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Integrating uncertainty quantification in reliability, availability, and maintainability (RAM) analysis in the conceptual and preliminary stages of chemical process design

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ABSTRACT

Traditional analysis of a proposed process design uses average input values in the performance assessment model, thereby generating single-point estimates. The resulting estimates ignore reliability, availability, and maintainability (RAM) considerations, or assume a fixed value based on prior experience. As a result, a probabilistic view of the impact of equipment unavailability on process profitability is not considered. Recent works have proposed a financial framework for incorporating safety and sustainability considerations in the analysis of proposed designs. Based on this research, we propose a framework to integrate RAM aspects during the conceptual design stage in a probabilistic manner using Monte Carlo simulation. Subsequently, full distribution profiles of key process performance indicators are generated, including system and section availability, annual net profit, and return on investment (ROI). Probabilistic characterization of equipment availability also facilitates the prediction of potential safety and sustainability issues, as more frequent process upsets may result in increased flaring and other potential negative consequences. A modified availability metric, using restoration instead of repair times, is used in this work to obtain a more accurate view of expected downtime and thus its effects on profitability. A propane dehydrogenation (PDH) process system is used to demonstrate the application and benefits of the framework. The proposed approach allows designers and decision-makers to comprehensively assess the impacts of equipment RAM characteristics on process availability and economic performance.

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1. Introduction

The chemical process design methodology involves determining specific objectives or customer needs, then developing and evaluating possible design solutions to ensure they satisfy those objectives in the best possible way. The number of feasible design alternatives is then further narrowed down by a variety of constraining factors. While some of these constraints are outside the design team's control (e.g., physical laws, government regulations, engineering standards), other critical factors, such as the choice of process or process conditions, materials, and equipment, are open in the trade space. Among the major constraints on any engineering design are economic considerations since prospective plants must also be profitable. Further, the number of alternative designs that can be evaluated is often also constrained by schedule considerations.

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Li and Kraslawski (2004) presented an overview of the development of conceptual process design in the context of three scales: micro- (molecules), meso- (unit operations), and macro-scale (plant). At the macro-scale, the authors identified the main research issues that will dominate conceptual design to be: (1) combining knowledge of different disciplines, (2) dealing with uncertainties at the top decision level, and (3) developing optimization and simulation techniques for complex systems. In this work, the proposed addition to the traditional process design approach is the integration of reliability, availability, and maintainability (RAM) considerations in the economic evaluation of design concepts for a proposed plant while taking into account the uncertainties involved in the process system.

1.1. Safety and sustainability considerations in process design

Within the approach outlined above, the evaluation of process technology is usually based purely on techno-economic analysis. However, this approach excludes consideration of other critical aspects, such as safety and sustainability, until after the detailed design has been completed. Alternatively, these considerations can be integrated earlier into evaluations of the design of the process. For example, inherent safety principles are applied in the early stages of design (e.g. screening of alternative technologies) to enhance the safety characteristics of the process (Rahman et al., 2005; Kidam et al., 2016; Park et al., 2019). Sustainability considerations, such as greenhouse gas emissions, total waste rate, and water footprint, have been used as indicators to assess the environmental impact of different process designs (Martinez-Gomez et al., 2016; Julián-Durán et al., 2014; Yang and You, 2017). Other process evaluation techniques include these considerations, but primarily from an economic perspective. El-Halwagi (2017a) developed a sustainability-weighted return on investment metric (SWROIM) to evaluate the viability of process improvement projects and their impact on sustainability relative to the requisite capital investment. Guillen-Cuevas et al. (2018) extended the previous work by including safety considerations to develop a safety-and-sustainability-weighted return on investment metric (SASWROIM). In addition to these metrics, another approach is the use of loss functions to model the economic consequences of process unit deviations from target values (Hashemi et al., 2014; Khan et al., 2016).

1.2. Reliability, availability, and maintainability (RAM) considerations in process design

Similar to other engineering systems, the expected function of a chemical process plant can be interrupted due to failure(s) in one or more of its units. Some systems or units are less inclined to fail, usually due to inherent design characteristics; thus, they are considered more reliable. While reliability engineering is relevant to all aspects of the design and operation of a process plant, applying reliability analysis and prediction techniques at the conceptual and preliminary stages of the design process significantly aids the design team in the technology selection decision. By analyzing the possible failure modes and mechanisms of process units or subsystems, the consequences of these failures and their effects on the economic potential or profitability of the design can be estimated. These consequences include revenue losses as a result of production slowdown or shutdown due to failure; costs of different maintenance regimes including labor (corrective, preventive, or predictive); environmental damages due to a large quantity of flaring; loss of life or injury to personnel or the public; and costs associated with environmental damages.

The problem of integrating RAM assessment and optimization into the conceptual design phase has been an active research area for many years. Early works examined the sensitivity of system reliability to parallel redundancies (Rudd, 1962; Henley and Gandhi, 1975). More recently, Goel et al. (2003) considered the effects of availability and maintenance in chemical plant economics and concluded that revenues and operational costs must be affected by the system inherent availability. Their approach used an exponential relationship, first reported by Ishii et al. (1997), between investment and availability to compute the capital cost of each equipment piece. However, it is further noted that it can be challenging to obtain real-world data on the link between capital cost and inherent availability. Sharda and Bury (2008) presented a discrete event simulation model to understand the impact of different critical subsystems on overall plant production capabilities using historical failure data. The disadvantage of using a discrete events approach is that it does not guarantee optimal solutions. Aguilar et al. (2008) considered redundancy alternatives to address reliability issues in utility plants. Recent works have utilized Markov chains to model utility systems and production sites and determine their optimal designs (Lin and Chang, 2012; Terrazas-Moreno et al., 2010). In addition, recent studies have utilized optimization methods to determine optimal allocation of redundancy (Ye et al., 2018; Andiappan et al., 2019). Al-Douri et al. (2020) introduced an economic framework for failure mitigation during the conceptual design stage utilizing a Bayesian updating procedure to update generic failure rate data with plant-specific data.

1.3. Uncertainty quantification

The previous survey shows that significant progress has been made in the inclusion of safety, sustainability, and reliability considerations as part of the evaluation of the design of chemical processes. However, these performance models are based on uncertain input variables and use average values leading to conclusions with significant levels of uncertainty regarding the overall performance profile of the process design. The use of average values is not recommended based on the "flaw of averages" concept in probability theory, which underscores that evaluating process performance at average conditions does not necessarily lead to an average process performance. In reality, different values for an input variable can have different consequences on the performance metric being examined. To address this, Monte Carlo (MC) simulation methods can be used to develop a model of the system in which uncertainties associated with key design variables are included. Seila et al. (2003) and Law and Kelton (2007) provided comprehensive reviews of simulation modelling methods and applications to operations research and finance. Monte Carlo techniques have been used to analyze complex industrial systems in areas such as project portfolio management, finance and accounting, and operational risk evaluation (Savage, 2003; Kuppens et al., 2018). Kazantzi et al. (2013) presented a systematic solvent selection approach for a safety-constrained system, using MC simulation to evaluate system performance in the presence of economic and regulatory uncertainties. Kazi et al. (2018) used an optimization framework and MC simulation to explore the effects of uncertainty in flaring sources of an ethylene process on the selection of flare reduction alternatives. Specific applications of MC simulation to systems availability analysis have been demonstrated for a cooling tower pump system (Alexander, 2003) and an offshore installation (Zio et al., 2006). Recent work has also combined structural reliability techniques and MC simulation to formulate stochastic performance models for optimizing the design and operational reliability of chemical processes (Abubakar et al., 2015a, b, c).

1.4. Problem formulation

The constraints on the solutions to a process design problem are both external and internal, but the decisive factor is the economic performance, as plants must be economically viable. Traditional economic performance assessment and valuation approaches have been proven inadequate when applied to complex engineering systems, especially in the early design phase, leading to insufficient outcome characterization (de Neufville and Scholtes, 2011; Savage, 2003). This kind of economic appraisal framework is usually based on specific economic metrics, such as ROI, IRR, NPV etc. at average conditions and does not correspond to realistic representations of uncertain input variables (such as equipment RAM characteristics in this case), which could have asymmetric impacts on economic performance outcome. Hence, there is a need to provide an explicit way to embed and quantify uncertain conditions in a process system, especially when RAM considerations are of particular importance at the early design stage.

In this work, the aim is to present an integrated framework which combines knowledge from the fields of process synthesis and design with reliability engineering into the economic analysis of process design alternatives in a probabilistic manner. RAM considerations will be included by collecting failure and repair data from two versions of the Offshore and Onshore Reliability Data (OREDA) Handbook—OREDA-02 and OREDA-15. Furthermore, the proposed approach enables the simultaneous inclusion of various sources of irreducible uncertainty (equipment RAM characteristics) as multiple model input (random) variables that becomes feasible (as opposed to the conventional sensitivity analysis where one model input at a time is considered varying).

As a result, full distribution profiles of economic performance outcomes are derived in the presence of uncertainty. The derived profiles are amenable to insightful statistical characterization, and risks and opportunities regarding the equipment and process design features can be identified and actively managed. According to the methodology followed in this study, all the uncertain model input variables are first identified and reasonable probabilistic representations through appropriately selected distribution profiles are assigned to them. Applying standard Monte Carlo techniques and performing random sampling from the above distributions, model input uncertainties are propagated through the model, and distribution profiles are generated that can be probabilistically characterized. The framework will be applied to a case study of a proposed propane dehydrogenation (PDH) plant using a RAM-weighted return on investment metric.

2. Description of proposed framework

2.1. *Classical process design and evaluation*

The framework presented in Fig. 1 begins with the same steps commonly used in the design process. These steps include identification of design objectives and sub-objectives, translation of customer needs into a design basis, development of block flow diagrams (BFDs) for promising alternative technologies, performing of stoichiometric targets of feed and product rates, and determination of profitability estimates for the alternative technologies. Evaluation of an alternative culminates in an estimate of a return on investment (ROI) value. The alternatives that do not meet the company's acceptable threshold ROI value are eliminated, and those that meet the criterion are considered for further study.

2.2. *Estimation of system RAM levels for proposed design*

At this stage of the design activity, the integration of reliability, availability, and maintainability (RAM) factors is considered. In order to estimate the availability of each process, preliminary knowledge of the equipment to be used for each major processing step is needed. This can be obtained through process flow diagrams (PFDs) of previous designs within a company or from literature references. Equipment failure rates (lower, mean and upper) and restoration manhours data (mean and maximum) for the proposed PDH plant were derived from two versions of the OREDA Handbook for Onshore and Offshore Reliability Data (OREDA, 2002, 2015). A weighted failure rate, $\hat{\lambda}$, was then calculated using the formula described by Vatn (1993):

$$\hat{\lambda} = \frac{\lambda_o^2 + \lambda_N^2(\lambda_o/\lambda_N + |\lambda_o - \lambda_N|/SD_N)^2}{\lambda_o + \lambda_N(\lambda_o/\lambda_N + |\lambda_o - \lambda_N|/SD_N)^2} \quad (1)$$

where SD_N is the failure rate standard deviation reported in the new edition, and λ_o and λ_N are the failure rate values from the old and new editions, respectively. In this work, the exponential distribution is used for failure and restoration times, meaning the failure and restoration rates are constant. Thus, the MTBF (mean-time-between-failures) value is the inverse of the weighted failure rate.

Conventional analysis of inherent availability utilizes the mean time to repair (MTTR) metric to represent the time that equipment or a system is not in operation. However, a more encompassing metric is the mean time to restoration (MTTRes), which is the time needed to restore an item to full operational status. It involves delays prior to and after repair actions, as well as time needed to ramp down and start up an equipment or system in the case of a failure event. The failure and restoration cycle described here is illustrated in a supplementary figure provided with this work.

The MTTRes metric captures important factors involved in the restoration process which can decrease the overall availability of a system and are important to consider when assessing its profitability. These factors include: ability of plant personnel to identify and mitigate failure events, responsiveness of management in allocating resources for maintenance needs, and the skill level of maintenance personnel. For a system in series, a modified system availability, A_{total}, using MTTRes can be estimated from the following equation:

$$A_{total} = \prod_{i=1}^{n} A_i = \prod_{i=1}^{n} \left(\prod_{k=1}^{m} \frac{MTBF_k}{MTTRes_k + MTBF_k}\right)_i \quad (2)$$

where A_i is the availability of a block, and $MTBF_k$ and $MTTRes_k$ are the mean time between failures and mean time to restoration, respectively, of the equipment making up the block. Then, the block with the lowest availability is identified as the critical process step causing the most significant downtime and having the most adverse impact on process profitability.

2.3. *RAM-weighted economic evaluation*

Using the estimated system availability range, a modified return on investment metric (ROI) range can be calculated as follows:

$$ROI\left(\frac{\%}{year}\right) = \frac{ANP\left(\frac{\$}{year}\right)}{TCI\ (\$)} * 100 \quad (3)$$

where ANP is the annual net (after-tax) profit and TCI is the total capital investment. This profit can be calculated by the following equation, modified from the profit equation in El-Halwagi (2017b):

$$ANP = \{Availability * (Annual\ Revenue - Annual\ Operating\ Cost) - Depreciation\} * (1 - Tax\ Rate) + Depreciation \quad (4)$$

The purpose of this modified profitability metric is to determine the inherent RAM characteristics of a process design alternative and their effect on profitability estimates. Different design modifications to improve RAM levels of critical equipment are then assessed to determine their feasibility and the extent to which they enhance process profitability. These modifications may include the quality of purchased process

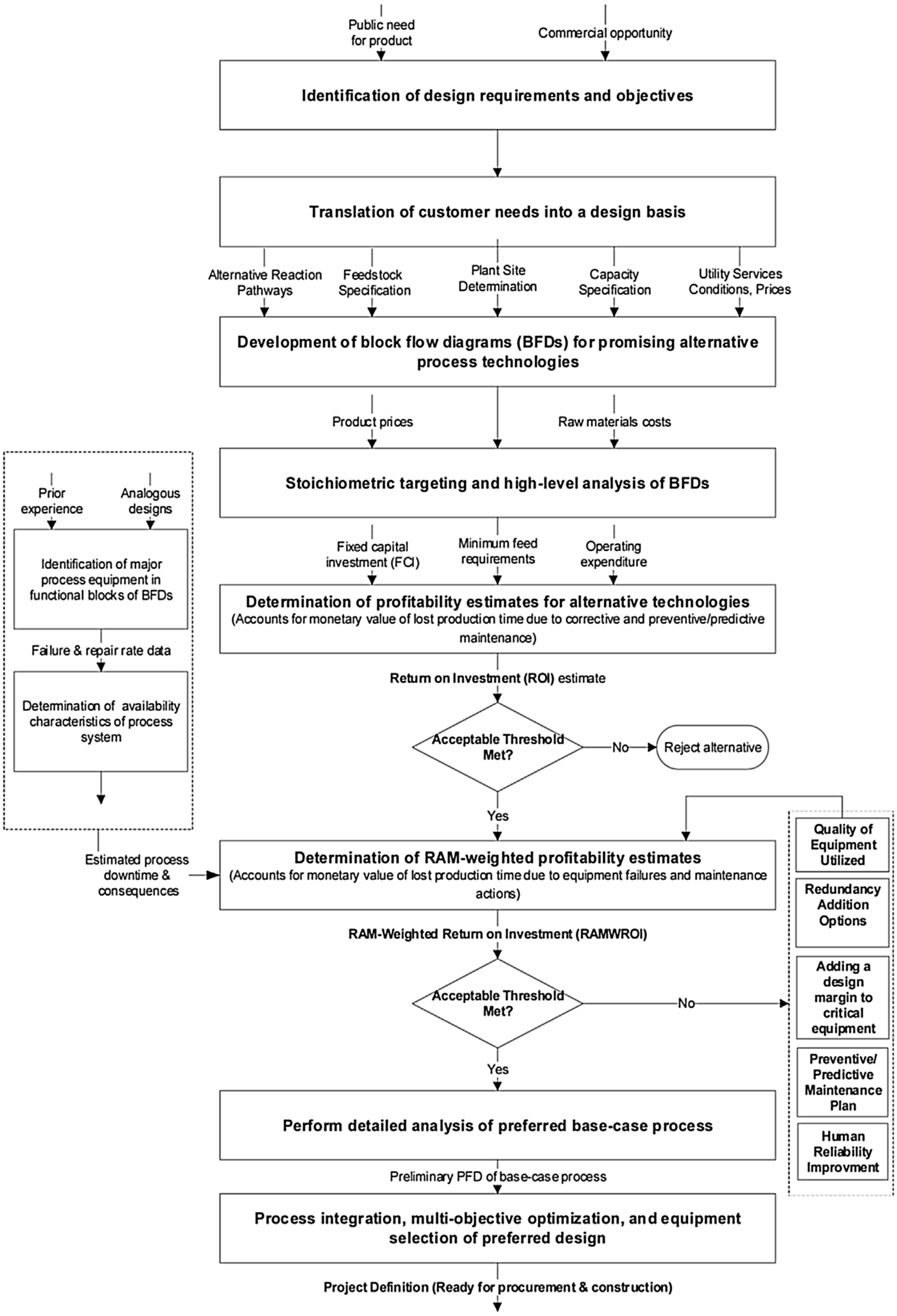

Fig. 1 – Framework for inclusion of reliability, availability, and maintainability (RAM) factors in process design.

equipment, over-design of equipment, addition of redundant components or subsystems, preventive and predictive maintenance plans, and measures to improve human reliability. The choice of design modification is made based on calculating its incremental return on investment (IROI) as follows:

$$IROI\left(\frac{\%}{year}\right) = \frac{\Delta ANP\left(\frac{\$}{year}\right)}{\Delta TCI\,(\$)} \quad (5)$$

2.4. Uncertainty quantification approach

Fig. 2 below illustrates the approach used to determine the expected ranges for process RAM characteristics and profitability. Using a representative distribution for the constituent equipment RAM characteristics (MTBF, MTTRes), a design team is able to obtain a range of values for process system availability and economic metrics such as annual profit and return on investment. For each major piece of equipment, both failure and restoration data represent uncertain variables and were assigned triangular distributions, selected due to limited data, as follows:

$$Triangular_{Failure}\left(MTBF_{Minimum}, MTBF_{Mean}, MTBF_{Maximum}\right) \quad (6)$$

$$Triangular_{Restoration}\left(MTTRes_{Minimum}, MTTRes_{Mean}, MTTRes_{Maximum}\right) \quad (7)$$

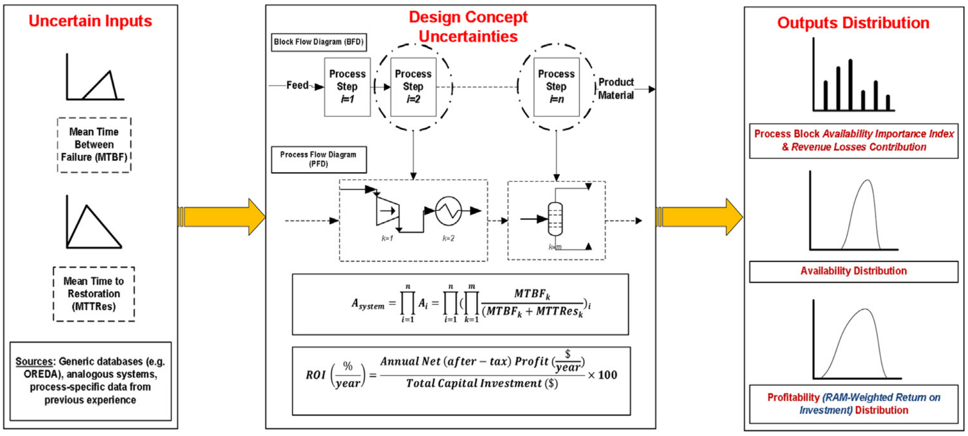

Fig. 2 – Uncertainty propagation of process RAM characteristics.

In this manner, the uncertainty inherent in RAM characteristics is propagated through the economic evaluation, thereby allowing decision-makers in technical and business divisions of an organization to make better-informed decisions about potential projects.

3. On-purpose propylene production

3.1. *Propylene production pathways*

Propylene is the petrochemical substance with the second-largest production volume after ethylene, and an important raw material for producing polypropylene and propylene oxide, both major building blocks in plastics production. Traditionally, propylene has been produced as a byproduct of ethylene from steam cracking of hydrocarbons, or as a byproduct of gasoline in fluid catalytic cracking (FCC) in refineries. In 2012, steam cracking and FCC accounted for 90% of the global production of propylene. However, the shale gas revolution has caused a shift in North American cracker feedstocks from naphtha to ethane, leading to an increase in ethylene yield and a decline in propylene production. For refineries, gasoline prices dictate the propylene production in those facilities. If prices are high, propylene is produced and used to make octane-boosting alkylates. If demand is low, gasoline production is lowered causing propylene output to fall. In these two pathways, propylene supply, unlike propylene demand, is subject to developments in the gasoline and ethylene markets. That demand is expected to grow from 109 million tons in 2014 to about 165 million tons in 2030, approximately 12–14% greater than the amount of propylene that can be produced as a by-product of steam crackers and in refineries (Wood Mackenzie, 2014). The resulting gap between supply and demand can be filled by on-purpose propylene (OPP) technologies such as propane dehydrogenation, methanol-to-propylene/methanol-to-olefins (MTP/MTO), and olefin metathesis. The optimal method of producing propylene is subject to factors such as geographic location, feedstock prices and availability, market conditions, technology maturity, sustainability and safety (Guillen-Cuevas et al., 2018; Roy et al., 2016).

3.2. *Propane dehydrogenation technologies*

According to (Eramo, 2017), propylene demand grew at an average rate of 3.5 million metric tons (MMT) from 2011 to 2015, and is expected to increase to 4.5 MMT in the period of 2017–2021. With the decline in propylene production due to lighter feedstock in crackers, it is projected that approximately 30% of propylene production (38 MMT) will be produced by on-purpose technologies in 2023. In North America, propylene demand is expected to reach 20 MMT (about 15% of global supply), of which 5 MMT is expected to be via on-purpose routes. Currently, there are three PDH plants in the U.S. producing about 2 MMT of on-purpose propylene (Galindo, 2019). These factors indicate that on-purpose propylene technologies will be essential to meet North American demand. Thus, this information establishes the need and commercial opportunity that exist for on-purpose propylene. In the PDH process, propane is converted to propylene over a platinum-alumina-based catalyst bed at high temperatures (550–650 °C) and low pressures (2–3 bar). Overall selectivity towards propylene is 90 mol%, and one-pass conversion is 40 mol% (Gregor and Wei, 2004). The PDH licensing is dominated by Honeywell UOP's OLEFLEX and CB&I CATOFIN technologies. Of the 28 PDH units operating worldwide, 18 use the OLEFLEX technology. In this work, the OLEFLEX process was selected for examination.

4. Application of proposed framework

4.1. *Propane dehydrogenation OLEFLEX process*

To begin the plant design process, a block diagram of the PDH process is constructed showing the major processing steps in each route (Fig. 3). The PDH process consists of the following major processing equipment and operations: depropanizer column, dehydrogenation reactors and interheaters, reactor effluent compressors and coolers, cryogenic refrigeration, pressure swing adsorption (PSA), propylene/propane separation. Fresh and recycled propane enter the depropanizer column where hydrocarbon (C4+) material is separated. The propane-rich stream in the overhead enters the refrigeration unit where its autorefrigeration property is utilized to cool the reactor effluent stream. The propane stream leaving the cold box is mixed with hydrogen and enters a fired heater where the mixture is heated to a temperature to 580–620 °C before entering the reactor system. The reaction occurs over a fluidized catalyst bed in a radial flow reactor to minimize pressure drop across the beds (Vora, 2012). To burn off resulting coke that is formed, a continuous catalyst regenerator (CCR) is used. The reaction is highly endothermic in nature (ΔH = 124.3 kJ/mol) and a considerable temperature drop occurs in each reactor. Therefore, interstage heaters are needed to raise the outlet stream temperature. The reactor

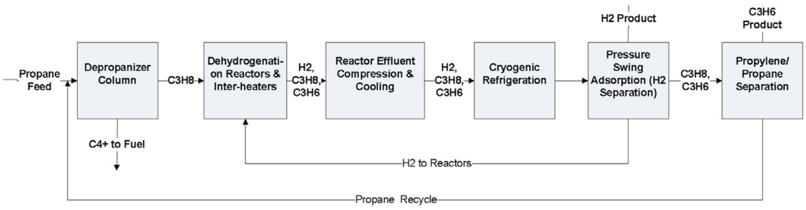

Fig. 3 – Block diagram of UOP OLEFLEX propane dehydrogenation (PDH) process.

system effluent is a mixture of propylene; unreacted propane; light gases, such as methane, ethane and ethylene; diolefins; and heavier hydrocarbon components formed in the reactor. The effluent is then cooled and compressed from 96.5 kPa psia to about 1380 kPa in a multistage compressor with interstage coolers. The next step is to liquefy the hydrocarbon material and separate out the hydrogen in the cold box unit. Part of the hydrogen produced is sent to the dehydrogenation reactors and the rest goes to the selective hydrogenation process (SHP) reactors. The net hydrogen is then sent to the pressure swing adsorption (PSA) unit to ensure it meets pipeline quality specifications. The liquefied hydrocarbons from the cold box are sent to SHP reactors to convert the diolefins to propylene. Then, a deethanizer column separates C2 components from the liquefied hydrocarbons and propane-propylene splitter (superfractionator) produces the final propylene product. Unconverted propane is sent from the superfractionator bottoms to the depropanizer column as part of the feed.

4.2. *High-level analysis of block flow diagrams*

A preliminary economic assessment of the proposed plant is performed using stoichiometric targeting to estimate the amount of raw materials needed for the process, operating expenditures, annual revenue and the capital investments. The capital and operating expenditures for the 450,000 MTA plant are estimated on the basis of the cost data in Agarwal et al. (2018), which reported on a simulation study with capital and operating investment estimates for a 600,000 MTA plant located on the U.S. Gulf coast. Those values and the prices for raw materials and product used in this study are shown in Table 1.

4.3. *Process design performance evaluation*

4.3.1. *Estimation of system RAM levels for proposed design*

After the major equipment in each processing step are identified, failure and restoration manhours data for these equipment are collected from two versions of the OREDA database. Table 2 includes this data for the equipment in a propane dehydrogenation (PDH) process. The ranges for MTBF and MTTRes values in this table are representative of different installations as well as varying environmental and operational conditions under which the data was collected.

The Monte Carlo simulation tool in the Palisade® @Risk software was used to generate 50,000 random samples for each equipment's MTBF and MTTRes values. Two sampling methods are available for use in this simulation feature: Latin Hypercube and Monte Carlo. For this work, Latin Hypercube sampling was used as the sampling method because it avoids the clustering that can occur with Monte Carlo sampling, providing a better chance for all values from the input distribution to be sampled. Eq. (2) is used to calculate availability for a subsystem or system in series. The resulting availability for each

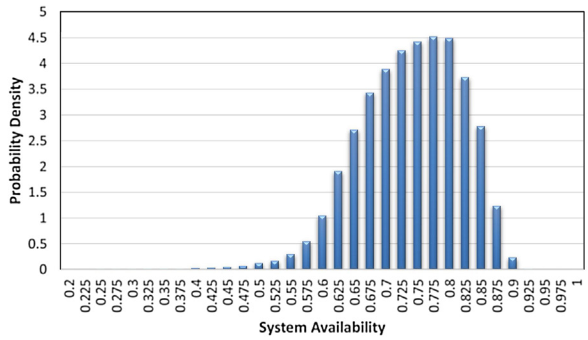

Fig. 4 – Probability density graph of overall PDH process availability.

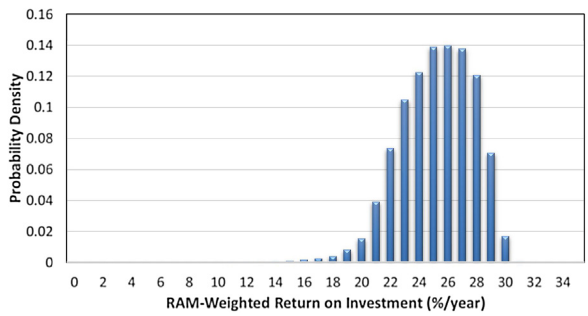

Fig. 5 – Probability distribution profile for the modified ROI of proposed PDH process.

major equipment piece, processing section, and the overall process are not point estimates, but rather a range of values that can be fit to a probability distribution using the @Risk software.

Fig. 4 shows the probability density distribution for the process system's availability. These results show that the standard deviation is low, indicating that the upper and lower confidence limits do not differ significantly from the mean value of total inherent availability (72.7%). The result is a range of estimated system availability that is significantly different from projections assuming a fixed system availability value of 80% or 85%. Greater accuracy with respect to system availability estimates allow for more accurate outlooks of a plant's projected profitability. Further refinement of the availability estimate is possible if in-house failure and repair data is available to the design team.

4.3.2. *RAM-weighted economic evaluation of proposed design*

Uncertainties in equipment RAM characteristics are included in the calculation of the process profitability using the modified return on investment (ROI) metric, as described previously. A Monte Carlo simulation was performed to obtain a distribution profile for this indicator. The probability distribution profile for the modified ROI is shown in Fig. 5. The results estimate a mean ROI value of 23.9 %/year and a standard deviation value of 7.45%/year. The coefficient of variation, defined as the

Table 1 – Feedstock/product prices and economics for PDH process.

Feedstock/Product	Minimum Flowrate in Metric Tons/Annum (MTA)		Price ($/MT)
Propane	524,000		375
Propylene	450,000		1100
Hydrogen	22,000		1600
Process economics results			
Fixed capital investment (FCI), $MM		534	
Total capital investment (TCI), $MM		628	
Annual net (After-Tax) profit (ANP), $MM/year		180	
Return on investment (%/year)		28.6	

Table 2 – Uncertain inputs into the availability estimation of a proposed propane dehydrogenation (PDH) design.

Processing step	Major equipment	Mean time between failure (Hours)			Mean time to restoration (Hours)		
		Lower	Mean/Most likely	Upper	Lower	Mean/Most likely	Upper
Separation of C4+ materials in feed and recycle	Depropanizer column	8174	10,146	12,695	10.0	44.5	359
Catalytic dehydrogenation reaction	Fired heater (charge heater)	266	909	41,239	2.0	66.7	706
	Dehydrogenation reactor	5255	10,632	50,383	1.0	47.0	474
	Reactor feed-effluent heat exchanger	13,325	15,838	20,017	1.0	55.4	419
Continuous catalyst regeneration (CCR)	Continuous catalyst regenerator	5255	10,632	50,383	39.0	47.0	474
Compression and cooling of reactor effluent	Turbocompressor feed cooler	13,325	15,838	20,017	1.0	55.4	419
	Steam turbine	6160	10,317	21,529	9.3	16.0	31
	Multi-stage centrifugal compressor	2700	3145	3815	16.9	28.9	1481
	Turbocompressor discharge cooler	13,325	15,838	20,017	1.0	55.4	419
	Heat exchanger	13,325	15,838	20,017	1.0	55.4	419
Cryogenic refrigeration	Flash drum	6849	13,522	37,823	5.9	16.9	409
	Isentropic expander	1207	3348	181,048	10.0	44.5	728
Hydrogen Separation	Selective hydrogenation process (SHP) reactor	5255	10,632	50,383	39.0	47.0	474
	Pressure swing adsorption (PSA) unit	8174	10,146	12,695	10.0	44.5	359
Product Recovery	De-ethanizer column	8174	10,146	12,695	10.0	44.5	359
	Propylene-propane splitter (superfractionator)	8174	10,146	12,695	10.0	44.5	359

ratio of the standard deviation to the mean, can be utilized to examine and compare the variability from the mean value for both availability and ROI. These values were determined to be 0.109 for system availability, and 0.312 for ROI. This indicates that there was less variability from the mean value (0.745) for system availability (Fig. 4) than from the mean value (23.7%) for ROI (Fig. 5).

A table in the supplementary materials of this work shows the range of results for the main economic parameters used to evaluate the proposed PDH process design. The 5% and 95% tails represent the lower and upper limits of the 90% confidence interval for all the parameters presented. The range of possible system availability is reflected in the annual revenue losses, annual profit, and return on investment. All of the categories displayed a moderate level of skewness (between −1 and 1), indicating the resulting distributions are moderately asymmetric.

The results of this work emphasize the importance of explicitly including uncertainty in all input variables used in the process performance assessment framework. Identification and characterization of the uncertainty associated with performance assessments improves the understanding of risks and design sensitivity, leading to more informed decisions regarding proposed designs.

4.3.3. *Section analysis of process RAM characteristics and profitability*

In addition to the results presented, the availability of individual process blocks can be estimated to identify critical units and determine the impact of their downtime in realtion to revenue losses. Fig. 6 shows the mean section availability for each of the process blocks, along with the 90% confidence bounds. This captures the range of possible availabilities for each section, depending on the equipment failure and restoration rates. Also, the figure illustrates that the compression and cooling of reactor effluent section has a significantly lower availability than the other section, even when considering the predicted upper limit of its availability. The compression and

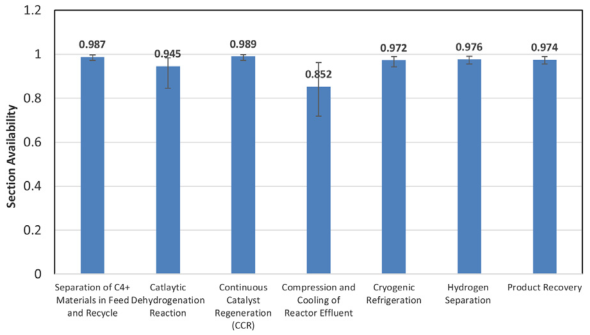

Fig. 6 – Section availability of individual process blocks for a proposed PDH process.

cooling of reactor effluent section includes a steam turbine-driven multi-stage centrifugal compressor, which typically experience higher failure rates than non-rotating machinery.

Using the section availability data, the contribution of each section to the overall process revenue losses (presented in the supplementary table) can be determined. From the results shown in Fig. 7, it is clear that the compression and cooling of reactor effluent section is the largest contributor to overall revenue losses due its significantly lower availability. In this case study, this section accounts for approximately 60% of annual revenue losses for a PDH process.

4.4. *Design modifications*

Four design modifications to the compression and cooling of reactor effluent section are evaluated to determine their effect on ROI. The proposed modifications for the multi-stage centrifugal compressor are as follows:

(1) Compressor with higher reliability (increased MTBF)
(2) Compressor with shorter restoration time (decreased MTTRes)
(3) Compressor with both a lower failure rate and shorter restoration time
(4) Addition of a second, parallel flow compressor train, with each train handling 50% of the flowrate.

The first three modifications can be realized by either obtaining equipment that are: (1) known to have enhanced RAM characteristics due to previous operating experience, or (2) larger vessels that provide a surge capacity in the case of process upsets. The latter case can be achieved by selecting a centrifugal compressor with a greater design pressure ratio and discharge temperature than needed for the process. The configuration for the base case and modifications 1–3 are illustrated in top part of Fig. 9.

For the compression and cooling section of a PDH process, the discharge temperatures for the two compressor stages are 138 °C and 355 °C, respectively. Accordingly, the compressor selected should have a higher specified discharge temperature than those values. This results in equipment that have higher pressure ratios and power rating, which typically incur higher capital costs. The desired margin between the discharge temperature and compressor design temperature limit depends on many factors including: (1) likely operating conditions (clean or fouling service), (2) operating environment due to location, and (3) an organization's financial resources. Higher design margins provide greater protection against failures, thus increasing overall equipment availability. The relationships between equipment capacity, availability, and cost is beyond the scope of this work and have not been established for the chemical process industries. Several works have examined those relationships for electronic equipment using correlations and discrete data (Fratta and Montanari, 1976; Majumder et al., 1976; Govil, 1985).

The fourth modification, a parallel flow configuration, employs two equal-size centrifugal compressors for the first and second stage of the compression system with the same design specifications and RAM characteristics as the base case. Each compressor in the parallel arrangement is designed to take 50% of the flowrate in the base case design. This configuration, shown in Fig. 8, incurs much higher capital costs than the other modifications due to the loss of economy-of-scale.

The availability, cost, and revenue losses associated with each modification are shown in Table 3. The parallel flow configuration has the highest availability and thus achieves the greatest reduction in revenue losses from equipment unavailability. However, it does present a significantly greater increase in installed costs over compared to the other modifications.

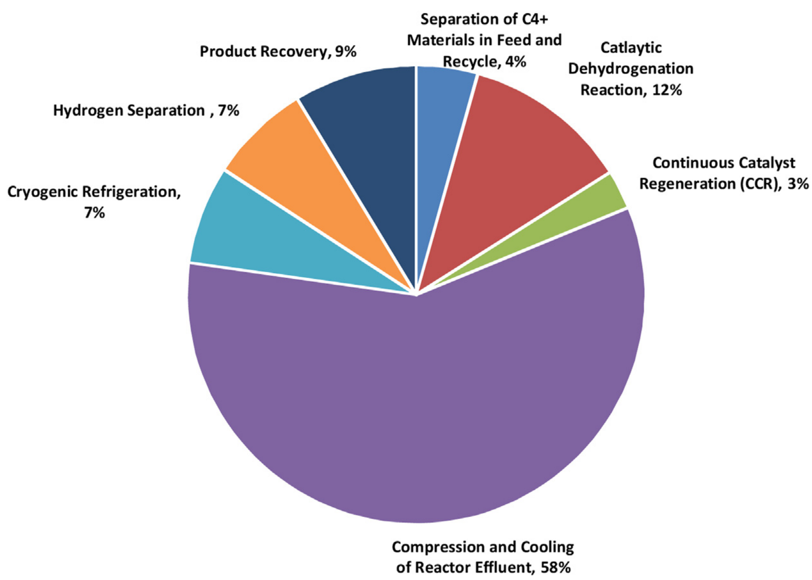

Fig. 7 – Contribution of processing sections to revenue losses.

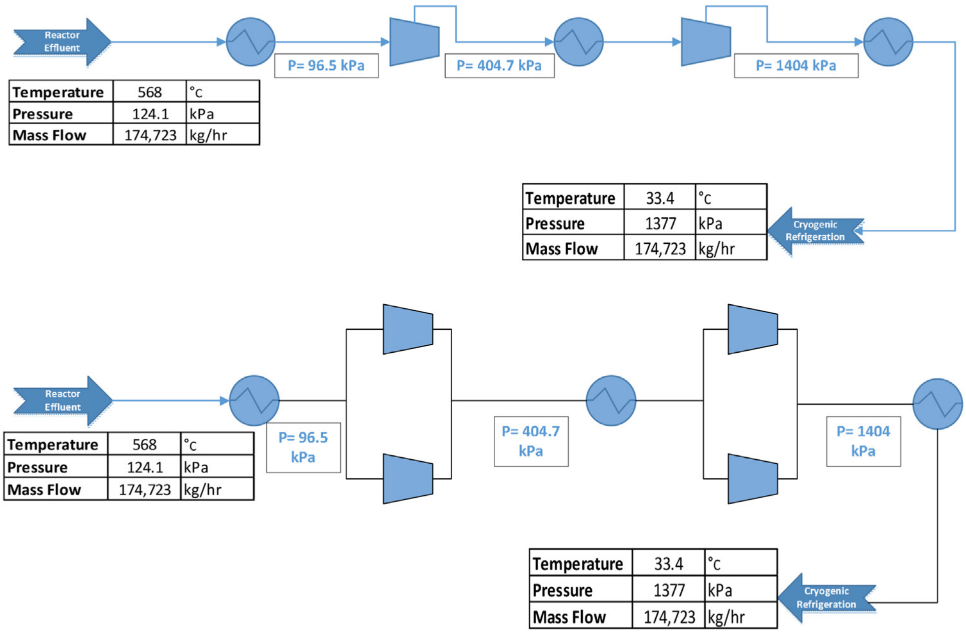

Fig. 8 – Compression and cooling section configurations for (top) base case design and modifications 1-3, and (bottom) modification 4 (parallel flow arrangement).

Table 3 – Availability and economic parameters for proposed design modifications.

Alternative	MTBF (Hours)	MTTRes (Hours)	Availabi-lity	Installed cost ($MM)	Revenue losses due to unavailabili-ty ($MM)	Reduction in revenue losses (%)
Base case	3226	509	0.845	34.1	94.7	–
Lower failure rate	3449	509	0.871	36.7	77.6	18.1
Shorter MTTRes	3226	458	0.876	37.1	75.3	20.5
Lower failure rate and shorter MTTRes	3449	458	0.883	37.7	71.6	24.4
Parallel flow with base case RAM levels	2419	208	0.921	51.8	51.9	45.2

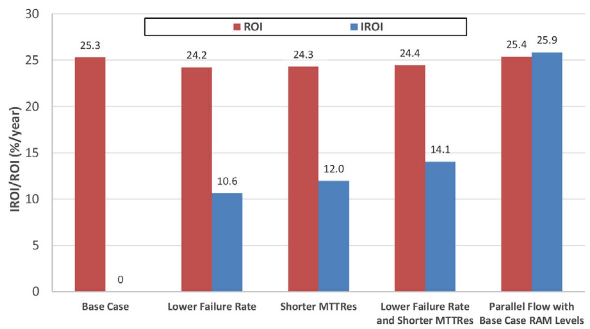

Fig. 9 – Comparison of ROI and IROI for alternative design scenarios of a PDH process compression system.

In this case study, a minimum ROI value of 15% was selected as an appropriate threshold for acceptability of a design. Fig. 9 presents the results for both the ROI and IROI metrics for the proposed designs for the cooling and compression section. Note that the base case, as well as all alternatives, exceed the ROI threshold. However, only the parallel flow configuration exceeds the 15% threshold for the IROI metric, with a value of approximately 26%/year. This configuration provides the most significant improvement in equipment availability and increase in annual profit over the base case. Despite the higher capital cost, the additional revenue generated by greater equipment availability results in the configuration having the highest IROI. Hence, it would be recommended as the optimal design configuration for the compression and cooling section of a PDH plant.

The improvement of system availability has a positive impact on both profitability and sustainability because it reduces flaring that occurs due to equipment failures. In the case of a PDH process, valuable propane feedstock, propylene product, and other chemicals can be flared in a failure event. This incurs additional costs to replace lost feedstock, reduces plant revenue, and results in fines due to the greenhouse gas emissions released during flaring. These fines can have an adverse effect on a company's reputation and future growth.

This approach can be further augmented by considering sustainability aspects along with RAM characteristics. For example, CO2 emissions reductions can be selected as a sustainability indicator. Two scenarios that can be considered are implementing: (1) a waste heat recovery (WHR) system to recover medium temperature heat from the fired boilers, and (2) an offgas recovery system to recover the deethanizer offgas stream and use it as fuel, thereby reducing natural gas consumption.

5. Conclusions

This paper presents a framework to integrate uncertainty quantification of equipment RAM characteristics into economic analyses of chemical process designs during the conceptual development stage. Instead of the standard practice of using average or fixed values, this framework employs distributions for failure and restoration data of process equipment to estimate an availability range for a base case design using Monte Carlo simulation. Using restoration instead of repair times accounts for delays in the maintenance process which increase downtime and negatively impact availability and economic performance. By doing so in a probabilistic manner, full distribution profiles of the key performance indicators, instead of single-point estimates which is the case in a deterministic approach, are generated and associated to their statistical characterization. These process economic performance indicators include: annual net profit, annual revenue losses, and return on investment. This approach also allows for identifying which specific section(s) in a process contribute significantly to revenue losses due to equipment unavailability. Proposed design modifications can then be examined to determine how best to improve availability for the section(s) in question in an economically-optimal way using an incremental return on investment (IROI) metric. A case study involving a propane dehydrogenation (PDH) plant was used to demonstrate the merits of integrating uncertainty quantification in RAM estimates used in system performance assessments. This approach differs significantly from practices which consider system design modifications to improve availability based solely on budgetary constraints. In summary, the proposed framework can be implemented by decision-makers, design engineers, and operations teams to make better-informed decisions on the economic potential of a project or design modification. This approach can also be extended to characterize the sustainability and process safety impacts of project or system modifications.

Declaration of Competing Interest

The authors report no declarations of interest.

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