

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY FUTURISTIC DEVELOPMENT

Integrating Reliability, Availability, and Maintainability Analysis into Production Facility Performance Optimization

Susan Ochi Makut ¹, Festus-Michael Uwagboe ², Henry Chukwuemeka Olisakwe ^{3*}

¹ Independent Researcher, USA

² Mining, Upgrading Operations, Suncor Energy, Fort McMurray, Alberta, Canada

³ Department of Mechanical Engineering, Faculty of Engineering, Nnamdi Azikiwe University, Awka, Anambra State, Nigeria

* Corresponding Author: **Henry Chukwuemeka Olisakwe**

Article Info

P-ISSN: 3051-3618

E-ISSN: 3051-3626

Impact Factor (RSIF): 7.6

Volume: 04

Issue: 02

Received: 14-09-2023

Accepted: 16-10-2023

Published: 18-11-2023

Page No: 99-121

Abstract

Reliability, availability and maintainability (RAM) studies of oil and gas production facilities usually assess a design after it has been fixed, not choose it. This study embeds RAM analysis in design optimization for a representative onshore central production facility with seven series subsystems. Eleven decisions were optimized: redundancy and unit sizing for each subsystem, emergency shutdown voting, compressor and turbine spares, and condition-based maintenance. Production efficiency was computed analytically by a multi-state universal generating function, with spare stock-outs and spurious trips represented. All 15,552 designs were enumerated to obtain the exact Pareto front against life-cycle cost. Inputs are representative published values, not field data. The base design achieved 95.3 percent production efficiency, with compression responsible for 2.2 of its 4.7 points of loss. Condition-based maintenance gave the highest return per dollar, and a third compression train the largest absolute gain. A knee design reached 98.1 percent for USD 10.8 million of life-cycle cost. The net-present-value optimum reached 98.7 percent for USD 20.9 million and added USD 60 million. Spares were valuable alone but redundant once a third train was installed. Discrete-event simulation agreed with the analytic model within 0.1 percentage points. Under a factor-of-two uncertainty in failure rates, the optimum had a mean regret of USD 1.1 million, against USD 5.5 million for the knee design.

DOI: <https://doi.org/10.54660/IJMFD.2023.4.2.99-121>

Keywords: reliability, availability and maintainability, production efficiency, universal generating function, redundancy allocation, spare parts, condition-based maintenance, oil and gas facilities

1. Introduction

Production efficiency, the ratio of actual to potential production, is one of the principal determinants of the value of an oil and gas facility. Each percentage point of production lost to equipment failures, spurious trips and planned shutdowns at a facility producing tens of thousands of barrels of oil equivalent per day represents millions of dollars of deferred revenue each year. The international standard ISO 20815 on production assurance and reliability management sets out how production availability should be analysed and managed through the facility life cycle ^[1], and the ISO 14224 standard and the Offshore Reliability Data (OREDA) handbook provide the failure data on which such analyses depend ^[2-4]. Reliability, availability and maintainability (RAM) analysis has been applied to subsea production systems ^[5, 6], floating production units ^[7], reciprocating compressor stations ^[8], gas re-injection plants ^[9] and offshore platform power systems ^[10, 11]. Reliability engineering and failure analysis of complex engineering systems more generally ^[12], and risk-based process engineering frameworks for natural gas infrastructure ^[13], provide the broader context in which these studies sit.

In practice, RAM studies are often performed late in design to verify that a chosen configuration meets a production availability target, rather than to choose among configurations. Studies of RAM practice describe the use of reliability block diagrams,

Monte Carlo simulation and Petri nets to estimate availability and identify critical equipment [14–17], but the design decisions that RAM results should inform, including redundancy, unit sizing, spares, maintenance strategy and safety system architecture, are typically settled separately [18, 19]. Meanwhile, a large literature on redundancy allocation and reliability optimization has developed exact and metaheuristic methods for allocating components in series-parallel systems [20–23], and multi-state reliability theory based on the universal generating function (UGF) has provided efficient ways to compute the performance distribution of systems with capacity-graded units [24–26]. These methods are rarely brought together with the production economics, spare parts and spurious trip behaviour that determine the value of availability at an oil and gas facility.

Three gaps follow. First, optimization studies seldom include the range of levers available to facility engineers, which go beyond component redundancy to unit sizing, spare parts holdings, condition-based maintenance (CBM) and emergency shutdown (ESD) voting [27–29]. Second, interactions between levers, for example between spares and redundancy, are rarely quantified, although they can make an individually attractive measure redundant [27, 30]. Third, the robustness of an optimized design to uncertainty in failure data, which in oil and gas is often generic and sparse, is rarely assessed [31–33].

This paper addresses these gaps with an RAM-based design optimization of a representative onshore central production facility. It makes four contributions. First, it formulates production efficiency as a function of eleven design and support decisions through a multi-state UGF model that includes spare stock-outs, spurious trips and turnarounds. Second, it enumerates all 15,552 designs to obtain the exact Pareto front between production efficiency and life-cycle cost, avoiding the approximation of metaheuristic search [22, 34]. Third, it quantifies the contribution of each subsystem and lever to production loss and the interactions between levers. Fourth, it verifies the analytic model by discrete-event simulation and tests the robustness of the optimal designs to failure-rate uncertainty through regret analysis. Section 2 reviews the literature, Section 3 describes the model, Section 4 presents the results, Section 5 discusses implications and Section 6 concludes.

2. Literature Review

This section reviews RAM and production availability analysis in oil and gas, system modelling methods, safety instrumented systems and common cause failures, redundancy allocation and multi-state systems, spare parts and maintenance optimization, maintainability, prognostics and digital twins, importance measures and resilience, and uncertainty in reliability data. It draws on textbooks and handbooks that establish the foundations of reliability engineering [18, 35, 36] and on the argument that reliability science has distinct foundations linked to risk science [37]. Production availability is treated as the central performance

measure for oil and gas facilities, consistent with ISO 20815 and the production assurance literature [1, 14, 38].

2.1. RAM and Production Availability in Oil and Gas

Production regularity assessment for subsea systems dates from the 1980s [38], and RAM analysis was adopted for deepwater subsea developments [5, 39, 40], subsea riser and deepwater system design [41], subsea blowout preventers [42], electrical submersible pumps [43], wellheads [44], distribution systems [6] and high integrity pressure protection systems [45, 46]. Topsides and onshore applications include natural gas compressor plants [47], ammonia plants [48], cogeneration plants [49], gas re-injection [9], production systems under fuzzy Bayesian analysis [50], ship-based carbon dioxide liquefaction [51], LNG fuel gas supply [52], floating production power generation [7], small offshore electric systems [53], offshore platform power [10, 11], oil production systems [54] and surface facilities [55]. Devices, converter topologies and system-level practice for energy efficiency in modern power systems have been reviewed [56], which bears on the power generation and distribution subsystems of production facilities. Quantitative risk assessment of submersible pump components with interval numbers [57], offshore system safety under microbiologically influenced degradation [58], studies of RAM indices for production systems [59, 60], RAM under uncertain data [61], sustainable production processes [62], RAM model development [17], RAMS overviews [63] and integration of RAMS with the safety life cycle [19] complete the picture. Equipment-level studies address compressor reliability from fleet data [64], reciprocating compressor RAM [8], centrifugal compressor maintenance [65], predictive maintenance specifications [66], next-failure prediction [67], efficiency deterioration [68], compressor networks with condition-based maintenance [69, 70], and compressor fault diagnosis [71, 72]. Reliability and integrity management of fired heaters, boilers and furnaces in upstream operations has been reviewed [73], and condition-based maintenance of CALM buoy bearings and swivels [74] and integrity assurance of FSO turret mooring systems [75] have been proposed to raise the availability of offshore crude export. Performance assessment of offshore equipment [76], maintenance criticality offshore [77], failure data analysis with degraded failures [78], competing risks [79], the basic concepts of failure analysis [80], oilfield development optimization under uncertainty [81] and risk assessment data directories [82] provide further context.

2.2. System Modelling Methods

Reliability block diagrams, fault trees, Markov models, Petri nets and Monte Carlo simulation are the main tools for availability modelling. Fault tree analysis has been reviewed [83, 84] and supported by new algorithms [85], analytical simulation tools [86] and time-dependent methods [87]. Petri nets [88] have been applied to dependability [89], production availability [14, 15] and multi-unit maintenance costs [90], and production trees provide a dedicated production availability formalism [16]. Bayesian networks support reliability evaluation [91, 92], compressor fault analysis [65] and dynamic operational reliability [93]. Failure mode and effects analysis has been reviewed [94], and complex systems have been evaluated through dynamic object-oriented methods [95], interval-valued fuzzy approaches [96] and degradation models [97].

2.3. Safety Instrumented Systems, Spurious Trips and Common Cause Failures

Safety instrumented systems (SIS) protect facilities but also cause production loss through spurious trips. Spurious activation in the oil and gas industry [28, 98], spurious activation and operational integrity of redundant SIS [99], MooN voting architectures [100], modelling patterns [101], Markov models [102, 103], analytical formulas with nonconstant failure rates [104], proof testing strategies [105–107], partial testing [108], multi-objective design and testing [109, 110], design optimization with genetic algorithms [111], unavailability of redundant SIS [112], functional analysis [113] and multi-state risk-based maintenance of safety systems [114] have been studied. Common cause failures reduce the value of redundancy and have been analysed using field experience [115], organizational factors [116], alpha factors [117], uncertainties in rates [118], single failure events in multiple groups [119], age-related degradation [120], updating for risk monitoring [121], inter-unit estimation [122], decision diagrams [123], multi-state systems [124, 125], redundant safety systems [126], optimization [127] and the value of redundancy [128].

2.4. Redundancy Allocation and Multi-State Systems

The redundancy allocation problem has been studied since Bellman's dynamic programming formulation [20]. Exact algorithms [21, 22, 34], multi-objective formulations [23, 129–142], mixed and universal redundancy strategies [143–148], time-dependent failure rates [149], survival signatures [150], load sharing [151], component supplier selection [152], strength redundancy [153], cold standby with inspection [154], k-out-of-n subsystems [155, 156], common cause failures [157], flow networks [158], electrical systems [159], bilevel formulations [160], two-stage approaches [161], particle swarm [162, 163], inventory-redundancy allocation [164] and production-reliability-inventory models [30] have been developed. Physical programming [165] and strategy-space reduction for multi-state maintenance optimization [166] show how large design spaces can be handled. Multi-state systems theory, built on the UGF [24, 167] and its engineering applications [25], has extended reliability to systems whose performance is graded, including extended block diagrams [26], combined stochastic process and UGF [168], weighted k-out-of-n systems [169, 170], three-state systems [171], swarm optimization [172], consecutively connected systems [173–175], dynamic series-parallel systems [176], common bus performance sharing [177, 178], confidence bounds [179], importance measures [180, 181], condition-based maintenance and performance control [182], manufacturing vulnerability [183], distributed generation [184], power reserves [185], critical failure modes [186], degraded systems with minimal repair [187], heterogeneous redundancy [188], phased missions [189, 190], maintenance policies [191, 192] and selective maintenance [193]. Availability of k-out-of-n systems with non-identical components [194], repairable k-out-of-n systems [195], warm standby [196, 197], general time distributions [198], load sharing with switching delays [199], selective maintenance of serial k-out-of-n systems [200] and failure dependencies [201] complete the modelling basis.

2.5. Spare Parts and Maintenance Optimization

Spare parts inventory theory, including the METRIC family of multi-echelon models [202, 203], has been reviewed [204–206] and applied to system availability constraints [207], design-

phase reliability [208], repairable stocking and expediting [209], exchangeable-item repair [210], fleet redundancy and spares [27], lateral transshipments [211, 212], demand forecasting [213, 214], emergency warehouses [215], dependent failures [216], time-varying installed bases [217], two-echelon control [218], classification [219], critical spare ordering [220], spare criticality [221], queuing models for aircraft [222], service logistics control towers [223] and the petroleum industry [224]. Models linking inventory availability to plant uptime in energy facilities [29], materials readiness to maintenance-driven supply chain performance [225], and strategic procurement to oil and gas operations [226] connect spares holdings to production, while supply chain risk management for EPC and gas processing projects [227] and supply chain resilience for gas processing plants [228] address disruption of the supply of parts. Joint optimization of maintenance and spares has been studied [229–232]. Opportunistic and grouping maintenance [233–240], dynamic predictive maintenance for multi-component systems [241], clustering of CBM with redundancy [242], preventive maintenance planning of series-parallel systems [243], genetic algorithm maintenance planning [244–246], maintenance and production interactions [247, 248], dependent two-component systems [249], offshore wind [250, 251], maintenance workforce planning [252, 253], turnaround criticality [254], linking maintenance strategy to performance [255], proactive maintenance cost reduction [256], computerized maintenance management of preventive and corrective work on static equipment [257], incident prevention in maintenance environments [258], maintenance with limited data [259], sustainability of maintenance practices [260] and life-cycle cost under dependent degradation [261] illustrate the breadth of the field.

2.6. Maintainability, Prognostics and Digital Twins

Maintainability determines how quickly failed equipment is returned to service. Lognormal repair time distributions [262, 263], maintainability indices [264], design for maintainability [36, 265], verification standards [266], limited-sample verification [267], clustering-based demonstration [268] and vehicle case studies [269] have been reported, and reliability-centered design that integrates finite element analysis with design failure mode and effects analysis has been proposed for mechanical components [270]. Reliability growth methods, including Crow-AMSAA models and military handbooks, track improvement during development [271–273], and reliability has been treated as a design variable in high-reliability industries [274–276]. Prognostics and health management reduce unplanned downtime [277], through remaining useful life estimation [278–282], multi-component predictive maintenance [283–285], condition-based maintenance with semi-Markov decision processes [286], degradation-threshold-shock models [287], structured replacement [288], fault monitoring [289], alarm-based scheduling [290], grouping [291], deep reinforcement learning for large systems [292], predict-then-optimize approaches [293], scheduling restricted by remaining life [294], safety and efficiency of maintenance strategies [295], the value of information from monitoring [296], condition monitoring filtering [297], predictive maintenance and condition monitoring in power and energy infrastructure [298], data-driven methods for industrial automation and process control [299] and interpretable machine learning for early failure prediction [300]. Non-destructive testing methods

for predictive failure analysis ^[301], NDT-based integrity management of refinery equipment ^[302], risk-based inspection for fitness-for-service of ageing pressure vessels ^[303] and non-intrusive inspection that reduces shutdown frequency ^[304] supply the condition data on which such methods depend. Digital twins support gas turbine degradation prognostics ^[305], predictive diagnostics at resource-constrained energy sites ^[306], fault diagnosis ^[307], fatigue monitoring ^[308] and nuclear applications ^[309], and hybrid models have been applied in petroleum systems ^[310].

2.7. Importance Measures and Resilience

Importance measures, from Birnbaum's original definition ^[311] to Fussell-Vesely and risk importance measures ^[312, 313], identify the components that most affect system performance. Their use in risk-informed decisions ^[314, 315], differential importance ^[316], dynamic and dependent systems ^[317], system-of-systems ^[318], inventory systems ^[319] and multi-state systems with external factors ^[320] has been studied. Resilience extends availability to the recovery from disruptions, with reviews of definitions and measures ^[321–323], metrics and frameworks ^[324–328], concepts ^[329], resilience-based importance measures ^[330–334], flow-based vulnerability ^[335], critical infrastructures ^[336–340], process plants ^[341], offshore facilities ^[342, 343], cogeneration ^[344, 345], mechanical structures ^[346], enterprises ^[347] and gas supply networks ^[348]. Combining system-theoretic process analysis with availability assessment ^[349] and dynamic risk assessment of deepwater operations ^[350] link resilience to safety.

2.8. Uncertainty in Reliability Data

Reliability data for oil and gas equipment are often generic, sparse and uncertain. Bayesian priors based on generic data and expert opinion ^[31], the influence of prior choice ^[32], rare event risk assessment ^[351], precursor data ^[352] and imprecise multi-source fusion ^[353] address sparse data, and statistical methods from quality engineering ^[354] and predictive modelling frameworks for forecasting energy yield ^[355] show how limited operating records can be turned into usable estimates. Sampling-based uncertainty and sensitivity analysis ^[33, 356], aleatory and epistemic uncertainty ^[357–359], uncertainty importance measures ^[360], evidence theory ^[361, 362], subset simulation ^[363], derivative-based global sensitivity measures ^[364], reliability-oriented sensitivity with epistemic uncertainty ^[365], imprecise probabilities ^[366], rare event estimation ^[367] and uncertainty in risk analysis of complex systems ^[368, 369] provide the methods used to test robustness.

2.9. Research Gap

The literature provides mature methods for RAM modelling, redundancy allocation, multi-state systems, spare parts,

maintenance optimization and uncertainty analysis. What is missing is their combination in a design optimization that treats redundancy, unit sizing, spares, maintenance strategy and SIS voting as joint decisions, values availability through production economics, quantifies interactions between levers and tests robustness to data uncertainty, for an oil and gas production facility ^[1, 27, 32]. The model presented next provides such a combination using an exact multi-state formulation that allows complete enumeration of the design space. Complete enumeration also allows the interactions between levers and the regret of each design under uncertainty to be computed exactly rather than estimated from a sample of designs ^[22, 34].

3. Methods

This section describes the representative facility, the multi-state availability model, the treatment of spares, CBM, spurious trips and turnarounds, the economic model, the enumeration and selection of designs, the simulation used to verify the analytic model, and the uncertainty analysis. The model follows the production availability principles of ISO 20815 ^[1], represents subsystems as multi-state elements combined by the UGF ^[24, 25] and uses data ranges of the kind reported in OREDA and related sources ^[2, 3, 82]. All parameter values are representative values chosen within published ranges; they are not data from a specific facility, and the results demonstrate the method and the relative value of design options rather than predict the performance of any particular facility.

3.1. Representative Facility

The facility is an onshore central production facility with a design throughput of 60 MMscf/d of gas and 15,000 barrels per day of oil. Its seven subsystems act in series, so that facility capacity at any time is the minimum of the subsystem capacities (Figure 1): inlet separation and slug catching, gas compression, glycol dehydration, oil export pumping, produced water treatment, gas turbine power generation and instrument air and utilities. Each subsystem consists of identical units whose capacities are fractions of design throughput, so that partial failures reduce rather than stop production, as in multi-state models of production systems ^[183, 184]. When all produced water treatment units are down, production can continue at 30 percent of capacity by diverting water to storage. Demand is at design throughput for the first six years and then declines linearly to 50 percent by year 20, a typical plateau and decline profile ^[81], and the subsystem structure follows risk-based process engineering practice for natural gas infrastructure ^[13]. The value of production at full throughput is USD 0.75 million per day. Table 1 lists the subsystem options and reliability parameters.

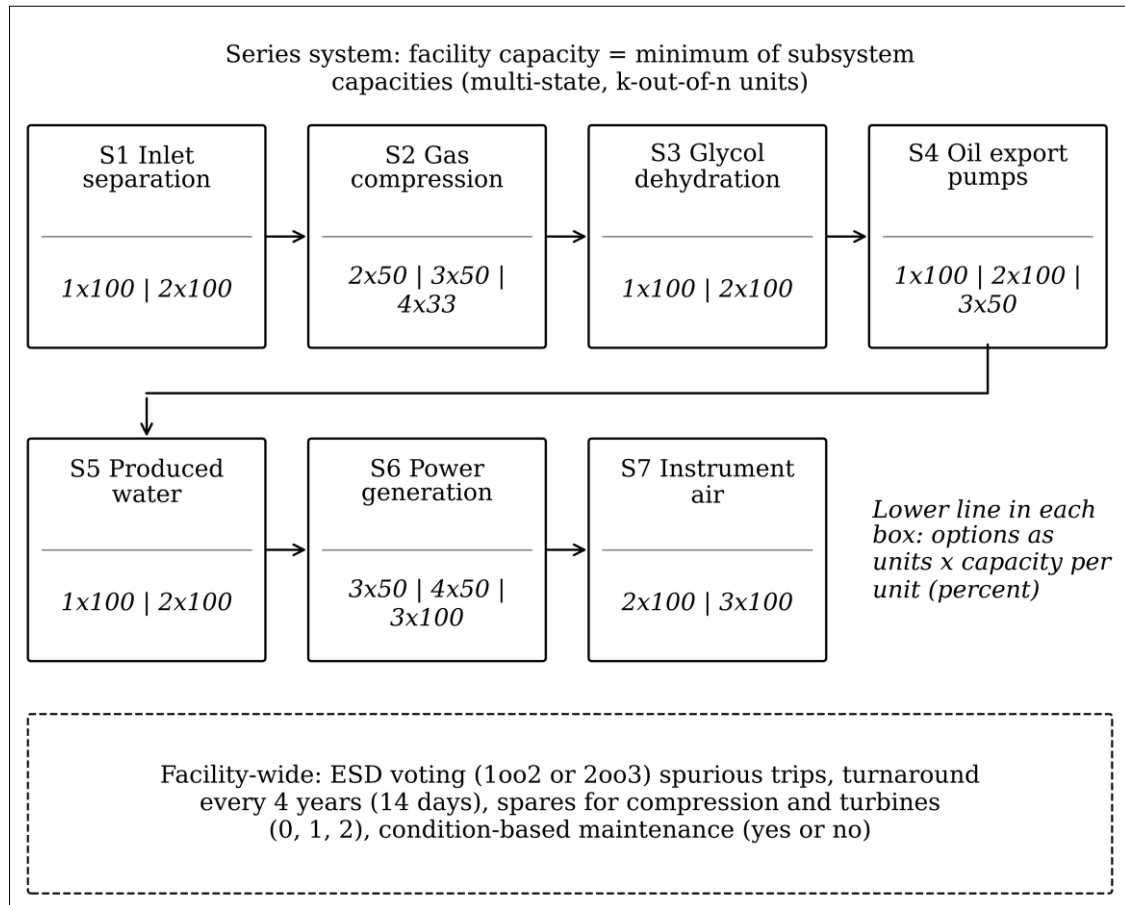


Fig 1: Series structure of the representative facility, subsystem configuration options and facility-wide decisions.

Table 1: Subsystem configuration options and representative reliability parameters.

Code	Subsystem	Options (units x capacity percent)	Base case	Failure rate per unit (per year)	Mean time to repair (h)	Reference unit cost (USD M)
S1	Inlet separation	1x100, 2x100	1x100	0.5	24	4.0
S2	Gas compression	2x50, 3x50, 4x33	2x50	6.0	36	6.0
S3	Glycol dehydration	1x100, 2x100	1x100	1.5	18	5.0
S4	Oil export pumps	1x100, 2x100, 3x50	2x100	3.0	30	1.2
S5	Produced water treatment	1x100, 2x100	1x100	2.0	20	3.0
S6	Power generation	3x50, 4x50, 3x100	3x50	4.0	48	8.0
S7	Instrument air and utilities	2x100, 3x100	2x100	2.0	8	0.6

3.2. Unit Availability, Spares and Condition-Based Maintenance

Each unit alternates between operation and repair. For compression and power generation, a fraction φ of failures (15 and 10 percent) requires a major spare such as a compressor cylinder assembly or a turbine hot-section module, with replenishment lead times of 21 and 45 days. If a spare is in stock, repair proceeds normally; otherwise the repair waits for the lead time. With s spares held and Poisson demand, the probability of a stock-out is approximated by the probability that demand during one lead time exceeds the stock, following the logic of repairable inventory models [202, 203] and of inventory availability models for energy facilities [29].

$$P_{\text{out}} = 1 - \sum_{j=0}^s \frac{\mu^j e^{-\mu}}{j!}, \quad \mu = \frac{n\lambda\varphi L}{365} \quad (1)$$

where n is the number of units, λ the failure rate per unit-year and L the lead time in days. The steady-state availability of a unit is then

$$a = \left[1 + \frac{\lambda}{8760} (\text{MTTR} + \varphi P_{\text{out}} 24L) \right]^{-1} \quad (2)$$

CBM on compression and power generation units reduces the rate of unplanned failures by 30 percent and the mean repair time by 20 percent, because degradation detected early is repaired in a planned way, consistent with reported benefits of condition monitoring for rotating equipment [66, 69, 74, 277, 298]. CBM costs USD 0.8 million to install and USD 0.1 million per year.

3.3. Multi-State Subsystem and Facility Model

The capacity distribution of a subsystem with n units of capacity c and availability a is obtained by the UGF [24, 25].

The UGF of a unit is $u(z) = a z^c + (1 - a) z^0$, and units in parallel are composed by the sum operator:

$$U_k(z) = \otimes_+[u_1(z), \dots, u_n(z)] = \sum_j p_{kj} z^{g_{kj}} \quad (3)$$

with capacities capped at 100 percent of design throughput and replaced by the residual capacity when all units are down. Subsystems in series are composed by the minimum operator:

$$U(z) = \otimes_{\min}[U_1(z), \dots, U_7(z)] = \sum_j p_j z^{g_j} \quad (4)$$

The expected deliverable fraction of demand D_t in year t is $\sum_j p_j \min(g_j, D_t)/D_t$. Spurious trips of the ESD system shut down the whole facility for a 10-hour restart; their rate is 6 per year with 1-out-of-2 (1oo2) voting and 1.5 per year with 2-out-of-3 (2oo3) voting, which costs USD 1.5 million, reflecting the trade-off between safety and production in SIS architectures [28, 98, 100]. A 14-day turnaround every 4 years removes a further 0.96 percent of time. Production efficiency over the life is

$$PE = \frac{\sum_t D_t (1 - f_{\text{trip}})(1 - f_{\text{TA}}) \sum_j p_j \min(g_j, D_t)/D_t}{\sum_t D_t} \quad (5)$$

where f_{trip} and f_{TA} are the fractions of time lost to trips and turnarounds.

3.4. Economic Model and Design Selection

Incremental capital cost of a configuration is the cost of its units relative to the base case, with unit cost scaling with capacity to the power 0.6, plus the cost of spares (USD 1.2 million per compression set and USD 3.0 million per turbine module), ESD upgrade and CBM. Operating costs are 3 percent of incremental capital per year and 5 percent of spares value per year. Incremental life-cycle cost (LCC) is the present value of incremental capital and operating costs, and net present value (NPV) is the present value of production less LCC, both at a 10 percent discount rate over 20 years [261]. The eleven decisions in Table 1 and Figure 1 define 15,552 designs, all of which were evaluated; because the UGF evaluation takes about a quarter of a millisecond, complete enumeration is faster than metaheuristic search and yields the exact Pareto front between production efficiency and LCC [22, 34]. Three designs were selected: the base case (D0), the knee of the Pareto front (D1), defined as the front point with maximum normalized distance from the line joining its extremes, and the NPV-maximizing design (D2).

3.5. Verification by Discrete-Event Simulation

To test the steady-state, independence and exponential repair assumptions of the analytic model, the selected designs were simulated over 20 years in 150 replications with a 2-hour time

step. Each unit followed an alternating renewal process with exponential operating times and lognormal repair times with a coefficient of variation of 0.8, consistent with evidence on repair time distributions [262, 263], spare stock-outs added the lead time with the computed probability; turnarounds occurred in years 2, 6, 10, 14 and 18; and spurious trips occurred as a Poisson process. Monte Carlo simulation of this kind is the standard method for production availability assessment [14, 16, 49].

3.6. Uncertainty and Regret Analysis

Failure rates in oil and gas are uncertain, especially for new facilities with generic data [31, 32]. Each subsystem failure rate was multiplied by an independent lognormal factor with an error factor of 2 (the 95th percentile twice the median), and 500 samples were drawn [33, 357]. For each sample, the production efficiency of the selected designs was computed, and the NPV of all 83 designs on the nominal Pareto front was evaluated to find the best design for that sample. The regret of a design is the difference between the best NPV for the sample and the NPV of the design [360]. A further analysis varied the value of production from USD 0.25 to 1.5 million per day to test how the NPV-optimal design changes with the value of availability.

4. Results

This section reports the base-case losses, the value of individual levers and their interactions, the Pareto front and selected designs, the simulation verification, the robustness to failure-rate uncertainty and the sensitivity to production value. Results are expected values unless stated otherwise. Because the inputs are representative, the ranking and relative size of effects are more informative than absolute values, as in other comparative RAM optimization studies [17]. The analytic results are reported first because they cover every design and every lever; the simulation results in Section 4.4 then check the analytic model for the three selected designs under more realistic repair time distributions.

4.1. Base-Case Production Losses

The base design achieved a production efficiency of 95.3 percent over the life and 94.7 percent during the plateau. Figure 2 decomposes the 4.7 percentage points of loss. Gas compression, with two 50 percent trains each failing about six times a year, caused 2.2 points, almost half the total, because any compressor failure halves throughput during the plateau. Turnarounds caused 0.9 points and spurious trips under 1oo2 ESD voting 0.7 points. Glycol dehydration and produced water treatment, both single-train, caused 0.3 points each, inlet separation 0.1 point and power generation, with 2-out-of-3 turbines, less than 0.1 point. This ranking, in which a frequently failing rotating subsystem without spare capacity dominates, is consistent with RAM studies of compressor stations and gas plants [8, 47, 73].

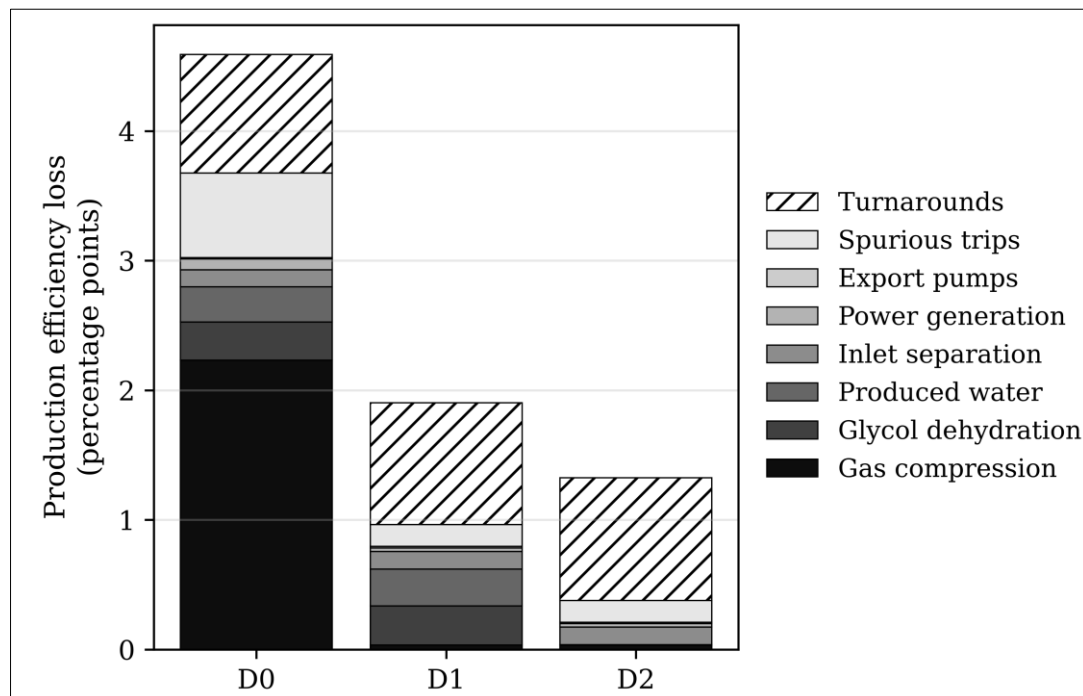


Fig 2: Production efficiency loss by cause for the base case (D0), knee design (D1) and NPV-optimal design (D2).

4.2. Value of Individual Levers and Their Interactions

Table 2 reports the effect of each lever applied alone to the base case. A third 50 percent compression train gave the largest gain, 2.1 percentage points and USD 45.6 million of NPV. CBM on compression and turbines gave 1.1 points and USD 24.7 million for a life-cycle cost of USD 1.7 million, the highest return per dollar at 14.6. 2003 ESD voting gave 0.5 point and USD 9.4 million. One set of compression spares

gave 0.4 point and USD 7.2 million, and a second produced water train gave 0.3 point and USD 2.5 million. A second dehydration train broke even, and additional inlet separation, turbines, turbine spares and air compressors destroyed value, because those subsystems already contributed little loss. Removing the standby export pump lost 1.0 point and USD 19.7 million, confirming the value of existing redundancy.

Table 2: Effect of individual levers applied to the base case.

Lever	Gain in production efficiency (percentage points)	Incremental life-cycle cost (USD M)	Change in NPV (USD M)	NPV gain per dollar of life-cycle cost
Third 50 percent compression train	2.12	7.61	45.6	6.0
Condition-based maintenance	1.05	1.69	24.7	14.6
2003 ESD voting	0.49	1.50	9.4	6.3
One compression spare set	0.36	1.74	7.2	4.1
Second produced water train	0.27	3.80	2.5	0.7
Second dehydration train	0.29	6.34	0.1	0.0
Second inlet separator	0.13	5.07	-2.2	-0.4
One turbine spare module	0.03	4.34	-3.5	-0.8
Fourth 50 percent turbine	0.08	10.14	-8.1	-0.8
Removal of standby export pump	-0.96	-1.52	-19.7	

Levers interact. Compression spares, worth USD 7.2 million alone, were not selected in any NPV-optimal design, because once a third compression train is installed, a spare stock-out removes only one of three trains and the facility continues at full capacity; spares and redundancy are substitutes. Conversely, CBM and the third train were complements in the sense that both remained in all high-value designs. Such interactions are invisible when levers are evaluated one at a time, which supports joint optimization of redundancy and spares [27, 30, 164].

4.3. Pareto Front and Selected Designs

Figure 3 shows all 15,552 designs and the exact Pareto front of 83 designs. Production efficiency rises steeply from 94.4

percent for the cheapest design to about 98 percent at USD 10 million of life-cycle cost and then flattens towards a ceiling of 98.8 percent, set by turnarounds and residual trips, which costs USD 54.6 million to reach. Table 3 compares the selected designs. The knee design D1 adds a third compression train, replaces the two 100 percent export pumps with three 50 percent pumps, adopts 2003 voting and CBM, and reaches 98.1 percent for USD 10.8 million, adding USD 57.0 million of NPV. The NPV-optimal design D2 adds a third compression train, second dehydration and water trains, 2003 voting and CBM, and reaches 98.7 percent for USD 20.9 million, adding USD 60.2 million. The last 0.6 percentage point between D1 and D2 therefore costs USD 10.2 million and adds USD 3.2 million of NPV. In D2,

turnarounds account for 0.95 of the 1.3 points of remaining loss (Figure 2). The shape of the front, steep and then flat, is characteristic of redundancy allocation problems in which a

few high-importance subsystems dominate the attainable improvement^[140, 180].

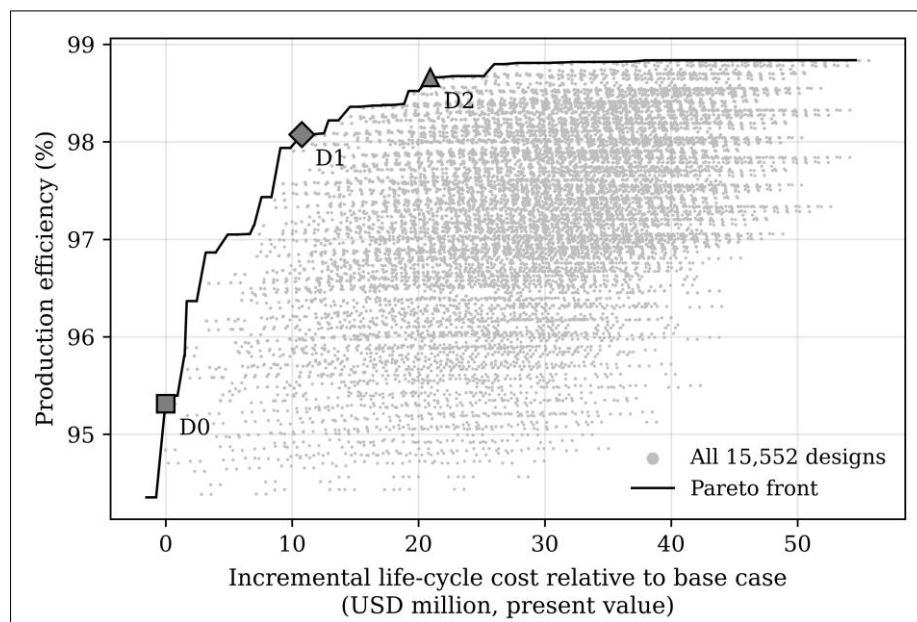


Fig 3: Production efficiency and incremental life-cycle cost of all 15,552 designs, with the exact Pareto front and the selected designs.

Table 3: Selected designs.

Measure	D0 Base case	D1 Knee design	D2 Maximum NPV
Compression	2x50	3x50	3x50
Dehydration; produced water	1x100; 1x100	1x100; 1x100	2x100; 2x100
Export pumps	2x100	3x50	2x100
ESD voting; CBM	1oo2; no	2oo3; yes	2oo3; yes
Spares (compression, turbine)	0, 0	0, 0	0, 0
Production efficiency, analytic (percent)	95.31	98.07	98.66
Production efficiency, simulation mean (percent)	95.21	98.00	98.65
Simulation 5th to 95th percentile (percent)	94.58 to 95.75	97.82 to 98.18	98.53 to 98.76
Incremental capital cost (USD M)	0.0	8.3	16.3
Incremental life-cycle cost (USD M)	0.0	10.8	20.9
Change in NPV (USD M)	0.0	57.0	60.2

4.4. Verification by Simulation

The discrete-event simulation agreed closely with the analytic model (Table 3 and Figure 4). Mean simulated production efficiency differed from the analytic value by 0.10, 0.07 and 0.01 percentage points for D0, D1 and D2. The small negative bias for D0 reflects the time-step discretization of the many short compressor outages. The

simulation also shows the variability of realized performance over a 20-year life: for the base case, the 5th to 95th percentile range spanned 1.2 percentage points, whereas for D2 it spanned 0.2 point, so redundancy reduces both the mean loss and its variability, consistent with evidence that redundancy improves the predictability of production^[14, 16].

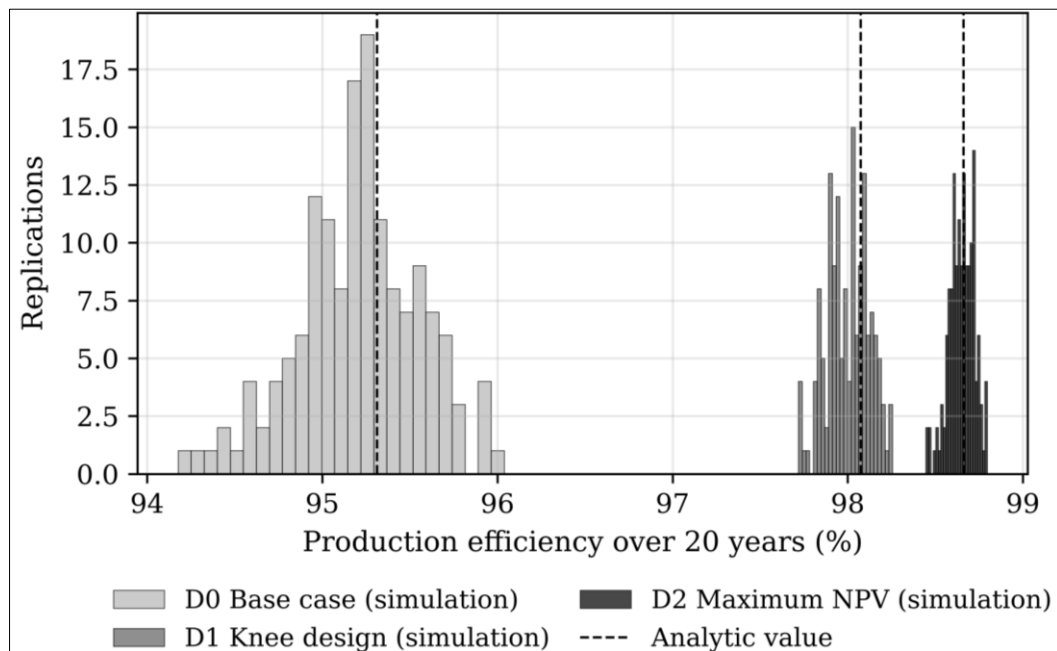


Fig 4: Distribution of production efficiency over 20 years from discrete-event simulation; dashed lines show the analytic values.

4.5. Robustness to Failure-Rate Uncertainty and Production Value

Figure 5a shows the effect of failure-rate uncertainty. With an error factor of 2 on each subsystem failure rate, the base case had a 90 percent range of production efficiency from 92.6 to 96.5 percent, whereas D1 ranged from 97.5 to 98.3 percent and D2 from 98.4 to 98.7 percent. The regret analysis confirmed that D2 is robust: across 500 samples, its mean regret relative to the best front design for each sample was USD 1.1 million, its 95th percentile USD 3.4 million, and it was within USD 1 million of the best design in 61 percent of samples. The knee design D1 had a mean regret of USD 5.5 million and the base case USD 68.6 million. Figure 5b shows

that the NPV-optimal design depends on the value of production. At USD 0.25 million per day, the optimum was D1 without CBM, with 97.9 percent efficiency for USD 9.1 million; at USD 0.5 million per day, it reached 98.4 percent for USD 14.6 million; between USD 0.75 and 1.0 million per day it was D2; and at USD 1.5 million per day a second inlet separator was added, reaching 98.8 percent for USD 26.0 million. The third compression train and 2003 voting were selected at every value. The robustness of D2 echoes the finding in the uncertainty analysis literature that decisions should be tested against epistemic uncertainty rather than nominal values alone [357, 360].

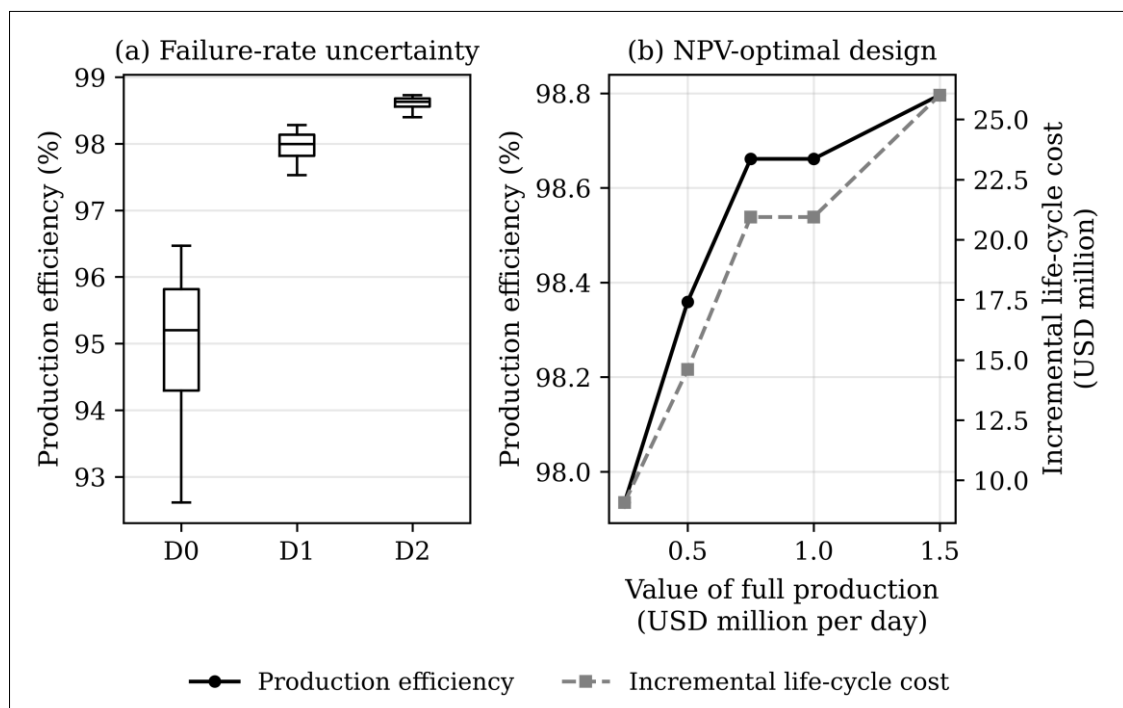


Fig 5: (a) Production efficiency under failure-rate uncertainty (box shows quartiles, whiskers 5th and 95th percentiles) and (b) production efficiency and incremental life-cycle cost of the NPV-optimal design as a function of the value of production.

5. Discussion

This section interprets the findings, draws implications for facility design and operation, considers how the method can be applied in practice and sets out its limitations. The discussion is framed by the production assurance principle that availability should be engineered through the life cycle rather than verified at the end of design ^[1, 19], and by the observation that the value of reliability improvements depends on their interaction with the system in which they are placed ^[27, 180, 314]. It also considers what the findings mean for brownfield facilities, where the design levers available are narrower than at the design stage ^[76, 77].

5.1. Principal Findings

Three findings stand out. First, production loss at the base facility was concentrated in a single subsystem. Gas compression, with frequent failures and no spare capacity, caused almost half the loss, and the most valuable measures were those that addressed it directly, a third train and CBM. This concentration is typical of oil and gas facilities, where rotating equipment dominates failure statistics ^[3, 8, 64], and it explains why RAM-based design choices can add tens of millions of dollars of value while most of the possible additions destroy value. Of the eleven levers, only four added significant value when applied alone, and five reduced NPV. Second, levers interact in ways that single-measure evaluations miss. Spares were valuable in the base design but redundant once a third compression train was installed, because a stock-out then left two trains in service, which still met plateau demand. This substitution between spares and redundancy, and the complementarity between CBM and redundancy, support the joint optimization of reliability, redundancy and spares advocated in the redundancy-inventory literature ^[27, 30, 164] and contrast with practice in which spares are planned after design is fixed ^[220, 224].

Third, complete enumeration was both feasible and informative. Because the UGF evaluates a design in a fraction of a millisecond, all 15,552 designs could be evaluated, giving the exact Pareto front and exact regret calculations without the convergence uncertainty of metaheuristic search ^[22, 34]. The NPV-optimal design was also robust to a factor-of-two uncertainty in failure rates, with a mean regret of USD 1.1 million, whereas the cheaper knee design carried a regret five times larger. Robustness to data uncertainty therefore favoured the more redundant design, a result consistent with the view that redundancy hedges against epistemic uncertainty ^[32, 357, 360].

5.2. Implications for Practice

For facility designers, the results suggest a sequence of steps. The first is to rank subsystems by their contribution to production loss using a multi-state model and importance measures before choosing any redundancy ^[180, 181, 311]. The second is to evaluate maintenance strategy and SIS architecture as design levers alongside redundancy, because CBM and 2oo3 voting delivered value at low cost ^[28, 98, 277]. The third is to optimize spares jointly with redundancy rather than sequentially ^[27, 207], and to link that plan to materials readiness and procurement lead times in the operating supply chain ^[225, 226]. The fourth is to test the selected design against failure-rate uncertainty and production value, because a design that is optimal for nominal data may carry large regret if the data are wrong ^[31, 33].

For operators of existing facilities, the same model supports brownfield decisions. Where adding a compression train is impractical, CBM and spares become the principal levers, and the base-case analysis shows that they recover about 1.4 percentage points together. Turnarounds became the largest residual loss in the optimized designs, which points to turnaround interval and duration optimization as the next frontier once equipment redundancy is adequate ^[238, 254]. Digital twins that update failure and repair parameters from operating data can keep such models current through the life of the facility ^[305, 306].

5.3. Application to Real Facilities

The approach requires reliability data for each unit type, repair times, spare lead times, trip rates and production values. Generic data from OREDA or ISO 14224 taxonomies ^[2, 3] can be updated with site data through Bayesian methods ^[31, 32, 354], and repair time distributions can be fitted from maintenance records ^[262, 268]. Where units are not identical or subsystems are not in simple series, the UGF extends to more general structures ^[26, 169, 176], and where dependencies such as common cause failures or shared maintenance crews matter, Petri nets or simulation can be used to verify the analytic model as was done here ^[15, 16, 115]. For larger design spaces, exact methods for multi-state redundancy allocation or metaheuristics can replace enumeration ^[23, 34].

5.4. Limitations

The study has several limitations. All parameters are representative values rather than data from a specific facility. The analytic model assumes independent units in steady state with exponential failures, although the simulation showed that lognormal repair times and finite horizons change the results by at most 0.1 percentage point. Common cause failures, shared repair crews and ageing were not modelled, and all of them would reduce the value of redundancy ^[115, 128, 252]; disruption of spare supply, which supply chain resilience frameworks for gas processing plants address ^[228], was also not modelled. The spare parts model uses a single-period stock-out approximation rather than a full inventory model ^[202]. The effect of CBM was represented by fixed reductions in failure rate and repair time rather than by a degradation model ^[286, 287]. Finally, safety consequences of trips and failures were not valued, so the analysis addresses production and cost only; in practice, SIS architecture is constrained by safety integrity requirements ^[103, 107].

6. Conclusion

This study embedded RAM analysis in the design optimization of a representative onshore oil and gas production facility, using a multi-state universal generating function model that included spare stock-outs, spurious trips and turnarounds, and enumerated all 15,552 combinations of eleven redundancy, sizing, spares, maintenance and safety system decisions.

Production loss at the base design was concentrated in gas compression. A third compression train and condition-based maintenance were the most valuable levers, and 2-out-of-3 shutdown voting and compression spares were also valuable when applied alone. Spares became redundant once a third train was installed. The exact Pareto front showed production efficiency rising steeply to about 98 percent for a modest life-cycle cost and then flattening towards a ceiling set by turnarounds. The value-maximizing design reached 98.7

percent and added about USD 60 million of net present value. It agreed with discrete-event simulation within 0.1 percentage point and remained close to optimal under a factor-of-two uncertainty in failure rates.

For designers and operators, the results support ranking subsystems by their contribution to production loss, treating maintenance strategy and safety system architecture as design levers, optimizing spares jointly with redundancy and testing designs against data uncertainty. Further work should add common cause failures, shared maintenance resources, ageing and turnaround optimization, and calibrate the model with field data.

References

1. International Organization for Standardization. ISO 20815:2018 Petroleum, petrochemical and natural gas industries - Production assurance and reliability management. ISO; 2018.
2. International Organization for Standardization. ISO 14224:2016 Petroleum, petrochemical and natural gas industries - Collection and exchange of reliability and maintenance data for equipment. ISO; 2016.
3. SINTEF, NTNU, & DNV GL. (2015). OREDA: Offshore reliability data handbook (6th ed.). *OREDA Participants*.
4. OREDA Participants. OREDA: Offshore reliability data handbook (4th ed.). OREDA Participants, Trondheim; 2002.
5. Brandt H, Eriksen R. RAM analysis for deepwater subsea developments. Offshore Technology Conference; 2001. doi:10.4043/13003-MS
6. Yasserli SF, Bahai H. Availability assessment of subsea distribution systems at the architectural level. *Ocean Engineering*. 2018;153:399-411. doi:10.1016/j.oceaneng.2018.01.099
7. Castro PF, Rodriguez YPM, Carvalho FBS. Application of generation adequacy analysis for reliability evaluation of a floating production storage and offloading platform power system. *Energies*. 2022;15(15):5336. doi:10.3390/en15155336
8. Corvaro F, Giacchetta G, Marchetti B, Recanati M. Reliability, availability, maintainability (RAM) study, on reciprocating compressors API 618. *Petroleum*. 2017;3(2):266-272.
9. Michelassi, C., & Monaci, G. (2008). Availability assessment of a raw gas re-injection plant for the production of oil and gas. *Proceedings of the 16th IMEKO TC4 International Symposium*, 777-783.
10. Wei, C., Du, W., Wang, X., Luo, X., & Li, Q. (2020). Reliability assessment of offshore oil platform power system based on state enumeration method. *IOP Conference Series: Earth and Environmental Science*, 431, 012029. <https://doi.org/10.1088/1755-1315/431/1/012029>
11. Du, W., Luo, X., Li, X., Guan, J., Xiong, C., & Li, D. (2019). Reliability evaluation of offshore oil platform power system. *Proceedings of the 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, 2754-2759. <https://doi.org/10.1109/ISGT-Asia.2019.8880880>
12. Gideon EN, Adaramola TS, Fadero S. Reliability engineering and failure analysis in complex engineering systems. *Iconic Research and Engineering Journals*. 2019;2(11):703-727. doi:10.64388/IREV2111-1722490
13. Asibor E, Isong DE. Risk-based process engineering framework for strengthening reliability across complex natural gas infrastructure systems. *Iconic Research and Engineering Journals*. 2019;3(2):1020-1060. doi:10.64388/IREV312-1723153
14. Signoret, J.-P. (2010). Production availability. In C. Guedes Soares (Ed.), *Safety and reliability of industrial products, systems and structures* (pp. 331-345). Taylor & Francis. <https://doi.org/10.1201/b10572-34>
15. Signoret JP, Dutuit Y, Cacheux PJ, Folleau C, Collas S, Thomas P. Make your Petri nets understandable: Reliability block diagrams driven Petri nets. *Reliability Engineering & System Safety*. 2013;113:61-75.
16. Kloul L, Rauzy A. Production trees: A new modeling methodology for production availability analyses. *Reliability Engineering & System Safety*. 2017;167:561-571.
17. Herder PM, van Luijk JA, Bruijnooge J. Industrial application of RAM modeling: Development and implementation of a RAM simulation model for the Lexan plant at GE Industrial, Plastics. *Reliability Engineering & System Safety*. 2008;93:501-508.
18. Calixto E. Gas and oil reliability engineering: Modeling and analysis (2nd ed.). Gulf Professional Publishing; 2016.
19. Lundteigen MA, Rausand M, Utne IB. Integrating RAMS engineering and management with the safety life cycle of IEC 61508. *Reliability Engineering & System Safety*. 2009;94:1894-1903.
20. Bellman R, Dreyfus S. Dynamic programming and the reliability of multicomponent devices. *Operations Research*. 1958;6(2):200-206.
21. Caserta M, Voß S. An exact algorithm for the reliability redundancy allocation problem. *European Journal of Operational Research*. 2015;244(1):110-116.
22. Cao D, Murat A, Chinnam RB. Efficient exact optimization of multi-objective redundancy allocation problems in series-parallel systems. *Reliability Engineering & System Safety*. 2013;111:154-163. doi:10.1016/j.res.2012.09.013
23. Yeh WC. BAT-based algorithm for finding all Pareto solutions of the series-parallel redundancy allocation problem with mixed components. *Reliability Engineering & System Safety*. 2022;228.
24. Levitin G. The universal generating function in reliability analysis and optimization. Springer (Springer Series in Reliability Engineering); 2005. doi:10.1007/1-84628-245-4
25. Lisnianski A, Frenkel I, Ding Y. Multi-state system reliability analysis and optimization for engineers and industrial managers. Springer; 2010.
26. Lisnianski A. Extended block diagram method for a multi-state system reliability assessment. *Reliability Engineering & System Safety*. 2007;92(12):1601-1607. doi:10.1016/j.res.2006.09.013
27. Jin T, Taboada H, Espiritu J, Liao H. Allocation of reliability-redundancy and spares inventory under Poisson fleet expansion. *IIE Transactions*. 2017;49(7):737-751.
28. Lundteigen MA, Rausand M. Spurious activation of safety instrumented systems in the oil and gas industry: Basic concepts and formulas. *Reliability Engineering & System Safety*. 2008;93(8):1208-1217.

29. Okonkwo CS, Ogunwale O, Okeke OT. Model for inventory availability and plant uptime improvement in energy facilities. *Iconic Research and Engineering Journals*. 2018;2(4):160-172. doi:10.64388/IREV2I4-1713120
30. Maji A, Bhunia AK, Mondal SK. A production-reliability-inventory model for a series-parallel system with mixed strategy considering shortage, warranty period, credit period in crisp and stochastic sense. *OPSEARCH*. 2022;59(3):862-907.
31. Maior CBS, Macedo JB, Lins ID, Moura MC, Azevedo RV, Santana JMM, *et al.* Bayesian prior distribution based on generic data and experts' opinion: A case study in the O&G industry. *Journal of Petroleum Science and Engineering*. 2022;210:109891. doi:10.1016/j.petrol.2021.109891
32. Leoni L, BahooToroodi F, Khalaj S, De Carlo F, BahooToroodi A, Abaei MM. Bayesian estimation for reliability engineering: Addressing the influence of prior choice. *International Journal of Environmental Research and Public Health*. 2021;18(7):3349. doi:10.3390/ijerph18073349
33. Helton JC, Johnson JD, Sallaberry CJ, Storlie CB. Survey of sampling-based methods for uncertainty and sensitivity analysis. *Reliability Engineering & System Safety*. 2006;91(10):1175-1209.
34. Li, Y.-F., & Zhang, H. (2022). The methods for exactly solving redundancy allocation optimization for multi-state series-parallel systems. *Reliability Engineering & System Safety*, 221.
35. Birolini A. *Reliability engineering: Theory and practice* (7th ed.). Springer; 2014. doi:10.1007/978-3-642-39535-2
36. Dhillon BS. *Engineering maintainability: How to design for reliability and easy maintenance*. Gulf Professional Publishing; 1999.
37. Aven T. The reliability science: Its foundation and link to risk science and other sciences. *Reliability Engineering & System Safety*. 2021;215.
38. Hokstad P. Assessment of production regularity for subsea oil/gas production systems. *Reliability Engineering & System Safety*. 1988;20(2):127-146. doi:10.1016/0951-8320(88)90093-2
39. Brandt H. Reliability management of deepwater subsea field developments. *Offshore Technology Conference*; 2003. doi:10.4043/15343-MS
40. Duell C, Fleming R. Implementing deepwater subsea reliability strategy. *Offshore Technology Conference*; 2001. doi:10.4043/12998-MS
41. Di Padova, A., Castello, F., Tallone, F., & Piccini, M. (2014). Reliability/availability methods for subsea risers and deepwater systems design and optimization. *Proceedings of the 12th International Conference on Probabilistic Safety Assessment and Management (PSAM 12)*.
42. Holland P. Reliability of subsea BOP systems for deepwater application, Phase II DW. SINTEF. 1999.
43. Alhanati FJS, Trevisan F. Reliability gaps in ESP technology for deepwater applications. *Offshore Technology Conference*; 2012. doi:10.4043/23341-MS
44. Wu, S., Zhang, Q., Li, B., Zhang, L., Zheng, W., Li, Z., Li, Z., & Liu, Y. (2023). Reliability analysis of subsea wellhead system subject to fatigue and degradation during service life. *Reliability Engineering & System Safety*, 239, 109494. <https://doi.org/10.1016/j.res.2023.109494>
45. Wang, C., Liu, Y., Hou, W., Yu, C., Wang, G., & Zheng, Y. (2021). Reliability and availability modeling of subsea autonomous high integrity pressure protection system with partial stroke test by dynamic Bayesian. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 235(2), 268-281. <https://doi.org/10.1177/1748006X20947851>
46. Wang, C., Gou, J., Tian, Y., Jin, H., Yu, C., Liu, Y., Ma, J., & Xia, Y. (2022). Reliability and availability evaluation of subsea high integrity pressure protection system using stochastic Petri net. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 236(3), 508-521.
47. Bosman M. Availability analysis of a natural gas compressor plant. *Reliability Engineering*. 1985;11:13-26. doi:10.1016/0143-8174(85)90012-5
48. Khan MR, Kabir AZ. Availability simulation of an ammonia plant. *Reliability Engineering & System Safety*. 1995;48:217-227. doi:10.1016/0951-8320(95)00020-3
49. Crespo Marquez A, Sanchez Heguedas A, Iung B. Monte Carlo-based assessment of system availability: A case study for cogeneration plants. *Reliability Engineering & System Safety*. 2005;88:273-289. doi:10.1016/j.res.2004.07.018
50. Gorkemli L, Ulusoy SK. Fuzzy Bayesian reliability and availability analysis of production systems. *Computers & Industrial Engineering*. 2010;59:690-696. doi:10.1016/j.cie.2010.07.020
51. Seo Y, You H, Lee S, Huh C, Chang D. Evaluation of CO2 liquefaction processes for ship-based carbon capture and storage (CCS) in terms of life cycle cost (LCC) considering availability. *International Journal of Greenhouse Gas Control*. 2015;35:1-12. doi:10.1016/j.ijggc.2015.01.006
52. Seo S, Chu B, Noh Y, Jang W, Lee S, Seo Y, *et al.* An economic evaluation of operating expenditures for LNG fuel gas supply systems onboard ocean-going ships considering availability. *Ships and Offshore Structures*. 2014;11:213-223. doi:10.1080/17445302.2014.984389
53. Guan, J., Du, W., Wang, X., Luo, X., Liu, X., & Li, X. (2021). A reliability evaluation method for independent small offshore electric systems. *Energies*, 14, 3035. <https://doi.org/10.3390/en14113035>
54. Ozor, P. A., & Mbohwa, C. (2018). Availability analysis of oil production systems. *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 1281-1289.
55. Antonius, A. (2010). Optimizing RAMS (reliability, availability, maintainability & safety) for surface equipment facilities using Markov modeling and sensitivity analysis method: A case study on CVC separator in a production plant. *Proceedings of the Indonesian Petroleum Association, 34th Annual Convention*.
56. Adenuga OM. Power electronics and energy efficiency in modern power systems: A comprehensive review of devices, converter topologies, and system level practice. *International Journal of Engineering and Modern Technology*. 2023;9(3):287-312. doi:10.56201/ijcsmt.v9.no3.2023.pg287.312

57. Bhattacharjee P, Dey V, Mandal UK, Paul S. Quantitative risk assessment of submersible pump components using interval number-based multinomial logistic regression (MLR) model. *Reliability Engineering & System Safety*. 2022;226.
58. Adumene S. Offshore system safety and reliability considering microbial influenced multiple failure modes and their interdependencies. *Reliability Engineering & System Safety*. 2021;215.
59. Sharma RK, Sharma P. Computing RAM indices for reliable operation of production systems. *Advances in Production Engineering & Management*. 2012;7(4):245-254.
60. Sharma RK, Kumar S. Performance modeling in critical engineering systems using RAM analysis. *Reliability Engineering & System Safety*. 2008;93:891-897.
61. Komal, Sharma SP, Kumar D. RAM analysis of repairable industrial systems utilizing uncertain data. *Applied Soft Computing*. 2010;10:1208-1221.
62. Soltanali, H., Garmabaki, A. H. S., Thaduri, A., Parida, A., Kumar, U., & Rohani, A. (2019). Sustainable production process: An application of reliability, availability, and maintainability methodologies in automotive manufacturing. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 233(4), 437-449.
63. Saraswat S, Yadava GS. An overview on reliability, availability, maintainability and supportability (RAMS) engineering. *International Journal of Quality & Reliability Management*. 2008;25(3):330-344.
64. Schulze Spuntrup, F., Londono, J. G., Skourup, C., Thornhill, N. F., & Imsland, L. (2018). Reliability improvement of compressors based on asset fleet reliability data. *Proceedings of the 3rd IFAC Workshop on Automatic Control in Offshore Oil and Gas Production*, 217-224.
65. Toufik, T., & Lakehal, A. (2023). Centrifugal compressor maintenance using fault tree and a Bayesian network methods for system reliability analysis and dependability. *2023 International Conference on Decision Aid Sciences and Applications (DASA '23)*.
66. Nordal H, El-Thalji I. Assessing the technical specifications of predictive maintenance: A case study of centrifugal compressor. *Applied Sciences*. 2021;11(4):1527. doi:10.3390/app11041527
67. Cho, S., Shin, J.-H., Jun, H.-B., Hwang, H.-J., Ha, C., & Hwang, J. (2016). A study on estimating the next failure time of compressor equipment in an offshore plant. *Mathematical Problems in Engineering*, 2016, 8705796. <https://doi.org/10.1155/2016/8705796>
68. Al-Busaidi W, Pilidis P. Investigation of efficiency deterioration causes in process centrifugal compressor operation. *Journal of Failure Analysis and Prevention*. 2016;16:19-36. doi:10.1007/s11668-016-0069-2
69. Xenos DP, Kopanos GM, Ciccotti M, Thornhill NF. Operational optimization of networks of compressors considering condition-based maintenance. *Computers & Chemical Engineering*. 2016;84:117-131. doi:10.1016/j.compchemeng.2015.08.008
70. Xenos DP, Ciccotti M, Kopanos GM, Bouaswaig AEF, Kahrs O, Martinez-Botas R, et al. Optimization of a network of compressors in parallel: Real time optimization (RTO) of compressors in chemical plants - An industrial case study. *Applied Energy*. 2015;144:51-63. doi:10.1016/j.apenergy.2015.01.010
71. Li, X., Duan, F., Loukopoulos, P., Bennett, I., & Mba, D. (2018). Canonical variable analysis and long short-term memory for fault diagnosis and performance estimation of a centrifugal compressor. *Control Engineering Practice*, 72, 177-191. <https://doi.org/10.1016/j.conengprac.2017.12.006>
72. Ciccotti, M., Xenos, D. P., Bouaswaig, A. E. F., Thornhill, N. F., & Martinez-Botas, R. F. (2015). Physical modelling of industrial multistage centrifugal compressors for monitoring and simulation. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 229, 3433-3448. <https://doi.org/10.1177/0954406215572433>
73. Obetta PC. Reliability and integrity management of fired heaters, boilers and furnaces in upstream oil and gas: A review. *Iconic Research and Engineering Journals*. 2019;3(5):599-626. doi:10.64388/IREV315-1722580
74. Obetta PC, Ninduwezuor-Ehiobu N. A condition-based maintenance concept for CALM buoy bearings and swivels to improve offshore crude export availability. *Iconic Research and Engineering Journals*. 2018;2(6):385-410. doi:10.64388/IREV216-1722579
75. Obetta PC, Ninduwezuor-Ehiobu N. Integrity assurance of FSO turret mooring systems: A review of inspection, monitoring and life-extension strategies. *Iconic Research and Engineering Journals*. 2019;3(6):599-629. doi:10.64388/IREV316-1722581
76. Ebrahimipour V, Suzuki K. A synergetic approach for assessing and improving equipment performance in offshore industry based on dependability. *Reliability Engineering & System Safety*. 2006;91(1):10-19.
77. Turan O, Lazakis I, Judah S, Incecik A. Investigating the reliability and criticality of the maintenance characteristics of a diving support vessel. *Quality and Reliability Engineering International*. 2011;27(7):931-946.
78. Haugen K, Hokstad P, Sandtorv H. The analysis of failure data in the presence of critical and degraded failures. *Reliability Engineering & System Safety*. 1997;58(2):97-107.
79. Langseth H, Lindqvist BH. Competing risks for repairable systems: A data study. *Journal of Statistical Planning and Inference*. 2006;136(5):1687-1700.
80. Rausand M, Oien K. The basic concepts of failure analysis. *Reliability Engineering & System Safety*. 1996;53:73-83.
81. Silva LMR, Guedes Soares C. Oilfield development system optimization under reservoir production uncertainty. *Ocean Engineering*. 2021;225:108758. doi:10.1016/j.oceaneng.2021.108758
82. OGP. (2010). Risk assessment data directory (Report No. 434-1). *International Association of Oil & Gas Producers*.
83. Baig AA, Ruzli R, Buang AB. Reliability analysis using fault tree analysis: A review. *International Journal of Chemical Engineering and Applications*. 2013;4(3):169-173.
84. Pan, K., Liu, H., Gou, X., Huang, R., Ye, D., Wang, H., Glowacz, A., & Kong, J. (2022). Towards a systematic description of fault tree analysis studies using informetric mapping. *Sustainability*, 14(18).

85. Rauzy A. New algorithms for fault trees analysis. *Reliability Engineering & System Safety*. 1993;40:203-211.
86. Khan FI, Abbasi SA. Analytical simulation and PROFAT II: A new methodology and a computer automated tool for fault tree analysis in chemical process industries. *Journal of Hazardous Materials*. 2000;75:1-27.
87. Vesely WE. A time-dependent methodology for fault tree evaluation. *Nuclear Engineering and Design*. 1970;13:337-360.
88. Murata T. Petri nets: Properties, analysis and applications. *Proceedings of the IEEE*. 1989;77(4):541-580. doi:10.1109/5.24143
89. Dutuit Y, Chatelet E, Signoret JP, Thomas P. Dependability modelling and evaluation by using stochastic Petri nets: Application to two test cases. *Reliability Engineering & System Safety*. 1997;55(2):117-124. doi:10.1016/S0951-8320(96)00108-1
90. Santos F, Teixeira AP, Guedes Soares C. Modeling, simulation and optimization of maintenance cost aspects on multi-unit systems by stochastic Petri nets with predicates. *Simulation*. 2019;95(5):461-478. doi:10.1177/0037549718782655
91. Cai, B., Kong, X., Liu, Y., Lin, J., Yuan, X., Xu, H., & Ji, R. (2019). Application of Bayesian networks in reliability evaluation. *IEEE Transactions on Industrial Informatics*, 15, 2146-2157. <https://doi.org/10.1109/TII.2018.2858281>
92. Jun HB, Kim D. A Bayesian network-based approach for fault analysis. *Expert Systems with Applications*. 2017;81:332-348. doi:10.1016/j.eswa.2017.03.056
93. Guo, Y., Wang, H., Guo, Y., Zhong, M., Li, Q., & Gao, C. (2022). System operational reliability evaluation based on dynamic Bayesian network and XGBoost. *Reliability Engineering & System Safety*, 225.
94. Huang J, You JX, Liu HC, Song MS. Failure mode and effect analysis improvement: A systematic literature review and future research agenda. *Reliability Engineering & System Safety*. 2020;199.
95. Yuan, X., Cai, B., Ma, Y., *et al.* (2018). Reliability evaluation methodology of complex systems based on dynamic object-oriented Bayesian networks. *IEEE Access*, 6, 11289-11300. <https://doi.org/10.1109/ACCESS.2018.2810386>
96. Zhang R, Zhang L, Wang N. Reliability evaluation of a multi-state system based on interval-valued triangular fuzzy Bayesian networks. *International Journal of System Assurance Engineering and Management*. 2016;7(1):16-24. doi:10.1007/s13198-015-0335-9
97. Guo J, Wang C, Cabrera J. Improved inverse Gaussian process and bootstrap: Degradation and reliability metrics. *Reliability Engineering & System Safety*. 2018;178:269-277.
98. Jigar AA, Liu Y, Lundteigen MA. Spurious activation analysis of safety-instrumented systems. *Reliability Engineering & System Safety*. 2016;156:15-23.
99. Qi, M., Kan, Y., Li, X., Wang, X., Zhao, D., & Moon, I. (2020). Spurious activation and operational integrity evaluation of redundant safety instrumented systems. *Reliability Engineering & System Safety*, 197.
100. Torres-Echeverria AC, Martorell S, Thompson HA. Modeling safety instrumented systems with Moon voting architectures addressing system reconfiguration for testing. *Reliability Engineering & System Safety*. 2011;96(5):545-563.
101. Meng H, Kloul L, Rauzy A. Modeling patterns for reliability assessment of safety instrumented systems. *Reliability Engineering & System Safety*. 2018;180:111-123.
102. Guo H, Yang X. Automatic creation of Markov models for reliability assessment of safety instrumented systems. *Reliability Engineering & System Safety*. 2008;93(6):829-837.
103. Innal F, Lundteigen MA, Liu Y, Barros A. PFDavg generalized formulas for SIS subject to partial and full periodic tests based on multi-phase Markov models. *Reliability Engineering & System Safety*. 2016;150:160-170.
104. Rogova, E., Lodewijks, G., & Lundteigen, M. A. (2017). Analytical formulas of PFD and PFH calculation for systems with nonconstant failure rates. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 231(4), 373-382.
105. Liu Y, Rausand M. Proof-testing strategies induced by dangerous detected failures of safety-instrumented systems. *Reliability Engineering & System Safety*. 2016;145:366-372.
106. Liu Y, Rausand M. Reliability effects of test strategies on safety-instrumented systems in different demand modes. *Reliability Engineering & System Safety*. 2013;119:235-243.
107. Torres-Echeverria AC, Martorell S, Thompson HA. Modelling and optimization of proof testing policies for safety instrumented systems. *Reliability Engineering & System Safety*. 2009;94(4):838-854.
108. Jin H, Rausand M. Reliability of safety-instrumented systems subject to partial testing and common-cause failures. *Reliability Engineering & System Safety*. 2014;121:146-151.
109. Longhi AEB, Pessoa AA, de Almada Garcia PA. Multiobjective optimization of strategies for operation and testing of low-demand safety instrumented systems using a genetic algorithm and fault trees. *Reliability Engineering & System Safety*. 2015;142:525-538.
110. Torres-Echeverria AC, Martorell S, Thompson HA. Multi-objective optimization of design and testing of safety instrumented systems with MoonN voting architectures using a genetic algorithm. *Reliability Engineering & System Safety*. 2012;106:45-60.
111. Riauke J, Bartlett L. Safety system design optimisation using a multi-objective genetic algorithm. *International Journal of Reliability and Safety*. 2009;3(4):397-412.
112. Alizadeh S, Sriramula S. Unavailability assessment of redundant safety instrumented systems subject to process demand. *Reliability Engineering & System Safety*. 2018;171:18-33.
113. Metatla H, Rouainia M. Functional and dysfunctional analysis of a safety instrumented system (SIS) through the common cause failures (CCFs) assessment. Case of high integrity protection pressure system (HIPPS). *International Journal of System Assurance Engineering and Management*. 2022;13(4):1932-1954. doi:10.1007/s13198-021-01608-8
114. Mohammad H, Pirouzmmand A. Multi-state risk-based maintenance analysis of redundant safety systems using

- the Markov model and fault tree method. *Frontiers in Energy Research*. 2021;9:685634.
115. Hauge S, Hokstad P, Habrekke S, Lundteigen MA. Common cause failures in safety-instrumented systems: Using field experience from the petroleum industry. *Reliability Engineering & System Safety*. 2016;151:34-45.
 116. Rahimi M, Rausand M. Monitoring human and organizational factors influencing common-cause failures of safety-instrumented system during the operational phase. *Reliability Engineering & System Safety*. 2013;120:10-17.
 117. Vaurio JK. Consistent mapping of common cause failure rates and alpha factors. *Reliability Engineering & System Safety*. 2007;92(5):628-645.
 118. Vaurio JK. Uncertainties and quantification of common cause failure rates and probabilities for system analyses. *Reliability Engineering & System Safety*. 2005;90(2):186-195.
 119. Kancev D, Cepin M. A new method for explicit modelling of single failure event within different common cause failure groups. *Reliability Engineering & System Safety*. 2012;103:84-93. doi:10.1016/j.ress.2012.03.009
 120. Zhou T, Drogue EL, Modarres M. A common cause failure model for components under age-related degradation. *Reliability Engineering & System Safety*. 2020;195.
 121. Zhang, M., Zhang, Z., Mosleh, A., & Chen, S. (2017). Common cause failure model updating for risk monitoring in nuclear power plants based on alpha factor model. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 231(3), 209-220.
 122. Soga S, Higo E, Miura H. A systematic approach to estimate an inter-unit common-cause failure probability. *Reliability Engineering & System Safety*. 2021;215.
 123. Mo, Y., & Xing, L. (2013). An enhanced decision diagram-based method for common-cause failure analysis. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 227(5), 557-566.
 124. Mi, J., Li, Y.-F., Peng, W., & Huang, H.-Z. (2018). Reliability analysis of complex multi-state system with common cause failure based on evidential networks. *Reliability Engineering & System Safety*, 174, 71-81.
 125. Qin, J., & Li, Z. (2019). Reliability and sensitivity analysis method for a multistate system with common cause failure. *Complexity*, 2019, 1-8.
 126. Alizadeh S, Sriramula S. Impact of common cause failure on reliability performance of redundant safety related systems subject to process demand. *Reliability Engineering & System Safety*. 2018;172:129-150.
 127. Ramirez-Marquez JE, Coit DW. Optimization of system reliability in the presence of common cause failures. *Reliability Engineering & System Safety*. 2007;92(10):1421-1434. doi:10.1016/j.ress.2006.09.004
 128. Hoepfer VM, Saleh JH, Marais KB. On the value of redundancy subject to common-cause failures: Toward the resolution of an on-going debate. *Reliability Engineering & System Safety*. 2009;94(12):1904-1916. doi:10.1016/j.ress.2009.06.007
 129. Salazar D, Rocco CM, Galván BJ. Optimization of constrained multiple-objective reliability problems using evolutionary algorithms. *Reliability Engineering & System Safety*. 2006;91(9):1057-1070.
 130. Taboada HA, Coit DW. A new multiple objective evolutionary algorithm for reliability optimization of series-parallel systems. *International Journal of Applied Evolutionary Computation*. 2012;3(2):1-18.
 131. Taboada HA, Baheranwala F, Coit DW, Wattanapongsakorn N. Practical solutions for multi-objective optimization: An application to system reliability design problems. *Reliability Engineering & System Safety*. 2007;92(3):314-322.
 132. Samanta A, Basu K. Multi-objective reliability redundancy allocation problem considering two types of common cause failures. *International Journal of System Assurance Engineering and Management*. 2019;10(3):369-383.
 133. Kundu P. A multi-objective reliability-redundancy allocation problem with active redundancy and interval type-2 fuzzy parameters. *Operational Research*. 2021;21(4):2433-2458.
 134. Cao R, Coit DW, Hou W, Yang Y. Game theory based solution selection for multi-objective redundancy allocation in interval-valued problem parameters. *Reliability Engineering & System Safety*. 2020;199.
 135. Zhang, E., Wu, Y., & Chen, Q. (2014). A practical approach for solving multi-objective reliability redundancy allocation problems using extended bare-bones particle swarm optimization. *Reliability Engineering & System Safety*, 127, 65-76.
 136. Zhao, J., Si, S., Cai, Z., Su, M., & Wang, W. (2019). Multiobjective optimization of reliability-redundancy allocation problems for serial parallel-series systems based on importance measure. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 233(5), 881-897.
 137. Zhang E, Chen Q. Multi-objective reliability redundancy allocation in an interval environment using particle swarm optimization. *Reliability Engineering & System Safety*. 2016;145:83-92.
 138. Zhao, J., Si, S., & Cai, Z. (2019). A multi-objective reliability optimization for reconfigurable systems considering components degradation. *Reliability Engineering & System Safety*, 183, 104-115.
 139. Abouei Ardakan M, Rezvan MT. Multi-objective optimization of reliability-redundancy allocation problem with cold-standby strategy using NSGA-II. *Reliability Engineering & System Safety*, 172, 225-238. 2018.
 140. Wang, W., Lin, M., Fu, Y., Luo, X., & Chen, H. (2020). Multi-objective optimization of reliability-redundancy allocation problem for multi-type production systems considering redundancy strategies. *Reliability Engineering & System Safety*, 193.
 141. Nath R, Muhuri PK. Evolutionary optimization based solution approaches for many objective reliability-redundancy allocation problem. *Reliability Engineering & System Safety*. 2022;220.
 142. Hsieh TJ. Performance indicator-based multi-objective reliability optimization for multi-type production systems with heterogeneous machines. *Reliability Engineering & System Safety*. 2023;230.
 143. Kong, X., Gao, L., Ouyang, H., & Li, S. (2015). Solving the redundancy allocation problem with multiple strategy choices using a new simplified particle swarm

- optimization. *Reliability Engineering & System Safety*, 144, 147-158.
144. Peiravi A, Nourelfath M, Zanjani MK. Redundancy strategies assessment and optimization of k-out-of-n systems based on Markov chains and genetic algorithms. *Reliability Engineering & System Safety*. 2022;221.
 145. Peiravi A, Ardakan MA, Zio E. A new Markov-based model for reliability optimization problems with mixed redundancy strategy. *Reliability Engineering & System Safety*. 2020;201.
 146. Peiravi A, Nourelfath M, Zanjani MK. Universal redundancy strategy for system reliability optimization. *Reliability Engineering & System Safety*. 2022;225.
 147. Gholinezhad H, Zeinal Hamadani A. A new model for the redundancy allocation problem with component mixing and mixed redundancy strategy. *Reliability Engineering & System Safety*. 2017;164:66-73.
 148. Golmohammadi E, Ardakan MA. Reliability optimization problem with the mixed strategy, degrading components, and a periodic inspection and maintenance policy. *Reliability Engineering & System Safety*. 2022;223.
 149. Zio E, Gholinezhad H. Redundancy allocation of components with time-dependent failure rates. *Mathematics*. 2023;11(16):1-27.
 150. Huang X, Coolen FPA, Coolen-Maturi T. A heuristic survival signature based approach for reliability-redundancy allocation. *Reliability Engineering & System Safety*. 2019;185:511-517.
 151. de Paula CP, Visnadi LB, de Castro HF. Multi-objective optimization in redundant system considering load sharing. *Reliability Engineering & System Safety*. 2019;181:17-27.
 152. Zaretabal A, Sharifi M, Guilani PP, Taghipour S, Niaki STA. A multi-objective model for optimizing the redundancy allocation, component supplier selection, and reliable activities for multi-state systems. *Reliability Engineering & System Safety*. 2022;222.
 153. Zhang, J., Li, L., & Chen, Z. (2021). Strength-redundancy allocation problem using artificial bee colony algorithm for multi-state systems. *Reliability Engineering & System Safety*, 209.
 154. Wang, W., Wu, Z., Xiong, J., & Xu, Y. (2018). Redundancy optimization of cold-standby systems under periodic inspection and maintenance. *Reliability Engineering & System Safety*, 180, 394-402.
 155. Kim H. Optimal reliability design of a system with k-out-of-n subsystems considering redundancy strategies. *Reliability Engineering & System Safety*. 2017;167:572-582.
 156. Zhang, J., Lv, H., & Hou, J. (2023). A novel general model for RAP and RRAP optimization of k-out-of-n:G systems with mixed redundancy strategy. *Reliability Engineering & System Safety*, 229.
 157. Sharifi, M., Sayyad, A., Taghipour, S., & Abhari, A. (2023). Optimizing a joint reliability-redundancy allocation problem with common cause multi-state failures using immune algorithm. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 237(1), 152-165.
 158. Zhang, H., Sun, M., & Li, Y.-F. (2022). Reliability-redundancy allocation problem in multi-state flow network: Minimal cut-based approximation scheme. *Reliability Engineering & System Safety*, 225.
 159. Guerraiche K, Dekhici L, Chatelet E, Zebblah A. Multi-objective electrical power system design optimization using a modified bat algorithm. *Energies*. 2021;14(13):1-19.
 160. Muhuri PK, Nath R. A novel evolutionary algorithmic solution approach for bilevel reliability-redundancy allocation problem. *Reliability Engineering & System Safety*. 2019;191.
 161. Ostadi B, Hamedankhah R. A two-stage reliability optimization approach for solving series-parallel redundancy allocation problem considering the sale of worn-out parts. *Annals of Operations Research*. 2021;304(1):381-396.
 162. Li, S., Chi, X., & Yu, B. (2022). An improved particle swarm optimization algorithm for the reliability-redundancy allocation problem with global reliability. *Reliability Engineering & System Safety*, 225.
 163. Ouyang Z, Liu Y, Ruan SJ, Jiang T. An improved particle swarm optimization algorithm for reliability-redundancy allocation problem with mixed redundancy strategy and heterogeneous components. *Reliability Engineering & System Safety*. 2019;181:62-74.
 164. Alikar N, Mousavi SM, Raja Ghazilla RA, Tavana M, Olugu EU. Application of the NSGA-II algorithm to a multi-period inventory-redundancy allocation problem in a series-parallel system. *Reliability Engineering & System Safety*. 2017;160:1-10.
 165. Tian Z, Zuo MJ. Redundancy allocation for multi-state systems using physical programming and genetic algorithms. *Reliability Engineering & System Safety*. 2006;91(9):1049-1056.
 166. Zhou, Y., Lin, T. R., Sun, Y., Bian, Y., & Ma, L. (2015). An effective approach to reducing strategy space for maintenance optimisation of multistate series-parallel systems. *Reliability Engineering & System Safety*, 138, 40-53.
 167. Ushakov I. The method of generalized generating sequences. *European Journal of Operational Research*. 2000;125(2):316-323.
 168. Lisnianski A, Ding Y. Redundancy analysis for repairable multi-state system by using combined stochastic processes methods and universal generating function technique. *Reliability Engineering & System Safety*. 2009;94(11):1788-1795.
 169. Li, W., & Zuo, M. J. (2008). Reliability evaluation of multi-state weighted k-out-of-n systems. *Reliability Engineering & System Safety*, 93(1), 160-167.
 170. Wang, Y., Li, L., Huang, S., & Chang, Q. (2012). Reliability and covariance estimation of weighted k-out-of-n multi-state systems. *European Journal of Operational Research*, 221(1), 138-147.
 171. Pourkarim Guilani P, Sharifi M, Niaki STA, Zaretabal A. Reliability evaluation of non-repairable three-state systems using Markov model and its comparison with the UGF and the recursive methods. *Reliability Engineering & System Safety*. 2014;129:29-35.
 172. Lai CM, Yeh WC. Two-stage simplified swarm optimization for the redundancy allocation problem in a multi-state bridge system. *Reliability Engineering & System Safety*. 2016;156:148-158.
 173. Xing L, Levitin G. Connectivity modeling and optimization of linear consecutively connected systems with repairable connecting elements. *European Journal of Operational Research*. 2018;264(2):732-741.

174. Yu, H., Yang, J., Peng, R., & Zhao, Y. (2016). Reliability evaluation of linear multi-state consecutively-connected systems constrained by m consecutive and n total gaps. *Reliability Engineering & System Safety*, 150, 35-43. <https://doi.org/10.1016/j.res.2016.01.010>
175. Levitin G. Optimal allocation of multi-state elements in linear consecutively connected systems with vulnerable nodes. *European Journal of Operational Research*. 2003;150(2):406-419.
176. Li, Y.-F., & Peng, R. (2014). Availability modeling and optimization of dynamic multi-state series-parallel systems with random reconfiguration. *Reliability Engineering & System Safety*, 127, 47-57.
177. Yu, H., Yang, J., & Mo, H. (2014). Reliability analysis of repairable multi-state system with common bus performance sharing. *Reliability Engineering & System Safety*, 132, 90-96.
178. Peng R, Xiao H, Liu H. Reliability of multi-state systems with a performance sharing group of limited size. *Reliability Engineering & System Safety*. 2017;166:164-170.
179. Ramirez-Marquez JE, Levitin G. Algorithm for estimating reliability confidence bounds of multi-state systems. *Reliability Engineering & System Safety*. 2008;93(8):1231-1243.
180. Zio E, Marella M, Podofillini L. Importance measures-based prioritization for improving the performance of multi-state systems: Application to the railway industry. *Reliability Engineering & System Safety*. 2007;92(10):1303-1314.
181. Ramirez-Marquez JE, Coit DW. Multi-state component criticality analysis for reliability improvement in multi-state systems. *Reliability Engineering & System Safety*. 2007;92(12):1608-1619.
182. Wang, J., Wang, Y., & Fu, Y. (2023). Joint optimization of condition-based maintenance and performance control for linear multi-state consecutively connected systems. *Mathematics*, 11(12), 1-19.
183. Gao, G., Wang, J., Yue, W., & Ou, W. (2020). Structural-vulnerability assessment of reconfigurable manufacturing system based on universal generating function. *Reliability Engineering & System Safety*, 203.
184. Li, Y.-F., & Zio, E. (2012). A multi-state model for the reliability assessment of a distributed generation system via universal generating function. *Reliability Engineering & System Safety*, 106, 28-36. <https://doi.org/10.1016/j.res.2012.04.008>
185. Ding Y, Wang P, Lisnianski A. Optimal reserve management for restructured power generating systems. *Reliability Engineering & System Safety*. 2006;91(7):792-799.
186. Abou SC. Performance assessment of multi-state systems with critical failure modes: Application to the flotation metallic arsenic circuit. *Reliability Engineering & System Safety*. 2010;95(6):614-622.
187. Soro IW, Nourelfath M, Ait-Kadi D. Performance evaluation of multi-state degraded systems with minimal repairs and imperfect preventive maintenance. *Reliability Engineering & System Safety*. 2010;95(2):65-69.
188. Li, C.-Y., Chen, X., Yi, X.-S., & Tao, J.-Y. (2010). Heterogeneous redundancy optimization for multi-state series-parallel systems subject to common cause failures. *Reliability Engineering & System Safety*, 95(3), 202-207.
189. Levitin G, Xing L, Amari SV, Dai Y. Reliability of non-repairable phased-mission systems with propagated failures. *Reliability Engineering & System Safety*. 2013;119:218-228.
190. Cheng, C., Yang, J., & Li, L. (2021). Reliability evaluation of a k-out-of-n(G)-subsystem based multi-state phased mission system with common bus performance sharing subjected to common cause failures. *Reliability Engineering & System Safety*, 216.
191. Nourelfath M, Ait-Kadi D. Optimization of series-parallel multi-state systems under maintenance policies. *Reliability Engineering & System Safety*. 2007;92(12):1620-1626.
192. Zhou, Y., Zhang, Z., Lin, T. R., & Ma, L. (2013). Maintenance optimisation of a multi-state series-parallel system considering economic dependence and state-dependent inspection intervals. *Reliability Engineering & System Safety*, 111, 248-259.
193. Liu Y, Chen Y, Jiang T. Dynamic selective maintenance optimization for multi-state systems over a finite horizon: A deep reinforcement learning approach. *European Journal of Operational Research*. 2020;283(1):166-181.
194. Khatab A, Nahas N, Nourelfath M. Availability of K-out-of-N:G systems with non-identical components subject to repair priorities. *Reliability Engineering & System Safety*. 2009;94(2):142-151. [doi:10.1016/j.res.2008.02.017](https://doi.org/10.1016/j.res.2008.02.017)
195. Li, X., Zuo, M. J., & Yam, R. C. M. (2006). Reliability analysis of a repairable k-out-of-n system with some components being suspended when the system is down. *Reliability Engineering & System Safety*, 91(3), 305-310.
196. Zhang T, Xie M, Horigome M. Availability and reliability of k-out-of-(M+N):G warm standby systems. *Reliability Engineering & System Safety*. 2006;91(4):381-387.
197. Guo, L., Li, R., Wang, Y., Yang, J., Liu, Y., Chen, Y., & Zhang, J. (2023). Availability for multi-component k-out-of-n: G warm-standby system in series with shut-off rule of suspended animation. *Reliability Engineering & System Safety*, 233.
198. Wang, N., Li, M., Xiao, B., & Ma, L. (2019). Availability analysis of a general time distribution system with the consideration of maintenance and spares. *Reliability Engineering & System Safety*, 192.
199. Shekhar C, Kumar A, Varshney S. Load sharing redundant repairable systems with switching and reboot delay. *Reliability Engineering & System Safety*. 2020;193.
200. Diallo C, Venkatadri U, Khatab A, Liu Z. Optimal selective maintenance decisions for large serial k-out-of-n: G systems under imperfect maintenance. *Reliability Engineering & System Safety*. 2018;175:234-245.
201. Yu, H., Chu, C., Châtelet, É., & Yalaoui, F. (2007). Reliability optimization of a redundant system with failure dependencies. *Reliability Engineering & System Safety*, 92(12), 1627-1634.
202. Sherbrooke, C. C. (2004). Optimal inventory modeling of systems: Multi-echelon techniques (2nd ed.). *Springer (International Series in Operations Research & Management Science, Vol. 72)*, 72. <https://doi.org/10.1007/b109856>

203. Guide VDR, Srivastava R. Repairable inventory theory: Models and applications. *European Journal of Operational Research*. 1997;102(1):1-20.
204. Zhang S, Huang K, Yuan Y. Spare parts inventory management: A literature review. *Sustainability*. 2021;13(5):2460. doi:10.3390/su13052460
205. Kennedy WJ, Patterson JW, Fredendall LD. An overview of recent literature on spare parts inventories. *International Journal of Production Economics*. 2002;76(2):201-215.
206. Hu, Q., Boylan, J. E., Chen, H., & Labib, A. (2018). OR in spare parts management: A review. *European Journal of Operational Research*, 266(2), 395-414.
207. van Houtum GJ, Kranenburg B. Spare parts inventory control under system availability constraints. *Springer (International Series in Operations Research & Management Science)*; 2015. doi:10.1007/978-1-4899-7609-3
208. Öner KB, Kiesmüller GP, van Houtum GJ. Optimization of component reliability in the design phase of capital goods. *European Journal of Operational Research*. 2010;205(3):615-624.
209. Arts J. A multi-item approach to repairable stocking and expediting in a fluctuating demand environment. *European Journal of Operational Research*. 2017;256(1):102-115.
210. Dreyfuss M, Giat Y. Optimal spares allocation to an exchangeable-item repair system with tolerable wait. *European Journal of Operational Research*. 2017;261(2):584-594.
211. Paterson C, Kiesmüller G, Teunter R, Glazebrook K. Inventory models with lateral transshipments: A review. *European Journal of Operational Research*. 2011;210(2):125-136.
212. Wong H, van Houtum GJ, Cattrysse D, Van Oudheusden D. Multi-item spare parts systems with lateral transshipments and waiting time constraints. *European Journal of Operational Research*. 2006;171(3):1071-1093.
213. Van der Auweraer S, Boute R. Forecasting spare part demand using service maintenance information. *International Journal of Production Economics*. 2019;213:138-149.
214. Zhu S, Dekker R, van Jaarsveld W, Renjie RW, Koning AJ. An improved method for forecasting spare parts demand using extreme value theory. *European Journal of Operational Research*. 2017;261(1):169-181.
215. van Wingerden E, Tan T, Van Houtum GJ. The impact of an emergency warehouse in a two-echelon spare parts network. *European Journal of Operational Research*. 2019;276(3):983-997.
216. Liu X, Tang LC. Reliability analysis and spares provisioning for repairable systems with dependent failure processes and a time-varying installed base. *IIE Transactions*. 2016;48(1):43-56.
217. Jin T, Tian Y. Optimizing reliability and service parts logistics for a time-varying installed base. *European Journal of Operational Research*. 2012;218(1):152-162.
218. Topan E, Bayındır ZP, Tan T. Heuristics for multi-item two-echelon spare parts inventory control subject to aggregate and individual service measures. *European Journal of Operational Research*. 2017;256(1):126-138.
219. Hu, Q., Chakhar, S., Siraj, S., & Labib, A. (2017). Spare parts classification in industrial manufacturing using the dominance-based rough set approach. *European Journal of Operational Research*, 262(3), 1136-1163.
220. Godoy DR, Pascual R, Knights P. Critical spare parts ordering decisions using conditional reliability and stochastic lead time. *Reliability Engineering & System Safety*. 2013;119:199-206.
221. Tsakatikas D, Diplaris S, Sfantsikopoulos M. Spare parts criticality for unplanned maintenance of industrial systems. *European Journal of Industrial Engineering*. 2008;2(1):94-107.
222. Mani V, Sarma V. Queuing network models for aircraft availability and spares management. *IEEE Transactions on Reliability*. 1984;33(3):257-262.
223. Topan, E., Eruguz, A. S., Ma, W., van der Heijden, M. C., & Dekker, R. (2020). A review of operational spare parts service logistics in service control towers. *European Journal of Operational Research*, 282(2), 401-414.
224. Gonçalves Calvacante D, Ferreira L, Borenstein D. Prevision and optimisation of repairable spare parts: A case study in the petroleum industry. *South African Journal of Industrial Engineering*. 2020;31(2):156-171. doi:10.7166/31-2-2221
225. Okonkwo CS, Agbabiaka J, Ogunwole O, Mayo W, Okeke OT. Conceptual model for materials readiness and maintenance-driven supply chain performance. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):584-594. doi:10.54660/IJMRGE.2021.2.6.584-594
226. Okonkwo CS, Ogunwole O, Okeke OT. Framework for strategic procurement optimization in oil and gas operations. *Iconic Research and Engineering Journals*. 2018;1(7):153-168. doi:10.64388/IREV117-1713119
227. Agbabiaka J, Okonkwo CS, Ogunwole O, Mayo W, Okeke OT. Supply chain risk management model for EPC and gas processing projects. *Iconic Research and Engineering Journals*. 2019;3(2):968-980. doi:10.64388/IREV312-1713124
228. Ogunwole, O., Okonkwo, C. S., Agbabiaka, J., Mayo, W., & Okeke, O. T. (2021). Supply chain resilience framework for critical infrastructure and gas processing plants. *Shodhshauryam, International Scientific Refereed Research Journal*, 4(4), 444-461. https://doi.org/10.32628/SHISRJR214462
229. Zhu M, Zhou X. Hypergraph-based joint optimization of spare part provision and maintenance scheduling for serial-parallel multi-station manufacturing systems. *Reliability Engineering & System Safety*. 2022;225.
230. Ighravwe DE, Oke SA, Adebisi KA. Preventive maintenance task balancing with spare parts optimisation via big-bang big-crunch algorithm. *International Journal of System Assurance Engineering and Management*. 2017;8(2):811-822.
231. Zhang X, Liao H, Zeng J, Shi G, Zhao B. Optimal condition-based opportunistic maintenance and spare parts provisioning for a two-unit system using a state space partitioning approach. *Reliability Engineering & System Safety*. 2021;209.
232. de Smidt-Destombes KS, van der Heijden MC, van Harten A. Joint optimisation of spare part inventory, maintenance frequency and repair capacity for k-out-of-N systems. *International Journal of Production Economics*. 2009;118(1):260-268.

233. Hu, J., Shen, J., & Shen, L. (2020). Opportunistic maintenance for two-component series systems subject to dependent degradation and shock. *Reliability Engineering & System Safety*, 201. <https://doi.org/10.1016/j.res.2020.106995>
234. Laggoune R, Chateaufneuf A, Aissani D. Impact of few failure data on the opportunistic replacement policy for multi-component systems. *Reliability Engineering & System Safety*. 2010;95(2):108-119.
235. Shafiee M, Finkelstein M, Bérenguer C. An opportunistic condition-based maintenance policy for offshore wind turbine blades subjected to degradation and environmental shocks. *Reliability Engineering & System Safety*. 2015;142:463-471.
236. Chen Y, Qiu Q, Zhao X. Condition-based opportunistic maintenance policies with two-phase inspections for continuous-state systems. *Reliability Engineering & System Safety*. 2022;228.
237. Melo, Y. R., Cavalcante, C. A. V., Scarf, P., & Lopes, R. S. (2023). A hybrid maintenance policy with fixed periodic structure and opportunistic replacement. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 237(3), 579-591.
238. Wildeman RE, Dekker R, Smit ACJM. A dynamic policy for grouping maintenance activities. *European Journal of Operational Research*. 1997;99(3):530-551.
239. Gan J, Zhang W, Wang S, Zhang X. Joint decision of condition-based opportunistic maintenance and scheduling for multi-component production systems. *International Journal of Production Research*. 2022;60(17):5155-5175.
240. Ding F, Tian Z. Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds. *Renewable Energy*. 2012;45:175-182.
241. Van Horenbeek A, Pintelon L. A dynamic predictive maintenance policy for complex multi-component systems. *Reliability Engineering & System Safety*. 2013;120:39-50.
242. Olde Keizer MCA, Teunter RH, Veldman J. Clustering condition-based maintenance for systems with redundancy and economic dependencies. *European Journal of Operational Research*. 2016;251(2):531-540.
243. Galante G, Passannanti G. An exact algorithm for preventive maintenance planning of series-parallel systems. *Reliability Engineering & System Safety*. 2009;94(10):1517-1525.
244. Lapa CMF, Pereira CMNA, de Barros MP. A model for preventive maintenance planning by genetic algorithms based in cost and reliability. *Reliability Engineering & System Safety*. 2006;91(2):233-240.
245. Volkanovski A, Mavko B, Bošević T, Čauševski A, Čepin M. Genetic algorithm optimisation of the maintenance scheduling of generating units in a power system. *Reliability Engineering & System Safety*. 2008;93(6):779-789.
246. Zhang T, Cheng Z, Liu Y, Guo B. Maintenance scheduling for multi-unit system: A stochastic Petri-net and genetic algorithm based approach. *Eksplatacja i Niezawodność - Maintenance and Reliability*. 2012;14(3):256-264.
247. Zhou, X., & Yu, M. (2020). Semi-dynamic maintenance scheduling for multi-station series systems in multi-specification and small-batch production. *Reliability Engineering & System Safety*, 195.
248. Zhang, N., Qi, F., Zhang, C., & Zhou, H. (2022). Joint optimization of condition-based maintenance policy and buffer capacity for a two-unit series system. *Reliability Engineering & System Safety*, 219.
249. Qiu, Q., Cui, L., & Kong, D. (2019). Availability and maintenance modeling for a two-component system with dependent failures over a finite time horizon. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 233(2), 200-210.
250. Nielsen JJ, Sørensen JD. On risk-based operation and maintenance of offshore wind turbine components. *Reliability Engineering & System Safety*. 2011;96(1):218-229.
251. Kang J, Wang Z, Guedes Soares C. Condition-based maintenance for offshore wind turbines based on support vector machine. *Energies*. 2020;13(14):3518.
252. Al-Zubaidi H, Christer AH. Maintenance manpower modelling for a hospital building complex. *European Journal of Operational Research*. 1997;99(3):603-618.
253. Ighravwe DE, Oke SA. A manufacturing system energy-efficient optimisation model for maintenance-production workforce size determination using integrated fuzzy logic and quality function deployment approach. *International Journal of System Assurance Engineering and Management*. 2017;8(4):683-703.
254. Bevilacqua M, Ciarapica FE, Giachetta G, Marchetti B. Development of an innovative criticality index for turnaround management in an oil refinery. *International Journal of Productivity and Quality Management*. 2012;9(4):519-544.
255. Swanson L. Linking maintenance strategies to performance. *International Journal of Production Economics*. 2001;70(3):237-244.
256. Eti MC, Ogaji SOT, Probert SD. Reducing the cost of preventive maintenance (PM) through adopting a proactive reliability-focused culture. *Applied Energy*. 2006;83:1235-1248.
257. Obetta PC, Ninduwezuor-Ehiobu N, Olisakwe HC. A CMMS-based concept for optimizing preventive and corrective maintenance of static mechanical equipment. *International Journal of Engineering and Modern Technology*. 2023;9(3):287-319. doi:10.56201/ijcsmt.v9.no3.2023.pg287.319
258. Obogo SF, Obriki OD, Arumosoye OM. Conceptual model for incident prevention in industrial maintenance engineering environments. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):847-858. doi:10.54660/IJMRGE.2021.2.6.847-858
259. Percy, D. F. (2008). Maintenance based on limited data. *Complex System Maintenance Handbook, Springer*, 133-154.
260. Ghaleb M, Taghipour S. Assessing the impact of maintenance practices on asset's sustainability. *Reliability Engineering & System Safety*. 2022;228.
261. Liu B, Zhao X, Liu G, Liu Y. Life cycle cost analysis considering multiple dependent degradation processes and environmental influence. *Reliability Engineering & System Safety*. 2020;197.
262. Kline MB. Suitability of the lognormal distribution for corrective maintenance repair times. *Reliability Engineering*. 1984;9(2):65-80. doi:10.1016/0143-8174(84)90041-6

263. Bovaird RL, Zagor HL. Lognormal distribution and maintainability in support systems research. *Naval Research Logistics Quarterly*. 1961;8(4):343-356. doi:10.1002/nav.3800080403
264. Wani MF, Gandhi OP. Development of maintainability index for mechanical systems. *Reliability Engineering & System Safety*. 1999;65(3):259-270.
265. U.S. Department of Defense. MIL-HDBK-470A: Designing and developing maintainable products and systems. U.S. Department of Defense; 1997.
266. International Electrotechnical Commission. IEC 60706-3: Maintainability of equipment, Part 3: Verification and collection, analysis and presentation of data. International Electrotechnical Commission; 2006.
267. Miao Q, Liu L, Feng Y. Complex system maintainability verification with limited samples. *Microelectronics Reliability*. 2011;51(2):294-299. doi:10.1016/j.microrel.2010.09.012
268. Wu, Z., & Hao, J. (2019). Clustering-based maintainability demonstration for complex systems with a mixed maintenance time distribution. *Journal of Systems Engineering and Electronics*, 30(6), 1260-1271. <https://doi.org/10.21629/JSEE.2019.06.20>
269. Budiul Berghian A, Vasiiu T, Birtok Băneasă C. Determination of maintainability for Dacia 1304, 1.9 D utility vehicle. *IOP Conference Series: Materials Science and Engineering*. 2018;294:012040.
270. Ogunnowo EO, Adewoyin MA, Fiemotongha JE, Igunma TO, Adeleke AK. A conceptual framework for reliability-centered design of mechanical components using FEA and DFMEA integration. *Journal of Frontiers in Multidisciplinary Research*. 2023;4(1):342-361. doi:10.54660/JFMR.2023.4.1.342-361
271. Ram, C., Krishnan, R. R., Siju, V., Subramanian, V. G., & Prasad, S. (2023). Reliability estimation of liquid rocket engine using Crow-AMSAA model. *Recent Advances in Mechanical Engineering (Lecture Notes in Mechanical Engineering)*, Springer, 127-136. https://doi.org/10.1007/978-981-19-2188-9_12
272. U.S. Department of Defense. MIL-HDBK-189A: Reliability growth management. U.S. Department of Defense; 2009.
273. Dawson, J. W. (2011). The use of Crow-AMSAA plots to assess mishap trends. *Proceedings of the 29th International System Safety Conference (ISSC29)*.
274. Guarro S. On the estimation of space launch vehicle reliability. *International Journal of Performability Engineering*. 2013;9:619-631.
275. Strunz R, Herrmann JW. Reliability as an independent variable applied to liquid rocket engine test plans. *Journal of Propulsion and Power*. 2011;27:1032-1044. doi:10.2514/1.B34279
276. Parkinson RC. The hidden costs of reliability and failure in launch systems. *Acta Astronautica*. 1999;44:419-424. doi:10.1016/S0094-5765(99)00093-4
277. Hu, Y., Miao, X., Si, Y., Pan, E., & Zio, E. (2022). Prognostics and health management: A review from the perspectives of design, development and decision. *Reliability Engineering & System Safety*, 217.
278. Chen N, Tsui K. Condition monitoring and remaining useful life prediction using degradation signals: Revisited. *IIE Transactions*. 2013;45(9):939-952.
279. Si, X.-S., Wang, W., Chen, M.-Y., Hu, C.-H., & Zhou, D.-H. (2013). A degradation path-dependent approach for remaining useful life estimation with an exact and closed-form solution. *European Journal of Operational Research*, 226(1), 53-66.
280. Li, N., Gebraeel, N., Lei, Y., Bian, L., & Si, X. (2019). Remaining useful life prediction of machinery under time-varying operating conditions based on a two-factor state-space model. *Reliability Engineering & System Safety*, 186, 88-100.
281. Li, X., Ding, Q., & Sun, J.-Q. (2018). Remaining useful life estimation in prognostics using deep convolution neural networks. *Reliability Engineering & System Safety*, 172, 1-11.
282. Li, T., Zhao, Z., Sun, C., Yan, R., & Chen, X. (2021). Hierarchical attention graph convolutional network to fuse multi-sensor signals for remaining useful life prediction. *Reliability Engineering & System Safety*, 215.
283. de Pater I, Mitici M. Predictive maintenance for multi-component systems of repairables with remaining-useful-life prognostics and a limited stock of spare components. *Reliability Engineering & System Safety*. 2021;214:107761. doi:10.1016/j.ress.2021.107761
284. Nguyen KTP, Medjaher K. A new dynamic predictive maintenance framework using deep learning for failure prognostics. *Reliability Engineering & System Safety*. 2019;188:251-262.
285. Mitici M, de Pater I, Barros A, Zeng Z. Dynamic predictive maintenance for multiple components using data-driven probabilistic RUL prognostics: The case of turbofan engines. *Reliability Engineering & System Safety*. 2023;234:109199. doi:10.1016/j.ress.2023.109199
286. Chen D, Trivedi KS. Optimization for condition-based maintenance with semi-Markov decision process. *Reliability Engineering & System Safety*. 2005;90(1):25-29.
287. Caballé NC, Castro IT, Pérez CJ, Lanza-Gutiérrez JM. A condition-based maintenance of a dependent degradation-threshold-shock model in a system with multiple degradation processes. *Reliability Engineering & System Safety*. 2015;134:98-109.
288. Elwany AH, Gebraeel NZ, Maillart LM. Structured replacement policies for components with complex degradation processes and dedicated sensors. *Operations Research*. 2011;59(3):684-695.
289. Jiao R, Peng K, Dong J, Zhang C. Fault monitoring and remaining useful life prediction framework for multiple fault modes in prognostics. *Reliability Engineering & System Safety*. 2020;203.
290. de Pater I, Reijns A, Mitici M. Alarm-based predictive maintenance scheduling for aircraft engines with imperfect remaining useful life prognostics. *Reliability Engineering & System Safety*. 2022;221.
291. Bouvard K, Artus S, Bérenguer C, Cocquempot V. Condition-based dynamic maintenance operations planning & grouping. Application to commercial heavy vehicles. *Reliability Engineering & System Safety*. 2011;96(6):601-610.
292. Andriotis CP, Papakonstantinou KG. Managing engineering systems with large state and action spaces through deep reinforcement learning. *Reliability Engineering & System Safety*. 2019;191.
293. van Staden HE, Deprez L, Boute RN. A dynamic “predict, then optimize” preventive maintenance

- approach using operational intervention data. *European Journal of Operational Research*. 2022;302(3):1079-1096.
294. He, X., Wang, Z., Li, Y., Khazhina, S., Du, W., Wang, J., & Wang, W. (2022). Joint decision-making of parallel machine scheduling restricted in job-machine release time and preventive maintenance with remaining useful life constraints. *Reliability Engineering & System Safety*, 222.
 295. Lee J, Mitici M. An integrated assessment of safety and efficiency of aircraft maintenance strategies using agent-based modelling and stochastic Petri nets. *Reliability Engineering & System Safety*. 2020;202.
 296. Zou G, Banisoleiman K, González A, Faber MH. Probabilistic investigations into the value of information: A comparison of condition-based and time-based maintenance strategies. *Ocean Engineering*. 2019;188:106181.
 297. BahooToroody A, Abaei MM, BahooToroody F, De Carlo F, Abbassi R, Khalaj S. A condition monitoring based signal filtering approach for dynamic time dependent safety assessment of natural gas distribution process. *Process Safety and Environmental Protection*. 2019;123:335-343.
 298. Adaramola TS, Fadero S, Gideon EN. Predictive maintenance and condition monitoring in critical power and energy infrastructure. *Iconic Research and Engineering Journals*. 2018;2(5):454-477. doi:10.64388/IREV2I5-1722489
 299. Adaramola TS, Gideon EN, Fadero S. Machine learning and data-driven methods for industrial automation and process control. *International Journal of Engineering and Modern Technology*. 2020;6(3):103-128. doi:10.56201/ijemt.vol.6.no3.2020.pg103.128
 300. Komi NM, Adamolekun A. Interpretable machine learning for early failure prediction in distributed renewable energy assets. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):1015-1038. doi:10.54660/IJMRGE.2021.2.6.1015-1038
 301. Ogunnowo EO, Adewoyin MA, Fiemotongha JE, Igunma TO, Adeleke AK. Systematic review of non-destructive testing methods for predictive failure analysis in mechanical systems. *Iconic Research and Engineering Journals*. 2020;4(4):207-222.
 302. Atta S, Tofah P, Kankam MA, Adenuga OM. A critical review of NDT based integrity management and corrosion risk assessment strategies for refinery process equipment. *International Journal of Engineering and Modern Technology*. 2020;6(2):19-46. doi:10.56201/ijemt.vol.6.no2.2020.pg19.46
 303. Obetta PC. A risk-based inspection concept for fitness-for-service assessment of ageing pressure vessels on offshore joint venture facilities. *Iconic Research and Engineering Journals*. 2018;2(5):497-520. doi:10.64388/IREV2I5-1722578
 304. Obetta PC, Ninduwezuor-Ehiobu N, Olisakwe HC. Advances in non-intrusive inspection of pressure vessels: Reducing shutdown frequency and OPEX in oil and gas operations. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2021;2(6):1137-1153. doi:10.54660/IJMRGE.2021.2.6.1137-1153
 305. Sun J, Yan Z, Han Y, Zhu X, Yang C. Deep learning framework for gas turbine performance digital twin and degradation prognostics from airline operator perspective. *Reliability Engineering & System Safety*. 2023;238.
 306. Komi NM, Adeniji IO. A tiered digital twin that brings predictive diagnostics to resource-constrained renewable energy sites. *International Journal of Engineering and Modern Technology*. 2023;9(3):287-347. doi:10.56201/ijemt.v9.no3.2023.pg287.347
 307. Xia, M., Shao, H., Williams, D., Lu, S., Shu, L., & de Silva, C. W. (2021). Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning. *Reliability Engineering & System Safety*, 215.
 308. VanDerHorn E, Wang Z, Mahadevan S. Towards a digital twin approach for vessel-specific fatigue damage monitoring and prognosis. *Reliability Engineering & System Safety*. 2022;219.
 309. Kochunas B, Huan X. Digital twin concepts with uncertainty for nuclear power applications. *Energies*. 2021;14(14).
 310. Zendejboudi S, Rezaei N, Lohi A. Applications of hybrid models in chemical, petroleum, and energy systems: A systematic review. *Applied Energy*. 2018;228:2539-2566.
 311. Birnbaum, Z. W. (1969). On the importance of different components in a multicomponent system. *Multivariate Analysis II, Academic Press*, 1-15.
 312. Fussell JB. How to hand-calculate system reliability and safety characteristics. *IEEE Transactions on Reliability*. 1975;24(3):169-174.
 313. Vesely, W. E., Davis, T. C., Denning, R. S., & Saltos, N. (1983). Measures of risk importance and their applications. *US Nuclear Regulatory Commission (NUREG/CR-3385)*.
 314. Vaurio JK. Importance measures in risk-informed decision making: Ranking, optimisation and configuration control. *Reliability Engineering & System Safety*. 2011;96(11):1426-1436. doi:10.1016/j.res.2011.06.012
 315. Vaurio JK. Ideas and developments in importance measures and fault-tree techniques for reliability and risk analysis. *Reliability Engineering & System Safety*. 2010;95(2):99-107.
 316. Zio E, Podofillini L. Accounting for components interactions in the differential importance measure. *Reliability Engineering & System Safety*. 2006;91(10):1163-1174.
 317. Lunt, S., & Andrews, J. (2023). The extension of commonly used measures of importance for dynamic and dependent tree theory (D2T2). *Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)*.
 318. Uday P, Chandrasaha R, Marais K. System importance measures: Definitions and application to system-of-systems analysis. *Reliability Engineering & System Safety*. 2019;191:106582. doi:10.1016/j.res.2019.106582
 319. Chen L, Kou M, Wang S. On the use of importance measures in the reliability of inventory systems, considering the cost. *Applied Sciences*. 2020;10(21):7942. doi:10.3390/app10217942
 320. Dui, H., Si, S., Wu, S., & Yam, R. C. M. (2017). An importance measure for multistate systems with external

- factors. *Reliability Engineering & System Safety*, 167, 49-57.
321. Hosseini S, Barker K, Ramirez-Marquez JE. A review of definitions and measures of system resilience. *Reliability Engineering & System Safety*. 2016;145:47-61.
 322. Righi AW, Saurin TA, Wachs P. A systematic literature review of resilience engineering: Research areas and a research agenda proposal. *Reliability Engineering & System Safety*. 2015;141:142-152.
 323. Bergström J, van Winsen R, Henriqson E. On the rationale of resilience in the domain of safety: A literature review. *Reliability Engineering & System Safety*. 2015;141:131-141.
 324. Francis R, Bekera B. A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliability Engineering & System Safety*. 2014;121:90-103.
 325. Henry D, Ramirez-Marquez JE. Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering & System Safety*. 2012;99:114-122.
 326. Tran HT, Balchanos M, Domercant JC, Mavris DN. A framework for the quantitative assessment of performance-based system resilience. *Reliability Engineering & System Safety*. 2017;158:73-84.
 327. Ayyub BM. Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making. *Risk Analysis*. 2014;34(2):340-355.
 328. Kammouh O, Gardoni P, Cimellaro GP. Probabilistic framework to evaluate the resilience of engineering systems using Bayesian and dynamic Bayesian networks. *Reliability Engineering & System Safety*. 2020;198.
 329. Woods DD. Four concepts for resilience and the implications for the future of resilience engineering. *Reliability Engineering & System Safety*. 2015;141:5-9.
 330. Whitson JC, Ramirez-Marquez JE. Resiliency as a component importance measure in network reliability. *Reliability Engineering & System Safety*. 2009;94(10):1685-1693.
 331. Barker K, Ramirez-Marquez JE, Rocco CM. Resilience-based network component importance measures. *Reliability Engineering & System Safety*. 2013;117:89-97.
 332. Xu, Z., Ramirez-Marquez, J. E., Liu, Y., & Xiahou, T. (2020). A new resilience-based component importance measure for multi-state networks. *Reliability Engineering & System Safety*, 193, 106591. <https://doi.org/10.1016/j.res.2019.106591>
 333. Baroud H, Barker K, Ramirez-Marquez JE, Rocco S. CM. Importance measures for inland waterway network resilience. *Transportation Research Part E: Logistics and Transportation Review*. 2014;62:55-67.
 334. Baroud H, Barker K. A Bayesian kernel approach to modeling resilience-based network component importance. *Reliability Engineering & System Safety*. 2018;170:10-19.
 335. Nicholson CD, Barker K, Ramirez-Marquez JE. Flow-based vulnerability measures for network component importance: Experimentation with preparedness planning. *Reliability Engineering & System Safety*. 2016;145:62-73.
 336. Johansson J, Hassel H, Zio E. Reliability and vulnerability analyses of critical infrastructures: Comparing two approaches in the context of power systems. *Reliability Engineering & System Safety*. 2013;120:27-38.
 337. Alderson DL, Brown GG, Carlyle WM. Operational models of infrastructure resilience. *Risk Analysis*. 2015;35(4):562-586.
 338. Ouyang M. Review on modeling and simulation of interdependent critical infrastructure systems. *Reliability Engineering & System Safety*. 2014;121:43-60.
 339. Zio E. Challenges in the vulnerability and risk analysis of critical infrastructures. *Reliability Engineering & System Safety*. 2016;152:137-150.
 340. Tabandeh A, Sharma N, Gardoni P. Uncertainty propagation in risk and resilience analysis of hierarchical systems. *Reliability Engineering & System Safety*. 2022;219.
 341. Khakzad N, Reniers G. Using graph theory to analyze the vulnerability of process plants in the context of cascading effects. *Reliability Engineering & System Safety*. 2015;143:63-73.
 342. Sarwar A, Khan F, Abimbola M, James L. Resilience analysis of a remote offshore oil and gas facility for a potential hydrocarbon release. *Risk Analysis*. 2018;38(8):1601-1617. doi:10.1111/risa.12974
 343. Abaei MM, Hekkenberg R, BahooToroody A, Banda OV, van Gelder P. A probabilistic model to evaluate the resilience of unattended machinery plants in autonomous ships. *Reliability Engineering & System Safety*. 2022;219.
 344. da Silva FS, Matelli JA. Resilience in cogeneration systems: Metrics for evaluation and influence of design aspects. *Reliability Engineering & System Safety*. 2021;212.
 345. Matelli JA, Goebel K. Conceptual design of cogeneration plants under a resilient design perspective: Resilience metrics and case study. *Applied Energy*. 2018;215:736-750.
 346. Zhang, Y., Cai, B., Liu, Y., Jiang, Q., Li, W., Feng, Q., Liu, Y., & Liu, G. (2021). Resilience assessment approach of mechanical structure combining finite element models and dynamic Bayesian networks. *Reliability Engineering & System Safety*, 216.
 347. Sheffi Y. The resilient enterprise: Overcoming vulnerability for competitive advantage. MIT Press; 2005.
 348. Shan, X., Yu, W., Gong, J., Huang, W., Wen, K., Wang, H., Ren, S., Wang, D., Shi, Y., & Liu, C. (2023). A methodology to evaluate gas supply reliability of natural gas pipeline network considering the effects of natural gas resources. *Reliability Engineering & System Safety*, 238.
 349. Zhang, J., Kim, H., Liu, Y., & Lundteigen, M. A. (2019). Combining system-theoretic process analysis and availability assessment: A subsea case study. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 233(4), 520-536. <https://doi.org/10.1177/1748006X18822224>
 350. Wang C, Cai B, Shao X, Zhao L, Sui Z, Liu K, et al. Dynamic risk assessment methodology of operation process for deepwater oil and gas equipment. *Reliability Engineering & System Safety*. 2023;239.
 351. Yang M, Khan F, Lye L, Amyotte P. Risk assessment of rare events. *Process Safety and Environmental Protection*. 2015;98:102-108.

352. Li, X., Chen, G., Khan, F., & Xu, C. (2019). Dynamic risk assessment of subsea pipelines leak using precursor data. *Ocean Engineering*, 178, 156-169.
353. Xiahou T, Liu Y. Reliability bounds for multi-state systems by fusing multiple sources of imprecise information. *IIE Transactions*. 2020;52(9):1014-1031.
354. Adaramola TS, Fadero S, Gideon EN. Statistical methods and quality engineering in advanced manufacturing. *International Journal of Engineering and Modern Technology*. 2023;9(3):287-312. doi:10.56201/ijcsmt.v9.no3.2023.pg287.312
355. Ezeugwa EC, Oluokun OA, Oggunnowo E. Predictive modeling framework for renewable energy yield forecasting. *Iconic Research and Engineering Journals*. 2023;6(9):514-544.
356. Saltelli A. Sensitivity analysis for importance assessment. *Risk Analysis*. 2002;22(3):579-590.
357. Hoffman FO, Hammonds JS. Propagation of uncertainty in risk assessments: The need to distinguish between uncertainty due to lack of knowledge and uncertainty due to variability. *Risk Analysis*. 1994;14(5):707-712.
358. Helton JC. Treatment of uncertainty in performance assessments for complex systems. *Risk Analysis*. 1994;14(4):483-511.
359. Sankararaman S, Mahadevan S. Separating the contributions of variability and parameter uncertainty in probability distributions. *Reliability Engineering & System Safety*. 2013;112:187-199.
360. Aven T, Nøkland TE. On the use of uncertainty importance measures in reliability and risk analysis. *Reliability Engineering & System Safety*. 2010;95(2):127-133. doi:10.1016/j.ress.2009.09.002
361. Helton JC, Johnson JD, Oberkampf WL, Sallaberry CJ. Sensitivity analysis in conjunction with evidence theory representations of epistemic uncertainty. *Reliability Engineering & System Safety*. 2006;91(10):1414-1434.
362. Zhang Z, Jiang C, Wang GG, Han X. First and second order approximate reliability analysis methods using evidence theory. *Reliability Engineering & System Safety*. 2015;137:40-49.
363. Song, S., Lu, Z., & Qiao, H. (2009). Subset simulation for structural reliability sensitivity analysis. *Reliability Engineering & System Safety*, 94(2), 658-665.
364. Sobol' IM, Kucherenko S. Derivative based global sensitivity measures and their link with global sensitivity indices. *Mathematics and Computers in Simulation*. 2009;79(10):3009-3017.
365. Sarazin G, Morio J, Lagnoux A, Balesdent M, Brevault L. Reliability-oriented sensitivity analysis in presence of data-driven epistemic uncertainty. *Reliability Engineering & System Safety*. 2021;215:107733. doi:10.1016/j.ress.2021.107733
366. Schöbi R, Sudret B. Global sensitivity analysis in the context of imprecise probabilities (p-boxes) using sparse polynomial chaos expansions. *Reliability Engineering & System Safety*. 2019;187:129-141.
367. Balesdent M, Morio J, Brevault L. Rare event probability estimation in the presence of epistemic uncertainty on input probability distribution parameters. *Methodology and Computing in Applied Probability*. 2016;18(1):197-216.
368. Bjerga T, Aven T, Zio E. Uncertainty treatment in risk analysis of complex systems: The cases of STAMP and FRAM. *Reliability Engineering & System Safety*, 156, 203-209. 2016.
369. Berner C, Flage R. Strengthening quantitative risk assessments by systematic treatment of uncertain assumptions. *Reliability Engineering & System Safety*. 2016;151:46-59.