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# Integration of Dynamic Probabilistic Risk Assessment and Decision Making Under Uncertainty Methodology for Hydrogen Fueling Station Deployment

Suroosh Mosleh

*Center for Risk and Reliability, Reliability Engineering, University of Maryland College Park USA. E-mail: smosleh@umd.edu*

Katrina M. Groth

*Director, Center for Risk and Reliability, Reliability Engineering, University of Maryland College Park USA. E-mail: kgroth@umd.edu*

The successful design, deployment, and management of complex engineering systems require an integrative framework that captures evolving risk dynamics, causal interdependencies, and explicit decision-making under uncertainty. This paper presents the first formal integration of Dynamic Probabilistic Risk Assessment (DPRA) with multistage stochastic optimization to support long-horizon planning under deep uncertainty. This methodology enables causal, risk-informed reliability modeling to be combined with decision analysis for modeling hydrogen fueling station deployment with the objectives of minimizing risk and maximizing profit and availability.
Traditional Probabilistic Risk Assessment (PRA) methods quantify what can go wrong, how likely it is, and what the consequences are, but they do not prescribe optimal actions for managing risk over time. Multi-horizon stochastic programming, a mathematical optimization framework for Decision Making under Uncertainty (DMU) models optimal actions when future states of the world are uncertain, but representable through probabilistic scenarios. By embedding a Dynamic Bayesian Network (DBN) within a multi-horizon stochastic programming framework, this work constructs a decision-dependent DPRA architecture in which reliability and risk evolve in response to design and operational decisions. This yields a fully dynamic, causal representation of system risk, as opposed to the static snapshots in more traditional techno-economic analyses and conventional PRA.
To enhance economic realism, the framework incorporates a capacity-constrained Cournot competition layer formulated as a stochastic mathematical program with equilibrium constraints (SMPEC). Rather than assuming exogenous hydrogen prices, the SMPEC computes endogenous market price–quantity outcomes each period by from strategic quantity decisions under a shared inverse demand curve, with the operator's feasible supply constrained by DBN derived availability. This hybrid integration captures how preventive maintenance policies, downtime, and capacity losses propagate into equilibrium revenue and long-horizon profits. The proposed DPRA–SMPEC hybrid model links engineering reliability, safety risk, operational policy, and economic performance in the market into a unified risk-informed tool for evaluating long-term hydrogen fueling station deployment.

*Keywords*: Hydrogen, Hydrogen Reliability, Quantitative Risk Assessment, Probabilistic Risk Assessment, Decision Making Under Uncertainty, Game Theory, Techno-Economic Assessment, Equilibrium, Optimization.

## 1. Introduction

Risk analysis of heavy-duty liquid hydrogen-based systems is a necessary tool for industry and decision-makers to push for wider deployment of hydrogen systems in industrial applications such as supporting drayage trucking for port operations. These uncertainties arise from many sources including technological reliability, regulatory frameworks, operational safety, variability in energy demands, economic conditions, and environmental factors. Probabilistic Risk Assessment (PRA), also known as Quantitative Risk Assessment (QRA) provides a structured, quantitative approach to identifying and analyzing risks that arise from uncertainties of many sources including technological reliability, regulatory frameworks, operational safety, variability in energy demands, economic conditions, and environmental factors (Modarres and Groth 2023). PRA methods and analysis generate information for the decision-making process to aid what is called "risk-informed" decision-making to assess what is known as the "risk triplet" — a concept introduced by Kaplan and Garrick (Kaplan and Garrick 1981). As PRA does not natively incorporate decision-making, recent literature has identified the need for "hybrid" models that incorporate PRA with decision-making under uncertainty and game-theory frameworks (Hausken et al. 2025; Mosleh and Groth 2026).

### 1.1. *Hydrogen fueling station PRA/QRA*

As many nations have identified hydrogen as an emphasis in their energy strategy, particularly in heavy-duty and industrial applications, uniform codes and standards have yet to be solidified for hydrogen fueling stations (Mosleh et al. 2025). The rapid interest in the expansion of the hydrogen economy has shown QRA to be a critical tool in the successful scaling of wider station deployment. Early hydrogen station QRA focused on identifying credible release scenarios, estimating frequencies, modeling physical effects, and quantifying consequences to people and assets. These QRAs led to the development of tools such as HyRAM and HyRAM+, developed by Sandia National Laboratories, for analysis of hydrogen system risk by identifying scenarios could lead to ignitions and their associated probabilities, as well as integrated consequence analysis of various risk scenarios including jet fires (Groth and Hecht 2017; Ehrhart et al. 2023). While HyRAM is used for QRA of gaseous hydrogen ($GH_2$) stations, as the industry is exploring liquid storage hydrogen fueling stations, integrated consequence analysis models are currently undeveloped. Thus, current QRA studies on $LH_2$ fueling stations use a mix of modeling methodologies including Bayesian networks for ignition and release, physical models, as well as commercial CFD tools (Mosleh et al. 2025).

Studies in risk analysis as well as operations research have looked at hydrogen fueling stations with on-site hydrogen production or off-site, where hydrogen is purchased and delivered and stored at the station. This study considers stations with off-site production, however the methodology can easily be modified to include on-site production (Apostolou and Xydis 2019).

Dynamic, or simulation-based PRA represents an evolution from traditional static PRA approaches, providing a more comprehensive analysis of complex system risks by explicitly incorporating time dynamics and physical phenomena (Siu 1994; Amendola and Reina 1981).This advanced methodology generates risk scenarios through stochastic branching processes driven by probabilistic models of system behavior and interactions. Such behavior models can take various forms, including logic-based models (such as fault trees or Bayesian networks), mathematical expressions, computer-based simulations, or hybrids combining these methods. By integrating these diverse modeling strategies, dynamic QRA effectively captures temporal dependencies and interactions within the system, offering greater precision and predictive capability.

### 1.2. *Techno-economic analysis of hydrogen stations*

Hydrogen fueling station techno-economic analysis (TEA) commonly uses discounted cash flow and cost-accounting approaches to estimate breakeven hydrogen selling cost or financial viability under assumed station capacity, utilization trajectories, and cost parameters.

Research on hydrogen fueling station design has developed increasingly detailed TEA pipelines and cost metrics, typically centered on levelized cost of hydrogen (LCOH) or a station-level levelized dispensing cost. Ade et al. exemplify an integrated safety–economics workflow by coupling station configuration and equipment sizing with quantitative risk assessment (QRA) outputs and economic performance indicators, enabling design trade-off studies between "safer" configurations and cost/return metrics (Ade et al. 2020). Widely used TEA tools such as Argonne National Lab's Hydrogen Delivery Scenario Analysis Model (HDSAM) estimate hydrogen fueling station levelized costs by sizing major components and applying discounted cash flow methods. These studies show that capacity utilization, component cost, and economies-of-scale can dominate the station contribution to delivered hydrogen cost, and therefore strongly influence LCOH or dispenser prices (Reddi et al. 2017). Complementary LCOH-focused life-cycle costing work similarly formalizes cost breakdowns (capex recovery + fixed and variable O&M) and highlights how utilization/operating hours and energy prices drive the levelized cost outcome (Viktorsson et al. 2017).

Most TEA assessments evaluate designs under assumed operating and pricing conditions but do not endogenize market outcomes (price/quantity/revenue) as a function of reliability and risk, nor do they represent sequential, risk-aware policy decisions over time. This is where hybrid PRA and DMU/game-theoretic models can offer perspective. Incorporating a market layer to existing TEA structures allows for increased realism to allow decision-makers to have more information about how major design investment and reliability decisions can affect their positioning in long-term deployments of stations.

## 2. System Description

The proposed methodology sets to analyze investment in the design and deployment of a retail hydrogen fueling station meant for high-capacity, heavy-duty applications such as port operation. The hydrogen fueling station owner and operator must choose between a set of design configurations with varying= storage and dispensing capacity, and varying component reliability. With the variance in the components from the selected configuration, the safety risk probabilities may differ as well. The baseline configuration of the hydrogen fueling station is from the QRA study in Mosleh et al. seen in Fig. 1 (Mosleh et al. 2025).

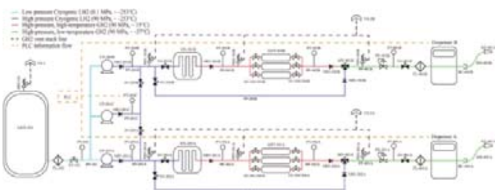

Fig. 1LH2 Hydrogen Fueling Station Configuration

The static QRA fault tree (FTA) and event sequence diagram (ESD) models ($LH^2$ rupture ESD shown in Fig. 3.) from Schaad et al. have been transformed to a be integrated with a reliability model, represented by the Dynamic Bayesian Network seen in Fig. 3 (Schaad et al. 2025). Underneath the LH2 and GH2 leak and rupture nodes are the embedded ESDs from Schaad & Mosleh, with the LH2 rupture ESD shown in Fig 2.

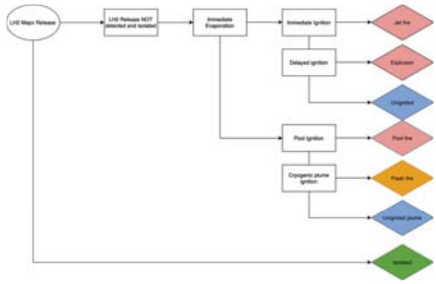

Fig. 2 LH2 Rupture ESD

The network has two main outputs, system availability and safety risk. Availability is influenced by component failures, and other component failure modes also influence risk invents identified as leak or rupture of gaseous or liquid hydrogen.

Fig. 3 LH2 Fueling Station DBN

The operator's choice in selecting a system design will directly affect capital expenditures, fixed operating costs, component reliability and replacement costs, as well as the fueling station's hydrogen storage and dispensing capacity.

## 3. DRPA-SMPEC Methodology

The proposed methodology follows from the DPRA-SDDiP methodology meant for integration of DPRA with decision making under uncertainty (DMU) for problems involving single agents (Mosleh and Groth 2026). Existing literature shows a gap in the full integration of Bayesian networks into as the scenario generator for multistage decision making, and especially multistage equilibrium problems. The proposed DPRA (DBN) based SMPEC, directly addresses these gaps by explicitly integrating causal risk and reliability models to dynamically update scenario information, and employing multi-horizon scenario tree structures to offering enhanced realism, computational efficiency, and practical utility for decision-making under uncertainty. The equilibrium aspect brings adds realism techno-economic realism by integrating market dynamics into the decision-maker's analysis. This methodology provides a structure for risk-informed analysis of long-term energy system infrastructure investment and deployment with many uncertainties, where decision-making has great implications on risk trajectories.

In formulating our methodology, we chose a DBN as the causal modeling vehicle for several reasons. First, DBN represents another popular method of PRA causal modeling, and it has been shown mathematically that FTA, ETA, and ES) are in fact special cases of Bayesian belief networks (Wang 2007). This has been shown mathematically. Furthermore, DBN is ideal as a causal model of situations where cause-effect relations are "soft" or non-deterministic.

In a standard multistage stochastic optimization formulation, representing both long-horizon strategic uncertainty and short-horizon operational uncertainty can lead to a combinatorial expansion of scenarios that quickly becomes computationally prohibitive.

By using a multi-horizon scenario tree, the model enhances computational efficiency and also supports long-term planning of strategic investments (e.g., design capacity and preventive maintenance policies) while explicitly accounting for short-term disruptions such as component failures, degraded operation, and other event-driven states that materially affect performance (Kaut et al. 2014). By embedding operational realizations inside each strategic period, the framework evaluates not only average profitability but also performance under probabilistic risk and reliability constraints, avoiding conclusions that can be masked by reliance on averaged inputs. The methodology follows the steps shown in Fig. 4.

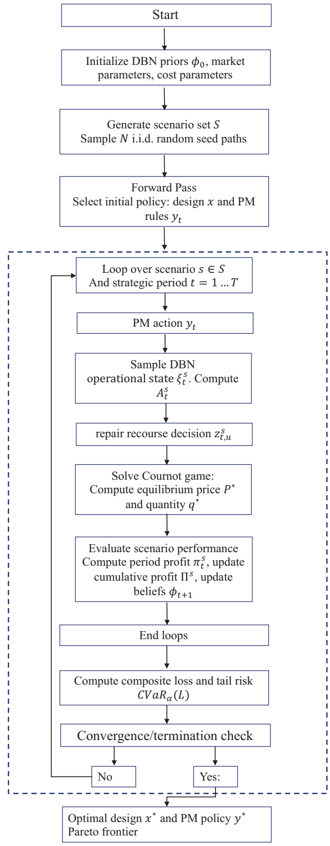


Fig. 4 DPRA-Stochastic MPEC methodology

### 3.1.1. *Scenario Generation*

The first phase of the framework involves initialization and scenario generation. The DBN is initialized using prior belief vectors $\phi_0$ that encode baseline component health and failure rates, along with the other state transition parameters such as safety risk and system availability. Market demand parameters $(a_t, b_t)$, rival capacity $K_{rival}$, and cost parameters (capital/design, preventive maintenance, repair, and operating costs) are specified. The design decision $x$ is interpreted as setting the station's nameplate capacity $K_{\text{design}}(x)$ and other physical limits.

Fig. 5 shows how a multi-horizon scenario tree is developed from the DBN causal model, where the red nodes are strategic nodes, defined as quarterly periods in the evaluation of the hydrogen fueling station problem, and the blue nodes are stochastic operational events within each strategic period.

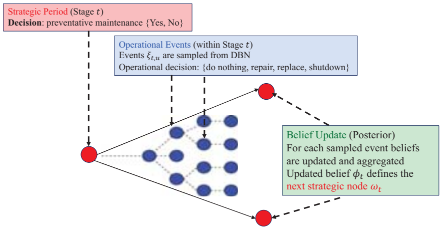


Fig. 5 Event-driven multi-horizon scenario tree generation

A set of $N$ seed paths $\{\omega_s\}_{s=1}^{N}$ is sampled a priori to drive DBN state transitions during forward simulation. This separates the generation of aleatory uncertainty from the subsequent policy evaluation step, enabling a Sample Average Approximation (SAA) interpretation in which expected performance and tail risk are estimated over the sampled scenario set.

### 3.1.2. *Foward Simulation*

The forward pass evaluates a candidate strategic policy $(x, y_{1:T})$ over the scenario set. For each scenario $s$ and strategic period $t = 1, ..T$, the framework transitions through strategic nodes (system PM intervention) and an operational node (reliability–market coupling).

**Strategic nodes:**

At the start of each strategic period $t$, the decision-maker applies the preventive maintenance (PM) rule $y_t$ conditional on the current belief state $\phi_{t,s}$. The PM action modifies the DBN transition probabilities for the upcoming period, reducing failure likelihood and/or improving the distribution over component health states. The strategic node outputs updated conditional probability tables (CPT) for period $t$, and the post-decision belief vector/parameterization used for sampling.

**Operational nodes:**

Along the pre-sampled seed $\omega_s$ and the updated transitions, a DBN realization $\xi_{t,s}$ is sampled. From $\xi_{t,s}$, an availability factor $A_{t,s} \in [0,1]$ is computed and mapped to available capacity: If the realized state indicates failure (or degraded-below-threshold), a recourse repair decision $z_{t,s}$ (or $z_{t,u,s}$ when multiple operational events are modeled within a period) is selected. This action incurs repair cost and influences subsequent beliefs and/or transitions by partially restoring condition or reducing future downtime.

**Cournot equilibrium:**

Conditional on the realized capacity $K_{\text{avail},t,s} = A_t^s K(x)$ and rival capacity $K_{\text{rival}}$, the model solves the stage-wise Cournot equilibrium. The equilibrium outputs include the operator's equilibrium quantity $q_{0,t,s}^*$, the rival's equilibrium quantity $q_{1,t,s}^*$, and the implied equilibrium market price: $P_{t,s}^*$. Revenue is then computed as $R_{t,s} = P_{t,s}^* q_{0,t,s}^*$. Importantly, $P_{t,s}^*$ is not an independently optimized profit-maximizing price; it is the *equilibrium price implied by equilibrium quantities* under the inverse demand curve. Period profit $\pi_{t,s}$ is computed and accumulated into discounted scenario-level profit $\Pi^s$. Then, beliefs are updated to $\phi_{t+1,s}$ using Bayesian updating conditional on observed outcomes $\xi_{t,s}$ and any repair action effects. Thus, the operational node outputs equilibrium outcomes $\left(q_{0,t,s}^*, q_{1,t,s}^*, P_{t,s}^*\right)$, period profit $\pi_{t,s}$, scenario profit $\Pi^S$, and updated beliefs $\phi_{t+1,s}$.

**Policy evaluation:**

After simulating all $(t, s)$ pairs for a candidate policy, the framework aggregates scenario performance and evaluates objectives and the expected profit $E[\Pi]$ is estimated

**Composite loss construction and CVaR:**

To unify safety risk and financial vulnerability in a single tail-risk measure, a composite scenario loss $\mathcal{L}$ is constructed where safety loss is computed from DBN safety outcomes along the path, and the economic loss represents downside financial shortfall relative to a reference profit $\Pi^{ref}$ The tail risk is then quantified via conditional value at risk (CVAR) $\mathrm{CVaR}_\alpha(L)$.

**Policy improvement:**

The strategic policy $(x, y_{1:T})$ is updated to improve risk-adjusted performance by subjecting the profit maximization the composite CVaR budget $\mathrm{CVaR}_\alpha(L) \le \epsilon$ (to trace a Pareto frontier over $\epsilon$). The framework is intentionally solver-agnostic at this stage. Options include policy MILP/MINLP reformulations (when complementarity conditions are linearized), decomposition-based methods (when horizon and scenario counts are large), or simulation-based learning (e.g., policy gradients, reinforcement learning).

## 4. Mathematical Formulation of

The formulation optimizes the hydrogen station operator's strategic policy—design selection $x \in X$ and preventive maintenance actions $\{y_t\}_{t=1}^{T}$—while embedding, in each $(t, s)$, a stage-wise Cournot equilibrium that is endogenously constrained by reliability through DBN-generated availability $A_t^s \in [0,1]$. The DBN provides (i) realized event outcomes $\xi_{t,u}^s$, (ii) a belief vector $\phi_t^s$ updated via Dirichlet counts, and (iii) an availability mapping $A_t^s = \text{Avail}(\xi_t^s)$ that scales the operator's capacity..

### 4.1.1. *Objective function*

The top-level objective maximizes the operator's expected total discounted profit across sampled DBN paths

$$\max \sum_{s \in S} p_s \Pi^s \tag{1}$$

Where $\Pi^s$ aggregates discounted operation profits along scenario $s$. The following constraints are imposed:

### 4.1.2. *Cournot market constraints*

For each period $t$ and scenario $s$, market price follows a linear inverse demand curve

$$P_t^s = a_t - b_t\left(q_{0,t}^s + q_{1,t}^s\right), \qquad \forall t, s \tag{2}$$

Such that the price $P_t^s$ is determined from the equilibrium quantities.

For the hydrogen fueling station capacity, the operator's feasible dispensing quantity is bound by the availability from the DBN reliability model

$$0 \leq q_{0,t}^s \leq A_t^s K(x), \qquad \forall t, s \tag{3}$$

Where $K(x)$ is the fully operational dispensing capacity\. $A_t^s \in [0,1]$ is the availability at $(t, s)$. The coupling of the reliability model to the economic analysis allows for a realistic evaluation of operational capability. The operator's competitor has an exogenous capacity limit

$$0 \leq q_{1,t}^s \leq \overline{\mathrm{K}}_1, \qquad \forall t, s \tag{4}$$

Given the constraints, the operator and the competing firm play a static Cournot game. The formulation enforces equilibrium using a compact mixed complementarity problem (MCP) with dual multipliers $\mu_{i,t}^s$ for the upper capacity bounds. For the operator, complementarity enforces either $q_{0,t}^s > 0$ and the marginal profit condition holds at equality, or $q_{0,t}^s = 0$ and the marginal profit condition is nonnegative together with complementarity on the capacity upper bound through $\mu_{0,t}^s$.

$$0 \leq q_{0,t}^s \perp c_{0,t}^s - a_t + b_t\left(2q_{0,t}^s + q_{1,t}^s\right) + \mu_{0,t}^s \geq 0, \forall_t, s \tag{5}$$

$$0 \leq \mu_{0,t}^s \perp A_t^s K(x) - q_{0,t}^s \geq 0, \qquad \forall t, s \tag{6}$$

Analogous complementarity conditions hold for the competitor, enforcing its best response subject to EQ#.

$$0 \leq q_{1,t}^s \perp c_1 - a_t + b_t\left(2q_{1,t}^s + q_{1,t}^s\right) + \mu_{0,t}^s \geq 0, \forall_t, s \tag{7}$$

$$0 \leq \mu_{1,t}^s \perp \left(\overline{K}_1 - q_{1,t}^s\right) \geq 0, \qquad \forall t, s \tag{8}$$

These constraints are imposed independently per period, i.e. the economic game is stage-wise rather than an intertemporal dynamic game. The equilibrium price and quantities arise form the simultaneous best-responses in equations

2.1.1.Physical operational constraints

The station maintains a hydrogen inventory $I_t^s$, replenished by procurement $h_{t,s}$ and depleted by dispensing $q_{0,t}^s$

$$I_t^s = I_{t-1}^s + h_{t,s} - q_{0,t}^s, \qquad \forall t, s \tag{9}$$

This couples the operational sales quantity to the procurement decisions upstream. Inventory is also constrained by the onsite storage capacity $H(x)$

$$0 \leq I_t^s \leq H(x), \qquad \forall t, s \tag{10}$$

This emphasizes the importance of the initial design investment, (decision $x$) and its associated capital costs on the overall viability of the station.

### 4.1.3. *Availability availability mapping*

Reliability outcomes are mapped via the availability from the DBN.

$$A_t^s = Avail(\xi_t^s) \in [0,1] \quad (12)$$

Availability $A_t^s$ then enteres the operator capacity constraint in equation (3).

#### 4.1.4. *Operator profit*

Scenario profit $\Pi^s$ aggregates discounted revenues and costs along the scenario path. The profit consists of capital cost $C^{capex}(x)$ of the chosen design $x$, strategic (quarterly) period operating profit which includes the equilibrium revenue $P_t^s q_{0,t}^s$, wholesale procurement cost $w_t^s h_t$, fixed operating cost $c_t^{fix}(x)$, PM cost $C_t^{PM}(y_t)$, and finally the failure-driven repair costs $c_{t,u}^{rep}(z_{t,u})$. Thus, the outputs of the Cournot game, $(P_t^s, q_{0,t}^s)$, are directly correlated to the station's reliability constraints.

#### 4.1.5. *Composite risk model*

Economic downside loss $g_s$ is defined relative to a reference profit level $\Pi^{ref}$, in this case 0.

$$g_s \coloneqq \max\{0, \Pi^{ref} - \Pi^s\} \quad (13)$$

Which is represented in the optimization problem by its linear epigraph

$$g_s \geq \Pi^{ref} - \Pi^s, g_s \geq 0, \qquad \forall s \quad (14)$$

This definition isolates tail losses. A composite loss metric $\mathcal{L}$ is constructed per scenario balancing economic risk with safety risk is defined

$$\mathcal{L}^s = \lambda_{safety} \sum_{t,u} \delta^{t-1} \ell^{safety}(\xi_{t,u}^s) + \lambda_{econ} g_s \quad (14)$$

This is used for having the conditional value at risk (CVaR) become a composite of safety consequence and economic loss. The weights $\lambda_{safety}, \lambda_{econ}$ control the decision maker's risk exposure trade-off preferences.

CVaR is enforced through the standard auxiliary variables $\eta$ representing the value-at-risk (VaR) threshold and $\rho_s$ representing the excess loss beyond that.

$$\rho_s \geq \mathcal{L}^s - \eta, \qquad \rho_s \geq 0, \qquad \forall s \quad (15)$$

CVaR at a confidence level $\alpha$ enforces the risk budget. $1 - \alpha$ defines the tail probability (e.g. at $\alpha = 0.95$) where CVaR averages the loss over the worst 5% of scenarios.

$$\eta + \frac{1}{1-\alpha} \sum_{s \in S} p_s \rho^s \leq \epsilon \quad (16)$$

This ensures the optimization maximizes expected profit subject to a hard constraint on the tail risk of the composite loss.

Finally, nonnegativity,

$$y_t \in \{0,1\}, z_{t,u}^s \in \{0,1\}, h_t \geq 0, \{I_t^s, q_{i,t}^s, P_t^s, \mu_{i,t}^s, g_s, \rho_s\} \geq 0 \quad (17)$$

And domain constraints

$$x \in X \quad (18)$$

Are enforced.

#### 4.1.6. *Full optimization problem*

Thus the full optimization problem becomes the objective function (1)

$$\max \sum_{s \in S} p_s \Pi^s \quad (20)$$
$$s.t.\ eq. (2) - (10)$$
$$eq. (14 - 19).$$

## 5. Methodology Focus: Hybrid Modeling

Integration of PRA/QRA with decision-making and game theory allows for operators to understand how investment strategies for design, maintenance scheduling, and risk tolerance perform over time in a complex engineered system operating in a highly uncertain techno-economic context. Traditional DPRA is primarily an analytical tool used to assess what could happen and with what likelihood, many times leaving the decision making to a human analyst to interpret the results. This framework advances the PRA from a purely evaluative model to a prescriptive one. It doesn't just simulate risk and reliability; it actively seeks to control it via integration of optimization to find a policy that explicitly achieves stated objectives and explicitly minimizing unwanted tail losses with the enforcement of a composite CVaR constraint. This provides clear and quantifiable answers for critical decisions, from inception, in the deployment of complex engineering systems. Further, the SPMEC allows for a market equilibrium layer that adds realism to the TEA as prices are not assumed but computed endogenously form the Cournot model.

## 6. Conclusion

This paper presents a hybrid PRA and game theory decision making methodology to better risk-inform investment and operation of hydrogen fueling stations in a period of rapid growth and high uncertainty. The methodology. The DPRA-SMPEC methodology integrates DBN based DPRA causal risk and reliability modeling with market equilibrium modeling to offer a generalizable framework that allows for enhanced risk and reliability driven economic realism through utilization of a multi-horizon scenario tree structure with equilibrium constraints, Bayesian updating, as well as modeling of decision-dependent probabilities. The aim is for the utilization of this methodology is to extend PRA's causal and probabilistic capabilities in evaluating risks to also providing the capacity for actively reducing risks through optimal decision-making in a realistic investment and operating framework, creatin better risk-informed outcomes in the deployment of complex engineering systems in

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**Appendix A. Nomenclature**

| | |
|---|---|
| **Sets and Indices** | |
| $T$ | Number of strategic periods |
| $t \in \{1, \dots, T\}$ | Strategic-stage index |
| $u \in \{1, \dots, S_t\}$ | Index of the $u$-th operational event in period $t$ |
| $I \coloneqq \{0,1\}$ | $H_2$ station operator firm |
| $i \in \{0,1\}$ | $H_2$ station firm index. Station operator = 0, competitor =1 |
| $S$ | Set of sampled scenario paths (full sequences of random events) |
| $s \in S$ | Sampled DBN scenario path, probability $p_s$ |
| $\Xi$ | Set of possible event outcomes |
| $\mathcal{U}$ | Set of all parent configurations for Dirichlet updating (e.g. design-action or design-failure combinations) |
| **Decision Variables** | |
| $x_0 \in X$ | Station design choice |
| $y_t$ | Preventive maintenance (PM) decision at strategic period $t$ |
| $z_{t,u}$ | Operational action taken immediately after $\xi_{t,u}^s$ on path $s$ |
| $h_t \geq 0$ | $H_2$ procured into storage at start of period $t$ (kg) |
| $I_t^s \geq 0$ | End of period inventory on path $s$ (kg) |
| **Equilibrium Variables** | |
| $q_{0,t}^s \geq 0$ | Operator equilibrium quantity (kg) in $(t, s)$ |
| $q_{1,t}^s \geq 0$ | Competitor equilibrium quantity (kg) in $(t, s)$ |
| $P_t^s \geq 0$ | Market price in period $t$ on path $s$ ($/kg) |
| $\mu_{0,t}^s \geq 0$ | Multiplier for operator capacity upper bound |
| $\mu_{1,t}^s \geq 0$ | Multiplier for competitor capacity upper bound |
| **Risk variables** | |
| $\eta$ | VaR threshold variable |
| $\rho_s \geq 0$ | Excess loss slack for scenario $s$ |
| $g_s \geq 0$ | Economic downside loss for scenario $s$ |
| $\mathcal{L}_s$ | Composite loss for scenario $s$ |
| $\Pi^s$ | Total discounted profit ($) along scenario $s$ |
| **Parameters** | |
| $p_s$ | Scenario-path probability |
| $\xi_{t,u}^s \in \Xi$ | DBN event outcome at $(t, u)$ on path $s$ |
| $\phi_t^s \in \Phi \subseteq \mathbb{R}^n$ | Belief-vector (Dirichlet counts → posterior mean) after all events in strategic period $t$ on scenario $s$ |
| $\epsilon(U, \xi)$ | Unit vector increment for parent configuration $U \in \mathcal{U}$ and event outcome $\xi \in \Xi$ |
| $A_t^s \in [0,1]$ | Availability of station from DBN for period $t$ |

| | |
|---|---|
| $K(x)$ | Dispensing capacity for design $x$ (kg/day) |
| $H(x)$ | On-site storage capacity for design $x$ (kg) |
| $w_t^s$ | Wholesale supply cost in period $t$ on path $s$ ($/kg) |
| $C^{capex}(x)$ | Capital cost of design $x$ |
| $c_t^{fix}(x)$ | Fixed O&M cost in period $t$ |
| $c_t^{PM}(y_t)$ | PM cost |
| $c_{t,u}^{rep}(z_{t,u})$ | Repair cost after operational event $u$ |
| $c_{0,t}^s$ | Operator's marginal cost ($/kg) of dispensing $H_2$ in period $t$ on path $s$ |
| $c_1$ | Competitor marginal cost ($/kg) |
| $\overline{K}_1$ | Competitor capacity (kg) per period $t$ |
| $a_t$ | Intercept/choke price ($/kg) |
| $b_t$ | Slope/price-impact ($/kg) marginal decrease in price per additional unite of $H_2$ supplied |
| $\epsilon \in (0,1)$ | Risk-event tolerance |
| $\alpha \in (0,1)$ | CVaR confidence level |
| $\delta \in [0,1]$ | Discount factor |
| $CVaR: \alpha, \eta, \rho_s$ | Confidence level, VaR variable, slack variables |
| $\lambda_{safety}, \lambda_{econ}$ | Weights for composite loss metric |
| $\Pi^{ref}$ | Reference profit level ($) used to define downside profit $\Pi^{ref} = 0$ |
| $\eta$ | VaR threshold variable |
| $\rho_s \geq 0$ | Excess loss slack for scenario $s$ |
| $g_s \geq 0$ | Economic downside loss for scenario $s$ |
| $\epsilon \geq 0$ | Risk tolerance (upper bound) on CVaR |