A Bayesian- Reliability Based Approach of Multi-agent System in Dynamic Environments

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Abstract: Dynamic modeling of multi-agent system interactions and modeling complex dynamic environments request devoted dynamic indicators. In complex dynamic environments under conditions of uncertainty, reliability targets have to be realistic and systematically defined in a meaningful way for marketing, engineering, testing, and production. Potential problems proactively identified and solved during design phase and products launched at or near planned reliability targets eliminate extensive and prolonged improvement efforts after start on. The real-life complex development situations express that the methods applied to new product development process content reliability risks which require assessment and quantification at the earliest stage, extracting relevant information from the process. The lecture proposes the computationally efficient adaptive multi-agent approach of estimation of the shape parameters in a complex data structures approached with exponential gamma distribution as model of life time, reliability and failure rate functions in multi-agent system in complex dynamic environments. The performances indices of studied systems, approached by the means of Extended Generalized Stochastic Petri Nets (EGSPN) and a method dedicated to nonlinear systems integrate the collaboration of multiple systems components for the purpose of proactive and adaptive management. The numerical simulation performed in the case study validates the correctness of the proposed methodology.

Key-Words: Bayesian model, Petri Nets, robots, reliability, estimation, adequate function distribution, simulation.

1 Introduction

Modeling reliability by means of artificial intelligence is increasingly required because of composite problems that systems are facing in socio-technical, and economical context. The risk prediction and decision making tools are converted or designed by means of interconnected structures. The risk estimation is aligning in the larger framework of solving business and technical issues by adopting solution and decision-making under the simultaneous multi-objective conditions Excluding requirements that systems face related to maintain nominal specification of states and conditions, a basic ones are dedicated to the error checking, recovery and protection against system. A shared vision in risk management regarding the stages of risk-based analysis include identification prioritization assess and decomposition of risk. Modeling the behavior of interconnected systems under realistic, time-dependent operational conditions, in order to allow an incremental development, requires assessment of architecture and core capabilities of a given system in the human – machine interactions and socio-technical cohesion conditions. The multi-agent abstraction allows the decomposition of complex system in interrelating components each represented by an agent, as self-organized, flexible and autonomous entity. Autonomous agents are computational systems that inhabit some complex dynamic environment, sense and act autonomously in this environment and by doing so realize a set of goals or tasks for which they are designed [1].

− The integration and cooperation between individual agents according the belief and goal of the agents, defined the collective agents which share the same goal or common task as a multi-agent system, thus:
multi-agent environments provide an infrastructure specifying communication and interaction protocols;
multi-agent environments are typically open and have no centralized designer;
multi-agent environments contain agents that are autonomous and distributed, and may be self-interested or cooperative [4].

In multi-agent systems, the agents can function as intelligent application programs, active information resources, and will be knowledgeable about information resources that are local to them, and cooperate with other agents to provide global view of the particular management information.

The environment types can be approach as:
- Fully observable (vs. partially observable): An agent's sensors give it access to the complete state of the environment at each point in time.
- Deterministic (vs. stochastic): The next state of the environment is completely determined by the current state and the action executed by the agent. (If the environment is deterministic except for the actions of other agents, then the environment is strategic)
- Episodic (vs. sequential): The agent's experience is divided into atomic episodes (each episode consists of the agent perceiving and then performing a single action), and the choice of action in each episode depends only on the episode itself.
- Static (vs. dynamic): The environment is unchanged while an agent is deliberating. (The environment is semidynamic if the environment itself does not change with the passage of time but the agent's performance score does)
- Discrete (vs. continuous): A limited number of distinct, clearly defined percepts and actions.
- Single agent (vs. multiagent): An agent operating by itself in an environment.

The mains features of multi-agent systems can be summarized as follows:
- Interaction
  - Communication languages
  - Protocols
  - Policies
- Co-ordination
- Co-operation
- Collaboration: Shared goals
- Negotiation

Multi agent technology is applied by intelligent systems to solve the problems of analysis of complex systems and intelligent management activities. Intelligent Multi-agent Systems (MAS) based learning combine collection of information from their environment, recognition data, intelligent classification data and prediction future data, storage data, delivery data to knowledge management systems such as Management Information System (MIS), Decision Support System (DSS), Enterprise Systems, (ES), Enterprise Intelligent Systems (EIS), and Business Intelligent Systems (BIS), [5].

When adapting agent technology to complex system, the collaboration between agents integrates local knowledge, effective to obtain a broader basis for decision support. The uncertain and incomplete knowledge which comes from the complexity, instability, or unknown factors of the managed system and the dependency between the management components or correlated management events are aspects added to form a global view of the whole system.

Agent refers to an entity that acts on behalf of other entities or organizations, and Multi-Agent System consists of several agents capable of common interaction with environment by perceiving though sensors and acting upon environment through effectors.

2 Instantaneous Availability

A particularly problem in determining the reliability of the elements is related to the complexity of environmental factors, acting simultaneously. Therefore, the usual models employed to describe the behavior over time of various applications are based on a large number of experiments, having a predictive character.

Given a random variable \( x \) whose probability distribution depends on a set of parameters \( P = (P_1, P_2, ..., P_p) \). Exact values of the parameters are not known with certainty, Bayesian reasoning assigns a probability distribution of the various possible values of these parameters that are considered as random variables. Bayes' theory is generally expressed through probabilistic statements as following:

\[
P(A / B) = \frac{P(A) \times P(B / A)}{P(B)} \quad (1)
\]

\( P (A / B) \) is the probability of A given the event B occurs or the posteriori probability. Using Bayes' theory may be recurring, that if exist an a priori distribution (\( P (A) \)) and a series of tests with experimental results \( B_1, B_2, ..., B_n, ... \), expressed according to successive equations:
\[
P(A / B_1) = P(A) \frac{P(B_1 / A)}{P(B_1)} \quad (2)
\]
\[
P(A / B_1, B_2) = P(A) \frac{P(B_1 / A) P(B_2 / A)}{P(B_1) P(B_2)} \quad (3)
\]
\[
P(A / B_1, B_2, ..., B_n) = P(A / B_1, B_2, ..., B_{n-1}) \frac{P(B_n / A)}{P(B_n)} \quad (4)
\]

A posteriori distribution is used as the test results are known, being obtained as a new function a priori. The start of operations sequences in the Bayesian method regards the transformation \( \gamma \).

In any transformation is looking to find invariant terms. The determination of \( \lambda_i \), invariants, Bayesian distribution is gamma. Admitting that for each individual component \( i \) of a batch, a resistance \( r_{i,j} \) for the requests spectrum \( j \), it is recognized that there is a statistical distribution \( g(r_{i,j}) \) of the quantities \( r_{i,j} \). As a consequence of univocal relationship \( r_{i,j} \rightarrow \lambda_i \), the distribution \( g(r_{i,j}) \) implies a distribution \( h(\lambda_i) \) of the components failure intensities of considered batch. The distribution \( h(\lambda_i) \) is a random distribution of values and reflects the statistical distribution \( \lambda \) of components that survive from batch at time \( t \).

Based on these definitions we can write the distribution \( f(t) \) expression in the terms of Bayesian method, corresponding to a limit likelihood the of the failure time taken to fall throughout the \( \lambda \) values, i.e. a priori distribution between zero and infinity:

\[
f(t) = \int_0^\infty f(t/\lambda) h(\lambda) d\lambda \quad (5)
\]

Moving in time to the left of the distribution \( h(\lambda) \) can be measured by the ratio between the distributions posteriori and a priori

\[
\frac{M[h(\lambda) / t]}{M[h(\lambda) / t]} = \frac{M(\lambda)}{Mo(\lambda)} = 1 + \beta t
\]

Also \( 1 + \beta t \) characterize the time restriction a posteriori distribution:

\[
\frac{\sigma'(\lambda)}{\sigma(\lambda)} = \frac{\beta \sqrt{\alpha + 1}}{\beta \sqrt{\alpha + 1}} = 1 + \beta t
\]

The aging phenomenon has a general model given by the equation:

\[
f(t) = \frac{(\alpha + 1)^\beta}{1 + \beta t} e^{\alpha t}
\]

The period of decline that characterizes hyperbolic useful life of components is followed by an exponential growth that characterizes aging components at time \( t \) in operational regime. In order to establish the period of time in which by an artificial aging of a batch of components is achieved a desired level of reliability, we assume the condition:

\[
z(kt^*) = \lambda^*
\]

where: \( \lambda^* \) is the reached target of components failure rate in operational conditions; \( k \) is acceleration coefficient; \( t^* \) is artificial aging duration.

A method for setting \( \alpha \) and \( \beta \) parameters based on available information, for a situation where prior information is limited to the estimated failure rate consider the empirical matching of random variables moments, consisting of observations performed at theoretical moments calculated using unconditioned probability density. The results show that in some cases reach an inadequate sensitivity distribution from the experimental results so that the uncertainty is either over or under estimated.

Assuming a distribution of gamma a priori:

\[
(\alpha + 1)\beta = \lambda^*, \quad (\alpha + 1)\beta > \lambda^*
\]

Relationship (27) relates parameters \( \alpha \) and \( \beta \) of a priori distribution:

\[
t^* = \frac{(\alpha + 1)\beta - \lambda^*}{k\beta\lambda^*}
\]

Estimated values of the parameters are:

\( \hat{\alpha} = -0.940 \) and \( \hat{\beta} = 6.19 \times 10^{-4} \). The instant failure rate is:

\[
z(t) = \frac{3.71 \times 10^{-5}}{1 + 6.19 \times 10^{-4} xt}
\]

The good correlation confirms between experimental and theoretical results which the adequacy of the law gamma for a priori distribution.

The failure and repair rates can have other representation than the constant function. These methods have some drawbacks, including:

- to enable calculations only some of the laws of distribution are consider (Weibull, Erlang, etc.);
- limitation to a number of system components.

To simplify and accelerate the deduction graph associated Markov process, the properties of extended generalized stochastic Petri net (EGSPN) are exploited. An EGSPN combines features of a Petri net with a generalized stochastic Petri nets. An EGSPN is a generalized stochastic Petri net in which the transitions have execution times distributed by any law of distribution. As a generalized stochastic Petri net, EGSPN have: immediate transitions, transitions validation functions, inhibitory arcs, arc multiplicity marking dependent and two types of markings, vanishing and tangible.
To obtain the instantaneous reliability $R(t)$ and availability, $A(t)$ functions are determined the vectors written as:

$$
R(T) = \sum_{i} P_{i}(T) = [R(t_0), R(t_1), ..., R(t_n)] = \left[\sum P_i(t_0), \sum P_i(t_1), ..., \sum P_i(t_n)\right]
$$

$$
A(T) = \sum_{i} P_{i}(T) = [A(t_0), A(t_1), ..., A(t_n)] = \left[\sum P_i(t_0), \sum P_i(t_1), ..., \sum P_i(t_n)\right]
$$

where $P_{i}(T)$, and $P_{i}(T)$ are vectors $P_{i}(T)$ (rel. 12) corresponding to the stable states of the system considered with, respectively without recovery.

Functions $R(t)$ and $A(t)$ is determined by interpolating vectors $R(T)$ and $A(T)$ properties using spline functions. We denote:

$$
\Delta: -\infty < x_1 < x_2 < ... < x_N < +\infty (x_0 = -\infty, x_{N+1} = +\infty)
$$

and with $P_{m}$ the set of real polynomials with degree less or equal to $m$.

Function $S: \mathbb{R} \rightarrow \mathbb{R}$ is called a spline function of degree $m$ with nodes $x_1 < x_2 < ... < x_N$, if it satisfies the following two conditions:

1) $S \in P_{m}(I_i)$, $I_i = [x_i, x_{i+1}], i = 1, 2, ..., N-1$, $I_0 = (-\infty, x_1], I_N = [x_N, +\infty)$;

2) $S \in C_{m-1}(\mathbb{R})$,

where $P_{m}(I_i)$ is the restriction of polynomials of degree $\leq m$ in the interval $I_i$.

The following $m+N+1$ functions: $\{1, x, ..., x_m, (x-x_1)^m, ..., (x-x_N)^m\}$ forms a basis for the set of all spline functions of degree $m$ with division nodes $\Delta$:

$$
S_{2m-1}(x) = \sum_{j=0}^{2m-1} a_j x^j + \sum_{i=0}^{N-1} c_i (x-x_i)^{2m-1}
$$

Applying the spline functions and using relations (13) we obtain the expressions for reliability and availability functions:

$$
R(t) = S_p(t), A(t) = S_{\Delta}(t)
$$

Considering the case of $R(t)$, and $A(t)$ similar. If the functions are cubic splines, $R(t)$ can be written as:

$$
R(t) = S_p(x) = \sum_{j=0}^{3} a_j x^j + \sum_{i=0}^{N-1} c_i (x-x_i)^3
$$

3. Task Assignment in Multi-agent Robotic in Dynamic Environment

Computation-based closed-loop controllers put most of the decision burden on the planning task. In hazardous and populated environments mobile robots utilize motion planning which relies on accurate, static models of the environments, and therefore they often fail their mission if humans or other unpredictable obstacles block their path. Autonomous mobile robots systems that can perceive their environments, react to unforeseen circumstances, and plan dynamically in order to achieve their mission have the objective of the motion planning and control problem [4, 9]. To find collision-free trajectories, in static or dynamic environments containing some obstacles, between a start and a goal configuration, the navigation of a mobile robot comprises localization, motion control, motion planning and collision avoidance. Its task is also the online real-time re-planning of trajectories in the case of obstacles blocking the pre-planned path or another unexpected event occurring. Inherent in any navigation scheme is the desire to reach a destination without getting lost or crashing into anything.

![Fig.1 Task assignment](image)

A higher-level process, a task planner, specifies the destination and any constraints on the course, such as time. Most mobile robot algorithms abort, when they encounter situations that make the navigation difficult. Set simply, the navigation problem is to find a path from start to goal and traverse it without collision. The relationship between the subtasks mapping and modeling of the environment; path planning and selection; path traversal and collision avoidance into which the navigation problem is decomposed, is shown in Figure 1.

4. Case study

The behaviour of an intelligent robot into can be decomposed in a hierarchy of skills, each defining a complete percept-action cycle for a very specific task [12]. Each action cycle can be modeled by a
finite-state with a few states (a state may correspond
to a complex function or module). The computation
module, a propulsion module, and a manipulation
module of a robot can be modeled by means of
Markov chains. The Markov modeling technique
requires to identify each intermediate state (in
practice, more neighboring levels can be grouped
together), to know the occupancy status of each
component \((T_i)\) and the number of transitions
between states \((N_{ij})\).
An individual navigation task is accomplished by
the cooperation a position localizer and a path
planner as a part of a complex overall mission goals.
Examining this task, we assign six possible sub-task
and represented as Petri system (Fig. 2). The
signification of the network elements is the
following: \(p_i\) (i = 1, ..., 6) - the component i is
working order; \(p_j\) (j = 7, ..., 12) - the component j is
failed; \(p_{13}\) - the system is defect; \(i\) (i = 1, ..., 6) -
component failures i with the rate \(\lambda_i(t)\); \(T_j\) (j = 7,
..., 12) - immediate transitions.
Accessibility graph and Associated Markov graph are
shown in Fig. 3 and respectively Fig. 4.

\[
\begin{align*}
P(t) &= \begin{bmatrix}
-P_1(t) & P_2(t) & P_3(t) & P_4(t) & P_5(t) & P_6(t) \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix} \\
Q(t) &= \begin{bmatrix}
-\sum_{i=1}^{6} \lambda_i(t) & \lambda_2(t) & \lambda_3(t) & \lambda_4(t) & \lambda_5(t) & \lambda_6(t) \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\end{align*}
\]

It results the following differential equations system:

\[
P_1'(t) = -P_1(t) \sum_{i=1}^{6} \lambda_i(t)
\]

Solving system (19) by Runge-Kutta numerical
method is determined \(R(t)\) and \(A(t)\) and
presented comparatively in the fig. 5.
Using Petri nets ease the system modeling if is based on the accessibility graph. Solving the differential equation system by Runge-Kutta method the inherent induced error is smaller than the one that consider constant the failure and repair rates.

Using cubic spline interpolation the reliability and instantaneous availability functions are determined at different time values than using the numerical method.

5. Conclusions
Evaluating the behavior of the in different operating conditions, the proposed method provides a robust estimation of performance indices of reliability and instantaneous availability even with an unspecified distribution function. The model is able to analyze multivariate data of the effects of failures. The checking up of simulation, experimental and analytical, shows a good concordance, the estimated parameters obtain by two ways have rigorous same values.

Fuzzy nets provide a promising solution towards the development quantitative approach of dynamic discreet / stochastic event systems of task planning of mobile robots. For a deeper insight into control and communication governing task assignment of the robot, the entire discrete-event dynamic evolution of task sequential process have to be linguistically described in terms of representations. A comprehensive inference framework is required in analyzing the database of rules of expert systems, Petri nets using a large amount of details for building analysis, even for small systems, which lead to high costs.

References: