Air Traffic Flow Management Data Mining and Analysis for In-flight Cost Optimization

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Abstract As the air traffic volume has increased significantly over the world, the great mass of traffic management data, named as Big Data, have also accumulated day by day. This factor presents more opportunities and also challenges as well in the study and development of Air Traffic Management (ATM). Usually, Decision Support Systems (DSS) are developed to improve the efficiency of ATM. The main problem for these systems is the data analysis to acquisition sufficient knowledge for the decision. This paper introduces the application of the methods of Data Mining to get the knowledge from air traffic Big Data in management processes. The proposed approach uses a Bayesian network for the data analysis to reduce the costs of flight delay. The process makes possible to adjust the flight plan such as the schedule of arrival at or departure from an airport and also checks the airspace control measurements considering weather conditions. An experimental study is conducted based on the flight scenarios between Los Angeles International Airport (LAX) and Miami International Airport (MIA).

1 Introduction

Air Traffic Management (ATM) is a complex process involving many attributes with on-line operation. Moreover, it is a chain with various factors that impacts the environment. A wrong or not previously evaluated decision in an interval could

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generate unexpected or unknown results in future instants. Hence, ATM is time contingent. Air traffic controllers do not have enough time to discover, analyze and evaluate potential impacts of previous decisions. Using well developed decision support system (DSS), the suggested actions to air traffic controllers can improve the air traffic flow management, safety, and also reducing the operational costs, etc.

To illustrate the possible chained impacts could be cited the overloaded maneuvering area, remote boarding and landing when this procedure is possible at the airport, retention of flights at the origin airport to wait for the flight crew or while the delayed flights are properly accommodated within the available air traffic flow. As the need to hold or forward aircraft in flight or wait on the runway, the operational cost with fuel and crew is affected and causes circular waiting en route near the airport until get authorization to land, and others.

The development of knowledge management has influenced many areas. However, there are two opportunities to scientific community: how lead with an amount of data so big in real-time and achieve useful results; and with Big Data available how improve the real-time decision support systems using historical information.

In the last decade, there has been a large increase in the number of databases, especially the unstructured data. To discover useful knowledge from these data is the new task for the government organizations and enterprises. This great mass of data, called Big Data, is presented in ATM environment too, which are from air traffic control process, whether information and airlines. In ATM systems, the study of Big Data is with the focus on the following two aspects: (1) ATM creates a huge amount of digital data such as radar data, restrict measurements applied by air traffic controllers, communication between pilots and controllers, flight plans, etc. [1]; (2) ATM needs to use information from various data sources such as meteorological data, GPS guidance, historical monitor images, etc.

Some approaches can be integrated to solve ATM problems such as to reduce operational in-flight costs for the airlines and passengers, improve airspace management and control with safety and cheaper air traffic fluency and reduce impact of decisions in airspace scenarios. Nowadays, there are conditions, data and knowledge to be used as input for intelligent systems to support decision process in air traffic management. The increasing amount of historical data provides both opportunities and challenges to improve the decision support systems.

The DSS comes as a great tool in the whole ATM environment, which can support in the automation processes with quick and easy information to controllers by impact evaluations, prediction analysis, improve the control on chained processes, and others. An important point of success in this domain is the air traffic controller confidence about each suggestion made by the system.

Considering the proposed suggestions are based on historical information, it will improve the acceptance by specialists day-by-day and also the speed of knowledge acquiring by new controllers. Hence, the knowledge acquired by the controller is transferred to the knowledge base. So, DSS will learn, adapt and suggest more appropriate decisions based on historical actions applied. The learning process of the system can be accomplished either on daily tasks as with the previously acquired knowledge.

This paper presents an approach in which Big Data structures are used to compile an appropriated knowledge for DSS in a real-time manner. The presented approach is developed in two steps. First, Bayesian network is used to conduct data mining in Big Data; second, a prediction rule structure is constructed in a real-time environment. The two-step approach involves the proposal of adjustment in a flight plan such as schedule of arrival/departure airport and checking in airspace controls considering schedule and/or weather conditions. The approach is demonstrated with air traffic between Los Angeles International Airport (LAX) and Miami International Airport (MIA).

The paper is organized in the following structure. Section 2, briefly reviews relevant research and concepts of Data Mining, Big Data, Bayesian network and ATFM. Section 3 proposes a Data Mining model for ATFM. Section 4 presents the case study and results. Section 5 concludes the paper with summaries and the direction of future study.

2 Related Concepts

This section briefly describe the related concepts of Data Mining, Big data, Bayesian network and also Air Traffic Flow Management.

2.1 Data Mining

Data mining is a process that aims to discover useful patterns and correlations through historical data [2–4]. This technique makes possible to discover relationships between business attributes and understand its process to take better actions based on real and specific knowledge for each situation.

The steps of data mining can be summarized such as business and data understanding; data preparation, selection, cleaning and modeling; knowledge discovery and evaluation; and data availability for use of specialists and/or decision support systems.

The Fig. 1 presents a basic Data Mining flow. It is possible to verify the process interactivity, which it is continuously improved, i.e., each phase or whole process is repeated according to how satisfactory it was the results or looking for business improvements.

Through Data Mining process is essential that DM experts work together with business specialists to achieve a better understanding about the business particularities. These specialists will interpret the achieved results, support the data correlation process, and others. The DM process can be explained in the following six steps.

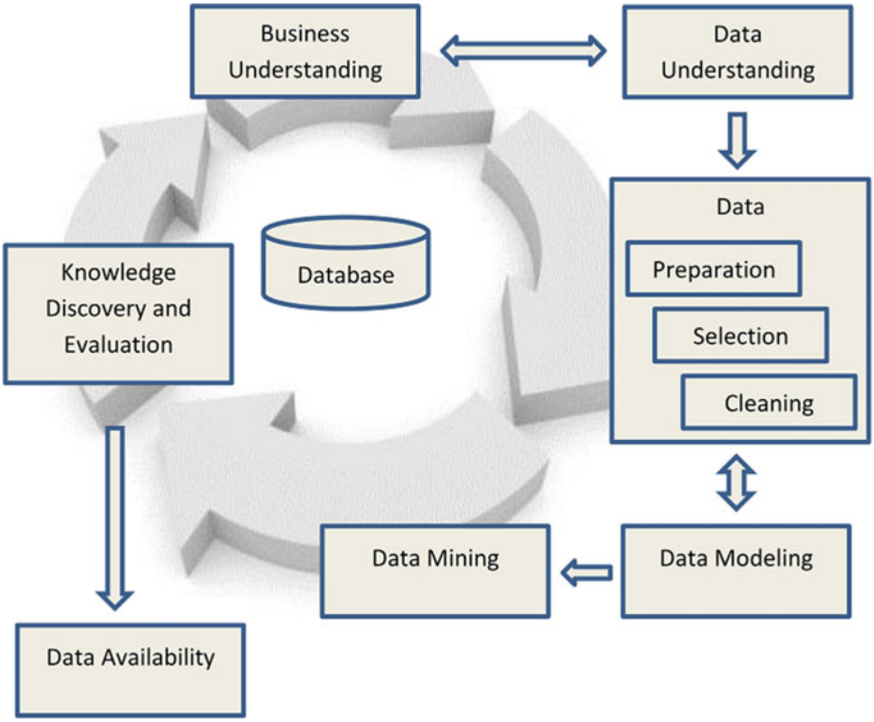

Fig. 1 Data mining flow

1. Business Understanding: This process will discover which goals might be achieved. The initial analysis of available data can determine which strategy will be used to select interest variables, evaluate information subgroups that are needed to develop the relationship among the data, and others.
2. Data Understanding: This step will analyze the data structures which will be processed and its computational requirements to be handled. Considering Big Data structures, it is important to perform tests in a reduced case study to evaluate and demonstrate that achieved results are relevant. Therefore, it will be possible a better data and business understanding about how all data are related and reduces the effort and time to develop the DM model.
3. Data Preparation, Selection and Cleaning: Considering Big Data structures, this step is the longest and hardest to complete due some reasons such as many different data sources, notations, values and meanings. The cleaning process will deal with missing, errors, outliers and integrity of preloaded data. This data processing must consider the business goals and its relationship among data.
4. Data Modeling: Considering Big Data structures, this step will create some Data Marts, which it will make possible to handle easier the data. These new structures organize the data as a Data Mining goal, which it can exists two or more goals in

the same DM process. Each Data Mart has all necessary related information to achieve the results of DM process.

5. Data Mining: This step is responsible to discover useful information in databases by data mining process and generate knowledge for decision process [4–8]. It is possible to be more specific about the tasks and its results such as description, classification, prediction, group and/or link. DM is a general concept which it can use many strategies and approaches to execute chosen task [9, 10]. There is a high computational demand to process all information in this phase.
6. Knowledge Discovery, Evaluation and Data Availability: After the Data Mining step, the information discovered will need to be analyzed by a business specialist to judge and understand the achieved results. This evaluation will determine if the process will need to be repeated from some specific step or the whole DM process again. In the evaluation task, it is possible to use statistics methods to prove and explain some discovered information which it will base the decision process with more confidence.

2.2 Big Data

The amount of available data is so big in many companies and authorities that a special term Big Data is referred to those data. Basically, Big Data is historical and useful data. As the time accumulated, the scale of data is so big and relates to many ones in the society. Data Mining can be used as a powerful technique to analyze and learn with Big Data and make structures that could be used as input for decision support system.

The major concern of using Big Data in real-time situations is how quick to achieve acceptable results. As it is necessary analyze so big and not-structured data or from many data sources, the DSS does not get to read these data and make available for the specialist in a real-time and critical environment, if it not be analyzed in a previous moment.

There is not a formal and unique Big Data definition for while. It can be described as a formal manner for knowledge discovery in so big data structures. Another way to explain this definition it is a manner used by companies to define strategies and tools to structure, handle, analyze and present the achieved results, expected or not, which it was discovered from big data structures. The complexity of analyzing big data is based on three factors: volume, velocity and variety, in order to base business specialists in their decision process.

- Volume: The size of data.
- Velocity: The speed of change in historical data.
- Variety: The number of data sources and how hard is to understand and merge.

These three factors make possible a better understanding about data fast increasing, variety about how these data are created, storage and made available for use and

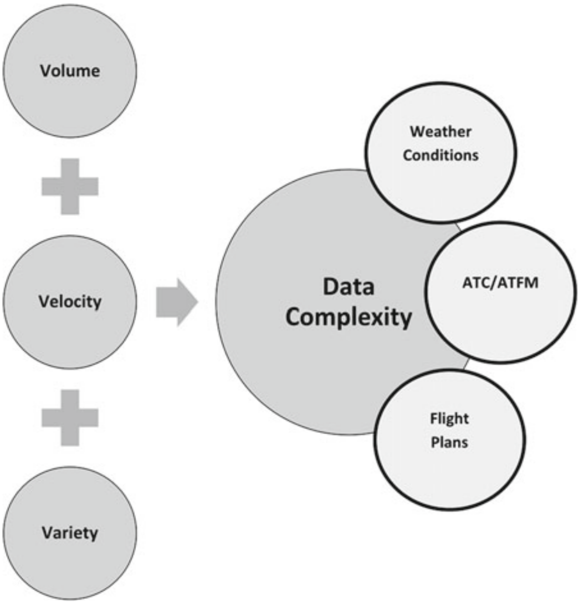

Fig. 2 Big data dimensions related with ATM

the impact of velocity on data that will be analyzed [11, 12]. Figure 2 presents the relationship of Big Data dimensions related with ATM.

To improve the data processing results, one manner is making the knowledge discovery process before the necessary time in two steps. First, it used a technique called Bayesian network that it will mining all available data and discover useful patterns and correlations. Second, it is created simple and fast structures to be used by decision support system in real-time. By this process, it will be created a prediction database, which contains rules identified by the first step ready to be read by DSS.

The use of historical data is an important step to improve and achieve a next step in decision support system. It is common using Data Mining techniques to acquire knowledge, however these data could be useful as input for other kind of systems, as it is proposed in this paper [13–15].

In the Air Traffic Management domain exists many opportunities to improve the decision support systems. Considering the critical real-time environment, the DSS suggestions might be clear and self-explained for air traffic controllers. Thus, the historical actions can improve the confidence of suggestions, once it is based on better similar historical actions.

2.3 Bayesian Network

Bayesian network is a structure which represent the correlations between attributes, in a specific domain, by using conditional probabilities [16–19]. Through these correlations are possible identify and understand how the domain is based on

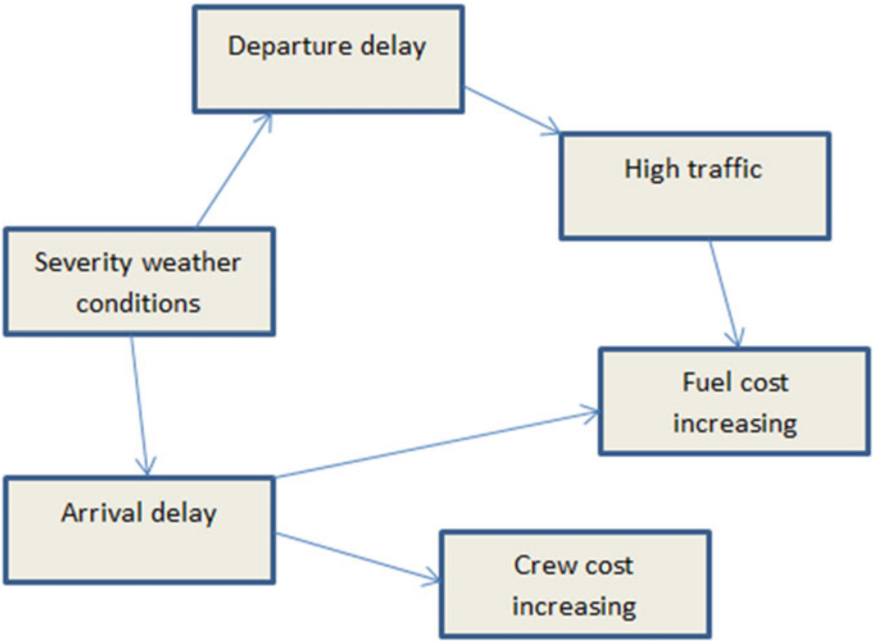

Fig. 3 Example of bayesian network

probability model and use this knowledge to take actions in similar situations. Figure 3 presents a basic example of how a Bayesian network could be constructed using ATM domain.

As it is detected probable association among variables and related uncertainty, Bayesian network arises as an important tool to identify and infer useful correlations which can be definitive, it usually happens due some aspects, or temporal, it was happening due some unusual environment.

To construct the network, it is necessary to perform a priori probability attribution for each correlation or use a learning algorithm. A Bayesian network is composed by following aspects [20]:

- Set of variables defined on a directed acyclic graph.
- The variables states are finite and mutually exclusive.
- For each variable X, with ascending $Y_1, \ldots, Y_n$, There is a conditional probability associated in $\mathrm{P}(X - Y_1, \ldots, Y_n)$.

The Bayes' Theorem can be applied as a way to calculate the posterior probability distribution based on the product proportion of priori distribution and the similarity function [21].

The priori distribution is an ad-hoc probability associated based on usual events in the environment, so using the theorem is possible to get a normalized probability which will represent better the probability for data analyzed.

$$\Pr(A|B) = \frac{\Pr(B|A)\Pr(A)}{\Pr(B|A)\Pr(A) + \Pr(B|\neg A)\Pr(\neg A)} \tag{1}$$

where:

$\Pr(A|B)$ it is the posterior probability distribution
$\Pr(A)$ it is the priori probability distribution
$\Pr(B|A)$ it is the conditional probability

2.4 Air Traffic Flow Management

ATM focuses on providing means to manage air traffic, taking into consideration factors such as security, planning, justice, finance and meteorology [22, 23]. By ATM the airspace can be monitored, controlled and the aircraft flow can be managed in an integrated manner. The ATM environment can be divided into three sectors:

- Air Space Management: ASM focuses on increasing the capacity of aircraft in the airspace, with the purpose of provide sufficient services for demand within the available structure.
- Air Traffic Control: ATC focuses on controlling the aircraft flight, providing mandatory information to preserve the safety.
- Air Traffic Flow Management: ATFM focuses on providing information to maintain the air traffic flow with safety and reduced impact on future scenarios.

ATFM is a complex procedure to avoid exceeding air traffic capacity and focuses on the supply of information to maintain the traffic flow with safety and less impact on scenarios that are necessary to take unexpected actions. The ATFM environment can be organized into three phases:

- Strategic Level: Considering tactical planning of flights and covering the period of forty-eight hours until the time before the flight.
- Operational Level: Focusing on strategic decision making and covering the period from forty-eight to two hours before the flight.
- Tactical Level: Considering tactical decision making and covering the period from 2 h before the flight until the aircraft arrives at its destination.

ATFM is responsible to assure aircraft traveling in a safe, quick, and economic way. It is responsible to avoid overloading facility capacity, optimize airspace usage, and provide information to responsible authority.

ATFM can guarantee that flights are conducted in a safe, quick, orderly and economic way. It is possible to avoid overloading in the air traffic capacity, optimize airspace and provide information to responsible authority [24–30].

Some activities from ATFM can be automate, partially or not, or improve using DSS. So, air traffic controller can monitor and analyze all aspects involved in the environment, such as meteorological aspects, evaluation of restrictive measures before to take some action, and verify alternatives for air traffic flows.

3 ATFM Data Mining Model

We proposed to use Big Data structures to discover an appropriated knowledge that is applied in real-time DSS for ATFM. The proposed method has two steps. First, Bayesian network is used to conduct data mining in Big Data; second, a prediction rule structure is constructed for real-time application environment. Figure 4 presents architecture that integrates Big Data analysis in decision support system for ATFM.

These rules are used to provide real-time knowledge for DSS in future times in order to reduce operating costs and increase safety with better-informed decisions. The proposed approach is performed in two stages: Preliminary Analysis and Data Analysis in Real Time.

It was developed a mechanism to discover patterns from historical information, considering big volume of data partial available. It aims to identify patterns on flights based on schedule, weather conditions, airports, and others, to use this information to conduct predictions.

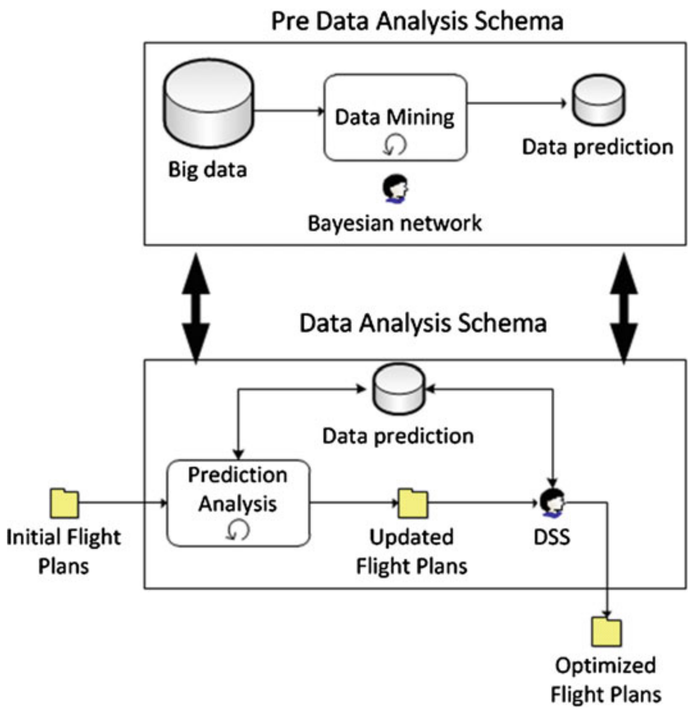

Fig. 4 ATFM data mining model overview

In the pre data analysis schema it is possible to develop a model which previous knowledge is analyzed offline with more time to create as many rules predictions as possible from data. During this first stage, Big Data structures are organized and analyzed to be handling by data mining process which uses Bayesian network to create this data prediction database. This step will be responsible for cleaning, organizing and structuring data and execute the processes of knowledge discovery to create forecasting rules, this will be used for Data Mining (DM) with the technique of Bayesian network. Data Analysis will use the knowledge generated in the previous step through the identified prediction rules. These structured rules will assist the decision making process of air traffic controller to be used, such as Multiagent Systems (MAS), Reinforcement Learning (RL) and Markov Decision (MDP) Processes.

Thus, it will be stored prediction rules based on historical information. The major objective is to discovery patterns that could be used to improve suggestions from DSS to airspace controllers. The model will combine the prediction rules and flight plans in a DSS simulated environment and suggest integrated actions to better decisions, i.e., considering the smallest impact on future scenarios. The smallest impact will be based on safety and reduce operating costs by improving the knowledge acquisition process in Big Data structures by own adaptation of decision support systems in real-time environments and improving on air traffic flow management.

At the end of this process, it had been created a data prediction database. Second phase will receive a group of flight plans to be analyzed in real-time environment. The prediction analysis process will verify the initial flight plans and compare with data prediction database, which it had been stored prediction rules based on acquired knowledge from Data Mining process.

At this moment, it generated updated flight plans that it could be used as input for DSS, which it can search more rules and create optimized flight plan as output from process.

The second phase aims to discovery similar situations and its variables looking for possible correlations between current situations and probability of achieve the results again. Considering this correlation, it is possible to select some actions as suggestions for airspace controllers, which will store all decisions taken to improve suggestions and learn with specialists.

4 Case Study

An experimental study is demonstrated with air traffic between Los Angeles International Airport (LAX) and Miami International Airport (MIA). This experiment is to identify patterns and correlations between departing and arriving flights in those two airports, and to update flight plans so that delay costs associated with extra crew hours and fuel burned.

More than 600,000 flights between 50 US airports were processed for this research, it was generated 25 tables with 25 GB of data. 719 flights from available data were analyzed. The major objective of this experiment is to create a schema that works and to achieve great results from a piece of big data, due the high cost of processing in this kind of structures. In this case study a big data structure was studied, however tests with a really big amount of data will be studied in future works.

The software were chosen with WEKA as it is one of the most popular applications in Data Mining area and the UnBBayes to generate the network. The task was association with Apriori algorithm, minimum support equals 90 % and minimum confidence equals 80 %. It was identified 42 attributes and chosen 7 to be used in first study: temperature, original departure, estimated departure, published departure, original arrival, estimated arrival and published arrival.

4.1 Results

The first study achieved promising results by identifying 6 rules from database structure available. These rules will compose data prediction database, which will be responsible to provide fast knowledge for DSS in real-time.

1. Original arrival between 5 and 7:30 pm and published departure delayed between 3 and 9 min, the published arrival delayed between 3 and 5 min in 64 % of cases.
2. Temperature is lower 55 F in arrival airport and published departure is delayed more than 4 min, the published arrival time increase about 20 %.
3. Estimated arrival is between 7 and 11 am and published departure was delayed until 7 min, the estimated arrival will be same as estimated arrival in 59 % of cases.
4. Temperature is lower 40 F in departure airport, the published departure increase more than 5 min in 27 % of cases.
5. Original departure between 6 and 8:15 pm, the flight period increases about 4 min in 70 % of cases.
6. Published arrival is delayed until 6 min from original arrival and temperature is higher 62 F, the aircraft will arrive in original time.

When initial flight plans are inside prediction analysis process, it will be evaluated if some flight plans match with some rule. In positive case, it will be adjusted by creating updated flight plans. This will be used in decision support system as suggestions for airspace controller verify and compare with original plan and take needed actions based on previous knowledge.

Considering these relationships the Bayesian network was developed. Figure 5 presents the influence correlation between each attribute. It is possible to verify that all attributes are much related, and this is a point that confirms a great chosen of attributes but this could limit more important and different patterns to be discovered.

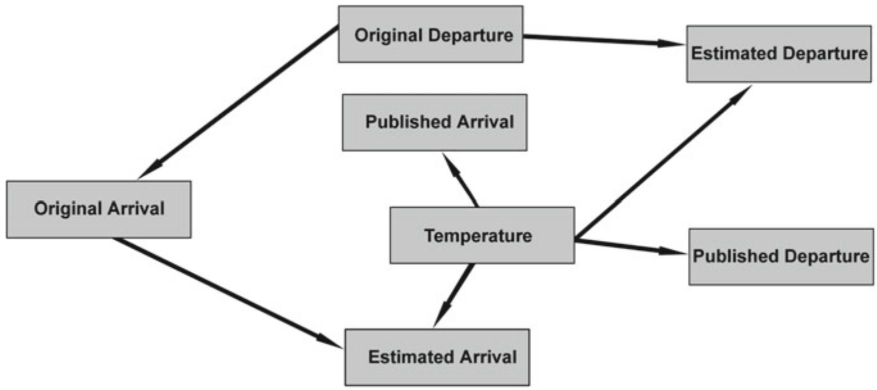

Fig. 5 Bayesian network

5 Conclusions

As the air traffic controller daily tasks are complex, there is necessary to provide decision support systems that could assists and provide suggestions and knowledge data to support their decisions. Nowadays, there are big amount of historical data which can be used to improve the decision process. Thus, it is possible to learn with this history, identify useful patterns, and make forecasts based on statistical events.

This proposal for ATFM domain is an experiment research to model these complex attributes and variables, which aims to create a fast process of data clean and load; data mining process that could identify attributes correlated as the influence of temperature, wind speed and forward a delayed flight in order to reduce operational costs; create a robust schema of predictions rules to support DSS operation; Based on these steps, the statistic makes better suggestions and adjustment in flight plans initially defined.

From the results achieved initially, it promises how to evaluate the complex process and to get the solutions for this kind of applications. It was identified 6 rules in the first study that it will be used to reduce in-flight costs considering costs of fuel and crew. When it is identified that some weather conditions repeats with great probability, the air traffic controller could take actions to make previous adjustment before aircraft take off, which will reduce many related risks.

The next steps for this research include more attributes for Bayesian network to identify new useful patterns and correlations, improve tests about minimum confidence and support to catch more possible patterns, increase amount of airports and flights, include more attributes and reports from METAR and TAF, and others. The DSS to support this kind of task will be developed based on presented approach, and used Reinforcement Learning and Multiagent System to model this approach. Moreover it will be created functions related with effectively crew and fuel cost to verify the financial impact of delays. Also, include the knowledge of the aircraft manufacturers, e.g., the speed at which the aircraft must fly at a certain altitude to have a great fuel consumption.

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