PASSIVE SYSTEM RELIABILITY ANALYSIS

By

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DECLARATION

I, hereby declare that the investigation presented in the thesis has been carried out by me. The work is original and has not been submitted earlier as a whole or in part for a degree / diploma at this or any other Institution / University.

Amit Chandrakar

DEDICATIONS

To my wife Akanksha

It’s a saying, “Behind every successful man there is always a woman,” is indeed true

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SYNOPSIS OF Ph.D THESIS

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SYNOPSIS

Passive safety systems are the systems which work based on natural laws, properties of materials, internally stored energy, etc. These passive safety systems do not require external sources of energy such as mechanical and/or electrical power, signals or forces. Many of the advanced reactors e.g. ESBWR, AP1000, CAREM, AHWR, etc. incorporate several passive systems in the design of the reactors. Deployment of passive systems in nuclear reactors provides several benefits, such as: avoidance of dependency on active components; such systems are simple and easy to build, operate and maintain. Elimination of operator intervention or dependency on external sources results in reduction of respective hazards. Despite the above, there are technological challenges and issues in order to engineer them in the reactor designs.

One of the issues with the passive systems is quantification of functional reliability for these systems during normal operation, transients including accidental conditions. The main challenge in assessing the reliability of passive system arises from the fact that the operating principles of these passive systems are based on the natural laws like buoyancy, gravity or natural convection, rather than being dependent on the active components. Since, these physical phenomena in itself never fails as long as the parameters governing them do not deviate from their nominal values, estimating the reliability for these passive system is indeed very subjective.

In this context, a few methodologies such as Reliability Evaluation of Passive Safety System (REPAS)[1], Reliability Methods for Passive Safety Functions (RMPS)[2] and Analysis of Passive Systems ReliAbility (APSRA)[3] have been developed in the past. One of the most important differences between these methodologies is the way these methods treat the variation of process parameters from their nominal values. In RMPS, variation of process parameters is considered by assigning probability density functions (pdf) based on engineering judgment; for example, the reactor has a nominal operating pressure which can vary within a range of pressure control system. This variation is treated by assigning a uniform distribution between minimum and maximum based on expert’s judgment. This approach (assignment of pdf based on expert’s judgment) adds uncertainties in the reliability estimates of the system because of the subjective nature of decisions of experts due to lack of sufficient plant data. Moreover, every process parameter cannot be said to have independent deviations on their own. These process parameters can have dependent variations as well. In APSRA, the variation of process parameters are treated by considering the root diagnosis of the component or sub-system causing these deviations, for example, the variation of pressure from the nominal value could be due to malfunction of the pressure control system which is basically failure of a hardware system. However, it is argued here that every process parameters cannot be treated by root diagnostics, for example, deviation of process parameters like atmospheric temperature cannot be assigned to failure of hardware or components.

Another difference is on the treatment of model uncertainty of the codes used for prediction of functional behavior of the system; RMPS treats this uncertainty by assigning a pdf to the key variable of the models employed. On the other hand, APSRA considers the uncertainty assessment of code/model on the basis of experimental validation. RMPS and APSRA also differ in the way the failure probability of passive system is evaluated. RMPS uses Monte-Carlo simulation or FORM/SORM (first/ second order reliability methods), whereas APSRA predicts failure surface and evaluates reliability using fault tree analysis of the hardware/ components responsible for the deviation of process parameters of passive system. Apart from the differences in these methodologies, they lack to explain some of the important issues related to passive system performance and reliability. These unresolved issues are:

1. Treatment of dynamic failure characteristics of components
2. Quantification of functional failure probability of components of passive systems

3. Treatment of independent process parameters variations
4. Treatment of model uncertainties

The objective of this thesis is to develop a new methodology for the reliability analysis of passive systems, which addresses the above mentioned issues in a consistent manner. In view of this, a methodology called APSRA$^+$ has been developed. The methodology APSRA$^+$ is presented in a hierarchical manner in Fig. 1.

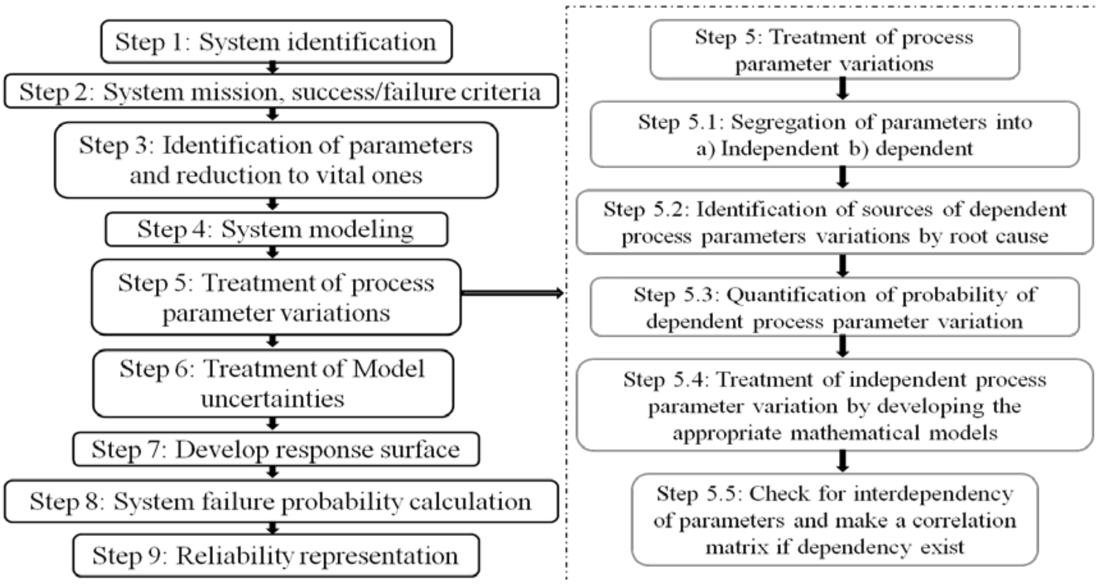

Fig. 1 APSRA$^+$ methodology

In APSRA+ methodology, the unresolved issues are treated in the following manner:

a. Treatment of dynamic failure characteristics of components: It is well understood that functional failure of passive system can be attributed to the deviation of process parameters and malfunctioning of components. During the mission of passive system execution, the process parameters may deviate and at the same time the components may fail stochastically based on the dynamics of operation. These complex interactions between hardware failure and process parameter deviation may further change the way the system is expected to behave during the rest of the operation, and can lead the system to failures which were not anticipated by the deterministic analysis or by static reliability analysis. Traditionally, the reliability analysis of passive safety systems is performed using fault tree (FT) and event tree (ET) analysis. FT/ET assumes that components of passive systems such as valves have binary-states of failure (stuck open and stuck closed). However, such components can fail at intermediate positions as well. Time to failure for these intermediate states of such components can have different probability which may vary from one state to another. In addition, the failed state of these valves also depends upon the process parameter variations and can increase or decrease during the rest of the mission time. These dynamic characteristics of components can have very high implications on the estimates of performance and failure of passive systems.

In the context of dynamic reliability analysis methodologies, one of the most commonly used methods is Markovian analysis. Markov models represent the system time evolution in terms of different states among which possible transitions may occur. This method can provide exact analytical continuous-time descriptions of systems which can be modeled by a discrete state space. The major drawbacks of Markov analysis technique are exponential explosion of state space for complex systems and only exponentially distributed failure and repair time distributions can be used. While making the Markov models, it is assumed that analyst has a wide knowledge of scenarios and it is his understanding which captures the dynamics of system in these models. There are, however, concerns that the analyst may not possess such detailed knowledge and runs the risk of overlooking some of the scenarios. For analyzing the multi-state system with fault increment/ decrement, the Markov models will require huge number of states, which is why this method cannot be used for such systems. In addition to Markovian framework, the methodologies like DYMCAM (Dynamic Monte Carlo Availability Model) and DYLAM (DYnamic Logic Analytical Method) have been proposed in the past. However, these methodologies follow either binary failure mode of components or they fail to model the fault transition during the mission time. In conclusion, the integrated effect of the dynamic failure characteristics of components has never been considered in any of the available methodologies for passive system reliability analysis.

In the framework of $APSRA^+$ methodology, a dynamic reliability methodology is developed and integrated to provide a consistent treatment of the dynamic failure characteristics of components and their interactions with process parameter variations. The developed methodology of dynamic reliability methodology incorporates the following features:

a. Multi state failure of mechanical components
b. Fault increment/decrement during the system evolution
c. Dependency and time dependent failures of components
d. Time treatment of chronology of events i.e. event sequence and order of failures

In order to benchmark the developed methodology, it has been applied to a benchmark system of a level controlled hold-up tank, which was earlier used by many researchers [4-5] in the dynamic reliability analysis domain. This system consists of a fluid containing tank, which has three separate level control units. Failure of the holdup tank system is ascribed as overflow and dryout. With the help of this initial assessment, it was found that developed methodology of dynamic reliability is able to reproduce the same results as published in the literature by Deoss [4] and Siu [5]. In this benchmark analysis, it was assumed that the components fail only in binary modes i.e. either stuck open or stuck closed. In addition to this, it was also assumed that time to failure of these components follow exponential distribution and the faults do not change during the mission time. In actual, these assumptions which were made for the simplification of analysis, often yields system failure estimates to be either too conservative or unrealistic. In view of this, a case of multi-state failure was simulated to assess the impact of dynamic failure characteristics such as multi-state failure on the obtained cumulative failure probabilities. In this case, the valves are assumed to fail at any of the state of opening. The time at which failure of these valves could happen is also assumed to be different for each state, i.e. the distribution of time to failure at each state is assumed to be different since control valves have this characteristic. The results for multi-state failure case along with the binary failure results is compared and shown in Fig. 2. With the help of this analysis, it was learnt that the traditional methods yields the erroneous estimates of system failure probability.

Thus, the methodology of dynamic reliability developed for APSRA$^+$ overcomes the problems of traditional reliability methodologies such as: binary failure mode assumption, exponentially distributed time to failure, no consideration of fault increment and inability to capture the interaction of process parameters with stochastic failure of components. In the present work it has been shown with the help of case studies that our dynamic reliability methodology is capable of handling the above issues. Implementation of this on the reliability methodology, yields significant improvement in the accuracy of estimates of system failure probability.

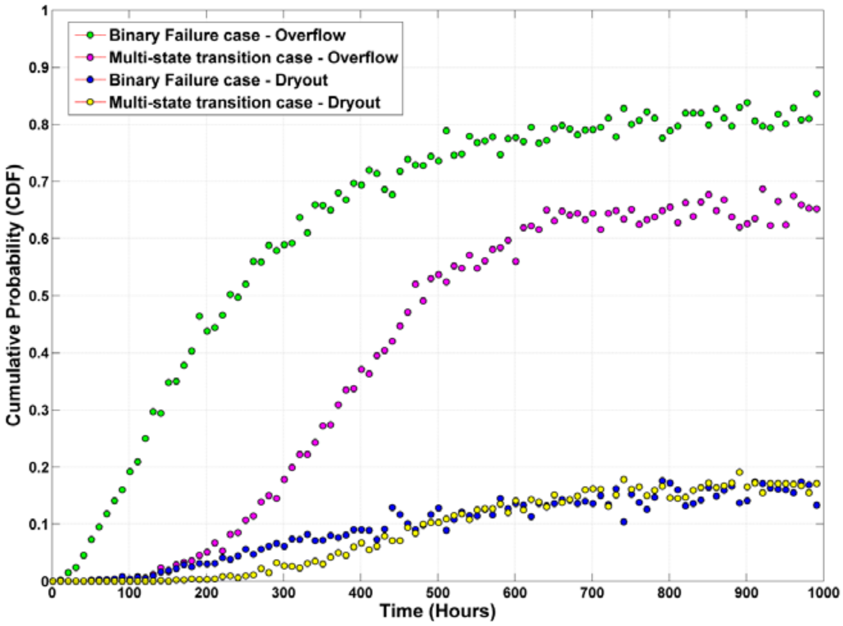

Fig. 2 Cumulative Probability of overflow and dryout for binary failure case and multi-state transition case

b. Quantification of functional failure probability of components: The advanced reactors are designed to utilize passive safety systems, which do not have any moving mechanical components; however most of the passive systems use valves for either activation or during the operation. Traditionally, reliability analysis of these systems is performed with the assumption that these valves have binary-states of failure (stuck open and stuck closed). However, these components can fail at intermediate positions as well. Currently the failure probability of such components at intermediate fault positions is not available in any failure databases. It has been recognized that lack of experimental evidence and validated data forces the analysts to resort to expert/engineering judgment to a large extent, hence making the results strongly dependent upon the expert elicitation process. This prompts the need for the development of a framework for constructing a database to generate probability distributions for the component failures and process parameters influencing the system behavior. In view of the requirement for generation of the databases for the probability distributions of the components of passive system like valves, an experimental facility of a benchmark setup consisting three control valves for a passive system was built and a series of experiments were performed to quantify the functional failure probability of these valves which play critical role in performance of passive safety system. Table 1 presents the failure probability of these valves at intermediate positions of openings. To compare the failure rates traditionally used in the static reliability methodologies, the derived failure rates at these intermediate failure positions has been shown along with the conventional failure rates obtained from the generic databases. It can be inferred from this table that the probability of intermediate faults is quite significant and hence should not be ignored while assessing the system failure and performance analysis. The effects of dynamic failure characteristics of the valves on the functional failure of the passive system were also assessed in this experimental facility. The implications of ignoring these characteristics in estimating the system failure probability were estimated and found to be very significant.

TABLE 1 Probability of valve failure at intermediate states

% Fault	**Probability of getting stuck**	**Derived failure rate (failure/demand)**	**Conventional failure rate (failure/demand)**
Stuck close – 100%	≈35%	3.50E-05	5.00E-05
Stuck intermediate-25%	≈5%	5.00E-06	0.00E+00
Stuck intermediate-50%	≈10%	1.00E-05	0.00E+00
Stuck intermediate-75%	≈15%	1.50E-05	0.00E+00
Stuck open - 100%	≈35%	3.50E-05	5.00E-05

c. Treatment of independent process parameters variations: Some of the advanced reactor designs incorporate emergency passive natural circulation cooling system to remove decay heat to the air through passive air cooled condensers. Performance of these systems is very sensitive to the parameters like atmospheric temperature or the environment temperature. These parameters vary in time along the mission period of system operation. In addition they have certain pattern depending on the season (summer/winter) and time of operation (day/night) including some random variations. Such parameters are called independent process parameters. Currently none of the methodologies for passive system reliability analysis have given due emphasis and treatment to variations of such independent process parameters. These independent parameters are time dependent and hence, cannot be treated by random probability distributions which are static with respect to time. Treatment of dynamic variation of such kind of parameters is another unresolved issue in reliability analysis of passive systems.

In APSRA^{+} methodology, quantification of probability of independent process parameter variations is performed by developing a mathematical model using the data collected for these process parameters over a time period. The methodology uses a special class of model called Auto Regressive Integrated Moving Average Model (ARIMA) for modeling the independent process parameters like atmospheric temperature. A detailed methodology of developing such time series models and synthetic data is developed in this thesis. As an illustration to the methodology of model fitting and synthetic data generation, a time series of monthly-maximum atmospheric temperature of district Chittaurgarh (Rajasthan, India) was considered. With the help of methodology, a non-contiguous ARIMA model of AR (1,3,6,9,12), MA(1,3,6,9,12) was found to represent the differenced (at lags 12) stationary series of monthly-maximum atmospheric temperature. A synthetic series of length 1224 months have been generated based on the finalized ARIMA model. The developed model could provide an accurate way for the treatment of dynamic variation of independent process parameter and was found to be significantly different from that conceived by using a pdf as in existing methods.

d. Treatment of model uncertainties: Currently, the performance of passive systems and their failure are predicted by so called ‘best estimate codes’. However, the applicability of the ‘best estimate system codes’ to assess the performance and failure of passive systems is not well established due to the lack of sufficient plant/experimental data. That introduces uncertainties and errors when such codes are applied to evaluate passive system performance. To address the issues associated with the treatment of model uncertainties, first an exhaustive literature survey has been performed to identify the uncertainties in the models which are generally used in the best estimate system codes to simulate the passive system behavior. Then these uncertainties associated with various models are propagated by modifying the corresponding model parameters in the best estimate system codes while performing the performance and failure analysis of passive system. The application of these uncertainties in system reliability analysis has been presented.

The methodology APSRA$^+$ has been applied to the passive isolation condenser system (ICS) of advanced heavy water reactor (AHWR) as an example. The failure probability of ICS with respect to the reactor years has been presented (shown in Fig. 5), which is of the order 1×10^{-10}. It has to be noted that the failure probability of ICS was earlier estimated to be of the order of 3.53E-07 using APSRA methodology. The failure probability of ICS obtained using APSRA methodology were found to be very conservative when compared with the failure probability obtained from APSRA^{+}.

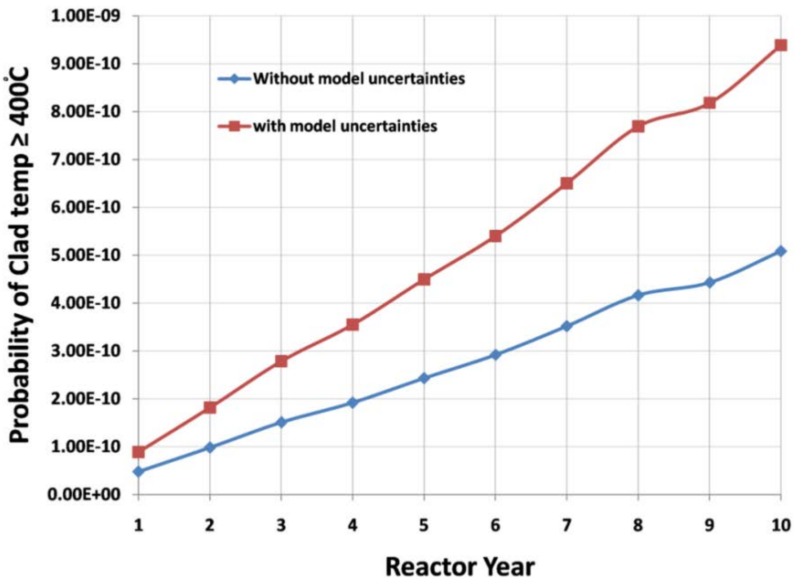

Fig. 4 Probability of failure of ICS with respect to the reactor years

Conclusions

Following are the main conclusions of this research work:

1. A critical review of the present methodologies of passive system reliability analysis was performed to identify the objectives and scope of work. With the help of the review of literature, four critical issues pertaining to passive systems performance and reliability have been identified. These issues are:
    - Treatment of dynamic failure characteristics of components
    - Quantification of functional failure probability of components of passive system

- Treatment of independent process parameters variations
- Treatment of model uncertainties

2. In view of the unresolved issues associated with the currently available methodologies of passive system reliability analysis, a methodology called APSRA$^+$ has been developed in this thesis to overcome the unresolved issues.
    - APSRA$^+$ provides an integrated dynamic reliability methodology for the treatment of dynamic failure characteristics such as multi-state failure, fault increment and time dependent failure of components of passive systems
    - With the help of benchmark system analysis, it was learnt that the conventional methods yields erroneous estimates of system failure probability

2. Since there is serious lack of the database for the probability distributions of the mechanical components of passive system like valves, an experimental facility of a passive system consisting of three control valves was built and a series of experiments were performed to quantify the functional failure probability of these valves. The following conclusions can be drawn from the findings of the experiments performed:
    - Intermediate state failure probabilities of valves were determined from the experiments performed
    - Implications of ignoring intermediate stuck failures and dynamic valve characteristics in estimating system failure probability was estimated and found to be very significant

3. For the treatment of independent process parameters variations for example, atmospheric temperature variations, $APSRA^+$ methodology suggest to rely on developing the time series models such as ARIMA and then use these models for generating synthetic data which can be used for uncertainty propagation. In this regard, the following developments were made in this thesis:
    - As an illustration, a time series of monthly-max. atmospheric temperature of district Chittaurgarh (Rajasthan, India) was considered
    - A non-contiguous ARIMA model of AR (1,3,6,9,12), MA(1,3,6,9,12) was found to fit the series. A synthetic series of length 1224 months have been generated
    - Developed model provides an accurate way for the treatment of dynamic variation of such parameter and was found to be significantly different from that conceived by using a pdf as in existing methods

4. $APSRA^+$ has been applied to passive isolation condenser system (ICS) of Indian advanced reactor: Advanced Heavy Water Reactor (AHWR). Failure probability of ICS with respect to the reactor years has been estimated, which is of the order 1×10^{-10}. It has to be noted that the failure probability of ICS was earlier estimated to be of the order of 3.703E-07 using APSRA methodology. APSRA methodology provides conservative estimates when compared with the $APSRA^+$ results. The large differences in the estimated probability is mainly because, in $APSRA^+$ the dynamic failure characteristics of components is considered while estimating the probability of variations of process parameters

Future Works

- Performing experiments to assess the variation of process parameters from its nominal values and generating the databases for functional failure of vital components of passive systems.
- Assessment and implementation of dynamic event tree methodology for integrating the passive system reliability into the plant specific PSA.
- Validation of system failure probability through functional and system level testing.

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4. A. CHANDRAKAR, A. K. NAYAK and V. GOPIKA, "Quantification of functional failure probability of a passive safety system," *SRESA Journal of Life Cycle Reliability and Safety Engineering* (Accepted for publication).

International Conferences:

1. Reliability Analysis of Process Controlled Systems Considering Dynamic Failure of Components. International Applied Reliability Symposium (ARS), September-2013

2. Passive System Reliability Analysis Challenges and a Step Towards Resolution. New Horizons in Nuclear Thermal Hydraulics and Safety, December, 2013

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NOMENCLATURE

List of Abbreviations

Abbreviation		Full Meaning
ACF	-	Auto Correlation function
AD	-	Anderson Darling
ADS	-	Automatic Depressurization System
AHP	-	Analytical Hierarchy Processes
AHWR	-	Advanced Heavy Water Reactor
AIC	-	Akaike Information Criterion
APSRA	-	Analysis of Passive Systems ReliAbility
AR	-	Auto-Regression
ARCH	-	Autoregressive Conditional Heteroskedasticity
ARIMA	-	Auto-Regressive Integrated Moving Average
ARMA	-	Autoregressive-Moving-Average
B.E.	-	Best Estimate Codes
BIC	-	Bayesian Information Criterion
C	-	Contiguous ARMA model
CDF	-	Cumulative Density Function
CMT	-	Core Makeup Tank
DDET	-	Discrete Dynamic Event Trees
DYLAM	-	DYnamic Logic Analytical Method
DYMCAM	-	Dynamic Monte Carlo Availability Model
ECDF	-	Empirical Cumulative Distribution Function
EJ	-	Expert Judgment
ESBWR	-	Economic Simplified Boiling Water Reactor
ETA	-	Event Tree Analysis
FIR	-	Fault Increment Rate

FORM	-	First Order Reliability Methods
FTA	-	Fault Tree Analysis
GFR	-	Gas-cooled Fast Reactors
IAEA	-	International Atomic Energy Agency
ICS	-	Isolation Condenser System
LERF	-	Large Early Release Frequency
LOCA	-	Loss of Coolant Accident
MA	-	Moving-Average
MLE	-	Maximum Likelihood Estimation
NC	-	Non-contiguous ARMA model
PACF	-	Partial Auto Correlation Function
PCCS	-	Passive Containment Cooling System
PCIS	-	Passive Containment Isolation System
PDF	-	Probability Density Function
PDHRS	-	Passive Core Decay Heat Removal System
PID	-	Proportional Integral Derivative
PRHR	-	Passive Residual Heat Removal Systems
PSA	-	Probabilistic Safety Assessment
PWR	-	Pressurized Water Reactor
RELAP	-	Reactor Excursion and Leak Analysis Program
REPAS	-	Reliability Evaluation of Passive Safety System
RMPS	-	Reliability Method for Passive Systems
SORM	-	Second Order Reliability Methods

List of Symbols

Symbol		Meaning	Units (SI)
A^2	-	Anderson darling test statistic	
c	-	Constant	
C	-	Choking Flow	
d	-	Degree of differencing	
e_t^2	-	Squared residuals	
f_n	-	Function	
F	-	Failure count	
H_0	-	Null hypothesis	
H_a	-	Alternate hypothesis	
k	-	Lags	
$L(\hat{\theta})$	-	Likelihood function of theta	
N	-	Number of runs	
p	-	Order of the autoregressive model	
P	-	Probability	
P_o	-	Cumulative probability of overflow	
P_d	-	Cumulative probability of dryout	
q	-	Order of the moving-average model	
R^2	-	Coefficient of determination	
$W(t)$	-	Residual series	Celsius
+X	-	Maximum level of tank	Meter
-X	-	Minimum level of tank	Meter
Y_t	-	A time series	Celsius
Y'_t	-	Differenced time series of Y_t	Celsius
+Y	-	Upper set point	Meter
-Y	-	Lower set point	Meter
Z_{MK}	-	Mann Kendal test statistic	

Greek symbols

Symbol		**Meaning**
α	-	Significance level
ΔP	-	Pressure Drop
θ_j	-	j^{th} moving average parameter
λ	-	Failure rate
ε_t	-	Residual series also called innovation
ρ_k	-	Correlation coefficient at lag k
σ_e^2	-	Residual variance
φ_j	-	j^{th} autoregressive parameter
χ^2	-	Chi-square distribution

Subscripts

Symbol		**Meaning**
t	-	At time t
o	-	Overflow
d	-	Dryout

Superscripts

Symbol		**Meaning**
‘	-	Estimated value

CHAPTER – 1

INTRODUCTION

1.1 General Considerations

Ever since the inception of nuclear fission, nuclear energy is considered as one of the potential sources of energy for electricity production, which can eliminate or reduce the dependency of human beings on the conventional sources of energy. Until December 2014, 438 nuclear reactors are in operations for electricity production [1]. Nuclear power reactors have two specific characteristics: first, during their operation, they accumulate a large quantity of radioactive fission products from which the public must be protected. Second, significant energy release continues for prolonged period due to the decay heat, even after the reactor is shutdown. Owning to these two specific characteristics of nuclear reactors, they are designed to be equipped with multiple layers of safety systems to minimize or eliminate the associated risk to public or to the environment. In the history of commercial nuclear power plants, there were three major accidents at Three Mile Island, Chernobyl and Fukushima leading to core melt down. Except Three Mile Island, large amount of radioactivity were released to the environment. To reduce the associated risk in nuclear power plants, several efforts have been made worldwide to improve the designs of safety systems. In addition, regulatory bodies have also revised the nuclear safety goals. Safety goals for the future nuclear reactors have been accordingly enhanced so that significant release of radioactive material to the environment is practically eliminated and the risk to public due to nuclear plants is negligibly small. The International Nuclear Safety Group (INSAG-12) and INPRO has set the targets of Core Damage Frequency of not more than 10^{-5} /reactor year for future nuclear power plants in comparison to the present goal of 10^{-4} for existing plants. The goal for Large Early Release Frequency (LERF) has been enhanced further to 10^{-6}/reactor year in place of present goal of 10^{-5}/reactor year.

The future reactor concepts are designed on the philosophy of "safety-by-design" for meeting the enhanced goals of nuclear safety. These concepts are designed with inherent safety features so that the reactor has the capability to return to stable safe conditions on its own in the event of any kind of accidents that may arise due to any internal or external events. Such safety characteristics are paramount important for these future reactors which can minimize or eliminate the necessity of evacuation of public. In the current operating reactors, most of the critical safety functions are provided by using active safety systems. However, in order to meet the revised goals of nuclear safety, relying on these active safety systems alone does not seem to be viable. One of the major problems with active safety systems is that the reliability of these systems cannot be improved beyond a threshold. In addition, active systems are prone to the errors made by operator's actions and their subjective decisions. Passive systems, on the other hand, are believed to be more reliable than the active safety systems and hence, can provide enhanced protection against any postulated accidents. This is because passive systems do not need human intervention or require external energy sources such as electricity or pneumatic supply for their operation.

1.2 Definition and application of passive safety systems

IAEA defines the passive safety system as “passive safety systems are the systems which works on the principle of natural laws, properties of materials, internally stored energy, etc. These passive safety systems do not require external mechanical and/or electrical power, signals or forces.” [2]. Many of the advanced reactors e.g. ESBWR [3], AP1000 [4] CAREM [5], AHWR [6], etc. incorporate several passive systems in the design of the reactors. Below are some of the examples of advanced water cooled reactor designs which implement passive safety systems:

AP600 and AP1000: The AP600 and AP1000 are PWRs designed by the Westinghouse Electric Corporation. Both designs employ passive safety systems that rely on gravity, compressed gas, natural circulation, and evaporation to provide for long term cooling in the event of an accident. Various passive safety systems in AP600/AP1000 are:

- Passive residual heat removal systems (PRHR)
- Core make-up tank (CMT)
- Containment sump recirculation
- Passive containment cooling system (PCCS)

Economic Simplified Boiling Water Reactor (ESBWR): The ESBWR developed by General Electric, is based on the previous simplified boiling water reactor (SBWR) design with some modifications of safety systems and the containment size relative to the reactor power. In ESBWR concepts, the safety is accomplished by eliminating the recirculation pump, thus relying on natural circulation cooling. The coolant is circulated by natural circulation as a result of the density difference between the high void, two-phase fluid in the chimney and the exterior single-phase liquid in the downcomer. The tall chimney not only enhances natural circulation flow, but also ensures ample time for core uncovery before the emergency core cooling system (ECCS) comes in play. The emergency core cooling and containment cooling systems do not have an active pump injecting flows and the cooling flows are driven by pressure differences. Large volumes of suppression pool functions not only acts as a primary heat sink during the initial blow down, but also as coolant inventory to prevent the core uncovery through the gravity equalization lines. Various passive safety features utilized in the ESBWR are:

- Natural circulation core cooling
- Gravity driven cooling system for Loss of Coolant Accident (LOCA)
- Automatic depressurization system (ADS)
- Isolation condenser system (ICS) for decay heat removal
- Passive containment cooling system (PCCS)
- Suppression pool

Advanced Heavy Water Reactor (AHWR): The AHWR is a vertical, pressure tube type, heavy water moderated and boiling light water cooled natural circulation reactor. AHWR employs several passive safety features in its design. Various passive safety systems of AHWR are:

- Passive Core Cooling System
- Passive Core Decay Heat Removal System using ICs
- Emergency Core Cooling System in Passive Mode
- Passive Containment Isolation System (PCIS)
- Passive Containment Cooling System (PCCS)

- Vapour Suppression in GDWP
- Passive Poison Injection System

1.3 Categorization of passive safety systems

As per IAEA-TECDOC-626[2], passive safety systems can be categorized into four categories, as described below.

Category A

This category is characterized by:

- No signal inputs of “intelligence”, no external power sources or forces;
- No moving mechanical parts;
- No moving working fluid.

Examples of safety features included in this category are:

- Physical barriers against the release of fission products, such as nuclear fuel cladding and pressure boundary systems;
- Hardened building structures for the protection of a plant against seismic and other external events;
- Core cooling systems relying only on heat radiation and/or conduction;
- Static components of safety related passive systems (e.g., tubes, pressurizers, accumulators) as well as structural parts (e.g., supports, shields).

Category B

This category is characterized by:

- No signal inputs of “intelligence”, no external power sources or forces;
- No moving mechanical parts; but

- Moving working fluids.

The fluid movement is only due to thermal-hydraulic conditions occurring when the safety function is activated.

Examples of safety features included in this category are:

- Reactor shutdown/emergency cooling systems based on injection of borated water from an external water pool;
- Reactor emergency cooling systems based on air or water natural circulation in heat exchangers immersed in water pools (inside the containment);
- Containment cooling systems based on natural circulation of air flowing around the containment walls;
- Fluidic gates between process systems, such as ‘‘surge lines’’ of PWRs.

Category C

This category is characterized by:

- No signal inputs of “intelligence”, no external power sources or forces;
- Moving mechanical parts, whether or not moving working fluids are also present;

The fluid motion is characterized as in category B; mechanical movements are due to imbalances within the system (e.g., static pressure in check and relief valves, hydrostatic pressure in accumulators) and forces directly exerted by the process.

Examples of safety features included in this category are:

- Emergency injection systems consisting of accumulators or storage tanks and discharge lines equipped with check valves;

- Overpressure protection and/or emergency cooling devices of pressure boundary systems based on fluid release through relief valves;
- Filtered venting systems of containments activated by rupture disks; and
- Mechanical actuator, such as check valves and spring-loaded relief valves, as well as some trip mechanisms (e.g. temperature, pressure and level actuators).

Category D

This category addresses the intermediary zone between active and passive where the execution of the safety function is made through passive methods as described in the previous categories except that internal intelligence is not available to initiate the process. In these cases an external signal is permitted to trigger the passive process.

Examples of safety features included in this category are:

- Emergency core cooling and injection systems based on gravity-driven flow of water that are initiated by battery powered electric or electro-pneumatic valves which break open on demand;
- Emergency reactor shutdown systems based on gravity-driven, or static pressure driven control rods, activated by fail-safe trip logic.

1.4 Issues of passive safety systems

Deployment of passive safety systems in nuclear reactors provides several benefits, such as: avoidance of dependency on active components; such systems are simple and easy to build, operate and maintain. Elimination of operator intervention or dependency on external sources results in reduction of respective hazards.

Despite the above, there are technological challenges and issues in order to engineer them in the reactor designs. One of the issues with the passive systems is quantification of functional reliability for these systems during normal operation, transients including accidental conditions. These functional failures are the type of failures, which happens because of deviations of the critical process or geometric parameters from their nominal values on which passive systems performance depends. The main challenge in assessing the reliability of passive system arises from the fact that the operating principles of these passive systems are based on the natural laws like buoyancy, gravity or natural convection, rather than being dependent on the active components. Since, these physical phenomena in itself never fails as long as the parameters governing them do not deviate from their nominal values, estimating the reliability for these passive system is indeed very subjective. The main difficulties in evaluation of functional failure of passive systems arise because of following:

- lack of plant operational experience;
- scarcity of adequate experimental data from integral test facilities or from separate effect tests in order to understand the performance characteristics of these passive systems, not only at normal operation but also during accidents and transients;

- lack of accepted definitions of failure modes for these systems; and
- difficulty in modeling certain physical behavior of these systems.

1.5 Literature on reliability analysis of passive safety systems

A historical perspective to this topic reveals that in mid-1990s, CEA and ENEA agreed to work to evaluate the reliability of passive systems. In University of Pisa (UNIPI), D'Auria and Galassi [7] studied it further and a few years later, a new methodology was proposed as REPAS (Reliability Evaluation of Passive Safety System). REPAS [8] methodology was a joint effort of UNIPI, ENEA, University of Rome and Polytechnic of Milan. In REPAS, failure probability of passive system was evaluated by propagating the epistemic uncertainties of important physical and geometric parameters which affects the system performance the most. The REPAS methodology recognizes the model uncertainties of the codes. In REPAS, the uncertainties in code predictions are evaluated by performing sensitivity study of input parameters and by code to code comparisons. Jafari et al. [8] applied this methodology to an experimental natural circulation test loop. Zio et al. [9] used REPAS for reliability analysis of an isolation condenser system. A drawback of REPAS was that, in order to assess the impact of uncertainties on the predicted performance of passive system, a large number of calculations with best estimate codes were needed. Thus, the reliability estimation using REPAS was found to be too expensive in terms of number of code runs, if complete sequences of passive system involvement are to be considered in the accident scenario.

Under the auspices of the European Union 5th Framework program, a comprehensive methodology Reliability Methods for Passive Safety Functions (RMPS) [10] was developed. RMPS inherited the methodological developments of REPAS and improved upon the shortcomings of it. The RMPS methodology in a hierarchical flow diagram is presented in Fig. 1.1. In RMPS, the most important parameters which affect the passive system performance are identified using Analytical Hierarchy Processes (AHP) and sensitivity analysis. These important parameters are chosen for further analysis. A probability distribution function (pdf) is assumed for treating the variation of input parameter. The pdf is assigned by using classical data fitting techniques (in case of data available about the parameters) or by expert judgment processes (in the absence of sufficient data). Once the distributions for the input parameters are determined, a Monte-Carlo sampling technique is used to sample a large number of samples for these parameters. The performance of passive system is then evaluated using best estimate codes such as RELAP or CATHARE. With the outcome of the results of these code runs, the probability of passive system failure is estimated. Various alternative techniques have been proposed in RMPS methodology to limit the large number of time consuming deterministic code runs. Some of such alternative techniques include the use of variance reduction techniques, FORM/SORM (first and second order reliability methods) and use of meta-models like response surface.

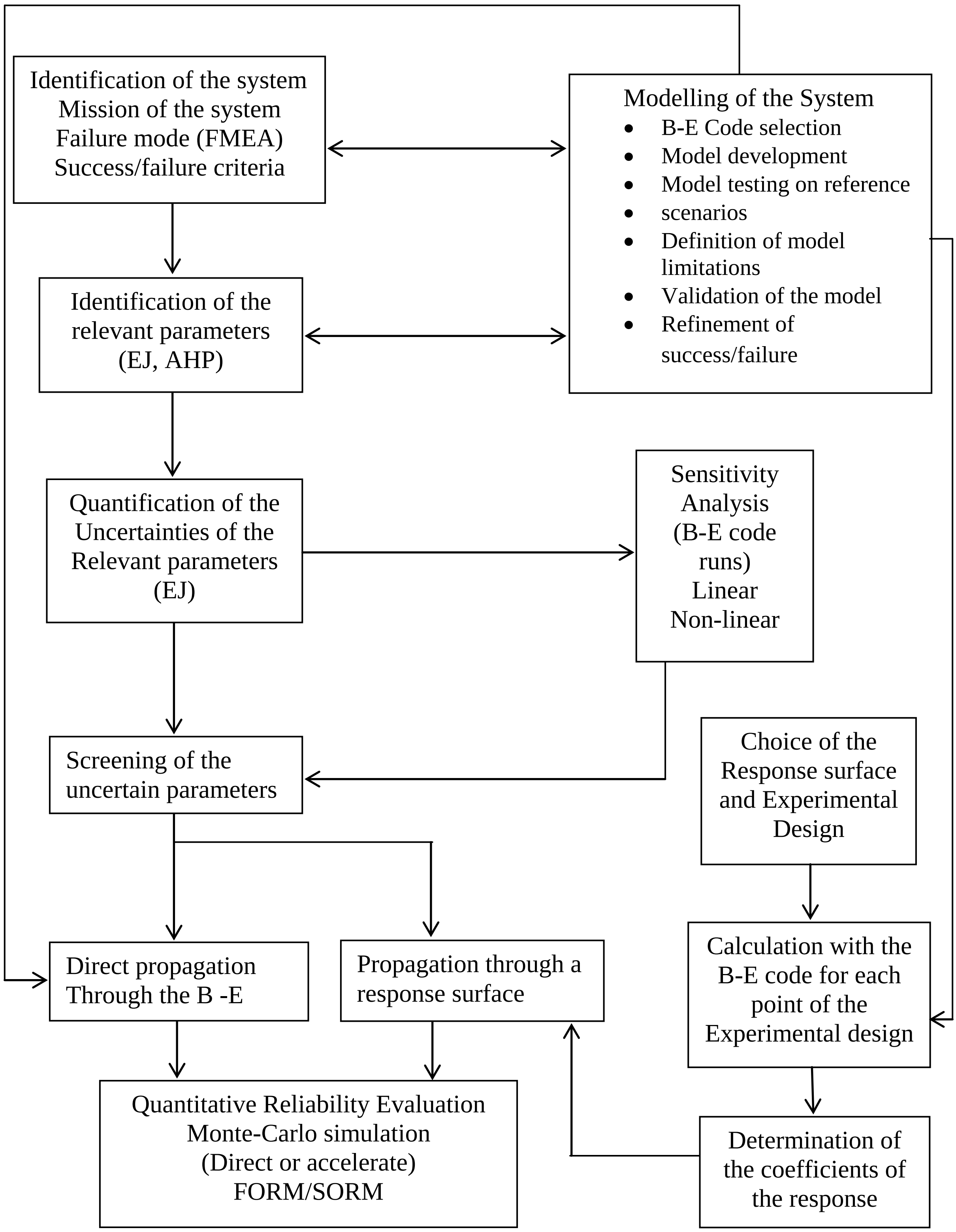


Fig 1.1 RMPS Methodology (Source: M. Marques et. al [10])

Two improvement areas have been identified for RMPS methodology after its inception and implementation to various passive systems of water cooled reactors based on natural circulation - first, for realistic estimation of probability density functions of the input parameters, a engineering judgment process needs to be implemented; second, to assess the impact of uncertainty in these input parameter's pdfs, appropriate sensitivity analysis must be incorporated [11].

Using a similar approach, Pagani et al. [12] evaluated the probability of failure of the gas-cooled fast reactor (GFR) natural circulation system. However, they used simpler conservative codes to evaluate the failure of a system.

A different methodology called Analysis of Passive Systems ReliAbility (APSRA) [13] was developed at BARC. Unlike RMPS, in APSRA methodology, it is attributed that the deviations of input parameters on which passive system performance depends, occur only because of malfunction or failure of mechanical components. In APSRA methodology, first a failure surface is generated by considering the deviations of all those critical parameters, which influence the system performance. These failure surfaces are generated by evaluating the effect of these deviations on passive system performance using qualified T-H codes (e.g. RELAP, CATHARE etc.). Then root cause analysis is performed to find the cause of these deviations. Once the causes of these deviations are determined, the failure probabilities of these causes are obtained from generic databases or from plant operational experience. Finally, the failure probability of passive system is evaluated using classical reliability analysis techniques like fault tree analysis. The top event for the fault tree is considered as passive system functional failures (for example, passive system unable to maintain the clad temperature below certain threshold, etc.) and the basic events are malfunctioning or failed component states. To reduce the uncertainty in code predictions, APSRA methodology suggests relying on experimental data from integral test facilities as well as from separate effect tests [14]. Fig. 1.2 illustrates the steps followed in APSRA methodology.

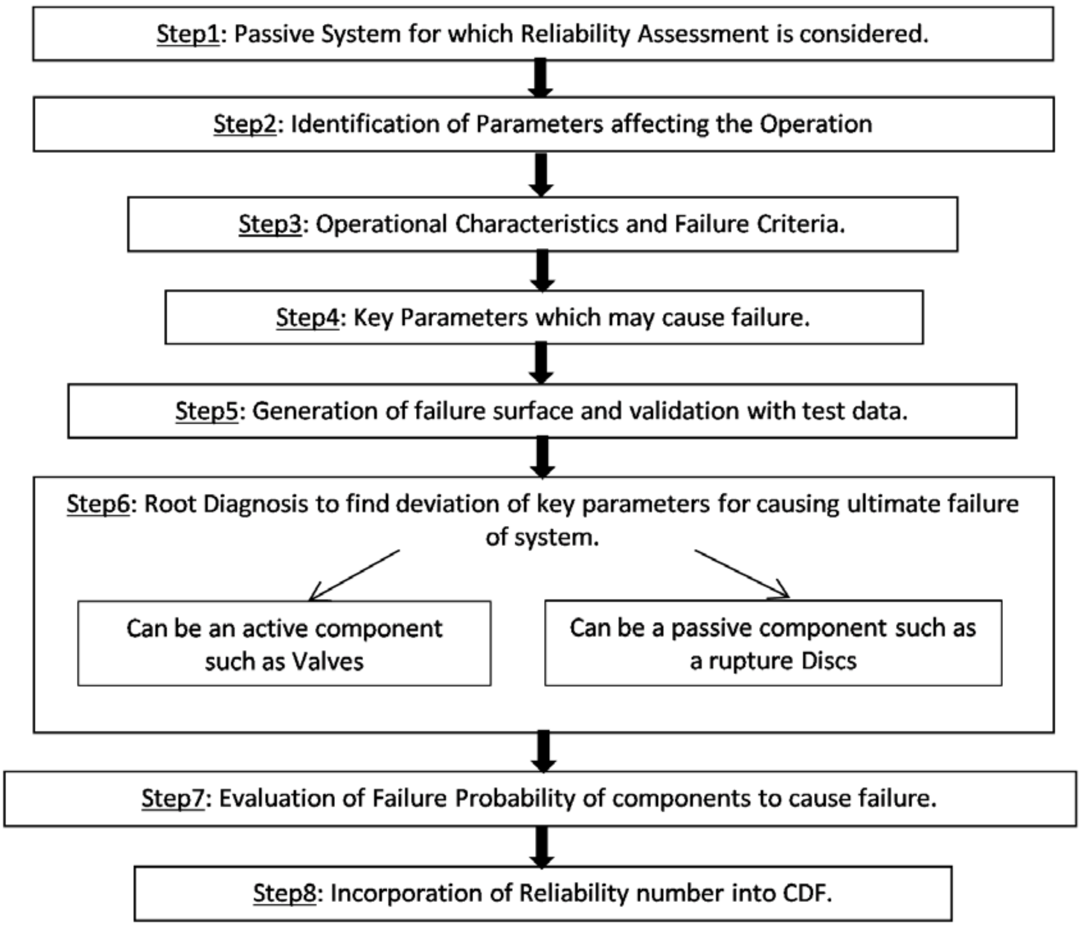


Fig 1.2 APSRA Methodology

Apart from RMPS and APSRA methodologies, a few alternative approaches have been attempted in the area of reliability assessment of passive systems. In one of the approach developed at ENEA by [15], the failure probability of passive system is linked only to mechanical component failure or degradation and is estimated from the surrogate models by replacing the T-H codes with fault tree. However, this approach does not treat deviation of initial and boundary conditions on passive system performance and reliability. Moreover, surrogate models used in this approach fails to capture the interactions among physical phenomena. In another approach, Burgazzi [16] proposed to predict, the probability of failure of passive system by multiplying the probability of independent failure modes. Only those failure modes were considered which had the potential to deviate from their nominal conditions or physical mechanisms, which in turn may deviate the passive system performance. This approach may result in providing very conservative estimates of failure probability. In addition to the above approaches, Zio [9] has illustrated a systematic methodology to guide the definition of the failure criteria of a passive system and the evaluation of its probability of occurrence, through the identification of the relevant system parameters and the propagation of their associated uncertainties. Within this methodology, Zio proposed the use of the analytic hierarchy process as a structured and reproducible tool for the decomposition of the problem and the identification of the dominant system parameters.

1.6 Accomplishments in passive system reliability analysis

The above methodologies REPAS, RMPS and APSRA have uncovered very important aspects related to passive safety system reliability. Following are noticeable accomplishments of the above methods:

- Definition of reliability of passive system: All the methodologies have a common opinion on the definition of reliability of passive system. Accordingly, passive system reliability can be defined as the probability of system or structure to carry out the defined function (like – decay heat removal, cooling of vessel, keeping clad temperature in a defined range etc) for a given mission time [0,t], when operated under specified conditions.
- It has been accepted by all the methods that passive system performance and reliability depends on the deviation of critical parameters from their nominal values. This is true because of the low driving forces of these systems.
- It is also accepted that input parameters and boundary conditions can vary between some limits. Some of these parameters and boundary conditions are critical for passive system performance. Key to quantify reliability lies in understanding the deviations and their effects on system performance during the operation and transient conditions. To name a few of initial and boundary conditions are– operating pressure, water level in reactor core, reactor power, environment temperature, etc. and some of physical properties like densities, thermal conductivity, specific heats of fuel, etc.
- In all the methods, defining failure of passive system is given the prime importance and it can be concluded that most of them have defined it as either

failure to meet the amount of heat exchanged or to keep maximal clad temperature in a safe range during the operation.

- Since there is limited experience in the operation of passive systems and lack of suitable experimental databases, all the methods rely on simulation by means of best estimate codes like RELAP5 or CATHARE, etc., which are 1-D thermal hydraulic code developed for forced circulation systems.

1.7 Open issues

One of the most important differences among these methodologies is in the way these methods treat the variation of process parameters from their nominal values. In RMPS, variation of process parameters is considered by assigning a probability density function (pdf) based on engineering judgment; for example, the reactor has a nominal operating pressure which can vary within a range of pressure control system. This variation is treated by assigning a uniform distribution between minimum and maximum based on expert's judgment. This approach (assignment of pdf based on expert's judgment) may add large uncertainties in the reliability estimates of the system because of the subjective nature of decisions of experts for the pdf assignment for the variation of process parameters without having enough database to substantiate the assumption. Moreover, every process parameter cannot be said to have independent deviations and cannot be assigned an independent pdf based on expert judgment, for example, variation of pressure from the nominal value could be due to malfunction of the pressure control system which is basically failure of a hardware system. The philosophy of considering these hardware dependent variations was considered in APSRA methodology. In APSRA, the variation of process parameters are treated by considering the root diagnosis of the component or sub-system causing these deviations, However, it is argued here that every process parameters cannot be treated by root diagnostics, for example, deviation of the atmospheric temperature on which performance of many passive decay heat removal system depends, cannot be assigned to the failure of hardware or component.

Another difference is on the treatment of model uncertainty of the codes used for prediction of functional behavior of the system; RMPS treats this uncertainty by assigning a pdf to the key variable of the models employed. On the other hand, APSRA considers the uncertainty assessment of code/model on the basis of experimental validation.

RMPS and APSRA also differ in the way the failure probability of passive system is evaluated. RMPS uses Monte-Carlo simulation or FORM/SORM (first/ second order reliability methods), whereas APSRA predicts failure surface and evaluates reliability using fault tree analysis of the hardware/ components responsible for the deviation of process parameters of passive system.

Apart from the above differences in these methodologies, all of them lack to explain some of the important issues related to passive system performance and reliability. These unresolved issues are:

1. Treatment of dynamic failure characteristics of components of passive system
2. Quantification of functional failure probability of components of passive systems

3. Treatment of independent process parameters variations
4. Treatment of model uncertainties

1.7.1 Treatment of dynamic failure characteristics of components of passive system

It is well understood that functional failure of passive system can be attributed to the deviation of process parameters and malfunctioning of components. During the mission of passive system execution, the process parameters may deviate and at the same time the components may fail stochastically based on the dynamics of operation. These complex interactions between hardware failure and process parameter deviation may further change the way the system is expected to behave during the rest of the operation, and can lead the system to failures which were not anticipated by the deterministic analysis or by static reliability analysis. Traditionally, the reliability analysis of passive safety systems is performed using fault tree (FT) and event tree (ET) analysis. FT/ET assumes that components of passive systems such as valves have binary-states of failure (stuck open and stuck closed). However, such components can fail at intermediate positions as well. Time to failure for these intermediate states of such components can have different probability which may vary from one state to another. In addition, the failed state of these valves also depends upon the process parameter variations and can increase or decrease during the rest of the mission time. These dynamic characteristics of components can have very high implications on the estimates of performance and failure of passive systems. The integrated effect of these dynamic failure characteristics has never been considered in any of the available methodologies of passive system reliability analysis.

1.7.2 Quantification of functional failure probability of components of passive systems

The advanced reactors are designed to utilize passive safety systems, which do not have any moving mechanical components; however most of the passive systems use valves for either activation or during the operation. Traditionally, reliability analysis of these systems is performed with the assumption that these valves have binary-states of failure (stuck open and stuck closed). However, these components can fail at intermediate positions as well. Currently the failure probability of such components at intermediate fault positions is not available in any failure databases. It has been recognized that due to the lack of experimental evidence and validated data, the analysts have to resort to expert/engineering judgment to a large extent, hence making the results strongly dependent upon the expert elicitation process. This prompts the need for the development of a framework for constructing a database by conducting a series of experiments to generate probability distributions for the component failures and process parameters influencing the system behavior.

1.7.3 Treatment of independent process parameters variations

Some of the advanced reactor designs incorporate emergency passive natural circulation cooling system to remove decay heat to the air through passive air cooled condensers, for example: Passive residual heat removal system via Steam Generator

(SG) in VVER-1000/V-392 [17] and Passive core cooling system using SG - open loop in APWR+ [18]. Performance of these systems is very sensitive to the parameters like atmospheric temperature or the environment temperature. These parameters vary in time along the mission period of system operation. In addition they have certain pattern depending on the season and time of operation (day/night) including some random variations. Such parameters are called independent process parameters. Currently none of the methodologies for passive system reliability analysis have given proper emphasis and treatment to variations of such independent process parameters. These independent parameters are time dependent and hence, cannot be treated by random probability distributions which are static with respect to time. Treatment of dynamic variation of such kind of parameters is another unresolved issue in reliability analysis of passive systems.

1.7.4 Treatment of model uncertainties

It is so far not established whether the so called best estimate system codes such as RELAP5 or CATHARE, etc are applicable for passive systems performance evaluation and their failure. Of course, these codes have been validated over several years using test data from separate effect facilities and integral experiments and it is now well recognized that they are acceptable for conventional water cooled reactors which have active safety systems. However, to use such best estimate codes for passive systems is still doubtful. Current methodologies treat the model uncertainties in different ways; RMPS follows a pdf treatment while APSRA methodology relies on estimating the uncertainties from the experimental data. Hence, there is difference in opinion on how to treat these model uncertainties while estimating the reliability of passive safety systems. It is thus required to reach a consensus on how to treat the model uncertainties in the context of reliability analysis of passive system.

1.8 Objectives and scope of work

The objective of this Ph.D research work is to develop a new methodology for passive system reliability analysis and implement it to a passive system of advanced reactor. This methodology should overcome the issues present in the current methodologies and must integrate the following:

1. **Treatment of dynamic failure characteristics of components of passive system**

   Development of a dynamic reliability methodology incorporating the following features:

   a. Multi state failure of mechanical components
   b. Fault increment during the system evolution
   c. Dependency and time dependent failure rates of components
   d. Time treatment of chronology of events i.e. event sequence and order of failures

   The methodology to be developed for the treatment of dynamic failure characteristics must be validated with the experiments. This dynamic reliability methodology must be integrated with the new methodology to be developed for passive system reliability analysis.

2. **Quantification of functional failure probability of components of passive systems**

   In view of the development of the databases for the probability distributions of the components of passive system like valves, a series of experiments must be performed to quantify the functional failure probability of these valves. In addition to this, the dynamic failure characteristics and dynamic operational characteristics of flow of such components and its effect on system failure and reliability must be assessed experimentally.

3. **Treatment of independent process parameters variations**

   The methodology to be developed for reliability analysis of passive system must provide a consistent treatment for the independent process parameters like atmospheric temperature.

4. **Treatment of model uncertainties**

   Since, there is difference in opinion on how to treat the model uncertainties of best estimate codes which have been developed and validated primarily for forced circulation based systems. It is thus required to understand how to treat and propagate the model uncertainties of best estimate system codes in the context of reliability analysis of passive system.

1.9 Organization of thesis

The above objectives are accomplished in the following chapters of the thesis.

In view of the open issues associated with the currently available methodologies of passive system reliability analysis presented in the introduction, a new methodology called APSRA$^+$ has been developed in this thesis. In chapter-2, this newly developed methodology called APSRA$^+$ is presented. The methodology has been described step by step with the help of a flow diagram.

In chapter-3, development of a new dynamic reliability methodology for the treatment of dynamic failure characteristics of components of passive systems is presented. Benchmarking analysis of this methodology on a system of hold-up tank consisting of three valves is presented and results are compared with the published literatures. The methodology is then demonstrated by considering the dynamic failure characteristics of components.

In chapter-4, the experiments performed for the quantification of functional failure probability of components of passive system is presented. This chapter presents the details of the experimental setup, experiments performed and the main findings from the analysis of the observations from the test results.

Chapter-5 discusses the methodology developed for the treatment of variation of independent process parameters. In this chapter, first the issue in treatment of independent process parameters of passive system is presented with an example; then the process of fitting the classical model of time series called Auto-Regressive Integrated Moving Average (ARIMA) to the independent process parameter is presented. With the help of this fitted ARIMA model, generation of the synthetic data of the independent process parameter is also presented. As an illustration to the methodology of model fitting and synthetic data generation, a time series of monthly-maximum atmospheric temperature of district Chittaurgarh (Rajasthan, India) has been modeled and presented.

In chapter-6, step by step application of APSRA^{+} on a passive safety system of an advanced reactor is presented. The results of the analysis are compared with the results obtained by the conventional methodology APSRA and are summarized to conclude the main findings.

Chapter-7 discusses the conclusions of this thesis, which is followed by the references and appendix.

CHAPTER – 2

DEVELOPMENT OF A NEW METHODOLOGY APSRA$^+$

2.1 Introduction

In the domain of passive system reliability analysis, it has been recognized that the unresolved issues like a) treatment of dynamic failure characteristics of components of passive system, b) treatment of independent process parameters variations and c) treatment of model uncertainties; must be addressed in a consistent manner in order to accurately assess the reliability of these systems. In view of these open issues, a new methodology called APSRA$^+$ (Analysis of Passive Systems ReliAbility Plus) is developed in this research work. APSRA$^+$ inherits the methodical developments of an existing methodology APSRA and hence is given the same name with suffix "+".

2.2 The APSRA$^+$ methodology

The methodology APSRA$^+$ in its hierarchical form is shown in Fig. 2.1.

APSRA$^+$ is described step by step as follows:

Step 1- System identification: System to be considered for analysis

In step 1, the passive system for which reliability will be evaluated is considered.

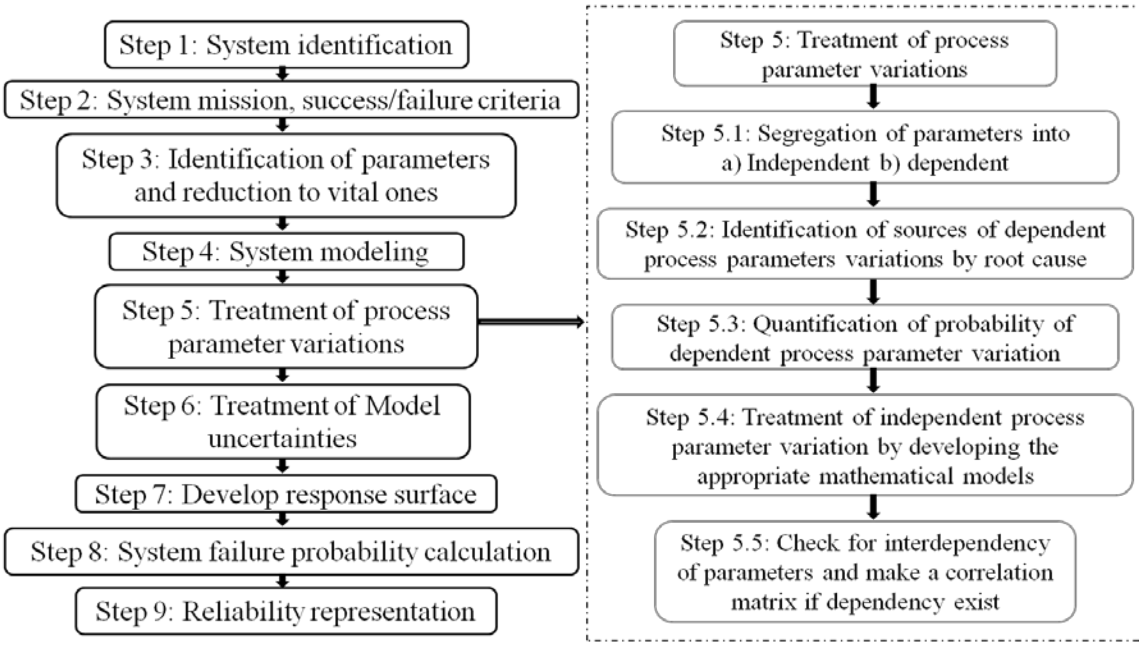


Fig. 2.1 APSRA$^+$ methodology

Step 2- System mission, success/failure criteria

The main challenge in defining the failure/success criteria of passive system arises from the fact that operating principles of these passive systems are based on the physical phenomena like buoyancy, gravity or natural convection, rather than being dependent on the active components. Since, these physical phenomena in itself never fails as long as the parameters governing them do not deviate from their nominal values, defining a failure for passive system is indeed very subjective. Since failure of the passive system cannot be defined in terms of some component failures, this must be defined in terms of not meeting certain functional criteria. For example, in advanced nuclear reactors, isolation condenser system (ICS) is used to remove the decay heat under station blackout conditions passively [6]. However, during the operation, the critical process parameters which govern the performance of ICS may deviate from their nominal values and degrade the heat transfer characteristics such that ICS fails to maintain the steam drum pressure in a given range, or to keep the clad temperature under certain threshold value. So the designer must define failure criteria in this step.

Step 3- Identification of critical process parameters and reduction to vital few

In a complex passive system, the performance can depend on a large number of parameters. These parameters could be geometric or process parameters or some initial and boundary conditions. To name a few parameters are operating pressure, water level in reactor core, reactor power, environment temperature, etc. and some of physical properties like densities, thermal conductivity, specific heats of fuel, etc. Identification of the process parameters is an important step in reliability analysis. To accomplish this step, a list of all the sensitive parameters is prepared and the effect of these parameters are analyzed using best estimate codes or by simplified codes (in case of time or resource constraints in simulation). If the number of parameters to be analyzed is more, global sensitivity analysis techniques such as Sobol and Fourier amplitude sensitivity testing (FAST) [19] are used to select the vital few among them.

Step 4- System modeling

The passive system chosen is modeled using a best-estimate system code such as RELAP, etc. Performance of passive system, under nominal conditions of the parameters identified in step-3, is determined.

Step 5- Treatment of process parameters

The parameters identified in step 4 are further analyzed in this step. Treatment of these process parameters is done in several steps, as follows:

Step 5.1: Segregation of parameters into: a) Dependent Parameters b) Independent Parameters

The parameters affecting passive system performance can be classified into two types: (a) dependent parameters and (b) independent parameters. Dependent parameters are the ones whose deviations depend on the output or state of certain hardware or control units, example of such dependent parameters are pressure, sub-cooling, non-condensable gas. Many of the parameters are not independent to have their own deviations; rather they are correlated or interdependent [20]. Independent parameters are the ones whose deviations do not depend upon any components rather they have their own patterns and deviations, which cannot be predicted easily; example of such parameter is atmospheric temperature.

Step 5.2: Identification and quantification of sources of dependent process parameters variations by root cause

For the dependent process parameters, the causes of the deviations are derived using root cause analysis techniques. For example, variation of pressure from the nominal value could be due to malfunction of the pressure control system which is basically failure/degradation of a hardware system.

Step 5.3: Quantification of probability of dependent process parameter variations

As pointed earlier, malfunctioning of the components causing deviation of dependent process parameters can have dynamic failure characteristics. The dynamism in the failure characteristics of these components has very high impact in the estimates of probability of failure of the system. Some of the most important dynamic failure characteristics involve: multi-state failure, failure increment, and process dependent failure rates. In order to capture these dynamic effects into the reliability analysis while quantifying the probability of variation of dependent process parameters, a new dynamic reliability methodology is used.

According to this new dynamic reliability methodology, the sub-system (malfunction of which causes deviation of dependent process parameters from its nominal value), is analyzed in a discrete time domain by considering the interaction of the process parameters with the stochastic failure of components. The process parameter values are estimated at the end of a given mission time for this sub-system. The whole process of this estimation is repeated for a predefined number of counts by repeating the simulation for different set of stochastic failure of components; at the end of each simulation the dependent process parameter values are recorded. This recorded process parameter values are then used for preparing the estimates of the probability of variation of the selected dependent process parameter. The newly developed methodology of dynamic reliability is discussed in the chapter 3.

Step 5.4: Quantification of independent process parameters variation

Since the deviation of independent process parameters cannot be assigned to a component or system failure, the feasible range of the deviation of these parameters and probability of falling in these ranges can be estimated only by collecting the data about these parameters over a period of time and then these data can be fitted into a suitable mathematical model. For example, the atmospheric temperature can be treated as an independent parameter since it does not depend on any component or system.

In order to quantify the variation of independent process parameters like atmospheric temperature, the temperature variations for the specific location of application of passive system is collected from measurement around the facility or from meteorological centers. Once the data about the parameter is collected, a classical time series modeling is performed and mathematical models based on auto regressive (AR), moving average (MA) or autoregressive integrated moving average (ARIMA) is developed. Using these models, the independent process parameters are modeled in the passive system reliability analysis. Within the APSRA$^+$ methodology a detailed methodology of developing such time series models is developed and is presented in chapter 5.

Step 5.5: Check for interdependency of parameters and make a correlation matrix if dependency exist

In this step, all the vital parameters are examined for the interdependency by performing a correlation analysis. If the correlation is found to be significant, the correlation matrix is prepared. This correlation matrix is used in the further steps during the generation of samples for Monte-Carlo simulations.

Step 6- Treatment of model uncertainty - Code validation and determination of errors and uncertainties in empirical models used for the performance and failure analysis of passive system

The use of best estimate codes that are validated for the forced circulation systems introduces uncertainties and errors when such codes are applied to evaluate passive system performance. The quantification and propagation of uncertainties in the empirical models used in the analysis of passive systems is performed in two steps:

Step 6.1: Identification of uncertainties/ errors in the empirical models:

In this step, the uncertainties in the empirical models are quantified by performing the experiments in the simulated environment or in integral test facilities. In the absence of such experimental data, the uncertainty in best-estimate calculations is modeled by considering the uncertainties in the empirical correlations used in these codes. As an example Table 2.1 shows some of the uncertainty ranges in correlations used in RELAP code.

Step 6.2: Propagation of uncertainties of the empirical models

In this step, the identified uncertainties are propagated by modifying the associated parameter in the best estimate system code using corresponding absolute mean errors. Table-2.1 lists absolute mean error of some of the models generally used in best estimate system codes.

Table 2.1. Various models and associated uncertainties

Sr.No.	Model	Uncertainty	Reference
1.	Heat Transfer		
1.1	Dittus-Boelter Correlation	25.0%	21
1.2	Sellars-Tribus-Klein Correlation	10.0%	22
1.3	Churchill-Chu Correlation	12.5%	23
1.4	Nusselt Correlation	07.2%	24
1.5	Shah Correlation	25.1%	24
1.6	Chato Correlation	16.0%	25
2	Wall Friction		
2.1	Colebrook-White Correlation with Zigrang-Sylvester Approximation	00.5%	26
2.2	Lockhart-Martinelli Correlation	25.6%	27
2.3	HTFS modified-Baroczy Correlation	21.2%	28
3	Interphase Friction		
3.1	Chexal-Lellouche Correlation (Drift Flux Model)	15.3%	29
3.2	Drag Coefficient Method	30.0%	30
4	Choking Flow	05.0%	31
5	Counter Current Flow Limitation	08.7%	32
6	Flow Stratification	20.0%	33
7	Thermal Front Tracking	13-19%	34

Step 7- Develop response surface: Develop a response surface of the important process parameters using best estimate codes

Passive system performance for the combination of important process parameters identified in step 3 is determined by the best estimate codes. The combinations of these important parameters are usually very high in number causing the simulation time to be very expensive in a fairly complex passive system. In order to reduce the number of repeated calculations by computationally expensive best estimate system codes, a technique of fitting response surface to the system output function in terms of input process parameters is utilized. The type of response surface that can be used depends upon the problem in hand.

Step 8- System failure probability calculation: Estimate system failure probability using Monte Carlo simulation

Once the parameter range with their associated probabilities has been identified and the correlations among the parameters are properly captured in correlation matrix, the system failure probability can be estimated using Monte Carlo simulation. Probability of system being in the failure zone is estimated by sampling and analyzing a sufficiently large number of samples for all the dependent and independent process parameters based on the probability of variations of these parameters, which were estimated using the newly developed dynamic reliability methodology.

Step 9- Reliability representation with uncertainty bounds of model errors:

In this step the probability of failure obtained in the step 8 is presented graphically. The probability without considering model uncertainties are generally represented as a plot consisting mission time in abscissa and probability value in ordinate. System failure or success probability considering the model uncertainties is also plotted in the same graph which can be treated as confidence bounds on probability of failure.

2.3 Comparison of RMPS, APSRA and APSRA$^+$

As mentioned earlier, APSRA$^+$ inherits the methodical developments of an existing methodology APSRA. There are significant improvements in APSRA$^+$ methodology when compared with the existing methodologies RMPS and APSRA. Table 2.2 provides a comparison among these methodologies.

Table 2.2. Comparison of RMPS, APSRA and APSRA$^+$

Criteria	**RMPS**	**APSRA**	**APSRA$^+$**
Definition of reliability	Functional failure	Functional failure	Functional failure
Passive system failure attributed to	Deviation of process parameters from nominal values	Deviation of process parameters from nominal values	Deviation of process parameters from nominal values
Reliability Estimation	FORM/ SORM/ Monte Carlo	Failure Surface and FT	Failure Surface + Monte Carlo + FT
Independent process parameter variation	PDF – Uniform [min-max]	Not considered/ Same as other process parameters	Time series ARIMA models

Criteria	RMPS	APSRA	APSRA+
Model Uncertainties	PDF – (Expert Judgement based)	Experimental Verification	PDF treatment from the available uncertainties from literature
Dynamic failure characteristics of components and their interaction with process parameters	Not considered	Not considered	Integrated Dynamic Reliability Methodology for capturing process parameter and hardware failure interaction while doing dependent process parameter treatment

2.4 Limitations of APSRA+

There are several limitations of APSRA+ methodology. Following is the list of a significant few:

- The failure rate of components such as valves was derived using a limited set of experiments.
- APSRA+ lacks the framework for validation of estimated failure probability of passive system.
- APSRA+ uses Monte Carlo simulations for estimating failure probability of passive system. The accuracy of estimates derived using Monte Carlo simulations depends on the total number of simulations.

- For estimating passive system performance, APSRA+ still depends upon the best estimate system codes. The best-estimate system codes in itself has many assumptions and limitations that should be validated for passive systems specifically.
- In modeling independent process parameters through time series, only temporal, seasonal and trend can be modeled. Any anomaly in the data due to some natural calamities and accidental conditions cannot be captured using this methodology.

2.5 Conclusions

In this chapter, a new methodology called Analysis of passive system reliability plus ($APSRA^+$) for evaluating reliability of passive systems is presented. This methodology is an improved version of existing methodology APSRA. Important features of $APSRA^+$ are: a) it provides an integrated dynamic reliability methodology for the consistent treatment of dynamic failure characteristics such as multi-state failure, fault increment and time dependent failure rate of components of passive systems; b) this methodology overcomes the issue of process parameter treatment by just probability density function or by root cause analysis, by segregating them into dependent and independent process parameters and then giving a proper treatment to each of them separately; c) treating the model uncertainties and independent process parameter variations in a consistent manner.

In $APSRA^+$, important parameters affecting the passive system under consideration are identified using sensitivity analysis. To evaluate the system performance, a best-estimate code is used with due consideration of the uncertainties in empirical models. Failure surface is generated by varying all the identified important parameters, variation of which from its nominal value affects the system performance significantly. These parameters are then segregated into dependent and independent categories. For dependent parameters, it is attributed that the variation of process parameters are mainly due to malfunction of mechanical components or control systems and hence root cause is performed. The probability of these dependent parameter variations is estimated using a newly developed dynamic reliability methodology. The dynamic failure characteristics of the identified causal component/system are accounted in calculating these probabilities. For the treatment of independent process parameters, APSRA^{+} adopts and integrate classical data fitting techniques or mathematical models: ARIMA. In the next steps, a response surface based meta-model is formulated using the generated failure points. Probability of system being in the failure zone is estimated by sampling and analyzing a sufficiently large number of samples for all the dependent and independent process parameters based on the probability of variations of these parameters, which were estimated using newly developed dynamic reliability methodology.

CHAPTER – 3

TREATMENT OF DYNAMIC FAILURE CHARACTERISTICS OF COMPONENTS OF PASSIVE SYSTEMS

3.1 Introduction

Functional failure of passive safety system can be attributed to the deviation of process parameters and malfunctioning of components. During the mission of passive system execution, the process parameters may deviate and at the same time the components may fail stochastically based on the dynamics of operation. These complex interactions between hardware failure and process parameter deviation may further change the way the system is expected to behave during the rest of the operation, and can lead the system to failures which were not anticipated by the deterministic analysis or by static reliability analysis. The integrated effect of stochastic failure of components and deviation of process parameters has never been investigated in the available methodologies of passive system reliability analysis. In RMPS, variation of process parameters is considered through a pdf treatment. These pdfs are assumed to be invariant in time. In fact, the parameter variations from their nominal values could be time dependent during the evolution of passive operation. RMPS follows classical event tree approach for integrating the passive system failure probability into PSA. Since RMPS methodology in itself, does not consider hardware/component failure or their degradation in passive system reliability evaluation, the dynamism in failure characteristics of hardware/components cannot be accounted in current version of RMPS. APSRA methodology relies in failure probabilities of hardware/ components for the treatment of process parameters variation and propagates them using classical fault tree and event tree approach for estimating the system failure probability. Both the methodologies only consider binary states of any component failure i.e. failure or success states; however, the components like mechanical, electrical, instruments and control systems may fail at intermediate states as well.

Fault tree (FT) and event trees (ET) are some of the widely used methodologies in quantitative reliability and safety analysis. However, these methodologies are static in nature and in their basic framework cannot be used in the safety assessment of the highly complex systems in which there is a significant interaction between the hardware/components of system and physical evolution of the important process parameters. These methodologies fail to capture the dynamic behavior of system failure, particularly when the accident progression completely depends on the instantaneous values of process parameters and on the working state of the components on demand. In order to overcome the static nature of the FT, the concept of dynamic fault trees [35-38] was introduced by adding sequential notion to the traditional FT approach. Using these dynamic FTs, system failures can be modelled when they depend on component failure order, failure characteristics as well as their combination. This is done by introducing dynamic gates into FTs. With the help of dynamic gates, system sequence-dependent failure behavior can be specified using dynamic FTs that are compact and easily understood. However, the method of dynamic FTs cannot account for the process parameter variations and their interaction with the hardware/component functional behaviour. A comparison of conventional PSA and dynamic safety analysis by Podofillinia [39] reveals that conventional FT and ET methodologies can capture some of the dynamics provided these criteria are well understood and are imposed in the FT/ET models by the analyst. However, in a highly complex continuous process controlled systems, defining such criteria are quite resource intensive and sometimes is impossible. In addition, it is also possible that the analyst may have forgotten or overlooked into certain phenomena or sequences which are of importance in defining the exact failure behavior of system.

Traditionally, reliability analysis of passive safety systems is performed using fault tree (FT) and event tree (ET) analysis [36]. FT/ET assumes that components of passive systems such as valves have binary-states of failure (stuck open and stuck closed). However, such components can fail at intermediate positions as well. Time to failure for these intermediate states of such components can have different probability distribution parameter which may vary from one state to another. For example, a control valve can fail at 10% stuck open or 25% stuck open or at any other percentage of openings. It is possible that the probability distribution of time to failure for 10% stuck may follow a Weibull 2 parameter distribution with scale - 100 hrs and shape - 1.75, whereas for the 25% state it could be another Weibull 2 parameter distribution with scale-125 hrs and shape-2. In addition, the failed state of these valves also depends on the process parameter variations and can increase or decrease during the rest of the mission time. These dynamic failure characteristics are often ignored in the static reliability analysis. Besides this, there can be certain other dynamic characteristics which may influence the reliability estimates of system.

One of the most commonly used method for solving dynamic system reliability problem is Markovian analysis. Markov models represent the system time evolution in terms of different states among which possible transitions may occur [40-41]. The states are defined based on the modes of operation of the hardware components, the values of the process variables and operator actions. The model yields the probability of finding the system in a given state at a given time. This method can provide exact analytical continuous-time descriptions of systems which can be modeled by a discrete state space. The major drawback of Markov analysis technique are exponential explosion of state space for complex systems and only exponentially distributed failure and repair time distributions can be used. While making the Markov models, it is assumed that the analyst has a wide knowledge of scenarios and it is his understanding which captures the dynamics of system in these models. There are, however, concerns where the analyst does not possess such knowledge and runs the risk of overlooking some of the scenarios. In Markov analysis, it is an assumption that there are no transitions simultaneously. So while doing the Markov analysis, these simultaneous transition events are ignored and are assumed as rare events. For analyzing the multi-state system with fault increment/ decrement, the Markov models will require huge number of states.

The methods of probabilistic dynamics [42-49] enable us to fully account for the interaction of dynamics and stochastic and for the temporal dependency in the evaluation of accident consequences. Probabilistic dynamics operate on the actual time/state space, but its computational effort is considerably larger compared to a conventional event tree analysis. For this reason, its application is still restricted to specific aspects of a PSA. Since, Monte Carlo simulation avoids the combinational explosion of DDET (Discrete Dynamic Event Trees), they are insensitive to the complexity and dimension of the system. Any modeling assumption could be included for the non-fixed failure rate assumption, random delays, interaction between components and process dynamics, etc. Dubi [50] claimed that Monte Carlo is the only practical approach to solve the realistic systems. So, the most straightforward numerical procedure for such an analysis would be a Monte Carlo simulation

3.2 The dynamic reliability methodology

To augment the methodology APSRA$^+$, a dynamic reliability methodology is developed incorporating the following features:

a. Multi state failure of mechanical components
b. Fault increment during the system evolution
c. Dependency and time dependent failure rates of components
d. Time treatment of chronology of events i.e. event sequence and order of failures

To understand the methodology let us move step by step:

I. First the simulation is started with resetting all the simulation parameters to its initial value and setting the simulation time to zero.
II. In step two sampling is carried out based on the fault state of all components considering their failure characteristics. The corresponding state probabilities are assigned based on the experimentally estimated probabilities or from the

generic databases. For example, for a control valve, the failure states could be stuck closed, partially open or stuck open completely. The corresponding probability of getting stuck at these positions can be different from one position to another.

III. Once the fault state of the components is decided in the step two, the time at which this particular failure occurs is sampled from the corresponding probability density functions of those states for all the components separately. These pdfs of time to failure are usually available in generic failure databases. The earliest among all the sampled time to failure of components is considered as the next transition time. At the earliest time, the system will go for a configuration change as per the new state of the corresponding component.

IV. Before the simulation advances, a check is performed to ensure that the next transition time is not greater than or equal to the mission time. If it is greater than the mission time, the mission is considered to be successful, else the simulation advances.

V. In this step, the system configuration is modified with the fault position determined in step II with the corresponding transition time identified in step III. The system response or system's required function is continuously evaluated by incrementing the time. This system evolution is checked with the threshold values during each time increment.

VI. While advancing the simulation, the faulty state of the component is updated with the new incremented values based on the rate of fault increment.

VII. If the system response(s) exceeds the threshold limit, the system demands configuration changes to prevent its failure.

VIII. The demand state is checked whether the demanded component is available or not; if it is not available, the system will be going towards failure and eventually when system responses reaches the failure limit, the system will be declared as failed and a failure count will be stored.

IX. Step I to VIII is repeated for N number of Monte Carlo runs. The estimators are then evaluated based on number of failure and success counts.

To this algorithm, an estimator P is associated for computing probability of failure. The estimator P is given by Eq. 3.1:

$$P = \frac{F}{N} \tag{3.1}$$

where, N is number of runs of the Monte Carlo algorithm and F is the number of times the system has failed during the total N Monte-Carlo simulations.

Fig. 3.1 shows the structure of the methodology for calculation of probability of failure of process controlled dynamic system.

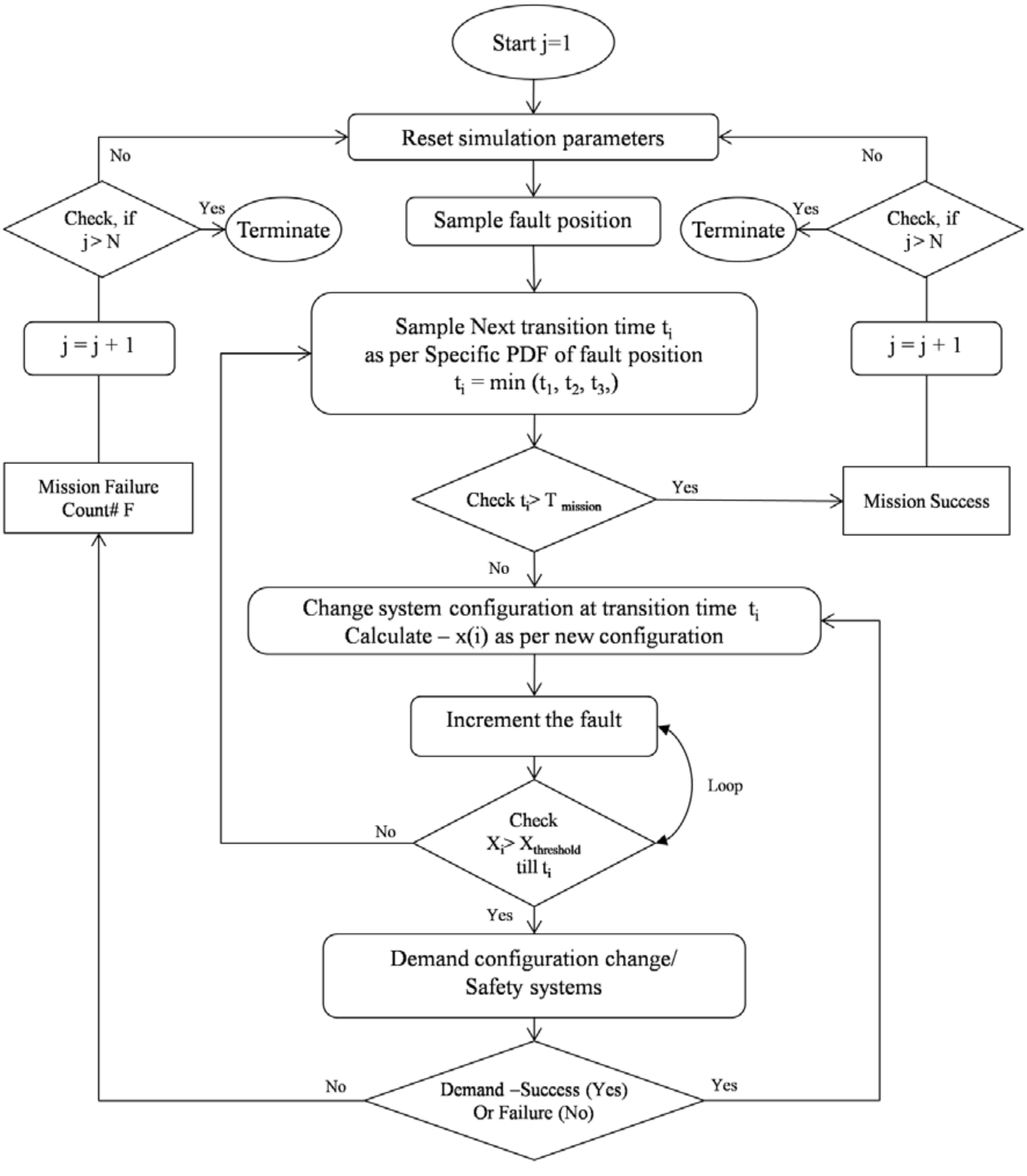


Fig. 3.1 Flow chart of dynamic reliability methodology

3.3 Application of the newly developed dynamic reliability methodology to a benchmark system

In order to check the applicability and correctness of the newly developed dynamic reliability methodology, it has been applied to a benchmark system of a level controlled hold-up tank with continuous inlet and outlet.

Several authors have considered similar benchmark problems for the dynamic probabilistic risk assessment. Aldemir [40] used the above problem as an example for his dynamic model based on Markov chain to analyze process control systems dynamics. However, this methodology was based on binary state and only exponential failure rates could be used in this method. Deoss and Siu [51] studied the same problem using DYMCAM (Dynamic Monte Carlo Availability Model) which was also based on binary state representation of component failure. Later, Siu [52] studied the problem to demonstrate different dynamic PRA methods. Cojazzi [53] applied DYLAM (DYnamic Logic Analytical Method) to study similar tank control risk analysis, but the bottle neck was that the methodology did not incorporate the fault increment. Besides, the complexity of implementation of the methodology without the DYLAM code is a challenge in itself. Dutuit et al. [54] used Petri nets to study a similar problem with Markov assumptions. Mechanistic modeling based on method illustrated by Hari et al. [55] provids the component level modeling of control valve for determining the probability of failure at any intermediate percentage of opening. However, this method can only be used for determination of failure probabilities of valves at any intermediate positions but cannot capture the dynamic aspect with respect to time.

In view of the above, the newly developed dynamic reliability methodology was first benchmarked against the findings of Aldemir [40], Deoss [51] and Siu [52] to check its applicability and correctness.

3.3.1 System details of benchmark system (hold-up tank)

As said before, the methodology was first applied to a level control system of a hold up tank. This consists of a fluid containing tank, which has three separate level control units. Fig. 3.2 shows a diagram of the system. Each control unit is independent of the other and has a separate level sensor associated with it. The level sensors measure the fluid level in the tank, which is a continuous process variable. Based on the information from the level sensors, the operational state of the control units is determined. Each flow control unit can be thought of as containing a controller which turns the unit "on" and "off" based on the signal from the level sensors, as shown in Fig. 3.2. These flow control units can be considered as pneumatic control valves. Failure of the system occurs when the tank either runs dry or overflows.

The tank has a nominal fluid level at the start of system operation. This nominal level is assumed as zero meters; all levels are measured with reference to this zero. The level which are above zero are referred as 'positive' whereas below ones are 'negative'. The maximum level of the tank is **+X** meters and the minimum level of the tank is **-X** meters. If the tank level moves out of this range, failure of the system will occur. Within this range, there are two set points at **-Y** meter and **+Y** meter. These set points define three control regions for system operation. Region 1 is defined from point **-X** to **-Y**, region 2 is from **-Y** to **+Y**, and region 3 is from **+Y** to **+X**. When the fluid level is in any of the three control region, there is a specific action required for each of the three control units. During normal operation the level is in region 2 (i.e. in between **-Y** and **+Y**). In this region, unit 1 and 2 are in ON position so the flow is coming from unit 2 and outgoing from unit 1. Due to any failures or transients, when level starts falling and reaches region 1 (i.e. in between -**Y** and **–X)** the system goes into a transition of state by turning OFF the unit 1 and switching ON the unit 3 and unit 2 so that the level in the tank starts getting rise to reach normal operating region 2. Similarly, when the level in the tank reaches upper control region 3 (in between **+Y** and **+X**) the system goes into transition of state by switching unit 2 and 3 OFF while keeping unit 1 in ON position so that level can drop to normal operating range (region 2). Table 3.1 shows the control unit states for each control region. Overflow failure occurs when level exceeds **+X** and dryout happens when it dips below **-X**.

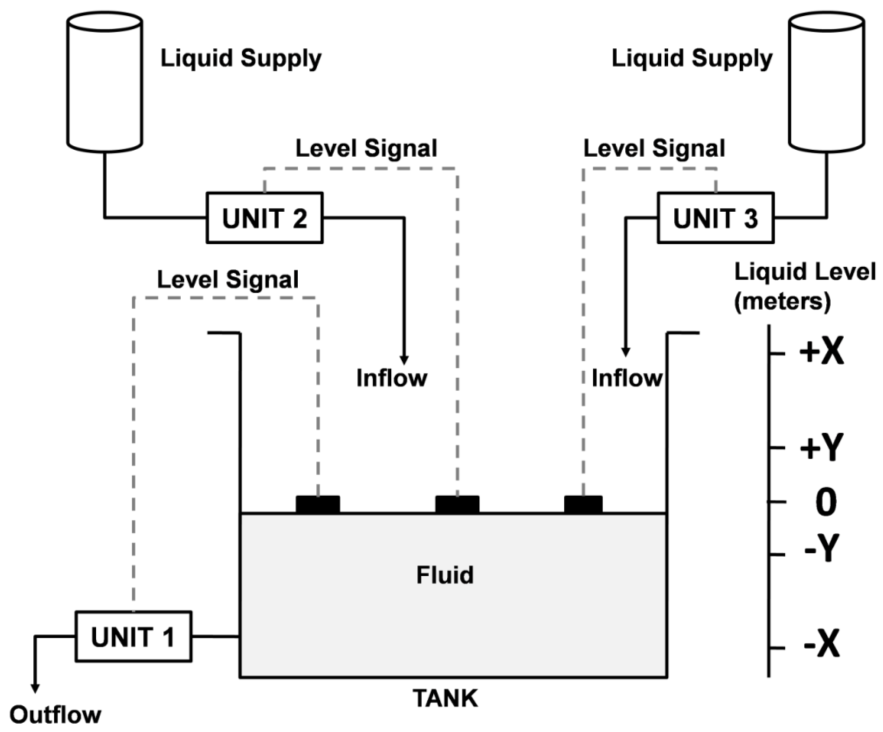


Fig. 3.2 Holdup Tank (Benchmark system)

Table 3.1 Control logic of component states

Liquid Level	Unit 1	Unit 2	Unit 3
$-Y \le x \le +Y$	ON	ON	OFF
$+Y < x$	ON	OFF	OFF
$-Y > x$	OFF	ON	ON

While solving this benchmark problem, there were certain assumptions made, which are as follows:

1. Failures are not repairable,
2. The response is instantaneous, and the time delay is negligible,
3. System evolution equation is known, as in this case it is Eq.3. 2,
4. Probability of getting stuck at any fault position is known or can be determined from databases,
5. Probability distribution of time to failure at each fault position is known or can be determined with the help of failure databases,
6. Each control unit acts independently and is not aware of the state of the other control units except through the change occurring in the process variable, and
7. The Unit 3 is supposed to be closed until the control logic calls for to open it up. Since this valve is still powered on when closed, this unit is considered as active not a standby. Hence the failure rate of active component is considered in this analysis.

Rate of liquid level change in the tank is expressed by Eq. (3.2) where f_n depends upon the state of each unit as shown in Table 3.2. The Q1, Q2 and Q3 in Table 3.2 are constants, which represent change in level per unit time caused by opening of respective units.

$$\frac{dx}{dt} = f_n \tag{3.2}$$

Table 3.2: Rate of liquid level change as a function of control unit states

Control Unit State			**Rate of**
Unit 1	Unit 2	Unit 3	Level Change f_n
ON	ON	ON	-Q1+Q2+Q3
ON	ON	OFF	-Q1+Q2
ON	OFF	ON	-Q1+Q3
ON	OFF	OFF	-Q1
OFF	ON	ON	Q2+Q3
OFF	ON	OFF	Q2
OFF	OFF	ON	Q3
OFF	OFF	OFF	0

There are two configurations of flow rates namely CASE - A, and CASE - F (names retained from [40]). For Case - A, flow rates are such that level change per min because of units 1, 2 and 3 are 0.01 m/min; whereas for Case - F, unit 1 and 2 are same 0.01 m/min only unit 3 has 0.005 m/min. Value of 0.01 signifies that when unit 1 is in open position for 1 minute, it will accumulate the amount of water in the tank such that the level will rise to 0.01 meters. This level change/min depends upon the flow rates of the respective valves (units). In this case it is an assumed value for analysis purpose. Control Levels are +1 meter (upper control limit) and -1 meter (lower control limit). Failure Limits considered for analysis are +3 meter for Overflow and -3 meter for Dryout. These levels are measured with respect to level zero meters.

3.3.2 Binary failure case

The two reported cases A and F are first solved by using simplified Markov modeling developed by Deoss [51], against which the Monte Carlo simulation based results are validated. In binary failure case, the failure rates of units are considered as constant. The failure rate of units has been taken from T. Ademir [40]. Failure rate per hour for unit 1 is λ_1 = 3.1250 E-03, unit 2 is λ_2 = 4.5662 E-03 and for unit 3 is λ_3 = 5.7143 E-03. The two cases will be discussed in the following sections:

3.3.2.1 Markov model

Aldemir [40] has described the algorithm for mechanized construction of transition matrix, using which the system can be analyzed for binary failure case using Markov chains. Also Deoss [51] mentioned an approximate solution using Markov modeling against which the results of the simulation approach for binary failure case can be compared. In both the methods it was assumed that the time required for the fluid level to transit between control regions is negligible in comparison with the time to failure of components. Time to failure of components was assumed to follow exponential distribution. In addition, it was also assumed that there are no transitions simultaneously.

With the assumptions mentioned, the state transition diagram for Case-A and Case-F are shown in Fig. 3.3 and Fig. 3.4. Table 3.3 describes the Markov states for Case-A and Case-F. Markov state equations for both the Cases A and F can be written in the following manner:

For case A, consider the system composed of only the first four states of the Fig. 3.3. The four Markov equations for this system are:

$$\frac{dP_0}{dt} = -[\lambda_1 + \lambda_2 + \lambda_3]P_0 \tag{3.3}$$

$$\frac{dP_1}{dt} = \lambda_1 P_0 \tag{3.4}$$

$$\frac{dP_2}{dt} = \lambda_2 P_0 \tag{3.5}$$

$$\frac{dP_3}{dt} = \lambda_3 P_0 \tag{3.6}$$

Noting that at time t=0.0 the system is initially in state 0 giving

$$P_0(t) = \exp[-[\lambda_1 + \lambda_2 + \lambda_3]\ t] \tag{3.7}$$

Substituting this result into equation 3.4 gives:

$$\frac{dP_1}{dt} = \lambda_1\ exp[-\ [\lambda_1 + \lambda_2 + \lambda_3]\ t] \tag{3.8}$$

This can be solved to yield:

$$P_1(t) = \left[\frac{-\lambda_1}{\lambda_1+\lambda_2+\lambda_3}\right] \exp[-\ [\lambda_1 + \lambda_2 + \lambda_3]\ t] + C \tag{3.9}$$

where

$$C = \left[\frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3}\right], since\ P_1(0) = 0.0 \tag{3.10}$$

The equation for state 1 can therefore be written:

$$P_1(t) = \left[\frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3}\right]\{1 - \exp[-\,[\lambda_1 + \lambda_2 + \lambda_3]\; t]\} \tag{3.11}$$

Using the same solution approach for states 2 and 3 it is found:

$$P_2(t) = \left[\frac{\lambda_2}{\lambda_1+\lambda_2+\lambda_3}\right]\{1 - \exp[-\,[\lambda_1 + \lambda_2 + \lambda_3]\; t]\} \tag{3.12}$$

$$P_3(t) = \left[\frac{\lambda_3}{\lambda_1+\lambda_2+\lambda_3}\right]\{1 - \exp[-\,[\lambda_1 + \lambda_2 + \lambda_3]\; t]\} \tag{3.13}$$

Cumulative probability of overflow and dryout for Case-A were estimated using equations 3.7 and 3.11-13. Results are plotted and shown in Fig 3.5.

Similarly for Case F, the Markov state equations can be written as follows:

$$\frac{dP_0}{dt} = -[\lambda_1 + \lambda_2 + \lambda_3]P_0 \tag{3.14}$$

$$\frac{dP_1}{dt} = -[\lambda_2 + \lambda_3]P_1 + \lambda_1 P_0 \tag{3.15}$$

$$\frac{dP_2}{dt} = -[\lambda_1 + \lambda_3]P_2 + \lambda_1 P_0 \tag{3.16}$$

$$\frac{dP_3}{dt} = -[\lambda_1 + \lambda_2]P_2 + \lambda_1 P_0 \tag{3.17}$$

$$\frac{dP_4}{dt} = \lambda_2 P_1 \tag{3.18}$$

$$\frac{dP_5}{dt} = \lambda_3 P_1 \tag{3.19}$$

$$\frac{dP_6}{dt} = -\lambda_3 P_6 + 0.5\, \lambda_1 P_2 \quad 3.20)$$

$$\frac{dP_7}{dt} = -\lambda_3 P_7 + 0.5\, \lambda_1 P_2 \tag{3.21}$$

$$\frac{dP_8}{dt} = -\lambda_1 P_8 + 0.5\, \lambda_3 P_2 \tag{3.22}$$

$$\frac{dP_9}{dt} = -\lambda_1 P_9 + 0.5\, \lambda_3 P_2 \tag{3.23}$$

$$\frac{dP_{10}}{dt} = \lambda_3 P_6 \tag{3.24}$$

$$\frac{dP_{11}}{dt} = \lambda_3 P_7 \tag{3.25}$$

$$\frac{dP_{12}}{dt} = \lambda_1 P_8 \tag{3.26}$$

$$\frac{dP_{13}}{dt} = \lambda_1 P_9 \tag{3.27}$$

$$\frac{dP_{14}}{dt} = \lambda_1 P_3 \tag{3.28}$$

$$\frac{dP_{15}}{dt} = \lambda_2 P_3 \tag{3.29}$$

Cumulative probability of overflow and dryout with respect to time for Case-F are estimated by solving the state equations 3.14-29. Results are presented in Fig 3.6. , the results obtained were verified by commercial software ISOGRAPH as well.

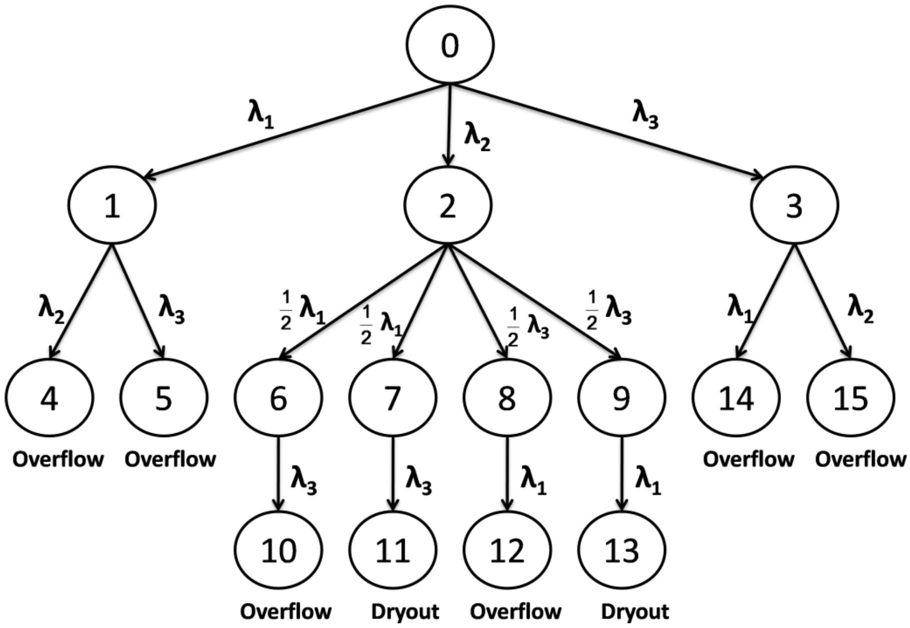


Fig. 3.3 Markov model (state transition diagram) for Case A

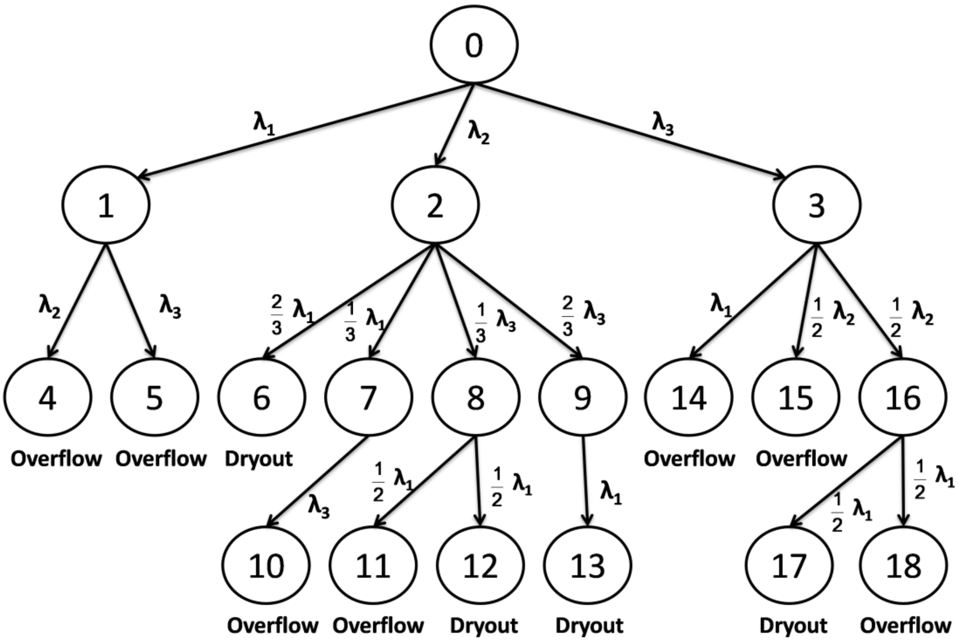


Fig. 3.4 Markov model (state transition diagram) for Case F

Table 3.3 Markov state description

CASE - A	
State	**Failure description**
0	All Units good
1	Unit 1 failed closed
2	Unit 2 failed closed
3	Unit 3 failed open
4	Unit 1 failed closed then Unit 2 failed open (Overflow)
5	Unit 1 failed closed then Unit 3 failed open (Overflow)
6	Unit 2 failed closed then Unit 1 failed closed
7	Unit 2 failed closed then Unit 1 failed open
8	Unit 2 failed closed then Unit 3 failed open
9	Unit 2 failed closed then Unit 3 failed closed
10	Unit 2 failed closed then Unit 1 failed closed then Unit 3 failed open (Overflow)
11	Unit 2 failed closed then Unit 1 failed open then Unit 3 failed closed (Dryout)
12	Unit 2 failed closed then Unit 3 failed open then Unit 1 failed closed (Overflow)
13	Unit 2 failed closed then Unit 3 failed closed then Unit 1 failed open (Dryout)
14	Unit 3 failed open then Unit 1 failed closed (Overflow)
15	Unit 3 failed open then Unit 2 failed open (Overflow)
CASE F	
State	**Failure description**
1	All units good
2	Unit 1 failed closed
3	Unit 2 failed closed
4	Unit 3 failed open
5	Unit 1 failed closed then Unit 2 failed open (Overflow)
6	Unit 1 failed closed then Unit 3 failed open (Overflow)
7	Unit 2 failed closed then Unit I failed open (Dryout)
8	Unit 2 failed closed then Unit 1 failed closed
9	Unit 2 failed closed then Unit 3 failed open
10	Unit 2 failed closed then Unit 3 failed closed
11	Unit 2 failed closed then Unit 1 failed closed then Unit 3 failed open (Overflow)
12	Unit 2 failed closed then Unit 3 failed open then Unit 1 failed closed (Overflow)
13	Unit 2 failed closed then Unit 3 failed open then Unit 1 failed open (Dryout)
14	Unit 2 failed closed then Unit 3 failed closed then Unit 1 failed open (Dryout)
15	Unit 3 failed open then Unit 1 failed closed (Overflow)
16	Unit 3 failed open then Unit 2 failed open (Overflow)
17	Unit 3 failed open then Unit 2 failed closed
18	Unit 3 failed open then Unit 2 failed closed then Unit 1 failed open (Dryout)

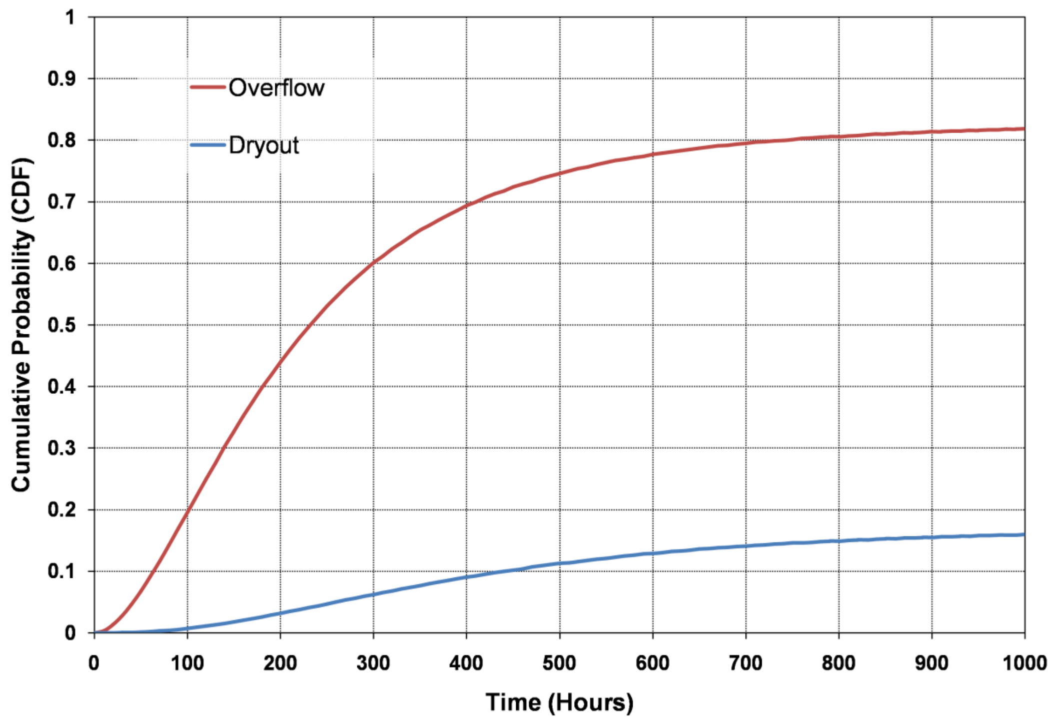


Fig. 3.5 Overflow and Dryout probability for Case A considering binary failures

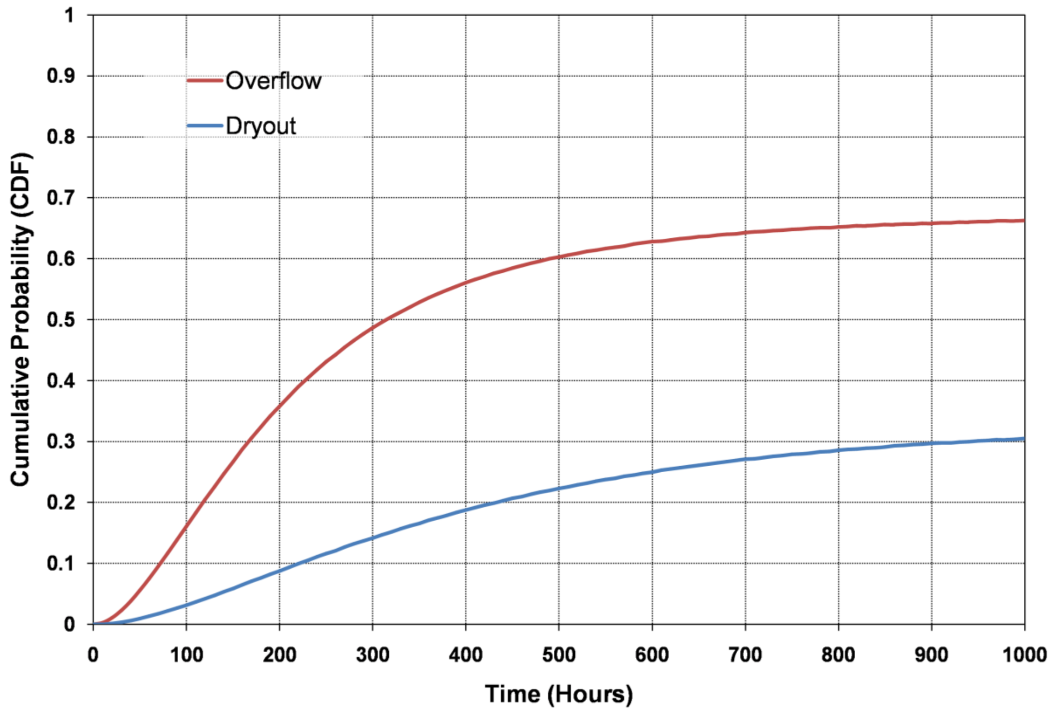


Fig. 3.6 Overflow and Dryout probability for Case F considering binary failures

3.3.2.2 Monte Carlo Simulation

Having solved the reported cases A and F by using a simplified Markov analysis, the same cases are solved by using Monte Carlo simulation as per the newly developed dynamic reliability methodology. A case with no fault increment, binary failure state and constant failure rate was simulated using the newly developed dynamic reliability methodology by disabling the fault increment rate and changing the sampling distributions to exponential, considering failure rates mentioned in section 3.3.2. It was assumed that whenever the fault occurs in any units, it behaves opposite to the current control law as stated by Aldemir [40]. For example, during the normal operating range, unit 1 is supposed to be open; but when fault occurs, it will close as opposite to the normal demand. Monte Carlo simulation with time step of 1 hr and total of 1000 runs was performed. In this Monte Carlo simulation, an estimator P_o and P_d of the probability of overflow and dryout is computed. The estimation P_o and P_d after N runs of the Monte Carlo algorithm is given by Eq. (3.30) and Eq. (3.31):

$$P_d = \frac{F(dryout)}{N} \tag{3.30}$$

$$P_o = \frac{F(overflow)}{N} \tag{3.31}$$

Where, *F(dryout)* is number of times the system has failed in dryout condition and *F(overflow)* is the number of times it has failed in overflow condition

Cumulative probability of Dryout and Overflow are plotted on the Y axis with respect to time in X axis. The results are shown in Fig. 3.7 and Fig. 3.8.

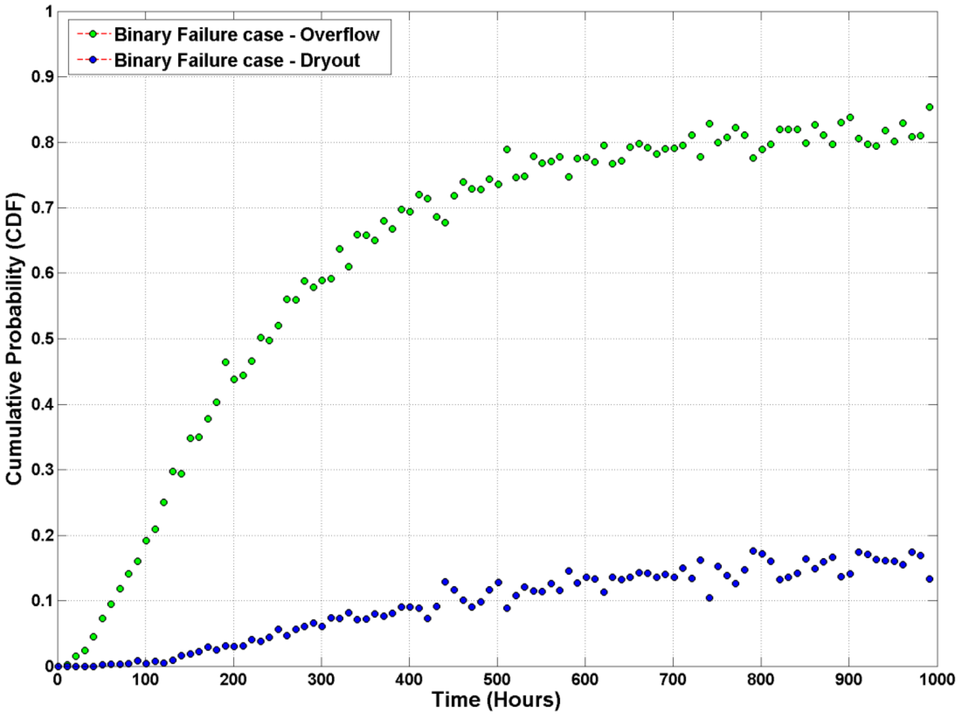


Fig. 3.7 Probability of Overflow and Dryout: binary case and const. failure rate-Case A

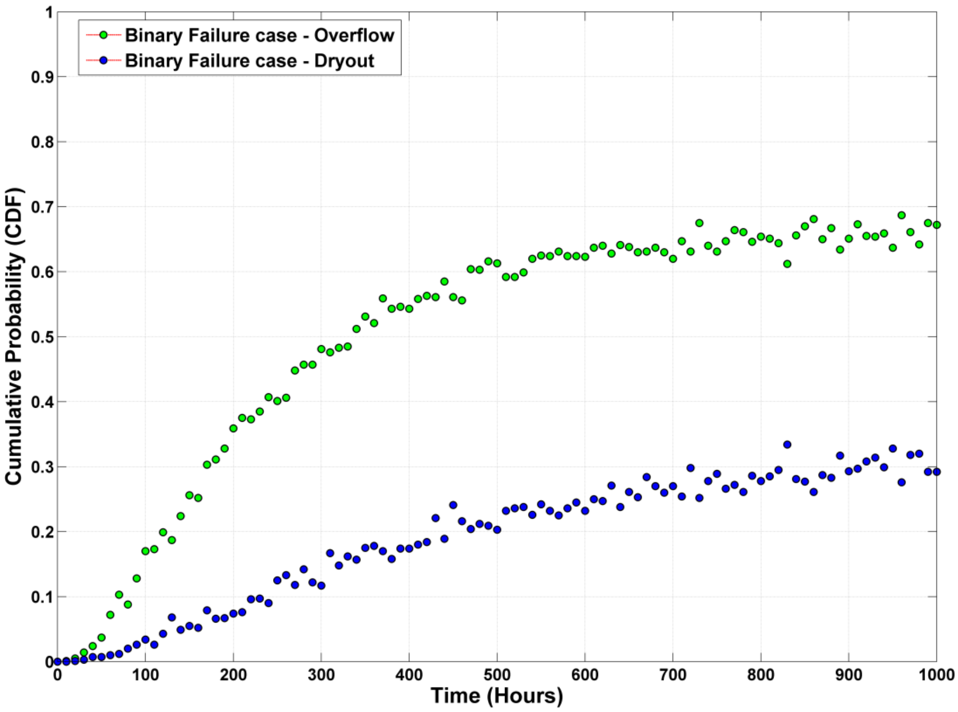


Fig.3.8 Probability of Overflow and Dryout: binary case and const. failure rate-Case F

The cumulative probabilities of overflow and dryout (presented in Fig. 3.7 and 3.8) of the hold-up tank system obtained by the newly developed dynamic reliability was compared with that of the results shown in Fig. 3.5 and 3.6. It was found that the newly developed dynamic reliability methodology could reproduce the exact results for the binary failure cases. The binary failure case was solved to benchmark the results of newly developed methodology. More complex cases of multi-state failures were then performed to assess the more realistic cases. The multi-state cases are discussed in the following section.

3.3.3 Multi-state failure case

Having solved the binary failure case, the objective of solving multi-state failure case was accomplished in two settings considering:

a) No-fault increment and
b) With fault increment.

3.3.3.1 Analysis without fault increment

As stated earlier, components like control valves can fail at any intermediate state as opposed to the assumption of binary state failure which restricts to only two failure cases (either stuck open or stuck closed). In this case, valves are assumed to fail at any of the states as mentioned in the Table 3.4 with certain probability. The time at which failure could happen is different for different states, i.e. the distribution of time to failure at different states is assumed to be different since control valves could have this characteristic.

Table 3.4 Assumed time to failure and distribution parameters of components

% Fault	Probability of getting stuck	Probability distribution	Distribution Parameter
Unit 1			
Close – 100%	35%	Weibull	Shape = 1, Scale = 300 hrs
Intermediate-25%	5%	Weibull	Shape = 1.5, Scale = 325 hrs
Intermediate-50%	10%	Weibull	Shape = 2, Scale = 350 hrs
Intermediate-75%	15%	Weibull	Shape = 2.5, Scale = 375 hrs
Open - 100%	35%	Weibull	Shape = 3, Scale = 400 hrs
Unit 2			
Close – 100%	35%	Weibull	Shape = 1, Scale = 200 hrs
Intermediate-25%	5%	Weibull	Shape = 1.5, Scale = 225 hrs
Intermediate-50%	10%	Weibull	Shape = 2, Scale = 250 hrs
Intermediate-75%	15%	Weibull	Shape = 2.5, Scale = 275 hrs
Open - 100%	35%	Weibull	Shape = 3, Scale = 300 hrs
Unit 3			
Close – 100%	35%	Weibull	Shape = 1, Scale = 100 hrs
Intermediate-25%	5%	Weibull	Shape = 1.5, Scale = 125 hrs
Intermediate-50%	10%	Weibull	Shape = 2, Scale = 150 hrs
Intermediate-75%	15%	Weibull	Shape = 2.5, Scale = 175 hrs
Open - 100%	35%	Weibull	Shape = 3, Scale = 200 hrs

Monte Carlo simulation with time step of 1 hr and total of 1000 runs was executed as per the flow diagram mentioned in Fig 3.1. Cumulative probability of Dryout and Overflow are plotted on the Y axis with respect to time in X axis. The results are shown in Fig. 3.9 and Fig. 3.10. To compare, previous graphs for binary state and constant failure case are also plotted and shown. It can be seen in Fig. 3.9 that cumulative probability of overflow for Case A has dropped from 0.810 (binary failure case) to 0.645 (Multi-state transition case) while, the cumulative probability of dryout is almost similar in both. In case of Case F the same phenomena can be observed in Fig. 3.10. The drop in cumulative probability of overflow can be attributed to the fact that in multi-state failure case, unit 1 and unit 2 can also fail at partial percentage of openings instead of completely stuck open/close as in case of binary failure. These partially open or close positions have a dominant effect on overflow probability since the system is so configured that chances of overflow is much higher than dryout.

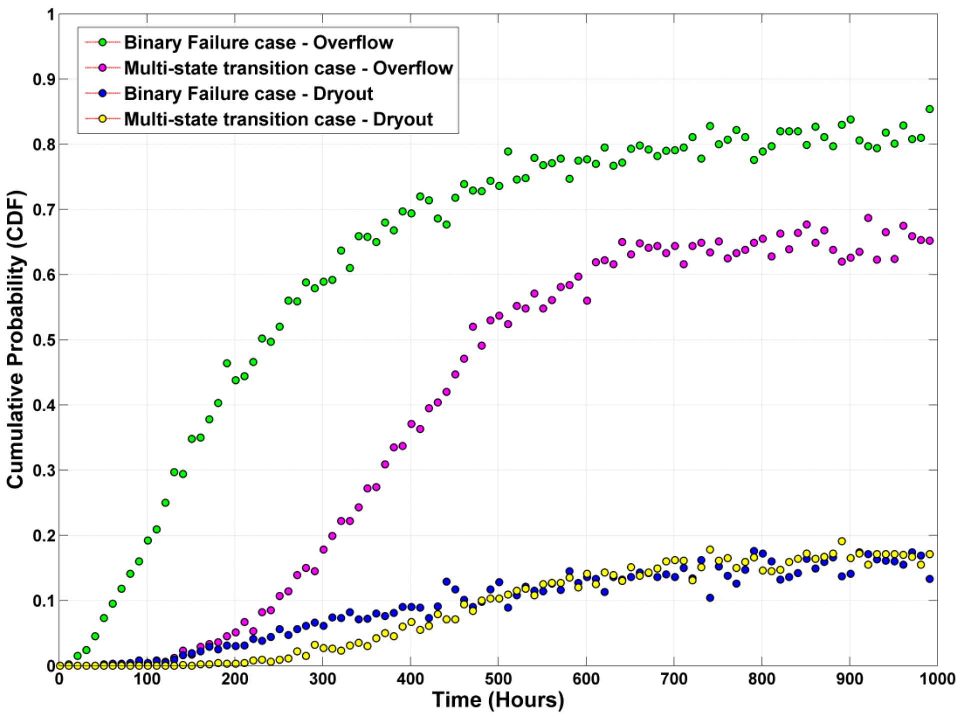


Fig. 3.9 Probability of Overflow and Dryout for binary and Multi-state transition Case -A

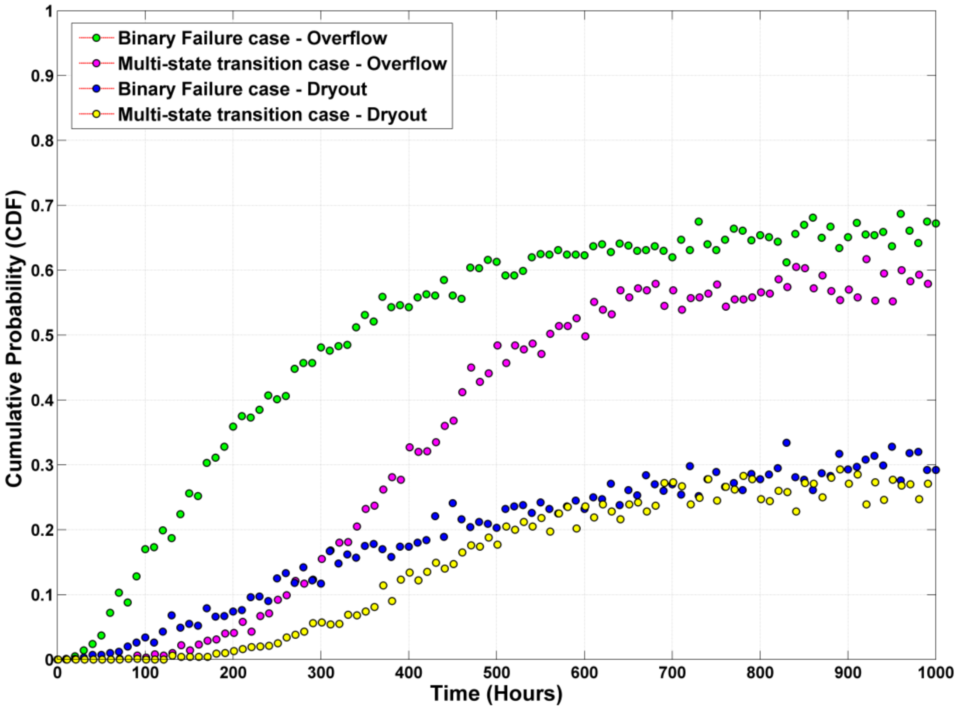


Fig. 3.10 Probability of Overflow and Dryout for binary and Multi-state transition Case-F

3.3.3.2 Analysis with fault increment

In order to understand the effect of fault increment during the system evolution in the estimation of probability of overflow and dryout, simulations with fault increment was preformed. It was assumed that valve fails in open position if power fails (loss of pneumatic pressure); so once the failure on any of the valves occurs, it gradually starts opening with the corresponding fault increment rate till it opens completely. Fault increment rate may differ from valves to valves, however for the simplicity it was assumed that all the three control valves have same fault increment rate (expressed in % increment per hour). Further, it was assumed that this rate of increment is linear. However, it is also possible to model a non linear rate of increment.

Monte Carlo simulation with time step of 1 hr and total of 1000 runs was performed as per the flow diagram mentioned in Fig 3.1. Cumulative probability of Dryout and Overflow are plotted on the Y axis with respect to time in X axis. The results are shown in Fig. 3.11 and Fig. 3.12 for Case A and Case F respectively. In order to understand the changes in the estimations for different fault increment rate, a number of cases with different fault increment valves were simulated. To compare, previous graphs for binary state and constant failure case are also plotted and shown. Results are summarized in Table 3.5.

It can be observed that for all the fault increment rates, the overflow probability was higher than the binary failure case and multi-state transition without fault increment; whereas the dryout probability in both Case A and F were less than that of the binary and multi-state transition case with no fault increment. The reasons for these overflow and dryout probabilities shooting up and dropping respectively is the directional fault increment, which opens the valve gradually after the fault has occurred.

Table 3.5 Overflow and dryout probabilities for Case A and F

CASE	Cumulative Overflow Probability					Cumulative Dryout Probability				
A		Multi-state failure case					Multi-state failure case			
Time (hr)	Binary case	No FIR	FIR – 1%	FIR – 10%	FIR – 50%	Binary	No FIR	FIR – 1%	FIR – 10%	FIR – 50%
200	0.326	0.044	0.112	0.310	0.133	0.021	0.005	0.001	0.000	0.000
400	0.584	0.357	0.559	0.707	0.537	0.070	0.056	0.004	0.000	0.000
600	0.729	0.594	0.883	0.918	0.869	0.119	0.124	0.003	0.000	0.000
800	0.772	0.651	0.946	0.983	0.947	0.155	0.148	0.006	0.000	0.000
1000	0.810	0.645	0.979	0.979	0.967	0.151	0.173	0.005	0.000	0.000
CASE	Cumulative Overflow Probability					Cumulative Dryout Probability				
F		Multi-state failure case					Multi-state failure case			
Time (hr)	Binary case	No FIR	FIR – 1%	FIR – 10%	FIR – 50%	Binary	No FIR	FIR – 1%	FIR – 10%	FIR – 50%
200	0.196	0.041	0.057	0.170	0.105	0.045	0.019	0.009	0.000	0.000
400	0.444	0.295	0.456	0.541	0.498	0.145	0.124	0.039	0.000	0.000
600	0.589	0.528	0.795	0.876	0.877	0.204	0.219	0.069	0.000	0.000
800	0.653	0.567	0.839	0.962	0.957	0.235	0.266	0.109	0.000	0.000
1000	0.654	0.573	0.884	0.987	0.971	0.279	0.281	0.099	0.000	0.000

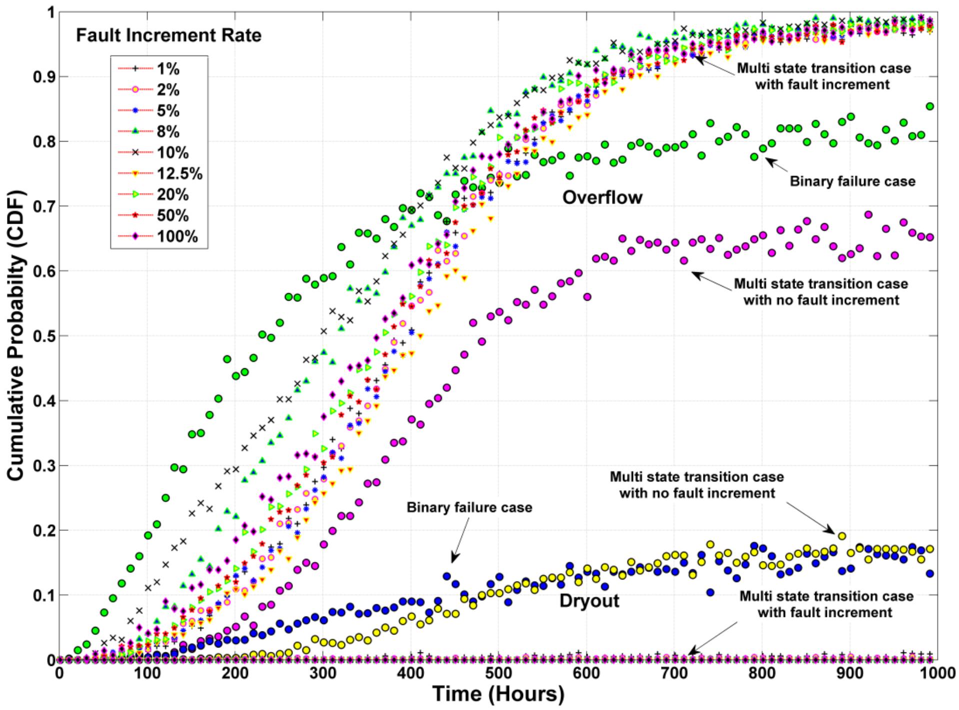


Fig. 3.11 Probability of Overflow and Dryout for multi-state transition case with fault increment rate - Case-A

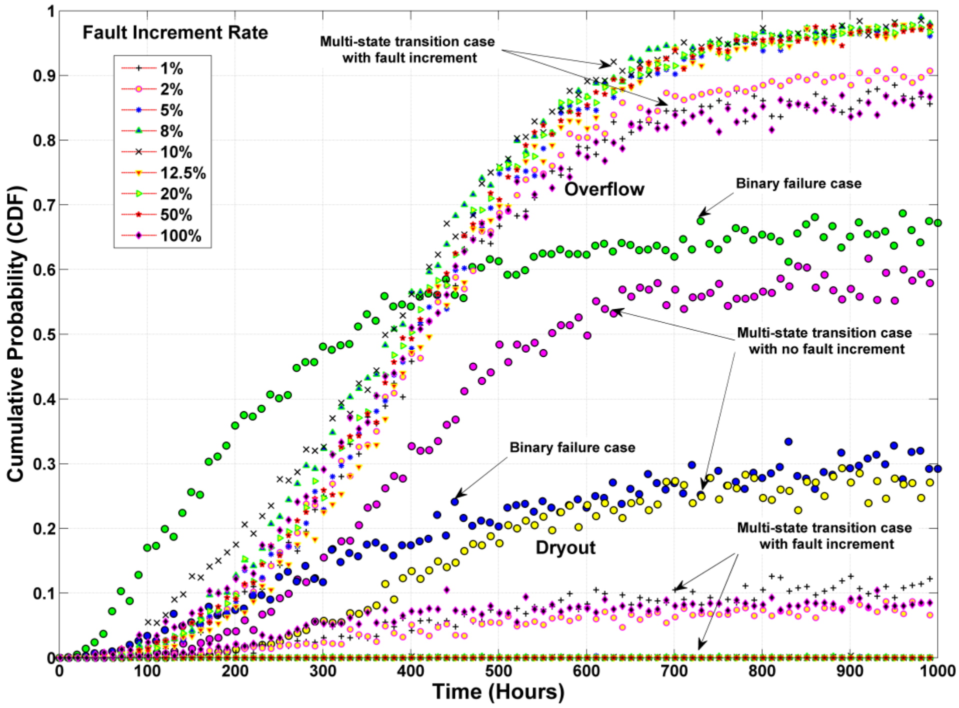


Fig. 3.12 Probability of Overflow and Dryout for multi-state transition case with fault increment rate - Case-F

3.4 Conclusions

Functional failure of passive safety system can be attributed to the deviation of process parameters and malfunctioning of components. During the mission of passive system execution, the process parameters may deviate and at the same time the components may fail stochastically based on the dynamics of operation. These complex interactions between hardware failure and process parameter deviation may further change the way the system is expected to behave during the rest of the operation, and can lead the system to failures which were not anticipated by the deterministic analysis or by static reliability analysis. Traditionally, the reliability analysis of passive safety systems is performed using fault tree (FT) and event tree (ET) analysis. FT/ET assumes that components of passive systems such as valves have binary-states of failure (stuck open and stuck closed). However, such components can fail at intermediate positions as well. Time to failure for these intermediate states of such components can have different probability distribution parameter which may vary from one state to another. In order to perform the reliability assessment of passive safety systems by considering the dynamic failure characteristics of components, a dynamic reliability analysis methodology has been developed and presented in this chapter.

In order to check the applicability and correctness of the newly developed dynamic reliability methodology, it was applied to a benchmark system of a level controlled hold-up tank. A binary failure case of components is first analyzed using the newly developed dynamic reliability methodology. The cumulative probability of overflow and dryout, obtained using the dynamic reliability methodology was compared with the respective probabilities published in the literatures [51-52]. With the help of this initial assessment, it was found that developed methodology of dynamic reliability is able to reproduce the same results as published in the literature by Deoss [51] and Siu [52].

A case of multi-state failure was simulated to assess the impact of dynamic failure characteristics such as multi-state failure on the obtained cumulative failure probabilities. In this case, the valves were assumed to fail at any of the states of opening. The time at which failure of these valves could happen were also assumed to be different for each state, i.e. the distribution of time to failure at each states were assumed to be different since control valves have this characteristic. The results for multi-state failure case along with the binary failure results were compared. It was observed that the cumulative probability of overflow had dropped while, the cumulative probability of dryout is almost similar in both the cases.

With the help of this analysis, it was learnt that the conventional methods yields erroneous estimates of system failure probability because the dynamic failure characteristics of components is not accounted in the existing methods. Keeping in view the above findings, it can be concluded that while estimating the failure probability of passive safety systems, the dynamic reliability methodology can provide realistic results.

CHAPTER – 4

QUANTIFICATION OF FUNCTIONAL FAILURE PROBABILITY OF COMPONENTS OF PASSIVE SYSTEM AND ITS IMPACT ON SYSTEM RELIABILITY ANALYSIS

4.1 Introduction

The advanced reactors are designed to utilize passive safety systems, which do not have any moving mechanical components; however most of the passive systems use valves for either activation or during the operation. Traditionally, reliability analysis of these systems is performed with the assumption that these valves have binary-states of failure (stuck open and stuck closed). However, these components can fail at intermediate positions as well. Currently the failure probability of such components at intermediate fault positions is not available in the available databases [56], [57] and [58]. It has been recognized that lack of experimental evidence and validated data forces the analysts to resort to expert/engineering judgment to a large extent, hence making the results strongly dependent upon the expert elicitation process. This prompts the need for the development of a framework for constructing a database by conducting a series of experiments to generate probability distributions for the component failures and process parameters influencing the passive system behavior. In addition, it is also important to assess the impact of considering these functional failures and dynamic failure characteristics in system reliability analysis.

4.2 Quantification of functional failure probabilities of valves at multiple state of opening

In view of the generation of the databases for the probability distributions of the components of passive system like valves, an experimental facility of a benchmark setup consisting three control valves for a passive system was built and a series of experiments were performed to quantify the functional failure probability of these valves which play critical role in performance of passive safety system.

4.2.1 Experimental set-up

The experimental set-up consists of a fluid containing tank, which has three separate level control units. Fig. 4.1 shows the actual photograph of the experimental set-up. Each control unit is independent of the other and has a separate level sensor associated with it. The level sensors measure fluid level in the tank, which is a continuous process variable. Based on the information from level sensors, the operational state of the control units is determined. Each flow control unit can be thought of as containing a controller which turns the unit “on” and “off” based on the signal from the level sensors, as shown in Fig. 4.1. Failure of the system occurs when the tank either runs “dry” or “overflows”.

Total length of the tank in the experimental setup is 1 meter. The tank has a nominal fluid level at the start of system operation. This nominal level is assumed as zero meters for the simulation which corresponds to 0.5 meters in the experimental set-up; all levels are measured with reference to this zero. The level which are above zero are referred as positive whereas level below zero are negative. The maximum level of the tank for experimental considerations is +0.4 meter and the minimum is -0.4 meter. If the tank level moves out of this range, failure of the system will occur. Within this range, there are two set points at -0.2 meter and +0.2 meter. These set points define three control regions for system operation. Region 1 is defined from -0.4 meter to -0.2 meter; region 2 is from -0.2 meter to +0.2 meter; and region 3 is from +0.2 meter to +0.4 meter. When the fluid level is in any of the three control regions, there is a specific action required for each of the three control units. During normal operation, the level is in region 2 (i.e. in between -0.2 meter and +0.2 meter). In this region, unit 1 and 2 are in ON position so the flow is coming from unit 2 and outgoing from unit 1. Due to any failure or transient when level starts falling and reaches region 1 (i.e. in between -0.2 meter and –0.4 meter), the system goes into a transition of state by turning OFF the unit 1 and switching ON the unit 3 and unit 2 so that the level in the tank rises to reach normal operating region 2. Similarly, when the level in the tank reaches upper control region 3 (in between +0.2 meter and +0.4 meter), the system goes into transition of state by switching unit 2 and 3 OFF while keeping unit 1 in ON position so that level can drop to normal operating range (region 2). Overflow failure occurs when level exceeds +0.4 meter mark and dryout happens when it dips below -0.4 meter mark.

In this experiment, three control valves were used. First control valve unit 1, has the highest level change rate while, the other two units 2 and 3 have lower level change rate as compared to unit 1. All the three valves were having linear flow characteristics ideally.

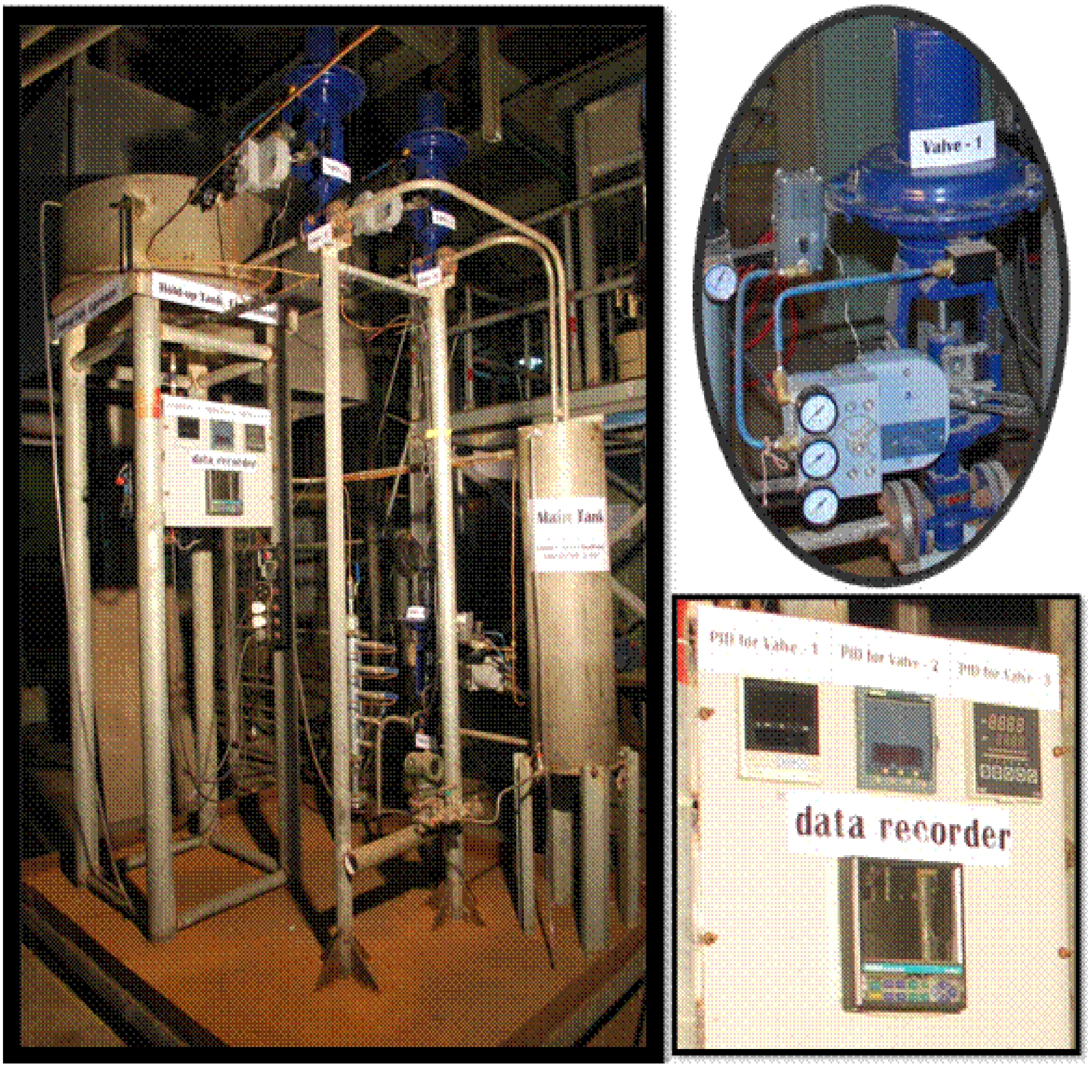


Fig. 4.1 Experimental set-up of Hold-up Tank

4.2.2 Experiments conducted

In order to simulate the actual failure of valves, the valves were made to fail in the experiment by disabling the control of that particular valve. Once the fault in the valve is initiated, it can get stuck at any position of operation. However, the stuck position of operation cannot be read by using the PID controller, because they were disabled to simulate the failure of valve. In order to get the failed position of these valves, the experiment was continued to record the actual failure of system (i.e. either overflow or dryout). In case the system does not fail by the end of predefined test duration (10 hrs.), the level of the tank was recorded in the end. Once the time to failure/ level of the system was recorded from the experiment, many configurations (different % of stuck conditions) of the faulty valve were simulated using the newly developed dynamic reliability methodology presented in chapter 3. From the output of the simulation of dynamic reliability analysis, the fault position was selected by comparing the system failure time/level obtained from the experiment and simulation. The above mentioned procedure is repeated for a large number of configurations of valve. The results so obtained are analyzed and a histogram of fault positions is plotted to get the probability of failure at intermediate states of operations of each valve. The above mentioned procedure is delineated in steps with one example illustrated below:

Step 1: Initiation of fault

In the experimental setup, the fault is induced in valves by disabling the automatic controller (PID). This fault is induced at the start of the operation when the main tank is at nominal operating condition. When the fault is induced in valve 1, other two valves were kept at 100% open condition. Similarly when the faults were induced in the valve 2 or 3, valve 1 was kept at closed condition and the other valve (either 2 or 3) was kept 100% open. This arrangement of keeping the good condition valves was done to simulate the system failure within the preset maximum test duration of 10 hrs.

Observation: The fault in valve 1 was induced. Once the fault in the valve is initiated, it can get stuck at any positions of operation.

Step 2: Recording the system failure time/ level at the end of experiment

The experiment is continued to record the system failure. If in case the system does not fail by the end of predefined test duration, the level of the tank is recorded in the end. Failure of the system can be overflow or dryout based on the system dynamics and state of the valve failure.

Observation: It was found that system failed in overflow state and time to failure recorded in the experiment was 220 minutes.

Step 3: Estimation of the fault position

Once the system failure time/ level of tank were recorded in the experiment, it is required to determine the exact fault position that occurred in the selected valve in which the fault was induced. In order to estimate this observed fault position of the valve, the recorded system failure time/ level of the tank at the end of the experiment was compared with the calculated failure time of this experimental facility using the newly developed dynamic reliability methodology presented in chapter 3. To compare the recoded failure time/ level, many configurations of different % of stuck condition of the selected faulty valve were simulated using the newly developed dynamic reliability methodology. From the output of the simulation, the fault position was selected by matching the system failure time/ level obtained from the experiment and simulation.

Observation: In the experiment, the recoded failure time of the system was found to be 220 min when the fault was induced in valve 1. To determine the fault position of the valve 1, a number of different cases of different fault positions were simulated using the dynamic reliability methodology presented in chapter 3. From the output of the simulation, the system failure time for many configurations of faulty valve was obtained. The recoded failure time in the experiment was then compared with the simulation output. The closest match of the failure time from the experiment and simulation was selected to represent the valve fault state. For example, Table 4.1 presents the simulated cases of different % of valve 1 fault. The failure times of the system for various fault configurations of valve 1 were determined using dynamic reliability methodology presented in chapter 3. The system failure time of 220 min. obtained in the experiment was found matching with the failure times obtained for various configurations of valve 1 fault simulated using dynamic reliability methodology. From the comparison, it was found that the valve 1 fault of 25% stuck open represents the fault position which occurred in the experiment. Hence, the observed fault position was 25% stuck open.

Table 4.1 Simulated cases of fault in valve 1

V1 (% open)	V2 (% open)	V3 (% open)	Failure type	Failure time in min.
100%	100%	100%	No failure	NA
75%	100%	100%	Overflow	652.9
50%	100%	100%	Overflow	301.3
25%	**100%**	**100%**	**Overflow**	**220.1**
0%	100%	100%	Overflow	156.2

Step 4: Repeat step 1-3

Steps 1-3, were repeated for a possibly large number of times. Accuracy of estimates of state probabilities increases by increasing the number of times the experiments are repeated. However, the constraints on the time and resources often put restrictions on this.

A total of 100 experiments were conducted as per the steps 1-3. Table 4.2 shows the details of the 100 experiments conducted. In Table 4.2, the component in which fault has been induced is represented as V1 for valve 1, V2 for valve 2 and V3 for valve 3. If the system failure happens before 10 hrs. in the experiment, failure time is recorded and if the system continues to degrade but does not fail till it reaches 10 hrs., the level at this time of operation has been recorded. These two quantities (i.e. system failure time and level at the end of 10 hrs.) have been used to identify the observed fault position of the respective valve.

Table 4.2 Observations of the experiments performed

Sr. No	Fault Induced in Component (In the experiment)	System Failure Time in min. (Observed in experiment)	Level (in meters) at 10 hrs. (Observed at the end of experiment)	Identified fault% from Simulation (Output of Step-3, fault matching using simulation)
1	V1	220	>0.4	25
2	V1	155	>0.4	0
3	V1	155	>0.4	0
4	V1	>600	0.29	88
5	V1	185	>0.4	12
6	V1	495	>0.4	70
7	V1	155	>0.4	0
8	V1	430	>0.4	66
9	V1	160	>0.4	2
10	V1	475	>0.4	69
11	V1	>600	0.23	97

Sr. No	Fault Induced in Component	System Failure Time in min.	Level (in meters) at 10 hrs.	Identified fault % from Simulation
12	V1	>600	0.39	75
13	V1	>600	0.27	91
14	V1	>600	0.26	92
15	V1	>600	0.27	91
16	V1	300	>0.4	51
17	V1	365	>0.4	60
18	V1	155	>0.4	0
19	V1	185	>0.4	12.5
20	V1	>600	0.24	95
21	V1	>600	0.21	100
22	V1	>600	0.27	90
23	V1	>600	0.21	100
24	V1	155	>0.4	0
25	V1	170	>0.4	6
26	V1	170	>0.4	8
27	V1	255	>0.4	40
28	V1	>600	0.22	98
29	V1	155	>0.4	0
30	V1	155	>0.4	0
31	V1	415	>0.4	65
32	V1	>600	0.21	100
33	V1	190	>0.4	15
34	V1	>600	0.21	100
35	V2	155	>0.4	100
36	V2	310	>0.4	0
37	V2	310	>0.4	0
38	V2	155	>0.4	96
39	V2	310	>0.4	0
40	V2	155	>0.4	98
41	V2	160	>0.4	90
42	V2	160	>0.4	91
43	V2	290	>0.4	6
44	V2	305	>0.4	1
45	V2	200	>0.4	55
46	V2	295	>0.4	5
47	V2	160	>0.4	95
48	V2	310	>0.4	0
49	V2	205	>0.4	50
50	V2	305	>0.4	2
51	V2	155	>0.4	100

Sr. No	Fault Induced in Component	System Failure Time in min.	Level (in meters) at 10 hrs.	Identified fault % from Simulation
52	V2	310	>0.4	0
53	V2	170	>0.4	80
54	V2	240	>0.4	30
55	V2	165	>0.4	88
56	V2	170	>0.4	82
57	V2	180	>0.4	72
58	V2	160	>0.4	90
59	V2	170	>0.4	79
60	V2	180	>0.4	70
61	V2	290	>0.4	7
62	V2	165	>0.4	89
63	V2	310	>0.4	0
64	V2	260	>0.4	20
65	V2	305	>0.4	1
66	V2	195	>0.4	58
67	V2	170	>0.4	79
68	V3	155	>0.4	99
69	V3	160	>0.4	90
70	V3	310	>0.4	0
71	V3	305	>0.4	1
72	V3	155	>0.4	100
73	V3	155	>0.4	98
74	V3	295	>0.4	5
75	V3	295	>0.4	5
76	V3	220	>0.4	41
77	V3	155	>0.4	100
78	V3	170	>0.4	79
79	V3	215	>0.4	45
80	V3	160	>0.4	95
81	V3	165	>0.4	86
82	V3	280	>0.4	10
83	V3	240	>0.4	28
84	V3	155	>0.4	96
85	V3	310	>0.4	0
86	V3	310	>0.4	0
87	V3	220	>0.4	39
88	V3	165	>0.4	89
89	V3	280	>0.4	11
90	V3	155	>0.4	98
91	V3	205	>0.4	50

Sr. No	Fault Induced in Component	System Failure Time in min.	Level (in meters) at 10 hrs.	Identified fault % from Simulation
92	V3	285	>0.4	8
93	V3	180	>0.4	70
94	V3	160	>0.4	95
95	V3	175	>0.4	77
96	V3	285	>0.4	9
97	V3	160	>0.4	92
98	V3	160	>0.4	91
99	V3	280	>0.4	10
100	V3	175	>0.4	75

The results obtained in the 100 experiments presented in Table 4.2 were further analyzed to derive meaningful conclusions about the failure rate of valves. The conventional failure rate of any system or unit is the frequency with which component fails, expressed in failure per unit of time or demand. This conventional failure rate is a statistical summary of past failures of valves. The derived failure rate is the weighted failure rate of the component or system, which is obtained by multiplying the weights to the conventional failure rate. These weights are derived by observing how the component fails in the given application and environment. For example, valves have a conventional failure rate of 1E-10 failure/ demand. However, in reality, the failure rate of valves or may vary based on the operation and environment. The derived failure rate of valves in muti-state failures would be the multiplication of convention failure rate and the probability of valve failing at a particular position of opening. Usually when any failure analysis is performed, the conventional failure rates are directly used without realizing that these are estimated values for some standard cases. The better estimate of failure rates are derived failure rate.

A histogram of fault positions obtained in 100 experiments was plotted (Fig. 4.2). The probability of failure at intermediate states of operations of valves is estimated by dividing the observed number of failures in a particular stuck position. For example, there were total 35 cases of valve stuck at 100% of opening was observed in total of 100 experiments, then probability of stuck close can be estimated as :

$$\text{Probability (100\% stuck open)} = \frac{\text{Observed events of 100\% stuck open}}{\text{Total no of observati ons}} \tag{4.1}$$

$$\text{Probability (100\% stuck open)} = \frac{35}{100} = 0.35$$

Table 4.3 presents the failure probability of these valves at intermediate positions of openings. To compare the failure rates conventionally used in the static reliability methodologies, the derived failure rates at these intermediate failure positions has been shown along with the conventional failure rates obtained from the generic databases.

Table 4.3 Probability of valve failure at intermediate states

% Fault	**Probability of getting stuck**	**Derived failure rate (failure/demand)**	**Conventional failure rate (failure/demand)**
Stuck close – 100%	≈35%	3.50E-05	5.00E-05
Stuck intermediate-25%	≈5%	5.00E-06	0.00E+00
Stuck intermediate-50%	≈10%	1.00E-05	0.00E+00
Stuck intermediate-75%	≈15%	1.50E-05	0.00E+00
Stuck open - 100%	≈35%	3.50E-05	5.00E-05

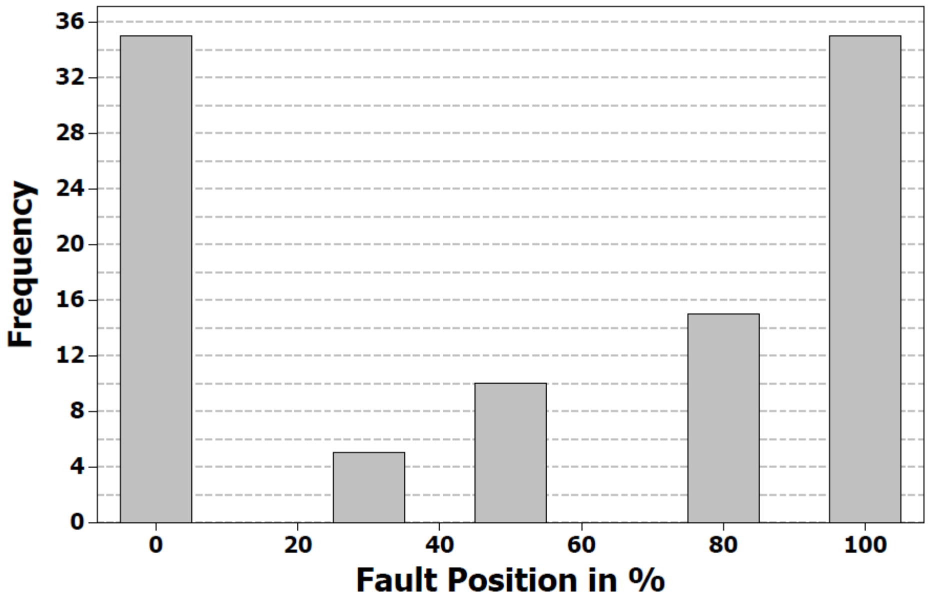


Fig. 4.2 Histogram of fault positions obtained from 100 experiments

It can be inferred from the Table 4.3 that the assumption of binary-states of failure of valves (stuck open and stuck closed) may not hold good in most of the practical cases. In the experiments, it was found that a significant percentage of cases of valve failure lie in between completely stuck open or closed. Currently, the failure probability of such components at intermediate fault positions is not available in the open databases [56], [57] and [58]. By conducting a series of experiments, we have generated the probability of intermediate faults of valves. Table 4.3 presents the failure probability of these valves at intermediate positions of openings. Since the impact of such intermediate failure can be very significant in the estimates of system performance and failure probability, it is important to quantify these effects. The quantification of impact of these failure probabilities has been carried out and presented in the following section.

4.3 Experimental observation of effects of dynamic failure characteristics of valves on the performance of passive system.

The effects of dynamic failure characteristics of the valves on the functional failure of the passive system were also assessed in this experimental facility. It is also important to assess the implications of ignoring these characteristics in estimating the system failure probability. Since intermediate failure and fault increment/decrement during the operation cannot be tested unless destructive tests are performed, it is important to notice if some other dynamic factors are involved which may affect the performance of the system. The following characteristics were observed in this experimental facility:

4.3.1 Observations from experiments

a) Valve characteristics: In this experiment, control valves were supposed to have linear flow characteristics. However when experiments were performed to check the linearity of these valves in actual setup, it was observed that flow characteristics of these valves were not linear. In order to verify linear characteristics of valves, flow rate causing change in level/min of each valve (1, 2 and 3) were measured at 0, 25, 50 and at 100% open conditions. Table 4.4 summarizes the experimental observations. Each observation presented in Table 4.4 is average of three repeated measurements. To avoid confusion, only average readings at each % of opening for the three valves are presented in the Table 4.4. It can be inferred from the Table 4.4 that these valves were having some non-linearity in their flow characteristics. The ideal versus actual flow characteristics of all the three valves for full tank condition is plotted and shown in Fig. 4.3(a) (b) and (c) for valves 1, 2 and 3 respectively. In general practice, such irregularity in the flow characteristics are often ignored while performing the reliability analysis of systems having components like valves. The implications of ignoring such important characteristics could be very significant as is discussed in the section 4.4.2.

Table 4.4 Measured flow characteristics of valves

Valve No.	Valve opening in %	Measured (Level change-meter/min)	Ideal (Level change-meter/min)
V1	100	0.003500	0.003500
V1	75	0.002850	0.002625
V1	50	0.002530	0.001750
V1	25	0.000974	0.000875
V1	0	0.000000	0.000000
V2	100	0.001280	0.001280
V2	75	0.001028	0.000960
V2	50	0.000563	0.000640
V2	25	0.000409	0.000320
V2	0	0.000000	0.000000
V3	100	0.001060	0.001060
V3	75	0.000617	0.000795
V3	50	0.000529	0.000530
V3	25	0.000221	0.000265
V3	0	0.000000	0.000000

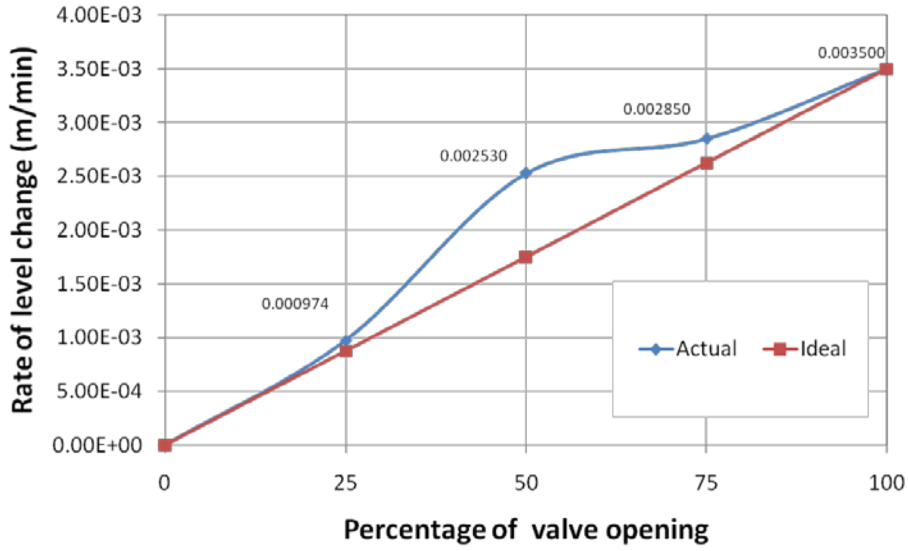


Fig. 4.3 (a)

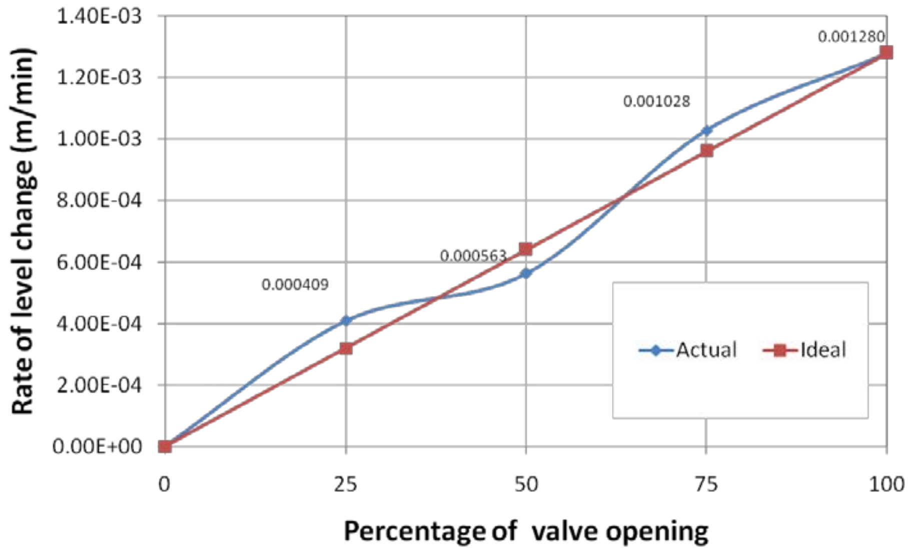


Fig. 4.3 (b)

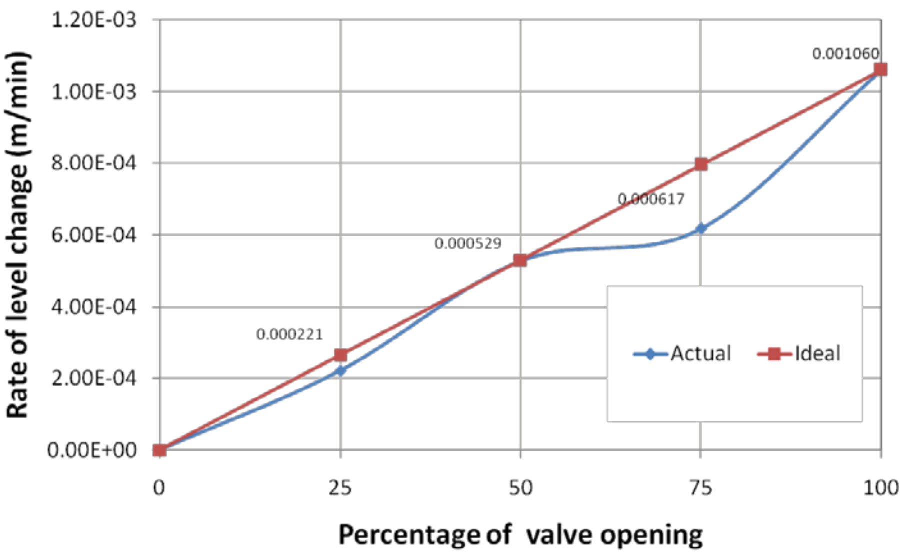


Fig. 4.3 (c)

Fig. 4.3 Ideal vs Actual flow characteristics of control valve units

b) Dynamic operational characteristics of valves: As said before, in this experiment, control valves were supposed to have linear flow characteristics. It was also observed that valve 1 is having different flow rates at different tank fill conditions, whereas the flow rates of valve 2 and 3 were not affected by tank fill conditions. This is practically true, since the pressure drop across the valve 1 changes with different tank fill conditions. However, such dynamic operational characteristics are often ignored when the system failure probability is estimated using static reliability methods. To capture this dynamic behavior of the valve 1, level change rate because of valve 1 at different tank fill conditions were measured. The resulting measured values were then used for calculating the level change rate for valve 1 at any intermediate tank fill condition and at any percentage of opening using a grid based linear interpolation method. Fig. 4.4 shows the surface plot of these gird based interpolated level change (meter/min) for valve 1 with respect to the varied percentage of openings. With the help of this surface plot, the flow rate causing the level change in the experimental main tank at any given % of operating condition can be easily determined.

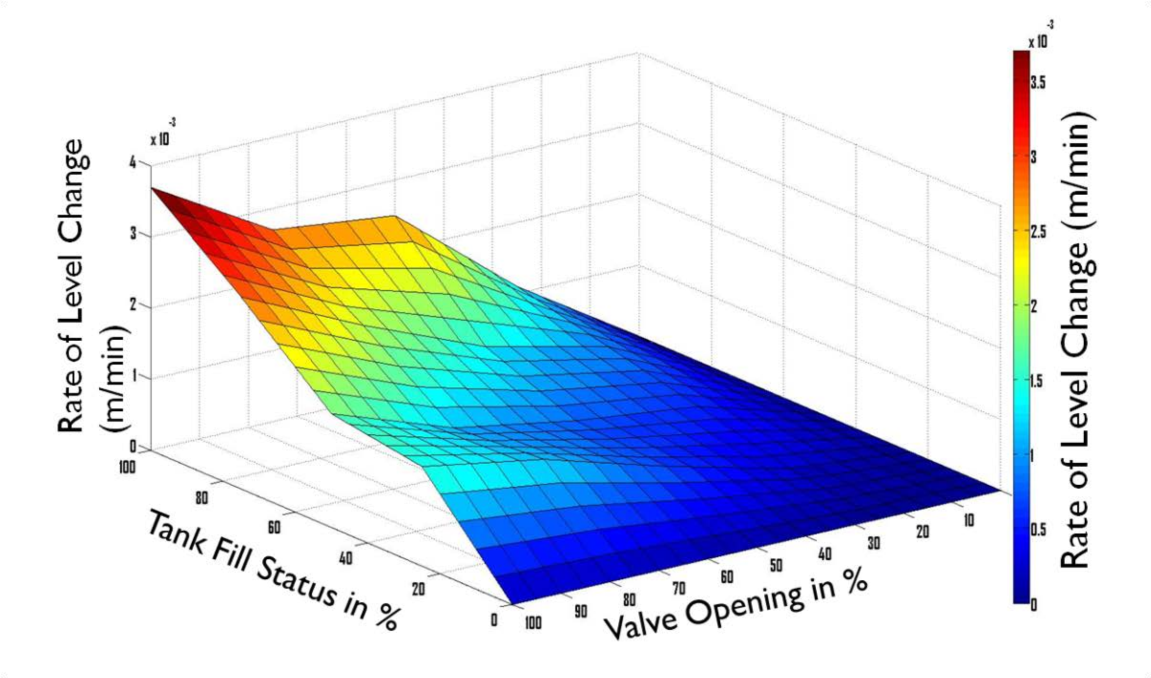


Fig. 4.4 Operational Characteristics of Valve 1

In most of the passive systems, failure mode of interest is dryout of the sink. The system failure analysis carried out using classical methods usually assume that the flow characteristics of the valve does not change over a varied condition of operation. Hence, the rate of level change is assumed as constant and not varying with tank fill conditions in most of the analysis. The implications of ignoring such important characteristics could be very significant while doing the system performance and failure analysis. The experimental data generated through this experiment can be directly used for doing a realistic system performance and failure analysis, which helps in accurate estimation of the system failure probability. Implementation of this experimental data and quantification of its impact on the system failure analysis is discussed in the next section.

4.4 Quantification of impact of identified dynamic failure characteristics and functional failure of components of passive system

In order to understand the impact of dynamic characteristics of valves on the system used in the test, the cumulative probability of overflow and dryout has been estimated and compared with that obtained considering only the binary failure case.

4.4.1 Binary failure case

As a base case, the binary failure mode with the ideal flow characteristics of valves was considered. In binary failure case, valves are assumed to fail only in binary mode, i.e. either stuck open or stuck closed. Failure rate of units are considered as constant. Failure rate per hour for unit 1 is λ_1 = 3.1250 E-03, unit 2 is λ_2 = 4.5662 E-03 and for unit 3 is λ_3 = 5.7143 E-03 [51]. In addition, as traditional reliability methodologies assume, the valve characteristics were assumed linear and dynamic operational characteristics were not considered in this case. The binary case was solved considering 1000 Monte Carlo runs with the time step of 1 hr. Results of this case are shown in Fig. 4.5. In this Fig., cumulative overflow and dryout probabilities of system are plotted with respect to the mission time in hours.

4.4.2 Multi-state failure case

In multi-state (dynamic) case, multi-state failure events are considered along with the valve characteristics and dynamic operational characteristic obtained from the experiments. In addition, the functional failure probability of valves (presented in Table 4.2) is considered as obtained from the tests. Monte Carlo simulation with time step of 1 hr and total of 1000 runs was executed using the newly developed dynamic reliability methodology presented in chapter 3. Cumulative probability of Dryout and Overflow are plotted on the Y axis with respect to time in X axis. To compare, binary failure case is also plotted and shown. It can be seen in Fig. 4.5 that cumulative probability of overflow for binary case has increased from 0.26 (binary failure case) to 0.40 (Multi-state dynamic case) while, the cumulative probability of dryout is dropped drastically from 0.710 (binary failure case) to 0.10 (Multi-state dynamic case). The drop in cumulative probability of dryout can be attributed to the fact that in multi-state failure case, valves can also fail at partial percentage of openings instead of completely stuck open/close as in case of binary failure. These partially open or close positions have a dominant effect on dryout probability. From the above analysis, it was found that classical method of treating binary failure and theoretical valve characteristics can result in very erroneous estimates of probability of failure of system.

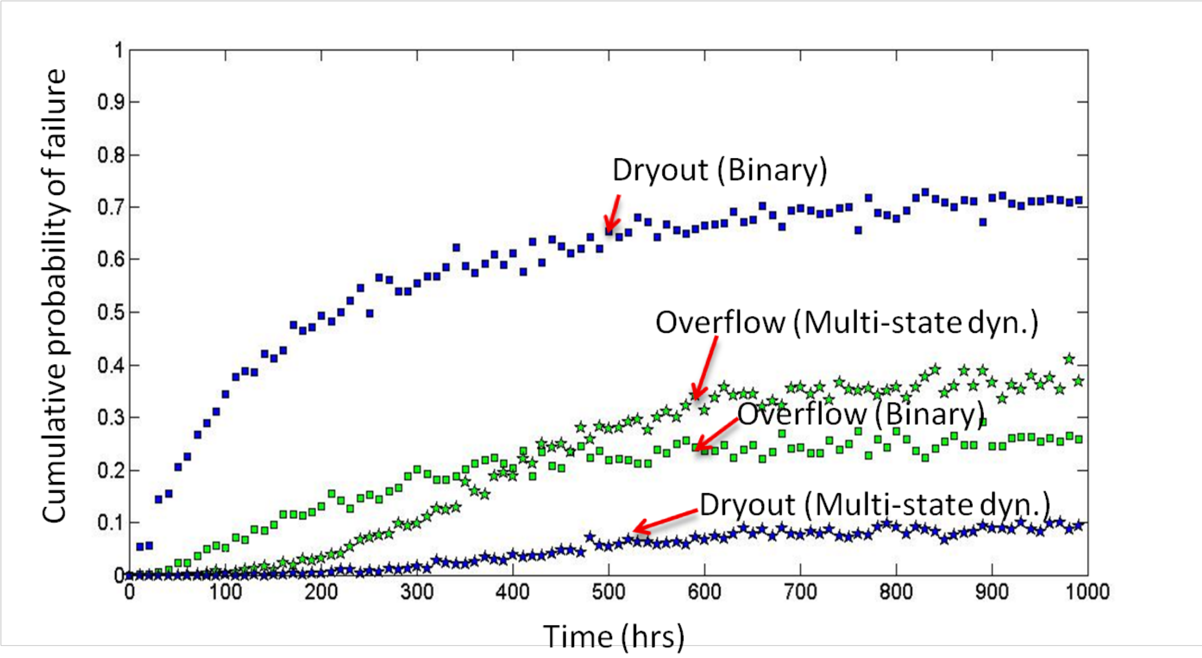


Fig. 4.5 Cumulative failure probabilities for binary and muti-state (dyn.) cases

4.5 Conclusions

In view of the generation of the databases for the probability distributions of the components of passive system like valves, an experimental facility of a benchmark setup consisting three control valves for a passive system was built and a series of experiments were performed to quantify the functional failure probability of these valves which play critical role in performance of passive safety system

In this chapter, we also investigated the impact of dynamic failure characteristics of valves on the performance of passive systems. When these dynamic characteristics were used along with multi-state failure, we observed that classical method of treating binary failure and theoretical characteristics of valve resulted in very erroneous estimates of probability of overflow and dryout which are considered as failure states of the passive system. Analysis of the results obtained by comparing both the dynamic and classical case draws two important conclusions. First, the classical reliability analysis produces erroneous estimates. Second, the failure probability when divided into the sub systems or to the failure modes, the usual assumption of classical methods yielding conservative estimates does not hold well, instead, the true estimates may lie on either side based on the parameter interactions with hardware/component failure dynamics. With the help of results of experiment and simulations, it can be concluded that dynamic failure characteristics of the valves must be accounted in doing reliability analysis of systems. The proposed dynamic reliability methodology used in this analysis proves very useful in getting the accurate estimates of reliability for passive safety systems.

CHAPTER – 5

TREATMENT OF VARIATION OF INDEPENDENT PROCESS PARAMETERS

5.1 Introduction

In APSRA[+], the process parameters affecting passive system performance are classified into two types: (a) dependent parameters and (b) independent parameters. Dependent parameters are the ones whose deviations depend upon the performance or state of certain hardware or control units, example of dependent parameters are pressure, sub-cooling, accumulation of non-condensable gas, etc. Independent parameters are the ones whose deviations do not depend upon certain components or systems, rather they have their own patterns and deviations; example of such parameter is atmospheric temperature. The dependence of system performance on these types of parameters is quite significant in many passive systems. Some of the advanced reactor designs incorporate passive natural circulation cooling system to remove decay heat to the air through passive air cooled condensers, for example: Passive residual heat removal system via Steam Generator (SG) in WWER-1000/V-392 [17], Passive core cooling system using SG - open loop in APWR+ [18] and prototype Indian Fast Breader Reactor, etc. Performance of these systems is very sensitive to the variation of atmospheric temperature or the environment temperature.

Assessment of probability of variation of dependent process parameter variations can be obtained by doing root diagnostics and then using failure probabilities of the identified hardware component or systems as discussed in chapter 3. However, independent process parameter variations cannot be modelled using similar approach. One of the prime reasons is that these parameters vary with respect to time along the mission time of system operation. In addition, parameters like atmospheric temperature also depend upon the geographical location; hence, classical treatment of probability density functions cannot be applied. As an example, let us look at the inlet water temperature variation (Fig. 5.1) for one of the natural circulation experimental facility in BARC [59], which depends on the ambient condition. One can easily infer from the data that this water temperature has seasonal and temporal variations.

In APSRA$^+$ methodology, quantification of probability of independent process parameter variations is performed by developing suitable mathematical models for these independent process parameters using data collected over a time period. The methodology uses a special class of linear stochastic model called Auto Regressive Integrated Moving Average Model (ARIMA) [60] for modeling the independent process parameters like atmospheric temperature. A detailed methodology of developing such time series models and generating synthetic data is developed and presented in this chapter. As an illustration to the methodology of model fitting and synthetic data generation, a time series of monthly-maximum atmospheric temperature of district Chittaurgarh (Rajasthan, India) [61] is considered.

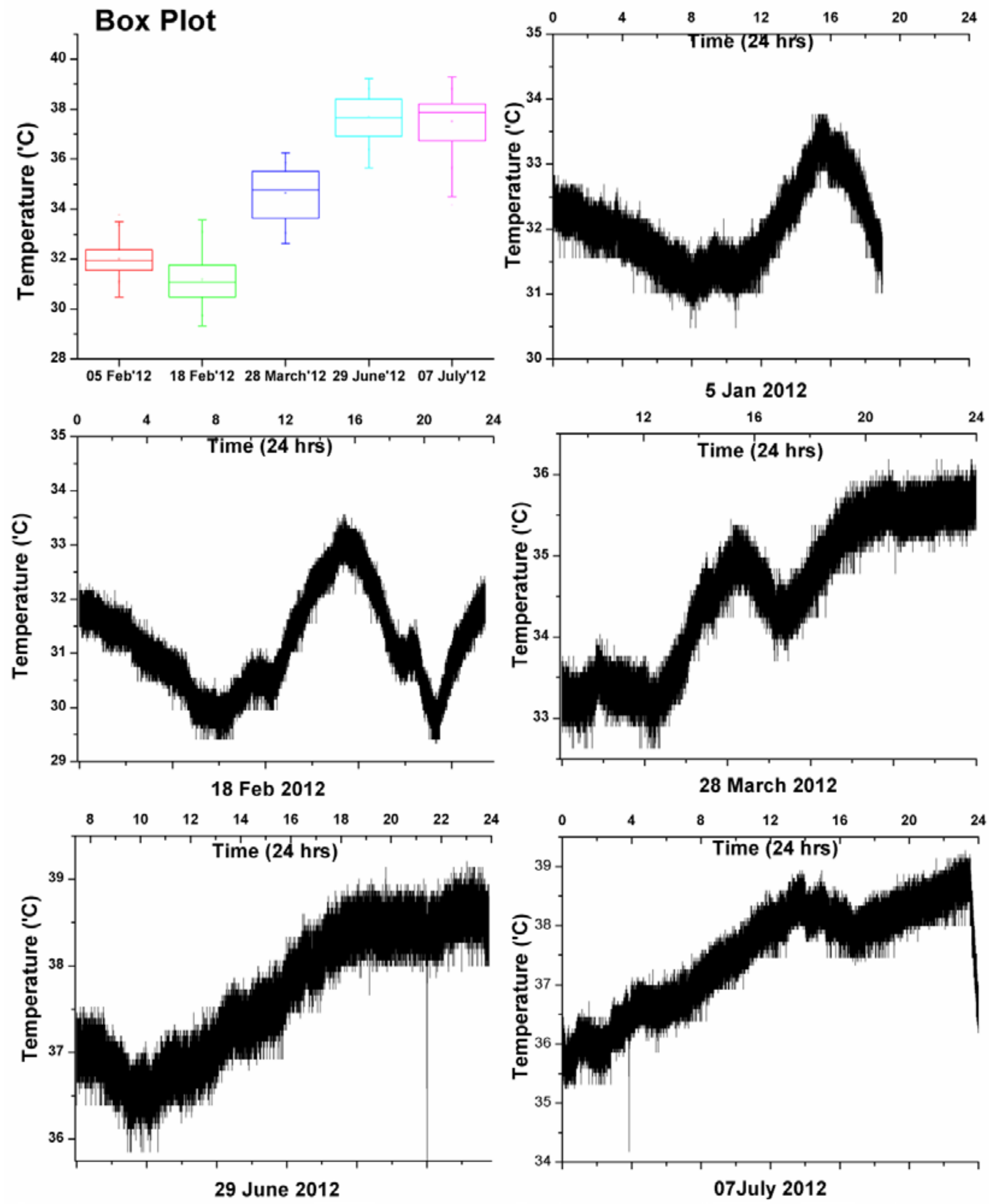


Fig. 5.1 Inlet water temperature variation for experimental natural circulation loop at BARC.

5.2 The Autoregressive–Integrated-Moving-Average (ARIMA) model

In the statistical analysis of time series, autoregressive–moving-average (ARMA) models provide a parsimonious description of a (weakly) stationary stochastic process in terms of two polynomials; one for the auto-regression (AR) and the second for the moving average (MA). In some cases when the time series data show evidence of non-stationarity, an initial differencing step (corresponding to the "integrated" part of the model) is applied. Non-seasonal ARIMA models are denoted as ARIMA(*p, d, q*) where parameters *p*, *d*, and *q* are non-negative integers, *p* is the order of the Autoregressive model, *d* is the degree of Differencing, and *q* is the order of the Moving-average model.

A time series Y_t, which is differenced over *d* degree to produce a stationary time series $\grave{Y}_t$, can be expressed as a non-seasonal ARIMA (*p, d, q*) in Eq. 5.1 :

$$\grave{Y}_t = c + \varphi_1 \; \grave{y}_{t-1} \ldots + \varphi_p \; \grave{y}_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{5.1}$$

where, $\{Y_t\,, t = 1,2,\ldots.\}$ - is time series being modelled,

Y'_t is differenced time series of original series Y_t ,

p is the order of the Autoregressive model,

φ_j is jth AR parameter,

d is the degree of differencing,

q is the order of the Moving-average model,

θ_j is jth MA parameter,

c is a constant,

$\{\varepsilon_t\,, t = 1,2,\ldots.\}$ - is residual series also called innovation, In lag operator notation, this ARIMA model can be represented as given by Eq. 5.2:

$$\varphi(L)(1-L)^d\, Y_t = c + \theta(L)\ \varepsilon_t \tag{5.2}$$

where, the lag operator L is defined as $L^i\, y_t = y_{t-1}$

$\varphi(L) = 1 - \varphi L - \varphi L^2 - \ldots\ldots\ldots.. - \varphi_p\, L^p$,is degree p autoregressive polynomial,

$\theta(L) = 1 + \theta L + \theta L^2 + \ldots\ldots\ldots.. + \theta_q\, L^q$, is degree q moving average polynomial,

The polynomial $(1-L)^d$ has a degree of non-seasonal integration d.

The important assumptions involved in such models are that ε_t has zero mean with the terms which are uncorrelated and form an independently identically distributed random variable.

A three stage methodology to fit the ARMA or ARIMA models to time series data consists of the following three stages:

1. Model identification

   The model identification stage is intended to determine the differencing required to produce stationarity, and the order of non-seasonal and seasonal AR and MA operators for a given series.

2. Parameter estimation

   Parameter estimation using computation algorithms to arrive at coefficients that best fit the selected ARIMA model. The most common methods use maximum likelihood estimation or non-linear least-squares estimation.

3. Model checking

   Model checking by testing whether the estimated model conforms to the specifications of a stationary univariate process.

5.3 Model identification

The model identification stage is intended to determine the differencing required to produce stationarity, and the order of non-seasonal and seasonal AR and MA operators for a given series. The ARIMA model requires the use of stationary time series data (Dickey and Fuller, 1981). A stationary time series has the property that its statistical characteristics such as the mean and the autocorrelation structure are constant over time.

When the observed time series presents a trend and heteroscedasticity, differencing and power transformation are often applied to the data to remove the trend and stabilize variance before an ARIMA model can be fitted. ARMA models may be used with different transformations of the original series. Commonly used transformations include logarithm transformations [60] and the square root transformations [62].

The existence or lack of stationarity in a time series can be detected by non-parametric tests such as Kendall's tau, Mann-Kendall and Sen tests [63-65].

5.3.1 Mann-Kendall test for detecting trend

The purpose of the Mann-Kendall (MK) test [63-65] is to statistically assess if there is a monotonic upward or downward trend of the variable of interest over time. A monotonic upward trend means that the variable consistently increases through time, but the trend may or may not be linear. The MK test can be used in place of a parametric linear regression analysis, which can be used to test if the slope of the estimated linear regression line is different from zero. The regression analysis requires that the residuals from the fitted regression line be normally distributed; an assumption not required by the MK test, that is, the MK test is a non-parametric (distribution-free) test.

The 'MK-test' tests whether to reject the null hypothesis (H_0) and accept the alternative hypothesis (H_a), where

H_0 : No monotonic trend

H_a: Monotonic trend is present

The MK test is conducted as follows:

1. The data is listed in the order in which they were collected over time, $y_1, y_2, y_3, \dots, y_n$, which denote the measurements obtained at times 1,2,3,…n, respectively.

2. The sign of all $n(n-1)/2$ possible differences of $y_j - y_k$, where $j>k$ are determined . These differences are:

$$y_2 - y_1, y_3 - y_1, \dots, y_n - y_1, y_3 - y_2, y_4 - y_2, \dots, y_n - y_{n-2}, y_n - y_{n-1}, \quad (5.3)$$

3. $sgn\,(y_j - y_k)$ is defined as an indicator function that takes on the values 1, 0, or -1 according to the sign of $y_j - y_k$, that is,

$$sign\,(y_j - y_k) = 1, \text{if } y_j - y_k > 0,$$

$$= 0, \text{if } y_j - y_k = 0,$$

$$= 1, \text{if } y_j - y_k < 0. \quad (5.4)$$

4. A quantity S is calculated, which is the number of positive differences minus the number of negative differences. If S is a positive number, observations obtained later in time tend to be larger than observations made earlier. If is a negative number, then observations made later in time tend to be smaller than observations made earlier.

$$S = \sum_{k-1}^{n-1} \sum_{j-k+1}^{n} sign(y_j - y_k) \tag{5.5}$$

5. Variance of S is calculated as follows:

$$VAR\ (S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p-1}^{g} t_p\left(t_p - 1\right)\left(2t_p + 5\right)\right] \tag{5.6}$$

Where, g is the number of tied groups and t_p is the number of observations in the pth group.

6. MK-test statistic, Z_{MK} is calculated using the following Eq. 5.7 :

$$Z_{MK} = \frac{S-1}{\sqrt{VAR\ (S)}}\ , if\ S > 0 \tag{5.7}$$

$$= 0, if\ S = 0$$

$$= \frac{S+1}{\sqrt{VAR\ (S)}}\ , if\ S < 0$$

A positive (negative) value of Z_{MK} , indicates that data tend to increase(decrease) with time.

7. At significance level (α), H_o is rejected and H_a is accepted if $Z_{MK} > Z_{(1-\alpha/2)}$, where $Z_{(1-\alpha/2)}$ is *100(1- α)th* percentile of the standard normal distribution.

5.3.2 Differencing

In general, if the original time series values are non-stationary and non-seasonal, performing the first or second differencing transformation on the original data usually produces stationary time series values. Eq. 5.8-5.9 shows how a first and second differencing are performed on a time series Y_t to produce a transformed stationary time series Z_t.

First Difference: $Z_t = y_t - y_{t-1}$, where t = 2, 3, 4,…………., n (5.8)

Second Difference: $Z_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})$, where t = 3, 4,…………., n (5.9)

5.3.3 Auto-correlation function

Autocorrelation is the correlation between observations of a time series separated by k time units (k-time units also referred as lags). The plot of autocorrelations is called the autocorrelation function (ACF) or correlogram. Correlogram is an important plot in analyzing time series data. It gives very important information about the randomness in any data-set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero. In addition, correlograms are used in the model identification stage for Box–Jenkins autoregressive moving average time series models.

For an observed series $Y_t = (y_1, y_2, y_3, \dots, y_t)$, denote the sample mean by $\bar{y}$, the sample lag-k autocorrelation is given by ρ_k in Eq. 5.10:

$$\widehat{\rho_k} = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \overline{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \tag{5.10}$$

Partial autocorrelation is the autocorrelation between Y_t and Y_{t-k} after removing any linear dependence on $y_1, y_2, y_3, \dots, y_{t-k+1}$.

In order to fit the non-seasonal ARMA models to any given time series, it is mandatory that the time series under consideration be stationary where it's mean and variance are constant through time. A common practice to identify the stationarity of the time series is to interpret the correlogram or ACF plot. If the ACF of the time series values either cuts off or dies down fairly quickly, then the time series values should be considered stationary. On the other hand, if the ACF of the time series values either cuts off or dies down extremely slowly, then it should be considered non-stationary.

The differences in ACF and partial autocorrelation function (PACF) among models are useful when selecting models. Table 5.1 summarizes the ACF and PACF behavior for these models.

Table 5.1 ACF and PACF behavior for conditional mean model

Conditional Mean Model	**ACF**	**PACF**
AR(*p*)	Tails off gradually	Cuts off after *p* lags
MA(*q*)	Cuts off after *q* lags	Tails off gradually
ARMA(*p*,*q*)	Tails off gradually	Tails off gradually

5.3.4 Candidate models

We start with a set of candidate models, and then find the models' corresponding AIC, BIC and L values. There will almost always be information lost due to using a candidate model to represent the "true" model (i.e. the process that generates the data). We wish to select, from among the candidate models, the model that minimizes the information loss (AIC and BIC) and maximizes the likelihood L in eq #. In present study, the time series $\grave{Y}_t$ is considered for selection of models. Both contiguous and non-contiguous models were considered. Based on the performance of these models, the best candidate models are selected for further validation tests.

Non-contiguous models accounts for the most significant periodicities without considering the intermediate terms which may be insignificant. The advantage of non-contiguous models is reduction in the number of parameters to be estimated while accounting for the most significant periodicities. An example of non-contiguous AR(1,3,6,9,12) model with significant periodicities at first, third, sixth, ninth and twelth lags would be :

$$\grave{Y}_t = c + \varphi_1 \ \grave{y}_{t-1} + \varphi_3 \ \grave{y}_{t-3} + \varphi_6 \ \grave{y}_{t-6} + \varphi_9 \ \grave{y}_{t-9} + \varphi_{12} \ \grave{y}_{t-12} + \varepsilon_t \quad (5.11)$$

5.3.5 Model selection criteria

Information criteria are model selection tools that are used to compare any models fit to the same data. Basically, information criteria are likelihood-based measures of model fit that include a penalty for complexity (specifically, the number of parameters). Different information criteria are distinguished by the form of the penalty, and can prefer different models.

Let log $L(\hat{\theta})$denote the value of the maximized loglikelihood objective function for a model with k parameters fit to N data points. Two commonly used information criteria are:

- **Akaike information criterion (AIC).** The AIC compares models from the perspective of information entropy, as measured by Kullback-Leibler divergence. The AIC for a given model is given by Akaike [66]

$$AIC = -2\,log\,L(\hat{\theta}) + 2k \tag{5.12}$$

  When comparing AIC values for multiple models, smaller values of the criterion are considered to be better.

- **Bayesian information criterion (BIC)**. The BIC, also known as Schwarz information criterion [67], compares models from the perspective of decision theory, as measured by expected loss. The BIC for a given model is by:

$$BIC = -2\,log\,L(\hat{\theta}) + k\,log(N) \tag{5.13}$$

  Under the assumption that the model errors or disturbances are independent and identically distributed according to a normal distribution and that the boundary condition that the derivative of the log likelihood with respect to the true variance is zero, BIC becomes:

$$BIC = -k\,log(\sigma_e^2) + k\,log(N) \tag{5.14}$$

  where, σ_e^2 is the residual variance

When comparing BIC values for multiple models, smaller values of the criterion are considered to be better.

- **Maximum Likelihood Rule (ML rule)**. Selection of a model by this criterion involves evaluating a likelihood value for each of the candidate models and choosing the model which gives the highest value. In general, as the number of parameters k, increases, the likelihood value decreases. This it is to be expected that the ML rule selects the models with a small number of parameters [68]. This is in line with the principle of parsimony propounded by Box and Jenkins [60]. The particular likelihood value L for a given model is [69]:

$$L = -\frac{N}{2} \; log(\sigma_e^2) - k. \tag{5.15}$$

where,σ_e^2 is the residual variance

When comparing L values for multiple models, maximum values of this criterion are considered to be better.

5.4 Parameter estimation

Parameter estimation using computation algorithms to arrive at coefficients that best fit the selected ARIMA model. The most common methods use maximum likelihood estimation or non-linear least-squares estimation.

5.5 Model checking

Model checking by testing whether the estimated model conforms to the specifications of a stationary univariate process. In particular, the residuals should be independent of each other and constant in mean and variance over time. If the model selected is inadequate, return to step one and attempt to build a better model.

Following tests were carried out to test the assumptions used in building the model are in fact valid for the model selected

- The residual series has zero mean
- No significant periodicity is present in the residual series
- The residual series is uncorrelated

5.5.1 Significance of residual mean and normality

A common assumption of time series models is a Gaussian innovation distribution with zero mean and constant variance. After fitting a model, residuals must be checked for normality and must be tested for significance of residual mean.

To test the validity of assumption that the mean of the residual series *W(t)* is not significantly different from zero, a test statistic $\eta(w)$ is defined as [70] :

$$\eta(w) = \frac{N^{1/2} \times \overline{\mathcal{W}}}{\widehat{\sigma_e}} \tag{5.16}$$

where: $\overline{\mathcal{W}}$ is estimate of residual mean and σ_e^2 is the residual variance

The test statistic is approximately distributed as $t(\alpha, N\text{-}1)$, where α is the significance level at which the test is being carried out. If the $\eta(w) \leq t(\alpha, N\text{-}1)$, then the mean of the residual is not significantly different from zero and hence the associated model passes the test.

If the Gaussian innovation assumption holds, the residuals should look approximately normally distributed. Some plots and test for assessing normality are listed below:

- Histogram
- Probability plot or Quantile-Quantile plot (QQ Plot)
- Anderson-Darling: an ECDF (empirical cumulative distribution function) based test

Anderson-Darling test for normality

The Anderson-Darling (AD) test is a member of the group of goodness of fit statistics known as empirical distribution function statistics. This test is widely used in practice to test normality. The test statistic is a squared distance that is weighted more heavily in the tails of the distribution. Smaller AD values indicate that the distribution fits the data better.

The Anderson Darling normality test is defined as:

H_0 : The data follow a normal distribution

H_a: The data do not follow a normal distribution

Test Statistic: The Anderson-Darling test statistic is defined as [71]

$$A^2 = -N - \left(\frac{1}{N}\right) \sum_{i=1}^{n} \Big((2i-1)\big((\ln F(z_I) + \ln\big(1 - F(z_{N+1-i})\big)\big)\Big) \tag{5.17}$$

where: F is the cumulative distribution function of the normal distribution

Zi are the ordered observations.

Let:

$$A'^2 = A^2 * \left(1 + \frac{0.75}{N} + \frac{2.25}{N^2}\right) \tag{5.18}$$

P-value for Anderson-Darling normality test can be calculated by Eq. (5.19):

$$If\ 13 > A'^2 > 0.600; \quad p = exp(1.2937 - 5.709 * A'^2 + 0.0186(A'^2)^2)$$

$$If\ 0.600 > A'^2 > 0.340; \quad p = exp\left(0.9177 - 4.279 * A'^2 - 1.38\left(A'^2\right)^2\right)$$

$$If\ 0.340 > A'^2 > 0.200; \ p = 1 - exp\left(-8.318 + 42.796 * A'^2 - 59.938\left(A'^2\right)^2\right)$$

$$If\ A'^2 < 0.200; \ p = 1 - exp(-13.436 + 101.14 * A'^2 - 223.73(A'^2)^2)$$

(5.19)

Null hypothesis of normal distribution can be rejected if p-value is less than the significant level.

5.5.2 Significance of periodicities

In time series ARMA models, the innovation process is assumed to be uncorrelated. For ARMA models to be applicable, the residual series *W(t)*, must not have any significant periodicities in it. Hence, after fitting a model, inferred residuals must be checked for any unmodeled autocorrelation.

As an informal check, the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of residuals can be plotted and checked for any significant autocorrelations. If either plot shows significant autocorrelations, the fitted model must be rejected and new models with additional autoregressive or moving average terms may be considered for further investigations.

In order to test the significance of autocorrelations, a Ljung-Box Q-test [72] on the residual series is performed. This tests the null hypothesis of jointly zero autocorrelations ρ_k up to lag k, against the alternative of at least one nonzero autocorrelation. The test can be conducted at several values of lags k. The degrees of freedom for the Q-test are usually k. However, for testing a residual series, degrees of freedom must be modified to dof = $(k - p - q)$, where p and q are the number of AR and MA coefficients in the fitted model, respectively. The choice of k affects test performance. If N is the length of observed time series, choosing $m \approx \ln(N)$ is recommended for power [73]. Test can be performed at multiple values of k. If seasonal autocorrelation is possible, one might consider testing at larger values of k, such as 10 or 15.

Null Hypothesis – H_0: $\rho_1 = \rho_2 = \rho_3 = \rho_4 = \rho_5 = \cdots = \rho_k = 0$;

Alternative Hypothesis – H_a: $at\ least\ one\ (\rho_1, \rho_2, \rho_3, \rho_4, \rho_5 \dots \rho_k) \neq 0$;

The test statistic for Ljung-Box Q-test is given by Eq. 5.20:

$$Q(k) = N(N+2)\sum_{h=1}^{k}\left(\frac{\rho_h^2}{(N-h)}\right), \tag{5.20}$$

Under the null hypothesis, Q(k) follows a χ^2(k) distribution. For the residuals resulted from fitting a model with p+q parameters, compare the test statistic Q(k) to a χ^2 distribution with $k - p - q$ degrees of freedom.

5.5.3 White noise test

In time series ARMA models, the innovation process is assumed to be Gaussian with zero mean and constant variance. For ARMA models to be applicable, the residual series *W(t)*, must not have any significant heteroscedasticity (nonconstant variance).

A white noise innovation process has constant variance. After fitting a model, residuals must be tested for heteroscedasticity. In order to check for the heteroscedasticity, Engle's Autoregressive conditional heteroskedasticity (ARCH) [74] test on the residual series is performed. This tests the null hypothesis of no ARCH effects against the alternative ARCH model with *k* lags. If all autocorrelation in the original series, Y_t, is accounted for in the conditional mean model i.e ARMA model, then the residuals are uncorrelated with mean zero. However, the residuals can still be serially dependent.

The alternative hypothesis for Engle's ARCH test is autocorrelation in the squared residuals, e_t^2, given by the regression

$$H_a\ :\ e_t^2 = \ a_0 + a_1 e_{t-1}^2 + \cdots \dots \dots .. + a_L e_{t-L}^2 + \varepsilon_t, \tag{5.21}$$

Where, there is at least one $a_j \neq 0,\ j = 0,..,L$; and ε_t denote the white noise error process.

The null hypothesis is

$$H_0 \colon a_1 = a_2 = a_3 = \cdots = a_k = 0; \tag{5.22}$$

The test statistic is the Lagrange multiplier statistic TR^2, where:

- T is the sample size.
- R^2 is the coefficient of determination from fitting the ARCH(k) model for a number of lags (k) via regression.

Under the null hypothesis, the asymptotic distribution of the test statistic is chi-square with k degrees of freedom. If TR^2 is greater than the Chi-square table value, reject the null hypothesis and conclude there is an ARCH effect in the ARMA model. If TR^2 is smaller than the Chi-square table value, do not reject the null hypothesis.

5.6 Sample generation (Synthetic data generation)

Once the ARIMA model is finalized, the synthetic data of length N can be generated using the algorithm mentioned in Fig 5.2.

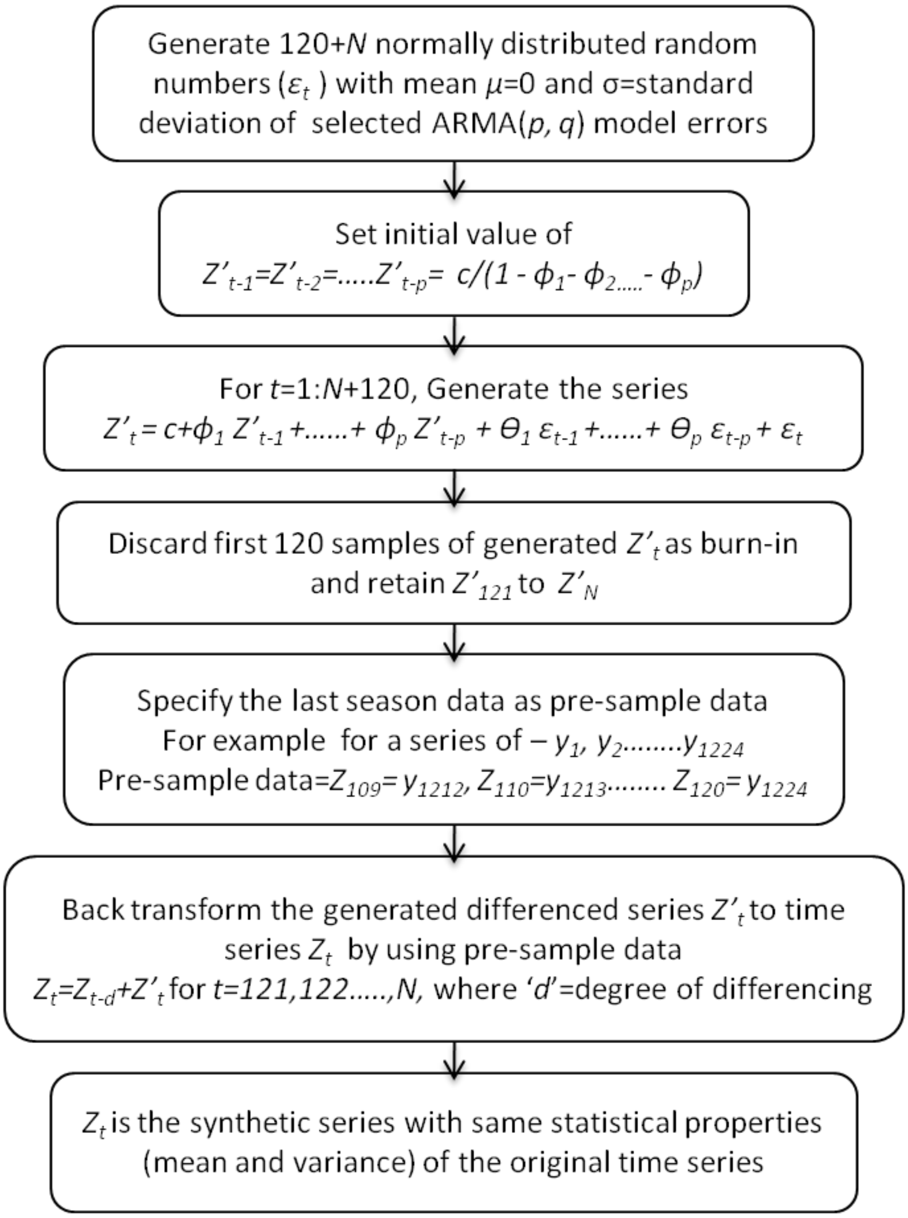


Fig. 5.2 Algorithm for generating samples of time series

5.7 Integration of treatment of variation of independent process parameters in the APSRA$^+$ methodology

In APSRA$^+$ methodology, probability of passive system failure is calculated by using Monte Carlo simulation, wherein a large number of sample values are generated for each of the process parameters. These samples are then analyzed to find the system response. The system response in terms of system failure, success or degraded is usually assessed by best estimate system codes. As presented in Fig. 5.3, the generated samples of dependent and independent process parameters are used for calculating the system response.

In order to generate the samples of a process parameter for the Monte-Carlo simulations to perform, typically, a probability density function (pdf) of the process parameter is used. However, if the parameter is time dependent like atmospheric temperature, the same pdf treatment becomes invalid. In such cases, the time dependent parameter is modeled using a mathematical function and then this developed mathematical function is used to generate the samples instead of pdfs. In APSRA$^+$, the independent process parameters are modeled using ARIMA model and then this model is used for generating the samples for Monte-Carlo simulations.

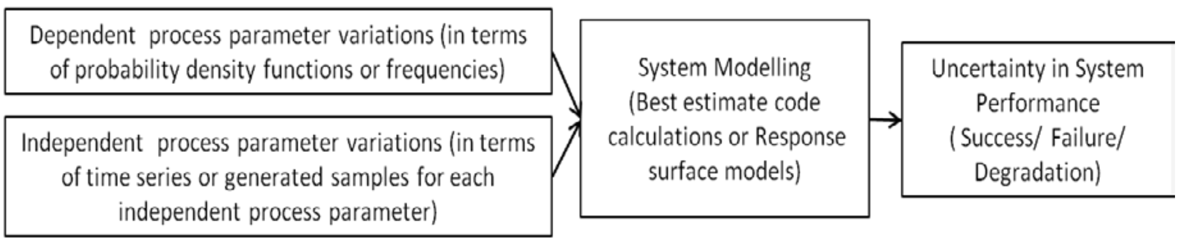


Fig. 5.3 Concept of uncertainty propagation in passive safety systems

5.8 Demonstration of methodology - Case study

The methodology of fitting a time series and generating the synthetic data is demonstrated by implementing the methodology to a time series data set collected from Indian Metrological Centre.

5.8.1 Study data

In this study, the monthly-maximum atmospheric temperature of district Chittaurgarh (Rajasthan, India), from month starting January -1901 till December-2002 were considered for building the model. Appendix A contains the time series data. The data was collected from the databases of Indian Metrological Centre [61].

Let the time series of maximum temperature be denoted by Y_t,

$$Y_t = (y_1, y_2, y_3, \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots, y_{1224}) \qquad (5.23)$$

Where: y_1 = Max temperature of Jan-1901

y_2 = Max temperature of Feb-1901

y_{12} = Max temperature of Dec-1901

y_{13} = Max temperature of Jan-1902

y_{1224} = Max temperature of Dec-2002

The time series data of max temperature from Year 1901 to 2002 is plotted and shown in Fig 5.4.

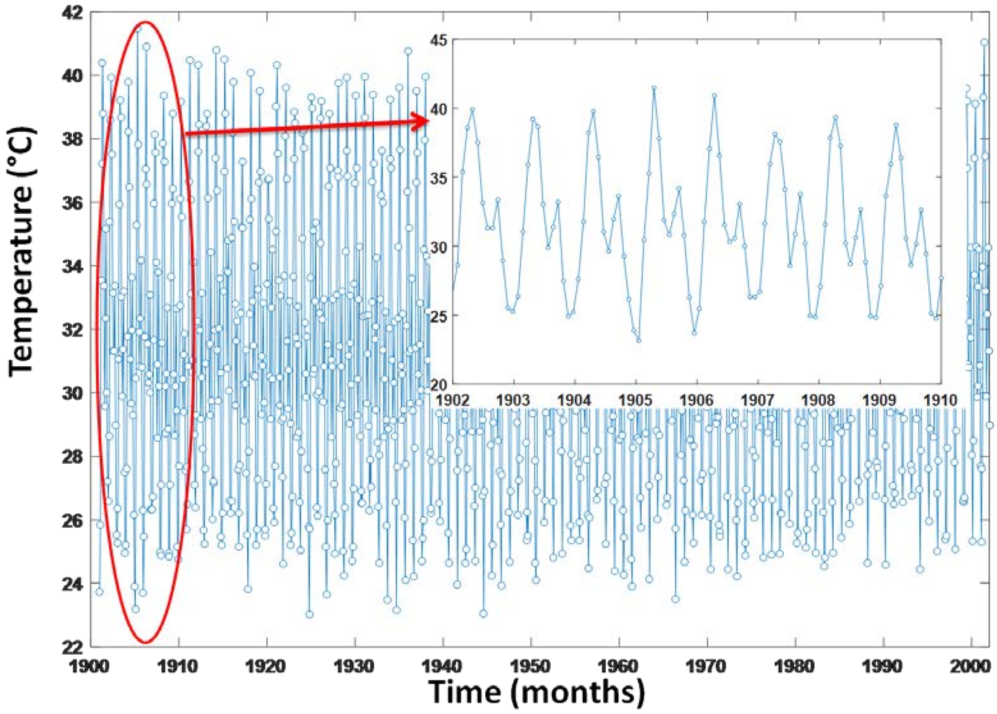


Fig. 5.4 Time series plot of the max atmospheric temperature series Y_t

5.8.2 Mann-Kendall test for detecting trend

The trend in the original time series Y_t is tested using Mann-Kendall's test. At significance level of 0.05, it can be concluded that there is no monotonic trend present in the time series, Y_t . The test statistic Z_{MK} and critical value $Z_{(1-\alpha/2)}$ is presented in Table 5.2.

Table 5.2 Mann-Kendall's test results at 0.05 significance level

Z_{MK}	$Z_{(1-\alpha/2)}$	p-value	Test Result
1.2579	1.9600	0.2084	No significant trend

5.8.3 ACF of time series

As said earlier, autocorrelation is the correlation between observations of a time series separated by k time units (k-time units also referred as lags). In order to compute the ACF of the time series at various lags (k) ranging from 1-75, the correlation between the time series Y_t and Y_{t-k} are calculated using the Eq. 5.10. The correlogram or ACF of time series Y_t is plotted and shown in Fig 5.5. It can be seen that the ACF of time series Y_t has significant peaks at various lags. Also, the autocorrelations do not have a decaying tendency which indicates that the time series in the present form is not stationary.

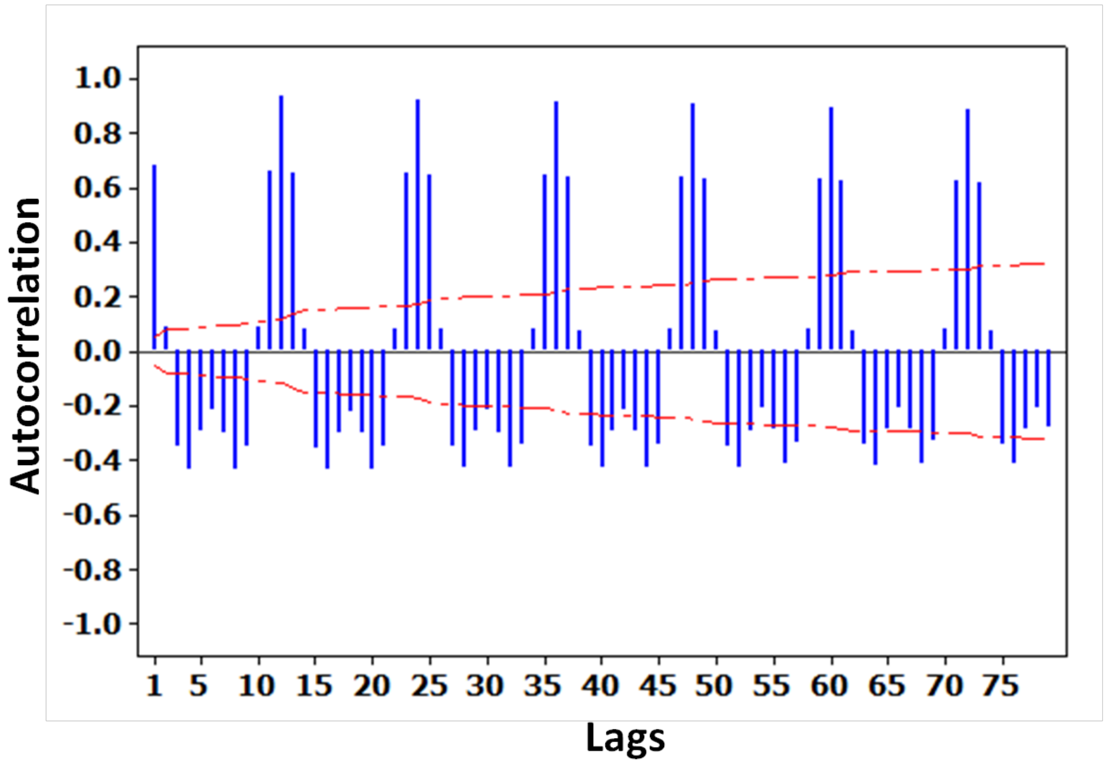


Fig. 5.5 Sample ACF of time series Y_t with 5% significance limits for ACF

5.8.4 Differencing

In this case, we performed the twelfth differencing transformation on the original time series Y_t which produced stationary time series $\acute{Y}_t$. The differenced series is plotted and shown in Fig 5.6. In order to compute the ACF of this diferenced time series at various lags (k) ranging from 1-75, the correlation between the time series Y_t and Y_{t-k} are calculated using the Eq. 5.10. Similarly the PACF are also computed using Eq. 5.10. The ACF and partial autocorrelation function (PACF) of the differenced series $\acute{Y}_t$ is plotted in Fig. 5.7 and 5.8 respectively.

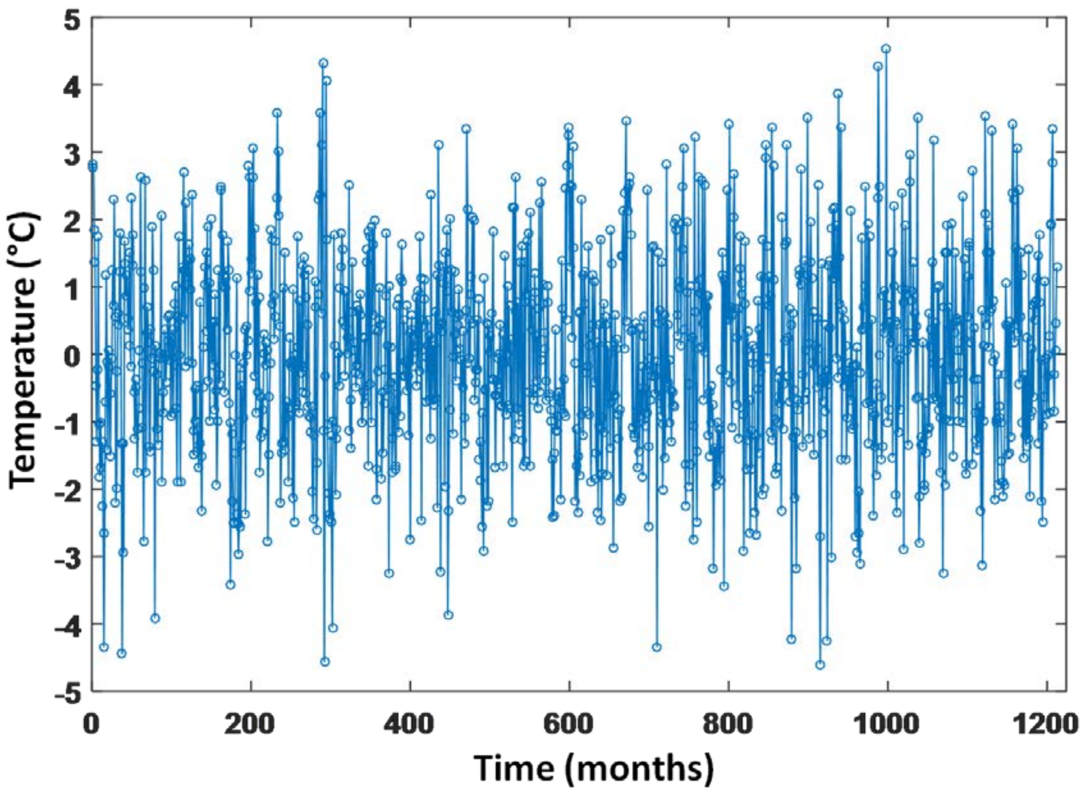


Fig. 5.6 Time series plot of the differenced stationary series $\grave{Y}_t$

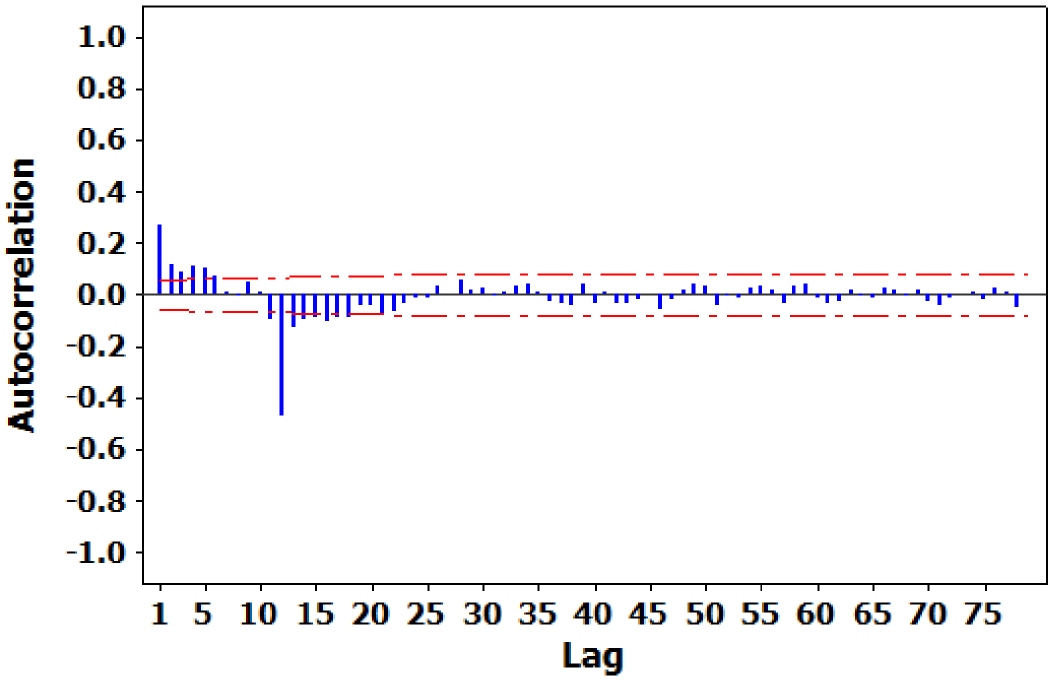


Fig. 5.7 ACF plot of time series $\grave{Y}_t$ with 5% significance limits for ACF

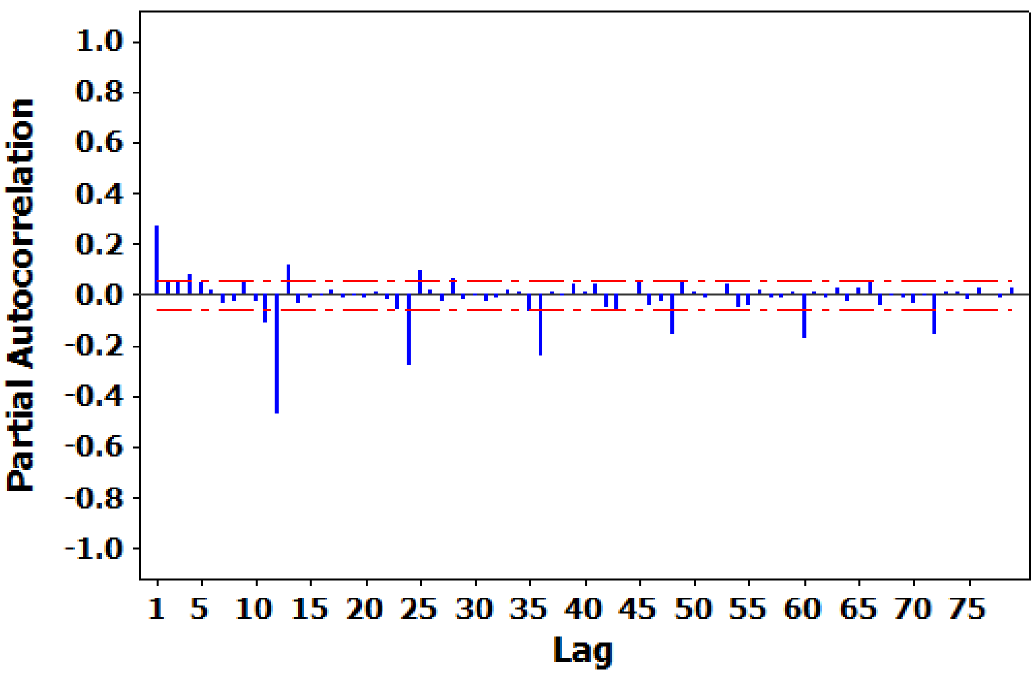


Fig. 5.8 PACF plot of time series $\grave{Y}_t$ with 5% significance limits for PACF

The ACF of the transformed time series $\acute{Y}_t$ has a damping sin-wave dying down tendency. PACF also has a decaying tendency with only exception at lags 12, 24, 36 and so on, indicating a strong seasonality of 12 months. This seasonality should be taken into account during the model selection.

5.8.5 Candidate models and model selection

For representing the time series $\acute{Y}_t$ various candidate models are considered. Both contiguous (C) and non-contiguous (NC) ARMA models are considered and the models which gives least AIC, BIC and highest likelihood L is selected for further validation tests. In Table 5.3, all the candidate models with the resulting AIC, BIC and likelihood value L are presented. Ranking of these candidate models based on AIC, BIC and L are also presented. Lower the rank, better the model is. Based on the information criteria model no. 18, 19, 20, 21 and 22 are selected for further validation tests.

5.8.6 Parameter estimation

Parameters of the selected models 18-22 were estimated using maximum likelihood estimation method. Through M. K test, it was concluded that there is no significant trend in our time series data, hence, the constant term has been assumed to be zero in all the models. Parameter values are presented in Table 5.4.

Table 5.3 Candidate models and their respective AIC, BIC and Max likelihood L

md. no	C/NC	AR	MA	AIC	BIC	L	Rank(AIC)	Rank(BIC)	Rank(L)
1	C	1	0	4254.53	4264.73	-407.51	22	17	22
2	C	1,2	0	4253.56	4268.86	-407.03	21	18	21
3	C	1,2,3	0	4252.74	4273.14	-406.61	20	21	20
4	C	1,2,3,4	0	4246.57	4272.07	-403.53	18	20	18
5	C	1,2,3,4,5	0	4245.38	4275.98	-402.93	17	22	17
6	C	1	1	4248.11	4263.41	-404.30	19	14	19
7	C	1	1,2	4243.51	4263.91	-402.01	14	15	14
8	C	1,2	1	4243.99	4264.39	-402.23	15	16	15
9	C	1,2	1,2	4189.56	4215.06	-375.01	13	13	13
10	C	1,2,3	1	4244.18	4269.68	-402.32	16	19	16
11	C	1,2,3	1,2	4163.85	4194.45	-362.16	12	12	12
12	NC	1,12	0	3948.54	3963.84	-254.50	11	11	11
13	NC	1,2,12	0	3943.17	3963.57	-251.84	10	10	10
14	NC	1,2,3,12	0	3935.75	3961.25	-248.12	9	8	9
15	NC	1,2,3,4,12	0	3928.93	3959.53	-244.72	8	6	8
16	NC	1,2,3,4,5,12	0	3925.46	3961.16	-242.97	7	7	7
17	NC	1,2,3,4,5,6,12	0	3921.94	3962.74	-241.22	6	9	6
18	NC	1,12	1,12	3572.51	3598.01	-66.492	4	1	4
19	NC	1,12	1,2,12	3574.35	3604.95	-67.437	5	3	5
20	NC	1,2,12	1,12	3570.72	3601.32	-65.628	2	2	2
21	NC	1,2,12	1,2,12	3572.41	3608.11	-66.463	3	4	3
22	NC	1,3,6,9,12	1,3,6,9,12	3557.374	3613.474	-58.927	1	5	1

Table 5.4 Parameter values of selected models

md. no	C/NC	AR	MA	Constant	AR parameters	MA parameters
18	NC	1,12	1,12	C=0	φ_1= 0.304367 φ_{12}= 0.0112195	θ_1= 0.00837056 θ_{12}= -0.896135
19	NC	1,12	1,2,12	C=0	φ_1= 0.302936 φ_{12}= 0.0107152	θ_1= 0.00771637 θ_2= 0.0058825 θ_{12}= -0.895959
20	NC	1,2,12	1,12	C=0	φ_1= 0.287647 φ_2= 0.0576933 φ_{12}= 0.00523008	θ_1= 0.00979417 θ_{12}= -0.895493
21	NC	1,2,12	1,2,12	C=0	φ_1= 0.287322 φ_2= 0.0661723 φ_{12}= 0.00504697	θ_1= 0.0107637 θ_2= -0.00938576 θ_{12}= -0.894949
22	NC	1,3,6,9,12	1,3,6,9,12	C=0	φ_1= 0.274743 φ_3= 0.0812419 φ_6= 0.0578781 φ_9= 0.0808885 φ_{12}= -0.0221227	θ_1= 0.0213305 θ_3= 0.00973465 θ_6= 0.00209352 θ_9= 0.00801166 θ_{12}= -0.897086

5.9.7 Model checking

5.9.7.1 Significance of residual mean

To test the validity of assumption that the mean of the residual series *W(t)* for each of the models 18-22, is not significantly different from zero, test statistic $\eta(w)$ is calculated and compared with the critical value $t(\alpha, N\text{-}1)$. At 95% significance level, it is observed that residual series of all the selected models 18-22 passes the test. Table 5.5 presents the test results along with critical value of test statistics.

Table 5.5 Results of test for significance of residual mean

md. no	C/NC	AR	MA	η(w)	t(0.95,1211)	Result
18	NC	1,12	1,12	-0.1426	1.6461	Pass
19	NC	1,12	1,2,12	-0.1168	1.6461	Pass
20	NC	1,2,12	1,12	-0.1496	1.6461	Pass
21	NC	1,2,12	1,2,12	-0.1947	1.6461	Pass
22	NC	1,3,6,9,12	1,3,6,9,12	-0.0938	1.6461	Pass

To test the Gaussian assumption of innovation, residuals should look approximately normally distributed in their histogram and in Quantile-Quantile (QQ plots). Histogram and QQ plot of residuals of the models 18-22 are plotted and shown in Fig 5.9-5.13. Table 5.6 presents the Anderson Darling (AD) normality test results of residuals. For all the selected models 18-22, p-value is greater than 0.05, hence null hypothesis of normality in residuals cannot be rejected at significance level of 0.05. Collectively from the histograms, QQ-plots and AD test results, it can be concluded that all the selected models 18-22 passes the Gaussian assumption of innovation.

Table 5.6 Results of Anderson Darling normality test on residuals

md. no	C/NC	AR	MA	AD	p-value	Result
18	NC	1,12	1,12	0.311	0.554	Residuals Normally Distributed
19	NC	1,12	1,2,12	0.288	0.619	Residuals Normally Distributed
20	NC	1,2,12	1,12	0.293	0.603	Residuals Normally Distributed
21	NC	1,2,12	1,2,12	0.315	0.544	Residuals Normally Distributed
22	NC	1,3,6,9,12	1,3,6,9,12	0.382	0.398	Residuals Normally Distributed

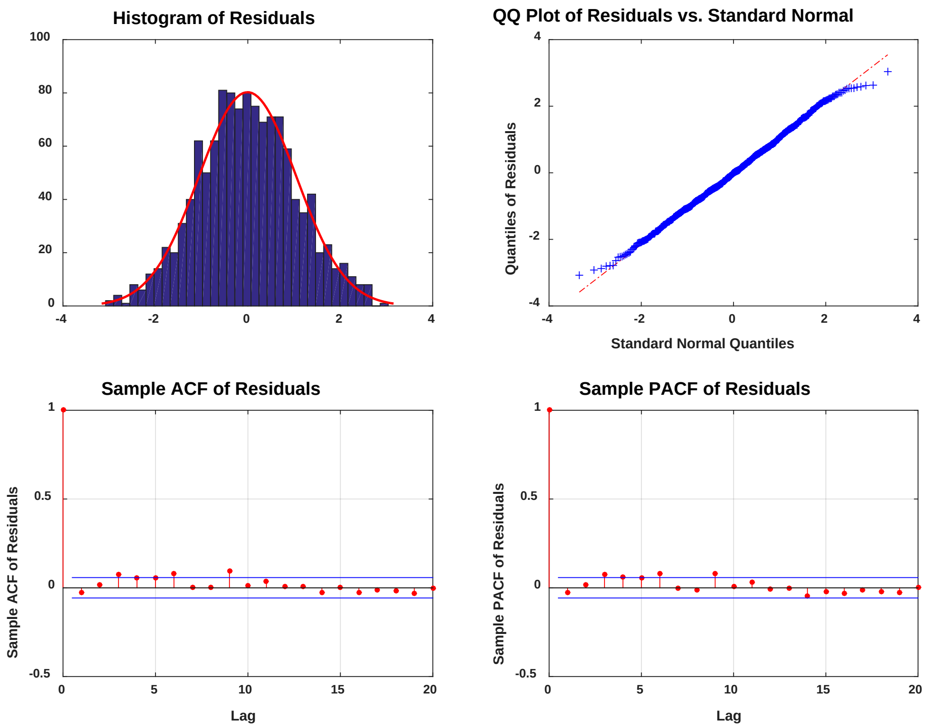


Fig. 5.9 Residual Analysis of AR (1,12) MA (1,12) model 18

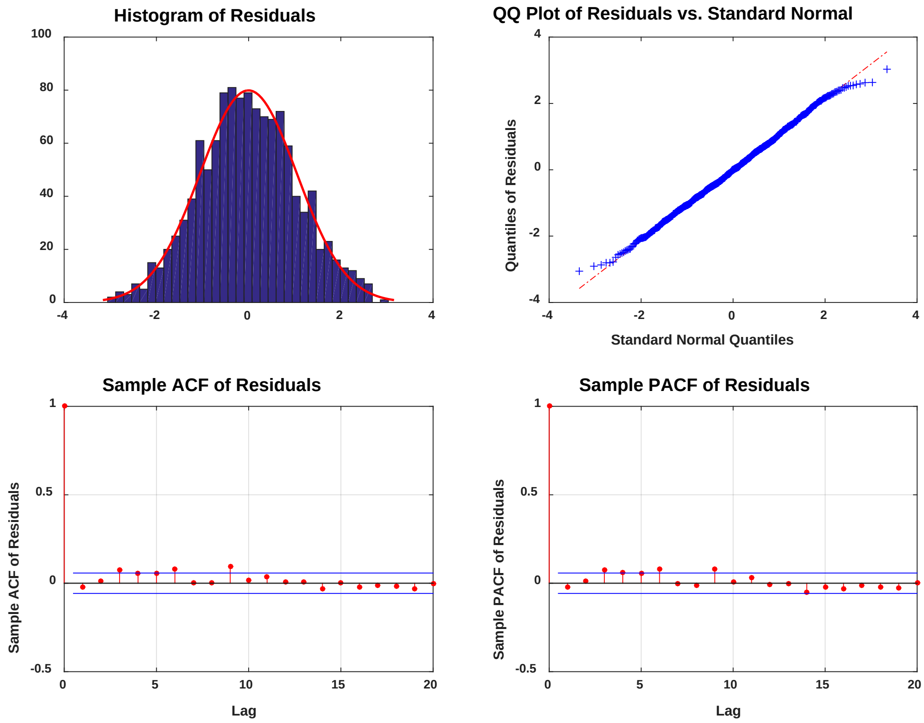


Fig. 5.10 Residual Analysis of AR(1,12) MA(1,2,12) model 19

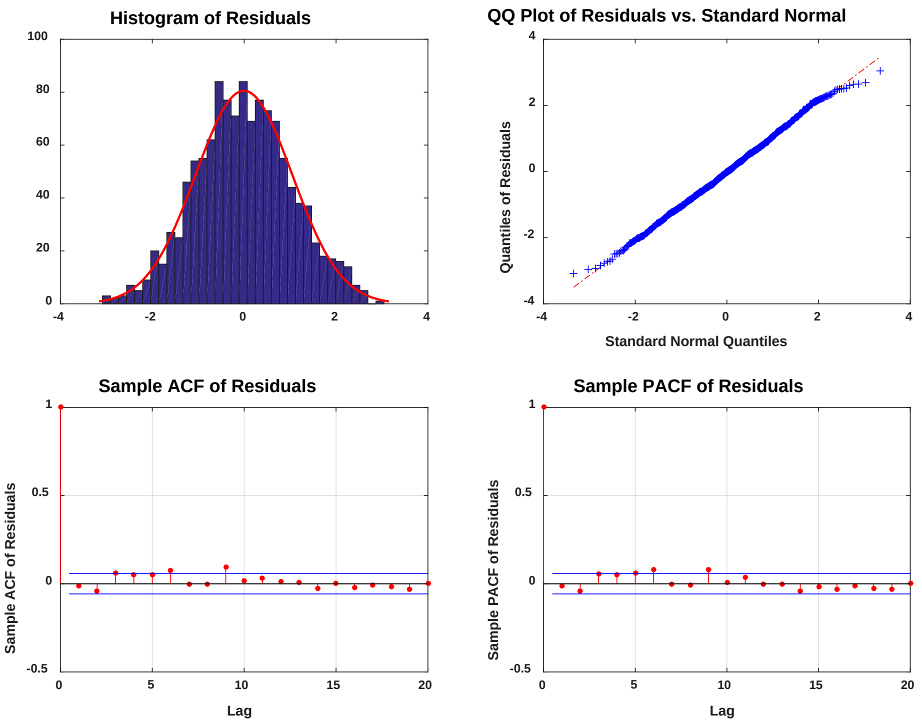


Fig. 5.11 Residual Analysis of AR(1,2,12) MA(1,12) model 20

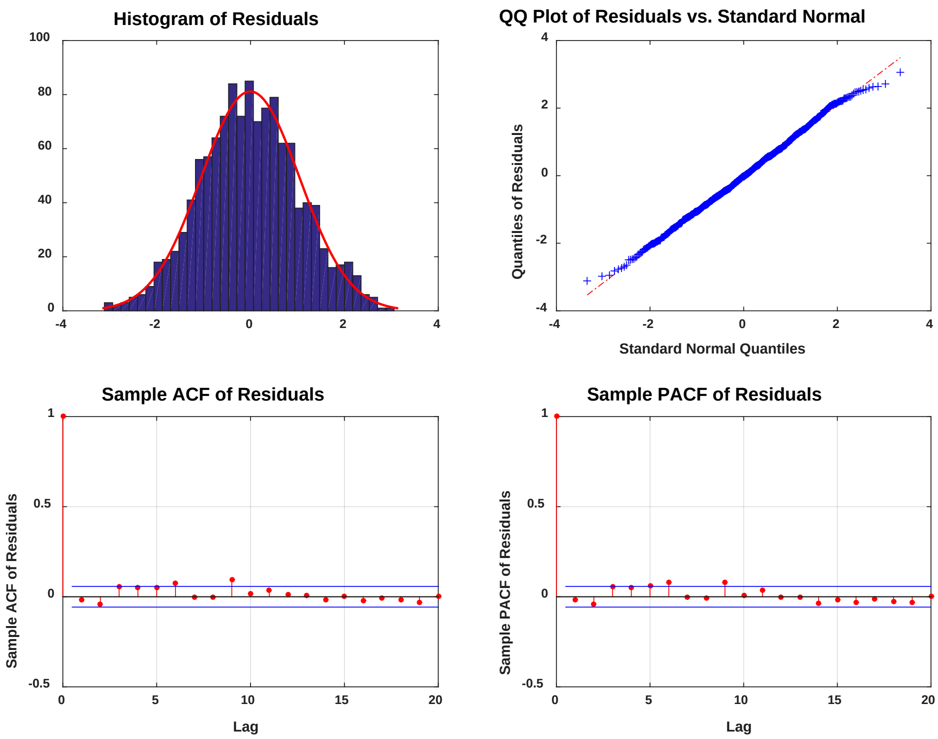


Fig. 5.12 Residual Analysis of AR(1,2,12) MA(1,2,12) model 21

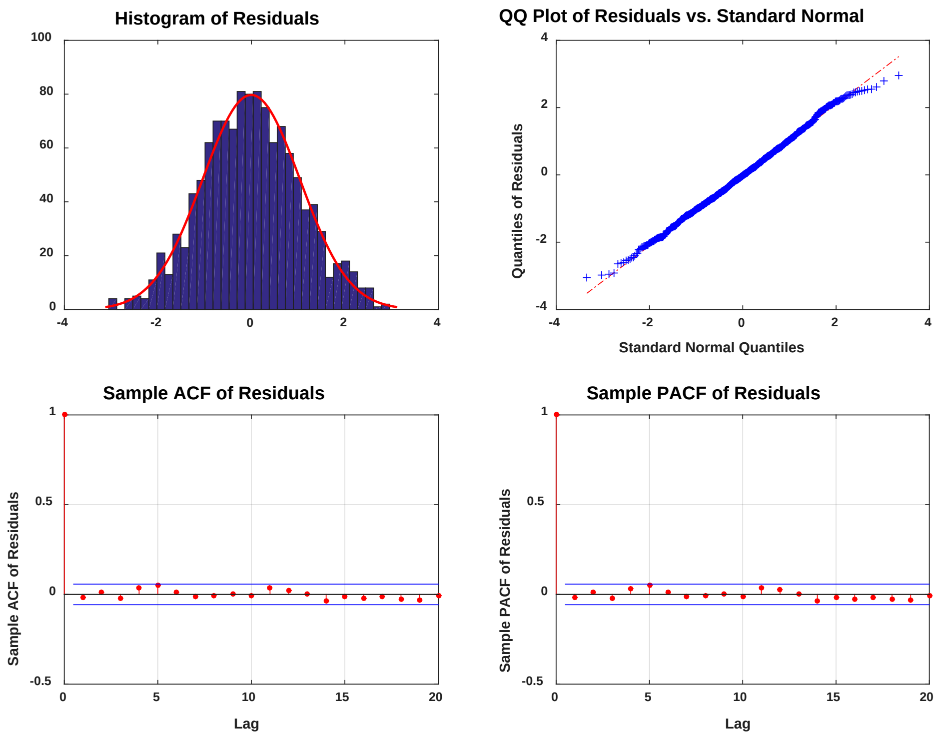


Fig. 5.13 Residual Analysis of AR(1,3,6,9,12) MA(1,3,6,9,12) model 22

5.9.7.2 Significance of periodicities

The ACF and PACF of residuals of models 18-22 is plotted and shown in Fig 5.9-5.13 respectively. It can be inferred from the plots of ACF and PACF of residuals that models 18-21 still have some ACF and PACF which appears to be significant. However, model 22 does not have any ACF or PACF which exceeds 5% significance limits. To test whether these ACF and PACF are statistically significant LBQ test was performed at till lag 24. Table 5.7 summarizes the LBQ test results. From LBQ test, ACF and PACF plots, it can be concluded that only model that does not have any significant periodicities in their residuals is model no. 22, which is AR(1,3,6,9,12) MA(1,3,6,9,12).

Table 5.7 Results of LBQ test on residuals

md. no	C/ NC	AR	MA	Q-stat	$\aleph^2$(0.95,24-no of parameters)	p-value	Result - Periodicity Significant/Insignificant
18	NC	1,12	1,12	42.5204	28.8693	9.35E-04	Significant
19	NC	1,12	1,2,12	41.9836	27.5871	6.74E-04	Significant
20	NC	1,2,12	1,12	37.3614	27.5871	0.003	Significant
21	NC	1,2,12	1,2,12	37.0766	26.2962	0.002	Significant
22	NC	1,3,6,9,12	1,3,6,9,12	14.6716	21.0261	0.2599	Insignificant

5.9.7.3 White noise test

In time series ARMA models, the residuals or innovations are assume to be Gaussian with zero mean and constant variance. Since a white noise process is a random process of random variables that are uncorrelated, have mean zero, and a finite variance, the innovations of the ARMA models should behave like a white noise. For ARMA models to be applicable, the residual series *W(t),* must not have any significant heteroscedasticity (nonconstant variance). In order to check for the heteroscedasticity, Engle's Autoregressive conditional heteroskedasticity (ARCH) [74] test on the residual series is performed. This tests the null hypothesis of no ARCH effects against the alternative ARCH model with *k* lags. Test statistics from Engle's ARCH test for any significant heteroscedasticity present in the residuals are presented in Table 5.8. These results imply that the residual variances are constant and i.e. no heteroscedasticity present in the residuals of any of the selected models 18-22.

Table 5.8 Results of Engle's ARCH test on residuals

md. no	**C/ NC**	**AR**	**MA**	**Tstat**	**Critical Value**	**P value**	**Result**
18	NC	1,12	1,12	3.0195	3.8415	0.0823	No heteroscedasticity
19	NC	1,12	1,2,12	3.0925	3.8415	0.0787	No heteroscedasticity
20	NC	1,2,12	1,12	2.8064	3.8415	0.0939	No heteroscedasticity
21	NC	1,2,12	1,2,12	2.6906	3.8415	0.1009	No heteroscedasticity
22	NC	1,3,6,9,12	1,3,6,9,12	2.6496	3.8415	0.1036	No heteroscedasticity

5.9.8 Finalized model

Based on the AIC, BIC and maximum likelihood rule the model which can be finalized to represent the differenced time series $\grave{Y}_t$ (ΔTemperature) is model no 22 i.e. AR (1,3,6,9,12) MA (1,3,6,9,12). The differenced time series $\grave{Y}_t$ (ΔTemperature) represented by AR (1,3,6,9,12) MA (1,3,6,9,12) is presented in the expanded form in Eq. 5.24. The parameters of the Eq. 5.24. i.e. $\varphi_{1,}$ $\varphi_{3,}$ $\varphi_{6,}\varphi_{9,}\varphi_{12,}$ $\theta_1, \theta_3, \theta_6, \theta_9$ and θ_{12} were estimated using maximum likelihood estimation (MLE) as presented in Table 5.4. The terms in the Eq. 5.24 as $\grave{Y}_{t-k}$, where k=1,3,6,9,12 represents $\grave{Y}$ at time k before t months. For example $\grave{y}_{t-1}$ represents the observed value of $\grave{Y}$ at 1 month before t. Similarly ε_t represents residual series also called innovation. Fig 5.14 shows the differenced series of maximum temperature with the fitted series based on the finalized model presented by Eq. 5.24.

$$\Delta \text{Temperature}\,(\grave{Y}_t) = 0.274743\,\grave{y}_{t-1} + 0.0812419\,\grave{y}_{t-3} + 0.0578781\,\grave{y}_{t-6} + 0.0808885\,\grave{y}_{t-9} - 0.0221227\,\grave{y}_{t-12} + 0.0213305\,\varepsilon_{t-1} + 0.00973465\,\varepsilon_{t-3} + 0.00209352\,\varepsilon_{t-6} + 0.00801166\,\varepsilon_{t-9} - 0.897086\,\varepsilon_{t-12} + \varepsilon_t \tag{5.24}$$

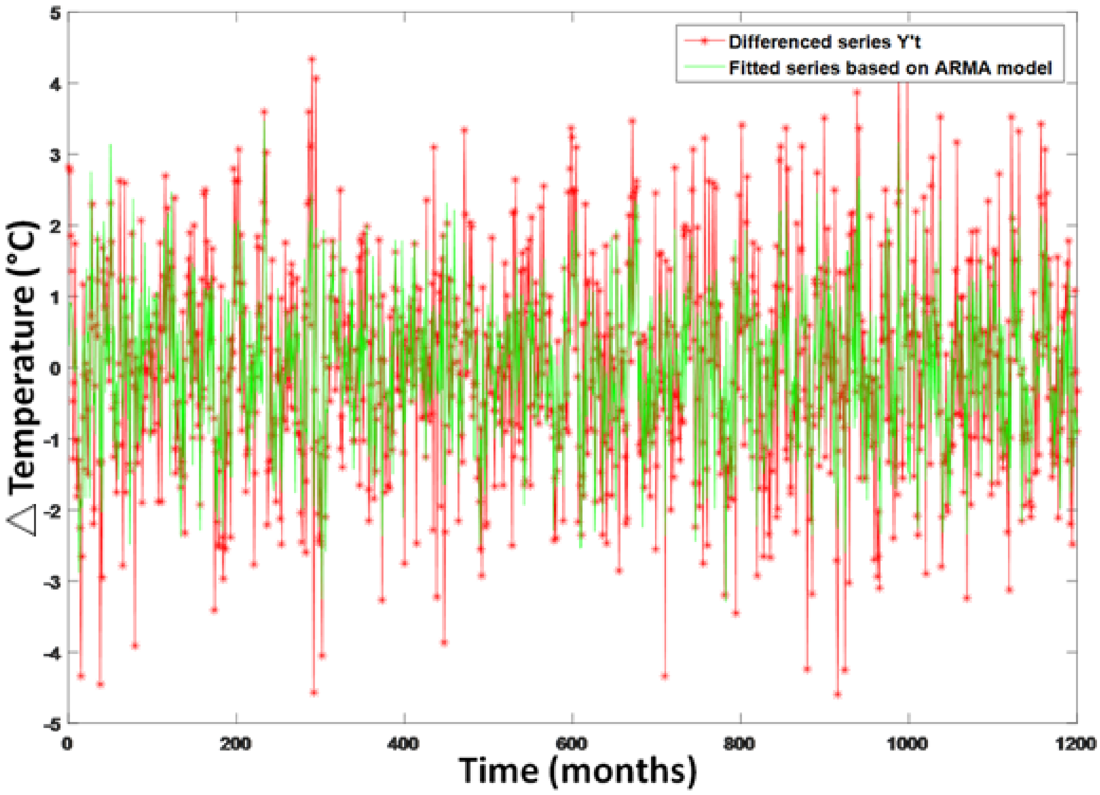


Fig. 5.14 Original differenced series and fitted ARMA series

5.9.9 Sampling and generating the synthetic data

As an illustration a time series of length N=1224 (i.e for the time period of 1224 month) is generated based on the finalized ARIMA model (Eq. 5.24). The time series that was considered for the analysis (Fig. 5.4) is plotted along with the synthetic series in the Fig. 5.15. It can be seen that the synthetic time series of the temperature has the same statistical properties (mean, variance and autocorrelation) as of the original time series.

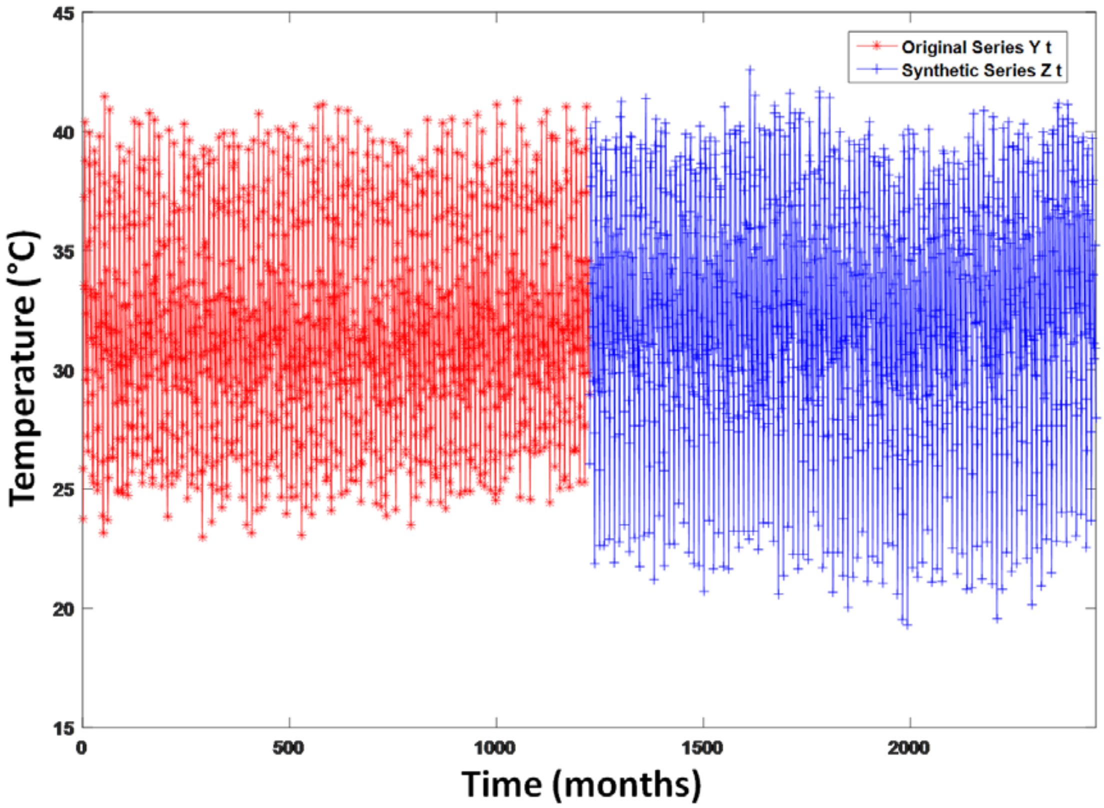


Fig. 5.15 Synthetic series plotted along with the maximum temperature data

As said earlier, in APSRA$^+$ methodology, probability of passive system failure is calculated by using Monte Carlo simulation, wherein a large number of sample values are generated for each of the independent process parameters such as atmospheric temperature. These samples are then analyzed to find the system response. The system response for each of the samples of these independent process parameters are assessed by best estimate system codes. For example, in isolation condenser system which dissipate heat in the atmosphere, the atmospheric temperature becomes an independent process parameter. The mathematical modeling of this independent process parameter accomplished using the methodology discussed. Once the model of the independent process parameter is ready, a sample of required size is conveniently generated using this model. These generated samples are then analyzed to check the system response.

5.10 Conclusions

Performance and reliability of passive safety systems is function of its process parameters which governs the passive operation. These process parameters can be broadly categorized as dependent and independent parameters. Probability density functions of dependent process parameter variations can be obtained by doing root diagnostics and then using failure probabilities of the identified hardware component or systems. However, independent process parameter variations cannot be modelled using similar approach. One of the prime reasons is that these parameters vary with respect to time along the mission time of system operation. In addition, parameters like atmospheric temperature also depend upon the geographical location; hence, classical treatment of probability density functions cannot be applied.

In this chapter, the methodology for fitting Auto-regressive integrated moving average (ARIMA) model to the independent process parameter of passive safety systems is presented. Algorithm for the generation of synthetic data of the modelled time series is also presented. In APSRA^{+} methodology the generated series of independent process parameters are used during the reliability estimation of passive safety systems. As an illustration to the methodology of model fitting and synthetic data generation, a time series of monthly-maximum atmospheric temperature of district Chittaurgarh (Rajasthan, India) has been considered. With the help of methodology, a non-contiguous ARIMA model of AR (1,3,6,9,12), MA(1,3,6,9,12) has been found to represent the differenced (at lags 12) stationary series of monthly-maximum atmospheric temperature. A synthetic series of length 1224 months have been generated based on the finalized ARIMA model. The developed model could provide an accurate way for the treatment of dynamic variation of independent process parameter and was found to be significantly different from that conceived by using a pdf as in existing methods.

CHAPTER – 6

APPLICATION OF APSRA$^+$ TO A PASSIVE SYSTEM OF AN ADVANCED REACTOR

The methodology "APSRA$^+$" has been applied for evaluation of reliability of passive Isolation Condenser System of an advanced reactor as an example.

6.1 System description

The Indian Advanced Heavy Water Reactor (AHWR) [6] is a 300MWe (920MWth) pressure-tube type boiling- water reactor employing many passive features. Natural circulation as the desired heat removal mode from the core under all conditions of operation. Decay heat removal is also accomplished in a passive manner by establishing a natural circulation path between the Main Heat Transport System (MHTS) and the Isolation Condenser System. Fig. 6.1 shows the general arrangement of MHTS and ICS of AHWR. The main heat transport system consists of a vertical core having coolant channels (452 numbers) arranged in a calandria. The two-phase mixture leaving the coolant channels is carried to the steam drum (4 numbers) through corresponding tail-pipes (risers). Steam drum is a horizontal cylindrical vessel with appropriate internals, where gravity separation of two-phase mixture is achieved. Nearly dry saturated steam leaves the steam drum through steam lines to feed the turbine. Recirculation water is mixed with feed water in the steam drum and it flows through the downcomer (4 numbers per steam drum) which are connected to a header, which in turn is connected to coolant channels through corresponding feeders.

Isolation Condenser System comprises of a set of immersed condensers located in an elevated water pool called gravity-driven water pool (GDWP), and associated piping and valves. A branch connection from the steam line carries the steam to tube bundle of immersed condenser through a distributor and top header. The steam condensation takes place in the tube bundle and the condensate returns to the downcomer region of steam drum through a bottom header and condensate return line. The condensate return line is provided with a set of active and passive valves in parallel. The heat removal capacity is regulated using a passive valve where the valve opening is regulated passively depending on steam drum pressure thus maintaining hot shutdown. Hot shutdown state refers to the condition of zero reactor power (core under decay heat) with the steam drum pressure in range of 76.5–79.5 bar (with corresponding saturation temperature) such that reactor can be started and powered after short duration outage. This is different from the cold shutdown state wherein the reactor coolant is cooled down to atmospheric pressure and temperature of about 40°C. The passive valve is a self-acting single-port spring-loaded valve with pressure balancing by stainless steel bellows, working in proportional mode requiring no external energy, like pneumatic or electric supply for its actuation. The valve uses the steam drum pressure as the signal and has the linear characteristic, i.e. valve opening varies from fully closed to fully open with the variation of steam drum pressure in the specified range. The active valve (pneumatically operated) provided in parallel serves the purpose of bringing system to cold shutdown condition, if required. Under normal operation, valves remain closed thus isolating the ICS from the MHTS, and steam flows to the turbine circuit. Whereas, under a station blackout condition when main condenser is unavailable, passive valve opens (and closes also) in response to steam drum pressure and a natural circulation path gets established between MHTS and ICS.

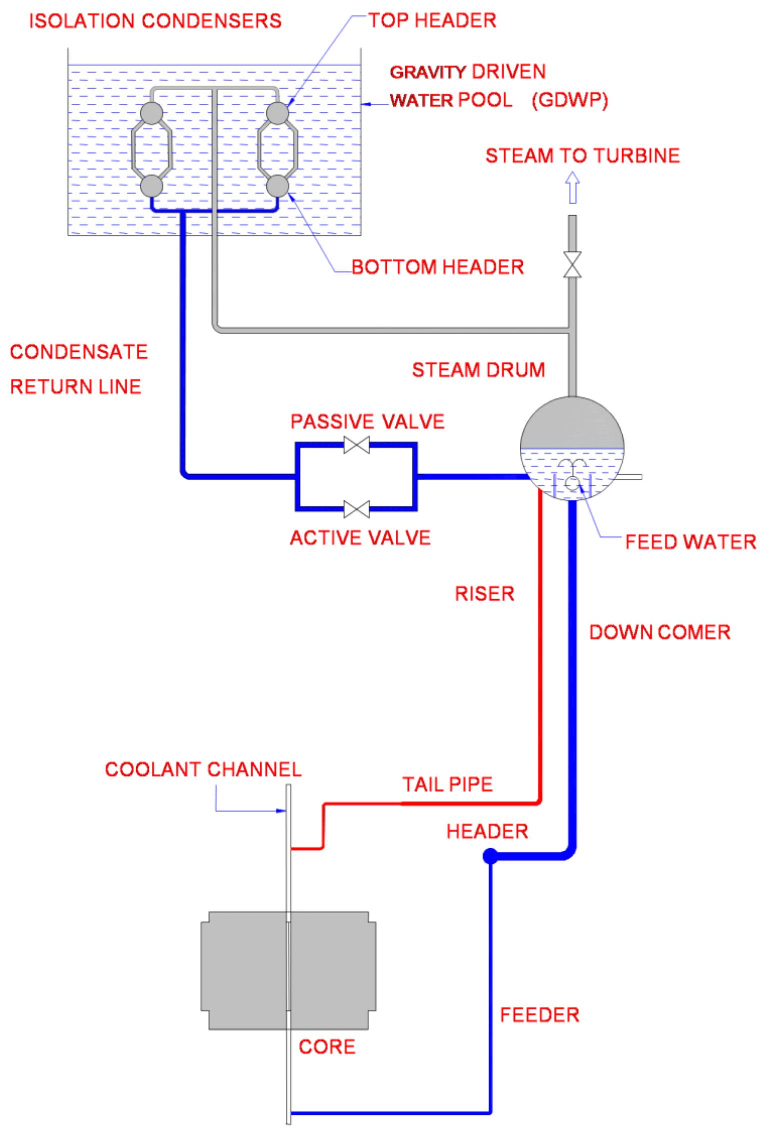


Fig. 6.1 Schematic MHTS and ICS of AHWR

6.2 Application of APSRA$^+$ in steps for reliability evaluation of ICS

The methodology APSRA$^+$ has been applied to the ICS in the following steps

Step 1: System identification: System to be considered for analysis

In step 1, the passive system for which reliability will be evaluated is considered. The system being considered is the Isolation Condenser System (ICS) of Advanced Heavy Water Reactor (AHWR).

Step 2: System mission, success/failure criteria

System mission: mission of the isolation condenser system is to provide a heat sink which would condense the steam generated by the stored heat, fuel decay heat and will limit the pressure rise in the steam drum and prevent the clad temperature under threshold for at least 3 days without operator intervention.

Failure Criteria: ICS is coupled to MHTS, any set of conditions that lead to excess peak clad temperature is ascribed to failure of ICS. Thus, ICS is considered to be failing if it fails to maintain the peak clad temperature under 400°C for the duration of 3 days.

Step 3: Identification of parameters and reduction to vital few

Initially a list of parameters that may affect the system performance was prepared. To identify the vital ones, effect of these parameters on system performance is calculated using RELAP5 code. The quantitative sensitivity analysis results are presented in step 4(b). Parameters that were initially identified in this step include the followings:

a. presence of non-condensables in IC;
b. water level in gravity driven water pool (GDWP);
c. GDWP water temperature;
d. active valve availability;
e. passive valve availability;
f. fouling and
g. stratification.

Among the above parameters, the ICS system performance is more sensitive to a few of them. Although the non-condensables are continuously removed during the operation, a little accumulation of these could greatly affect the isolation condenser. Water level in GDWP is very important as reduction of the level leads to the exposure of IC tubes and hence may stall the heat transfer process. Also, reduced water inventory may result in insufficient water availability during the long term cooling of the core. Increased water temperature may reduce the heat transfer process in the IC tubes. Active valve and passive valve availability is very important as they perform the most vital operation of initiation and control of flow in the IC tubes during the operation. Since the water chemistry is strictly controlled and to eliminate stratification GDWP an innovative technique of multiple shroud concepts[34] is adopted, phenomena like fouling and stratification are highly unlikely. Hence, fouling and stratification was discarded from the list of important parameters.

Step 4: System modeling

The performance of ICS coupled with MHTS was modeled using RELAP5/mod 3.2. The nodalization scheme followed is presented in Fig. 6.2. Following assumptions were made to simulate the system behavior:

- Non-condensable were modeled as air,
- MHTS coolant channels were lumped together,
- IC tube bundles were lumped together,
- A quarter symmetric section of MHTS and ICS was considered for analysis.

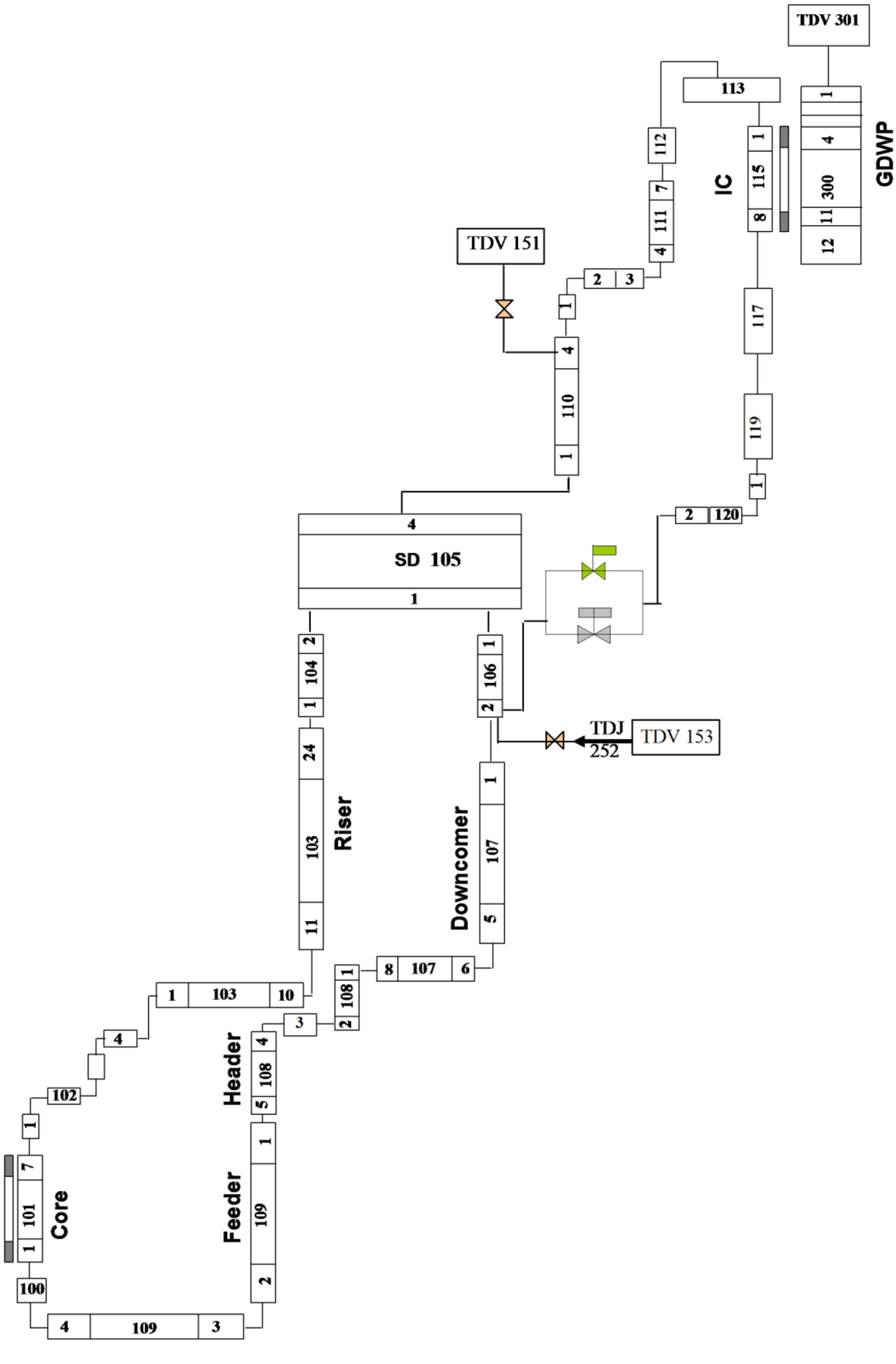


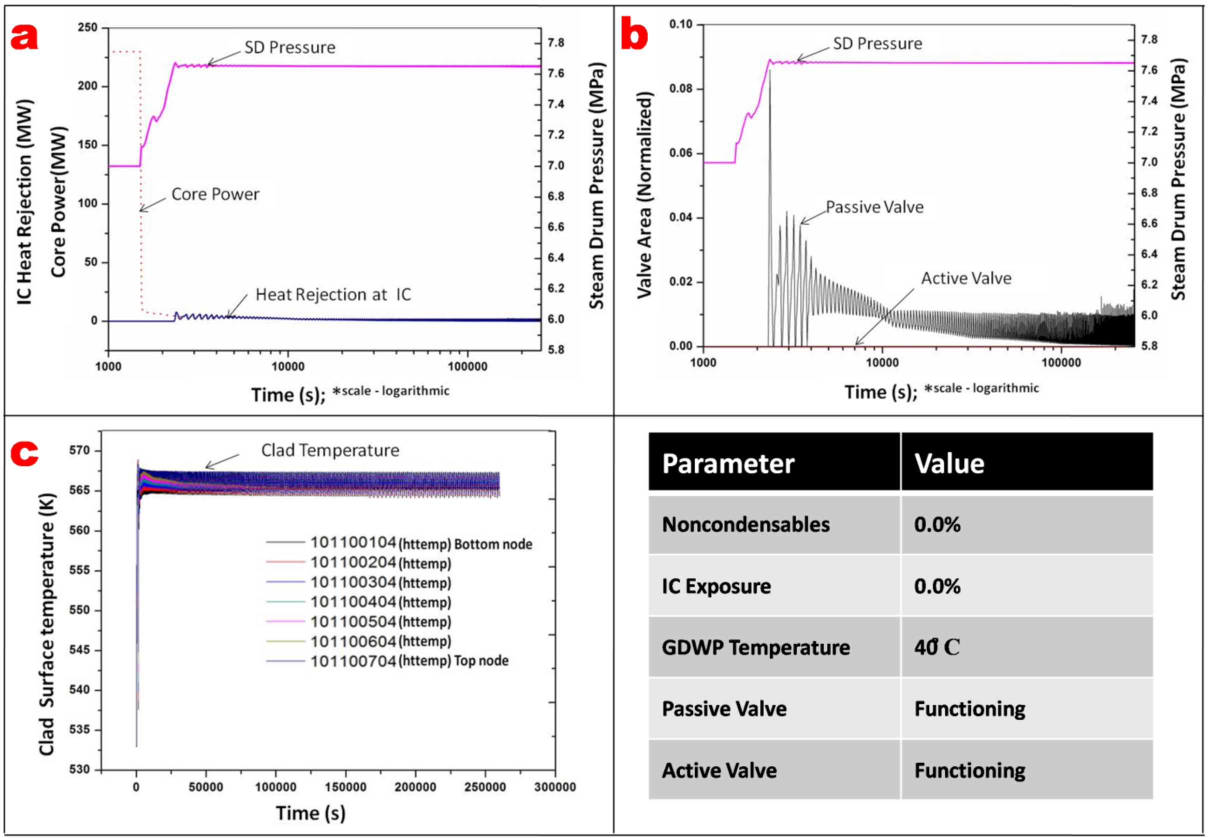
Fig. 6.2 Nodalisation of MHTS and ICS of AHWR for RELAP5/ Mod 3.2

Step 4(a): Performance under normal operating range of process parameters

Isolation condenser along with main heat transport system was analyzed for the normal condition of operation as a base case. This normal operating condition of ICs corresponds to 0% non-condensable, 100% submergence of IC tubes in GDWP water and 40ºC normal operating temperature of GDWP water. Performance under normal condition is depicted in Fig. 6.3. With initiation of decay heat transient at t=1500 s, main heat transport system is boxed. At this point (at t=1500 s) main condenser including feed water becomes unavailable. As a consequence of this, steam drum pressure increases from normal operating value of 7.00MPa to 7.65MPa over the period of 700 s. At this pressure (7.65 MPa), passive valve begins to open and thereafter pressure is maintained by regulating passive valve opening area as shown in Fig. 6.3(b). Core decay power and heat rejection in IC are closely matching, and, in turn maintaining the SD pressure constant. Under this condition active valve remains closed, as it opens only when steam drum pressure reaches 8.0 MPa or after 30 minutes of operation of Isolation condenser, However for understanding the effect of dynamism involved in the operation of valves and their effect on the passive system operation, in this analysis active valve is restricted to open only when SD pressure rises beyond 8.0 MPa. As shown in Fig. 6.3(c), clad temperature remains constant and under the threshold 400ºC.

Step 4(b): Performance under degraded conditions

In order to determine the effect of the parameters identified in Step 3 on system performance, sensitivity analysis of the various parameters is performed using RELAP5/mod 3.2. The parameters are varied over a range as given in Table 6.1 and their effects on system performance are described in the following sections.



Parameter	Value
Noncondensables	0.0%
IC Exposure	0.0%
GDWP Temperature	40° C
Passive Valve	Functioning
Active Valve	Functioning

Fig. 6.3 (a) Variation of SD pressure, core decay power and heat rejection through IC with time during SBO transient in absence of degrading factors, (b) Passive and active valve during the operation of IC, (c) Clad temperature during the operation of IC

Table 6.1 Parameters affecting system performance

SI. No.	Parameter	Normal operating condition	Range of variation
1.	Non condensables in IC circuit	0%	0-100%
2.	GDWP water temperature	40ºC	30-90ºC
3.	Water level in GDWP	9 m	0-9 m
4.	Active valve availability	100%	0-100%
5.	Passive valve availability	100%	0-100%

Active and Passive valve availability: The passive and active valves in isolation condenser can fail at any intermediate positions other than stuck open or stuck closed. In order to understand the system behavior when active and passive valves fail at intermediate positions of opening, valve failures were simulated using RELAP5/mod3.2. It was observed in simulations, clad temperature rises beyond 400ºC only when both valves fail during the assumed SBO transient. Various failure cases obtained by individual and combined variations of the parameters along with the valve failures are discussed below.

Effect of non-condensables: For the purpose of this analysis, non-condensables (NC) are assumed to be initially present in the system. Steam drum to IC line is filled with steam-air mixture of a different concentration as an initial condition. GDWP water is at 40ºC and IC tubes are fully submerged in water. The assumed transient is initiated. At NC mass fraction of 6.5%, IC is found to fail to maintain hot shutdown, as shown in Fig. 6.4 (a). At this NC fraction, it is found that though the passive valve is fully open, it is not able to maintain the SD pressure, due to degraded condition of heat transfer resulting in poor condensation of steam, and hence the pressure rises. As the pressure reaches 80 bar, active valve opens. With opening of active valve, SD pressure reduces to 76.5 bar that leads to closing of passive valve, but pressure continues to drop as active valve continues to remain open. Under such conditions, system inadvertently undergoes cold shutdown. During this scenario of NC mass fraction of 6.5%, if passive and active valve fails stuck (total passive+active valve opening area <0.2%) on demand, the clad temperature rises beyond 400°C within 3 days of grace period as depicted in Fig. 6.4 (b).

Effect of GDWP water temperature: With the simulation results, it was observed that, even at GDWP water temperature 90ºC, the system is maintained under hot shutdown as shown in Fig. 6.5(a). Under this condition it was found that heat transfer condition has rather improved due to local boiling in the pool near the top node of IC tubes. A typical case of failure (i.e. clad temperature exceeding 400ºC) at GDWP temperature of 50ºC and 5.5% NC (shown in Fig. 6.5(b)), is observed in case of passive and active valve fails stuck closed partially (total <0.2% of their opening area) during SBO.

Effect of GDWP water level: As an initial condition, the steam drum to IC line is filled with pure steam and GDWP temperature is at 40ºC. IC tubes external surface is partially exposed by reducing GDWP water level. The hot shutdown is successfully maintained with 75% exposed IC tubes. This may be attributed to huge coolant inventory available in the pool. At 87.5% exposure of IC tubes, the SD pressure rises even after the opening of active valve (Fig. 6.6(a)). Under this set of degrading factors, a different mode of failure is observed, where in the pressure continues to rise even after opening of active valve as shown in Fig. 6.6(a) as very small heat transfer surface is in contact with pool water, resulting in very little condensation. At this condition, if the passive and active valve fails in stuck closed condition partially (total <0.2% of their opening area), the clad temperature rises above 400ºC as shown in Fig. 6.6(b).

Combined effect of NC, GDWP water level and temperature: Based on the effect of degrading factors individually various combinations are considered. IC performance at a combination of degraded parameters (62.5% exposed tubes with 4.2% NC and 90ºC pool water temperature) is shown in Fig. 6.7(a). A typical failure case is observed when along with these degraded parameters active and passive valve fails stuck partially (total <0.2% of their opening area), as shown in Fig. 6.7(b).

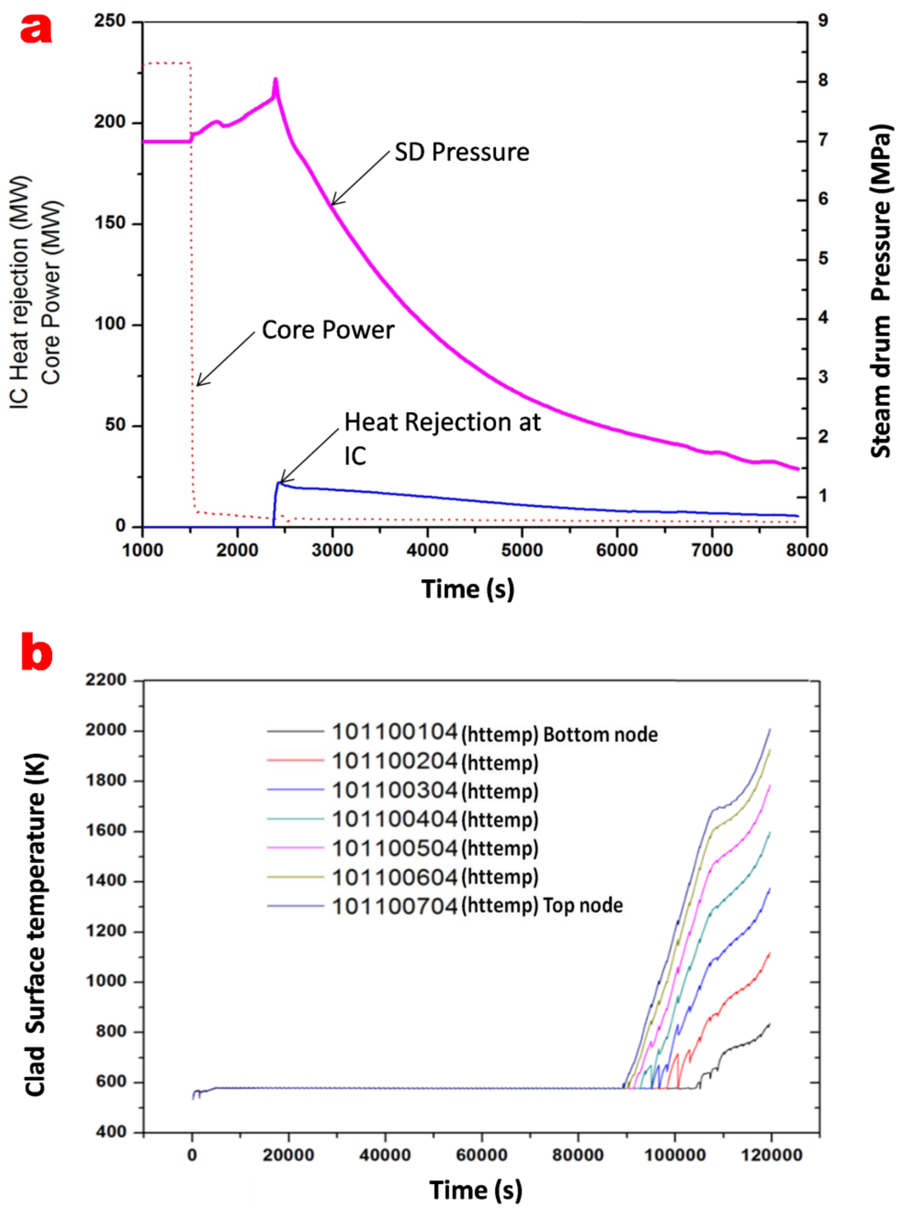


Fig. 6.4 (a)Variation of SD Press, core power and heat rejected at IC in presence of 6.5% NC; (b) Clad temperature in presence of 6.5% NC with active and passive valve failed stuck closed <0.2%

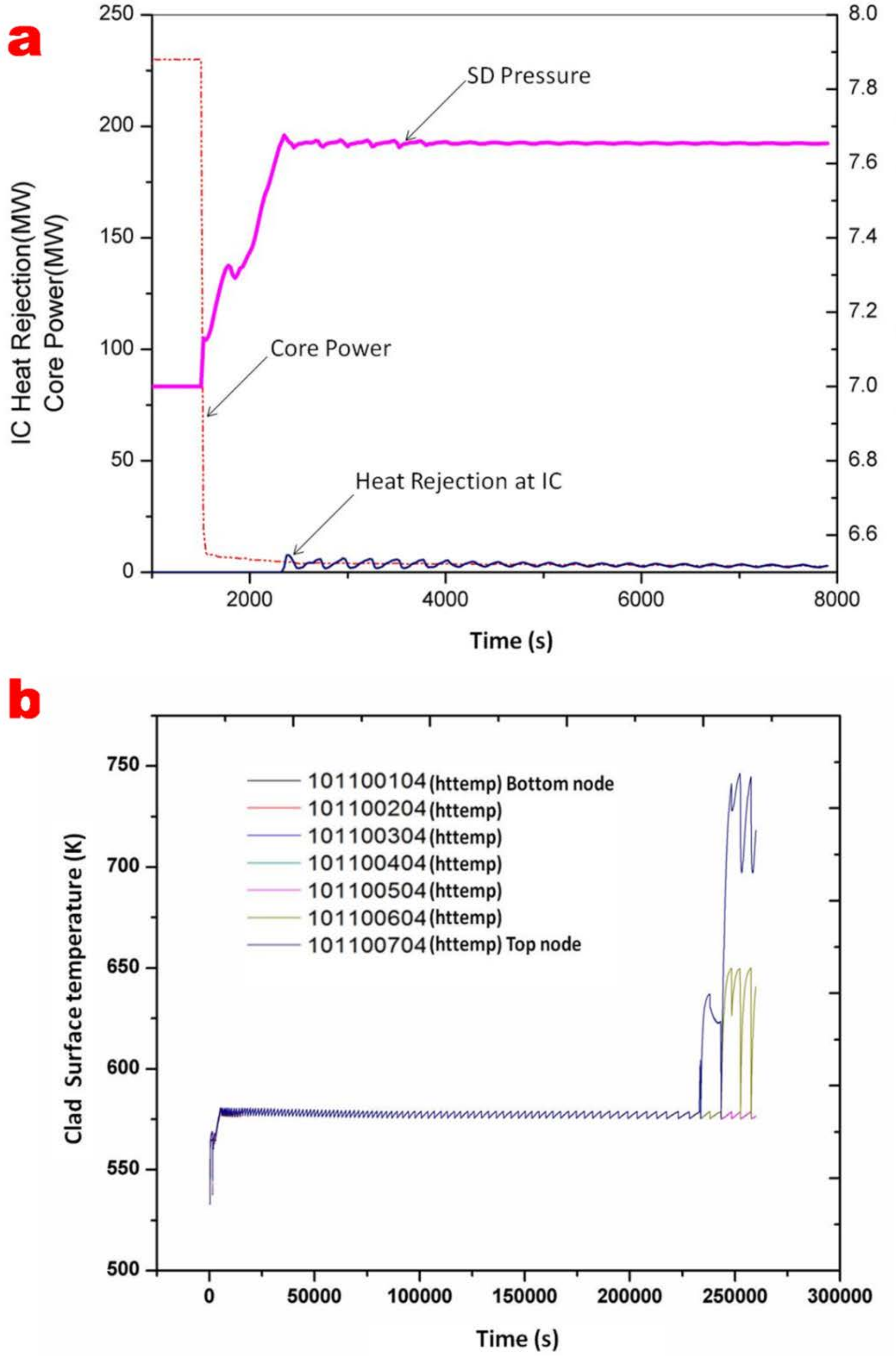


Fig. 6.5 (a) IC performance with 90°C GDWP water temperature without NC in ICS; (b) Clad temperature in presence of 5.5% NC and 50°CGDWP water temperature with active and passive valve failed stuck closed <0.2%

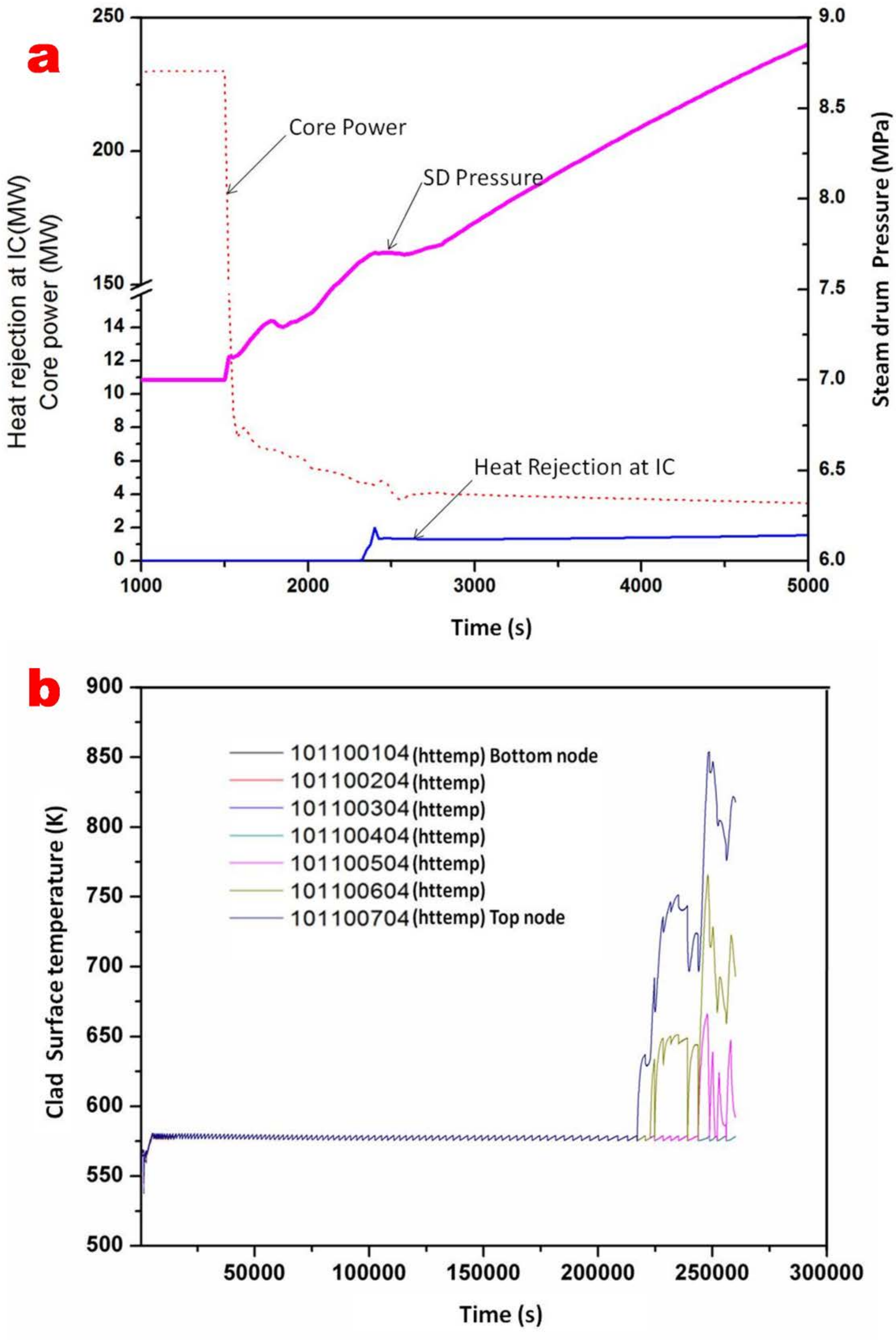


Fig. 6.6 (a) IC performance with 87.5% exposure of IC tubes; (b) Clad temperature at IC exposure of 87.5% with active and passive valve failed stuck closed <0.2%

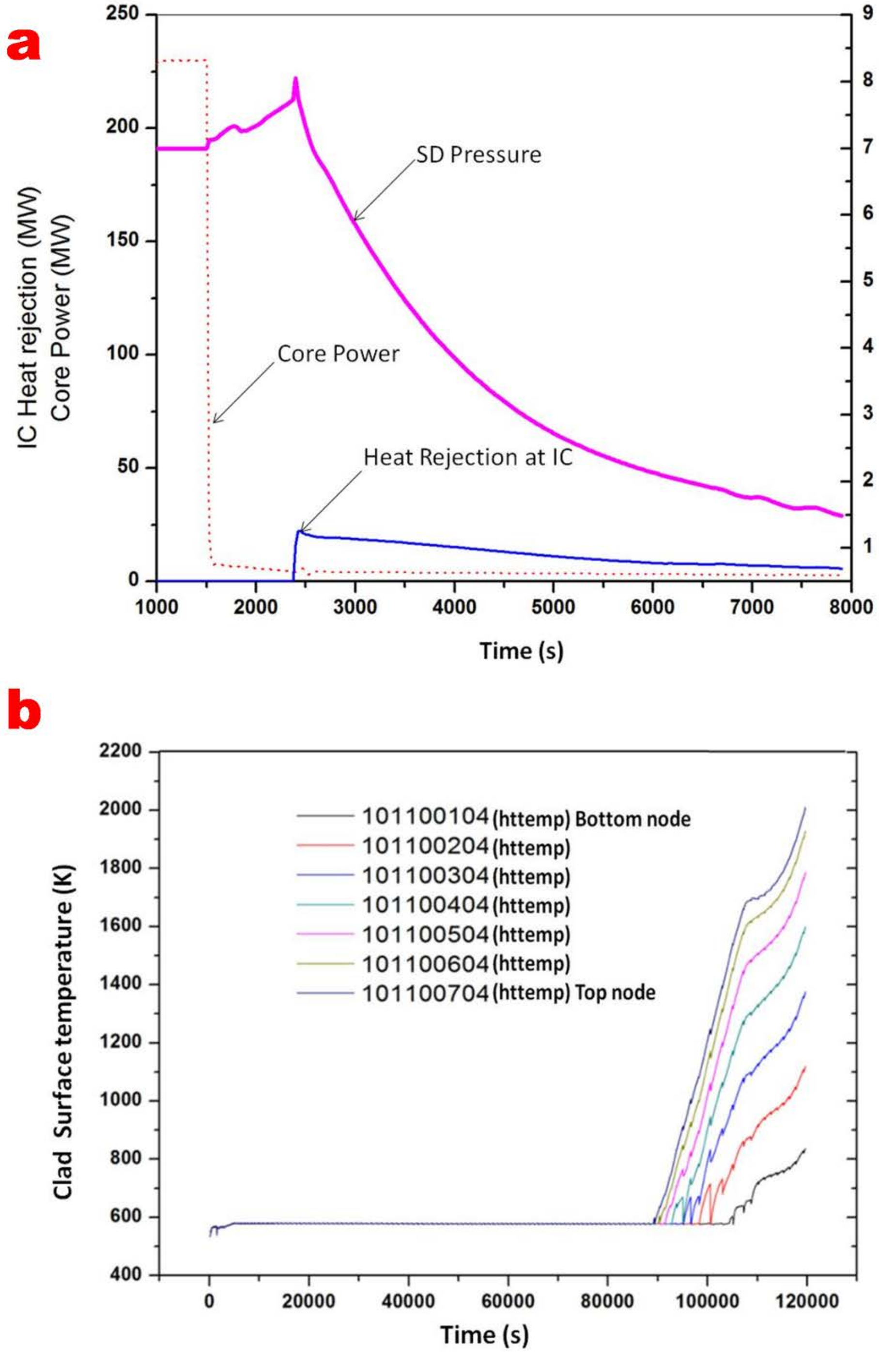


Fig. 6.7(a) IC performance with combination of degraded parameters; (b) Clad temperature at IC exposure of 62.5%, GDWP temperature 90°C and NC 4.2% along with active and passive valve failed stuck closed <0.2%

Step 5: Treatment of process parameters

Treatment of process parameter variations is performed in several steps:

Step 5.1: Segregation of parameters into: a) Dependent Parameters b) Independent Parameters

Process parameters are segregated as follows:

Dependent Parameters: Non condensables, GDWP Temperature, GDWP level and passive and active valve availability

Independent Parameters: None

Step 5.2: Identification and quantification of sources of dependent process parameters variation by root cause

a) Non-condensables: A close examination to the system reveals that control valves were used in the purging/ venting system of non-condensables. The accumulation of non-condensable can be attributed to the failure of these control valves to remain open during the normal operation of reactor.

b) GDWP Level: The root cause for this parameter reveals that the cause for this parameter variation is failure of makeup circuit.

c) Active and Passive valve availability: Valve failure in itself is a hardware failure, hence no further root cause was performed. However, the valve failure can be further explored to the basic cause and its mechanism of failure by using physics of failure models.

d) GDWP Temperature: The primary cause of high temperature of GDWP water is the failure of GDWP recirculation system.

Step 5.3: Quantification of probability of dependent process parameter variations

a) **Non Condensables:** Accumulation of non-condensable is attributed to the failure of the purging/vent valves to remain open during the normal operation of reactor. A simplified schematic of the venting valves for one set of isolation condenser is presented in the Fig. 6.8.

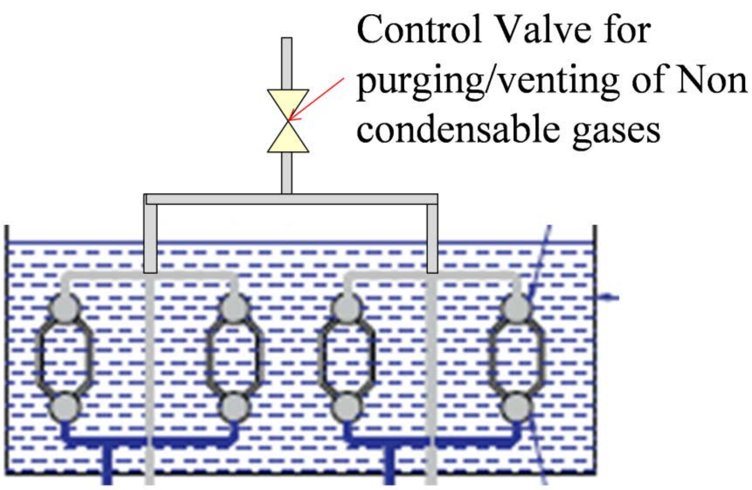


Fig. 6.8 Schematic of purging/vent system for one set of isolation condensers

To quantify the probability of presence of non-condensable during the startup of isolation condenser operation, the following assumptions were made:

- The inspection time for the purging/vent control valves is considered to be 12 hrs.

- If purge valve fails in between the inspections, NC gases will accumulate till the next scheduled inspection.
- For the worst case analysis, it is assumed that the SBO transient may occur before the inspection is scheduled, hence the total NC gases accumulated till the scheduled inspection because of the failure of purge valve is considered as the initial condition for IC system.
- In actual reactor, for quarter core ($1/4^{th}$ total power) the non-condensable accumulation over a 3 hrs period will be 6.2 kg
- Purging valve failure probability is 1E-4 [56].
- Valve stuck probabilities considered in this analysis were derived by performing a series of experiments in chapter 4 are presented in the Table 6.2.

Table 6.2 Control valve stuck probabilities at different states of operation

Fault	Occurrence Probability%
Stuck Close (0% open)	35.00
Stuck Intermediate (1-99% open)	30.00
Stuck Open (100% open)	35.00

* Equi-probable in getting stuck in between – 1% - 99% open

With the above mentioned assumptions, the total amount of NC generated (expressed in NC mass fraction in %, present at the start of ICS operation) in the IC circuit is calculated by using Eq. 6.1.

NC mass fraction in %= NC accumulation in % per hour * No of hours spent after valve failure (6.1)

The newly developed methodology of dynamic reliability presented in chapter 3 was used to get the estimate of frequency of non condensable gases.

The flow diagram of the methodology adopted for this case is presented in Fig. 6.9. The procedure is described step by step as:

I. Start with the decided number of Monte Carlo simulation runs. Initialize j=1 and reset all the other simulation parameters to default values.

II. Sample the fault position of vent valve as per Table III.

III. Sample undetected failure time for vent valve t_i assuming uniform distribution for failure time in between 0-12 hrs.

IV. Check for t_i, if it is greater than 12 hrs. then set NC% =0.

V. If t_i is less than 12 hrs. calculate NC% using equation 1.

VI. Store and repeat the step I-V for N number of Monte Carlo runs.

VII. Make a frequency table for NC% from the stored results.

VIII. Determine the probability of each bin by dividing the frequency count with the total number of Monte Carlo runs (in this case N=1e6).

IX. Multiply the purge valve failure probability (1e-4) with each bin probabilities to get the occurrence of probabilities of NC%.

X. Plot the probabilities obtained in step IX in Y-axis with the NC% in X-axis.

Non-condensable gas present during the startup of the operation of isolation condenser system, based on this analysis is shown in Fig. 6.10. It is to be noted that the probability of non-condensables present in the ICS was considered as a constant (Probability of high NC=1e-4) [56] in case of APSRA

[75] methodology. However, $APSRA^+$ methodology considers this probability to be varying with respect to the percentage of non-condensable present during the start of the operation. The probability values are conservative in APSRA when compared to the $APSRA^+$ methodology. In APSRA, the probability of presence of non-condensable gases is attributed to the failure of the purging valve. It was assumed that this valve fails in binary mode (i.e stuck closed or suck open) and whenever the valve fails in stuck closed mode, it causes the non-condensable gases to accumulate. However, in actual fact the valve can fail in intermediate positions as well, and the partial failure will not always lead to very high non-condensable gas accumulation. In addition, the accumulated time after the failure of the valve was not considered when probability of NC was assigned in APSRA methodology. These two factors: a) partial failure of purging valve b) time accumulated after the valve failure; were considered in $APSRA^+$ methodology to estimate the presence of non-condensables probability. When these factors were considered, the probability of non-condensables present during the startup of the ICS was estimated to be very less than the one considered in APSRA methodology.

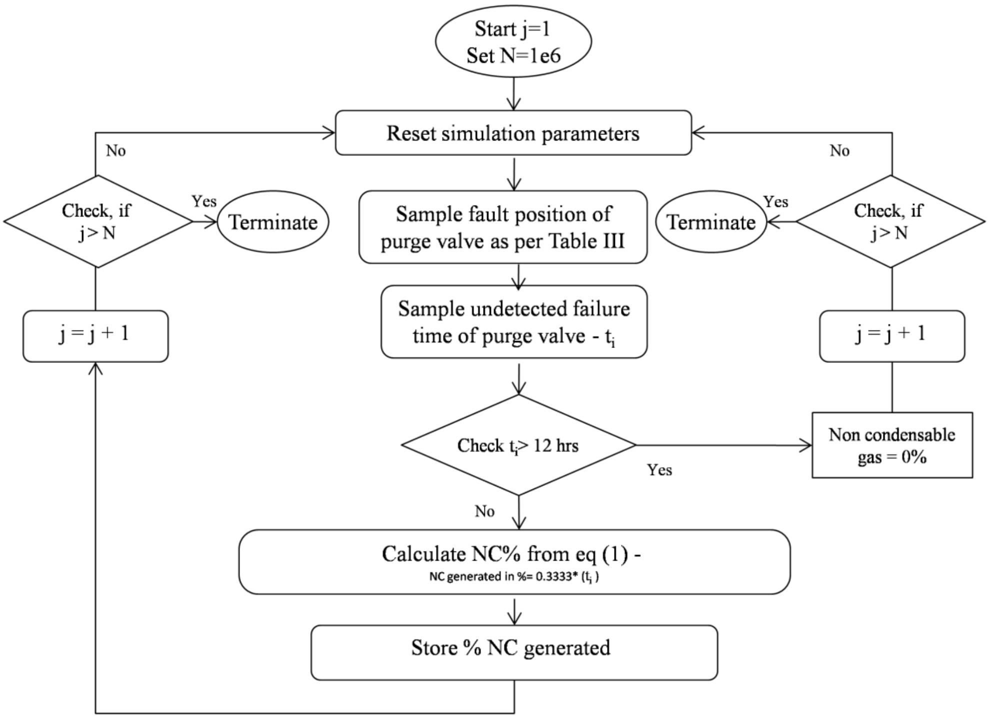


Fig. 6.9 Flow chart of the methodology for deriving the probability of non-condensable% present during the startup of ICS

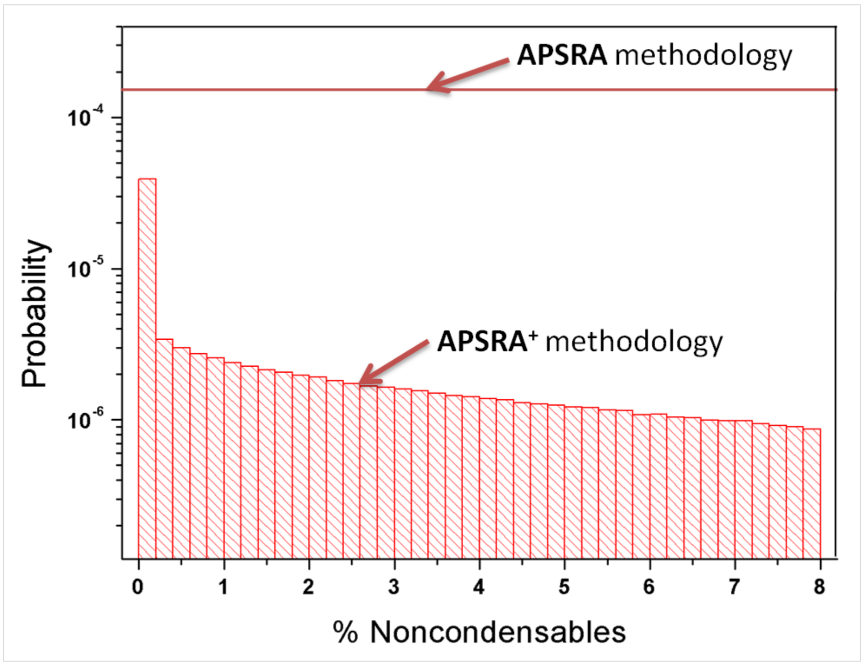


Fig. 6.10 Probability of non-condensable present at the startup of ICS operation

b) **GDWP Level and Temperature:** The GDWP level fall causes IC tubes to be exposed to the atmosphere. The effect of GDWP level can be directly represented by IC exposed. Hence the effect is represented by the %IC exposed. Since the GDWP level can fall primarily because of the failure of the makeup circuit, which consists of many valves (schematic presented in Fig. 6.11), a simulation similar to non-condensable gas probability estimation was adopted with appropriate modifications to model the behavior of these valve failures. The simulation result is shown in the Fig. 6.12. Due to the similar reasons mentioned in the non-condensable case, in this case also, the probability values considered in APSRA appeared to be very conservative and constant as shown in Fig. 6.12. GDWP water temperature is maintained by the heat dissipation in the recirculation loop. Hence the GDWP water temperature rise is attributed to the failure of recirculation loop, which consists of many valves (schematic presented in Fig. 6.11). A simulation, similar to non-condensable gas probability generation was adopted with appropriate modifications to model the behavior of these valve failures. The simulation result is shown in the Fig. 6.13. Unlike the above two cases (non-condensable and GDWP level/IC exposure), in this case the probability of high GDWP water temperature considered in APSRA [75] methodology appeared to be lesser than the ones estimated by the APSRA$^+$. It is to be noted that, when considering the single parameter, high GDWP water temperature that affects the ICS performance ranges from 80-90°C. However, when combined with the other process parameters like non-condensable and GDWP level, failure of the system can happen even at lower GDWP temperatures (as low as 50°C).

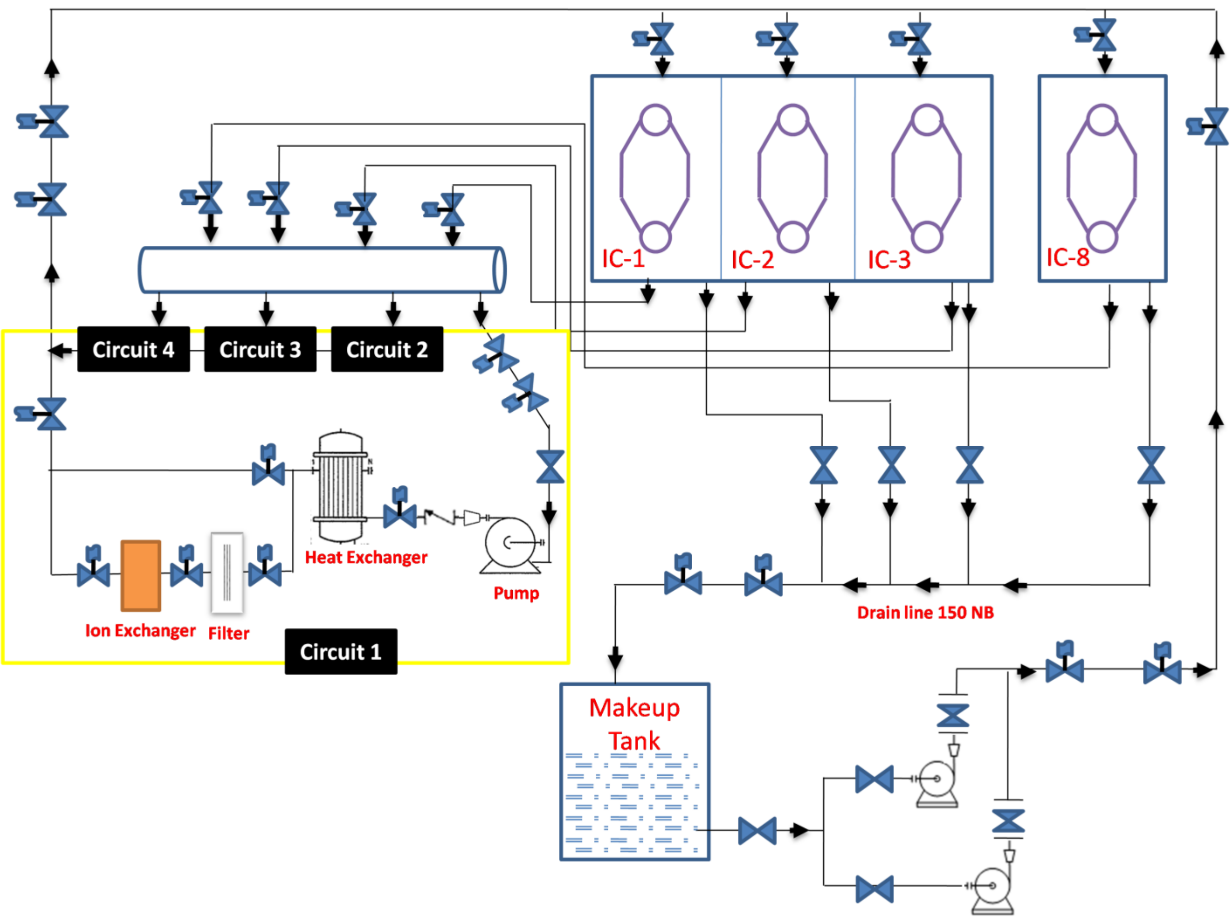


Fig. 6.11 GDWP makeup and recirculation schematic

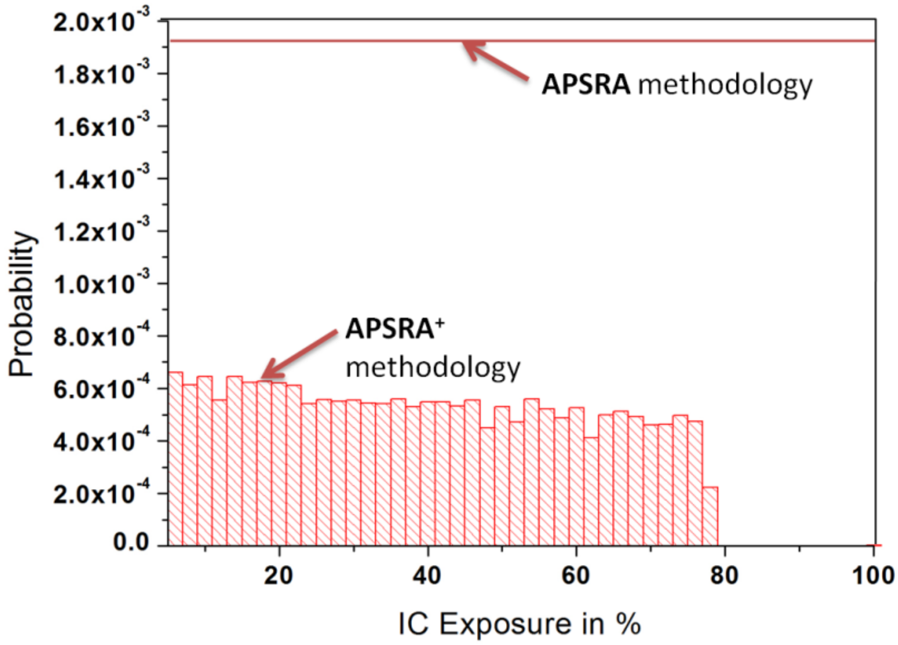


Fig. 6.12 Probability of percentage of IC exposure

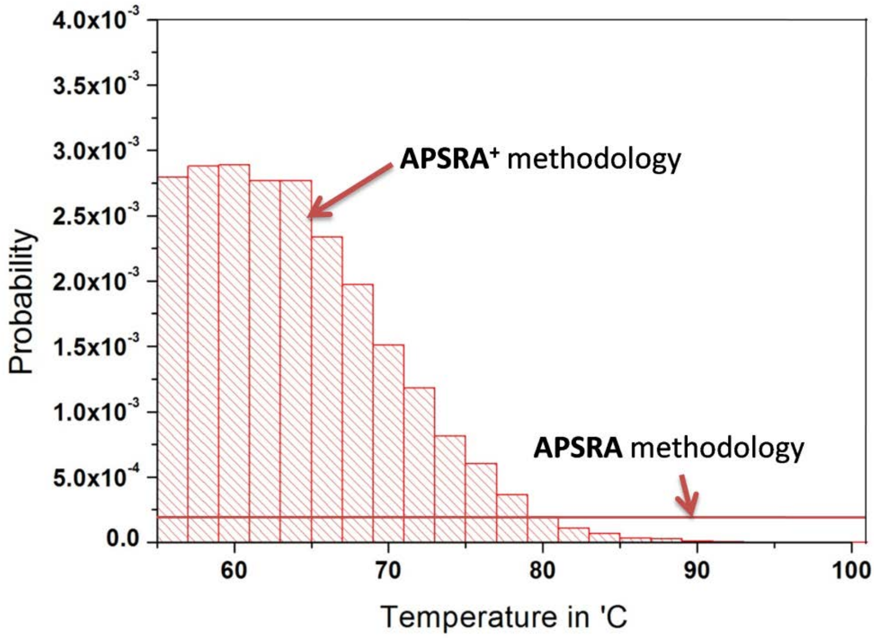


Fig. 6.13 Probability of high GDWP temperature

c) **Valve Failure:** Valve failure rates were taken from the results derived from the series of experiments performed on a passive system consisting of similar valves. The derived failure rates considered are presented in chapter 4 Table 4.2.

Step 5.4: Quantification of probability of independent process parameter variation

In the present analysis, GDWP water temperature is considered as dependent process parameter because there is a dedicated makeup and cooling system in place. However, in many of the passive systems, the ultimate heat sink is ambient atmosphere. In such cases, the temperature of atmosphere is considered as independent process parameter. In order to generate the samples for independent process parameters, first the mathematical models of such parameters are developed as per the procedure mentioned in chapter 5. Once the mathematical models are developed, the synthetic series of the independent process parameters is generated which possess the same statistical properties as of the selected independent process parameter.

Step 5.5: Check for interdependency of parameters and make a correlation matrix if dependency exist

There was no correlation found in between the parameters of ICS for this application.

Step 6: Treatment of model uncertainty

In absence of adequate operational experience with passive systems, it is customary to depend on the prediction of their performance by best estimate codes. The applicability of best estimate system codes such as RELAP5/mod 3.2 to model such systems and capture various phenomena associated with such systems is questionable as the currently available best estimate codes were developed mainly for active systems. As a consequence of this, prediction of passive system performance is associated with uncertainties which can significantly influence the prediction of natural circulation characteristics and hence its reliability.

Various models of RELAP5/mod 3.2 which can significantly affect the system performance were presented in chapter-2 Table-2.1. The model uncertainties considered for this analysis are: (1) Heat Transfer (HTC), (2) Pressure Drop (ΔP), (3) Choking Flow (c), (4) Abrupt Area Change (a), (5) CCFL (f), and (6) Modified Energy Term (e). To model the uncertainties in heat transfer coefficient, HTC was decreased by 25% in the simulation input. Since there is no direct method to modify the heat transfer coefficients in RELAP5/mod 3.2, the heat transfer coefficient uncertainty is implemented by modifying the associated heat transfer surface area. In the present case, the surface area is decreased by 25 %. The pressure loss uncertainty was implemented by modifying the junction energy loss coefficients, in the present situation being increased by 10%. Similarly the uncertainty in choking flow was implemented by modifying the associated flow area. In the present case, it was increased by 5%. All the other model uncertainties were modeled by switching the corresponding models on or off i.e. 0 or 1 in the RELAP5. On the basis of analysis of all the combinations of the degrading factors, various failure points have been generated.

Step 7: Develop a response surface of the important process parameters using best estimate codes

Response surface of limiting surface for cases a) without model uncertainties and b) with model uncertainties was developed (Fig. 6.14).In both the cases the limiting value of non-condensable was considered as response and % IC exposed and GDWP temperature were considered as input variables. For estimating the probability of parameters falling outside the limiting surface, all three parameter values were generated for 1E+07 number of Monte Carlo runs based on their mathematical models or pdf developed. The limiting value of non-condensables were calculated from the response surface equation using % IC exposed and GDWP temperature as inputs. The sampled non-condensable values were then compared with the limiting value of the non-condensable calculated from response surface equation. If sampled value of non-condensable was found more than the limiting value, this indicated that point lies beyond the limiting surface.

Response surface for case a) without considering model uncertainties: A full quadratic model was used to model the response surface. The fitted model has R^2 – 88.7% and R^2-adjusted -84.0%, which ensures that the fitted model is good approximation of the response surface. The equation for response surface without considering model uncertainties is given by Eq. 6.2:

$$\% NC = 6.52468 - 0.00207*\%IC\_exposed - 0.01407*gdwp\_temp - 0.00058*\%IC\_exposed^2 - 0.00003 * gdwp\_temp^2 + 0.00017*\%IC\_exposed*gdwp\_temp \quad (6.2)$$

Response surface for case b) with considering model uncertainties: A full quadratic model was used to model the response surface. The fitted model has R^2 – 98.3% and R^2-adjusted -97.7%, which ensures that the fitted model is good approximation of the response surface. The equation for response surface with considering model uncertainties is given by Eq. 6.3:

$$\% NC = 2.32193 + 0.00787*\%IC\_exposed + 0.01637*gdwp\_temp - 0.00032*\%IC\_exposed^2 - 0.00014* gdwp\_temp^2 - 0.00005*\%IC\_exposed*gdwp\_temp \quad (6.3)$$

Step 8: System failure probability calculation

From the analysis of isolation condenser system, it was found that clad temperature exceeds the threshold value of 400ºC in the events when process parameters affecting the performance lie on or outside the failure surface and both passive and active valves fail stuck $\leq$ 0.2% of the their combined opening area. The event that leads to clad temperature exceeding the threshold value of 400ºC is represented as a fault tree in Fig. 6.15.

Probability of IC fail to maintain the clad temperature below 400ºC was estimated by multiplying the failure probabilities of valves and process parameters exceeding the failure surface. It can be noted that the probability of parameters falling on or above the limiting surface is invariant with time. However, the active and passive valve failure probability increases with time. Probability of parameters falling outside the limiting surface was estimated by using a Monte Carlo simulation. For the Monte Carlo simulation, process parameter values were sampled based on the probabilities generated by dynamic reliability analysis in step 6.3. Each generated sample combination of process parameters were checked to find if it lays above or below the failure surface. Probability of the combination of valve failure with respect to the reactor years of operation were estimated using Monte Carlo simulation. Flow diagram of the Monte Carlo simulation algorithm adopted for one mission time is shown in Fig. 6.16.

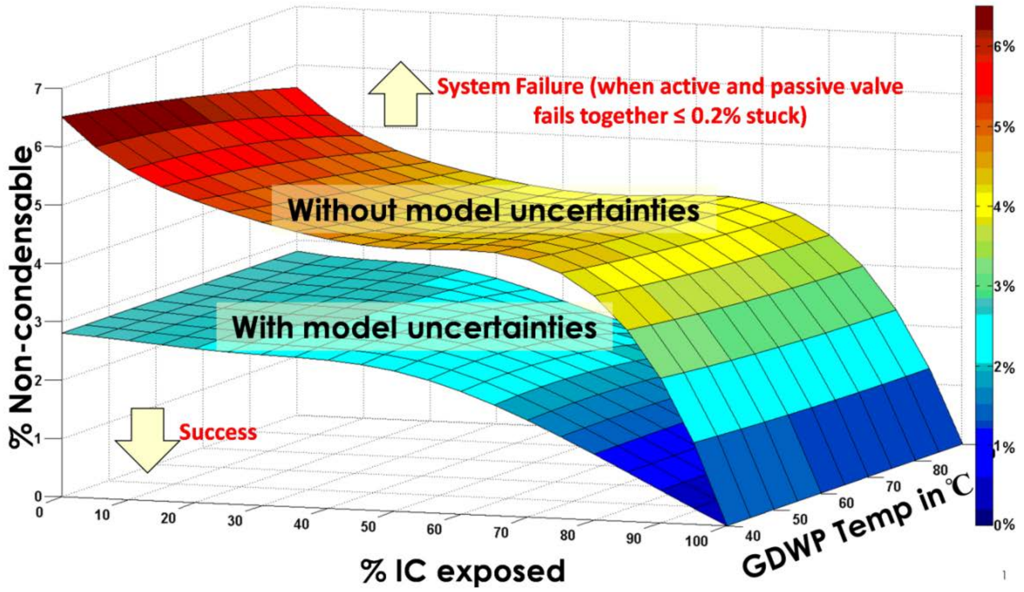


Fig. 6.14 Failure surface with and without considering model uncertainties

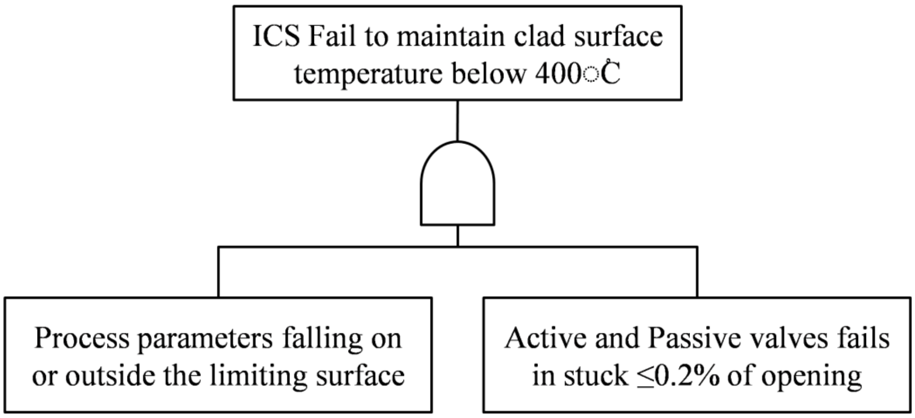


Fig. 6.15 Fault tree representation of events leading to clad temperature exceeding threshold 400°C

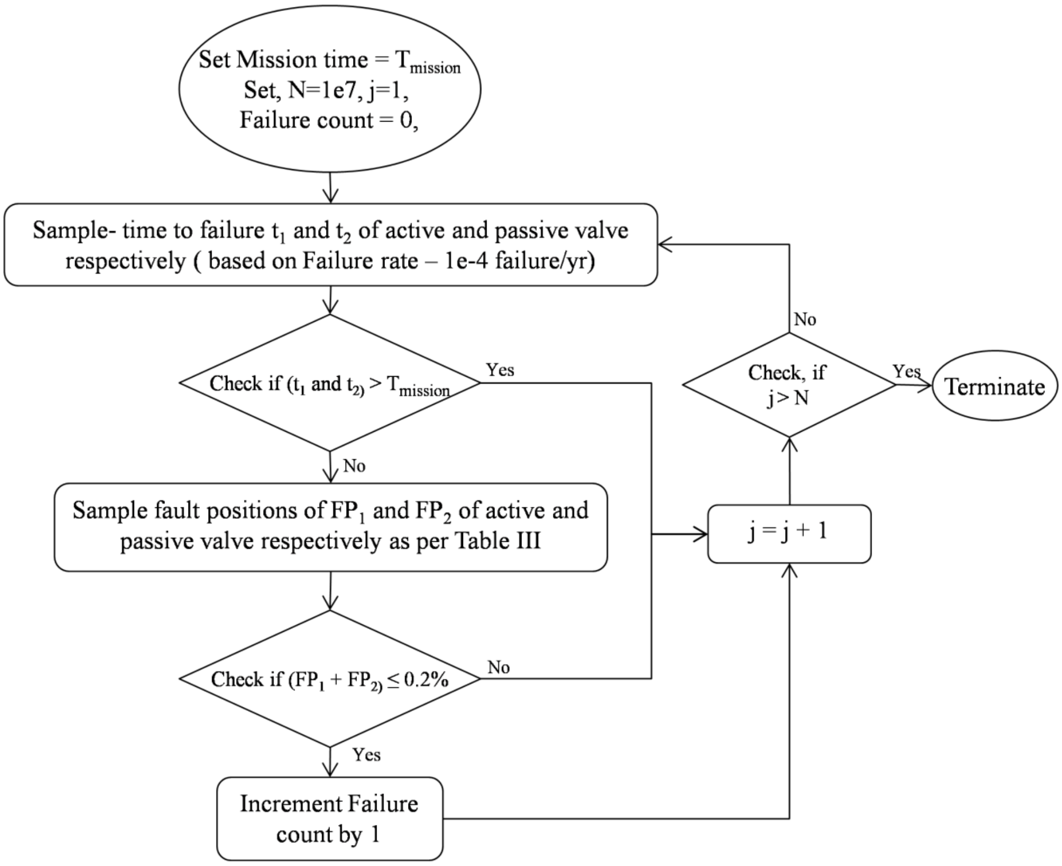


Fig. 6.16 Flow diagram for estimation of failure probability of active and passive valve fail stuck ≤ 0.2%

Step 9: Reliability representation with uncertainty bounds of model errors

Probability of ICS failure is presented in Fig. 6.17. Probability of failure with considering the model uncertainties can be treated as confidence bounds on probability of failure. It can be seen that the probability of failure considering model uncertainties is higher than without considering the model uncertainties for isolation condenser system.

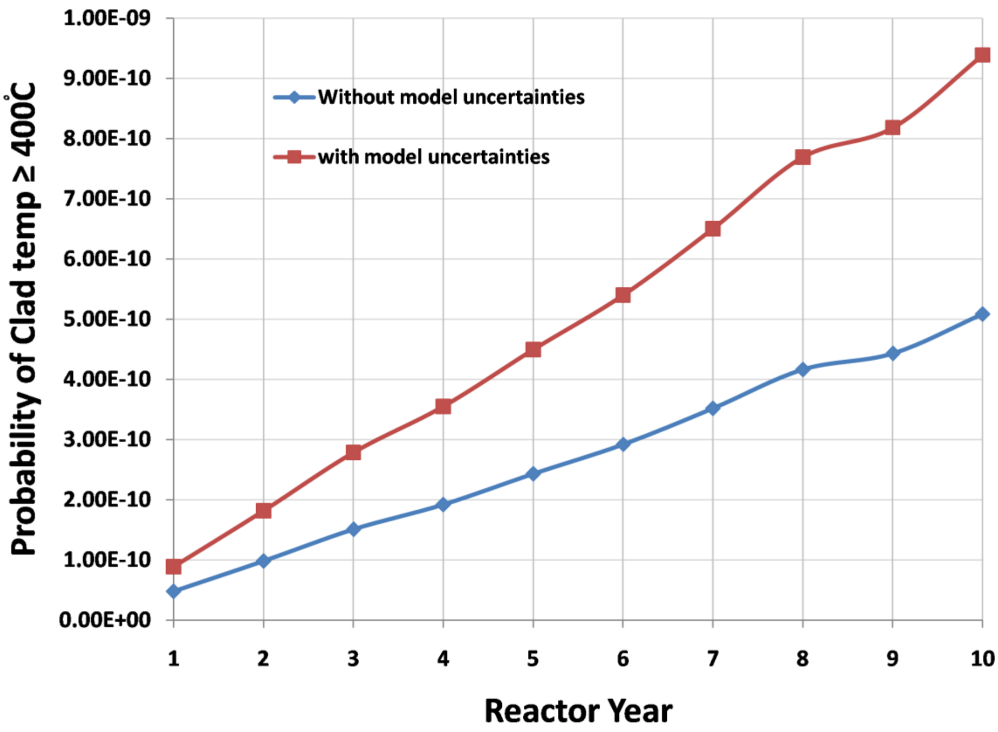


Fig. 6.17 Probability of failure of ICS with respect to the reactor years

The estimated conditional probability of failure of ICS is of the order of 1×10^{-10}. It has to be noted that the failure probability of ICS was earlier [75] estimated to be of the order of 3.53E-07 using APSRA methodology. The failure probability of ICS obtained using APSRA methodology were found to be very conservative when compared with the failure probability obtained from APSRA$^+$. The large differences in the estimated probability of failure is mainly because in APSRA$^+$ the dynamic failure characteristics of components is considered while estimating the probability of variations of process parameters.

6.3 Conclusions

In this chapter, the application of methodology Analysis of passive system reliability plus (APSRA$^+$) is presented. The methodology has been applied to the passive isolation condenser system of advanced heavy water reactor (AHWR). In APSRA$^+$, important parameters affecting the passive system under consideration were identified using sensitivity analysis. The five important parameters identified were: a) presence of non-condensables in IC, b) water level in gravity driven water pool (GDWP), c) GDWP water temperature, d) active valve availability and e) passive valve availability. To evaluate the system performance, a best-estimate code was used with due consideration of the uncertainties in empirical models. Failure surface was generated by varying all the identified important parameters, variation of which from its nominal value affects the system performance significantly. These parameters were then segregated into dependent and independent categories. All the five important parameters were categorized as dependent parameters and no independent process parameter was found to be significantly important in this passive system (ICS). For the dependent parameters, it was attributed that the variation of process parameters are mainly due to malfunction of mechanical components or control systems and hence root cause was performed. The probability of these dependent parameter variations was then estimated using the newly developed dynamic reliability methodology presented in chapter 3. The dynamic failure characteristics of the identified causal component/system were accounted in calculating these probabilities. In the next steps, a response surface based meta-model was formulated using the generated failure points. Probability of system being in the failure zone was estimated by sampling and analyzing a sufficiently large number of samples for all the important process parameters based on the probability of variations of these parameters, which were estimated using newly developed dynamic reliability methodology. The estimated failure probability of ICS with respect to the reactor years was found to be of the order of 1×10^{-10}. It has to be noted that the failure probability of ICS was earlier estimated to be of the order of 3.53E-07 using APSRA methodology. The failure probability of ICS obtained using APSRA methodology were found to be very conservative when compared with the failure probability obtained from APSRA^{+}. The large differences in the estimated probability of failure is mainly because in APSRA^{+} the dynamic failure characteristics of components is considered while estimating the probability of variations of process parameters.

CHAPTER – 7

CONCLUSIONS

This chapter discusses the conclusions of the thesis. Important conclusions are as follows:

- A critical review of the present methodologies of passive system reliability analysis was performed to identify the objectives and scope of work. With the help of the review of literature, four critical issues pertaining to passive systems performance and reliability have been identified. These issues are:
  - Treatment of dynamic failure characteristics of components of passive systems
  - Quantification of functional failure probability of components
  - Treatment of independent process parameters variations
  - Treatment of model uncertainties

- In view of the unresolved issues associated with the currently available methodologies of passive system reliability analysis, a methodology called APSRA$^+$ has been developed in this thesis to overcome the unresolved issues.

- APSRA+ provides an integrated dynamic reliability methodology for the treatment of dynamic failure characteristics such as multi-state failure, fault increment and time dependent failure rate of components of passive systems.
    - — In view of this a dynamic reliability methodology has been developed and is integrated in APSRA+ methodology.
    - — The dynamic reliability methodology has been applied to a benchmark dynamic system of hold-up tank to demonstrate the applicability of this methodology.
    - — With the help of benchmark system analysis, it was learnt that the conventional methods yields erroneous estimates of system failure probability.
    - — In addition to this, it was found that dynamic failure characteristics of components such as multi-state failure and fault increment, etc. cannot be accounted in the conventional methods of reliability analysis.
    - — Keeping in view the above findings, it can be concluded that while estimating the failure probability of dynamic systems like passive safety systems, the dynamic reliability methodology must be used.

- Since there is serious lack of the database for the probability distributions of the mechanical components of passive system like valves, an experimental facility of a passive system consisting of three control valves was built and a series of experiments were performed to quantify the functional failure probability of these valves. The following conclusions can be drawn from the findings of the experiments performed:

— From the experiments performed, the intermediate state failure probabilities of valves were determined.

— The probability of valves failing at the intermediate positions of opening was found to be very significant which cannot be ignored while estimating system failure and performance.

— Valve characteristics were found to seriously affect the passive system performance and failure.

— The implications of ignoring the intermediate stuck failures and dynamic valve characteristics in estimating the system failure probability was estimated and found to be very significant.

- For the treatment of independent process parameters variations for example, atmospheric temperature variations, APSRA$^+$ methodology suggest to rely on developing the time series models such as ARIMA and then use these models for generating synthetic data which can be used for uncertainty propagation. In this regard, the following developments were made in this thesis:

— In this framework, the methodology for fitting Auto-regressive integrated moving average (ARIMA) model to the independent process parameter was developed. With the help of this fitted ARIMA model, the data were synthesized.

— As an illustration to the methodology of model fitting and synthetic data generation, a time series of monthly-maximum atmospheric temperature of district Chittaurgarh (Rajasthan, India) was considered. With the help of methodology, a non-contiguous ARIMA model of

AR (1,3,6,9,12), MA(1,3,6,9,12) was found to represent the differenced (at lags 12) stationary series of monthly-maximum atmospheric temperature. A synthetic series of length 1224 months have been generated based on the finalized ARIMA model.

— The model could provide an accurate way for the treatment of dynamic variation of independent process parameter and was found to be significantly different from that conceived by using a pdf as in existing methods.

- To address the issues associated with the treatment of model uncertainties, first an exhaustive literature survey has been performed to identify the uncertainties in the models which are generally used in the best estimate system codes to simulate the passive system behavior. Then these uncertainties associated with various models are propagated by modifying the corresponding model parameters in the best estimate system codes while performing the performance and failure analysis of passive system.

- $APSRA^+$ has been applied to passive isolation condenser system (ICS) of Indian advanced reactor: Advanced Heavy Water Reactor (AHWR). Failure probability of ICS with respect to the reactor years has been estimated, which is of the order 1×10^{-10}. It has to be noted that the failure probability of ICS was earlier estimated to be of the order of 3.703E-07 using APSRA methodology. The failure probability of ICS obtained using APSRA methodology were found to be very conservative when compared with the failure probability obtained from APSRA$^+$. The large differences in the estimated probability is mainly because, in APSRA$^+$ the dynamic failure characteristics of components is considered while estimating the probability of variations of process parameters.

FUTURE SCOPE OF WORKS

- Performing experiments to assess the variation of process parameters from its nominal values and generating the databases for functional failure of vital components of passive systems.
- Assessment and implementation of dynamic event tree methodology for integrating the passive system reliability into the plant specific PSA.
- Validation of system failure probability through functional and system level testing.
- Implementation of advanced sampling techniques (variance reduction samplings) while performing Monte Carlo simulations.
- Advanced sensitivity analysis to identify the important parameters can be implemented to augment the APSRA$^+$ methodology.
- The confidence bounds on cumulative failure estimates of system were estimated by propagating the uncertainties of empirical models used to simulate the passive system. The methodology of computing the confidence bounds on system reliability can be further improved by using statistical confidence bounds.

- The methodology of modeling the independent process parameter of the passive system could be implemented to a real world system to understand the potentials and pitfalls of methodology.

APPENDIX – A

Data for the period of Year 1901 – 2002

Location: Chittaurgarh, Rajasthan, India,

Sampling frequency - Monthly

Table A.1 Time series of monthly maximum atmospheric temperature in ℃

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1901	23.74	25.85	33.54	37.23	40.39	38.79	33.36	29.58	32.35	35.18	29.99	27.22
1902	26.57	28.62	35.39	38.59	39.92	37.50	33.14	31.32	31.32	33.37	28.98	25.53
1903	25.27	26.36	31.05	35.93	39.22	38.67	33.04	29.90	31.38	33.20	27.48	24.94
1904	25.21	27.62	31.78	38.23	39.78	36.47	31.05	29.65	31.98	33.64	29.28	26.16
1905	23.89	23.17	30.46	35.28	41.47	37.82	31.91	30.82	32.34	34.18	30.80	26.28
1906	23.70	25.48	31.77	37.05	40.90	36.56	31.53	30.33	30.58	33.08	30.01	26.33
1907	26.33	26.71	31.65	35.97	38.12	37.55	34.12	28.58	30.90	33.79	30.20	24.97
1908	24.88	27.08	31.58	37.86	39.36	37.29	30.21	28.72	30.60	32.68	28.86	24.94
1909	24.83	27.10	33.65	35.96	38.79	36.41	30.57	28.66	30.19	32.66	29.43	25.15
1910	24.75	27.68	32.73	36.12	39.16	35.53	30.42	29.41	31.20	31.87	27.54	25.70
1911	26.50	27.66	30.84	36.64	40.46	36.08	33.12	30.67	31.02	34.11	28.69	27.09
1912	26.39	29.29	32.25	37.60	40.32	38.46	31.98	29.18	30.50	33.13	28.22	25.66
1913	25.25	27.60	30.92	38.38	38.80	36.13	31.49	29.29	31.53	34.42	29.74	26.01
1914	27.15	27.20	31.97	37.39	40.80	36.36	31.34	29.76	32.02	33.60	30.63	25.48
1915	25.22	26.21	33.21	36.96	40.50	38.80	33.83	30.78	33.79	34.79	30.06	26.60
1916	26.21	26.59	34.88	38.20	39.78	35.39	32.81	29.59	31.62	32.27	27.58	25.14
1917	26.20	27.73	32.50	35.23	37.27	35.19	30.26	29.13	30.28	31.34	27.46	25.52
1918	23.82	28.15	32.48	35.44	40.06	36.12	32.88	30.54	31.48	33.97	30.52	25.20
1919	25.69	27.27	33.25	36.63	39.50	36.96	31.14	29.31	30.85	32.82	29.69	25.50
1920	25.69	27.11	33.42	36.70	36.73	35.48	30.51	29.18	32.69	34.52	30.44	26.36
1921	25.92	27.68	35.09	39.02	40.32	37.54	33.53	29.60	30.48	33.06	29.12	27.35
1922	24.62	29.19	33.68	38.07	39.61	36.75	31.64	29.48	30.72	32.88	29.02	25.22
1923	25.59	26.71	33.66	37.36	38.85	38.50	31.74	28.61	31.51	32.72	28.75	26.54

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1924	25.04	28.16	34.85	38.20	38.27	37.72	32.19	29.86	30.59	31.78	27.60	25.77
1925	23.00	25.71	33.64	39.29	38.97	35.12	30.59	30.75	32.88	35.37	29.96	26.37
1926	26.11	30.04	32.50	34.72	38.66	39.18	32.30	29.71	30.82	32.93	27.59	25.16
1927	23.63	25.99	31.52	36.50	38.80	37.09	31.04	28.60	30.84	32.94	27.12	26.15
1928	24.93	27.78	33.08	36.99	39.75	36.78	31.45	29.53	30.84	33.20	29.62	25.01
1929	24.24	26.38	34.45	37.61	39.93	36.83	31.17	29.04	31.57	33.05	30.27	24.71
1930	25.14	26.97	33.43	36.59	39.37	37.07	30.44	29.30	32.93	34.60	28.62	26.52
1931	26.90	26.52	32.41	38.48	39.95	38.69	32.42	29.67	31.22	32.45	28.96	26.28
1932	27.89	27.03	32.85	36.64	39.38	37.23	31.69	29.45	32.09	34.25	28.44	26.40
1933	24.63	28.04	32.95	36.23	37.62	35.99	31.34	28.61	30.43	32.55	29.16	25.82
1934	23.48	28.85	32.04	37.36	39.24	37.08	31.03	29.11	30.32	32.23	28.62	26.54
1935	23.15	27.65	32.35	34.61	39.62	37.66	30.85	29.15	30.56	32.49	29.47	26.07
1936	24.10	27.75	32.10	36.35	40.76	35.19	31.26	29.66	31.37	33.59	29.44	25.36
1937	24.22	28.26	31.41	36.63	39.50	37.55	30.58	29.70	31.51	32.84	30.08	24.70
1938	25.40	25.98	34.51	37.96	39.95	34.32	31.04	30.05	32.56	34.14	28.12	26.22
1939	26.35	27.83	30.64	35.65	39.14	36.34	31.67	31.30	31.37	34.11	29.35	26.52
1940	25.95	27.89	31.08	36.26	40.11	36.92	31.75	29.15	31.29	33.63	29.70	25.57
1941	24.63	28.55	34.42	38.41	39.99	37.42	31.69	30.05	32.45	35.67	30.16	27.55
1942	23.95	28.14	34.19	38.92	39.76	38.23	30.14	28.76	30.57	33.12	29.30	24.63
1943	25.07	27.61	33.69	36.68	40.23	36.05	30.57	28.79	30.84	32.76	29.91	26.45
1944	24.71	27.01	32.02	36.29	39.62	36.00	30.14	28.79	31.29	31.98	29.16	26.74
1945	23.05	26.88	33.49	36.18	38.72	37.01	30.15	29.52	30.53	32.20	28.36	24.24
1946	25.22	29.07	32.23	38.82	39.36	36.21	30.92	28.48	30.80	33.56	27.51	25.85
1947	23.94	27.41	33.61	37.24	40.14	37.88	31.82	30.28	30.25	31.90	29.62	26.23
1948	24.68	26.89	32.93	38.44	41.06	37.49	32.09	29.49	30.92	34.16	29.07	26.15
1949	27.24	27.92	33.69	38.76	41.14	36.81	31.70	30.26	31.92	33.58	28.44	25.34
1950	26.25	25.50	32.13	36.36	39.68	37.18	30.58	29.35	30.79	33.03	27.87	24.63
1951	24.10	26.90	32.80	35.50	39.31	36.27	33.05	29.87	33.59	36.39	31.11	25.93
1952	26.60	29.38	33.06	38.59	40.90	36.14	30.88	28.76	31.94	34.04	29.59	26.54
1953	24.80	30.01	35.36	37.69	39.69	37.31	32.10	29.51	31.66	33.19	29.41	28.15
1954	24.92	29.11	33.47	37.96	40.88	37.75	31.68	30.59	30.19	31.34	29.59	25.80
1955	25.36	28.05	35.18	35.49	39.10	36.81	32.44	29.43	30.64	31.89	27.79	25.93
1956	25.35	27.32	33.79	37.33	40.45	36.11	29.58	28.83	31.23	31.28	27.88	26.16
1957	24.46	26.06	31.60	36.51	38.33	37.58	31.72	30.29	31.31	33.68	31.34	26.65
1958	26.93	28.19	34.22	39.05	40.11	37.92	30.63	30.65	30.14	32.45	30.31	27.11
1959	25.24	27.34	34.61	37.61	39.60	37.01	30.44	28.84	30.42	33.01	29.26	26.59

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1960	24.38	29.79	32.06	36.23	38.92	36.96	32.03	28.51	32.03	32.81	28.67	26.28
1961	24.27	25.45	33.56	36.70	39.58	36.24	31.12	29.89	30.03	31.78	29.26	24.74
1962	23.90	28.26	33.14	37.15	38.58	36.16	30.58	28.59	29.48	31.04	28.49	26.68
1963	25.75	30.26	33.73	37.42	39.56	37.25	32.51	28.72	31.03	33.53	31.56	27.06
1964	24.13	28.02	34.64	39.39	39.12	35.29	30.89	29.72	31.29	33.79	28.81	26.00
1965	27.35	28.65	33.21	36.90	39.20	37.91	31.99	30.63	31.40	34.68	31.40	26.46
1966	26.68	31.17	33.24	37.78	39.91	36.71	32.87	29.13	30.83	34.21	30.39	25.72
1967	23.49	29.74	31.85	35.83	38.44	35.71	31.05	28.02	29.42	32.35	30.17	27.24
1968	24.67	26.29	32.96	36.87	38.14	38.14	31.58	28.52	32.83	33.06	29.76	26.16
1969	25.26	28.33	35.64	37.51	38.81	37.40	31.84	29.20	31.58	34.34	31.52	27.23
1970	26.15	27.43	32.72	38.25	40.48	35.70	31.91	29.54	30.31	33.67	28.86	26.10
1971	24.45	27.56	32.58	38.33	38.14	34.49	29.24	29.02	31.11	32.21	29.22	25.85
1972	25.61	25.47	34.29	36.35	39.26	37.40	32.35	30.63	31.06	33.37	29.94	26.72
1973	24.45	28.84	33.01	39.14	40.36	36.44	30.58	28.95	30.06	33.02	29.31	25.99
1974	24.20	26.53	35.04	38.04	39.91	36.64	32.22	30.64	33.17	33.27	29.00	25.28
1975	24.88	26.96	30.81	36.82	40.51	36.10	30.08	29.49	29.99	32.60	28.18	26.52
1976	26.06	27.99	33.55	36.53	39.13	35.43	31.48	28.92	30.05	33.79	31.69	26.67
1977	24.80	29.35	35.51	37.65	39.00	36.05	29.99	28.75	30.19	34.32	31.21	29.17
1978	24.89	26.64	30.91	36.48	40.34	35.35	29.58	28.40	30.62	33.48	30.95	24.92
1979	26.22	26.19	31.30	37.87	37.32	37.22	31.74	29.52	32.80	34.61	30.89	26.84
1980	25.88	30.06	32.75	38.61	40.69	35.67	31.48	30.18	32.34	35.11	31.02	25.28
1981	25.59	29.11	32.62	38.49	40.00	37.80	31.13	29.07	32.17	34.05	28.32	25.13
1982	25.69	26.17	30.59	35.84	36.90	37.53	32.86	29.44	32.57	34.75	29.33	27.62
1983	24.96	26.59	32.52	34.52	38.64	36.83	32.12	29.96	31.65	32.36	28.44	26.24
1984	24.52	24.80	34.83	38.80	41.12	36.82	31.50	28.40	30.29	33.24	29.39	26.55
1985	24.95	29.33	35.56	37.80	40.30	37.29	31.67	28.88	31.79	31.71	30.41	28.75
1986	25.43	27.25	33.21	38.24	39.14	37.21	30.84	28.96	32.76	34.11	31.19	25.86
1987	26.40	29.17	34.11	38.30	37.79	37.52	33.39	31.92	33.71	34.90	31.36	27.22
1988	26.58	29.77	33.45	38.71	41.31	36.90	30.59	29.82	32.37	33.68	30.05	27.41
1989	24.64	27.75	32.72	37.24	40.13	35.80	31.20	28.74	32.47	34.04	31.42	26.76
1990	27.81	27.63	32.08	37.70	39.44	36.79	30.39	29.74	30.71	33.10	30.73	26.63
1991	24.57	28.33	33.59	36.73	37.51	38.29	32.30	29.38	31.41	33.49	29.74	27.06
1992	26.50	26.83	33.23	37.05	39.01	38.83	32.78	29.43	30.42	32.80	29.47	27.56
1993	26.56	29.17	32.21	37.28	40.42	37.05	31.16	30.58	30.98	34.46	31.07	27.73
1994	26.75	27.54	34.94	36.92	40.81	36.18	29.89	29.17	30.61	33.23	30.19	26.96
1995	24.44	28.19	31.82	37.04	39.83	39.71	31.98	29.62	32.12	35.15	30.29	27.60

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1996	25.95	28.87	35.14	37.83	39.73	37.55	31.96	28.60	31.16	33.21	29.99	26.83
1997	25.02	27.86	33.55	35.94	37.63	35.60	31.66	29.65	31.60	31.72	30.40	25.37
1998	25.50	28.25	32.33	38.33	41.05	37.90	31.83	31.24	32.04	34.79	30.71	27.82
1999	25.07	28.81	33.85	39.50	40.04	36.36	31.53	30.03	31.73	33.43	30.96	26.56
2000	26.62	26.70	32.93	39.58	39.19	37.08	30.90	30.81	32.24	34.57	31.75	28.03
2001	25.31	28.48	33.70	37.39	39.11	34.60	29.85	30.19	33.33	34.52	30.85	27.70
2002	25.30	27.60	33.98	39.30	41.05	37.45	33.19	29.89	32.48	34.57	31.32	28.99