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Regression Methods Applied to Flight Variables for Situational Awareness Estimation Using Dynamic Bayesian Networks

Carlos Morales CMORRAM@CORREO.UGR.ES
Directorate General of Armament and Materiel
Ministry of Defence
28071 Madrid, Spain

Serafín Moral SMC@DECSAI.UGR.ES
Department of Computer Science and Artificial Intelligence
University of Granada
18071 Granada, Spain

Abstract

Situational awareness can be a valuable indicator of the performance of flight crews and the way pilots manage navigation information can be relevant to its estimation. In this research, dynamic Bayesian networks are applied to a dataset of variables both collected in real time during simulated flights and added with expert knowledge. This paper compares different approaches to the discretization of continuous variables and to the estimation of pilot actions based on variable regression, in order to optimize the model performance.

Keywords: dynamic Bayesian networks, regression, discretization, flight simulation, aviation, human factors, situational awareness

1. Introduction

Situational (or situation) awareness (SA) can be defined as the field of study concerned with quantifying the perception of the environment critical to decision-makers in complex and dynamic areas (Fracker, 1988). In the context of human factors applied to aviation, SA of flight crews usually depends on how the pilots receive and interpret a large amount of information. Their SA drives their actions during the flight and is reckoned to be a reliable indicator of the ability of flight crews to perform their missions safely.

Based on this assumption, a simulation environment has been implemented with the aim of creating a dataset with variables that mainly contain data from aircraft parameters, aircraft situation, pilot control actions and pilot management of flight information using an electronic flight bag (EFB). A post-flight analysis tool adds expert knowledge and performs calculations to summarize information and reduce time dependency of data, to make a selected group of variables in the dataset more suitable for Dynamic Bayesian Networks (DBN) to learn variable dependencies from data. This research previously focused on the issues of DBN for handling continuous variables and the impact of discretization alternatives on the performance metrics (Morales and Moral, 2015). This paper revisits the topic from the perspective of applying variable regression as a method to improve computational efficiency of DBN and contribute to the discovery of the relationships between the dataset variables that may drive the strategy to estimate SA in the future. The current experiment is performed using 10 datasets produced from 10 repetitions of a commercial flight plan, flown by several experienced pilots who control the aircraft changing the autopilot settings.

Our objective is to learn a dynamic Bayesian network modelling the relationships between the measured variables. It is important to remark that we have continuous and discrete variables. In a previous paper (Morales and Moral, 2016) we built a model based on discretizing the continuous variables and we applied an approach based on using linear regression to predict the continuous variables and discretize the error variables.

Section 2 explains the main characteristics of the dataset and how it has been complemented to allow DBN learning the dependencies between variables: including expert knowledge to help the DBN learn the correctness of pilot actions. The criteria to add summary variables that include information of past phases of the flight in the immediate previous time step, as required by DBN is also explained, relating the dataset variables to SA levels in terms of pilot perception and time dependencies.

Section 3 presents the research line followed to translate aeronautical and human factors criteria into a model for measuring SA with DBN. The focus is set on explaining how the model has been tested to compare direct discretization of continuous dataset variables with a discretization of the error from regression variables. Sections 4 and 5 present the results that show how regression-based DBN obtain better scores when they learn pilot actions, and highlight the next steps of the research.

2. The Dataset

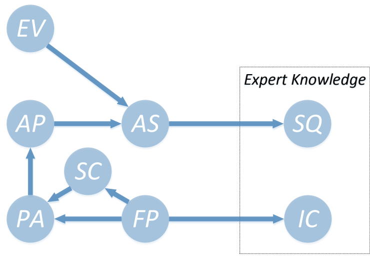
The simulation environment developed for this research collects data in real-time from a commercial flight simulator and from a desktop application in charge of the user interface. These applications are connected with software sockets to a local server that hosts the databases where the variables are stored. A post-flight application is used to add variables that require further calculations, including the ones that contain expert knowledge. A more detailed description of the simulation environment was provided in the previous work (Morales and Moral, 2016), together with an introduction to the criteria for producing summary variables. For offering a better understanding of the dataset, this section contains a short description of the variable categories and their relationships.

2.1 Categories of variables in the dataset

Although it is not required by DBN to establish categories among the variables in order to learn their relationships, the dataset variables have been tagged. The following groups have been identified for the sake of improving the understanding of the variables and to facilitate the detection of unexpected relationships:

- Aircraft situation (AS): these are parameters that contribute to define the position of the aircraft in the different axis, also taking into account the flight plan route that the aircraft is expected to fly. Parameters like aircraft altitude, geographic coordinates, distance to flight plan waypoints, etc. are included in this group.

- Aircraft parameters (AP): they may be directly or indirectly set by the pilot and their value can typically be checked in an aircraft instrument. These parameters may vary or oscillate without human intervention due to aerodynamics and thrust force momentum. At this stage of the research only engine power settings and aircraft pitch and bank angles are included in the dataset.



AS	Aircraft Situation	19
AP	Aircraft Parameters	4
EV	Environment Variable	4
PA	Pilot Action	21
IC	Information Check	37
SC	Situation Check	14
FP	Flight Plan	9
SQ	Situation Accuracy or Quality	11

119 variables, sampled every 7 seconds, 10 flights with durations from 54 to 64 minutes.

Figure 1: The dataset variables categories with their main expected dependencies before the regression experiment.

- Environment variables (EV): the current list includes wind speed and direction, external ambient temperature, and atmospheric pressure.
- Pilot actions (PA): these include actions to control the aircraft. For this experiment only the autopilot actions have been recorded, including those for setting aircraft altitude, speed and heading. This approach provides relevant data of the pilot intention to control the aircraft, without the simulation bias associated to manual control.
- Information checks (IC): these are pilot actions to check documents included in the EFB. This category also contains some variables with *a priori* incorporated expert knowledge for assessing if the information checked by the pilot is relevant for the current or the next leg (or segment) of the flight plan route. More details are provided in section 2.2.
- Situation checks (SC): these are based on pilot queries to obtain information about the position of the aircraft, based on a simulation of navigation instruments. Additional SC variables are calculated after the flight with enhanced context information about the anticipation taken by the pilot to perform these queries.
- Flight plan (FP): these variables contain flight plan information and are used to compare the flight path with the expected route.
- Situation accuracy or quality (SQ): including expert knowledge applied to AS and FP variables, to assess if the aircraft situation is suitable with respect to the flight plan or other factors related with the desired aircraft trajectory. Section 2.2 explains the principles that will be followed to add more expert knowledge once the regression experiment is finished.

Fig. 1 shows the dependencies between the identified variable types, that can be initially expected from domain knowledge. They are not the dependencies learned by the DBN, but a comparison of both may be relevant in future stages of this research. The number of variables for each category included in the dataset is also indicated.

2.2 Characteristics of the added expert knowledge

The current dataset includes two different types of expert knowledge: SQ variables contain *a priori* expert knowledge not particularized to any particular flight, that is based on general assumptions of compliance with standard flight quality criteria. Their discrete values indicate if the aircraft is too separated from the expected flight path or the required altitude.

On the other hand, IC variables have also been produced integrating *a priori* expert knowledge, but in this category the assessment is particularized to the planned route and should be adapted if the flight plan is modified. This expert knowledge consists on different discrete variables that rate the information checked by the pilot in terms of relevance, i.e., the query performed by the pilot is relevant according to the instant when it happens and it contains information that is necessary to ensure flight safety; and exclusiveness, i.e., the query provides information that can more or less be obtained from other sources.

Different values of IC values will vary to indicate from beneficial to distractive queries, whereas SQ values will indicate deviations based on the flight safety impact. In both cases the applied expert knowledge is causal, not requiring the knowledge of the future development of the flight to provide a SA estimation, even in real time. Future stages of the research may focus on adding *a posteriori* expert knowledge to the dataset in order to help training the DBN.

2.3 Summary variables

The DBNs we are considering are such that each variable depends only on the variables in previous time (Markov condition). In order to alleviate this restriction and to introduce dependences from a full time interval, we have created summary variables that contain information about what happened in the past. Since the current stage of the process is focused on the improvement brought by regression rather than summary variables, these are kept simple and no significant model performance increase is expected from them. Therefore, they basically perform a calculation of the average error of the aircraft position (SQ variables) and the expert assessment about relevance and exclusiveness of pilot information queries (IC variables). These averages are calculated for the total flown time, and for the last two and four minutes of flight, at each time step.

2.4 Dataset variable groups from the perspective of SA levels

The classical approach to provide a definition of SA based on three levels of perception was introduced by Endsley (1995), and it drives our strategy for the SA estimation.

- Level 1 SA - Perception of the elements in the environment: The measurement of perception-related variables for the current dataset is focused on the navigation information management, expecting low simulation bias as discussed in (Morales and Moral, 2016). Dataset IC and SC variable types are expected to contain information about level 1 SA, monitoring real-time pilot activities related to the retrieval of navigation information.

- Level 2 SA - Comprehension of the current situation: The most common approach to measure level 2 SA is based on techniques like the situational awareness Global Assessment Technique (SAGAT, Endsley et al. (1998)) that rely on obtaining direct and explicit feedback from the subject. As already discussed in our previous work (Morales and Moral, 2016), when the pilot behaviour is monitored in real time, the assessment on the pilot's comprehension of the situation is preferably inferred from his actions rather than from a conscious feedback. Variable types IC, SC, PA (containing pilot actions) and AS, AP, EV, FP, SQ (containing aircraft situation/condition) are therefore related to level 2 SA.

- Level 3 SA - Projection of the near future: The most important conclusion of Endsley (1995) is that pilots with correct SA not only perceive and comprehend, but also are able to predict the future flight evolution. This can not be reduced to associating good SA to the absence of crew mistakes or inaccuracies. Specially in high workload situations, pilot actions should be more focused on avoiding future problems rather than fixing past mistakes. The expert knowledge variables incorporated during the present stage of the research contain assessments related to pilot mistakes or inaccuracies during the flight and their evolution. DBN are expected to extract level 3 SA information from them.

3. SA measurement based on the estimation of pilot actions

As introduced in section 2, pilot actions are contained in PA, IC and SC variables of the dataset. This dataset contains ”correct” flights in which no important pilot actions are present. So, the learned model corresponds to good SA. Our plan for the future is: in a second stage we will learn a model in which each variable can only depend on the same variable in a former period of time: the idea is that this is the model corresponding to a bad SA. Finally we will define a Markov chain for the value of SA in different time points. As we have a model for SA and two different models depending on the value of SA, by applying probabilistic inference, we can compute in real time the probability of the SA of the pilot given the current set of measurements.

3.1 The Model

We will assume that we have repeated measures of a basic set of variables $\mathbf{X}$ in different time instants $t = 1, \ldots, m$. We will denote the variables $\mathbf{X} = \{X_1, \ldots, X_n\}$ on time t as $\mathbf{X}_t$ and the variable X_i on time t, as X_{it}. The model will be a dynamic Bayesian network (DBN) which has been implemented in Elvira environment Consortium (2002). At a first stage, we will consider the following assumptions:

- Markovian processes: probabilities at a given time step depend only in former time step, i.e. the set of parents for each variable X_{it} (denoted by Π_{it}) is included in $\mathbf{X}_{t-1}$. In some cases, this condition can be too restrictive, as there can be variables depending of a full period of time: $\mathbf{X}_{t-k}, \ldots, \mathbf{X}_{t-1}$ with $k > 1$. The objective of introducing summary variables is precisely this: to include on each instant of time $\mathbf{X}_{t-1}$ variables containing information depending of an interval of time and that it is considered as relevant to predict the values of variables in time $\mathbf{X}_t$.

- Stationary: transition probability between time steps is time independent, i.e. the conditional probability $P(X_{it}|\Pi_{it})$ is the same for any value of t.

In some cases, dynamic networks also include links between variables in the same period of time. In a first stage we will not include these links as in Morales and Moral (2016), but when introducing linear regression we will add some additional instrumental variables and we will make use of these links to relate them to the initial measured variables.

3.2 Discretization of Variables

Our problem contains continuous and discrete variables. A first approach is to discretize continuous variables as in Morales and Moral (2016). First, we introduce some notation: if X_i is a continuous variable taking values on U_i we will assume that U_i is an interval $[a^i, b^i]$. A discretization of this variable is a finite partition of $[a^i, b^i]$ in a finite set of subintervals $r^i_j = [a^i_j, b^i_j)$, $j = 1, \ldots, k_i$. Then the possible values of the discretized variable X^d_i will be the finite set of intervals $R^i = \{r^i_1, \ldots, r^i_{k_i}\}$. A probability distribution P about this variable will be a mapping $P : R^i \to [0, 1]$ such that $\sum_{j=1}^{k} P(r^i_k) = 1$. This probability distribution will be considered as an approximate density of the original continuous variable X_i. This density will be constant in each interval r^i_j and the total density of the interval will be $P(r^i_j)$, i.e. the associated density about X_i will be:

$$f(x) = \frac{P(r^i_j)}{b^i_j - a^i_j} \tag{1}$$

where r_j is the interval containing x ($x \in [a^i_j, b^i_j)$).

A first approach has been to consider several discretizations with thresholds provided by experts: *min Thr* contains a discretization with a number of intervals between 2 and 5, also determined by an expert as a minimum to avoid meaningless values. In the case of *10 Thr*, *20 Thr*, *50 Thr* and *100 Thr*, the number represents the number of intervals per variable.

3.3 Learning a Model

Once a discretization has been obtained, we can learn the structure of a DBN from a set of data with the measurement of variables in several flights $\mathcal{D} = \{D_i\}_{i=1}^{m}$ where each $\mathcal{D}_i$ contains the measurement of all the variables on a flight. To learn an optimal set of parents for each variable X_i, learning is based on finding for each variable X_i the set of parents Π_i optimizing one of the following metrics:

- BIC information criterion:

$$BIC(X_i, \Pi_i, \mathcal{D}) = \sum_{j=1}^{h_i} \sum_{k=1}^{l_i} N_{ijk} \log \frac{N_{ijk}}{N_{ij}} - (1/2) h_i (l_i - 1) \log(N)$$

- Akaike information criterion:

$$Akaike(X_i, \Pi_i, \mathcal{D}) = \sum_{j=1}^{h_i} \sum_{k=1}^{l_i} N_{ijk} \log \frac{N_{ijk}}{N_{ij}} - h_i (l_i - 1)$$

- K2 metric (usually the logarithm of this value is computed):

$$K2(X_i, \Pi_i, \mathcal{D}) = \prod_{j=1}^{h_i} \prod_{k=1}^{l_i} \frac{\Gamma(l_i)}{\Gamma(l_i + N_{ij})} \Gamma(1 + N_{ijk})$$

where N_{ijk} are the frequencies in the data $\mathcal{D}$ for which X_i takes the value x_k in time t given that the parents Π_i take the combination of values number j in time $t - 1$. It is assumed that there are l_i different values for variable X_i and h_i possible combinations of values of the parents. Also $N_{ij} = \sum_{k=1}^{l_i} N_{ijk}$ and $N = \sum_j N_{ij}$.

$BDEu$ is not used in this case, as in Morales and Moral (2016) we found that in some cases this metric was always increasing with the number of parents till the memory was exhausted. This happened when a variable has an almost constant value during the whole flight, so we do not use this metric. After the structure, the parameters for each conditional probability are estimated with Laplace correction (Neapolitan, 2004).

3.4 Learning a Discretization

In above subsection, the discretization was provided by an expert. Now we will consider the case, in which the discretization is also learned from data.

Given the hypothesis we have done about the densities associated to a discretization (see Equation (1)), this can be achieved by adding to the scores (in case of $K2$ to the logarithm of the expression we have given) the following value:

$$-\sum_{i\in C}\sum_{j=1}^{k_i} N_{ij}\log(b_j^i - a_j^i) \tag{2}$$

where C is the set of indexes of continuous variables that we want to discretize. This method is based on the procedure in Monti and Cooper (1998) for discretizing variables in a Bayesian network based on the same assumptions we have done and a non-supervised problem. If BIC score is used, it represents the application of the minimum length description principle.

With this complement, we have a score for a graph and a discretization. We could compute the graph and the discretization optimizing this score. However, we will perform a two step optimization: first we compute an optimal discretization for each variable with the empty graph (no parents for any variable) and then we learn the optimal structure as in the previous subsection.

To find an optimal discretization we use a greedy algorithm in which the possible interval limits are the middle points between the actual points of this variable in the learning data.

The search of a discretization of variable X_i starts with a discretization in which the interval $[a^i, b^i]$ is divided in two parts with equal frequency. Then a greedy procedure is repeated while there are improvements in the score: each actual interval is tested to be splitted in two parts with equal frequency, and when there are no improvements dividing intervals, then each interval is tested to be merged with the consecutive interval on its right.

3.5 The regression based model

Our previous experiments in Morales and Moral (2016) showed an improvement in performance when the number of intervals in the discretization was increased. When learning the discretization the performance was intermediate. The problem is that most of the continuous variables are such that its value on a time t is a small variation of its value on previous time $t-1$. In this way, it would have been more reasonable to discretize the differences $X_{it} - X_{i(t-1)}$. In this paper, we have gone an step forward, by trying first to make a numerical estimation of each continuous variable X_{it} using linear regression and with variables in previous time as predictors. In this way, the variable $X_{i(t-1)}$ will be considered as possible predictor of X_{it}. This has been done with R package `bestglm`. As the number of predictors is very high and to avoid overfitting, the number of variables in regression is limited to a maximum and the best model is chosen with BIC criterion. In our case, the maximum number of predictors has been selected to be 4 (this number of variables has shown to be enough to produce good estimations and though `bestglm` has a procedure to determine the optimal number of variables, it this maximum is not limited, the procedure is very time consuming given the large number of measured variables). . In all the cases, the most important variable to precitor of X_{it} has been $X_{i(t-1)}$ with a regression coefficient close to 1.0.

Assume that we have predicted X_t by means of a linear combination $a + b_1 Y_{t-1}^1 + \cdots b_k Y_{t-1}^k$, then our model includes in time $t-1$ the deterministic variable $Z_{i(t-1)} = a + b_1 Y_{t-1}^1 + \cdots b_k Y_{t-1}^k$. The values of this variable can be computed with the values of other variables in the same time.

Then in time t we add another variable, the error variable: $E_{it} = X_{it} - Z_{i(t-1)}$. Once, the regression is computed, then the dataset is expanded by including the artificial variables Z_{it} and E_{it}: $Z_{it} = a + b_1 Y_t^1 + \cdots b_k Y_t^k$, $E_{it} = X_{it} - Z_{i(t-1)}$.

With the expanded dataset, we estimate the model structure in the following way:

- Each variable Z_i is a deterministic variable depending of other variables in the same period of time, through its linear equation.
- Each continuos variable X_{it} is a deterministic variable equal to the sum of the artificial variable in previous period $Z_{i(t-1)}$ and the error variable of the same period, E_t.
- Each error variable E_{it} is discretized with the procedure of above subsection and its set of parents is computed by optimizing the score with a set of parents $\Pi_{i(t-1)}$ selected from variables in previous time, in the same way that it was done with continuous variables in previous approach.

It is important to remark that though E_{it} is computed from X_{it} and $Z_{i(t-1)}$, in the model is considered that E_{it} is random and that X_{it} is the sum of $Z_{i(t-1)}$ and E_{it}. This is the usual assumption in regression models, where it is assumed that a variable of interest is the sum of a deterministic function (in our case the value of $Z_{i(t-1)}$) and a noise (in our case E_{it}), though in the data the noise or error is computed by measuring the difference between the real value and the value of the deterministic function.

In classical regression, it is assumed that variable E_i is Gaussian and independent from the rest of the variables in the problem. In our case, we do not assume this hypothesis and consider that E_i is a variable which can depend on any variable in the previous period. We do not consider either that the errors are Gaussian, learning a generic distribution through the discretization and conditional probability estimation.

In the regression problem, the discrete variables X_i can also be an explanatory variable, with values $0, 1, \ldots, l_i - 1$ with l_i the number of elements of variable X_i. We also compute a discretization for variables Z_i and continuous variables X_i. This discretized variables can be parents of any discrete or error variable. The full model is represented in Fig. 2.

3.6 Testing a Model

Once a model is learned, its performance is measured using new observations of variables $\mathbf{X}$ in a new flight. Assume that we have a measurement of the variables $\mathbf{X}_t$ for a finite set of time steps $t \in T$. The idea is to compute the logarithm of probability (LP), $LP = \log(P((\mathbf{X}_t)_{t\in T}|M)) = \log(P(\mathbf{X}_{t_0})) + \sum_{t\in T\setminus\{t_0\}} \log(P(\mathbf{X}_t|M, \mathbf{X}_{t-1}))$, where M is the learned model and $t_0 \in T$ is the initial time.

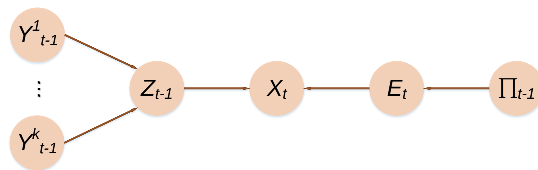


Figure 2: Regression model for the estimation of pilot actions.

If only discretization is used, then we start with $LP = 0$ and for each t and for each variable X_i in this interval we add the following values to LP: first we compute the observed values of its parents in former time interval $\Pi_{t-1} = \pi_{t-1}$, with these values and the conditional probability of the variable given its parents, we can select a discrete probability P_i for the values of this variable in time t. Then,

- If it is discrete and $X_{it} = x_i$, then we add $\log(P_i(x_i))$ to LP.
- If X_i is continuous and $X_{it} = x_i$ and x_i belong to interval r^i_k, then $\log(P_i(r^i_k)) - \log(b^i_k - a^i_k)$ is added to LP.

In the case of using linear regression, the computation is done in a similar way, but first we have to compute the values of instrumental variables Z_i (linear combinations) and E_i (error variables). Then, we take into account that variables Z_i and continuous variables X_i are considered as deterministic variables and then its true value is predicted with probability one (given the other measured and error variables). So, these variables add a value of $\log(1.0) = 0.0$ to LP. We have to apply above computations only to discrete variables and to error variables (with the same procedure that was applied to discretized continuous variables).

The greater LP results for model M than for model M', it should be assumed that the model M has better predicted the values of variables $\mathbf{X}_t$ than model M'.

If we are interested only in a subset $\mathbf{Y} \subset \mathbf{X}$ of the variables (for example the variables describing pilot actions) we could compute this value, but adding the computation of LP only for the variables in that subset (or the corresponding errors in the case of continuous variables with the regression model).

4. Results of the variable regression experiment

We have carried out a series of experiments in which we have repeated the learning of the model with 9 flights and tested it with the remaining one (as in 10-fold cross validation). We report the results of LP for the different discretizations and the regression model in the following experiments:

- Experiment 1: All the variables are used in the model and LP is measured for all the variables.
- Experiment 2: The summary and expert knowledge variables are not used and LP is only measured for pilot actions.
- Experiment 3: All the variables are used in the model and LP is measured only for pilot actions including consulting information (PA and IC variables).

When regression is not used, the discretizations we have tested are provided by the expert. Experiments for learning discretizations without regression are reported in Morales and Moral (2016) are they are not better than the results obtained with a large number of intervals. In the LP model the error variable is not known in advance and therefore the intervals have to be learned with the procedure in Subsection 3.4. Other continuous variables are also discretized with the automatic method, but this discretized variables can only appear as parents variables.

The results of these experiments are given in Tables 1, 2, and 3, respectively. We see the following facts:

- Without regression: using a large number of discretization intervals is better, also with the extra variables added, and when we focus on pilot actions. This is in accordance with the previous discretization experiment. This is due to the fact that in our model we assume that the density is constant in each interval of the discretization and then $-\log(r_i)$ is added to the likelihood where r_i is the length of the interval to which the value of X_i belongs. This factor has a big impact and gives rise to a preference for larger discretizations with smaller a_i values.

- Using regression plus discretization is always better than just discretization. The differences are of several orders of magnitude with models that are of smaller size than the large discretizations, though we have not carried out statistical tests. Here the impact of using a high number of intervals is not so important, as only error variables are involved in the likelihood computation and the values of these variables are concentrated around 0 (in contrast with initial variables that have their values distributed in a large domain).

- Regression benefits from the use of summary variables and expert knowledge, however the differences are not very important. In the case of discretization, the use of summary variables does not change the results of the experiments.

- There are no meaningful differences between using the different scores: if we focus on the regression model, the model learned with K2 is better when estimating all the variables (experiment 1) but BIC it is the best one when learning only the pilot actions (experiment 2).

5. Conclusions and future work

As a project to on-line assess the aircrew SA, we have considered several alternative models to estimate the pilot actions as a function of variables measures during a flight. In this paper, we have proposed a model in which linear regression is used, but as the produced errors are not assumed to be independent Gaussian, we have considered that they can follow an arbitrary distribution that can depend on any of the measured or artificially built variables. The dependences and the distribution are estimated by discretizing the error variables and applying methods based on learning discrete dynamic Bayesian networks. The use of this procedure is shown to have a much better performance than our previous approach based only on discretizing the continuous variables.

We see two directions for the future: first try to improve the model to predict pilot actions, by adding more artificial summary variables (their suitability can be tested by checking improvements in the LP measure), to consider a more proper treatment of discrete variables by considering for example a different regression model for the different values of a discrete variable having influence in a continuous variable or using alternative models for continuous variables as the ones in R. Rumí

	min Thr	10 Thr	20 Thr	50 Thr	100 Thr	regression
BIC Score	$-9.300e5$	$-6.690e5$	$-5.699e5$	$-6.360e5$	$-5.676e5$	$-2.475e5$
Akaike Score	$-9.310e5$	$-6.682e5$	$-5.655e5$	$-4.271e5$	$-5.075e5$	$-2.450e5$
K2 Score	$-9.305e5$	$-6.694e5$	$-5.653e5$	$-4.188e5$	$-3.602e5$	$-1.989e5$

Table 1: LP values for the estimation of all variables and using summary variables.

	min Thr	10 Thr	20 Thr	50 Thr	100 Thr	regr. w/o
BIC Score	$-1.408e5$	$-1.034e5$	$-9.680e4$	$-1.034e5$	$-9.280e4$	$-2.162e4$
Akaike Score	$-1.398e5$	$-1.021e5$	$-9.235e4$	$-8.082e4$	$-8.966e4$	$-2.378e4$
K2 Score	$-1.409e5$	$-1.032e5$	$-9.330e4$	$-7.886e4$	$-6.548e4$	$-2.184e4$

Table 2: LP values for the estimation of pilot action variables, without using summary variables.

and Moral (2006); but we think that the most meaningful step would be to include SA variables in the model considering that the model in this paper corresponds to a good SA and building a simple model in which each variable depends only on the same variable in the previous period time, corresponding to the case of a bad SA, so that we can compute and only probability for SA variables given the available observations.

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	min Thr	10 Thr	20 Thr	50 Thr	100 Thr	regr. w/
BIC Score	$-1.408e5$	$-1.034e5$	$-9.680e4$	$-1.034e5$	$-9.280e4$	$-2.109e4$
Akaike Score	$-1.398e5$	$-1.021e5$	$-9.235e4$	$-8.078e4$	$-8.974e4$	$-2.281e4$
K2 Score	$-1.409e5$	$-1.032e5$	$-9.330e4$	$-7.886e4$	$-6.548e4$	$-2.148e4$

Table 3: LP values for the estimation of pilot action variables, with the use of summary variables.

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