SEVEN Expert System: A Decision Support Tool for Fire Safety Analysis in the Nuclear Area

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ABSTRACT

For fire safety studies in nuclear facilities, IRSN uses the SYLVIA software to simulate fire scenarios in highly confined and mechanically ventilated compartments and airborne contamination transfers inside nuclear facilities. In order to take into account the different sources of uncertainty resulting from initial and boundary conditions as well as from model parameters, the SYLVIA software is associated with the SUNSET statistical software. However, such a use of SYLVIA requires a large number of runs and a significant statistical analysis what is not always compatible to the requirements of safety assessments in terms of deadlines. To overcome this difficulty, IRSN is currently developing expert systems based on SYLVIA result databases. This approach allows deriving the most likely diagnosis or prognosis in a very short time, but also deriving a more complex form of reasoning intertwining prognostic and diagnostic inferences.

These expert systems are based on the Bayesian Belief Network methodology and consist in two steps: first, a large database obtained from SYLVIA runs allows the estimation of conditional probability tables; then, a message passing algorithm is used to dynamically exploit this database. The illustrating example is based on the study of the behavior of the final level of aerosol filtration in nuclear facilities, in a fire situation. The holding of the final level of filtration is conditioned by the thermal and mechanical stresses experienced by high-efficiency particulate air filters. The database of the expert system SEVEN is built from the results of ten million calculations performed with the SYLVIA software.

This example illustrates how an expert system can be used as a decision support tool for fire safety analysis in the nuclear area. Expert systems represent a new generation of calculation tools in the field of probabilistic fire simulation and contribute to building the enhanced expertise of tomorrow.

INTRODUCTION

The SYLVIA software system [1] has been developed by the Institut de Radioprotection et de Sûreté Nucléaire (IRSN) to simulate a complete ventilation network, fire scenarios in a highly confined and mechanically ventilated facility, and airborne contamination transfers inside nuclear facilities. This software is based on a two-zone approach and is used by IRSN for fire safety studies.

To evaluate the impact of uncertainties, the SYLVIA software is coupled to the SUNSET software [2], one of IRSN's statistical tools, used in support of risk analysis studies. This coupling makes it possible to directly carry out a set of parametric studies and then measure the impact on some selected responses. A typical use of the SYLVIA/SUNSET coupling is to perform a Monte Carlo simulation in which a set of variables, known as study parameters, is modeled by random variables. The results obtained from a Monte Carlo simulation constitute a database linking parametric configurations determined by the set of values assigned to the study parameters and uncertainties to the corresponding results. However, the direct use of this database in the context of a safety assessment encounters two main difficulties:

- The database is necessarily very limited considering the possible configurations. The SYLVIA simulations constituting the database represent a small percentage of the possible parametric configurations. This is due to the combinatorial explosion of the configurations as a function of the possible values taken for each parameter and the number of parameters considered. For instance, if we consider 16 parameters and each of them can take only three values, the number of combinations of values is 3^{16}, i.e. approximately 43 million configurations.
- The database is not specific to the characteristics of a safety assessment. It is necessary to extract from the database the information compatible with the specificities of the case of interest. For example, a safety assessment can focus more specifically on large volumes, low air renewal rates, etc. and seek to discriminate configurations compatible with safety issues, such as maximum pressure difference through High-Efficiency Particulate Air (HEPA) filters of the final level of aerosol filtration.

To meet this dual challenge, it is necessary to be able to correctly update the information contained in the database by integrating the characteristics of each safety assessment. One solution is to use an expert system [3]. This approach allows deriving in a negligible time prognostic and diagnostic like inferences, but also more complex forms of reasoning intertwining prognostic and diagnostic inferences. To achieve this goal, a large SYLVIA result database has to be built.

The illustrating example is based on the study of the behavior of the final level of aerosol filtration in nuclear facilities in a fire situation. The holding of the final level of filtration is conditioned by the thermal and mechanical stresses experienced by HEPA filters. The database of this expert system, named SEVEN, is built from the results of ten million calculations performed with the SYLVIA software. This example illustrates how an expert system can be used as a decision support tool for fire safety analysis in the nuclear area.

THE EXPERT SYSTEM

An expert system is a tool that aims to simulate the cognitive mechanisms of an expert in a particular field. This is one of paths leading to artificial intelligence. More precisely, an expert system in artificial intelligence is defined as a computer program that has the ability to represent and reason from observations and generic knowledge. In fire safety, it is useful to be able to quickly discern the configurations of a facility at risk. The idea behind the expert system approach is to make the most benefit of the SYLVIA software to build a database covering a wide range of configurations, and then to use the expert system reasoning abilities to discern configurations of this database useful to one specific case of interest.

An expert system can be divided into three separated components [4], as shown in Figure 1:

- **The knowledge base** that contains all the generic information in which the expert system will operate. This information will be encoded by means of conditional probability tables (CPTs, cf. the green rectangle in Figure 1).
- **The observation base** that gathers all the contingent or specific information from which inferences can be performed. This information has to be provided by the users in terms of likelihood or probability.
- **The inference engine**, a set of algorithms (the yellow arrows in Figure 1) that propels the information coming from the observation base through the knowledge base. Contrary to "physical" computer codes that intertwine the numerical data coming from initial and boundary conditions with the solving algorithms, the expert systems algorithms are designed to be independent and separated from the data.

The general principle is to update in a real-time process the knowledge related to the variables defined in the expert system. More precisely, the expert system objective is to have a numerical tool able to perform three types of inferences:

1. In a forward chaining (prognostic inference), to determine for a configuration of input data the possible responses;
2. In a backward chaining (diagnostic inference), to identify for a given configuration of the responses the compatible input data;
3. In a mixed chaining, an inference that intertwines prognostic and diagnostic inferences.

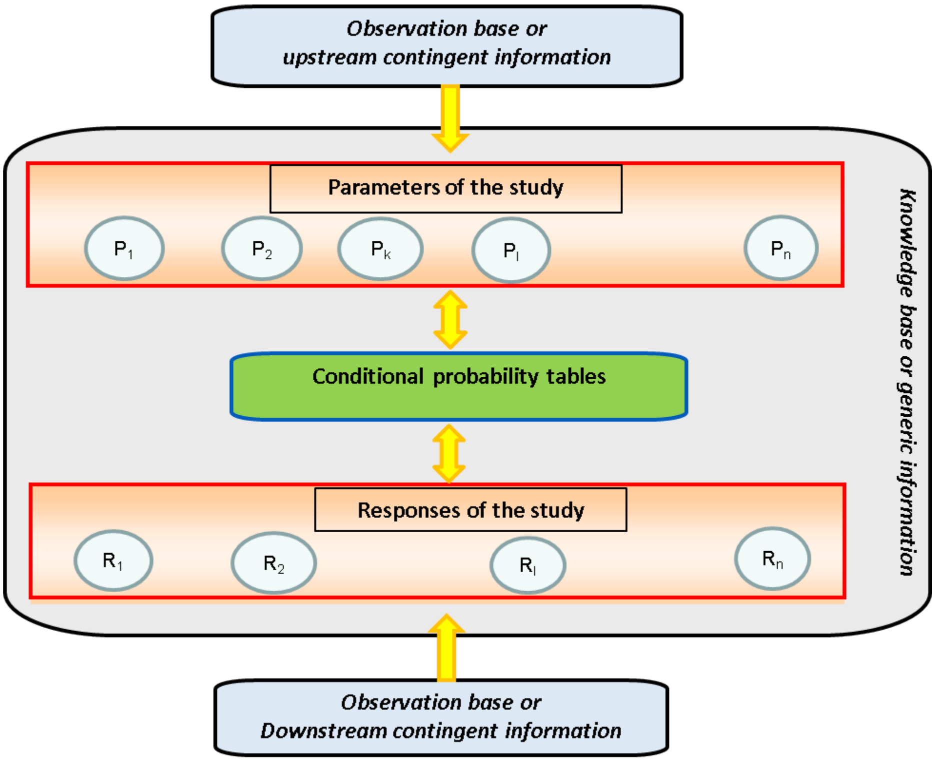

Figure 1 Flow chart of the expert system

The Knowledge Base

Since the computation time is short enough to perform many calculations, our approach consists in building a database, which relates to the case studied – such as the behavior of the final level of aerosol filtration in nuclear facilities, in a fire situation – by performing a stratified Monte Carlo study by a Latin Hypercube Sampling (LHS) method [5]. This Monte Carlo study is carried out by varying the input parameters of the calculation code in the study area under consideration. Thus, if we want the expert system to be able to answer to queries for compartment volume ranges between 100 and 500 m^3, we have to model this parameter by a random variable between 100 and 500 m^3 in the Monte-Carlo simulation. This way, we can build a large database made of SYLVIA calculations. This database is made up of all the data corresponding to both parameters and outputs. Then, this database can be interpreted as a numerical transcription of the generic knowledge carried by the SYLVIA software.

In a formal way, the SYLVIA software can be seen as a mapping of the parameters´ domain to the responses´ domain (see Figure 2). This can be written as:

$$R_i = S(P_1, \dots , P_N) \qquad (1)$$

where R_i is any response of interest, P_j, the parameters and S, the SYLVIA software acting as a transfer function.

With this formalism, a SYLVIA computation is defined by fixing values p_j to each parameter P_j and by calculating the values r_i of any code output R_i. It should be noted that the independent variables P_j and the response R_i of the equation (1) can be either continuous or discrete.

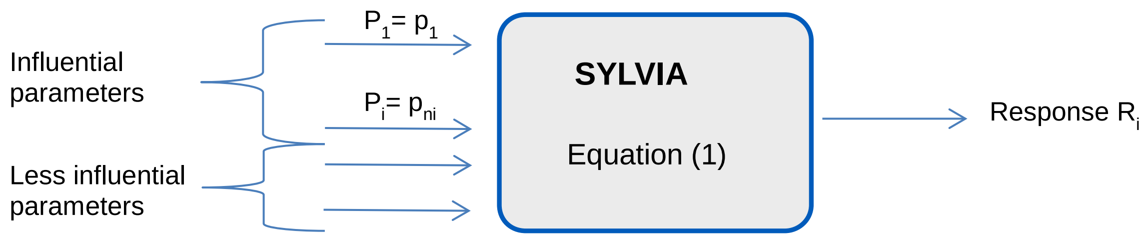

Figure 2 The formal model of SYLVIA

The principle followed to establish the SYLVIA knowledge base consists in transcribing the transfer function S into numerical tables (one for each response). In order to carry out this transcription of SYLVIA into numerical tables (see Figure 3), two simplifications are necessary. The first one consists in discretizing all the continuous variables of the equation (1) as:

$$R_i^* = S(P_1^*, \dots, P_N^*) \quad (2)$$

where R_i^* and P_j^* can only take discrete values.

The second simplification [6] concerns the identification of influential parameters for each response to limit the combinatorial aspect induced by the numerical transcription of the equation (2). Therefore, a preliminary step before making the knowledge base is the identification, for each response R_i, of its most n_i influential parameters. It has been done with a covariance analysis. Thus, equation (2) becomes:

$$R_i = S(P_1, \dots, P_{ni}, U_i) \quad (3)$$

where U_i is a random variable modeling the loss of information induced by the discretization step and by neglecting the less influential variables of the response R_i. It is worth noting that this model is stochastic, since for a given parametric configuration of $P_1, \dots, P_{ni}$, R_i may have different values.

From these simplifications, each SYLVIA calculation is replaced by a set of discrete values: the levels of the parameters and of the responses. Then, the whole set of SYLVIA simulations is used to calculate the conditional probability of each response knowing the combination of its influential parameters.

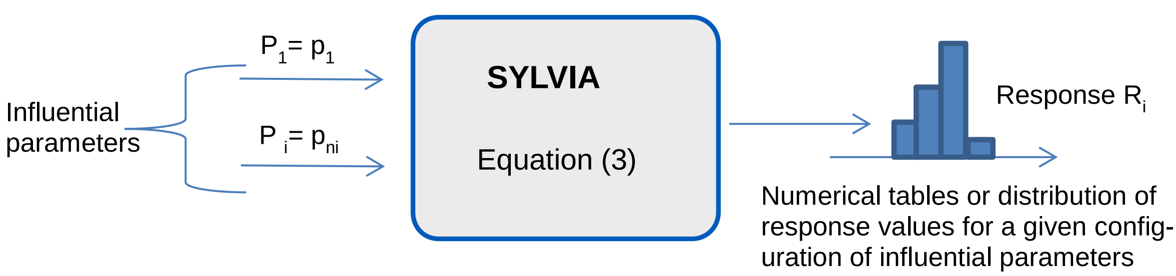

Figure 3 The structural model of SYLVIA

The Observation Base

In the expert system based on a SYLVIA database, the variables of the observation base are identical to the variables of the knowledge base. Unlike the knowledge base that encodes the generic information (i.e. the information carried out through the SYLVIA code), the observation base encodes the contingent knowledge for which we wish to solicit the expert system.

In a Bayesian network, each variable receives two kinds of information: an upstream information and a downstream information [4]. This distinction is essential to correctly perform the information propagation in a network. We will come back to this notion in the next section, as for now, it is sufficient to know that upstream information is required for the parameters and downstream information for the responses. This information is given by means of probability or likelihood. For example, if a variable V (associated to either a parameter or a response) is discretized into four levels (very low, low, high, very high), a (2, 1, 1, 0) u-plet is equivalent to the (0.5, 0.25, 0.25, 0) u-plet and means that the very low level is twice likely as the low or high level and the very high level is either impossible or not considered. More generally, the observational database consists in providing for each parameter P_i and for each response R_j some information that specifies (by means of vectors π_{Pi} and λ_{Rj}) the domain in which the expert system will operate.

The Inference Engine

A Bayesian network is not merely a passive tool storing factual knowledge, but also a computational architecture reasoning on that knowledge. This means that the links in the network have to be seen as mechanisms that propel information in order to update it. The CPTs (Conditional Probability Tables) attached to the nodes (cf. the left-hand variables of the equations in the system 3) act as single processors so that the inference engine is the set of processors (as many single processors as equations in the system 3).

To propagate and update information, the inference engine distinguishes upstream and downstream information. For a parameter P_i, the upstream information is the information provided by the vector π_{Pi} defined in the observation base and the downstream information is the vector λ_{Pi}which will be calculated by the inference engine. In a similar way, for a response R_j, the downstream information is the information provided by the vector λ_{Rj} defined in the observation base and the upstream information is the vector π_{Rj}, which will be calculated by the inference engine.

From this distinction between upstream and downstream information, each single processor is able to perform three kinds of local computation independently of other things happening in the network:

- **A forward propagation mechanism**. It consists of gathering all the upstream information coming from the right-hand variables and transforming it into upstream information of the left-hand variables.
- **A backward propagation mechanism**. It consists of gathering all the downstream information coming from the left-hand variables and transforming it into downstream information of the right-hand variables.
- **An updating mechanism**. It consists for a variable X of combining all the downstream information coming from the equations, where X is on the left-hand side, with all the upstream information, where X is on the right-hand side.

As each processor is connected to another in a Bayesian network, the local information can circulate through the whole network. These propagation mechanisms proposed by J. Pearl [7] are called the "message passing" algorithms: they act as information propellers from one variable to its neighbors.

BUILDING THE KNOWLEDGE BASE OF THE EXPERT SYSTEM SEVEN

The knowledge base collects all the generic information from which the expert system will perform inferences. It determines the application domain of the expert system. Thus, a first step consists of delimiting the general framework of the study and in defining the parameters and responses of the study and their variation ranges. In a second step, the SYLVIA database is built, and the conditional probability tables are computed.

Delimitation of the General Framework

In the presence of radioactive materials a fire can become a vector of resuspension and dissemination of these materials, and thus, can generate uncontrolled radio exposure of workers or even a release of radioactive materials into the environment. The estimation of the fire source term (total activity corresponding to the release of radioactive materials into the environment) allows IRSN to assess the sufficiency of the risk control measures taken by the operator of a nuclear facility and to apprehend the decisions to be taken in a crisis situation as the delimitation of a security perimeter. The study of the behavior of the final level of aerosol filtration in nuclear facilities in a fire situation is a major step in the assessment of the fire source term by simulation tools.

The perimeter of the knowledge base determines the scope of the expert system. It is delimited by the general framework of the study. This one is presented in Figure 4.

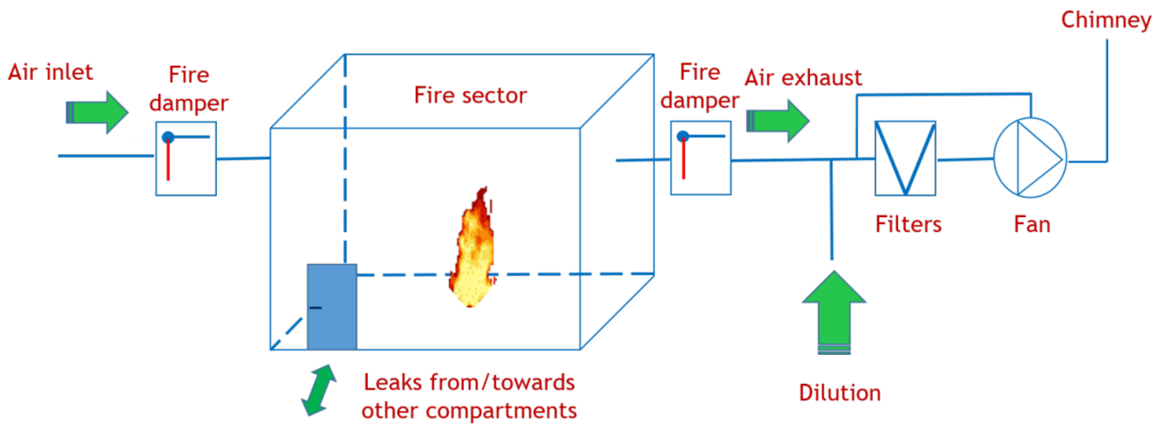

Figure 4 Topology scheme of the general framework of the study

It consists in a fire sector, represented by a 4 m high compartment, whatever the considered volume. This one is provided with fire dampers at the inlet and the exhaust air vents. A leak representative of all the leaks of the compartment (including leaks through doors) is modeled. The ventilation network is composed of an air inlet line and an air exhaust line with a dilution line. The air flow is ensured by two fans located, for one, at the entrance of the inlet line and modeled by a boundary condition node (80 Pa, characteristic value of what is usually observed), and for the other, at the end of the exhaust line, upstream of which a battery of HEPA filters (final level of aerosol filtration) is connected. A regulation of the exhaust fan is taken into account in the study. This one is equipped with a rotation speed control device allowing to assign the pressure upstream of the filters to a set value (- 2000 Pa, characteristic value of what is usually observed). Nevertheless, cases without regulation are also taken into account in order to cover non-regulated historical facilities.

In the nominal state, the compartment pressure is set at – 100 Pa relative to the atmospheric pressure. This value was chosen in coherence with the under-pressure value recommended in ISO 17873 standard (criteria for the design and operation of ventilation systems of nuclear facilities other than nuclear power plants, 2004) for C2 confinement class rooms [8].

Assumptions of the Study

The expert system SEVEN is based on the following assumptions:

- The modeling of the ventilation network adopted in the study is based on the methodology for the simplification of the ventilation networks, developed and validated at IRSN for fire scenarios using the SYLVIA software. This methodology is very conservative because it does neither take into account thermal losses nor the deposition of combustion aerosols occurring in the ventilation ducts between the fire room and the final level of aerosol filtration. Since these phenomena are highly dependent on the geometry of the ventilation network (duct diameter, number of bends, duct length, etc.), the deposition rate of soot particles upstream of the filters is therefore a parameter of the study. Similarly, thermal losses in the ventilation ducts are not taken into account, only the cooling of the gases of a dilution located downstream of the fire room is taken into account.
- The deposition of soot particles in the fire room is in particular due to the thermophoresis phenomenon (deposition related to a thermal gradient at the vicinity of the deposition surface). To take into account this phenomenon, a fine description of equipment in terms of surface and materials is required. These aspects are not taken into account in this version of the expert system. Thus, the parameter characterizing the deposition rate of soot particles upstream of the filters also integrates the soot particle deposition in the fire room.
- The modeling of the ventilation network of the study does not allow to study the effect of the shift to the half-regime of ventilation on the behavior of the filters of the final level of aerosol filtration, in a fire situation. Indeed, the study of this ventilation management strategy requires the modeling of two inlet fans and two exhaust fans, which considerably increases the number of parameters to take into account. Since this strategy is not part of the strategies commonly used by operators in their safety analysis, it is not integrated in the knowledge base of the expert system SEVEN. However, the knowledge base could be completed later, if necessary.
- The fire source is modelled by a design fire [9] in order to cover all the kinetics of fire growth in the study. A design fire is characterized by its maximum heat release rate in open atmosphere and by its fire growth factor:

$$HRR = \alpha t^2 \tag{4}$$

  where HRR [kW] is the heat release rate, α [kWs^{-2}] the fire growth factor and t [s] the time.
- The filter clogging model [10] was developed at IRSN from data acquired during the combustion of different fuels studied at IRSN. This model only retains direct parameters known to have an influence on the filter clogging, in order to be easily usable. The empirical law elaborated is in the form:

$$\begin{cases} R(t=0) = R_0 \\ \frac{d}{dt}(R) = \left(\frac{a(1-FC)}{d_p} + 2b\left(\frac{1-FC}{\max(v_f, v_0/9)d_p}\right)^2 m_{ae}\right)\frac{dm_{ae}}{dt} \end{cases} \tag{5}$$

  with:
  - R: aeraulic resistance of the filter [kg m^{-4} s^{-1}];
  - R_0: initial aeraulic resistance of the filter [kg m^{-4} s^{-1}];
  - FC: Mass fraction of condensate contained in aerosols and deposited on filters [-], set to 0 in the study;
  - m_{ae}: mass of aerosols deposited on filters per unit surface area [kg^{-2}];

- d_p: characteristic diameter of soot particles: diameter of the monomers constitutive of the aggregates for particles of fractal morphology, or volume-equivalent diameter for particles of compact morphology [m];
- v_f: filtration velocity [m s^{-1}];
- v_0: nominal filtration velocity [m s^{-1}];
- a, b: empirical clogging constants (a = 2.8 10^{-5} <m^3 kg^{-1}; b = 5.5 10^{-15} m^8 kg^{-2} s^{-2}).

- Fire scenarios with rupture of a fire break door are not taken into account in the study. They require the modeling of adjacent compartments as well as their ventilation system in order to take into account a recovery of a part of the soot inventory by the ventilation. However, these scenarios could enrich the knowledge base of the expert system later.
- In order to cover the various ventilation regimes of the study, a parametrization of the characteristic curve of the exhaust fan is achieved. This curve links the volume flow rate of the gas passing through the fan (Qv) to the total pressure difference at its edges (manometric height H) and is in the form of a polynomial of the second degree:

$$H = C_2 Q_v^2 + C_1 Q_v + H_0 \tag{6}$$

Coefficients H_0, C_1 and C_2 were deduced from the observation of 39 exhaust fan curves studied at IRSN (see Figure 5).

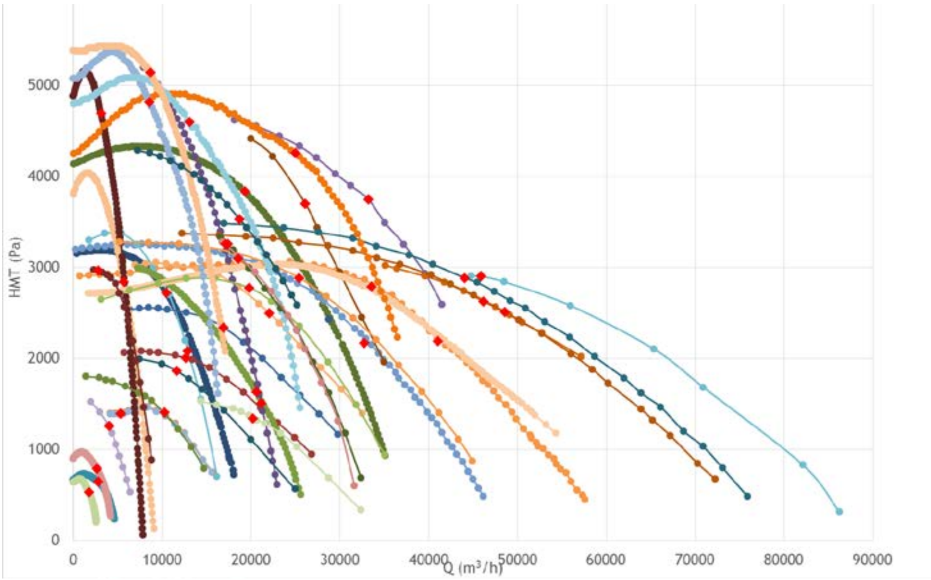

Figure 5 Characteristic curves of exhaust fans studied at IRSN

Parameters and Responses of the Study

According to the issue addressed in this study, three responses were retained: the maximum pressure difference and the maximum gas temperature through HEPA filters of the final level of aerosol filtration as well as the initial dilution rate of the gas upstream of the filters. The latter is defined as the ratio of the air volume flowrate in the dilution line to the gas volume flowrate at the exhaust of the fire room. The discretization of these three responses is reported in Table 1. The classes of response constitute the columns of the conditional probability tables.

Table 1 Discretization of the responses of the study

Responses	Discretization
Maximum pressure difference through filters [Pa]	< 500 [500; 1000] [1000; 1500] [1500; 2000] > 2000
Maximum gas temperature through filters [°C]	[20; 50] [50; 100] [100; 150] [150; 200] > 200
Initial dilution rate of gas [-]	< 5 [5; 50] [50; 500] [500; 1000] > 1000

According to the responses of the study, 20 parameters have been identified as influencing these responses. They are split into three categories, as reported in Table 2 to Table 4. The discretization of the variables is also specified in these tables.

Table 2 Parameters related to the fire, D {discrete values}, C [continuous values]

Parameters	Type	Discretization
Mass of fuel [kg]	C	[100; 400] [400; 700] [700; 1000] [1000; 1500] > 1500
Fire growth factor [kWs^{-2}]	D	{$3\ 10^{-3}$; 0.012; 0.047; 0.19}
Maximum HRR in open atmosphere [kW]	C	[200; 800] [800; 1500] [1500; 3000] [3000; 5000]
Heat of combustion [$MJkg^{-1}$]	C	[15; 25] [25; 35] [35; 50]
Fire extinction on O_2 criterion [v/v %]	D	{8; 12}
Soot production rate [%]	C	[1; 5] [5; 10] [10; 15] [15; 20]
Soot particle diameters [µm]	C	[0.005; 0.02] [0.02; 0.06] [0.06; 0.1] [0.1; 0.3] [0.3; 1]

Table 3 Parameters related to filters

Parameters	Type	Discretization
Initial filtration velocity [$cm\ s^{-1}$]	C	[1.7; 1.9] [1.9; 2.1]
Initial pressure difference through filters [Pa]	C	[250; 500] [500; 1000]

Table 4 Parameters related to the ventilation network

Parameters	Type	Discretization
Compartment volume [m^3]	C	[50; 300] [300; 700] [700; 1000] [1000; 1500]
Compartment air renewal rate [vol h^{-1}]	C	[1; 3] [3; 7] [7; 10]
Location of the inlet air vent [-]	D	{Low; High}
Location of the exhaust air vent	D	{Low; High}
Compartment leak rate [vol h^{-1}]	C	[0.1; 0.4] [0.4; 0.7] [0.7; 1]
Fire dampers closing times inlet/exhaust [s; s]	D	{150; 0} {150; 1800} {150; 3600} {1200; 0} {1200; 0} {1200; 1800} {1200; 3600} {∞ ; ∞}
Fire dampers aeraulic resistance in closed position [m^{-4}]	D	{10^4; 10^6}
Soot deposition rate [%]	C	[0; 20] [20; 40] [40; 60]
Dilution volume flow rate [m^3h^{-1}]	C	[4.5 10^3; 2 10^4] [2 10^4; 4 10^4] [4 10^4; 6 10^4] [6 10^4; 8 10^4] [8 10^4; 10^5]
Slope of the fan curve at functional point [-]	C	[-0.6; -0.2] [-0.2; -0.1] [-0.1; -0.01]
Regulation index [-]	D	{0; 1}

Size of the Database

To study a set of configurations, the SYLVIA software is coupled to the SUNSET software. This coupling directly allows Monte Carlo simulations. For this, a set of variables, known as study parameters, is modeled by random variables. Thus, each study parameter is associated to a variation domain and a distribution function (a uniform distribution function is used in the study). For each study parameter, a value is randomly drawn in its range of variation (or imposed as for the closing time of the fire dampers), creating a set of values for the parameters characterizing the SYLVIA calculation to be performed. By performing this simulation, one obtains the values of the responses associated with this parametric configuration. The Monte Carlo method consists in reiterating this procedure a large number of times. The storage of the values taken by the study parameters and by the responses for all the runs constitutes the SYLVIA database. The Monte Carlo simulation allows to explore the whole variation range of the study parameters and to estimate the impact of these variations on responses of interest.

The size of the database depends on the number of influential parameters and on the level of discretization of these parameters. The minimum number of SYLVIA calculations to be performed is given by the product of the highest value of the number of classes of individuals among the responses by a number of runs to have a sufficient statistic for each combination of classes. For a given response, the number of classes of individuals is the sum of all the class combinations of its influential parameters and corresponds to the number of rows of the conditional probability table associated with this response.

The identification of the influential parameters of a response is based on its correlations with the parameters determined from the Monte Carlo simulation. It was obtained from the results of a Monte-Carlo simulation performed on a sampling of 100,000 runs, by a covariance calculation. Results are reported in Table 5. Less influential parameters do not explicitly appear in the knowledge base. Nevertheless, the variability induced by these parameters is taken into account in the conditional probability tables.

Table 5 Correlations of the responses [%] according to the parameters of the study; most influential parameters are highlighted with orange background

Parameters	ΔP Filters	T° Filters	Gas Dilution Rate
Mass of fuel	0.00	0.00	0.00
Fire growth factor	0.02	0.14	0.00
Maximal HRR in open atmosphere	0.05	0.28	0.00
Heat of combustion	-0.12	-0.01	0.00
Fire extinction on O_2 criterion	-0.07	-0.02	0.00
Soot production rate	0.26	-0.01	0.00
Soot particle diameters	-0.44	0.00	0.00
Compartment air renewal rate	0.05	0.16	-0.31
Compartment volume	0.10	0.12	-0.46
Compartment leak rate	0.05	0.01	0.05
Location of the inlet air vent	0.00	0.00	0.00
Location of the exhaust air vent	0.12	0.28	0.00
Fire dampers closing times	0.26	0.14	0.00
Fire damper resistance	-0.17	-0.01	0.00
Soot deposition rate	-0.10	0.00	0.00
Dilution volume flow rate of gas	-0.25	-0.43	0.31
Slope of the fan curve at functional point	-0.01	0.01	0.00
Initial filtration velocity	0.01	0.00	0.00
Initial pressure difference through filters	0.38	0.00	0.00
Pressure regulation at exhaust	0.03	-0.03	0.00

For this study, based on the ten most influential parameters of the response “maximum pressure difference through the filters”, the conditional probability table associated with this response contains $3 \times 4 \times 5 \times 4 \times 2 \times 7 \times 2 \times 3 \times 5 \times 2 = 201{,}600$ configurations. A base of simulations of ten million calculations guarantees over 99 % that each parametric configuration will be observed in the database. Thus, ten million runs were performed with the SYLVIA software to build the knowledge base of the expert system SEVEN. For information, this number of runs required seven full days of CPU time distributed on 144 cores.

APPLICATION OF THE EXPERT SYSTEM SEVEN

The graph of the knowledge base

The graphical user interface is composed of two main sheets: the graph of the knowledge base, as shown in Figure 6, that gathers data entered for the analysis and the associated results and a sheet to visualize a priori and a posteriori likelihood in the form of histograms. The graph of the knowledge base is divided into three zones: at the top, the fourteen influential parameters of the study on which the expert system can make inferences; at the bottom, the three responses of interest on which the expert system can also make inferences; and in the center, a button to launch a query. Three columns are associated to each influential parameter and each response of interest reported on the graph of the knowledge base. The first column corresponds to the discretization of the variable, the second column to the a priori likelihoods taken by the variable and the third column to a posteriori likelihood of the variable (results of the query). The computing time required for a query is negligible.

Application

To illustrate the potential interest of an expert system as an aid tool for safety assessment, we consider the following issue: What are the configurations leading to the loss of the final level of aerosol filtration due to filter clogging during an in-cell solvent fire in a reprocessing facility? The organic phase considered in this example is composed of a solvent mixture of 30 % in volume of tributyl phosphate (TBP) and 70 % in volume of HTP (hydrogenated tetrapropylene).

If the expert system is used as a prognostic tool or in a forward chaining, the result of the expert system is rather like a direct exploitation of the database. In this case, only the knowledge relative to the parameters can be used: a fast kinetics of fire growth, a heat of combustion in the range of 25 to 35 MJ/kg, a soot production rate in the range of 10 to 15 %, soot particle sizes in the range of 0.1 to 0.3 µm according to [11] and a soot deposition rate in the range of 0 to 20 %]. The lowest class retained for the particle deposition rate upstream of the filters is justified by the size of the soot particles that corresponds to the minimum efficiency of particle deposition [12].

If the expert system is now used as a diagnostic tool or in a backward chaining, only the knowledge relative to the responses is used: a pressure difference through the filters greater than 2000 Pa, corresponding to the loss of filters.

To fully answer the question, it appears necessary to combine the forward and the backward reasoning. Three cases are here illustrated: (1) a conventional closing time of the fire dampers at 2 min and 30 s, corresponding to a servo control of the fire dampers to the automatic fire detection (cf. Figure 6); (2) a manual closing of the fire dampers by the shift personal at 20 min, to consider the case of an aleatory failure of the automatic closing of the fire dampers (cf. Figure 7) and (3) a fire damper closing time at the inlet air vent at 2 min and 30 s and a fire damper closing delay at the exhaust air vent of 30 min, to consider one of the ventilation management strategies, in a fire situation, used by operators in their safety analysis (cf. Figure 8).

The crossing of the upstream information (kinetics of fire growth, heat of combustion, soot production rate, soot particle sizes, soot deposition rate and fire dampers closing times) and downstream information (pressure difference through filters) indicates that, for a closing time of the fire dampers at 2 min and 30 s (see Figure 6), the compartment volume has low effect on filter clogging due to an early closing of the fire dampers, that 60 % of cases leading to a loss of filters are predicted for an exhaust air vent in the upper part of the fire room, that 76 % of cases are given for pre-clogged filters (initial pressure difference through filters in the range of 500 to 1000 Pa) and that 100 % of cases are predicted for fire dampers of low aeraulic resistance in a closed position and dilution volume flow rates lower than 60000 m^3h^{-1}, with 76 % of cases in the class of 4500 to 20000 m^3h^{-1}. Leaks in the compartment and through fire dampers of low aeraulic resistance contribute to maintain the fire and allow soot transfer in the ventilation network. Since the number of filters depends on the value of the dilution flow rate, low dilution flow rates lead to filter clogging in this configuration.

Fire growth factor		
slow	☐	0%
medium	☐	0%
fast	☑	100%
ultrafast	☐	0%

Maximum HRR in open atmosphere (kW)		
200-800	☑	25%
800-1500	☑	25%
1500-3000	☑	25%
3000-5000	☑	25%

Heat of combustion ($MJ\ kg^{-1}$)		
15-25	☐	0%
25-35	☑	100%
35-50	☐	0%

Fire dampers closing times Inlet (s)/Exhaust (s)		
150 / +0	☑	100%
150 / +1800	☐	0%
150 / +3600	☐	0%
1200 / +0	☐	0%
1200 / +1800	☐	0%
1200 / +3600	☐	0%
∞ / ∞	☐	0%

Fire dampers aeraulic resistance (m^{-4})		
10^4	☑	100%
10^6	☑	0%

Soot particle diameters (µm)		
0.005-0.02	☐	0%
0.02-0.06	☐	0%
0.06-0.1	☐	0%
0.1-0.3	☑	100%
0.3-1	☐	0%

Soot production rate (%)		
1-5	☐	0%
5-10	☐	0%
10-15	☑	100%
15-20	☐	0%

Soot deposition rate (%)		
0-20	☑	100%
20-40	☐	0%
40-60	☐	0%

Initial pressure difference through filters (Pa)		
250-500	☑	24%
500-1000	☑	76%

Compartment volume (m^3)		
50-300	☑	30%
300-700	☑	25%
700-1000	☑	24%
1000-1500	☑	22%

Compartment renewal rate ($vol\ h^{-1}$)		
1-3	☑	33%
3-7	☑	33%
7-10	☑	33%

Compartment leak rate ($vol\ h^{-1}$)		
0.1 - 0.4	☑	33%
0.4 - 0.7	☑	33%
0.7 - 1	☑	33%

Dilution volume flow rate ($m^3\ h^{-1}$)		
$4.5\ 10^3 - 2\ 10^4$	☑	76%
$2\ 10^4 - 4\ 10^4$	☑	19%
$4\ 10^4 - 6\ 10^4$	☑	4%
$6\ 10^4 - 8\ 10^4$	☑	0%
$8\ 10^4 - 10^5$	☑	0%

Exhaust vent location		
Low	☑	40%
High	☑	60%

Maximum pressure difference through filters (Pa)		
500	☐	0%
500-1000	☐	0%
1000-1500	☐	0%
1500-2000	☐	0%
>2000	☑	100%

Maximum gas temperature through filters (°C)		
20-50	☑	93%
50-100	☑	7%
100-150	☑	0%
150-200	☑	0%
>200	☑	0%

Initial dilution rate (-)		
5	☑	18%
5-50	☑	65%
50-500	☑	17%
500-1000	☑	0%
>1000	☑	0%

Figure 6 Results for a closing time of the fire dampers at 2 min and 30 s

If we now consider a manual closing of the fire dampers by the shift personnel at 20 min (case of an aleatory failure of the automatic closing of the fire dampers, cf. Figure 7), the expert system indicates that the size of the fire room has more effect than in the previous case (only 18 % of the cases in the range of 50 to 300 m^3 against 30 % for an early closing of the fire dampers) that 71 % of cases are predicted with a high position of the exhaust air vent, due to higher soot concentrations in the upper part of the fire room, that the percentage due to pre-clogged filters is equivalent to the previous case (78 %), that 29 % of cases are found with a high aeraulic resistance of the fire dampers, due to their late closing and that all levels of dilution of the study are involved in filter clogging, with 67 % of cases in the lowest class ranging from 4,500 to 20,000 m^3h^{-1} against 2 % of cases in the highest class ranging from 80,000 to 10,0000 m^3h^{-1}.

Consider now the case a fire damper closing time at the inlet air vent at 2 min and 30 s and a fire damper closing delay at the exhaust air vent of 30 min (see Figure 8). In this case, the expert system informs us that the compartment volume has still low effect on filter clogging in this configuration, that an early closing of the fire damper at inlet does not change significantly the percentage of cases leading to a loss of filters with an exhaust air vent in the upper part of the fire room (66 % against 60 % in case 1 and 71 % in case 2) that 80 % of cases are predicted for pre-clogged filters, a higher percentage compared to case 2 due to a longer delay of the fire damper closing at exhaust, that 81 % of cases are given for fire dampers of low aeraulic resistance in a closed position and that all levels of dilution are involved in filter clogging, with a slightly higher percentage in the lowest classes compared to case 2 (72 % of cases in the lowest class (from 4,500 to 20,000 m^3h^{-1}) against 1 % of cases in the highest class (from 80,000 – 100,000 m^3h^{-1}).

Fire growth factor		
slow	☐	0%
medium	☐	0%
fast	☑	100%
ultrafast	☐	0%

Maximum HRR in open atmosphere (kW)		
200-800	☑	25%
800-1500	☑	25%
1500-3000	☑	25%
3000-5000	☑	25%

Heat of combustion (MJ kg^{-1})		
15-25	☐	0%
25-35	☑	100%
35-50	☐	0%

Fire dampers closing times Inlet (s)/Exhaust (s)		
150 / +0	☐	0%
150 / +1800	☐	0%
150 / +3600	☐	0%
1200 / +0	☑	100%
1200 / +1800	☐	0%
1200 / +3600	☐	0%
∞ / ∞	☐	0%

Fire dampers aeraulic resistance (m^{-4})		
10^4	☑	71%
10^6	☑	29%

Soot particle diameters (µm)		
0.005-0.02	☐	0%
0.02-0.06	☐	0%
0.06-0.1	☐	0%
0.1-0.3	☑	100%
0.3-1	☐	0%

Soot production rate (%)		
1-5	☐	0%
5-10	☐	0%
10-15	☑	100%
15-20	☐	0%

Soot deposition rate (%)		
0-20	☑	100%
20-40	☐	0%
40-60	☐	0%

Initial pressure difference through filters (Pa)		
250-500	☑	22%
500-1000	☑	78%

Compartment volume (m^3)		
50-300	☑	18%
300-700	☑	26%
700-1000	☑	29%
1000-1500	☑	28%

Compartment renewal rate (vol h^{-1})		
1-3	☑	33%
3-7	☑	33%
7-10	☑	33%

Compartment leak rate (vol h^{-1})		
0.1 - 0.4	☑	33%
0.4 - 0.7	☑	33%
0.7 - 1	☑	33%

Dilution volume flow rate (m^3 h^{-1})		
$4.5\ 10^3 - 2\ 10^4$	☑	67%
$2\ 10^4 - 4\ 10^4$	☑	20%
$4\ 10^4 - 6\ 10^4$	☑	8%
$6\ 10^4 - 8\ 10^4$	☑	3%
$8\ 10^4 - 10^5$	☑	2%

Exhaust vent location		
Low	☑	29%
High	☑	71%

Maximum pressure difference through filters (Pa)		
500	☐	0%
500-1000	☐	0%
1000-1500	☐	0%
1500-2000	☐	0%
>2000	☑	100%

Maximum gas temperature through filters (°C)		
20-50	☑	67%
50-100	☑	27%
100-150	☑	4%
150-200	☑	1%
>200	☑	0%

Initial dilution rate (-)		
5	☑	18%
5-50	☑	65%
50-500	☑	17%
500-1000	☑	0%
>1000	☑	0%

Figure 7 Results for a manual closing of the fire dampers at 20 min

Fire growth factor		
slow	☐	0%
medium	☐	0%
fast	☑	100%
ultrafast	☐	0%

Maximum HRR in open atmosphere (kW)		
200-800	☑	25%
800-1500	☑	25%
1500-3000	☑	25%
3000-5000	☑	25%

Heat of combustion (MJ kg^{-1})		
15-25	☐	0%
25-35	☑	100%
35-50	☐	0%

Fire dampers closing times Inlet (s)/Exhaust (s)		
150 / +0	☐	0%
150 / +1800	☑	100%
150 / +3600	☐	0%
1200 / +0	☐	0%
1200 / +1800	☐	0%
1200 / +3600	☐	0%
∞ / ∞	☐	0%

Fire dampers aeraulic resistance (m^{-4})		
10^4	☑	81%
10^6	☑	19%

Soot particle diameters (µm)		
0.005-0.02	☐	0%
0.02-0.06	☐	0%
0.06-0.1	☐	0%
0.1-0.3	☑	100%
0.3-1	☐	0%

Soot production rate (%)		
1-5	☐	0%
5-10	☐	0%
10-15	☑	100%
15-20	☐	0%

Soot deposition rate (%)		
0-20	☑	100%
20-40	☐	0%
40-60	☐	0%

Initial pressure difference through filters (Pa)		
250-500	☑	20%
500-1000	☑	80%

Compartment volume (m^3)		
50-300	☑	19%
300-700	☑	28%
700-1000	☑	27%
1000-1500	☑	27%

Compartment renewal rate (vol h^{-1})		
1-3	☑	33%
3-7	☑	33%
7-10	☑	33%

Compartment leak rate (vol h^{-1})		
0.1 - 0.4	☑	33%
0.4 - 0.7	☑	33%
0.7 - 1	☑	33%

Dilution volume flow rate (m^3 h^{-1})		
$4.5\ 10^3 - 2\ 10^4$	☑	72%
$2\ 10^4 - 4\ 10^4$	☑	22%
$4\ 10^4 - 6\ 10^4$	☑	4%
$6\ 10^4 - 8\ 10^4$	☑	2%
$8\ 10^4 - 10^5$	☑	1%

Exhaust vent location		
Low	☑	34%
High	☑	66%

Maximum pressure difference through filters (Pa)		
500	☐	0%
500-1000	☐	0%
1000-1500	☐	0%
1500-2000	☐	0%
>2000	☑	100%

Maximum gas temperature through filters (°C)		
20-50	☑	72%
50-100	☑	24%
100-150	☑	3%
150-200	☑	1%
>200	☑	0%

Initial dilution rate (-)		
5	☑	18%
5-50	☑	65%
50-500	☑	17%
500-1000	☑	0%
>1000	☑	0%

Figure 8 Results for a fire damper closing time at the inlet air vent at 2 min and 30 s and a fire damper closing delay at the exhaust air vent of 30 min

CONCLUSIONS

In fire safety assessment, it is essential to be able to quickly discern configurations at risk in a nuclear facility. For that purpose, an expert system approach, based on the Bayesian Belief Network methodology, was undertaken to take advantage of the SYLVIA software. A knowledge base including the results of ten million runs performed with the SYLVIA software was built to study the behavior of the final level of aerosol filtration in nuclear facilities, in a fire situation. The first results confirm the interest of the expert system approach in order to dynamically use large databases as part of a fire safety analysis. Indeed, it can help the identification of configurations increasing the risk for a particular scenario from the exploitation of a large database of SYLVIA runs.

The perimeter of the knowledge base determines the scope of the expert system. If the framework of the study were to change, it would then be necessary to integrate the new generic knowledge (enrichment of the knowledge base). For any other safety assessment needs the database, the identification of the responses of interest and their influential parameters as well as the characterization of the conditional probability tables are likely to be different. However, the general framework is generic. Thus, for new issues coming from some fire safety analysis, another study done with SYLVIA / SUNSET software may be necessary. Nevertheless, the algorithmic part of the expert system (the inference engine) is, in principle, unchanged, but may, however, need to be adapted in order to take into account the characteristics specific to the new question of interest in terms of parameters and responses.

In the approach of the assessment of the fire source term by simulation tools, the next step would be to develop "satellite" expert systems for the fire room and the ventilation network that would be plugged to the SEVEN expert system. These expert systems would integrate the geometry and the specificities of the installation to be studied. This step would make it possible to calculate the soot deposition in the fire room and the ventilation network as well as thermal exchanges. The ultimate step would consist in introducing radionuclides in the SYLVIA simulations in order to calculate the fire source term.

To achieve the coupling of different expert systems, a possible solution would consist in introducing intermediate responses to aggregate the effect of subsets of upstream parameters. This approach has the advantage of increasing the number of modelled parametric configurations while maintaining the computational efficiency but requires identifying and validating appropriate intermediate responses. A difficulty lies in taking into account the feedback of the filter clogging effects on the ventilation and the fire, such as the rise in pressure.

The development of Bayesian Belief Network tools based on large simulation database can be considered as a complementary way to take advantage of the SYLVIA software allowing an expert to quickly target the configurations at risk in a specific safety assessment. Moreover, the computing time required by such expert systems being negligible, this kind of tools can be highly profitable for training. To the authors´ opinion, expert systems represent a new generation of computational tools in the field of probabilistic fire simulation.

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