Towards a method to analyze the problematic level of Barrier Crossing
(Vers une méthode d'analyse de la problématique du franchissement de barrière)

Zhicheng Zhang, Philippe Polet, Frédéric Vanderhaegen, Patrick Millot

LAMIH -SHM, UMR CNRS 8530,
University of Valenciennes,
Le Mont Houy, Valenciennes, 59313
{zzhang; ppolet ; frederic.vanderhaegen; patrick.millot}@univ-valenciennes.fr

Summary

Barrier Crossing (BC) is one safety related violation, and the analysis of BC can be undertaken in term of benefit, cost, and possible deficit. In order to integrate the BC theory into the new BC analysis for the designer during the early design phase or in the re-design work, a method integrating the Self-Organizing Map (SOM) is proposed. This is an artificial neural network which, on the basis of the information contained in a multi-dimensional space, generates a space of lesser dimensions. The proposed method can be used, in one part, to foreseen the problematic level of a new barrier (prospective analysis), and in another part, to identify or to regroup synthetically the barriers of a given Human-Machine System (HMS) which were often crossed (retrospective analysis). Finally, application of this method into the BC analysis on experimental railway simulator has been implemented, and some results have been presented.

Le Franchissement de Barrière (FB) est une violation de la sûreté, et l'analyse du FB peut être entrepris en terme du bénéfice, du coût, et du déficit potentiel. Afin d'intégrer la théorie du FB dans l'analyse du franchissement d'une nouvelle barrière au début de la conception ou pendant la re-conception, une méthode basée sur des cartes auto-organisatrices (SOM) est donc proposée. C'est un réseau de neurones artificiel qui, sur la base de l'information contenue dans un espace multidimensionnel, produit un nouvel espace de dimension moindre. La méthode proposée peut être utilisée, d'une part, pour prévenir le comportement humain face à une nouvelle barrière (analyse prospective), et d'autre part, pour identifier ou regrouper synthétiquement les barrières d'un Système Homme-Machine donné qui ont été souvent franchies (analyse rétrospective). Finalement, l'application de cette méthode dans l'analyse du FB dans un simulateur ferroviaire a été mise en application, et quelques résultats sont présentés.

Introduction

The traditional approaches to HRA became the target of widespread criticism in the beginning of the 1990s. Researches on the 1st generation HRA approaches show that the results obtained by different human centered methods often differ one from another [1]. They have been considered to be inadequate in explaining the real issues confronting operators and maintainers in Human-Machine System (HMS).

- There has not yet been a demonstration of satisfactory levels of between-expert consistency/agreement in use of expert-judgment methods, the accuracy of predictions is not satisfied.
- Some approaches require a strong operational database or knowledge on human error in order to assess or estimate the probability of human error occurrence. Most industrial application cannot use those methods because this database or knowledge does not exist or is incomplete [2].
- Insufficient calibration of simulator data because the simulator is not the real world, the problem remains of how raw data from training simulators can be modified to reflect real-world performance; The other disadvantage is that the simulation experiment data did not always support this kind of model [3].
- Most of them did not realize that Performance Shaping Factor (PSF) difficult to be dealt with alone, it should be treated with system conditions; The relationship between various PSFs was not taken into account; Thirdly, some PSFs, such as managerial methods and attitudes, organizational factors, cultural differences, and irrational behavior were not adequately treated.

As a result of this awareness, a number of different methods and models (so-called 2nd generation HRA) have been proposed, e.g. ATHEANA [4], CAHR [5], COGENT [6], CREAM [7], HDT [8], HERMES [9], MERMOS [10], RECUPERARE [11] etc. Based on a requirements table structured according to the criteria of objectivity, validity and reliability, these methods/models were comprehensively evaluated [12].

After systematic survey on 2nd generation HRA methods, one may find that few of them can be used to accomplish the on-line safety analysis; In addition, it should be noted that many of these methods have not yet matured into full-blown HRA methods.

In order to consider both off-line and on-line prevention support specification into the global system development during the safety analysis phase, a new approach APRECIH (French acronym for Preliminary Analysis of Consequences of Human Unreliability) [13, 14] is therefore proposed. It is divided into four main steps: functional analysis, procedural and contextual analysis, human task feature identification, consequence analysis. APRECIH was firstly extended to specify a multi-objective analysis of safety related violation called Barrier Crossing (BC) [15].

BC is a safety related violation. The analysis of BC can be undertaken in term of benefit, cost, and possible deficit. To integrate the BC theory into the new BC analysis for the designer during the early design phase or in the re-design work, after discussing the existing problematic and the selection of adopted neural network model, a method integrating the Self-Organizing Map (SOM) is proposed in the following section, and then, we present experimental results from the application of SOM to our BC experimentation data. The final section provides conclusions and offers future research directions.

Reminder of BC analysis

There are often some differences between the task prescribed by the designer and the effective task in its operational context due to various individual or technical or environmental factors. In some industry fields, for instance NPP, there is "waiver" which sometimes occurs. In this case, the utility waiver report should be submitted for the approval of safety authorities prior to execution.

During the review of waiver report, it is always difficult to evaluate and then judge if it is acceptable, as there is no existing guideline or technical issue to be followed. In fact, even if both of normal operation condition (including start-up, power operation and outage) and incident/accident condition have generally been taken into account during the design period, this kind of activity is rarely predicted by the designers as it belongs neither to the designer's normal operation condition, nor to the incident/accident one.

For the user of HMS, the routine operation condition is sometimes different from the one of designer, it includes,

a. The work conditions predicted and defined by the designer;
b. The work conditions accepted by the user, they can be further divided into two subgroups:
   b1. Some conditions which have been listed by the designer as the unacceptable conditions during previous design phase, they are accepted by user after a compromise among various individual or technical or environmental factors;
   b2. Some conditions that have not yet been taken into account by designer, or have been realized ambiguously and have not been written down.
   User tolerates both of subgroups after an operation period without occurrence of any incident/accident.

The waiver can be seen as the case (b). The activities relative to this kind of work condition have occasionally been implemented by the utilities. Unfortunately most of 2nd generation HRA methods have not taken into account this issue, neither does the traditional risk analysis methods for designer. "Rule violation tasks should be assessed where the technique claims to be able to quantify such error types"[1].

BC can be considered as migration. Figure 1 is one simplified process of migration mode in the operation of HMS. In the figure, "decommissioning" means the action of taking a HMS out of service.

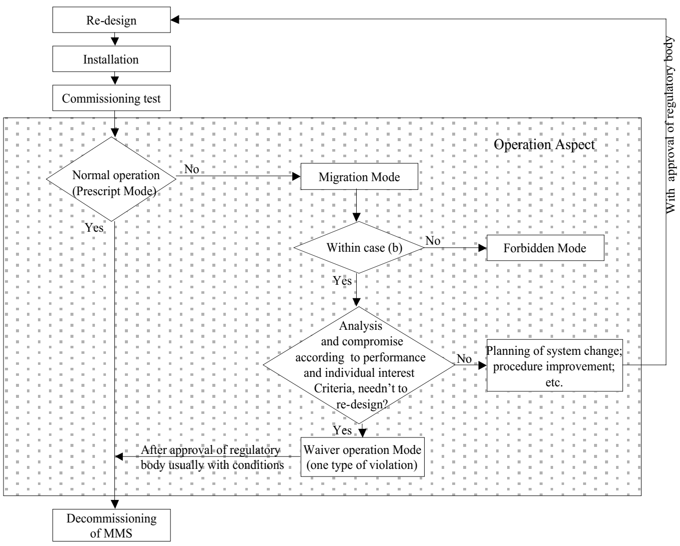

Figure 1 – Process of migration mode in the operation of HMS

The BC can be analyzed according to three attributes [2],
The immediate cost of crossing: in order to cross or remove a barrier the human operator has to modify sometimes the material structure, and/or the operational mode of use. That usually leads to an increase in workload and can have negative consequences on productivity or quality.
The expected benefit: a barrier crossing is goal driven. Crossing a barrier is immediately beneficial and the benefits outweigh the costs.
The possible deficit: a barrier that is crossed introduces a potentially dangerous situation. So, the crossing of a barrier has also a possible deficit due to the related risk.

Table 1 gives an example of the different qualitative probability values for BC taking a binary viewpoint (either High or Low). In general speaking, the probability of crossing a barrier will be high when the benefit outweighs the cost and the perception of the possible deficit.

As indicated in the table 1, the probability of the particular cases (e.g. case 1 and case 8) can be easily determined: case 1 represents a situation with a high benefit, low cost and low possible deficit, so it is very likely that such barriers will always be crossed; Case 8 represents a situation with low benefit, high cost and high possible deficit, so, it is very likely that this case will never be crossed.

For other cases, it is not so easy to classify or distinguish the level of the probability (or consequence) of BC (whose outcome is undetermined (?)); Secondly, if the sub-category regarding each criterion is divided into more detail (e.g. benefit may be determined as very low, low, normal, high, very high, as well as the cost and possible deficit), the classification of the final probability of BC will be more difficult (i.e. more numerous the sub-levels are, more difficultly the identification of probabilistic level of BC is).

Case	Benefit	Cost	Possible deficit	Probability of crossing
1	HIGH	LOW	LOW	HIGH
2	HIGH	LOW	HIGH	?
3	HIGH	HIGH	LOW	?
4	HIGH	HIGH	HIGH	?
5	LOW	LOW	LOW	LOW
6	LOW	LOW	HIGH	LOW
7	LOW	HIGH	LOW	LOW
8	LOW	HIGH	HIGH	LOW

Table 1: Example of probability of barrier crossing [16]

Moreover, during the BC analysis, for each barrier class, the levels of all three indicators (benefit, cost, possible deficit) are usually provided in term of four sub-criteria _ productivity, quality, safety and workload (usually, some of them may consist of several aspects, e.g. safety may be considered as, in railway domain, e.g. face-to-face collision, overtaking collision, derailment etc.). It will be more complicated to directly identify the final probabilistic level of one BC, to easily group the similar BCs in synthetic way, and will be more difficult to make the prediction for the probabilistic level of new BC.

To solve this kind of problem, furthermore, and to integrate the BC theory into the new BC analysis for the designer during the early design phase or in the re-design work, a method integrating the Self-Organizing Map (SOM) is then proposed.

A method to analyze the problematic level of BC

Based on the BC analysis according to the benefit, cost and possible deficit, we would like to easily find out how these indicators influence the final crossing/non crossing result, the intra-relations (between the different sub-criteria for same indicator) and/or inter-relations (between three indicators), and which barriers are similar (they have similar features) among all barriers of HMS, or in other words, grouping or classification of all these barriers in several categories.

Normally, for the given barriers (e.g. during the simulator experiment), crossing of a barrier can be easily observed, it means that all these barriers can be divided into two groups _ barriers crossed and barriers respected/non crossed. However, it isn't easily to know which barriers are similar ones among all barriers. In addition, for the barriers to be studied in a HMS, their final synthetic/probabilistic levels of the crossing are unknown in advance, i.e. we are not sure how many final output classes are suitable. Thirdly, when the (re)design of a new barrier needs to be implemented, it's better to predict, first of all, its final probabilistic level of the crossing, then retrospectively, integrating the user's viewpoint during the early phase of the (re)design. So it evokes the artificial neural network, Self-Organizing Map (SOM).

Setting up of Self-Organizing Map (SOM)

As an artificial neural network model, the Self-Organizing Map (SOM) as originally proposed by Kohonen (1982) is designed for multidimensional data reduction with topology-preserving properties, and thus they are also known as Kohonen maps. Previous applications of SOM methodology resulted in some successful implementations for solving a variety of categorization, pattern recognition tasks, reduction of dimensions and the extraction of features [17].

As there are a number of technical issues that must be dealt with in the application of both neural network logics in general and Kohonen's algorithms in particular. The explanation of these issues in detail is beyond the scope of this paper. So, only the aspects that are relative with our project will be introduced briefly.

Generally, the SOM network is based on an unsupervised learning algorithm [18]. A supervised-learning algorithm can be sometimes used if the input vectors are known to belong to some predefined classes, a more detailed description of the training process for the supervised-learning algorithm can be found in [17, 19]. In other words, there is no outside information that denotes a correct classification of the input data vectors. A SOM network constructs a low- (one or two-) dimensional mapping in order to detect the inherent structure of high-dimensional input data in a visually easily unsupervised manner.

The SOM network architecture consists of two neural layers (see figure 2 for a graphical illustration of a SOM).

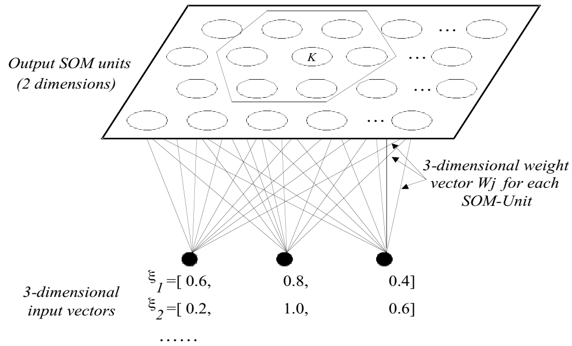

Figure 2: Graphical illustration of an SOM architecture (notice that the input data is 3-dimentional in the figure, it can be more than 3-dimentions, e.g. 21 dimensions in the application section)

The input layer has as many neurons as it has indicators (e.g. benefit, cost, possible deficit). Let *m* be the number of neurons in the input layer; and let $n_x{*}n_y$ the number of neurons in the output layer which are arranged in a rectangular or hexagonal patterns with *x* rows and *y* columns, which is called "the map". Each neuron in the input layer is connected to each neuron in the output layer. Thus, each neuron in the output layer has *m* connections to the input layer. Each one of these connections has a synaptic weight associated with it. Let W_j the weight vector associated with the connection between m input neurons $i=1,\ldots, m$ and one output j $(j=1,\ldots, n_x{*}n_y)$ (see figure 2).

The SOM tries to project the multidimensional input space into the output space (SOM map) in such a way that the input patterns whose variables present similar values appear close to one another. In our case, the input data could be BC indicator information. Each neuron in the output layer learns to recognize similar input patterns whose images, therefore, will appear close one another on the created map. In this way, the essential topology of the input space is preserved in the output space. To achieve this, SOM uses a competitive algorithm known as "winner takes all".

The SOM algorithm can be briefly described by the following iterative procedure (see figure 3):

Firstly, the initial W_j $(j=1,\ldots, n_x{*}n_y)$ are given small random values, or other initialization method can be adopted which allows the computation/training of the SOM faster (e.g. W_j are initialized linearly) [17]. These values will be corrected as the algorithm progresses (training). Training proceeds by presenting the input layer with barrier indicators.

The input indicator vectors ξ can be presented sequentially (one barrier at a time) or in batch (the data set is presented to the SOM as a whole such that the SOM is trained faster, and the new weight vectors are weighted averages of the data vectors) from the set of training vectors and compute the Euclidean distances $D_j = \| \xi - W_j \|$ $(j=1,\ldots, n_x{*}n_y)$ between this input indicator vector and each of the present values for the units' weights vectors. Here is an example of input vector, if "benefit"= normal, "cost"=very low, "deficit"=low, then input vector ξ is [0.6, 0.2, 0.4]; The Euclidean distances of map units $1, \ldots, n_x{*}n_y$ are computed through this input vector ξ [0.6, 0.2,0.4] minus the current weight vector for each SOM-unit (Cf. figure 2). The output neuron for which $min\| \xi - W_j \|$ is the "winner neuron".

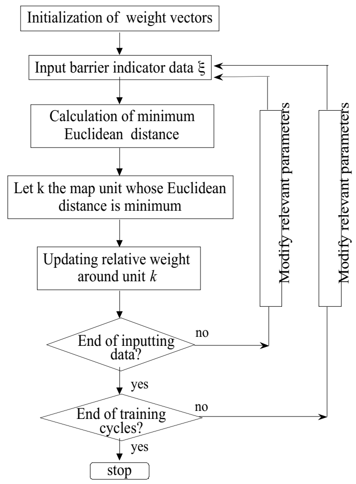

Figure 3 SOM training algorithm flowcharts

Let such neuron be "*k*". The algorithm now proceeds to change the synaptic weight vector W_j in such a way that the Euclidean distance is reduced. Then a correction takes place, which depends on the number of iterations already performed and on the absolute value of the difference between ξ and W_j. But other synaptic weight vectors are also adjusted in function to how near they are to the Best-Matching Unit (BMU)[1] neuron *k* and the number of iterations that have already taken place [19, 20]. Update of weight vector W_j is performed by

$$Wj \leftarrow Wj + \eta\phi(\xi - Wj) \qquad [1]$$

_ – learning rate

ϕ – neighborhood function

For instance, in the figure 2, neuron *k* is BMU, W_k will be updated according formula [1]. In the formula [1], the learning rate _ controls the magnitude of weight updates and is reduced gradually. In addition, the SOM learning uses a neighborhood function $\phi\,(j, k)$ whose value represents the strength of the coupling between unit *k* and its neighbor units *j* during the training process [20]. For example, if the current training radius in the neighborhood function $\phi(j, k)$ is 1 (see figure 2), the weights of six neurons/units around the neuron *k* will be also adjusted respectively.

The training is done in two phases: rough training with large (initial) neighborhood radius and large (initial) learning rate, and fine-tuning with small radius and learning rate.

With proceeding sequences of input vector presentations (i.e. one input vector or one batch at each iteration), the weights vectors corresponding to respective winning units rapidly become prototypes or "representatives" of a specific type of input indicator data set. The procedure is repeated until complete training stops.

For the SOM output layer, firstly, one or two dimensions can be given for testing. The number of output layer neurons may be reduced according to the training situation so that the optimal SOM map size can be found.

[1] BMU: the output layer neuron whose weight vector is closest to the input vector ξ is called Best-Matching Unit (BMU).

Proposed method integrating SOM for the analysis of BC

Safety structure of each given HMS can be interpreted in terms of several barriers. The designers implement their system design works complying with the relative regulations (particularly safety aspects), standards, technical guidelines, etc. In order to reduce the occurrence of human error or to limit failure propagation or to protect the human operator from technical failures, designers provide users with barriers. The objective of design should be to make the benefit low, the cost high and the human operator's perception of the deficit high [2].

To achieve or achieve as optimally as possible the objectives, a method integrating SOM network is proposed. During the analysis of BC, the effective cooperation between designer and utility/user is indispensable. The general process of this analysis is outlined as following (see figure 4):

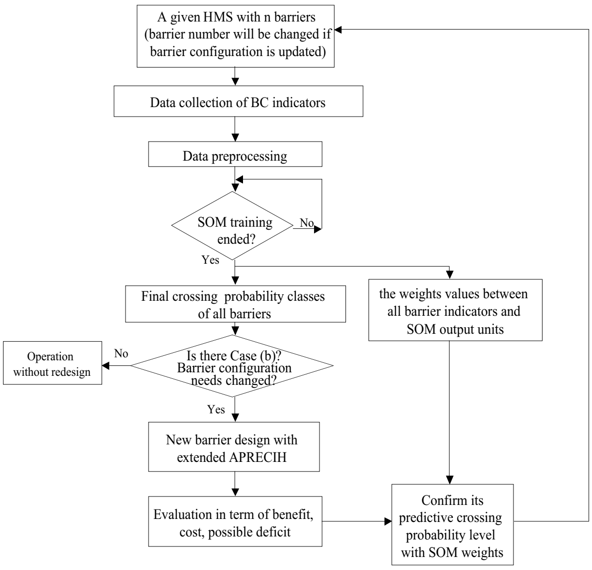

Figure 4 General process of the Barrier Crossing analysis. The work conditions in a given HMS have been predicted and defined by the designer; The case (b) includes two subgroups (see the relative section).

Firstly, all barriers of a given HMS should be identified, including material barriers, functional barriers, and immaterial barriers. In fact, during the design phase, most barriers have been taken into consideration, anyway, these barriers are designed from the point of view of designer, especially for a new HMS.

After identification of the barriers of a given HMS system, data collection may be implemented. Data sources include, for instance, operation experience feedback. For those barriers of case (b), they can be adjusted only after the good operation record has been shown with the crossed barrier. The barrier indicator data may be obtained during each time of crossing; The second important data source is simulator data. The simulator experimental data can meet two aspects of demand: one is to collect the barrier indicator data that can fill up the blank in previous human events; the other is to enhance understanding of operator performance during the crossing of barrier. Of course, BC data can be derived sometimes from various user-related report (e.g. near-miss report, internal audit report, surveillance report etc.) and observations on the real expertise and operator interview are usually helpful.

Thirdly, in order to do the SOM training in the next step, preprocessing of raw data is needed. For each performance criterion (row) in table 3, there are, in our case, 5 sublevels for each barrier indicator (column): benefit very high, benefit high, benefit normal, benefit low, and benefit very low, same thing with the cost and possible deficit.

Barriers	Level of benefit	Corresponding input data for SOM
No. 1	High	0.8
No. 2	Normal	0.6
No. 3	Very high	1.0
...	...	...
No. n	Very low	0.2

Table 2 An example of data transformation

To be able to transform these qualitative data into numerical data, which are recognizable for the SOM training (the transformation will be unnecessary if three indicator numerical data can be provided), one can treat them into some discrete data: very high _ 1, high _ 0.8, normal _ 0.6, low _ 0.4, and very low _ 0.2. An example for one criterion "benefit" is shown in table 2. It should be noted that there are of course another transformation methods.

Regarding to the parameter setting or initialization for the SOM training, refer to the application section. The training is done in two phases: rough training with large (initial) neighborhood radius and large (initial) learning rate, and fine tuning with small radius and learning rate. Output of SOM consists of two aspects:

- Group classification of final problematic level of given barrier data set;
- Weights trained by SOM, which can be used to predict the final location probability of new barrier.

In the former aspect, the group classification may be more than two, their corresponding output unit/location can be always found on the output map layer for all the barrier patterns which have participated to the SOM training. Anyway, one can usually find out the limit between the barriers that are often crossed, as well as ones that are seldom crossed. In addition, successful grouping of all the barriers can be used to verify the pertinence of indicator determination for the BC analysis.

During the followed analysis of BC, if there is no group in which the barriers are often crossed, i.e. there isn't case (b), this HMS can be operated without any change of barrier configuration (Cf. figure 4); If not, some supplementary works will be needed for these barriers that are often crossed. In the case (b), two subgroups of work conditions should be treated respectively following the extended APRECIH procedure [15],

- Firstly, for those conditions that have been listed by the designer as the unacceptable conditions during previous design phase but accepted by user after a compromise among various individual or technical or environmental factors, the barrier may be modified. As it is tolerated by the user during routine operation, after relative parameters of the barrier have been modified, e.g. procedure or technical specification modification, set point modification, even the physical modification etc., usually the relaxation of requirement compared to the old one. This activity will be allowed to be implemented in the future so that this barrier can be respected by operator as one non-crossing barrier. In a word, the barrier is transformed from crossed one to respected one.
- Secondly, for those conditions that have not yet been taken into account by designer, or have been realized ambiguously and have not been written down, new barrier needs to be designed/established. It can be any kind of barrier, e.g. physical material, regulatory instruction etc.
- In the extreme case, if this barrier is observed often crossed during normal operation without any negative record in the experience feedback, i.e. the benefit is very high, the cost and the possible deficit are almost neglectable, reference to the output map location of this barrier in the SOM network, it can be finally removed.

In the two former conditions, one barrier should be modified or new barrier should be added, with the well-trained SOM structure in which the weights have been trained for this given HMS system, designer may present the indicator data of new barrier or changed one into the SOM network, the region where the maximum activity takes place can be found out, it indicates the final probabilistic class that the present input barrier belongs to. Based on this predictive result, one can retrospectively reconsider the configuration pertinence of this barrier (see figure 4), final objective is to reduce the probability of crossing by making the benefit low, the cost high and the human operator's perception of the deficit high.

One may find out, from above procedure, that the method proposed can be used, in one part, to foreseen the problematic level of a new barrier (***prospective analysis***), and in another part, to identify or to regroup synthetically the barriers of a given HMS system such that those barriers which were often crossed can be taken into account, and this HMS system is finally optimized (***retrospective analysis***).

Application in railway experimentation

An application of proposed method has been implemented during a railway experiment on the simulator.

Railway simulator experimentation

In order to study the risk perception and acceptability of human operators when they cross barriers, and to study dependencies between the criteria (benefit, cost, possible deficit), an experimental platform was developed to simulate train movements from depots to another one crossing transformation stations on which humans operate the products on trains. Figure 5 is an interface sample of the experiment simulator.

There are three depots and three transformation stations, along the depots, tracks and stations, several barriers were defined. For example, different traffic lights _ depot, station and switching device signals: red to stop a train or green to authorize it to proceed; When a train has passed the signal, the traffic light should be switched to red, etc.

There are so far 19 persons who have participated to the simulator experiment as "traffic controller". They come from different countries, have different educational level and different regional performance characteristics. The experiment in which the proposed method was applied consists of two steps:

- First step of the experiment with all the designed barriers active,
- Second step of the experiment with only barriers that are selected by the human operator who controls the traffic, that means he/she may cross several barriers which were being judged as crossable,

In these two experiments, 7 classes of barrier have been taken into account:

- Signals for input/output movements at the depots;
- Signals for input/output movements at transformation areas;
- Signals before and after the shunting device;
- Stop signals at the transformation areas to transform the goods;
- Announcement message for input/output movement into the transformation areas;
- Direction of the movement of the train;
- Respect of the procedure that says that a signal has to be putting at the red colour after the crossing of a train;

As for three BC indicators (e.g. benefit) of a same barrier, there will be different values in term of different performance criteria of the HMS (i.e. quality, productivity, safety, and workload). So, several performance criteria should be considered for each barrier:

- The respect to the scheduled time,
- The number of treated products per train,
- The traffic safety, includes collision face to face, overtaking, derailment, synchronisation of the announcement made by the operator before train dispatch and arrival,
- The human task demand load (or workload).

After each step of the experiment, a questionnaire, focused on the evaluation of the performance interests of all barriers in terms of benefit, cost, potential deficit and utility, is undertaken (Cf. table 3).

One example of data collection is shown in table 3. The evaluation of crossing a barrier is implemented in terms of benefit, cost, potential deficit and utility. By utility we mean the overall experts judgement of the reliability related to the barrier crossing (in term of quality, productivity, safety, and work load) [2].

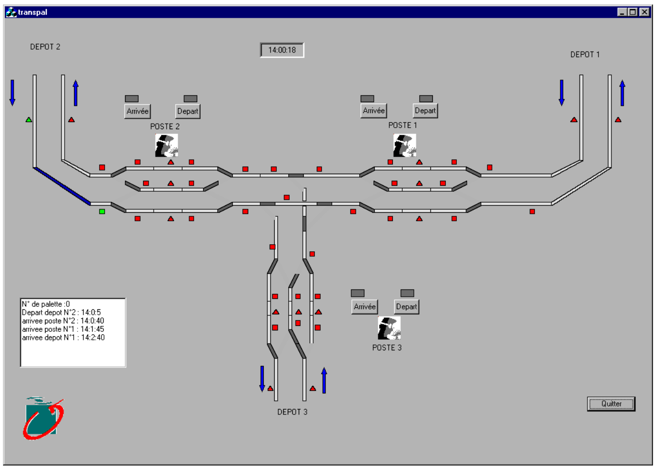

Figure 5 An interface sample of the experiment simulator

For a same barrier and its three crossing indicators (e.g. benefit), there will be different values from the different performance criteria of the human-machine system, i.e., quality, productivity, safety, and workload. BC indicators can be compared between different barriers and different controllers in term of 7 different performance criteria, in term of entire performance criteria as well.

Barriers	Criteria	Utility of Barrier	Crossing of Barrier		
			Benefit	Cost	Possible deficit
Signals for input/output movements at the depots	Advance on the planning	0	3	0	0
	Number of products treated by train	0	0	0	0
	Safety: face-to-face collision	2	0	0	3
	Safety: overtaking collision	2	0	0	3
	Safety: derailment	0	0	0	0
	Safety: input/output movement message	0	0	0	0
	Workload	0	3	0	0

Table 3 Example of data collection table for BC analysis (0: very low; 1: low; 2: normal; 3: high; 4: very high)

Result and analysis

In 7 classes of the defined barriers, there are four former barriers' classes whose crossing results have been recorded during the experimentation. So, as the preliminary result, our analysis focuses on these four kinds of barriers, i.e. four kinds of traffic signals have been analyzed.

In these experimental data, two different SOM training modes may be divided:

- First one is mono-criteria mode, SOM network is trained with the barrier data in term of each performance criterion, i.e. seven barrier data sets can be derived: Data set of respect to the scheduled time; Data set of number of treated product per train; Data set of safety: face to face collision; Data set of safety: overtaking collision; Data set of safety: derailment; Data set of safety: synchronisation of the announcement; Data set of workload.
- Regarding to the second data type _ multi-performances mode, the barrier indicator data set consists of entire performance criteria, i.e., for each barrier, there will be 21 variables, i.e. 21 dimensional input data (e.g. all item data in table 3 are spread out sequentially). It allows us to synthesize the former seven mono-performance modes, and to analyse the independence between these variables.

Experimental applications were performed on a Pentium _ PC (Genuine Intel x86 Family 6 Model 8 Stepping 1, 128 Mo RAM). In early analysis phase, SOM training maps is implemented in C++. To improve the visualization level of training results (e.g. weight distribution, U-matrix diagram, output visualization grouping map with the label of each input barrier pattern, etc.), final running environment has been chosen as Matlab 5.3. SOM Toolbox has been used to some basic function computations.

1. Looking up the optimal SOM map parameters

The barrier indicator data set has labels associated with the data samples. In the unsupervised SOM training, there is only one label that indicates the identification and the observation result of corresponding barrier, e.g. "*Cro1B1*" means controller No.1 and the first barrier for him, the observation result is 'crossing".

Besides of this kind of label, in the supervised SOM training, there is another separate label that contains the crossing information that was recorded during the experiment. The difference between the supervised SOM and the unsupervised one is that, in supervised-learning algorithm, the crossing information (first label of each barrier indicator data, e.g. "Yes") participates to the computation [17].

An input data example for the supervised SOM training is shown hereafter,

Benefit	*Cost*	*Deficit*	*Crossing*	*Identification*
0.8	*0.2*	*0.2*	*Yes*	*Cro1B1*
0.8	*0.2*	*0.2*	*Yes*	*Cro1B3*
……				
0.2	*0.2*	*1.0*	*No*	*Non7B4*
……				

One can see that each of the data lines gives one input data sample beginning with numerical variables and followed by two labels. The map can be labelled with these labels. The best matching unit (BMU) of each barrier sample is found from the map, and the two barrier labels are given to the map unit respectively (see figure 6).

The network parameters include the map size and the training cycles, learning rate _, the neighborhood function ϕ etc. For the SOM training, one dimensional output layer was tested firstly, the grouping result was not satisfied (the frontier between different problematic groups was not very clear) because of the irregular grouping region on the output layer, better results has been found in the case of two dimensional output. The number of output layer neurons became important during the followed process.

After our several tests, it was found that the map size (11×4 for mono-criteria mode, 8×5 for multi-performances mode) gave satisfactory grouping results. According to this map size, the investigation indicated that stable and satisfactory grouping results could be obtained by setting the rough training iteration and then fine-tuning iteration. Usually, the number of the fine-tuning cycles is 4 times of rough training one. The learning rate _ is 0.5 for the rough training, and 0.05 for the fine tune training.

2. Analysis results in term of mono-performance mode

In this first mono-performance analysis, all barrier data in the training set were presented into SOM training network in term of 7 different performance criteria. A supervised SOM training result in term of mono-performance mode is shown in the figure 6. In this example, the barrier indicator data were derived in term of the respect to the scheduled time. There are four barrier (four different traffic signals) indicator data for each controller, and the data of 15 former controllers were provided to the SOM network for training, and the data of 4 latter controllers were used to validate the prediction rate of this method.

Two maps in figure 6 represent the same SOM output map with the different labels. Each hexagon corresponds one neuron in the output layer, there are 4×11 = 44 neurons. The left map in figure 6 indicates the output map units labeled with the first label of the input barrier indicator data, and the right one in the figure indicates the map units labeled with the second label.

From the left figure it is easy to see that all the input barriers have been classified into two clusters. "Yes" in the hexagon means "crossing", and "No" means "non crossing". By looking at the second labels that are shown in the right figure, it is immediately seen that the corresponding location of all the trained data samples has been found out, and the similarity between different clusters has been visualized.

The left figure is often useful during the prediction of the final problematic level of one new barrier or one modified barrier. If the BMU of one barrier is located at the unit which was activated by one or several training set data samples, the membership (final problematic level) of this barrier can be easily determined; If it's located at one empty neuron which was not activated by any training set data sample, the membership of this barrier can be then determined by comparing with the status label of corresponding unit in the left figure.

It should be noted that cluster number may be more than two if the problematic level for all the barriers in the input set of SOM can be given in more detail.

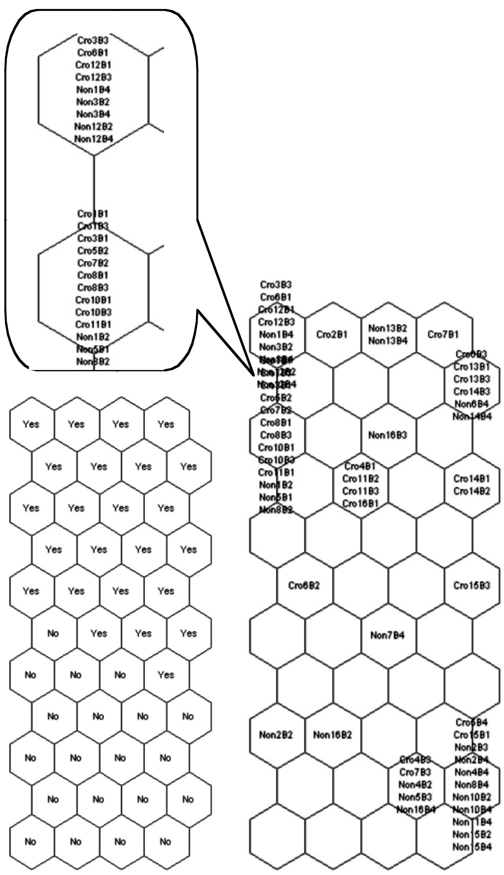

Figure 6 the supervised SOM training result in term of the respect to the scheduled time

3. Analysis results in term of multi-performance mode

The analysis of barrier crossing may be undertaken in term of multi-performance criteria. In this mode, 7 performance criteria can be partly studied, they can be also taken into account entirely and comprehensively. The training result of 72 barrier data samples (15 controllers) is given in figure 7 in term of their entire performance criteria. In this case, there are 21 variables (21 dimensional input data) for each barrier in the input layer, output is two-dimension layer.

Compared with the mono-performance mode (Cf. figure 6), one can find the better classification result in the multi-performance mode, as the analysis in term of mono-performance mode is sometimes lack of another impacting factors. For example, for the barrier "Non13B2", it was trained in the crossing cluster (see the right map in the figure 6) in term of mono-performance mode (the criterion respect to the scheduled time) whereas it was trained in the non-crossing cluster (see the figure 7) in the multi-performance mode, because, in the former case, this barrier data (benefit "3", cost "0", possible deficit "2") can be considered as "crossing" according to the barrier theory in term of the respect to the scheduled time, but its final problematic level has been classified in the non-crossing cluster if another 6 performance criteria are also taken into account.

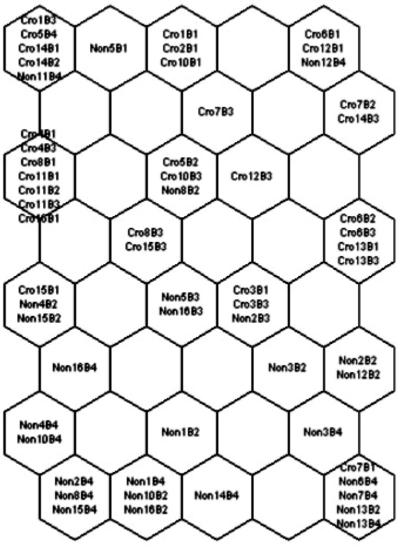

Figure 7 training results in term of multi-performance mode

Besides of the map labels figures, the component planes (e.g. 'Benefit', 'Cost', and 'Possible deficit') can be shown. Component planes are very convenient when one want to visualize correlation between different performance criteria or between different barrier indicators. This is sometimes helpful during the retrospective analysis for a given HMS, particularly in case of large number of input dimensions. It allows us to visualize the layout of all the barrier data in term of the combination between any barrier indicator and any performance criterion.

4. Prediction with the SOM training result and its accuracy

There are totally 76 sample data (19 'traffic controllers') for the simulator experiment. Along the experiment schedule, previous 60 sample data (15 controllers) were selected as the training set. Once the training is completed, from now on, the following remaining 16 samples (4 controllers) were the prediction set.

When a new barrier indicator pattern in the prediction set (16 latter data) is presented, each neuron computes in parallel the distance between this input indicator vector and the weight vectors that it stores in the SOM network, and a competition starts that is won by the neuron whose weights are more similar to the input vector.

During the prediction process, if the prediction sample falls into an active output map neuron (in the right map of figure 6), by comparing with the left map of figure 6, it is classified as belonging to the class corresponding to this active neuron. The prediction rate in term of criterion of respect to the scheduled time is 75% (see table 4).

The column of observation is the result for all the barriers during the experiment. 4 barriers crossing results were recorded automatically for each controller. These are the reference values for the computation of the prediction accuracy of the proposed method.

The column of prediction is the prediction result for all barriers by computing with weight vectors stored in the SOM network. The location of the BMU in the SOM map will be the prediction result for each barrier. This is a parallel process with the controller experiment. The final accuracy can be calculated by comparing between two columns.

Serial no.	Observation	Prediction	Accuracy
S17B1	Crossed	Non crossed	
S17B2	Non crossed	Non crossed	
S17B3	Crossed	Crossed	
S17B4	Non crossed	Crossed	
S18B1	Crossed	Crossed	
S18B2	Crossed	Non crossed	
S18B3	Crossed	Non crossed	(16-6)/16=75%
S18B4	Non crossed	Non crossed	
S19B1	Crossed	Crossed	
S19B2	Crossed	Crossed	
S19B3	Crossed	Crossed	
S19B4	Non crossed	Crossed	
S20B1	Crossed	Crossed	
S20B2	Crossed	Crossed	
S20B3	Crossed	Crossed	
S20B4	Non crossed	Crossed	

Table 4 Prediction result after SOM training in term of criterion of respect to the scheduled time. In the table, "Serial no." means the controller number and the corresponding barrier number, e.g. "S18B1" means controller No.18 and the first barrier for him. The underlined items in column "Prediction" are the prediction results with the SOM network, and may be different from the actual controller behaviors on the simulator.

Conclusion and perspective

This paper has discussed a method integrating a neural model, namely the Self-Organising Map, to the analysis of BC. For all barriers in a given HMS, their final synthetic/probabilistic level of crossing can be firstly classified as several classes, all the barriers are categorized successfully showing the pertinence of indicator determination for the BC analysis.

Retrospective analysis can be undertaken to identify or to regroup synthetically the barriers of a given HMS system with non-supervised or supervised SOM such that those barriers that were often crossed can be taken into account.

Based on the SOM map obtained from the training set, predictions can be made for the unknown/new barriers. Prospective analysis can be equally implemented to foreseen the problematic level of a new barrier. This can be used to support evaluation of present barriers and the (re)design process so that the HMS system is finally optimized.

The experimental data have been analyzed in term of mono-performance mode (3 input dimensions) and multi-performance mode (21 input dimensions), it is noted that these data can be analysed in term of any combination of the performance criteria if necessary.

Analysis of all the barriers that were often crossed may lead to some new event indicators that are useful for the designer, the user and the regulatory body.

Until now, the railway simulator experiment is still undertaken. Results presented above are only preliminary analysis for our experiments. A lot of further research works will be done, e.g., with the SOM training result, the statistic layout (distributions) in term of each pair of variable(s) both in the input data layer and in the output map can be displayed so that the correlation between some sub-barrier indicators may be found out. From this kind of visualization we can conform many of the earlier conclusions derived from the component plane visualization. This may be useful during the retrospective analysis of BC for a given HMS.

It should be noted that there are only two predefined groups whose status labels have been input into the SOM network during the supervised training, in the future, after the identification of more groups in the trained data, the number of the final problematic levels of these barriers may increase.

During the identification of the final crossing result, a barrier has been judged "crossed" so long as one barrier in same class is crossed. In fact, in a same class, several barriers have same features and functions, e.g. there are totally 6 signals for input/output movements at the depots. Some controllers removed a few signals, and the others removed all 6 signals, both of cases have been identified "crossed" at this experiment stage. This phenomenon can be taken into account during the identification of the final problematic levels/classes of crossing in the future.

Moreover, it has been found out that there is even difference between the barriers which belong to same barrier class in the questionnaire sheet, e.g. it was observed that the signals for output movements at the depots are always removed, in contrary, the ones for input movement were sometimes respected. So the barrier class may be further detailed in the questionnaire.

The judgment of whether a barrier will be crossed or not is subjective and is, at this stage of the experiments, the controllers' opinion. Depending on the experience feedback and PRA in some real industry fields, the collection of objective data should be started.

Based on the simplified simulator experiment, the application of the proposed method will be finally applied for an urban-guided transport management system.

References

[1] Kirwan B., Validation of human reliability assessment techniques: part 2 – Validation results. Safety Science, 27, pp 43-75, 1997.

[2] Vanderhaegen F. et al., Risk analysis method of human deviation in operational situations, Safety, Risk and Reliability – Trend in Engineering, International conference, Malta, March 21-23, 2001.

[3] Zhang Z. et al., Study of Chinese operator reliability using NPP simulator and application of HRA in PSA, IAEA-J4-RC589.3A, Heidelberg, Germany, 1998.

[4] NUREG-1624, Technical Basis and Implementation Guidelines for A Technique for Human Event Analysis (ATHEANA). USNRC, United States, 2000.

[5] Sträter, O., Evaluation of Human Reliability on the Basis of Operational Experience, Report GRS-170, Cologne, Germany, 2000.

[6] Gertman, D., Blackman, H., Human Reliability and Safety Analysis Data Handbook, A Wiley-Interscience Publication, 1994.

[7] Hollnagel, E., Cognitive Reliability and Error Analysis Method (CREAM). Elsevier Science, 1998, New York.

[8] Baumont G. et al., Method for quantifying human and organizational factors in accident management, using Decision Tree - The HORAAM method, Reliability Engineering and System Safety, 70, Elsevier, 2000.

[9] Pédrali, M., Vers un environnement multimédia pour l'analyse vidéo des causes d'erreurs humaines, application dans les simulateurs d'avions. Thèse de l'Université de Toulouse, janvier 1996.

[10] Bieder, C., Le-Bot, P., Desmares, E., Bonnet, J-L., Cara, F. MERMOS: EDF's new advanced HRA method, Probabilistic Safety Assessment and Management (PSAM 4), Mosleh, A. and Bari, R.A. (eds), Springer-Verlag, New York, 1998.

[11] Baumont G., Modèle et Méthode RECUPERARE, une méthode d'analyse des incidents intégrant la fiabilité humaine, Rapport DES 371, IPSN, février 1999.

[12] Zhang Z., Spécifications d'une méthode pour analyser les conséquences d'erreur humaine, working paper of LAMIH, pp 11-14, 2001.

[13] Vanderhaegen F., APRECIH: a human unreliability analysis method – application to railway system, Control Engineering Practice 7 (1999).

[14] Vanderhaegen F., A non-probabilistic prospective and retrospective human reliability analysis method – application to railway system, Reliability Engineering and System Safety, 71, pp1-13, 2001.

[15] Polet, Vanderhaegen, 2000. Analysis of deviated modes for risk assessment, ESREL 2000, Foresight and Precaution Conference, May 2000.

[16] Polet et al., Theory of barrier crossing. EAM'2000, European Annual Conference on Human Decision Making and Manual Control, pp 67-73, Ispra, Italy, June 2000.

[17] Kohonen T., Self-organizing map, Neurocomputing, 21(1), pp 1-6, 1998.

[18] Rousset P., Applications des algorithmes d'auto-organisation à la classification et à la prévision, PhD Thesis, University of Paris 1, 1999.

[19] Hérault J. et al., Réseaux neuronaux et traitement du signal, Hermès, 1994, Chapitre VII, pp 173-204.

[20] Rojas R., Neural Networks – A Systematic Introduction. Springer-Verlag, 1996.