Robotic Process Automation of Inventory Demand with Intelligent Reservation

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Abstract: The paper describes a solution that automates the inventory demand process for supporting facilities of a fixed service capacity, based on reservation with cost-effective overbooking strategy. This process, part of the back-office service management in the hospitality industry, is implemented in the robotic process automation (RPA) technology and integrated with front-office, customer interaction workflows in an operations management software (OMS) system. The main idea that led to this service model was the end-to-end (E2E) automation of the organisation, which is a new direction to merge AI techniques into one E2E platform with RPA capabilities at its basis: building, managing, and running software robots with process analytics tools to tackle a wider spectrum of business functions and knowledge intensive services with quick report of the business impact. Experimental results are reported for the RPA bot that establishes the overbooking strategy in the back-office.

Keywords: Service management, Inventory demand, Overbooking, RPA, OMS.

1. Introduction

The main concern that the management of service providing companies has to deal with is matching daily service capacity with customer demand in a dynamic business and market environment. Two strategies address the problem of variable service demand: operations-oriented and marketing-oriented. *Operations-oriented* strategies adjust the level of service capacity; they increase capacity utilization by better matching the available service capacity to the demand. This approach is centred around the concept of productive capacity and on the management's ability to exploit the forms of productive capacity - work, equipment, facilities, and infrastructure - efficiently (produce maximum output with fixed or limited resources in a short-term, yield-oriented perspective) and effectively (ensure excellent service delivery in a long-term, result-oriented perspective), as profitably as possible (Fitzsimmons & Fitzsimmons, 2008). Marketing-oriented strategies consist in managing the level of service demand by altering or smoothing customer demand, which requires knowledge of demand patterns and drivers as well as the ability to segment market into customer classes (Wirtz, 2018). Most service firms combine these two approaches in yield strategies (Rajani, Heggde and Kumar, 2022).

Service capacity, defined in terms of an achievable level of output per unit time (e.g., workload of busy hotel staff) and of a constrained supporting facility (e.g., number of hotel rooms), respectively, is a perishable commodity because producing and consuming a service occur simultaneously (e.g., accommodation); this means that service capacity cannot be saved for sale at a later time in many service sectors, including hospitality.

Managing productive service capacity requires permanent service quotation, i.e., identifying the costs related to design, delivery and support of the service for which facilities, equipment, infrastructure and staff work represent direct key cost components (Stanford University, 2022). In the hospitality sector, facilities critical to capacity management are constrained by strategic decisions taken at the investment and design level regarding the site geography (hotel location), service capacity (number of rooms), and level of services (accommodation category, facilities for extra services, e.g., fitness, pool, restaurant, bar, sport courts, etc.). They have been set up for a certain market segment, cannot be easily extended and, therefore, limit the productive service capacity compared with infrastructure and equipment which, even if initially selected to meet the requirements of the facility, they can be much easier upgraded, extended or renewed.

In the present analysis, it is also considered that capacity in this high-contact service sector is not limited by factors such as work skills classification or availability of equipment and consumables, as proper actions can be taken whenever necessary: professional staff selection and training, well-organized procurement, efficient supply and logistics (Li et al., 2013).

Chasing demand is a first operations-oriented strategy to expand or shrink productive capacity in order to adapt to the expected level of demand.

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Expanding the capacity level can be used to absorb an extra demand on short or a priori estimated periods of time without modifying the limited capacity level, e.g., staff trained to work at higher levels of efficiency at peak hours, cross-trained employees to shorten service time and thus reduce the level of demand exceeding the maximum available capacity, using facilities for longer periods, minimizing slack times or temporarily reducing the level of services. These techniques are flexible in taking up extra demand, being also referred as indirect capacity adjustments because they change the service context and work conditions of staff in order to absorb temporary excess demands (Fisk, 2018).

Adjusting capacity to match demand is a second operations-oriented strategy derived from the chasing demand approach which, unlike expanding capacity, directly adjusts the productive capacity in the [optimum-maximum available] range level as needed to balance demand fluctuations (primarily increases). Multiple capacity adjustment methods can be used and combined: scheduling downtime during periods of low demand, variable capacity sharing, creating flexible capacity to serve the needs of market segments (e.g., changing the hotel room category from premium to standard to match the dominant demand during peak seasons), scheduling the work shift by optimizing the staffing level, using part-time employees, etc. (Chetty, 2010; Morariu, Morariu & Borangiu, 2014). Yet, stretching or adjusting capacity ensure only temporary changes that do not guarantee a permanent, long-term increase of facilities of the service capacity.

Smoothing demand is a marketing-oriented strategy that consists in influencing or even modifying the type of demand by trying to move customer requests to time periods with lower capacity utilization, i.e., by decreasing demand when it exceeds the optimum level of productive capacity. Any of the key elements of a customary marketing strategy can be used for this: a) product: the service sold must meet the customer's expectations; b) price: a service should be always correctly priced; c) fair customer information about the characteristics of the service; d) place: the location of service delivery must be known (Granger, 2022).

An important first step in balancing demand and capacity is to establish the nature of service demand patterns by market segments: predictable cycle of demand levels or random variations of the demand. For *predictable cyclical demand*, it is necessary to establish the reasons for cyclical variations and the cycle length which are usually influenced by the location of the facility, market segment and societal context. In the hospitality industry, the duration of the demand cycle varies from one week (for urban hotel location and business/weekend segments) to one year (for tourist resorts, month/season segments, and it reflects seasonal climate characteristics, school vacation, employment calendars, public and religious holidays). *Random changes in the demand levels* are caused by factors beyond the provider's control: weekly or daily weather changes, natural disasters, damages provoked to facilities by fires, unforeseen customer health problems or accidents. If in this preliminary analysis demands for particular services over time can be separated on market segments, then the disaggregated patterns can be used to influence demand for special categories of customers or types of services and to drive operating margin relative to the finalized transactions per segment (Ross, 2022). Creating records of service requests, weather and context influencing the demand, service level agreement (SLA) and delivery allows further analysis of historical demand patterns by market segment (customer and service type) and date, and predicting further evolutions of the demand.

A *mix of marketing elements* can be used to influence patterns of segmented demand, e.g., reducing or shifting demand during periods of insufficient capacity: differentiating and reducing prices, offering price incentives, scaling down service elements during peak demand periods, developing complementary services for waiting clients. In business-oriented strategies, the most profitable segments identified will be stimulated by granting them priority relative to limited capacity, while demand reduction will be applied to lower yield segments.

When demand frequently exceeds limited capacity, the above actions may fail to balance supply and demand; then it is necessary to *inventory demand* at the time it occurs, which can be performed in two ways: <u>establishing a reservation system</u> (e.g., preselling the accommodation service in the hospitality industry), and <u>using a formal queuing system</u> that includes a mechanism to comfort waiting customers. Inventory demand is further refined in demand forecast and made operational by inventory planning, demand forecasting and analytics (Thomopoulos, 2015).

Most service firms use a mix of operations- and marketing-oriented approaches: adjusting the capacity level, i.e., increasing the utilisation of facilities essential to service capacity (e.g., hotel rooms in the hospitality business), and smoothing demand by applying marketing strategies to patterns of segmented and inventoried demand (e.g., inventory demand through reservation systems, prioritizing capacity to less price-sensitive customers, focus on yield, etc., in the hospitality sector). *Yield strategies* combine operations- and marketing-oriented methods.

For a service organization, coordinating service capacity with dynamic varying, market-driven customer demand implies the correlation and synchronization between front-office and back-office processes - the first category addressing customer relationship management (CRM) and the second inventory planning, forecasting demand, analytics, and strategic decision making. *Operations management software* (OMS) systems assist, plan, coordinate and monitor back-office service operations, digitalize daily front-office work-flows of front-line personnel, identify and mitigate operational process bottlenecks (ScienceSoft, 2023). Service operations management refer to task automation, business process management and streamlining operations to improve the efficiency of employees in service delivery.

Intelligent Process Automation (IPA) uses IT capabilities to automate OMS systems and network operational processes while interacting with elements like user platforms, databases and hardware infrastructure. While service automation focusses on automation of end-to-end service as a design-oriented approach that considers the whole service value chain, *Robotic Process Automation* (RPA) is more business-focused on the automation of back-office processes of the organisation. RPA represents a promising solution based on software robots (bots) to automate OMS tasks (Fung, 2014). To implement OMS for services, RPA must be extended beyond its rigid rule-based methods by combining bots with artificial intelligence (AI) techniques to forecast demand, analyse (big) market data, optimize capacity utilization, operations planning and staffing levels, and extract insights on customer perception of service quality (Kumar, 2020; Sutherland, 2013).

The paper describes a solution that automates the inventory demand process for support facilities (hotel rooms) of fixed service capacity in hospitality, based on reservation with cost-effective overbooking strategy. This process, part of the back-office service management, is linked through the RPA technology to customer interaction workflows in an integrated OMS system with IPA capabilities. Section 2 presents the global OMS system for services that controls demand and adjusts capacity in yield strategy. Section 3 describes the software robots developed for RPA of intelligent reservation configured in overbooking mode. Experimental results are given in Section 4 that presents the advantages of equipping RPA bots with AI techniques for end-to-end process automation. Finally, section 5 provides the conclusion of the research proposed in this paper.

2. Service OMS System Integrating Front-and Back-Office Tasks

The OMS 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 activity workflows involving customers (service requests, service quality assessment) and front-line personnel (check in, check out, taxation and invoicing). To streamline demand forecasting, inventory planning, coordinating, monitoring and valuing service delivery, the service OMS integrates the following back-office subsystems:

- *CRM software*: for quick scheduling of service requests at any time, updating and optimized allocation to service personnel and for the segmentation of the request (ScienceSoft, 2023);
- *Analytics software*: to identify demand patterns, establish best reservation policy by market segment, optimize capacity utilization from predicted demand. The support to these decisions needs integrating in the OMS big data and AI techniques for market analysis, forecasting and sentiment analysis (Kovács et al., 2015);

- *Customer portal*: to speed up capacity adjustment and keep customers up to date regarding service availability, delivery options and price incentives (SoftSuggest, 2022);

- *Accounting software*: for the efficient tracking and billing of customers' expenses, for scheduling the work shift of the staff and for an accurate recording of the revenue;

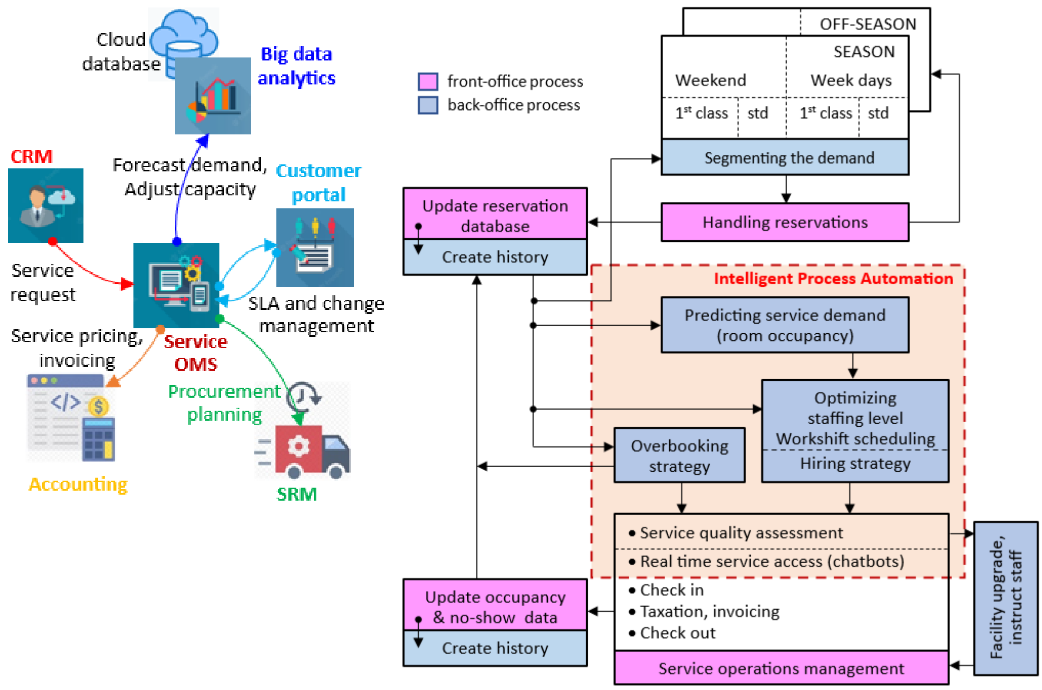
Figure 1a) shows the main activity classes integrated as back-office workflows in the service OMS system.

They are interconnected with customer-related, front-office processes to optimally control the problem of demand inventory - capacity adjustment, according to the end-to-end automation approach that will need to be integrated in the OMS for hospitality services software robots extended with AI techniques. Thus, the service OMS is driven by the *intelligent process automation* (IPA) technology (Figure 1b), which is currently considered strategic for higher productivity, higher quality of services, increased customer satisfaction, and cost saving.

The main idea that led to the proposed service OMS model is the end-to-end automation (E2E) of the service organisation, which is a new direction to combine technology into one end-to-end automation platform with RPA capabilities at its centre: building, managing, and running software robots with process analytics tools to tackle a wider spectrum of business functions and knowledge intensive services with a quick business impact report. For the considered service OMS, E2E was extended with IPA technologies to confer hyperautomation attributes to the global service system (Flowable, 2022):

1. *Integration* of front-office and back-office processes, with stronger coupling of operation workflows and their context-driven orchestration. This enables the engagement of the firm's management and contact personnel, and of the customers to contribute to the automation process;

2. *Artificial intelligence* techniques like machine learning (ML), natural language processing (NLP), optical character recognition (OCR), and process mining are used to develop methods and tools for intelligent process automation: i) segmentation and forecasting of service demand; sentiment analysis to evaluate customer's expectation and perception and assess service quality; simulating human-like conversation to understand customer questions and automate responses to them,



a) b)

Figure 1. End-to-end automation of OMS model proposed for the service system: a) back-office workflows; b) front- and back-office processes linked by Intelligent Process Automation

and ii) assisting software robots to read, see, learn, compare, analyse and provide decision support (Gartner Inc., 2021);

3. *Advanced analytics* to establish the most cost-efficient booking policy and yield strategy, to adjust service capacity and increase utilisation of service facilities and to optimize staffing levels, which justifies the return on investment in automation and its impact on key business outcomes (Udroiu et al., 2022).

Figure 1b) represents the front-office and back-office process workflows that will be automated with software robots and driven by AI-based techniques. This will lead to the optimization of the yield strategy used to permanently control the request for services and to correspondingly adjust the utilisation of facilities, resources and facilitating goods which are critical to service capacity.

Inventory demand is represented by front-office processes that handle service requests (active and cancelled reservations), confirmed requests (check-ins, no-shows) and accomplished requests (completed and interrupted services, check-outs) and update related data bases (reservations, hotel occupancy, no-shows). The content of these data bases is accessed by software robots that automate front-office service operations: check-in, check-out, taxation and invoicing.

The elements of the yield strategy are selected and configured by a set of interconnected back-office processes that use market data, information about competitors and domain regulations:

- Marketing-oriented processes: segmenting the demand by season, week days and service category; service pricing; sizing the reservation system by seasonal prediction of the service demand and calculating the best overbooking level to compensate for no-shows; relating price incentives to categories of service cost and customer loyalty (Li et al., 2013);

- Operations-oriented actions: adjusting capacity utilisation by changing the facility category or sharing facility units; optimizing staffing level and part-time hiring from predicted demand; planning fair work shift schedules and calculating employee remuneration and taxes.

The automation of these workflows needs *aggregation* from different OMS data sources like the booking platform, registration desk, back-office management data, service delivery list, human resource directory, and *integration* in the data base that keeps historical logs and is continuously updated to allow intelligent process automation of a) inventory demand (the reservation system) and b) service delivery (the registration system) back-office processes, as it can be seen in the central area of Figure 1b). IPA uses the AI techniques in this process as follows: the reservation system is controlled to adapt the level of services and prices to customer profiles modelled on market segments and identified by NLP methods; it is also scaled by a reservation overbooking strategy based on the probability theory and prediction to compensate last-moment random changes in demand relative to service delivery that lead to no-shows and, hence, to economic losses. As for the registration system, in the IPA context it is based on demand forecasting, i.e., on predicting the degree of facility (hotel room) occupancy. This is done by analysing previous trends, seasonal demands, customer expectations, upcoming marketing campaigns, and market research to predict how much of the service will be sold in the near future (e.g., in the weeks and months of the current season). In back-office, demand forecasting - a very proactive process - is used to determine the number of employees needed weekly, the facilitating goods and stock levels, the marketing budget, etc. The demand forecast for the IPA of the registration system forms the basis of the business plan to meet demand and improve profitability of the service business (Schmid et al., 2022).

3. Selecting the Cost-Effective Over-booking Strategy with RPA Bots

As discussed in section 2, configuring the reservation system for inventory demand is one of the main back-office processes to be automated by software robots that integrate IPA algorithms in the RPA implementation of the service operations management system.

Setting up a reservation system allows preselling potential services, focusing on the most profitable market segments and smoothing for the standard ones. As reservations are made within segments of service categories (e.g., first class or standard hotel rooms) and time periods (e.g., peak season, weekend, week days), additional demand might be deflected to other categories and time slots from the same facility or to other facilities of the same organisation when the customers' first choice is not available (Li et al., 2013). Reservations also guarantee customers service availability and reducing the time needed to get a particular type of service. The number of reservations per service segment is limited by the available productive capacity; for the case analysed, there is a fixed service capacity which is limited by the accommodation facility expressed in the number of hotel rooms CM=160 rooms (120 standard hotel rooms and 40 first class rooms).

A problem that reservation systems face occurs when customers fail to honour their reservations, situations designated as *no-shows*. To counter them, the reservation system will be provided with an *overbooking strategy* that redefines the number of reservations per service segment in time: at peak period/off-season, monthly, for weekends/ national holidays. By accepting reservations that exceed the maximum capacity CM the service management hedges against important numbers of no-shows; however, if too many facility units (hotel rooms) are overbooked, the risk of turning away customers with reservations should be minimized. A cost efficient overbooking strategy should minimise the expected opportunity cost of idle service capacity as well as the expected cost of turning away reservations and offering overbooked customers the same category of service at a near hotel free of charge.

Establishing the overbooking strategy will be performed as back-office IPA process by a dedicated software robot implemented in RPA technology and integrated in the OMS.

Since the pattern of service demand is predictable cyclical (six-month peak season annually), and assuming that an exact record of no-shows for this representative time period is available, it is possible to compute the probability of no-shows when the ensemble of service facilities (the hotel) was fully booked in the past season. The critical fractile criterion (critical probability), derived from perishable goods, will be applied to the inventory of rooms:

$$P(ns<ro) \leq C_u/(C_u+C_o)$$

where *ns* is the number of no-shows in the past peak season, computed by the OMS from the registration data base; *ro* is the number of rooms to be overbooked during the current peak season according to the cost-efficient reservation strategy that will be established; C_u[€] is the lost room payment when a reservation is not honoured, i.e., the number of no-shows is *underestimated*; C_o[€] is the opportunity loss when a room is not available for an overbooked customer, i.e., the number of no-shows is *overestimated*. According to the marginal analysis made, the number ro of rooms overbooked should cover only the cumulative probability of no-shows; this choice minimizes cost losses with no-shows.

The pseudo code below synthetises the back-office workflows carried out by the RPA bot to establish the monthly overbooking coefficient *ro*(*m*[*y*]) for the current peak season [*y*] from data stored during the past year [*y-1*] in the reservation and registration data bases of the service OMS. The RPA bot is activated automatically in two series of repetitive tasks:

<u>STAGE 1</u>: In year *y-1* after each of the six months *m*[*y-1*] May-October of the peak season, to set up one year in advance the overbooking index *ro*(*m*[*y*]) for the corresponding month of the peak season in year *y*.

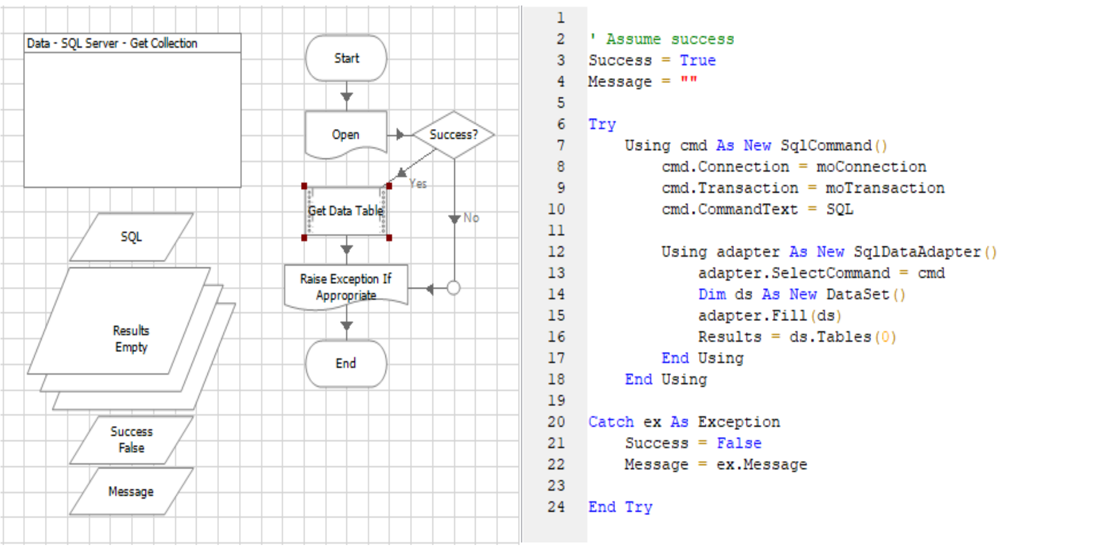
```
for m = May to October of year y-1     ; m = m[y-1]
    wait time event end_of_month m
    read Res_DB (m)
       ; read reservation data base for m[y-1]
    identify days (m) with fully booked hotel, df(m)
                             ; df(m) = df1, ..., dfm
    read Reg_DB (m)
       ; read registration data base for m[y-1]
    for all ϵ dfi df(m), 1≤ i ≤ m
        read no. of active check-ins in dfi, ck(i)
        calculate and store ns(i) = Cmax – ck(i)
                 ; ns(i) is the number of no-shows in df(i)
    end
    calculate nsm = max {ns(i)}, 0≤ i ≤ m
          ; nsm is the max. no. of no-shows in one df(m)
    sump = 0
          ; initializing the sum of no-show probabilities
    for j = 0 to nsm
        for i = 1 to m
           count no. of ns(i) equal to j, tns(j)
            ; tns(j) is the total no. of j no-shows in month
                                          ; m, 0≤ j ≤ nsm
        end
        store tns(j) in No-Sh_DB
               ; store all no-shows of all types in month m
                                      ; in no-show data base
        sump = sump + tns(j)
    end
    cup(0) = 0
              ; cumulative probability for zero no-shows
    for i = 0 to nsm
```

```
    compute no-show probabilities p(i) = tns(i) / sump
                ; total no. of no-shows per category in m
      compute cumulative probabilities cup(i+1) =
      cup(i) + tns(i) per no-show category 0≤j ≤nsm
  end
  calculate cp(m) = Cu(m) / (Cu(m) + Co(m))
       ; compute the critical probability for month m
                       ; apply critical fractile criterion
  i = 0
  while [cp > cup(i) AND cp ≤ cup(i+1)] false  do
     i = i+1
     ro = i               ; update the overbooking index
  end
  ro = ro(m)          ; the coefficient for cost-effective
                      ; overbooking for month m[y]
end
```

<u>STAGE 2</u>: In year y, at the end of the month before any of the months *m*[*y*] May-October of the peak season, the overbooking coefficients computed in Stage 1 will be eventually updated using seasonality prediction (Kliewer, Ehmke & Borndörfer, 2017).

```
; It is assumed that no-shows have been recorded for
; months 1 … 12 of year [y-1] before prediction starts
; and are available in the No-Sh_DB
 for m = April to September of year [y]
            ; m = 16 (April [y]), m= 21 (September [y])
    wait time event end_of_month m = 16 … 21
; a seasonality index I(m) is defined to de-
; seasonalize observation data (no. of no-shows) in
; the 12-month length (L) cycle; the 6 indices for 5 ≤
; m ≤ 10 in year y-1 have been already computed by
; the bot in Step 1 and stored in the no-show data
; base No-Sh_DB as tns(m).
; I(m) is the set I(m,j) of all categories of actual no-
shows 0 ≤ j ≤ nsm(m) recorded in month m.
; I(m) is then used to de-seasonalize the observations
; for the corresponding months of year [y] with
; exponential smoothing in which tns(m) is adjusted
; to account for seasonality with the index I(m-L)
; 0.1≤ α ≤0.5
  S(m) = α·(tns(m)/I(m – L) + (1 – α) · S(m – 1))
                                        ; 5 ≤ m = m[y] ≤ 10
; the prediction of no-shows for month (m + 1), i.e.,
; months May-October of year [y] is then made by
; seasonalizing the smoothed value for period :
   compute p_tns(m+1) = S(m) · I(m – L + 1)
; the value assigned to the subunit coefficient  is a
; trade-off between reacting excessively to random
; variations about a constant mean and identifying a
; change in the mean value; higher values of this
; coefficient in the range [0.4 – 0.5] determine more
; responsiveness to changes in recent observations.
; from the predicted values for the no-shows, the RPA
; bot will eventually adjust successively the over-
booking coefficients for the months May – October
; [y] applying the same critical fractile criterion.
end
```

The RPA bot is developed using the Blue Prism software tool (Blue Prism, 2022), in which the overbooking process is run on a predefined scheduler that automates the computing workflows and data base handlings. The bot is trained: 1) to access the data bases of the OMS system, see Figure 2a) and b) and learns when to access the data bases, where to look for data, what is the data format, how to schedule sequences of SQL interrogations, how to manage pointers to variables of given data types and how to assess the veracity of data; 2) to compute the



a) b)

Figure 2. SQL interrogation of the Res_DB and Reg_DB data bases

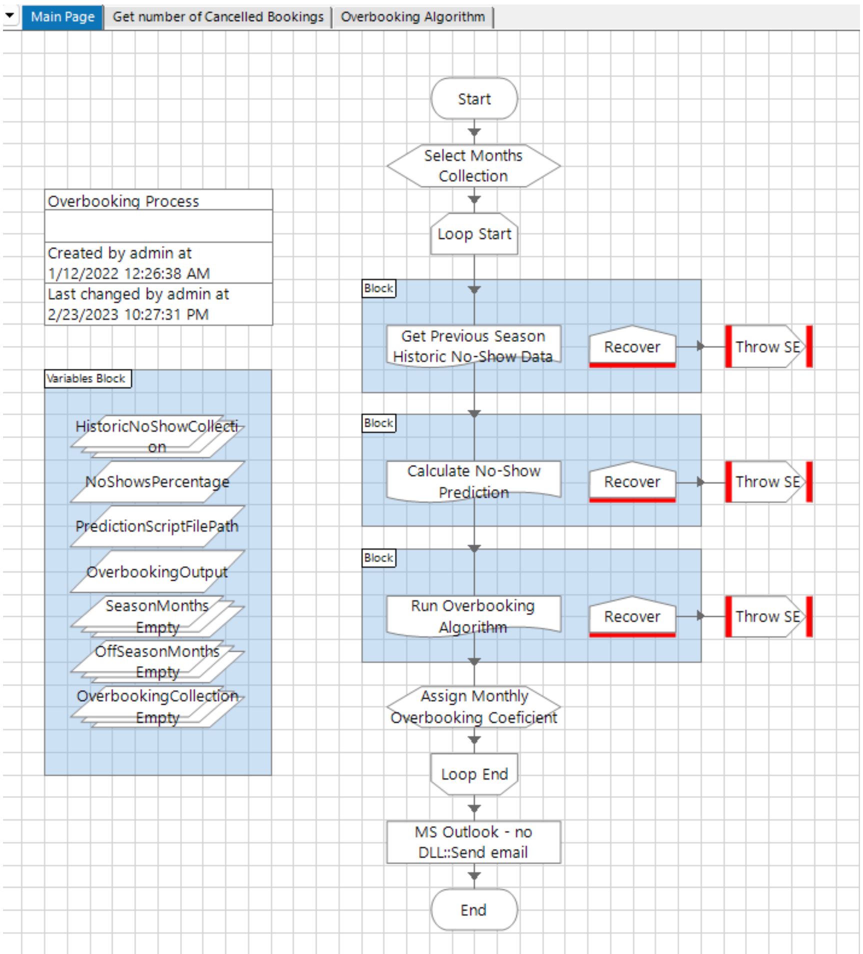


Figure 3. The RPA bot kernel for the monthly computation of the overbooking coefficient

probabilities of no-shows from real observations recorded and stored in the Res_DB and Reg_DB data bases; 3) to apply prediction and marginal analysis algorithms to control demand using IPA tools (UiPath, 2022).

The RPA kernel of the Blue Prism software robot for monthly update of the overbooking coefficient is represented in Figure 3; the results are transferred to the provider's management as support for the decision to influence the service demand by reconfiguring the reservation portal of the service OMS system.

4. Experimental Results with the RPA Bot

The back-office process for monthly computation of the overbooking cost-effective coefficient has been automated with an RPA bot developed in Blue Prism version 7.1.1 tool and run with the following data: C_u = 126€ per facility unit contribution lost for any non-honoured hotel room reservation; C_o = 164€ opportunity loss for unavailable room for an overbooked client; one-month records available in the reservation and registration data bases of the OMS system. The software robot implements the overbooking algorithm described in section 3; the screen capture in Figure 4 shows the results obtained by running the RPA bot.

The analysis of the Res_DB and Reg_DB data bases revealed 13 no-show categories (from 0 to 12 = *nsm*) in the analysed month; for the C_u and C_o values, a critical probability of 0.434 results. Applying the critical fractile criterion, the cumulative probability 0.34 is selected by the bot, which gives the value 6 for the overbooking coefficient. The expected opportunity losses with overbooking factor $ov = 6$ (expL_ov) and without overbooking (expL_ns) are, respectively:

$$expL_{ov} = \sum_{i=0}^{ov-1} (ov - 1) \cdot C_o + \sum i \cdot C_u = 289.60\,€$$

$$expL_{ns} = \sum_{i=1}^{nsm} i \cdot C_u = 790.02\,€$$

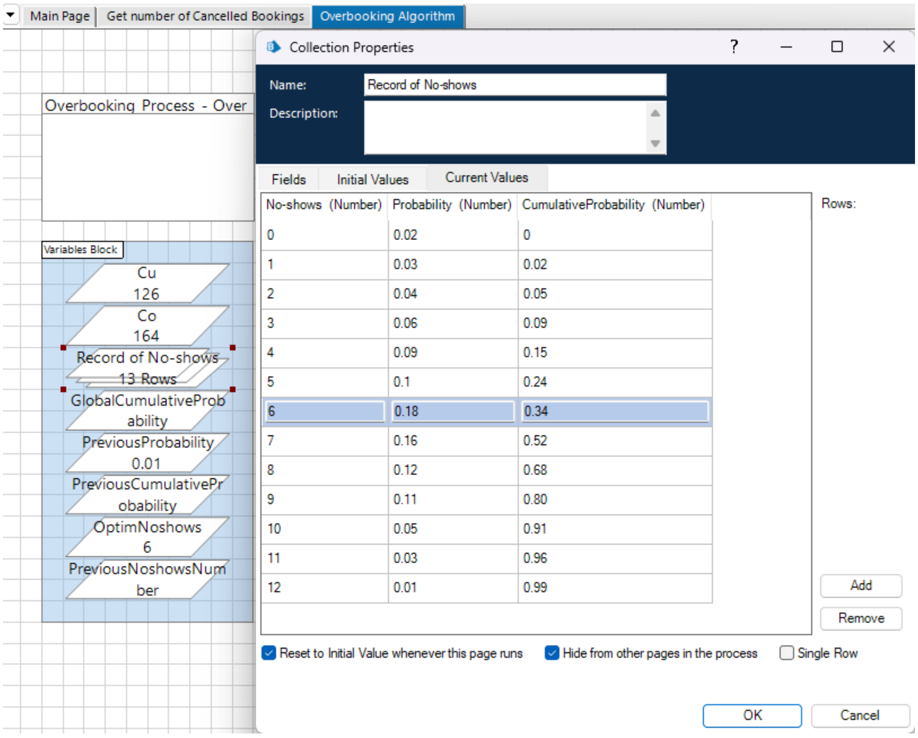


Figure 4. Results obtained at RPA bot run for a monthly overbooking coefficient

which indicates a gain of 790.02€ – 289.60€ = 500.42€, if this strategy is adopted. By comparing all the 12 possible overbooking policies, it can be seen that the best one is $ov = 6$.

5. Conclusion

The present paper describes a solution that automates the back-office process of balancing service capacity and demand using a mixed yield strategy. The marketing-oriented component of this strategy is represented by the inventory demand based on service request reservations with cost-effective overbooking policy. This process, part of the back-office service management, is coordinated using the RPA technology with customer interaction workflows in an integrated operations management software system with intelligent process automation capabilities.

The main contribution of the reported research is the development of a service OMS model with end-to-end automation of front- and back-office workflows, implemented with the RPA technology. The software robots of the proposed RPA solution include AI-based algorithms that are able to forecast demand, analyse (big) market data, optimize capacity utilization and extract information about customer's perception on service quality.

The intelligent bots automating the back-office service management are validated by the experimental results obtained with the Blue Prism RPA software; they run repetitively, according to a demand-driven timing, are connected with front-office processes, and use historical observations of client requests (reservations, registrations) to predict and control future evolutions in demand segments. The main advantages offered are: operating autonomy in dynamic context, high-speed (15 times faster than human experts) error-free computation, and intelligent process automation.

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