Complex systems modelling and optimization

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ABSTRACT: This communication presents two systems modelling methods which can be coupled directly with automatic optimization tools: A hybrid method based on Fault Trees and Markovian process is proposed when systems are made of independent sub-systems of average complexity and a recursive simulation method proposed in the other cases.

1 INTRODUCTION

The optimization of complex systems under availability constraints has become one of the major challenges in all engineering domains (aeronautic or space systems for example). Usually based on cost criteria (Life Cycle Cost), this optimization is built on the availability evaluation of complex systems made of many different equipments organized on particular redundancy patterns. In addition to corrective maintenance the planned maintenance is implemented in order to avoid wear phenomena and hidden failures. Several stocks of spare equipments avoid long supply and repair delays.

The optimized configuration might take into account big number of independent parameters. This is why the pseudo-manual approaches, such as the analysis of sensitivity, are impossible.

The evaluation methods have to model the true systems behavior and be validated by designers. Moreover, those methods shall lead to fast computing in order to be directly coupled with automatic optimization methods that need big numbers of evaluations to converge (Goldberg 1994).

No evaluation method is the perfect answer to this point:

- Reliability block diagrams and fault trees allow fast processing but can not take into account the dynamic behaviors.
- Markovian solver is as fast and precise but is quickly limited by the big number of Boolean combinations.
- Stochastic PETRI nets have a great quality for representation but are difficult to use and their processing very slow (The simulation of a Monte-Carlo type is 1000 times longer than an equivalent analytic or Markovian type for 2 to 3 digits of accuracy).

This paper proposes two original techniques that seem to be the adequate answers when those methods are inappropriate:

- A hybrid method based on fault trees and Markovian processes when systems are made of independent sub-systems of average complexity.
- A recursive simulation model when the sub-systems are dependent or too complex.

2 HYBRID MODEL

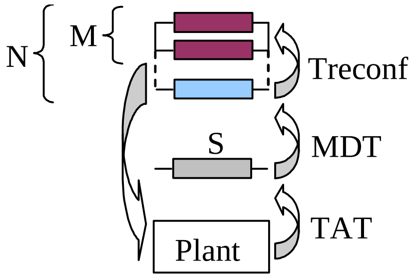
When systems consist of independent sub-systems, each one of limited size, a hybrid technique using fault trees and Markovian processes is a good alternative solution. But this joint use of two well-known methods curiously constitutes originality in a reliability field characterized by practices of work and schools of thought.

Markovian process can take into account the dynamic aspects of sub-systems (reconfiguration, repair, return to shop) as well as some stochastic dependence between their equipments (cold redundancy, limited number of operators or repairers). In order to limit the effort of modeling significantly, various tools can be used.

Thus, a Markovian models generator (Cabarbaye and all 1999) allows automatically to build the Markov matrix of a system thanks to the input of logical equations describing its good functioning and potential stochastic dependences. The tool groups together equivalent system states.

In the same way, redundancy parametric formula (Laulheret 2003), as shown on figure 1, allows to automatically generate the corresponding Markovian model and then obtain reliability or availability data.

The redundancies can be of M among N type, active or passive, with a spare stock of size S.



= *Redundancy(M, N, λ_{ON}, λ_{OFF}, T, T_{reconf}, MDT, $Nb_{operators}$, S, TAT, $N_{repairers}$, Active/passive, Reliability/Availability)*

Figure 1. Parametric redundancy formula

The maintenance is characterized by the Mean Down Time (MDT) value (repair by replacing failed equipment by an identical new one) and Turn Around Time (TAT) value (repair in shop or stock supply delays). The passive, hot or cold ($\lambda_{OFF} \neq \lambda_{ON}$) redundancies are characterized by the reconfiguration time to switch on redundant equipments.

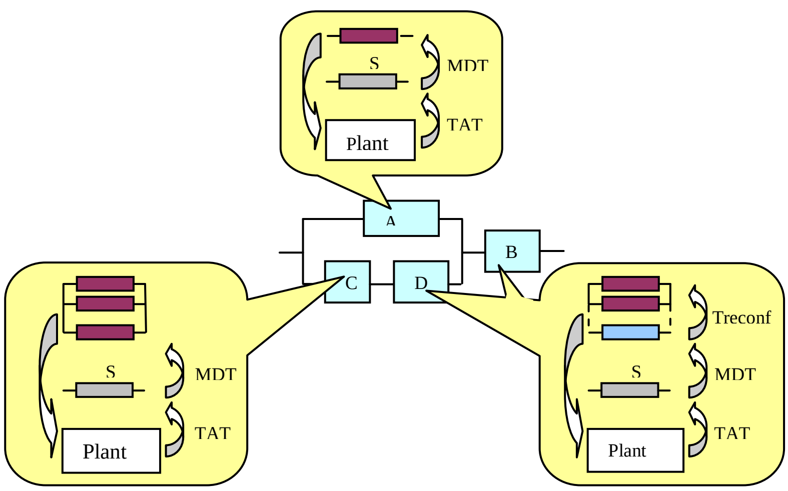
As an example, figure 2 shows the Markovian matrix of a passive redundancy of one equipment among two plus one spare (M=1, N=2 and S=1). Equivalent system states are grouped together in this redundancy model. Failures are taken into account only when at least M equipments are operational among the N+S equipments (outside long duration unavailability).

MAT :	1	2	3	4	5	6	7	8
Ok: 1	-	λ_{ON}	λ_{OFF}		λ_{OFF}			
Reconfiguration: 2		-	$1/T_{reconf}$	λ_{ON}		λ_{OFF}		
Loss of redundancy: 3			-	λ_{ON}	1/MDT		λ_{OFF}	
Not available: 4				-			1/MDT	λ_{OFF}
Ok and loss of spare: 5	1/TAT				-	λ_{ON}	λ_{OFF}	
Reconfiguration and loss of spare: 6		1/TAT					$1/T_{reconf}$	λ_{ON}
Loss off redundancy and loss of spare: 7			1/TAT				-	λ_{ON}
Not available and loss of spare: 8				1/(TAT+MDT)				-

Figure 2. Markovian matrix

As an example, the availability of architecture shown on figure 3 was calculated by the SUPER-CAB tool that uses this hybrid technique.

This example is evaluated thanks to the redundancy formula of figure 1 and also to a form of logical solver of the same type of those used in fault trees, but limited to the logical operators: OR (+), AND (*), NO (~). In the example, the equation is: (A+C*D)*B.



	M	N	S	$MTBF_{ON}$ (hr)	$MTBF_{OFF}$	T_{reconf}	MDT	TAT	Availability
A	1	1	2	10000	100000	-	15	70	0.99850177
B	1	2	1	2000	20000	10	20	500	0.97875901
C	1	3	2	3000	30000	-	30	650	0.9884445
D	2	3	1	2000	20000	10	20	500	0.91104693
					Complete System		(A+C*D)*B		0.978613126

Figure 3. Example of hybrid model

The evaluation tool is coupled to an optimization tool (GENCAB) (Cabarbaye 2003) that is based on an hybrid method using genetic algorithms, differential evolution (Feoktistov 2004) and non-linear simplex (Nelder Mead algorithm). Spare equipments stock can then be automatically optimized on cost and availability criteria (for example, availability ≥0.99 in the example of figure 4). The convergence is very fast. (a few minutes with a Pentium 4)

	M	N	S	$MTBF_{ON}$ (hr)	$MTBF_{OFF}$	T_{reconf}	MDT	TAT	Availability	Unit cost	Spare cost
A	1	1	0	10000	100000	-	15	70	0.99304866	1000	0
B	1	2	3	2000	20000	10	20	500	0.99327934	9000	27000
C	1	3	1	3000	30000	-	30	650	0.98039992	5000	5000
D	2	3	1	2000	20000	10	20	500	0.91104693	2000	2000
			↑	Complete System			(A+C*B)*B'		0.99254186		34000
									≥ 0.99		⇓

Figure 4. Optimization of spare stock

In the same way, the optimization can be done simultaneously on many parameters: components reliability (quality level), redundancy levels, spare stock size or repair and supply time. Each of those parameters has an influence on acquisition and operating costs. On the example shown on figure 5, 20 parameters are taken into account for the optimization (bold red figures).

DEMO16.XLS

Equipment	MTTF ON (hour)	Nb	Type of redundancy	Stock of spares	Unit cost (Euros)	MDT (hour)	TAT (hour)	Operational availability	Cost (Euros)
Engine az/el	100000	2	serie	**1**	4500	28	2400	0,9972	13500
Coders	100000	2	serie	**1**	1500	28	2400	0,9972	4500
Receiver / transmitter	**2003**		**Passive 1/2**	**1**	15039	28	1000	0,9113	45116
Processor	**2059**		**Passive 1/3**	**0**	4237	25	800	0,9456	12711
A - STATION TTC								**0,8569**	**75827**
Archive processor	33000	1	serie	**0**	4500	**35**	500	0,9851	4500
Production processor	**2183**		**Passive 2/2**	**1**	1775	**35**	500	0,9736	5324
Supervision	10000		**Active 1/3**	**2**	500	**35**	300	0,9965	2500
Memory disc	50000	2	serie	**2**	4000	**35**	600	0,9986	24000
B - USER CENTER								**0,9544**	**38056**
Antenna	33000	1	serie		4500		1000	0,9706	4500
Receiver / transmitter	**4811**	1	serie	**2**	19053	**26**	2400	0,9177	57160
Supervision	127000	1	serie	**3**	500	**26**	100	0,9998	2000
C - REDUNDANT CENTER								**0,8905**	**68309**
TOTAL SYSTEM:	A*B+C							**0,9800**	**182192**

Availability > Objective: 0,98

KE

Optimization of a satellite ground station

Figure 5. Multi-parameters optimization

In the example of the figure 3, if it is supposed that the equipment B and D are identical and there is a common shared stock of spares, this hybrid method is not working because there is dependence between subsystems. In that case, it is not possible anymore to evaluate the availability of the system but only to find the probability of a stock interruption, by considering a strategy of maintenance consisting in using, if necessary, the same units located in redundancy chains in the whole system. Such a model is proposed in the form of a Markovian parametric formula considering, by type of unit, the numbers of active elements, redundant elements at ON state and elements at OFF state (redundant or spare). Another solution consists in evaluating the availability of the system by Monte-Carlo simulation.

3 RECURSIVE SIMULATION MODEL

When a system can not be split into independent sub-systems, or when those sub-systems are too complex, the simulation is the appropriate method. A technique based on recursive simulation model and effective optimization coupling allows optimizing the system without taking too much processing time. This method is the subject of another ESREL 2006 article entitled: “Optimization and Recursive Simulation modelling”. Included in an Excel-based simulation tool (SIMCAB), it is illustrated on the Figure 6.

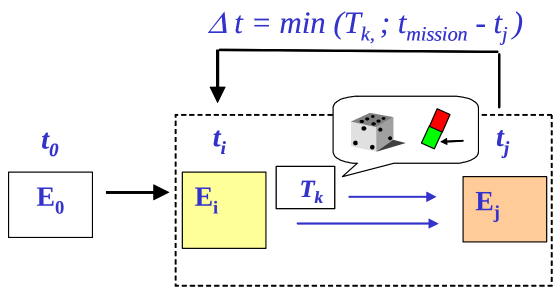


Figure 6. Recursive Model

This evaluation method of discrete states systems consists in defining a generic transition between a state Ei (at ti) and a state Ej (at tj). This transition is built by means of logical operators and of calculation between both states defined in cells of the spreadsheet. The tool algorithm copies the Ej state into the Ei state during all the mission time, starting from the initial E0 state (at t0). The time slot between ti and tj is the duration of two events following each other. This duration is defined as the smallest computed value, at the current time, among the time increments Tk corresponding to system status random changes or to the overstep of thresholds by continuous parameters.

The considered systems can be Markovian or not (without influence of the preceding states) and possibly of hybrid type, defined by dependences between continuous and stochastic parameters. (Labeau 2003) (Castagna 2003)

The simulation can be done with a step by step mode in order to validate the hypothesis or for a complete mission that is re-processed numerous times depending on the targeted results precision.

An original coupling technique between optimization and simulation algorithms allows decreasing the processing time (Cabarbaye and all 2006) (Chen and all 2000). This technique is very efficient and divides the processing time by 30 on several test examples.

This technique performs a rough estimation of the quality of each candidate solution (50 simulations of the mission for example) before evaluating it with a higher precision (between 50 to 2000 simulations for example).

The figure 7 shows an example of a similar redundancy model as the one processed previously thanks to a Markovian model.

Three cells of the spreadsheet are respectively the number of active elements (M), passive elements (N-M) and stock size (S), at the T0, Ti and Tj time.

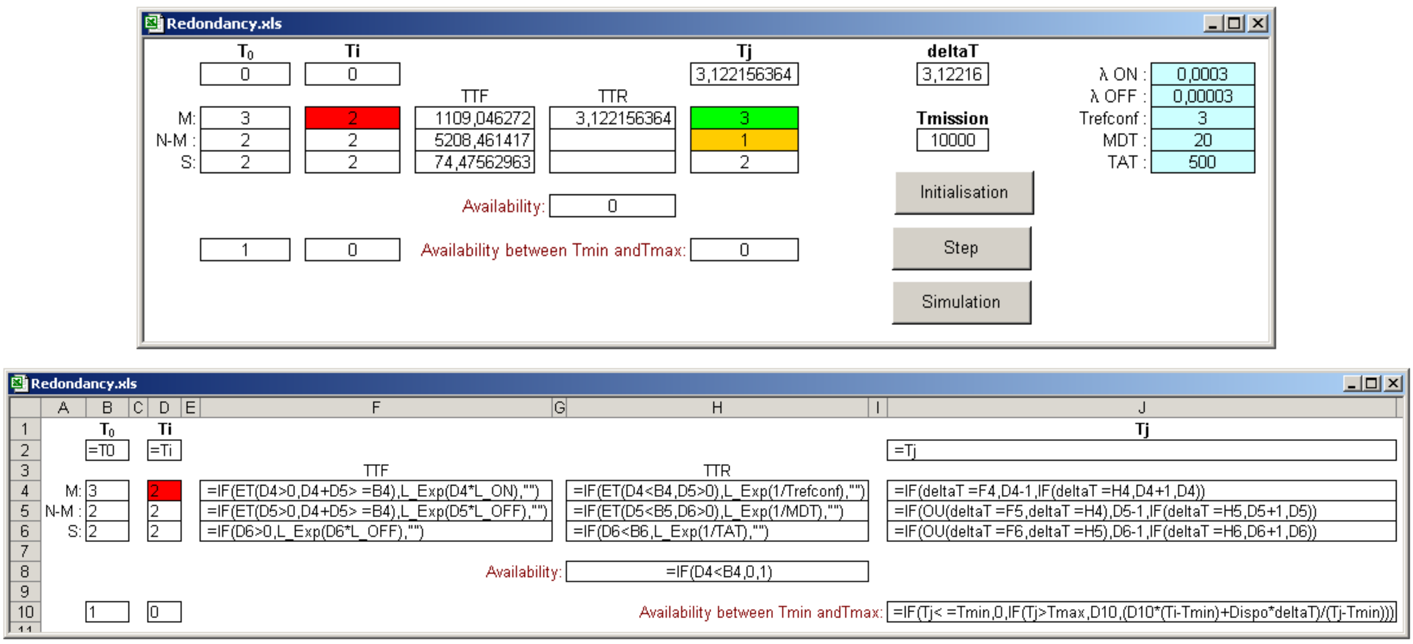
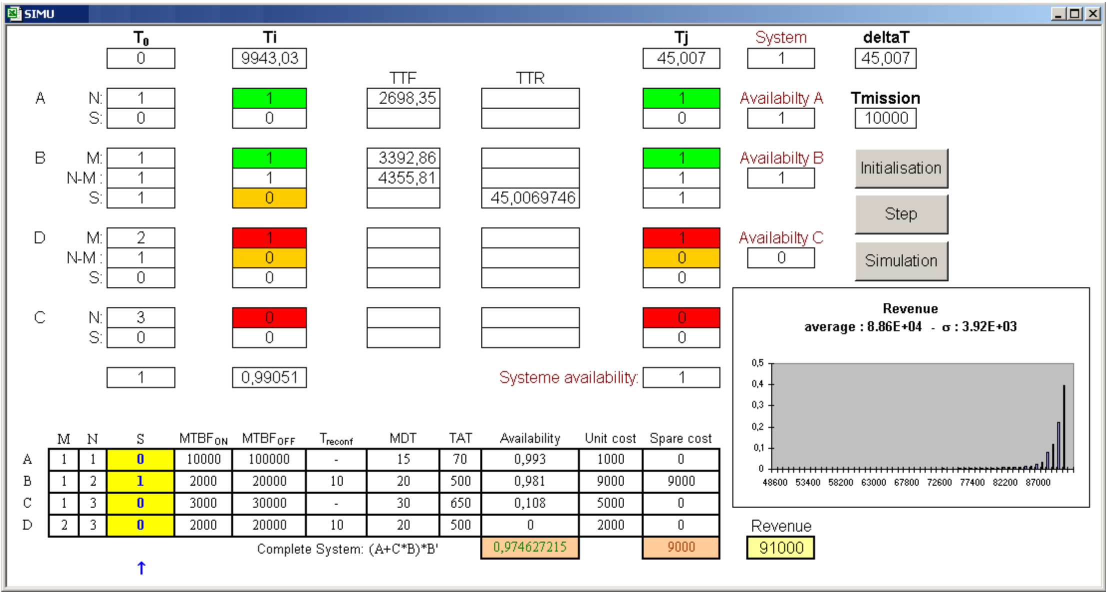


Figure 7. Redundancy model of M active elements among N elements with a S size spare stock

The Time To Failure (TTF) and Time To Repair (TTR) are defined by equations where the function L_Exp() performs a randomized drawing of the exponentional law (20 different laws are available in the tool). Reconfigurations and standard exchanges are authorized only if redunded or spare equipments are present. The system is available as long as there are enough active elements. The average availability is computed on all the mission’s duration.

The architecture of Figure 3 previously processed with hybrid model can be evaluated and optimized with a recursive model method as shown on figure 8.



	M	N	S	$MTBF_{ON}$	$MTBF_{OFF}$	T_{reconf}	MDT	TAT	Availability	Unit cost	Spare cost
A	1	1	0	10000	100000	-	15	70	0,993	1000	0
B	1	2	1	2000	20000	10	20	500	0,981	9000	9000
C	1	3	0	3000	30000	-	30	650	0,108	5000	0
D	2	3	0	2000	20000	10	20	500	0	2000	0

Figure 8. Optimization of preceding architecture

However, the coupling of optimization and stochastic simulation has a difficulty concerning the availability constraint. Indeed, spare equipments costs and system availability are antagonist. Therefore is the optimum located on the border of the constraint limit. But, because of the variance of the results obtained by simulation, several evaluations of a same solution at close range of the limit can strongly vary and lead to discarding a previously optimum-graded result. The penalty associated to the amplitude of the distance with the constraint border limit becomes a parameter difficult to set. That is why the optimization was done on the revenue performance defined as follow:

Revenue = 100000 * Availability – Costs.

Nevertheless, this model can deal with more complex systems, with dependences between subsystems such as shared spare stock of B and D equipments if they are identical.

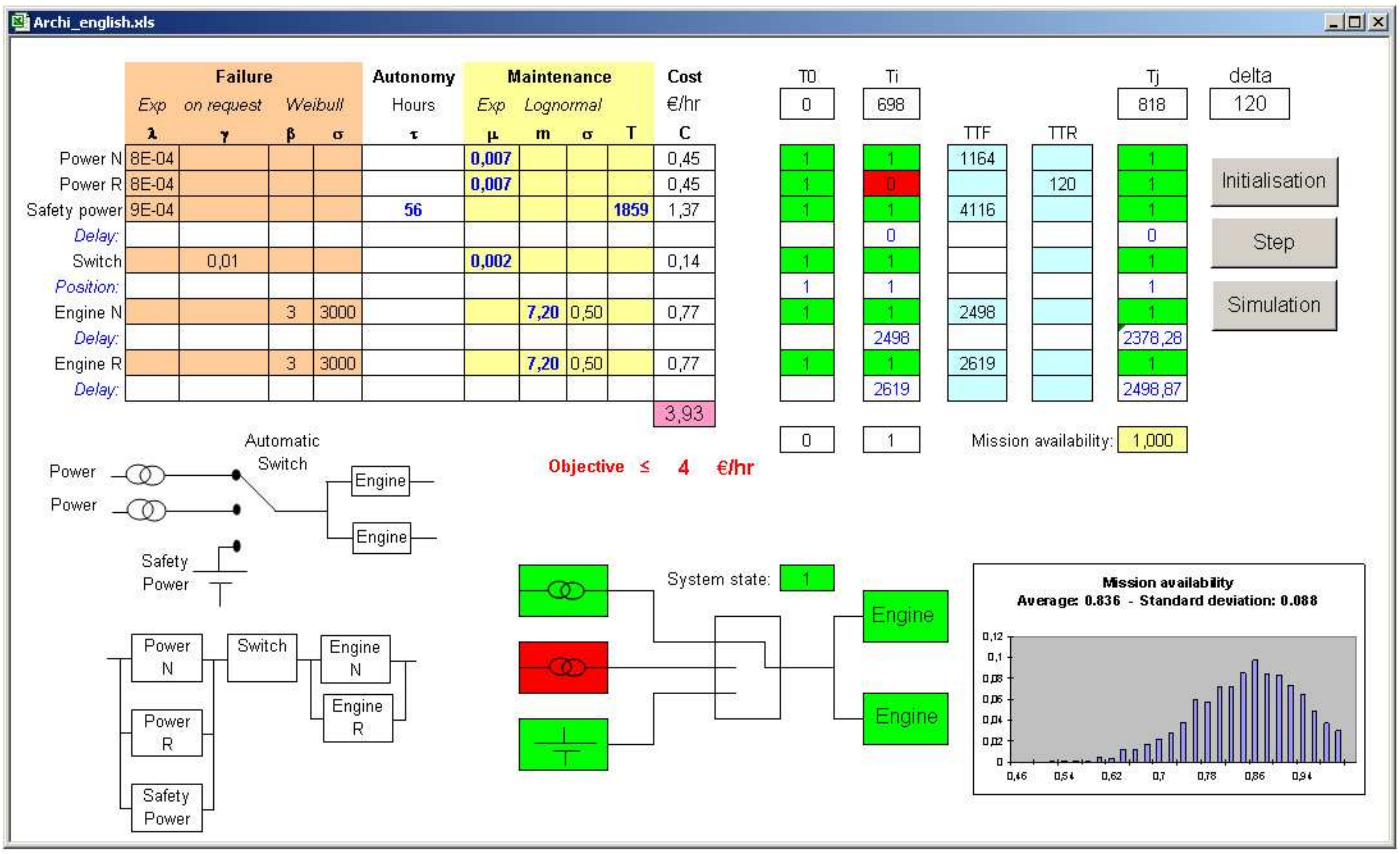


Figure 9. Architecture optimization

In the same way, the example of figure 9 illustrates a simple academic case relating to the optimization of the preventive and corrective maintenance of a system. This one is composed of two engines in redundancy supplied with two electric sources or an accumulator battery, through an automatic relay.
The optimization relates simultaneously to the battery sizing and maintenance parameters:

- Power supply MTTR (Mean Time To Repair): between 100 to 500 hours
- Engine MTTR: between 500 to 200 hours
- Automatic switch MTTR: between 100 to 500 hours
- Battery autonomy between 25 to 100 hours
- Periodicity of battery maintenance operation: between 500 to 2000 hours

The availability of the system is maximized here in a limited cost (4 €/hour) by using a parametric function of cost.
We can notice that this system is only partially Markovian. Indeed, the battery autonomy duration is deterministic and the reliability of the engines is modelled by a Weibull probability law and their maintenance by a lognormal law. This is why durations of engine operation and those of repair are random simulated only one time, then decremented with the occurrence of each event. It is the same for the battery autonomy duration.
The validation of the simulation model is facilitated by an animated representation of the system which is directly coupled with the model. In this example this one allows visualizing, step by step, the state of equipment as well as the position of the automatic switch which can fail when it is requested.

4 CONCLUSION

Whatever their complexity, the reparable systems can be the subject of optimization in order to propose the best compromises between the availability of service and the costs. This optimization can be performed by coupling of evaluation and optimization tools. Thus, it is possible to optimize overall various parameters concerning architectures, operating conditions, maintenance policy and logistical support.
The techniques of evaluation per Monte-Carlo simulation are much more constraining, in term of computing time, than those performed by calculation, such as the hybrid method proposed in this paper. But the latter are not possible when the systems are too complex.
The coupling between simulation and optimization tools is however feasible. Indeed such a coupling was implemented in a simulation tool for discrete states systems with an improvement allowing to reduce the computing times significantly (divided by 30 approximately).

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