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A risk-sharing-based resilient renewable energy supply network model under the COVID-19 pandemic

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Abstract

Over the past few months, the COVID-19 pandemic has postponed many renewable energy projects because of disruptions in the technology and finance supply. Additionally, the existing power plants are inefficient because of a record drop in demand for goods and services caused by lockdowns in cities. This situation poses huge challenges to the resilience of renewable energy supply networks in the face of deeply hazardous events, such as the COVID-19 pandemic. Therefore, the purpose of this study was to design a resilient renewable energy supply network considering supply, demand, and payment risks caused by COVID-19. The objective of the proposed model was to determine the optimal amount of electric power generated and stored to meet the demands and the risk-sharing effort index to maximize the total resilient profit of the power plant and determine the optimal price adjustment index to minimize the cost to consumers. A government subsidy-based risk-sharing model was developed to enhance the resilience of the concerned renewable energy supply network under the pandemic. To overcome uncertainties in both random and risk events, a robust fuzzy-stochastic programming model was proposed to solve these research problems. Computational experiments were conducted on the test supply network in Vietnam. The results showed that the resilient energy supply network with the risk-sharing model tended to stabilize the total profit with the different impact levels of COVID-19 compared to the network without risk-sharing. The proposed model efficiently tackled both uncertainties in random and hazardous events and had a higher profit and shorter CPU time compared to the robust optimization mode.

Keywords: COVID-19; Resilience; Renewable energy; Supply network; Risk-sharing; Robust fuzzy stochastic model.

Nomenclature

Sets and indices	
I	set of RE generation units , $i = 1,....,\lvert I \rvert$
M	set of consumers, $m = 1,....,\lvert M \rvert$
T	set of time, $t = 1,....,\lvert T \rvert$
S	set of supply disruption scenarios, $s = 1,....,\lvert S \rvert$
Decision variables	

q_{it}	amount of electric power generated from RE generation units i at time slot t
v_{it}	amount of electric power storaged at RE generation units i at time slot t by using storage capacity
α	risk-sharing effort coefficient
φ_m	price adjustment coefficient for consumer m under risk-sharing model
Parameters	
e_t	electric power price at time slot t [$/kwh]
d_{tm}^{critic}	critical load of consumer m at time solt t [kwh]
d_{tm}^{curt}	curtailable load of consumer m at time slot t [kwh] (uncertainty)
D_{tm}	energy consumption demand of consumer m at time slot t [kwh] (uncertainty)
$d_m^{\min}$	minimum demand reduction of consumer m [kwh]
$d_m^{\max}$	maximum demand reduction of consumer m [kwh]
τ	price elasticity coefficient of electric power demand [dimensionless]
fc_i	fixed cost of RE generation unit i [$] (uncertainty)
vc_i	variable operating cost of RE generation unit i [$/kwh] (uncertainty)
r	interest rate [percentage]
h	payment delay of consumer due to the Covid-19 impacts [day]
ϕ	impact of Covid-19 on total output capacity of power plant [dimensionless]
β	impact of Covid-19 on energy demand [dimensionless]
N	number of days in a year [dimensionless]
g	unit government subsidy [$]
G	maximum government subsidy [$]
V_i	maximum capacity of storage device at RE generation unit i [kwh]
Q_{it}	maximum capacity of RE generation unit i at time solt t [kwh] (uncertainty)

1. Introduction

As a promising alternative to fossil fuel-based power systems (e.g., coal, oil, and gas) and an effective solution to environmental and social issues related to the rapidly increasing energy demand, renewable energy (RE) sources (e.g., wind, solar, and hydro power) have played an increasingly important role in the global society over the past few decades (Owusu and Asumadu-Sarkodie, 2016; Liang et al., 2019). However, some barriers (e.g., policy, technology, and intermittency) pose challenges to the development of RE sources. Additionally, hazardous events (e.g., earthquakes, floods, and fires) cause a high level of uncertainty in the supply, production, and consumption of RE sources. In power systems, the disruption risks may be derived from both internal factors (e.g., capacity and equipment failures) and external conditions (e.g., natural disasters and policies). Supplying enough electric power to consumption areas (e.g., residential, commercial, and industrial consumers) is usually difficult when disruptions related to capacity and equipment failures occur in the power system. For example, in the California electricity crisis of 2000–2001, only a few consumption areas were allowed to receive power from suppliers when a capacity failure occurred in the electrical systems (Dulude, 2006). A variety of other utilities (e.g., transportation systems and manufacturing entities) may shut down following an extended time without electricity. In some cases, the disruption risks caused by natural disasters (e.g., earthquakes, floods, and pandemics) usually affect both the supply and demand sides of the power system. These disruptions may result in drops in energy consumption demand and system capacity. It can be extremely difficult for the government and energy regulators to balance the supply and demand in the wake of disruptions. Additionally, some financial risks (e.g., payment ability) may also arise after a disaster in consumption areas, especially for industrial consumers.

Recently, the outbreak of the COVID-19 pandemic has been considered a specific example of a disaster, which has significantly affected all aspects of life, including the supply and demand sides of the RE sector. For example, 3,000 MW of RE projects in India were delayed because of COVID-19, according to a report from Wood Mackenzie. Without proper resilience solutions from government, consumers, and power system operators, the crisis caused by COVID-19 could considerably disrupt the development progress of RE sources for global long-term sustainable energy goals. Consequently, a resilient RE supply network (RRESN) to cope with disruptions on both the supply and demand sides becomes important in this situation. This study proposes a risk-sharing-based RRESN model in the face of the COVID-19 pandemic. Permissible delays in payment of utility bills by end-users are applied as a short-term solution to stabilize demand during the pandemic. However, the impacts of COVID-19 on the energy supply and the demand of the power supply network were not analyzed. Furthermore, the financial support packages of the government are critically important for post-pandemic economic recovery plans, especially in the RE field, to meet its climatic goals (Bahar, 2020). To help governments and energy regulators enact timely policies based on quantitative analyses, this study distinguished contributions from practical and theoretical perspectives as follows:

- **Practical:** This study proposes a mathematical model to explore the effects of deeply hazardous events (e.g., the COVID-19 pandemic) on the resilience of RE supply networks. The proposed model is expected to maximize the total profit of the power plant and minimize the total energy cost to industrial consumers, simultaneously under disruption risks in the output capacity of RE generation units, energy consumption demand, and payment by consumers. Additionally, a risk-sharing model among the government, power plant, and consumer is developed to enhance the resilience of the RE supply network under disruption risks. In the proposed risk-sharing model, the power plant considers a price adjustment coefficient and allows a delay of payment from consumers to stimulate demand in the crisis, and governments provide a subsidy to power plants based on the risk-sharing effort between the power plant and consumers. The numerical analysis discusses the influence of deeply hazardous events on energy supply and demand. The results are also expected to support the power plant by effectively applying the risk-sharing model to optimize the total profit under disruption risks.
- **Theoretical:** To successfully overcome a high degree of uncertainty in random (e.g., demand, intermittence of RE) and deeply hazardous (e.g., COVID-19 pandemic) events, a robust fuzzy-stochastic programming (RFSP) model is proposed based on the extension of robust optimization into fuzzy and stochastic programming. Fuzzy and stochastic programming provide powerful tools to deal with a variety of uncertainties in both random and deeply hazardous events. Fuzzy numbers are applied to express the business-as-usual uncertainties, such as the demand and costs of power plants. This helps save considerable time and resources for collecting historical data to manage the

probability distribution of the random variables related to the real-life problem. For deeply hazardous events, stochastic scenarios-based robust optimization is used to model disruption risks. It is possible to deal with numerous scenarios simultaneously in relation to the uncertainties in risks. Additionally, robust optimization also ensures a feasible solution to the optimization problems by determining the trade-off between feasibility and optimization robustness. Thus, the proposed model would be dominant over others in dealing with hybrid uncertainties and ensuring a feasible solution to uncertainties in random and deeply hazardous events.

The remainder of this paper is organized as follows. Section 2 presents a review of the relevant literature on risk-sharing models and resilient solutions in power systems. The description of the study problem, formulation of the model, and solution approach to overcome business-as-usual and deeply hazardous uncertainties is developed in Section 3. Section 4 reports the numerical results and discussions from a case study in Vietnam. Section 5 includes conclusions, managerial insights, and directions for future research.

2. Literature review

RE sources with significant environmental, economic, and social benefits have been noted by scholars and practitioners in recent years. Along with solar photovoltaic and wind turbines, biogas is also an RE source that has significant environmental benefits. According to Lyytimäki (2018), the development of RE sources, including biogas, will deliver multiple environmental benefits, such as the reduction of nutrient discharge and greenhouse gases, while the relevant costs (e.g., investment and operation cost) are not significant. Ikram et al. (2020) revealed that there is a strong relationship between RE consumption and CO_2 emission reduction. Additionally, some other benefits (e.g., increased access to electricity and improved energy efficiency awareness) have also been drawn from their results regarding the developing social sustainability in the energy mix by enhancing RE sources. To ensure environmental and social sustainability, countries should increase their investments in the RE sectors and consider plans for research and development of RE as a national development policy (Zafar et al., 2020). However, the production and consumption of RE sources are challenged by several barriers, such as technology and finance. Several recent studies have put substantial effort into finding optimal policies for RE development. For example, Tsao and Thanh (2021) introduced an optimization model for financial incentives (e.g., bank credit and trade credit) in the RE sector. Their results revealed that the effective use of financial instruments, such as trade and bank credit and pricing policy, can stimulate the penetration of RE sources. Some feed-in tariff policies have also been introduced for RE technology development based on many different programming models, such as statistical (He et al., 2019), dynamic (Ding et al., 2020), and network analysis models (Li et al., 2020). Along with the technological and financial barriers, the development of RE sources is also affected by intermittent power generation because of their dependency on local weather. Thus, the integration of RE sources into the grid poses challenges to the resilience of the network (Mousavizadeh, 2018; Shahid et al., 2020; Tsao and Thanh, 2020).

In power systems, resilience reflects the ability of a system to adapt to changing conditions and recover rapidly from unpredictable disruptions in an efficient manner while ensuring the smallest possible interruption in the electricity supply (Khodaei, 2014). Numerous studies have proposed solutions to enhance the resilience of RE supply networks caused by supply disruptions. For example, Kosai and Cravioto (2020) used storage systems as a resilient solution for a standalone hybrid RE system under sudden disturbances in output capacity. Microgrids with distributed RE resources and demand response programs have been considered to improve the resilience of a power distribution system under extreme events in Gilani et al. (2020). To deal with supply influences because of natural disasters, an emergency budget was formulated in their model. Jabbarzadeh et al. (2018) considered disruptions in the generation, transmission, and distribution systems to maximize the resilience of electricity supply networks using distributed generation. The robust model used successfully overcame the uncertainties in business-as-usual, including generation capacities and demand, but hazardous events were not mentioned in their study. Mousavizadeh et al. (2018) integrated advanced technologies, including energy storage units, distributed generations, and demand responses, to improve the resiliency of smart distribution systems in the face of disasters. Dehghni et al. (2018) developed a scenario-based robust optimization model to solve a resilient solar photovoltaic supply network design problem under both business-as-usual and hazard uncertainties. However, the results did not explicitly mention the solutions for increasing the resilience of the network in the face of hazardous events. A risk-sharing model between the power plant and farmers that provides cassava for bioethanol production has been proposed by Ye et al. (2017) to improve the resiliency of the supply network. These models considered uncertainties in demand and yield, but demand disruption risks were not integrated into their models.

Because of global economic development and climatic changes, disruption risks derived from both internal factors (e.g., economic cycle, demand, and costs) and external conditions (e.g., natural disasters and policies) deeply affect the operational efficiency of RE supply networks. Thus, the RRESN must be able to operate effectively in a high-risk environment with the presence of two basic types of uncertainties: random and deeply hazardous events. According to Klibi and Martel (2013), random events refer to uncertainties in the business-as-usual operations of the supply network. It is usually estimated using probability distributions of random variables. Deeply hazardous events describe incidents affecting the network resources on both supply and demand sides with an unpredictable time and likelihood of occurrence. For such events, robust optimization with impact scenarios can be applied to enhance the resilience of the supply network (Lempert et al., 2006). The COVID-19 pandemic is considered a deeply hazardous event that has affected all aspects of life and led to major business failures (Majumdar et al., 2020). In the energy sector, many European countries have faced a record drop in electricity prices because of falling demand related to the lockdown policies for treating COVID-19. A report from ICIS showed a significant reduction in electric power consumption demand (more than 20%) in epidemic regions, such as Italy and France. Additionally, there is widespread tolerance from energy regulators and governments regarding the delay in payment or nonpayment for utility bills by end-users. This helps consumers by providing peace of mind to maintain energy consumption demand during the peak of the COVID-19 pandemic. However, the default risks caused by payment delays cause cascade effects and affect the entire energy market if there is not a proper policy from energy regulators and timely support from governments.

Regarding the COVID-19 pandemic as a deeply hazardous event affecting several adjacent planning periods and creating critical network disruptions, a risk-sharing-based RRESN model is essential for facing and recovering the economy post-COVID. The world is witnessing a record drop in demand for goods and services, while the global supply chain networks are vulnerable because of logistical delays. As with SARS, lessons from the COVID-19 pandemic are a great motivation for scholars and practitioners to contribute innovative solutions for sustainable and resilient supply networks in the face of pandemics. There have been many studies from the theoretical perspective that focus on technical solutions (e.g., storage capacity, distributed generations, demand-side management, and maintenance policies) to improve resilience in the energy supply networks. Additionally, some risk-sharing models have also been introduced in the literature. However, there are still some research gaps that ensure the resilience of the supply networks in the face of the pandemics where both the supply and demand sides are interrupted. To the best of our knowledge, the aspects not considered in the existing literature are as follows: (i) there is a scarcity of studies in the energy sector that consider risk-sharing in the entire supply network, including upstream and downstream, as a resilient solution for network disruption risks; (ii) the previous studies did not consider the impact of delayed payment on the total profit of a power plant from a risk management perspective.

3. Methods

In this section, a mathematical model for the risk-sharing-based RRESN design problem was developed. Additionally, the RFSP approach was introduced to overcome a high degree of the intermittent nature of RE sources and deeply hazardous events, such as the COVID-19 pandemic.

3.1. Problem description

The structure of the proposed RRESN includes three objects: governments, power plants, and consumers (see Fig.1). The power plant consists of a group of RE generation units (e.g., solar photovoltaics and wind turbines), whereas consumers are composed of a group of industrial factories. During the COVID-19 pandemic, many countries applied a lockdown policy to prevent its spread. This has seriously affected the energy consumption demand of industrial factories. Additionally, the global logistic delay is one of the main problems related to the delayed delivery of equipment to power plants, causing negative impacts on the output capacity of power plants. To overcome this crisis, a performance-based risk-sharing model was proposed in this study. In the proposed model, governments provide financial support to power plants based on the risk-sharing effort between the power plant and consumers by reducing electricity prices and delaying payments of consumers.

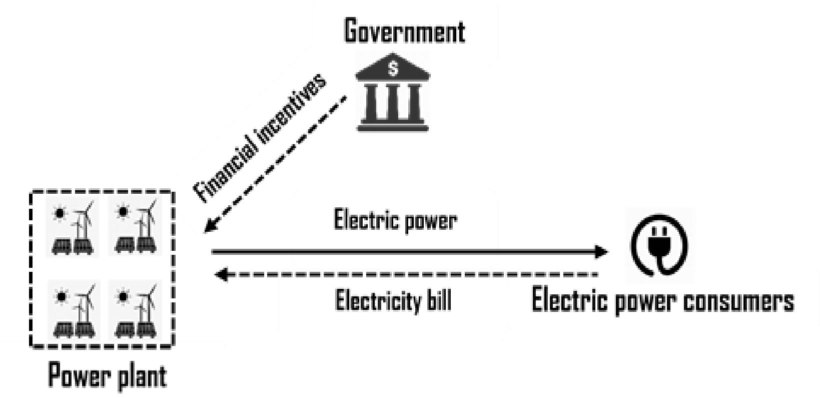

Fig. 1. Underlying structure of proposed resilient RE supply network.

The described research problem entails decisions regarding not only the amount of electric power generated and stored to meet the demands but also the price adjustment coefficient for consumers and risk-sharing effort index between the power plant and consumers. The objective was to maximize the total resilient profit of a power plant while minimizing the electricity bill of consumers. The following assumptions were made to formulate the research problem:

(i) The COVID-19 effects on the output capacity of power plants, energy consumption demand, and payment delays of consumers are independent uncertain parameters.
(ii) The risk-sharing effort index increases linearly with the payment delay of consumers.
(iii) Consumers would prefer less demand reduction because of COVID-19 when the power plant puts a larger effort into risk-sharing with them.
(iv) Government subsidies to power plants subject to a fixed budget.

The following sections present the proposed dual-objective optimization model for power plants and consumers. To simultaneously guarantee the maximum resilient profit of the power plant and the minimum electricity bill of consumers, the proposed models of the power plant and consumers were considered sequentially.

3.1.1. Utility function of consumers

The baseline demand functions assumed that the energy demand was sensitive to changes in electricity prices (Lu et al., 2018; Tsao et al., 2019). In this study, to consider the effects of COVID-19 on energy consumption in industrial areas, we assumed that the energy demand of industrial consumer *m* at time slot *t* is given by Eq. (1). This demand function enabled us to capture that consumers are sensitive to both the price adjustment coefficient (φ_m) and COVID-19 impacts (β).

$$D_{tm} = \left[d_{tm}^{critic} + d_{tm}^{curt} \left(1 + \tau\left(1 - \beta\varphi_m\right)\right)\right] \tag{1}$$

The energy consumption demand of consumer *m* can be classified as a critical load (d_{tm}^{critic}) and curtailable load (d_{tm}^{curt}). The critical load was critically met and was not affected by external factors, such as price and COVID-19, whereas the curtailable load is apart from the critical load and it may be affected by external factors, such as that consumers usually decrease curtailable loads as the electricity price increases. Therefore, COVID-19 and the price adjustment coefficient only affected the curtailable load of consumers. Under the performance-based risk-sharing model. The objective of each consumer *m* was to minimize costs, as presented below:

$$Min\pi_1 = \sum_{t\in T}\sum_{m\in M}\varphi_m e_t\left[d_{tm}^{critic} + d_{tm}^{curt}\left(1+\tau\left(1-\beta\varphi_m\right)\right)\right] + \frac{\alpha}{2}\left[d_{tm}^{curt} - d_{tm}^{curt}\left(1+\tau\left(1-\beta\varphi_m\right)\right)\right]^2 \quad (2)$$

In utility function (2), the first term represents the cost of consumer *m* for buying electric power from the power plant, and the second term denotes the attitude of consumers with respect to the risk-sharing strategy. A greater value of the risk-sharing effort coefficient *(α)* ensures that consumer *m* prefers less of a demand reduction because of the COVID-19 pandemic when a risk-sharing strategy is applied. Because the second term is not an actual expense incurred by consumers for energy consumption, the value of α was set to $\alpha/2$ (Yu and Hong, 2017). The optimal price adjustment coefficient φ_m can be obtained by solving the first-order derivative of the objective function (2). The value of φ_m is a function defined in Eq. (3):

$$\varphi_m = \frac{e_t\left(d_{tm}^{critic} + d_{tm}^{curt} + d_{tm}^{curt}\tau\right) - \alpha d_{tm}^{curt\,2}\beta\tau^2}{d_{tm}^{curt}\tau\beta\left(2e_t - \alpha d_{tm}^{curt}\beta\tau\right)} \quad (3)$$

When COVID-19 occurs, customers tend to reduce energy consumption in the range of demand reduction between d_m^{min} and d_m^{max} to save on the electricity bill. To ensure that the objective function (2) is a concave function in the range from d_m^{min} to d_m^{max} (its second-order derivative is always greater than zero), the risk-sharing effort index (α) must satisfy the condition in Eq. (4). The detailed first-order and second-order derivatives of the objective function (2) can be found in Appendix A.

$$\alpha > \frac{2e_t}{d_{tm}^{curt}\tau\beta} \quad (4)$$

To minimize the electricity bill of each consumer *m* during the COVID-19 pandemic under the risk-sharing model, the price adjustment coefficient φ_m and the risk-sharing effort index α of the power plant must satisfy constraints (3) and (4). This may result in a loss of revenue for the power plant. However, this loss will be compensated by government subsidies in the optimization model for the power plant in the following section.

3.1.2. Objective function of power plant

The profit of the power plant under the risk-sharing model is described below:

$$Max\pi_2 = \sum_{t\in T}\sum_{m\in M}\varphi_m e_t \min\left[\sum_{i\in I}Q_{it}(1-\phi); D_{tm}\right] + \sum_{m\in M} g(1-\varphi_m)h\alpha - \sum_{t\in T}\sum_{i\in I} fc_i + vc_i\left(q_{it} + v_{it}\right) - \quad (5)$$

$$\sum_{t\in T}\sum_{m\in M}\frac{rh\varphi_m e_t \min\left[\sum_{i\in I}Q_{it}(1-\phi); D_{tm}\right]}{N}$$

In objective function (5), the first term represents the revenue from selling electric power to consumers. It is estimated based on the minimum value of the output capacity of the power plant and the energy consumption demand of consumers because COVID-19 has affected both the supply and demand sides. The parameter ϕ in the range [0; 1] reflects the impact of COVID-19 on the total output capacity of the power plant from RE generation units i. A higher value of ϕ indicates a higher impact of the COVID-19 pandemic. The second term is the amount of subsidy from the government. This subsidy will cover losses of energy prices and provide financial support to the power plant when allowing customers to delay payment. The third term calculates the fixed cost and variable operating cost of the power plant based on the amount of electric power generated and stored at RE generation units. Because the performance-based risk-sharing model is applied to stimulate energy consumption during the pandemic, consumers postpose electricity bill payments for the period h. Then, the RE generation units will suffer a loss of financial costs based on the revenue and interest rate during the deferral period. This is expressed in the final term of the objective function.

The constraints of the RRESN are presented in Eqs. (6)–(14). The inequality constraint (6) ensures that the amount of generated and stored electric power at the RE generation units is larger than the demand loads of all consumers during the planning time. Equations (7) and (8) are the capacity limitation constraints of the storage devices and RE generation units, respectively. Constraint (7) states that the stored power amount cannot exceed the limited capacity of the storage device. Constraint (8) ensures that the amount of electric power generated and stored cannot exceed the total output capacity of the power plant. To guarantee the minimum electricity bill of consumers according to the proposed risk-sharing model, Eqs. (3)–(4) in Section 2.2.1 become constraints (9) and (10) in the power plant optimization model. Equation (9) is applied to calculate the price adjustment coefficient for each consumer under the COVID-19 effects. Constraint (10) is established to ensure that the energy consumption cost of consumers in the objective function (2) is a concave function of the optimal value of the risk-sharing effort index. Constraint (11) limits the range of energy consumption demand reduction of consumers because of the COVID-19 pandemic. Constraint (12) guarantees that subsidies cannot exceed the government's budget. Constraint (13) guarantees the nonnegativity of the decision variable regarding the amount of generated and stored electric power. Constraint (14) is the condition for the risk-sharing model to be applied. When the value of φ_m equals 1, it indicates that the risk-sharing model has not been applied to enhance the resilience of the supply network.

$S.t.$

$$\sum_{t\in T}\sum_{i\in I} q_{it} + v_{it} \geq \sum_{t\in T} d_{tm}^{critic} + d_{tm}^{curt}\left[1+\tau\left(1-\beta\varphi_m\right)\right], \forall m \in M \tag{6}$$

$$\sum_{t\in T} v_{it} \leq V_i, \forall i \in I \tag{7}$$

$$q_{it} + v_{it} \leq Q_{it}(1-\phi), \forall t \in T, i \in I \tag{8}$$

$$\varphi_m = \frac{e_t\left(d_{tm}^{critic} + d_{tm}^{curt} + d_{tm}^{curt}\tau\right) - \alpha d_{tm}^{curt\,2}\beta\tau^2}{d_{tm}^{curt}\tau\beta\left(2e_t - \alpha d_{tm}^{curt}\beta\tau\right)}, \forall m \in M \tag{9}$$

$$\alpha > \frac{2e_t}{d_{tm}^{curt}\tau\beta}, \forall m \in M \tag{10}$$

$$d_m^{\min} \leq \sum_{t\in T} d_{tm}^{curt} - d_{tm}^{curt}\left(1+\tau\left(1-\beta\varphi_m\right)\right) \leq d_m^{\max} \tag{11}$$

$$\sum_{m\in M} g(1-\varphi_m)h\alpha \leq G \tag{12}$$

$$q_{it}, v_{it} \geq 0, \forall t \in T, i \in I \tag{13}$$

$$\varphi_m \leq 1, \forall m \in M \tag{14}$$

3.2. Solution approach

The RRESN model must be able to overcome a high degree of intermittent nature from RE sources. Additionally, the deeply hazardous events, such as the COVID-19 pandemic, are taken into account for assessing the RRESN, such that a high degree of uncertainty in input data and risk situations have posed substantial difficulties to solution approaches. As a result, deterministic models are not able to provide a precise analysis of the resilient supply network. Although there are many probabilistic models to deal with uncertain factors, such as stochastic and simulation models (Bhuiya et al., 2020; Snoeck et al., 2019; Irawan et al., 2019, Rajesh, 2019). According to Pishvaee and Torabi (2010), there are two main disadvantages in applying stochastic models: (i) it is difficult to accurately estimate the probability distribution of random variables in many real-world situations where there is not enough historical data; (ii) a large number of scenarios are used to model uncertain parameters that can lead to computation time challenges in the original model.

As an alternative, the fuzzy set theory of Zadeh (1965) provides a concept, called membership function, which may be of use in dealing with the absence of sharply defined criteria of uncertainties rather than the presence of random variables. In classical fuzzy approaches, Bellman and Zadeh (1970) laid the first foundation for developing decision-making methods in a fuzzy environment. Their method has focused on dealing with the fuzziness in goals and constraints by using the fuzzy set theory, called possibility theory instead of using the probability theory. Several years later, Zadel (1978) developed the possibilistic programming theory for fuzzy sets, which has been widely applied in many studies related to system optimization under uncertain environments (Pishvaee et al., 2012; Tsao et al., 2018). Owing to the dynamic nature of complex systems, such as power systems and supply chains, uncertain planning conditions lead to variability in the operation and business environment. This has led to the development of numerous hybrid fuzzy approaches, such as fuzzy stochastic programming (Vahdani, 2015; Wu et al., 2016; Ji et al., 2020) and robust fuzzy programming (Tsao and Thanh, 2019; Goodarzian et al., 2020) to cope with hybrid uncertainties more effectively. In this hybrid fuzzy research stream, this study introduces an interactive fuzzy method called the robust fuzzy stochastic programming model. This method is expected to successfully overcome many different types of uncertainty, as well as different levels of risk situations because of COVID-19.

The solution approach is an extension of robust optimization into fuzzy programming and stochastic programming based on Tsao et al. (2019). For uncertain environments, fuzzy programming provides a powerful tool to tackle a variety of uncertainties in parameters, objective functions, and soft constraints (Inuiguchi and Ramik, 2000), whereas the stochastic model helps to model disruption risks through probability theory (Zhou et al., 2013). For optimal solutions, robust optimization ensures a feasible solution to the optimization problems by trade-offs between feasibility and optimality robustness (Mulvey et al., 1995). The effectiveness of the RFSP model on the optimal solution and computation time compared with that in other methods, such as robust stochastic programming model and robust fuzzy programming model, has been considered in several studies (Fazli-Khalaf et al., 2017; Farrokh et al., 2018; Nasiri et al., 2019; Gholizadeh et al., 2020). To overcome uncertainties in both random and hazardous events, the RFSP model should be applied to this research problem. The following sections briefly describe the methods applied to deal with the business-as-usual uncertainty and deeply hazardous events, such as the COVID-19 pandemic.

3.2.1. Dealing with the business-as-usual uncertainty

In the proposed mathematical model, the business-as-usual uncertainties, including demand loads of consumers, fixed and variable costs of the power plant, and interest rate can be described as triangular fuzzy numbers. Compared to stochastic programming methods, the use of fuzzy numbers to express the uncertainties helps save considerable time and resources when collecting historic data to estimate the probability distribution of the random variables related to practical real-life problems. However, it requires an in-depth understanding from the experts and decision-makers to perform the fuzzification and defuzzification processes of the random variables. In the RFSP model, the expected interval and expected value method of Jimenez (1996) are applied to the defuzzification process to generate an exact value of a triangular fuzzy number. This method does not increase the number of objective functions and constraints; therefore, it is computationally efficient for solving a mathematical programming model in a highly uncertain environment.

For a triangular fuzzy number with three prominent points, for example, the curtailable load of consumer *m* at time slot *t* is, $d_{tm}^{curt} = (d_{tm1}^{curt}; d_{tm2}^{curt}; d_{tm3}^{curt})$ as illustrated in Fig. 2, and the fuzzification process with the membership function is in the range [0; 1] (Fig.3) and can be described as Eq. (15). According to the defuzzification process of Jimenez (1996), the expected interval and expected value of d_{tm}^{curt} can be defined as in Eqs. (16)–(17). It is noted that the same equations can be used for all other business-as-usual uncertainties in the model, including $d_{tm}^{critic}, d_{m}^{min}, d_{m}^{max}, \xi, fc_i, vc_i$, and r.

$$\mu_{d_{tm}^{curt}}(x)=\begin{cases} f_{d_{tm}^{curt}}(x)=\dfrac{x-d_{tm1}^{curt}}{d_{tm2}^{curt}-d_{tm1}^{curt}} & \text{if } d_{tm1}^{curt}\le x\le d_{tm2}^{curt}\\ 1 & \text{if } x=d_{tm2}^{curt}\\ g_{d_{tm}^{curt}}(x)=\dfrac{d_{tm3}^{curt}-x}{d_{tm3}^{curt}-d_{tm2}^{curt}} & \text{if } d_{tm2}^{curt}\le x\le d_{tm3}^{curt}\\ 0 & \text{if } x\le d_{tm1}^{curt} \text{ or } x\ge d_{tm3}^{curt} \end{cases} \tag{15}$$

$$EI(d_{tm}^{curt})=\left[\int_0^1 f_{d_{tm}^{curt}}^{-1}(x)dx;\int_0^1 g_{d_{tm}^{curt}}^{-1}(x)dx\right]=\left[\frac{1}{2}\left(d_{tm1}^{curt}+d_{tm2}^{curt}\right);\frac{1}{2}\left(d_{tm2}^{curt}+d_{tm3}^{curt}\right)\right] \tag{16}$$

$$EV(d_{tm}^{curt})=\frac{\int_0^1 f_{d_{tm}^{curt}}^{-1}(x)dx+\int_0^1 g_{d_{tm}^{curt}}^{-1}(x)dx}{2}=\frac{d_{tm1}^{curt}+2d_{tm2}^{curt}+d_{tm3}^{curt}}{4} \tag{17}$$

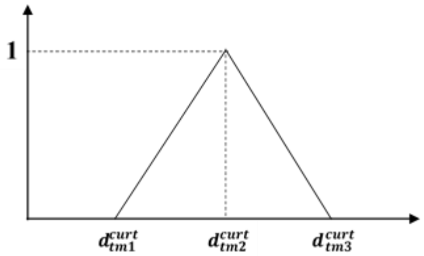

Fig. 2. Triangular fuzzy number for curtailable load of consumer *m* at time slot *t*.

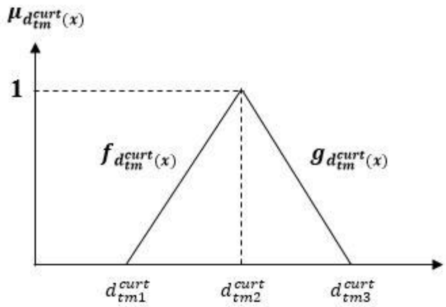

Fig. 3.Membership function for curtailable load of consumer *m* at time slot *t*.

3.2.2. Dealing with the hazardous event

COVID-19 is considered a hazardous event affecting several adjacent planning periods and creating supply network disruptions. In the proposed mathematical model, COVID-19 effects are formulated by the disruptions on both the supply and demand sides through two parameters, ϕ and β, respectively.

Let S_ϕ be a set of stochastic scenarios for the effect of ϕ on the output capacity Q_{it} of each RE generation unit *i* with associated probability $p_{s\phi}$ ($\sum_{S\phi} p_{s\phi}=1$). Because of the intermittent nature of RE sources, Q_i is an uncertain parameter in the triangular fuzzy number form. According to the Eqs. (15) – (17), the membership function, expected interval, and the expected value of Q_{it} can be defined as $\mu_{Q_{it}}(x), EI(Q_{it})$, and $EV(Q_{it})$, respectively. According to the guidance of Tsao et al. (2019), to measure the impacts of ϕ on Q_{it}, constraint (8) can be reformulated as Eq. (18)

$$q_{it} + v_{it} \le EV(Q_{it}) - EV(Q_{it})\left(1 - \sum_{s\phi \in S_\phi} \phi_{s\phi} p_{s\phi}\right), \forall t \in T, i \in I \qquad (18)$$

The terms on the right side of Eq. (18) measure the change in the fuzzy values of Q_i caused by the impact of each stochastic scenario $s_\phi \subset S_\phi$ on the output capacity of RE generation units. This is called the scenario variability for all considered stochastic scenarios. A decrease in the value of the variability, accomplished by decreasing the value of ϕ, can increase the optimality robustness of the optimal solution.

Similarly, let S_β be a set of stochastic scenarios to denote the effect of β on the energy consumption demand (d_{tm}^{curt}) of consumers with associated probability $p_{s\beta}$ ($\sum_{s\beta} p_{s\beta} = 1$). Taking into account the uncertain nature of consumer demand, d_{tm}^{curt} is also a triangular fuzzy number, and its expected value can be obtained by Eq. (17). Disruption uncertainties in consumer demand can cause variability in the objective function. To measure this change, the objective function (5) can be a reformulation of Eq. (19), as follows:

$$Max\pi_2 = \sum_{t\in T}\sum_{m\in M} \varphi_m e_t \min\left[\sum_{i\in I} M\left(Q_{it}\right); M\left(D_{tm}\right)\right] + \sum_{m\in M} g(1-\varphi_m)h\alpha - \qquad (19)$$

$$\sum_{t\in T}\sum_{i\in I} EV(fc_i) + EV(vc_i)\left(q_{it}+v_{it}\right) - \sum_{t\in T}\sum_{m\in M} \frac{rh\varphi_m e_t \min\left[\sum_{i\in I} M\left(Q_{it}\right); M\left(D_{tm}\right)\right]}{N}$$

In Eq. (19), two terms $M(Q_{it})$ and $M(D_{tm})$ measure the effects of the operational and disruption uncertainties on the capacity output of each RE generation unit i and the energy consumption demand of each consumer m at time slot t, respectively. According to Tsao et al. (2019), the values of $M(Q_{it})$ and $M(D_{tm})$ are functions defined by Eqs. (20) and (21) as follows:

$$M\left(Q_{it}\right) = EV(Q_{it}) - EV(Q_{it})\left(1 - \sum_{s\phi\in S_\phi} \phi_{s\phi} p_{s\phi}\right) \qquad (20)$$

$$M(D_{tm}) = d_{tm}^{critic} + EV(d_{tm}^{curt}) - EV(d_{tm}^{curt})\left[1 + \tau\left(1 - \sum_{s\beta\in S_\beta} p_{s\beta}\beta_{s\beta}\varphi_m\right)\right] \qquad (21)$$

Eq. (20) consists of the possibilistic variability ($EV(Q_{it})$) caused by the intermittent nature of RE sources and scenario variability ($EV(Q_{it})(1 - \sum_{s\emptyset\in S_\emptyset} p_{s\emptyset}\emptyset_{s\emptyset})$) caused by the effects of ϕ on the capacity output of RE generation units. Similarly, Eq. (21) consists of the possibilistic variability ($EV(d_{tm}^{curt})$) caused by the uncertain nature of consumer demand and scenario variability ($EV(d_{tm}^{curt})(1 + \tau(1 - \sum_{s\beta\in S_\beta} p_{s\beta}\beta_{s\beta}\varphi_m))$) caused by the effects of β on consumer demand. High variability for the objective function indicates that the solution is a high-risk one. In other works, a small change in the values of uncertainty can cause large variability in the objective function.

3.2.3. Proposed robust fuzzy-stochastic programming model

In this section, an RFSP approach is proposed to cope with both operational and disruption risks in the considered RRESN model. The proposed approach is based on the integration of fuzzy programming and scenario-based stochastic programming into robust optimization. Based on the fuzzy methods and scenario-based stochastic programming described in Sections 3.1 and 3.2, the robust objective function, including three components, expected value, optimality robustness, and feasibility robustness, according to Mulvey et al. (1995), is defined in Eq (23) as follows:

$$Max(OF) = EV(\pi_2) + \gamma \sum_{S_\phi} p_{s\phi} \sum_{S_\beta} p_{s\beta} \left[EV(\pi_2) - \pi_{2(S_\phi S_\beta)} \right] - \eta\theta \left[M\left(Q_{it}\right) - M(D_{tm}) \right] \tag{23}$$

In Eq. (23), the first term measures the expected resilient performance of the RRESN. It can be determined by the expected objective function in Eq. (19). The second term measures the optimality robustness of a robust solution by realizing the difference between the expected profit in Eq. (19) and the profit obtained by solving the deterministic model under each scenario s_ϕ and s_β ((π_2 (s_ϕ s_β)). The last term is a penalty cost function for unsatisfied demand caused by realizing the difference between the possibilistic and scenario variability of the capacity and the possibilistic and scenario variability of the demand. The parameter θ represents the penalty cost for each unit of possible violation. It is determined through supply contracts and can be adjusted based on the agreement between the stakeholders in the network or government regulations. Here, γ and η are the importance weights of the optimality robustness and the feasibility robustness in the robust objective function, respectively. These parameters reflect the preference of the decision-maker. For example, if planners wish to produce RE with low variability but higher penalty costs, they must increase the weight of η or vice versa.

According to the guidance in Sections 3.1 and 3.2, the constraint system of the original power plant optimization model [Eqs. (6) – (14)] can be formulated in the proposed RFSP model as follows:

$S.t$

$$\sum_{t\in T}\sum_{i\in I} q_{it}+v_{it} \ge \sum_{t\in T} d_{tm}^{critic} + EV(d_{tm}^{curt}) - EV(d_{tm}^{curt})\left[1+\tau\left(1-\sum_{s\beta\in S_\beta} p_{s\beta}\beta_{s\beta}\varphi_m\right)\right], \forall m\in M \quad (24)$$

$$q_{it}+v_{it} \le EV(Q_{it}) - EV(Q_{it})\left(1-\sum_{s\phi\in S_\phi}\phi_{s\phi}p_{s\phi}\right), \forall t\in T, i\in I \quad (25)$$

$$\varphi_m = \frac{e_t\left(d_{tm}^{critic}+EV(d_{tm}^{curt})+EV(d_{tm}^{curt})\tau\right)-\alpha EV(d_{tm}^{curt2})\tau^2\sum_{s\beta\in S_\beta} p_{s\beta}\beta_{s\beta}}{EV\left(d_{tm}^{curt}\right)\tau\sum_{s\beta\in S_\beta} p_{s\beta}\beta_{s\beta}\left(2e_t-\alpha\tau EV(d_{tm}^{curt})\sum_{s\beta\in S_\beta} p_{s\beta}\beta_{s\beta}\right)}, \forall m\in M \quad (26)$$

$$\alpha > \frac{2e_t}{EV(d_{tm}^{curt})\tau\sum_{s\beta\in S_\beta} p_{s\beta}\beta_{s\beta}}, \forall m\in M \quad (27)$$

$$d_m^{\min} \le \sum_{t\in T} EV(d_{tm}^{curt}) - EV(d_{tm}^{curt})\left[1+\tau\left(1-\sum_{s\beta\in S_\beta} p_{s\beta}\beta_{s\beta}\varphi_m\right)\right] \le d_m^{\max} \quad (28)$$

Constraints (7) and (12 - 14) remain unchaged

The steps of the proposed RFSP model are summarized in the form of an algorithm as follows:

Step 1: Determine the expected profit under hybrid uncertainties in the objective function (19) and the profit of the deterministic model under each scenario, s_ϕ and s_β

Step 2: Transform the original model into the proposed RFSP model according to the explanation in Section 3.3.

Step 3: Identify all relevant system parameters (e.g., θ, γ, and η) of the decision-makers.

Step 4: Solve the RFSP model. If the decision-maker is satisfied with the proposed solution, stop. Otherwise, another solution is sought by adjusting the values of one of the system parameters (e.g., η). Return to Step 3.

4. Results and discussion

The market structure of Vietnam was selected to undertake case studies, and industrial consumer information regarding electric power demand can be found in Vu et al. (2017). Along with Taiwan and Korea, Vietnam has successfully faced two waves of COVID-19. The Vietnamese government has accepted economic losses to prevent the spread of the pandemic in society through a nationwide lockdown of 15 d from 1 April to 15 April. Currently, the government has introduced financial incentives to spur economic growth. For the energy sector, large-scale investments in RE energy projects continue to be developed and are included in the national master plan of electricity development. Credit support packages, such as low-interest rates and payment delays, have also been launched by the government to support power plants and consumers for recovering the economy post-COVID (Thuy et al., 2020). Thus, the results presented and discussed below are expected to help planners make informed decisions regarding the policies to recover the economy of Vietnam post-COVID in the RE energy sector.

The proposed model and solution approach were tested on the 110 kV distribution feeder network, including a single power plant with six RE generation units and a consumption area with 150 consumers. The designed capacity and relevant costs of six RE generation units based on solar photovoltaics and wind turbines are given in Table 1 according to a report by the Vietnam Electricity (EVN) Company. The electric power price in the normal state is based on the time-of-use electricity tariff of the EVN, as shown in Fig. 4. The proposed model of the case study was solved using MATLAB 2013 optimization software running on a dual-core 3.40 GHz computer with 8.0 GB of RAM. The significant results are presented and discussed below.

Table 1. Design capacity and relevant costs of RE generation units.

RE units	Technology	Design capacity (kW)	Fixed cost ($/kW)	Variable cost ($/kW)
RGU1	Solar	(450, 550, 650)	(0.02, 0.03, 0.04)	(0.02, 0.03, 0.04)
RGU2	Solar	(350, 450, 550)	(0.03, 0.04, 0.05)	(0.03, 0.04, 0.05)
RGU3	Solar	(200, 400, 600)	(0.04, 0.05, 0.06)	(0.04, 0.05, 0.06)
RGU4	Wind	(250, 350, 450)	(0.03, 0.04, 0.05)	(0.02, 0.03, 0.04)
RGU5	Wind	(300, 400, 500)	(0.02, 0.03, 0.04)	(0.03, 0.04, 0.05)
RGU6	Wind	(350, 450, 550)	(0.01, 0.02, 0.03)	(0.02, 0.03, 0.04)

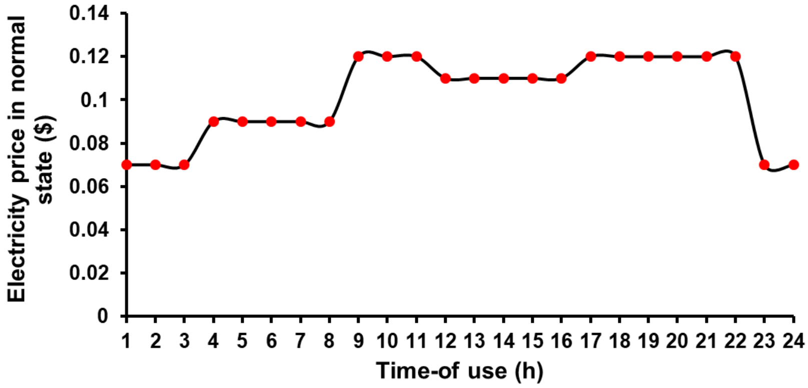

Fig. 4. Time-of-use electricity tariff in normal state.

4.1. Risk-sharing-based resilient renewable energy supply network-related decisions

According to the results from the proposed model, the decisions related to the amount of electric power generated and stored in the planning time (1 d) are shown in Fig. 5. It was seen that 148,608 kWh of electric power would be generated from the six RE generation units to meet the energy consumption demand during the pandemic. Additionally, to enhance resilience from the supply side caused by the intermittent nature of RE resources, 54,800 kWh of electric power should be stored in the RE generation units. The energy consumption demand is concentrated in the period from 10:00 to 20:00, accounting for more than 57% of the total demand. This was explained by the impact of the lockdown policy because of the COVID-19 pandemic, which has shifted the energy consumption time of industrial consumers.

Table 2 presents the resilient RE supply network-related results using the proposed risk-sharing model. When the values of β (the COVID-19 impact on demand), ϕ (the COVID-19 impact on supply), and h (the payment delay), θ, γ, and η were set to 0.4, 0.1, 20, 3.14, 0.5, and 0.5, respectively. The average price adjustment coefficient of each consumer m in the supply network (φ_m) was 0.86. This corresponded to a 16% reduction in the electricity price in the normal state to achieve 9.68×10^8 ($) resilient profit in the supply network.

Based on the risk-sharing effort index (α = 1.56), a 1.46×10^4 ($) grant was supported by the government to increase the resilience of the supply network. In the proposed risk-sharing model, two decision variables regarding the price adjustment coefficient (φ_m) and the risk-sharing effort index (α) will help the government determine the proper amount of subsidy for power plants to increase the resilience of the supply network during the pandemic. Finally, the proposed RFSP model can help planners to obtain a Pareto optimal solution with a CPU time of less than 2 min in our examples.

Table 2. Relevant information of the resilient RE supply network.

Indicators	Value
Total resilient profit [π_2]	9.68×10^6 ($)
Average price adjustment coefficient [φ_m]	0.86
Risk-sharing effort [α]	1.56
Government subsidy [$g(1- \varphi_m)\alpha h$]	1.46×10^4 ($)
CPU time	98 (sec)

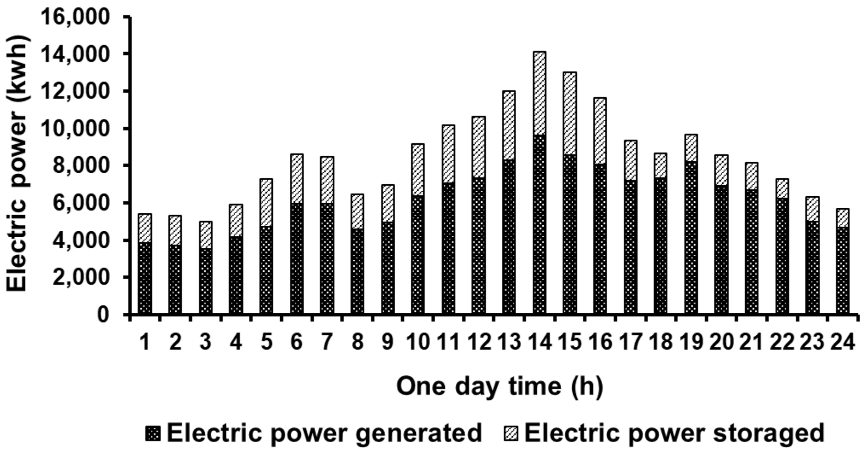

Fig. 5. Amount of electric power generated and stored to meet demand.

4.2. Sensitivity analysis

This section investigates the effects of system parameters, including ϕ, β, h, and G, on the decision variables and total resilient profit of the RE supply network. Table 3 illustrates the stochastic scenarios under the different values of ϕ and β to express the COVID-19 effects on both the supply and demand sides of the resilient RE supply network. The main results are shown in Figs. 6–9.

Table 3. Stochastic scenarios for supply and demand disruption due to COVID-19.

Scenarios	Supply side		Demand side	
	Value of ϕ	Value of $p_{s\phi}$	Value of β	Value of $p_{s\beta}$
No effect (SC1)	0.00	0.15	0.00	0.10
Little effect (SC2)	0.00 – 0.15	0.15	0.00 – 0.30	0.15
Moderate effect (SC3)	0.15 – 0.30	0.45	0.30 – 0.70	0.45
Considerable effect (SC4)	0.30 – 0.50	0.25	0.07 – 1.00	0.30

4.2.1. COVID-19 impact on the total resilient profit of the network

From Fig. 6, an increase in the COVID-19 impact on the energy supply of the power plant led to an increase in the average price adjustment coefficient and a decrease in the total resilient profit of the power plant. When the COVID-19 impact on the energy supply increased, it was reasonable to increase the average price adjustment coefficient for consumers because the output capacity of the power plant decreased. A larger average price adjustment coefficient corresponds to a slight reduction of the electricity price in the normal state. As a result of the power shortage, electricity pricing often rises dramatically (Nooij et al., 2007). However, this value tends to have stability at approximately 0.89 when the COVID-19 pandemic has a considerable effect on the energy supply (ϕ in the range 0.3–0.5). This is explained by the effect of risk-sharing on the supply network. The output capacity of the RE generation units decreases because of the COVID-19 impacts, but the power plant still holds an approximate 11% discount in the energy price to consumers when the COVID-19 impacts on the energy consumption demand of consumers was set to 0.4. The power plant loses part of its revenue from capacity reduction. Additionally, a larger average price adjustment coefficient results in lower subsidies from the government to the power plant. Thus, the total resilient profit of the power plant tends to decrease (approximately 1.00×10^4 \$) when COVID-19 has a tremendous impact on the energy supply.

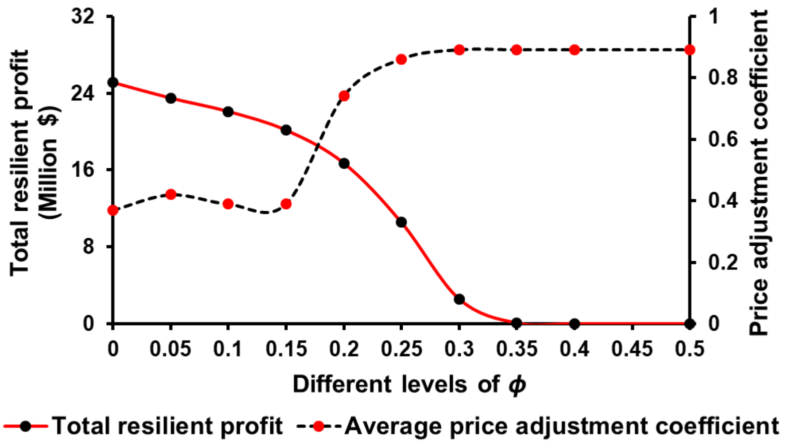

Fig. 6. Total resilient profit and price adjustment coefficient under different value of ϕ at $\beta = 0.4$ and $h = 30$.

Regarding the different effect levels of the COVID-19 pandemic on the energy consumption demand of consumers, Fig. 7 shows the behavior of the proposed model for different β levels from 0.1 to 1.0. An increase in the effect level of the pandemic leads to a decrease in the average price adjustment coefficient for consumers. When the effect of the pandemic on the economy is large, it is reasonable to decrease electricity pricing to enhance the resilience of the supply network. Lu et al. (2018) and Tsao et al. (2019) emphasized that energy demand is sensitive to changes in the electric power price. A decrease in electricity price results in an increase in demand. In some cases (e.g., economic crisis or inelastic goods), reducing prices to stimulate demand often results in less overall revenue (Adenso-Díaz et al., 2017). In the proposed risk-sharing model, a larger subsidy from the government is also expected to improve the resilience of the distribution network on the supply side as electricity pricing falls to maintain the demand side.

There is a significant change in the total resilient profit of the power plant under different influence levels of the COVID-19 pandemic. The total resilient profit tends to decrease when the impact level of the pandemic increases from 0.1 to 0.6. This is explained by the fact that the electricity price adjustment coefficient at these impact levels is not larger to maintain the energy consumption demand of consumers. Additionally, a long payment delay (h = 30 d in this case) led to an increase in the financial cost and a decrease in the total resilient profit of the power plant. However, the total resilient profit tends to recover when the impact level of the pandemic is larger than 0.6. A greater impact level of the COVID-19 pandemic allows the power plant to offer lower electricity prices to maintain the demand. Thus, a smaller electricity price adjustment coefficient at a greater impact level of pandemic ($\beta > 0.6$) allows a power plant to receive more revenue to stimulate demand. Government subsidies are also greater to enhance the resilience of the supply network at the same payment delay (h = 30 d).

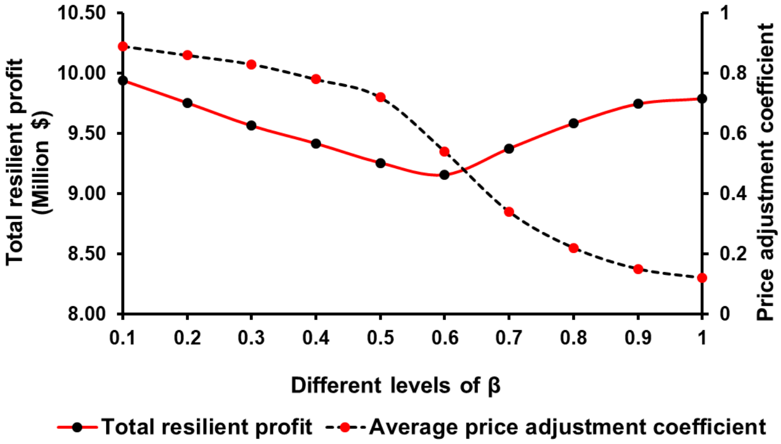

Fig. 7. Total resilient profit and price adjustment coefficient under different value of β at ϕ = 0.2 and h = 30.

4.2.2. The impact of delayed payment on the total resilient profit of the network

From Fig. 8, a longer delay in the payment credit period of consumers leads to an increase in the risk-sharing effort index. When the delay in payment increases, it is reasonable to put more effort into risk-sharing between power plants and consumers. Consequently, a greater risk-sharing effort allows a power plant to receive more subsidies from the government. However, the total resilient profit of the power plant tends to approach zero when the delay in payment is longer than 60 d. This is explained by the budget constraints of the government for supporting the energy sector when a pandemic occurs. According to Mylenka (2020), the default risks on payments cause cascade effects and affect the entire energy market. Thus, permissible delays in payment are expected not only to assist consumers in a crisis but also to maintain the resilience of suppliers (Jamal et al., 2000). In our numerical example, the optimal payment delay to achieve the maximum resilient profit for the power plant is approximately 30 d. The risk-sharing effort index is 2.78, and the price adjustment coefficient is 0.53, which satisfies the conditions in Eqs. (2) and (3) to ensure the minimum electricity costs of consumers.

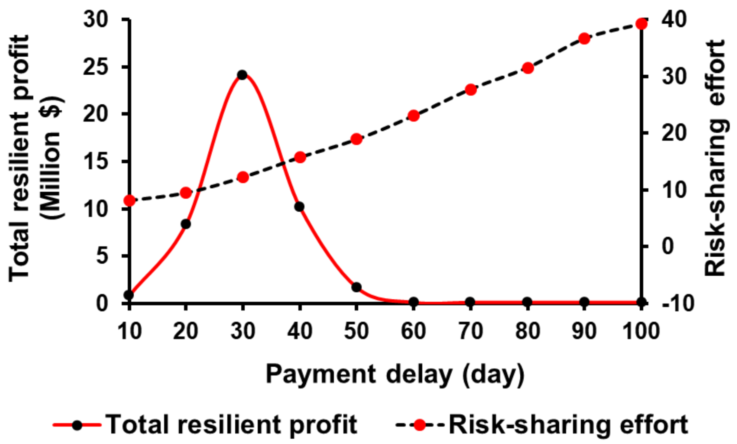

Fig. 8. Total resilient profit and risk-sharing coefficient under different value of h at ϕ = 0.2 and β = 0.4.

4.2.3. The impact of government subsidy on the total resilient profit of the network

To evaluate the effects of the government subsidy budget (G) on enhancing the resilience of the RE supply network, a sensitivity study on the amount of government subsidy was conducted in this section. The values of ϕ and β were 0.4 and 0.3, respectively. Fig. 9 shows the behavior of the total resilient profit, and the risk-sharing effort of the power plant increases as the values of G increase.

As shown in Fig. 9, an increase in the government subsidy budget leads to increases in the total resilient profit and the risk-sharing effort of the power plant. When the government subsidy G increases, it is reasonable to put more effort into risk-sharing between power plants and consumers. A greater value of α reflects a longer payment delay (h) for consumers. Consequently, a greater risk-sharing effort and a longer payment delay allow the power plant to receive more subsidies from the government.

The role of the government in recovering the post-pandemic RE market has been mentioned in many reports and studies (Bahar, 2020, and Hosseini, 2020). In COVID-19, government support focuses on community benefits, such as healthcare systems and unemployment assistance; therefore, subsidies to power plants are also limited. In a budget constraint, the power plant needs to consider the tradeoff between the loss of financial costs because of a longer payment delay for consumers and the subsidy received from the government to make an appropriate decision for the value of h.

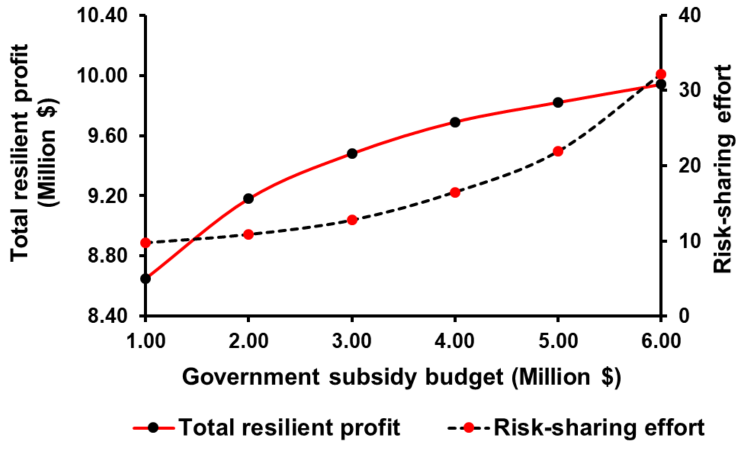

Fig. 9. Total resilient profit and risk-sharing coefficient under different value of G.

4.3. Performance assessment of the proposed model

In this section, the effectiveness of the risk-sharing model with the government subsidy and the performance of the proposed RFSP model are assessed by comparing it with other existing models.

4.3.1. Effectiveness assessment of the risk-sharing model

The effectiveness of the proposed risk-sharing-based RRESN model in the face of the COVID-19 pandemic is assessed by comparing the total resilient profit (with risk-sharing) and the total profit (without risk-sharing) of the power plant under different degrees of impact of the COVID-19 on the energy consumption demand of consumers. Both models are simulated with a planning time extension of 3600 h corresponding to the impact of the COVID-19 pandemic over 5 months. Table 4 shows the comparison of results with four different impact levels of COVID-19 on the energy consumption demand of the consumer (0.4, 0.6, 0.8, and 1.0).

As can be seen in Table 4, it is clear that the proposed risk-sharing model has a better performance in enhancing the resilient profit of the power plant in the face of the COVID-19 pandemic. With the increase in the COVID-19 impact levels and the planning time, the supply network model without risk-sharing (with the values of φ_m and h set to 1 and 0, respectively, in the proposed model) tends to decrease the total profit of the power plant by approximately 1.00×10^6 ($) at $\beta = 1$ and $t = 3600$ h. The resilient supply network with the risk-sharing model tends to stabilize the total resilient profit of the power plant at the approximate value of 4.00×10^9 ($) with different levels of the COVID-19 impacts at the same planning time of 3600 h. To enhance the resilience of the supply network in the face of the COVID-19 pandemic, a 2.56×10^7 ($) subsidy is supported by the government, whereas the average price adjustment coefficient is 0.42 and the risk-sharing effort between the power plant and consumer is 22.68.

Table 4. Comparing the total resilient profit and total profit of the power plant with different values of β.

β	*0.4*		*0.6*		*0.8*		*1.0*	
Time	Total profit ($)	Total resilient profit ($)	Total profit ($)	Total resilient profit ($)	Total profit ($)	Total resilient profit ($)	Total profit ($)	Total resilient profit ($)
720	5.57×10^8	5.77×10^9	5.08×10^8	5.37×10^9	4.29×10^8	5.28×10^9	4.09×10^8	4.99×10^9
1440	2.36×10^8	3.97×10^9	2.21×10^8	3.65×10^9	1.68×10^8	3.36×10^9	1.06×10^8	2.90×10^9
2160	8.09×10^7	4.39×10^9	8.08×10^7	4.12×10^9	6.55×10^7	4.06×10^9	5.25×10^7	3.93×10^9
2880	4.57×10^7	4.69×10^9	4.08×10^7	4.50×10^9	3.08×10^7	4.37×10^9	2.89×10^7	4.28×10^9
3600	1.09×10^7	4.47×10^9	1.08×10^6	4.26×10^9	1.05×10^6	4.07×10^9	1.02×10^6	3.96×10^9

4.3.2. Performance assessment of the proposed model

In this step, the RFSP model was compared with the robust optimization (RO) model in Diabat et al. (2019). The RO model only considers the scenario variability caused by the risk scenario while ignoring the possibilistic variability caused by uncertain parameter deviation in each risk scenario. Thus, the weight factor for the feasibility robustness (η) in the RFSP model was zero. The details of the RO model can be found in Diabat et al. (2019).

The total resilient profit and the optimality robustness of both models for different impact levels of COVID-19 on the energy supply and demand are shown in Figs. 10 and 11, respectively. This revealed that the results obtained from the proposed RFSP model were better than those of the RO model in most of the risk scenarios. This can be explained by the fact that the RFSP model can capture uncertainties in both random and hazardous events. The comparison of the average CPU time of both models is shown in Table 5. For all considered risk scenarios, the proposed RFSP model achieves an efficiency for the average CPU time (reducing CPU time by approximately 5.6%) than that of the RO model.

Table 5. Comparing the CPU time of both models.

	RFSP model	RO model
Average CPU time	118 (sec)	125 (sec)

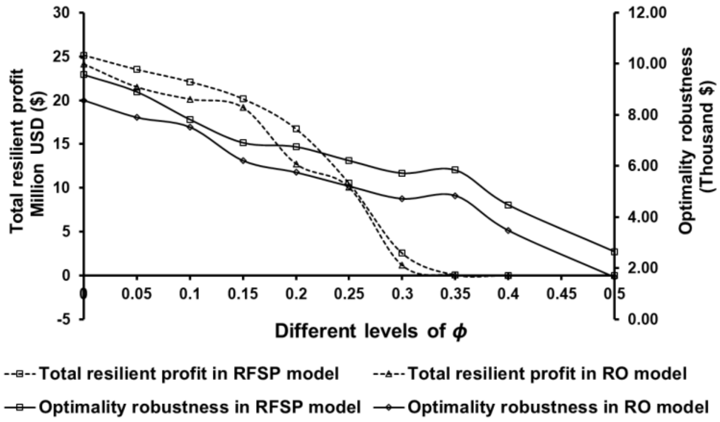

Fig. 10. Comparative results of both models under different value of ϕ at β = 0.4 and h = 30.

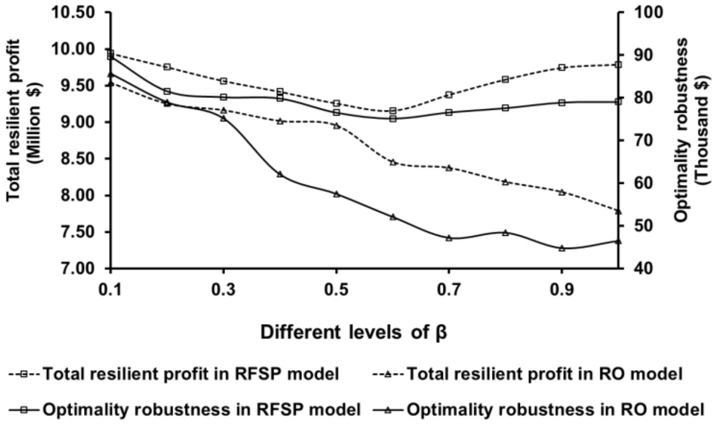

Fig. 11. Comparative results of both models under different value of β at ϕ = 0.2 and h = 30.

5. Conclusions

The world is going through a stressful period to overcome the COVID-19 pandemic. The outbreak of COVID-19 has created tremendous waves of death and economic crises. Lockdown is the world's biggest challenge in treating COVID-19 and recovering the economy. At this time, it will need all support and efforts to help all aspects of the economy recover, including the energy sector because it is extremely important to ensure the prosperity of a county and its society. This study contributes a resilient renewable energy supply network model based on risk-sharing between the government, power plant, and consumers in the face of the COVID-19 pandemic. The proposed model aims to minimize the electricity bill cost of the consumer while maximizing the total resilient profit of the power plant. The effects of the COVID-19 pandemic on the energy sector were modeled through the negative impacts on the energy consumption demand and payment delay in electricity bills of consumers, as well as the disruptions in the energy supply of the power plant. With the performance-based risk-sharing model, the government subsidies to the power plant are considered based on the risk-sharing effort and the electricity price adjustment coefficient that the power plant will provide to consumers during the COVID-19 pandemic.

A test of the energy supply network was simulated to validate the efficacy and efficiency of the proposed model. The main results were as follows: (i) there was a significant fluctuation in the total resilient profit of the power plant when the COVID-19 pandemic affects both the energy supply and demand sides; (ii) the power plant tended to have a lower electricity price reduction when the COVID-19 pandemic creates considerable disruptions in the energy supply; (iii) a greater impact level of COVID-19 on the energy consumption demand of consumers allows the power plant to offer lower electricity prices to stimulate demand, and government subsidies are also greater to enhance the resilience of the supply network at the same risk-sharing effort index; (iv) government subsidies play an important role in enhancing the resilience of the supply network; (v) the supply network with risk-sharing model showed a better performance in maintaining the total resilient profit compared to the supply network without risk-sharing.

Some policy implications were also drawn from the main results. First, for an RE supply network affected by the deeply hazardous events, such as COVID-19 on both the supply and demand sides, the government and energy regulators should consider risk-sharing for power plants and consumers because the analysis results showed that government subsidies play an important role in enhancing the resilience of the network. Second, along with another incentive on the demand side (e.g., permissible delay in payment of consumers), the pricing decision is also expected to maximize the total profit of power plant during the crisis. The results demonstrated that a pricing policy consistent with the different influence levels of disruption risks allows the power plant to reap higher profits and better risk management in disruptions. Finally, compared to disruption risks on the demand side, disruptions in the supply side result in more significant fluctuation in the total resilient profit of the power plant. Moreover, more government efforts to restore the energy supply network are also required.

The proposed model has some limitations and can be extended in several directions. First, the proposed risk-sharing model considers only government subsidies to the power plant based on the price adjustment coefficients and risk-sharing effort, which does not consider the effects of capacity interruption on the amount of government subsidies. Incorporating effects of COVID-19 on the output capacity of power plants into risk-sharing models with government subsidies could be an important issue for further research to help the economy recover after the pandemic. Additionally, the proposed model could be enriched by considering various types of diversity impacts of deeply hazardous events (e.g., COVID-19) on the global renewable energy sector, such as interest rate problems and international investment projects. Finally, along with government subsidies, the solution initiatives and other risk-sharing policies could be investigated to support the post-pandemic economic recovery towards "resilient" supply networks (Rajesh, 2018), which is a valuable research topic to consider based on our model.

Appendix A. The detailed first and second-order derivative of the objective function for consumers.

The objective function (1) of consumers

$$Min\pi_1 = \sum_{t\in T}\sum_{m\in M}\varphi_m e_t\left[d_{tm}^{critic} + d_{tm}^{curt}\left(1+\tau\left(1-\beta\varphi_m\right)\right)\right] + \frac{\alpha}{2}\left[d_{tm}^{curt} - d_{tm}^{curt}\left(1+\tau\left(1-\beta\varphi_m\right)\right)\right]^2 \quad (1)$$

First-order derivative of the objective function (1)

$$\pi_1(\varphi_m)' = e_t d_{tm}^{critic} + e_t d_{tm}^{curt} + e_t d_{tm}^{curt}\xi - 2\varphi_m e_t d_{tm}^{curt}\xi\beta + \alpha d_{tm}^{curt\,2}\xi\beta - \alpha d_{tm}^{curt\,2}\xi\beta - \alpha d_{tm}^{curt\,2}\beta\xi^2 + \alpha d_{tm}^{curt\,2}\beta^2\varphi_m\xi^2$$

Solving the equation $\pi_1(\varphi_m)' = 0$, the pattern of φ_m can be obtained as follows:

$$\pi_1(\varphi_m)' = 0$$

$$\varphi_m = \frac{e_t\left(d_{tm}^{critic} + d_{tm}^{curt} + d_{tm}^{curt}\xi\right) - \alpha d_{tm}^{curt\,2}\beta\xi^2}{d_{tm}^{curt}\xi\beta\left(2e_t - \alpha d_{tm}^{curt}\beta\xi\right)}$$

Second-order derivative of the objective function (1)

$$\pi_1(\varphi_m)'' = -2e_t d_{tm}^{curt}\xi\beta + \alpha d_{tm}^{curt\,2}\beta^2\xi^2$$

To ensure that the objective function (1) is a concave function, its second-order derivative is always greater than zero.

$$\pi_1(\varphi_m)'' > 0$$

Solving the above inequation, the condition for α can be obtained as follows:

$$\alpha > \frac{2e_t}{d_{tm}^{curt}\tau\beta}$$

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