Development of a Station Blackout Benchmark Case Study for Dynamic Probabilistic Risk Assessment

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Abstract: Probabilistic Risk Assessment (PRA) has been widely used to estimate the risk of engineering systems including nuclear power plants. Dynamic PRA represents a category of advanced methods for PRA and improves upon conventional PRA. Dynamic PRA methods generate scenarios using a computational process, typically simulation of scenarios, which allows the analysis to consider significantly more scenarios and complex dependencies. Existing dynamic PRA studies make use of many differing case studies to demonstrate their contributions, such as the integration of operator performance models, passive component modeling, and computational cost reduction. It is challenging to use the existing case studies in the literature to compare existing methods, and to clearly demonstrate the capabilities of dynamic PRA. In this paper, a new case study for dynamic PRA studies is designed and proposed as a common test case. Station blackout is selected as the initiating event for the case study because of its relatively large contribution to system risk as well as the strongly physics-dependent nature of the corresponding accident progression. This allows the results of the case study to clearly demonstrate the capabiliteis of dynamic PRA on an important type of accident in a practical system. In addition to the initiating event, the case study includes a list of stochastic events to consider along with corresponding probabilistic models. The stochastic events can be categorized as failure on demand, time distributed failure to run, operator actions, and physics dependent failures. These categories are representative of the variety of possible events in a nuclear power plant risk assessment.

1. INTRODUCTION

Dynamic probabilistic risk assessment (PRA) methodologies were developed to address certain limitations in conventional PRA. Specifically, dynamic PRA methods were designed to explicitly handle variable event timing and ordering, and to directly model complex dependencies [1, 3, 12, 15]. These abilities are useful when assessing the risk of systems with highly physics-dependent failure behavior, such as nuclear power plants. There are many examples of dynamic probabilistic risk assessment methods being demonstrated using nuclear power plant case studies, and in particular, many examples using the station blackout (SBO) accident [2, 7, 9, 18]. Previous work has also highlighted a lack of a common case study for dynamic PRA studies [12, 17], resulting in challenges assessing the relative usefulness of various dynamic PRA methods. For example, many dynamic PRA methods are computationally expensive [12], and deciding which method to use for a practical, cost limited risk assessment is challenging without a common point of comparison. To address this gap, a new case study based on SBO of a nuclear power plant is developed and proposed.

SBO is selected because it has been commonly used in previous dynamic PRA studies [12] and because it is a significant contributor to nuclear power plant risk [5, 8]. The key features of this case study include the definition of the possible stochastic events to be modeled, context-based operator performance, and physics dependent component failure behavior [17]. These case study features demonstrate the ability of dynamic PRA methods while performing risk assessment of a reasonably large-scale system.

2. SYSTEM DESCRIPTION

To demonstrate the capabilities of various dynamic PRA methodologies, a level 1 PRA of a representative pressurized water reactor (PWR) experiencing station blackout is proposed. The system is defined by two models. The first model is the risk assessment or PRA model, consisting of a set of components and functions that must be performed in order to respond to the station blackout initiating event. The second model is the physics model, to be used to compute the evolution of the system dynamics over time during the accident. This model can be developed using many nuclear power plant simulation codes, but for the purposes of this case study, it is developed using RELAP5-3D [16].

The PRA model is used to estimate the frequency of the many possible scenarios corresponding to the response of a PWR to SBO. The model includes the frequency of the initiating event, the loss of offsite power followed by the loss of onsite AC power, and the probabilities of the possible stochastic events. These stochastic events can occur at branching points in the dynamic PRA simulation, and are used to represent events like the failure of the automatic start of the turbine driven auxiliary feed water (TDAFW) pump and the depletion of the DC batteries. For each stochastic event, a probabilistic model is developed which is used in conjunction with the probabilities of other stochastic events and the frequency of the initiating event to compute the frequencies of scenarios which include said event. This estimation can be done using Monte Carlo simulation (e.g. [4]), dynamic event tree methods (e.g. [7]), or other dynamic PRA methods such as the Exploratory Nuclear Tree Sampler (ENTS) [13].

For each scenario included in the dynamic PRA analysis, a system dynamics simulation is carried out using the physics model of the plant. This model is used primarily to estimate the system dynamics as a function of time throughout each of the generated scenarios, as well as to estimate the consequences associated with the occurrence of each scenario. The frequencies computed using the PRA model can then be combined with the consequences estimated using the physics model to estimate the overall plant risk given the occurrence of the initiating event. The remainder of this paper is primarily focused on the PRA model.

3. INITIATING EVENT

Station blackout (SBO) is the result of the complete loss of AC power at a nuclear power plant. Nuclear power plants require a connection to the external power grid to power many critical systems, including the primary coolant pumps, and many auxiliary systems. When this power is lost, the event is termed loss of offsite power (LOOP). A LOOP event does not necessarily progress into an SBO event, because there are emergency backup generators present at nuclear power plants that can provide backup AC power in the case of LOOP. If these backup diesel generators are unavailable or fail to operate, the event becomes an SBO.

During an SBO, the only electrical power available at the plant is stored in large batteries. The batteries can provide DC power to instrumentation in the control room and some plant elements that use DC power (e.g. power operated relief valves) for a limited time. Because all AC power is lost, most of the primary cooling systems for the nuclear reactor are lost, which if not addressed, can lead to the overheating of the reactor core and possible core damage. The crew of the nuclear power plant and the automatic systems that can operate using the DC power from the batteries must ensure that the reactor core does not overheat by ensuring continuous cooling of critical parts of the reactor systems. For the purposes of this proposed case study, scenarios that lead to the temperature of the fuel cladding in the reactor core exceeding a threshold are deemed to have consequences, and the scenario generation process is terminated at that point. This definition is somewhat conservative, as it is possible that after reaching the melting point of the cladding, the temperature decreases fast enough that no risk-significant melting actually occurs in the core. An example scenario that leads to the occurrence of consequences is the uncovery of the fuel due to leakage of primary side coolant. When the fuel is uncovered the local reactivity increases resulting in an increase in the peak temperature within the core. If this temperature is high enough, such scenarios are deemed to have consequences.

4. PLANT RESPONSE

As discussed in section 3, the crew and available automated systems must respond to the occurrence of SBO by ensuring that the reactor systems are appropriately cooled. There are several ways this cooling can be maintained even with no AC power available, such as use of the turbine-driven auxiliary feedwater pump, or the timely recovery of AC power (either onsite through the backup diesel generators or offsite power). In a dynamic PRA analysis, these events should each be considered, and the time at which each event occurs within individual scenarios is also considered. The stochastic events considered in the PRA model generally correspond to the plant response, and for each stochastic event there is an impact on the system dynamics evolution within the simulation model.

The stochastic events considered in this case study were selected to demonstrate the capabilities of dynamic PRA methods, including the modeling of physics-dependent failures, context-based operator interactions, and the variety of possible hardware failures (i.e. failure on demand, failure to run, etc.). This case study was designed to be representative of a nuclear power plant response, and therefore does not include all possible events, only those that are expected to be of interest from a PRA perspective. The events were determined to be of interest based on the existing literature on station blackout accidents at existing nuclear power plants as well as existing PRA analyses of nuclear power plants [2, 7, 9, 10, 18].

The stochastic events considered in this case study are categorized as failure on demand, time distributed, operator actions, and physics dependent. A single stochastic event may fit multiple categories, for example, an event may occur according to a time distribution that is a function of physics, making the event both time distributed and physics dependent. Each stochastic event considered in this case study is categorized by its most specific category, so the example event described above would be categorized as physics dependent.

4.1. Failure on Demand

The category of failure on demand describes events that may occur whenever a system is demanded to respond to a condition during a scenario. For example, immediately following the initiating event (i.e. the loss of all AC power at the nuclear power plant) the reactor should automatically trip. The initiating event corresponds to the demand for the trip system to actuate. Another example of demand is overpressure opening a spring actuated safety relief valve.

The first failure on demand considered is the failure of the automatic reactor trip following the initiating event. This event results in the reactor remaining at full power longer than expected, resulting in the production of additional heat that must be removed to prevent core damage. If there are no other interventions following the failure of the automatic reactor trip, the likelihood of core damage is very high, since the emergency cooling systems are insufficient to provide cooling to a reactor core at full power. In the event the automatic trip fails, it is assumed that the operators are able to manually trip the reactor after a time delay. Additional information about the operator model for manual reactor trip is discussed in Section 4.3. If the automatic reactor trip is successful, it is assumed that the control rods are fully inserted into the reactor core, and the production of new heat by nuclear fission is stopped. Under other transient conditions such as a condition with partial core damage already, it is possible that the trip would not fully insert some or all of the control rods. However, because the reactor is assumed to be operating normally prior to the initiating event, partial insertion is not considered in the proposed case study.

The second failure on demand considered is the failure of the main steam isolation valves to close following the initiating event. Similarly to the failure of the automatic reactor trip, the main steam isolation valves should close immediately following the initiating event, and in the event that they do not close automatically there is an operator action that occurs after a time delay to close them. The main steam isolation valve serve to block the flow of secondary side steam from the steam generators through the turbines, preserving containment.

The third failure on demand considered is the failure of the TDAFW pump to start automatically. The TDAFW pump is expected to start automatically one minute after the initiating event, and injects fresh coolant into the secondary side to remove additional heat from the steam generators. The proposed case study also considers a manual backup to start the TDAFW pump with a time delay following its failure on demand. The TDAFW pump is one of the most critical components in an SBO accident, and has been modeled extensively in this case study. Additional information about the TDAFW pump state is given in Section 6.

The next failures on demand considered are the failure of various relief valves. The proposed case study considers both pressurizer power operated and safety relief valves, as well as steam generator power operated and safety relief valves. The pressurizer relief valves allow the flow of primary side coolant (in the form of steam) into containment, reducing the pressure in the primary side. Similarly, the steam generator relief valves allow the flow of secondary side coolant (also in the form of steam) into containment, reducing pressure in the secondary side. Power operated relief valves require the availability of DC power (either through the batteries not being depleted or through the availability of AC power from any source). Safety relief valves have a higher pressure set point and do not require power to operate. These valves are expected to be opened when the pressure in the primary or secondary side exceeds a set point, whose value depends on the particular valve in question. Once open, any of the four valve types discussed can also fail to close. This is also a failure on demand (where the demand is the pressure falling below a set point). Note that while these demands are physics-dependent because they are a function of the pressure, the failure behavior is only determined on demand.

The final failure on demand considered in the proposed case study is the failure of the emergency core cooling system (ECCS) to start automatically. The ECCS consists of two independent parallel equipment trains, one for high pressure injection and one for low pressure injection. Each train can supply additional coolant in the primary loop, and the train that is used depends on the pressure present in the primary loop and the required flow rate of injected coolant. The ECCS operates only when AC power is available, which in the case of SBO is the result of either the restoration of offsite power or the restoration of onsite power. When the AC power is restored, the ECCS system may fail to start automatically. It is possible that the ECCS system is started manually following the failure of the automatic system. Since the manual start of the ECCS is an operator action it is discussed in Section 4.3.

4.2. Time Distributed Events

The category of time distributed events describes events that occur with a probability computed using a probability distribution of time. Events in this category may have a probability distribution that is defined over the entire accident scenario, or may be partially dependent on other events. For example, a backup system failure to run may occur at any time after the backup system is activated, but cannot occur prior to its activation.

The first two time distributed events considered in the proposed case study are the recovery of offsite and onsite AC power. Because SBO requires the loss of all AC power to the nuclear power plant, and the proposed case study assumes all power is lost as part of the initiating event, both recovery of offsite and onsite AC power can occur at any time during a scenario. When either source of AC power is restored, AC powered equipment, such as the ECCS becomes available. If the DC batteries are depleted when AC power is recovered, then DC powered equipment (made unavailable by the battery depletion) also becomes available. Recovery of either source of AC power is assumed to be sufficient to power all modeled AC powered equipment for the remainder of the accident duration. This assumption is reasonable for accident scenarios that are relatively short, although for scenarios where offsite AC power is unavailable for an extremely long time, it is possible that onsite AC power fails because the generators run out of fuel. The case of the onsite generators running out of fuel is not considered in the proposed case study. It is assumed that recovery of either source of AC power is independent of the other.

The next time distributed event is the failure to run of the TDAFW pump. As discussed in Section 4.1, the TDAFW pump is expected to start one minute after the initiating event and inject fresh coolant into the secondary side to remove heat from the steam generators. Once the TDAFW pump is active, either due to the success of the automatic start system or a successful start by the operators, it may fail to run at any time during an accident scenario. This failure causes the pump to completely stop supplying coolant injection, and is modeled using a time distribution. Additional information about the TDAFW pump state is given in Section 6.

The fourth and final time distributed event considered in the proposed case study is the depletion of the DC batteries. The DC batteries are used to supply electric power to control room instrumentation and limited plant components such as power operated relief valves. As discussed previously, it is assumed that the restoration of AC power also supplies DC power if the DC batteries are depleted. The batteries are placed under load immediately following the initiating event (because all AC power is lost) and may be depleted at any time between 2 and 8 hours after the initiating event. More information about this particular model is given in Section 5.

4.3. Operator Actions

Operator actions are included in the proposed case study to reflect the potential impact of delayed and potentially neglected human actions that are required to prevent core damage. As is often the case in human reliability analysis, only operator errors of omission are considered in the proposed case study. This corresponds to the crew forgetting to take an action rather than the crew taking an incorrect action relative to the emergency operating procedures relevant to SBO. The operator actions considered in the proposed case study are manual backups to automated systems in the event that the automated system fails.

The first operator action considered is the manual trip of the reactor following the failure of the automatic trip system. Immediately following the initiating event, the automatic trip system is expected to trip the reactor and insert the control rods, but it is possible that the system fails on demand (see Section 4.1). In the case that the automatic trip system fails, the reactor will remain at full power until the operators notice the issue, diagnose the failure as caused by the automatic trip system not inserting the control rods (instead of e.g. an incorrect readout on their instrument panel), and correctly activate the manual trip system. It is possible that the operators complete the first two items (noticing the issue and diagnosing the failure) at any time after the failure occurs, but there is expected to be some delay between the failure and the completion of these two items. Once the diagnosis is complete, the operators must actuate the manual trip system, which they may forget to do. If the operators do not actuate the manual trip system, either because they do not finish the diagnosis before core damage or because they omit the step to actuate it, the scenario is likely to correspond to a severe accident.

Similarly, the second operator action considered in the proposed case study is the manual closure of the main steam isolation valve following the failure of the valve to close automatically. Immediately following the initiating event, the main steam isolation valves are expected to close to block the flow of secondary side steam from the steam generators through the turbines. In the case that the valves are not closed automatically, the operators must diagnose the failure and then manually close the valves. The diagnosis step takes some time, and there is a chance that the operators neglect to manually close the valves.

The TDAFW pump may fail on demand (Section 4.1), and can be manually started if this occurs. The third operator action, starting the TDAFW pump, is again similar to the other operator actions discussed here. The operators must diagnose that the TDAFW pump has not started automatically, corresponding to a time delay, and then must manually start the pump with a potential to neglect this step in the emergency operating procedures. Failure to start the TDAFW pump or a long delay before it is started due to the diagnosis process may result in the scenario resulting in consequences because inadequate cooling is provided to the reactor core without additional coolant injected by the TDAFW pump. More information about the TDAFW pump is given in Section 6.

The fourth and final operator action considered in the proposed case study is the manual start of the ECCS following its failure on demand. Once AC power is restored to the nuclear power plant, the ECCS should start automatically to provide additional cooling to the reactor core. If the ECCS fails on demand, the operators must diagnose the failure and then manually activate the system. As with the other operator actions considered in the proposed case study, there is a time delay associated with the diagnosis step and a possibility that the operators omit the manual activation of the system.

4.4. Physics Dependent Events

Physics dependent events are stochastic events whose probability is computed as a function of the system dynamics within each accident scenario. The dominant behavior of events in this category is that accidents with more severe physical conditions (i.e. high temperature, high pressure) have a higher likelihood of including stochastic events within the category. These events are challenging to include in a conventional PRA since the system dynamics are not an explicit part of generating scenarios in conventional PRA methods. Dynamic PRA methods, however, provide an easier way to include such events.

The first physics dependent event included in the proposed case study is the degradation of the reactor coolant pump (RCP) seal. Immediately following the initiating event, it is assumed that the RCP begins to leak at a constant rate. The rate of leakage remains constant until the time at which the temperature and pressure in the primary side reach saturation conditions. This time is directly related to the system dynamics associated with each accident scenario. Once saturation conditions are reached, the leakage rate may remain the same, slightly increase, or substantially increase each with a given probability.

The second and third physics dependent events included in the proposed case study are the creep rupture of the pressurizer surge line and the creep rupture of the steam generator tubes. Because the creep failure mechanism is a result of elevated mechanical stress and temperature, the probability of creep rupture events is computed as a function of the pressure and temperature in the primary side in the case of the pressurizer surge line and the secondary side in the case of the steam generator tubes. Creep failure is a cumulative process, so the entire history of the pressure and temperature is considered for both events. These events also consider uncertainty in the process, so even if creep rupture is expected from a deterministic physics model, it may not occur during a particular scenario due to this uncertainty.

5. SELECTED PROBABILISTIC MODELS

Each of the stochastic events described in Section 4 has a corresponding probabilistic model that gives its probability of occurrence. These models range in complexity from simply a constant probability, to highly complex, such as a human reliability model. An example of a probabilistic model for each category of stochastic event in Section 4 is given in this section. Detailed probabilistic models for all stochastic events are required in order to implement the proposed case study, but because the purpose of this work is to outline the events considered, only a selected few models are discussed.

Most of the failure on demand events (Section 4.1) are modeled using a simple constant probability. For example, the automatic start of the TDAFW pump may fail to occur with a probability of 3.79×10^{-3} (Table 48, Row 8 [11]). This probability is estimated from industry-wide operational data at US commercial nuclear power plants.

The probability of the depletion of the DC batteries is computed from a time distribution (Section 4.2). As discussed previously the time at which the DC batteries are depleted is modeled using a triangular distribution with a minimum of 2 hours, mode of 6 hours, and maximum of 8 hours [10]. The probability that the stochastic event "DC batteries depleted" occurs at some time is the value of the triangular cumulative density function conditioned on the fact that the batteries have not failed at an earlier time.

Operator actions (Section 4.3) are modeled using a combination of the Human Cognitive Reliability (HCR) method [14] and the Standard Plant Analysis Reliability - Human Reliability Analysis (SPAR-H) method [6]. The HCR method is used for the time delay associated with the diagnosis step, and the SPAR-H method is used to estimate the probability that the operators omit whatever action is under study. For example, the manual start of the TDAFW pump is modeled as follows. The time at which the operators complete the diagnosis that the automatic start of the TDAFW pump has failed to occur and that they must manually actuate the pump is given by a lognormal time distribution with a median time of 365 seconds and a standard deviation of 0.57. These parameters are estimated using the HCR manual [14], specifically the median is estimated from Table 3-3, using the value for the establishment of main feedwater flow following the loss of the secondary heat sink. This value is chosen because the table does not include manual actuation of the TDAFW pump, but the selected event is expected to be of similar complexity. The standard deviation is given by Table 3-1 of Reference [14], as it is expected that this interaction follows an alarm, and is therefore of type CP-1. The SPAR-H method [6] estimates the probability that the operators omit the actuation of the TDAFW pump using performance shaping factors (PSFs) and a nominal failure probability. For simplicity, it is assumed that all the PSFs are fixed and nominal except for complexity, experience/training, and stress. Complexity is assigned a value of moderately complex and multiplier of 2.0, while experience/training is assigned a value of high and a multiplier of 0.5. Stress is assigned a value of high with a multiplier of 2.0 if the fluid level in the reactor core is far above the top of the fuel rods, or a value of extreme with a multiplier of 5.0 if the fluid level is close to the top of the fuel rods. This reflects the operators' response to the perceived risk during the accident scenario. The probability at any time that the operators successfully manually start the TDAFW pump is therefore the joint probability that the diagnosis is completed at that time and that they do not omit the action.

Physics dependent failure (Section 4.4) models use a probability distribution in combination with a physics function to determine failure probability over time. In the case of the pressurizer surge line creep rupture, the model uses a cumulative creep rupture parameter that is updated at each time step during each scenario based on the previous system dynamics. This parameter is then used in combination with a lognormal distribution to compute the probability of creep rupture. The creep rupture parameter is computed as

$$R(t_f) = \int_0^{t_f} 10^{(-p(t)/T(t))-20} dt \tag{1}$$

where $p(t)$ is the pressure over time and $T(t)$ is the temperature over time [2]. The probability of creep rupture at any time t_f is computed using the value of $R(t_f)$ and the lognormal cumulative density function with parameters $\mu = 0$ and $\sigma = 0.4$.

6. EXAMPLE COMPLETE COMPONENT MODEL: TDAFW PUMP

The stochastic component of the nuclear power plant state evolves in response to the occurrence of the previously discussed stochastic events. These events, however, are not all independent and unrelated. One of the key capabilities of dynamic PRA methods is their ability to handle complex dependencies, and as a result, the proposed case study includes such dependencies. As a simple example of these dependencies, this section discusses the TDAFW pump state evolution through potential scenarios. The TDAFW pump is demanded to activate at one minute after the initiating event. At that time it is possible that the TDAFW pump is unavailable due to a standby failure, the TDAFW pump may activate automatically, or the automatic activation signal fails, and a manual start is required. If the manual start is required, the TDAFW pump may be activated at any time following the failure of the automatic signal, or may fail to be activated because the operators omit the step in their emergency operating procedures. While the pump is running, it may stop running if it experiences a failure to run, or if the DC batteries are depleted. If the DC batteries are depleted but DC power is later recovered due to the recovery of either the offsite or onsite AC power, the TDAFW pump may be restarted automatically or manually following the recovery of power. The possible state evolution of the TDAFW pump is shown in Figure 1.

As can be seen in Figure 1, there are many possible ways in which the TDAFW pump state may change throughout any given scenario. These different evolutions may result in the pump being available or unavailable at many different times during a scenario, including the possibility for the pump to be available, fail due to loss of DC power, and then recovered due to the recovery of AC power. The TDAFW pump state is therefore dependent on a number of other events. This model would be extremely challenging to incorporate in a conventional PRA model because of its dependencies, including time dependence. However, this complex model of the TDAFW pump (and similar complex models for other system components like the ECCS) is expected to be less challenging to include in a dynamic PRA model, showcasing the capabilities of dynamic PRA methods.

7. CONCLUSIONS

This paper describes a proposed dynamic PRA case study based on SBO of a PWR. The case study includes a comprehensive list of stochastic events that may influence the outcome of any given scenario and probabilistic models of each stochastic event. In order to demonstrate the capabilities of dynamic PRA methods, and to highlight the differences between different dynamic PRA methods, the case study includes events categorized as failure on demand, time distributed failures, operator actions, and physics dependent events. These different categories are sometimes easy to include in conventional models, such as failure on demand, but others, like physics dependent events can be challenging to include. Additionally, many of the considered stochastic events have complex dependencies. The possible state evolution of the TDAFW pump is given as an example of a set of interdependent stochastic events from multiple categories. The TDAFW pump may fail on demand, experience a time-distributed failure to run from two different sources (mechanical failure to run or failure to run due to loss of DC power from battery depletion), and physics-dependent operator actions

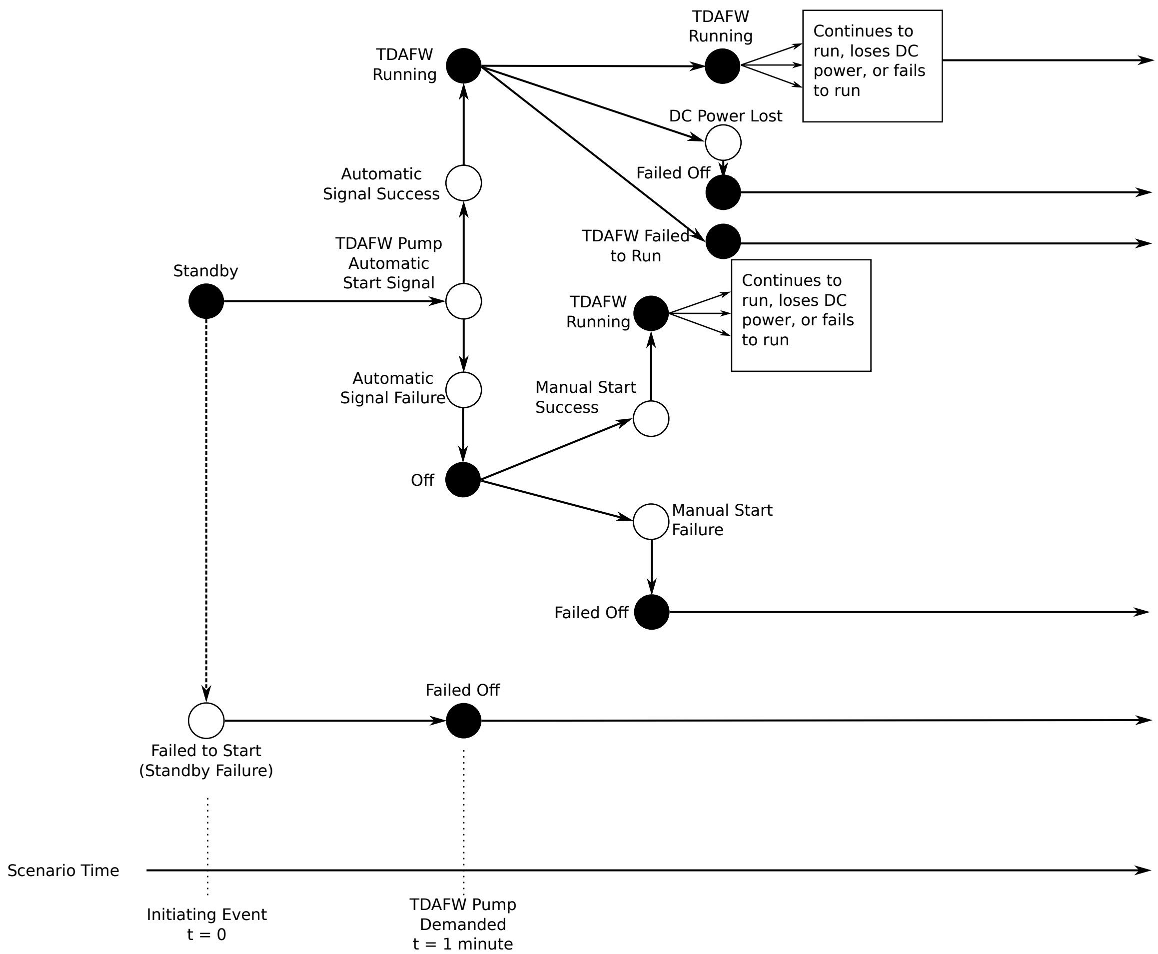

Figure 1: Possible Evolutions of TDAFW Pump State

in the case that the pump fails to start automatically but is not failed during standby. If adopted by the wider dynamic PRA research community, the proposed case study will highlight the capabilities of dynamic PRA methods as well as allow different dynamic PRA methods to be compared using a moderately scaled realistic system.

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