# An Agent Framework to Support Air Passengers in Departure Terminals

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***Abstract*—Airports are complex nodes performing several roles such as interchange terminal, shopping and relaxing center, meeting area for short-time business activities. Airport operators pay great attention to financial profits from their managed assets, while passengers desire spending their slack time inside the terminal in a pleasant way after wasting time in queues and controls to access the gate areas. In such a context, an agent framework is proposed to support travelers' slack time by providing purchase suggestions potentially interesting for them. Recommendations are computed by taking into account passengers' interests, their current position inside the departure terminal and the commercial opportunities available therein.**

***Index Terms*—Airport terminal; Arrivals distribution; Multi-agent system; Recommender system**

## I. Introduction

Airports play a fundamental role in the mobility of people and goods for middle-long range trips and a significant number of studies exist on the different aspects involved in their management (e.g., transport, financial and security issues) [1]–[6], included strict regulatory constraints to cope with air travelers inside the departure terminals [7].

Three main facilities can be identified for a given airport [8]: *i*) service areas, *ii*) waiting areas and *iii*) commercial activities. More in detail, in the service areas passengers access all the services addressed to process the flow of travelers departing from the airport (e.g., check-in, passport and security controls, baggage drop) [9]. Waiting areas, where passengers may wait before boarding their flight, are equipped with seats (e.g., lounges and open seating areas, usually close to the departure gates) and free services for travelers (e.g., information desks, Wi-Fi, toilets). Finally, commercial areas consists of shops, food courts, currency exchange and so on, available to air travelers waiting their flights.

In this scenario, air passengers desire to both avoid wasting time in queues and controls and spend pleasantly their slack time inside the terminal [10], [11]. On the other hand, airport operators have to optimize all the terminal activities and, at the same time, give profitability to the assets directly or indirectly managed by them [12] (e.g., commercial areas inside the terminal, car parks outside the terminal and so on) by complying with national and international rules [7].

The challenge of satisfying both the passengers' desire of enjoying their slack time and the airport operator's needs of increasing the revenues from the airport commercial areas is of great interest. As for the first goal, which is the focus of this study, a possible approach is that of providing air travelers with personalized recommendations [13], [14] about the available commercial facilities that suit as more as possible their preferences and interests. This task is rather complex to realize because it requires several steps, namely:

- acquiring preliminary information about passengers and their interests by complying with privacy rules at the same time [15];
- tracking passengers' movements around the terminal [16];
- taking into account passengers' slack time [17].

Providing passengers with a personalized support requires the knowledge of some information about them (i.e., age, sex, job) and their main interests (i.e., preferences for product categories). As for personal information, some of them could be obtained/deduced when a passenger is processed at security checkpoints before entering the departure area[1]. Unfortunately, data gathered at airport security checkpoints are subjected to manifold restrictions mainly due to privacy rules [20], which can also differ among countries, and are not available for the above aims. Therefore, the main way to acquire the desired information is that of requiring it directly to passengers [21], for instance in return for the access to some reserved terminal services offered for free (e.g., Wi-Fi connection, discounts).

The second listed step is addressed to identify the current traveler's position inside the terminal for providing him/her with suitable personalized suggestions, offers and so on, by following a "*now*, *here*, *only-for-me*" approach. As the precise tracking of passengers' movements by using GPS[2] is practically impossible, the remaining opportunities are *i*) the analysis of the images by dedicate cameras (e.g., different from those belonging to the security system) and/or *ii*) the explotation of Wi-Fi [22]/Bluetooth [23] connections used by smarthphones and tablets. In particular, the analysis of camera images also provides people density information [24], while each Wi-Fi and Bluetooth fingerprints can return the number of connected devices for each of their hot-spot (note that these two wireless technologies should be set with different and suitable operating ranges and that, in the proposed framework, very low power Bluetooth connections will work only as detection points).

[1] In large airport, security checkpoint operators realize the first identification by using ticket and document [18], while a further identification may be based on video analysis processes realized by specialized softwares, which also allows the traveler' movements around the terminal to be tracked [19].

[2] The use of the GPS technology is very difficult inside the terminal.

The final required step is addressed to know in advance the number of passengers that could be present in the departure terminal at a given time and their estimated slack time. Generally, the whole amount of demand on a yearly basis is estimated to understand the development opportunities for both airlines and airports [25], [26]. However, in this case it is more relevant to identify not simply the number of departing passengers but mainly the air terminal processing procedures [27].

In particular, processing procedures are modeled by queuing theory approaches, which include the estimate of the time required to carry out a terminal procedure, roughly made by the time necessary to provide the service to the passenger and the time the passenger has to spent in queue. The service time depends by both the nature of the service and the specific adopted procedure, which often follows service requirements and/or security regulations. The time spent in queue depends on the length of the queue that, in turn, depends on *i*) the number of passenger requiring the service at the same time interval and *ii*) the efficiency of the service process [16]. The set of terminal procedures can be summarized as a chain of processes, where two consecutive processes are separated by time varying intervals. In large airports also acting as hubs, the number of passengers increases quickly during peak hours and generates congestion and delays, which generally increase the time required to perform terminal procedures [27]. Modeling the probability density function describing passengers arrivals at airport facilities allows better managing airport resources [28].

In the context above described, this paper intends to contribute by designing an agent-based framework where each traveler inside the airport departure area is associated with a personal agent whose goal is to provide personalized suggestions for enjoying slack times. More in detail, the personal agent runs on a traveler's mobile device, by exploiting a free app required for accessing some reserved free terminal services, and by interacting with both its user and other components of the agent-based framework, will build a light user profile as closed as possible to his/her interests [29]. In such a scenario, the user will be supported with some suggestions potentially interesting for him/her generated by using both content-based (CB) [30] and collaborative filtering (CF) [31] techniques. Such recommendations will take into account *i*) the user profile, *ii*) the current position of the traveler (determined by exploiting his/her device and the terminal hot-spots), *iii*) his/her slack time also depending on the crowd degree of the terminal areas and the amount of time remaining before the scheduled departing time and *iv*) the terminal resources available for the traveler.

The remaining of the paper is organized as follows. The proposed agent-based framework is described in detail in Section II, while Section III introduces some information about the computation of the slack time, and Section IV deals with the proposed recommender algorithm. Section V presents the relevant literature related to the matter presented here and, finally, in Section VI some conclusions are drawn.

## II. The proposed Agent-based Framework

The structure of the proposed agent-based framework (from hereafter only AF) is quite simple (see Figure 1) and consists of three mutually interacting components which are:

- the *Personal Agent* (PA);
- the *Commercial Agent* (CA);
- the *Terminal Agent* (TA);

Tasks, profiles and behaviors of all the AF components will be briefly described in the following sections.


Fig. 1. The Agent-based Framework

### A. The Personal Agent (PA)

A PA is an agent pre-activated and identifiable (i.e., equipped a unique identifier) associated with a free app running on a passenger's device (i.e., a smartphone, a notebook or a tablet). This app is provided by the airport company and it is necessary to access to some services provided for free to the passengers. The PA does not require expensive computational tasks and/or a great amount of storage resources to its host device.

The main tasks carried out by a PA include:

- interacting with its owner both for:
  - acquiring some personal information;
  - acquiring the product categories meeting the owner's interest with respect to the terminal resources;
- interacting with CAs and TAs agents.

Each PA builds, manages and updates a light XML agent profile [32], represented in Fig. 2, consisting of:

- the PA Identifier (PAId), which is unique into the AF;
- some basic personal owner data[3];

[3]Note that the system recognizes a traveler by means of the identifier of its associated PA and, therefore, the required personal data only consists of age, sex, job, trip reason and similar information voluntarily provided by the traveler in the respect of his/her privacy.

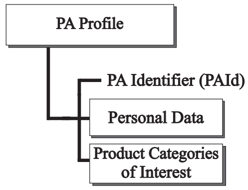


Fig. 2. The PA Profile

- the product categories of interest selected by the owner [4] from a list taking into account the commercial resources available inside the terminal (see below).

The PA behavior consists of two main activities, namely:

- ***setup***: The first time it is active, it receives the list of the AF product categories of interest (from a TA) and interacts with the PA owner to acquire both personal and interests information.
- ***operative***: To support its owner, the PA:
  - interacts with CAs and TAs, associated with Bluetooth/Wi-Fi hot-spots, each time its device enters into their operating ranges[5];
  - updates its profile and sends a copy to the nearest TA (see below);
  - computes (CB) and presents (CB and CF) recommendations generated for the PA owner (see Section IV) and other opportunities (like advertising, discount codes and so on) proposed, also based on his/her current position inside the terminal (see below).

### B. The Commercial Agent (CA)

This agent is associated with both a commercial facility placed inside the departure terminal and a Bluetooth hot-spot. The main activities of a CA consist of:

- storing and updating the list of the product categories made available by the associated commercial facility;
- considering the number of devices and PAs active in the operating range of its associated Bluetooth hot-spot;
- taking into account the detected purchases performed with the PA assistance (e.g., by using a TA discount code).
- interacting with PAs and TAs agents;

The CA behavior consists of the following activities:

- ***setup***: The first time the CA is active, it registers its presence with the closer TA from which receives its identifier and the AF list of all the product categories available into the terminal.
- ***operative***: The CA : *i*) selects from the AF list of product categories those present into its associated commercial facility (when this CA list changes, it sends a copy to the nearest TA[6]); *ii*) sends its product category list to all the PA connected to its associated hot-spot; *iii*) sends periodically the number of devices and the identifiers of the PAs connected to its associated Bluetooth hot-spot and the identifiers of the PAs that interacted with the CA, to assist a traveler in a purchase, to the nearest TA.

### C. The Terminal Agent (TA)

A TA is an agent associated with a Wi-Fi hot-spot. A TA also generates CF recommendations (for all the PAs connected with its associated Wi-Fi hot-spot) by taking into account both the travelers' interests and the commercial resources available inside its operating range.

More TAs can be active into the AF and, from a functional point of view, they are interchangeable.

Each TA performs manifold activities, more precisely it:

- takes into account the number of wireless connections and agents (e.g., PAs and CAs) active in the operating range of its associated Wi-Fi hot-spot;
- stores the resources available in its operating range.
- stores the profiles of each connected PA agent;
- collects the information received by CAs (see above) to roughly monitor the travelers' position inside the terminal and their potential interests;
- generates CF recommendations (see Section IV);
- maintains an updated list of the AF product categories;

To realize its goals a TA builds, manages and updates a XML profile [34], represented in Fig. 3, and uses the information stored in its profile to realize its goals. In particular, a TA profile is formed by the three sections *i*) *Working Data*, *ii*) *PA Data* and *iii*) *CA Data*. More in detail:

- the *Working Data* section stores:

[4]Note that for privacy reasons the PA will not monitor the traveler's activity on his/her device for automatically extracting his/her interests [33].

[5]Note that the PA exploits Bluetooth connections only to communicate its presence in a narrower range with respect to that of a Wi-Fi hot-spot.

[6]When a new product category needs, its insertion into the AF list of product categories can be required to a TA by the associated CA.

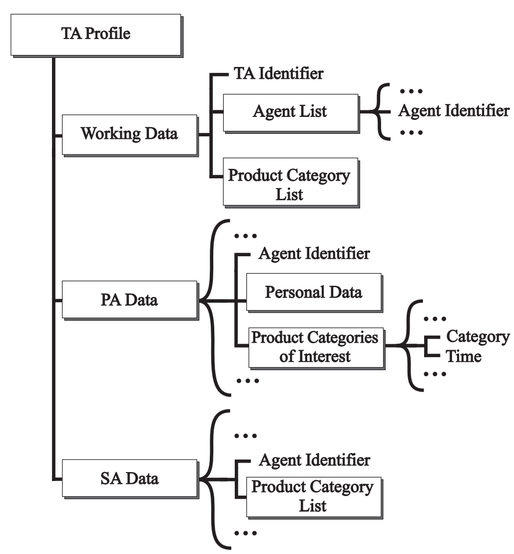


Fig. 3. The TA Profile

- the TA Identifier;
- the Agent List containing the identifiers of all the contacted PAs and CAs;
- the Product Category List storing all the product categories managed by the TA.

- The PA Data stores the PA profiles and, for each product category of interest, takes into account the PA owner's interest (see Section IV);
- The CA Data stores the identifier of each CA and the product categories made available by its associated commercial facility.

The behavior of a TA consists of the following activities:

- assigning an identifier (unique into the AF) to all the CAs requiring to be registered and providing PAs and CAs with the updated list of the Categories of Interest managed by the AF;
- interacting with PAs in both receiving their profiles and transmitting the CF recommendation suitably generated for their associated travelers (see Section IV) for supporting their slack time;
- interacting with CAs to receive the product categories available in their associated commercial facility and (periodically) the number of devices connected to the associated hot-spot, the identifiers of all the connected PAs at a given time and those of the PAs assisting a passenger in a purchase;
- maintaining updated the list of the AF categories of interest.

## III. Estimation of the Traveler's Slack Time

The recommender algorithm works by considering the slack time of each traveler, which depends on the arrival time at the terminal checkpoints with regard to the expected take-off time of his/her flight. The slack time can be estimated based on data collected at the security control desks. In fact, collecting data coming from the automatic detection of the bar-coded *Boarding Pass* (BP) (e.g., the barcode reading of paper and/or mobile boarding cards) of each passenger identifies both his/her arrival time at security checkpoints and the time he/she enters inside the departure area to take his/her flight, other than information on departure and boarding times.

By following [28], an estimate of the slack time can be obtained by the *Early Scheduled Delay* ($ESD$) measuring the earliness arrival of passengers at checkpoints, which is here defined as the difference between the *BP scan Time* ($BPT$) and the *Scheduled Boarding Time* ($SBT$) for the detected flight. Therefore, for passenger $i$ his/her $ESD$ is obtained as $ESD_i = SBT_i - BPT_i$ and may represent an estimate of the slack time $ST_i$ for each passenger $i$. However, the reliability of this estimate depends on the nature of $BPT$:

- If $BPT$ refers to the time the passenger scans the boarding pass just before passing through the metal detector, the corresponding slack time is very close to $ESD$ and can be estimated as:

$$ST_i \cong ESD_i = SBT_i - BPT_i \tag{1}$$

- If $BPT$ is obtained when the passenger accesses to the security area, before queuing for the security service, the related slack time computed by Eq.1 is overestimated. To obtain a more reliable estimate, the time spent in queue by each passenger should be used. It is worthwhile to note that only the average waiting time can be estimated under the hypothesis that there is no other automatic detection system before passing through the metal detector. To this aim, the approach proposed in [28] is briefly summarized. Each 15 minutes data are aggregated and the discrete arrival distribution is obtained based on how many passengers arrive in each time interval. Once obtained this discrete arrival distribution, the underlying probability density describing the arrival process is identified by means of a Chi-Square test. The estimated passenger probability density function $f(x)$, where $x$ is the Early Scheduled Delay $ESD$, is then used to forecast the number of *Expected Passengers* $EP$ of flight $j$ in the given interval $\Delta t$ , computed as $EP^j_{\Delta t} = N_j \cdot \int_{\Delta t} f(x)dx$, where $N_j$ is the expected number of passengers on flight $j$. The total number of Expected Passengers in interval $\Delta t$ is then given by $EP_{\Delta t} = \sum_j EP^j_{\Delta t}$. Finally, the *Slack Time* $ST$ of passenger $i$ during $\Delta t$ can be estimated as:

$$ST_i = ESD_i - LT_i \tag{2}$$

where $LT_i$ is the time spent by passenger $i$ at the checkpoint, while queuing to be processed, which depends on the expected number of passengers in $\Delta t$, $EP_{\Delta t}$ and the expected number of passengers for all flights $j$ in $\Delta t$, $N_{\Delta t} = \sum_j N_j$.

## IV. The Recommender System

Travelers are supported by personalized suggestions generated by an hybrid approach adopting both CB and CF techniques. In particular, the CB recommendation system are computed by PAs, while the CF component is generated by TAs. Recommendations take into account information coming from: *i*) PA profiles; *ii*) positions and time spent inside the hot-spots ranges; *iii*) detected purchases; *iv*) travelers' slack time. The recommender process consists of three main steps, namely: *i*) selecting the categories potentially interesting for a traveler; *ii*) locating the resources (i.e., commercial facilities) also based on the traveler's position; *iii*) generating some personalized suggestions by considering the traveler's slack time $ST$.

To realize the CB stage, a PA selects for its owner the first $m$ (a system parameter) categories on the basis of a measure of his/her interest. In particular, the measure of interest for the $k$-th category (i.e., $I_k$) is computed as:

$$I_k = (w_1 \cdot l_k + w_2 \cdot \overline{TB}_k + w_3 \cdot \overline{TW}_k) \cdot p_k \tag{3}$$

where:

- $l$ is set to 1 / 0 if the associated category was selected or not by the traveler as a category of his/her interest.

- $\overline{TB}$ (i.e., $\overline{TW}$) is a parameter, belonging to $[0.1] \in \mathbf{R}$, which considers the time $TB$ (i.e., $TW$) spent in Bluetooth (i.e., Wi-Fi) hot-spot ranges, where there are items belonging to the $k$-th category, as a rough measure of the interest for those categories. $\overline{TB}$ is computed as:

$$\overline{TB} = \begin{cases} 0 & \text{if } \tau_1 > TB \\ TB/\tau_2 & \text{if } \tau_1 < TB \leq \tau_2 \\ 1 & \text{if } \tau_2 < TB \end{cases}$$

  where $\tau_1$ and $\tau_2$ are system time thresholds (note that after a time greater than $\tau_2$ the value of $\overline{TB}$ is set to 1). $\overline{TW}$ is computed in a similar way.
- $p$ is set to 0.5 / 1 if an item of that category has been purchased or not. It decreases the value of $I_k$ if an item belonging to $k$-th category has been already purchased in order to give priority to other categories.
- $w_1$, $w_2$ and $w_3$ are system weights ranging in $[0.1] \in \mathbf{R}$, with $w_1 \ll w_2 \ll w_3$ and $\sum_{i=1}^{3} w_i = 1$.

Similarly, a TA will select, for each PA in its operating range, the first $m$ categories popular among similar travelers (based on their interest degree measures). The similarity between two travelers $u$ and $q$ (i.e., $\sigma_{u,q}$) is calculated by using the Jaccard similarity measure [35] on the basis of their associated PA profiles ($P$) as $\sigma_{uq} = \frac{|P_u \cap P_q|}{|P_u \cup P_q|}$, where the number of categories shared by $u$ and $q$ is divided by the total number of unique categories in $u$ and $q$.

Finally, let $X$ be the set of the $m$ CB and the $m$ CF categories selected for each traveler. Then the commercial facilities where there are items belonging to the selected categories will be identified by the PA (by using the data stored in its profile). Based on the current traveler's position, his/her data (i.e., age, sex, job and so on) and his/her slack time $ST$, the most relevant personalized suggestions will be presented to the traveler.

## V. Related Work

Recommender systems ($RS$s) have been widely investigated in the literature and their contextualization is beyond our aims. However, interested readers can refer to [36]–[38]

$RS$s are generally classified in [39]: (*i*) *Content-based* (CB), based on past users' interests [40]; (*ii*) *Collaborative Filtering* (CF), searching people having similar interests [41], [42]; (*iii*) *Demographic*, identifying people belonging to the same demographic niche [43]; (*iv*) *Knowledge-based*, inferring people's needs and references [44]. However, the most performing $RS$s are usually the hybrid systems [45], which combine several approaches to promote mutual synergies, as in [46].

Another common way to classify $RS$s is based on the adoption of a centralized or distributed architecture. The first one is adopted by many $RS$s because it is easy to implement given that it exploits a unique server and a unique database to perform all the tasks. Many e-Commerce sites like Amazon (www.amazon.com) and eBay (www.ebay.com) implement this type of $RS$, mainly by combining CB and CF techniques. However, these $RS$s are affected by efficiency, fault tolerance, scalability and privacy problems. Differently, distributed $RS$s exploit more computational resources but guarantee openness, accessibility, transparency and scalability [47]; although these $RS$s are very attractive, only a few systems are really operative given their intrinsic complexity.

The proposed $RS$ is characterized by locating travelers in order to identify both their interest and the better facilities for them. Different localization schemes (based on wireless connections and a wide range of different sensors) have been investigated [48] for understanding shoppers behavior within retail spaces. In [49] a framework that should identify customers malling behaviors by using smartphones, named *MallingSense*, is presented. It consists of three steps; customer data collection, customer trace extraction, and behavior model analysis. MallingSense was positively tested on real data. A store-type $RS$ for physical stores considering the learned customers' preference' and temporal influence is proposed in [50]. It finds customers' preferences in physical stores from their interaction behaviors, non-intrusively generated from WiFi logs, confirming that customers preferences are influenced by intrinsic interests and temporal data. In the same context, [51] describes a location-aware $RS$ matching customers shopping needs with location-dependent vendor offers and promotions.

The other main considered question is how identifying specific travelers' interests on the basis of their location. In this paper, it is proposed to assign the same value of interest to all the categories present in the range of a hot-spot on the basis of his/her stop time therein. This solution is due to the impossibility of identifying a specific topic of interest. The problem is similar to that of measuring the interest in the topics contained into a visited Web page. In this case, the same measure of interest is assigned to all the topics present in a visited page, for instance, based on the time spent by a user on the Web page, its length or a score assigned by the visitor. A $RS$ using a similar approach is described in [52] where the visiting time of a Web page is the main parameter to estimate the user's interest in the instances present therein, while in [53], [54] the typology of the device exploited in the page access is also considered.

## VI. Conclusions and Future Work

This paper proposed the design of an agent framework to support air travelers slack time inside departure terminal. To this aim, for each passenger some suggestions about the commercial opportunities available inside the terminal, potentially interesting for him/her, are generated. Such recommendations suitably take into account traveler's interest, current position inside the terminal and slack time.

Currently, an app for the free access to some terminal services is in the designing phase. This app also should contribute to collect data coming from both travelers and some hot-spots to perform a preliminary check about the potential feasibility of the proposed framework.

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## References


[1] G. Francis, I. Humphreys, and J. Fry, “The benchmarking of airport performance,” *J. air Transport Manag.*, vol. 8, no. 4, pp. 239–247, 2002.

[2] R. Guimera and L. A. N. Amaral, “Modeling the world-wide airport network,” *The European Physical J.*, vol. 38, no. 2, pp. 381–385, 2004.

[3] A. Kazda and R. Caves, *Airport design and operation*. Emerald, 2010.

[4] M. N. Postorino and F. G. Praticò, “An application of the multi-criteria decision-making analysis to a regional multi-airport system,” *Research in Transportation Business & Management*, vol. 4, pp. 44–52, 2012.

[5] M. N. Postorino, L. Mantecchini, and F. Paganelli, “Green airport investments to mitigate externalities: Procedural and technological strategies,” in *Sustainable Entrepreneurship and Investments in the Green Economy*. IGI Global, 2017, pp. 231–256.

[6] C. Malandri, L. Mantecchini, and M. N. Postorino, “Airport ground access reliability and resilience of transit networks: a case study,” *Transportation Research Procedia*, vol. 27, pp. 1129–1136, 2017.

[7] M. Milde, *Int. air law and ICAO*. Eleven Int. Pub., 2008, vol. 4.

[8] B. Edwards, *The modern airport terminal: New approaches to airport architecture*. Taylor & Francis, 2004.

[9] N. Ashford, P. Coutu, and J. Beasley, *Airport operations*, 2013.

[10] D. Fodness and B. Murray, “Passengers’ expectations of airport service quality,” *J. of Services Marketing*, vol. 21, no. 7, pp. 492–506, 2007.

[11] Y. Lin and C. Chen, “Passengers’ shopping motivations and commercial activities at airports–the moderating effects of time pressure and impulse buying tendency,” *Tourism Management*, vol. 36, pp. 426–434, 2013.

[12] K. A. Mew, P. C. Alexander, I. Bergera, M. Chanes, G. Crysler, K. Dana, and M. Desai, *Airport financial management*. Ashgate, 2012.

[13] L. Palopoli, D. Rosaci, and G. M. L. Sarnè, “A multi-tiered recommender system architecture for supporting e-commerce,” in *Intelligent Distributed Computing VI*. Springer, 2013, pp. 71–81.

[14] M. N. Postorino and G. M. L. Sarnè, “A neural network hybrid recommender system,” in *Proceedings of the 2011 conference on neural Nets WIRN10*, 2011, pp. 180–187.

[15] L. Palopoli, D. Rosaci, and G. M. L. Sarnè, “Introducing specialization in e-commerce recommender systems,” *Concurrent Engineering*, vol. 21, no. 3, pp. 187–196, 2013.

[16] S. Takakuwa and T. Oyama, “Modeling people flow: simulation analysis of international-departure passenger flows in an airport terminal,” in *Proc. 35th conf. on Winter simulation: driving innovation*. Winter Simulation Conf., 2003, pp. 1627–1634.

[17] M. L. Tam, W. H. Lam, and H. P. Lo, “Modeling air passenger travel behavior on airport ground access mode choices,” *Transportmetrica*, vol. 4, no. 2, pp. 135–153, 2008.

[18] K. Artur and K. Tomasz, “A model of check-in system management to reduce the security checkpoint variability,” *Simulation Modelling Practice and Theory*, vol. 74, pp. 80–98, 2017.

[19] K. Yoo and Y. Choi, “Analytic hierarchy process approach for identifying relative importance of factors to improve passenger security checks at airports,” *J. of Air Transport Manag.*, vol. 12, no. 3, pp. 135–142, 2006.

[20] K. W. Bowyer, “Face recognition technology: security versus privacy,” *IEEE Technology and society magazine*, vol. 23, no. 1, pp. 9–19, 2004.

[21] G. M. L. Sarnè, “A collaborative filtering recommender exploiting a som network,” in *Recent Advances of Neural Network Models and Applications*. Springer, 2014, pp. 215–222.

[22] F. Ohrtman and K. Roeder, *Wi-Fi handbook: Building 802.11 b wireless networks*. McGraw-Hill New York, NY, 2003, vol. 67.

[23] B. A. Miller and C. Bisdikian, *Bluetooth revealed: the insider’s guide to an open specification for global wireless communication*. Prentice Hall PTR, 2001.

[24] S. A. M. Saleh, S. A. Suandi, and H. Ibrahim, “Recent survey on crowd density estimation and counting for visual surveillance,” *Engineering Applications of Artificial Intelligence*, vol. 41, pp. 103–114, 2015.

[25] A. Andreoni and M. N. Postorino, “Time series models to forecast air transport demand: a study about a regional airport,” *IFAC Proceedings Volumes*, vol. 39, no. 12, pp. 101–106, 2006.

[26] M. Postorino, “A comparison among different approaches for the evaluation of the air traffic demand elasticity,” *WIT Transactions on Ecology and the Environment*, vol. 67, 2003.

[27] R. De Neufville, “Airport systems planning and design,” *Air Transport Management: An International Perspective*, p. 61, 2016.

[28] M. N. Postorino, L. Mantecchini, C. Malandri, and F. Paganelli, “Airport passenger arrival process: Estimation of earliness arrival functions,” *Transportation Research Procedia*, In Press.

[29] D. Rosaci, G. M. L. Sarnè, and D. Ursino, “A multi-agent model for handling e-commerce activities,” vol. 2002-Jan. IDEAS, 2002, pp. 202–211.

[30] P. Lops, M. De Gemmis, and G. Semeraro, “Content-based recommender systems: State of the art and trends,” in *Recommender systems handbook*. Springer, 2011, pp. 73–105.

[31] X. Su and T. M. Khoshgoftaar, “A survey of collaborative filtering techniques,” *Advances in artificial intelligence*, vol. 2009, p. 4, 2009.

[32] P. De Meo, D. Rosaci, G. M. L. Sarnè, D. Ursino, and G. Terracina, “Ec-xamas: supporting e-commerce activities by an xml-based adaptive multi-agent system,” *Applied Artificial Intelligence*, vol. 21, no. 6, pp. 529–562, 2007.

[33] D. Rosaci and G. M. L. Sarnè, “Masha: A multi-agent system handling user and device adaptivity of web sites,” *User modeling and user-adapted interaction*, vol. 16, no. 5, pp. 435–462, 2006.

[34] P. De Meo, D. Rosaci, G. M. L. Sarnè, G. Terracina, and D. Ursino, “An xml-based adaptive multi-agent system for handling e-commerce activities,” in *Web Services-ICWS-Europe ’03*. Springer, 2003, pp. 152–166.

[35] Grefenstette G., *Explorations in Authomatic Thesaurus Construction*. Hingham, MA, USA: Kluwer Academic Pub., 1994.

[36] G. Adomavicius and A. Tuzhilin, “Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions,” *IEEE trans. on knowledge and data engineering*, vol. 17, no. 6, pp. 734–749, 2005.

[37] F. Ricci, L. Rokach, and B. Shapira, “Introduction to recommender systems handbook,” in *Recommender systems handbook*. Springer, 2011, pp. 1–35.

[38] X. Yang, Y. Guo, Y. Liu, and H. Steck, “A survey of collaborative filtering based social recommender systems,” *Computer Comm.*, vol. 41, pp. 1–10, 2014.

[39] R. Burke, “Hybrid Web Recommender Systems,” in *The Adaptive Web*, ser. LNCS, vol. 4321. Springer, 2007, pp. 377–408.

[40] P. Lops, M. Gemmis, and G. Semeraro, “Content-based Recommender Systems: State of the Art and Trends,” in *Recommender Systems Handbook*. Springer, 2011, pp. 73–105.

[41] J. Breese, D. Heckerman, and C. Kadie, “Empirical Analysis of Predictive Algorithms for Collaborative Filtering,” in *Proc. 14th Int. Conf. on Uncertainty in Artificial Intell.* Morgan Kaufmann, 1998, pp. 43–52.

[42] X. Su and T. Khoshgoftaar, “A Survey of Collaborative Filtering Techniques,” *Adv. in Artif. Intell.*, vol. 2009, pp. 4:2–4:2, 2009.

[43] C. Stiller, F. Ross, and C. Ament, “Demographic Recommendations for WEITBLICK, an Assistance System for Elderly,” in *Comm. and Information Technologies, 2010 Int. Symp.* . IEEE, 2010, pp. 406–411.

[44] S. Trewin, “Knowledge-based recommender systems,” *Encyclopedia of Library and Information Science*, vol. 69, no. Suppl. 32, p. 69, 2000.

[45] R. Burke, “Hybrid Recommender Systems: Survey and Experiments,” *UMUAI*, vol. 12, no. 4, pp. 331–370, 2002.

[46] D. Rosaci and G. M. L. Sarnè, “Multi-agent technology and ontologies to support personalization in b2c e-commerce,” *Electronic Commerce Research and Applications*, vol. 13, no. 1, pp. 13–23, 2014.

[47] A. S. Tanenbaum and M. Van Steen, *Distributed systems: principles and paradigms*. Prentice-Hall, 2007.

[48] S. Rallapalli, “Mobile localization: approach and applications,” Ph.D. dissertation, 2014.

[49] S. Lee, C. Min, C. Yoo, and J. Song, “Understanding customer malling behavior in an urban shopping mall using smartphones,” in *Proc of ACM conf. on Pervasive and ubiquitous comp.* ACM, 2013, pp. 901–910.

[50] Y. Chen, Z. Zheng, S. Chen, L. Sun, and D. Chen, “Mining customer preference in physical stores from interaction behavior,” *IEEE Access*, vol. 5, pp. 17 436–17 449, 2017.

[51] J. Bao, Y. Zheng, and M. Mokbel, “Location-based and preference-aware recommendation using sparse geo-social networking data,” in *Proc. of conf. on advances in geographic inform. sys.* ACM, 2012, pp. 199–208.

[52] J. Parsons, P. Ralph, and K. Gallagher, “Using Viewing Time to Infer User Preference in Recommender Systems,” in *AAAI Work. on Semantic Web Personalization*. Menlo Park, CA, USA: AAAI., 2004, pp. 52–64.

[53] D. Rosaci, G. M. L. Sarnè, and S. Garruzzo, “Muaddib: A distributed recommender system supporting device adaptivity,” *ACM Transactions on Information Systems (TOIS)*, vol. 27, no. 4, p. 24, 2009.

[54] D. Rosaci and G. M. L. Sarnè, “A multi-agent recommender system for supporting device adaptivity in e-commerce,” *Journal of Intelligent Information Systems*, vol. 38, no. 2, pp. 393–418, 2012.