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Analysis and Insights from a Dynamical Model of Nuclear Plant Safety Risk

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ABSTRACT

In this paper, we expand upon previously reported results of a dynamical systems model for the impact of plant processes and programmatic performance on nuclear plant safety risk. We utilize both analytical techniques and numerical simulations typical of the analysis of nonlinear dynamical systems to obtain insights important for effective risk management. This includes use of bifurcation diagrams to show that period doubling bifurcations and regions of chaotic dynamics can occur. We also investigate the impact of risk mitigating functions (equipment reliability and loss prevention) on plant safety risk and demonstrate that these functions are capable of improving risk to levels that are better than those that are represented in a traditional risk assessment. Next, we analyze the system response to the presence of external noise and obtain some conclusions with respect to the allocation of resources to ensure that safety is maintained at optimal levels. In particular, we demonstrate that the model supports the importance of management and regulator attention to plants that have demonstrated poor performance by providing an external stimulus to obtain desired improvements. Equally important, the model suggests that excessive intervention, by either plant management or regulatory authorities, can have a deleterious impact on safety for plants that are operating with very effective programs and processes. Finally, we propose a modification to the model that accounts for the impact of plant risk culture on process performance and plant safety risk. We then use numerical simulations to demonstrate the important safety benefits of a strong risk culture.

KEYWORDS: Nonlinear Dynamical Systems, Process Model, Risk Management

INTRODUCTION

In a previous paper [1], we presented an alternative approach to addressing the issue of the impact of plant programmatic and process performance on nuclear power plant safety risk. We developed a dynamical systems model that describes the interaction of important plant processes on nuclear safety risk and discussed development of the mathematical model including the identification and interpretation of significant inter-process interactions. We also performed a preliminary analysis of the model that demonstrated that its dynamical evolution displays features that have been observed at commercially operating plants. From this analysis, a few significant insights were presented with respect to the effective control of nuclear safety risk, the most important example being that significant benefits in effectively managing risk can be obtained by integrating the plant operation and work management processes such that decisions are made utilizing a multidisciplinary and collaborative approach. Finally, we noted that although the model was developed specifically to be applicable to nuclear power plants, many of the insights and conclusions obtained are likely applicable to other process industries.

In this previous paper, a dynamical systems model was developed that accounted for the impact of the operations (O), work management (W), equipment reliability (E) and loss prevention (L) functions on plant risk (R). These functions were defined as a mapping over the domain space [-1, 1] with $X_i = -1$ defined to correspond to completely ineffective process performance (i.e. a process for which there is no confidence that it will achieve its intended function), $X_i = 1$ to completely effective process performance (i.e. a process for which there is complete confidence that it will achieve its intended function) and $X_i = 0$ to be the point of indifferent performance. Here we obtained the model (1)

$$\begin{gathered} R(t+1) = O(t) + W(t) \\ O(t+1) = O(t) + \lambda_{WO} W(t) + \mu_{WO} W(t) O(t) \\ W(t+1) = W(t) + \lambda_{OW} O(t) + \lambda_{EW} E(t) + \lambda_{LW} L(t) + \mu_{OW} O(t) W(t) + \mu_{EW} E(t) W(t) \\ E(t+1) = a_1 E(t) + a_2 E(t)^3 \\ L(t+1) = b_1 L(t) + b_2 L(t)^3 . \end{gathered} \tag{1}$$

In this model, the coefficient λ_{jk} represents the linear coupling of process j on process k. As an example, λ_{OW} represents the influence of the operations process on decisions made in the work management process. Similarly, λ_{WO} represents the influence of the work management process on decisions made in the operations process. The λ_{jk} thus provide a representation of how much one process influences the other process in a unilateral manner. The coefficients μ_{jk} represent the interactive (collaborative) coupling that occurs from process j on process k. Thus, μ_{WO} represents the degree to which the operations and work management functions collaborate in operational decision-making. In both cases, small values of the coupling coefficients (λ, $\mu \sim 0.01 – 0.05$)

indicate minimal interaction between the processes, whereas large values ($\lambda, \mu \sim 1$) indicate significant levels of interaction.

As discussed in [1], we wish to reiterate that the primary benefit of this model is not in its capacity to provide detailed quantitative estimates of changes in plant risk. The significance of the model is that it provides a theoretical construct that can account for some of the features of the impact of plant management and processes on commercial nuclear power plant safety risk. As such, its analysis permits the development of insights that can be used to develop and implement effective strategies to control safety risk at these facilities. As will be discussed in this paper, the insights obtained from the model analysis qualitatively corroborate the results of previous research and the opinion of numerous experts on the importance of management and process factors to plant risk. Thus, the model can provide a construct from which these strategies can be evaluated prior to implementation.

In the analysis of this model in [1], we demonstrated that the risk mitigating functions (equipment reliability and loss prevention) possessed stable operating points at E = L = 0 (i.e. the point of indifferent operation). Thus, we obtained an important simplification which permitted use of analytical techniques. This simplification resulted in what we termed the "ROW" model

$$\begin{aligned} R(t+1) &= O(t) + W(t) \\ O(t+1) &= O(t) + \lambda_{WO} W(t) + \mu_{WO} W(t) O(t) \\ W(t+1) &= W(t) + \lambda_{OW} O(t) + \mu_{OW} O(t) W(t)\,. \end{aligned} \tag{2}$$

In addition to its utility in facilitating analysis, this simplified model also is important in that it is generically applicable across a wide variety of process industries that either have not implemented risk management functions and processes or where their impact is not significant.

BIFURCATIONS AND CHAOTIC DYNAMICS OF ROW SYSTEM

In [1], we demonstrated the system (1) possesses two fixed points. The first is located at the origin (i.e. $(R^*,O^*,W^*,E^*,L^*) = (0,0,0,0,0)$) and corresponds to the level of risk inherent in the plant design and that which is estimated in the probabilistic risk assessment (PRA). Analysis of this fixed point demonstrated that it is a point of unstable equilibrium with respect to programmatic and process performance. The model also produced a second fixed point at

$$(R^*,O^*,W^*,E^*,L^*) = \left(-\frac{(\lambda_{WO}\mu_{OW} + \lambda_{OW}\mu_{WO})}{\mu_{WO}\mu_{OW}}, -\frac{\lambda_{WO}}{\mu_{WO}}, -\frac{\lambda_{OW}}{\mu_{OW}}, 0, 0\right). \qquad (3)$$

Analysis of the stability of this fixed point demonstrated that, for values of the coupling constants that are not too large, the point represents a stable equilibrium. This fixed point lies in the negative portion of the {R,O,W} phase subspace. Thus, operation at this fixed point is indicative of a higher level of plant risk than that inherent in the design and estimated in a PRA. This result is not unexpected. In practice, routine operational and maintenance activities constantly alter the risk profile and the plant will not remain at its level of inherent design risk.

One of the characteristics of nonlinear dynamical systems is that small changes in the system parameters can lead to large qualitative changes in the behavior of the system. Because the model presented here is nonlinear, it also can be expected to demonstrate these characteristics. From a nuclear safety viewpoint, since these regions are indicative of less predictable dynamics, they are regions to be avoided. To analyze our system for these effects, we use the simplified

ROW model (2) assuming the additional simplification in the interprocess couplings described in [1]; i.e., we set $\lambda_{WO} = \lambda_{OW} = \lambda$ and $\mu_{WO} = \mu_{OW} = \mu$. With this simplification, the system of equations becomes

$$\begin{aligned} R(t+1) &= O(t) + W(t) \\ O(t+1) &= O(t) + \lambda W(t) + \mu W(t) O(t) \\ W(t+1) &= W(t) + \lambda O(t) + \mu\, O(t) W(t)\,. \end{aligned} \tag{4}$$

For this system, the origin is an unstable fixed point and the second fixed point reduces to ($-2\lambda/\mu$, $-\lambda/\mu$, $-\lambda/\mu$). The primary motivation for this simplification is to facilitate analysis of the model and develop useful insights. We note that setting the interprocess coupling parameters equal to each other may not be appropriate for all applications of the model to real plants. However, there are situations in which it is reasonable to expect the couplings between processes to be roughly equal. As one example, when collaborative decision-making between processes is strong (i.e. μ predominates over λ), it is likely that this collaboration will be reciprocal. Thus, if the work management process inputs collaboratively in operational process decision-making, it is reasonable that the converse also will apply.

For many dynamical systems, a stable fixed point can change stability as a control parameter is varied. At a critical threshold of the parameter, this stable fixed point can become unstable and be replaced by a system which oscillates between two points which are different from the original stable point. For a system $\mathbf{X}(t)$, a period two solution occurs for $\mathbf{X}(t+2) = \mathbf{X}(t) \neq \mathbf{X}(t+1)$ [2]. Solving (4) for this condition indicates a period two bifurcation can occur for $\lambda > 2$. At values greater than this, system bifurcations are possible. Thus, the model indicates that as the individual processes are driven by internally generated objectives, their integrated impact on other plant programs and safety risk can result in unanticipated results. Additionally, as this linear coupling term is increased further, the system can undergo additional bifurcations leading to the period doubling route to chaos. To provide an example of this behavior, Figure 1 shows a bifurcation diagram for $\lambda = 5$ as the parameter μ is increased. In this diagram, performance of the operations function (O) is displayed. Behavior of plant risk and the work management process is similar.

In this diagram, the system bifurcates to a period two attractor at the value $\mu = 4.0$. At approximately $\mu = 4.74$ the system bifurcates again into a period four attractor. This process continues with further period doubling bifurcations. Between approximately 4.8 and 4.94, a period three attractor is present. This region is particularly significant because existence of a period three orbit implies chaotic dynamics [3]. This follows from Sharkovskii's Theorem [4, 5]. This theorem provides a scheme for ordering the integers such that the existence of a period k orbit implies the existence of periodic orbits for every higher ordered period. In this scheme, consider the following ordering of all integers [12, p.135]

$$3 \blacktriangleright 5 \blacktriangleright 7 \blacktriangleright \ldots \blacktriangleright 2\cdot 3 \blacktriangleright 2\cdot 5 \blacktriangleright 2\cdot 7 \blacktriangleright \ldots \blacktriangleright 2^n\cdot 3 \blacktriangleright 2^n\cdot 5 \blacktriangleright 2^n\cdot 7 \blacktriangleright \ldots \blacktriangleright 2^n \blacktriangleright \ldots \blacktriangleright 2^4 \blacktriangleright 2^3 \blacktriangleright 2^2 \blacktriangleright 2^1 \blacktriangleright 1 \qquad (5)$$

with $n \rightarrow \infty$. In this sequence, the symbol $\blacktriangleright$ should be understood to mean "follows" in the sequence. Sharkovskii's theorem states that the existence of a period j orbit implies the existence of all periodic orbits of period k where k follows j in the ordering given in (5). For example, a period 8 orbit implies at least one period 4 orbit, which implies at least one of periods 2 and 1 also. Since three is the last number in the sequence, existence of a period three orbit implies all other periodicities, and thus chaotic dynamics. Thus, the presence of a period three orbit in Figure 1 indicates that this system is capable of producing chaotic dynamics.

There are two additional items of significance with respect to this diagram. First, from a risk management perspective, since performance changes rapidly in this region of the {R,O,W} phase space, it will be difficult to effectively manage plant risk. Thus, these regions should be avoided. Since values of λ this large are indicative of the individual process decision-makers driving the decisions to meet their own objectives, these results indicate that individual departments and work groups unilaterally pursuing their own agendas can have a detrimental impact on risk, with the results of the decision-making process not always being adequately foreseen. However, a second significant item relates to the behavior as μ is increased. At a sufficiently large value of μ, which is indicative of the degree of collaboration between the operations and work management processes, the results again become completely predictable (with significant risk reduction). This is indicative of the collaboration between the majority of the organization's members outweighing the individual agendas of the few individuals attempting to control the decision process. In the illustration presented here, μ is extremely large ($\mu = 5$) which is indicative of an extremely high level of interorganizational cooperation; and one which probably is not achievable in practice. Thus, we obtain the insight that collaboration between the organizations responsible for the operations and work management processes is an important component in effectively managing plant risk and it can be concluded that it is not just the interaction between the processes which is the important characteristic for managing risk, but the extent to which this interaction is collaborative in nature. Therefore, to effectively control plant risk, organizations should strive to maximize the degree of collaboration in the operations and work management decision-making processes.

IMPACT OF RISK MITIGATION FUNCTIONS

In a commercial nuclear power plant, both the equipment reliability and loss prevention functions are specifically intended to monitor performance, detect degraded conditions and specify appropriate corrective actions for plant structures, systems and components. Thus, these functions can be viewed as specifically addressing nuclear safety risk. Equipment reliability encompasses those engineering and maintenance functions that specifically address the reliability and availability of plant hardware. This function includes activities such as:

- developing and maintaining a long-term maintenance plan (preventive and predictive maintenance programs),
- conducting surveillance and performance tests,
- analyzing performance and reliability of structures, systems and components,
- performing predictive maintenance.

Similarly, loss prevention encompasses those engineering and business functions that specifically address the effectiveness of processes that prevent or mitigate safety consequences that may occur due to unexpected events. This function includes activities such as:

- providing security measures,
- providing performance monitoring and improvement services,
- maintaining licenses and permits,
- performing emergency planning,
- providing fire protection.

The first question to be addressed is to what extent does good performance of either of these programs compensate for poor performance in plant operations and work management. To investigate this relationship, plant operations and work management performance were simultaneously set to poor performance at a level which is representative of the lowest level which likely would be tolerated by either plant management or the regulatory authorities. This minimum level of acceptable performance was set at $X = -0.1$ for any of the modeled processes, (i.e. $X = \{R,O,W,E,L\}$). This level was selected based on the following reasoning. Since the industry is strictly regulated, the permitted level of plant performance will not be allowed to deviate far from the level of inherent risk. Historical actions of the United States Nuclear Regulatory Commission issuing shutdown orders to plants for management deficiencies and plant operators taking similar self imposed actions when performance degradations are identified lend support to the conclusion that significant performance degradation will not be tolerated. Thus, choosing a negative 10% deviation within the domain space of one or more of the modeled processes provides a reasonable estimate of the maximal degraded condition that would be considered acceptable before significant corrective actions (i.e. plant shutdown by the plant operator or regulatory body) would be taken.

The benefit of the risk mitigating functions can be shown explicitly by observing their effects on plant risk. Figure 2 provides an example of where effective risk mitigating functions can operate to overcome poor initial performance of the operations and work management functions. In this simulation, the representative values for process couplings were chosen so that the dominant interactions were linear; thus the beneficial impact of interactive decision-making was present but not dominant. Also, the couplings of the risk mitigation functions were taken to be only half that of the quadratic couplings between the operations and work management processes. This led to the following selection of coupling parameters for the demonstration: $\lambda_{WO} = \lambda_{OW} = \lambda = 0.5$, $\mu_{WO} = \mu_{OW} = \mu = 0.2$, and $\lambda_{LO} = \lambda_{EW} = \lambda_{LW} = \mu_{EW} = 0.1$. To permit illustration of the effect of these functions, both were assumed to possess highly qualified staff with significant plant experience ($a_1 = b_1 = 0.8$). For this case, increasing the initial performance of the equipment reliability and loss prevention functions to E(0) = L(0) = 0.4474 results in these processes eventually reversing the trend in increasing plant risk and reducing it below the inherent level. Note that this initial value of E(0) / L(0) represents a critical value (to four significant figures). For initial performance below this point, the loss prevention functions are not capable of restoring risk performance to an acceptable level; whereas better initial performance of these functions will restore performance faster. We note that we interpret $R \rightarrow 1$ for $t > 30$ as the risk mitigating functions operating at a sufficiently high level of performance that they are capable of reducing plant risk well below the inherent level. An example of this would be the case where the plant's predictive and preventive maintenance programs are functioning effectively so that observed equipment failure rates are significantly below the levels that have been assumed in the PRA.

The results displayed in Figure 2 provide an additional insight which is significant to the management of nuclear plant safety risk. In this example, the equipment reliability and loss prevention functions were capable of altering the performance of the operations and work management processes sufficiently to reverse the deleterious trend in plant risk. However, these dynamics required a significant period of time to occur. During this time, plant risk performance remained in a degraded state. This behavior reinforces the conclusion that management must continually focus on maintaining strong performance for those plant processes that provide a direct impact on risk, i.e. operations and work management. It also indicates that the specific risk mitigation processes will be maximally effective at controlling risk only if the operations and work management functions are already operating at an effective level.

EFFECTS OF ADDITIVE NOISE

In any practical application of the dynamical risk model to analyze actual plant data, there is anticipated to be a significant degree of uncertainty in the values of the estimated coupling constants and in the actual level of process performance. This problem is exacerbated by the fact that there do not exist any direct measures of these parameters. Currently, an assessment approach has been developed [6] and preliminary results reported [7] that utilizes a structured assessment to evaluate the effectiveness of risk management at operating plants. Further research is being conducted to quantify these results so that they can be trended over time and used to develop estimates of the model parameters. Because the model is nonlinear, system dynamics possess strong sensitivity to initial conditions. Thus, these uncertainties will result in uncertainty in the model predictions. Due to this, it is important to analyze these effects. An effective method of simulating this effect is to introduce noise into the model equations. This noise can be viewed as being from two distinct sources. First, the uncertainty of the values of the coupling constants and actual performance provide a source that is internal to the system. This type of noise is usually called “multiplicative noise” or “dynamical noise” and is expected to be random in nature. Thus, it is well modeled as white noise. Second, the external environment also provides a source of noise. This type of noise typically is referred to as additive noise. Sources of this type of noise can include implementation of new regulatory requirements, application of new business practices, etc. However, many of these external contributions (for example, implementation of U. S. Nuclear Regulatory Commission (NRC) Regulatory Oversight Program (ROP) requirements safety system performance monitoring) specifically are intended to improve plant safety or performance. In the long term, they would be manifest as improvements in the couplings between the plant processes or as reductions in observed equipment failure rates or frequency of human error. However, in the short term, their effects could be manifest as colored noise, i.e. noise which does not have the same power distribution per unit bandwidth anywhere in the spectrum [8]. However, since this noise is expected to provide a positive bias, modeling it as white noise will provide conservative results from a plant safety perspective. Thus, in this study only white noise was considered.

To study this effect, the nuclear plant risk model equations were modified to provide additive noise to each term. Thus, for the model in which risk culture is not included (see next section), the model equations become

$$\begin{gathered}
R(t+1) = O(t) + W(t) + \varepsilon_R(t) \\
O(t+1) = O(t) + \lambda_{WO} W(t) + \mu_{WO} W(t) O(t) + \varepsilon_O(t) \\
W(t+1) = W(t) + \lambda_{OW} O(t) + \lambda_{EW} E(t) + \lambda_{LW} L(t) + \mu_{OW} O(t) W(t) + \mu_{EW} E(t) W(t) + \varepsilon_W(t) \\
E(t+1) = a_1 E(t) + a_2 E(t)^3 + \varepsilon_E(t) \\
L(t+1) = b_1 L(t) + b_2 L(t)^3 + \varepsilon_L(t)
\end{gathered} \tag{6}$$

with $\varepsilon_i(t)$ additive random noise for the i-th process. For this study, both uniformly and normally distributed noise centered about zero were analyzed. Results obtained were similar, thus we will report on the results obtained from the uniformly distributed case. For each calculation, the system evolution for 60 iterates (representative of 5 years at a specified monthly monitoring interval) was determined. At the end of this period, the systems were evaluated to ascertain if the risk had increased or decreased at the end of the period. An ensemble of 1000 systems were permitted to evolve for each set of noise over the range [-e, e] with e varied from 0 to 0.30 in increments of 0.005. In all simulations, the plant initially was set at the inherent level of risk due to its design (i.e. R(0) = 0) and all programs were set to the indifferent level of performance (O(0) = W(0) = E(0) = L(0) = 0). The statistic measured was the fraction of systems which achieved improved risk performance at the end of the simulated period, i.e.

$$S \equiv \text{Number of systems with } R(t=60)>0 \text{ / Total number of systems.} \qquad (7)$$

We note that simulating system evolution over a 5 year timeframe without any modification to the coupling parameters may be considered to be unrealistic. Changes in business and regulatory conditions certainly require some response to plant operating practices over this time period. However, as described in [1] (and additional references cited therein), nuclear power plant operation has been characterized as a “machine bureaucracy”. Thus, any changes that are implemented require significant periods of time to propagate through the system and the impact of them to be made manifest. Experience with regulatory enforced shutdowns in the United States indicates a long time is required to improve poor performance (typically two years duration for the plant shutdown with several more years of closely monitored operation required to attain strong levels of performance). Thus, by examining the evolution of the system over the identified 5 year period, one can obtain some insight into the magnitude and relative timeframe of a perturbation required to impact performance.

For the initial application of noise to the model, each program was assumed to operate independently of every other program; i.e., all coupling constants were set equal to zero. As expected, the system obtained a value of approximately 0.5 for the S statistic regardless of the level of noise input. Next, the Operations and Work Management functions were assumed to be present and interactive. However, the risk mitigating Equipment Reliability and Loss Prevention functions were assumed to not contribute. As discussed earlier, this model is representative of a much broader class of industrial facilities for which the risk mitigating functions are either not present or only recently implemented. Direct couplings between O and W were assumed to be moderate ($\lambda_{WO} = \lambda_{OW} = 0.25$) and the interactive coupling to be occasional ($\mu_{WO} = \mu_{OW} = 0.1$) where the interpretation of the coupling values is as described in [1]. These values were selected because they are believed to represent typical values for domestic commercial nuclear plants currently in operation. They also are values which are well below that required for bifurcations to occur. Since the additive noise is symmetrically distributed about zero, we expect the S statistic also should be near S = 0.5 for all values of additive noise. This result was obtained via the simulation and is shown in Figure 3. Similar results were obtained when the equipment reliability and loss prevention functions were included under the same conditions.

Next, we investigated the impact of additive uniformly distributed noise for the case of an initial positive performance of the risk mitigating Equipment Reliability and Loss Prevention functions. Because these programs explicitly are intended to limit plant safety risk and improve operational performance, they would be expected to increase the plant's risk performance (R). Thus, as E(0) and L(0) are increased, the statistic S also should increase with S $\rightarrow$ 1 as the initial performance of these functions becomes sufficiently effective. Since the noise is symmetrically distributed about zero, higher amounts of noise would be expected to impact performance by reducing S as the noise level increases. Figures 4(a) and (b) provide results for two of the cases analyzed. Figure 4(a) displays results for the equipment reliability and loss prevention functions initially slightly effective ($E(0) = L(0) = 0.01$) while Figure 4(b) provides results for the case of moderately effective initial performance ($E(0) = L(0) = 0.1$). From these curves, one can see that as the initial performance level of E or L increases, S also increases. However, for a given initial condition, increasing the amount of noise limits the extent to which S increases; i.e. if ε_l represents the low noise state and ε_h the high noise state with $|\varepsilon_l| < |\varepsilon_h|$, then $S(\varepsilon_l) > S(\varepsilon_h)$). Similar calculations were performed for an initial negative performance of the risk mitigation functions with results that basically mirrored those for the case of E and L having initially good performance.

In the previous analyses, the additive noise was considered to be induced external to the system and provide a stochastic component to performance. This noise can be interpreted as the effects due to the external environment and includes factors such as perturbations due to the general business climate and responses to regulatory mandates. The results obtained can be interpreted in the following manner. For initial operation of the plant at indifferent levels of performance and coupling parameters that are believed to be representative of current commercial plants, deviation from the inherent risk level is sensitive to the external noise imposed on the system. This result can be explained by the external environment having a roughly equal potential to provide a positive or a negative effect. As an example of a negative impact, a general economic slowdown can result in decreased operating revenue for the plant owner. These business conditions will impose additional economic constraints on the plant that can be manifest by items such as staff reductions or deferred maintenance. An example of a positive effect would be the implementation of new information management software that increases personnel efficiency and, thus, results in improved performance. However, there is concern that some recent changes in the industry, particularly the effects due to the deregulation of electrical generation, could result in economic pressures to reduce costs with potential for concomitant reduction in effective risk management. This external influence could be modeled by the addition of colored noise that provides a negative performance bias to each of the processes. In contrast, programmatic and process changes that are intended to address identified deficiencies can be modeled (at least in the short term) by the addition of colored noise that provides a positive performance bias to each of the processes. These conditions were not evaluated here and constitute a task for future research.

These results suggest several conclusions that could be drawn with respect to the effect of external influences and the interactions with the specific risk management functions of equipment reliability and loss prevention. For cases where performance of these functions is poor, external perturbations typically produce a beneficial effect. This effect also increases as the magnitude of the influence is increased. This result can be interpreted in the following manner. Since performance of these functions is initially poor, externally induced events have a greater likelihood of providing beneficial changes in performance. As an example, for plants with identified degraded performance levels, either the plant owner or the regulatory authority will attempt to identify the degradation and implement actions to address their basic causal factors. Although not all of these changes will provide the intended effect, the majority will, and thus overall performance can be anticipated to improve. Additionally, the poorer the initial performance, the greater are the changes that are necessary to correct the situation. Thus, the dynamical systems model provides support for the commonly accepted premise that, for complex technologies which have the potential to impact public health and safety, regulation by an unbiased external agency is an important element in ensuring that performance degradations that can impact the public do not occur. Additionally, the result of these simulations also suggests that these regulatory resources are best expended on facilities which demonstrate deficient performance levels.

A second conclusion can be drawn from the case of effective performance of the risk management functions. In this case, the addition of external noise typically produces a detrimental effect which increases as the noise level increases. This result indicates that for well functioning programs, most external stimuli are more likely to degrade performance than to enhance it. This result also is not surprising. Systems that are operating at high efficiency typically require significant effort to maintain this high level of effectiveness. For plants which have developed effective risk management, the resources required to achieve these benefits need to be used in a manner which is effective and efficient. Because these resources are limited, responding to external perturbations will detract from performing the required beneficial risk management functions. Since most of these external influences will not provide as much benefit to performance as the functions typically performed by these resources, they will tend to detract from the good overall performance. From a regulatory perspective, this suggests that the amount of external intervention should be minimized at plants which exhibit effective risk management and operational performance. For example, in the extreme case of a plant that possesses comprehensive and effective risk management and demonstrates exemplary performance, the regulatory function could theoretically be limited to monitoring and trending performance. We note that this constitutes the basic premise of a regulatory structure that is risk-informed and performance-based. Thus, this characteristic of the dynamical risk model provides additional support to the safety and economic benefits that can be achieved by transforming to this regulatory structure.

ADDITION OF RISK CULTURE TO THE MODEL

An important component to controlling plant risk is the development of a plant risk culture. This culture can be characterized by understanding and awareness, by all plant personnel, of the potential impact of operational and maintenance tasks on plant safety. Additionally, in an effective risk culture, plant decision-making processes incorporate an explicit consideration of the potential safety impact of plant activities and decisions and provide appropriate levels of oversight and controls to mitigate risk. Although not formally demonstrated via specific results obtained from traditional plant risk assessment models, it is logically consistent to assume that the stronger the risk culture is made at a plant, the safer the plant will operate. In terms of the dynamical systems model, this contribution should be manifest both directly in the coupling of the risk mitigation processes to plant risk performance and also in the performance of the individual processes themselves. In this section, we specifically address a modification to the model (1) to address the impact of risk culture on performance.

In this discussion, we explicitly use the term “risk culture” as the defining characteristic that impacts nuclear plant safety risk. The use of this terminology is deliberate. Recently, significant research has been conducted throughout process industries, including nuclear power generation, on the impact of what has been called a plant “safety culture”. However, although this terminology has become accepted, it does not have a standard definition, meaning different things to different researchers and across different industries [9, 10]. For applications to commercial nuclear power plants, the term has been defined by the International Nuclear Safety Advisory Group (INSAG). INSAG-4 [11] defines safety culture as "…that assembly of characteristics and attitudes in organizations and individuals which establishes that, as an overriding priority, nuclear plant safety issues receive the attention warranted by their significance". However, as discussed in [10], there are several problems with this approach; the most significant being lack of development of a linkage between safety culture and how it impacts human performance and reliability and the inability to establish the link between achieving a "good" safety culture and safe plant performance. Additionally, from our perspective, by including attitudes and values within the operational definition, safety culture possesses a very broad context, for example including those attributes associated with normal industrial safety practices. Because of this broad definition of the term safety culture, for the dynamical systems model, we define a much more limited concept which we call risk culture. By this term, we refer to the extent to which the plant considers nuclear safety risk as a fundamental input into the various decision-making processes. Additionally, we consider the extent to which this occurs to be measurable and demonstrable [7]. Thus, as defined here, risk culture can be considered as a subset of safety culture with the specific objective of effectively controlling plant safety risk.

Modeling of Risk Culture

We propose to incorporate the effect of risk culture in the dynamical systems model by making the following assumptions. First, the extent to which an effective risk culture has been achieved predominantly is a plant level effect. This is due to the organization's culture being strongly dependent upon the facility's management philosophy and business practices. Thus, in the model, the effect of the risk culture will apply to each plant process in the same way. Second, the impact of risk culture is expected to have the following effects on the individual plant processes. First, a point of operational indifference should be a fixed point of the system. This assumption is due to a combination of economic and regulatory factors. From an economic standpoint, implementing an effective risk culture is expensive in terms of resource application. Providing appropriate personnel training, obtaining necessary technology and assigning qualified personnel to analyze the risk associated with various activities all require a significant commitment of human and monetary resources. Because these resources are limited by economic considerations, there will be strong incentives to minimize their application, and thus limit their effectiveness. This characteristic has been, in a qualitative sense, observed both at nuclear plants and throughout industrial facilities in general, particularly in businesses in which competitive pricing pressures are manifest. Conversely, poor operational performance can result in significant regulatory pressure (including, if necessary, regulatory mandated plant shutdowns) to force enhanced management effectiveness and improve operational performance. These competing forces thus will tend to drive the risk culture to its point of indifferent performance, i.e. one that utilizes a minimal level of resources to achieve a level of performance that is acceptable from the viewpoint of both plant management and the regulatory authority. Second, for a plant with an effective risk culture, this culture is expected to support maintaining effective process performance, i.e. it should impede process performance from returning to the point of indifference. Conversely, if process performance is poor, an effective risk culture should cause a rapid improvement in the performance, at least back to a level of indifferent performance.

Finally, the model should revert to the previous model for a plant in which no discernable risk culture has developed.

A mathematical function that provides the characteristics described above is a quadratic. Thus, for each process, the effect of the plant risk culture can be incorporated into the process model by including a term of the form

$$X_c(t+1) = \beta_I X_c(t)^2 \tag{8}$$

where X_C represents the culture component of the I-th program performance (I = {O, W, E, L}) at the t-th iterate and β_I represents the risk culture of the I-th process. Further, because a major determinant of the risk culture possessed by different plant organizations is determined by global management factors, the risk culture of each of the individual processes can be modeled as

$$\beta_X = \beta(1+\delta\beta_X) \tag{9}$$

where β is the global component of the risk culture and $\delta\beta_X$ is the deviation from this value for the particular process. For this analysis of the impact of risk culture, we assume the culture is set at the global level, thus we set $\delta\beta_X = 0$ for all processes. With these modifications to incorporate the effect of the plant risk culture, the dynamical systems risk model becomes

$$\begin{gathered} R(t+1) = O(t) + W(t) \\ O(t+1) = O(t) + \lambda_{WO} W(t) + \mu_{WO} W(t) O(t) + \beta O(t)^2 \\ W(t+1) = W(t) + \lambda_{OW} O(t) + \lambda_{EW} E(t) + \lambda_{LW} L(t) + \mu_{OW} O(t) W(t) + \mu_{EW} E(t) W(t) + \beta W(t)^2 \\ E(t+1) = a_1 E(t) + \beta E(t)^2 + a_2 E(t)^3 \\ L(t+1) = b_1 L(t) + \beta L(t)^2 + b_2 L(t)^3 . \end{gathered} \tag{10}$$

The effect of risk culture on a process function is shown in Figure 5 which shows a cobweb plot [12] of the equipment reliability function with the cultural term included. Notice at these values of the coupling parameters, there is a stable fixed point at the origin (the point of indifferent performance). There also is an unstable fixed point near E ~ 0.6. From the cobweb plot, for initial performance $0 < E(0) < \sim 0.6$, process performance will slowly decay to the point of indifferent performance. Conversely, if initial performance is poor, $E(0) < 0$, performance will rapidly improve towards the point of indifferent performance. For E(0) to the right of the unstable fixed point, performance remains good for all $t > 0$. Thus, this model suggests that once a very strong risk culture is established, it will tend to remain in place until changed by some external perturbation, for example budget constraints which cause a reduction in available resources. Also note that these conclusions become more pronounced as the risk culture is improved, i.e. as β increases.

Analysis of Risk Culture Impact on Plant Risk

As a first task, we wish to analyze the impact of a positive risk culture in isolation from those activities which have been identified previously as providing important contributions to effective risk management. Thus, we examine the effects of risk culture for the case of a plant that does not possess the explicit risk mitigation functions of equipment reliability and loss prevention. This permits analyzing the impact of the risk culture term in its simplest form. This is achieved by incorporating the risk culture term into the simplified ROW model where the Operation – Work Management linear and quadratic interaction coupling terms are set equal to each other; i.e. $\lambda_{WO} = \lambda_{OW} \equiv \lambda$ and $\mu_{WO} = \mu_{OW} \equiv \mu$. To further isolate the impact of the risk culture term, we look at the case of a plant with minimal collaborative decision-making between the operations and work management processes, i.e. we set the quadratic operations to work management coupling to zero ($\mu = 0$). This results in the following simplified model

$$\begin{aligned} R(t+1) &= O(t) + W(t) \\ O(t+1) &= O(t) + \lambda W(t) + \mu W(t)O(t) + \beta O(t)^2 \\ W(t+1) &= W(t) + \lambda O(t) + \mu O(t)W(t) + \beta W(t)^2 \end{aligned} \tag{11}$$

To analyze the effect of the culture terms on plant risk, we assume the plant initially possesses poor operational and work management performance and the impact on plant risk is investigated as the effectiveness of the plant risk culture is increased. For this analysis, we arbitrarily set $\lambda = 0.25$ and the initial conditions to be at the previously identified level of maximal allowed poor performance (i.e. $O(0) = W(0) = -0.1$). For the case of no positive risk culture, plant risk performance will decrease to $R = -1$, implying an unacceptable increase in plant risk. This is shown in Figure 6(a) where the decrease to $R = -1$ is very rapid. As a positive risk culture is instituted at the plant, the rate at which plant risk performance continues to decrease will slow. This can be seen in Figure 6(b) where risk performance vs. time is displayed for the same conditions but where a positive risk culture exists, with $\beta = 2\lambda$. At risk culture couplings greater than this value, a stable operating point at a risk performance of $R = -2\lambda/\beta$ occurs. This is demonstrated in Figure 6(c) where the risk culture is set at $\beta = 1.0$. As the plant risk culture is further improved, plant risk performance also will continue to improve with $R \rightarrow 0$ in the limit of $\beta >> 2\lambda$.

Next, we examine the synergistic effects that can be obtained for a plant which possesses a strong risk culture and utilizes a collaborative decision-making process. This can be demonstrated by comparing the results shown in Figures 7(a) and (b). Figure 7(a) shows the risk evolution for a plant with a strong risk culture with $\beta = 2$, $\lambda = 0.25$ and initial poor operations and work management performance ($O(0) = W(0) = -0.1$). As can be seen, this system will reach a stable operating point at the very poor risk performance level of $R = -0.25$. For this plant, improvement in risk performance above this level can be obtained by increasing the level of collaboration in the operations and work management decision-making processes. Figure 7(b) shows this improvement for a plant that possesses both a very strong risk culture and strongly collaborative decision-making processes. For this case, ($\lambda = 0.25$, $\mu = \beta = 2$), plant risk performance is seen to be much improved above the level shown in Figure 7(a). Thus, the impact of an effective risk culture can be viewed as similar to that due to effective collaboration between the operations and work management decision processes. Note however, that because the specific risk management processes (equipment reliability and loss prevention) are not present, risk performance will still be below the inherent level due to the plant design. Thus, a significant conclusion from this analysis is that a strong plant risk culture combined with effective interactive decision-making in the operations and work management processes can result in a significant improvement in plant safety risk with the two attributes combining to provide benefits beyond those which can be obtained from either attribute by itself.

Effects of Positive Risk Culture

A question of fundamental importance with respect to risk culture is to what extent can it impact (i.e. improve) safety performance. A second related question is what time frame is required for this impact to be observed. A fruitful approach to evaluate these questions is to apply the methods used in the analysis of dynamical systems to identify conditions necessary for the system to remain in the region where $R > 0$. This analysis requires identification of the basin of attraction for initial conditions and model coefficients to obtain performance such that R remains positive and is similar to those which are employed to numerically generate the Mandelbrot set. In this paper we provide a very brief discussion of the concept of basin of attraction in the one-dimensional case. We then employ this concept to demonstrate how an increasingly effective risk culture contributes to achieving effective risk management by driving the system to operate in the region where R > 0.

An important question in the analysis of all physical systems is the determination of the ultimate fate of an arbitrary initial point in the system. This question essentially asks what is the behavior for an arbitrary point as $t \to \infty$. A system for which all initial conditions approach a single point is termed globally stable. This can be demonstrated in a simple manner via the elementary ordinary differential equation

$$\dot{x} = -ax \tag{12}$$

for a > 0 subject to the initial condition $x(0) = x_0$. In this discussion, we illustrate the concepts using differential equations because they are more familiar. However, they apply equally to maps such as the dynamical risk model. One can solve (12) via elementary means to obtain the simple exponential decay

$$x(t) = x_0 e^{-at} \tag{13}$$

One can see from this solution that $x \to 0$ as $t \to \infty$ for any finite initial condition x_0. Thus, the basin of attraction for the origin is the entire interval $(-\infty, \infty)$.

However, most systems do not possess dynamics that are so simple. A slightly more complicated example is the nonlinear system

$$\dot{x} = x^2 - 1 \tag{14}$$

For this system, where x is defined to exist on the real line, the points $x = \pm 1$ are fixed points with –1 being stable and +1 unstable. Analysis of this system shows that any initial point $x_0 < 1$ will be attracted to the stable fixed point at $x = -1$. All initial points $x_0 > 1$ escape to infinity. Thus the basin of attraction of the stable fixed point is $(-\infty, +1)$ and the basin of attraction of infinity is $(1, \infty)$. This can be seen graphically by plotting the phase space (on the real line) for (14) in Figure 8.

The system (14) provides an example where the boundary between the basins of attraction is simple. However, as the complexity and dimensionality of the system increase, the long-term behaviors exhibited also can become more complex. More complex systems can exhibit behaviors that lead to multiple asymptotic outcomes. In some instances, the long-term behavior of different points can be characterized in a compact manner; in other cases, this behavior is extremely complicated with points that are initially close asymptotically approaching vastly different end states. For systems that can exhibit chaotic dynamics, the property of sensitive dependence on initial conditions permits exceedingly complex behaviors. For these systems, two points initially arbitrarily close together may diverge in their long-term behavior. One manifestation of this characteristic is that the boundaries between the basins of attraction may possess a fractal structure. In this instance, the boundaries between the different regions are not simple curves or surfaces. They possess an interleaved structure that is manifest at many different scales [12]. There are numerous examples of this behavior, the most famous of which is that due to Mandelbrot (which results in the Mandelbrot set) [13].

The Mandelbrot set is obtained by consideration of the map [14]

$$z(k+1) = z(k)^2 + c \tag{15}$$

where z is a complex variable and c a complex constant. This system has fixed points at values $z^* = [1 \pm (1 - 4c)^{1/2}] / 2$. Fixed points z* for which $-\frac{3}{4} < c < \frac{1}{4}$ are stable. Iterates of the map for values of $c < -2$ or $c > \frac{1}{4}$ escape to infinity. The dynamics of (15) can be analyzed by iterating the initial value $z(0) = 0$ for many values of the constant c and observing whether the point escapes to infinity. The result of this process produces the Mandelbrot set. This set exhibits a complicated structure with increasing detail as we look at smaller regions of the parameter c. For each point c in the set, there are orbits that remain bounded and orbits that do not. The boundary of the basin of infinity is called a Julia set. We can analyze the points that are not in the Mandelbrot set by characterizing their rate of divergence. For these points, we find their structure to be fractal. We now make use of this technique to analyze the effect of plant risk culture on the dynamics of the nuclear plant risk model.

To analyze the impact of risk culture on the dynamical systems risk model, we perform a numerical simulation to estimate the basin of attraction for $R \rightarrow 1$ assuming initial poor operational and work management performance $O(0) = W(0) = -0.1$. Since these conditions are expected to be near the limit of what would be permitted by either plant management or the regulatory authority, they provide a very stringent test of the impact of a beneficial plant risk culture. To simplify the calculations, we set model coefficients that are anticipated to be similar equal to each other. This results in the following system of equations

$$
\begin{aligned}
R(t+1) &= O(t) + W(t) \\
O(t+1) &= O(t) + \lambda W(t) + \mu W(t)O(t) + \beta O(t)^2 \\
W(t+1) &= W(t) + \lambda O(t) + \omega E(t) + \omega L(t) + \mu O(t)W(t) + \omega E(t)W(t) + \beta W(t)^2 \\
E(t+1) &= a_1 E(t) + \beta E(t)^2 + a_2 E(t)^3 \\
L(t+1) &= b_1 L(t) + \beta L(t)^2 + b_2 L(t)^3 .
\end{aligned}
\tag{16}
$$

In the simulations, like coefficients were set equal to each other with $a_1 = b_1 = 0.7$ and $\omega = 0.05$. For each calculation, 50000 points were obtained and classified into the six categories listed in Table 1. In the figure that displays the results (Figure 9), only orbits that reached the "perfect" risk condition R = 1 within 60 iterations are shown. Thus, these points clearly are within the basin of attraction of R = 1. Regions shown in white indicate that the system has not evolved to R = 1 within this timeframe. Thus, it is indeterminate whether these points are within this basin of attraction. Note that from a strictly risk management viewpoint, the objective would be to avoid operation in these regions in preference to regions where $R \rightarrow 1$ much more rapidly. The calculations shown here were conducted assuming good equipment reliability and loss prevention performance E(0) = L(0) = +0.1. Results are provided in Figures 9(a) through (d) for risk culture values of β = 0.1, 1.0, 2.0 and 3.0 respectively.

As expected, a small positive risk culture will provide a small impact on plant risk. This can be seen in Figure 9(a) where a very large value of the operations – work management coupling (μ) is required to drive risk performance to its maximal value within a reasonable time. Recall that the iteration interval of the model was defined in [1] to be 1 month; thus at the small beneficial risk culture assumed in this simulation ($\beta = 0.1$), μ must be very large (of the order 4 or more) to significantly improve plant risk within the space of a few years. However, this figure provides an important insight into the importance of a strong risk culture. Notice that once we enter the basin of attraction for $R \rightarrow 1$, small improvements in the operations – work management collaborative interaction term result in a very rapid decrease in the time required to reach $R = 1$. This is demonstrated in Figure 9(a) by the fact that the region where the time required to reach $R = 1$ is long ($50 < t < 60$ iterations represented by the dark blue region) is very thin. This effect is seen to persist as risk culture is improved as shown in Figures 9(b) through (d) ($\beta = 1$, 2 and 3 respectively). This result suggests that there is a synergistic effect between a strong risk culture, the plant decision-making processes and improved safety risk.

As plant risk culture improves further, it becomes readily apparent that a strong risk culture can have a tremendous impact on improving plant risk performance. As expected, at modest levels of plant risk culture, the operations and work management functions must be strongly interactive to overcome the initial degree of poor performance assumed in these simulations. However, as the plant risk culture becomes stronger, the degree to which this interaction must occur diminishes. As plant risk culture further improves to a high level, e.g. $\beta \sim 3$, the culture is strong enough to be effective at reducing plant risk in a very rapid manner. Notice that this effect occurs regardless of the interactive coupling between the operations and work management processes. From a practical standpoint, development of a strong risk culture also could be expected to provide an impact on improving the dynamics of this interaction. Since this is not included in the model (the interaction coefficients are treated as constants), the actual effectiveness of the plant culture is most likely understated by the model for plants that have developed a strong risk culture.

Finally, model simulations using this approach reveal a rich and complex structure inherent in the system dynamics. Figure 10 provides results for a simulation for a plant where the risk mitigating functions are assumed to operate at the indifferent level of performance. In this simulation, the initial conditions were set to $O(0) = 0.05$ and $W(0) = -0.025$ and β was set to $\beta = 0$ (no risk culture). For this system, the operations process performance is sufficiently strong to overcome the initial poor work management performance and permit the plant to evolve to a state where risk performance can be sustained at $R > 0$. Figure 10 provides results for 25,000 trajectories over the subinterval $0 \leq \lambda \leq 0.2$ and $0 \leq \mu \leq 5$. In this figure, we can see that different combinations of λ and μ in this region can result in a wide range of the number of iterations required to reach $R = 1$. This behavior of arbitrarily close points (in $\lambda - \mu$ space) resulting in significantly different times required to reach $R = 1$ suggests the boundary of the basin of attraction is fractal. This fact is important from a nuclear safety perspective. Because small changes in the parameters can result in large changes in risk, operation in regions near the basin boundary are unstable. Since this would be indicative of a potential loss of ability to effectively control risk, these operational regimes should be avoided.

CONCLUSIONS

In this paper, we expanded upon previously reported results for a dynamical systems model that accounts for the impact of plant processes and programmatic performance on nuclear plant safety risk. We employed both analytical techniques and numerical simulations to obtain insights from the model that identify important attributes of effective risk management. These insights can be summarized as follows.

1) Use of collaborative decision-making between the operations and work management processes provides important benefits to ensure plant risk impact is considered from multiple viewpoints. This type of decision-making helps to ensure that operational and maintenance decisions are well planned and robust with appropriate contingency plans and management attention provided when anomalies are encountered.
2) The equipment reliability and loss prevention functions are capable of controlling plant risk. For the case of some degradation in operations and / or work management performance, these functions are capable of reversing these trends and restoring the plant to an acceptable risk profile. However, because these functions require a significant period of time for their impact to be observed, plant management and regulatory authorities must be vigilant in ensuring the operations and work management functions are effective. Contrariwise, for the case where the operations and work management functions are already operating at an effective level, the equipment reliability and loss prevention functions can provide additional risk mitigation and result in the plant achieving risk levels that are less than the levels inherent in the plant design. In this instance, the plant is capable of operating at a level of risk which is less than may be inferred from the PRA.
3) Analysis of the model with additive noise indicates that regulation by an unbiased external agency is an important element in ensuring that performance degradations that can impact the public do not occur, or if they do, they are identified at an early stage

where the potential impact is minimal. This result also suggests that these resources would best be expended on facilities which demonstrate deficient performance levels. For plants which have achieved effective risk management, excessive intervention may result in reduced efficiency and effectiveness and thus provide results that are the opposite of what is desired. Thus, this model suggests that the amount of external intervention should be limited at plants which exhibit effective risk management and operational performance. Thus, the model supports the basic premise of a regulatory structure that is risk-informed and performance-based. Additionally, it suggests that when high levels of performance are achieved, both plant management and regulatory authorities should carefully consider the potential impact on resource effectiveness and plant performance before implementing any significant changes to plant processes or the resources required to implement them.

4) Analysis of a modification to the model demonstrated the important impact and safety benefits of a strong plant risk culture. Also, for plants with a very strong risk culture, the model shows that the beneficial effects can perpetuate over long periods of time.
5) When a positive risk culture is combined with effective risk mitigation processes (i.e. equipment reliability and loss prevention), the combined impact of these positive influences provides significant safety benefits. Once good performance in all processes that impact risk is in place, this level of performance can become self propagating and persist for long periods of time.

Thus, the results obtained from the model provide useful insights and an underlying theoretical construct which can be used to provide more effective risk management and help ensure activities that are important to manage nuclear plant risk are performed in a manner that maximizes their effectiveness.

We wish to close this paper with a few comments on how the insights obtained from the model could be used to further the safe and efficient operation of commercial nuclear generating stations. We also provide some ideas for future research to permit validation and application of the model. At this time, the transition to a risk-informed, performance-based regulatory structure is in the early stages of development and implementation. Additionally, the concept of risk culture (or the more broadly defined safety culture) is only beginning to be understood and incorporated into a plant management paradigm. However, as shown in Figure 11, over the past decade both operational performance and plant safety have improved significantly at commercial U. S. nuclear power plants [15]. These improvements can be attributed to many factors including application of advanced technologies such as condition based maintenance approaches (e.g. vibration, infrared thermographic analysis and ferrographic oil condition monitoring technologies), use of analytical techniques such as reliability centered maintenance to specify appropriate preventive and predictive maintenance activities, and implementation of comprehensive work management information management systems. These systems (and others) have contributed to reduced failure rates as observed in the various PRA updates. Additionally, specific risk management processes (such as ORAM/SENTENEL, EEOS, etc.) coupled with implementation of comprehensive system health and performance monitoring programs have resulted in additional observed reductions in plant risk. Thus, there is significant evidence that risk management is effective at controlling plant safety risk. The results obtained from analysis of the dynamical systems model indicate that these improvements are both effective and sustainable. Thus, important elements of ensuring this performance (both economic and safety) is sustained and improved even further will be to (1) continue further use of advanced technologies to transition from diagnostic to prognostic capabilities, (2) develop a deeply rooted risk culture and (3) provide the capability to monitor and trend the performance of those plant processes that have been identified as significant contributors to safety risk.

Based on the above discussion, future research with respect to the approach described in this paper should be performed to address two specific issues. First, and most significantly, the insights obtained from the model should be validated using actual plant data. As discussed previously, a comprehensive risk management effectiveness assessment process has been developed [6]. The process has been demonstrated in several pilot plant applications. However, because of the limited number of these applications to date, insufficient data have been obtained to provide statistically significant results. Integration of the assessment results with the model represents an area for future research with the following objectives:

- Develop methods to estimate both current program performance and process interaction coefficients from the assessment data.
- Evaluate the model predictions of future performance against existing qualitative metrics (e.g. NRC Reactor Oversight Program) to determine the capability of the model to predict incipient degraded performance.

The second area is to further analyze the model for robustness and fidelity. As an example, in the model, the equipment reliability and loss prevention functions were modeled such that there is no correlation between them; although in practice there should be some degree of correlation between these functions. As discussed in [1], we did not include any coupling between these two functions for several reasons. First, the SNPM provides a clear distinction between the two processes (i.e. E represents engineering activities with direct and short term impact such as preventive and predictive maintenance; whereas L represents those with longer term and more indirect impact such as security and emergency planning). Thus, the degree of interaction between them is assumed to be small compared with their interactions with O and W. Second, both of these functions only impact risk indirectly through the O and W processes. These assumptions should be investigated by analysis of the results obtained from plant risk management assessments. They also can be validated by introducing coupling between these functions in the model and determining at what level interactions impact the results.

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FIGURES

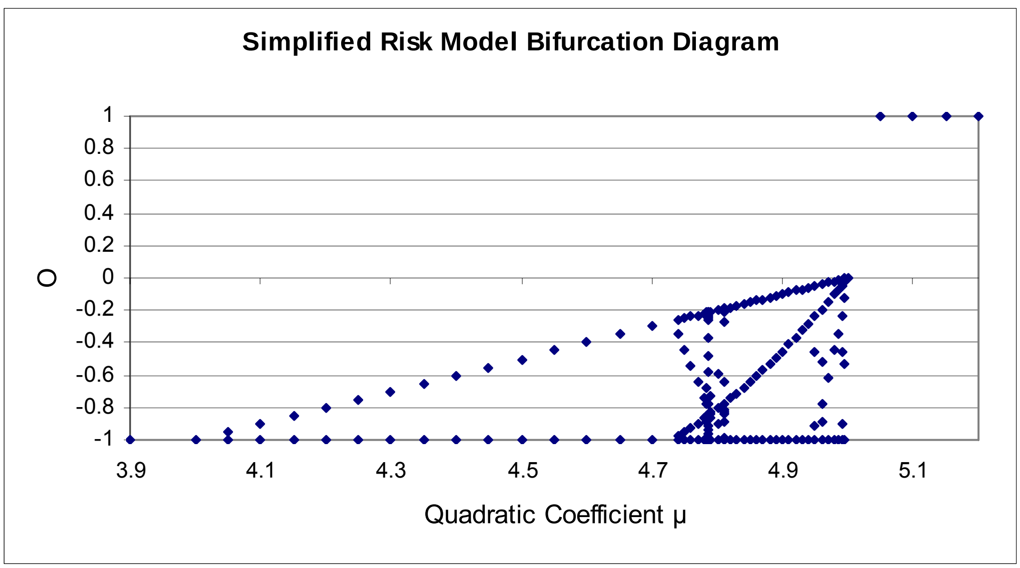


Figure 1: Example bifurcation diagram for simplified ROW risk model.

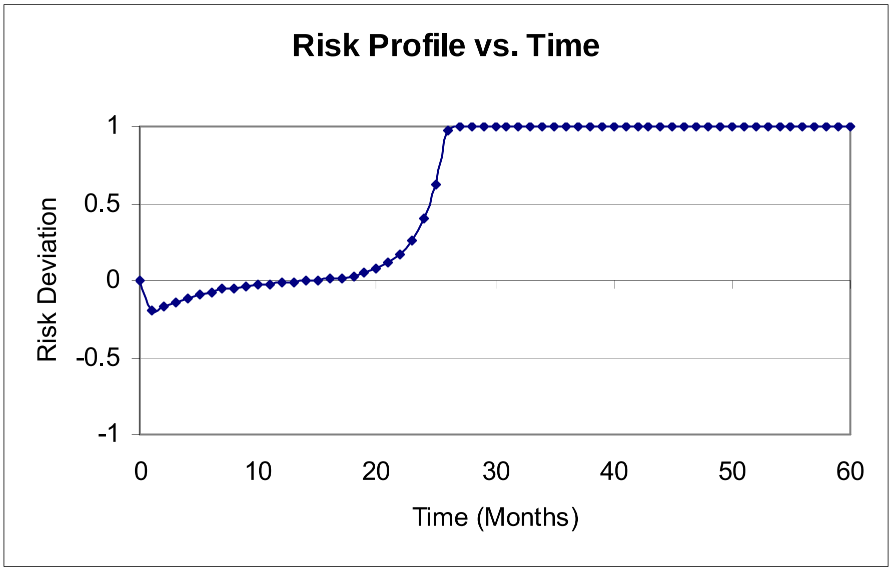


Figure 2: Demonstration of capability of equipment reliability and loss prevention functions to overcome poor operations and work management performance.

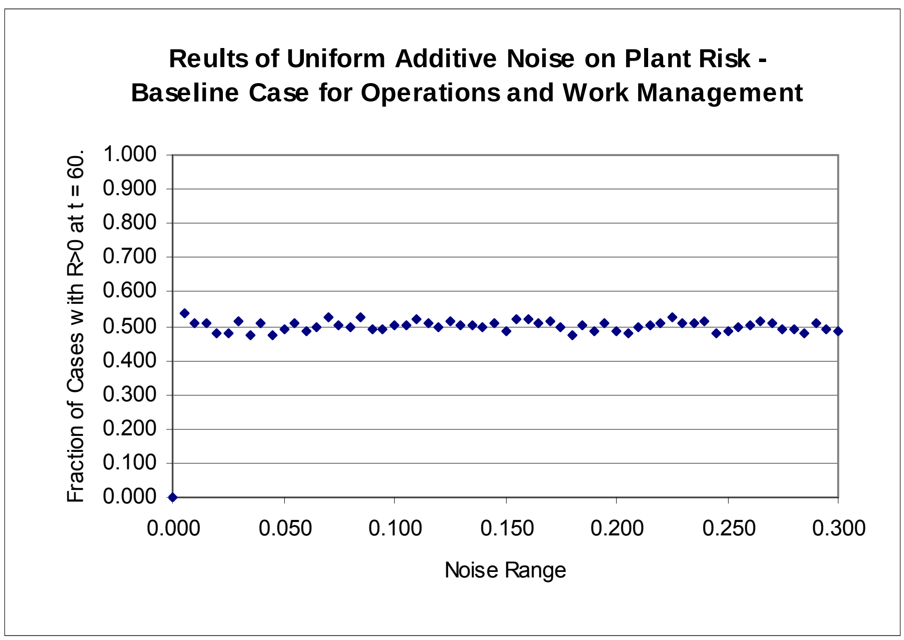
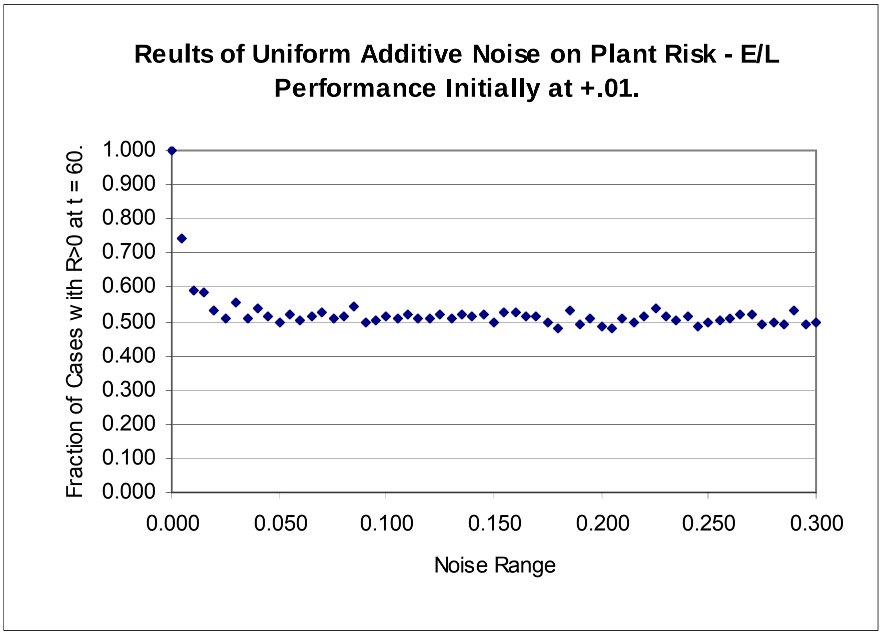
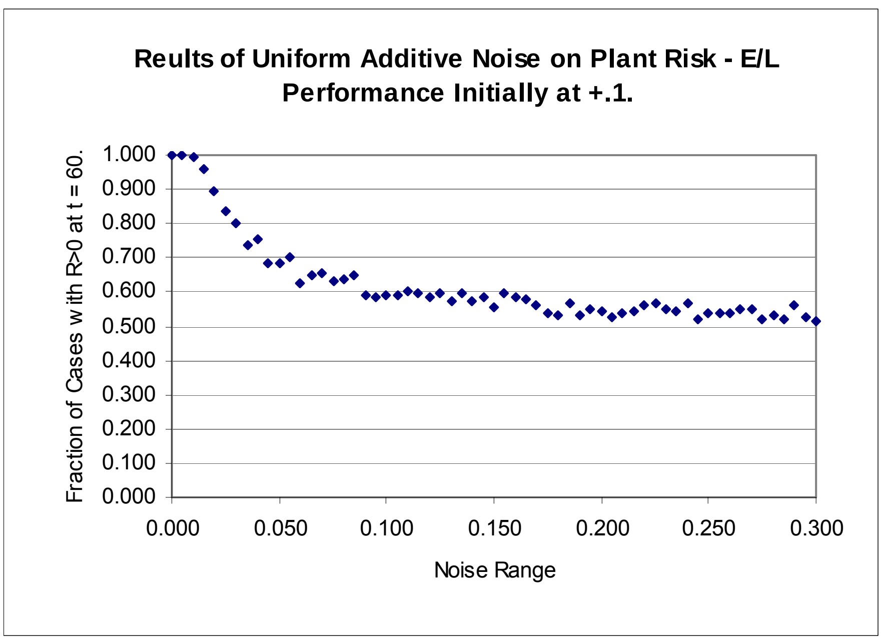


Figure 3: Results for addition of additive uniformly distributed noise for Operations / Work Management program interactions.



(a)



(b)

Figure 4: Results for addition of additive uniformly distributed noise for plant with effective equipment reliability and loss prevention functions. (a) E(0) = L(0) = 0.01. (b) E(0) = L(0) = 0.1.

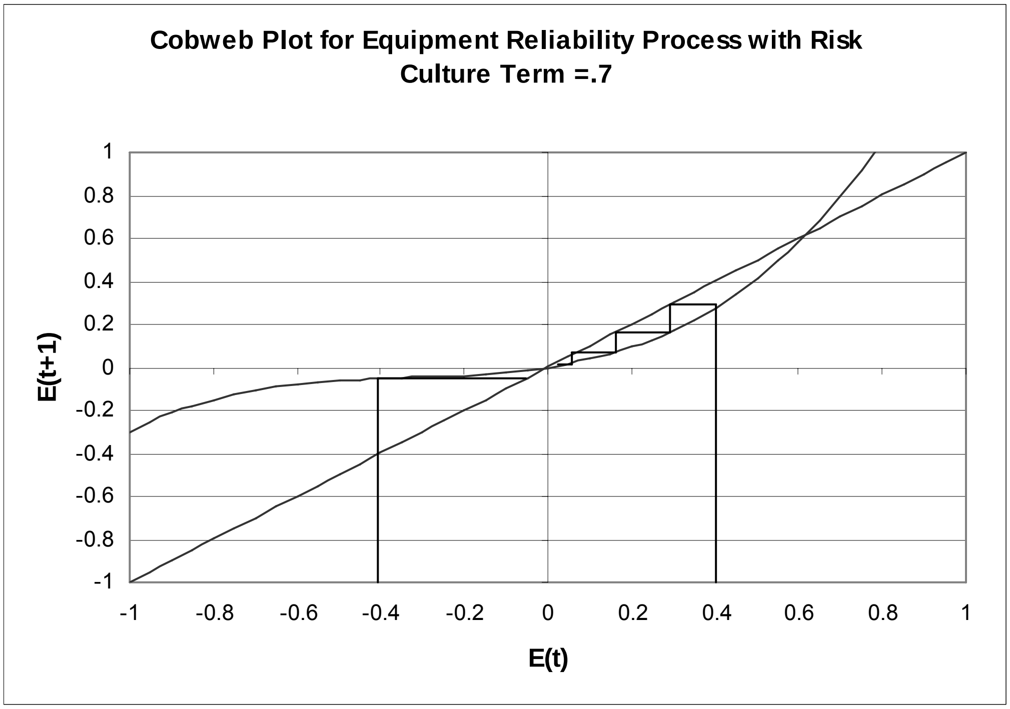
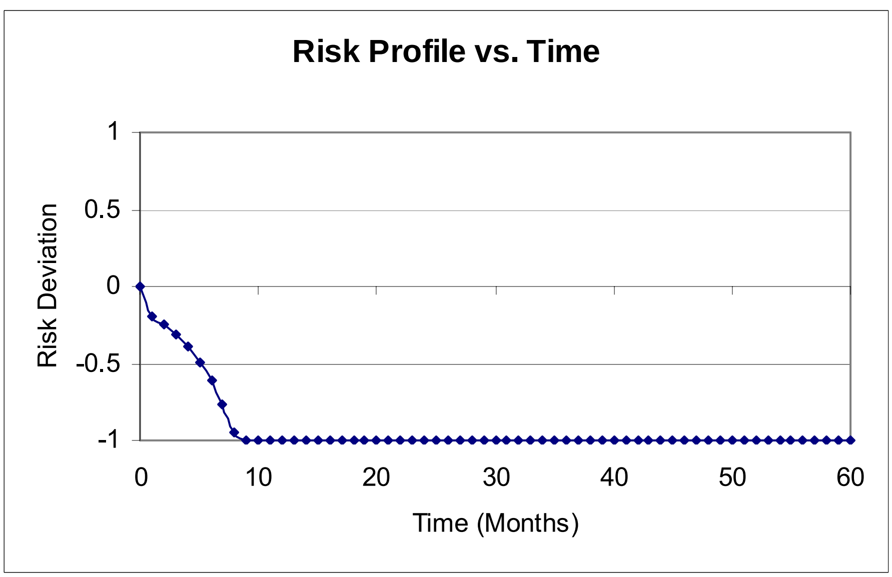
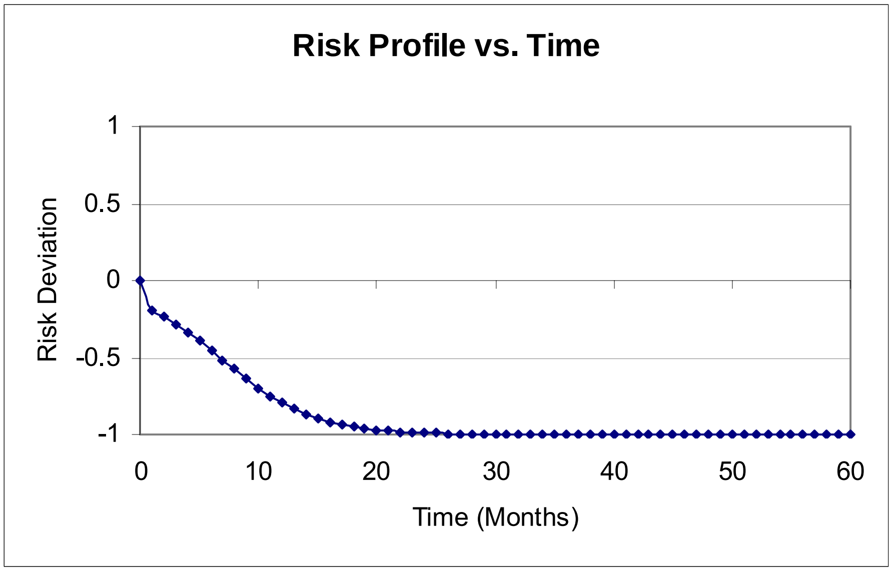


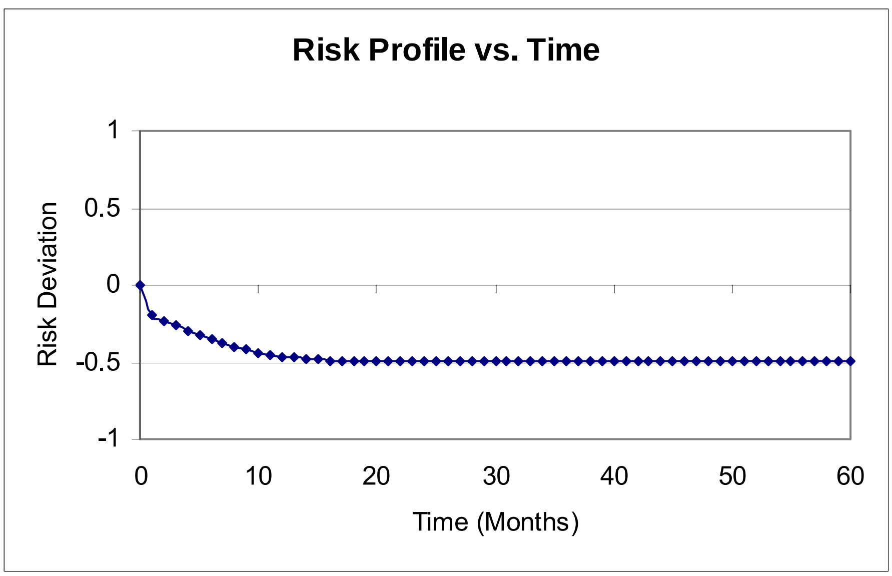
Figure 5: Cobweb plot of E(t+1) vs. E(t) for coupling parameters a_1= 0.7, a_2 = 0.3 and β_E = 0.2.



(a)

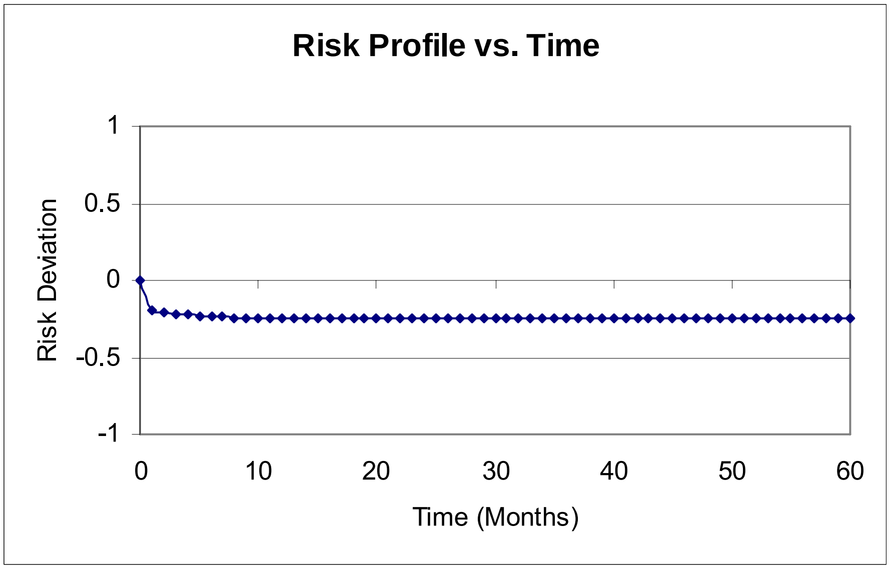


(b)

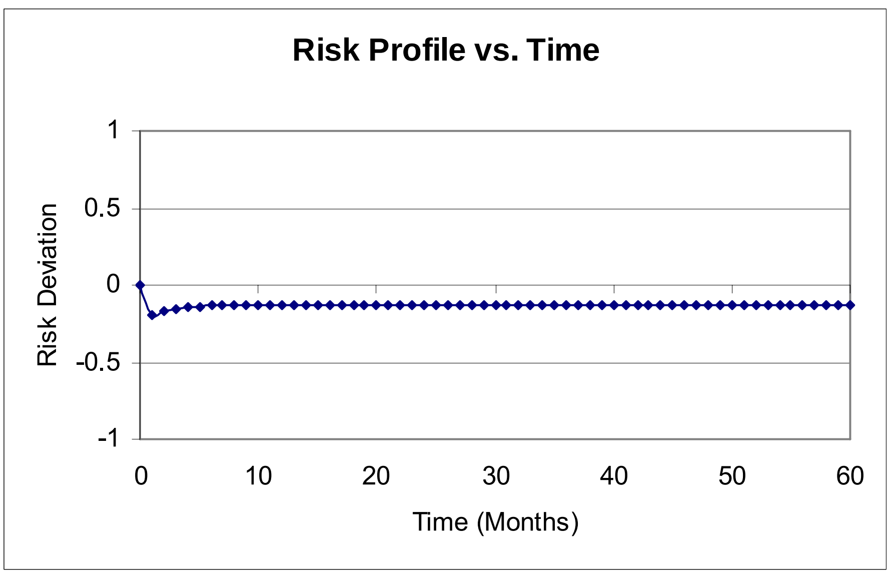


(c)

Figure 6: Impact of risk culture for case of initial poor operational and work management performance. (a) No effective risk culture. (b) Risk culture sufficiently positive to slow the rate of decay. (c) Risk culture sufficiently positive to limit the increase in plant risk.



(a)



(b)

Figure 7: (a) Evolution for plant with strong risk culture but with no collaboration between plant operations and work management processes. (b) Case of strong plant risk culture coupled with strong collaboration between operations and work management decision-making processes.

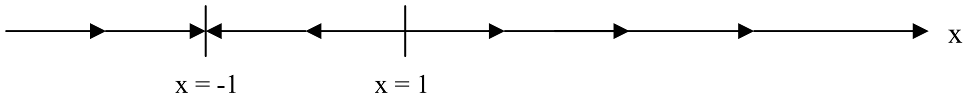
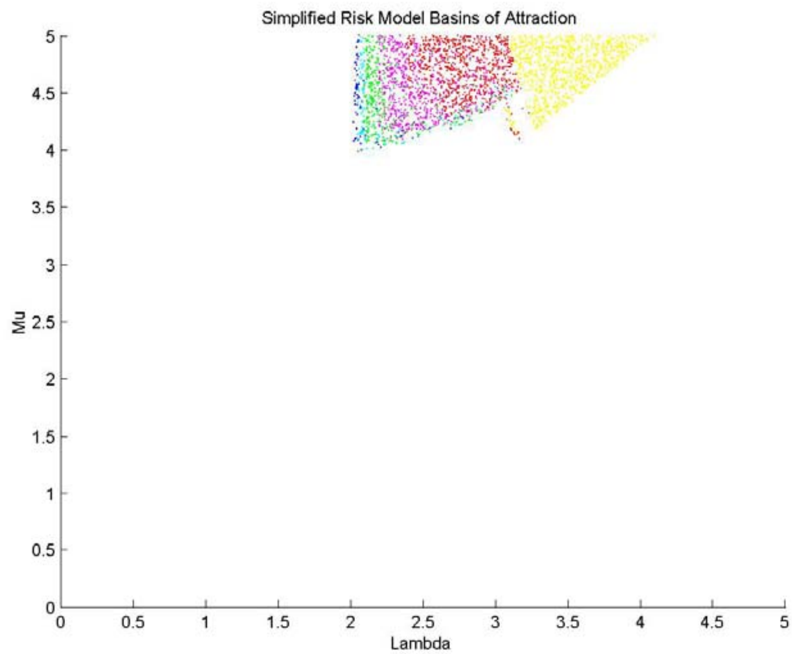
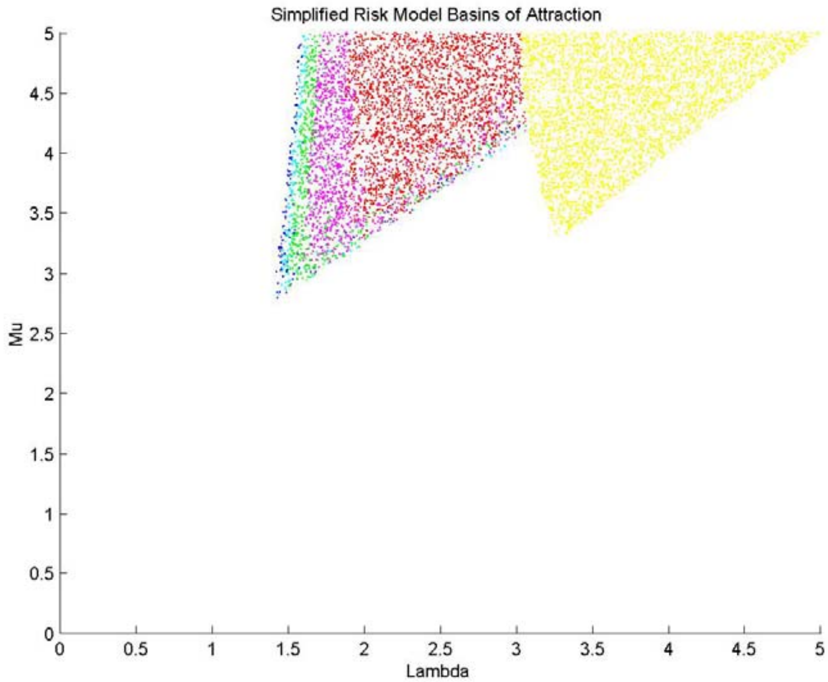


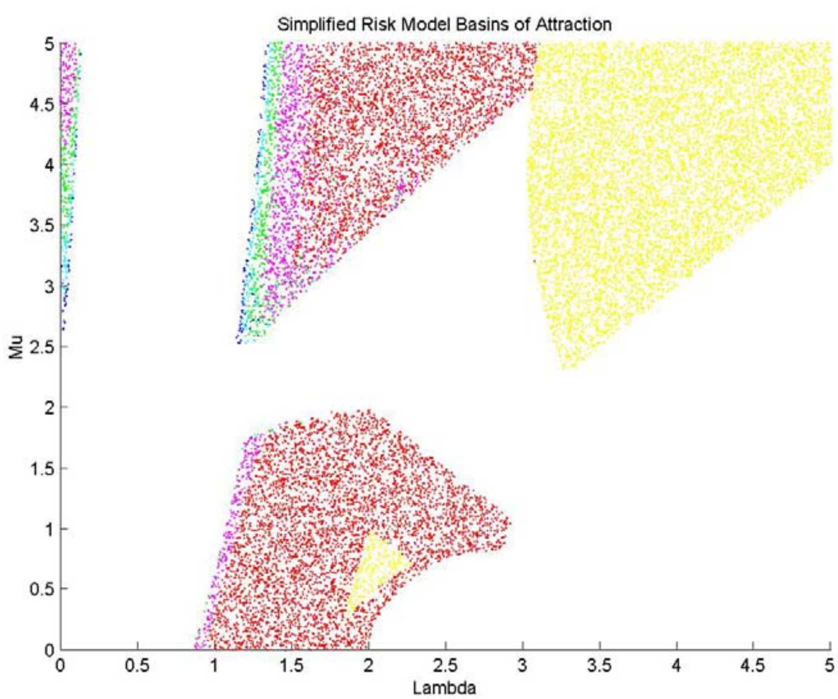
Figure 8: Phase portrait for nonlinear differential equation (14).



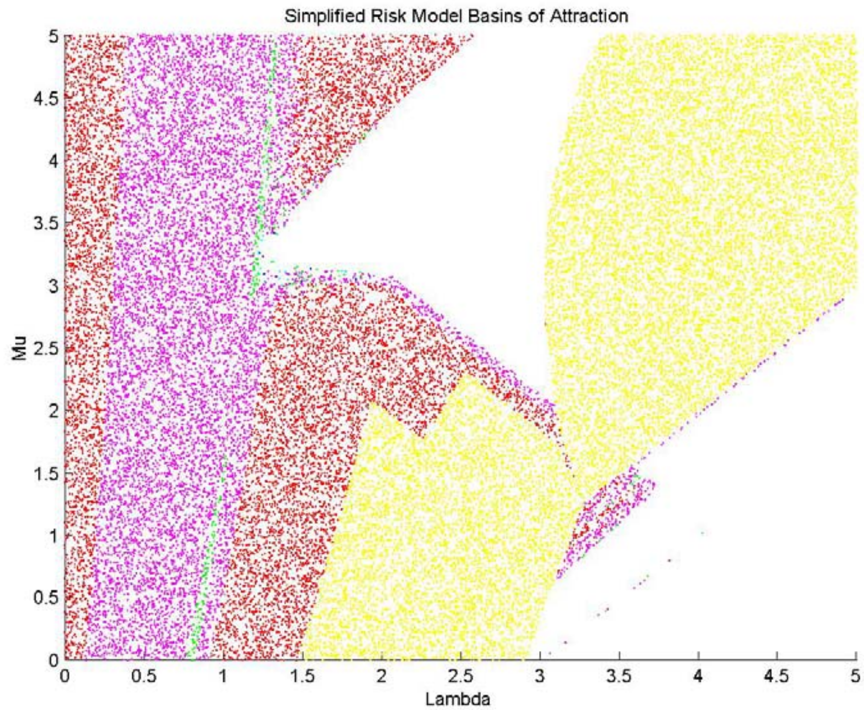
(a)


Simplified Risk Model Basins of Attraction
Mu
Lambda
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5

(b)


Simplified Risk Model Basins of Attraction
Mu
Lambda
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5

(c)



(d)

Figure 9: Basins of attraction for positive risk culture. Initial conditions set to O(0) = W(0) = -0.1, E(0) = L(0) = +0.1. (a) β = 0.1, (b) β = 1.0, (c) β = 2.0 and (d) β = 3.0.

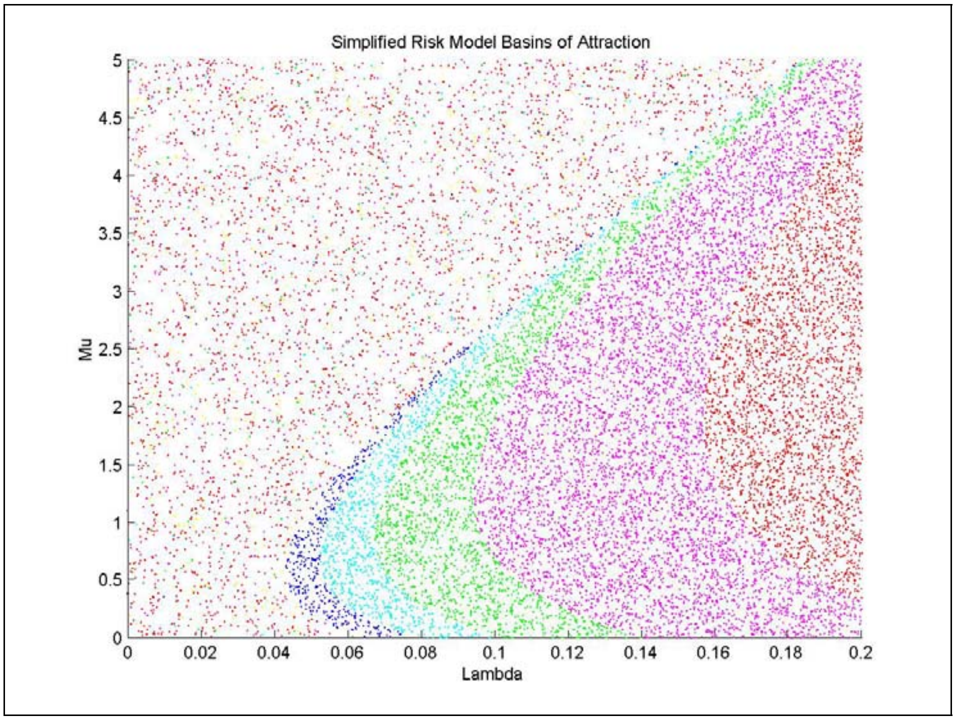


Figure 10: Basin of attraction for risk model without risk culture for $0 \leq \lambda \leq 0.2$ and $0 \leq \mu \leq 5$.

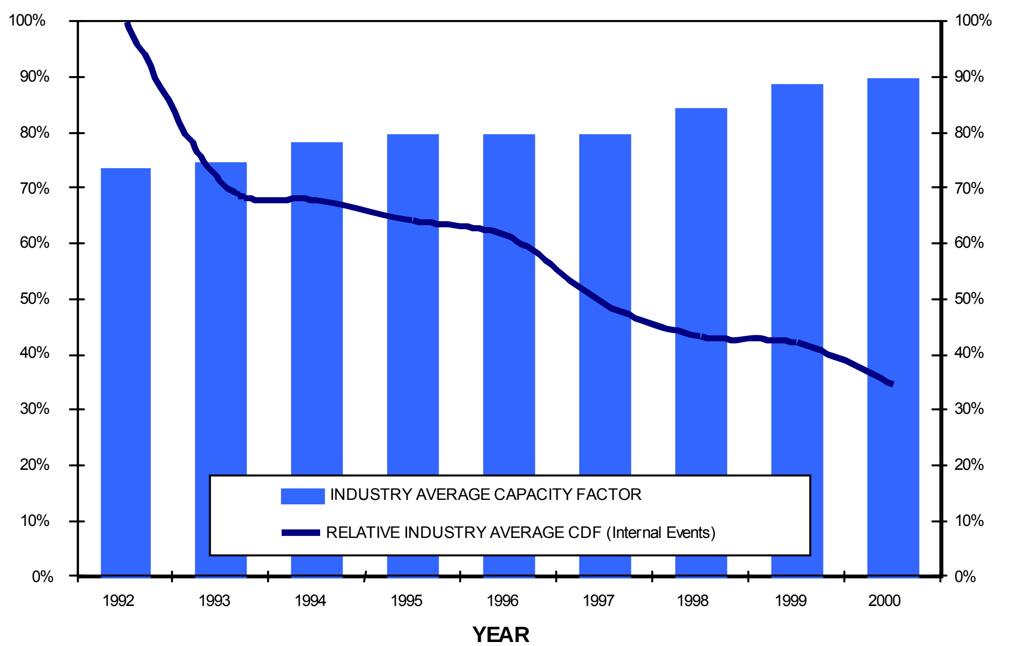


Figure 11: U. S. commercial nuclear power plant performance and relative calculated core damage frequency 1992 – 2000.

TABLES

Time to Reach R = 1	**Data Point Color**
t < 10	Yellow
10 < t < 20	Red
20 < t < 30	Magenta
30 < t < 40	Green
40 < t < 50	Cyan
50 < t < 60	Blue

Table 1: Classification scheme for basin of attraction R→ 1.