Prediction-based Optimization of Service Capacity using the Robotic Process Automation technology

Radu Florin Negoiţă, Theodor Borangiu, Silviu Răileanu

Dept. of Automation and Industrial Informatics, University Politehnica of Bucharest, Romania
(e-mail: radu_florin.negoita@stud.acs.upb.ro, theodor.borangiu@upb.ro, silviu.raileanu@upb.ro)

Abstract: The research described in this paper concerns the automation of back-office workflows for the capacity management of hospitality services: continuously monitoring clients' reservations and hotel registrations and automatically updating the decisions that establish optimal staffing levels to assure dependable and accurate services with minimum personnel cost, and maintaining a minimal stable workforce level. The service capacity management workflows connect multiple instances of online reservation and front-office customer registration processes (booking, check-in taxation, check-out invoicing according to the back-office strategy) with a combination of marketing- and operations-oriented back-office processes that: a) best match capacity and demand for quality services, and b) optimize the staffing levels and personnel workshift schedules. These workflows with many operations and complex timing are automated with the Robotic Process Automation (RPA) technology that uses AI techniques for seasonality prediction of confirmed service demand. A case study of optimal hotel staff assignment with RPA using the Blue Prism scheduler is included, and the gains of using RPA solutions are presented.

Keywords: Service capacity management, seasonality prediction, service demand, staffing optimization, work shift scheduling, RPA.

1. INTRODUCTION

Several approaches are used for capacity management to achieve maximum efficiency. Among these, level capacity and chase demand are pure strategies generally adopted - the first in the production sector, the latter mostly in the service industry. Some attributes of these pure strategies may be highlighted or adapted to the service capacities of interest and merged with strategies that manage the demand for services - leading thus to combination strategies that are customized to analyse, forecast and influence the demand of customers for services and the process by which the capacity needed to match the demand is ensured, (Wirtz, 2018). The following are examples of *capacity management* methods derived from the chase demand strategy: creating variable capacity sharing, daily workshift scheduling and weekly workshift scheduling with day(s)-off constraints, using part-time employees, cross-training staff, (Fitzsimmons and Fitzsimmons, 2008; Gordon, 2022). These methods are combined with strategies *managing the demand* level, e.g., segmenting demand, offering price incentives, promoting off-peak demand, reservation systems and overbooking, (Kliewer et al., 2017).

The general sense of the chase demand strategy is to track the demand placed by the market. In the hospitality industry, services are set in the provider's back office to match the customer demand known or estimated in advance. In the chase strategy, service capacity will be varied monthly as demand - expressed by confirmed customer reservations or room occupancy - varies, (Welp, 2020).

For the problem of managing the capacity for hospitality services, *service capacity* is defined in terms of: i) a feasible level of staff workload per unit time (e.g., hotel rooms and common spaces cleaning per day for a busy employee), and ii) the utilised supporting facility (e.g., number of occupied hotel rooms) which is limited by the fixed room capacity of the building. Also, service capacity is not limited by factors such as available labour skill classification, equipment or consumables, because adequate measures are put in place: careful personnel selection and training, well-organized procurement, efficient supply and logistics. In back-office capacity management, the objective is to develop work schedules that meet the employees' requirements for weekdays and weekends with the smallest number of staff members possible.

Recent developments of custom service Operations Management Software (OMS) allow digitising related workflows in view of their optimization and provide deep visibility into service operations. To streamline planning, control and analysis of service operations, service OMS should be integrated with the following back-office systems: Customer Relationship Management (CRM - handling service requests); Analytics software (managing resource availability and utilization, establishing business strategies); Customer portal (solving customer change requests, activity progress reports); Accounting software (service time and expense log data, financial data) (SciSoft, 2022). The key features set of integrated service OMS systems that allow continuous service operations offering functionality for multiple users (operations, infrastructure and strategy managers, service delivery teams and customers) are: a) service planning and optimization - for managers, setting up service-related workflows; b) human resource management - centralized view of human resource (HR) data, AI-driven HR allocation based on forecasted capacity occupancy, configura-ble capacity utilization dashboards; c) service request manage-ment - task assignment, progress status tracking; d) time and expense management - automated invoice generation, configu-rable timesheets and expense claim forms; e) document mana-gement - centralized storage of service-related documents, search engine with document metadata querying, template-based document creation; f) supply management; g) service analytics - change impact analysis, resource utilization reports, preventive asset maintenance, revenue forecasting based on real-time monitoring of service delivery, AI-based service risk assessment, (SoftSug, 2022; HUK, 2022).

The motivation for the presented research is the necessity to automate service management operations in the hospitality industry. For the hotel business, coordinating service capacity with dynamic varying, market-driven demand implies the correlation and synchronization of front-office and back-office processes - the first category addressing customer relationship management (CRM) and the second one inventory planning, forecasting demand, analytics, and strategic decision making.

Duetto, a hospitality application supplier, conducted a market survey of hospitality professionals in their Revenue Outlook & Trends report (Duetto, 2022). The report concluded that hotel automation and OMS integration are fast becoming critical tools for success, especially for hotels located in competitive markets, and that automation will be extremely important to hotel revenue management in the future.

By automating a variety of hotel operations, it is possible to minimize operational expenses while maximizing the value offered to guests. Automating time-consuming hotel operating processes can benefit the business by: reducing labour costs, supporting short-staffed teams, streamlining operational services, powering up hotel sales management, improving the guest experience, forecasting demand more accurately, increasing occupancy percentage, enhancing hotel communications, cutting hotel expenses (Campbell, 2022). Two typical OMS systems in the hospitality service area, partially automated, are further referred.

Frontdesk Anywhere is a cloud-based hotel management software dedicated to independent hotels and management groups. The features of this Performance Management System include: easy reservation management, reporting, group bookings, commission free booking engine, revenue management, payment processing and channel manager with OTA connections (Frontdesk Anywhere, 2022). The system's functionalities cover mainly the back-office area: reservations management; reporting and statistics; third party integrations; activity dashboard; reporting/analytics.

Duve is a OMS platform (Duve, 2022) built for a modern hotel experience that includes general operations management components: task management, key provider integrations, in-app chat, analytics, and digitalizes some front-office processes like: i) online check-in: collect guest details, arrival coordination, document scan, registration card - E-signature; ii) upsells: 2) upselling: early check-in, room upgrades, late check-out; in-house services; iii) guest communication: omnichannel unified inbox, prescheduled messages; live guest broadcasting; iv) digital check-out: check-out coordination, smart late checkout upsell, review optimization; payment for stay.

The proposed approach intends to integrate front-office and back-office service processes with highest possible level of automation using a digital OMS system to complete hotel processes formerly completed by hotel staff. This service automation system is designed to segment and influence customer demand, adjust supporting facilities of limited capacity and optimize work (staffing level and assignment); these are back-office workflows that are kept consistent with the business strategy of the organization's management and assist front-office workflows involving customers (service request, quality assessment) and front line personnel (check in, check out, taxation and invoicing).

In this approach, the proposed service OMS is driven by the *intelligent process automation* (IPA) technology, a combination of robotic process automation and artificial intelligence, machine learning, process mining, prediction, decision management and optimization used together in an end-to-end automation solution (UiPath, 2022) - currently considered as strategic for higher productivity and quality of services, increased customer satisfaction, and cost saving.

The expanding *Robotic Process Automation* (RPA) software technology represents a promising solution to implement OMS systems. RPA incorporates a recent software technology in the ICT area specialised in creating virtual robots (BOTs) that are able to reproduce human activities with improved efficiency and productivity, (Kumar, 2020; UiPath, 2022).

The RPA-based service OMS platform will operate with two types of software robots:

1. *Front office robots*: they share the same workstation as an employee who has control over its utilisation (context, time); the staff launches these robots that run only under the operator's surveillance; front office software robots reside on the employee's local workstation and cannot be run or scheduled remotely, (Saul, 2022).
2. *Back-office robots*: they run unattended in batch mode in virtual environments; back office robots send heart-beats to the OMS server, so that it knows instantly when a robot is down.

Businesses that adopt the RPA technology improve their processes by increasing agility, processing speed and efficiency in scalable manner, reducing costs and eliminating errors caused by human operators, (Jovanović, 2018). RPA robots interact with the front-end part of the information systems as humans do, performing well-structured, rule-based repetitive actions, (Correia and Da Silva, 2022). Actual information-based service systems show an increasing interest in combined RPA-IPA solutions, (Magrin and Costa, 2020; Varshini et al., 2021).

The paper presents an RPA solution that automates the service capacity management processes for prediction-based optimization of the staffing level needed in hotels. Chapter 2 describes the back-office processes that compute updates for the personnel staffing problem, based on seasonality prediction of service demand. The staffing and workshift scheduling problem is formulated and a solution for its optimization is proposed. Chapter 3 presents an aggregate RPA system developed to automate capacity management processes. Experiments with the Blue Prism RPA scheduler of the main processes and the results obtained are described in Chapter 4. Conclusions and perspectives of future work are outlined in Chapter 5.

2. WORKFLOWS OF CAPACITY MANAGEMENT PROCESSES

The problem will be defined for a season-specific capacity segmentation (fixed number of standard and first-class rooms) that holds for six full (peak) months in the period May-October and involves three steps: 1) computing the necessary weekly staffing level; 2) weekly workshift scheduling; 3) monthly workshift scheduling of established staff (cleaning personnel). This computation process uses two input data sets:

- *Service workload* expressed in hours per day for the maintenance of supporting facilities: room set up at check out, daily cleaning of rooms and common spaces; this workload is defined before season start.
- *Short-term room occupancy forecast*: prediction is made for the next month based on historical data from the previous year and actual tenancy in the current month, e.g., for a 6-month current season.

The workflows for service capacity management interconnect multiple instances of online reservation and front-office customer registration processes (booking, check-in taxation, check-out invoicing according to the current business strategy) with a combination of marketing- and operations-oriented back-office processes that: a) best match capacity and demand for quality services, and b) optimize the staffing levels and personnel workshift schedules (customer segmentation, overbooking, offering price incentives, sharing capacity, monthly updating workshift schedules). Automating these workflows needs data aggregation from different sources like the booking platform, hotel registration desk, back-office management data, service delivery list, human resource directory, and integration in a registration data base that is updated according to a timing that provides the input for the processes predicting the monthly room occupancy and on this basis controlling the optimal staffing level.

The processes included in these workflows and their interconnections are represented in Fig. 1.

The active tables of the registration data base store information about the current season (months 13-24 in year $[y]$) and the previous one (months 1-12 in year $[y-1]$) for a cycle length $L=12$. Based on these data, the staffing level will be optimised for the current 6-month peak season (May-October of $[y]$). The history of statistics about booking and real room occupancy $O_t, 1 \le t \le 12$ is first created in year $y=1$ and will be used to forecast monthly the actual room occupancy for the next year. At the end of the current year $[y]$, the actual occupancy values will replace the historical ones : $O_{t-L}[y-1] = O_t[y]$, $13 \le t \le 24$. The room occupancy for the next month $t+1$ of a new season $[y]$ will be predicted using the actual number of registrations confirmed in month $t[y]$ and the 1-year seasonality history $O_{t-L}[y-1]$, $13 \le t \le 24$ that was updated at the end of the year that just expired.

Using the hotel accommodation predicted in month $t[y]$ for the next month $(t+1)[y]$ and the updated service workload, the minimal staffing level can be calculated monthly and updated whenever major changes in demand are expected.

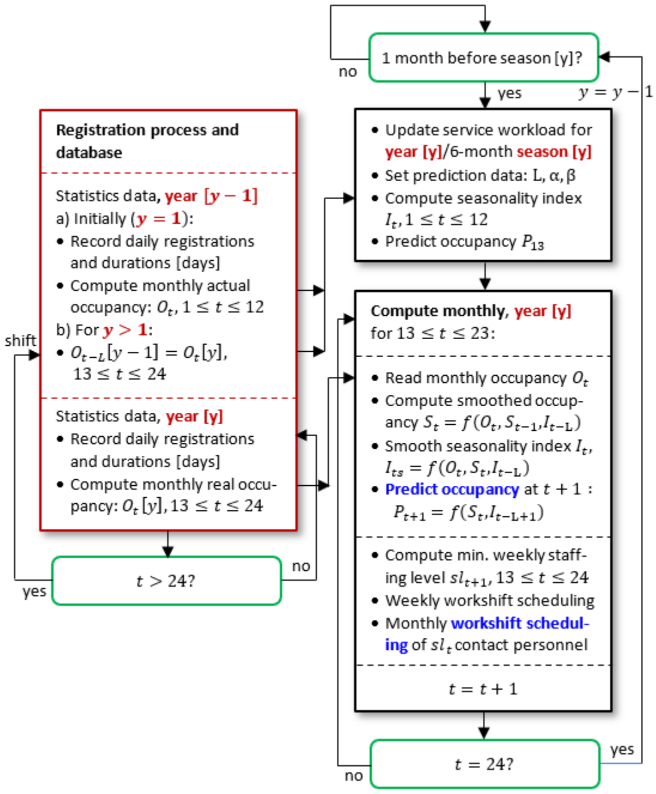

Fig. 1. Capacity management process workflows for prediction-based optimisation of staffing level.

In the hospitality service industry, important variations in demand levels occur in the season and off-season periods, which impose re-establishing the service staff level. In the case studied, service workload is set at season start (yearly in May) and the staffing level is updated monthly during the peak demand season May-October.

2.1 Seasonality prediction of service demand

Time series models are applicable for short-term predictions of the accommodation service demand because in general the values of observations, in this case confirmed registrations (actual hotel occupancy values), fit in patterns that can be recognized over time. Predicting demand to manage service capacity requires generating accurate forecasts that can be achieved by evaluating the baseline, smoothing out blips from observations over established periods, addressing exceptions, and considering trend, seasonality and causal components by data segment. The time series models have been investigated:

- *Exponential smoothing model* is customized to track elements of a forecast such as average, trend, and seasonality which are then combined to calculate the forecast. The method eliminates blips in observed data by feeding back a fraction α, $0.1 \le \alpha \le 0.5$ of the prediction error (the difference between the actual observation O_t in the current period t and the smoothed value S_{t-1} calculated in the prior period $t-1$) to correct the previous smoothed value, thus obtaining the new smoothed value S_t. Although the calculation requires the most recent observed data, old data is never ignored but its importance is gradually reduced. In general, the smoothed value S_t is based on actual observed value O_t

that is given the weight α, and on N-period older observations O_{t-N} that are given the weights $\propto (1-\propto)^N$.

- *Trend adjustment model* considers the average rate at which the observed values O_t change from one period t to the next one $(t+1)$ over time; this is the slope of the demand curve. The trend for period t is defined by $S_t - S_{t-1}$, i.e., the rate of change in smoothed value from one period to the next.
- *Seasonal adjustment model* is based on seasonality i.e., the presence of variations that occur at certain regular intervals e.g., on weekly or monthly basis. Seasonality is a recurring cycle whose fluctuations in actual observations occur at certain regular intervals such as monthly confirmed registrations and generate repetitive, periodic, in general regular patterns that are predictable in a time series. Seasonal variation is calculated in terms of a so-called *seasonal index* - an average that can be used to compare a real observation subject to seasonality with its value in the absence of seasonal change.

The service demand forecast using a time series model is a continuous process based on daily observations that are aggregated monthly over time. The perspective of maintaining and improving the prediction process is twofold: 1) Measuring and tracking forecast accuracy: consist in identifying and analysing the causes of forecast errors and tracking improvements by customer demand segments; 2) Enhance prediction models with built-in intelligence and contextual insight extracted from big data: evaluate intermittency, collinearity, anomalies, level shifts, price changes, events and holidays from big data streaming, and make intelligent reconfiguring decisions with built-in machine learning.

A combination of the exponential smoothing and seasonality adjustment models will be adopted for the prediction of service demand. In this case, seasonality is caused by two factors: weather and holidays. The length of the seasonality cycle is $L = 12$ months. Confirmed service demand (room occupancy) P_t will be predicted monthly for $13 \le t \le 24$ of the current year $[y]$ based on observations from the previous month $O_{t-1}[y]$ and the time series of observations $O_t, 1 \le t \le 12$ recorded in the preceding year $[y-1]$. The values P_t predicted at the end of months April-September $[y]$ will be then used to exemplify the calculation of the monthly optimal staffing level for service capacity management during the 6-month season May-October $[y]$.

Seasonal prediction involves two steps in which actions are taken on the set of actual observations: first, the seasonality is removed from the data that is exponentially smoothed; then, seasonality is introduced back to make the forecast. We assume that observations have been recorded for one season $[y-1]$ before prediction starts and are available in the registration database, see Fig. 2.

A first seasonality index I_t is defined to de-seasonalise observation data in the 12-month cycle $[y-1]$, for $1 \le t \le 12$; these 12 indices are defined as the ratio between the monthly actual room occupancy O_t and the average value O_{av} for all periods t in cycle $[y-1]$:

$$I_t = O_t / \sum_{i=1}^{L} O_i \qquad (1)$$

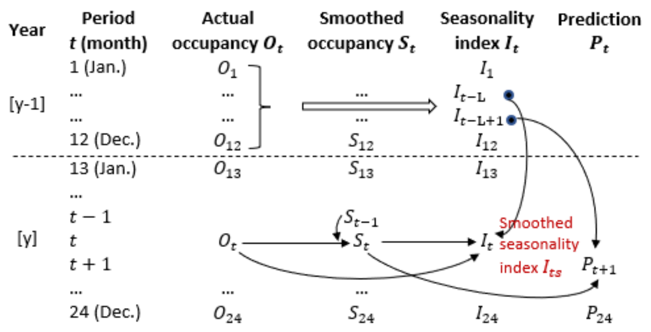

Fig. 2. Seasonality prediction of service demand with exponential smoothing.

The indexes I_t calculated for $t = 1, \dots, 12$ according to eq. (1) are available in column 5 of the scheme represented in Fig. 2, being then used to de-seasonalize the observations for the corresponding months of year $[y]$ with exponential smoothing in which O_t is adjusted to account for seasonality with the particular index I_{t-L}:

$$S_t = \propto \cdot (O_t / I_{t-L}) + (1-\alpha) \cdot S_{t-1} \qquad (2)$$

The prediction of room occupancy for month $(t+1)$ is then made by seasonalizing the smoothed value for period t according to eq. (3):

$$P_{t+1} = S_t \cdot I_{t-L+1} \qquad (3)$$

The data from the 12 observations in year $[y-1]$ is used to compute the initial estimates of the seasonality indices. New smoothed data can be computed beginning with month $t = 13\ [y]$; to start the process, it can be considered that $S_{12} = O_{12}$ if there are no observations available from year $[y-2]$.

If the seasonality indices are not sufficiently stable they can be smoothed by help of a constant coefficient γ that takes values in the range $[0.1, 0.5]$; the smoothed estimate $I_{t,s}$ of the seasonality index for any month $t[y]$ will be calculated with eq. (4) for future use:

$$I_{t,s} = \gamma \cdot (O_t / S_t) \cdot (1-\gamma) \cdot I_{t-L} \qquad (4)$$

As can be seen from the schematic representation in Fig. 2, smoothed values, indices and predictions are calculated progressively for $t[y]$, on a month-to-month basis as the most recent observations O_t become available, i.e.:

$$P_{t+1} = f(\underbrace{O_t, S_t}_{\text{Most recent observations}}; \underbrace{I_{t-L}, I_{t-L+1}}_{\text{L-cycle history}})$$

A key performance indicator of prediction accuracy is the mean absolute deviation D_{ma} expressed as average of the absolute values of prediction errors ($t = 13$ for accuracy analysis of predictions in $[y]$):

$$D_{ma} = \frac{1}{L} \sum_{t}^{t+L-1} |O_t - P_t| \qquad (5)$$

The values assigned to the subunit coefficients $\propto, \gamma$ are trade-offs between reacting excessively to random variations about a constant mean and identifying a change in the mean value; higher values of these coefficients in the range $[0.4 - 0.5]$ determine more responsiveness to changes because of the greater importance that is granted to recent observations. The values of the coefficients $\propto, \gamma$ can be also calculated to minimize the forecast error D_{ma} over a complete seasonality cycle L in which trends are identified systematically.

2.2 Optimizing staffing level and work shift scheduling

The service capacity planning process computes the minimum staffing level that covers the weekly service workload for an accurate seasonality prediction of room occupancy on short term, i.e., monthly during the period of peak demand May-October of season $[y]$: $17 \leq t[y] \leq 22$. Next, work shifts are scheduled to match the established staffing profiles as closely as possible with the smallest number of staff members.

The forecast of room occupancy for month $(t+1)$ is an automated process linked to the registration process as follows: 1) the customers' registration and the duration of their stay [days] are daily recorded and stored in the *registration data base*; each day d, the actual room occupancy $O_{d,t}$ is recorded; 2) at month end, i.e., after $D(t)$ days, the actual room occupancy (confirmed demand) O_t is computed for the entire period $t[y]$: $O_t = \frac{1}{D(t)}\sum_{d=1}^{D(t)} O_{d,t}$ or $O_t = \sum_{d=1}^{D(t)} O_{d,t}$; it can be also expressed as a percent of the maximum (fixed) accommodation capacity of C_M [rooms], e.g., for $C_M = 160$, an average monthly occupancy of 152 represents an O_t percent of 95%.

The service workload is expressed relative to units of accommodation (e.g., rooms) and access spaces (staircases, corridors, sanitary groups), and types of operations (daily room cleaning, room preparation at customer check out, etc.). This activity profile is translated in standard time durations necessary for a busy employee to perform the operations. Table 1 centralises the standard time slots for room preparation at check-out (1.5 h), daily room cleaning (0.5 h) and access space cleaning (2 h and 3 h) per day. By distributing the daily service workload in two 8-hour work shifts from which 7 hours are dedicated to the cleaning activity profile above described, the necessary staffing level per day results in the rightmost column of Table 1.

Table 1. Staffing levels per day calculated for 100% monthly predicted occupancy of 40-room segment.

Work profile / Day	Check-outs [rooms]	Prepare room [h]	Daily room clean [h]	Corridor, stair, bath [h]	Concierge desk, hall [h]	Daily workload [h]	Staffing level [people]
Sa	2	3	19	2	1	25	4
Su	8	12	16	2	1	31	5
Mo	12	18	14	3	2	37	6
Tu	4	6	18	2	1	27	4
We	4	6	18	2	1	27	4
Th	2	3	19	2	1	25	4
Fr	8	12	16	2	2	32	5

To exemplify the calculation of the necessary staffing level with busy personnel for each day d in a week of the period $t[y]$, we assume that the confirmed accommodation O_t predicted for month t is 100% of the hotel's max. capacity $C_M = 160$, i.e., peak demand. Because this accommodation capacity is evenly distributed on four floors each of them with 40 rooms (30 standard and 10 1st-class rooms) of the same type and hence with the same workload for cleaning services, the personnel scheduling problem will be analysed for a 40-room segment.

After computing the necessary staffing levels for each day in the week, the problem is formulated by help of an integer linear programming (ILP) model in order to determine the minimum number of employees required for assignment to each of seven possible work shifts (tours). Each tour consists of 5 days *on* and 2 consecutive days *off* (DO), each beginning on a differrent day of the week and lasting for 5 consecutive working days. The ILP model is formulated like follows:

- *Variables*:
  - x_i: number of employees assigned to tour i that has two successive days off
  - b_j: staffing level needed for day j
- *Objective function*: minimize the sum $\sum_{i=1}^{7} x_i$
- *Constraints* ($x_i \geq 0$ and integer):

Sunday (Su): $x_2 + x_3 + x_4 + x_5 + x_6 \geq b_1 = 5$
Monday (Mo): $x_3 + x_4 + x_5 + x_6 + x_7 \geq b_2 = 6$
Tuesday (Tu): $x_1 + x_4 + x_5 + x_6 + x_7 \geq b_3 = 4$
Wednesday (We): $x_1 + x_2 + x_5 + x_6 + x_7 \geq b_4 = 4$
Thursday (Th): $x_1 + x_2 + x_3 + x_6 + x_7 \geq b_5 = 4$
Friday (Fr): $x_1 + x_2 + x_3 + x_4 + x_7 \geq b_6 = 5$
Saturday (Sa): $x_1 + x_2 + x_3 + x_4 + x_5 \geq b_7 = 4$

which leads to the equation:

$$x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 = 7 \quad (6)$$

ILP-type scheduling problems have multiple optimal solutions. One solution, shown in Table 2, is: $x_2 = 1$, $x_3 = 1$, $x_4 = 1$, $x_5 = 1$, $x_6 = 1$, $x_7 = 2$; hence, there is one tour with Mo and Tu off, one tour with Tu and We off, one tour with We and Th off, one tour with Th and Fr off, one tour with Fr and Sa off, and two tours with Sa and Su off. Also, 1-member of staff in excess occurs on Tu, We and Th; other workloads can be assigned to the staff in excess in these three workdays, e.g., care of the open air food serving area. The ILP model is replicated for the other three 40-room workloads, leading to a total of 28 staff for two 8-hour daily tours in month $t[y]$.

Table 2. Optimal weekly employee work shift scheduling with 2 day-off constraints.

Employee	Su	Mo	Tu	We	Th	Fr	Sa
A	x	DO	DO	x	x	x	x
B	x	x	DO	DO	x	x	x
C	x	x	x	DO	DO	x	x
D	x	x	x	x	DO	DO	x
E	x	x	x	x	x	DO	DO
F	DO	x	x	x	x	x	DO
G	DO	x	x	x	x	x	DO
Total	5	6	5	5	5	5	4
Required	5	6	4	4	4	5	4
Excess	–	–	1	1	1	–	–

Because of the strong seasonality of hospitality services, business efficiency can be increased in the 6-month peak demand while keeping a suitable effectiveness for service workloads; this can be reached by widening the staff working profile, e.g., using part time employees or relaxing the day-off constraints (two non-consecutive days-off or one day-off per week). Thus, the same maximal workload can be achieved by: i) 24 full-time employees working five days weekly in one 8-hour tour with two consecutive days-off plus one part-time employee working weekly 8-hour tours in two days (on Friday and Sunday); ii) 16 full-time staff working six days weekly in one of two 8-hour tours with one day off plus 4 part-time employees working weekly 8-hour tours in two days (two tours on Mo, and one tour in the other six days of the week).

3. THE RPA SOLUTION

The RPA system is based on the Blue Prism software tool, Blue Prism (2022) in which the OMS solution for service capacity optimization is run on a predefined scheduler that automates all the processes of the workflows defined in Chapter 2.

The RPA solution automates two main processes, the activities of which are interconnected in a specific timing: "Occupancy Aggregation" and "Prediction and Staff Allocation".

Occupancy Aggregation, the first principal RPA process, automates the online reservation and front-office customer registration processes (booking, check-in taxation, check-out invoicing) according to a continuously updated back-office strategy. The related BOT will collect data and information from two databases - *Booking Platform* and *Registration Desk*, launch the CheckIn, CheckOut and Reservation activities (triggered by external events), and will calculate daily at 11:59 p.m. the room "Occupancy Percentage" that will be used by the second main RPA process to optimize the staffing activity (Fig. 3).

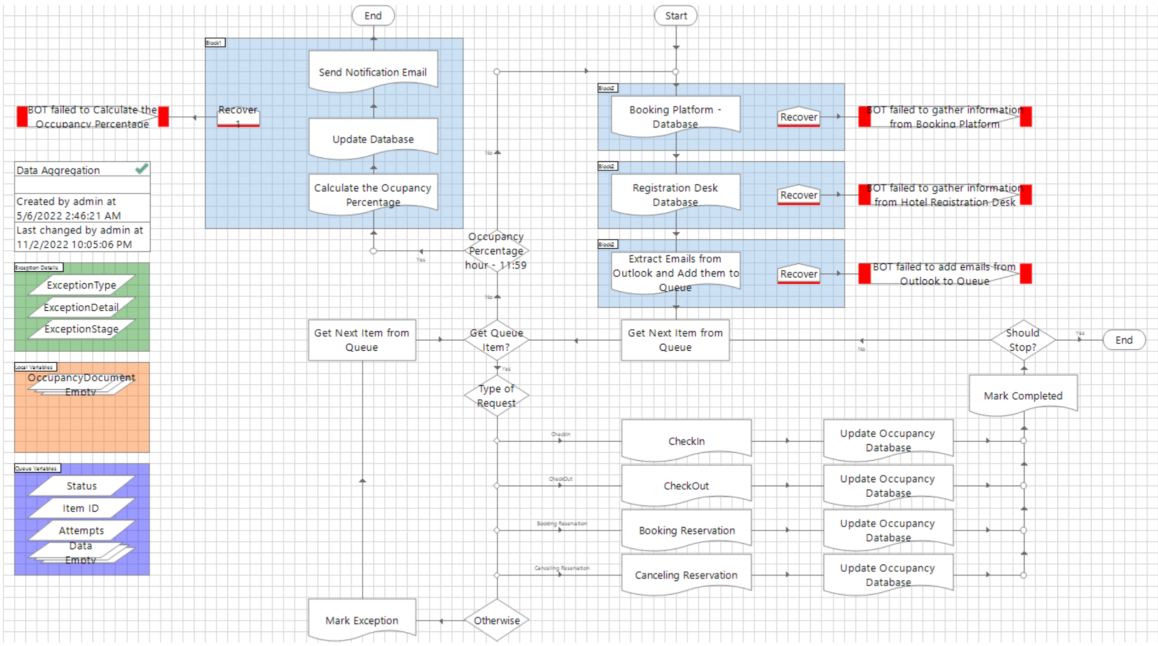

Fig. 3. RPA representation of the Occupancy Aggregation process.

The information extracted from the two databases are of the types String(name, surname, address, type of reservation, …), Int32(no. of days/reservation, no. of persons/stay, no. of. children/stay, …) and Date(date of reservation, date of CheckIn, date of CheckOut), and is stored in a temporary document, saved locally, every time the BOT will run (thus avoiding duplicate values). This document will be used to automate the second main process (Prediction and Staff Allocation) of the RPA solution every last Friday of a month after which it is permanently deleted.

After mapping the information from the two databases, the available input data is read, sorted, interpreted and process-ed according to its type. After a reservation is created (in Booking Platform or Registration Desk processes) an auto-mated email containing all the information required for the reservation (name, address, contact data, no. of persons, no. of days, date of CheckIn, additional services requested, etc.) is sent to the Hotel Management mailbox, and serves as input data for the robot. In a similar way, the CheckIn and CheckOut sub-processes are started by a human agent who launches the run; they send in a similar mode the input data to the robot by an email that contains all the information needed to finalize the check-in or check-out process.

The BOT of the first RPA main process has thus access to the hotel's email mailbox, reads all emails from Outlook's Inbox received during the current day and adds those result-ed from reservations, check-ins and check-outs to its proce-sssing queue. The email reception represents for this RPA process the trigger to automate the CheckIn, CheckOut and Reservation sub-processes. After adding the emails to the queue, the BOT takes them successively (Get Next Item from Queue), verifies their type using the email's subject, and processes them accordingly. If the decision stage "Get Queue Item" returns the value "False", then the working queue is empty and there is no other element to be process-ed. Each email has a dedicated subject that corresponds to the type of sub-process ("Type of Request") associated with it. For example, if the subject is "CheckIn" activity, then the BOT will update the "Update Occupancy Database" with the information related to the room to be occupied, making it unavailable for upcoming reservations in the next "Date" period of this confirmed reservation. If the email contains the "CheckOut" activity, then the BOT will update the database as well (“Update Occupancy Database”), this time freeing the hotel room and making it available for incoming reservations and launching the “invoicing” subprocess.

For a “Reservation” email, the BOT checks in the *Hotel database* the availability of the request in the “Date” period specified and, depending on the current situation, updates the *Occupancy database* or generates a “Fully booked” message, see the subprocess “Booking Reservation” in Fig. 4. If the requested reservation interval is available, then the next step is to verify whether the client is a new one, case in which the client’s personal information (name, address, contact data) is entered in the database. The BOT will upda-te the “Available booking” list and will finish this subpro-cess by sending an email via Outlook to the client confirm-ing that the reservation has been successfully completed.

For the last type of request “Cancelling Reservation”, the BOT will extract the client information, remove the reserva-tion and update the *Reservation database* accordingly.

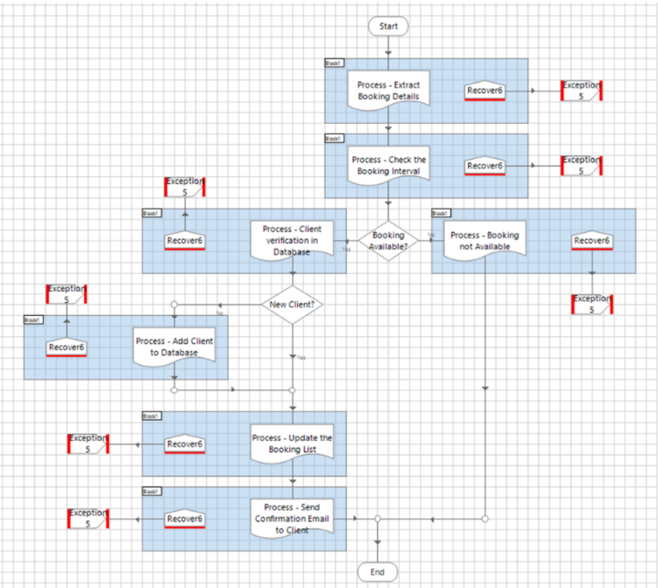

Fig. 4. Automating the Booking Reservation process.

After successfully finishing the queue item, the “Occupancy Aggregation” BOT marks the item as completed (“Mark Completed”); if an error of any kind will appear during the run, it will be labelled as an exception. After marking com-pleted the element from the queue, the BOT will go through a ”Should Stop?” decision stage, where the decision is made by factors external to the process, e.g., the support team may stop the process because of technical matters. The BOT of the “Occupancy Aggregation” RPA process runs continu-ously; daily, at 11:59 p.m., it automatically starts the pro-cess “Calculate the Occupancy Percentage”, updates the *Hotel Occupancy database* with the result of the calculation and sends an email to the business department notifying the occupancy percentage for the day that has just expired.

The left side of Fig. 3 groups the variables used to develop the Occupancy Aggregation RPA process:

- *Exception Details Variables*: specify the type of excep-tion with some details or the exception stage where the error is reported and the BOT execution is stopped.
- *Queue Variables*: store the information of each element of the queue, its unique identifier, number of processing attempts, and the status of the run.
- *Local Variables*: are the variables needed in the current page of processing.

The exception handling procedure is very important in the RPA solution; hence, “Recover” activities were used to cap-ture errors and release them for Exception handlings; e.g., when the BOT extracts information from the Booking Data-base, an unexpected error might occur; then, an exception handling mechanism is placed to avoid process stops.

Prediction and Staff Allocation is the second principal RPA process that: a) automates the 1-month forecast of room occupancy based on the “Occupancy percentage” of the current month and the 1-year history of actual occupan-cy in the past year, and b) optimizes the necessary staffing level using the service workload data established at the beginning of the current peak season. The BOT uses a “Months” collection that includes the 12 months of the year, in which it will iterate to extract the occupancy percentage to be then used in the “Prediction” and “Staff Allocation” RPA blocks. Based on the output from the “Data Aggregati-on” process, the BOT will extract the percentage required for the iterated month.

This process is essential for updating personnel staffing; therefore, an exception handling rule is applied to all its three component blocks (“Get Occupancy Percentage”, “Recover”, “Staff Scheduling”) allowing three retry decisi-ons when the BOT encounters an exception. If, after three retries, the exception is still present, the BOT will send an exception email (“Send Exception Email”) and abort the process (Fig. 5).

After getting the occupancy percentage for the current month, the BOT calculates in the “Prediction” subprocess the room occupancy for the next month based on the season-al time series method given in eq. 1-5 of chapter 2.1 and the historical data from the previous year. Then, the BOT uses the result of the forecast to weight the staffing level based on the service workload established by the management for the current year, optimizes the weekly work shift scheduling with predefined work policy constraints, assigns employees to work shifts for the entire month based on the computed weekly schedule and predefined equity rules, and calculates the monthly personnel costs for the established schedules. The BOT of the “Prediction and Staff Allocation” process runs once per month (at the end of the current month) and finalizes the RPA process by sending the computed staffing, work shift schedule and personnel cost data for the next month by email to the financial department.

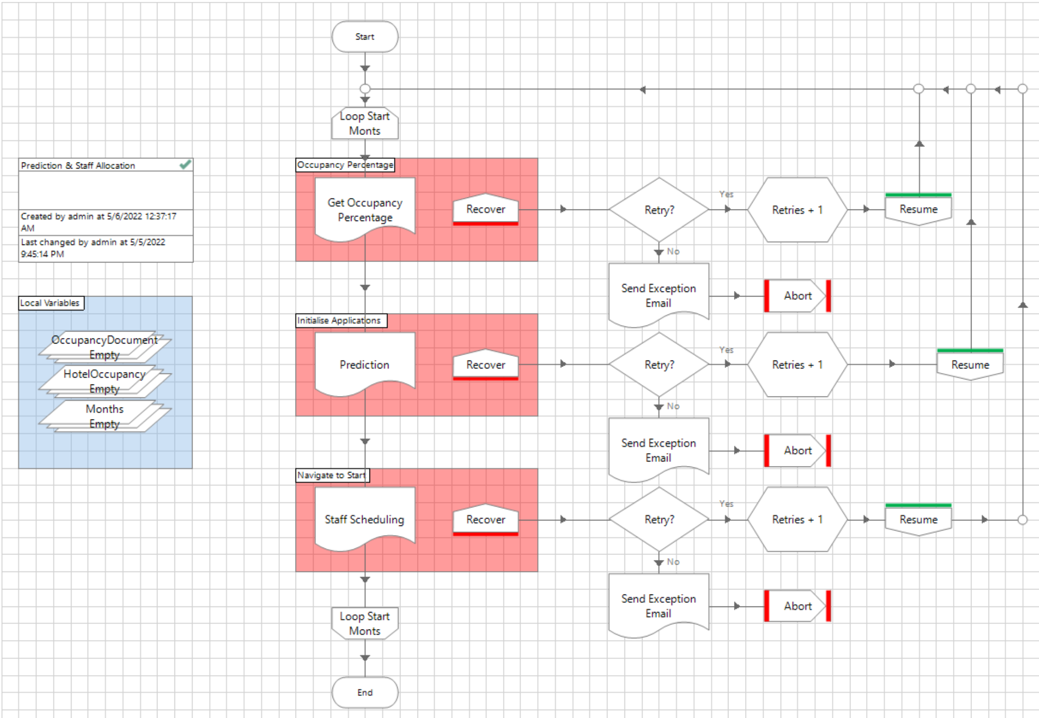

Fig. 5. RPA representation of the Prediction and Staff Allocation process.

4. EXPERIMENTAL RESULTS

The two RPA processes have been scheduled in Blue Prism, based on different calendars, Blue Prism (2021). A screen capture of the Blue Prism Scheduler for the principal RPA process "Occupancy Aggregation" is shown in Fig. 6.

While this RPA process runs continuously managing the reservation process and computing daily the input data nee-ded for service delivery (CheckIn, Checkout, invoicing) and occupancy update (Hotel Occupancy Database), the second RPA process runs once per month computing the optimal staffing level, work shift schedule, personnel assignment and cost for the next month, based on seasonal prediction.

Experiments have been carried out with the BOT automat-ing the CheckIn and Checkout subprocesses of "Occupancy Aggregation", for which processing times of 45-50 seconds per process were obtained. Considering that a human agent needs 4-5 minutes to complete manually these processes, it results that for a daily number of 100 transactions the BOT needs 1.3-1.5 hours as compared with 6.7-8.3 hours needed by human operators. Tests with simulated reservation and check-in data showed that the daily evaluation of the hotel occupancy for the accommodation infrastructure described in chapter 2.2 (involving database analysis, computation of occupancy percentage, update of the prediction database and sending the confirmation email) takes the BOT 2.6-2.8 minutes. The rate of success for 500 evaluation runs with randomly generated data was 100%.

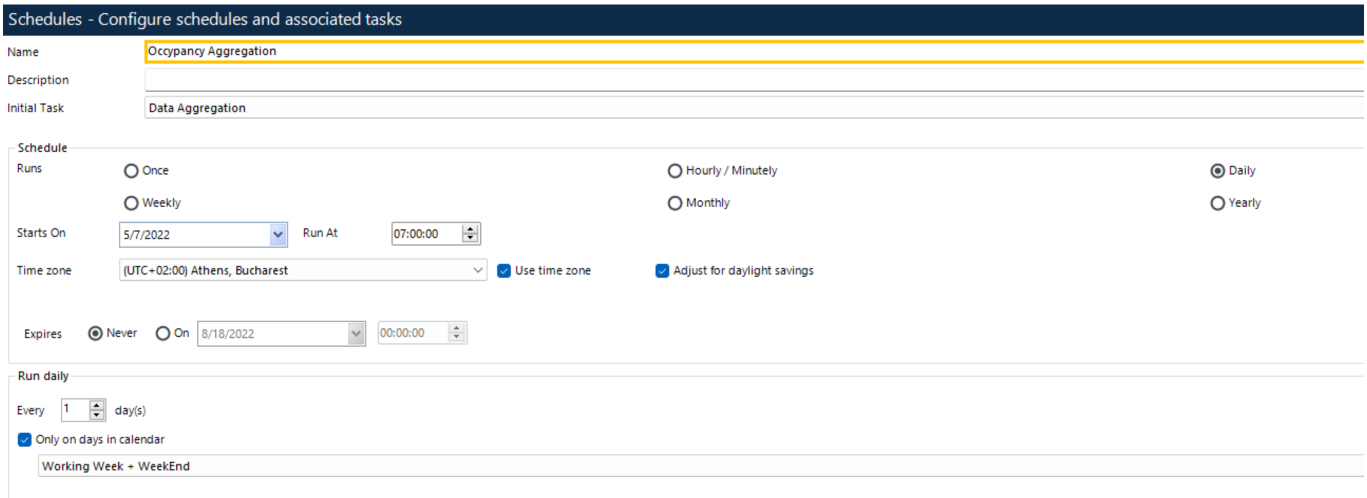

Fig. 6. Blue Prism Scheduler of the "Occupancy Aggregation" RPA process.

For the second RPA process, the BOT extracted the real occupancy data from 12-month history database that inclu-des the occupancy percentage of the current month comput-ed by the "Occupancy Aggregation" BOT in 40 seconds, predicted the occupancy for the next month in 35 seconds and generated the optimal staffing, work shift scheduling and manpower cost data in 50 seconds, that is in a total solution processing time of about 2 minutes.

The results obtained confirm the viability and data processing efficiency of the RPA solution for automated reservation and back-office service management based on seasonal service demand prediction.

5. CONCLUSIONS

The paper describes a Robotic Process Automation solution for a service Operations Management Software system that automates and integrates the principal back-office work-flows for capacity management in the hospitality industry: management of the reservation process, prediction-based optimization of the staffing level, work shift scheduling and calculation of manpower cost.

These workflows include repetitive, continuously execut-ing, asynchronous event-driven processes that are intercon-nected in variable timing, depending on the service context. Automating these processes improves work productivity, eliminates errors in document management, and significant-ly reduces personnel costs. The designed BOTs are trained to reproduce human activities for document generation, handling and transfer, verify content, access and update databases, and to communicate with customers and business managers; they are able to execute the processes 8-10 times faster than busy human operators.

The RPA solution described in the paper optimizes service capacity in terms of staffing level for predefined, known service workloads with the support of two BOTs that apply AI techniques: 1) the first one runs seasonal weighted pred-iction algorithms to forecast the degree of hotel occupancy on short time horizon based on the current month occupancy and the historical occupancy data from the past year; 2) the second one runs an optimization algorithm based on Integer Linear Programming to establish the most economic service staffing level constrained by human resource policies: employment type, time shift and work intensity.

The research contribution relates the service OMS design to the end-to-end automation of the service organisation which is a new direction to unite technology into one end-to-end hotel automation platform with RPA capabilities at its core: developing, training, managing, and running software ro-bots with process analytics tools to tackle a wider spectrum of business functions and knowledge intensive services with quick report of the business impact. For the OMS system considered, software robots were extended with intelligent process automation technologies to confer hyperautomation attributes to the global service system:

1. *Integration* of front-office and back-office processes, with stronger coupling of operation workflows and their context-driven orchestration.
2. *Artificial intelligence* techniques (machine learning, na-tural language processing, optical character recognition, process mining) are used to develop IPA methods and tools: i) segmenting and forecasting customer demand; sentiment analysis to evaluate customer expectation and perception and assess service quality; emulating human-like conversation to understand guest questions and au-tomate responses to them; ii) assisting software robots to read, see, learn, compare, analyse and provide support for optimized decisions.
3. *Advanced analytics* to establish the most cost-efficient reservation policy and yield strategy, to adjust service capacity and increase utilisation of service facilities, and to optimize staffing levels; this justifies the return of investment of automation and its impact on significant business outcomes.

Future research will be directed to develop and integrate software technologies for the end-to-end automation of ser-vice management systems for the hotel business:

- Automation development tools: RPA bots, low-code development tools, iPaaS for integrations, and workload automation tools.
- Business intelligent reporting tools logic tools to stay up-to-date on changes in the market
- Automated retargeting tools to capture customers who visited the hotel's website and showed interest.
- AI and machine learning tools to extend the capabili-ties of automations: natural language processing, machine vision, virtual agents and chatbots.

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