Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
R.Graph: A new risk-based causal reasoning and its application to COVID-19 risk analysis

Hamidreza Seiti\textsuperscript{a}, Ahmad Makui\textsuperscript{a,}\textsuperscript{*,} Ashkan Hafezalkotob\textsuperscript{b}, Mehran Khalaj\textsuperscript{c}, Ibrahim A. Hameed\textsuperscript{d}

\textsuperscript{a} Department of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran
\textsuperscript{b} College of Industrial Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran
\textsuperscript{c} Department of Industrial Engineering, Islamic Azad University, Robat Karim Branch, Tehran, Iran
\textsuperscript{d} Department of ICT and Natural Sciences, Norwegian University of Science and Technology, 6009 Alesund, Norway

\textbf{Abstract}

Various unexpected, low-probability events can have short or long-term effects on organizations and the global economy. Hence there is a need for appropriate risk management practices within organizations to increase their readiness and resiliency, especially if an event may lead to a series of irreversible consequences. One of the main aspects of risk management is to analyze the levels of change and risk in critical variables which the organization’s survival depends on. In these cases, an awareness of risks provides a practical plan for organizational managers to reduce/avoid them. Various risk analysis methods aim at analyzing the interactions of multiple risk factors within a specific problem. This paper develops a new method of variability and risk analysis, termed R.Graph, to examine the effects of a chain of possible risk factors on multiple variables. Additionally, different configurations of risk analysis are modeled, including acceptable risk, analysis of maximum and minimum risks, factor importance, and sensitivity analysis. This new method’s effectiveness is evaluated via a practical analysis of the economic consequences of new Coronavirus in the electricity industry.

© 2022 Institution of Chemical Engineers. Published by Elsevier Ltd. All rights reserved.

1. Introduction

COVID-19 has rapidly led to unprecedented health, economic, and political crises across the globe (Djalante et al., 2020), becoming a major risk factor for many organizations. Many companies have indicated that the impact of Coronavirus COVID-19 is, or will be, a significant source of uncertainty. According to the OECD Economic Outlook Interim Report (March 2020), annual global GDP growth projections for 2020 have dropped by half a percentage point to 2.4%, largely due to the coronavirus outbreak. However, a longer-lasting and more intense coronavirus outbreak could even slow global growth to 1.5% (OECD, 2020). The coronavirus pandemic may eventually fade, as the Ebola, Zika, and SARS viruses have in recent history. However, even if it does, the next as-yet-unknown devastating outbreak is not so much a matter of “if” but “when.” How, then, should organizations, societies and governments prepare for similar future possibilities? Even with the knowledge that such events may occur, there is a significant difference between mere awareness and the actual experience; evaluating the correct response to these potential future situations is vital for any company, institution, or country which wishes to remain competitive in the current globalized world (“Embed. Resil. A Guid. to Bus. Implic. COVID-19,” 2020).

One solution to increase resiliency is risk-informed development. Risk can be defined as the probability of a certain deviation in achieving a goal, which can be determined by modeling the

\textbf{Keywords:}

R.Graph, Risk analysis, Causal chain, COVID-19
interacting risk factors (Seiti and Hafezalkotob, 2020). Risk factors can be considered as effective factors which may cause variations in predictions (Seiti et al., 2020). Risk analysis constitutes a family of approaches to aid top managers in assessing all potential impacts through considering the criticality of various risk factors within systemic procedures.

Two significant aspects of specific risk are the probability of a risk occurring (known as stochastic uncertainty) and the variability and changes in predictive consequences (aleatoric uncertainty) (Hillson, 2016). Therefore, the risk of interactive risk factors on each other can be assumed in three different ways: 1) the effect of a specific risk factor on the probability of an event; 2) the effect of the risk factor on the severity of an event; and 3) the combined effect of the risk factor on the probability and severity of a consequence. For instance, let us assume the probability of a person being imprisoned for a certain period of time. For this, finding a new document in court or a further witness, as a factor, can have an effect on reducing or increase in the length of imprisonment, an increase/decrease in the probability of incarceration, as well as the simultaneous effect on the probability and duration of confinement.

One of the most effective methods for modeling and determining the probability and variability in a system is to break it down into smaller components through causality analysis models. These components can then be used to identify a set of factors that affect each other, examining a chain of causes and effects to make better predictions of risk and variability. The motivation for conducting this study is based on the fact that, in some risk analysis problems, the decision-maker is interested in knowing various change rates. These can relate to the occurrence of events that: have not been previously predicted; have already occurred; or have not yet occurred but may alter relevant predictions and variables. In many cases, either events happen or it is obvious to the decision-maker that the event will happen eventually. In such cases, the models can be assumed to be definite (Hillson, 2016), thus only variability needs to be considered. Since, in the real world, many variables are continuous, it is necessary to develop a suitable model that can find the percentage of change predicted in the desired variables. The challenge for some of these issues is that the probability of certain events occurring may be very low, meaning that there is little data available for risk analysis. In these cases, therefore, instead of empirical or statistical data, the knowledge of experts in related fields can be employed during the process of evaluating the relationships between the model components (Panula-Onotto, 2016).

There are several causal methods in the literature for risk analysis, whose various characteristics and disadvantages are investigated in Section 2. The motivation of this study is then to overcome these disadvantages and to find an appropriate solution; a causal mathematical model is proposed, called R.Graph. This model has the ability to estimate variability and risk while considering different scenarios in a causal chain of various factors. It uses data gathered from experts, while its outputs are easily interpretable and explicable by decision-makers.

The current paper is arranged in the following order: Section 2 surveys existing literature on causality models and methods of risk analysis, while Section 3 discusses the preliminaries of risk and aggregation operators. Section 4 sets out the R.Graph model. A relevant case study is presented in Section 5, and Section 6 summarizes the findings, and proposes insights for future research.
2. Literature review

In this section, the literature survey on causality models and their applications in risk analysis is provided in Section 2.1; the limitations of these methods, and the novel contributions of this paper are then presented in Section 2.2.

2.1. Literature survey on causality models and applications in risk analysis

There are various methods in the existing literature to analyze these causal chains, which can be divided into two categories: deterministic models including structural models (Bashir et al., 2020), multi-criteria based models (MCBMs) (Zhang et al., 2019) and probabilistic models, such as cross-impact analysis models (CIAMs) (Kadaifci et al., 2020), Bayesian models (BMs) (George and Renjith, 2021), risk-based approaches (RBAs) (Amin et al., 2019), which are displayed in Fig. 1. In these approaches, the impacts of various scenarios are measured in different ways. For instance, CIAMs, BAs, and RBAs use probabilistic inference to deal with a variety of interactive risk analyses based on probabilistic input data. They can be used to examine the effects of event probability changes, and then identify requisite actions and interventions to reduce adverse effects (Panula-Ontto and Pirhonen, 2018). In MCBMs and cognitive maps (Liu et al., 2019), the cause and effect between various interactive concepts are modeled.

Various studies have been conducted to analyze the different aspects of risk analysis in distinct organizations, including Li et al. (2020), who proposed a causal analysis based on the STAMP model for a safety risk analysis of underground gas pipelines. In this study, CAST analysis was adapted to examine safety flaws, revealing the series of reasons behind decisions made leading up to a catastrophic gas explosion. Yazdi et al. (2020a) augmented a new integrated approach – based on DEMATEL, BWm, and Bayesian network approaches – to assess the dependency between risk factors and information sources. BWm was employed to compute relative expert opinion weights, then DEMATEL was mapped into the BN in order to identify critical factors in a dynamic structure. The proposed method was utilized in high-tech safety management. In another study, Yazdi et al. (2020b) introduced an improved solution, termed Pythagorean fuzzy DEMATEL, to evaluate the interrelation of corrective actions within a probabilistic safety analysis of an offshore platform facility. Pythagorean fuzzy numbers were applied to conjoin expert judgment and the DEMATEL method to encompass randomness and uncertainty. Li and Wang (2019) developed a fuzzy risk assessment methodology by integrating a fuzzy ANP and interpretive structural modeling, which captured interrelationships and interdependencies between risk factors and risk priorities to avoid data inaccuracy. ISM was used to identify critical risk factors, while fuzzy ANP was utilized to capture the fuzziness of neutral, optimistic, and pessimistic expert opinions, before ranking risk factors. This proposed method was implemented in construction and engineering risk management. A new risk analysis approach was proposed by Huang and Zhang (2020) combining FMEA and pessimistic-optimistic FAD, while accounting for an acceptable risk coefficient. The method was employed in evaluating dangerous goods transportation system risk on a railway. Tran et al. (2016) published a hybrid CIAM and factor analysis model for modeling cost variances in highway project-delivery decisions. Chen et al. (2019) proposed a model for the risk analysis of a multi-reservoir system, employing Monte Carlo simulations, dynamic Bayesian networks, and risk-informed inference. In this paper, Monte Carlo simulations were utilized to provide inputs for DBN, then DBN was built through expert knowledge uncertainty interrelationships. Finally, risk-informed inference provided risk information by a trained DBN. Drakaki et al. (2019) proposed a risk-informed supplier selection based on integrating fuzzy cognitive maps and a risk-based FAD (RFAD). Here, FCM was used to capture between-criteria dependencies, while RFAD was used to rank suppliers. Li et al. (2019) proposed a three-stage approach integrating DEMATEL, ISM, and BN. As a first step, a hierarchical network model was presented combining DEMATEL and ISM methods, thus investigating the coupling relationships between various accident-related factors and BN structure. The hierarchical structure was mapped onto a BN in order to quantify the strength of relationships between accident leading systems, specifying the main resultant systemic cause.

2.2. Limitations of existing methods and novel study contributions

Each available causality analysis method (Fig. 1) has certain drawbacks in terms of analyzing the main research problem. For example, existing risk analysis methods, such as fault tree (Kabir, 2017) and event tree (Purba et al., 2020), only determine the probability of risk occurrence or the probability of occurrence of the desired outcome. They are thus unable to determine the rate of change and the new values of variables due to risk factors. In CIAMs, the effect of a risk factor is modeled only on probability. When the goal is to investigate the impact of a risk factor on the severity and probability of an event, this can be achieved by defining discrete or different scenarios (states) and assigning probabilities to each of them. However, increasing states requires a large number of evaluations, causing the complexity of the problem to grow exponentially (Premchaiswadi, 2012). Moreover, due to a consideration of discrete values, it does not provide a good estimate of the continuous values provided to decision-makers. Bayesian methods can be divided into two categories: discrete and continuous. Discrete methods have the same drawbacks as the CIAM, while continuous methods first require sufficient data to estimate the probability function. This is often unavailable in the problem, and is used less frequently by decision-makers due to its computational complexity. In definite methods such as MCDM, structural models, and cognitive maps, only the degree of importance and effectiveness of a risk factor is considered among all factors, not the percentage of variability. For these reasons, they are more useful for ranking risk factors rather than for risk prediction, and thus are not suitable for use in the problem mentioned. Finally, the limitations of certain traditional data-driven methods like structural equation modeling (Ali et al., 2018) include a lack of access to data, due to quantification problems within the essential systemic parts. Moreover, decision-makers are often reluctant to rely on data-based models unless it is immediately clear what the results will (Arrieta et al., 2020). If this clarity is lacking, it provides a major concern for management, since they wish to take appropriate decisions with confidence, comprehension, and clarity.

According to the above, the purpose of this paper is to develop a new method of causes and effects which considers the impacts of different factors on each other in a network structure. The aims are to be able to: 1) estimate a risk degree of a factor according to other inputs, instead of considering an overly extensive number of discrete scenarios; 2) use the data obtained from experts to perform risk analysis in cases where data is not available; 3) consider different configurations of risk analysis (such as acceptable risk, maximum and minimum risks, factor ranking and sensitivity analysis); and finally, 4) be analyzable, interpretable, and explicable for decision-makers. The resulting new method is termed R.Graph within this paper. To test the effectiveness of this new model, a case study is presented in order to investigate the effects of COVID-19 on financial parameters of Iranian electricity industry.
3. Preliminaries

In this section, the required prerequisites for developing the proposed R.Graph model are presented. These include the definitions of relative difference and risk, as well as the operators of the aggregation process, in Sections 3.1 and 3.2, respectively.

3.1. Relative risk

Absolute difference refers to the difference between a compared value and a specified reference value. Considering two variables, $y$ and $x$, however, allows the absolute difference to be described in comparison with a reference value (Törnqvist et al., 1985). The relative difference between $x$ and $y$ can be measured, then defined as a real-value function $R(x, y)$ (Törnqvist et al., 1985). This function involves positive arguments $x$ and $y$, $R : \mathbb{R}^2 \to \mathbb{R}$, and possesses the following properties (Törnqvist et al., 1985):

\begin{align}
(a) &\quad R(x, y) = 0, \text{ if } x = y. \\
(b) &\quad R(x, y) > 0, \text{ if } y > x. \\
(c) &\quad R(x, y) < 0, \text{ if } y < x. \\
(d) &\quad R \text{ is a continuous, increasing function of } y \text{ when } x \text{ is fixed.} \\
(e) &\quad \forall x \geq 0 \to R(ax, ay) = R(x, y).
\end{align}

The risk or error of definite data can be defined as the deviation of the exact parameter from the predicted value using relative change measure, which can be determined as follows (Seiti et al., 2019):

\begin{equation}
R = \frac{|\text{Predicted value} - \text{Exact value}|}{\text{Exact value}} \quad (1)
\end{equation}

Therefore, the risk of $E_2$ in accordance with $E_1$ can be defined by employing Eq. (1) (Seiti et al., 2020):

\begin{equation}
R = \left| \frac{E_2 - E_1}{E_1} \right| \quad r \geq 0 \quad (2)
\end{equation}

in which we have:

\begin{equation}
E_2 = \begin{cases} (1 + R)E_1 & \text{if } E_2 \geq E_1 \\
(1 - R)E_1 & \text{if } E_2 < E_1 \end{cases}
\end{equation}

3.2. Aggregation operators

In this section, several fundamental definitions are introduced with regard to aggregation operators used in the R.Graph methodology.

**Definition 1.** (Lin and Jiang, 2014). The weighted arithmetical averaging (WAA) operator with dimension $n$ is a mapping $\mathbb{R}^n \to \mathbb{R}$. This is defined by the following formula:

\begin{equation}
\text{WAA}(a_1, a_2, ..., a_n) = \sum_{i=1}^{n} w_i a_i \quad (4)
\end{equation}

where $W = (w_1, w_2, ..., w_n)^T$ is the weighting vector of real numbers $a_1, a_2, ..., a_n$, such that $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0, 1]$. $\mathbb{R}$ is the set of the real numbers

**Definition 2.** (Lin and Jiang, 2014). The ordered weighted average (OWA) aggregation operator of dimension $n$ is a mapping $\mathbb{R}^n \to \mathbb{R}$. It possesses the weighting vector $W$ as follows:

\begin{equation}
W = (w_1, w_2, ..., w_n)^T \quad (5)
\end{equation}

where the component $w_i \ (i = 1, 2, ..., n)$ of weighting vector $W$ is subject to the following constraints: $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$.

Following on from this, an OWA operator can be expressed as:

\begin{equation}
\text{OWA}(a_1, a_2, ..., a_n) = \sum_{i=1}^{n} w_i d_i \quad (6)
\end{equation}

with $d_i$ being the $i$-th largest of the $a_i \ (1, 2, ..., n)$.

Using the various advantages of operators WAA and OWA, a hybrid weighted averaging (HWA) operator may thus be defined:

**Definition 3.** (Lin and Jiang, 2014). The HWA operator of dimension $n$ is a mapping $\mathbb{R}^n \to \mathbb{R}$. It is defined by an associated weighting vector $W = (w_1, w_2, ..., w_n)^T$, such that $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0, 1]$, and may be expressed as the following formula:

\begin{equation}
\text{HWA}(a_1, a_2, ..., a_n) = \sum_{i=1}^{n} w_i d_i \quad (7)
\end{equation}

where $d_i$ is the $i$-th largest of weighted arguments $n w_1 a_i (i = 1, 2, ..., n)$, and $W = (w_1, w_2, ..., w_n)^T$ is the weighting vector of $a_i (i = 1, 2, ..., n)$, with $\sum_{i=1}^{n} w_i = 1$ and $w_i \in [0, 1]$. $n$ here is a balancing coefficient.

4. Risk analysis using R.Graph methodology

In this section, the proposed R.Graph method is developed, and its various configurations are investigated (Section 4.1). In addition, a new group risk analysis framework based on the proposed R.Graph is presented (Section 4.2).

4.1. R.Graph methodology

The purpose of this section is to examine the different risk scenarios and changes in the causal chain, utilizing expert knowledge and presenting the concepts of the R.Graph model. Therefore, the main definitions and ideas of the R.Graph methodology are discussed in Section 4.1.1. Consistency checking; acceptable risk; determining pessimistic and optimistic risk values; identifying critical factors; and sensitivity analysis are laid out in Sections 4.1.2, 4.1.3, 4.1.4, 4.1.5, and 4.1.6, respectively.

4.1.1. R.Graph definitions and concepts

Considering a chain of acyclic causes and effects influencing each other, the goal of the R.Graph method is to investigate the percentage change in each factor due to changes in other factors, or the occurrence of different events over a fixed period of time. In this case, assuming the model is definite, the following concepts are first defined:

**Variable:** The variable in this study is set as any factor that has the ability to accept a value and a quantity as intensity, and all variables are considered to be continuous and definite. If there is a causal relationship between the two variables, a change in the cause variable can lead to a change in the effect variable. Generally, mathematical functions can be defined for variables. For instance, cost, time, and speed can be examples of a variable. In the proposed R.Graph method, the $i$th variable is shown as $V_i$ and in the form of a circle.

**Event:** Event is a factor without intensity and quantity, or is the variable whose change in value is not examined; it is generally stated by zero and one values. The occurrence of one event can cause the presence of other events, or change the value of other variables. For instance, the existence of natural disasters, such as floods and earthquakes, can be considered an event. In the proposed R.Graph, an event $j$ is shown as $E_j$ and in the form of a rectangle.

**Factor:** Each variable or event is called a factor.

**Parent:** If there is a cause and effect relationship between two factors, the parent is the factor that affects the influenced factor.

**Arc:** This is a directional vector drawn from cause to effect, and shows the causal relationship. It is worth noting that R.Graph edges do not form a loop, because the proposed model is acyclic.
The possible states and factors affecting the RGraph method, as shown in Fig. 2, are briefly examined in the following.

**State 1) The effect of an event on another event.**

Since the present paper aims to investigate the extent of changes in the problem variables, and also since the problem is considered to be definite, and the event probability is deemed to be 1, the cause and effect events are represented in this state, according to Fig. 2-a, that shows which events influence other events, or are influenced by them. In Fig. 2-a shows the existence of a causal relationship between events j and e, which takes values of zero and one. If b_{j,e} is one, it shows the existence of causality, otherwise, it indicates the absence of such a relationship.

**State 2) The effect of a variable on an event.**

Similar to the first state, according to Fig. 2-b, it can be determined which events are caused by changes in one variable, in which b_{j,v} indicates the existence of a causal relationship between the i-th variable and e-th event; this takes zero and one values.

**State 3) The effect of one variable on another variable.**

In this state, according to Fig. 2-c, the goal is to examine the change in the variable V_i due to the change in the variable V_j.

**Proposition 1.** Suppose the changes in V_i and V_j are called ΔV_i and ΔV_j, respectively. Now, if V_i is considered as a function of the variable V_j, we will have:

\[ \Delta V_i = V_i(V_j + \Delta V_j) - V_i(V_j) \]  

Eq. (8) can be called the ‘change rate’ to understand the changes better. In this study, the change rate of a variable is called the risk of that variable, which is generally shown by R. Now, if we write the change rate of V_i (risk of V_i) according to the change rate of V_j (risk of V_j), we have:

\[ R(V_i | V_j) = \frac{V_i(V_j \times (1 + R(V_j)))}{V_i(V_j)} - 1 \]  

where \( R(V_i | V_j) \) indicates the amount of V_i risk due to the existence of the risk in V_j. In this relation, the positive value of \( R(V_i | V_j) \) indicates that by increasing the risk of V_j, the risk of V_i also increases (positive correlation), while the negative values indicate that increasing the risk of V_j reduces the risk of V_i (negative correlation).

**Proof.** By dividing ΔV_i by V_i(V_j), the growth rate or the risk of V_i is obtained, and we have:

\[ R(V_i | V_j) = \frac{\Delta V_i}{V_i(V_j)} = \frac{V_i(V_j + \Delta V_j) - V_i(V_j)}{V_i(V_j)} - 1 \]

If \( V_i(V_j + \Delta V_j) \) is also written as a growth rate, i.e., \( V_i(V_j(1 + R(V_j))) \), Eq. (9) is proven.

For a real problem, the relationship between the variables is either already known (in which Eq. (12) can be used to determine the risk of the variables) or unknown. If the relationship between the two variables is unknown, we can suppose the relationship between the two variables is \( V_i = a_0V_j^n + a_{n-1}V_j^{n-1} + \ldots + a_1V_j + c \). Using this, it can be shown from Eq. (9) that the relationship between the risks of two variables is as follows:

\[ R(V_i | V_j) = a_0R(V_j)^n + a_{n-1}R(V_j)^{n-1} + \ldots + a_1R(V_j) \]  

To correctly estimate the type of relationship between two variables and its coefficients, a sufficient amount of data is needed. However, many real-world problems are caused by lack of accurate knowledge of the V_j function in terms of V_i, since there is often not enough data to estimate the functions of the intended variables. In these cases, as is often applied to predictive intelligence in the case of little data (Deeh, 2015), it can be better to utilize simpler models such as linear models. Considering linear relationships for many variables, such as the values of profit and cost, can be a rational assumption. In this paper, due to the lack of available data, and since it is assumed that all data are obtained from experts, an approximate linear method for determining the risk of V_i with respect to the risk of V_j is presented in the following.

**Definition 4.** Let the function V_i be assumed to be linear in terms of V_j. If the unit risk of V_j is specified in terms of V_i risk, then we have:

\[ R(V_i | V_j) = a_0R(V_j) \]

where \( a_0 \) indicates the amount of risk V_i per unit increase or 100% increase in the risk of V_j, which can be obtained according to experts’ opinions. It is worth noting that in this article, all variables are considered continuous and definite, and if the nature of the variable is probabilistic in the real world, its expected value can be entered into the problem.

**State 4) The effect of an event on one variable.**

In this state, according to Fig. 2-d and assuming the model to be non-probabilistic, it can be said that if \( E_i \) occurs as a parent of the variable \( V_i \), \( V_i \) grows to a constant and definite amount.

**Definition 5.** If the risk of the variable \( V_i \) due to the occurrence of \( E_i \) is \( I_{i,j} \), then we have:

\[ R(V_i | E_i) = I_{i,j} \]

**State 5) The effect of several factors on another variable**

**Definition 6.** Suppose that a set of \( V \) variables and \( E \) events affects a specific variable \( V_i \), and \( i = 1, \ldots, V, j = 1, \ldots, E \) (Fig. 3); now, if the purpose is to investigate the change rate (risk) of the variable \( V_i \) in terms of all these factors, assuming all the factors are independent, we have:

where \( \text{Par}(V_i) \) represents all parents of \( V_i \), \( R(V_i) \) is the risk of the \( i \)-th variable and \( R(V_i | \text{Par}(V_i)) \) is the change rate (risk) due to changes in or occurrence of \( \text{Par}(V_i) \).

Now, a separate parent can be assumed for the \( \text{Par}(V_i) \) members which can be seen in Fig. 4. In this state, Eq. (12) can be generally written as follows:

---

Fig. 2. Different types of causality between two factors in RGraph.

Fig. 3. The effect of different factors on a variable.
Fig. 4. A typical R.Graph diagram.

\[
R(V_i | \text{Par}(V_i)) = \sum_{j=1}^{\mathcal{E}} x_{ij} R(V_j | \text{Par}(V_i)) + \sum_{j=1}^{\mathcal{F}} l_{ji}
\]

(13)

In Eq. (13), the risk of the variable \( V_i \) was calculated according to its parent. However, we can determine the risk of the variable \( V_i \) relative to the risk of an influential variable.

**Definition 7.** If we want to define the risk of the variable \( V_i \) relative to its influential variable \( V_j \), namely \( R(V_i | V_j) \), we will have:

\[
R(V_i | V_j) = \alpha_{ij} R(V_i) + \sum_{l=1}^{L} \alpha_{ijl} R(V_l | V_j) + \sum_{k=1}^{K} l_{ijk} \text{Var} \text{Par}(V_i)
\]

(14)

where \( V_i \) represents the variables that are directly or indirectly affected by \( V_j \); \( l_{ij} \) shows the effect of events on \( V_i \) that are the parents of \( V_j \), and \( l_{ij} \) affects their occurrence. Consequently, from Eq. (14), we have:

\[
R(V_i | V_j) = 0
\]

(15)

Moreover, from Eq. (14), it can be argued that if \( V_i \) does not affect \( V_j \) in any way, we have:

\[
R(V_i | V_j) = 0
\]

(16)

**Definition 8.** The risk of the variable \( V_i \) can be defined according to the desired event \( E_j \), i.e., \( R(V_i | E_j) \) as follows:

\[
R(V_i | E_j) = l_{ij} + \sum_{k=1}^{L} l_{ijk} \alpha_{ij} R(V_j | E_j) \] \( E_j \text{Var} \text{Par}(V_i)
\]

(17)

In the above relation, \( l_{ij} \) shows the effect of events on \( V_i \), which is the parent of \( V_j \), and also shows that \( E_j \) affects their occurrences. \( V_i \) also indicates variables directly or indirectly affected by \( E_j \). On the other hand, it can be said that if \( E_j \) does not affect \( V_i \) in any way, we have:

\[
R(V_i | E_j) = 0
\]

(18)

After calculating the risk value for each variable, the new value of each variable can be updated using **Definition 9**.

**Definition 9.** Suppose the initial value of the variable \( V_i \) is denoted by \( V_i^{old} \); now, if the new value of \( V_i \) is displayed as \( V_i^{new} \), according to the risk value \( R(V_i | \text{Par}(V_i)) \), its value is obtained as follows:

\[
V_i^{new} = (1 + R(V_i | \text{Par}(V_i)))V_i^{old}
\]

(19)

The R.Graph data can be displayed through the R.Graph matrix as follows.

**Definition 10.** Assume that the whole problem includes \( V \) variables and \( E \) events; the basic values of the effectiveness of the variables (for 100% risk) and the events can be displayed by the R.Graph matrix which is denoted by \( R_{\text{Graph}} \). For simplicity, the \( R_{\text{Graph}} \) may be defined as:

\[
R_{\text{Graph}} = \begin{bmatrix}
V - V & V - E \\
E - V & E - E
\end{bmatrix}
\]

(20)

where the R.Graph matrix consists of 4 separate sub-matrices: \( V - V, V - E, E - V, \) and \( E - E \). These are defined as follows:

\[
V - V = \begin{bmatrix}
0 & \alpha_{12} & \ldots & \alpha_{1\mathcal{V}} \\
\alpha_{21} & 0 & \ldots & \alpha_{2\mathcal{V}} \\
\ldots & \ldots & \ldots & \ldots \\
\alpha_{\mathcal{V}1} & \alpha_{\mathcal{V}2} & \ldots & 0
\end{bmatrix}, \quad v = 1, \ldots, \mathcal{V}, \quad \forall i
\]

(21)

\[
V - E = \begin{bmatrix}
b_{11}^e & b_{12}^e & \ldots & b_{1\mathcal{E}}^e \\
b_{21}^e & b_{22}^e & \ldots & b_{2\mathcal{E}}^e \\
\ldots & \ldots & \ldots & \ldots \\
b_{\mathcal{E}1}^e & b_{\mathcal{E}2}^e & \ldots & b_{\mathcal{E}\mathcal{E}}^e
\end{bmatrix}, \quad v = 1, \ldots, \mathcal{V}, \quad e
\]

(22)

\[
E - V = \begin{bmatrix}
0 & b_{12}^e & \ldots & b_{1\mathcal{E}}^e \\
b_{21}^e & 0 & \ldots & b_{2\mathcal{E}}^e \\
\ldots & \ldots & \ldots & \ldots \\
b_{\mathcal{E}1}^e & b_{\mathcal{E}2}^e & \ldots & 0
\end{bmatrix}, \quad v = 1, \ldots, \mathcal{V}, \quad \forall j
\]

(23)

\[
E - E = \begin{bmatrix}
0 & b_{12}^e & \ldots & b_{1\mathcal{E}}^e \\
b_{21}^e & 0 & \ldots & b_{2\mathcal{E}}^e \\
\ldots & \ldots & \ldots & \ldots \\
b_{\mathcal{E}1}^e & b_{\mathcal{E}2}^e & \ldots & 0
\end{bmatrix}, \quad v = 1, \ldots, \mathcal{V}, \quad e
\]

(24)

where the \( V - V \) matrix describes the impact of variables’ risks on other variables; the \( V - E \) matrix defines the impact of variables on events; the \( E - V \) matrix describes the impact of events’ risks on variables; and the impact of events’ risks on other events are defined by the \( E - E \) matrix. In the \( V - V \) matrix, \( \alpha_{ij} \) shows the risk of the \( v \)-th variable per 100% increase in risk of the \( i \)-th variable. Since the graph is acyclic, if \( \alpha_{ij} \) adopts a value, we will have \( \alpha_{ij} = 0 \). In the \( V - V \) matrix, \( l_{ij} \) indicates the risk of the \( i \)-th event due to the occurrence of the \( j \)-th event. Finally, in the \( E - V \) and \( E - E \) matrices, \( b_{ij}^e \) and \( b_{ij}^e \) indicate how the occurrence of \( i \)-th event is affected by the occurrence of the \( j \)-th event and \( i \)-th variable, respectively. If \( b_{ij}^e \) and \( b_{ij}^e \) take values of one, indicate that the occurrence of the \( e \)-th event is affected by the \( j \)-th event and \( i \)-th variable. If \( b_{ij}^e \) and \( b_{ij}^e \) are zero, it indicates that there is no effect.
One of the things that should be considered in the R.Graph method is to check the inconsistency of the evaluations. On this basis, after obtaining the results through the R.Graph method, the following condition should be considered for each variable:

\[ R(V_{i})^{\text{min}} \leq R(V_{i} | \text{Par}(V_{i})) \leq R(V_{i})^{\text{max}} \]  

(25)

where \( R(V_{i})^{\text{min}} \) and \( R(V_{i})^{\text{max}} \) are the lowest and highest possible risk values that \( R(V_{i} | \text{Par}(V_{i})) \) can take, respectively.

### 4.1.3. Acceptable risk

In the proposed method of R.Graph, if there is a risk in a parent, the risk is passed on to its offspring, which increases the risk values of the downstream variables. Since one of the goals of the R.Graph method is to identify events that affect critical variables and plan to reduce their risk, high risk demands greater efforts in decreasing the risk. Therefore, in some decision-making problems, decision-makers accept some level of risk due to organizational goals and the degree of risk-taking, which is called 'acceptable risk' (AR) in the literature (Seiti et al., 2019).

In this paper, the acceptance level of risk and changes in a variable is defined as the percentage change for a one hundred percent risk in the desired variable that can be accepted and compensated by the relevant organization which is not included in the calculations. This can be expressed as:

\[ \text{Acceptable risk for a one hundred percent risk of a variable} = \text{Risk-taking degree} + \text{Risk-compensation degree} \]

In the R.Graph method, some of the risk levels of each variable can therefore be considered acceptable. However, since the risk value of one variable depends on the risk values of other variables, the acceptance and compensation of some risks affects the risks of other variables, so the risk values of each variable should be calculated by considering the acceptable risk of the variables. Therefore if the AR value is defined as a percentage between 0 and 100, each risk value can be modified based on Definition 11.

### Definition 11

Assume that the risk-taking for a one hundred percent risk of the \( i \)-th variable is shown by \( \text{AR}_{i} \), considering the level of risk-taking, Eq. (13) can be rewritten as follows:

\[ R(V_{i} | \text{Par}(V_{i})) = \left( \sum_{j=1}^{\text{v}} \alpha_{ij} R(V_{i} | \text{Par}(V_{i})) + \sum_{j=1}^{\text{v}} \beta_{ij} \right) \times \left( 1 - \text{AR}_{i} \right) \]  

(26)

where the values of acceptable risk are considered simultaneously for inputs and outputs, and \( 1 - \text{AR}_{i} \) is the percentage of risks not accepted and entered into the problem. Generally, the matrix of acceptable risk for \( V \) variables, which is displayed by \( \text{AR}^{V} \), can be defined as follows:

\[ \text{AR}^{V} = [\text{AR}_{1}, ..., \text{AR}_{v}, ..., \text{AR}_{V}] \]  

(27)

where \( 0 \leq \text{AR}_{i}^{V} \leq 1 \).

### Example 2

Considering Example 1 and the acceptable risk values, the risk values of each variable in Example 1 can be calculated as follows:

\[ \text{AR}^{V} = [\text{AR}_{1} = 0.3, \text{AR}_{2} = 0, \text{AR}_{3} = 0.5, \text{AR}_{4} = 0.2] \]

\[ R(V_{1} | E_{2}) = I_{h1} (1 - \text{AR}_{1}) = -0.3 (1 - 0.3) = -0.21 \]

\[ R(V_{2} | E_{2}) = I_{h2} + I_{l2} (1 - \text{AR}_{2}) = (0.4 - 0.25) (1 - 0) = 0.15 \]

\[ R(V_{3} | E_{2}) = \alpha_{23} R(V_{2} | E_{6}, E_{2}) = 0.2 \times 0.15 \times (1 - 0.5) = 0.015 \]

\[ R(V_{4} | E_{2}) = \alpha_{42} R(V_{2} | E_{6}, E_{2}) \times (1 - \text{AR}_{4}) = -0.5 \times 0.21 + 0.3 \times 0.15 + 0.6 \times 0.015 \times (1 - 0.2) = 0.1272 \]
4.1.4. Determining pessimistic and optimistic risk values

In some decision-making and risk analysis problems, the decision-maker is interested to know the value of the highest and lowest risks that will be experienced in each variable, terming them pessimistic and optimistic values, respectively. Since the risk values of each variable or event on a specific variable are either positive or negative, Proposition 2 can be formulated.

Proposition 2. The maximum and minimum amount of risk of a variable can be determined as follows:

\[
\begin{align*}
\text{max}(R(V_i)) &= \sum_{v=1}^{V} \alpha_{iv} \cdot \text{max}(R(V_i)) + \sum_{v=1}^{V} \alpha_{iv} \cdot \text{min}(R(V_i)) \\
&\quad + \sum_{j=1}^{E} \xi_{ij} \cdot \text{max}(R(V_i)) \geq 0 \\
\text{min}(R(V_i)) &= \sum_{v=1}^{V} \alpha_{iv} \cdot \text{min}(R(V_i)) + \sum_{v=1}^{V} \alpha_{iv} \cdot \text{max}(R(V_i)) \\
&\quad + \sum_{j=1}^{E} \xi_{ij} \cdot \text{min}(R(V_i)) \leq 0
\end{align*}
\]

where \( \text{max}(R(V_i)) \) shows the highest value of risk (pessimistic risk) and \( \text{min}(R(V_i)) \) shows the lowest amount of risk (optimistic risk) of the variable \( V_i \). Also, in these relations, \( \xi_{ij} \) represent the effects of event risks on variables which are positive and negative, respectively. Moreover, \( \alpha_{iv}^+ \) and \( \alpha_{iv}^- \) indicate positive and negative values, which are defined as follows:

\[
\begin{align*}
\alpha_{iv}^+ &= \begin{cases} 
\alpha_{iv} & \text{if } \alpha_{iv} > 0 \\
0 & \text{otherwise}
\end{cases} \\
\alpha_{iv}^- &= \begin{cases} 
\alpha_{iv} & \text{if } \alpha_{iv} < 0 \\
0 & \text{otherwise}
\end{cases} \\
\xi_{ij}^+ &= \begin{cases} 
\xi_{ij} & \text{if } \xi_{ij} > 0 \\
0 & \text{otherwise}
\end{cases} \\
\xi_{ij}^- &= \begin{cases} 
\xi_{ij} & \text{if } \xi_{ij} < 0 \\
0 & \text{otherwise}
\end{cases}
\end{align*}
\]

(29)

Proof. For \( R(V_i) \) to reach its maximum value, namely \( \text{max}(R(V_i)) \), only sentences with positive or zero values must be included. If \( R(V_i) \) is itself affected by other events and variables, only its positive sentences should be considered. Hence, only positive values of \( \xi_{ij} \), i.e., \( \xi_{ij}^+ \), are entered into the \( \text{max}(R(V_i)) \) calculation. However, since the values of \( \alpha_{iv} \) are multiplied by \( R(V_i) \), this multiplication is positive when either both \( \alpha_{iv} \) and \( R(V_i) \) are negative, or both are positive. Thus, the \( \text{max}(R(V_i)) \) value is obtained. Similarly, the relation of \( \text{min}(R(V_i)) \) can be proven.

Example 3. Considering Example 1, optimistic and pessimistic values for each of the variables can be calculated as follows:

\[
\begin{align*}
\text{max}(R(V_1)) &= 0 \\
\text{min}(R(V_1)) &= h_{13}^- = -0.3 \\
\text{max}(R(V_2)) &= 0.25 \\
\text{min}(R(V_2)) &= h_{24}^+ = 0.4 \\
\text{max}(R(V_3)) &= \alpha_{31}^+ \cdot \text{max}(R(V_2)) = 0.2 \times 0.15 = 0.03 \\
\text{min}(R(V_3)) &= 0 \\
\text{max}(R(V_4)) &= \alpha_{44}^+ \cdot \text{min}(R(V_1)) + \alpha_{45}^+ \cdot \text{max}(R(V_2)) + \alpha_{41}^+ \cdot \text{max}(R(V_3)) = 0.213 \\
\text{min}(R(V_4)) &= 0
\end{align*}
\]

4.1.5. Identifying critical factors

One of the goals of cause and effect methods, including the proposed R-Graph method, is to identify the events or variables with the most significant impact on other variables, as considered by an organization. Indeed, the organization or managers can identify these critical factors and plan to reduce related negative consequences. The following outlines the prioritization of factors in the proposed R-Graph method.

Proposition 3. Assume that the total number of variables is \( V \), and the total number of events is \( E \); then, the relative importance of factors is obtained from the following relation:

\[
\begin{align*}
\sum_{v=1}^{V} |R(V_v|V_i)| + |R(V_i)| \\
\sum_{j=1}^{E} |R(V|E_j)| + |R(E_j)|
\end{align*}
\]

(30)

where \( w_v^+ \) shows the weight of the \( i \)-th variable and \( w_j^+ \) shows the weight of \( j \)-th event among all factors.

Proof. The change rates in the risk of all variables can be written, considering the \( i \)-th variable, as follows:

\[
\sum_{v=1}^{V} |R(V_v|V_i)| + |R(V_i)|
\]

Also, the change rates of the risk of all variables can be obtained, considering the importance of the \( j \)-th event, as follows:

\[
\sum_{j=1}^{E} |R(V_j|E_j)|
\]

To obtain the significance of the \( i \)-th variable or the importance of the \( j \)-th event among \( V \) variables and \( E \) events, it must be divided by the sum of the changes. In this way, Eq. (30) can be proven.

Example 4. Suppose the causal is in the form of Fig. 5, and its binary display, which is indicated by arrows, can be seen in Fig. 6. To find the effect of the variable \( V_3 \) on the problem, it is necessary to find the effects of the variable \( V_9 \) on other variables, and then remove the

Fig. 6. Variable \( V_3 \) removal and the interaction of factors in Example 1.
Proposition 4. If the amount of the intended change to the sensitivity analysis of the variable \( v \) (for a 100% increase in the risk of \( v \)) is called \( \Delta v_{\text{irr}} \), then the sensitivity of the whole problem over the variable \( v \) will be obtained as follows:

\[
S^v|\Delta v_{\text{irr}} = \sum_{i=1}^{V} R(V_i|V_j + \Delta v_{\text{irr}}) - \sum_{i=1}^{V} R(V_i|V_j)
\]  

(31)

where \( S^v|\Delta v_{\text{irr}} \) indicates problem sensitivity (total changed risk) to the \( i \)-th variable on the \( v \)-th variable, considering \( \Delta v_{\text{irr}} \) can be positive or negative. Also, \( \sum_{i=1}^{V} R(V_i|V_j + \Delta v_{\text{irr}}) \) indicates the sum of the \( V_i \) risk calculation for \( V_j \) among \( V \) variables, assuming the value of \( \Delta v_{\text{irr}} \) for the variables risk calculation with a 100% change in \( V_i \). Similarly, sensitivity analysis can be performed on a specific event as follows.

Proposition 5. If the sensitivity change of the \( j \)-th event over the \( v \)-th variable is called \( \Delta V_{\text{irr}} \), then we will have:

\[
S^v|\Delta V_{\text{irr}} = \sum_{i=1}^{V} R(V_i|E_j + \Delta V_{\text{irr}}) - \sum_{i=1}^{V} R(V_i|E_j)
\]  

(32)

where \( S^v|\Delta V_{\text{irr}} \) shows the sensitivity of the problem over the \( j \)-th event for \( \Delta V_{\text{irr}} \), and \( \sum_{i=1}^{V} R(V_i|E_j + \Delta V_{\text{irr}}) \) shows the risk calculation of \( V_i \) for the event \( E_j \) among \( V \) variables, assuming the value of \( \Delta V_{\text{irr}} \) indicates more risk due to the \( E_j \) event.

Example 5. Considering the R.Graph matrix in Example 1, and assuming \( \Delta V_{\text{irr}} = \Delta V_{\text{irr}} = 0.2, \forall i, j \), the sensitivity of the problem to all factors will thus be as follows:

- For Event 1:
  \[ R(V_1|E_1 + 0.2) = l_{11} + 0.2 = -0.3 + 0.2 = -0.1 \& R(V_1|E_2) = -0.3 \]
  \[ R(V_2|E_1 + 0.2) = l_{21} + 0.2 = 0.4 + 0.2 = 0.6 \& R(V_2|E_1) = 0.4 \]
  \[ R(V_2|E_2 + 0.2) = \alpha_{23} R(V_2|E_1 + 0.2) = 0.2 \times 0.6 = 0.12 \]
  \[ & R(V_2|E_2) = 0.08 \]
  \[ R(V_1|E_1 + 0.2) = \alpha_{14} R(V_1|E_1 + 0.2) = 0.5 \times \times 0.1 + 0.3 \times 0.6 + 0.3 \times 0.12 = 0.302 \]
  \[ & R(V_1|E_2) = 0.318. \]

Therefore, according to Eq. (32), we have:

\[ S^y|\Delta V_{\text{irr}} = \sum_{i=1}^{V} R(V_i|E_1 + 0.2) - \sum_{i=1}^{V} R(V_i|E_1) = 0.424 \]

For Event 2:

\[ R(V_1|E_2 + 0.2) = 0 \& R(V_1|E_2) = 0 \]

\[ R(V_2|E_2 + 0.2) = l_{21} + 0.2 = -0.25 + 0.2 = -0.05 \& R(V_2|E_2) = -0.25 \]

4.2. The risk analysis framework using the proposed R.Graph method

As mentioned in the introduction, the purpose of developing the R.Graph approach is to provide a cause and effect model using expert knowledge. In fact, it aims at analyzing risk and changes in important organizational parameters, based on risk factors with a low probability of occurrence, to provide preventive solutions and relative preparedness. The way of modeling in R.Graph method and its mathematical relations were presented in Section 4.1. Additionally, different cases of the risk analysis were considered, such as considering acceptable risk, optimistic and pessimistic situations, the importance of factors, and sensitivity analysis. The following section aims to provide a group risk analysis framework by experts, based on the proposed R.Graph method, and is summarized as follows:

4.2.1. Phase I: data preparation

4.2.1.1. Step zero

Identifying the set of events and variables affecting each other, and the degree of acceptable risk.

In this step, the organization’s intended variables are considered, examined, and determined according to organizational purposes. In addition to the factors leading to changes in intended variables or other events, the organization also wants to investigate how these effects are specified. In this step, the interrelations between variables and events are determined using expert opinions and by a moderator. Then, a graph of causes and effects is drawn, from which the event-variable matrix (i.e., \( E - V \)) and the event-event matrix (i.e., \( E - E \)) can be created. Additionally, the experts are asked to determine the effects and risks of events on variables (\( E - V \) matrix) and the effects of variables on variables (\( V - V \) matrix) by defining a specific percentage. The sample questionnaire for obtaining the \( E - V \) and \( V - V \) matrices is provided in Appendix I. It is worth noting that, since R.Graph relations are developed based on the unit value of these changes, after determining the impact percentage by
experts, the evaluation values are converted to unit values in terms of percentage (dividing by 100).

Finally, according to organizational macro policies, goals, and perspectives, values are determined relating to the acceptability of risks of variables. A sample questionnaire for obtaining acceptable risk values is shown in Appendix 2.

4.2.1.2. Step 1

Aggregating the $E - V$ and $V - V$ matrices and determining the R.Graph matrix.

In this step, the R.Graph risk matrix can be determined, according to the 4 matrices $E - E$, $E - V$, $V - E$, and $V - V$. It should be noted that evaluation values obtained directly by each expert (which can contain continuous values) occur in matrices $V - V$ and $E - V$. These represent the impacts of variables and events on other variables. Since the values of these two matrices may be different for each expert's evaluations, the aggregated values of all the expert opinions must first be calculated for each of these two matrices.

Let us denote the $E - V$ and $V - V$ matrices of the $t$-th expert as $(E - V)^j$ and $(V - V)^j$. If there are $T$ experts in the problem, the aggregated values of these two matrices are determined through the HWA operator. Let us consider $(V - V)^j = [a_{ij}^j]$ and $(E - V)^j = [b_{ij}^j]$; if we denote the aggregated matrices of $(V - V)^j$ and $(E - V)^j$ as $(V - V)^i$ and $(E - V)^i$, using the HWA operator, we have:

$$(V - V)^i = HWA((V - V)^j, (V - V)^j, ..., (V - V)^j) = \left[ \sum_{t=1}^{T} w_t a_{ij}^t \right]$$

$$(E - V)^i = HWA((E - V)^j, (E - V)^j, ..., (E - V)^j) = \left[ \sum_{t=1}^{T} w_t b_{ij}^t \right]$$

where vector $\hat{W} = (\hat{w}_1, \hat{w}_2, ..., \hat{w}_T)$ is the weighting vector associated with OWA, $a_{ij}^t$ and $b_{ij}^t$ are the $t$-th largest of the weighted arguments $T w_t a_{ij}^t$ and $T w_t b_{ij}^t$ ($t = 1, 2, ..., T$), $\hat{W} = (\hat{w}_1, \hat{w}_2, ..., \hat{w}_T)$ is the weighting vector of the experts, with $\sum_{t=1}^{T} w_t = 1$ and $w_t \in [0, 1]$, and $T$ is the balancing coefficient.

Now the aggregated R.Graph matrix $(R_{R, Graph}^i)$ can be defined based on the $E - E$ and $V - E$ matrices obtained at Step zero. The aggregated matrices $(V - V)^i$ and $(E - V)^i$ may be described as follows:

$$R_{R, Graph}^i = \begin{bmatrix} (V - V)^i & V - E \\ (E - V)^i & E - E \end{bmatrix}$$

4.2.2. Phase II: processing

4.2.2.1. Step 2

Determining the risk of each variable.

Now, according to the aggregated R.Graph matrix $(R_{R, Graph}^i)$, the risk value of each variable can be obtained through considering the acceptable risk matrix $AR^i$ using Eq. (26) or without considering $AR^i$ by employing Eq. (13).

4.2.2.2. Step 3

Calculating the value of pessimistic and optimistic risks.

At this stage, the maximum risk values (pessimistic risks) $\max R(V_i)$ and the lowest risk values (optimistic risks) $\min R(V_i)$ are calculated for each variable according to Eq. (28).

4.2.3. Phase III

Consistency checking.

4.2.3.1. Step 4

Consistency checking of risk values.

In this step, the risk values obtained without considering AR values are checked against the consistency constraint of Eq. (25). If this condition is not met, the values of the matrices $(V - V)^j$ and $(E - V)^j$ must be revised or adjusted.

4.2.4. Phase IV

Post-processing.

4.2.4.1. Step 5

Calculating the weights of all variables and events.

In this step, Eq. (30) is used to determine the importance of each factor, whether variable or event.

4.2.4.2. Step 6

Sensitivity analysis.

To identify the sensitivity analysis of different factors in their input parameters, considering different values for $\Delta V_i$ and $\Delta V_{iv}$, Eqs. (31) and (32) are employed to calculate the sensitivities of the variables and events, respectively.

The R.Graph algorithm is represented in Algorithm 1 and Fig. 7.
The COVID-19 epidemic in Iran is part of the worldwide Coronavirus pandemic, which has had various consequences, including social and economic implications, for the entire country. One of the most critical parts of Iran's economy that has been significantly affected by the Coronavirus is the electricity industry. COVID-19 is projected to reduce production volumes and shut down manufacturing, contracting, and consulting units, leaving manufacturing units temporarily closed and costing a large number of jobs (Asadi, 2020). The volume of executive activities will be reduced, and ongoing projects may also be delayed; with the disruption of trade, imports and exports related to the electricity industry will additionally be severely disrupted (Asadi, 2020). The power grid is unstable, and blackouts occur. Delays in the private sector, due to the Coronavirus pandemic, as shown in Table 1. Additionally, the causal relationships of these factors have been identified by relevant experts and drawn into the R.Graph Diagram (Fig. 8), which led to the determination of the E – E (Table 2) and V – E matrices (Table 3).

The six steps of the proposed methodology (Section 4.2) have been utilized to evaluate the risk of each variable in different scenarios, and risk analysis has been carried out using the R.Graph method.

5. Case study

The COVID-19 epidemic in Iran is part of the worldwide Coronavirus pandemic, which has had various consequences, including social and economic implications, for the entire country. One of the most critical parts of Iran's economy that has been significantly affected by the Coronavirus is the electricity industry. COVID-19 is projected to reduce production volumes and shut down manufacturing, contracting, and consulting units, leaving manufacturing units temporarily closed and costing a large number of jobs (Asadi, 2020). The volume of executive activities will be reduced, and ongoing projects may also be delayed; with the disruption of trade, imports and exports related to the electricity industry will additionally be severely disrupted (Asadi, 2020). The power grid is unstable, and blackouts occur. Delays in the private sector, due to the Coronavirus pandemic, as shown in Table 1. Additionally, the causal relationships of these factors have been identified by relevant experts and drawn into the R.Graph Diagram (Fig. 8), which led to the determination of the E – E (Table 2) and V – E matrices (Table 3).

The six steps of the proposed methodology (Section 4.2) have been utilized to evaluate the risk of each variable in different scenarios, and risk analysis has been carried out using the R.Graph method.

5.1. Determining the R.Graph and acceptable risk matrices and aggregating expert opinions

In the initial stage, by determining the R.Graph diagram of Fig. 8, two sub-matrices of the R.Graph matrix (i.e. E – E and V – E) were first determined in order to obtain the other two matrices, namely the matrices of the event on variable effect (E – V) and the variable on variable effect (V – V). Three experts from the field of the electricity industry were recruited to cooperate with the study. The participants were then analyzed demographically. Two experts held doctorates in related fields, while one held a related postgraduate degree. The decision-makers had high levels of experience in the field, ranging from 5 to 25 years. As per the data collected, the decision-makers involved in this study were the researchers from two research centers (namely from a high-capacity power transmission center, and from a group planning and operating power systems).

In order to analyze the risk of each variable, the three experts were asked to specify the impact and risk of potential events on each of the affected variables. They were also asked to estimate the effect (risk) of each variable on other variables, in case of a 100% increase in the effective variable. For example, experts were asked the following question to determine the effect of the event “new safety regulations” on the variable “job difficulty”:

How many percentage points do you think new safety regulations will alter job difficulty?

In order to determine the effects of variable “personnel medical expenses” on “total cost”, the following question was asked:

How many percentage points do you think a 100% increase in personnel medical expenses will alter total cost?

In both types of questions, participants were requested to indicate an increase in the percentage changes with a positive sign, and a decrease with a negative. The questionnaire used for obtaining the V – V and E – V matrices of each expert can be found in Appendix 1. Next, since the V – V and E – V matrices in the R.Graph method were developed based on the unit value of the changes, after determining the percentage impacts by experts, the evaluation values were converted to unit values in terms of percentage (dividing by 100). Finally, equal weights were considered for each ordered aggregation, and equal weights given to each expert. The V – V and E – V matrices obtained from each expert were aggregated using Eqs. (33) and (34), and can be seen in Tables 4 and 5.

In the next stage, an expert in the organization's policies was asked to determine acceptable risk values for each of the variables in Table 6. For example, the related expert was asked:

What percentage do you accept for a one hundred percent risk in personnel medical expenses, according to organizational policies?

The questionnaire used for obtaining acceptable risk values can be found in Appendix 2.
5.2. Determining the risk of each variable in different cases

At this stage, the risk in different situations was calculated, taking into account the potential risk with and without considering the acceptable risk, and while calculating the maximum and minimum risks. A software code based on Algorithm 1 was developed using MATLAB software; the results can be seen in Table 7. For further explanation, the following describes how to obtain the risk values in different cases. For example, the risk of variable $V_1$ (number of key personnel) is affected by events $E_2$ (refusal to attend the workplace), $E_3$ (staff first-degree relative infection) and $E_4$ (staff infection). Assuming $AR = 0.8$, the calculations are made using Eqs. (26) as follows:

$$R(V_1|E_2, E_3, E_4) = (P_{21} + P_{31} + P_{41}) \times (1 - AR)$$

$$= (-0.075 - 0.075 - 0.15) \times (1 - 0.5) = -0.15$$

and without considering $AR$, we have:

$$R(V_1|E_2, E_3, E_4) = (P_{21} + P_{31} + P_{41}) = (-0.075 - 0.075 - 0.15)$$

$$= -0.3$$

In addition, the highest and lowest values of $V_1$ can be calculated using Eqs. (31) as follows:
Without considering $AR$

The $(E - V)^2$ matrix.

| Variable | $V_1$ | $V_2$ | $V_3$ | $V_4$ | $V_5$ | $V_6$ | $V_7$ | $V_8$ | $V_9$ | $V_{10}$ | $V_{11}$ | $V_{12}$ | $V_{13}$ |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|----------|----------|----------|
| $E_1$    | 0     | 0     | 0     | 0     | 0     | 0     | 0.2   | -0.3  | -0.5  | 0        | 0        | 0        | 0        |
| $E_2$    | -0.075| 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0        | 0        | 0        | 0        |
| $E_3$    | -0.075| 0     | 0     | 0.5   | 0     | 0     | 0     | 0     | 0     | 0        | 0        | 0        | 0        |
| $E_4$    | -0.15 | 0     | 0     | 0.2   | 0     | 0     | 0     | 0     | 0     | 0        | 0        | 0        | 0        |
| $E_5$    | 0     | 0.25  | 0.39  | 0     | 0.3   | 0     | 0     | 0     | 0     | 0        | 0        | 0        | 0        |

Now, since the risk results in the "without considering" mode are consistent, the analysis proceeds to the next section in order to carry out the weight calculation and sensitivity analysis.

5.3. Determining the weights of each factor and sensitivity analysis

In this section, in order to prioritize all factors for planning risk management and determining preventive measures, the importance of each factor was determined and ranked using Eq. (30), as shown in Table 8. Also, to investigate problem sensitivity to increases and decreases in the constant value in the risk of various factors, three cases of sensitivity analysis were considered as follows:

**Case 1.** To determine the risk of each of the variables for each factor, the effect of each of the affecting factors is considered to be 0.1 greater, thus:

$\forall j = 1, ..., 13, \quad \Delta V_{ij} = \Delta V_{ji} = 0.1$

**Case 2.** To determine the risk of each of the variables for all factors, the effect of each of the affecting factors is considered to be 0.2 greater, thus:

$\forall j = 1, ..., 13, \quad \Delta V_{ij} = \Delta V_{ji} = 0.2$

**Case 3.** To determine the risk of each of the variables for all factors, the effect of each affecting factor is considered to be 0.1 lower, thus:

$\forall j = 1, ..., 13, \quad \Delta V_{ij} = \Delta V_{ji} = -0.1$

The sensitivity analysis values of each of the factors in these three cases are shown with the indices $(S_1|\Delta i = 0.1), (S_1|\Delta i = 0.2),$ and $(S_1|\Delta i = -0.1)$, respectively. The results of the sensitivity analysis are provided in Table 8 and Fig. 9.

5.4. Robustness analysis

An analytical method's robustness may be defined as an estimation of its capability to remain unaffected by small but deliberate methodological changes across variables (César and Pianetti, 2009). The sensitivity analysis in Section 5.3 showed how much a constant change in values of a factor would change the aggregated risks of all variables. This section investigates to what degree small changes in the most influential factors will have an impact on each specific result. Therefore, the most influential factors should first be identified; as can be seen in Table 8 and Fig. 9, the greatest sensitivities are related to factors $E_1, E_2, E_3, E_4,$ and $V_6$. 

### Table 6
The acceptable risk values for each variable.

| Variable | $V_1$ | $V_2$ | $V_3$ | $V_4$ | $V_5$ | $V_6$ | $V_7$ | $V_8$ | $V_9$ | $V_{10}$ | $V_{11}$ | $V_{12}$ | $V_{13}$ |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|----------|----------|----------|
| $AR$     | 0.5   | 0.8   | 0.25  | 0.5   | 0.8   | 0.1   | 0.3   | 0.3   | 0.5   | 0.3       | 0.5       | 0.1       | 0.1       |
Table 9
The robustness analysis results at 2% error level.

| Cases     | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ | $V_1$ | $V_2$ | $V_3$ | $V_4$ | $V_5$ | $V_6$ | $V_7$ | $V_8$ | $V_{10}$ | $V_{11}$ | $V_{12}$ | $V_{13}$ | SCC  |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|---------|---------|---------|-----|
| Default case | 1 18 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 17 | 13 | 2 | 10 | | | | | | |
| $E_1$ | 1 17 7 | 11 4 | 12 16 | 9 5 | 15 8 | 6 3 | 14 | 18 | 13 | 2 | 10 | 0.913 | | | | | |
| $E_3$ | 1 17 7 | 11 3 | 12 16 | 9 4 | 15 8 | 6 5 | 14 | 18 | 13 | 2 | 10 | 0.897 | | | | | |
| $E_4$ | 1 18 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 17 | 13 | 2 | 10 | 0.897 | | | | | |
| $E_5$ | 1 18 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 17 | 13 | 2 | 10 | 0.897 | | | | | |
| $V_8$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5, E_3$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5, E_3, E_4$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_3, E_4$, $E_5, V_8$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |

Table 10
The robustness analysis results at 4% error level.

| Cases     | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ | $V_1$ | $V_2$ | $V_3$ | $V_4$ | $V_5$ | $V_6$ | $V_7$ | $V_8$ | $V_{10}$ | $V_{11}$ | $V_{12}$ | $V_{13}$ | SCC  |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|---------|---------|---------|-----|
| Default case | 1 18 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 17 | 13 | 2 | 10 | | | | | | | |
| $E_1$ | 1 17 8 | 11 4 | 12 16 | 9 5 | 15 7 | 6 3 | 14 | 18 | 13 | 2 | 10 | 0.91 | | | | | |
| $E_3$ | 1 18 7 | 11 3 | 12 16 | 9 4 | 15 8 | 6 5 | 14 | 17 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_4$ | 1 18 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 17 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_5$ | 1 18 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 17 | 13 | 2 | 10 | 0.916 | | | | | |
| $V_8$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5$ | 1 17 8 | 11 3 | 12 16 | 9 5 | 15 7 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5, E_4$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5, E_3, E_4$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_3, E_4$, $E_5, V_8$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |

Table 11
The robustness analysis results at 6% error level.

| Cases     | $E_1$ | $E_2$ | $E_3$ | $E_4$ | $E_5$ | $V_1$ | $V_2$ | $V_3$ | $V_4$ | $V_5$ | $V_6$ | $V_7$ | $V_8$ | $V_{10}$ | $V_{11}$ | $V_{12}$ | $V_{13}$ | SCC  |
|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|---------|---------|---------|-----|
| Default case | 1 18 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 17 | 13 | 2 | 10 | | | | | | | |
| $E_1$ | 1 17 8 | 11 4 | 12 16 | 9 6 | 15 7 | 5 3 | 14 | 18 | 13 | 2 | 10 | 0.907 | | | | | |
| $E_3$ | 1 18 7 | 11 3 | 12 16 | 9 4 | 15 8 | 6 5 | 14 | 17 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_4$ | 1 18 7 | 11 3 | 12 16 | 9 4 | 15 8 | 6 5 | 14 | 17 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_5$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $V_8$ | 1 17 7 | 11 4 | 12 16 | 9 5 | 15 8 | 6 3 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5$ | 1 17 8 | 11 3 | 12 16 | 9 6 | 15 7 | 5 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5, E_3$ | 1 17 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 18 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_5, E_3, E_4$ | 1 18 7 | 11 3 | 12 16 | 9 5 | 15 8 | 6 4 | 14 | 17 | 13 | 2 | 10 | 0.916 | | | | | |
| $E_1, E_3, E_4$, $E_5, V_8$ | 1 18 7 | 11 4 | 12 16 | 9 5 | 15 8 | 6 3 | 14 | 17 | 13 | 2 | 10 | 0.916 | | | | | |

598
Since one of the main outputs of the R.Graph method is the ranking of factors, some dummy values were deliberately entered into each of these factors in order to measure their impacts on the overall ranking of factors. For this purpose, three error levels of 2%, 4%, and 6% were entered into each of the values related to each of the factors. Then the effect of each factor on the results was first examined individually, then the changes entered into a set of influential factors. Overall, 9 separate cases were examined at three error levels, namely, cases \( E_1 \), \( E_2 \), \( E_3 \), \( E_4 \), \( E_5 \), \( E_6 \), \( E_7 \), \( E_8 \), \( E_9 \), and \( E_{10} \). This means that each of these sets entered 2%, 4%, and 6% errors in their values, respectively, and the result of the overall ranking of all factors in all these cases was obtained, as can be seen in Tables 9–11. In each of these tables, the ranks that differ from the main case are distinguished in blue. Additionally, to check the closeness of these answers with the answers of the main case, Spearman’s correlation coefficient (SCC) (Seiti et al., 2020) was applied, which is a measure of the correlation between the ranking and its values. These SCC results can also be seen in Tables 9–11.

5.5. Comparing current results with other methods

In this section, the aim is to compare the results obtained from the R.Graph method with other existing methods from the relevant literature. Since the proposed method is definite, it is necessary to examine existing definite approaches in the literature, some of which were previously mentioned in Section 2. In general, though, the results of the proposed R.Graph are not comparable to any of the existing methods, since each one has its own assumptions with different input meanings. However, with some simplifying assumptions, it is possible to compare the EXIT (Panula-Ontto and Pirinen, 2018) and fuzzy cognitive maps (Stylios and Groumpos, 2004) methods, which are most similar to the present method, assuming that the inputs of the R.Graph have the same interpretation as the inputs in these methods. Table 12 presents the results of comparing the obtained ranks from the R.Graph method and the ranking results based on the total impact measure of the EXIT method and centrality measure of fuzzy cognitive maps approach.

5.6. Comparing risk analysis with results observed

As discussed in Section 4, the risk analysis horizon was considered for the case study for a period of one year. However, at the time of writing this article, 6 months have elapsed since the risk analysis was conducted. Thus, Table 13 is provided in order to compare how close the R.Graph risk prediction results obtained were to the changes observed after 6 months, according to available data. Of course, it is worth noting that the values of risk analysis are substantially different from the observed values, due to the existence of the acceptable risk factor. Moreover, using forecasts as inputs in decision-making processes often results in self-predicted outcomes – a problem known as self-negating forecasts, or the prophet dilemma (Petropoulos et al., 2020). However, it can be seen that the predicted and observed values in many cases are relatively close.

### Table 12

| Factor | Proposed R.Graph | EXIT | Fuzzy cognitive maps |
|--------|------------------|------|----------------------|
| Ranking |
| \( E_1 \) | 1 | 1 | 1 |
| \( E_2 \) | 18 | 18 | 9 |
| \( E_3 \) | 7 | 7 | 6 |
| \( E_4 \) | 11 | 11 | 7 |
| \( E_5 \) | 3 | 3 | 3 |
| \( V_1 \) | 12 | 12 | 16 |
| \( V_2 \) | 16 | 16 | 17 |
| \( V_3 \) | 9 | 9 | 15 |
| \( V_4 \) | 5 | 5 | 13 |
| \( V_5 \) | 15 | 15 | 18 |
| \( V_6 \) | 8 | 8 | 11 |
| \( V_7 \) | 6 | 6 | 12 |
| \( V_8 \) | 4 | 4 | 14 |
| \( V_9 \) | 14 | 14 | 5 |
| \( V_{10} \) | 17 | 17 | 10 |
| \( V_{11} \) | 13 | 13 | 8 |
| \( V_{12} \) | 2 | 2 | 2 |
| \( V_{13} \) | 10 | 10 | 4 |
| SCC | | | 0.43 |

Table 13

| \( V_i \) | Predicted risk | Observed values |
|--------|----------------|-----------------|
| \( V_1 \) | -0.15 | NA |
| \( V_2 \) | 0.05 | 0.25 |
| \( V_3 \) | 0.29 | 0.29 |
| \( V_4 \) | 0.35 | 0.25 |
| \( V_5 \) | 0.06 | 0.2 |
| \( V_6 \) | -0.18 | -0.15 |
| \( V_7 \) | -0.21 | -0.2 |
| \( V_8 \) | -0.35 | -0.2 |
| \( V_9 \) | -0.063 | -0.2 |
| \( V_{10} \) | 0.054 | 0.2 |
| \( V_{11} \) | 0.12 | 0.1 |
| \( V_{12} \) | -0.315 | -0.2 |
| \( V_{13} \) | -0.32 | -0.2 |

NA=Not available
The aim now, then, is to rank these actions based on their suitability in reducing the risks of the entire problem. It should be noted that the effects of corrective actions are examined even when there is no acceptable risk in the problem, because in this case, the effect of corrective actions on the absolute risk is modeled. It is worth noting that any corrective action which has a positive effect on improving the risk value of one variable may have negative effects on the risk values of other variables. If the percentage of improvement and worsening in the risk value of variable \( V_i \) due to taking action \( j \) are denoted with \( PR(V_i)^j \) and \( NR(V_i)^j \), the modified amount of risk assuming corrective action \( j \) can be obtained as follows:

\[
R(V_i)^m = R(V_i) \times (1 - \theta)
\]

where \( R(V_i) \) denotes the amount of risk without considering any acceptable risk value, and \( R(V_i)^m \) is the modified risk value. Also, we have:

\[
\theta = \begin{cases} 
PR(V_i)^j & \text{in the case of risk improvement} \\
NR(V_i)^j & \text{in the case of risk worsening}
\end{cases}
\]

Finally, the total effect of \( j \)-th corrective action on the whole problem, which is shown by \( TE^j \), can be defined as:

\[
TE^j = \sum_{i=1}^{V} R(V_i)^m - \sum_{i=1}^{V} R(V_i)
\]

where lower values indicate greater effectiveness of the suggested action in reducing the risk of the problem. On this basis, the total effects of the suggested corrective actions of Table 14 can be calculated. For example, for analyzing the total effect of periodic Corona tests, we have:

\[
R(V_1) = -0.3, \ PR(V_1)^3 = 0.6 \rightarrow R(V_1)^m = -0.12.
\]

\[
R(V_2) = 0.7, \ PR(V_2)^3 = 0.6 \rightarrow R(V_2)^m = 0.28.
\]

\[
R(V_3) = 0.39, \ NR(V_3)^3 = 0.2 \rightarrow R(V_3)^m = 0.468
\]

\[
TE^3 = \sum_{i=1}^{13} R(V_i)^m - \sum_{i=1}^{13} R(V_i) = -1.021
\]

The total impacts of all suggested actions are presented in Table 14.

6. Discussion

- Risk values for each of the variables, provided in Table 7, indicate how much the value of the variable will change, assuming that all events and variables affecting a variable are considered. Positive values indicate an increase and negative values indicate a decrease. According to Table 7, the amount of risk variable of total profit is calculated at \(-0.15\), which shows that if the previous profit forecast (pre-Coronavirus) was 1000 monetary units, the new forecast (according to Eq. (19) and the calculated risk) would be \(1000 \times (1-0.15) = 850\) monetary units, considering the occurrence of the influential factors. It is also possible to see the effect of considering or not considering acceptable risk in Table 7. Many risk values in the real world can be compensated for, which is considered in the RGraph model as an acceptable factor for the correction of risk values. Also, according to the results of Table 7, it can be seen that the maximum or minimum values of each variable are equal to the risk values of that variable. The main reason for this is when all the factors affecting the risk of that variable have moved in the same direction, or when all of them have increased the risk of the desired variable, or when all of them have been used to reduce the risk of that variable.

- Table 8 shows the importance of each factor on the total risks of problem variables, and also their ranking. It can be seen that the Coronavirus pandemic is the most important of all the factors that could have already been predicted, because all the values of
the risks were due to its occurrence. It is also observed that the highest importance among the variables is related to the power branch sales revenue, and the lowest concern belongs to the variable of degree of work difficulty. Decision-makers and managers in the organization can thus design and implement preventive plans according to the importance of each individual factor, in order to reduce its risk and its consequences.

- According to Table 8, the effect of increasing or decreasing the values of each factor on the risk of its children can be examined, which is termed the amount of sensitivity analysis of that factor. It can be observed that the highest sensitivities to changing values are seen in power branch sales revenue in variables. Moreover, it is also observed that the problem is very sensitive to changes in the new safety regulations, in addition to the Coronavirus pandemic. It can also be seen that, for each factor, the following is apparent:

\[ \text{S}_{ij} | \Delta t = 0.1 = -\text{S}_{ij} | \Delta t = -0.1 \]

Generally, it can be said that the problem sensitivity to increases or decreases in a certain value are opposites in the R.Graph method, thus:

\[
\begin{align*}
\text{S}_i | \Delta V = -\text{S}_i | -\Delta V \\
\text{S}_i | \Delta V_T = -\text{S}_i | -\Delta V_T
\end{align*}
\]

- To investigate the degree to which the model ranking results are robust subject to minor changes, three different scenarios of change in the values of the influencing factors were carried out. The results are presented in Tables 9 to 11; it can be seen that the Spearman’s correlation coefficient values changed from 0.898 to 0.916 in worst and best cases. This indicates slight changes in the ranking results, and an acceptable degree of robustness within the model.

- In Section 5.7, a framework for evaluating the effectiveness of corrective measures was presented by the R.Graph method through examining which measures had the highest priority in reducing the overall risk of the problem. It was observed that periodic corona tests were the first priority. The proposed framework can be a useful tool for ranking various factors, allowing for appropriate planning to implement preventive measures. It permits decision-makers to effectively determine policies and interventions affecting system outputs, and to examine their impact on reducing adverse effects or increasing.

- For many problems, modeling with traditional techniques is difficult or even impossible. This is especially true when certain statistical data related to the model and its parameters are not available, and/or it is difficult to extract the relationships between the components of the modeled system from the quantitative prediction models such as time series models. In such cases, opinions provided by knowledgeable individuals are the best available data. The R.Graph method can be seen as a tool for modeling and simulating systems, using data obtained from experts in the field, thus providing an appropriate, interpretable framework for decision-makers and system modelers. In this method, the intended data can be collected and aggregated through interviews, workshops, or surveys, or by using the Delphi method and questionnaire, or a combination of these methods. Additionally, experts can be asked to vote on entries...
Table 15
Comparison of causal models from different perspectives.

| Method                        | Input Nature | Event Nature | Deterministic | Probabilistic | Static | Dynamic | Discrete | Continuous |
|-------------------------------|--------------|--------------|---------------|---------------|--------|---------|----------|------------|
| MICMAC (Bashir et al., 2020) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| EXIT (Panula-Onnonta and Pirainen, 2018) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| DEMATEL (Zhang et al., 2019)  | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| Cognitive maps (Liu et al., 2019) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| Structural equation modeling (Tolrak et al., 2021) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| Bayesian networks (Premchaiswadi, 2012) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| Dynamic Bayesian networks (Wang et al., 2020) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| BASICS (Honton et al. (1985)  | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| AXIOM (Panula-Onnonta, 2016)  | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| Fault tree (Lindhe et al., 2009) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| Event tree (Purba et al., 2020) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| Petri nets (Zhou and Wu, 2018) | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |
| Proposed R.Graph              | ✓            | ✓            | ✓             | ✓             | ✓      | ✓       | ✓        | ✓          |

- The proposed R.Graph method has been developed based on three simplifying assumptions that can be called the method limitations:
- The first simplification assumption is that in the proposed model, events are assumed to be definite and the probability of occurrence was not considered for each event. This is because definite consideration of the occurrence of events and their impact is based on the assumption that it is known that the event in question will occur sooner or later; the purpose is to determine its impact. However, in the real world and especially in risk management over longer periods of time, this is not the case; the probability of each event should be considered for each variable.
- The second simplification assumption is that the relationships between the variables are considered to be unknown and statistical data are unavailable. Since it was assumed that the data was obtained through experts, the risk of each variable was considered in terms of the linear sum of changes in the influential variables, as well as in terms of influential events which affect a variable independently. However, the process to obtain the risk of each variable in a general case was described in Section 4. In general, how much data is needed to reliably obtain the risk of one variable based on other variables depends on the degree of relationship between the variables and the number of variables: this can involve the use of statistical methods such as regression analysis (Fox, 1997).
- The third simplifying assumption was that the initial and subjective weight was not considered for any of the risk factors (i.e., for both events and variables the same initial weight was considered). The initial weight can be easily determined by extending 30(30) on this basis.

An important point to be noted is that in this study, when collecting data from experts, attention was paid to the quality of experts and not the quantity, although the number and access to experts in this field were limited. Therefore, due to the lack of sufficient statistical data, it was not possible to analyze the dimensions related to gender and age; only the quality and subjective importance of each expert was aggregated by the HWA operator and entered into the problem. In group decision-making, there is no specific rule for determining the minimum number of experts needed to achieve a reliable result, but if the decision-maker believes in the high reliability of data from statistical methods, more experts guarantee a better and more reliable result.

In this section, the advantages and disadvantages of the proposed R.Graph method in risk analysis and management are briefly mentioned, and its differences and similarities with existing methods were discussed. It should be mentioned that the development of the proposed method and its innovations, with all
its positives and negatives, is a step toward a longer-term goal and has been developed to provide new ideas for researchers in the relevant field and decision-makers in their future decision-making issues.

7. Conclusion

Risks and disruptions, especially unforeseen ones, have led many companies today to be concerned about the consequences on the complex, global business environment. The Coronavirus pandemic represents such a specific disruptive case. Epidemic/pandemic outbreaks lead to long-term disruptions, which are unpredictable in terms of time, severity, and scale. Even with certain known, low-probability, high-impact events, many traditional risk analysis methods have proven insufficient in assessing their risks and outcomes.

The present paper presented a new risk analysis method to measure the risk of interactive factors in the causal chain which can be fully explainable for decision-makers. Its application was studied in a risk analysis of Coronavirus on the Iranian electricity industry. The advantages of the proposed model included: determining the amount of change in variables; accounting for preferred organizational parameters, such as acceptable risk; determining the importance and ranking of factors; analyzing sensitivity; and interpretability and explicability for decision-makers.

Simplified assumptions were made in the development of the R.Graph method in order to better comprehend this new model and its applicability. Consequently, new assumptions can be introduced as future research topics developing upon the current study. For instance, the R.Graph model has been developed assuming that the problem in hand is definite, so its extension into a probabilistic model to capture randomness can provide useful future research. Moreover, linearity is one of the main assumptions in the R.Graph method, but the linearity assumption is not always established in certain risk analysis problems. It is also suggested to employ supervised (Osarogiagbon et al., 2020) or unsupervised learning (Michau and Fink, 2021) methods in cases where sufficient data is available for statistical interpretation. Another issue not discussed in the R.Graph method is how to combine the information obtained from experts with methods to consider the reliability of their evaluations (Wang et al., 2019); this can be considered as another future research area. Finally, other areas of research might pursue the development of the R.Graph model in a dynamic mode (Wang et al., 2021), while considering other uncertainties (Jianxing et al., 2021) in input data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The present investigation is supported under the Iran University of Science and Technology, Tehran, Iran, Postdoctoral Fellowship granted by the Iran National Science Foundation (INSF), and Iran’s National Elites Foundation, Iran (Grant No. 99003878).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.psep.2022.01.010.
Panula-Ontto, J., 2016. AXIOM Method for Cross-Impact Modeling and Analysis (Master’s thesis).

Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M.Z., Barrow, D.K., Taieb, S.B., Ziel, F., 2020. Forecasting: theory and practice. arXiv Prepr. 01854.

Premchaiswadi W. Bayesian Networks, 2012.

Purba, J.H., Tjahyantri, D.S., Widodo, S., Ekariasyah, A.S., 2020. Fuzzy probability based event tree analysis for calculating core damage frequency in nuclear power plant probabilistic safety assessment. Prog. Nuclear Energy 125, 103376.

Richard Gall P. Machine Learning Explainability vs. Interpretability: Two concepts that could help restore trust in AI n.d. https://www.kdnuggets.com/2018/12/machine-learning-explainability-interpretability-ai.html, 2018.

Seiti, H., Hafezalkotob, A., 2020. A new risk-based fuzzy cognitive model and its application to decision-making. Cogn. Comput. 12, 309–326. https://doi.org/10.1007/s12559-019-09701-8

Seiti, H., Hafezalkotob, A., Martínez, L., 2019. R-numbers, a new risk modeling associated with fuzzy numbers and its application to decision making. Inf. Sci. https://doi.org/10.1016/j.ins.2019.01.006

Seiti, H., Hafezalkotob, A., Herrera-Viedma, E., 2020a. A novel linguistic approach for multi-granular information fusion and decision-making using risk-based linguistic D numbers. Inf. Sci. 530, 43–65.

Stylios, C.D., Groumpos, P.P., 2004. Modeling complex systems using fuzzy cognitive maps. IEEE Trans Syst Man. Cyber A Syst. Hum. 34, 155–162.

Tolak, N.G., Demir, A., Badur, T., 2021. Using VIBOR with structural equation modeling for constructing benchmarks in the Internet industry. Benchmarking Int. J.

Törnqvist, L., Vartiainen, P., Vartia, Y.O., 1985. How should relative changes be measured? Am. Stat. 39 (1), 43–46.

Tran, D.Q., Molenaar, K.R., Alarcón, L.F., 2016. A hybrid cross-impact approach to predicting cost variance of project delivery decisions for highways. J. Infrastruct. Syst. 22 (1), 04015017.

Wang, H., Xu, C., Xu, Z., 2019. An approach to evaluate the methods of determining experts’ objective weights based on evolutionary game theory. Knowl. Based Syst. 182, 104862.

Wang, S., Zhang, S., Wu, T., Duan, Y., Zhou, L., Lei, H., 2020. FMDBN: a first-order Markov dynamic Bayesian network classifier with continuous attributes. Knowl. Based Syst. 195, 105638.

Wang, Y., Wang, K., Wang, T., Li, X.Y., Khan, F., Yang, Z., et al., 2021. Reliabilities analysis of evacuation on offshore platforms: a dynamic Bayesian Network model. Process Saf. Environ. Prot. 150, 179–193.

Yazdi, M., Khan, F., Abbassi, R., Rusli, R., 2020a. Improved DEMATEL methodology for effective safety management decision-making. Saf. Sci. 127, 104705.

Yazdi, M., Nedjati, A., Zarei, E., Abbassi, R., 2020b. A novel extension of DEMATEL approach for probabilistic safety analysis in process systems. Saf. Sci. 121, 119–136.

Zhang, L., Sun, X., Xue, H., 2019. Identifying critical risks in Sponge City PPP projects using DEMATEL method: a case study of China. J. Clean. Prod. 226, 949–958.

Zhou, M., Wu, N., 2018. System modeling and control with resource-oriented Petri nets. CRC Press.