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A Data Warehouse Solution for Analyzing RFID-Based Baggage Tracking Data

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***Abstract*—Today, airport baggage handling is far from perfect. Baggage goes on the wrong flights, is left behind, or gets lost, which costs a lot of money for the airlines, as well as frustration for the passengers. To remedy the situation, we present a data warehouse (DW) solution for storing and analyzing spatio-temporal Radio Frequency Identification (RFID) baggage tracking data. Analysis of this data can yield interesting results on baggage flow, the causes of baggage mishandling, and the parties responsible for the mishandling(airline, airport, handler,...), which can ultimately lead to improved baggage handling quality. The paper presents a carefully designed data warehouse (DW), with a relational schema sitting underneath a multidimensional data cube, that can handle the many complexities in the data. The paper also discusses the Extract-Transform-Load (ETL) flow that loads the data warehouse with the appropriate tracking data from the data sources. The presented concepts are generalizable to other types of multi-site indoor tracking systems based on Bluetooth and RFID. The system has been tested with large amount of real-world RFID-based baggage tracking data from a major industry initiative. The developed solution is shown to both reveal interesting insights as well as being several orders of magnitude faster than computing the results directly on the data sources.**

***Index Terms*—RFID; data warehouse; data cube; data analysis; baggage tracking; moving objects; indoor tracking;**

I. Introduction

A recent report[1] discloses the enormous loss caused by baggage mishandling in the aviation industry. Each year more than 31M passengers and 34M bags are affected by baggage mishandling which costs the aviation industry 3,300 M USD. A passenger wastes on average 1.7 days of his vacation or business trip waiting for the mishandled bag. Typical baggage mishandling problems include flight delay, bag loss, wrong bag destination, failure to load bags at the origin airport, missed connection at transit hubs, etc. During the travel from the origin airport to the final destination, a bag is moved over different places in multiple steps: check-in, screening, sortation, loading, transition, arrival, etc. In these steps, a bag is handed over between a large number of stakeholders. In contrast with the visibility of passengers' movement steps during the end-to-end journey, the baggage movement is considerably less visible due to the very limited information to passengers. A single error or inefficacy in a handover can cause a bag not to reach its intended destination with its owner [12].

[1]SITA Baggage Report 2012 www.sita.aero/content/baggage-report-2012

Radio Frequency Identification (RFID) technology is used in many applications for monitoring object movement. The use of RFID in baggage tracking systems enables to track a bag in an airport as well as along its travel route cross airports. RFID tracking systems generate huge amounts of data. For example, Walmart has recently started using tags at the item level and research firm Venture Development Corporation predicts that this will generate up to 7 terabytes of data per day [5]. In RFID-based airport baggage tracking systems, these huge amounts of RFID data can be very useful for analyzing and mining purposes. Coupled with other kinds of information about routes, transit airports, transit durations, flights and punctuality, airlines, handler, special events, etc., RFID baggage tracking data can reveal a lot of information about baggage handling quality. Analyzing these data will open the door to identifying the different problems in baggage handling and finding solutions for the problems. This is exactly the goal of the BagTrack project (www.daisy.aau.dk/bagtrack), within which this work took place. Here, a number of important industry players have teamed up with our data management team to revolutionize baggage handling using RFID.

In this paper, we present a multidimensional database warehouse solution for RFID-based baggage tracking data. To the best of our knowledge, this paper is the first to design a multidimensional data warehouse, including a relational DW schema with a data cube on top, for this important domain. The proposed data warehouse contributes to the airline baggage handling process by providing a framework for data analysis and answering complex queries that can ultimately improve the baggage handling quality. For example, the manager of Copenhagen airport may ask a query like *how many bags were sent to wrong destination from Copenhagen airport in the Easter holidays of 2012*. Another query can be *find the average number of baggage traveling from Copenhagen airport in the afternoon of each Sunday*. Our data warehouse supports such useful queries effectively and efficiently.

Our data warehouse design features several novelties. First, it captures not only the RFID baggage tracking data but also baggage flow along different dimensions like airport, airline, date and time, all at several levels of granularity. We also handle the complex many-to-many relationship between bag and flight effectively. Second, our design treats date and time as different dimensions, each with different hierarchical

levels. Each date is *localized* to a particular airport, to allow capturing special local events, like strikes, sports games, etc. This localization makes it easy to ask complex queries about baggage movement in a particular event or occasion. Third, our data warehouse design supports powerful data analysis queries in a both easy and efficient way. The relevant results enable the users (e.g., an airline) to find out the places (e.g., a particular airport) where mishandling occurs most of the time, and thus to determine the reasons of baggage mishandling. The paper also discusses the complexities of performing Extract-Transform-Load (ETL) to load the DW from the source data, including our solutions to the encountered challenges.

The remainder of the paper is organized as follows. Section 2 reviews related work. Section 3 presents an overview of RFID-based airport baggage handling process and the structure of RFID data. Section 4 presents the relational data warehouse design and the multidimensional data cube design. Section 5 represents the ETL steps to load the data from source schema into the data warehouse. Section 6 presents the experimental results. Finally, Section 7 concludes the paper and points to the challenges for future work that we encountered.

II. Related Work

Data warehousing, mining and work flow analysis techniques have been proposed for RFID-based supply chain systems [3], [4], [5], [6]. Those proposals take advantage of bulky movement of objects in supply chains to compress the massive RFID data. Efficient storage scheme and encoding the object paths are designed [9], [10] to support faster query performance for supply chain RFID data. RFID data warehousing for tracking patients and drugs has been studied [2]. The general challenges and solutions for RFID data management are also discussed [1], [13].

The scenario of airport baggage management in this paper differs from the settings of previous research. Unlike objects in supply chain management, airport bags do not move in a bulky way. In addition, the bag locations in airport baggage management are much more fine grained so that places and reasons of mishandling can be identified at a satisfactory level. Further, the time dimension in airport baggage management is also much more fine grained so that complex time-dependent queries can be supported. Last but not least, our data warehouse design considers other important dimensions which enable complex analysis on baggage tracking data.

III. RFID-Based Airport Baggage Handling

In airport baggage management a bag needs to pass different stages to go from origin to final destination. Suppose that Lisa needs to travel from Aalborg Airport (AAL) to Arlanda Airport (ARN) via Copenhagen Airport (CPH). First, Lisa has to check-in and handover her bag to the check-in desk staff. Then the staff puts the bag into the conveyor belt for automatic baggage sortation system. After passing all the stages inside AAL, the bag is loaded into the aircraft using belt loader for the targeted flight. As the bag has to be transferred to ARN, upon arrival at CPH it is shifted to the transfer system. After all the required stages at CPH, the bag is loaded to the aircraft for its next flight to ARN. After arriving at ARN, the bag is shifted to arrival belt and finally Lisa collects the bag from the arrival belt.

Figure 1 shows an example of RFID reader deployment at different locations of a baggage management system. An RFID reader corresponds to the location where it is deployed. For example, *reader1* in Figure 1 corresponds to *check-in1*, *reader6* corresponds to *Gateway-1* etc. The circles represent the RFID reader and their activation range.

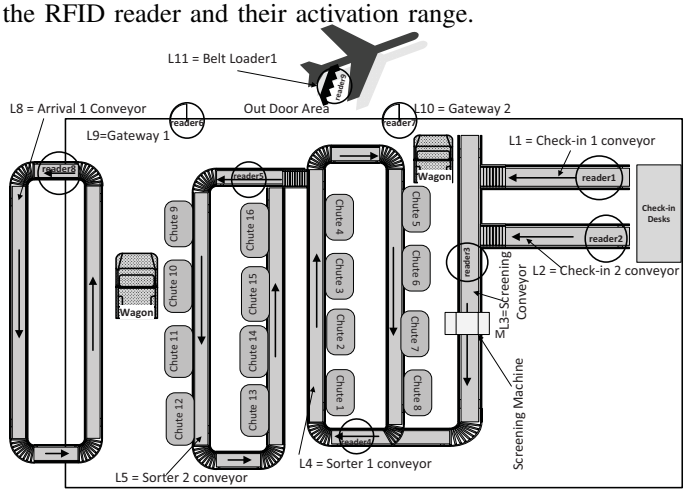


Fig. 1: RFID reader deployment for airport baggage handling

At check-in, an RFID tag is attached to the bag. The tag is then read by readers is passes through their respective activation ranges. An RFID reader continuously detects the tags, and the reader's controller software determines which actual records are stored: if the read rate is 1 sec, an object staying under a reader for 30 sec will generate 30 records, unless it is specified that only one record can be sent per 15 sec, which will yield only 2 records.

An RFID tag has small built-in memory that stores bag information.An example of this data is {*0123456789, 28APR, AAL, SK1234, 28APR, CPH, LH2345, 28APR, ARN*}. The first 10 digits are the *LicensePlate*[2]. Specifically, the 1st digit is a flag, the 2-4th digits state the bag issuer code (e.g., 117 for SK (SAS)) and the 5-10th digits are the baggage tag number. Next, the flight date is 28APR, the tag is printed in AAL(borg), the first flight leg is SK1234 on 28APR to CPH, the second leg is LH2345 on 28APR to ARN.

Due to the huge number of taggings, the 10 digit integer *LicensePlate* is reused after some time. Thus, a *BagID* is added to uniquely identify a bag. The records are stored in the format: $\langle$*BagID, L, T, info*$\rangle$, meaning that a reader at location *L* detects a bag with ID *BagID* at timestamp *T* and the tag stores the information *info*. Considering only location and time related information, some example tracking records are shown in Table I. The records are represented in the form: $\langle$*ReadingID, BagID, LocationID, ReadingTime*$\rangle$.

[2]The license plate is a unique 10 digit code encoding bag information. IATA specifies the rules for using the (Baggage) License Plate in Resolution 740B of their Passenger Services Conference Resolutions Manual.

TABLE I: Raw Baggage Tracking RFID Data

⟨ *ReadingID, BagID, LocationID, ReadingTime* ⟩
(r1, b1, L1, 1) *(r2, b2, L2, 2)* *(r3, b1, L3, 4)* *(r4, b1, L3, 5)* *(r5, b2, L3, 5)* *(r6, b2, L3, 6)* *(r7, b1, L4, 8)* *(r8, b1, L4, 9)* *(r9, b2, L4, 9)* (r10, b2, L4, 10) (r11, b2, L5, 14) (r12, b2, L5, 15) (r13, b1, L4, 19) (r14, b1, L4, 20) . . .

As explained earlier, the raw readings contain many redundant records. A *LocationTrace* table can be constructed from the raw tracking sequence after eliminating the multiple readings. The format of the records in *LocationTrace* table is: *(recordID, BagID, LocationID,* t_{in}*,* t_{out}*)*, where *recordID* is the identifier of each location trace record and t_{in}, t_{out} respectively represent the timestamps of first reading and last reading of *BagID* by the RFID reader deployed at location *LocationID*. This means that the bag was within the readers activation range during time t_{in}, t_{out}. An example of a table containing location trace records from Table I is shown in Table II. In this table the record rec_3 represents, a bag $b1$ is observed by RFID reader at location $L3$ from time t_4 to time t_5, and record rec_5 means that $b1$ is observed by reader at location $L4$ from time t_8 to t_9. This is a lossless compression with huge data reduction in volume.

TABLE II: Tracking records after duplicate elimination

ObjectID	*TrackingRecord⟨RecordID,ObjectID, LocationID,* t_{in}*,* t_{out}*⟩*
b1	*(rec1, b1, L1, 1, 1) (rec3, b1, L3, 4, 5) (rec5, b1, L4, 8, 9) (rec8, b1, L4, 19, 20)*
b2	*(rec2, b2, L2, 2, 2) (rec4, b2, L3, 5, 6) (rec6, b2, L4, 9, 10) (rec7, b2, L5, 14, 15)*
...	...

IV. Data Warehouse Design

To support business intelligence analysis using complex analytical queries, we propose a data warehouse design, shown in Figure 2. The proposed multi-dimensional data warehouse schema is a mixture of a star and a snow-flake schema with one fact table and eight dimension tables. A star schema is less complex compared to a snow-flake schema where the dimensions are partly normalized, but in some places, a snow-flake schema is needed, as discussed in the following. In the following, the different dimensions are described, after which the fact table is introduced to link all the dimensions to the facts and calculated measures. As seen in the Figure 2, all the dimension tables follows the standard data warehouse convention of having auto-generated surrogate keys.

A. Dimension Descriptions

The different dimensions of the data warehouse presented in Figure 2 are described in this section.

1) **Date and TimeOfDay Dimension:** As seen in Figure 2, date and time has been split up into two dimensions in order to save records compared to a combined dimension table. If date and time were modeled in one table there could be over 86400 records for each day. In a year that would give over 31 million records in the dimension which could result in a slow query performance. Another reason for splitting up the two

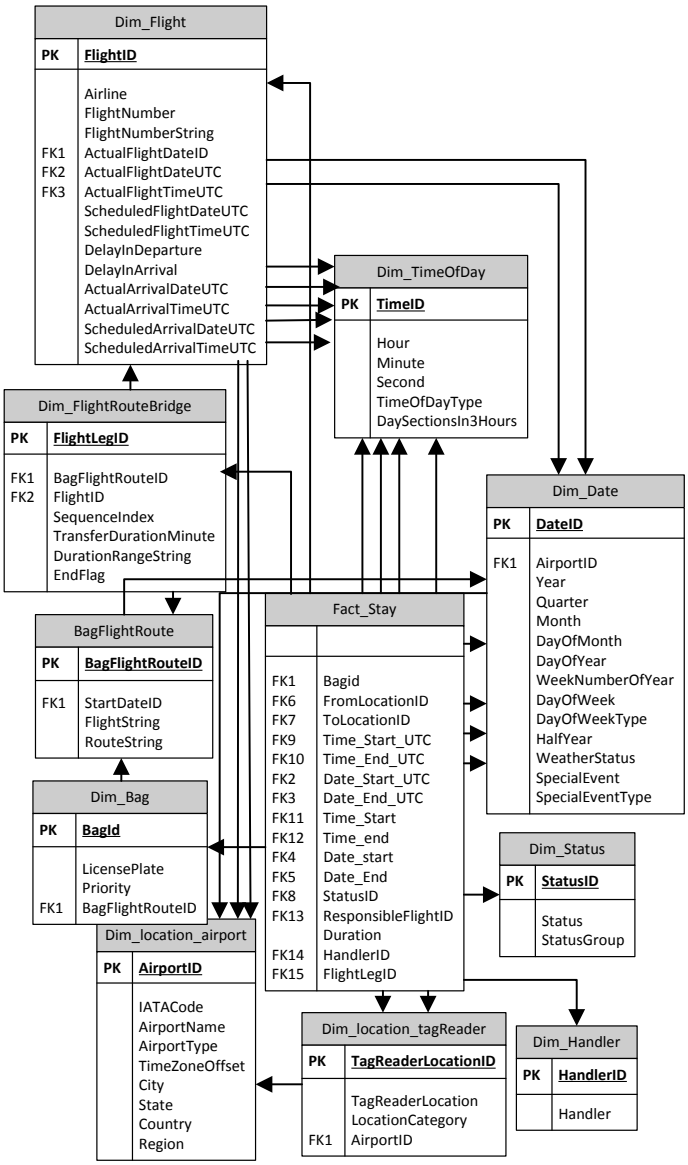


Fig. 2: Relational Data Warehouse Schema

dimensions is that queries are normally performed on either a date basis or a time of day basis.

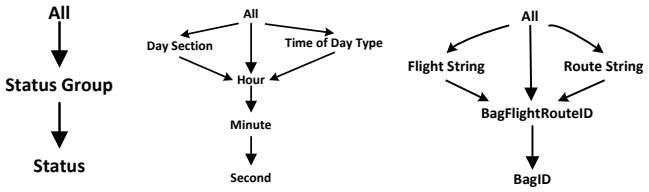
The main hierarchy of the $Date$ dimension consists of: *Year, Month, and DayOfMonth*. To allow more detailed analysis, the dimension includes the following attributes: *HalfYear, Quarter, WeekNumberOfYear and DayOfYear*. *DayOfWeek* is included as a one level hierarchy to specify the specific days of the week. The *HalfYear* attribute indicates if it is the first or last half of the year. The *DayOfYear* attribute enables queries on a specific day or range of days (1..365). The *WeekNumberOfYear* attribute enables queries on specific weeks of a year. The *DayOfWeek* makes it possible to query on a specific weekday and the last attribute *DayOfWeekType* enables classification of days, e.g. holiday, weekend, weekday, etc.

Location based events may occur on a particular date. For example Aalborg, Denmark celebrates a special occasion

called Aalborg Carnival which is one of the biggest carnivals in Europe. As a result lot of people from Europe come to Aalborg to celebrate this occasion. Another example can be a strike in the city of an airport or conveyor belt broken of an airport etc. Additionally, bad weather in the area of an airport should be captured to relate baggage handling quality with the weather. So, it is very important to *localize* each date to the airport for capturing these types of location based special events and weather status. We use two special attributes: *SpecialEvent, EventType* which allow queries on a specific event or type of event. For localizing each date and date related information to a particular airport, we use *AirportID* as an attribute of the *Date* dimension. As a result the *Date* dimension has to store a copy of same date for each airport. Figure 4b shows the hierarchy of the *Date* dimension.

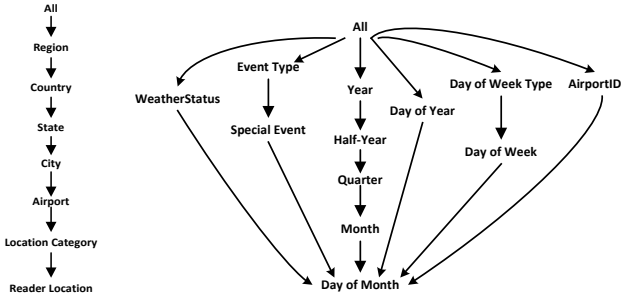
The *Date* dimension stores a copy of all stored dates for UTC which is independent of the airport. We store a default *AirportID, (AllAirports)*, which indicates all airports and the other attributes also store default values for the corresponding UTC date. An example of date localization concept is shown in Fig. 5a. From Fig. 5a we can see that date May, 29, 2012 is localized for each airport and as a result it is possible to capture an special event i.e., *ConveyorBeltBroken* at AAL airport.

The *Time* dimension called *TimeOfDay* consists of the three necessary attributes to specify a time hierarchy down to a specific second: *Hour, Minute, and Second*. Attribute *TimeOfDayType* indicates whether this is rush hour or normal hour, and *DaySections3Hours* divides the 24 hours of a day into eight 3-hour sections. As a result it will be easier to analyze the baggage movement at different parts of the day. Figure 3b shows the hierarchy of the *TimeOfDay* dimension.



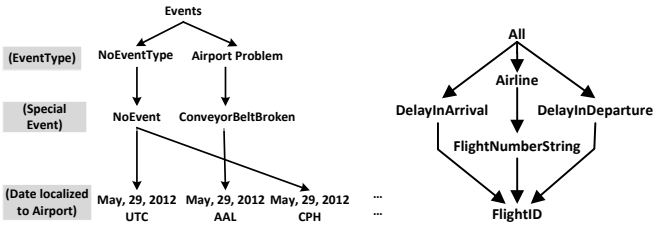
(a) Status (b) Time of Day (c) Bag

Fig. 3: Hierarchy of Status, Time of Day and Bag



(a) Location (b) Date

Fig. 4: Hierarchy of Location and Date



(a) Date localization (b) Flight

Fig. 5: Date localization example and Flight hierarchy

2) **Location Dimension:** In order to refer to different points of interest in the airport, a hierarchy of seven levels is introduced to handle the various degrees of detail. The lowest level in the hierarchy is denoted as a *TagReaderLocation*, which describes the specific location of an RFID reader like Check-in-1, Sorter-1, Sorter-2, Gateway-1, Arrival-1 etc. A location belongs to a category e.g., Sorter-1, Sorter-2 belongs to the location category Sorter. A number of location categories are grouped into an airport. The other levels of hierarchy of *Location* dimension are showed in Figure 4a.

The location hierarchy enables queries for the baggage movement at different abstraction levels, e.g., from one tag reader location to another tag reader location at the lowest level, and from one region to another region at the top level. Here, the meaning of region indicates the baggage movements between North America, Europe, Middle East and Africa (EMEA), Latin America (LATAM) and Asia-Pacific etc,. The *Location* dimension is snow-flaked at airport level and we use *Dim_airport* as an outrigger dimension [7] as some other dimensions like *Dim_Date, Dim_Flight* etc., depend on the location at the airport level not at the tag reader level.

3) **Status Dimension:** The $Status$ dimension captures the status of a bag while moving from one location to another. The status domain is $\{$*WrongDestination, OK, LeftBehind, TrackedInNonRouteAirport, StillTrackedInNonRouteAirport, LongerDurationThanExpected, UnexpectedReader*$\}$. To make a hierarchy, another column *StatusGroup* is introduced which contain the group of the status, e.g., *WrongDestination, LeftBehind, TrackedInNonRouteAirport* belong to *mishandled group* etc. Figure 3a shows the hierarchy of *Status* dimension.

4) **Bag Dimension:** The *Bag* dimension contains the identifier of the bag, *LicensePlate* and other planned travel information of bags like route, airline, date of departure etc. To keep track of the bags planned to move together in the same route and the same flight on the same date, we create a separate ID called *BagFlightRouteID*. This ID is generated while loading the data from the source schema. As a result, it creates a hierarchy in the *Bag* dimension. Each *BagFlightRouteID* corresponds to a given combination of *StartDateID, FlightString* and *RouteString*. Here, *StartDateID* is the departure date, *FlightString* contains a sequence of flights, e.g., "SK1202-QI1354-#"; *RouteString* contains a sequence of airports of the route, e.g., "AAL-CPH-ARN-#". In both strings '#' indicates the end of the sequence. Use of these strings enables queries on flight and route sequences more easily. For example, to find the number of mishandled bags starting from AAL and

ending at ARN, the route string wild-card "AAL%ARN:#" can be used. Figure 3c represents the hierarchy of *Bag* dimension.

5) **Flight Dimension:** In addition to the general information of a flight like *FlightID, Airline, FlightNumber, departure date* and *time* etc., we also store the *source airport, destination airport, delay in departure, delay in arrival etc.* Storing this delay information enables queries that can give an idea about how baggage mishandling is related with punctuality of flights. We store *FlightNumberString* which includes airline and flight number together e.g., *"SK1202"* indicates a flight of SAS (SK) Airline with flight number 1202. Instead of querying only on a flight number it is common to query on a flight based on *FlightNumberString* which can be rolled up to the airline level. Hierarchy of *Flight* dimension is represented in Figure 5b.

6) **Handler Dimension:** While traveling from origin to destination a bag is handled by many handler organizations at different stages of baggage movement. So handler is an extremely important entity related to baggage management. The *Dim_Handler* table represents the *Handler* dimension. It contains attributes *HandlerID* and *Handler*. The *Handler* dimension enables to find relationship between baggage handling quality and handlers.

B. Many-to-Many Relationship Between Flight and Bag

A bag can travel in many flights and a flight can carry many bags, and therefore the relationship between bag and flight is many-to-many. Additionally a sequence number is maintained when a bag is planned for traveling more than one flight. It also includes a transit duration i.e., duration between scheduled departure time of next flight and actual arrival time of the current flight. If a flight is the final flight of a bag in its sequence of flights then the transit duration is remain null. A standard approach of handling many-to-many relationship is the use of a bridge table that use foreign keys from both entities [8] e.g., *Bag-Flight-Bridge*$\langle$*BagID, FlightID, SequenceIndex, TransitDuration*$\rangle$ where *BagID* and *FlightID* are foreign keys taken from *Bag* table and *Flight* table respectively.

However this type of implementation produces huge amount of data in the bridge table which results a low query performance due to join lot of data. In Figure 6 the *bag-flight bridge* table shows some examples of association between bags and flights. Even though bags *B1, B2* and *B6* follows same flights with same sequences, due to the database design they have to be inserted thrice. Moreover in the whole table there are 2 different collection of pairs for $\langle$*FlightID, Sequence*$\rangle$ i.e., $\{\langle F1, 1\rangle, \langle F1, 2\rangle\} \rightarrow 1$ and $\{\langle F1, 1\rangle\} \rightarrow 2$. The process of transformation this table is exemplified in Figure 6.

Specifically, we create a separate table called *BagFlightRoute* table. It contains an ID *BagFlightRouteID* for each distinct set of pairs. Also, we store the *flight string* and *route string* for each *BagFlightRouteID*. The features of these two strings are described in the earlier sub section. For each *BagFlightRouteID* the pairs and its related info is stored in the *FlightRouteBridge* table. Finally in the *bag* table each bag is assigned with its relevant *BagFlightRouteID*. It makes a one-to-many relationship between *BagFlightRoute* table and *bag* table. The discussed transformation reduces huge amount of rows which results better query performance.

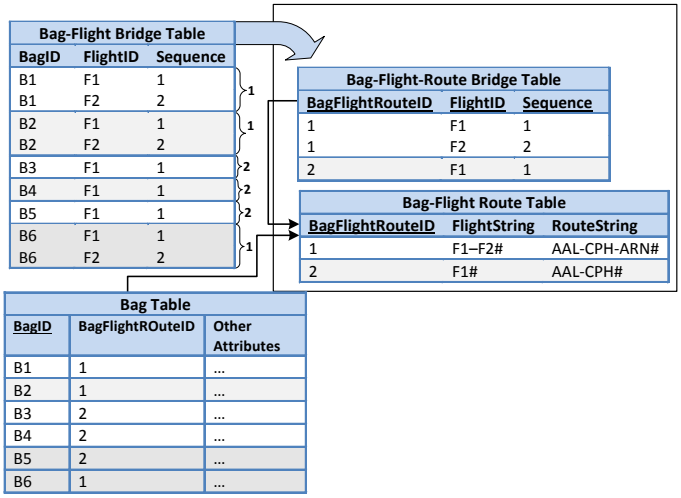


Fig. 6: Example of bag-flight many-to-many relationship

C. Fact Table

The *Fact_Stay* is the fact table and it binds the tracking records to the relevant entries in the dimensions. The relations to the *TimeOfDay* and *Date* dimension are represented twice for each *datetime* attribute from the source data. This is to store both the wall clock time, and the UTC time when considering tracking records from different sites, e.g. AAL where the standard time zone is UTC/GMT+1 hour, Los Angeles International Airport (LAX) where the standard time zone is UTC/GMT-9 hours etc. As an RFID reader does not cover the whole area of a location, the value of t_{out} in Table II does not necessarily give us the time when an object actually get out from a location. As in the airport baggage tracking scenario a bag moves from one symbolic location to another symbolic location sequentially, instead of storing this t_{out} we store the $time_{end}$ in the fact table which specify when the object reaches another location.

Attributes $FromLocation$ and $ToLocation$ specify the baggage movement from one tag reader location to the next tag reader location in its path sequence. Usually *time_start* and *time_end* of a particular bag indicates the $time_{in}$ at *FromLocation* and $time_{in}$ at *ToLocation*, respectively. However for the final location (which means there is no reading of a bag after this location), *FromLocation* is same as *ToLocation* and *time_end* specify the last reading time of the bag at this final location which is $time_{out}$ at *FromLocation*. The duration taken by a bag to go from *FromLocation* to *ToLocation* is stored in the *Duration* attribute. If *FromLocation* to *ToLocation* both are from same airport then the value of *Duration* also represents the time spent by a bag at *FromLocation*.

We store *HandlerID* for each movement of a bag to track the responsible handler of the bag for that specific location. If it takes longer than expected to transfer the bag between the tracked location or the movement of the bag is not correct, then it will be possible to know which handler actually handled that

section and this mishandling can be attributed to the quality of that handler. The status of a bag at each stay is stored in *StatusID* attribute. Storing both source and destination for each tracking record enables lot of opportunity for analysis of baggage flow from one location to another in an easy and efficient way. This technique also allows giving a status to each movement of a bag from one tag reader location to another. The *ResponsibleFlightID* column points to the *Flight* dimension to keep track which flight is responsible for the movement. It allows to find the baggage handling quality of different flights and airline. Additionally we store *FlightLegID* that points to *Dim_FlightRouteBridge* table. It helps to find how baggage handling quality affects for transit duration.

D. Cube Design

A multi-dimensional cube is built on top of the data warehouse described above. There can be various types of measures for answering different types of analytical questions on RFID baggage data. We give a few examples of analytical questions: a) *Average time taken by bags to move from sorter to gateway in Aalborg airport*, b) *Total number of bags handled by Copenhagen airport in the Christmas holiday*, c) *Total number of bag sent to wrong destination from Gteborg airport in weekends of January 2012*, d) *Maximum time taken by bags to go from check-in to sorter in Stockholm airport*. To answer these queries we used the following measures.

Duration, maximum duration, minimum duration, average duration. The *duration* column itself is used as measure and also enable other relevant measures like *maximum duration, minimum duration, total duration* taken by objects to go from one location to another. The *Duration* is also used for a computed measure *avg duration* i.e., the average duration taken by objects to move between locations. These measures are semi-additive and should be used with appropriate dimension to get relevant results. Because this is not meaningful to find the average, maximum, minimum duration without considering the *FromLocation* dimension. Moreover finding the sum of duration regardless of *Bag* dimension is also not meaningful. The use of maximum duration measure is shown in the following example MDX query in Q1. It returns a matrix showing max time taken by all bags to go from one tag reader location to another at AAL. In the query the parameter 2 for *descendants* function indicates two levels down from the airport level i.e., the tag reader level.

```
Q1. SELECT DESCENDANTS([FromLocation].[
    LocationHierarchy].[Airport].&[AAL], 2)
    on Axis(1),
    DESCENDANTS([ToLocation].[
        LocationHierarchy].[Airport].&[AAL],
        2) on Axis(0)
    FROM [cube_name]
    WHERE [Measures].[Maximum Duration]
```

BagID distinct count. The number of distinct *BagIDs* in the fact table and grouping this on interesting dimensions give lot of interesting results. For example, the number of bags traveled from one tag reader location to another, and one country to another or region to region, number of bags mishandled at different airports, number of bags traveled in different routes, etc. For example the following MDX query, Q2 shows the number of bags mishandled at different airports and the result is ascending order based on number of bag(s) mishandled.

```
Q2. SELECT [Measures].[Bagid Distinct Count]
     ON COLUMNS,
    ORDER(NonEmpty([FromLocation].[IATACode
        ].members),[Measures].[Bagid Distinct
         Count], DESC) On ROWS
    FROM [cube_name]
    WHERE DESCENDANTS([Dim Status].[Status
        Group].&Mishandled, 0)
```

Fact stay count. The number of stay records in the fact table can be used for many types of computed measures like percentage calculation, average calculation, etc. For example finding the average duration taken by bags to go from one tag reader location to another at Aalborg airport can be calculated by the following MDX query, Q3 where we use the measure Fact Stay Count.

```
Q3. WITH MEMBER[measures].[avgDuration]
     AS '[Measures].[Duration]/[Measures].[
         FactStayCount]'
    SELECT DESCENDANT([FromLocation].[
        LocationHierarchy].[Airport].&[AAL],
        2) on Axis(1),
    DESCENDANTS([ToLocation].[
        LocationHierarchy].[Airport].&[AAL],
        2) on Axis(0)
    FROM [cube_name]
    where [Measures].[avgDuration]
```

Incorporating Flight and Bag many-to-many relationship into the cube. Incorporating many-to-many relationship into a cube needs extra care. Because improper relationship between the dimensions and measures produce wrong aggregation results. As mentioned earlier we store both planned route and actual route of bags. The actual route taken by a bag is found from the tracking records stored in the fact table *Fact_stay*. On the other hand a long chain of relational tables are maintained between *Flight* and *Bag* table for planned route and flights. To get the aggregate results like the number of bags planned for traveling by particular flight or airline, the *Dim_Bag* table is used as fact table and a measure *Bag Count* is created on this fact. Here the dimensions to be used by the measure are *Dim_Bag, Flight* and *BagFlightRoute*. As *Dim_Bag* and *Flight* is related by the *Dim_FlightRouteBridge* table through *BagFlightRouteID*, an intermediate fact table is required to incorporate them in the cube. So the *Dim_FlightRouteBridge* table is considered as an intermediate fact table where this fact is related with the *Flight* table by *FlightID* and to the *Dim_Bag* table by *BagFlightRouteID*. Now the *Bag Count* measure of *Dim_Bag* has a many-to-many relationship in the cube through the intermediate fact table *Dim_FlightRouteBridge*. The implementation of this concept in MS Analysis Services can be seen in Appendix A-A. An example query on this relation can be *total number of bags planned to be carried by each airline* and this can be answered by the following MDX query.

```
Q4. SELECT [Measures].[Dim Bag Count] on
    COLUMNS,
    [Flight].[Airline].members on ROWS
    FROM [cube_name]
```

V. ETL Design

In this section, we present the Extract-Transform-Load (ETL) design for loading relevant data from source databases to the data warehouse. The design is shown in Figure 7.

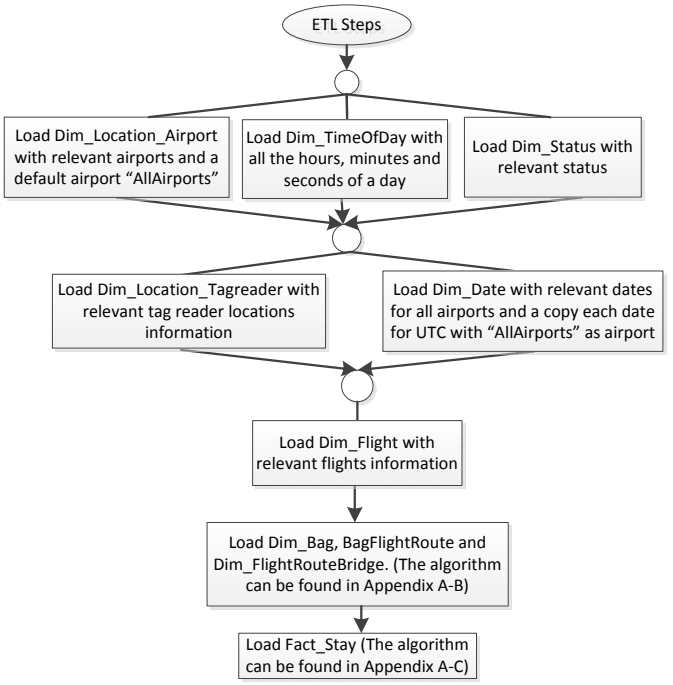


Fig. 7: Steps of ETL operation

First *Dim_Location_Airport* is loaded with the relevant airports as this table is independent of any other dimension. This table is also loaded with a default airport *"AllAirports"* and an airport *"INVALIDAirport"*. The default airport is used as a reference from the $Date$ dimension to handle UTC date and time. On the other hand *INVALIDAirport* is referred when there are some records containing some invalid values or null values. The *Dim_Location_TagReader* is loaded with tag reader information from the source data. Here also we have a default tag reader *UnknownReader* which points to *INVALIDAirport*. The name of the tag reader is made self contained, e.g., check-in1 reader of Aalborg Airport of Denmark is stored as *'DK.AAL.Check-in'*.

The *Date* dimension is preloaded with relevant years and the *TimeOfDay* dimension is preloaded with each second of a day. Both *Date* and *TimeOfDay* dimension is loaded for the airports where RFID readers are deployed and reading records are coming from these airports. There is a copy of Date for the default airport which is discussed earlier.

The *flight* table is loaded directly from the source data where date and time of departure and arrival is pointed to the *Date* and *TimeOfDay* dimension respectively. The departure airport and arrival airport points to the *Dim_Location_Airport* table.

The *Bag, BagFlightRoute* and *Dim_FlightRouteBridge* are loaded together at the same time from the source data. The detailed algorithm can be seen in Appendix A-B.

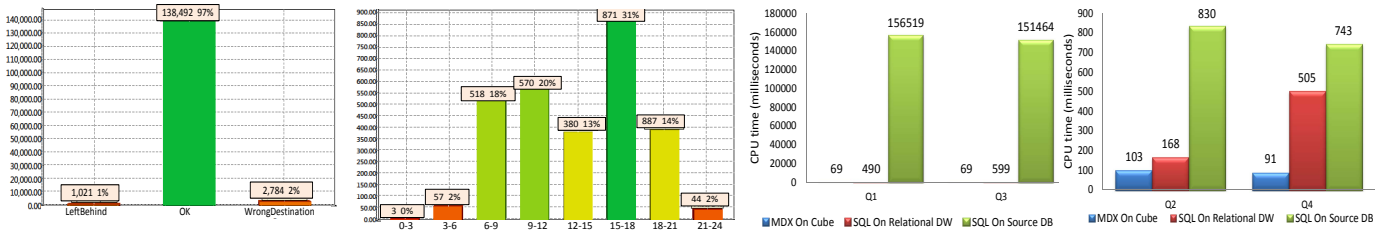
The fact table *Fact_Stay* is loaded by the tracking records and relevant data from the source schema. Some preprocessing like creating some views in the source data can make the loading steps much easier and faster. We create two database view for this purpose. One view is created inside data warehouse schema with structure: *v_bag_flight*$\langle$*BagID, FlightId, sequenceIndex, FromAirportID, ToAirportID, ActualDepartureTimeUTC, FlightLegID*$\rangle$ where the columns are taken by joining *Dim_Bag, Flight, Dim_FlightRouteBridge* tables of data warehouse schema. Another view is created inside source schema with structure:*v_track_airport*$\langle$*BagID, LocationID,* t_{in}, t_{out}, *AirportID*$\rangle$, where the columns are taken from the location tracking records of Table II and *Airport* Table of source schema. The *v_track_airport* includes *AirportID* which helps to easily track, when actually a bag changed its airport as well as tracking the responsible flight of a bag for the tracked airport. The overall algorithm to load the fact table can be seen in Appendix A-C.

VI. Experimental Results

We implemented the relational data warehouse in SQL Server 2008 R2 and the cube in SQL Server Analysis Services 2008 using MS Business Intelligence Development Studio 2008. The source data is stored in Oracle 11g. The ETL loads the source data from Oracle into the SQL Server DW and is implemented in C# with .Net framework 4.0. For advanced querying and visualization, TARGIT BI suite 2K11 is used. The experiments are conducted on a laptop with an Intel Core i7 2.7 GHz processor with 8 GB main memory. The operating system is Windows 7 64 bit. We use RFID-based airport baggage tracking data collected from 57 RFID readers deployed at 57 different baggage handling locations at 7 airports in 7 cities in 2 countries. There were 149K bags with 4M filtered RFID readings. There was a huge data reduction after conversion of the RFID readings into location tracking records where it becomes 483K records. The readings were taken between 15-Dec-2011 and 17-Apr-2012 and the bags traveled on 36K flights.

Example Analysis Results We have generated many analysis results from the cube using through TARGIT BI suite, some are described here. The bar chart of Figure 8a shows *bagID distinct count* per *Status* where the status is one of $\{$*OK, Left Behind, and WrongDestination*$\}$. This shows that 97% of the bags are OK, 2% bags sent to the wrong destination, and 1% is left behind. Figure 8b shows the value of *bagID distinct count* grouped by the dimensions $\{$*Status, and TimeOfDay*$\}$. The status is drilled down to *Wrong Destination* and the *TimeOfDay* is at the *DaySectionsIn3Hours* level. This shows that among the 2% bags sent to wrong destination, 31% of the mishandlings happened between 15 PM to 18 PM, i.e., improvement efforts should focus here.

Performance We tested the above MDX queries on the MS Analysis Services cube and produced equivalent SQL



(a) Overall baggage status (b) WrongDest/DaySectionsIn3Hours (c) Query Q1 and Q3 (d) Query Q2 and Q4

Fig. 8: Some analysis results and performance study

queries for both of the source database and the relational data warehouse. To allow direct comparison, the source data was migrated from Oracle into SQL Server 2008. To observe MDX query performance, MDX Studio[3] was used. To observe SQL query performance, SQL Server 2008 Profiler was used and the queries is executed in SQL Server Management Studio. Each query is executed 5 times and for each execution, the query editor software is restarted and the cache is cleared. Finally, the average execution time is reported in Figure 8c and 8d for each query.

Query Q1 and Q3 is reported together in Figure 8c as both of them works with duration between tag reader locations of Aalborg airport. For the source data the value of duration, FromLocation and ToLocation is calculated using complex SQL queries and some intermediate views on the filtered RFID readings. Due to the complexity some criteria e.g., the final location of an object is not considered (In DW FromLocation and ToLocation is same for the final location of an object). The results show that, for Q1, the CPU time on cube is 7 times faster compared to relational data warehouse and 2.3K times faster compared to source data. For the same query CPU time on relational data warehouse is 313 times faster compared to source data. Similarly for other queries, the results show that, the CPU time for all of the cases cube is significantly faster whereas the source database is significantly slower. The queries on relational data warehouse are also much faster compared to source database. The queries on the source database are very slow due to the huge data volume which is also not structured for analysis purposes. On the other hand, the proposed relational data warehouse is specially structured for analysis purposes and we also have reduced the data volume. Finally, the designed cube employs specialized MOLAP storage and has pre-computed aggregate results, which make the queries much faster. The differences between the execution times will become even larger for larger data sets.

VII. Conclusion and Future Work

In this paper we proposed a data warehouse solution for analysis of RFID-based airport baggage tracking data. We designed DW, including a number of complex dimensions and measures, in order to provide insight into the baggage tracking data and the reasons of baggage mishandling. We localized each date to a particular airport to capture special events related to that airport. We handled the many-to-many relationship between *Bag* and *Flight* dimension effectively both in the relational data warehouse and cube the design. The proposed data warehouse concepts can be used in similar types of indoor tracking application.

Future work will aim to solve the challenges encountered during this work as well as planned work. One important aspect is to scale the solutions to handle data from thousands of airport over long time periods, along with more precise capturing of the bag movement. This will require developing new pre-aggregation techniques. Another important aspect is to develop native support for *spatio-temporal sequences*, e.g., flight sequences, within the DW and BI tools, in order to get both more seamless querying and better performance.

[3]www.sqlbi.com/tools/mdx-studio/

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APPENDIX A

A. Implementation of Many-To-Many Relationship into Cube

Implementation of many-to-many relationship into cube in MS Analysis services is shown in Figure 9. The figure shows the dimension usage of SQL Server Business Intelligence Development Studio 2008 for the cube containing many-to-many relationship between *Bag* and *Flight*. For generating the figure, a Visual Studio add-in BIDS Helper[4] is used. From the figure we can see that *Dim_Bag* is used as both fact and dimension. Two measure groups on *Dim_Bag* and *Dim_FlightRouteBridge* are created. For *Dim_Bag* measure group the *Flight* dimension is used as many-to-many relationship where *Dim_FlightRouteBridge* is used as intermediate measure group. The *BagFlightRoute* is in regular relationship with the *Dim_Bag* measure group. Here the dimension column is *BagFlightRoute.BagFlightRouteID* and measure group column is *Dim_Bag.BagFlighRouteID*. Both *Flight* and *BagFlightRoute* dimension is in regular relationship with *Dim_FlightRouteBridge* measure group. For *BagFlightRoute* dimension the dimension column is *BagFlightRoute.BagFlightRouteID* and measure group column is *Dim_FlightRouteBridge.BagFlightRouteID*. On the other hand for *Flight* dimension the dimension column is emphFlight.FlightID and measure group colum is *Dim_FlightRouteBridge.FlightID*.

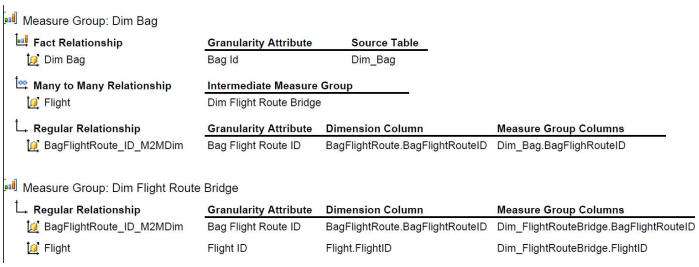

Fig. 9: Incorporating Flight and Bag relationship into cube

B. Algorithm: LoadBag_BagFlightRoute_FlightRouteBridge

The algorithm for loading *Dim_Bag, BagflightRoute and Dim_FlightRouteBridge* is shown in Algorithm 1 . In the algorithm at line 1, all the bags information is stored into variable*B* in the form ⟨*BagID, LicensePlate, FlightDate, Priority*⟩ as *BagID* wise ascending order. It helps to track easily which bags are already inserted into the data warehouse. If any error/failure occurs at the mid step during loading, we can quickly know which bags are already loaded by checking only the last inserted *BagID*. Putting additional condition: *Where BagID>Last inserted BagID* in line 1 of the algorithm can avoid reloading of existing bags and decreased the loading time. For each bag in the source data the algorithm gets all the flight info and the sequence of flights the bag has planned to travel. To find out the existence of a *BagFlightRouteID* for the bag with exact same number of pairs of ⟨*FlightId, SequenceIndex*⟩ we use the concept of relational algebra for *exact relational division* [11] or *relational division without reminder*. A general relational division does not consider exact number of pair. For example consider the data of table *Bag-Flight Bridge* of Figure 6. Let us assume in *Bag-Flight-Route Bridge* table there be only one *BagFlightRouteID* exist which is 1: {⟨*F1, 1*⟩, ⟨*F1,2*⟩}. To find out the existence of *BagFlightRouteID* for bag *B3* in *Flight-Route Bridge* table, the relational algebra expression for general division operation can be: ($\Pi_{BagFlightRouteID,FlightID,Sequence}$⟨*Flight-Route Bridge*⟩)÷($\Pi_{FlightID,Sequence}\sigma_{BagID=B3}$⟨*Bag-Flight Bridge*⟩). For example the operation: {⟨*1, F1, 1*⟩, ⟨*1, F1,2*⟩}÷{⟨*F1, 1*⟩} results 1. It seems that trying to find out the existence of *BagFlightRouteID* for bag *B3* by the given general division operation returns 1 which is not correct. Because *BagFlightRouteID* 1 contains more flight sequences and we need to get a *BagFlightRouteID* containing exactly the set of value pair⟨*FlightID, Sequence*⟩ of bag *B3* i.e., { ⟨*F1, 1*⟩}.

Algorithm 1 LoadBag_BagFlightRoute_FlightRouteBridge()

1: *B* := Set of all bags from the source data in the form ⟨*BagID, LicensePlate, FlightDate, Priority*⟩ in bagid wise ascending order;
2: *BR* := Set of routes of all the bags in the form ⟨ *Bagid, Flightid, Sequenceindex* ⟩ from the source data;
3: **for** each record $b_i \in B$ **do**
4: *R* := all the route info of bag b_i.*Bagid* from *BR*;
5: $U := \bigcup_{j=1}^{SizeOf(R)}$ ⟨ R_j.*flightid,* R_j.*Sequenceindex*⟩;
6: *result* := ExecuteQueryInDataWarehouse ⟨ *"WITH pair AS (SELECT U) SELECT b.BagFlightRouteID as BagFlightRouteID FROM Dim_FlightRouteBridge b LEFT JOIN pair p ON (b.SequenceIndex = p.SequenceIndex AND b.FlightID = p.FlightID) GROUP BY b.bagFlightRouteID HAVING count(CASE WHEN p.flightid IS NULL THEN 1 END) = 0 AND count(*) = (SELECT count(*) FROM pair)"* ⟩;
7: **if** *result.RowCount* $\neq$ *0* **then**
8: Insert into $Dim\_Bag\langle\ b_i.Bagid,\ b_i.Licenseplate,\ result.BagFlightRouteID,\ b_i.Priority\rangle$;
9: **else**
10: Generate FlightString and RouteString from BR and flight's source and destination information;
11: Add a new record to $BagFlightRoute$ table with a new $BagFlightRouteID$. This can be done by using database sequence or auto generated identifier;
12: Add records to *Dim_FlightRouteBridge* table with all the values of U and the new $BagFlightRouteID$. For *TransferDuration* subtract actual arrival time of current flight sequence from the schedule departure time of next flight. For the final flight of a $BagFlightRouteID$ put *TransferDuration* as 0 (Zero);
13: Insert into $Dim\_Bag\langle b_i.Bagid,\ b_i.Licenseplate,$ *The new BagFlightRouteID,* $b_i.Priority\rangle$;

To match the exact pairs it is important to count the number of pair(s) at divisor and divide it only with those dividend which contain the same number of pair(s) as the divisor. The concept of exact relational division is implemented by a complex SQL query shown in line 6 of Algorithm 1. Getting any row by executing this SQL indi-

[4]http://bidshelper.codeplex.com/

cates there exist a *BagFlightRouteID* with the given set of pairs (U of line 5 in Algorithm 1). If the SQL returns any *BagFlightRouteID* for this SQL, it inserts the bag with the returned *BagFlightRouteID* into the *Dim_Bag* table (line 8). In contrast with that, if the SQL does not return any *BagFlightRouteID* then a new record is inserted into the *BagFlightRoute* table with a new *BagFlightRouteID* (line 11). In line 13 it inserts the bag with this new *BagFlightRoute*.

C. Algorithm: LoadFactStay

The algorithm for loading the *Fact* table *Fact_Stay* is shown in Algorithm 2. As mentioned in the paper we have used some views to make the steps easy. The structure of the views are: *v_bag_flight*⟨*BagID, FlightId, sequenceIndex, FromAirportID, ToAirportID, ActualDepartureTimeUTC, FlightLegID*⟩ and *v_track_airport*⟨*BagID, LocationID,* t_{in}*,* t_{out}*, AirportID*⟩. At the beginning of the algorithm the tracking records, distinct *BagID* and flight info is loaded into variables (lines 1-3).

Algorithm 2 LoadFactStay()

1: *TR* := Set of all tracking records from *v_track_airport* in *BagID* and t_{in} wise ascending order ;
2: *B* := Set of distinct *BagID* in *TR* on *BagID* wise ascending order;
3: *BF* := Set of all flight records from *v_bag_flight* in *BagID* and *SequenceIndex* wise ascending order ;
4: **for** each BagID $b_i \in B$ **do**
5: *F* := All records for bag b_i from *BF*;
6: *R* := All tracking records for bag b_i from *TR*;
7: R_{end} := Last record of *R*; *seq* := 1;
8: **for** each record $r_i \in R \setminus R_{end}$ **do**
9: *fromLoc* := r_i.*LocationID; toLoc:=* r_{i+1}.*LocationID*;
10: *fromAirport* := r_i.*AirportID; toAirport:=* r_{i+1}.*AirportID*;
11: $time_{start}$:=$r_i.t_{in}$;$time_{end}$:=$r_{i+1}.t_{in}$;
12: *Duration* := $time_{end}$ - $time_{start}$; *Status* := "OK";
13: **if** *fromAirportID* = *toAirportID* **then**
14: Find the status of the movement and the responsible flight with the help of *F*.;
15: **else** ▷ // *fromAirportID* $\neq$ *toAirportID*
16: **if** *toAirportID*$\neq$ Airport of planned destination. Check this from *F* with the help of *seq* **then**
17: *Status* := "WrongDestinaion";
18: Find *ResponsibleFlightID* from *F* with the help of *seq*;
19: *seq*++;
20: **Insert** a new record into the Fact table with b_i, *fromLoc, toLoc, StatusID* for *Status, Duration, ResponsibleFlight, DateID* and *TimeID* of $time_{start}$, $time_{end}$ for both UTC, *fromAirportID* and *toAirportID*;
Now for the last tracking record *R_end*,
21: *fromLoc* := R_{end}.*LocationID; toLoc* := *fromLoc*;
22: $time_{start}$:= $R_{end}.t_{in}$; $time_{end}$:= $R_{end}.t_{out}$;
23: $Duration$:= $time_{end}$ - $time_{start}$; $Status$:= "OK";
24: Find the *status* and other attributes based on the above logic;
25: **Insert** a new record into the Fact table with b_i, *fromLoc, toLoc, StatusID* for *Status, Duration, ResponsibleFlight, DateID* and *TimeID* of $time_{start}$, $time_{end}$ for both UTC, *fromAirportID* and *toAirportID*;

For each bag the algorithm retrieves and determine necessary fields for each tracking record and insert it into *Fact_Stay* table (lines 4-27). For each bag the algorithm filters the records of the particular bag and keep them into variables (lines 5-6). As for the final tracking record of a bag the *FromLocation* and *ToLocation* is same in the *Fact_Stay* table, we separate that tracking record into a variable R_{end} (line 7). This record is handled separately for each bag (lines 22-27). For each tracking record of a bag except R_{end} (line 8), the algorithm determine the *FromLocation* and *ToLocation* (line 10), $time_{start}$ and $time_{end}$ (line 11), check whither the bag changes the airport or not (lines 13 and 16) and based on the information it determines the *Status* of that particular tracking record (lines 14 and 17). The variable *seq* is used to track how many airport is changed by the bag which helps to retrieve flight info for that particular sequence and also to determine the *Status*. For R_{end} the operations are very similar to the other records except the value of *ToLocation* (line 21) and $time_{end}$ (line 22). After retrieving and determining the values of necessary fields a record is inserted into *Fact_Stay* (lines 20 and 25).