A Decision Analytics Pipeline for Balancing Business, Environmental and Social Impacts of Supply Chain Disruptions ⋆

Reza Babazadeh * **Cemalettin Ozturk** * **Barry O'Sullivan** **

* *Munster Technological University, Bishopstown, Cork, Ireland, (e-mail: {reza.babazadeh,cemalettin.ozturk}@mtu.ie).*
** *University College Cork, Cork, Ireland, (e-mail: b.osullivan@cs.ucc.ie)*

Abstract: Supply chain resilience is essential for maintaining global economic stability and ensuring the continuous delivery of goods and services. This study introduces a new decision analytics framework to stress test supply chains by improving robustness, addressing network vulnerabilities, and developing adaptive mitigation strategies. The proposed approach includes a modified Time to Survive (TTS) model, a sustainable mitigation planning Time to Recover (TTR) model, and a sequential Monte Carlo simulation to measure variability in mitigation plans. It focuses on reducing business, environmental, and social impacts while supporting strategies such as dual sourcing and capacity reallocation. Multi-objective mathematical programming and open-source technologies are used to develop the framework. Computational experiments with a synthetic supply chain network generator confirm its scalability, efficiency, and practical value.

Keywords: Supply chain resiliency, Stress testing, Time to Survive, Time to Recover, Variable quantification.

1 INTRODUCTION

Supply chain disruptions and their propagation have been the major risks in the continuity of business, health, education, and social services. Ongoing pressure on supply chains due to political instability, and increasing energy prices/availability keep supply chain disruptions still the priority in risk scale and will preserve its position in the foreseeable future (Forum, 2023). An effective solution to mitigate supply chain disruptions has a direct and significant impact on strengthening business and public service organisations' resilience, as well as securing the economic and social well-being of society by facilitating accessibility to goods and essential health and public services.

Understanding the impact of disruptive events on suppliers and their propagation is still subjective and there is a strong need for quantifying these ripple effects. This paper addresses these points by incorporating supply chain network-related KPIs and considering compound disruption scenarios while developing mitigation plans. Mapping interaction between supply chain actors via the proposed pipeline in terms of product/service flow enables practitioners to identify and eliminate vulnerabilities. Making environmental and social indicators a part of the proposed solution engages supply chain practitioners to be more responsible for environmental, social, and governmental (ESG) concerns.

In the next, Section 2, we will give a discussion of the recent supply chain resilience literature. Then, in Section 3 details of the analytical pipeline will be presented. An illustrative demonstration of the pipeline will be provided in Section 4. Computational results for scalability of the pipeline are presented in Section 5 and the paper will conclude with insights and future research directions at Section 6.

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2 BACKGROUND

The global disruptions encountered in the last decades enforced a paradigm shift from "cost first" to "resiliency first" (Ivanov and Dolgui, 2022). Hence, buffer inventory and redundancy become more significant strategies for enhancing supply chain resiliency (Sheffi (2005)). Ivanov (2022) introduced a concept called viable supply chain in which viability is considered a fundamental feature of the supply chain that includes three key dimensions, namely agility, resilience, and sustainability. Simchi's pioneering work (Simchi-Levi et al., 2015) introduced two novel concepts for incorporating stress testing and mitigation strategies, time to survive (TTS) and time to recover (TTR). TTS of a supply chain is defined as the maximum amount of time that it can continue at decreased capacity before it does not perform vital functions. Conversely, TTR refers to the time it takes to restore a disrupted supply chain to its original state. Indeed, these two concepts originated from earlier infrastructure resilience studies such as (Cimellaro et al., 2010), (Tierney and Bruneau, 2007). In collaboration with Ford Motor Company, Simchi presented a successful implementation of these models that facilitates identifying hidden vulnerabilities, evaluating mitigation strategies, and designing contingency plans. The increasing impact of climate change brings additional challenges to global supply chains due to the major responsibility of greenhouse gas emissions (GHG) from manufacturing and transport activities. Therefore, supply chain resilience strategies need to take into account environmental impact they cause and include strategies for reducing emissions (Koh et al., 2023). Besides business and the environmental impacts, Unitied Nations Sustainable Development Goals and EU Corporate sustainability due diligence enforce humanization of supply chains by better protection of human and labor rights, increased trust in businesses, more transparency, biodiversity, and circularity (Truant et al., 2024), (Longoni et al., 2024).

Recent contributions to the supply chain resilience indicates the timeliness and relevance of our work. Chari et al. (2024) developed a Resilience Compass assessment tool to enhance manufacturing resilience and Singh et al. (2024) showed how AI-driven transparency enhances supply chain resilience. In another work, Yadav and Singh (2024) explored blockchain technology for supply chain information flow resilience and proposed a machine learning enhanced optimization model for procurement decisions. Blockchain technology is being exploited also for resilience of non-manufacturing supply chains (Ekinci et al. (2024)).

There are several software companies such as Everstream Analytics, (Analytics, 2024), providing solutions for supply chain resilience analytics. However, these tools are not capable to fully capturing all three business, sustainability, and social impacts of disruptions, mostly relying on the alert notification and monitoring, shallow learning curves, and lack of customization for different business rules and modularity of the technology being used.

Therefore, there is a need in the literature to extend the current business-oriented TTS and TTR concepts to include the environmental and societal impacts of supply chain disruptions, quantifying their variability with simulations. In the next section, we will propose our decision analytics pipeline along with extended models and explain their interactions.

3 DECISION ANALYTICS PIPELINE

As demonstrated in Figure 1, the proposed decision analytics pipeline first identifies disruption scenarios and then solves the TTS analytic model. After calculatingthe TTS value, TTR values are collected from suppliers. To incorporate TTRs in the mitigation planning model, we have considered three perspectives: (1) optimistic: considering the minimum value of TTRs, (2) pessimistic: considering the maximum value of TTRs, and (3) most likely: considering the mean of TTRs. If the resulting TTR value is less than the TTS value, we can execute the TTR model to generate a sustainable mitigation plan. Otherwise, risk management principles like time to value analysis (TTV) are adopted. Notably, TTS is computed using known supply chain parameters, meanwhile, the TTR model depends on all supply chain capabilities, facilities, supports, and external uncertainties, requiring estimation with pessimistic, most likely, and optimistic scenarios. After generating the mitigation plan, indicating the revised production, sourcing, and distribution strategies in the given disruption scenario, the variability of the plan is quantified through the Monte Carlo simulation method, and confidence intervals for the performance criteria are reported. As Simchi-Levi et al. (2015) reported, TTR is supplier-reported and hence may be underestimated, which could delay mitigation decisions. The proposed framework addresses this by focusing on pessimistic estimates and using Monte Carlo simulations to account for variability, ensuring a robust mitigation plan.

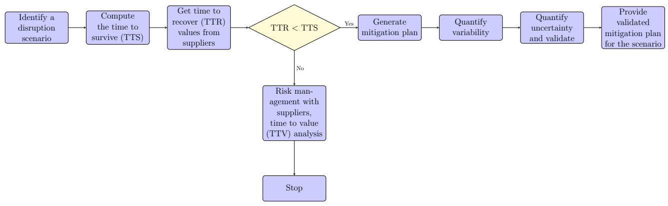

Fig. 1. Decision Analytics Pipeline

In the following subsections, we provide linear programming formulations for TTS and mitigation planning models.

3.1 *Time to Survive Model*

Once the disruption scenarios are identified, pipeline (Figure 1) executes the TTS model to estimate the longest duration the supply chain can still operate under given scenarios. The proposed model extends the conventional TTS model by (1) considering the simultaneous disruption of multiple factories with different rates, (2) alternative facilities for producing items (3) as well as production of multiple items in a factory. The nomenclatures in TTS and TTR models are described below.

Set and Indices

i, j, k: indices for components, sub-assemblies, and final assemblies which are nodes in Bill of Material (BOM),
$Nodes$: set of all nodes in BOM,
α, α': indices for factories that are nodes in the supply chain network,
n: indices for disruption scenarios,
$\Phi^{(n)}$: set of nodes (factories) disrupted in scenario n,
Ω_{jk}: set of all nodes in BOM that are in the upstream of node j and of part type k,
$N^{+}(i)$: set of subassembly or final assemblies that require component or subassembly i,
$N^{-}(i)$: set of subassemblies or components that are required to produce subassembly or final assembly i,
D: set of all final assembly and subassemblies in BOM (except the last tier),
U: set of all nodes except the final (assembly) nodes,
Υ: set of final products /assemblies,
A: set of all supplier sites (factories),
A_{α}: set of all nodes (components, subassemblies and assemblies) produced in plant α,
Ψ_i: set of all supplier sites (factories) that can produce item i in BOM

Parameters

$TTR^{(n)}$: Time to recover of the supply chain for disruption scenario n,
$PGHG_{\alpha i}$: greenhouse gas(GHG) emission of factory α for each unit production of item i,
$TGHG_{\alpha\alpha'}$: greenhouse gas emission of transportation a unit item from factory α to factory α',
SI_{α}: societal impact (employability, following legislation) index of factory α,
f_j: unit lost revenue of final item j,
$S_{\alpha j}$: available inventory of item j at factory α,
c_{α}: capacity of factory α,
$c_{\alpha} TTR^{(n)}$: capacity of factory α during the time to recover

period of the supply chain,
$p_{k\alpha}$: unit processing time of item k at factory α,
$dr_{\alpha}^{(n)}$: disruption rate of factory α in disruption scenario n,
r_{kj}: number of item k used for making a unit of item j (BOM),
d_j: demand of final item j per week,

Decision Variables
$TTS^{(n)}$: Time to survive of the supply chain for disruption scenario n,
l_j: lost production amount of final item j,
$y_{i\alpha j\alpha'}$: amount of item i in BOM sent from factory α to be used in producing item j in BOM at factory α' during disruption duration,
$u_{\alpha j}$: total production quantity of item j at factory α during disruption scenario n.

$$\text{maximize} \quad TTS^{(n)} \tag{1}$$
Subject to:
$$u_{\alpha j} \leq \sum_{i \in \Omega_{jk}} \left(\frac{\sum_{\alpha' \in \Psi_i} y_{i\alpha j\alpha'}}{r_{kj}} \right) \quad \forall k \in N^-(j), \forall j \in D, \forall \alpha \in \Psi_j \tag{2}$$
$$\sum_{j \in N^+(i)} \sum_{\alpha' \in \Psi_j} y_{i\alpha j\alpha'} \leq u_{\alpha i} + s_{\alpha i} \quad \forall i \in U, \forall \alpha \in \Psi_i \tag{3}$$
$$\sum_{\alpha \in \Psi_j} u_{\alpha j} + s_{\alpha j} \geq d_j TTS^{(n)} \quad \forall j \in \Upsilon, \forall \alpha \in \Phi^{(n)} \tag{4}$$
$$\sum_{k \in A_\alpha} p_{\alpha k} u_{\alpha k} \leq c_\alpha TTS^{(n)} \left(1 - dr_{\alpha}^{(n)}\right) \ \forall \alpha \in \Phi^{(n)} \tag{5}$$
$$TTS^{(n)},\ u_{\alpha j},\ y_{i\alpha j\alpha'} \geq 0 \quad \forall i \in U, \forall j \in \Upsilon, \forall \alpha \in \Phi^{(n)} \tag{6}$$

Objective function (1) maximizes time to survive (TTS) values for each disruption scenario (n). Constraints (2) consider the BOM relationship for the quantities of components and subassemblies required to produce a finished item or an intermediate item in the supply chain. Constraints (3) ensure that the amount of production flow sent from the origin factory to the destination factory is less than the production amount and available inventory of the item in the origin factory. Constraints (4) ensure that all demands during disruption scenario (n) are satisfied through the production and available inventory without any shortage. Without loss of generality, we assume weekly demand for each item. The time unit for each item may be varied for different industries. So, the total demand would be a multiplication of weekly demand by the TTS value which means total demands happen in disruption duration. Constraints (5) imply the capacity of each factory for producing the items. The capacity of each factory under disruption scenario (n) is degraded according to disruption rate. For example, disruption $dr_{\alpha}^{(n)} = 1$ means fully disruption of the corresponding factory. Also, the capacity is presented in terms of production time. Thus, the production amount is multiplied by the processing time of each item. Note that the capacity of factories is defined for each week. So, the total capacity of the factory is multiplied by the TTS of the supply chain. Constraints (6) imply non-negativity conditions for the decision variables.

3.2 *Sustainable Mitigation Planning Model*

After calculating the TTS for the supply chain, the Time to Recover (TTR) at each node, which is equal to the time needed to return operational functionality to the initial status, is asked from suppliers, and if $TTS < max(TTR)$ then the mitigation plan for the given disruption scenario is executed (Figure 1). The sustainable mitigation planning model is the extended version of TTR model in Simchi-Levi et al. (2015) which improves it as a lexicographically formulated multi-objective mathematical model. The model is capable of employing multiple sustainable performance measures while mitigating the given disruption scenario including economic, environmental, and social impacts through inventory reallocation, and supply redirection.

$$\text{Minimize} \left\{ \sum_{j \in \Upsilon} f_j l_j ; \left\{ \sum_{i \in \text{Nodes}} \sum_{\alpha \in \Psi_i} (\text{PGHG}_{\alpha j} u_{\alpha j} + \sum_{i \in \text{Nodes},\ j \in N^+(i)} \sum_{\alpha \in \Psi_i, \alpha' \in \Psi_j} \text{TGHG}_{\alpha\alpha'} y_{i\alpha j\alpha'} \quad) \right\} \right\} \tag{7}$$
$$\text{Maximize} \sum_{\alpha \in A} \text{SI}_\alpha \sum_{i \in \text{Nodes} | \alpha \in \Psi_i} u_{\alpha i} \tag{8}$$
Subject to:
$$u_{\alpha j} \leq \sum_{i \in \Omega_{jk}} \left(\frac{\sum_{\alpha' \in \Psi_i} y_{i\alpha j\alpha'}}{r_{kj}} \right) \quad \forall k \in N^-(j), \forall j \in D, \forall \alpha \in \Psi_j \tag{9}$$
$$\sum_{j \in N^+(i)} \sum_{\alpha' \in \Psi_j} y_{i\alpha j\alpha'} \leq u_{\alpha i} + s_{\alpha i}, \quad \forall i \in U, \forall \alpha \in \Psi_i \tag{10}$$
$$l_j + \sum_{\alpha \in \Psi_j} u_{\alpha j} + s_{\alpha j} \geq d_j TTR^{(n)}, \quad \forall j \in \Upsilon, \forall \alpha \in \Phi^{(n)} \tag{11}$$
$$\sum_{k \in A_\alpha} p_{\alpha k} u_{\alpha k} \leq c_\alpha TTR^{(n)} \left(1 - dr_{\alpha}^{(n)}\right), \ \forall \alpha \in \Phi^{(n)} \tag{12}$$
$$u_{\alpha j},\ l_{\alpha j},\ y_{i\alpha j\alpha'} \geq 0, \quad \forall i \in U, \forall j \in \Upsilon, \forall \alpha \in \Phi^{(n)} \tag{13}$$

The objective function minimizes total lost revenue due to disruption and corresponding GHG of the production and distribution of the mitigation plan (7), and maximizes the societal impact of the plan by giving priority to the alternative facilities for production with higher social performance (8). The societal impact (SI) is quantified on a 1–10 scale, with higher scores indicating full compliance. We refer readers to Fahimnia and Jabbarzadeh (2016) and Network (2023) for quantification of supplier social impact performance and Babazadeh et al. (2017) for methods to compute GHG values. We handle multi-objectives lexicographically; the model is solved only by minimizing the business impact of disruptions (lost revenue). Then, the optimal value of the first objective found is added as a constraint and the model is solved to minimize only the GHG impact of the mitigation plan. And finally, optimal values of lost revenue and GHG found in the first two iterations are added as a constraint and the model is solved by maximizing the societal impact of the mitigation plan. The rest of the constraints (9)–(13) are the same as the TTS model except using the given TTR value in (11) and (12).

3.3 *Variability quantification with Monte Carlo Simulation*

To take into account the stochasticity of the input parameters and quantify the variability of TTS and sustainable mitigation planning models, we follow the Monte Carlo simulation procedure. The method is illustrated in Algorithm 1 which is adapting the sequential sampling method (De Freitas, 2001) with a given confidence level β in estimating the TTS and mitigation planning model objectives functions.

Algorithm 1 VariabilityQuantification Algorithm(model(), ϵ, β, n, seed, stepsize)

```
Let obj_i be the objective function values of each model run
Let obj be the list of objective function values for all model runs
Seed ← seed
for i = 1 to n do
    Run model(seed) and obtain obj_i
    Update obj with obj_i
    Seed ← Uniform(Seed + 1, i× Seed)
end for
Compute confidence_interval(obj, β) and precision(obj)
if precision(obj) > ϵ then
    while precision(obj) > ϵ do
        for i = n + 1 to n + stepsize do
            Run model(seed) and obtain obj_i
            Update obj with obj_i
            Seed ← Uniform(Seed + 1, i× Seed)
        end for
        Compute confidence_interval(obj, β) and precision(obj)
    end while
end if
Return confidence_interval(obj, β)
```

4 A DEMONSTRATED EXAMPLE

The decision analytic pipeline in 1 is demonstrated using a selected part of the Irish pharmaceutical supply chain. Bill of material graph presented in Figure 2 is taken from the literature (Oztürk and Ornek (2010)) which indicates a supply chain with 20 items, 3 tires, 3 final products, and 15 factories (Figure 3) in which factory 3 is disrupted partially 25 % and factory 7 is fully disrupted. As the model in Section 3.2 works with a single TTR value, we got the maximum TTR of factories 3 and 7 as the conservative approach. Processing times for each item and alternative factories are generated randomly with a uniform distribution. The complete code and data for the demonstrated example can be found in Ozturk (2024). TTS and sustainable mitigation planning models were implemented in Python via Pyomo environment (Bynum et al. (2021)) and solved with CBC solver (Forrest and Lougee-Heimer (2014)) on a 64-bit laptop with an Intel Core Ultra 7 165H processor (1.40 GHz) and 16 GB RAM. The desired confidence level is considered to be 95 percent for each model as a stopping criterion of the sequential Monte Carlo simulation method.

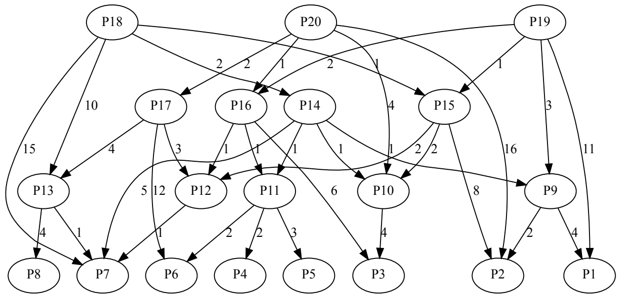

Fig. 2. Illustrative Bill of Material (BOM)

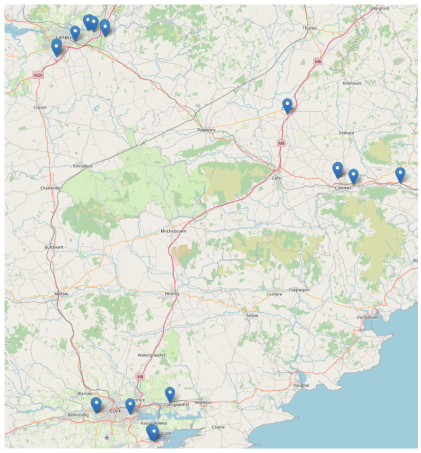

Fig. 3. Illustrative factory locations (Getreskilled (2024))

Objective Criteria	Lower Bound	Upper Bound
TTS (weeks)	4.81	6.61
Lost Revenue (€)	0	468150
PGHG (100 metric tons CO_2)	76.08	101.50
TGHG (100 metric tons CO_2)	1621.53	2380.24
Social Impact (10^4)	153.82	232.54

Table 1. Resulting pipeline objective criteria.

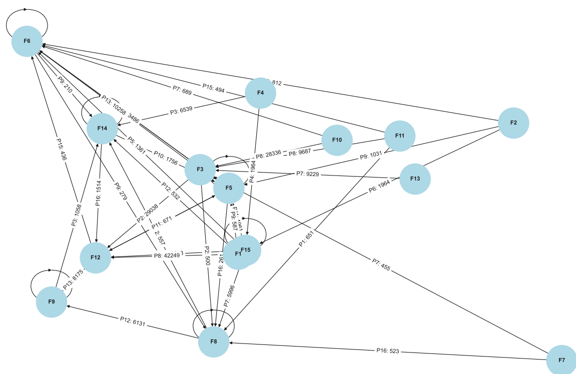

Fig. 4. Distribution plan in the mitigation plan

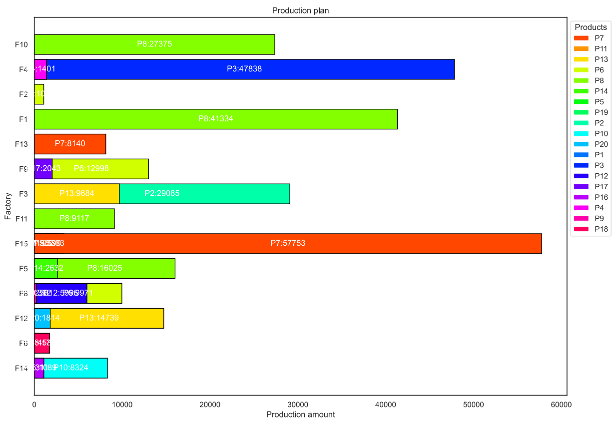

Fig. 5. Production plan in the mitigation plan

Table 1 summarizes 95% confidence interval values of objective function values for both models. Notably, TTS and mitigation planning models are converged to the mentioned confidence level through Monte Carlo Simulation procedure after 20 and 70 iterations, respectively. Distribution and production decisions of the mitigation planning model are shown in Figure 4 and 5 respectively.

5 COMPUTATIONAL RESULTS

In this section, we provide numerical experiments to demonstrate the scalability of the decision analytics pipeline for large and complex supply chain networks. We first summarize the methodology we follow for data acquisition and then describe the results of experiments.

5.1 Supply Chain Network Generator

Testing the efficiency of the developed pipeline requires a diverse set of supply chain networks which is impossible to access real data due to confidentiality. Therefore, we developed a supply chain network generator (SCNG) (Algorithm 2) to produce realistic instances. SCNG follows the reasoning in previously published papers (Öztürk and Ornek (2010) and Quetschlich et al. (2021)) and has three components, the first produces a BOM as an acyclic-directed graph with the desired depth (tiers), size, and complexity. In parallel, random facility locations worldwide are generated and the Haversin distances between them are computed. Finally, a mapping algorithm matches nodes in the BOM graph with facilities and generates inventory and demand levels, substitutes plants, and production capacities. As SCNG is polynomial, it is computationally very effective to create many instances in a short time. Details of SCNG as well as the code are publicly available through GitHub (Ozturk (2024).

5.2 Numerical experiments

As illustrated in Table 1, we generated different supply chain network instances starting from small (11 items, 9 factories, and 3 tires) to very large (105 items, 53 factories and 11 tiers) sizes. Multiple factories could be randomly disrupted within each instance. The average disruption rate of disrupted facilities is reported in Table 2. All instances achieve 95% confidence level in several minutes. The last two columns represent the solution time for TTS and mitigation planning models at the end of Monte Carlo simulation replications.

Algorithm 2 Supply Chain Network Generator (SCNG)

n: Number of items in the BOM, default $n \sim U(8, 20)$
`root`: Number of root items, default `root` $\sim U(2, n/2)$
`depth`: Maximum tier or depth of the BOM tree, default `depth` $= 3$
`max_parents`: Maximum number of parents an item might have, default `max_parents` $= 2$
`seed`: Random number seed for reproducibility, default `seed` $\sim U(0, 10000)$
`min_demand`: Minimum demand for final items (leaf nodes), default `min_demand` $= 10$
`max_demand`: Maximum demand for final items (leaf nodes), default `max_demand` $= 100$
`nb_locations`: Number of facility locations to be generated, default `nb_locations` $\sim U(n/2, n)$
`BOM` $\leftarrow$ `BOM_generator(n, root, depth, max_parents, min_demand, max_demand, seed)`
`Facilities` $\leftarrow$ `Facility_generator(nb_locations, seed)`
`SCN` $\leftarrow$ `Mapping(BOM, Facilities, seed, min_demand, max_demand)`
return `SCN`

Items	Tiers	Fact.	Ratio Disrupt. Fact.	Avg. Disrupt. Rate	TTS (s)	TTR (s)
11	3	9	0.39	0.43	4	10
16	4	10	0.16	0.58	4	11
19	3	11	0.39	0.62	5	11
19	4	12	0.32	0.49	19	47
20	4	14	0.29	0.40	5	11
26	5	18	0.14	0.76	6	14
26	6	23	0.21	0.62	7	16
29	6	22	0.23	0.57	9	20
32	5	26	0.11	0.41	9	20
38	5	27	0.19	0.44	10	21
44	5	33	0.15	0.77	17	33
62	9	32	0.11	0.74	22	41
63	5	46	0.21	0.67	43	76
65	12	59	0.27	0.68	177	292
65	8	47	0.20	0.51	45	71
68	7	52	0.14	0.58	52	83
72	6	49	0.17	0.61	70	104
74	8	53	0.20	0.55	67	107
87	7	65	0.17	0.55	166	271
91	9	47	0.23	0.68	203	271
92	5	77	0.23	0.49	159	221
93	10	85	0.18	0.61	363	552
93	9	46	0.12	0.73	77	121
93	7	87	0.22	0.52	285	418
95	8	89	0.26	0.60	423	653
95	7	80	0.17	0.69	234	334
97	8	92	0.30	0.57	349	546
97	10	56	0.26	0.54	93	129
102	8	53	0.28	0.67	280	382
105	11	53	0.21	0.59	240	321

Table 2. Numerical experiments

6 CONCLUSION

This paper proposes an innovative decision analytic pipeline for evaluating and enhancing supply chain resilience under disruptions. The main contributions of the pipeline include (1) an extended Time to Survive (TTS) linear programming model, which assesses a supply chain's ability to endure disruptions and allow alternative factories, partial and multiple disruptions, (2) a novel multi-objective sustainable mitigation planning linear programming model to be executed during the Time to Recover (TTR) that considers business, environmental and societal impacts of disruptions and (3) a Monte Carlo simulation to account for variability in supply chain parameters. The computational results confirm the scalability and reliability of the pipeline.The developed pipeline can be incorporated into a decision support system (DSS) and extended with situational awarenessand anomaly (risk) prediction and detection. Real-time data connection can enhance the capabilities of the DSS into a digital twin. Bayesian inference of TTR, critical node, and path analysis can be incorporated. A sensitivity analysis to understand the relative importance of input parameters would be worth investigating. Publicly available industrial data can be adapted for verifying the pipeline [1] and dynamic lead times can be incorporated. Additional ESGs such as renewable energy usage, and waste management can be included in the mitigation planning. Integrating the pipeline with existing ERP systems is envisaged as the biggest challenge in practice.

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