the time of broadcasting. Our forecasting model differs from traditional models, which emphasize advertising heterogeneity and disregard cycles in autoregressive (AR) terms. The seasonal heterogeneous structure becomes more complicated for data at 15-minute intervals. However, the model fit remains approximately 90%, which is similar to the model fit that is obtained at hourly data intervals (Kiygi-Calli et al., 2012). The implications from our simulations are that the adjustments in manpower between active weeks and inactive weeks have caused an improved (on average 6 calls/agent in an hour) ratio of calls to agents. Therefore, from a managerial point of view, this study focused on the balance between excess capacity and waiting times.

For further research, alternative aggregation levels of data can be analyzed to examine the most effective forecasting system. This study can be conducted with a different periodicity of the estimation, that is, shorter than 15-minute intervals.

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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.

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