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A Resilience Analysis Approach for Process Design, Integration and Optimization

Jian Gong, Fengqi You*

Cornell University, Ithaca, New York 14853, USA
fengqi.you@cornell.edu

Resilience in response to disruption events is critical to the economic performance of process systems, but this concept has received limited attention in the literature. A general framework for resilience optimization is proposed to incorporate an improved quantitative measure of resilience and a comprehensive set of resilience enhancement strategies for process design and operations. The proposed framework identifies a set of disruptive events for a given system, and then formulates a multiobjective two-stage adaptive robust mixed-integer fractional programming model to optimize the resilience and economic objectives simultaneously. The model accounts for network configuration, equipment capacities, and capital costs in the first stage, and the number of available processes and operating levels in each time period in the second stage. The applicability of the proposed framework is demonstrated through an application on process network design and planning.

1. Introduction

A major goal of risk management is to avoid the occurrences of undesired events by implementing effective prevention and protection strategies (Hosseini et al., 2016). However, many disruptive events, such as Hurricane Sandy in 2012 and the Haiti and Chile Earthquake in 2010, suggest that not all unexpected events can be avoided (Bhamra et al., 2011). Common disruptive events include natural disasters (such as tornados, earthquakes, and hurricanes), process accidents (such as faulty operations), and intentional man-made attacks (such as terrorism and sabotage) (Dinh et al., 2012). Disruptive events usually strike a process system and cause critical failures in vulnerable processes (Rehak & Novotny, 2016). System-level resilience was first introduced in ecology as the persistence of systems regarding unexpected change and disturbance (Holling, 1973). Although resilience may be interpreted by different terminologies in various contexts (Vugrin et al., 2010), a resilient system is always capable of absorbing a portion of the impacts from disruptive events and recovering to the original state rapidly (Miranda et al., 2017). A resilient plant could move fast and smoothly from one operating condition to another and dealt effectively with disturbances (Morari, 1983). A relevant concept of resilience was flexibility (Grossmann et al., 2014) which can help predict the probability of feasible operation for a design (Straub & Grossmann, 1990). Another relevant concept of resilience was reliability, which described the failure rate due to equipment aging. As the resilience of a process system is relevant to both safety and operability, the system performance under the worst-case realization of disruptive events is of paramount importance. However, resilience was not quantified explicitly as an intrinsic property of the system and there is no systematic framework for resilience optimization of process systems.

In this work, a novel quantitative measure of resilience is proposed as the ratio of the quantity of products manufactured with disruptive events to that without disruptive events. Based on the quantitative measure of resilience, a general framework for resilience optimization with three steps is proposed. First, a preliminary risk assessment is performed to identify the disruptive events and the numbers of failed processes for the identified disruptive events. Then a multiobjective two-stage adaptive robust mixed-integer fractional programming (ARMIFP) model is formulated to maximize the resilience under the worst-case realization of disruptive events, and to minimize the total capital cost. Future work is to include utility cost in the cost objective. The applicability of the proposed framework is illustrated through the design and planning of a chemical process network.

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2. General framework for resilience optimization

A general framework for resilience optimization is proposed that incorporates the quantitative measure of resilience and the five resilience enhancement strategies. As shown in Figure 1, there are three steps in the proposed resilience optimization framework. In the first step, a preliminary risk assessment is performed for a given system. A set of disruptive events are identified, and the related information, such as the number of failed processes in the given system and the recovery time of each process, is used as input parameters in the second step to formulate a multiobjective two-stage ARMIFP model. In the third step, the multiobjective two-stage ARMIFP problem is solved by a tailored global optimization method that integrates the parametric algorithm and the column-and-constraint generation algorithm.

Figure 1: Three steps in the general framework of resilience optimization

2.1 Novel quantitative measure of resilience

Common disruptive events include natural disasters (such as tornados, earthquakes, and hurricanes), process accidents (such as faulty operations), and intentional man-made attacks (such as terrorism and sabotage) (Dinh et al., 2012). Many system performance indicators, such as the flow rates of key streams and the number of normally functioning processes, respond to disruptive events dynamically and reflect the impacts of disruptive events to a given system. There are three sequential phases of a system performance function $F(t)$. The disruptive events occur at t_0 and cause initial failures in the process system. The first phase, or the impact propagation phase, lasts from t_0 to t_1. During this period, the initial failures cause additional failures in other normally functioning processes. Therefore, the system performance function keeps declining until t_1, which corresponds to the lowest operating level. In the system recovery phase from t_1 to t_2, the failed processes in the given system recovers gradually and the system performance function increases to its original operating level. In the last phase from t_2 to t_n, the system maintains the operating level.

$$\text{Resilience} = \sum_{w=0}^{\frac{t_n-t_0}{ti}-1} \left[F\left(t_0 + w \cdot ti\right) \cdot ti \right] \Big/ \left[F\left(t_0\right) \cdot \left(t_n - t_0\right) \right] \tag{1}$$

where $F(t) = \sum_k \left[\omega_k \cdot M(t)_k \right]$; $M(t)_k$ and ω_k are the flow rate and the weight of product k, respectively; ti is the length of each time period.

A novel quantitative measure is proposed in Eq(1). The disruptive events occur at t_0 and the time horizon is [t_0, t_n]. The denominator calculates the accumulated system performance from t_0 to t_n and the numerator calculates the accumulated system performance in the same period but assumes that no disruptive event occurs. This quantitative measure accounts for recovery time and performance degradation simultaneously. Moreover, as the quantitative measure is normalized by the accumulated system performance without disruptions, the resilience analysis results can be compared among distinct process systems. The failed processes of a given system can be reused only if they are fully repaired and tested. Therefore, system performance remains flat in each time period, and the system performance functions are step-wise functions.

2.2 Uncertainty set

The concept of uncertainty set is used in robust optimization to capture the uncertain disruptive events (Shang et al., 2017). A disruptive event can impact only one process or multiple processes in the given system. External factors include, but not limit to, the type, scale, and severity of the disruptive event, the starting time of the disruptive event, the duration of the disruptive event, and the environment of the given system. Internal factors include, but not limit to, the use of advanced sensors, monitors, and process control technologies, the precautions against the disruptive event, and the contingency plans for the disruptive event. However, due to the uncertain nature of disruptive events, it is impossible to predict whether a process will be affected or not.

$$\sum_{i \in ID_d} SI_{i,d} \le \Gamma_d \cdot \left(1 - \varepsilon_d\right), \quad \forall d \tag{2}$$

$$\sum_{i \notin ID_d} SI_{i,d} = 0, \quad \forall d \tag{3}$$

The availability of process *i* after the occurrence of disruptive event *d* is modeled as an uncertain 0-1 variable $SI_{i,d}$. $SI_{i,d}$ is equal to one if the operating units in process *i* fail after the occurrence of disruptive event *d*, and 0 otherwise. Given the same operating conditions, parallel operating units are assumed to show the same availability after the occurrence of disruptive event *d*. Additionally, constraints (2) and (3) are introduced to provide an upper bound of the number of failed processes in the given system. Γ_d denotes the number of failed processes of disruptive event *d* based on historical records or simulation results. As a decision-maker may consider it too conservative to hedge against the realization where Γ_d processes fail, a tolerance level ε_d is introduced to adjust the degree of conservatism of the optimal solution. Since a disruptive event may influence only a set of processes, the summation in constraint (2) are limited to a subset of sections ID_d. The processes not in subset ID_d are fixed to be 0 as enforced by constraint (3). The uncertainty set for the availability of each process can thus be formulated with the above-mentioned constraints: $U = \{\text{constraints } (2) - (3)\}$.

2.3 Two-stage adaptive robust nonlinear programming model and tailored solution algorithm

Given the definition of resilience and the uncertainty set, a multiobjective two-stage ARMIFP model is developed for resilient design and operations (Gong et al., 2016). The decisions are determined sequentially in two stages (Shi et al., 2016). The first-stage decisions, including network configuration, equipment capacities, and capital costs, are determined before the occurrence of the disruptive events; the second-stage decisions, including the number of available processes and operating levels in each time period, are determined after the occurrence of the disruptive events. There are two objective functions in the general form of the proposed model (shown below). The first objective is to maximize the resilience under the worst-case realization of the availability of process units, and the second objective is to minimize the total capital cost of the given system.

$$\max_{C1} \min_{U} \max_{C2} \quad \text{Resilience}$$

$$\min_{C1} \quad \text{Total capital cost}$$

where $C1 = \{\text{network design; equipment capacity constraints; capital cost evaluation}\}$,

$C2 = \{\text{recovery constraints; operating level constraints}\}$.

Since the proposed multiobjective two-stage ARMIFP model has a multilevel structure, it cannot be handled directly by any off-the-shelf optimization solvers. Additionally, due to the combinatorial nature and nonconvexity stemming from the mixed-integer terms and the fractional objective function, the optimization problem is challenging to solve. To tackle the computational challenge, a tailored optimization algorithm is used to efficiently solve this ARMIFP problem (Gong and You, 2017). Specifically, the optimization algorithm employs the parametric algorithm in the outer loop to tackle the computational challenge stemming from the fractional objective function. Instead of solving the original optimization problem with the fractional objective function directly, an auxiliary parameter *r* and an auxiliary parametric problem *P*(*r*) are introduced. The optimal solution of the orginal optimization problem is identical to the optimal solution of the auxiliary parametric problem with the parameter r^* such that $P(r^*) = 0$ (Zhong and You, 2014). Each iteration of the parametric algorithm needs to solve a two-stage adaptive robust MILP problem *P*(*r*), which cannot be tackled directly by any off-the-shelf optimization solvers. Instead, a master problem and a subproblem of *P*(*r*) are developed and solved iteratively. This solution algorithm is guaranteed to converge within finite iterations (Ning and You, 2017). A conventional design and operations problem that minimizes the total capital cost without disruptive events is solved after the initialization step, and the optimal first-stage solutions are used by the first subproblem in each inner loop.

3. Application to chemical process network design and planning

The application of the proposed resilience optimization framework is illustrated thorough the resilient design and planning of a chemical process network with ten chemicals and six processes as shown in Figure 2 (You & Grossmann, 2011). The feedstock materials include acetylene, propylene, benzene, and nitric acid; the products include acetaldehyde, acrylonitrile, isopropanol, phenol, acetone, and cumene (Yue and You, 2013). The correlation parameter is 1 for all processes and disruptive events. The tolerance level is equal to 5 % for all disruptive events. There are 4 case studies: Case studies 1 – 3 involve only one disruptive event, and case study 4 involves two disruptive events. The numbers of failed processes in case studies 1 – 3 are 2, 4, and 6, respectively. In case study 4, the numbers of failed processes of the first and second disruptive events are 3 and 2, respectively.

All computational experiments are performed on a DELL OPTIPLEX 7040 desktop with Intel(R) Core(TM) i7-6700 CPU @ 3.40GHz and 32 GB RAM. The solution procedure is coded in GAMS 24.8.5 (Rosenthal, 2016), with CPLEX 12.7 used as the MILP solver. The relative optimality tolerances for the inexact parametric algorithm and the column-and-constraint generation algorithm are 10-6. The subproblem of all case studies and instances consist of 6 integer variables, 1,766 continuous variables, and 1,690 constraints. All instances in the first application can be solved in less than 2 min.

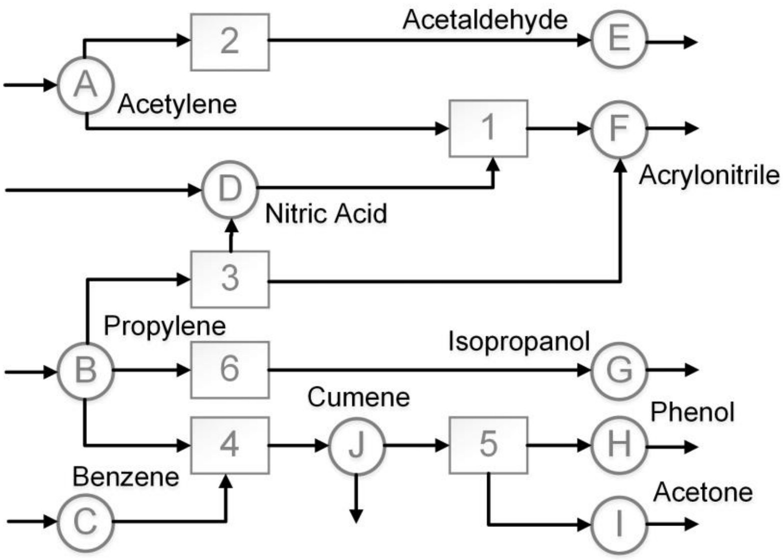

Figure 2: Chemical process network of the case studies.

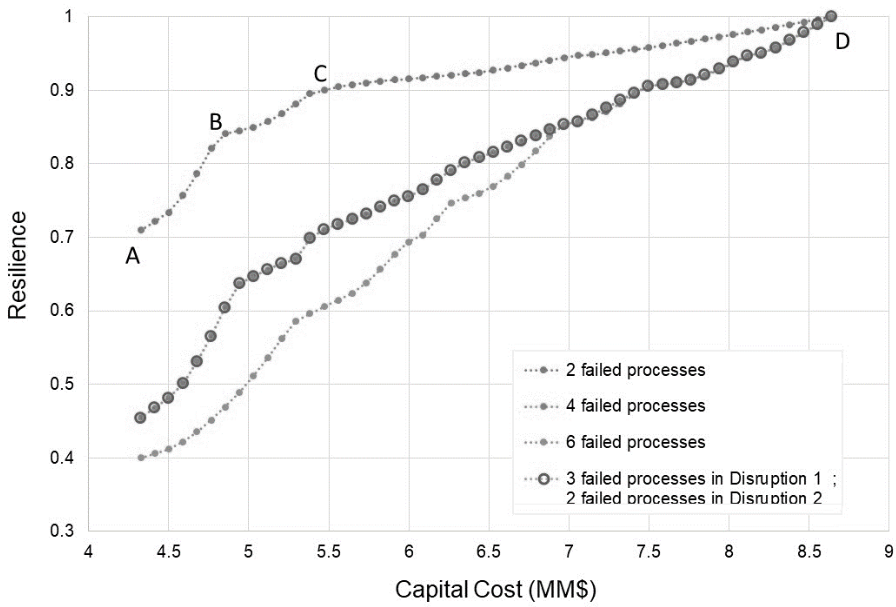

Figure 3: Pareto-optimal curves of the four case studies.

The optimal solutions of the multiobjective two-stage ARMIFP problems can be plotted as Pareto-optimal curves in Figure 3. Each point on the Pareto-optimal curves corresponds to an optimal solution of the optimization problems. On the Pareto-optimal curves, an increase in resilience corresponds to an increase in the total capital cost. For case study 1, the most resilient solution demonstrates a resilience of 1 and a capital cost of $8.64 M, while the most cost-effective solution demonstrates a resilience of 0.71 and a capital cost of $4.32 M. Both optimal solutions employ the same operating processes, but the minimum capital cost of the most resilient solution is twice of that of the most cost-effective solution. It is noted that the most resilient solution includes a set of backup processes with the same capacities of the corresponding operating processes, while no backup process is built for the most cost-effective solution. The optimal capital cost ranges from \$4.32 M to \$8.64 M across all the case studies. If the optimal capital cost is fixed, the optimal resilience decreases as more failed processes are considered in the optimization problem. The Pareto-optimal curve in case study 2 overlaps with that in case study 4, because the total numbers of failed processes adjusted by the tolerance level are the same in these two case studies.

Each point on a Pareto-optimal curve corresponds to an optimal process design. Figure 4 presents the optimal capital costs as well as the worst-case realization of the optimal solutions A, B, C, and D in Figure 2. To satisfy the product demands, the optimal solutions A, B, and D select the same processes with the same equipment capacities of the operating processes. The difference lies in the capacities of the backup processes. There is no backup process in the optimal solution A in order to minimize the total capital cost. With a higher capital investment, a backup process is built for process 4 in the optimal solution B. Although the capacity of this backup process is smaller than that of the corresponding operating process, it effectively increases the worst-case operating levels from 230 ton/day to 330 ton/day in time periods 1–3. As an extreme case of the optimal solution B, the optimal solution D establishes backup processes for all the operating processes and the capacities of the backup processes are the same as the corresponding operating processes. In the optimal network designs of solutions A, B, and D, only process 1 is employed to produce acrylonitrile. A different process design is selected for the optimal solution C and both process 1 and process 3 are employed to produce acrylonitrile. Accordingly, the capacity of process 1 in the optimal solution C is lower than those in the optimal solutions A, B, and D.

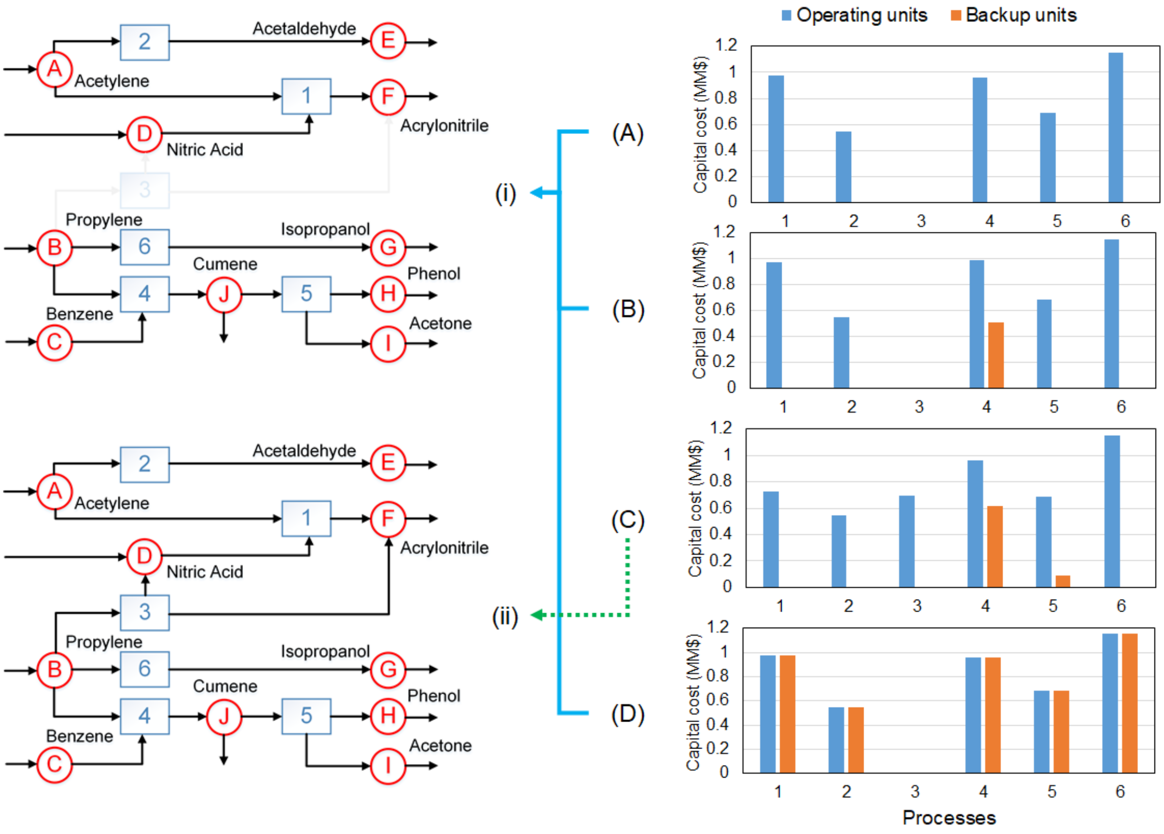

Figure 4: Capital cost breakdowns and worst-case realizations of four optimal solutions. Network design (i) corresponds to the optimal solutions A, B, and D. Network design (ii) corresponds to the optimal solutions C.

4. Conclusions

A general framework for resilience optimization is proposed to incorporate a quantitative measure and the resilience enhancement strategies. The framework involves developing a multiobjective two-stage ARMIFP model after performing a preliminary risk assessment to identify the disruptive events and the numbers of failed processes for the identified disruptive events. The applicability of the proposed resilience optimization framework is illustrated through the design and planning of chemical process networks. The maximum resilience of the chemical process network ranges from 0.71 to 1 if two out of six processes in the network fail after the occurrence of a disruptive event, while the corresponding minimum capital cost ranges from $4.32 M to $8.64 M.

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