Official Transcript of Proceedings ACRST-3335

NUCLEAR REGULATORY COMMISSION

ORIGINAL

Title: Advisory Committee on Reactor Safeguards Human Factors and Reliability & Probabilistic Risk Assessment Subcommittees Meeting

Docket Number: (not applicable)

PROCESS USING ADAMS
TEMPLATE: ACRS/ACNW-005

Location: Rockville, Maryland

Date: Friday, December 16, 2005

Work Order No.: NRC-775

Pages 1-111

TR04

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UNITED STATES NUCLEAR REGULATORY COMMISSION'S

ADVISORY COMMITTEE ON REACTOR SAFEGUARDS

December 16, 2005

The contents of this transcript of the proceeding of the United States Nuclear Regulatory Commission Advisory Committee on Reactor Safeguards, taken on December 16, 2005, as reported herein, is a record of the discussions recorded at the meeting held on the above date.

This transcript has not been reviewed, corrected and edited and it may contain inaccuracies.

1 UNITED STATES OF AMERICA

2 NUCLEAR REGULATORY COMMISSION

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4 ADVISORY COMMITTEE ON REACTOR SAFEGUARDS (ACRS)

5 HUMAN FACTORS AND RELIABILITY & PROBABILISTIC RISK

6 ASSESSMENT SUBCOMMITTEE MEETING

7 + + + + +

8 FRIDAY,

9 DECEMBER 16, 2005

10 + + + + +

11 The meeting was convened in Room T-2B3 of

12 Two White Flint North, 11545 Rockville Pike,

13 Rockville, Maryland, at 8:30 a.m.

14 MEMBERS PRESENT:

15 GEORGE E. APOSTOLAKIS ACRS Member

16 MARIO V. BONACA ACRS Member

17 THOMAS S. KRESS ACRS Member

18

19 ACRS STAFF PRESENT:

20 ERIC A. THORNSBURY ACRS Staff

21 ALSO PRESENT:

22 ZOUHAIR ELAWAR

23 BRUCE HALLBERT

24 ALI MOSLEH

25 ERASMIA LOIS

A-G-E-N-D-A

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ALI MOSLEH, UMD 33

Halden Experiments,

A. BYE, HRP

1 P-R-O-C-E-E-D-I-N-G-S

2 8:28 a.m.

3 CHAIRMAN APOSTOLAKIS: This is the second
4 day of the Advisory Committee on Reactor Safeguards,
5 Subcommittees on Human Factors and Reliability and
6 Probabilistic Risk Assessment. I'm George
7 Apostolakis, Chairman of the Reliability and
8 Probabilistic Risk Assessment Subcommittee.
9 Members in attendance are Mario Bonaca,
10 Chairman of the Human Factors Subcommittee, and Tom
11 Kress.
12 The purpose of this meeting is to review
13 the status of the Agency's current research and human
14 reliability analysis. The subcommittee will gather
15 information, analyze relevant issues and facts, and
16 formulate proposed positions and actions as
17 appropriate for deliberation by the full committee.
18 Eric Thornsbury is the Designated Federal
19 Official for this meeting.
20 The rules for participation in today's
21 meeting have been announced as part of the notice of
22 this meeting previously published in the Federal
23 Register on November 28, 2005.
24 A transcript of the meeting is being kept
25 and will be made available as stated in the Federal

1 Register notice. It is requested that speakers first
2 identify themselves and speak with sufficient clarity
3 and volume so that they can be readily heard.
4 We have received no written comments or
5 requests for time to make oral statements from members
6 of the public regarding today's meeting.
7 We will now proceed with the meeting, and
8 I call upon Mr. Bruce Hallbert to begin the
9 presentations.
10 DR. LOIS: I would like to start out the
11 meeting.
12 CHAIRMAN APOSTOLAKIS: Okay, Dr. Lois.
13 DR. LOIS: I just want to note that Dr.
14 Mosleh is here representing himself. He has a long-
15 time interest in the area of human reliability and the
16 use of Bayesian frameworks for improving the human
17 reliability technology, and he offered to address the
18 committee. However, he's not in any capacity --
19 contracted capacity for the NRC.
20 And, with that, I will ask Dr. Hallbert to
21 start the discussion on HERA database development, and
22 then pursue the discussion on Bayesian frameworks.
23 DR. HALLBERT: Thank you, Dr. Lois.
24 We are happy to be here this morning to
25 talk about two activities that we're conducting for

1 the Nuclear Regulatory Commission.

2 One is the development of the Human Event

3 Repository and Analysis Database, HERA database, and

4 I'm going to provide you with some information about

5 the project status, what's going on, and sort of

6 refamiliarize members of the ACRS and the other people

7 who are here today with what HERA is, and what we are

8 hoping to do with HERA to support human reliability

9 analysis.

10 And secondly, I'm going to provide a short

11 introduction to, and a summary of, a workshop that we

12 had related to the use of Bayesian methods for

13 employing information, such as information in HERA, to

14 support human reliability analysis.

15 As always, our purpose for being here is

16 not only to tell you about what we are doing, but also

17 to get feedback from you on where you think areas of

18 our research are practical within the field of PRA and

19 what areas you'd like to make recommendations on.

20 The background for the HERA project is, to

21 some extent, similar to the current state of the art

22 in human reliability. HRA methods use structured

23 processes to identify the kinds of situations that are

24 likely to produce errors, and the ways in which errors

25 occur.

1 Most of the methods direct analysts to try
2 to account for variously termed elements of the
3 environment, whether you call it context, PIFs, PSFs,
4 whatever. They are a way to say that we know that
5 human performance is causally connected to variables
6 that are internal to the human and external within the
7 environment and in the work setting.
8 Identifying these things is somewhat
9 challenging, because from person to person, or context
10 to context, or accident scenario to scenario, the
11 influence of these things varies, and even the factors
12 that contribute to performance, they themselves vary.
13 So, accounting for these things is
14 important, yet is somewhat difficult. As a result,
15 there's a lot of analyst judgment that's applied in
16 the process.
17 The concern is that differences employed
18 in the judgment process can materially affect the risk
19 methods that are produced by the HRA process.
20 The objective of the HERA project is to
21 collect data and information about human performance
22 in PRA relevant settings. The approach has been, and
23 we briefed the ACRS on this a couple of years ago in
24 April, and the approach is still the same, to identify
25 information sources that could be used and that are

1 PRA relevant, develop a formal process for taking
2 information from those relevant settings and putting
3 it into a database, and in parallel, the new thing
4 that we've been doing over the course of the last year
5 or so is developing approaches to use the information
6 that we're collecting in a quantitative framework.
7 The approach to extracting information is
8 based upon this layered model that I'm showing here.
9 At the bottom here, we talk about very objective
10 information, and this model is especially relevant to
11 the activities that we are conducting where we are
12 extracting human performance information from
13 operating events, LERs and things like that.
14 We look at the information source and we
15 identify, you know, specifically, what happened, when
16 it happened, where it happened, what the consequence
17 of this occurrence was, and in looking into it, where
18 human performance comes into play, we identify
19 instances where human performance was successful, and
20 instances where it was not successful, in terms of its
21 intended consequences.
22 CHAIRMAN APOSTOLAKIS: So, you are
23 including successes?
24 DR. HALLBERT: Yes, absolutely.
25 CHAIRMAN APOSTOLAKIS: How do you get

1 those? Operators do things all the time.

2 DR. HALLBERT: Yeah.

3 CHAIRMAN APOSTOLAKIS: They don't submit

4 LERs for those things, so unless there's something,

5 you know, going on, and they are successful, is that

6 the space?

7 DR. HALLBERT: Well, the space, the space

8 of our analysis is in LER, at least for this portion

9 that I'm presenting to you now. There's other sources

10 of information that we are looking at as well, too,

11 where it will be slightly different. But, the source -

12 - but the frame of reference for this is in LER.

13 Within every LER, there are things that

14 were done right and there are some things that were

15 not done as well, or things that went awry, and we

16 capture all those things.

17 DR. LOIS: This is Erasmia.

18 Therefore, we are to capturing the success

19 in terms of number of opportunities versus number of

20 failures. We are not saying that so many times the

21 operators or the maintenance groups are out there and

22 basing this specific involvement on this specific

23 valve. It's not that the concept is to -- when we

24 have an event, we analyze what went wrong, and then

25 how they recovered from that event and did not evolve

1 into a more serious event.

2 CHAIRMAN APOSTOLAKIS: So, you already have

3 something going on if you operate your site correctly,

4 like what they did at Brown's Ferry with the -- source

5 of water that they were not supposed to use.

6 DR. HALLBERT: That's right.

7 CHAIRMAN APOSTOLAKIS: But, not routine

8 operation.

9 DR. HALLBERT: No.

10 The setting for this analysis is really in

11 the context of an LER report, so it implies that

12 something didn't go right.

13 CHAIRMAN APOSTOLAKIS: That's very

14 interesting, because usually we focus on failures, and

15 looking at some successes is probably a good idea.

16 DR. HALLBERT: Well, we have to, because,

17 you know, -- well, at least we believe we have to,

18 because, you know, what differentiates success and

19 failure sometimes in certain environments is a very

20 small margin, and sometimes, you know, the context is

21 the same for success as well as failure. And, we are

22 trying to collect evidence of both kinds.

23 CHAIRMAN APOSTOLAKIS: Good. Good.

24 DR. HALLBERT: Yes.

25 CHAIRMAN APOSTOLAKIS: Now, why is the

1 triangle going like that? I mean, what does it mean,
2 the dependencies of the -- there?
3 DR. HALLBERT: Well, what we are trying to
4 show is that, you know, at the beginning, and this is
5 sort of a time flow as well too, at the beginning of
6 the analysis there's a lot of information to be
7 extracted, and that as we go through sequentially and
8 extract more information about human performance, we
9 eventually get to the point where we think we've
10 extracted -- we've extracted all the information
11 that's available to us about the factors that
12 influence behavior in that context. That's all the
13 pyramid really represents.
14 CHAIRMAN APOSTOLAKIS: Remind us what error
15 mechanisms and error types are.
16 DR. HALLBERT: Okay.
17 Well, we started at the lower level here
18 on the diagram, and we are dealing with objective,
19 almost demographic information, what happened, where
20 it happened, and I'll show you an example of this in
21 a few minutes.
22 The next thing we look at is, we try to
23 identify what went right and what went wrong, and that
24 starts to get into judgmental processes. Okay,
25 somebody didn't do something right. You know, we have

1 to have some criterion for making that decision.

2 Beyond that, we try to understand what

3 influenced their performance, so that either they did

4 something well or they didn't do it well.

5 In the case of an error, you know, we

6 would call those error mechanisms. So, if somebody

7 was out, and I'll give you an illustration in a few

8 minutes, if somebody was out applying, you know, a

9 piece of equipment to another piece of equipment, and

10 set it up incorrectly, and detected that, okay, you've

11 made a mistake, now can you recover from that?

12 If they stop and they formally analyze it

13 and figure out the best way to approach, then they

14 might do it correctly, but if they don't, if they just

15 reflexively try to take it off the device, it might

16 cause the device to trip. And then you have an error.

17 CHAIRMAN APOSTOLAKIS: As you know in

18 literature, the psychology literature, human failure,

19 the words mechanism and types means something

20 specific. That's not what you mean. Error types, you

21 know --

22 DR. HALLBERT: Phenotypes, or whatever --

23 CHAIRMAN APOSTOLAKIS: You don't mean that.

24 DR. HALLBERT: No, I don't.

25 CHAIRMAN APOSTOLAKIS: And, mechanisms you

1 don't mean that either, because mechanisms I think
2 really go into the minds of people.
3 DR. HALLBERT: Sort of the causes.
4 CHAIRMAN APOSTOLAKIS: Yeah, it's just the
5 causes.
6 DR. HALLBERT: What triggered behavior in
7 that particular context.
8 CHAIRMAN APOSTOLAKIS: And, maybe you can
9 put error/success.
10 DR. HALLBERT: Yes.
11 CHAIRMAN APOSTOLAKIS: Since you are
12 looking at successes too.
13 DR. HALLBERT: Yes. Okay.
14 I'm going to give you sort of a short
15 description here of the information that's in HERA,
16 and by the way I think, and correct me if I'm wrong
17 here, Erismia, but I believe that you have a copy of
18 the HERA draft NUREG?
19 DR. LOIS: Yes.
20 DR. HALLBERT: Okay.
21 CHAIRMAN APOSTOLAKIS: The NUREG? We have
22 a bunch of slides.
23 DR. LOIS: You should have received a draft
24 report on HERA.
25 CHAIRMAN APOSTOLAKIS: Let me see, Bayesian

1 Methods Workshop.

2 DR. HALLBERT: The one before that.

3 CHAIRMAN APOSTOLAKIS: The one before that,

4 yes.

5 DR. HALLBERT: Yeah, I believe in Appendix

6 B of that report there is a detailed summary and

7 description of the data fields in HERA. So, what I'm

8 going to do here is just describe some of these

9 things.

10 There's two main sections of a HERA -- of

11 an event that's coded in HERA. The front part is what

12 we refer to as the event main profile, and it includes

13 some of that, you know, factual demographic

14 information that we pull off of the LER, the name of

15 the plant, the LER, the event type, which involves

16 whether it was an initiating event or whether the

17 event resulted in either an active or a latent

18 condition, and I'll describe those in just -- the next

19 slide, I believe, and plant mode, power levels,

20 losses, and system unavailabilities as a consequence

21 of the event.

22 Initiating events, we are using the same

23 terminology for initiating events as are used in PRA

24 and elsewhere within the Agency, conditions that lead

25 to shutting down, new products processes, and they

1 include the same types of initiating events that are
2 commonly used in PRA.
3 Conditions, not every event results in an
4 initiating event, or every LER results in an
5 initiating event. Some produce conditions, and these
6 are, basically, undesired outcomes. They don't
7 require shutting down the reactor or removing decay
8 heat, but they result in some sort of an off-normal
9 condition, and there's two kinds that we look for.
10 One is an active condition, and that is where somebody
11 does something and the effects of their performance
12 are immediately observed. They do something,
13 something trips, that's an example, or something
14 becomes unavailable, and it's clear it's unavailable.
15 A latent condition is something where
16 somebody performs an action, or a series of actions,
17 and a system is rendered inoperable or unavailable,
18 but it is undemanded. And so, the condition may lay
19 dormant for some period of time before its effects are
20 observed
21 CHAIRMAN APOSTOLAKIS: Some of the latent
22 conditions are very difficult to find, though, right,
23 if there is an error in the procedure?
24 DR. HALLBERT: Well, an error in a
25 procedure is not a latent condition that we would be

1 -- we would be looking for a latent condition that
2 would be reported in an LER, like an emergency diesel
3 generator was determined to be inoperable six months
4 after some maintenance was conducted on it, and it was
5 later determined that that maintenance rendered it
6 inoperable. That would be a latent condition. The
7 fact that the emergency diesel generator would not
8 function, but was not detected to be inoperable is a
9 latent condition. It would also be an LER.
10 CHAIRMAN APOSTOLAKIS: Well, that's --
11 DR. HALLBERT: Yes, but it would also be
12 reported under the LER rule, most probably.
13 CHAIRMAN APOSTOLAKIS: Okay.
14 DR. HALLBERT: Okay.
15 Every time -- we typically break an event
16 down into constituent pieces, and there's some
17 subjectivity involved in this now. We've gone from
18 very objective description to now our own assessment
19 of what happened in what sequence of time, and how it
20 played out.
21 And, basically, there's a couple of things
22 we look for. We look for human actions, and the kinds
23 of human actions we look for are successful human
24 actions, as well as human errors, or human failure
25 events, as well as equipment actions. Sometimes

1 equipment fails, and sometimes it actuates in a way
2 that it should.
3 In addition, you see that we have these
4 designations for positive and negative, and, actually,
5 there's a typo on this slide here, it says positive
6 human action and negative human action, really, this
7 should be, you know, positive context and negative
8 context, and what we are talking about are conditions
9 that are either present or produced by equipment and
10 human actions.
11 We refer to these things as sub events, so
12 we'll decompose, if you will, an LER into a series of
13 sub events.
14 MR. BONACA: Could you give me an example
15 of the difference between human error and negative
16 human action?
17 DR. HALLBERT: Actually, it wouldn't be
18 negative human action, it would be negative context,
19 in fact, this is --
20 MR. BONACA: Okay, so --
21 DR. HALLBERT: This is a typo, it should
22 have said negative context or positive context. I'm
23 sorry. I just caught that. Yeah.
24 And, the wording up here also for many of
25 these things also corresponds to similar wording

1 conventions that are used in a PRA model, except for
2 pos and neg, that doesn't occur in a PRA model. So,
3 you can see, as we are going through and we are
4 decomposing a series of human and equipment actions we
5 are trying to render some information about the causes
6 and consequences that can also be related to a PRA
7 model of activities.
8 Dependency, we know that dependency
9 occurs, there have been a lot of discussions of
10 dependencies, and, indeed, one of the analyses that we
11 perform of human actions is to understand how series
12 in human behaviors influence one another, and whether,
13 in fact, there are dependency between actions, because
14 we are trying to, again, use this information as an
15 evidentiary basis to inform HRA methods and to inform
16 the treatment of human actions in PRAs. And, our
17 definitions of dependency come straight out of the
18 Good Practices NUREG. So again, we are building on --
19 and you'll see, if you've noticed already, much of
20 what we are doing here is building on work that's
21 already been performed and thoughts and ideas that
22 have been promoted by others. So, we are striving for
23 commonality in our thinking with HERA, that, you know,
24 meets and intersects with different HRA methods and
25 models.

1 For each human sub event, where human
2 performance is analyzed, we then go into more detailed
3 analysis of the human action itself. We look at,
4 first of all, you know, any cognitive components that
5 we can identify from the report, or from our knowledge
6 of the operation of that plant in the specific action,
7 and we look at the PSFs using the same -- most of the
8 same PSFs as are in this SPAR-H method, but we are
9 also adding a few more PSFs based upon the
10 recommendations of a peer review group.
11 We'll also look at the action portion of
12 the behavior and do the same thing. We'll identify
13 what kind of personnel were involved in the sub-event,
14 whether it was maintenance people, operations people,
15 engineering, management, supervisors, whoever, and
16 we'll look at contributory plant factors.
17 Contributory plant factors is, essentially, an
18 amalgamation of factors that represent context, and
19 the definition of contributory plant factors were
20 taken from research that was conducted by the Halden
21 Reactor Project, where they studied and worked on
22 defining context, if you will, for our purposes.
23 Contributory maintenance factors are those
24 things in, specifically, maintenance operations, that
25 are suspected to contribute to human performance.

1 As I mentioned, a lot of actions that we
2 analyzed will be successful human actions, because
3 it's just a fact that all these LERs have resulted in
4 successful termination of the events, whatever they
5 were. So, there are successful human actions as part
6 of most every analysis. And similarly, you know,
7 where there were errors we'll try to relate the error
8 to something like slips, lapses, mistakes, something
9 like that.
10 Every time an analyst goes through and
11 performs one of these analyses, and notes where PSFs
12 or conditions contributed to performance, we asked the
13 team to document their comments, in other words, how
14 did they arrive at that conclusion, because we know
15 that this is based upon judgment and expertise.
16 There's no clear criteria for these things yet, and,
17 in fact, this still is a research project. We are
18 trying to demonstrate the principles of doing this.
19 So, you know, we want to look back through
20 these things and judge for ourselves, you know, a year
21 later do we still agree with that assessment, would
22 somebody else make the same assessment?
23 And, here's an example. I said I'd give
24 you an example, here's one. The event is designated
25 and the LER from which it came is up on the top here.

1 Now, this kind of a time line is produced for every
2 LER that we analyze. Our system automatically
3 produces this, automatically now, and what it does is,
4 the way that we store the data, it extracts it and it
5 puts it up on a time line like this.
6 Now, time lines differ because sometimes
7 we don't know when some things occurred, especially
8 like latent errors and stuff, we just know that some
9 time in the past something happened.
10 Similarly, not all events will have this
11 fine of a detailed time line in terms of hours,
12 minutes and seconds on the bottom here, because we
13 simply don't have that information. In this event, we
14 do. What was happening was, at this particular plant
15 there was a positive activity that was going on, a
16 positive context. The operators were preparing to
17 perform a monthly surveillance of the Turbine
18 Protection System. Now, they had made their
19 notifications to the control room, they had gotten all
20 their work orders, it was an approved work package,
21 and it was properly done. There was nothing wrong.
22 So, they were doing things the right way. Things were
23 set up for success.
24 At some point, just after midnight, and
25 this is 12:16 in the morning, so it's just after

1 midnight, two auxiliary operators, non-licensed, went
2 out to work on the system, and one operator mistakenly
3 placed a lever actuating tool on the TRIP lever, not
4 the test lever. Okay, it's a simple mistake. Okay?
5 MR. BONACA: He did not actuate anything.
6 DR. HALLBERT: He just put it on, okay,
7 that's what's designated as XHE01, that is an error.
8 It's a mistake.
9 Now, something positive happened right
10 here, which is that the same operator realized that
11 the tool was on the wrong lever. He himself said, oh,
12 I've gone and put this on the wrong thing.
13 However, there was a second error that
14 occurred because he attempted to remove it from the
15 TRIP lever reflexively. He could have stopped and
16 thought about, what's the best way to do this, maybe
17 I should notify someone that this is a potential
18 problem. But, what he thought was, well, maybe I can
19 just fix it real quickly here. So, he attempted to
20 take it off himself, without analyzing how to best
21 handle that.
22 As a consequence, he rotated the lever
23 enough just so it caused a main turbine trip. Okay?
24 Now, there's a line between XHE01, XHE02,
25 this line on a HERA time line indicates dependency.

1 It means if you look -- if you now look in the HERA
2 record you'll see that we noted a dependency between
3 XHE01 and XHE02. If you want to know what that
4 dependency is, you just have to go and look it up.
5 One of the features that we're going to
6 have in the future, actually, is to have a dependency
7 table that prints out along with the time line.
8 So, there's an actuation here. There's a
9 main turbine trip, and because the reactor was above
10 30 percent the turbine trip caused an automatic
11 reactor trip, which should be an EQA01 not an EAQ01,
12 it's just a small typo.
13 CHAIRMAN APOSTOLAKIS: So, this is not to
14 scale, I mean, I see. The turbine trip occurred one,
15 what, 1/10th of a second?
16 DR. HALLBERT: Yeah, yeah, yeah, that's
17 right.
18 CHAIRMAN APOSTOLAKIS: Okay.
19 DR. HALLBERT: That's right.
20 CHAIRMAN APOSTOLAKIS: So, EAQ01 is really
21 very close to XHE02, huh?
22 DR. HALLBERT: Yes. This is cognitive
23 time.
24 CHAIRMAN APOSTOLAKIS: Very good.
25 DR. HALLBERT: Okay.

1 So, what happened then was, two successful
2 human actions then ensued. The main control room
3 entered into the emergency procedures of the plant,
4 and they stabilized the unit in Mode 3, and there's a
5 dependency here between the decision to enter into the
6 procedures and to successfully stabilize the plant
7 subsequently in Mode 3.
8 CHAIRMAN APOSTOLAKIS: Uh-huh.
9 DR. HALLBERT: So, that's an example of a
10 HERA time line.
11 And for everything on this time line here
12 there will be an entry in the HERA database.
13 CHAIRMAN APOSTOLAKIS: How many events like
14 this do you have, roughly, do you remember?
15 DR. HALLBERT: We have -- we have about 47
16 LERs and about 700 records in HERA right now, and that
17 was the next slide, George.
18 MR. BONACA: So, but you are adding LER,
19 there are many, many LERs.
20 DR. HALLBERT: Yes, yes, and, in fact, we
21 just received funding through continuing resolution
22 that we'll have to discuss with our project manager
23 what to do next.
24 CHAIRMAN APOSTOLAKIS: Do you -- project?
25 DR. LOIS: No, we don't have funding.

1 CHAIRMAN APOSTOLAKIS: Geez.

2 MR. BONACA: Now, the LERs are a particular

3 subset of events that happen at the plants.

4 DR. HALLBERT: Yes.

5 MR. BONACA: They have to have some

6 licensing significance. I can't remember exactly the

7 specifics.

8 DR. HALLBERT: They are threshold events.

9 MR. BONACA: That's right.

10 So, but, they have to be, you know, an

11 event that affects other tech specs or whatever.

12 DR. HALLBERT: Yes.

13 MR. BONACA: And, does that limit very much

14 the information you put in?

15 DR. HALLBERT: Well, it means we are

16 limited to just that one source presently.

17 MR. BONACA: I was thinking about, you

18 know, INPO has --

19 CHAIRMAN APOSTOLAKIS: Yeah, the APEX.

20 MR. BONACA: -- the APEX system that you

21 wonder at some point if that would be a worthwhile as

22 a minimum sampling just to evaluate what kind of

23 information is not being, you know, provided, by the

24 LER system.

25 DR. HALLBERT: Uh-huh.

1 CHAIRMAN APOSTOLAKIS: You are also using
2 augmented inspection -- reports.
3 DR. HALLBERT: Yes.
4 CHAIRMAN APOSTOLAKIS: These are really
5 very detailed.
6 Question, isn't one LER giving you one
7 time line, so how can you have 700 data records, what
8 does that mean? If you have 45 LERs, why don't you
9 have 45 data records?
10 DR. HALLBERT: Well, what it means is that,
11 45 LERs, you know, if you divide 700 by 45 you find
12 the number -- the average number of sub events that
13 are coded per LER.
14 CHAIRMAN APOSTOLAKIS: But, the time line
15 included the sub events.
16 DR. HALLBERT: Yeah.
17 CHAIRMAN APOSTOLAKIS: So, by data records
18 you don't mean the time lines.
19 DR. HALLBERT: No, no, what --
20 CHAIRMAN APOSTOLAKIS: There are 45 time
21 lines.
22 DR. HALLBERT: -- there's 45 time lines.
23 CHAIRMAN APOSTOLAKIS: Okay, okay.
24 DR. HALLBERT: That's right.
25 CHAIRMAN APOSTOLAKIS: Yes, Erismia?

1 DR. LOIS: I just wanted to note that we
2 would like to load many data, but these activities are
3 really resource drive, because of the analysis that go
4 in, and we -- so far we were not able to load as many
5 events as we wanted.
6 The other issue that in actuality we are
7 still striving with quantifying the data the way it's
8 better, so as we are having meetings with our HRA
9 users we are changing the structure, if you wish, of
10 the database constantly, and we have to go back and
11 recode some of the data.
12 So, so far we are not still in -- we are
13 not in the production mode of the database yet.
14 DR. HALLBERT: That's true. This is
15 definitely a research project.
16 However, you know, my perspective, my
17 perspective on that is, is that, you know, we started
18 thinking about this a couple of years ago before this
19 project was really initiated formally by the NRC, and
20 we've done some thinking about it, and over time I
21 would say that the number of changes is gradually
22 reducing to the point where we are not conducting
23 major changes to our structures and definitions, but
24 we are really, you know, improving and refining the
25 information that's in it, I think.

1 Would you agree with that, Erismia?

2 DR. LOIS: Yes.

3 DR. HALLBERT: Okay, yeah.

4 CHAIRMAN APOSTOLAKIS: Okay.

5 DR. HALLBERT: Let me just mention also,
6 I'm not going to talk about this very much, but we
7 also have an arrangement with Halden, where Halden has
8 been going through some of their experiments, and you
9 heard about the experiments yesterday, and they sent
10 a visiting scientist to Idaho for six months for the
11 express purpose of working on the HERA structure for
12 encoding information from their experiments into the
13 HERA database, and so that is happening now.

14 CHAIRMAN APOSTOLAKIS: So now, this is on
15 top of the 45 LERs.

16 DR. HALLBERT: That's right.

17 CHAIRMAN APOSTOLAKIS: But, their events
18 are on the simulators.

19 DR. HALLBERT: That's right.

20 So, what we are probably going to do is
21 partition the database and have a portion of the
22 database that's from operating experience and a
23 portion of the database from simulators.

24 And, the other thing I was going to
25 mention is, we have currently one doctoral student,

1 and we are planning on a second doctoral student, and
2 that's partly why Professor Mosleh is here today, a
3 couple of doctoral students working on new approaches
4 for data generation and utilization. We have one
5 doctoral student at Vanderbilt, and she's working on
6 taking information from the psychological literature,
7 and focus on a particular topic, and trying to extract
8 information from that and make it, you know, into HERA
9 records.
10 MR. BONACA: My reason for asking the
11 question before is the fact that, let's take the
12 example where the operator is placing the lever on the
13 wrong component, okay, and then this results in a trip
14 now.
15 DR. HALLBERT: Uh-huh.
16 MR. BONACA: There are many events that are
17 planned to happen that are successful, in the sense
18 that he actually is able to remove the lever, nothing
19 happens, so the first error is occurring there, a
20 second one does not occur because it recovers from it,
21 so, therefore, there's not a reportable event. In
22 fact, the problem isn't -- it would be reported within
23 the plant. I mean, the plant will know.
24 DR. HALLBERT: Perhaps, yes, yes.
25 MR. BONACA: And, in most cases that will

1 be a condition that happened and was encoded, but is
2 successful.
3 So, my question is mostly, are there a lot
4 of successful actions that happen at the plant which
5 are not really listed or recognized into a repository
6 of this type, and, therefore, they are somewhat
7 biased, you know, ultimately, the views that you get
8 of how these events occur.
9 DR. HALLBERT: If you think about it that
10 way, then yes. I mean, we are only looking at, you
11 know, some portion of the iceberg that's above sea
12 level.
13 MR. BONACA: Yes.
14 DR. HALLBERT: There's a much larger
15 portion that we are not observing.
16 MR. BONACA: And, in the portion that ends
17 up with the negative events, I mean, they are
18 reportable.
19 DR. HALLBERT: Yeah, that's exactly right.
20 MR. BONACA: Okay.
21 DR. HALLBERT: But again, remember also
22 that PRA is focused on unreliability.
23 MR. BONACA: True.
24 DR. HALLBERT: And, we are concerned about
25 unreliability, specifically, of human performance in

1 these complex operational contexts. What we are
2 trying to learn from HERA is, you know, how people end
3 up in situations where they make mistakes that are of
4 significance, enough significance that they have to
5 report them, and as well, how people behave in those
6 situations and recover. Both pieces of information,
7 we think, are highly relevant to informing our
8 assessment of how to apply human reliability methods
9 and specific parameters that ought to be included in
10 human reliability methods.
11 So, this is sort of an empirical source of
12 information give that some failure events have
13 occurred. It doesn't give us everything, it's not a
14 great estimator of the number of opportunities for
15 success.
16 MR. BONACA: Okay.
17 DR. HALLBERT: Okay.
18 MEMBER KRESS: This setting of this lever
19 that started everything off is a relatively simple
20 thing to do, and if I were going to try to program
21 something in a PRA what I'd want to know is how often
22 that happens compared to how many of these simple
23 events occur during the year of a plant, or averaged
24 over its lifetime.
25 DR. HALLBERT: Yeah.

1 MEMBER KRESS: How do you get that
2 denominator?
3 DR. HALLBERT: We don't.
4 MEMBER KRESS: You don't get that
5 denominator?
6 DR. HALLBERT: We don't presently.
7 MEMBER KRESS: So, you can't really use
8 that particular part of the thing. It's what comes
9 after that that you have to use?
10 DR. HALLBERT: Not in a frequentist sort of
11 way, you know a frequentist approach would say, you
12 know, error probability is the number of errors
13 divided by number of opportunities. We don't have --
14 well, we are not currently estimating the number of
15 opportunities, although there have been some
16 approaches that have been used in PRA with equipment
17 to estimate, you know, estimate exposure in some way
18 or the other.
19 We talked a little bit about that. We
20 don't have anything yet to discuss about that, but we
21 have discussed it.
22 Rather, what we are proposing to do at
23 this time is to use Bayesian methods, to take evidence
24 and information that we do have, recognizing that it's
25 sparse, it's incomplete, and it may be partially in

1 some situations, and to employ that systematically so
2 that we can, you know, estimate the likelihood of
3 specific human actions, and that's what the rest of
4 the presentation relates to.
5 So, if you are ready, what I'm going to do
6 is I'm going to really breeze -- I think I've
7 explained already sort of what the intent of the
8 Bayesian activity is. We have data and observations
9 from a variety of sources, experience, research,
10 training, the literature, and at the same time we are
11 trying to make improvements about the kind of
12 predictions that we make of human actions in PRA-
13 relevant context.
14 And so, a number of us decided, with the
15 encouragement of our program manager, to get together
16 to share some ideas, to discuss some ideas, related to
17 how you would use information from a source like HERA
18 and apply it formally to PRA-type applications. So,
19 we had a workshop.
20 And, this morning, you know, time
21 permitting, and we are going to try to move through
22 these fairly quickly, we are going to talk about a
23 couple of things. The first one, Professor Mosleh is
24 going to give a very important introduction about, you
25 know, what exactly is it that we are making

1 predictions of in HRA? What's the quantity of
2 interest, and what do we know about the quantity of
3 interest, and how could we use information in
4 something of a Bayesian framework to do that?
5 I'm going to follow up with two
6 presentations, and I'll try to speed through these a
7 little bit. One is on using information from
8 simulator research, and how that can inform the
9 Bayesian process, and then Professor Mahadevan from
10 Vanderbilt University has been sponsored to do some
11 research and thinking on this project previously, and
12 I'm going to talk about his thoughts on how you could
13 use data from a source like HERA to estimate model
14 parameters from an HRA method.
15 So, with that, I'm going to turn this over
16 to Professor Mosleh.
17 DR. MOSLEH: Okay, good morning, Ali
18 Mosleh, University of Maryland, and following what
19 Bruce's introduction to the objectives of the
20 workshop, this effectively represents some of the
21 proposal's ideas that I presented at the workshop and
22 following the workshop in a couple of meetings with
23 other researchers in the discipline. And, the idea
24 was to see if there are things in the Bayesian
25 framework of probabilistic thinking that could be used

1 in the HRA field and the estimation of error
2 probabilities.
3 So, some of the material that I will
4 present are typical things that we have seen in the
5 past, some new material, and the key objective is to
6 relate the two, effectively.
7 We started by asking questions that you
8 would ask within the Bayesian framework broadly, that
9 we need to identify the quantity that we are trying to
10 estimate, so the unknown of interest as I call it.
11 You have some information about that from whatever
12 source or whatever type, it's just generally the
13 information that you have, that you would put in what
14 is known in a Bayesian framework as a prior
15 distribution of the unknown, and the additional
16 evidence that you have, so that's E. evidence
17 information. You gather this evidence based on some
18 assumption, some process of observing the evidence.
19 So, the model of the process that generates the
20 evidence is called a likelihood function, and then you
21 put all these things together through the Bayesian
22 inference to obtain the posterior combined state of
23 knowledge about the unknown of interest.
24 So, base theorem here is what we have
25 there. P is the quantity of interest we are

1 estimating, pi-zero is the prior distribution, the
2 likelihood function and the posterior distribution,
3 and base theorem.
4 So, given that, we started asking the
5 basic questions. What is the unknown of interest in
6 the HRA? And so, well, from a PRA perspective what
7 you are looking at the operator response objectively,
8 what is happening, and what kind of physical action
9 outcome is on the system. And, normally labeled as
10 success and failure using some reference point that is
11 model dependent.
12 And, particularly of interest in PRA is
13 the probability of action failure or error failure.
14 So, P is defined as such, and we have seen in the HRAs
15 and PRAs that people put the probability distribution
16 over that p, so pi of p is the probability
17 distribution of p, and the questions are why are we
18 uncertain about the action outcome. So, what is the
19 source of the uncertainty in that? Why a p between
20 zero and one, not zero and one, why is it not the kind
21 of a deterministic? And, what is the uncertainty
22 about p? You know, what are the sources of
23 uncertainty about p, and why are we uncertain? Okay.
24 Now, in form of reference I put a couple
25 of major frameworks that people have used in

1 estimating error probabilities, I call them blue model
2 and yellow model, and I'm sure you recognize what's
3 blue and what's yellow, that in the blue model you are
4 calculating the error probability, probability of
5 response as the condition of probability of error or
6 response given a particular condition or context, and
7 you multiply it by the probability of context, and you
8 sum over, so that's kind of a partition of the space
9 of possibility leading to a particular response.
10 The yellow model, which is the vast
11 majority of HRA models, you have a probability of
12 response directly as a function of something that kind
13 of characterizes the context and in form of
14 performance influence the factors of performance
15 safety factors. And, examples of the gap in this
16 function, function of relationship that we have, the
17 tabular form, such as in the CREAM methodology, you
18 have a table relating conditions, values, parameters,
19 to response probability, mathematical functions such
20 as the one that you see in the SLIM, which is an
21 exponential function, and expert judgment is,
22 essentially, the approach that is taken in ATHEANA.
23 So, these are different forms of the function relating
24 PIFs to response.
25 In an attempt trying to kind of describe

1 the meaning of p, by no means this is something that
2 is a consensus, just an idea it is, but trying to
3 clarify some of the elements that contribute to the p
4 being a number between zero and one, and then zero and
5 one, is we thought that maybe if you look at it the
6 following way, that given a very specific condition,
7 external or internal to the operator, cognitive or
8 physical, response is predictable as either success or
9 failure, make this assumption.
10 Now, one of the reasons that we have a
11 probability is that in reality we can only specify a
12 class of similar but not identical conditions, that
13 the level of modeling and specificity that we have
14 only reflect a class of conditions.
15 And, in that class some of those are
16 really deterministically leading to failure, some of
17 the are deterministically leading to success, and
18 depending on where you fall in the spectrum a fraction
19 of those that lead to success is 1 minus p, and the
20 other fraction p is the error, error probability. So,
21 it refers to the fraction of conditions that produce
22 the error versus success in a grouped -- you know, the
23 definition of a context.
24 So, p, therefore, is the product of
25 grouping a spectrum of conditions into one class. And

1 maybe an additional layer or contributor to the p
2 could be this kind of questioning the validity of the
3 first assumption, that the behavior is
4 deterministically determined given the condition, that
5 maybe that's not correct and there is still a residual
6 randomness in one behavior. So, that contributes to
7 p also.
8 CHAIRMAN APOSTOLAKIS: I don't know why you
9 say that. I mean, if you say that there is p, that
10 implies there is randomness, there is a probability
11 that it will do something wrong, but if you consider
12 many, many contexts like that, precisely because
13 there's a probability, sometimes it will fail,
14 sometimes it will succeed. I mean, the randomness is
15 there in what you call the outcome. I mean, the
16 random variable is the outcome, success/failure, then
17 you have a probability for that outcome, that
18 probability reflects the context. But, it is still a
19 probability.
20 DR. MOSLEH: Yes.
21 CHAIRMAN APOSTOLAKIS: So, every time you
22 have that context you are not guaranteed that there
23 will be success or failure, because it's a probability
24 that will go one way or the other.
25 So, this residual randomness is not clear

1 to me.

2 DR. MOSLEH: Well, it, effectively, means,

3 for instance, a specified condition, according to your

4 model and resolution of the model. You may still say

5 we do not fundamentally know whether people behave in

6 a predictable way, so you have --

7 CHAIRMAN APOSTOLAKIS: Well, that's what p

8 is, that it is not predictable.

9 DR. MOSLEH: -- no, but I think the kind

10 of unraveling is kind of peeling it off layer by

11 layer, so like we have specified a set of conditions

12 that there -- it kind of basically is the version

13 between the subset of those conditions that would lead

14 to success, some subset that would lead to failure,

15 and really don't know which ones are those within the

16 class of conditions that they have defined.

17 MEMBER KRESS: Would those conditions be a

18 combination of the performance shaping factors, for

19 example?

20 DR. MOSLEH: Yes, normally the performance

21 shaping factors are supposed to kind of characterize

22 such conditions, so, yes, yeah.

23 CHAIRMAN APOSTOLAKIS: Are you saying that

24 there is not a single p even if you have the

25 conditions, in other words that --

1 DR. MOSLEH: Yes.

2 CHAIRMAN APOSTOLAKIS: -- there is some --

3 DR. MOSLEH: Correct.

4 CHAIRMAN APOSTOLAKIS: -- group

5 variability or something like that?

6 DR. MOSLEH: I tried to separate that in

7 terms of uncertainty about p.

8 CHAIRMAN APOSTOLAKIS: Yeah, but there is

9 uncertainty about p --

10 DR. MOSLEH: Right.

11 CHAIRMAN APOSTOLAKIS: -- even though p

12 has a unique value.

13 DR. MOSLEH: Yes.

14 CHAIRMAN APOSTOLAKIS: Or you can say, p

15 itself does not have a unique value, because there is

16 some variability, okay, and then I'm uncertain about

17 the curve itself.

18 DR. MOSLEH: Right.

19 CHAIRMAN APOSTOLAKIS: So, this residual

20 randomness is not clear to me. You are saying that

21 even in a very specific condition the operator

22 response is predictable. Well, it's not.

23 DR. MOSLEH: No, that's an assumption. You

24 say, let's assume that --

25 CHAIRMAN APOSTOLAKIS: If you have a p,

1 it's not predictable, because, you know, it's a
2 probability. You may do right or wrong. So, that --
3 DR. MOSLEH: That assumption -- that is --
4 the fourth bullet is questioning that assumption, that
5 things re predictable.
6 CHAIRMAN APOSTOLAKIS: What I'm saying is
7 that, perhaps, it's not stated well. Given a very
8 specific condition, the operator response is not
9 predictable, it's always probabilistic.
10 DR. MOSLEH: Yes.
11 CHAIRMAN APOSTOLAKIS: But, given a
12 specific condition, we are making the assumption that
13 there is a probability of behavior, in a certain way,
14 that we can deal with, that we can do something about
15 on variability. But, the behavior itself is still
16 uncertain.
17 DR. MOSLEH: Perhaps, this points to more
18 like from a modeling perspective, whether some of
19 those conditions that lead to behavior randomness are
20 fundamentally identifiable.
21 CHAIRMAN APOSTOLAKIS: I think the first
22 bullet, Ali, you have to reword. It says, "Given a
23 condition the operator response is predictable
24 value," and then you give a p. So, obviously, it's
25 not predictable, because there is a p. I mean, it can

1 be ten to the minus three, but if they do it a
2 thousand times one time they will fail.
3 DR. MOSLEH: Are you referring to what I
4 say in the fourth bullet?
5 CHAIRMAN APOSTOLAKIS: The first bullet.
6 DR. MOSLEH: The first bullet says --
7 CHAIRMAN APOSTOLAKIS: Predictable is the
8 wrong word in my view.
9 DR. MOSLEH: Oh, no, no, but the first
10 bullet said, let's assume that this is the case, that
11 given well specific condition the behavior is
12 predictable.
13 CHAIRMAN APOSTOLAKIS: Oh, so the second
14 bullet modifies it.
15 DR. MOSLEH: Right.
16 DR. HALLBERT: Or, I think the first bullet
17 is saying, you know, given some condition, and a
18 demand on the operator, their behavior will be either,
19 you can classify it as either successful or
20 unsuccessful.
21 CHAIRMAN APOSTOLAKIS: Yeah, that's the
22 fundamental around the variable, but then you have a
23 model for that, which has a p in it.
24 DR. MOSLEH: And then you say, the reason
25 for that p is that you really can't identify that

1 specific very well-defined condition, therefore, we
2 attribute p to the variability of the condition.
3 CHAIRMAN APOSTOLAKIS: Variability of the
4 condition, plus we don't have enough evidence to say
5 that --
6 DR. MOSLEH: So, that's kind of basing --
7 the second bullet says the variability of the
8 condition, and the last bullet says, even then you may
9 say, well, we really don't know or we cannot really
10 predict in a deterministic way, given precisely
11 defined conditions. Therefore, there is --
12 CHAIRMAN APOSTOLAKIS: Well, your next
13 slide probably explains a little bit more.
14 DR. MOSLEH: So, if you are putting another
15 layer of uncertainty on p now, the value, then what
16 could be potential sources of that variability.
17 CHAIRMAN APOSTOLAKIS: So, am I to
18 interpret this that when we say context there is some
19 randomness within the context.
20 DR. MOSLEH: Right.
21 CHAIRMAN APOSTOLAKIS: Yesterday we saw
22 results from Halden that showed us that they had seven
23 crews responding to the same sequence, and there was
24 randomness in the response time, right? So, how would
25 I take those times then?

1 No, it's not the response time, the
2 response time does not define the context. The
3 response time is the outcome, where there was
4 something there that made one crew do the right thing
5 in five minutes, and another crew do it in 11 minutes.
6 So, it's this underlying cause that could be random,
7 right? We don't know what it is.
8 DR. HALLBERT: Well, in the case of Halden,
9 in the case of the Halden research, this is Bruce
10 Hallbert again, they were attributing the variability
11 in performance, to some extent, to the variables they
12 were manipulating.
13 However, as you started digging in deeper,
14 what you found was that they were crew-related
15 factors.
16 CHAIRMAN APOSTOLAKIS: Additional.
17 DR. HALLBERT: Right.
18 CHAIRMAN APOSTOLAKIS: And, I think what
19 Ali is trying to say, actually, he is saying, he is
20 not trying to say, he is saying, is that there is
21 variability that is not of the state of knowledge
22 type.
23 DR. HALLBERT: Right.
24 CHAIRMAN APOSTOLAKIS: There are some other
25 factors, like maybe the experience of the crew or

1 whatever, which -- anyway, I don't know where you are
2 going with this.
3 DR. MOSLEH: Okay, stochastic --
4 CHAIRMAN APOSTOLAKIS: What's PIF, by the
5 way, PIF is what?
6 DR. MOSLEH: Performance influency factors
7 of PSFs.
8 CHAIRMAN APOSTOLAKIS: Yeah.
9 DR. MOSLEH: So, you see, there is
10 stochastic variability in characterizing the condition
11 variability and time pressure and other conditions,
12 crew-to-crew characteristics variability, are the
13 types of things that one could kind of basically use
14 as a basis for varying p for the same class of
15 conditions.
16 CHAIRMAN APOSTOLAKIS: So, are you going to
17 the two-stage Bayesian here approach?
18 DR. MOSLEH: Yes.
19 CHAIRMAN APOSTOLAKIS: Okay. All right.
20 DR. MOSLEH: And then, the other thing is,
21 uncertainty of the values of specific PIFs, that could
22 be treated as -- PSFs, that could be treated as
23 parameter uncertainty. And, the model uncertainty,
24 whether you have the right set of PIFs, for instance,
25 the PSFs.

1 CHAIRMAN APOSTOLAKIS: And, how they
2 influence the behavior.
3 DR. MOSLEH: How they influence, right.
4 CHAIRMAN APOSTOLAKIS: So, all these
5 factors, the adjustment factors, the other report from
6 Idaho --
7 DR. MOSLEH: Yeah, all the structure.
8 CHAIRMAN APOSTOLAKIS: -- this is major
9 model uncertainty.
10 DR. MOSLEH: Yes.
11 So, some way, one way you are supposed to
12 cover that under pi of p, the variabilities and these
13 uncertainties. Okay.
14 Given that, we kind of made an attempt to
15 try to see what is it that we were estimating, and
16 where were the uncertainties go, I see three areas
17 where we could use Bayesian methods in HRA. One is in
18 development of generic reference HEPs, most vast
19 majority of HRA methods we use a reference number, a
20 set of reference numbers, whether they are judgmental
21 or based on experience, or otherwise, generic
22 reference values from different types and sources of
23 information.
24 And, so far this is still unavoidable
25 because of the questions that you raised earlier, the

1 success database doesn't exist, we don't have the
2 denominator. So, we still need to use some sort of
3 generic reference values.
4 Expanding and extending the data
5 classification, bringing the Bayesian kind of
6 philosophy into the data classification. Bruce showed
7 an example of how the events were divided into sub
8 events. All these involve judgment. Analysts need to
9 make judgments, assigning, defining PIF values,
10 connections, relations, all these are judgmental to a
11 large extent, based on the evidence that you have.
12 So, one area is really to bring the --
13 allow the analyst to record their level of subjective
14 judgment about different parameters or attributes of
15 an event, and also relax the requirement of quality
16 and quantity of data. So, if you don't have success
17 there that can be distribution of a success data, as
18 opposed to a precise point estimate.
19 So, these are departures from the
20 classical thinking, classical statistical thinking,
21 bringing a little bit of a Bayesian flavor into the
22 data collection and classification.
23 A third area is the exploration of the
24 role of causal factors. You have -- you record data
25 in HERA or other databases, and then you identify

1 PIFs, PSFs, you build some cause of connections,
2 relations between the error forcing or error
3 influencing factors and behavior, in construction of
4 such causal models one could see a role for Bayesian
5 methods, in particular, Bayesian Belief Network for
6 constructing causal models, and if you follow that
7 you've got use of evidence to update or estimate the
8 probabilities that you need in the Bayesian Belief
9 Networks.
10 These are the three top areas.
11 So, this probably is quite evident by now
12 that, obviously, the nature of the evidence in HRA
13 involves a lot of subjectivity. You have different
14 estimates, estimation forms, estimates based on data
15 from other situations, expert estimate, numbers that
16 are coming from other HRA methods, the non-homogeneity
17 of information source, different pieces from different
18 sources of information, and, obviously, the
19 incompleteness of data sets, whether the -- database
20 is, in fact, a failure-biased database.
21 Indirect or partially relevant
22 observations, when you observe behavior based on PIFs
23 as an indirect observation, partially relevant
24 information, when you are using, for instance, pilots
25 landing commercial airline data for space shuttle crew

1 landing space shuttles, it's evidence, but it's
2 partially relevant only.
3 Now, we go to the formalism of base
4 theorem Bayesian methods, you need to consider the
5 fact that in constructing the likelihood function that
6 relates the evidence to the estimate, the fact that
7 you have multiple types of information, you have the
8 issue of dependence among the different sources of
9 information, the issue of credibility of the data
10 sources, data from experts and models, the homogeneity
11 of the data points, the fact that you have multiple
12 conditions for which you might have estimate, and the
13 question is, how do we put all that together to
14 represent a development estimate for a particular
15 condition, applicability of sources of information to
16 the HEP human error if interest, and evidence
17 uncertainty, and then more, perhaps.
18 Step by step, again now, we are looking at
19 the techniques introduced, Bayesian techniques
20 introduced in other parts of PRA, and see which ones
21 would be useful in this case.
22 The question of using multiple sources of
23 multiple types of information is a simple one. In
24 fact, you can construct likelihood functions that
25 speak --

1 CHAIRMAN APOSTOLAKIS: -- conceptually.

2 DR. MOSLEH: Pardon?

3 CHAIRMAN APOSTOLAKIS: Simple conceptually.

4 DR. MOSLEH: Yes.

5 CHAIRMAN APOSTOLAKIS: Trying to do that

6 thing there in real life is not simple.

7 DR. MOSLEH: Yes, that's why you still need

8 experts on Bayesian methods.

9 CHAIRMAN APOSTOLAKIS: They have to make

10 assumptions on the second role of dependence, then it

11 becomes significantly simpler, but --

12 DR. MOSLEH: Absolutely right.

13 CHAIRMAN APOSTOLAKIS: -- boy, defending

14 the assumption is -- how many people do you think copy

15 other sources when they report human error

16 probabilities?

17 DR. HALLBERT: I'm sorry, can you repeat

18 that?

19 CHAIRMAN APOSTOLAKIS: I mean, there is a

20 number of methods out there, right?

21 DR. HALLBERT: Yes.

22 CHAIRMAN APOSTOLAKIS: Do you think these

23 methods are independent? I believe most of them are

24 caught in Swain and Gutman, or at least calibrating

25 what they are reporting using Swain and Gutman.

1 DR. MOSLEH: In fact, if you look at some
2 of the sections of the reports that talk about
3 evaluation of their method, evaluation means we looked
4 at PRA numbers that they provide.
5 DR. HALLBERT: Oh, and specifically, you
6 know, some methods have said, and, you know, we heard
7 from SPAR-H yesterday, one of the things that they did
8 in coming up with the base HEPs in the model was, they
9 looked to see -- they looked for conversions between
10 their numbers and what was prevalent out there.
11 And, I have heard other HRA people at
12 conferences say that they have, you know, validated
13 curve numbers. So, it is still a benchmark.
14 CHAIRMAN APOSTOLAKIS: Well, the fact, of
15 course, that they decided -- it depends who is doing
16 it, but if they decide to be influenced by Swain and
17 Gutman, maybe make some changes, is also useful
18 information, that means that they find what is in
19 Swain and Gutman reasonable estimates.
20 DR. MOSLEH: Partially relevant.
21 CHAIRMAN APOSTOLAKIS: You know, also with
22 the failure rates, it seems to me that there is
23 tremendous dependence to this day of the failure rates
24 on the Reactor Safety Study.
25 DR. HALLBERT: Yeah.

1 CHAIRMAN APOSTOLAKIS: I mean, they set the
2 standard, and then, you know, so the issue of
3 independence is a serious one.
4 But anyway, yeah, conceptually, this is --
5 DR. MOSLEH: Conceptually, that's the kind
6 of framework. So, if you have multiple sources of
7 information, depending on the type of information you
8 can construct the likelihood function for these
9 different types. So, that's, you know, the --
10 CHAIRMAN APOSTOLAKIS: And then you have a
11 student do the integral, the denominator, right?
12 DR. HALLBERT: Or, do it numerically. You
13 know, in Maha's presentation he did go ahead and, you
14 know, we'll talk about that, but, you know, he had to
15 do the denominator numerically through simulation.
16 CHAIRMAN APOSTOLAKIS: In very rare cases
17 it's analytical.
18 DR. MOSLEH: We now have algorithms that do
19 a 20 parameter base integration in a fraction of a
20 second, in a very precise way.
21 CHAIRMAN APOSTOLAKIS: I've always wanted
22 to do that in a fraction of a second.
23 Now, Ali, I don't know, do you want to
24 show these equations?
25 DR. MOSLEH: No.

1 CHAIRMAN APOSTOLAKIS: Okay.

2 DR. HALLBERT: Why don't you just do --

3 DR. MOSLEH: Well, in any case, I think

4 those are kind of ways of mapping the techniques to

5 the specific situation.

6 CHAIRMAN APOSTOLAKIS: Sure.

7 DR. MOSLEH: So, let me --

8 CHAIRMAN APOSTOLAKIS: The mechanics of

9 doing it is not of interest today. I mean, we believe

10 -- but the other stuff, how to do what, that's of

11 interest. In other words, to show an equation.

12 DR. MOSLEH: Well, one area that I

13 mentioned earlier, in terms of bringing -- capturing

14 the subjectivity of the analysis, the data analysis,

15 is what we are suggesting proposing that what we did

16 in the case of Common Cause failures could apply here,

17 there we took data, this is an example from Common

18 Cause, the event, the LER, where data is classified

19 different ways and the analysts put the weight or

20 level of confidence on each data record, and the two

21 Bayesian methods, you know, one can, basically, roll

22 up all that set of weights and subjectivity to the

23 level of estimation. So, there are formulas and

24 methods for doing that.

25 Another area, the issue of success data

1 not being available, it's a major issue, major problem
2 we need to wrestle with, and the fact that, again, we
3 can use estimates or ranges of values has helped, you
4 know, that the formalism allows us to be uncertain
5 about success, the amount of data.
6 Okay, so I mentioned the fact that we can
7 deal with uncertain evidence and data, there's more on
8 formalism, on how to do that, so these have been tried
9 and tested before.
10 CHAIRMAN APOSTOLAKIS: Wait, wait, wait,
11 come back. The first one there is exact numbers,
12 right?
13 DR. MOSLEH: Weighted posterior.
14 CHAIRMAN APOSTOLAKIS: The others are
15 approximate.
16 DR. MOSLEH: I can't say that. Actually,
17 we can show that the first two -- the third one is
18 definitely an approximate, it's just an ad hoc method.
19 The first two are both correct under different sets of
20 -- different interpretations of interpretation
21 evidence.
22 CHAIRMAN APOSTOLAKIS: I would say the
23 first one is the really accurate one. Maybe the
24 others, the second one gives reasonable results, too.
25 But, the first one really, because you say this is the

1 evidence, this is what my state of knowledge will be,
2 and I have three different kinds of evidence, so I'll
3 weigh the results and add them up.
4 DR. MOSLEH: Yes.
5 CHAIRMAN APOSTOLAKIS: But also in some
6 other cases, I think what you did with the outcome
7 model, even the last one, is --
8 DR. MOSLEH: Okay result, yeah, for the
9 value, right, yeah.
10 CHAIRMAN APOSTOLAKIS: -- and it's easier
11 to do.
12 DR. MOSLEH: Yes, it's a five-second
13 procedure.
14 CHAIRMAN APOSTOLAKIS: But, I think the
15 first one is really --
16 DR. MOSLEH: I published a paper showing
17 the relation between the first two theoretically, so
18 I think -- I believe that the two, both are correct on
19 their own set of conditions.
20 The third one is certainly an
21 approximation.
22 Okay, well, the issue of using partially
23 relevant information, you can go from standard base
24 theorem to a modified base theorem. This is a little
25 bit ad hoc, but still something that we have done in

1 the component failure probability -- you know, --
2 failure probability.
3 Let me talk a little bit about this part,
4 which I think kind of basically is a background and
5 lead to what Bruce will present. We mentioned the
6 possible role of Bayesian Belief Network in developing
7 and establishing causal connections, causal models, so
8 this slide shows the principles of Bayesian Belief
9 Network, for the record, basically. You are talking
10 about fuzzy, uncertain and less than a clear
11 connection between causes and effects. And,
12 therefore, you make probabilistic and non-
13 deterministic kind of statements about the causal
14 relations. That's, basically, the essence of what you
15 do in Bayesian Belief Networks, relating what we call
16 input nodes to output or target nodes to probability
17 relations.
18 And, you can capture dependencies in a
19 very, very formal way. In fact, initially, it was
20 invented, you know, to, basically, trace
21 interdependencies of the variables.
22 We have seen the beginning of, actually,
23 a few attempts in formally using BBNs in relating PIFs
24 to performance, so this schematically shows, you know,
25 that we can put the --

1 CHAIRMAN APOSTOLAKIS: How are the BBN
2 different from inference diagrams?
3 DR. MOSLEH: BBNs, I would say, are a sub
4 class of inference diagrams, that when you use
5 formally base theorem Bayesian condition of
6 probability to --
7 CHAIRMAN APOSTOLAKIS: Okay, but in
8 inference diagrams base theorem is the main tool.
9 DR. MOSLEH: Maybe I'm referring to maybe
10 a broader class of inference diagrams, where the
11 connections are not probabilistic.
12 CHAIRMAN APOSTOLAKIS: Yeah, it could be
13 done both ways.
14 DR. MOSLEH: Yeah, that's what I meant.
15 CHAIRMAN APOSTOLAKIS: But, here -- well --
16 DR. MOSLEH: Here it is, essentially -- in
17 all application of BBN to our own HRA, that's the --
18 model, the causal model is not purely BBN, it's a mix
19 of BBN and some other types of relations. But, that's
20 for maybe --
21 DR. HALLBERT: Aren't these also acyclic,
22 the BBNs?
23 DR. MOSLEH: BBNs have some restrictions.
24 They are acyclic, so feedback and cross correlations
25 that of a feedback nature cannot be modeled. There

1 are limitations.

2 This is an example of what we mean by,

3 basically, a rough high-level BBN of different

4 influencing factors. You have the PIFs and the PIFs,

5 and then you show the interdependency, and then you

6 try to put numerical scale on probability for the

7 conditional connection.

8 CHAIRMAN APOSTOLAKIS: So, this is an

9 example.

10 DR. MOSLEH: This is an example, yes, yeah.

11 This is what you are using --

12 CHAIRMAN APOSTOLAKIS: Emotional arousal is

13 something we're never going to use. That's what it

14 says there, "emotional arousal."

15 DR. MOSLEH: Is not what, sir?

16 CHAIRMAN APOSTOLAKIS: Most likely this

17 Agency is not going to use that as a PIF. We are --

18 DR. MOSLEH: Well, it depends on whether

19 you --

20 CHAIRMAN APOSTOLAKIS: -- to stay away

21 from the mental state of our subjects.

22 DR. HALLBERT: You know, on the other hand

23 if what you are concerned about is, you know, fatigue,

24 well, maybe take the word emotional out and just say

25 level of arousal or something.

1 MR. BONACA: It's interesting, looking at
2 p-related factors, yesterday we were talking about
3 control room crews, and we were trying to identify
4 causal factors of why one was successful and the other
5 wasn't. And, what was striking, from the observation
6 I've done when I used to work at plants, was that, you
7 know, among the individuals I knew personally, they
8 were operators who were capable, and yet I saw them
9 working on a crew where the supervisor was dominant as
10 an individual, and clearly the operator accepted this
11 dominance, even on a technical basis. It seemed as if
12 all the calls the supervisor made he accepted blindly,
13 and I really wanted to -- it's something of that, you
14 know, chemistry within your crew represented here, p-
15 related factors, how would you -- because those are
16 very important factors. I mean, the human
17 relationship or how people relate to each other in a
18 crew, it becomes very dominant.
19 DR. MOSLEH: In my opinion also, they are
20 extremely important factors, and then we are trying to
21 capture those.
22 Now --
23 MR. BONACA: Really, the influence among
24 individuals cannot be captured.
25 CHAIRMAN APOSTOLAKIS: Yeah, I don't think

1 we are really trying to capture the team effects. We
2 are assuming the team acts in a certain way. I'm not
3 sure to what extent the team effects are important.
4 DR. HALLBERT: We haven't really thought
5 about using that level of data yet, and, actually, to
6 be honest with you, I hadn't really thought about the
7 availability of that.
8 First, the first that we've even seen any
9 of that is really coming out of Halden over the course
10 of last year.
11 CHAIRMAN APOSTOLAKIS: I think the Navy has
12 done some work on submarines.
13 MR. BONACA: You see, to me when I think
14 about, you know, even big events like Chernobyl, I
15 mean, you know, there was an issue within the control
16 room that left open questions, you know, people that
17 are very knowledgeable.
18 CHAIRMAN APOSTOLAKIS: Well, Ali has the
19 team-related factors.
20 MR. BONACA: Yeah, that's why I raise that
21 question.
22 CHAIRMAN APOSTOLAKIS: This is the
23 exception, rather than the rule with the models.
24 DR. MOSLEH: We have a lot of detail on
25 that category of team-related factors, but I didn't

1 put those in here because I didn't want to make this
2 kind of presentation on a specific model.
3 CHAIRMAN APOSTOLAKIS: Maybe Halden could
4 shed some light again on this, as we were saying
5 yesterday.
6 DR. HALLBERT: We really hope to use more
7 of Halden data to --
8 CHAIRMAN APOSTOLAKIS: Yeah, and there was
9 some work in Germany I remember. It was published in
10 Reliability Engineering years ago, where they actually
11 looked at team effects, and, in fact, there was a
12 domineering person there. I don't remember what the
13 conclusion was.
14 MR. BONACA: It's startling to sit back
15 behind a glass and they don't know you are there, and
16 see the chemistry.
17 CHAIRMAN APOSTOLAKIS: Well, I mean, all
18 you have to do is come to an ACRS meeting.
19 DR. HALLBERT: You think that goes on
20 there?
21 CHAIRMAN APOSTOLAKIS: I don't know, we'll
22 ask Halden.
23 DR. MOSLEH: In most recent experiments, we
24 see clear evidence of team effect from the Halden, and
25 they are here, they can tell you more.

1 CHAIRMAN APOSTOLAKIS: So, you are really
2 going beyond the Bayesian framework. I mean, you are
3 using subjective theory of probability to propose a
4 framework within which people can make judgments.
5 DR. MOSLEH: Precisely.
6 CHAIRMAN APOSTOLAKIS: Bayesian -- okay,
7 fine.
8 Okay, let's go on.
9 DR. MOSLEH: Okay.
10 So now, one of the things about the
11 Bayesian inference is, and then if you use BBNs or
12 Bayesian Belief Networks, it gives you a framework to
13 explore the causal connections, causal relations, from
14 data and information. In fact, you can do a backward
15 and forward inference from informational causes given,
16 informational error given causes, to go to kind of
17 understanding of causes when there is a particular
18 error.
19 This is a very powerful -- I mean, that
20 blue box will give you tremendous flexibility to
21 extract information from limited data, from say 40, or
22 50, or 700 events that we heard. And, some of the
23 effort I think that has been labeled as Bayesian
24 inference has been basically focused on use of this
25 type of backward and forward inference.

1 The other thing is that you can really use
2 the Bayesian framework for BBNs to modify generic
3 data, and for that I -- let me go to this particular
4 vu-graph where I have put, say, imagine that you have
5 a Bayesian Belief Network representing the relation
6 between PIFs and performance, and I've color coded
7 them differently, that means it's the same structure
8 but if you go -- if you look at HERA database for
9 instance, and you look at what influences the
10 behavior, you can take that limited data set, this is
11 all in the space of events, it doesn't really need
12 success or failure data, you can classify them into
13 maybe a countable number of sub classes, each
14 representing -- so these BBNs represent those classes.
15 And, if you have a number of those, 45 or
16 100 events, you can see what fraction of events fall
17 in context alpha 1, what fraction in alpha 2, and so
18 on and so forth. So, you divide now the space of
19 observation into specific situations which can be
20 characterized by the PIFs that have been observed in
21 here.
22 Therefore now, we have, these alpha
23 factors could be correction factors, basically. If
24 you have a reference number, you can use these to
25 modify those reference numbers, reference human error

1 probabilities, and get error probabilities that are
2 more specific to context 1 versus context 2.
3 And so, that's I think something that is
4 quite doable with the HERA database. HERA will provide
5 the top distribution, the alphas, and the generic HEPs
6 need to be developed some other way, and there are
7 some ideas about how to do that, and then you can
8 modify the results using the alpha factors.
9 This follows to a large extent the
10 philosophy behind like the beta factor in common cause
11 failure analysis. You know, it's kind of the same
12 basic philosophy.
13 Bruce mentioned some of the limitations of
14 BBNs. They really cannot really capture dynamic
15 factors and the feedback effects, and the
16 quantification is difficult. If you really want to do
17 this quantitatively it's very difficult, because now
18 you are going to deeper layers of the influencing
19 factors when you are revealing with cognitive factors,
20 putting numbers and probabilities on those would be
21 very difficult.
22 So, what we did, I did, in a different
23 environment, for different application, in fact, for
24 modeling the role of organizational factors in
25 behavior, was to kind of relax the requirement of

1 quantitative scales for BBNs by dividing the BBN into
2 a qualitative segment and a quantitative segment. So,
3 the deeper roots would be qualitative, you know, high,
4 low, medium, and the more observable layers would be
5 quantitative.
6 And, we have developed some algorithms to
7 kind of connect these two, and therefore they are a
8 little bit more flexible framework.
9 I guess these are some ideas that we have
10 been basically looking to in terms of kind of basis
11 for the methodology.
12 CHAIRMAN APOSTOLAKIS: Thank you.
13 DR. HALLBERT: Thank you.
14 So, the things that we are presenting here
15 are suggestions or ideas. They are proposals for
16 where we might go with the use of data from a source
17 such as HERA, using Bayesian methods.
18 Now, one of the things -- I'm going to
19 take a technical pause here for a moment, the computer
20 is --
21 CHAIRMAN APOSTOLAKIS: Close it.
22 DR. HALLBERT: Oh, I have to close it, it's
23 trying to do something.
24 CHAIRMAN APOSTOLAKIS: There is Hallbert up
25 there, the second one, is that Hallbert, too, from the

1 top, that one? What is that one? No. What is that,
2 reliability data, no? We want something that says
3 extending Bayesian methods.
4 DR. HALLBERT: It's this one right here, by
5 process of elimination I found it.
6 CHAIRMAN APOSTOLAKIS: All right, boy, look
7 at that.
8 Does this show the level of stability in
9 organizational terms?
10 DR. THORNSBURY: This is sort of like a
11 Rorschach test.
12 DR. HALLBERT: Okay.
13 CHAIRMAN APOSTOLAKIS: Oh, there's an
14 orbiter?
15 DR. HALLBERT: It's predictable as well.
16 MEMBER KRESS: Heisenberg would have liked
17 this.
18 DR. HALLBERT: All right.
19 In -- I'm thinking about tying this
20 presentation -- and this is Bruce Hallbert again for
21 the record, tying this to some of the preceding
22 discussions that we've had.
23 One of the things that we've heard from
24 all the people who are either developing HRA methods
25 or applying HRA, is that they are looking for

1 information about how to take information about the
2 environment and use it in a human reliability
3 analysis.
4 The question is, is where does that
5 information come from? And, what we know about
6 performance shaping factors, and I'll use that word
7 throughout my presentation, not because there's a
8 specific technical distinction between what I'm saying
9 here and any methods that are used today, but where is
10 that information coming from, and how do we use it?
11 Now, I'm focusing here more on the
12 Bayesian context. Ali was talking earlier about one
13 form of representing outcomes as being either success
14 or failure, and that's true. If you were to look at
15 many instances in performance, you could classify them
16 as successful or unsuccessful, success or failure.
17 That's only using part of the information that we have
18 available to us.
19 What I'm going to propose, and what I
20 propose at the workshop, is in addition to looking at
21 whether performance is successful or not, we look at
22 the factors that contribute to successful as well as
23 unsuccessful performance, and try to systematically
24 relate that through a formal model.
25 And, what I propose at the workshop is

1 that, our likelihood models should try to become as
2 parametrically elaborate as they need to be, in order
3 to represent the dynamics of human behavior in these
4 operational contexts.
5 Now, I know that's challenging and
6 daunting from a mathematical standpoint, but we've
7 done some preliminary work on this sort of stuff,
8 showing that it can be done, although you have to do
9 it numerically. But, what we want to do is take
10 information, relate it to the success and failure
11 model, but include parameters about PSFs
12 systematically so that we can talk about where
13 performance shaping factors drive performance to
14 success and failure.
15 In a sense, it's common, it's similar to
16 like limit state determination for systems, except we
17 are talking about the human system.
18 And, the issue is that, you know, most
19 methods today come with causal models, and most of the
20 causal models that they use at human performance are
21 related to an information processing model. Everybody
22 is using information processing models to represent
23 cognition.
24 CHAIRMAN APOSTOLAKIS: So, this is one of
25 the equations that Ali showed, right, on the bottom

1 there?

2 DR. HALLBERT: Yeah.

3 CHAIRMAN APOSTOLAKIS: The blue one, that's

4 the blue equation.

5 DR. HALLBERT: This is the blue equation.

6 Yeah, and --

7 CHAIRMAN APOSTOLAKIS: How did you manage

8 to make it illegible?

9 DR. HALLBERT: I think I had a little help

10 from Microsoft.

11 DR. MOSLEH: It was an error producing

12 condition.

13 DR. HALLBERT: It's error producing

14 software.

15 CHAIRMAN APOSTOLAKIS: Or, is it the

16 operator himself?

17 DR. HALLBERT: It actually looks okay on my

18 computer.

19 CHAIRMAN APOSTOLAKIS: Actually, you know,

20 the problem is that you probably tried to enlarge it

21 after you typed it, and you have to do it

22 symmetrically, otherwise the letters go on over the

23 others.

24 DR. HALLBERT: I think it's a problem

25 between Mac translation to --

1 CHAIRMAN APOSTOLAKIS: It could be too.

2 DR. HALLBERT: -- because I did this on

3 a Mac.

4 CHAIRMAN APOSTOLAKIS: Well, that will show

5 you.

6 DR. HALLBERT: That's what I get for trying

7 to do something on a Mac.

8 CHAIRMAN APOSTOLAKIS: Okay.

9 DR. HALLBERT: Okay.

10 What this is showing is that, these

11 different models acknowledge the role of a variety of

12 different performance shaping factors, such as

13 individual history, learning, heuristics, biases, and

14 the situation, to produce conditions that they

15 describe as either error forcing, or shaping and

16 influencing, or common performance conditions. If we

17 look beyond those terminologies, what we find is that

18 the quantification process is trying to relate

19 information about the performance environment to a

20 model of human behavior to predict a metric of risk.

21 That's all they are doing. And, these are different

22 ways down here of doing that.

23 In terms of my proposal at the Bayesian

24 meeting, it was to look at extending the Bayesian

25 framework to address more parametrically elaborate

1 solutions to making predictions about the likelihood
2 of success and failure, using many of the things that
3 Ali was talking about previously.
4 The goal is to be able to systematically,
5 as I was saying earlier, systematically relate
6 information about the environment to our model of
7 human behavior, and use that model of human behavior
8 that's empirically calibrated to make predictions of
9 outcomes that are related to our metrics of interest
10 for the HRA.
11 We'd like to, in doing this, in using
12 information from relevant operational contexts to
13 inform our models, we'd like to improve the accuracy
14 of the HEP estimates. We know there are right now
15 sources of data that are used in HRA commonly come
16 from look-up tables, or from sort of a static
17 deterministic or predictive model in some way.
18 The question is, is could we use data to
19 feed into our model, and at the same time attempt to
20 try to account for the multi variate nature context,
21 and then the SPAR-H presentation yesterday, you heard
22 about the -- or we discussed the APSFs. That's,
23 essentially, a multi variate explanation of context,
24 it's saying that at any given time of writing things,
25 it could be influencing the behavior of a crew.

1 And, what we are talking about is trying
2 to figure out comparatively-based ways of developing
3 those models of likelihood.
4 The illustration that I'm going to talk
5 about here is something that I discussed with the ACRS
6 probably three years ago, maybe four years ago now,
7 and it's related to data that I've been collecting
8 over the years on performance shaping factors.
9 One of the recommendations from the ACRS
10 was, well, why don't you write up this research, and
11 I've done that. I have a draft manuscript about what
12 I'm presenting here, and my plans are to submit that
13 to the Reliability Engineering Journal.
14 The study focuses on different kinds of
15 PSFs and how they relate to performance, and how to
16 use them in models such as Bayesian models is what I
17 discuss at the workshop or suggest at the workshop.
18 So, in order to do that, you need to have
19 a set of PSFs that are in some way predictive of crew
20 performance, and there's been a lot of discussion
21 about, how do you take performance related data, or
22 performance data, and relate it to a failure model?
23 And so, we discuss that, and we're in the process of
24 discussing that still with Halden, for example. How do
25 we figure out how important some PSFs are relative to

1 one another. How do we express the relationship
2 between PSFs.
3 So, in this research we've collected data
4 on performance shaping factors, and the kinds of PSFs
5 that we were looking at at the time were procedures,
6 training, stress, workload, information, system
7 feedback and other elements of the human-machine
8 interface. And, during a series of experiments over
9 a number of different years, we asked operating crews
10 at different reactors, as they went through a set of
11 similar scenarios, to rate the effects of these PSFs
12 on their own performance.
13 And --
14 MEMBER KRESS: High, medium, low?
15 DR. HALLBERT: No, we used a Licard scale,
16 it was a 7 point Licard scale.
17 And, we were interested in knowing how
18 they believed that these things influenced their
19 ability to carry out some critical tasks related to
20 mitigation of the transient that were clearly a PRA-
21 relevant gate. In other words, if you failed this
22 gate, you'd go down a leg in your event sequence. So,
23 it was a critical path.
24 We had the operators rate these PSFs on
25 their performance after the scenario, and we collected

1 the data now, you know, in the U.S. and abroad, with
2 licensed operators in simulated operational settings,
3 and the types of scenarios that were used were broadly
4 representative, over heating, over cooling, loss of
5 coolant accidents, and these were specifically
6 pressurized water reactors.
7 And, George, as I was relating this
8 information to the other members I was saying that,
9 when I was here three or four years ago I presented
10 this study, and one of the recommendations from the
11 committee was, well, why don't you write that up, and
12 why don't you come back and consider how to use this
13 in a reliability way, so that's what I'm doing. I
14 have written it up, and I'm preparing to submit it to
15 the Reliability Journal.
16 CHAIRMAN APOSTOLAKIS: This is a paper?
17 DR. HALLBERT: Yes.
18 CHAIRMAN APOSTOLAKIS: Okay.
19 DR. HALLBERT: And then, there's an excerpt
20 of the paper in what you have.
21 CHAIRMAN APOSTOLAKIS: Yeah, I know this.
22 This was, basically, your presentation to the
23 workshop, right?
24 DR. HALLBERT: Yes, exactly.
25 So, we used a linear model of multiple

1 regression.

2 CHAIRMAN APOSTOLAKIS: Some people made

3 some interesting comments there.

4 DR. HALLBERT: I'm sorry?

5 CHAIRMAN APOSTOLAKIS: Some people made

6 some interesting comments in their presentations

7 there. I purposely went back to the ACRS transcripts

8 and found the guy that says this is incorrect.

9 DR. HALLBERT: I think he was sort of

10 lambasting me, wasn't that me?

11 CHAIRMAN APOSTOLAKIS: No.

12 DR. HALLBERT: I think it was. I thought

13 that it was -- well, we can talk about this later, but

14 I thought it was your question to me about if we had

15 20 trials from Halden could we use that to estimate a

16 reliability metric, and I don't remember the exact

17 context, but --

18 CHAIRMAN APOSTOLAKIS: I'd have to go back

19 to it.

20 DR. HALLBERT: Yeah, I think it was our

21 conversation anyway.

22 But anyway, we looked at this linear model

23 and related to performance, where Y was the critical

24 mitigation time, and so we were looking at time from

25 initiation of the event sequence to mitigation. And,

1 the different Xs in this model were the different
2 PSFs, and the ratings of the PSFs made by the
3 operators, and the Bs are the weights that were
4 determined through multiple linear regression.
5 And, what we found was that this model was
6 predictive of performance and accounted for the
7 majority of variability in -- majority of crew
8 variability in mitigation time.
9 We found that the model became more
10 predictive on a scenario-specific basis, so if you
11 aggregate the data the model would be predictive
12 across scenarios, but became more predictive at an
13 individual scenario level.
14 And, furthermore, differences in the model
15 predictions were observed across plants. So, really,
16 what it's saying is, there is predictive ability in
17 these PSFs. The operators understand their influence.
18 They are able to express their influence. We find an
19 association between their perceptions of the PSFs and
20 their actual performance, and we find differences in
21 the PSFs themselves across scenarios and across
22 plants.
23 CHAIRMAN APOSTOLAKIS: This point is
24 extremely important, of course, and you were here
25 yesterday when we had the expression of two different

1 viewpoints from Susan and David. Somehow, I mean, you
2 are arguing now that, yes, the PSFs do make a
3 difference, and they probably define a lot of the
4 context.
5 DR. HALLBERT: Uh-huh.
6 CHAIRMAN APOSTOLAKIS: What do you think,
7 Ali? The difference was -- you have to go with the
8 concept of context from the beginning, because if you
9 don't do that, you know, you go with the PSFs, you
10 will never really manage to define -- to describe the
11 context.
12 The counter argument from David Gertman,
13 which I believe you support, is that, look, the PSFs
14 are an approximation, but if you have a good set of
15 eight, or ten, or whatever, maybe you capture 80
16 percent or even more of the context.
17 Have you thought about it at all?
18 DR. MOSLEH: Oh, yeah, a lot.
19 CHAIRMAN APOSTOLAKIS: Just, give us a
20 short answer.
21 DR. MOSLEH: I think what we -- I have done
22 in the past ten years about modeling, called
23 development of the causal model, you know, basically,
24 had to address this issue, what do we mean by causal
25 kind of relations, and whether you need the level of

1 detail that, say, you see in real events from kind of
2 a predictive perspective.
3 And, I think the truth is really somewhere
4 in between. This really highly abstract that some
5 PSFs, with no clear correlation or connection with
6 performance, probably are not sufficient to identify
7 the types of errors people make, the specific errors.
8 At the same time, I don't think that the
9 extreme view that you really need to know the precise
10 set of conditions in order to make any meaningful
11 prediction is kind of extreme view.
12 CHAIRMAN APOSTOLAKIS: Well, I asked, if
13 you were to do an HRA tomorrow, or a PRA, okay,
14 somebody comes to you and says we are going to do a
15 PRA for this plant, Professor Mosleh, we want you to
16 help the HRA part, but the high level, how would you
17 proceed? You would say, gee, you know, and this HRA
18 is going to be used before the NRC, those guys are
19 going to review it, you know how picky they are.
20 Would you immediately go to ATHEANA, would you go to
21 SPAR-H, would you go to IDAC, what would you do? They
22 want HRA contribution to the PRA, which has to be done
23 in a year and a half.
24 DR. MOSLEH: I think the right balance
25 between the two would be the right solution in the

1 short term.

2 CHAIRMAN APOSTOLAKIS: Between the two?

3 DR. MOSLEH: Between the two, and I would

4 say extremes, I'm not characterizing SPAR-H or ATHEANA

5 as really extremes, but, you know, they could think of

6 two extreme points of view, where you really look at

7 correlated factors correlation as indication of B, and

8 the other one really looks at a very detailed context

9 analysis.

10 CHAIRMAN APOSTOLAKIS: But, we should do

11 them in parallel? Would you do one first and then the

12 other?

13 DR. MOSLEH: The framework would be --

14 CHAIRMAN APOSTOLAKIS: I'm sorry, Bruce.

15 DR. MOSLEH: -- yeah, I think the

16 framework would be something that is closer to a set

17 of PIFs through some causal model that is -- I think

18 has the right level -- like the type that I showed

19 earlier, you know, that kind of 10, 15 factors, but

20 causally connected, not just a linear list. I think

21 that's dangerous, meaning everything --

22 CHAIRMAN APOSTOLAKIS: Taking the sum.

23 DR. MOSLEH: -- yeah, right, that is

24 absolutely -- I think that is incorrect.

25 But, some model of causal relation between

1 the PIFs, their interdependencies, and performance, on
2 top of kind of a review and analysis of the situations
3 under which the operators will have to deal with an
4 accident, which is part of, actually, any PRA or
5 credible HRA, people look at the scenarios, look at
6 the conditions, but quantitatively you characterize
7 those and then come up with some mapping between the
8 situation and analyzing the set of PIFs and the causal
9 model, and you go to to the quantitative procedures
10 that the model presents, somewhere in between.
11 I think the hybrid methodology would be
12 most meaningful at this stage of the state of
13 knowledge that we have.
14 CHAIRMAN APOSTOLAKIS: Okay, thank you.
15 Okay, Bruce.
16 DR. HALLBERT: Okay.
17 So, this slide sort of illustrates the
18 point I was making on the previous slide, simply
19 showing that the correlations between, you know,
20 predicted mitigation time and observed mitigation
21 time, you know, can be largely accounted for by the
22 PSFs, at least in the scenarios we studied and the
23 crews that we collected data from.
24 I know that Halden is continuing to
25 collect data on PSFs, I can't remember exactly how

1 they are using it, or what analysis they might
2 perform, but that's something I will be talking more
3 about.
4 CHAIRMAN APOSTOLAKIS: What variable are
5 you plotting there?
6 DR. HALLBERT: Observed values predicted.
7 CHAIRMAN APOSTOLAKIS: Of what?
8 DR. HALLBERT: Oh, actual mitigation time
9 versus predicted mitigation time.
10 CHAIRMAN APOSTOLAKIS: Mitigation time.
11 DR. HALLBERT: Yes, mitigation time.
12 I wanted to use an objective measure,
13 because, you know, we already had subjectivity in the
14 ratings of the PSFs, and we weren't exactly sure
15 whether, you know, whether we could get people to
16 understand the definitions of those PSFs, and whether
17 they would agree upon the PSFs, and so we wanted to
18 have an objective measure to see if these things could
19 be systematically related to some outcome.
20 CHAIRMAN APOSTOLAKIS: Now, the time, of
21 course, is the actual random variable, right?
22 DR. HALLBERT: Yes.
23 CHAIRMAN APOSTOLAKIS: It's a random
24 variable.
25 DR. HALLBERT: Yeah.

1 CHAIRMAN APOSTOLAKIS: But, in our -- well,
2 I guess if you have an allowed or available time that
3 you compared it to, then you get 01, which is the
4 success or failure of the human performance, right?
5 DR. HALLBERT: And, we didn't actually look
6 at that in these situations.
7 CHAIRMAN APOSTOLAKIS: No, but I'm saying -
8 -
9 DR. HALLBERT: Yeah.
10 CHAIRMAN APOSTOLAKIS: -- in the big
11 context that you and Ali have described, you have the
12 observable variables, right?
13 DR. HALLBERT: Yup.
14 CHAIRMAN APOSTOLAKIS: Here we have two in
15 this context, one is the actual time that it can take
16 compared to available time, and say that was a 01,
17 which is a fundamental variable of human action, then
18 I start saying I don't know whether it's 01, or p, p
19 itself may have a distribution in it, the whole thing
20 that Ali described.
21 DR. HALLBERT: Right.
22 CHAIRMAN APOSTOLAKIS: It's very important
23 for people to understand these things, by the way. I
24 don't mean you two, but it's really important.
25 DR. HALLBERT: Yeah.

1 CHAIRMAN APOSTOLAKIS: Because these
2 variables and all that, and then Ali introduced as
3 randomness in p, it's not an easy thing to comprehend.
4 DR. HALLBERT: No, it's not, and one of the
5 questions you ask yourself is, so, where does the data
6 come from for me to initialize those models, or to
7 define the relationships among PSFs? How do I develop
8 those Bayesian Belief Networks, and what I'm
9 suggesting is, you know, there's a variety of sources
10 of information. Some of that information can come
11 from a source like HERA, where we have information
12 that's retrospectively available.
13 In addition, a source like simulator
14 studies, where you can actually observe the dynamic
15 interaction and interplay between PSFs, and study the
16 correlations and the causal connections between PSFs
17 on performance, help you to develop a more empirical
18 basis for developing your reliability model.
19 CHAIRMAN APOSTOLAKIS: Absolutely.
20 DR. HALLBERT: In that particular context.
21 CHAIRMAN APOSTOLAKIS: Here's a thought
22 that just occurred to me, though. What I just
23 described, there is a response time of the operators,
24 available time, and compare it til you get to 01.
25 But then, if you look at the models, the

1 available time, and one of the PSFs in SPAR-H is that,
2 or time pressure, that is used as a performance
3 shaping factor, not as a fundamental random variable.
4 DR. HALLBERT: Right.
5 CHAIRMAN APOSTOLAKIS: Why not? Why not as
6 a fundamental variable, and then all the PSFs affect
7 the length of that time.
8 DR. HALLBERT: Well, I believe you are
9 right. I think it could be a dependent measure.
10 CHAIRMAN APOSTOLAKIS: Could be actually
11 the outcome.
12 DR. HALLBERT: Yeah.
13 CHAIRMAN APOSTOLAKIS: Instead of saying
14 success/failure of the operator, you are looking now
15 at the time the operators take to do something, like
16 in the example you showed earlier.
17 DR. HALLBERT: Yes.
18 CHAIRMAN APOSTOLAKIS: The guy realized
19 there was an error within a period of time, and that
20 was before something bad happened, but then he made a
21 mistake again. You know, he put the thing -- the
22 lever at the wrong place.
23 I wonder whether that would be a more
24 reasonable way to proceed.
25 DR. MOSLEH: To the extent that it's an

1 observable, of course, is one of the more favored kind
2 of elements of this model, because you can measure,
3 you can talk about it, you can see. But, I don't
4 think that it is really the most representative
5 parameter or characteristics for all situations.
6 CHAIRMAN APOSTOLAKIS: This is the
7 fundamental outcome. In other words, all the PSFs,
8 all the BBNs that you presented and so on, ultimately
9 feed into how long the operators will take to do
10 something.
11 DR. HALLBERT: Or, perhaps, the quality of
12 -- the quality of the behavior that they --
13 CHAIRMAN APOSTOLAKIS: The whole ting.
14 DR. HALLBERT: Yeah.
15 CHAIRMAN APOSTOLAKIS: The quality of the
16 behavior might be poor, so they take a long time, like
17 we saw yesterday, 11 minutes or so.
18 DR. HALLBERT: Uh-huh.
19 CHAIRMAN APOSTOLAKIS: But, the problem
20 that I see with that, and it would be nice to have
21 someone trying it, but the problem you see with that
22 it negates all the models that are out there.
23 DR. LOIS: Well, this is the typical TLC.
24 CHAIRMAN APOSTOLAKIS: No, it's not a TLC.
25 DR. LOIS: Why not?

1 CHAIRMAN APOSTOLAKIS: No, because EPRI
2 said, well, EPRI, everybody would, they said if the
3 available time is five minutes this is the probability
4 that they will not do.
5 What I'm saying is, forget about that, I'm
6 not talking about TLC, I'm talking about all the
7 models that Bruce, and Ali, and others are developing,
8 should serve as a fundamental focus the time it takes
9 for the operators to do something. So, you are going
10 to have PSFs, you are going to have the whole works,
11 like we saw yesterday from Halden. So, all these PSFs
12 now will lead to some probability distribution at that
13 time, and if that time exceeds the available time then
14 you have a failure.
15 We're not talking about TLCs at all,
16 nothing, TLCs are out.
17 MEMBER KRESS: I think you want
18 distribution on both of those, available time --
19 CHAIRMAN APOSTOLAKIS: The available time
20 distribution comes from thermal hydraulic observation
21 or something.
22 MEMBER KRESS: Yeah, and the overlap will
23 give you that.
24 CHAIRMAN APOSTOLAKIS: And, the overlap
25 will give you that, yeah.

1 DR. MOSLEH: If the time to perform
2 something is really what is impacting the PRA model,
3 or the sequence of events, of course, time is the
4 underlying parameter of everything, obviously.
5 But, whether that's the real anchor
6 parameter, or factor, to look at --
7 CHAIRMAN APOSTOLAKIS: Look at what Bruce
8 presented a half an hour ago, how does he present the
9 information, he has a time line.
10 DR. MOSLEH: Yeah, but he chose to --
11 CHAIRMAN APOSTOLAKIS: They did it here,
12 they did it there, thank God the core damage was down
13 there. You know, it's a fundamental random variable,
14 that the operators do something, and then all the
15 models will try to figure out what are the factors,
16 what are the contexts, if you go ATHEANA will be the
17 context that affects, that influences, that length,
18 because this is really -- and I mean in practice, too,
19 you see, when you do -- because this ties -- there are
20 several reasons, first of all, I'm not really saying
21 do that, I'm saying here is another way of approaching
22 human error that may or may not be better than this,
23 by this I mean, you know, all the models.
24 DR. MOSLEH: Yeah.
25 CHAIRMAN APOSTOLAKIS: It ties the human

1 performance to the thermal hydraulic and neutronic
2 behavior of the reactor, because the available time
3 comes from thermal hydraulics, right, only sometimes,
4 but usually thermal hydraulics, and then you have a
5 benchmark. I mean, if they do it within ten minutes
6 or so.
7 The other thing is that in licensing
8 actions, when you -- when a licensee asks to raise the
9 power, the allowed power, by 20 percent, the main
10 impact on human performance is the shortening of the
11 available time, right, the available time. So, the
12 crews do take 15 minutes, but before the available
13 time was 18, now it's 11. Okay?
14 So, you are really dealing in all
15 applications with the actual times. Now, what the
16 licensees say and what the reviewers agree with, is
17 that, okay, so there is a shortening of the time, but
18 it's not very big, so even though we may not know the
19 probability of doing something wrong, the new
20 probability is not that different, so accept. But,
21 nobody really knows what happens to that probability,
22 and probably the reason is that the focus is not on
23 the time.
24 I don't know, this is something to think
25 about.

1 MEMBER BONACA: We will go through some of
2 the sequences they have tested on the simulators, they
3 know how long it takes for that parameter to respond
4 to it. So, they have some indications there, but you
5 are right.
6 CHAIRMAN APOSTOLAKIS: There are some
7 indications, but also --
8 MR. BONACA: The time --
9 CHAIRMAN APOSTOLAKIS: -- for some reason,
10 from the beginning, and maybe that's an
11 interdependence on Swain and Gutman, we have all
12 focused, including me, on the probability of the
13 operators doing the right thing or the wrong thing,
14 but it seems to me the fundamental random variable
15 underneath is really the time --
16 MR. BONACA: Especially some fundamental
17 operator action, for example, clearly, -- for PWRs is
18 a fundamental decision.
19 CHAIRMAN APOSTOLAKIS: Yes.
20 MR. BONACA: Now, if you look at how -- for
21 certain plants, like the C plants with small PRBs and
22 small charging flow, very small actually, you have a
23 very narrow window for success. Either you enter --
24 within, I believe, it's like two hours or one half
25 hour, or you just don't succeed, there's no way to

1 succeed.

2 CHAIRMAN APOSTOLAKIS: Yea.

3 MR. BONACA: Okay.

4 Now, the pressure on the operators to make
5 the right decision, the right call, is tremendous. I
6 mean, you know, because they know that once you get
7 into bigger figure, the whole containment, and you may
8 just -- and that's a big issue, time is just a factor.

9 CHAIRMAN APOSTOLAKIS: This is critical, I
10 can't think of a case where it's not. So, you should
11 go back to Ali's presentation, for example, the second
12 slide, the amount of interest now will be the time,
13 and the formulation still applies, but you have a
14 different amount of interest in this third slide where
15 you say, the amount of interest is the operator
16 response failure or success, you said it was 01, now
17 you say time to do something, and then I have some
18 estimate from the hard sciences, thermal hydraulics
19 and so on, to tell me how much time I have.

20 And, ideally, as Dr. Kress said, if you
21 also have uncertainty on the available time, then you
22 do this convolution thing there.

23 Anyway, I mean, that's just a thought.

24 DR. MOSLEH: The operator action could
25 change the time scale of things, basically, by the

1 action, the error, they could change the sequence,
2 they could change the time scale.
3 CHAIRMAN APOSTOLAKIS: But, that's the
4 reality of it, and also it would be very consistent
5 with HERA.
6 HERA cries for time, it says, you know,
7 here is a sequence, so how do we use that information,
8 and maybe your Bayesian calculations would be, in
9 fact, easier.
10 DR. HALLBERT: Yeah, we --
11 CHAIRMAN APOSTOLAKIS: Because you are
12 having evidence directly on time.
13 DR. HALLBERT: -- no, time is clearly the
14 stream in which all behavior occurs. I mean,
15 everything unfolds in time, over time.
16 CHAIRMAN APOSTOLAKIS: Right.
17 DR. HALLBERT: And, I suppose to some
18 extent all the data that we have reflects outcomes in
19 time. The question, though, of conversion, or
20 considering the use of time as the performance metric,
21 and what that tells us, I think we have to --
22 CHAIRMAN APOSTOLAKIS: Oh, I'm not saying
23 it's obvious, far from it. I'm not saying, no, here is
24 a good way to do it, you dummies haven't thought about
25 it. No. All I'm saying is, perhaps, we should be

1 focusing on that as the random variable, which would
2 be completely consistent with what you are doing in
3 HERA, and again, I'm not using it as a performance
4 shaping factor, no, this is now the true random
5 variable. And, if it's very short, if the available
6 time is very short, then a performance shaping factor
7 will tell me the stress level is high.
8 Dr. HALLBERT: Well, let us consider that.
9 CHAIRMAN APOSTOLAKIS: SO, I still have
10 these things.
11 MEMBER KRESS: Yes, I think you would find
12 this to be a unanimous recommendation from the ACRS,
13 even though they are not all here.
14 DR. HALLBERT: Okay.
15 CHAIRMAN APOSTOLAKIS: It's the domineering
16 effect.
17 Anyway, that's a thought, Bruce.
18 DR. HALLBERT: See, we have team factors
19 that play here even.
20 CHAIRMAN APOSTOLAKIS: Yes, that's what I
21 say.
22 Can you wrap it up in ten minutes?
23 DR. HALLBERT: Sure, sure, actually, I've
24 got one more slide.
25 CHAIRMAN APOSTOLAKIS: Summary, well, gee,

1 I like to see that.

2 DR. HALLBERT: And then, I'll just -- I

3 don't know, should I wrap it up?

4 CHAIRMAN APOSTOLAKIS: We have read the

5 other stuff, this is from Mahadevan?

6 DR. HALLBERT: Yeah, right.

7 CHAIRMAN APOSTOLAKIS: Yeah, it's in the

8 book.

9 DR. HALLBERT: Yeah, so we could just --

10 CHAIRMAN APOSTOLAKIS: This is not HERA.

11 DR. HALLBERT: We can wrap this up, and

12 then if you have some questions on Mahadevan's stuff,

13 otherwise we can come back to that.

14 DR. MOSLEH: It's a fundamental variable we

15 need to finish in ten minutes.

16 CHAIRMAN APOSTOLAKIS: And, I'm trying to

17 influence you.

18 DR. HALLBERT: I think the likelihood is

19 high because I've been drinking so much water here

20 this morning.

21 CHAIRMAN APOSTOLAKIS: We can stop for a

22 few minutes if you need.

23 DR. HALLBERT: Ali can talk, but I have to

24 leave.

25 Summary, we have -- I mean, we have

1 demonstrated this link between performance shaping
2 factors and performance. You know, we argue, we
3 discuss, we question, we disagree about whether
4 performance shaping factors are important, how they
5 are important, whether we should or should not use
6 them. I think fundamentally we are missing a huge
7 piece of very informative information if we don't
8 account for these things we call performance shaping
9 factors. And, I don't care whether your method calls
10 them PIFs, or common performance conditions, or
11 context, you know, it's important that we account for
12 these things in some systematic way.
13 Moreover, it's important that we collect
14 data on these variables. It's important that we
15 collect data and have a source of information that we
16 can use to understand the interactions between PSFs
17 and performance, so that we can have, in fact,
18 predictive models.
19 It's also important that we start thinking
20 about collecting human performance data in ways that
21 allow it's direct use in reliability type models. The
22 information I've been showing you in this presentation
23 is simply performance, it's not related to any model
24 of reliability. And so, when we do research, when we
25 do collect data, it is important that the performance

1 domain also include occurrences of failure, and that
2 way it's possible that we can start using information
3 about human performance outcomes in ways similar to
4 what we do with structural reliability and system
5 reliability, and that is, to develop formal models of
6 human performance, like limit state conditions. And,
7 I say that with a full understanding of what we do in
8 developing limit state conditions.
9 We need to have data that relate human
10 performance, elements of the context, and be able to
11 derive limit states, so that we can make some real
12 statements about human reliability, and not just
13 estimates.
14 But, that has to be based in data, it has
15 to be -- and even if we disagree about what to call
16 specific elements, we can agree on specific outcomes.
17 The other thing that I would say that I
18 feel strongly about in this research is that we didn't
19 begin with any assumptions or models about PSFs in
20 performance. What we allowed to happen was for those
21 relationships to emerge as they naturally occurred.
22 This was naturalistic research. We observed the
23 operators, we collected the data after the fact, and
24 we used, you know, standard parametric statistical
25 analysis techniques to identify or to understand how

1 the evidence supported model development, and that's
2 what I'm a proponent for.
3 CHAIRMAN APOSTOLAKIS: Good.
4 Finished? Any questions?
5 MR. ELAWAR: I am Zouhair Elawar from the
6 Apollo Nuclear Power Plant, I work with HRAs
7 extensively. I just want some clarification or,
8 perhaps, a recommendation to your project.
9 I hope you don't intend on giving the
10 industry work for them to do, that Bayesian updating,
11 to keep doing -- you know, improving their HRAs. I
12 hope your bottom line will be maybe generating some
13 generic HEPs by whichever means you reach them, and
14 they will be given to the industry with guidelines as
15 to how to use it, because I believe, and I know for
16 sure that at least I am of that frame of mind, there
17 is a deep skepticism about using Bayesian methods on
18 human performance. People don't believe in it,
19 frankly, to say to you.
20 So, you need to come with a very
21 convincing reason as to why you think it applies,
22 first of all, and secondly, you will need to make it
23 so simple for the end user to be able to apply it
24 without being a mathematician, let's say.
25 Thank you.

1 CHAIRMAN APOSTOLAKIS: Okay.

2 Any other comments?

3 Well, thank you very much, gentlemen.

4 As usual, this was very interesting,

5 always incites interesting comments and debates,

6 appreciate it.

7 Ali, thank you for coming.

8 I think maybe we can go now around the

9 table and get some views, although we are not writing

10 a letter on the whole program. We will be briefed in

11 February, and we will write a letter on the evaluation

12 of the models against -- you don't have to leave, by

13 the way, it's up to you -- go if you like.

14 DR. HALLBERT: No, well, are we done with

15 our --

16 CHAIRMAN APOSTOLAKIS: We are done with

17 your presentation.

18 DR. HALLBERT: Okay.

19 CHAIRMAN APOSTOLAKIS: This is now among

20 the committee members.

21 What was I saying? Oh, yeah, we will

22 review and write a letter on the evaluation of the

23 models against the best practices, but what we are

24 planning to do, as we discussed with the staff

25 yesterday, is in a few months afterwards -- well,

1 actually, not even a few, one or two months
2 afterwards, we can review SPAR-H or other pieces of
3 work that Dr. Lois feels are ready for review, and
4 write comments, I mean, a letter, because as I said
5 yesterday, the committee communicates its views only
6 through letters, what individual members say, you
7 know, their individual opinions.
8 But anyway, from what we heard yesterday
9 and today, what are the views?
10 MEMBER BONACA: Well, first of all, I
11 appreciated very much the evaluation of the HRA
12 methods against the best practices. I thought that it
13 was a very clear document, lot of information, it
14 allowed me to really understand much better the HRA
15 tools available.
16 And, I must say that also it gave me a
17 sense of the value of the best practices document
18 which was developed a year ago, or whatever, I don't
19 think I appreciated it as much before, until I saw the
20 comparison perform, and that was very helpful. That's
21 my sense, and I think that probably the whole
22 committee will recognize the value of this NUREG.
23 Second, I think I was quite impressed, I
24 must say, by SPAR-H. I mean, from the various
25 indications, it seems to be an effective tool. I also

1 appreciate much more the importance of having
2 separately SPAR-H and ATHEANA.
3 Now, ATHEANA I made some statement
4 yesterday about, you know, -- motivated by the fact
5 that I would like to see some application of ATHEANA
6 to better understand how it is being applied.
7 CHAIRMAN APOSTOLAKIS: We can ask the staff
8 to come and show us some of their applications that
9 they have.
10 MR. BONACA: Because again, I mean, you
11 know, at least to my sense it has been kept hidden and
12 is not used.
13 CHAIRMAN APOSTOLAKIS: HE called it a
14 nuclear weapon.
15 MR. BONACA: Well --
16 CHAIRMAN APOSTOLAKIS: You are threatening
17 people here, but you never use it.
18 MR. BONACA: -- you never use it, you
19 know, and you also threaten people with it.
20 But, I think, you know, I can see now
21 there is an application that is being made, and I
22 understand better the differences between what you get
23 out of ATHEANA versus SPAR-H, okay, given that SPAR-H
24 seems to be already a tool that is being used by, I
25 guess, LLR, right, for evaluation. So, we need to

1 look at it more closely as we go and review SPAR, as
2 we've done in the past, we are going to do more of
3 that.
4 By the way, I was impressed by all the
5 presentations to the subcommittee. I mean, that was
6 a very valuable subcommittee meeting that we had.
7 The Halden project, it was very
8 interesting to me, I mean, again, particularly the
9 work -- the people working in crews, and that's
10 opening in my mind the question of, you know, how to
11 model this issue of temperament, personalities, how
12 people relate to each other, and those are issues
13 which are dominant in the team. And, you know, it's
14 a mystery to me right now how you are going to effect
15 that, or to use that, although I believe the work from
16 Halden may shed some incite on that, and we don't
17 really pursue that enough.
18 But, maybe the crews that they used were
19 not -- didn't have that make-up, but I've seen some
20 U.S. crews where, you know, you can see a dominant
21 individual on a crew, and that seems as if -- and
22 people follow pretty much the leader. And so, you are
23 losing the ability of having the crew individuals
24 separately thinking about it and feeding back
25 information.

1 And, I don't know about using Bayesian
2 methodology for human reliability analysis. I heard
3 this comment here, but I thought that some of the
4 incites were valuable, I appreciate the presentation
5 that you provided us.
6 That's pretty much my comments.
7 CHAIRMAN APOSTOLAKIS: Thank you, Mario.
8 Tom?
9 MEMBER KRESS: Well, first off, I think as
10 far as risk assessments are concerned, the
11 quantification of human reliability is very important.
12 CHAIRMAN APOSTOLAKIS: It's very important.
13 MEMBER KRESS: We are showing that it tends
14 to dominate a lot of the sequences.
15 And, I think the view that the whole
16 reliability is greatly determined by the performance
17 shaping factors is the right view.
18 CHAIRMAN APOSTOLAKIS: Is the right view?
19 MEMBER KRESS: It's the right view. I
20 think definitely those things are what are going to
21 influence it.
22 Now, I've known -- this thing for
23 quantifying the influence of the performance shaping
24 factors, I think the Halden project gives some incites
25 on what these might be and how they might be, but I

1 don't see how to go from what they have to a
2 quantification, but what I saw by this Bayesian
3 process in the University of Maryland work, using the
4 influence diagrams for example, can have promise, I
5 think, of determining the interdependence of the
6 various performance shaping factors, and come up with
7 a way to actually quantify their influence, and their
8 own particular conditions, how many of them -- how
9 many of these are available, and to what extent they
10 are available in a given call for operator action for
11 some critical action.
12 So, I'm really encouraged by what I saw
13 from this Bayesian approach, and I encourage them to
14 keep on with it. I think George's recommendation that
15 the focus should be on the time was a marvelous one.
16 I think that should influence how they think about
17 these things, and how they look at them and all, I
18 think they need to take that very seriously.
19 I guess my final comment was working with
20 the various models, there is a need to put the ISPER
21 study to bed, and I don't know how we do that, but we
22 need to do that.
23 So, I guess those are my major thoughts
24 right now, George.
25 CHAIRMAN APOSTOLAKIS: Very good, thank

1 you, Tom.

2 Well, I also was very -- I'm very pleased

3 with what I heard yesterday and today. I think we are

4 making significant progress. The staff is to be

5 congratulated for running a very good program in the

6 human reliability analysis.

7 I appreciated the presentation from EPRI

8 and the industry. I must say that I wasn't too

9 favorable towards the calculator before I heard you,

10 you know, based on what I knew, but now I think there

11 is a lot of value to it. The fact that you are

12 developing software that attempts to make the process

13 more systematic and so on, the benefits that you have

14 when you have a software package I think this is very

15 good.

16 I was also pleased to hear you say that

17 not too many people, in fact, possibly none, are using

18 HCR. Then the staff presentations were excellent, all

19 of them actually. You know, we learned from all of

20 them, you know, we made comments in the spirit of

21 being constructive.

22 I'm still now -- not still, I mean, now I

23 am a little bit disturbed by the exchange yesterday

24 between Dr. Cooper and Dr. Gertman, especially since

25 as Mario said the Agency is, in fact, using SPAR-H in

1 regulatory actions as we speak, and then to hear that,
2 you know, the right way to go is to use context is
3 disturbing. Maybe people in the heat of the debate
4 took extreme positions that they really didn't mean,
5 I don't know, but that has to be resolved.
6 I did appreciate, as always, the
7 presentation from Halden. They are doing very good
8 stuff. A few years ago, I thought you couldn't do
9 anything about human reliability in terms of
10 experiments and so on, but they are doing good stuff.
11 We are getting good incites. I mean, when you see all
12 the crews responding in a short period time, and then
13 one crew is way out there, you ask why, which is a
14 good step, actually, you know, but you ask questions
15 that you might not have asked without this evidence.
16 And, today's presentation, too, from Bruce
17 and Ali, I thought were very good. I mean, the
18 framework is the proper one, I think. That doesn't
19 mean that, you know, you are going to tell the
20 industry or the staff, go out and use these formulas
21 that Ali showed and do it, no, I mean, the research
22 project has to produce results that are usable by
23 somebody who is not a mathematician, I agree with you,
24 but that's the intent. I don't think they intended to
25 throw out a huge Bayesian thing and say --

1 MR. ELAWAR: Just want to make sure.

2 CHAIRMAN APOSTOLAKIS: -- you guys, okay,

3 it doesn't hurt to do that, reduce the uncertainty,

4 very good.

5 So --

6 MEMBER KRESS: It seems to me the Bayesian

7 updates on the probabilities, seemed to me like the

8 repository for this should be NRC.

9 CHAIRMAN APOSTOLAKIS: Oh, absolutely.

10 MEMBER KRESS: Yes.

11 CHAIRMAN APOSTOLAKIS: But, the NRC --

12 MEMBER KRESS: That's their job to do that.

13 CHAIRMAN APOSTOLAKIS: -- everything we do

14 is public.

15 MEMBER KRESS: Right.

16 CHAIRMAN APOSTOLAKIS: Unlike some

17 organizations.

18 And, the first presentation by the staff

19 yesterday, and its contractors, on the evaluation of

20 the various models against the Good Practices

21 Document, I thought was excellent.

22 MEMBER KRESS: Yes.

23 CHAIRMAN APOSTOLAKIS: The document is

24 excellent. I was so pleased when I read it, especially

25 when I read the criticism of -- the commentary, not

1 criticism, the commentary on models that have been
2 developed by the NRC. I thought that was a brilliant
3 move on your part, to have outsiders review it, and
4 then, of course, it's your document, I mean, you have
5 to edit it and so forth, but Jeff did not object to
6 anything.
7 So, I thought this was an excellent piece
8 of work.
9 MR. BONACA: -- because, you know, I mean
10 at some point I questioned in my mind how much the
11 EPRI calculator is influenced by the fact that the
12 presence there is influenced by the fact that the
13 industry has been using this approach for a long time,
14 there are other ways maybe to skin the cat, and I
15 think the document of this NUREG offers you some
16 incite.
17 CHAIRMAN APOSTOLAKIS: It's the very first
18 step, but a very significant step, what I've always
19 wanted, a benchmark exercise.
20 MEMBER KRESS: Why would you want to skin
21 a cat?
22 MR. BONACA: That's the point I wanted to
23 make, by the way, that, you need, we need -- one of
24 the things that we need to see is more a benchmark
25 exercise.

1 CHAIRMAN APOSTOLAKIS: Yes.

2 MR. BONACA: I mean, there's always some
3 between different users with the calculator, but also
4 different ways of doing this work, because one is then
5 left with a question of, you know, when you put the
6 right numbers in, like with the calculator, and you
7 add factor, after factor, after factor, how credible
8 all these factors are, what kind of numbers do you get
9 at the end of the process.

10 CHAIRMAN APOSTOLAKIS: Yeah.

11 MR. BONACA: And, you know, you may train
12 people to come out with the same numbers, that doesn't
13 give me the comfort that the number is the right
14 number, and it may be simply that we are all thinking
15 that and moving in one direction, but comparing with
16 different kind of code or model, that would be a
17 benchmark that would be significant to me.

18 CHAIRMAN APOSTOLAKIS: Yeah, and I -- as
19 Tom said, I mean, even though that benchmark exercise
20 from the European Union is now, I don't know, 20 plus
21 years old, we can't ignore it. You can't have a paper
22 like that out as that infamous table, that shows the
23 results being all over the place.

24 MR. BONACA: Yes.

25 CHAIRMAN APOSTOLAKIS: You can't do that.

1 You have to respond, either the benchmark exercise was
2 wrong, or inadequate, or whatever, or we have
3 progressed now and we have better results or
4 something.
5 Now, doing benchmark exercises is not a
6 trivial matter. I mean, it's expensive, it requires
7 the cooperation of many, many groups, but, I mean, we
8 have to do something, and I think the NUREG that the
9 staff is about to issue on their evaluation is really
10 an excellent first step.
11 So, unless there are any other comments
12 from the members, public.
13 DR. LOIS: I have --
14 CHAIRMAN APOSTOLAKIS: Yes.
15 DR. LOIS: If you -- it will help us if we
16 know which of the projects that we presented you would
17 like to present to the full ACRS committee.
18 The methods evaluation has been planned.
19 CHAIRMAN APOSTOLAKIS: SPAR-H.
20 DR. LOIS: SPAR-H.
21 CHAIRMAN APOSTOLAKIS: And then you decide.
22 The others is not obvious to us how ready they are, so
23 you decide that.
24 DR. LOIS: Okay. It doesn't have to be
25 this year, are you looking forward to --

1 CHAIRMAN APOSTOLAKIS: Not just this year,
2 I mean, but certainly SPAR-H, some time March or
3 April. You know, are there any other projects that
4 are near to --
5 DR. LOIS: We intend to --
6 CHAIRMAN APOSTOLAKIS: You can always come
7 to us without the request for a letter, if you feel
8 that, you know, you are going to take a major step in
9 one of the projects, and you would like to have the
10 subcommittee's input. I mean, we do that a lot.
11 DR. LOIS: Absolutely.
12 We are developing the ATHEANA users'
13 guide, which addresses some of the --
14 CHAIRMAN APOSTOLAKIS: Absolutely.
15 DR. LOIS: -- committee's concerns.
16 CHAIRMAN APOSTOLAKIS: Absolutely, yes.
17 DR. LOIS: So, that may show up some time.
18 CHAIRMAN APOSTOLAKIS: You know, following
19 up on Mario's comment, maybe we can have a
20 demonstration, a presentation on the actual
21 application, to PPS, or -- or both, and that can be in
22 the context of the guide you are developing. And,
23 when do you think we will be ready for that?
24 DR. LOIS: Summer, not before summer.
25 CHAIRMAN APOSTOLAKIS: Okay, that's fine.

1 MR. BONACA: PPS will be very interesting,
2 because the PPS --
3 CHAIRMAN APOSTOLAKIS: I mean, the PPS, I -
4 -
5 MR. BONACA: -- the human performance, you
6 know, will change the whole dynamics of that issue, I
7 mean, all the crew members, will be eliminated as
8 contributors, okay, because --
9 CHAIRMAN APOSTOLAKIS: And, the paper that
10 Bye and others, -- and John, on how to use expert
11 judgment in this context, I mean, oh, absolutely, that
12 can be the third one, that can be the third one, and
13 you judge what.
14 DR. LOIS: Okay, thank you.
15 CHAIRMAN APOSTOLAKIS: Okay?
16 DR. LOIS: Thank you.
17 CHAIRMAN APOSTOLAKIS: But also, don't
18 hesitate to come when you are about to make a major
19 decision, because we've done that with the Regulatory
20 Guide 1174 and after that a lot of the groups come
21 here and they say, look, this is what we are thinking,
22 what do you guys think, rather than coming at the end
23 and having us disagreeing or whatever.
24 DR. LOIS: Thank you very much.
25 CHAIRMAN APOSTOLAKIS: Okay, thank you.

1 Okay, so this subcommittee meeting is
2 adjourned.
3 (Whereupon, the above-entitled matter was
4 concluded at 10:41 a.m.)
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CERTIFICATE

This is to certify that the attached proceedings before the United States Nuclear Regulatory Commission in the matter of:

Name of Proceeding: Advisory Committee on Reactor Safeguards Human Factors & Reliability & Probabilistic Risk Assessment Subcommittee Meeting

Docket Number: n/a

Location: Rockville, MD

were held as herein appears, and that this is the original transcript thereof for the file of the United States Nuclear Regulatory Commission taken by me and, thereafter reduced to typewriting by me or under the direction of the court reporting company, and that the transcript is a true and accurate record of the foregoing proceedings.

Charles Morrison
Official Reporter
Neal R. Gross & Co., Inc.

Idaho National Laboratory

Extending Bayesian Methods: Causal Models and Context in HRA Methods

Bruce P. Hallbert
Idaho National Laboratory

December 15-16, 2005

Bruce.Hallbert@inl.gov (208) 526-9867

Background

- The use of readily available information about human performance in HRA is limited
  - Some HRA methods include data—however, their quality and suitability for HRA analysis is questionable
  - Available sources are not typically used for reasons, such as:
    - HRA is modeling rare events—limited relevant operational data available
    - Thus far, operational experience or other sources have been regarded as not suitable for HRA—do not resemble the conditions analyzed in HRA
- Bayesian methods are used in other fields dealing with rare events (or sparse data) to support/inform their analysis
- Therefore, we believe that the Bayesian framework can be used for HRA as well

Objective

- Objective: Improve our capability to incorporate information about human performance from various resources in HRA
- Bayesian –type techniques for incorporating different types of information are available
- Currently we are focusing on developing approaches and associated technical bases that will lead to improvements in Bayesian methods for HRA
  - For example, causal models and context serve as a basis for explaining why people behave certain ways. Linking that to performance prediction is an aim of HRA.
  - An illustration of extending Bayesian methods to explicitly account for causal mechanisms and context will be presented next
- Other frameworks may also be explored in the future

Issue

- Many methods come with causal models identified via models of human performance.
  - Information processing model employed in many methods (e.g., ATHEANA, IDAC, SPAR-H, CREAM, etc.)
- Further acknowledge role of individual history, learning, heuristics, biases, & situational elements that were missing.
  - Error forcing conditions, performance shaping/influencing factors, common performance conditions, etc.
- Quantification entails relating information about specific elements from the performance environment to the model of human behavior to predict the risk metric of interest.

$$P(HF|S) = \sum_i P(EF_i|S) * P(UA|EF_i, S)$$

$$HEP = Nominal_{HEP} * \prod_{i=1}^{n} PSF_i \qquad MFR = MFR_0 * 10^A$$

Approach (cont'd)

- Extending Bayesian methods to employ information about causal and contextual factors can assist in implementing advanced in HRA.
- Need to address:
  - Definition(s) of data and evidence;
  - Use of partial & incomplete evidence;
  - Cases of success and failure;
  - How to employ information about PSFs & context;
  - Identifying & selecting sources of information and methods to derive prior probabilities;
  - Suitability of different distributions (i.e., likelihood functions) and important assumptions they employ;
  - How to extend both the mathematical and conceptual basis in Bayesian methods to be able to employ all of the available evidence.

Research Aims

- Be able to systematically relate elements of environment to performance using models of human performance.
  - Test model assumptions about potential causes;
  - Identify relevant causes and classes of outcomes;
  - Improve the kinds of causal mechanisms that are able to be considered in HRA.
- Improve accuracy of resulting HEP estimates.
  - Account for causal mechanisms with greater fidelity
  - Account for multivariate nature of context
  - Improve our knowledge of uncertainty.
- Develop, test, and employ empirically-based effects models.
  - Similar in concept to limit-state determination for systems
  - Attempt to identify how individual and groups of EFCs interact and dynamically shape performance
- Support validation or benchmarking of HRA methods

Concept Illustration: Operator Performance and PSFs

- Intuitive linkage between PSFs and operator performance.
- Types of PSFs and their effects on error rates vary among HRA methods.
- Assessment of PSFs estimated; uncertainty remains high in most applications.
- Need for better benchmarking and understanding of PSF relationship with performance.
- Linkage needed to build better models of failure.

Purpose

- Explore how data collected in human factors studies could support HRA.
  - Identify a set of PSFs that are predictive of crew performance.
  - Determine the weighting of these factors relative to one another.
  - Demonstrate a general model in which the PSFs can be expressed.
  - Measure the factors affecting the predictive validity of PSFs.
  - Replicate the results and model developments at different plants and at different times.

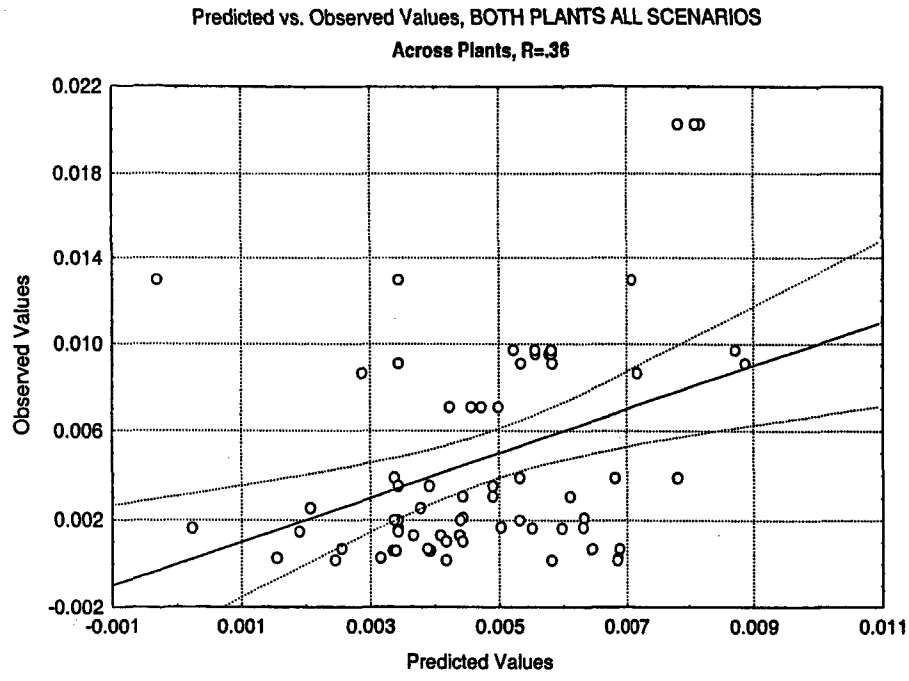
Approach

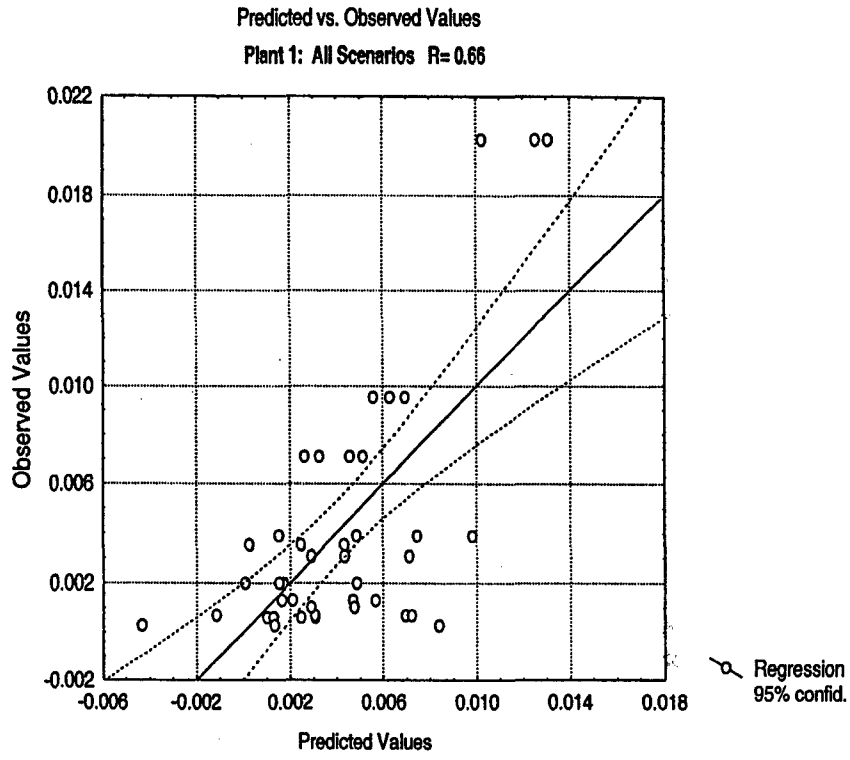
- Set of 10 PSFs tested for use in predicting crew performance:
  - 7 demonstrated predictive power: Procedures, Training, Stress, Workload, Information Available, System Feedback, HMI.
- Data collection instrument developed to measure "experienced" effects of PSFs.
  - Critical Tasks (mitigation)
  - Simulator trials
  - Rating by operators on the effect of PSFs on performance after scenario.
- Data collected on:
  - 4 crews in U.S. plant (3 Scenarios used: LOFW, SG overfill, SB-LOCA) NUREG/CR-4966
  - 4 crews in Loviisa and 4 crews in HAMMLAB
  - 3 common scenarios: overheating, overcooling, loss of coolant

Results

- Linear model with combined PSF weightings
- $$Y=a + b_1x_1 + b_2x_2 + ... + b_nx_n$$
  - Where Y= critical task mitigation performance
- Sensitive to scenario differences
- Sensitive to plant differences
- Demonstrated predictive ability (critical task performance)

Plant-specific predictive power





All crews, all plants, all scenarios

Plant 1, all scenarios

Idaho National Laboratory

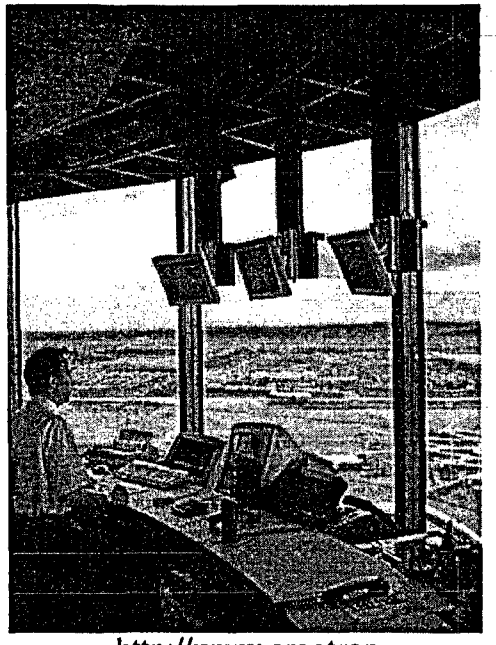
Summary

- Demonstrated link between performance shaping factors and operator performance.
- Model, technique show promise for explaining variability in task performance
  - Limited to situations in which the defined set of PSFs are, in fact, influencing performance
- Potential use for data collection using plant-specific simulators
  - Time and training demands are small
- No assumptions about strength of relationship between PSFs and performance: empirically established in each data collection trial.
- Potential for reducing uncertainty in HRA.

Additional Thoughts

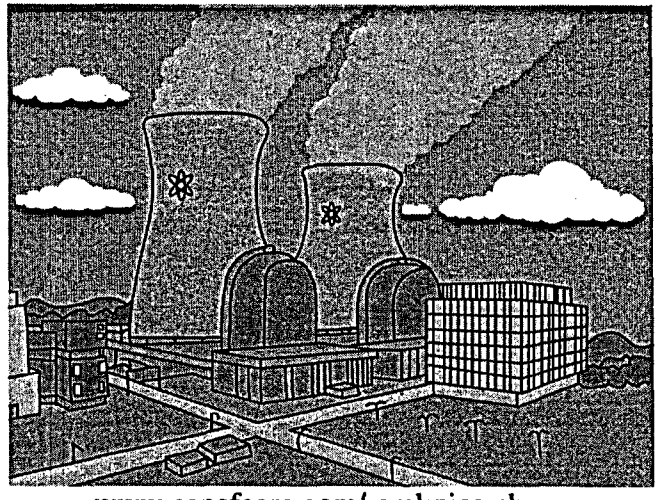
- Question remains of how to take performance (which we can observe) and predict quantities of interest that we don't.
- Focus attention on sources of data that include successful and unsuccessful performance in challenging contexts.
- Need development of formalisms that are multivariate in nature and allow incorporation of more information.
- Consider how advances in other areas of reliability engineering can help (e.g., BBNs, MCMC, importance sampling, variance reduction techniques, design of experiments, etc.)

Bayesian Analysis of Human Reliability and Performance Shaping Factors



http://www.ergotron-europe.com/europa/products_in_use.asp

Sankaran Mahadevan
Vanderbilt University



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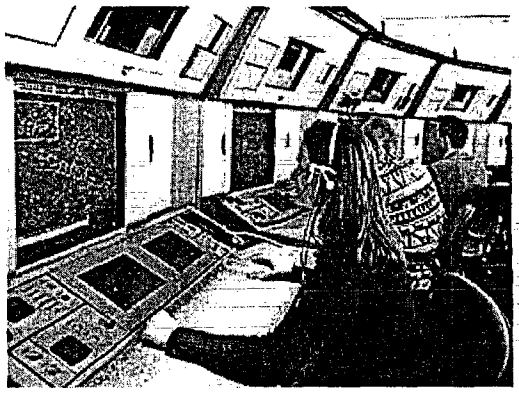
Overview



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Quantitative HRA

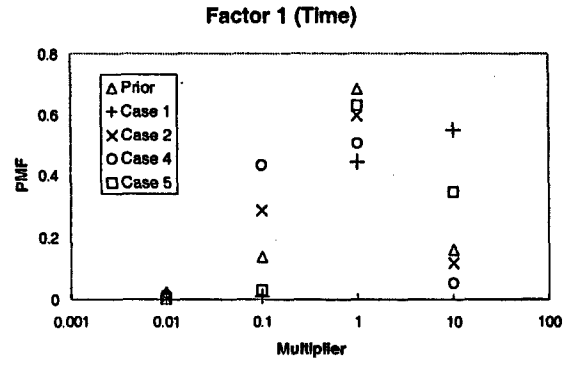
PSF	
Stress	5
Time	10
Complexity	3

SPAR-H model

$$P(E_i \mid A) = \frac{P(A \mid E_i)P(E_i)}{\sum_{i=1}^{n} P(A \mid E_i)P(E_i)}$$

Bayes' Theorem

Update model



Numerical example

Our analysis uses the SPAR-H model

Uses 8 PSFs

- Stress
- Complexity
- Available Time
- Ergonomics
- Experience/Traning
- Fitness for Duty
- Procedures
- Work Processes

Each PSF is a discrete variable with several possible values

The value of each PSF multiplies a nominal error probability

$$P_r = P_0 \prod_{i=1}^{m} F_i$$

Bayes' theorem allows us to combine experience, judgment, and observational data

We are interested in the probability of event E_i

Given:

- Prior estimate of $P(E_i)$, (judgement or experience)
- Occurrence of a related event, A, (observed data)
- Relationship between A and E_i, $P(A \mid E_i)$, (Likelihood)

Likelihood

Prior

Posterior

$$P(E_i \mid A) = \frac{P(A \mid E_i)P(E_i)}{\sum_{i=1}^{n} P(A \mid E_i)P(E_i)}$$

Update performance factor PMFs using human reliability data

Case 1: Data on binomial output

Given:

- Prior PMF estimates, $P(f_1), P(f_2), \ldots, P(f_n)$
- Failure data, k and n

$$\overbrace{P(p_r \mid n,k)}^{\text{Posterior}} \propto \overbrace{P(k,n \mid p_r)}^{\text{Likelihood}} \overbrace{P(p_r)}^{\text{Prior}}$$

Case 1 cont…

Assumptions:

- Each opportunity for human error is independent (trials are independent)
- Performance conditions occur independently (PSFs are independent)

$$P(p_r \mid n,k) \propto P(k,n \mid p_r)P(p_r)$$

$$\binom{n}{k} p_r^k (1-p_r)^{n-k} \qquad \prod_{i=1}^{m} P(f_i)$$

Now have data on failures *and* occurrences of performance factors

<u>Case 2:</u> *Data on input and output*

Given:

- Prior PMF estimates, $P(f_1), P(f_2), \ldots, P(f_8)$
- Failure data, k and n
- PSF occurrence data, $n_{f1i}, n_{f2i}, \ldots, n_{f8i}$

$$(2) \quad \overbrace{P(p_r \mid n,k)}^{\text{Posterior}} \propto \overbrace{P(k,n \mid p_r)}^{\text{Likelihood}} \overbrace{\cancel{P(p_r)}}^{\text{Prior}}$$

$$(1) \quad n_{f1i}, n_{f2i}, \ldots, n_{f8i} \quad + \quad P(p_r) \quad \Rightarrow \quad P2(p_r)$$

Correlation between trials can be dealt with by using a generalized binomial distribution

Case 4: Correlated trials

$$P(X=x)=\frac{\binom{n}{x}p^{x}(1-p)^{n-x}\theta^{x(n-x)}}{f(p,\theta,n)}$$

Generalized binomial distribution
(multiplicative form)

$\theta = 1$	Binomial	Independent
$\theta < 1$	Variance greater	Positive correlation
$\theta > 1$	Variance less	Negative correlation

Interpretation of the correlation factor, θ

Estimation of p and θ requires multiple data sets

$(n_1, k_1), (n_2, k_2), (n_3, k_3), \ldots$

Must simulate the joint PMFs of the correlated factors

Estimate correlation coeff. from data → Generate correlated normals

↓

CDF inverse transformation

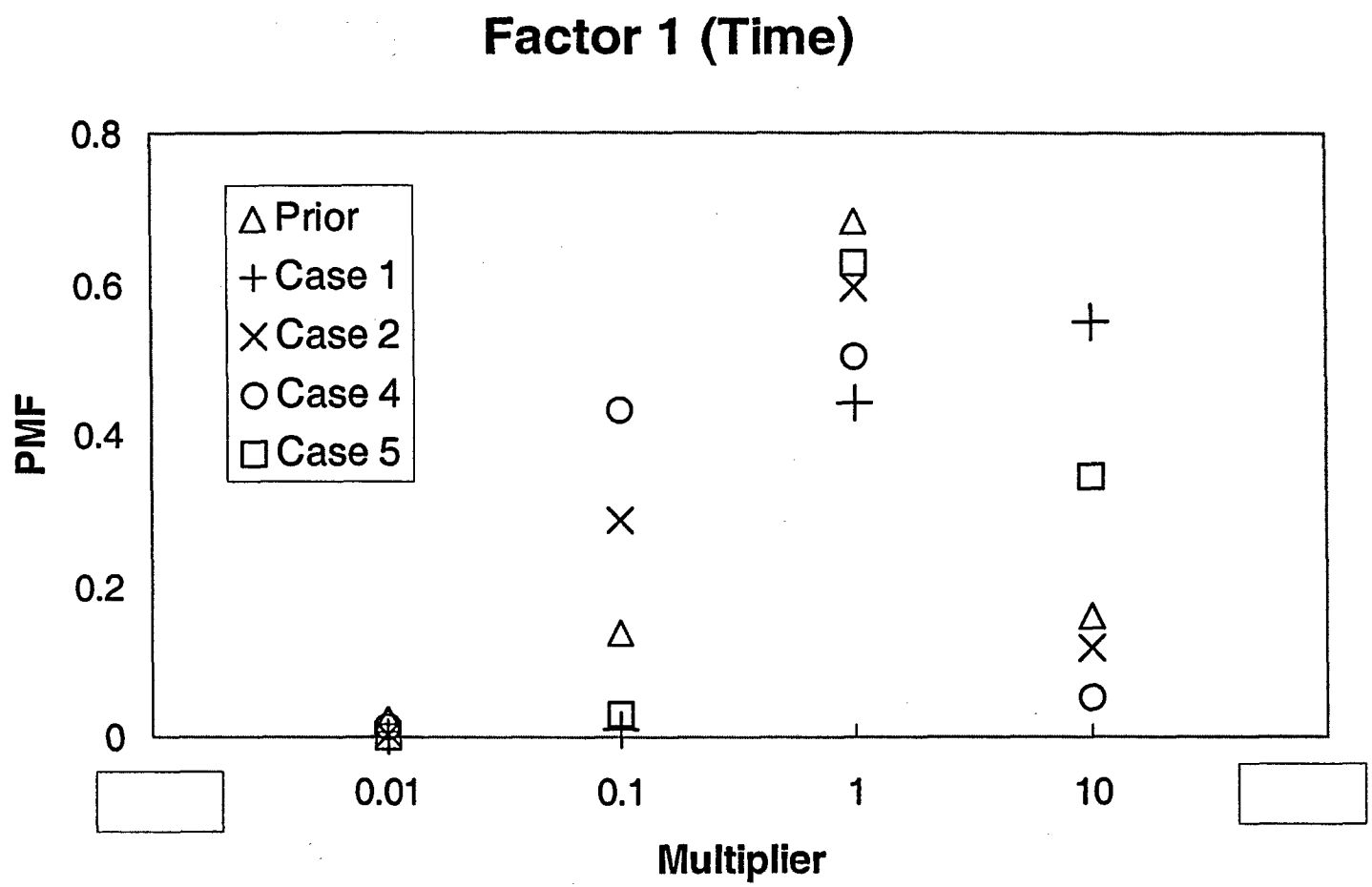
↓

Correlated discrete variables

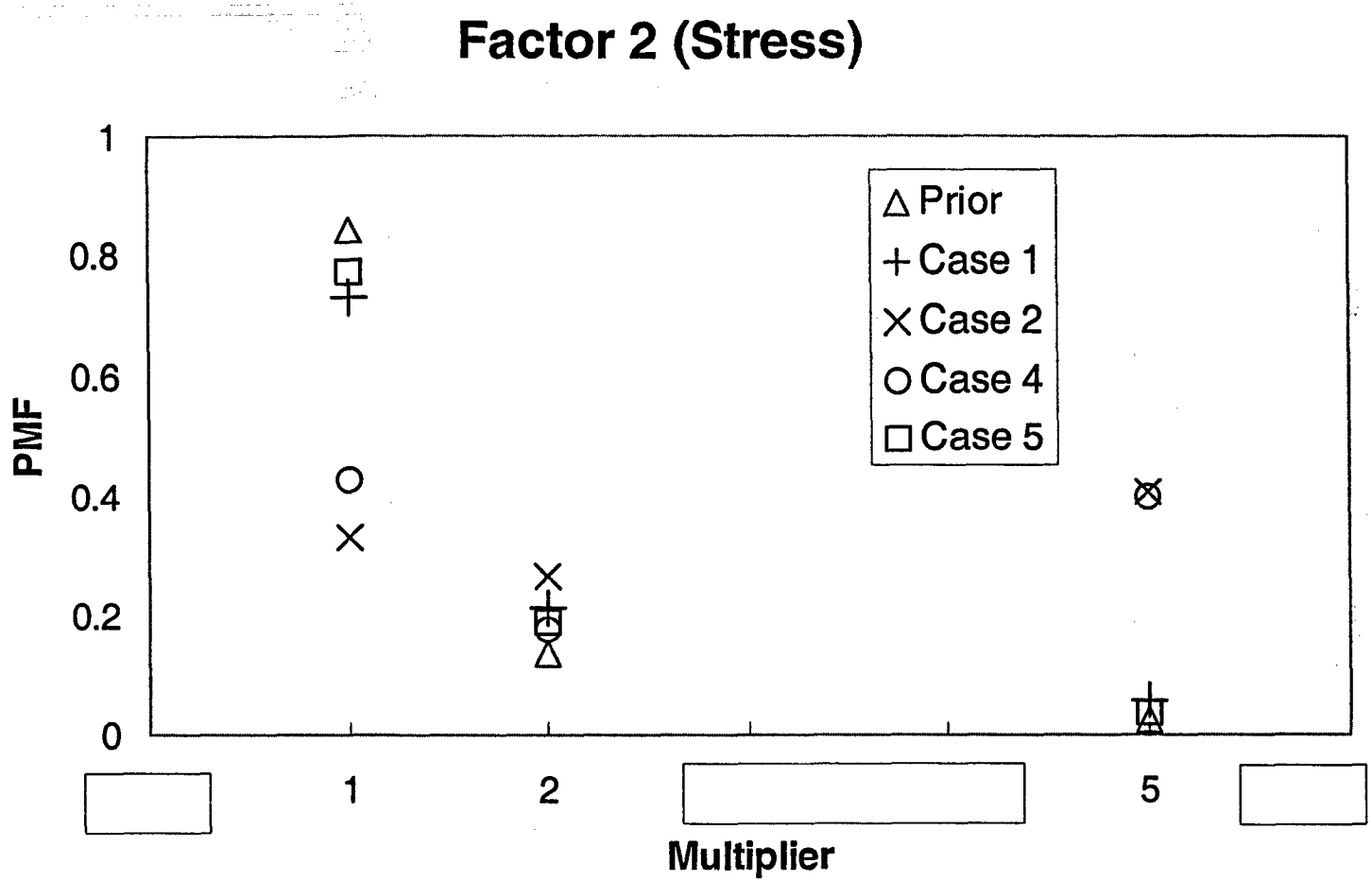
Repeat until desired correlation coeff. is achieved

Since not independent: $\cancel{P(p_r) = \prod_{i=1}^{m} P(f_i)}$

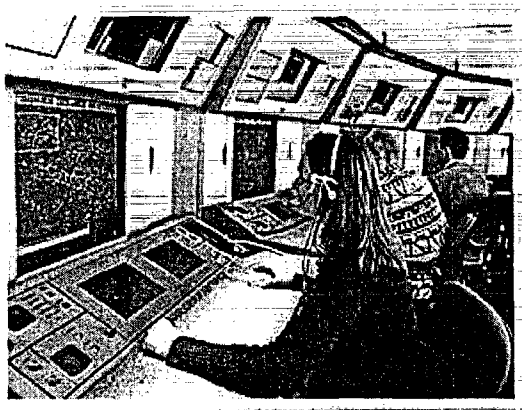
Numerical example results



Numerical example results cont…



Conclusion



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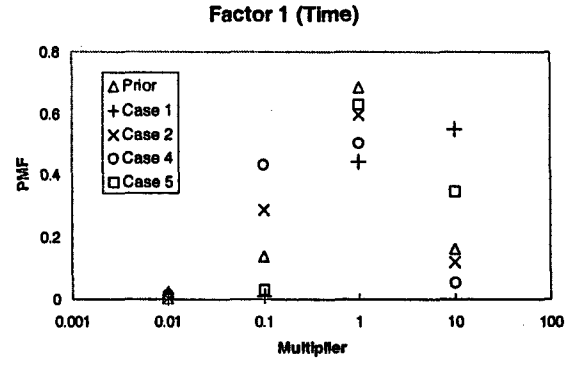


Numerical example

Bayesian Methods and HRA

Ali Mosleh
Center for Risk and Reliability
University of Maryland

Presented to

Advisory Committee on Reactor Safeguards
US Nuclear Regulatory Commission
December 15-16, 2005

BAYESIAN INFERENCE

- The unknown of interest (UOI)
- What we know about the UOI (Prior)
- Other evidence (E)
- Model of the process generating the evidence (Likelihood)
- Combined state of knowledge about the UOI (Posterior)

$$\pi(\mathrm{p}|\mathrm{E}) = \frac{L(\mathrm{E}|\mathrm{p})\pi_0(\mathrm{p})}{\int L(\mathrm{E}|\mathrm{p})\pi_0(\mathrm{p})\mathrm{dp}}$$

UNKNOWN OF INTEREST

Unknowns of Interest

- AO ≡ Operator Response or Action Outcome:
  - Failure
  - Success
- p = Probability (AO = Failure)
- Π (p) ≡ Probability Distribution of p

Questions:

- Why are we uncertain about AO? (why p and not "0" or "1"?)
- Why are we uncertain about p?

ESTIMATION FRAMEWORKS

Blue Model

$$P(\text{response}) = \sum_i P(\text{response} \mid \text{condition } i)\, P(\text{condition } i)$$

Yellow Model

$$P(\text{response}) = f(\text{PIF})$$

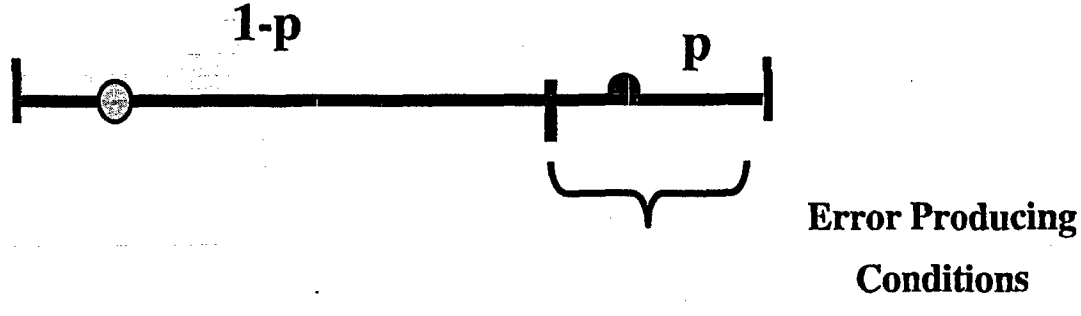
Examples of f:

- Tables (e.g., CREAM)
- Mathematical Function (e.g., SLIM)
- Expert Judgment (e.g., ATHEANA)

A POSSIBLE EXPLANATION FOR "p"

- Given a very specific condition (external and internal) the operator response is predictable as either success or failure.
- However in reality we can only specify a class of similar but not identical conditions, a fraction of which lead to failure and the rest result in success. That fraction is "p".

- Therefore "p" is the product of grouping a spectrum of conditions (external and internal) as one context



- The main assumption may be incorrect: Behavior is subject to a "residual randomness" - a source of "p" .

A POSSIBLE EXPLANATION FOR $\pi(p)$

- Variability of p from subclass to subclass (of conditions) within a super-class (e.g., generic context). Examples
  - Stochastic (aleatory) variability in factors, e.g.,
    - in PIFs characterizing the condition (e.g., variability in time pressure due to timing of events)
    - Crew-to-crew characteristics variability

- Uncertainty about the assessed values/states of PIFs for the specific condition or state of interest ("parameter uncertainty")
- Model Uncertainty
  - E.g., Incompleteness of PIFs (or factors used to characterize the condition or context) to represent the condition class

POSSIBLE AREAS OF APPLICATION OF BAYESIAN METHODS (1/3)

1. Developing "**generic or reference**" **HEPs** form different types and sources of information

POSSIBLE AREAS OF APPLICATION OF BAYESIAN METHODS (2/3)

2. Extending **data classification** and event coding frameworks to

- explicitly capture and record unavoidable use of analyst judgments and interpretations
- relax the requirements for the quality and quantity of data elements
  - exposure/success data, i.e., the number of opportunities to make a particular type error

POSSIBLE AREAS OF APPLICATION OF BAYESIAN METHODS (3/3)

3. Exploring the **role of causal factors** in "forcing" or "influencing" performance

- Use of Bayesian Belief Network for constructing causal models based on soft evidence
- Use of evidence to assess probabilities needed in such BBNs.

NATURE OF THE EVIDENCE

- Types of evidence available in HRA are often different than conventional statistical evidence. Some of the characteristics of the information are:

- Different forms of information:
  - o Estimates based on data from situations other the error of interest
  - o Expert estimates
  - o HEPs generated by applying HRA Models

- Non-homogenous evidence (different pieces of information from multiple sources)

- Incomplete, indirect, or partially relevant observations

FACTORS IN CONSTRUCTING THE LIKELIHOOD FUNCTION

- Type of Information
- Dependence (of information sources)
- Credibility (of data from experts and models)
- Homogeneity (of data points)
- Applicability (to the HEP of interest)
- Evidence Uncertainty
- ...

MULTIPLE TYPES OR SOURCES OF INFORMATION

$$\pi\left(p \middle| I_i,\ i=1,2,3,\ldots,n\right)=\frac{L\left(I_i,\ i=1,2,3,\ldots,n \middle| p\right)\pi_0(p)}{\int L\left(I_i,\ i=1,2,3,\ldots,n \middle| p\right)\pi_0(p)\,dp}$$

$$L\left(I_i,\ i=1,2,3,\ldots,n \middle| p\right)=\prod_{i=1}^{N} L\left(I_i \middle| p\right)$$ (For Independent Types)

Examples of I:

- I_1 = Actual Event Counts
- I_2 = Expert Estimates
- I_3 = Estimates Based on HRA Models

GENERIC DISTRIBUTION OF "p"

- Evidence: HEP estimates from different sources and reflecting different context or conditions

$$E = \{p_1, p_2, p_3, \ldots, p_n\}$$

1. Assume a beta distribution for p:

$$f(p|\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1}(1-p)^{\beta-1}$$

2. Use E to estimate distribution of α and β:

$$\pi(\alpha,\beta|E) = \frac{L(E|\alpha,\beta)\pi_0(\alpha,\beta)}{\int_\alpha \int_\beta L(E|\alpha,\beta)\pi_0(\alpha,\beta)\,d\alpha\,d\beta}$$

3. Estimate f(p):

$$f(p) = \int_\beta \int_\alpha f(p|\alpha,\beta)\pi(\alpha,\beta)\,d\alpha\,d\beta$$

UNCERTAINTY IN DATA ANALYSIS

- Uncertainty in event interpretation
- Partial Failures (quickly recovered error)
- Uncertainty about the success data (error opportunities)
- Uncertainty in cause classification (e.g., PIFs involved and their values /states)
- .....

DATA UNCERTAINTY: CLASSIFICATION OF CCF EVENT

- ***Impact Vector Method*** and ***Bayesian Estimation*** techniques used to extract information from uncertain and partially relevant data

- **Motivation:** Maximize the use of available information

  - CCF events are often highly system and situation specific
  - Limited in quantity - need to apply data from one situation to another
  - Analysis and classification involve significant judgment

EXAMPLE CCF EVENT CLASSIFICTION

LER Event Description :	Two of three independent switches failed due to higher than normal levels of fine dust in the environment. Fine dust deposit was also found on the third switch upon inspection.
Failure Mode:	Fail to Operate
Common Cause Component Group Size:	3

Hypotheses for Event

	Hypothesis	Probability	Elements of Impact Vector			
			F_0	F_1	F_2	F_3
1.	Two of three components fail	0.9	0	0	1	0
2.	All three components fail	0.1	0	0	0	1
Average Impact Vector ($\bar{I}$)			$\overline{F_0}$	$\overline{F_1}$	$\overline{F_2}$	$\overline{F_3}$
			0	0	0.9	0.1

DATA UNCERTAINTY: EXPOSURE DATA

- Exposure or success data are typically unavailable for HEP calculations. In some cases, however, one might be able to develop upper and lower bounds based on auxiliary information.

- Conventional statistical evidence;

$$E = \{N_O \text{ and } N_E\}$$

- Uncertain Evidence

$$UE = \{ f(N_O),\ f(N_E) \}$$

- Bayesian framework allows us to use uncertainty distribution for the exposure/success data (N_O) and number of errors (N_E)

DEALING WITH UNCERTAIN EVIDENCE

- Weighted Posterior Method

$$\pi(p|UE) = \int \pi(p|E) f(E) dp$$

- Weighted Likelihood Method

$$\pi(p|UE) = \frac{\left[\int L(E|p) f(E)\right] \pi_0(p)}{\int \left[\int L(E|p) f(E)\right] \pi_0(p) dp}$$

- Evidence Averaging Method

$$\pi(p|UE) = \frac{L(\bar{E}|p)\pi_0(p)}{\int L(\bar{E}|p)\pi_0(p) dp}$$

$$\bar{E} = \int E f(E)$$

MODELING PARTIALLY RELEVANT EVIDENCE

- Totally Relevant

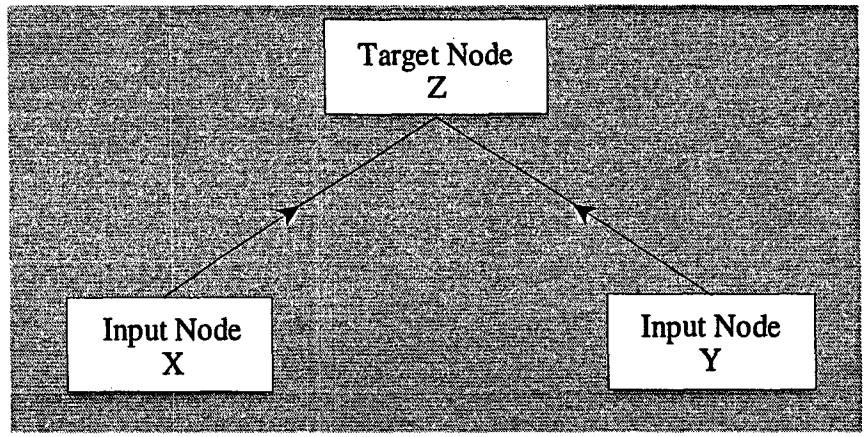
$$\pi(\mathrm{p}|\mathrm{E}) = \frac{L(\mathrm{E}|\mathrm{p})\pi_0(\mathrm{p})}{\int L(\mathrm{E}|\mathrm{p})\pi_0(\mathrm{p})\mathrm{dp}}$$

- Partially Relevant (one of a number of options)

$$\pi(\mathrm{p}|\mathrm{E}) = \frac{[L(\mathrm{E}|\mathrm{p})]^{\omega}\pi_0(\mathrm{p})}{\int [L(\mathrm{E}|\mathrm{p})]^{\omega}\pi_0(\mathrm{p})\mathrm{dp}}, \qquad 0 \le \omega \le 1$$

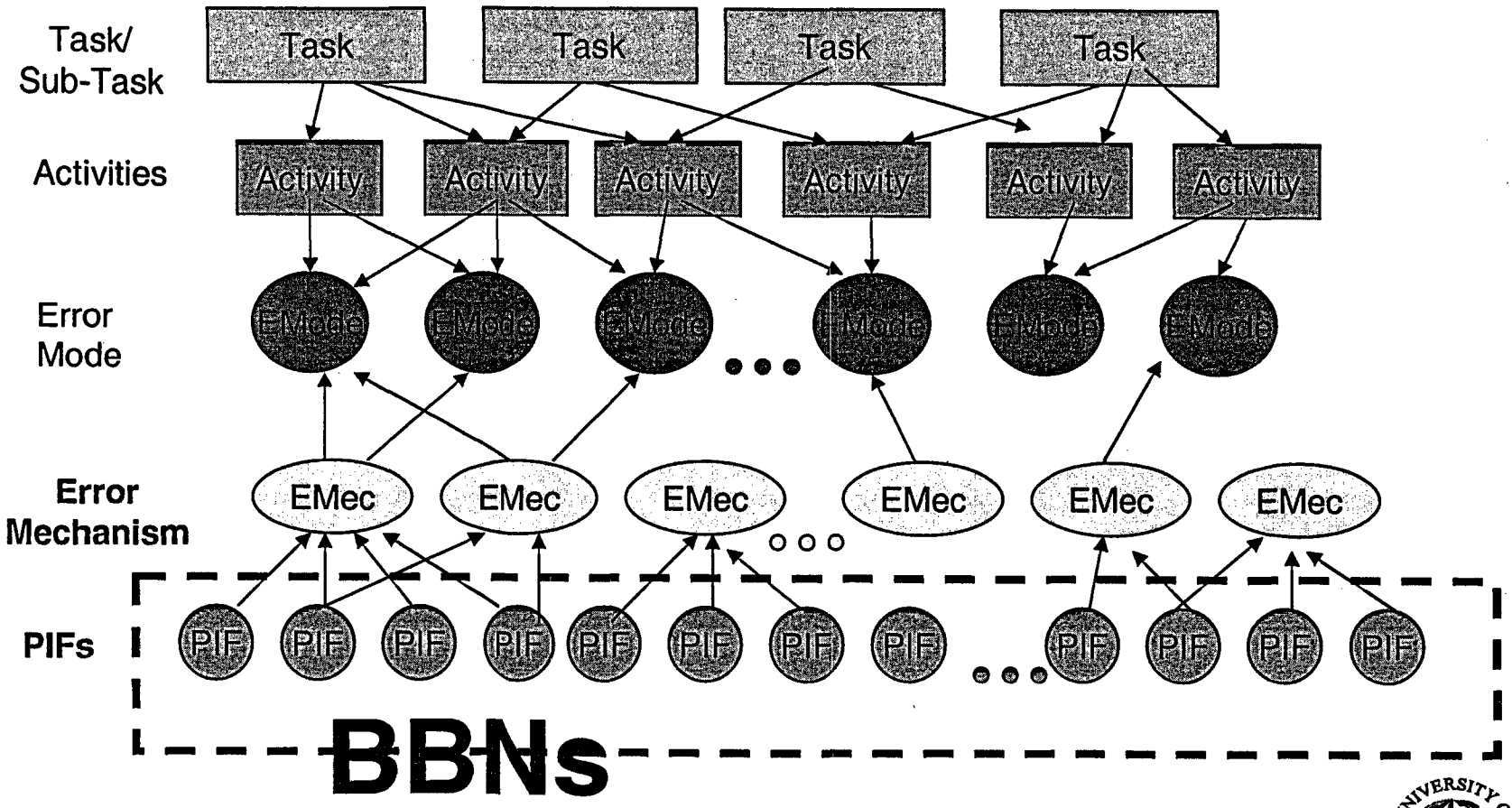
USE OF BBN TO CONSTRUCT CAUSAL MODELS

Bayesian Belief Network (BBN) Basic Concepts



State of X	State of Y	Joint Prob.	**Conditional Prob (Z=0)**	**Unconditional Prob (Z=0)**
X=1	Y=1	pq	r_1	r_1 pq
X=0	Y=1	(1-p)q	r_2	r_2 (1-p)q
X=1	Y=0	p(1-q)	r_3	r_3 p(1-q)
X=0	Y=0	(1-p)(1-q)	r_4	r_4 (1-p)(1-q)

USE OF BBN TO CONSTRUCT A CAUSAL MODEL



EXAMPLE: IDAC PIF Group Dependencies

Independent PIF Group \ Dependent PIF Group		Mental State							External Factors			
		Cognitive Modes and Tendencies	Emotional Arousal	Strains and Feelings	Perception and Appraisal	Intrinsic Characteristics	Physical Factors	Memorized Information	Team-Related Factors	Organizational Factors	Environmental Factors	Conditioning Events & Hidden Faults
Mental State	Cognitive Modes and Tendencies		--	--	--	--	--	(1)*	--	--	--	--
	Emotional Arousal	X		--	--	--	(3)*	(1)*	--	--	--	--
	Strains and Feelings	X	X		--	--	(3)*	--	--	--	--	--
	Perception and Appraisal	X	X	X		--	--	--	--	--	--	--
	Intrinsic Characteristics	X	X	X	X		--	(4)*	(5)*	(5)*	--	--
Physical Factors		X	X	X	X	--		--	--	--	--	--
Memorized Information		--	--	--	X	--	--		--	--	--	--
External Performance Influencing Factors	Team-Related Factors	X	X	X	X	(6)	(6)	(6)		--	--	--
	Organizational Factors	X	X	X	X	(6)	(6)	(6)	--		--	--
	Environmental Factors	--	--	--	--	--	--	--	--	--		--
	Conditioning Events & Hidden Faults	--	--	--	--	--	--	--	--	--	--	

INFERENCE WITH BBNs

- Forward Inference - Backward Inference

$$P(\text{Cause } x \mid \text{Error}) \Longleftrightarrow P(\text{Error} \mid \text{Cause } x)$$

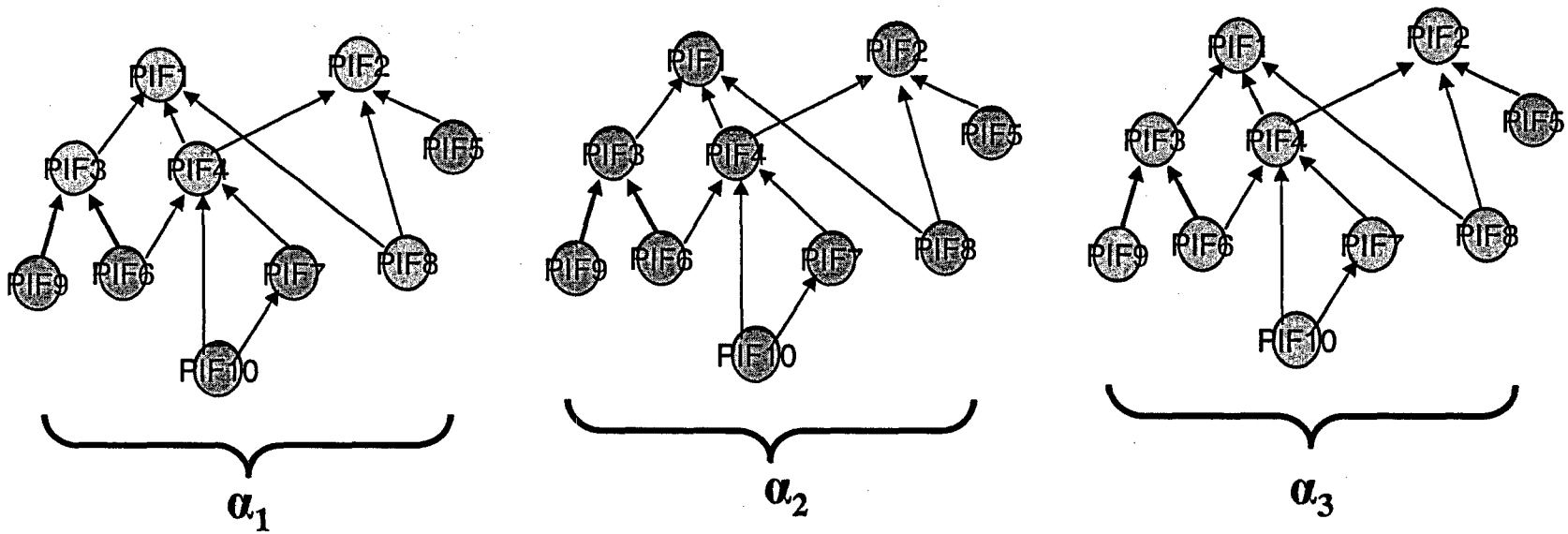
- Allows
  - o use of data to estimate causal link conditional probabilities
  - o quantification of HEPs once the network is populated

- Can be used to define a limited number of "generic Contexts" in terms of states of various PIFs

USE OF DATA (1/2)

- BBN construction:
  - o Test/ Identify BBN Links
- BBN Quantification:
  - o Psychological Literature
  - o Halden data
  - o HERA data
- Modification of generic estimates based on data-based distribution of contexts

USE OF DATA (1/2)



Distribution based on HERA Data

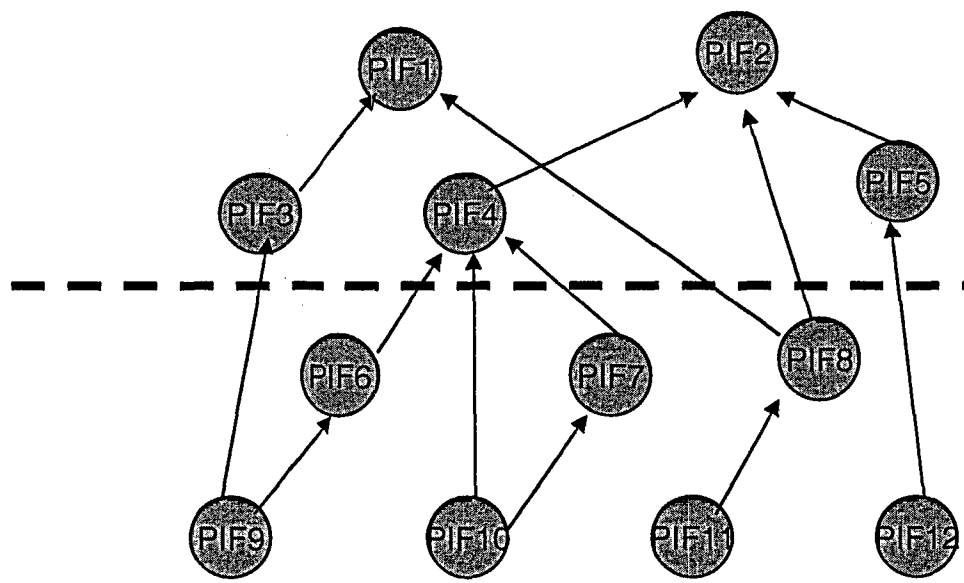
Generic HEP (Q): 10^{-4} — 10^{-2}

Modified HEPs: $Q_i = \alpha_i Q$

ADEQUACY OF BBN

- Pure BBN may be too restrictive
  - o Dynamic factors
  - o Feedback (BBNs are acyclic)
- Quantification is difficult for "inner nodes"
- Quantification requirements can be relaxed using the QQ-BBN Methodology

Qualitative-Quantitative BBN
(Mosleh et al, 2005)



Quantitative
Probability scale

Qualitative
Likelihood scale

Human Event Repository and Analysis (HERA) Project

Bruce Hallbert, INL
Erasmia Lois, US NRC

Advisory Committee on Reactor Safeguards (ACRS)

Human Factors & Probabilistic Risk Assessment Subcommittees Meeting

Rockville, MD
December 15-16, 2005

Briefing Overview

- Update ACRS on the status of efforts related to data production and system development for the HERA database.
  - Data description and system architecture
  - Data types and efforts to incorporate various kinds of human performance evidence
- Describe efforts to address use of data to estimate likelihood of human failure events (HFEs) and HRA model parameters.
  - Summary of workshop on Bayesian methods
  - Discussion of several promising ideas.
- Feedback sought on current direction and approaches to data production and use of data in HRA.

Background

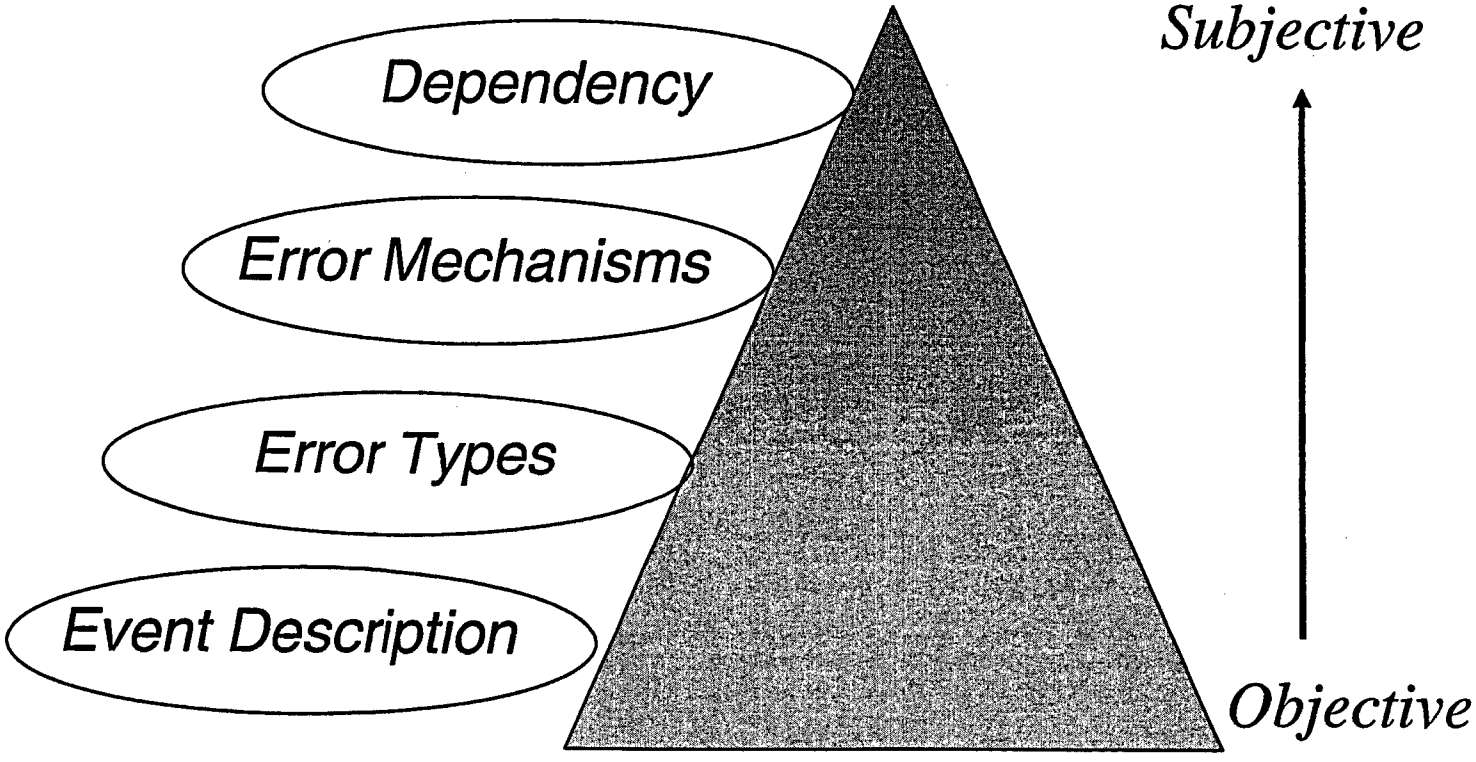
- HRA methods use structured processes to identify potential human failure events and to estimate their likelihood.
- Most methods permit or direct the analyst to account for performance conditions and context.
- Identifying important conditions and accounting for their effects continue to be a challenge for HRA.
- HRA methods may account for different Performance Shaping Factors (PSFs) and may treat them each differently.
- As a result, considerable analyst judgment is required.
- Differences in the magnitude of effect of such factors contribute to the uncertainty in the resultant risk metric.

HERA Objective and Approach

- Objective: Systematic collection of information about human performance in PRA-relevant settings
- Approach:
  - Identify information sources that can be used to inform HRA activities.
  - Develop a formal process for extracting HRA-relevant information.
  - Extract the information/ develop a repository to make information readily available to NRC users.
  - Develop quantification approaches (e.g., Bayesian type methods) to allow the use of various types of evidence in estimations.

Process model

- **Extraction based on concept of layering:**



HERA Main Event Profile

Section I. Plant & Event Overview

1. **Name of Nuclear Plant**
2. **LER #**
3. **Event Type – broken down into 3 types:**
   - **Initiating event**
   - **Condition (Latent)**
   - **Condition (Active)**

Also important in Section I:

- **Date/Time**
- **Mode**
- **Plant Power Level**
- **Potential/ Actual Losses**
- **Components Unavailable**

Plant & Event Overview
Event Types

Initiating Event: **Plant upset condition that leads to shutting down the reactor neutronics process and subsequent removal of decay heat from the reactor core.**

Common Initiating Events include:

- **Reactor trip (TRANS or SCRAM)**
- **Loss of offsite power (LOOP)**
- **Loss of coolant accident (LOCA)**
- **Steam generator tube rupture (SGTR)**
- **Loss of DC bus accident (LDCA)**
- **Loss of service water system (LOSWS), and**
- **Loss of component cooling water (LOCCW)**

Plant & Event Overview
Event Types

Condition: **An event, which, when left unattended, either**

receiving no response from operators or automatically actuated systems would result in an undesired outcome, but that would not require shutting down the reactor neutronics process or removal or decay heat from the reactor core.

2 types of conditions, or off-normal events:

- Active condition: **An off-normal event which occurs as a result of an undesired outcome is an active condition**
- Latent condition: **A latent condition is an off-normal event which has the potential for an undesired outcome, but that outcome doesn't occur at the time the condition is created.**

Section II: Index of Subevents

Main event broken down into subevents

- Subevents coded*
  XHE – Human Error (through unsafe action or inaction)
  HS – Successful Human Action (or recovery)
  XEQ – Equipment Failure
  EQA: Equipment Actuation
  POS: Positive Human Action
  NEG: Negative Human Action

- Subevents – coded consecutively on timeline
  (e.g. XHE1, XHE2, HS1)

*** Subevent codes adapted from SPAR**

Section III: Human Subevent Dependency

Dependency: The means by and extent to which an action or event influences a subsequent action or event. Dependency increases the probability of success or failure of a human action that occurs serially in relation to other actions or events.

- Examples include:
  - Whether subevents involved the same crew or different crews;
  - Whether or not the subevents occurred within a close range of time such that a crew "mindset" or interpretation of the situation might carry over from one event to the next;
  - The procedures and cues used along with the plant conditions related to performing the actions are identical (or nearly so) or related, and the applicable steps in the procedures have few or no other steps in between the applicable steps;
  - Similar PSFs apply to actions;
  - How the actions are performed is similar and they are performed in or near the same location;
  - There is reason to believe that the interpretation of the need for one action might bear on the crew's decision regarding another action, i.e., the basis for one decision in a scenario may influence another decision later in the scenario.

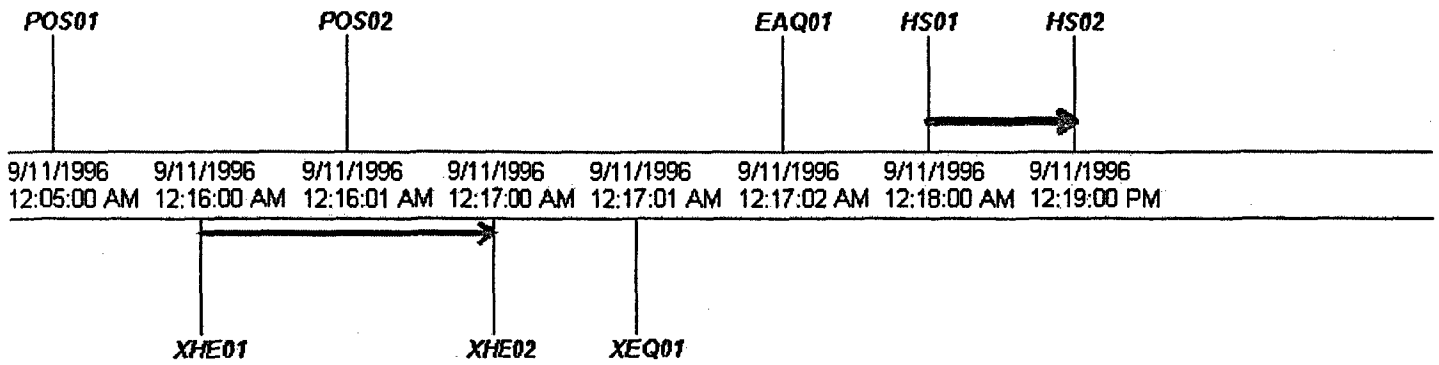
Part B: HERA Subevent Profile

Separate Part B worksheet required for each human subevent :

Each Part B Worksheet broken down into 8 sections:

- **Diagnosis and Planning**
- **Action**
- **Personnel Involved in Subevent**
- **Contributory Plant Factors**
- **Contributory Maintenance Factors**
- **Successful Human Actions**
- **Error Type**
- **Subevent Comments**

Byron Unit 1 (LER 4541996017)



POS01 Operators were preparing to perform a monthly surveillance of the Turbine Protection System

XHE01 Auxiliary Operator (Non-licensed) #2 mistakenly placed the lever actuating tool into position on the TRIP lever, not the TEST lever as he intended.

POS02 AO#2 realized the tool was on the wrong lever

XHE02 AO#2 attempted to remove the lever actuating tool from the TRIP lever reflexively, without taking the time to analyze how best to handle the situation, he rotated the lever enough that is caused a Main Turbine trip.

XEQ01 Main Turbine Trip

EAQ01 Because the reactor was above 30% power, the turbine trip caused an automatic reactor trip, which resulted in actuation of Unit 1 Engineered Safety Features equipment. All automatic safety system actuation occurred as designed.

HS01 Main Control Room entered into Byron Emergency Procedures

HS02 Operators stabilized the unit in Mode 3

Idaho National Laboratory

Status

- 45 LERs form the basis for information in HERA
- ~700 data records (end of FY 05)

Bayesian Methods

Bruce Hallbert, INL
Ali Mosleh, University of Maryland
Erasmia Lois, US NRC

December 14-15, 2005

Background

- Data and observations from experience, research, training & other sources can improve our assessments.
- Improvements needed in making predictions about the kinds of human human performance possible in PRA-relevant contexts.
- Improvements also needed in ability to make predictions about the likelihood of their occurrence.
- Workshop goal and subsequent activities aimed at improving methods for predicting human performance outcomes and likelihood.
- Bayesian methods focus of the workshop.

Presentation Overview

- Three ideas illustrate some promising approaches:
  - Considerations about the nature of the measure(s) we are predicting and ways of combining evidence to facilitate their prediction (Professor Mosleh).
  - Approaches to using human performance research to develop parametrically elaborate, contextually sensitive models (Hallbert).
  - Using operational experience to improve knowledge of HRA model parameters (Professor Mahadevan).