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Building organizational resilience in the face of multiple disruptions

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A B S T R A C T

The increasing number of natural and man-made hazards is forcing organizations to build resilience against numerous types of disruptions that threaten continuity of their business processes. This paper presents an integrated business continuity and disaster recovery planning (IBCDRP) model to build organizational resilience that can respond to multiple disruptive incidents, which may occur simultaneously or sequentially. This problem involves multiple objectives and accounts for inherent epistemic uncertainty in input data. A multi-objective mixed-integer robust possibilistic programming model is formulated, which accounts for sensitivity and feasibility robustness. The model aims to plan both internal and external resources with minimal resumption time, restoration time, and loss in the operating level of critical functions by making tradeoffs between required resources for continuity plans, recovery time, and the recovery point. A real case study in a furniture manufacturing company is conducted to demonstrate the performance and applicability of the proposed IBCDRP model. The results confirm the capability of the proposed model to improve organizational resilience. In addition, the proposed model demonstrates the interaction between the organizational resilience and required resources, particularly in respect to the total budget and external resources, which is necessary for developing continuity and recovery strategies.

1. Introduction

Organizations are increasingly realizing the importance of taking proactive approaches such as Integrated Business Continuity and Disaster Recovery Planning (IBCDRP) for protecting personnel lives, preserving reputation/brand, reducing financial losses, and continuous serving of products/services (Woodman and Musgrave, 2013). Continuity plans focus on resuming phase immediately after a disruption (i.e. initial recovery) while recovery plans cover the restoring phase after resumption (i.e. final recovery). Typically, there are alternative continuity and/or recovery plans for the same disruptive incidents with different resource requirements. IBCDRP can help managers to analyse different continuity and recovery plans for the effective use of limited resources and budget after disruption (Sahebjamnia et al., 2015). In this way, organizations will be able to keep their critical functions running within the predetermined maximum downtime after disruptions. As a result, an organization can transform itself into a *resilient organization* by the best allocation of available resources to continuity and recovery plans (Ates and Bititci, 2011; Boin and van Eeten, 2013; Llorens et al., 2013).

There has been a limited attention in the literature to developing IBCDRP decision models for providing organizational resilience. These include, for instance, the research by Bryson et al. (2002) who developed a mathematical model for the selection of the most suitable recovery plan in the context of organizational disaster management. Also, Sahebjamnia et al. (2015) demonstrated the capability of using Management Science/Operations Research (MS/OR) tools by developing an effective IBCDRP framework to deal with a single disruptive incident. However, the impact of multiple simultaneous or consecutive disruptions and the inherent uncertainty of the input parameters on the organizational resilience were neglected in their model. Despite limited work on developing IBCDRP models for building organizational resilience, many researchers have focused on the response and recovery planning for the society and urban areas in response to natural disasters in the context of disaster operations management (Galindo and Batta, 2013). Several scholars such as Altay and Green (2006), Galindo and Batta (2013), and Zobel and Khansa (2014) emphasized that the scholars should pay more attention to developing novel quantitative models in the field of organizational resilience. Building the resilient supply chains or urban areas requires development of special organizational processes and resources to guarantee resilience at the organizational level (Kamalahmadi and

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Parast, 2016). Recently, Annarelli and Nonino (2016) reviewed the organizational resilience and found out the extant literature is still far from a consensus on developing the organizational resilience. Developing organizational resilience measures as well as continuity and recovery plans for resuming and restoring of organization's critical functions at post-disaster are highlighted as two main gaps in the organizational resilience literature.

To address these gaps, this paper develops a novel IBCDRP model to cope with multiple disruptive incidents, which may occur simultaneously or sequentially. Also, a new resilience measure is developed to optimize the resuming and restoration times as well as the loss of operating level. Since each disruptive incident has its own characteristics that further limits accumulation of historical data for non-repetitive events, we would face with the epistemic uncertainty in input data (i.e. lack of knowledge about their exact values). Hence the model's parameters are formulated through the possibility theory in the form of linear fuzzy numbers using the experts' judgmental data (Pishvaee and Torabi, 2010). Subsequently, a multi-objective mixed integer possibilistic linear programming model is formulated to find an efficient resource allocation pattern among candidate continuity and recovery plans.

To solve the proposed model, a two-phase method is developed. In the first phase, it is converted to a single objective possibilistic mixed integer linear programming model by utilizing the weighted augmented ε-constraint method. Then, in the second phase, three tailored Robust Possibilistic Programming (RPP) approaches with different risk attitudes (i.e. Hard-Worst case RPP, Soft-Worst case RPP and Realistic RPP) are applied to find robust solutions. Finally, the proposed IBCDRP model is validated through application to a real case study in a manufacturing company. The main contributions of this paper can be outlined as follows:

- demonstrating the merits of Management Science/Operations Research (MS/OR) for measuring the organizational resilience;
- proposing a new IBCDRP model to select the most efficient and effective continuity and recovery plans through a novel resource allocation model;
- considering multiple disruptive incidents which might happen simultaneously or consecutively;
- incorporating three quantitative measures of resilience, i.e., loss of operating level, resumption time, and restoring time by extending the existing organizational resilience concepts;
- evaluating the applicability of the proposed model through implementation in a real case study.

The rest of the paper is organized as follows. The relevant literature is reviewed in Section 2. The proposed IBCDRP model for building resilient organization is formulated in Section 3. Section 4 presents the proposed two-phase solution approach along with a brief review of the weighted augmented ε-constraint method and RPP approaches. The proposed two-phase approach for developing an IBCDRP model is applied to an industrial case study in Section 5. Finally, Section 6 provides concluding remarks and directions for further research.

2. Literature review

Based on characteristics of the proposed IBCDRP, the most relevant literature is reviewed in this section in three different but related streams: organizational resilience, Business Continuity Management System (BCMS) and disaster operations management.

2.1. Organizational resilience

The concept of resilience has emerged in several fields to highlight the need to increase the continuity capability of any system against disruptive incidents including internal or external variations, changes, disturbances, disruptions, and surprises (Hollnagel et al., 2007). Following recent major disasters such as September 11 terrorist attacks, 2004 Tsunami in Asia, and 2009 earthquakes in Indonesia, resilience has gained the attention of academics and practitioners working in disaster operations management (Bhamra et al., 2011). Boin et al. (2010) outlined characteristics and challenges of a resilient supply chain as the key features of humanitarian relief chains. Pal et al. (2014) developed a conceptual framework to determine level of economic resilience of Swedish textile and clothing SMEs. To increase resilience of systems, scholars often focus on descriptive methods based on resilient principles such as robustness against initial loss, rapidity, flexibility, redundancy, adaptability, and dependency (Boin et al., 2010; Boin and McConnell, 2007; Boin and van Eeten, 2013; Pal et al., 2014; Pettit et al., 2013; Sheffi and Rice, 2005). Bhamra et al. (2011) reported that theory (Usman Ahmed et al., 2014), empirical case studies (Thun and Hoenig, 2011) and conceptual models (Filippini and Silva, 2014) are more applied than MS/OR methodologies among scholars in the organizational and supply chain resilience literature.

Bruneau and Reinhorn (2007) evaluated resilience of an organization based on the single resilience metric i.e., the disaster resilience triangle which depends on operating level loss and recovery time. Zobel (2010) provided both graphical and analytical approaches by considering the trade-offs between operating level loss and recovery time based on the Bruneau's resilience triangle. In another work, Zobel and Khansa (2014) quantified the resilience of a multi incidents situation using the concept of disaster resilience triangle. Sahebjamnia et al. (2015) developed a new framework for organizational resilience by controlling two resilience measures i.e., loss of resilience and recovery time objectives. They highlighted different research gaps and recommended future research including: i) considering simultaneous or consecutive multiple disruptive incidents over the planning horizon, ii) proposing new quantitative measures of resilience iii) demonstrating the capability of MS/OR tools in this area by developing new mathematical models for building organizational resilience and validating them using real case studies, iv) considering the inherent uncertainty in the model's parameters to find robust solutions, and v) using suitable uncertainty programming techniques such as fuzzy/possibilistic programming and robust possibilistic programming to cope with imprecise data. Indeed, this paper extends the model proposed by Sahebjamnia et al. (2015) in different ways as elaborated in Supplementary material S1.

Tang (2006) reviewed different methods in the literature of supply chain risk management and identified two major risk categories as disruption and operational risks. They emphasized that researchers should pay more attention on developing quantitative approaches for managing disruption risks. Mizgier et al. (2015) proposed a quantitative model to design a supply chain network considering two types of disruptions including idiosyncratic and systematic incidents. They considered direct and indirect impacts of disruption on an organization and its supply network. Wagner et al. (2017) analysed the impact of supply chain operational disruptions on organizations. Operational disruptions are internal or external incidents that could lead to failure of critical functions as a result of organization's resource loss. They explored the relationship between the business cycles and operational disruptions due to internal incidents (e.g. personnel disease, system failures and malfunctions) and supply chain incidents (e.g. sanctions, currency change, transportation mishaps, and intentional attacks). Furthermore, they highlighted different directions to enhance the understanding of operational disruptions such as modelling the impact of operational disruptions on organizations beyond the economical view point. Mizgier (2017) introduced the concept of global sensitivity analysis to aggregate risk in a multi-product supply chain network problem and used Monte Carlo simulation to analyse the impact of multiple consecutive disruptions on the network. He called for future research on interactions among multiple disruptions and their influence on the organization. In response to this call, we propose a new IBCDRP model, which considers the likelihood and impact of multiple simultaneous or consecutive disruptions. In addition, we assume that the impacts of disruptions on organizational resources are independent across disruptive incidents over the planning horizon. In practice, we would face with epistemic uncertainty about the likelihood and impact of disruptive incidents whose impreciseness is originated from the lack of knowledge regarding their exact values. In such cases, experts' judgmental data are often used for providing reasonable estimations for imprecise parameters, which are originated from their past experiences and professional opinions/feelings (Pishvaee and Torabi, 2010). Accordingly, we formulate the likelihood and impact of disruptive incidents through the possibility theory in the form of fuzzy numbers.

Based on the definition of resilience by International Organization for Standardization (ISO22301, 2012), an organization could be considered *resilient* if it is able to continue its critical functions at least in the Minimum Business Continuity Objective (MBCO) level within the Maximum Tolerable Period of Disruption (MTPD) after any disruption. In this way, we consider the trade-offs between the three quantitative factors, i.e., operating level loss, resumption time, and restoring (recovery) time. Notably, resumption time refers to the required time for initial recovery of disrupted functions to their at least MBCO level through BC plans, and the restoration time includes the required time for final recovery of disrupted functions to their normal level through recovery plans. Therefore, our IBCDRP model aims to build resilience in an organization so that: (i) the operating level of each disrupted critical function is increased to at least its MBCO level before its MTPD, (ii) the operating level of each disrupted critical function never falls below the respective MBCO level in the case of happening consecutive disruptive incidents, (iii) both restoration and resumption times of each critical function are decreased, and (v) the loss of resilience is minimized. To this end, a Multi-Objective Mixed Integer Possibilistic Linear Programming (MOMIPLP) model is developed to optimize the three measurable resilience factors i.e. the critical functions' loss of operating level, resumption and restoring times following disruptive incidents.

2.2. Business Continuity Management System

To plan business continuity and disaster recovery in BCMS, organizations frequently rely on two standards: ISO22301(2012) and BS2599-2(2007) developed by International Organization for Standardization and British Standards Institute, respectively. However, these standards only set out general requirements for setting up and managing effective BC/DR plans (Tammineedi, 2010). Despite numerous publications on developing BC/DR plans in BCMS context such as frameworks (Gibb and Buchanan, 2006; Järveläinen, 2013; Lin et al., 2012), guidelines (Sarkoni and Fariza, 2011; Sharp, 2008), success reports (Lokey, 2009; Smith, 2005), and patents (Mehrdad, 2011), the subject has received limited attention in the Management Science/Operations Research (MS/OR) field (Altay and Green, 2006; Galindo and Batta, 2013). Indeed, managers need to address specific features of BC/DR plan for implementing effective BCMS by prescriptive rather than descriptive approaches.

However, there is no unified BC/DR planning model in the literature addressing all required resources and their allocation for proactive development of appropriate BC/DR plans in an efficient and effective manner. More specifically, within the limited body of literature on application of MS/OR in BCMS, there is a gap in considering aforementioned issues when applying effective MS/OR techniques to IBCDRP (Millar et al., 2002; Sahebjamnia et al., 2011). To address this gap, we propose a new model for IBCDRP that can develop BC/DR plans addressing all required resources and their allocation to critical functions of organization.

2.3. Disaster operations management

Disaster operations management is a multi-disciplinary research field bringing together academics and practitioners from several disciplines such as urban administration, organizational crisis management, and supply chain disruption management. Altay and Green (2006) and Galindo and Batta (2013) presented a holistic literature review on disaster operations management and showed the deficiency of methodological direction for BC/DR planning in organizational (business) disaster management. There is a limited body of literature on developing decision models for business continuity and recovery planning. These include, for instance recovery of computer networks (Ambs et al., 2000), and selection of disaster recovery alternatives for organizational crisis management (Bryson et al., 2002). Millar et al. (2002) presented the advantage of MS/OR models as an appropriate tool for developing a disaster recovery plan. They emphasized that managers must consider different options/issues for effective planning and proposed a mathematical model to select a plan which maximizes the efficiency of the disaster recovery plan. Sahebjamnia et al. (2011) developed a mathematical programming model for disaster recovery plan problem by considering the business continuity planning characteristics. They considered *Recovery Time Objective (RTO)* and *Recovery Point Objective (RPO)* for each critical function based on Cervone's definition (Cervone, 2006). Although many researchers have addressed immediate response and recovery planning for supply chain management (Fujimoto and Park, 2014; Kumar and Havey, 2013) and humanitarian relief chains (Chakravarty, 2014; Heaslip et al., 2012), very little attention has been paid on developing an integrated MS/OR model of BC/DR planning and organizational disaster management. Bajgoric (2006) argued that continuity and recovery plans do not mark the start and end of plans after incidents for organizations. The IBCDRP model developed in this paper address this gap by joint development of BC/DR plans which specifies the end of continuity and start of recovery for each critical function of the organization.

3. Problem description

Herbane (2010) pointed out that organizations could protect and enhance their value through the implementation of an IBCDRP model. IBCDRP came out as a response to the need to resume and restore disrupted critical functions towards creating resilient organizations. Moreover, organizations' functions need various resources such as personnel (human resource), information and data, facilities and raw materials (ISO22301, 2012). In this manner, critical functions of an organization along with their required resources are the two main parts of an IBCDRP model. The model is developed to find efficient and effective resource allocation patterns among candidate continuity and recovery plans. In this way, selected continuity plans are invoked right after a disruptive incident (if needed) to increase the operating level of critical functions to their respective minimum business continuity objective levels within their maximum tolerable period of disruption (resumption phase of IBCDRP). Subsequently, the selected recovery plans are performed to rise the operating level of critical functions to their normal (100%) level (restoring phase).

We assume that each critical function (f) could be executed at several discrete modes (m). Each mode needs specific amount of resources and leads to a specific operating level (l_f^m) where κ_f is the number of possible executing modes for critical function f. Also, execution of a critical function f in mode m needs fixed amount of resource type r denoted by θ_{fr}^m. The first mode of a critical function f needs the least amount of resources which might lead to an operating level equal or lower than the lowest acceptable operating level (i.e., MBCO level) from a business continuity management viewpoint, while the mode κ_f leads the function to its normal (100%) operating level. In this way, a lower executing mode needs less resources than higher modes for each critical function.

When a disruptive incident (i) happens, a particular set of circumstances are changed and several causes can affect different resources. This situation could lead to a disruption and the organization may lose some of its resources partially or completely. Since both natural and man-made incidents are largely unpredictable, each disruptive incident i is characterized by two prominent parameters including the likelihood of occurrence (β^i) and the impact on resource r (e_{ir}) in terms of disrupted operating level. Furthermore, we take into account multiple disruptive incidents introduced by Zobel and Khansa (2014) as depicted in Fig. 1. In this figure, we assume that two disruptive incidents (e.g. an earthquake and a subsequent fire) strike at time t and ($t + T_1$) which decrease the operating level of a critical function f to $l_f^{1\prime}$ and $l_f^{1\prime\prime}$ respectively. Since the operating levels of the critical function f after these incidents (i.e. $l_f^{1\prime}$, and $l_f^{1\prime\prime}$) are lower than minimum business continuity objective, the first mode of the critical function f ($m = 1$) is activated. Similarly, the operating level of critical function f is increased to $l_f^{2\prime\prime\prime}$ at times t'' and t''' which belongs to the second mode ($m = 2$). Hence the mode of the critical function might be changed after incidents or resuming and restoring plans along the planning horizon.

According to the ISO terminology in regards to BCMS, we define Recovery Time Objective (RTO) for each critical function as the time following an incident within which the function should be resumed. Also, the Recovery Point Objective (RPO) is defined as the restored operating level that enables the function to be operated on resumption along the planning horizon (ISO22301, 2012). As shown in Fig. 1, the RPO at time *(t')* is increased to MBCO and the critical function is resumed. The restoring process is continued until the operating level of the critical function f is increased to its initial level before the disruptive incident at point T and operating level $l_f^{\kappa_f}$ under mode κ_f. However, the amount of required resources and time for resumption and restoring a function depends on the functions' modes. An IBCDRP is called effective when (a) the RTO of each disrupted function is less than or equal to its MTPD (γ_f), (b) the respective RPO is more than or equal to its MBCO (λ_f), and (c) the operating level of each disrupted critical function is increased to at least its MBCO level during the respective MTPD *(t''-t)*.

As shown in Fig. 1, to decrease the resumption or restoring time of critical functions, more resources need to be allocated to continuity or recovery plans, respectively. This is to ensure that total loss in operating level of critical functions will be decreased. On the other side, if more resources are allocated to keep the operating level of critical functions at predefined minimum level (maximum acceptable loss of operating level) after disruptive incidents, less resource will be available for recovering and restoring plans. This in turn will increase the restoration and resumption time. Hence there are obvious conflicts between loss of operating level, resumption and restoring times functions (Zobel and Khansa, 2014). To overcome this, the proposed IBCDRP model is developed to generate the Pareto set of compromise plans with different resource allocation patterns so that disaster managers can select the most preferred continuity and recovery plans.

3.1. Assumptions

The main characteristics and assumptions used in the formulation of IBCDRP model are as follows:

- a multi-period planning horizon with given length is considered to derive the detailed continuity and recovery plans in order to resume and restore disrupted functions;
- several disruptive incidents can occur simultaneously or consecutively along the planning horizon;
- simultaneous or consecutive disruptive incidents have not any interdependent effect on each other;
- each disruptive incident has its own effects which impact organizational resources and may disrupt a number of critical functions of the organization;
- the continuity and recovery plans are restricted to the organization's critical functions according to the BCM concepts and scope;
- the set of critical functions have already been identified through Business Impact Analysis (BIA) process;
- each critical function can be executed under several modes, each with known operating level and resource requirement;
- the MBCO and MTPD measures of each critical function have been defined through the BIA process;
- the RPO and RTO (i.e., the actual resumption level and time) for each critical function are obtained endogenously by the IBCDRP model whereby the associated MBCO and MTPD act as lower and upper bounds, respectively;
- there is a limited amount of each internal resource but the amount of external resources are unlimited;
- the remaining internal resources after a disruptive incident are available for resumption and restoring the organizations' critical functions. Furthermore, the amount of resources will be revived along the planning horizon;

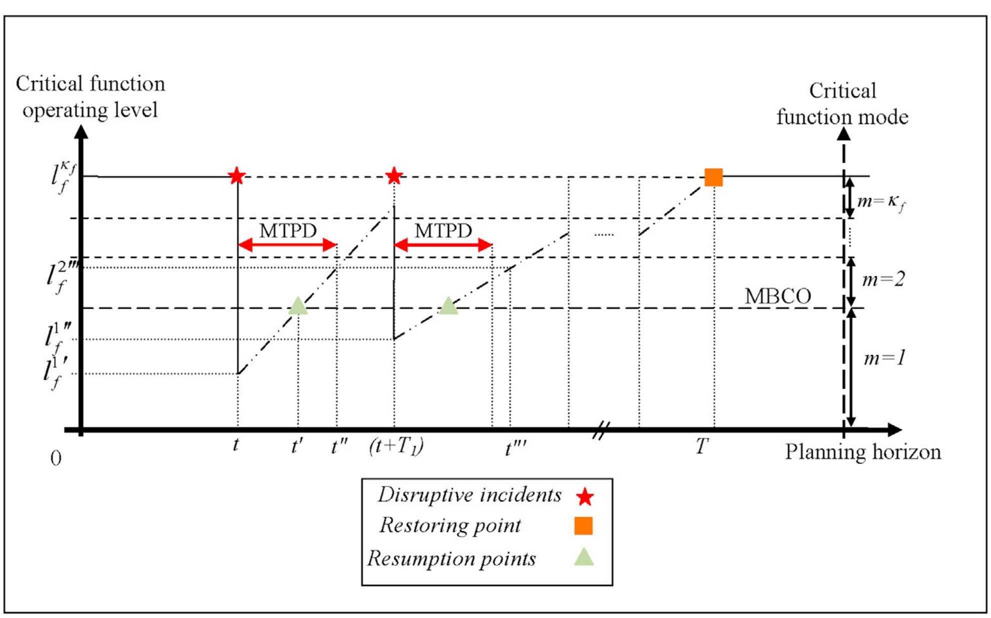


Fig. 1. Multiple disruptive incidents paradigm for a critical function.

- resumption and restoration of each critical function requires allocation of some pre-determined resources according to selected executing modes;
- Since the organization's resources are limited and may decrease after a disruption, disaster managers prefer to resume and restore the disrupted functions based on their relative importance. As such, we use profit ratio as the relative importance of each critical function. The profit ratios of critical functions were determined based on the net profit of the company's key products (see Appendix I);
- because of unpredictable nature of disruptive incidents, their likelihoods and impacts are tainted with epistemic uncertainty; which are then represented as triangular fuzzy numbers (TFNs);
- due to impreciseness and/or unavailability of required data over the planning horizon, significant parameters including the amount of required resources for critical functions at each mode, the total budget of organization, the unit cost of each external resource, and profit ratio of each critical function are formulated as imprecise/possibilistic data in the form of TFNs.

Indices:	
i	Index of disruptive incidents (i = 1, …,I)
f	Index of critical functions (f = 1, …,F)
l	Index of operating levels (l = 1, …,L)
m	Index of critical functions' modes
r	Index of resources (r = 1, …,R)
t,t'	Index of time (t = 1, …,T)
Parameters:	
γ_f	The MTPD for critical function f
λ_f	The MBCO for critical function f
κ_f	Number of possible modes for function f
l_f^m	Operating level of critical function f in mode m
θ_r^I	Total amount of internal resource type r during the planning horizon
$\tilde{\theta}_{fr}^m$	The amount of required resource type r for critical function f in mode m
$\tilde{\beta}^i$	Likelihood of disruptive incident i
$\tilde{e}_{ir}^t$	The impact of disruptive incident i on resource r at time t
$\tilde{\omega}_f$	Profit rate of the critical function f
$\tilde{B}$	Total budget for acquiring external resources
$\tilde{C}_r^E$	The unit cost of external resource r
Variables:	
x_f^{mt}	1, if the critical function f at time t is operating in mode m; 0, otherwise;
θ_r^{Et}	The amount of external resource r utilized at time t
ϖ_f^t	The recovery level of critical function f at time t
ϑ_f	The restoration time (RTO) of critical function f

3.2. Problem formulation

In practice, the critical input parameters of an IBCDRP model, i.e., the likelihood and impact of each disruptive incident, the amount of required resources for each critical function at each mode, the total budget of organization for developing continuity and recovery plans and profit ratio of critical functions are tainted with a high epistemic uncertainty due to lack of knowledge about their precise values (Pishvaee and Torabi, 2010; Sahebjamnia et al., 2016; Tofighi et al., 2016). Hence, we present a new IBCDRP model to guarantee the continuity and recovery of an organization's operations. The proposed MOMIPLP model for the IBCDRP problem under consideration is as follows:

$$Min\, f_1 = \sum_{f=1}^{F}\sum_{t=1}^{T}\tilde{\omega}_f\cdot\left(l_f^{\kappa_f} - \varpi_f^t\right) \tag{1}$$

$$Max\, f_2 = \sum_{f=1}^{F}\sum_{m \mid l_f^m \geq \lambda_f}\sum_{t=1}^{\gamma_f}\tilde{\omega}_f\cdot t\cdot x_f^{mt} \tag{2}$$

$$Min\, f_3 = \sum_{f=1}^{F}\tilde{\omega}_f\vartheta_f \tag{3}$$

Such that:

$$\sum_{m=1}^{\kappa_f} x_f^{mt} = 1 \quad \forall f,t \tag{4}$$

$$\sum_{m=1}^{\kappa_f} l_f^m\cdot x_f^{mt} \geq \lambda_f \quad \forall f, t \geq \gamma_f \tag{5}$$

$$\sum_{m=1}^{\kappa_f} l_f^m.x_f^{mt} - \sum_{m=1}^{\kappa_f} l_f^m.x_f^{m1} \geq 0 \qquad \forall f,t \tag{6}$$

$$\sum_{t=1}^{T}\sum_{r=1}^{R}\theta_r^{Et}.\tilde{C}_r^E \leq \tilde{B} \tag{7}$$

$$\sum_{f=1}^{F}\sum_{m=1}^{\kappa_f}\tilde{\theta}_{fr}^m.x_f^{m1} \leq \theta_r^I - \sum_{i=1}^{I}\tilde{\beta}^i.\tilde{e}_{ir}^1 + \theta_r^{E1} \qquad \forall r \tag{8}$$

$$\sum_{f=1}^{F}\sum_{m=1}^{\kappa_f} x_f^{mt}\cdot\tilde{\theta}_{fr}^m \leq Max\left\{0, \sum_{f=1}^{F}\tilde{\theta}_{fr}^{\kappa_f} - \sum_{i=1}^{I}\tilde{\beta}^i\cdot\sum_{t'=1}^{t}\tilde{e}_{ir}^{t'-1}\right\} + \theta_r^{Et} \quad \forall r, t \geq 2 \tag{9}$$

$$\sum_{m=1}^{\kappa_f} l_f^m\cdot x_f^{mt} \geq \varpi_f^t \quad \forall f,t \tag{10}$$

$$\left(T - \sum_{t=1}^{T} x_f^{\kappa_f t}\right) \leq \vartheta_f \quad \forall f \tag{11}$$

$$x_f^{mt} \in \{0,1\} \quad \forall f,m,t \tag{12}$$

$$\varpi_f^t, \vartheta_f, \theta_r^{Et} \geq 0 \quad \forall f,r,t \tag{13}$$

Objective function (1) minimizes the weighted sum of critical functions' loss of operating level during the IBCDRP time horizon. Since multiple disruptions might happen during the planning horizon, equation (2) aims to minimize the resumption time by maximizing the number of periods following a disruption during which, the operating level of critical function is more than MBCO. Objective function (3) minimizes the weighted sum of restoring times following disruptive incidents. While equation (11) restricts the RTOs based on the critical functions' modes, equation (3) forces to decrease ϑ_f as decreasing ϑ_f leads the critical function $(\sum_{t=1}^{T} x_f^{\kappa_f t})$ to return to normal situation as soon as possible. The proposed multi-objective model of IBCDRP helps the decision makers when choosing the final solution by allowing trade-offs among the three resilience quantitative measures. Constraints (4) warrant that only one mode is assigned to each critical function at any given time. Constraint (5) ensures that the operating level of the selected mode for each critical function after its MTPD is greater than respective MBCO. Constraint (6) guarantees that the operating level of each critical function does not fall below its initial operating level during the IBCDRP planning horizon. As shown in Fig. 1, this constraint ensures the business continuity in the event of multiple disruptive incidents. Constraint (7) sets the budget limitation for provision of required external resources during the IBCDRP planning horizon. Disruptive incidents have their own effects, which impact organizational resources. Decreasing organizational resources (such as human recourse, facility and equipment) can disrupt a number of critical functions of the organization. In this manner, constraints (8) make sure that the amounts of required resources are less than accessible (remaining) internal and external resources in the first period after disruptive incidents. Constraint (9) guarantees that the required resources for the active mode of critical functions during IBCDRP time horizon do not exceed the available internal and external resources while accounting for the expected value of capacity losses affected by possible (multiple) disruptive incidents. Constraints (10) determine the operating level of the selected mode for the critical functions in each time. Constraints (11) specify the restoration time of the critical functions. Finally, Constraints (12) and (13) enforce the binary and non-negativity restrictions on corresponding decision variables. The resulting model is a MILP model with $T(2R+F)+F$ continuous variables and $\sum_f (F \times \kappa_f \times T)$ binary variables. The number of constraints is $4FT+F+RT-\sum_{f=1}^{F} F\cdot\gamma_f$, excluding constraints (12) and (13).

The proposed IBCDRP formulation is explained further using an illustrative example. Assume that an organization with one critical function (*f*) and three executing modes for each critical function as a percentage of normal operating level, i.e., 50%, 70%, and 100%. If a disrupted critical function is to be continued in the first mode with 50% of normal operating level, at least 50 units of its required resources should be available. Likewise, at least 70 and 100 units of required resources should be accessible to continue a disrupted critical function in the second and third mode. Let's assume that three disruptive incidents (D1, D2, and D3) strike at time *2* and 5, which decrease the operating level of a critical function *f* as reported in Appendix II. Let θ_r^{Et} to be zero along the planning horizon and MBCO and MTPD are $\lambda_f = 70$ and $\gamma_f = 6$ respectively. According to equation (8) at the first period, 100 unit of resource is available (no disruptive incident happened and impact is zero $\sum_{i=1}^{I}\beta^i\cdot e_{ir}^1 = 0$). Therefore the critical function can operate in mode 3 ($x_f^{31} = 1$).When $x_f^{31} = 1$ then objective function (1) and constraint (10) set operating level to 50 ($\varpi_f^1 = 100$). At time 2, disruptive event D1 happens with impact 50 units of resource. Based on equation (9), the available resource decrease to 50 unit ($\boldsymbol{Max}\{0, \sum_{f=1}^{F}\tilde{\theta}_{fr}^{\kappa_f} - \sum_{i=1}^{I}\tilde{\beta}^i\cdot\sum_{t'=1}^{t}\tilde{e}_{ir}^{t-1}\} = \boldsymbol{Max}\{0, 100-50\} = 50$) and the critical function mode is changed to 1 ($x_f^{12} = 1$). When $x_f^{12} = 1$, objective function (1) and constraint (10) set operating level to 50 ($\varpi_f^2 = 50$). Although in times 3 and 4 no disruptive incident happens, the impact of D1 is still there. In this manner, the right hand side of equation (9) restricts the available resource as 70 and 95 for time 3 and 4 respectively. Similarly $x_f^{23} = 1$, $x_f^{24} = 1$, $\varpi_f^3 = 70$, and $\varpi_f^4 = 70$. At time 5, two disruptive incidents D2 and D3 happen while the impact of D1 is extricated. Equation (9) restricts ($\boldsymbol{Max}\{0, \sum_{f=1}^{F}\tilde{\theta}_{fr}^{\kappa_f} - \sum_{i=1}^{I}\tilde{\beta}^i\cdot\sum_{t'=1}^{t}\tilde{e}_{ir}^{t-1}\} = \boldsymbol{Max}\{0, 100-20-20\} = 60$) the available resource such that the mode of critical function *f* is changed from 2 ($x_f^{24} = 1$) to 1 ($x_f^{15} = 1$). While objective function (1) aims to increase the operating level, equation (10) restricts it to 50 ($l_f^1\cdot x_f^{35} + l_f^2\cdot x_f^{35} + l_f^3\cdot x_f^{35} = 50\times 1 + 70\times 0 + 100\times 0 = 50 \geq \varpi_f^5$). Finally at time 6, the impacts of disruptive incidents decrease approaching zero and the critical function mode change to 3 with operating level 100. Objective function (3) and Equation (11) determine the RTO of the critical function *f*. While objective function (3) tries to minimize the RTO, constraint (11) restrict the RTO with executing mode of critical function. In this example, critical function *f* is restored at the end of time 5. According to constraint (11), just at time 6 the critical function mode *f* is changed to 3 (the highest mode that shows restoration of *f*). So, equation (11) restricts the RTO as 5 ($(T - \sum_{t=1}^{T} x_f^{\kappa_f t} + 1) = (6-1) \leq \vartheta_f$) indicates that *f* can be back to normal situation after 5 periods. When objective function (3) aims to minimize the RTO, objective function (2) maximizes the number of times that the operating level of critical function is higher than MBCO. In this example at three times i.e. 3, 4, and 6 the operating level of the *f* is increased upper than MBCO.

4. Solution methodology

To cope with epistemic uncertainty and multiple objectives in the developed possibilistic model, a two phase approach is proposed. First, the weighted augmented ε-constraint method (Esmaili et al., 2011) is applied to convert the original multi-objective model into its equivalent single objective problem. Then, three variants of robust possibilistic programming models employing different risk attitudes are used to cope with imprecise/possibilistic parameters.

4.1. Weighted augmented ε-constraint method

In multi-objective programming, the concept of optimality is replaced with efficiency in order to find the most preferred compromise solution. The efficient solution in multi-objective programming is defined as a solution that cannot be improved in one objective function without deteriorating at least one other objective function (Cakici et al., 2011; Cao et al., 2014). Several methods have been developed in the literature to solve the multi-objective programming (MOP) models (e.g. Weighted Sum Method (WSM), goal programming and ε-constraint method). According to the literature of MOP, WSM is not appropriate to estimate the Pareto front (i.e. the set of non-dominated solutions) as it cannot guarantee finding an efficient solution or reaching to a new efficient solution in each run of the equivalent single-objective program (SOP). The ε-constraint method is another well-known technique to solve multi-objective programs. It keeps the main or first objective function and adds the others as constraints to the feasible solution space (Pieragostini et al., 2012). Nevertheless, the ε-constraint method has some disadvantages as well (see Mavrotas, 2009 for details). For example, this method does not guarantee the efficiency of the obtained solutions and may reach to weakly efficient solutions. Various variants of ε-constraint method have been proposed in the literature, trying to improve its presentation or to tune it for particular problems (Behnamian et al., 2009; Fazlollahi et al., 2012; Khalili-Damghani et al., 2013; Liu and Papageorgiou, 2013; Mavrotas and Florios, 2013; Olivares-Benitez et al., 2013; Soysal et al., 2014). In this paper, we adopt the weighted augmented ε-constraint method. This method not only guarantees the efficiency of the yielded solution in each run, but also considers the relative importance of each objective function explicitly in the related SOP (Esmaili et al., 2011). The method is implemented as follows:

Consider an MOP with p objective functions of $f_p(x)$, $p = 1, \ldots, P$, subject to $x \in S$, where x is the vector of decision variables and S is the feasible solution space of original MOP. Without loss of generality, we assume that all objective functions are to be minimized. The weighted augmented ε-constraint method is formulated as follows:

$$Min\ F = f_1(x) + r_1 \sum_{p=2}^{P} \frac{\alpha_p s_p}{r_p} \tag{14}$$

$$s.t.\ f_p(x) = \varepsilon_p + s_p \quad \forall p \geq 2 \tag{15}$$

$$x \in S, s_p \in R^+, \alpha_p = \frac{w_p}{w_1} \tag{16}$$

In order to properly apply the ε-constraint method, we need to know the range of at least (*P-1*) objective functions for generating different ε vectors through constructing the pay-off table. To ensure that resultant solutions are Pareto optimal, the lexicographic optimization (Mavrotas, 2009) is used for constructing the pay-off table. Moreover, the decision maker needs to know the relative importance of the objective functions (w_p) to select the most preferred efficient solution from among the obtained Pareto-optimal solutions. Analytic Hierarchy Process (AHP) is applied to calculate the weights of objective functions (Parthiban and Abdul Zubar, 2013).

Mavrotas (2009) proved that by adding the slack variables ($s_p \in R^+$) to constraints (15) and using them as the augmented term in the objective function (14), the solutions found by the weighted augmented ε-constraint approach will be definitely efficient. Finally, to avoid scaling problem, the slack variables are normalized to the main objective function (f_1) by using r_p values as the ranges of objective functions.

4.2. Robust possibilistic programming

For dealing with epistemic uncertainty of the critical parameters, we adopted three tailored variants of the Robust Possibilistic Programming

(RPP) approach proposed by Pishvaee et al. (2012).

To guarantee robustness against such uncertainties, two main concepts, i.e., *sensitivity (optimality) robustness* and *feasibility robustness* must be addressed at the same time within a mathematical programming framework (Hasani et al., 2011; Torabi and Amiri, 2011). To this end, several robust programming approaches have been developed by scholars for example robust convex optimization (Ben-Tal et al., 2011), scenario-based robust programming (Klibi et al., 2010) and RPP (Fan et al., 2013; Pishvaee et al., 2012). Pishvaee et al. (2012) classified RPP approaches based on sensitivity and feasibility robustness into three categories: (i) Hard Worst case RPP (HW-RPP), (ii) Soft Worst case RPP (SW-RPP) and (iii) Realistic RPP (R-RPP). HW-RPP method ensures that the objective function never violates the obtained value of the solved mathematical programming model. In the meantime, SW-RPP does not aim to satisfy the whole constraints in their extreme worst case. Finally, The R-RPP tries to trade-off between sensitivity robustness and feasibility robustness cooperatively (Ben-Tal et al., 2009; Beyer and Sendhoff, 2007; Pishvaee et al., 2012).

To simplify the RPP for IBCDRP formulation, we propose a unified version of the model as follow:

$$\mathrm{M}inF = \tilde{c}y + G \tag{17}$$

$$\text{s.t.} f_p(x) = \varepsilon_p + s_p \tag{18}$$

$$Ax \le b \tag{19}$$

$$\tilde{N}x + Sy \ge \tilde{q} \tag{20}$$

$$Uy \ge \tilde{d} \tag{21}$$

where vector x and y denote the binary and continuous variables, respectively. The second term of the objective function (G) is equal to $\left(r_1 \sum_{p=2}^{P} \frac{\alpha_p s_p}{r_p}\right)$. Constraints (19)–(21) correspond to constraints (4–6), (9–11), and (7) respectively. Due to inherent uncertainty of disruptive incidents and dynamic nature of real world problems,$\tilde{c}$,$\tilde{N}$,$\tilde{q}$, and $\tilde{d}$ are considered as imprecise data. Accordingly, we adopted possibility distributions for modelling these parameters in the form of triangular fuzzy numbers such as $\tilde{\eta} = (\eta_{(1)}, \eta_{(2)}, \eta_{(3)})$. Moreover, $\tilde{q}$ and $\tilde{d}$ are obtained by multiplying two fuzzy numbers $\tilde{\beta}^i$ and $\tilde{e}^t_{ir}$ (i.e. disruptive incidents likelihood ($\tilde{\beta}^i$) and impact ($\tilde{e}^t_{ir}$)). Now, we develop three variants of RPP models including the HW-RPP, SW-RPP, and R-RPP which can help decision makers (DMs) to develop different IBCDRP models to keep the continuity of the business under different preferences from the best to worst. Incidentally, Wang and Lin (2006) and Sasikumar and Haq (2010) used this approach for partner selection and network design in supply chain management.

4.2.1. Hard worst case robust possibilistic programming (HW-RPP)

In HW-RPP, the final solution must be feasible in all possible situations (feasibility robustness). So, we try to minimize the objective function under the worst case of all possibilistic constraints (worst real situation). Accordingly, the HW-RPP model can be formulated as follows:

$$\text{Min } F_{HW-RPP} = F^+ \tag{22}$$

$$\text{s.t.} f_p(x) = \varepsilon_p + s_p \tag{23}$$

$$Ax \le b \tag{24}$$

$$Sy \ge \sup(\tilde{q}) - \inf(\tilde{N})x \tag{25}$$

$$Uy \ge \sup(\tilde{d}) \tag{26}$$

where F^+ indicates the worst possible value of F and can be defined as $F^+ = c_{(1)}y + G$. Since it is assumed that the imprecise parameters have been modelled as triangular fuzzy numbers, equations (25) and (26) are reformulated as follows:

$$Sy \ge q_{(3)} - N_{(1)} \cdot x \tag{27}$$

$$Uy \ge d_{(3)} \tag{28}$$

It is clear that the HW-RPP only uses extreme values of constraints to guarantee the feasibility robustness under all possible situations. In this manner, the decision makers only need to determine the pessimistic values instead of possibility distribution for the likelihood and impact of disruptive incidents. Although, it may not be common that all disruptive incidents occur at highest intensity, in cases such as earthquake, flood, and war it is possible that corresponding parameters take their worst values.

4.2.2. Soft worst case robust possibilistic programming (SW-RPP)

In SW-RPP approach, the feasibility robustness is considered in a more realistic way compared to HW-RPP. In this approach, the sum of the objective values and the penalty of constraints' violations is minimized. To cope with imprecise parameters in the possibilistic constraints (20) and (21), we use necessity measure to form a possibilistic chance constrained programming model (Liu and Iwamura, 1998; Pishvaee et al., 2012). Accordingly, the SW-RPP for IBCDRP model can be formulated as follows:

$$\begin{aligned} Min\, F_{SW-RPP} = F^+ + \delta\Big(\big[q_{(3)} - (1-\alpha)\cdot q_{(2)} - \alpha\cdot q_{(3)}\big] - \big[N_{(1)} - (1-\alpha)N_{(2)} \\ - \alpha N_{(1)}\big]x\Big) + \varphi\big(\big[d_{(3)} - (1-\alpha)d_{(2)} - \alpha d_{(3)}\big] \end{aligned} \tag{29}$$

$$\text{s.t.} f_p(x) = \varepsilon_p + s_p \tag{30}$$

$$Ax \le b \tag{31}$$

$$Nec\big(\tilde{N}x + Sy \ge \tilde{q}\big) \ge \alpha \tag{32}$$

$$Nec\big(Uy \ge \tilde{d}\big) \ge \alpha \tag{33}$$

The first term of the objective function (29) minimizes the worst possible value of initial objective function similar to HW-RPP formulation. Also, the second term determines the confidence level of each possibilistic chance constraint (32) and (33). δ and φ denote the penalty rates for possible violation of possibilistic constraints. Meanwhile, $[q_{(3)} - (1-\alpha)\cdot q_{(2)} - \alpha . q_{(3)}]$ and $[d_{(3)} - (1-\alpha)d_{(2)} - \alpha d_{(3)}]$ determine the distance between the worst case value and the used value of imprecise parameters in the chance constraints.

Let us now extract the equivalent constraints for (32) and (33). Inuiguchi and Ramik (2000) defined the necessity (*Nec*) measure as the degree of certainty regarding the extent at which Sy and Uy are not smaller than $\tilde{q} - \tilde{N}x$ and $\tilde{d}$ respectively. In other words, it means that $Nec(Sy \ge \tilde{q} - \tilde{N}x) = 1 - \sup\{\mu_Q(q) | q - Nx > Sy\}$. According to Inuiguchi and Ramík (2000), the possibilistic chance constraint (32) and (33) can be rewritten as follow:

$$Nec\big(Sy \ge \tilde{q} - \tilde{N}x\big) = \begin{cases} 1 & Sy \ge q_{(3)} - N_{(1)}x \\ \dfrac{Sy - q_{(2)} - N_{(2)}x}{q_{(3)} - N_{(2)}x - q_{(2)} + N_{(1)}x} & q_{(2)} - N_{(1)}x \le Sy < q_{(3)} - N_{(2)}x \\ 0 & q_{(2)} - N_{(2)}x > Sy \end{cases} \tag{34}$$

$$Nec\left(Uy \geq \tilde{d}\right) = \begin{cases} 1 & Uy \geq d_{(3)} \\ \dfrac{Uy - d_{(2)}}{d_{(3)} - d_{(2)}} & d_{(2)} \leq Uy < d_{(3)} \\ 0 & d_{(2)} > Uy \end{cases} \tag{35}$$

Accordingly, based on (34) and (35) with confidence level (α) more than or equal to 0.5 (see also Appendix III), constraints (32) and (33) can be replaced by equations (36) and (37) as follow (Inuiguchi and Ramík, 2000; Pishvaee et al., 2012):

$$Sy \geq \left[(1-\alpha).q_{(2)} + \alpha.q_{(3)}\right] - \left[(1-\alpha).N_{(2)} + \alpha.N_{(1)}\right]x \tag{36}$$

$$Uy \geq (1-\alpha)d_{(2)} + \alpha d_{(3)} \tag{37}$$

Noticeably, SW-RPP approach does not satisfy all constraints at their extreme worst case. In this method, both optimally and feasibility robustness are considered jointly. In this paper, we added the violation degree of chance constraints to the objective function with penalty rates δ and φ. Since these conditions are extracted from constraints (8) and (9) of IBCDRP model, we can determine these values according to the risk appetite and main goals of BCM in an organization. For example, greater penalty rate leads to lower violation degree, higher feasibility robustness, and increased capability of organizations to cope with disruptive incidents.

4.2.3. Realistic robust possibilistic programming (R-RPP)

R-RPP aims to guarantee the optimality and feasibility of the obtained solution under unstable situations by utilizing feasibility and optimally robustness concepts. Feasibility robustness minimizes the violation degree of constraints and optimally robustness minimizes the deviation of the objective function in presence of uncertain parameters. To doing so, R-RPP approach minimizes the deviation of objective and the violation degree of uncertain constraints as objective function simultaneously. Thus the R-RPP approach for IBCDRP model can be formulated as follows:

$$\begin{aligned} Min\ F_{R-RPP} = {} & E(c).y + G + \chi\cdot\left(F^{+} - F^{-}\right) + \delta\cdot\left(\left[q_{(3)} - (1-\alpha).q_{(2)} - \alpha.q_{(3)}\right]\right. \\ & + \varphi\left(\left[d_{(3)} - (1-\alpha)d_{(2)} - \alpha d_{(3)}\right] - \left[N_{(3)} - (1-\alpha)N_{(2)}\right.\right. \\ & \left.\left. - \alpha N_{(3)}\right]x\right) \end{aligned} \tag{38}$$

$$\text{s.t.} f_p(x) = \varepsilon_p + s_p \tag{39}$$

$$Ax \leq b \tag{40}$$

$$Sy \geq \left[(1-\alpha).q_{(2)} + \alpha.q_{(3)}\right] - \left[(1-\alpha).N_{(2)} + \alpha.N_{(3)}\right]x \tag{41}$$

$$Uy \geq (1-\alpha)d_{(2)} + \alpha d_{(3)} \tag{42}$$

The first term of the objective function (38) minimizes the initial objective function F by considering the expected value of $\tilde{c}$. According to Heilpern (1992), the expected value of fuzzy number $\tilde{c}$ is defined as (43). The second term $(F^{+} - F^{-})$, is the possible deviation of the objective function F between the two extreme possible values of F. As mentioned previously, F^{+} is the worst possible value of F and F^{-} is the best possible value of F and can be determined as $F^{-} = c_{(3)}y + G$. Similar to the SW-RPP, the violation degree of the uncertain constraints i.e. (41) and (42) are added to the objective function. In addition, Constraints (20) and (21) are replaced by (41) and (42).

$$\begin{aligned} & E^{+}(\tilde{c}) = c_{(2)} + \textstyle\int_{c_{(2)}}^{c_{(3)}} \mu_{\tilde{c}}(x)dx \\ & E^{-}(\tilde{c}) = c_{(2)} - \textstyle\int_{c_{(1)}}^{c_{(2)}} \mu_{\tilde{c}}(x)dx \\ & EV(\tilde{c}) = \left(\frac{E^{+}(\tilde{c}) + E^{-}(\tilde{c})}{4}\right) = \left(\frac{c_1 + 2c_2 + c_3}{4}\right) \end{aligned} \tag{43}$$

4.3. Solution procedure

Our proposed solution procedure can be summarized as follows:

Step 1: Calculate the weights of objective functions through AHP or other weighing methods. Noteworthy, if the certainty level of manager's opinions is low, Fuzzy AHP or other fuzzy MADM approaches might be more useful than the classic AHP;
Step 2: Generate ε-vectors for *(P-1)* objective functions (i.e. f_2 and f_3). To this end, consider the extreme points of imprecise parameters in possibilistic constraints to guarantee the feasibility of obtained solution in any situation. Then, use the lexicographic optimization to calculate the upper bounds $(\overline{f}_p, p = 2, 3)$ and lower bounds $(\underline{f}_p, p = 2, 3)$ of objective functions. Finally, divide the range of each objective function into a number of grid points ($k = 2, \ldots, K$).
Step 3: Set $k = 1$ and find the following solutions while $k \leq K$:

- HW-RPP (F^{HW-RPP}): Formulations (22)–(24) and (27)–(28)
- SW-RPP (F^{SW-RPP}): Formulations (29)–(31) and (36)–(37)
- R-RPP (F^{R-RPP}): Formulations (38)–(42)

5. Case study

To evaluate the proposed IBCDRP model and the solution approach, we applied them to a real case study. Performance of the proposed IBCDRP model is demonstrated during a 30-days period. Then, the results are analysed and evaluated by implementing the proposed plan in a three month period.

5.1. Outline of the case study

The case company is a furniture manufacturer who produces different types of furniture such as kid's furniture, bed and sofa. The company is ISO9000/2008 accredited. A consulting team was formed involving three members of the board, an executive manager, four experts of disaster operations management, and three academics. We held various meetings in each step of the proposed solution procedure to analyse the gathered real data. Also, for some meetings, other experts were invited from different departments of the organization as required. To obtain the primary data, each meeting was held in two sub-sessions. In the first sub-session, we explained our approach, the goals of the meeting, and the results of previous meetings. Then, in the second sub-session, we utilized Delphi method to gather required data. To test the concordance of the results, Kendall's Coefficient of Concordance W was calculated for each meeting (Field, 2005). Since the number of members of the meetings was more than 10, the agreement level of W was set to 0.75.

An expert-based BIA methodology developed in (Torabi et al., 2014) has been used to identify critical functions and main resources of the company. To this end, we asked the consulting team to identify major departments. As a result, finance, product design, marketing and sales, customer relationship, production and production planning departments were selected for the study. Subsequently, we conducted several meetings with the consulting team and five representative experts from selected departments who were introduced by the departments' managers; to gather required information. To determine critical function(s) in each department, the relationships between nine criteria (see Supplementary material S.2) were evaluated by consulting team (including sixteen experts). First, the initial direct influence matrix of criteria (Supplementary material S.3) was formed to consider the correlation among criteria through DEMATEL (see more details about DEMATEL technique in Torabi et al. (2014)). Second, the value of each function in respect to each criterion was determined by the consulting team and representative experts. The well-known ANP method (Torabi et al., 2014) was finally used to rank the functions and to recognize the critical ones at each department. Then, we asked managers of each department for recognizing the main resources of their critical function(s). In doing so, the consulting team recognized four types of resources as the main resources consisting of human resources, equipment, facilities, and raw material. Then, the related information were gathered through the work sheet presented in Supplementary material S.4.

We proposed three executing modes to the consulting team including the low, medium and high operating levels for each critical function as a percentage of normal operating level, i.e., 40%, 65%, and 100% respectively. To simplify the case study presentation, the amounts of resources were normalized in the range of one to hundred units (i.e. the amount of each resource required for each operation is divided by the total amount of available resource and then multiplied by hundred). For instance, if a disrupted critical function is to be continued in the low mode with 40% of normal operating level, around 40 out of 100 units of its required resources should be available. Likewise, around 65 units of required resources should be accessible to continue a disrupted critical function in the medium mode with 65% of normal operating level. Information regarding the critical functions and their MTPD and MBCO measures were obtained by the consulting team through the BIA process (see Table 1).

To determine model parameters, required data were collected from different sources. The profit ratio (ω_f) of critical functions were determined based on the net profit of the company's key products. The net profits of key products were obtained from finance department based on financial balance of the last year. In this manner, the profit ratio of a critical function is calculated as the summation of the net profit of the key products depending to that critical function.

For analysing disruptive incidents, which threaten the company's critical functions, two steps i.e. disruption identification as well as estimation of likelihood and impact of each disruption scenario must be conducted. To identify the disruptive incidents, a comprehensive survey in the literature along with reviewing relevant reports regarding the past records available in the company and other similar companies were carried out. In this way, possible disruptive incidents were listed (see Supplementary material S.5). Then, a pairwise comparison matrix (PCM) was constructed by asking the consulting team (including six department managers and eight workshop supervisors) and some external experts (including five people from disaster management organization in Mazandaran province and Mazandaran Red Cross Society, a faculty member from Mazandaran University, and two executive managers from similar companies in the Mazandaran province who had valuable experiences about the past and potential disruptive incidents in the region) about the relative importance degree of each disruptive incident (see Supplementary material S.6). To fill out the disruption pairwise comparison matrix, the main question was: “how important is the disruptive incident X (row) compared to disruptive incident Y (column) for the company?”. Furthermore, to increase the familiarity of experts about the company and helping them to fill out disruption pairwise comparison matrix properly, we provided background information to participators. For this, they were provided documents regarding previous incidents, environmental conditions and geographical position of the company. Subsequently, five distinctive types of disruptive incidents with higher relative importance degree were selected. These include flood, fire, personnel sabotage, supply chain interruption, and disease outbreak (see Supplementary material S.6).

In the next step, likelihood ($\tilde{\beta}^i$) and impacts ($\tilde{e}^t_{ir}$) of these incidents should be estimated. It should be noted that the impact and likelihood of disruptive incidents may be different based on their scale, the company's vulnerability degree to each incident, and the nature of disruptive incidents. For example, a flood may have low, medium or high impact while high, medium, or low likelihood based on its scale, and the company's infrastructures. Hence to simplify the data collection phase, we asked from the aforementioned experts to comment on the disruptive incidents under normal condition. Notably, as the internal and external experts' subjective opinions were the main source of our gathered data, we used the possibilistic approach by which the imprecise data extracted from the experts are formulated as fuzzy numbers. Indeed, likelihoods and impacts of disruptive incidents are the most difficult parameters that should be manipulated subjectively.

Due to lack of explicit historical data for impact and likelihood of disruptive incidents, it was obvious that we could obtain different imprecise values for each parameter in our several meetings with experts. To tackle this issue, we asked from participators to give us their estimations about impact and likelihood of each disruptive event under optimistic, realistic and pessimistic conditions. In this way, we could define a suitable possibility distribution in the form of a triangular fuzzy number for impact and likelihood of each disruptive incident. Since Kendall's concordance coefficient level was 0.714 at the third round and the opinions of the experts were not similar even under optimistic, realistic and pessimistic viewpoints, uniform distributions were considered for them. For example $\tilde{e}^t_{ir} = (e^t_{ir(1)}, e^t_{ir(2)}, e^t_{ir(3)}) = (U[12,15], U[22,25], U[32,35])$ refer to uniform distributions of optimistic, realistic and pessimistic values obtained from external and internal experts for the impact of flood on human resource (see Table 2). Since the impact of disruptive incidents can be decreased during the planning horizon as a result of implementing the BC/DR plans, it is calculated by $\tilde{e}^t_{ir} = \left(\frac{\tilde{e}^{t'}_{ir}}{t-t'+1}\right); \quad \forall t > t'$ where t' denotes the time when a disruptive incident is happened and $\underset{t\to\infty}{Lim}\ \tilde{e}^t_{ir} = \underset{t\to\infty}{Lim}\left(\frac{\tilde{e}^{t'}_{ir}}{t-t'+1}\right) = 0$. The final IBCDRP model was solved by the proposed solution procedure to identify the most suitable BC/DR plans based on different RPP categories.

The consulting team evaluated the proposed IBCDRP model for 30 days with 30 million Rials budget (B) for providing the required external resources. Consequently, the model was solved for the planning horizon of 30 days length.

5.2. Results

For solving the resultant IBCDRP model of the case company, CPLEX solver in GAMS 22.1 was used. According to step 1 of the proposed solution procedure, the AHP was used to determine the relative importance of each objective function. This resulted in the weight vector w= (0.42, 0.37, 0.21). Then, the upper and lower bounds of the second and third objective functions (i.e. resumption and restoring times) were obtained by lexicographic optimization as ($\underline{f}_2 = 4232.32, \bar{f}_2 = 7027.2, \underline{f}_3 = 1795.2$ and $\bar{f}_3 = 1180.8$). Subsequently, the epsilon vectors were generated by dividing the range of objective functions into two equal intervals by one grid point. The IBCDRP model was run with two confidence levels of α equal to 0.7 and 0.9 with penalty rates $\delta = \varphi = U[875, 1000]$. The obtained results are reported in Table 3. Furthermore more computational information about solution methodology is provided in Table D.1 of Appendix IV.

Table 1
Critical functions' information and unit cost of external resources.

Critical functions	γ_f(Days)	λ_f(%)	$\tilde{\omega}_f$(1000 Rials)	Resources	C^E_r(1000 Rials)
Finance	4	50	(1152,3840,6528)	Human	400
Product design	7	80	(5126,17088,29049)	Equipment	500
Marketing and sales	5	70	(2150,7168,12186)	Facilities	2000
Customer relationship	5	70	(2266,7552,12838)	Raw materials	1000
Planning	3	60	(3744,12480,21216)		
Production	3	70	(4762,15872,26982)		

Table 2
Impact and likelihood of disruptive incidents.

Disruptive incident	$\tilde{\beta}^i$	Resource	Impact
Flood (*i* = *1*)	$\beta^1_{(1)} = 0.04\beta^1_{(2)} = 0.06\beta^1_{(3)} = 0.08$	Human	$(e^t_{1r(1)} = U[12,15], e^t_{1r(2)} = U[22,25], e^t_{1r(3)} = U[32,35])$
		Equipment	$(e^t_{1r(1)} = U[8,14], e^t_{1r(2)} = U[18,24], e^t_{1r(3)} = U[28,34])$
		Facilities	$(e^t_{1r(1)} = U[36,40], e^t_{1r(2)} = U[46,50], e^t_{1r(3)} = U[56,60])$
		Raw materials	$(e^t_{1r(1)} = U[64,68], e^t_{1r(2)} = U[74,78], e^t_{1r(3)} = U[84,88])$
Building/site fire (*i* = *2*)	$\beta^1_{(1)} = 0.01\beta^1_{(2)} = 0.03\beta^1_{(3)} = 0.05$	Human	$e^t_{2r(1)} = e^t_{2r(2)} = e^t_{2r(3)} = 0$
		Equipment	$(e^t_{2r(1)} = U[42,48], e^t_{2r(2)} = U[54,60], e^t_{2r(3)} = U[66,74])$
		Facilities	$(e^t_{2r(1)} = U[72,76], e^t_{2r(2)} = U[80,84], e^t_{2r(3)} = U[88,92])$
		Raw materials	$(e^t_{2r(1)} = U[70,73], e^t_{2r(2)} = U[80,83], e^t_{2r(3)} = U[90,93])$
Personnel sabotage (*i* = *3*)	$\beta^1_{(1)} = 0.01\beta^1_{(2)} = 0.03\beta^1_{(3)} = 0.05$	Human	$(e^t_{3r(1)} = U[3,8], e^t_{3r(2)} = U[10,15], e^t_{3r(3)} = U[20,25])$
		Equipment	$(e^t_{3r(1)} = U[10,15], e^t_{3r(2)} = U[22,27], e^t_{3r(3)} = U[29,34])$
		Facilities	$(e^t_{3r(1)} = U[3,8], e^t_{3r(2)} = U[11,15], e^t_{3r(3)} = U[18,22])$
		Raw materials	$(e^t_{3r(1)} = U[45,50], e^t_{3r(2)} = U[60,65], e^t_{3r(3)} = U[65,70])$
Supply chain interruptions (*i* = *4*)	$\beta^1_{(1)} = 0.03\beta^1_{(2)} = 0.05\beta^1_{(3)} = 0.07$	Human	$e^t_{4r(1)} = e^t_{4r(2)} = e^t_{4r(3)} = 0$
		Equipment	$e^t_{4r(1)} = e^t_{4r(2)} = e^t_{4r(3)} = 0$
		Facilities	$e^t_{4r(1)} = e^t_{4r(2)} = e^t_{4r(3)} = 0$
		Raw materials	$(e^t_{4r(1)} = U[70,75], e^t_{4r(2)} = U[80,85], e^t_{4r(3)} = U[90,95])$
Disease outbreaks (*i* = *5*)	$\beta^1_{(1)} = 0.02\beta^1_{(2)} = 0.04\beta^1_{(3)} = 0.06$	Human	$(e^t_{5r(1)} = U[64,68], e^t_{5r(2)} = U[72,76], e^t_{5r(3)} = U[70,74])$
		Equipment	$e^t_{5r(1)} = e^t_{5r(2)} = e^t_{5r(3)} = 0$
		Facilities	$e^t_{5r(1)} = e^t_{5r(2)} = e^t_{5r(3)} = 0$
		Raw materials	$e^t_{5r(1)} = e^t_{5r(2)} = e^t_{5r(3)} = 0$

Table 3
Solutions of HW-RPP, SW-RPP, and R-RPP approaches.

α	k	$\vec{\varepsilon}_p$		F^{HW-RPP}			F^{SW-RPP}			F^{R-RPP}		
		ε_2	ε_3	f_1	f_2	f_3	f_1	f_2	f_3	f_1	f_2	f_3
0.7	1	4232.32	1795.2	235852.8	4384	1728	204818.6	4262.4	1795.2	212064	4323.2	1761.28
	2	4232.32	1488	292320	4358.4	1491.2	207984	4240.64	1488	237595.5	4299.52	1484.8
	3	5629.44	1795.2	217190.4	5632	1760	185532.8	5644.16	1795.2	185532.8	5637.76	1777.28
	4	5629.44	1488	308889.6	5676.8	1401.6	186876.8	5644.16	1488	246812.8	5660.16	1444.48
0.9	5	4232.32	1795.2	235852.8	4384	1728	217634.6	4262.4	1795.2	217634.6	4300.8	1763.2
	6	4232.32	1488	292320	4358.4	1491.2	216448	4243.84	1488	253283.2	4300.8	1488
	7	5629.44	1795.2	217190.4	5632	1760	200192	5644.16	1795.2	200192	5632.64	1776
	8	5629.44	1488	308889.6	5676.8	1401.6	198339.2	5630.72	1488	253066.9	5654.4	1443.2
Average RTO (days)				5.27			2.13			3.08		

As it can be seen from Table 3, four Pareto-optimal solutions were found for each confidence level by the weighted augmented ε-constraint method. The results demonstrate that the proposed objective functions conflict with each other. When the loss of resilience objective f_1 is increased from 235852.8 to 292320, the recovery objective is decreased from 1728 to 1491.2. The selected modes for critical functions by HW-RPP, SW-RPP and R-RPP during IBCDRP planning horizon (i.e. X^{HW-RPP}, X^{SW-RPP}, and X^{R-RPP}) for $k = 4$ and $\alpha = 0.7$ are shown in Figs. 2–7 and summarized in Supplementary material S.7. As shown in these figures, the MTPD and MBCO related constraints are satisfied for the obtained IBCDRP plan. For example, the MTPD and MBCO of the finance's critical function is set to four days and 50%, respectively (see Table 1). It means that the mode of finance's critical function should not be less than two (since the operating level of mode two is 60%) for more than four successive days. For HW-RPP solution, only for two times the mode of finance's critical function fell down to the first mode (under 40%), i.e. during the first and second days, and also during 21st and 23rd days (see Fig. 2). As another example, the mode of product design's critical function should not be less than three for more than seven successive days. Fig. 3 shows that the mode of product design's critical function does not come down to three for seven successive days. The obtained solutions by HW-RPP, SW-RPP, and R-RPP approaches satisfied the MBCO and MTBD constraints as the basis for an effective IBCDRP.

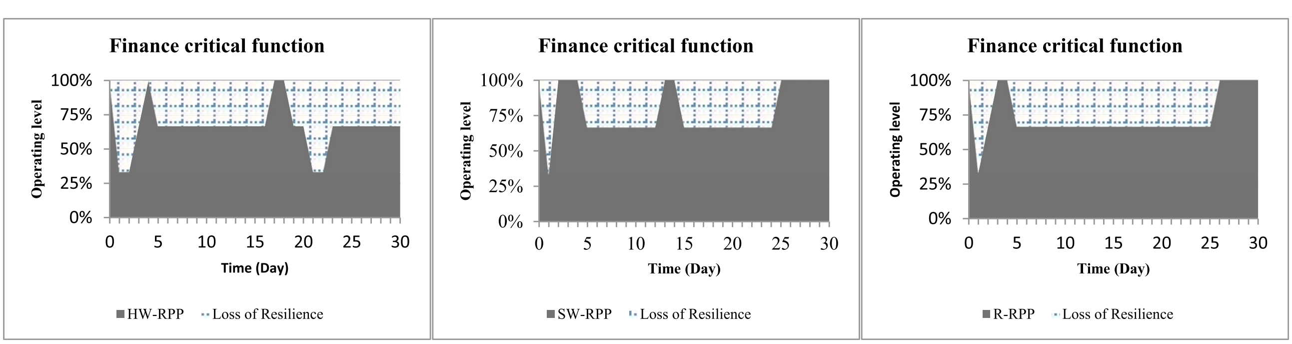


Fig. 2. The operating level of the finance for $k = 4$.

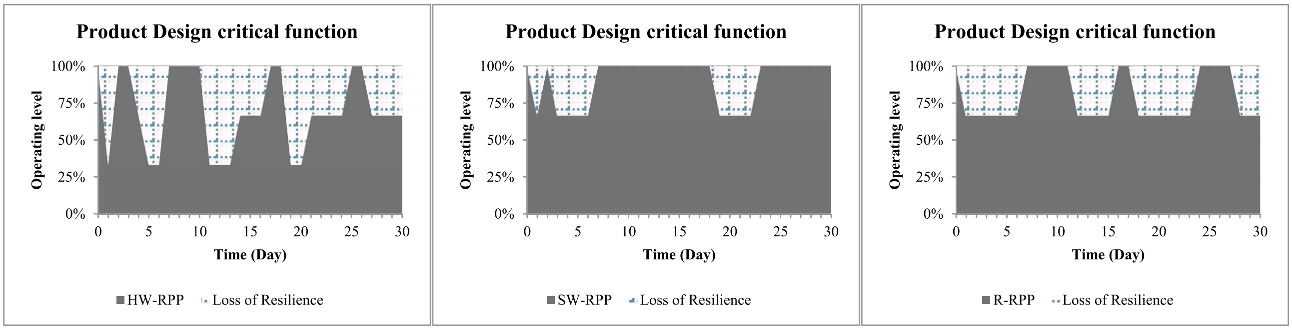


Fig. 3. The operating level of the product design's for $k = 4$.

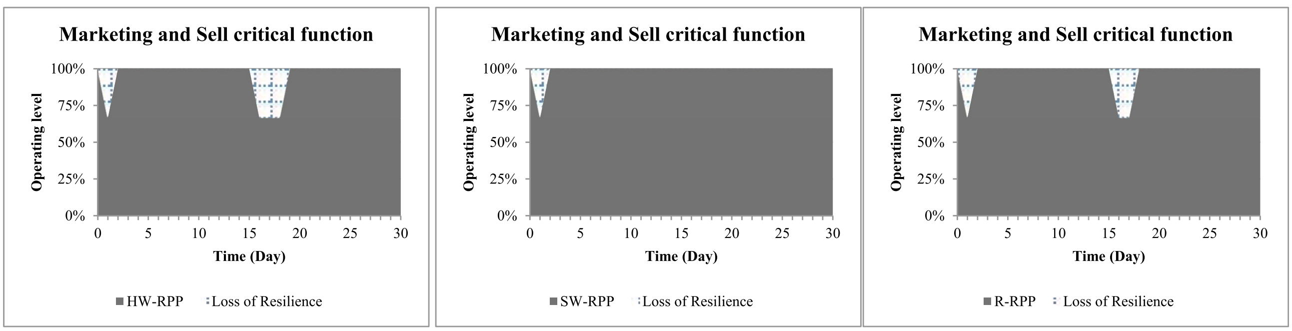


Fig. 4. The operating level of the marketing and sales for $k = 4$.

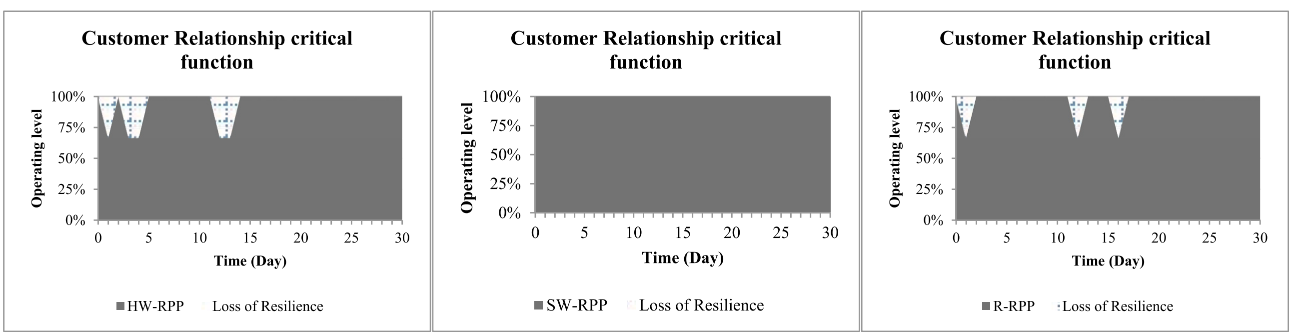


Fig. 5. The operating level of the customer relationship for k = 4.

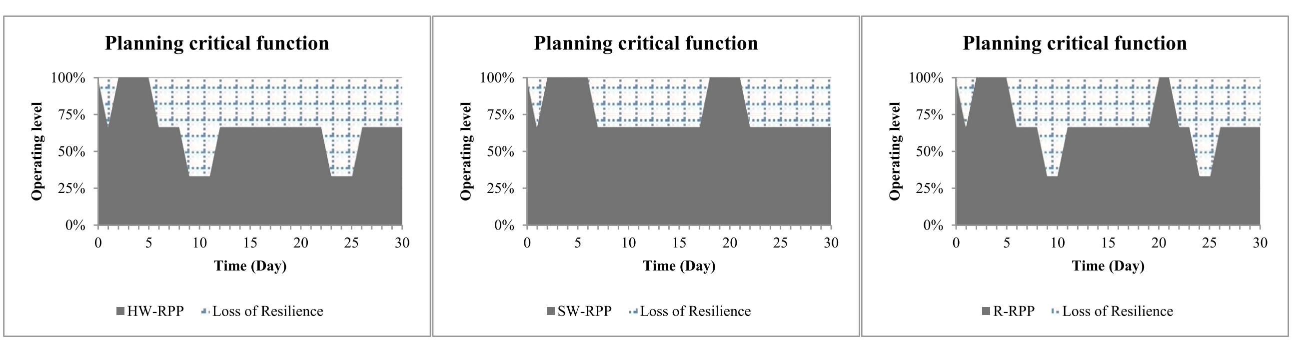


Fig. 6. The operating level of the planning for $k = 4$.

The proposed IBCDRP model aims to build a resilient organization by suitably allocating the available internal resources of the organization and external resources after disruptive incidents to critical functions. According to constraints (8) and (9) of IBCDRP model, the critical functions' modes depend on both the available internal and external resources. Although the organization could bounce back to the normal situation with 100% operating level after disruptive incidents rapidly, constraint (7) restricts the total amount of external resources to the total budget assigned to the BCM. To evaluate the interaction between the organizational resilience and the total budget of BCM, we relaxed constraint (7). In this regard, the total amount of budget was obtained for restoring and recovering each critical function rapidly after disruptive events (i.e. RTO = 0) under HW-RPP, SW-RPP, and R-RPP methods with $k = 4$ and $\alpha = 0.7$ whose results were summarized in Table 4. For

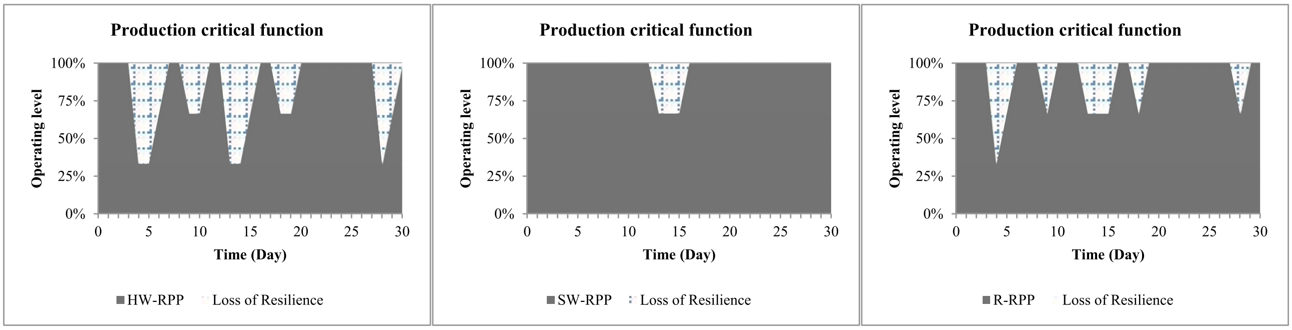


Fig. 7. The operating level of the production for $k = 4$.

Table 4
The obtained RTO and additional budget for RTO = 0.

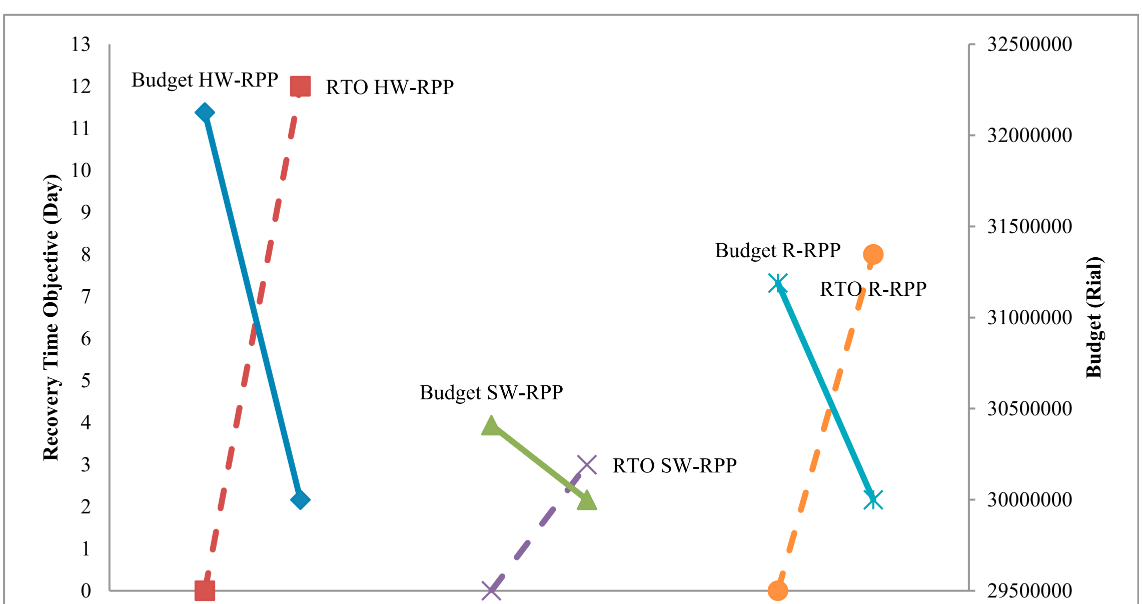
Critical Functions	HW-RPP		SW-RPP		R-RPP	
	RTO	AB	RTO	AB	RTO	AB
Production	12	2125500	3	409500	8	1189500
Marketing and sell	4	546000	1	136500	3	409500
Financial	26	4075500	18	2691000	22	3237000
Product design	11	3510000	8	1228500	19	2593500
Planning	26	4134000	21	2866500	23	3666000
Customer relationship	5	682500	0	0	3	409500
Average of RTO	14		8.5		13	
Total AB	15073500		7332000		11505000	

* Additional Budget: AB.

example, the operating level of the production critical function was under its normal situation (i.e. 100% operating level) for 12, 3, and 8 days according to HW-RPP, SW-RPP, and R-RPP methods respectively (As shown in Fig. 7 and summarized in Table S.5 of the Supplementary material). By relaxing the right hand side of constraint (7), the RTO was decreased to 0 while the total budget was increased to 2125500, 409500, and 1189500, respectively, for the production critical function under HW-RPP, SW-RPP, and R-RPP. The interaction between the budget and RTO for the production critical function and organization were shown in Figs. 8 and 9, respectively. The results show that the organization could increase the total budget up to 50.2, 24.4, and 38.3 percentage of the initial budget to decrease the RTO of critical functions.

To determine the continuity and recovery strategies of the organization, the total amount of available resources should be evaluated over the planning horizon. To this end, we eliminate the external resources' variable from equations (8) and (9) and relax the total budget in equation (9). Then, the total amount of external resources' variable is inserted to the objective function and minimized subject to equations (1)–(3). Therefore, the minimum amount of each resource is obtained that would be supplied for satisfying the MBCO and MTPD constraints after happening disruptive incidents. In this regard, the proposed IBCDRP model was solved under HW-RPP, SW-RPP, and R-RPP methods with $k = 4$ and $\alpha = 0.7$ whose resource usage pattern over the planning horizon are shown in Fig. 10.

The external resources were obtained as 20.77, 10.10, and 14.91 percentages for HW-RPP, SW-RPP, and R-RPP methods. These values helped decision makers of the organization to develop the continuity and recovery strategies. The developed strategies should provide operational solutions that are able to supply a certain amount of resources (i.e. 20.77, 10.10, and 14.91 percentages of resources for HW-RPP, SW-RPP, and R-RPP methods). In fact the proposed IBCDRP model could be used as a quantitative method for developing continuity and recovery strategic plans. For example, the following continuity and recovery strategies were suggested to the organization's decision makers based on the R-RPP result of the proposed IBCDRP model:



Note: Dot line is related to left vertical axis (i.e. RTO) and the line is related to right vertical axis (i.e. budget)

Fig. 8. Interaction of the budget and RTO for production critical function.

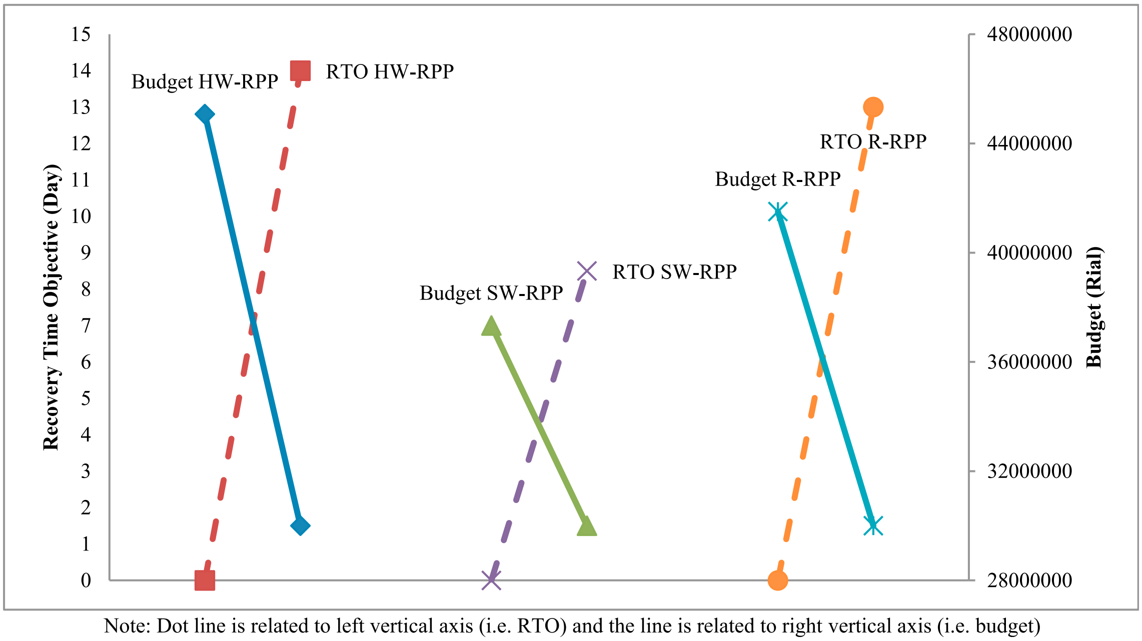


Fig. 9. Interaction of the budget and RTO for organization.

- *Signing a contract with an organization located in neighboring province for relocating the critical function(s) to an alternative facility.* We assumed that both organizations are not affected by the same disruptive incident at the same time. The area of the office is determined according to the results of the proposed IBCDRP model i.e. about 14.91 percent of the office area used for each critical function in the normal situation. In this way, the required area is determined as 300 square meters in the contract.
- *Contracting with a company to provide backup server for the company.* In addition, they will provide secure link for staff after disruptive incidents. In this way, the organization's information would be fully accessible from anywhere at any time. In this way, official employees of the company can continue their daily activities by connecting to the organization's portal after any disruptive incident.
- *Hiring part time experts for assisting organization after disruptive incidents through organization's portal.* We suggested that part time experts to be selected from other geographical locations. According to the results of the proposed IBCDRP model under the R-RPP method, about 5 percent of each critical function's staff should be employed. We assumed that about 9 percent of current staff can perform their duties after disruptive incidents through the organization's portal remotely (i.e. 14.9 percent of the IBCDRP model minus 5 percent of external experts).
- *Finding a shop with the similar equipment to those of current organization's production line.* It was a main challenge of continuity and recovery strategic planning in our case study. Indeed, the case company could not use their competitors' production equipment. According to the IBCDRP results, about 14.9 percent of the production critical function's equipment should be provided in continuity and recovery strategies, and there is no alternative solution for this. Therefore, we suggested the organization should rent a warehouse and setup part of the required equipment inside it. As a practical strategy, we suggested that the organization could join a consortium with other organizations to share the associated cost.

5.3. Evaluation of results

We evaluated the robustness and accuracy of the proposed solutions by the IBCDRP model during a three months period using real data. The impact of disruptive incidents on each resource was recorded during this period. For disruptive incidents which happened during the implementation period, RTO values were measured (number of periods that the operating level of critical function is under normal situation). Since the RTO indicated the needed time for backing to normal situation based on the BC/DR plans, the average values of RTO obtained by IBCDRP model were compared with observed values as a performance measure. During the three months, two disruptive incidents occurred in the company including a supply chain disruption and flood. The supply chain disruption was due to sanctions which decreased the supply of raw material (consumable resources such as MDF and wood) by about 80 percentage. As a result, operational disruption has happened in the marketing and sales, production, and finance departments. The actual modes of critical functions were determined after supply chain disruption as shown in Fig. 11. The average RTO of disrupted critical functions is 2.66. The deviation between RTO which was obtained by HW-RPP, SW-RPP, and R-RPP approaches and supply chain disruption were 2.61, 0.53, and 0.42 days, respectively.

The other disruptive incident was a flood which happened in the North of Iran during the case study. The disruptions as a result of flood are included personnel absence due to travel disruption, and loss of equipment, facility and raw material which were recorded as 26, 18, 45, and 60 percentages respectively. Thus, all critical functions of the company were disrupted. The real modes of critical functions were determined after the flood as shown in Fig. 12. The average RTO of disrupted critical functions was 3.5 days. The deviation between RTO which was obtained by HW-RPP, SW-RPP, and R-RPP approaches and flood were 1.77, 1.37, and 0.51 days, respectively.

The following were the key observations of the case study:

- The values of RTO which were obtained by SW-RPP and R-RPP approaches were closer than HW-RPP to the observed values of the two real disruptive incidents.
- Since HW-RPP solution was obtained under the worst possible values of imprecise parameters, the determined real RTO value was less than HW-RPP solution in both incidents.
- By increasing the impact of disruptive incident, the RTO was increased and the results tended to favour HW-RPP approach. For example, the RTO deviation between HW-RPP and flood (1.77) was less than that of HW-RPP and supply chain disruption (2.61) since the impact of flood was more than that of supply chain disruption.

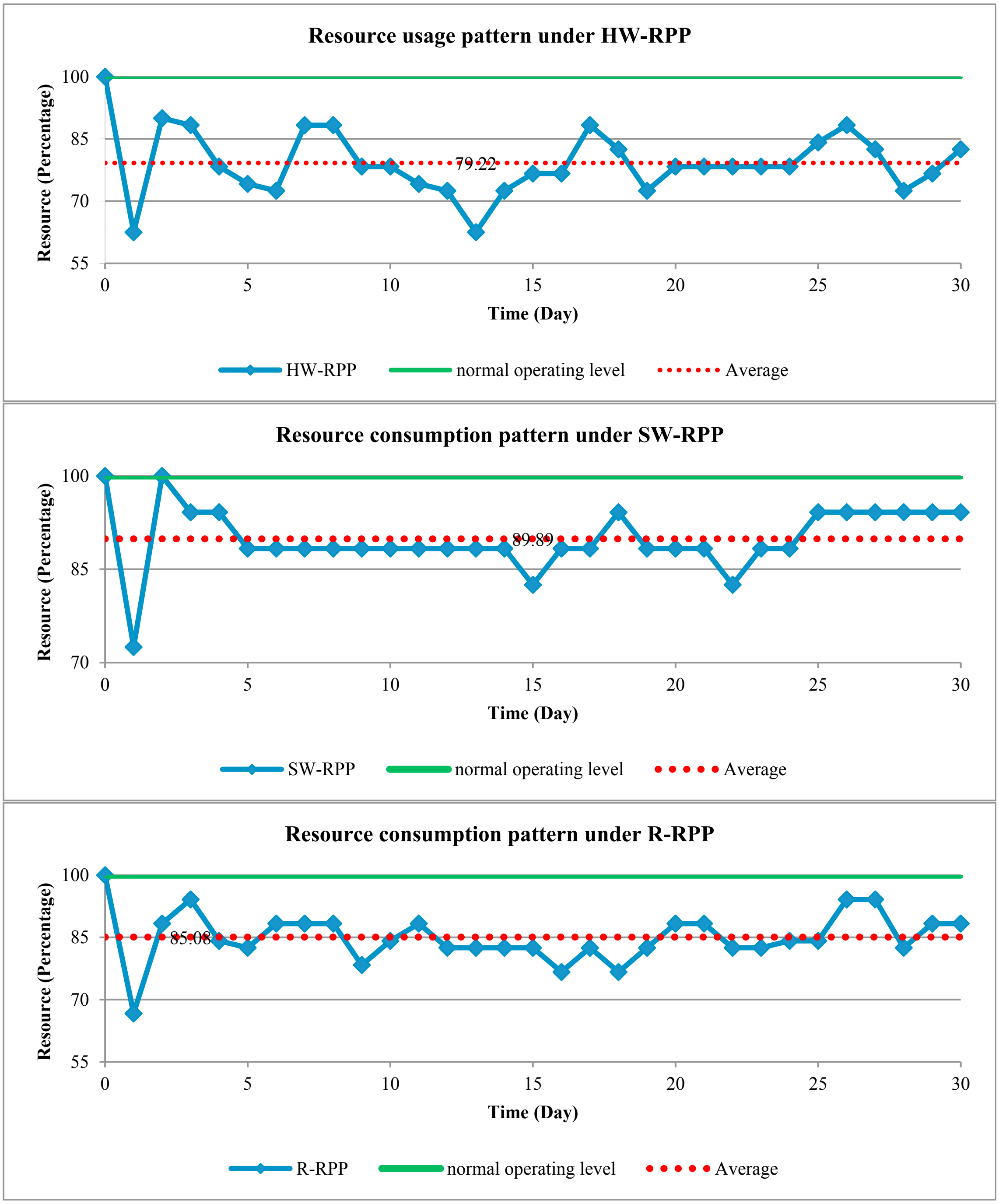


Fig. 10. Resource usage pattern along planning horizon under HW-RPP, SW-RPP, and R-RPP.

- The R-RPP approach provided the closest result to the two real disruptive incidents. While the average deviation between R-RPP and the two disruptive incidents was 0.465, the average deviation between HW-RPP and SW-RPP and the two disruptive incidents were 2.19 and 0.95, respectively.
- The amounts of available external resources are limited for organization (particularly at the early stage of the post-disruption). If an organization spends more budget for continuity and recovery plans, it can decrease MTPD measure.

It should be noted that the selection of final solution among HW-RPP, SW-RPP, and R-RPP approaches for developing the IBCDRP plan in an organization depends on the decision makers' preferences given the preferred level of BCMS. As emphasized in the BCMS literature and guidelines, BCMS implementation is a step by step procedure. The results of case study indicated that it would be preferred for the case organization to start with SW-RPP and after promoting the continuity capability, develop BCM program according to R-RPP and HW-RPP approaches respectively. Indeed the effectiveness of the continuity and recovery plans depend on the total amount of budget. More explicitly, if the organization managers supply the whole disrupted resource from external resources, they can reduce resumption and restoration time to around zero. On the other hand by decreasing the recovery and continuity budget, the resumption and restoration time can be increased. Hence, the organization managers may consider the resilience budget in the

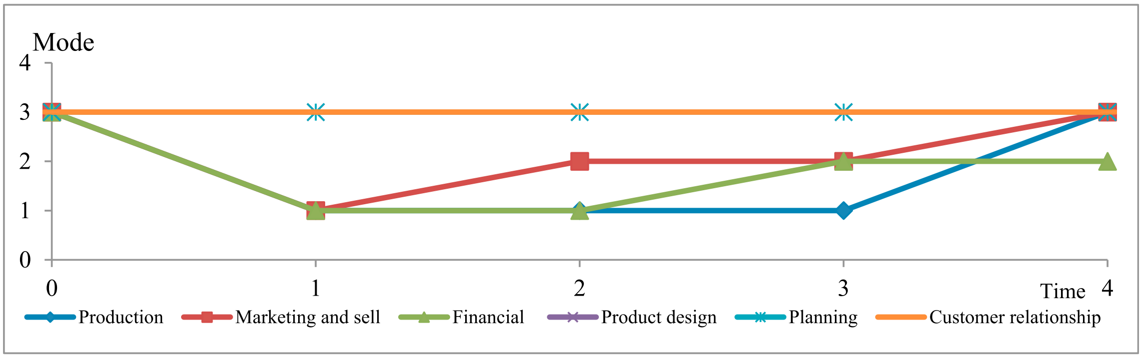


Fig. 11. Critical functions' modes after supply chain disruption.

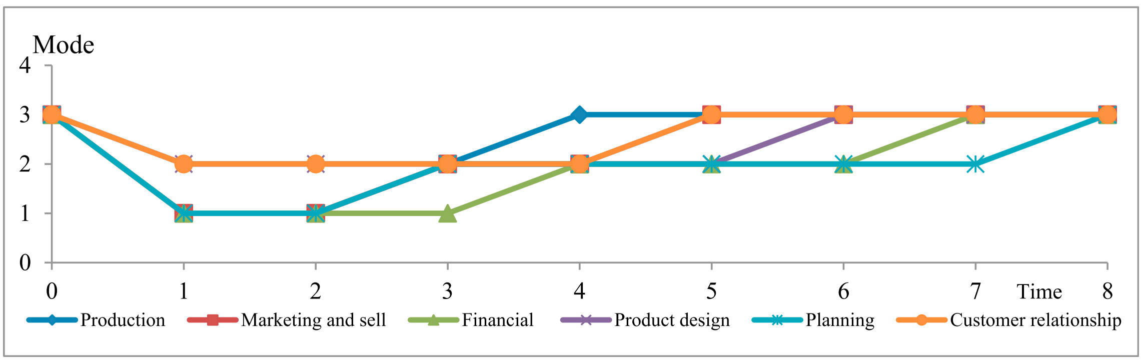


Fig. 12. Critical functions' modes after flood.

financial plans of organization according to upper and lower bounds for budget, which is indicated by the IBCDRP model.

5.4. Illustrative comparison

To evaluate the application and performance of the proposed IBCDRP model compared to the proposed model by Sahebjamnia et al. (2015), an illustrative and comparative study is provided here. In doing so, we assume that two disruptions happen simultaneously and consecutively at times $t = 0$ and $t = 6$. Therefore, the model presented by Sahebjamnia et al. (2015) (called the 'benchmark model' hereafter) is solved two times consecutively at times $t = 0$ and $t = 6$. Notably, the amount of available external resources for the second period (i.e. [6–15]) is equal to the remained external resources from the first period [0,6].

To adapt the parameters of the case study, the benchmark model is extended to a multi-objective mixed integer possibilistic linear programming model by considering same uncertain parameters and solved with the proposed solution procedure in this paper using the R-RPP approach. Since the operating level of the benchmark model is changed continuously, we set the operating levels from 0 to 40 as the critical functions' mode 1, from 40 to 65 as the critical functions' mode 2, and more than 65 as the critical functions' mode 3. The obtained results are shown in Figs. 13–18.

The main comparative results between the proposed IBCDRP model and the benchmark model can be summarized as follows:

- At the first period (i.e. after happening disruptions at time t = 0), the proposed IBCDRP aims to firstly resume all the critical functions at their MBCO levels. After resuming all the critical functions, it then

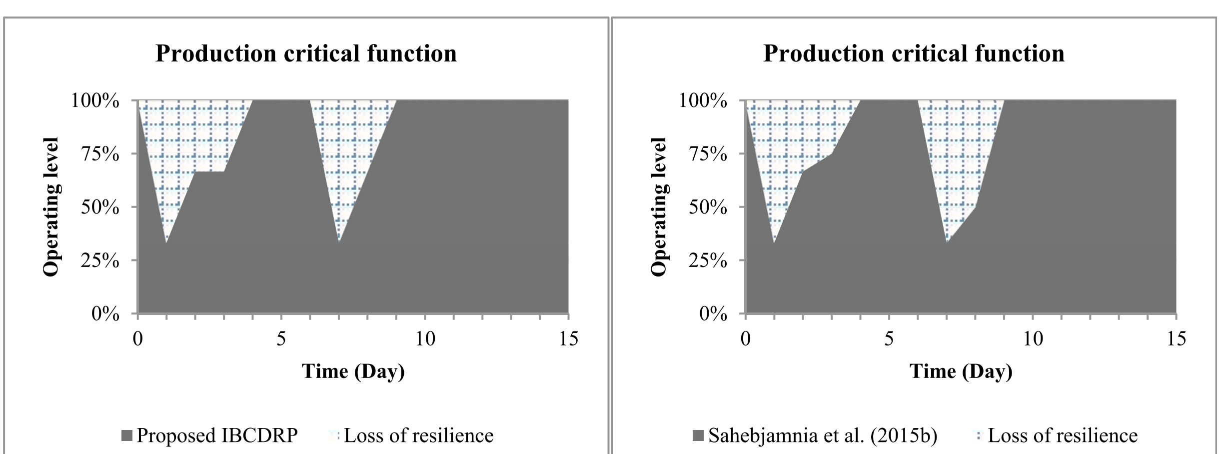


Fig. 13. The mode of the production critical function during 15 days with disruptions at t = 0 and t = 6.

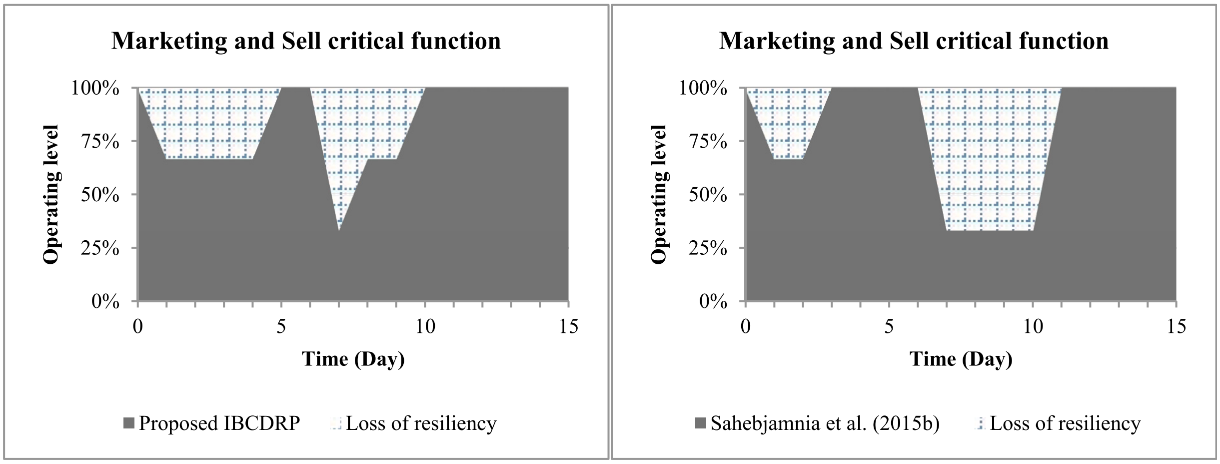


Fig. 14. The mode of the marketing and sales critical function during 15 days with disruptions at t = 0 and t = 6.

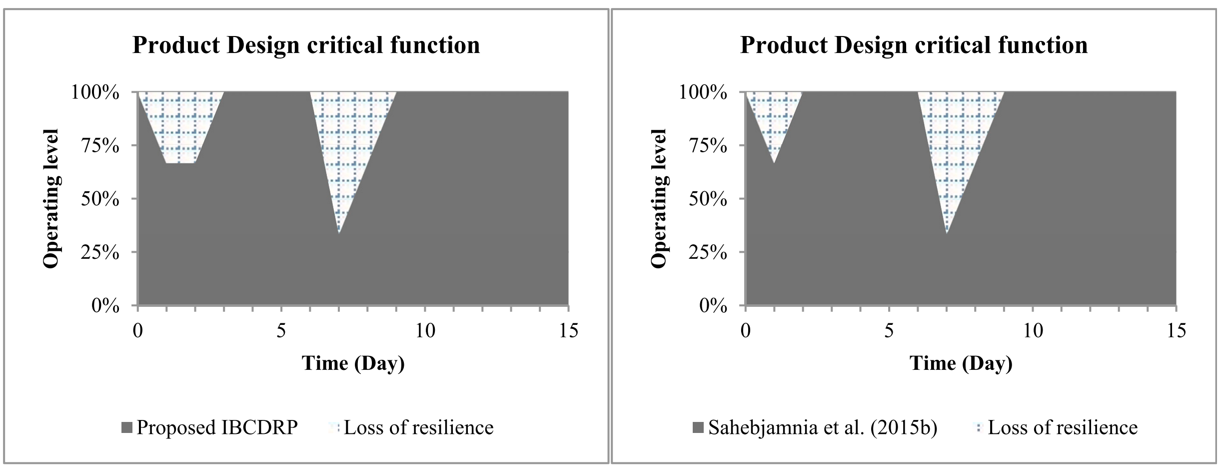


Fig. 15. The mode of the product design critical function during 15 days with disruptions at t = 0 and t = 6.

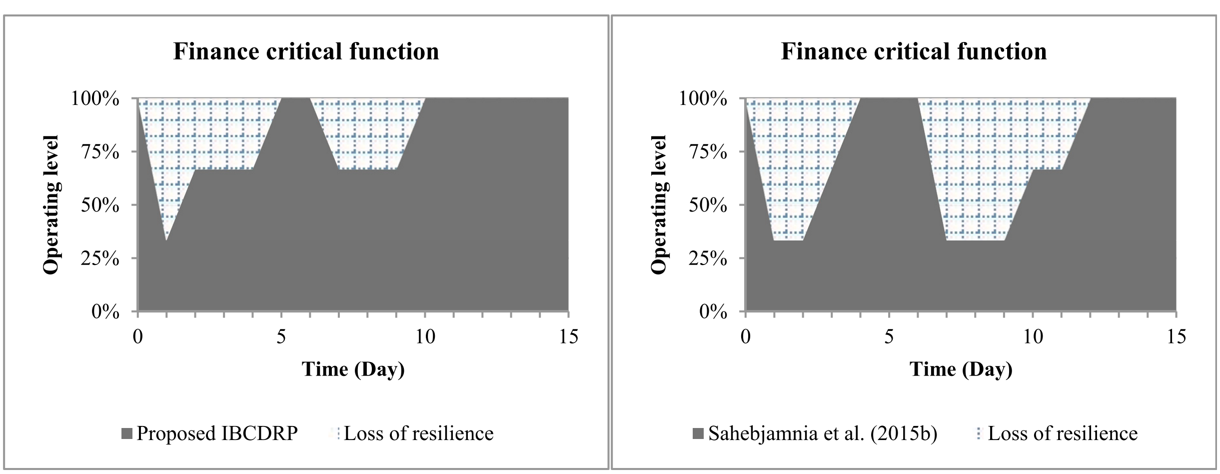


Fig. 16. The mode of the financial critical function during 15 days with disruptions at t = 0 and t = 6.

tries to recover the critical functions to their normal situation (i.e. their operating level 100% in mode 3). For example, the mode of the customer relationship critical function obtained by the benchmark model is more than that proposed by IBCDRP model (see Fig. 17).

- The benchmark model only restores critical functions based on their relative importance levels. In contrast with the proposed IBCDRP model that considers both resuming and restoring times, the benchmark model only considers restoring time. Therefore, it suggests increasing the critical functions' mode to the recovery level faster than the proposed IBCDRP model. As shown in Figs. 13, 14 and 17, the proposed IBCDRP keeps the modes for production, marketing and sales, and customer relationship critical functions at their MBCO

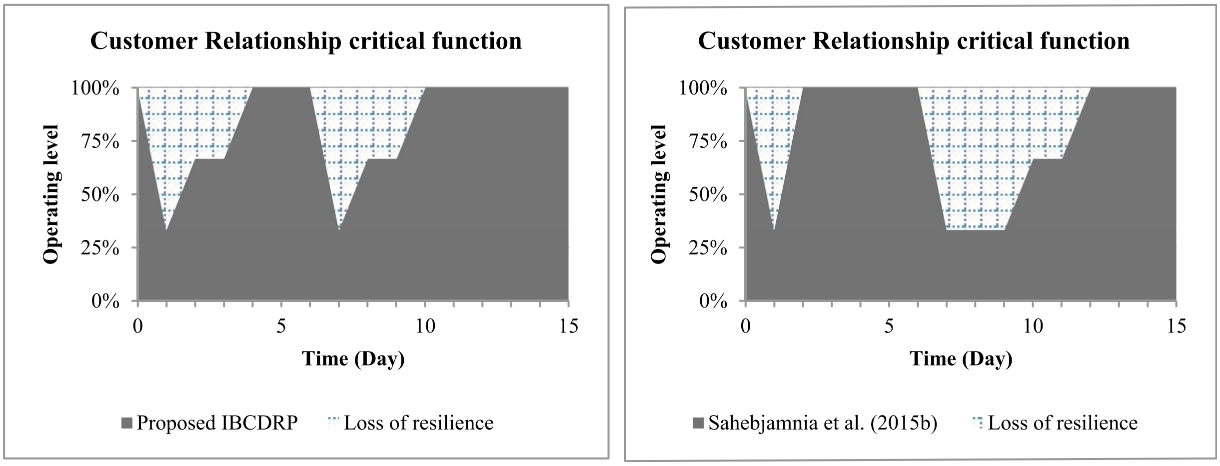


Fig. 17. The mode of the customer relationship critical function during 15 days with disruptions at t = 0 and t = 6.

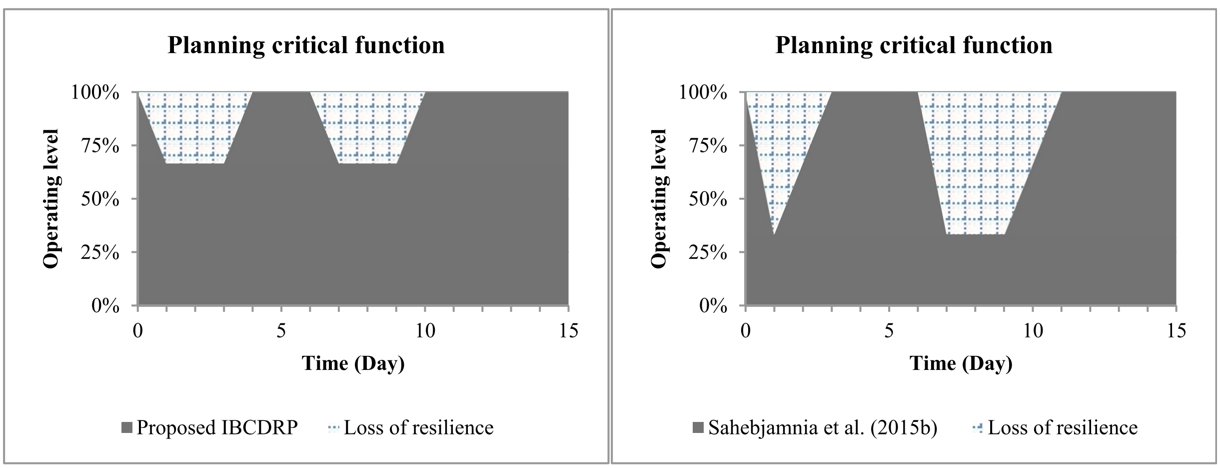


Fig. 18. The mode of the planning critical function during 15 days with disruptions at t = 0 and t = 6.

levels during the first six days. However, the results of the proposed IBCDRP shows that the critical functions could be recovered before the next disruptions at time 6.

- Indeed, in the second period (after happening consecutive disruptions at time t = 6), the proposed IBCDRP outperforms the benchmark model. That is, while the proposed IBCDRP model solves the problem for two periods jointly, the benchmark model considers these two time horizons separately for t = 0 and t = 6. Hence, the amount of reduction in the operating level by the proposed IBCDRP model at time t = 7 was less than that of the benchmark model. For example, the operating level of financial critical function mode planned by the proposed IBCDRP model was more than that of the benchmark model.
- As shown in Figs. 13–18, the restoring and recovering times of the proposed IBCDRP model are less than those of the benchmark model at the second period [6,15]. In fact, the proposed IBCDRP model aims to increase the critical functions' mode based on both simultaneous and consecutive disruptions.
- In terms of the external resource utilization, there is a significant difference between the results of the proposed IBCDRP model and the benchmark model. While the proposed IBCDRP model balances external resources utilization rates, the benchmark model dedicates more resources at the first period. In this manner, the remained external resources of the proposed IBCDRP for the next period [6,12] are more than those of the benchmark model.

Consequently the proposed IBCDRP aims to balance the utilization of the external resources when consecutive disruptions might happen. In addition, Figs. 13–18 show that the proposed IBCDRP model tries to first resume and then restore all critical functions. When the probability of happening consecutive disruptions is low and external resources are not limited, the benchmark model can recover critical functions faster than the proposed IBCDRP model. However, top managers need to choose one of the models according to their own situations.

5.5. Managerial implications

This section summarizes practical implications for implementing the proposed IBCDRP model, which could be useful for managerial decision process:

- The proposed IBCDRP model is a capable quantitative model for calculating the resilience level of organizations. The practitioners could utilize the proposed model as the core of the BCMS framework (Sahebjamnia et al., 2015) in the tactical decision level for building resilient organization.
- To implement the proposed IBCDRP model effectively, the continuity measures (i.e. MTPD and MBCO) as well as the impact and likelihood of disruptive incidents should be estimated through the business impact analysis and risk management processes. In the literature, scholars (e.g. Radeschütz et al., 2015; Torabi et al., 2014) presented quantitative frameworks for calculating MTPD and MBCO measures. In addition, to estimate the impact and likelihood of disruptions, practitioners could refer to Dong and Cooper (2016) and Torabi et al. (2016).

- For the effective implementation of the obtained plans, a consulting team should be formed consisting representatives of the directory board and executives of the organization as they have useful information about the available budget and the future situation of the organization, which are necessary information for continuity and recovery planning. In addition, department managers should attend in the related meetings, since they have exact information about their departments (e.g. amount of resource consumption). To increase the quality of the results, the proposed IBCDRP model and solution procedure should be presented for the members of the consulting team step by step during the implementation phase.
- Our observations in the three months period using the real data demonstrate that the RTO level never exceeds the solution of HW-RPP. Although HW-RPP plans are the most appropriate ones for building the organization's resilience, they need more budget than those of SW-RPP and R-RPP approaches. In general, the directory board members are not interested in allocating high budget at the beginning of the BCMS implementation. Hence, the R-RPP solution with the average deviation 0.465 and lower budget could be suggested. Indeed, the resilience level of the organization could be improved gradually over the time.
- Other insights from implementing the proposed IBCDRP model during the three months horizon are about the effects of source diversification and facilities' fortification strategies. As noted in other studies (such as Kamalahmadi and Parast, 2017; Mizgier et al., 2015; Wagner et al., 2009), a supply chain disruption could decrease the supply amount of raw material intensively. Diversification and fortification strategies not only could decrease the impact of supply chain's disruptions on the operations' of the organization but also could save continuity and recovery budget that can then be used for supplying other resources after disruptive incidents.
- To determine a suitable amount of budget for continuity and recovery planning in the implementation phase, the decision makers can solve the IBCDRP model with an initial budget and obtain the restoring and resuming times accordingly. Then, for decreasing the RTO to zero, the constraint (7) is released and the total additional budget is calculated. As shown in Figs. 8 and 9, increasing the budget of BCM led to the decrease of resuming and restoring times. The decision makers could allocate appropriate budget to continuity and recovery plans based on the resuming and restoring times by solving the proposed IBCDRP.

6. Conclusions and future research

In this paper, a new model for integrated business continuity and disaster recovery planning was presented which is able to cope with multiple disruptive incidents that might happen simultaneously or consecutively. A MOMIPLP model was developed to allocate both internal and external resources of organization by considering MTPD and MBCO measures of critical functions. The proposed model aims to minimize resumption and restoring times and loss of resilience among critical functions during the IBCDRP time horizon for establishing a resilient organization. A two phase solution procedure was developed to solve the proposed model. In the first phase, the proposed model is converted to a single objective counterpart. Then, three variants of robust programming approach including HW-RPP, SW-RPP, and R-RPP are applied to cope with uncertain (possibilistic) parameters. To evaluate the applicability of the proposed IBCDRP model and robustness of the crisp counterparts, they were applied to a real case study in furniture industry. We solved the model by robust programming approaches based on the data gathered during the first 30 days. Then, we compared the results with two disruptive incidents (i.e. flood and supply chain disruption) which happened during a 90-days observation period. The results demonstrate the robustness and capability of the proposed IBCDRP model and its solution approach.

The results of case study showed that the proposed IBCDRP model can play a positive role in the improvement of organizational resilience to encounter with disruptive incidents. The quantitative model developed in this research can help managers of organizations proactively select and implement effective business continuity and disaster recovery plans. The main advantages of the proposed IBCDRP model can be highlighted as follow:

- It can help selecting the most effective and efficient business continuity and recovery plans among the candidate solutions while accounting for resource limitations to build a resilient organization;
- The model enables evaluation of capability of organizations against possible disruptive incidents in pre-disaster phase by solving the proposed model under different situations;
- It assesses the outcome of selected continuity and recovery plans based on three quantitative measure of resilience;
- The developed model is able to cope with inherent epistemic uncertainty in characteristics of disruptive incidents and other parameters while accounting for sensitivity and feasibility robustness by adopting robust possibilistic programming approach.
- The IBCDRP model helps organization managers to prepare resources such that to avoid resource shortage in post disaster phase for continuity and recovery plans.
- It can evaluate the strategic and tactical decisions regarding disaster response across the organization.

The outcomes of this paper emphasise that the capability of organizations for restoring or resuming critical functions is highly dependent on their resources. For example, if an organization was disrupted due to Fukushima nuclear disaster in Japan, it could continue and recover their critical functions for example in its pre-determined secondary site. In fact, top managers should determine their critical functions' continuity measures (i.e. MBCO and MTPD) according to their internal and external resources. As another example, we can point out to Cloud-based back up system. If an organization loses its critical information due to a catastrophe (e.g. a terrorist attack, flood, etc.), it could retrieve its information from anywhere, at any time if using cloud technologies. Consequently, the MTPD depends on selected continuity and recovery plans while accounting for available resources. Given the nature of the robust possibilistic approach in this research, both possible fluctuations in imprecise parameters and the solution robustness (including the feasibility and optimality robustness) are assured through the RPP models tailored to the problem. As a result, we expect similar results to be achievable in other cases where inputs are realized within the specified ranges of imprecise parameters and even in similar organizations in response to simultaneous or consecutive disruptions.

Future research could explore more quantitative measures of resilience to illustrate of merits and capability of MS/OR tools in this area. Although dealing with multiple disruptive incidents 'simultaneously' is an important issue in the context of organizational resilience, the challenging part is to handle those 'interdependent' events. Probing such interdependency could be another avenue for further research. Since the organization is influenced by other nodes in the related supply chain network, the interactions between the organization's resilience and its supply chain resilience should be studied. Also, the correlation among disruptive incidents that might have direct and indirect impacts on the organization and its supply chain must be focused. The impact of disruption on each node of the supply chain can be considered with the proposed IBCDRP model including the resuming and restoring times, as well as the loss of operating level in each period. In addition, an appropriate aggregation function should be developed to integrate the loss of resilience of different nodes of the supply chain. In this way, simulation could be an applicable approach to estimate the overall supply chain resilience. This approach is particularly appealing for cases in which historic data is available to develop reliable simulation models.

In addition, use of other uncertainty programming techniques such as mixed fuzzy stochastic programming to cope with uncertainties in the model's parameters is another avenue for further research. Finally, developing more efficient and faster solution techniques like multi-objective evolutionary algorithms could facilitate implementation of the proposed model in larger organizations with several critical functions.

Appendix I

Table A.1 shows how the profit ratio is calculated for two products A and B and five products with profit net.

Table A.1
Example of profit ratio calculation

Function	Related product	Profit ratio (relative importance)
A	X (net profit = 2$), Y (net profit = 4$)	(2 + 4)/(2 + 4+1 + 3+5) = 0.4
B	Z (net profit = 1$), W (net profit = 3$), K (net profit = 5)	(1 + 3+5)/(2 + 4+1 + 3+5) = 0.6

Appendix II

Table 1
Information of illustrative example

Time	1	2	3	4	5	6
Disruptive event (impact)	D1(0) D2(0) D3(0)	D1(50) D2(0) D3(0)	D1(30) D2(0) D3(0)	D1(5) D2(0) D3(0)	D1(0) D2(20) D3(20)	D1(0) D2(0) D3(0)
Available resource	100	50	70	95	60	100
x_f^{mt}	$x_f^{31} = 1$	$x_f^{12} = 1$	$x_f^{23} = 1$	$x_f^{24} = 1$	$x_f^{15} = 1$	$x_f^{36} = 1$
ϖ_f^t	$\varpi_f^1 = 100$	$\varpi_f^2 = 50$	$\varpi_f^3 = 70$	$\varpi_f^4 = 70$	$\varpi_f^5 = 50$	$\varpi_f^6 = 100$

Appendix III

According to (Inuiguchi and Ramík, 2000), the necessity (*Nec*) degree of possibilistic/fuzzy event $\tilde{A} \le B$ is calculated as follows:

$$Nec(\tilde{A} \le B) = 1 - \sup_{x>B} (\mu_A(x))$$

If $\tilde{A}$ is a triangular fuzzy number, the necessity of $\tilde{A} \le B$ is shown in Fig. I.A and is written as follow:

$$Nec(\tilde{A} \le B) = \begin{cases} 0 & B < a_2 \\ \dfrac{a_3 - x}{a_3 - a_2} & a_2 \le B \le a_3 \\ 1 & a_3 < B \end{cases}$$

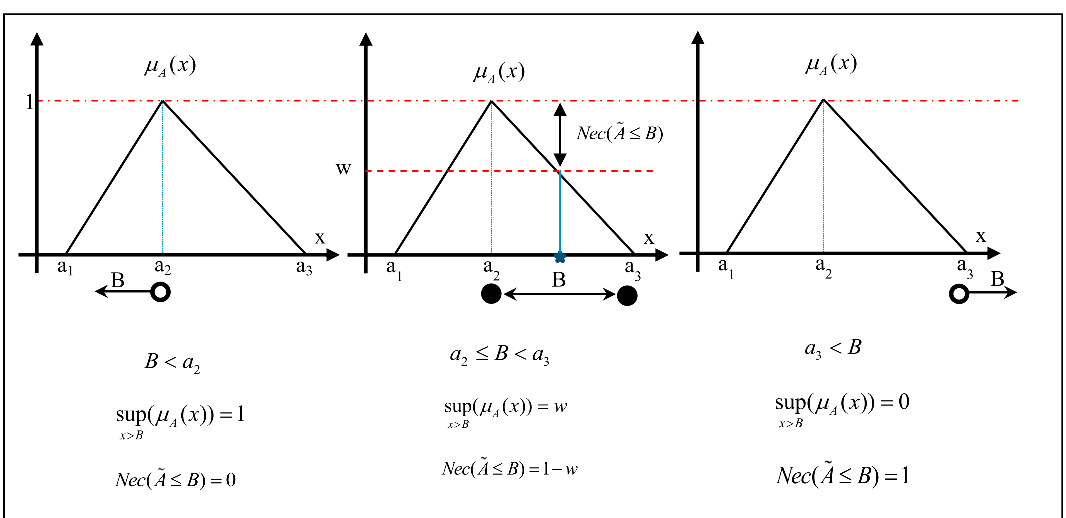


Fig. I.1. Necessity diagrams of $\tilde{A} \le B$.

Consequently, $Nec(\tilde{A} \le B) \ge \alpha$ for $\alpha \ge 0.5$ is reformulated as:

$$Nec(\tilde{A} \le B) \ge \alpha \rightarrow \frac{a_3 - x}{a_3 - a_2} \ge \alpha \rightarrow x \le \alpha . a_2 + (1 - \alpha) . a_3$$

Accordingly, for equations (32) and (33) we have:

$$Nec\left(\tilde{N}x + Sy \geq \tilde{q}\right) \geq \alpha \rightarrow Nec\left(Sy \geq \tilde{q} - \tilde{N}x\right) \geq \alpha$$
$$\rightarrow \left[1 - \sup\left(\underset{Sy<x}{\mu_q(x)}, \underset{Sy>t}{\mu_N(t)}\right)\right] \geq \alpha \rightarrow \frac{Sy - q_{(2)} - N_{(2)}x}{q_{(3)} - N_{(2)}x - q_{(2)} + N_{(1)}x} \geq \alpha$$

$$Nec\left(Uy \geq \tilde{d}\right) \geq \alpha \rightarrow \left[1 - \sup\left(\underset{Uy<x}{\mu_d(x)}\right)\right] \geq \alpha \rightarrow \frac{Uy - d_{(2)}}{d_{(3)} - d_{(2)}} \geq \alpha$$

Therefore, we can replace equations (20) and (21) as follow:

$$Sy \geq \left[(1-\alpha)\cdot q_{(2)} + \alpha . q_{(3)}\right] - \left[(1-\alpha)\cdot N_{(2)} + \alpha \cdot N_{(1)}\right]x$$

$$Uy \geq (1-\alpha) d_{(2)} + \alpha d_{(3)}$$

Appendix IV

Table D.1
The performance of the proposed model

k	Continues variable	Discrete variables	Constraints	Computational time (s)		
				F^{HW-RPP}	F^{SW-RPP}	F^{R-RPP}
1	428	3240	690	14	9	15
2				18	14	18
3				12	8	14
4				24	16	22
5				9	15	10
6				14	23	9
7				11	14	14
8				21	22	19

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.ijpe.2017.12.009.

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