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COVID-19: Government subsidy models for sustainable energy supply with disruption risks

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Abstract

The outbreak of the COVID-19 pandemic poses great challenges to the current government subsidy models in the renewable energy sector for recovering in the post-pandemic economy. Although, many subsidy models have been applied to accelerate renewable energy investment decisions. However, it is important to develop a new model to ensure the sustainability of the renewable energy supply network under disruptions on both the supply and demand sides due to hazardous events. This study investigates different subsidy models (renewable credit, supplier subsidy, and retailer subsidy) to find a win-win subsidy model for sustainable energy supply under disruption risks. The objective is to determine the optimal capacity of renewable energy added to the grid, the optimal wholesale price of the power plant, and the optimal retail price of the aggregator under different subsidy models to maximize the economic, social, and environmental benefits of the whole network. A novel scenario-based robust fuzzy optimization approach is proposed to capture the uncertainties of business-as-usual operations (e.g., some relevant costs and demand) and hazardous events (e.g., COVID-19 pandemic). The proposed model is tested in a case study of the Vietnamese energy market. The results show that for a high negative impact level of hazardous events on the supply side, the renewable credit and supplier subsidy models should be considered to recovery the renewable energy market. Further, the proposed approach has a better performance in improving the power plant's robust profit for most of the hazard scenarios than the robust optimization model.

Keywords: COVID-19; Renewable energy; Sustainable supply; Government subsidy; Robust fuzzy model; Hazardous scenario.

Nomenclature

Abbreviation

Coronavirus disease of 2019	COVID-19
Electricity of Vietnam	EVN
Novel scenario-based robust fuzzy	NSRF
Robust optimization model	RO
Renewable energy	RE
Renewable generation	RG
Renewable credit	RC
Retailer subsidy	RS
Supplier subsidy	SS
Sustainable energy supply	SES
United Nations Sustainable Development Goals	UNSDGs

Sets and indices

I set of RG units , $i = 1,....,|I|$

M set of industrial loads, $m = 1,....,|M|$

T set of time, $t = 1,....,|T|$

S set of disruption scenarios, $s = 1,....,|S|$

Decision variables

$$x_i = \begin{cases} 1 & \text{RG unit } i \text{ is established in the grid} \\ 0 & \text{otherwise} \end{cases}$$

g_i installed capacity at RG unit

w_t wholesale energy price of power plan at time slot t

p_{tm} retail energy price of aggregator at time slot t for consumer m

Parameters

D_{tm}	energy demand of load m at time slot t [kWh]
d_{tm}^{ifle}	inflexible load of load m at time solt t [kWh] (uncertainty)
d_{tm}^{fle}	flexible load of load m at time solt t [kWh] (uncertainty)
τ	price elasticity coefficient of energy demand [percentage] (uncertainty)
β	impact of Covid-19 on energy demand [percentage]
α	subsidy rate from government to aggregator [percentage] (uncertainty)
ε	subsidy rate from government to power plant [percentage] (uncertainty)
c_i	investement cost of RG unit i [$] (uncertainty)
a	initial capital of power plant [$]
v_i	marginal cost of power plant [$/kW] (uncertainty)
r	interest rate of bank [percentage] (uncertainty)
φ	subsidy rate from government to bank [percentage] (uncertainty)
δ	impact of Covid-19 on maximum capacity of RG unit [percentage] (uncertainty)
$G_i^{\max}$	maximum capacity of RG unit i [kWh]
q	energy from the grid [kWh]
B	maximum loan from bank [$]
G	maximum subsidy from governement [$]
$p_t^{\max}$	maximum energy price that consumer willing to pay [$]
H	carbon cap [kg]
h	unit carbon emission per unit energy [kg/kW]
ξ	carbon emission price [$/kg] (uncertainty)

1. Introduction

Renewable energy (RE) sources are a promising solution to the United Nations Sustainable Development Goals (UNSDGs) related to environmental and social issues caused by the rapidly increasing energy demand [1]. However, there seem to be few possible ways of achieving this goal because of barriers in policy, technology, and finance [2]. In addition, the unexpected risks (e.g., floods, earthquakes, and pandemics) create difficulties for the production and consumption of RE sources. Recently, the outbreak of the coronavirus disease of 2019 (COVID-19) has had wide-ranging effects across all sectors and strata of society, including the RE sector. It has slowed down the transition to a global sustainable low-carbon energy system due to disruptions on both the supply and demand sides of the global economy. For example, the penetration level of solar photovoltaics was planned to be decreased by 17% in the fourth quarter of 2020 in the United States [3]. In addition, the logistics delay caused by COVID-19 has disrupted the supply chain from China, slowing down under-construction RE projects worldwide [4]. Meanwhile, many countries will certainly tighten budgets to treat COVID-19 and the implementation of new RE projects will undoubtedly be postponed [5]. This situation poses great challenges to the current subsidy models in the RE sector for recovering in the post-pandemic economy. Thus, the effective use of subsidy models to achieve a sustainable energy supply (SES) network in the framework of the UNSDGs in the current situation is crucial.

In the energy sector, government subsidies play an important role in promoting the penetration of RE in power grids to meet global climate goals. In practice, many subsidy models, such as green credit, feed-in tariffs, tax exemptions, and tenders, have been applied in many countries to accelerate RE investment decisions [6]. Green credit and feed-in tariffs refer to financial supports that a utility or energy supplier can be received based on their installed renewable energy capacity. Tax exemptions and tenders aim to provide a guaranteed tariff based on the amount of generated and consumed renewable energy for a specified period. To facilitate this process, many theoretical studies [7–16] attempted to find an optimal subsidy model for RE supply chains for sustainable development goals. For example, Chen and Su [7] determined the optimal subsidy rate in a RE supply network to maximize total system profit and social welfare simultaneously. Consumer surplus was used as a measure to evaluate the effectiveness of the subsidy model for social welfare in their study. A combination of renewable credit and carbon policy was applied in a government subsidy model to minimize the total cost of hybrid energy systems while increasing the share of RE sources in Martelli et al. [8]. The results showed that in a certain environment, the proposed subsidy model reduces carbon emissions by 25%. Suh and Yoon [9] investigated the impact of subsidy budgets on solar photovoltaic development. Their results highlighted that for subsidies allocation problems a simple rule of an optimal subsidy policy is used to allocate subsidies to equalize regional marginal net benefits of all eligible regions. Under uncertain energy demand and costs, RE subsidies are expected to improve social welfare by adjusting carbon emission abatement costs. Lecuyer and Quirion [10] revealed that a larger subsidy rate in low electricity price cases brings higher expected welfare for consumers. A noteworthy issue in above publications is that uncertainty has not been comprehensively investigated for both business-as-usual operations (e.g., demand and costs) and hazardous events (e.g., pandemics and earthquakes) (see Table 1). Ignoring uncertainties in decision-making processes leads to additional risks and costs [17].

Regarding uncertainty, disruptions arising from both internal factors (e.g., demand and cost) and external conditions (e.g., policies and disasters) deeply affect the operational performance of SES networks in the future. Therefore, the SES network must be able to operate effectively in a high-risk environment in the presence of two basic types of uncertainty: random and risk events. According to Klibi and Martel [18], random events refer to uncertainties in input parameters due to a lack of knowledge or historical data. Such events are usually tackled using probability distributions of random variables. Risk events describe incidents with unpredictable timing and likelihood of occurrence, and usually result in major business failures. For such events, robust optimization with impact scenarios can be applied to enhance the robustness of the network [19]. The COVID-19 pandemic is considered a risk event that has affected all aspects of life and led to critical network disruptions. Several previous studies have developed uncertain programming models to overcome the uncertainty in parameters and risks in the power system planning field with or without government subsidies [20 – 26]. For example, Tsao el al. [20] applied an integrated approach to deal with hybrid fuzzy-stochastic vagueness in smart electricity distribution networks. The applied model can cope with both operational and disruption risks to enhance the sustainability of the intelligent grid. Regulatory uncertainty in the feed-in tariff model was highlighted by [21] by using a Poisson process for incentivizing RE projects. The authors in [22] applied an approach based on the fuzzy set theory and stochastic variables to tackle various uncertainties in input parameters for planning energy systems with varied subsidies for stimulating RE technologies. The disruption risks, however, were not addressed in the studies by [21 - 22]. In a different study, a simulation approach was applied to evaluate the battery distribution network based on the resilience indices considering the material input risks [23]. However, resilient solutions, such as government subsidies and risk-sharing policies, are not discussed.

There have been many studies from the theoretical perspective that focus on mathematical models to tackle the uncertainty of different parameters and disruptions. In addition, some government subsidy models have also been introduced and evaluated in the literature. However, to ensure sustainability of the RE supply network in the face of disruptions on both the supply and demand sides due to hazardous events additional research is necessary, and the COVID-19 pandemic provides an excellent research opportunity. Table 1 presents a summary of studies on RE development in terms of efficiency index, subsidy model, uncertainty, and approach. To the best of our knowledge, the aspects not considered in the existing literature are as follows: (i) no previous study addressed the effects of various subsidy models on RE development and attempted to find a win–win subsidy model for the SES network under disruptions on both the supply and demand sides. Within a limited government budget, the flexible application of subsidy models will contribute to strengthening the sustainability of the entire network, especially in hazardous situations; (ii) there is a scarcity of studies in the RE sector on government subsidy models that consider the uncertainty of both business-as-usual operations and risk events. This was resulted in a limited ability of the existing approaches to provide a precise analysis of the SES network planning problem in uncertain environments. From the practical perspective, the world is witnessing a record drop in demand for energy sources and the global supply chain networks are vulnerable due to logistics delays caused by COVID-19. Along with efforts to deal with the huge public health challenges created by the pandemic, policy makers and governments also focus on taking necessary measures to maintain RE goals for post-pandemic economic recovery plans. The continuation and extension of existing policy measures are required to ensure progresses of on-going projects. Additional economic incentives, such as renewable credit, investment subsidies, and discount loan schemes, can stimulate demand for the highly vulnerable RE sector. 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 networks in the face of pandemics.

Table 1. Review of some relevant researches.

Reference	**Efficiency index**			**Subsidy model**	**Uncertainty**		**Approach**
	Eco	Env	Soc		Random	Risk	
[7]	●		●	SS			Game-theory
[8]	●			SS			Black-box optimization
[9]	●			SS			Game-theory
[10]	●			SS	●		Stochastic
[11]	●			SS		●	Poisson process
[12]	●	●	●	SS	●		Stochastic
[13]	●			SS			Algebraic Modelling
[14]	●	●	●	SS			Game-theory
[15]	●			SS, RS			Game-theory
[16]	●	●		SS	●		Stochastic
[17]	●	●	●	N/A	●	●	Robust fuzzy stochastic
[21]	●			SS	●		Simulation
[22]	●			SS	●		Possibilistic-stochastic

[23]	●			N/A		●	Simulation
[24]	●			N/A	●		Stochastic fuzzy
[25]	●			RC,SS			Game-theory
This study	●	●	●	RC, SS, RS	●	●	Scenario-Robust fuzzy

SS: supplier subsidy (feed-in tariff); **RC**: renewable credit; **RS**: retailer subsidy: **N/A**: No subsidy.

Considering all above issues, this study aims to investigate different government subsidy models, including renewable credit (RC), supplier subsidy (SS), and retailer subsidy (RS), and find a win-win subsidy model for sustainable energy supply under disruption risks. The objective is to determine the optimal capacity of RE added to the grid, the optimal wholesale price of the power plant, and the optimal retail price of the aggregator under different subsidy models while maximizing the total profit of the network, including the profit of power plants and aggregators. In addition to the economic benefits of power plants and aggregators, the influence of the government subsidies on social welfare and environmental benefits are also evaluated to ensure the sustainability of the network. A novel scenario-based robust fuzzy (NSRF) optimization approach is proposed to capture the uncertainties of business-as-usual operations (e.g., some relevant costs and intermittency of RE sources) and hazardous events (e.g., the COVID-19 pandemic). This study distinguishes contributions from practical and theoretical perspectives as follows:

- **Practical:** This study formulates a dual-objective optimization model for SES planning with disruption risks on both the supply and demand sides. To meet the UNSDGs in the RE sector, three different government subsidy modes (RC, SS, and RS) are considered simultaneously in the proposed model. The effects of the COVID-19 pandemic on the SES network are formulated by the disruption risks on the output capacity of renewable generation (RG) units and the energy demand of consumers. The numerical results are expected to help energy regulators and governments with finding a win–win subsidy model for SES networks under disruption risks through quantitative analysis of the influence of COVID-19 on energy supply and demand.
- **Theoretical**: To successfully overcome a high degree of uncertainty of the input parameters and risks, a new NSRF approach, based on the combination of scenario-based robust optimization and fuzzy programming, is developed in this study. The proposed approach poses several advantages for dealing with different types of uncertainty owing to the use of fuzzy numbers for discrete distributions. This is suitable for practical real-world problems where historical data, essential for determining uncertainties, is lacking. Furthermore, scenario-based robust optimization is an effective approach to address hazardous events without increasing computational challenges in the model. It is also possible to deal with numerous scenarios simultaneously in relation to uncertainties in disruption risks.

The remainder of this paper is organized as follows: In Section 2 the problem addressed in this study is outlined and the proposed model is formulated. An NSRF approach is developed in Section 3 to overcome business-as-usual and hazard-related uncertainties. A numerical analysis is conducted in Section 4. Section 5 details conclusions, managerial insights, and directions for future research.

2. Problem definition and model formulation

2.1. Problem description

Fig.1 shows the proposed SES network structure, including a government, a single bank and power plant, and an aggregator. The power plant is considering setting up new RG units to meet climate change goals, while the aggregator buys electric power from the power plant at the wholesale price to provide power to consumption areas at the retail price. During the COVID-19 pandemic, the entire energy supply network is severely affected by the falling demand associated with the lockdown of cities to curtail the spread of the pandemic. As a result, the power plant faces financing obstacles when establishing RG units that can be resolved by means of financing with a bank. To encourage post-pandemic RE development, the government may adopt three types of subsidy models: RC, SS, and RS.

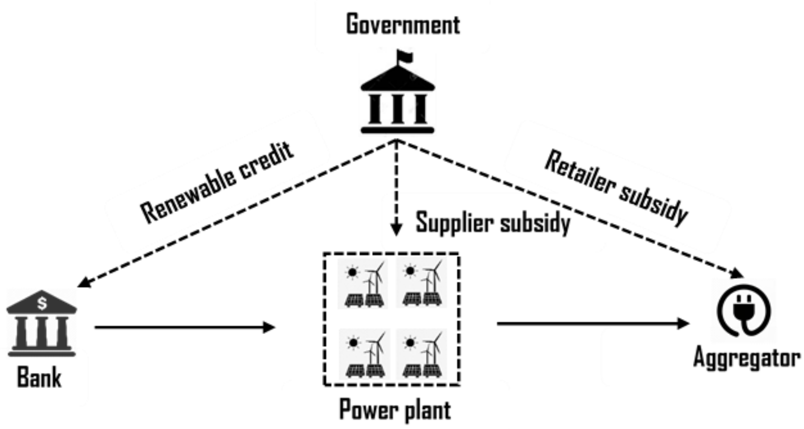

Fig. 1. Underlying structure of proposed SES network.

As shown in Fig.1, under the RC model the government subsidy is given directly to the bank, and the power plant gets a loan from the bank at a relatively low interest rate. Under the SS model, the government will give the subsidy directly to the power plant and under the RS model, the government subsidy is given directly to the aggregator. The research problem addressed in this study entails optimizing decisions regarding not only the amount of RE injected into the grid but also the wholesale energy price of the power plant and the retail energy price of the aggregator to maximize the total profit of the SES network, including the profit of both the power plant and aggregator. Along with the economic benefits, the effects of the government subsidies on social welfare and environmental benefits are also evaluated to ensure the sustainability of the network. The energy demand of consumers is satisfied by the power from the power plant and RG units. In addition, the following assumptions are made to define the research problem:

(i) The COVID-19 effects on energy supply and demand are independent and uncertain parameters.
(ii) The total government subsidies are subject to a fixed budget.
(iii) The SES network is a capital-constrained model.

In Section 2.2 the proposed dual-objective optimization model is presented for both power plant and aggregator under different government subsidy rates.

2.2. Mathematical model

2.2.1. Demand function with the effects of energy price and COVID-19 pandemic

The energy demand is assumed to be dependent on electricity price when developing the demand response programs for energy efficiency goals [20]. However, energy is a primary and essential need for life. The highly elastic in energy demand is not realistically possible, according to [27]. To consider the effects of COVID-19 on energy demand, this study assumes that the energy demand of consumers m at time slot t is given by Eq. (1). This demand function enables us to capture that consumers are sensitive to both energy prices and COVID-19, where the price elasticity coefficient of energy demand (τ) is set based on Ref. [20] and the effects of COVID-19 on energy demand (β) is an uncertain parameter. Because the COVID-19 effects on energy supply and demand are assumed to be independent and uncertain parameters, the value of parameter β is not affected by various conditions of elasticity.

$$D_{tm} = d_{tm}^{ifle} + d_{tm}^{fle}\left(1 - \tau\frac{p_t - w_t}{w_t} - \beta\right) \tag{1}$$

For each consumer m, the energy demand is a combination of inflexible (d_{tm}^{ifle}) and flexible load (d_{tm}^{fle}). The inflexible load is the demand load to which power supply has to be maintained under any circumstances, and it is not affected by external factors, such as energy price or the COVID-19 pandemic. The flexible load is the demand load that consumers can reduce owing to the effects of external factors. For example, consumers usually decrease heating and air conditioning as the electricity price increases. Therefore, the COVID-19 pandemic and the electricity price only affect the flexible load of consumers in the demand function.

2.2.2. Aggregator model

The objective of the aggregator is to maximize profit under the unit of money form by determining the dynamic pricing (p_{tm}) for each consumer m at each time slot t based on the energy demand (D_{tm}) of the consumer and the wholesale electricity price (w_t) of the power plant. Under the RS model, the total profit of the aggregator is obtained using the objective function described by Eq. (2).

$$Max\pi_1 = \sum_{t\in T}\sum_{m\in M} p_{tm}D_{tm}(1+\alpha) - w_t D_{tm} \tag{2}$$

In Eq. (2), the sales revenue (p_{tm} D_{tm}) and the government subsidy at a subsidy rate α (p_{tm} $D_{tm}\alpha$) of the aggregator are presented in the first term. In the proposed RS model, the government subsidy is allocated to the aggregator based on its sales revenue with a subsidy rate α. In other words, the aggregator's sales revenue is the basis for the government to determine the amount of subsidies money. The final term is the cost of the electric power from the power plant at the wholesale price (w_t) that the aggregator purchases. By solving the first-order derivative of the objective function (Eq. (2)), the optimal retail price for each consumer m at time slot t is a function defined by Eq. (3).

$$\frac{\partial\pi_1(p_{tm})}{\partial(p_{tm})} = 0 \Rightarrow p_{tm} = w_t\frac{(1+\alpha)\left(d_{tm}^{ifle} + d_{tm}^{fle} + d_{tm}^{fle}\tau - d_{tm}^{fle}\beta\right) + d_{tm}^{fle}\tau}{(1+\alpha)2d_{tm}^{fle}\tau} \tag{3}$$

The second-order derivative of the objective function (Eq. (2)) in Eq. (4) is always less than zero. Therefore, the objective function (Eq. (2)) is a strictly concave function of p_{tm}.

$$\frac{\partial^2\pi_1(p_{tm})}{\partial(p_{tm})^2} = -(1+\alpha)\left(\frac{2d_{tm}^{fle}\tau}{w_t}\right) \tag{4}$$

The optimal retail price of the aggregator in Eq. (3) is influenced by the following three points: (i) the optimal retail price of the aggregator for each consumer m at time slot t depends on the demand parameters of the consumers, including d_{tm}^{ifle} and d_{tm}^{fle}, and the wholesale price (w_t) of the power plant; (ii) a higher subsidy rate α allows the aggregator to offer a lower optimal retail price to consumers to stimulate demand; (iii) finally, a higher impact level of COVID-19 (β) on the electricity consumption demand of consumer m results in a reduction of the optimal retail price of the aggregator.

The following section presents the power plant optimization model that determines the decision-making factors related to the number and capacity of established RG units and the wholesale price of the power plant. Based on the modeling results, the aggregator will decide on the retail price that maximizes the profit.

2.2.3. Power plant model

The profit model of the power plant is as follows:

$$Max\pi_2 = \sum_{t\in T}\sum_{m\in M} w_t D_{tm}\left(1+\varepsilon\right) - \sum_{i\in I}\left[\left(c_i - a\right)x_i + v_i g_i\right]\left(1+r-\varphi\right) \tag{5}$$

In the objective function described by Eq. (5), the first term represents the wholesale revenue (w_tD_{tm}) and the government subsidy under the SS model at a subsidy rate ε ($w_tD_{tm}\varepsilon$) of the power plant. The final term is the financing cost arising from both establishment (e.g., investment cost) and operation (e.g., maintenance cost) of the RG units. The term (c_i – a) denotes the required amount of capital for establishing the RG unit i^{th}, where c_i is the total required investment cost and a is in-hand money (initial capital) of the power plant. Thus, to establish a new RG unit i, the power plant gets a loan including (c_i – a) for establishing and v_ig_i for operating a RG from a bank. These costs are supported by the bank at a certain interest rate r. Under the RC model, the government first provides financing discounts to the bank, then the power plant borrows $[(c_i - a)x_i + v_ig_i]$ from the bank at a relatively low interest rate (r – φ). The power plant must repay the bank loan $[(c_i - a)x_i + v_ig_i](1 + r - \varphi)$ after it gains the wholesale revenue (w_tD_{tm}) from the aggregator and the subsidy ($w_tD_{tm}\varepsilon$) from the government.

The following constraints define the impact of COVID-19 on the capacity output of RG units as well as several constraints on both demand and budget considered in the power plant optimization model.

$$S.t.$$

$$g_i \le \delta G_i^{\max} x_i \tag{6}$$

$$q + \sum_{i\in I} g_i \ge D_{tm}, \forall t \in T, m \in M \tag{7}$$

$$\left(c_i - a\right)x_i + v_i g_i \le B, \forall i \in I \tag{8}$$

$$\left[\left(c_i - a\right)x_i + v_i g_i\right]\varphi + w_t D_{tm}\varepsilon + p_t D_{tm}\alpha \le G \tag{9}$$

$$p_{tm} > w_t \tag{10}$$

$$x_i \in \{0,1\}; g_{i,} w_t > 0 \tag{11}$$

The inequality constraint (6) states that the capacity output of each RG unit cannot exceed its limited capacity. An uncertainty parameter (δ), added to the right-hand side, considers the effects on the

COVID-19 pandemic on the capacity of RG units. Constraint (7) ensures that the amount of electric power generated from new RG units (g_i) and the traditional power plant (q) is larger than the demand loads of consumer m at the planning time. Constraints (8) and (9) are the budget constraints of the bank and government, respectively. According to constraint (8), the bank has a budget limitation (B) for the loans for the power plant, while constraint (9) guarantees that the total subsidies under the three models (RC, SS, and RS) cannot exceed the government's budget. Constraints (10) and (11) are the conditions for the decision variables in the model. Constraint (10) ensures that the wholesale price is always less than the retail price, while constraint (11) ensures that the decision variables are binary and non-negative.

The following section presents our NSRF programming approach, proposed to tackle the uncertainties associated with business-as-usual operations (e.g., some relevant costs and intermittency of RE sources) and deeply hazardous events (e.g., the COVID-19 pandemic) of the power plant optimization model.

3. Scenario-based robust fuzzy programming approach

The SES network model must be able to overcome a high degree of uncertainty of the business-as-usual operations, including relevant costs and the intermittent nature from RE sources. In addition, risk events, such as earthquakes, floods, and pandemics, have posed substantial difficulties to solution approaches. Deterministic approaches, for example, are unable to provide a precise analysis of the SES network planning problem under uncertain environments. Although previous studies have discussed a number of uncertain programming methods, such as stochastic models [10, 16, 28 - 29] and simulation models [21 - 23, 30], these methods are accompanied by two major drawbacks: (i) a large amount of historical data is required to estimate the probability distribution for the uncertain parameters, which is generally not available for most real cases; (ii) a large number of scenarios are used to model uncertain parameters that can lead to computation time challenges in the original model. In this study, an NSRF model is proposed based on the combination of a scenario-based robust optimization model by [31] and fuzzy programming by [32]. Compared with other methods applied in recent publications, such as the robust fuzzy stochastic programming of [20], the robust fuzzy programming of [33], and the robust stochastic programming of [34], our proposed approach has a number of advantages for dealing with uncertainties in both random and hazardous events:

(i) Fuzzy programming is a powerful method to overcome different types of uncertainty, including imprecise parameters caused by a lack of historical data and flexibility in goals and constraints. Fuzzy programming is also much more efficient than stochastic models regarding the use of time and resources when collecting data to manage probability distributions for practical real-world problems.

(ii) Scenario-based robust optimization is an effective approach to address hazardous events by trading off the feasibility and optimality robustness of major hazard scenarios to provide a robust solution to the optimization problems. In addition, it does not increase the inequality constraints of the original model, which can lead to computational challenges.

The following sections will present how the fuzzy method and robust optimization are applied to convert the original power plant optimization model [Eqs. (5) – (11)] into our NSRF model.

3.1. Dealing with uncertainty and flexibility in the objective function

To describe the proposed NSRF model, $s = \{1 ..., S\}$ is set as a finite set of disruption scenarios caused by the COVID-19 pandemic with a fixed probability of occurrence ϕ_s. The NSRF model for the power plant optimization problem is as follows:

$$MaxW = EV\left(\pi_{2(s)}\right) + \eta Max\left[EV\left(\pi_{2(s)}\right) - \pi_{2(s)}\right] - \rho \sum_{s \in S} \zeta \phi_s \pi_{2(s)} \tag{12}$$

The robust objective function defined by Eq. (12) consists of three components according to the robust optimization approach by [35]: the expected value, the feasibility robustness, and the optimality robustness in the first, second and last terms, respectively. The first term in Eq. (12) $EV(\pi_{2(s)})$ denotes the expected value function of the power plant's initial objective function in Eq. (5) under considered hazard scenario *s*. The second term in Eq. (12) measures the optimality robustness of an optimal solution by realizing the difference between the optimal profit resulting from the occurrence of each scenario *s* at given fuzzy values of uncertain parameters ($\pi^*_{2(s)}$) and the optimal profit obtained by solving the deterministic model under each scenario *s* ($\pi_{2(s)}$). The last term of Eq. (12), accounting for the feasibility robustness, is a penalty cost (ξ) caused by ignoring uncertain parameters in the original model under each scenario *s*. The value of ξ is determined through supply contracts and can be adjusted based on the agreement between the stakeholders in the network or government regulations. The two parameters η and ρ are parameters that weigh the importance of the optimality robustness and the feasibility robustness in the robust objective function, respectively. These parameters thus reflect the preference of the decision-maker. For example, if planners wish to produce RE with low variability but high penalty cost, they must increase the weight of η and vice versa.

Because the initial objective function of the power plant (Eq (5)) includes a number of uncertain parameters (e.g., demand, investment cost c_i, and marginal cost v_i). Thus, fuzzy programming is applied to estimate the expected value function $EV(\pi_{2(s)})$ in the first term of Eq. (12) under each hazard scenario *s* as follows:

A triangular fuzzy number with three prominent points, for example $c_i = (c_{i1}, c_{i2}, c_{i3})$ with its membership function in the range [0, 1], is estimated as described in Eq. (13). According to the defuzzification process of [32], the expected value of c_i can be defined by Eq. (14). It is noteworthy that the same equations can be used for all other fuzzy parameters in the model.

$$\mu_{c_i}(c) = \begin{cases} g_{c_i}(c) = \dfrac{c - c_{i1}}{c_{i2} - c_{i1}} & \text{if } c_{i1} \le c \le c_{i2} \\ 1 & \text{if } c = c_{i2} \\ h_{c_i}(c) = \dfrac{c_{i3} - x}{c_{i3} - c_{i2}} & \text{if } c_{i2} \le c \le c_{i3} \\ 0 & \text{if } c \le c_{i1} \ or \ c \ge c_{i3} \end{cases} \tag{13}$$

$$EV(c_i) = \frac{\int_0^1 g_{c_i}^{-1}(c)dc + \int_0^1 h_{c_i}^{-1}(c)dc}{2} = \frac{c_{i1} + 2c_{i2} + c_{i3}}{4} \tag{14}$$

According to Eqs. (13) and (14), the first term in Eq. (12) can be estimated in Eq. (15) as follows:

$$EV\left(\pi_{2(s)}\right)=\sum_{t\in T}\sum_{m\in M} w_t EV\left(D_{tm}\right)\left(1+\varepsilon\right)-\sum_{i\in I}\left[\left(EV\left(c_i\right)-a\right)x_i+EV\left(v_i\right)g_i\right]\left(1+r-\varphi\right) \quad (15)$$

where $EV(D_{tm})$, $EV(c_i)$, and $EV(v_i)$ denotes the expected value of uncertain parameters regarding demand, investment cost, and operating cost of power plant under triangular fuzzy number form.

3.2. Dealing with flexibility within constraints

In the original power plant optimization model, constraints (6) and (7) are flexible constraints on the capacity output of RG units and the demand of consumers, respectively. For the capacity output of RG units, owing to the intermittent nature of RE sources, G_i^{max} is an uncertain parameter in the triangular fuzzy number. According to Eqs. (13) and (14), the membership function and expected value of G_i^{max} can be defined as $\mu_{G_i^{max}}(G_i)$ and $EV(G_i^{max})$, respectively. In addition, the effect of COVID-19 on the energy supply (δ) is also taken into account in the model. Thus, constraint (6) contains the hybrid uncertainty between the imprecise parameter (G_i^{max}) and the hazard scenario (δ_s). To measure the impact of δ on G_i^{max} under each disruption scenario s, constraint (6) can be reformulated as Eq. (16).

$$g_i \le \left[EV\left(G_i^{\max}\right)-EV\left(G_i^{\max}\right)\sum_{s\in S}\phi_s\delta_s\right]x_i \quad (16)$$

The right side of Eq. (16) measures the change in the expected value of the fuzzy parameter G_i^{max} caused by the impact of each hazard scenario δ_s on the output capacity of the RG units. This is called the scenario variability for all considered hazard scenarios. A decrease in the value of the variability, resulting from a decrease of δ, can increase the optimality robustness of the optimal solution in the NSRF model.

For the energy demand constraint (7), D_{tm} on the right hand side is an imprecise parameter caused by the uncertainty in the values of the flexible load (d_{tm}^{fle}) and COVID-19 impact (β). Taking into account the uncertain nature of energy demand and the effect of hazardous events, both d_{tm}^{fle} and β are considered as triangular fuzzy numbers and their expected values can be obtained as defined by Eq. (14). The uncertainty of D_{tm} can cause changes in the decisions (x_i and g_i) related to the penetration of RE sources. This can lead to variabilities in the feasibility robustness of the optimal solution in the NSRF model. To measure this change, constraint (7) can be reformulated as Eq. (17).

$$q+\sum_{i\in I} g_i \ge EV\left(D_{tm}\right), \forall t\in T, m\in M \quad (17)$$

in which

$$EV\left(D_{tm}\right)=d_{tm}^{ifle}+EV\left(d_{tm}^{fle}\right)\left(1-\tau\frac{p_t-w_t}{w_t}-EV\left(\beta\right)\right)$$

Based on the above guideline, the original power-plant optimization model [Eqs. (5) – (11)] can be converted into the proposed NSRF model as follows:

$$MaxW = EV\left(\pi_{2(s)}\right) + \eta Max\left[EV\left(\pi_{2(s)}\right) - \pi_{2(s)}\right] - \rho\sum_{s\in S}\zeta\phi_s\pi_{2(s)} \tag{18}$$

$$S.t$$

$$g_i \le \left[EV\left(G_i^{\max}\right) - EV\left(G_i^{\max}\right)\sum_{s\in S}\phi_s\delta_s\right]x_i \tag{19}$$

$$q + \sum_{i\in I} g_i \ge EV\left(D_{tm}\right), \forall t\in T, m\in M \tag{20}$$

Constraints (8 - 11) remain unchaged

The steps of the proposed NSRF model can be summarized in the form of an algorithm as follows:

Step 1: Determine the expected profit under hybrid uncertainties in the objective function (Eq. (15)) and the profit of the deterministic model each scenario s_ϕ and s_β

Step 2: Transform the original model into the proposed NSRF model according to the explanation in Sections 3.1 and 3.2

Step 3: Identify all relevant system parameters (e.g., ξ, ρ, and η) of the decision-makers and solve the NSRF model to determine the decisions of the power plant, including w_t, x_i, and g_i.

Step 4: Determine the electricity retail price of the aggregator based on Eq. (3). Due to the uncertain parameters in Eq. (3) and the form of triangular fuzzy numbers, it is converted into Eq. (21) to capture the uncertainties.

$$p_{tm} = w_t\,\frac{\left(1+\alpha\right)\left[d_{tm}^{ifle} + EV(d_{tm}^{fle}) + EV(d_{tm}^{fle})\tau - EV(d_{tm}^{fle})EV(\beta)\right] + EV(d_{tm}^{fle})\tau}{\left(1+\alpha\right)2\tau EV(d_{tm}^{fle})} \tag{21}$$

Step 5: 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. Computational results

The market structure of Vietnam was selected for a case study to demonstrate the viability of the proposed modeling approach. Along with Taiwan and Korea, Vietnam has successfully weathered two waves of COVID-19. The Vietnamese government has accepted economic losses to prevent the spread of the pandemic in the community through a nationwide lockdown that lasted 15 days (1 – 15 April, 2020). Currently, the government provides financial incentives to spur economic growth. In the energy sector, large-scale investments in RE energy projects continue and are included in the national master plan for electricity development. Credit support packages, such as low interest rates and payment delays, have also been launched by the government to support both power plants and consumers during the recovery of the economy post-COVID-19 [36]. Thus, the results presented and discussed below are expected to help planners make informed decisions regarding policies for the recovery of Vietnam's economy post-COVID-19 in the RE energy sector.

To deliver sufficient electric power to satisfy post-COVID-19 economic recovery plans and meet global climate change goals, the Electricity of Vietnam (EVN) Company is considering the establishment of new RG units for a 110-kV distribution feeder network, including a single traditional power plant, 10 potential locations for establishing new RG units, and an industrial consumption area with 100 factories. Information regarding the electric power demand of industrial consumers can be found in [37]. The designed capacity and relevant costs of 10 potential RG units based on wind turbines and solar photovoltaics are given in Table 2 and were taken from the EVN feasibility report [38]. To express the impact of COVID-19 on the energy supply and demand, a set of hazard scenarios under different values of δ and β (see Table 3) were created based on the COVID-19 report in the Vietnam's energy sector ([39] and [40]). All remaining flexible parameters of the proposed model, including the subsidy rate of the government subsidy models and the weight of the robust objective function, are shown in Table 4. The impact of varying flexible parameters in the range [0, 1] was investigated to evaluate the effectiveness of the proposed model.

All tests were performed using MATLAB 2013 optimization software running on a dual-core 3.40-GHz computer with 8.0 GB of random-access memory. The results presented and discussed below are expected to assist planners in making informed decisions regarding the development of RE in an SES network

Table 2. Designed capacity and relevant costs of potential RG units.

Potential RG units	Technology	Design capacity (kW)	Fixed cost ($/kW)	Variable cost ($/kW)
RG1	Solar	(250, 350, 450)	(0.03, 0.04, 0.05)	(0.02, 0.03, 0.04)
RG2	Solar	(450, 550, 650)	(0.02, 0.03, 0.04)	(0.01, 0.02, 0.03)
RG3	Solar	(200, 400, 600)	(0.04, 0.05, 0.06)	(0.04, 0.05, 0.06)
RG4	Solar	(350, 450, 550)	(0.03, 0.04, 0.05)	(0.03, 0.04, 0.05)
RG5	Solar	(300, 500, 700)	(0.03, 0.04, 0.05)	(0.04, 0.05, 0.06)
RG6	Solar	(350, 450, 550)	(0.01, 0.02, 0.03)	(0.02, 0.03, 0.04)
RG7	Wind	(250, 350, 450)	(0.04, 0.05, 0.06)	(0.02, 0.03, 0.04)
RG8	Wind	(450, 550, 650)	(0.02, 0.03, 0.04)	(0.02, 0.03, 0.04)
RG9	Wind	(450, 550, 650)	(0.02, 0.03, 0.04)	(0.02, 0.03, 0.04)
RG10	Wind	(300, 400, 500)	(0.02, 0.03, 0.04)	(0.03, 0.04, 0.05)

Table 3. Hazard scenarios for supply and demand disruptions due to COVID-19.

Scenarios	Supply side		Demand side
	Value of δ	Value of ϕ_s	Value of β
No effect (SC1)	0.00	0.15	(0.00, 0.00, 0.00)
Little effect (SC2)	(0.00 – 0.15]	0.15	(0.04, 0.05, 0.06)
Moderate effect (SC3)	[0.15 – 0.30)	0.45	(0.08, 0.10, 0.12)
Considerable effect (SC4)	(0.30 – 0.50]	0.25	(0.14, 0.17, 0.19)

Table 4. Flexible parameters of the NSRF model.

Parameter	Value
α (subsidy rate in RS model)	0.5
ε (subsidy rate in SS model)	0.5
φ (subsidy rate in RC model)	0.50
η (weight of optimality robustness)	0.60
ρ (weight of feasibility robustness)	0.40

4.1. SES network-related decisions

The decisions related to the amount of electricity generated by new RG units, the wholesale price of the power plant, and the retail price of the aggregator at the planning time (one day) determined by the proposed NSRF model applied to the power plant optimization problem, are shown in Fig. 2. With 7 RG units established (*RG1, RG2, RG4, RG5, RG7, RG9,* and *RG10*), the total electric power from RE sources injected into the grid is 203,408 kWh, accounting for more 72% of the total energy demand.

The total government subsidy in the three models (RC, SS, and RS) is 2.56E+06 ($), the total profit of the aggregator (π_1) is 1.01E+01 ($), and the robust profit of the power plant (W) is 9.87E+06 ($).

As can be seen in Fig.2, the average retail price of the aggregator for 100 industrial consumers ranges from 0.06 ($) to 0.13 ($), with significant variations for peak hours (from 9:00 to 22:00), while the wholesale price of the power plant ranges from 0.04 ($) to 0.11 ($). Because the aggregator determines the retail price after receiving the wholesale price from the power plant, both prices have similar trends during the planning time. This reflects the consistent nature of the proposed model. In other words, the proposed model guarantees sustainable economic benefits for the SES network.

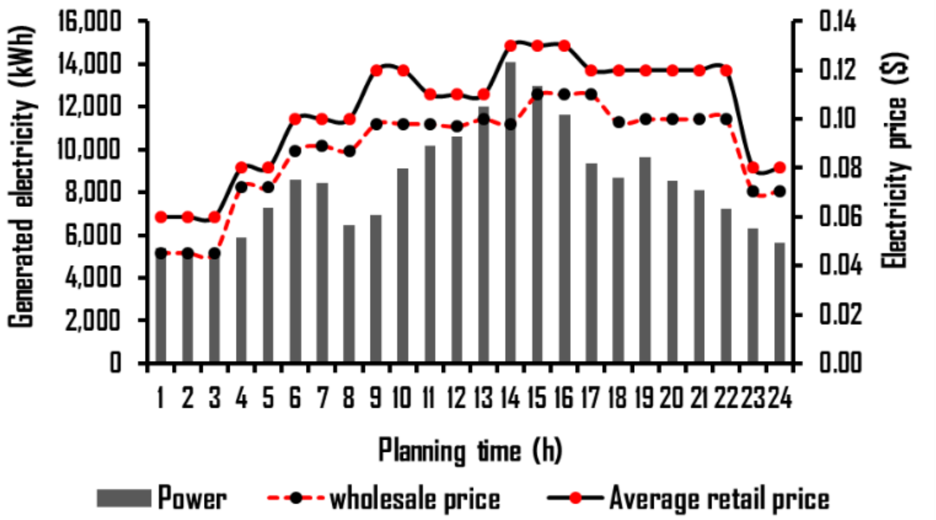

Fig. 2. Wholesale price, retail price, and generated power-related decisions

4.2. Effects of government subsidy models

In this section the effects of the three government subsidy models (RC, SS, and RS) on the sustainability of the energy supply network are investigated. For economic benefits, the government subsidy models are adopted to enhance the total profit of aggregators and the robust profit of power plants under the disruption risks related to the COVID-19 pandemic. This is accomplished by increasing the penetration of RE in the grid and promoting the energy consumption of industrial consumers. However, an important goal for subsidy models is to increase social welfare and to meet global climate change goals in the energy sector. Therefore, Eqs. (22) and (23) are developed to calculate the environmental benefits and social welfare in terms of saving costs, respectively.

$$E = \left[H - \left(\sum_{t\in T} q - \sum_{i\in I} \sum_{t\in T} g_i \right) h \right] \xi \tag{22}$$

$$S = \sum_{t\in T} \sum_{m\in M} \left(p_t^{\max} - p_{tm} \right) D_{tm} \tag{23}$$

The carbon emission reduction level is one of the indexes used to evaluate the environmental benefits of increased penetration of RE sources. The function of the environmental benefits can be defined by Eq. (22), which means that the larger the electric power from RE sources (g_i), the higher the environmental benefits from reducing carbon emissions. Social welfare is measured as the total consumer surplus in Eq. (23). According to Ref. [7], the total consumer surplus is calculated as the difference between the consumer's willingness to pay at the price p_t^{max} and the optimal retail price of the aggregator determined by the proposed model after adopting the government subsidy models. Tables 5 – 7 illustrate the effect of different values of α, ε, and φ in the RS, SS, and RC models, respectively, on the sustainable aspects of the energy supply network.

Clearly, an increase in the subsidy rates α, ε, and φ leads to an increase in the economic benefits of power plants (W) and aggregators (π_1), environmental benefits (E), and social welfare (S). The reason is that a higher subsidy rate in all three models will decrease the total financing cost of the power plant; thereby, the wholesale and retail electric power price also decreases to expand the market demand, which will improve the social welfare, the profit of the aggregator, and the robust profit of the power plant. In addition, when the value of ε increases, the power plant can access more bank credit, thereby opening many new RG units. In other words, many electric power sources are generated from RE sources, which will improve the environmental benefit by decreasing the carbon emissions.

Table 5. Effect of different value α on the sustainable aspects of the network.

$\varepsilon = 0.5$ & $\varphi = 0.5$	***$\alpha = 0.5$***	***$\alpha = 1.0$***	***$\alpha = 1.5$***	***$\alpha = 2.0$***
Total profit of aggregator [π_1] ($)	1.01E+07	1.17E+07	1.20E+07	1.31E+07
Total robust profit of power plant [W] ($)	9.87E+06	9.91E+06	9.23E+07	9.36E+07
Environmental benefit [E] ($)	1.21E+05	1.21E+05	1.23E+05	1.23E+05
Social welfare (S) ($)	1.05E+03	1.54E+03	1.62E+03	1.67E+03

Table 6. Effect of different value ε on the sustainable aspects of the network.

$\alpha = 0.5$ & $\varphi = 0.5$	***$\varepsilon = 0.5$***	***$\varepsilon = 1.0$***	***$\varepsilon = 1.5$***	***$\varepsilon = 2.0$***
Total profit of aggregator [π_1] ($)	1.01E+07	1.28E+07	1.37E+07	1.42E+07
Total robust profit of power plant [W] ($)	9.87E+06	1.01E+07	1.25E+07	1.34E+07
Environmental benefit [E] ($)	1.21E+05	1.42E+05	1.56E+05	1.64E+05
Social welfare (S) ($)	1.05E+03	1.56E+03	2.78E+03	2.98E+03

Table 7. Effect of different value φ on the sustainable aspects of the network.

$\alpha = 0.5$ & $\varepsilon = 0.5$	***$\varphi = 0.5$***	***$\varphi = 1.0$***	***$\varphi = 1.5$***	***$\varphi = 2.0$***
Total profit of aggregator [π_1] ($)	1.01E+07	1.32E+07	1.41E+07	1.61E+07
Total robust profit of power plant [W] ($)	9.87E+06	1.24E+07	1.34E+07	1.56E+07
Environmental benefit [E] ($)	1.21E+05	1.56E+05	1.62E+05	1.71E+05
Social welfare (S) ($)	1.05E+03	1.48E+03	1.51E+03	1.62E+03

Considering the different hazard scenarios for supply and demand disruptions due to COVID-19 in Table 3, Figs. 3 and 4 show the effect of the government subsidy models on the recovery of the post-pandemic RE market. As can be seen in Fig. 3, with an increase in the COVID-19 impact on the energy supply, the government subsidy models play an important role in maintaining the robust profit of power plants and the total profit of the aggregator. When the COVID-19 impact on the energy supply increases, it is reasonable to increase the wholesale and retail electric power price as the capacity output of RG units decreases. Consequently, the robust profit of the power plant and the total profit of the aggregator decrease as the energy demand is reduced. However, the subsidy models, particularly the RS model, have helped sustain demand. In addition, the RC and SS models helped reduce the financial burden of the power plant in the face of the pandemic. Thus, the robust profit of the power plant and the total profit of the aggregator tend to be stable, which will improve the social welfare because the consumer surplus increases with the RS model. In addition, due to the reduced capacity output of RG units, the power plant will use power from traditional plants to meet the demand. Thus, it is reasonable to decrease environmental benefits.

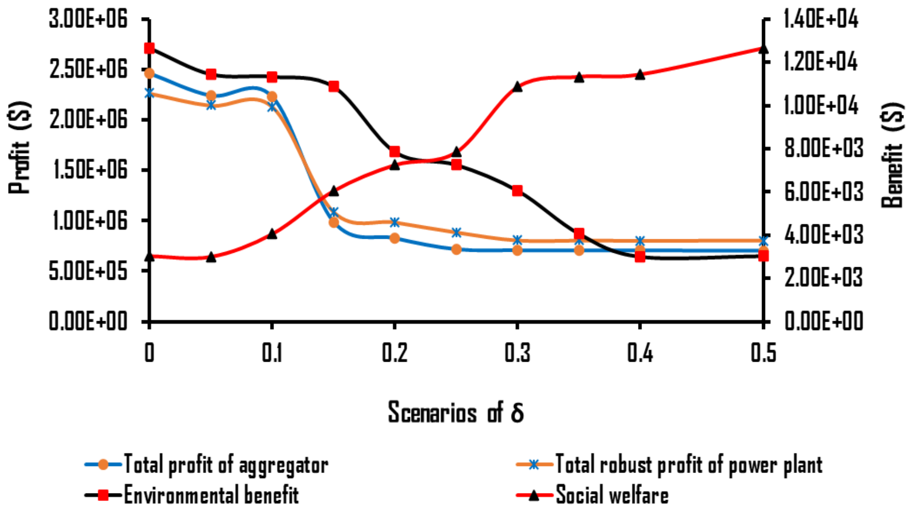

Fig. 3. Behavior of the proposed model for different hazard scenarios of δ

Regarding different impact levels of COVID-19 on energy demand, Fig. 4 shows the behavior of the proposed model for different β. Clearly, an increase in the effect level β leads to a decrease in the robust profit of the power plant and the total profit of the aggregator and an increase in the social welfare and the environmental benefits. When the energy demand decreases (a larger value of β), it is reasonable to decrease the wholesale and retail energy prices to expand the market demand. In addition, the government subsidy models are adopted in the network, which will improve the robust profit of the power plant and the total profit of the aggregator to a certain degree (β from 0.00 to 0.20). At values of β larger than 0.2, the strategy of price reduction to stimulate demand is no longer effective, which means that a large discount rate generates only a very small increase in demand. Consequently, the robust profit of the power plant and the total profit of the aggregator decrease with an increase in the effect of COVID-19 on energy demand. However, subsidy models have contributed to the stability of the profits of the energy market. Due to the reduced energy price in both wholesale and retail markets, it is reasonable to increase social welfare by way of consumer surplus. In addition, at a certain impact level of δ, the capacity output of RG units is unchanged, and the RC and SS models are applied within the network. Thus, a larger amount of electric power from RE sources is injected into the grid, which will improve the environmental benefits.

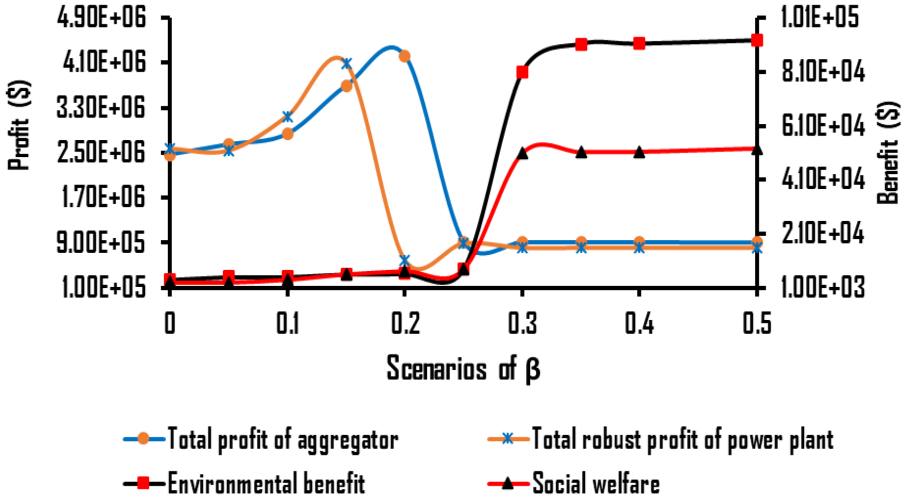

Fig. 4. Behavior of the proposed model for different hazard scenarios of β

4.3. Performance assessment of the proposed model

The effectiveness of the proposed SES network model in the face of the COVID-19 pandemic is evaluated by comparing the amount of RE injected into the grid, the total profit of the aggregator, the total robust profit of the power plant, the environmental benefits, and social welfare under the different government subsidy schemes. Table 8 lists the results from applying the proposed model with eight different combinations from the three government subsidy models (RC, SS, and RS). Thus, it provides an overview of the effectiveness of each subsidy scheme combination on the sustainability of the grid compared to the baseline model without government subsidies (values of α, ε, and $\varphi = 0$). Clearly, the sustainability values are the lowest in the baseline model without government subsidies. In addition, when all three models are adopted simultaneously, the energy supply network achieves outstanding sustainability in terms of economic efficiency, environmental benefit, and social welfare compared to the remaining combinations. Finally, when the government adopts a subsidy model, the sustainable benefits in terms of economy, environment, and society are always higher than those in the baseline model without the government subsidy.

During the COVID-19 pandemic, government support focuses on community benefits, such as healthcare systems and unemployment assistance; therefore, subsidies to power plants are limited. Thus, the effective application of subsidy models is a major constraint for planners. The proposed model provides insight into the application of government subsidy models in the RE field. It is obvious that these schemes not only revive the economy (increase the whole network profit) but also increase the environmental benefits associated with carbon emissions and social welfare in the form of consumer surplus.

Regarding the effectiveness of the proposed NSRF model in tackling the uncertainty of input parameters and hazardous events, Figs. 5 and 6 illustrate the comparative results of the robust profit of the power plant resulting from the proposed NSRF model with the robust optimization (RO) model proposed by Tsao et al. [20]. The NSRF model was developed to solve the power plant optimization problem. Therefore, the three components of a robust objective function (expected values, optimality robustness, and feasibility robustness) only affect the power plant profit. However, based on the optimal decisions of the power plant (e.g., the wholesale price, the number of established RG units, and the amount of generated power), the aggregator will decide the retail price and the environmental benefits and social welfare are also calculated. Thus, based on higher values of power plant decisions, it is reasonable to create a larger profit for the aggregator and stronger benefits for the environment and society. With the different hazard scenarios in the energy supply and demand due to COVID-19, Figs. 5 and 6 reveal that the proposed NSRF model has a better performance in improving the robust profit of power plants and CPU time in most hazard scenarios.

Table 8. Comparing the sustainable aspects of the network under different combinations of 3 subsidy models

Subsidy models	Generated power from RG units [g_i]	Total profit of aggregator [π_1]	Total robust profit of power plant [W]	Environmental benefit [E]	Social welfare [S]
No subsidy	109,600 (kWh)	2.72E+06 ($)	2.31E+06 ($)	6.50E+04 ($)	5.68E+02 ($)
RC, SS, and RS models	203,408 (kWh)	1.01E+07 ($)	9.87E+06 ($)	1.21E+05 ($)	1.05E+03 ($)
RC and SS models	148,608 (kWh)	3.69E+06 ($)	3.13E+06 ($)	8.81E+04 ($)	7.70E+02 ($)
RC and RS models	189,705 (kWh)	4.70E+06 ($)	4.00E+06 ($)	1.12E+05 ($)	9.82E+02 ($)
SS and RS models	126,802 (kWh)	3.14E+06 ($)	2.67E+06 ($)	7.52E+04 ($)	6.57E+02 ($)
RC model	162,970 (kWh)	4.04E+06 ($)	3.43E+06 ($)	9.66E+04 ($)	8.44E+02 ($)
SS model	120,314 (kWh)	2.98E+06 ($)	2.54E+06 ($)	7.13E+04 ($)	6.23E+02 ($)
RS model	118,072 (kWh)	2.83E+06 ($)	2.49E+06 ($)	7.00E+04 ($)	6.12E+02 ($)

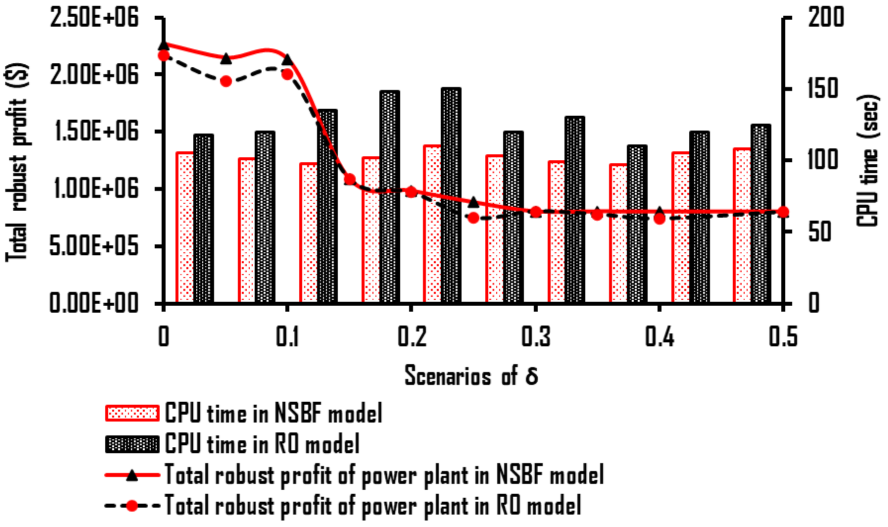

Fig. 5. Comparing the robust profit of power plant and CPU time of both approach for different scenarios of δ

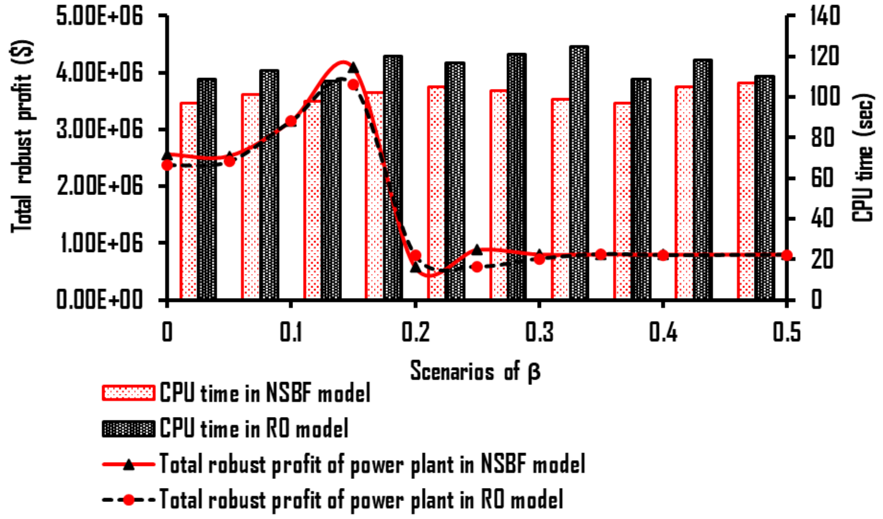

Fig 6. Comparing the robust profit of power plant and CPU time of both approach for different scenarios of β

5. Conclusion

Among the many adverse consequences of COVID-19, the pandemic has slowed the transition to a global sustainable low-carbon energy system due to disruptions on both supply and demand sides. This crisis requires tremendous government support and effort to recover all aspects of the economy, including the energy sector, to ensure the prosperity of each country and its communities. In this regard, this paper highlights the role of different government subsidy schemes, including RC, SS, and RS models, to achieve the sustainable goals (economy, environment, and society) in the RE sector under hazardous events, such as the COVID-19 pandemic. A dual-objective optimization model was developed to maximize the network profit of both the power plant and aggregator under different subsidy schemes by determining the optimal capacity of RE added to the grid, the optimal wholesale price of the power plant, and the optimal retail price of the aggregator simultaneously. Based on the optimal decisions of the power plant and aggregator, the environmental benefits related to carbon emission reduction and the social welfare, as consumer surplus, are also calculated to evaluate the effect of the subsidy schemes on the UNSDGs. To tackle the hybrid uncertainty of input parameters and hazardous events, an NSRF approach is proposed to solve the power plant optimization problem.

The proposed model was tested in a case study of the Vietnamese energy market. The results demonstrate that: (i) the RS model promotes consumer energy demand, but does not increase the penetration level of RE in the grid to meet climate change goals; (ii) an increase in the subsidy rate of the RC, SS, and RS models leads to an increase in the economic benefits of both the power plant and aggregator, the environmental benefits, and social welfare; (iii) for different hazard scenarios for both energy supply and demand due to COVID-19, the proposed NSRF model has a better performance in terms of improving the robust profit of the power plant for most of the hazard scenarios than that of the robust optimization model. With the increasing intensity of hazardous events, such as the COVID-19 pandemic, the SES networks have been facing challenging tasks to recover all aspects of the economy after a crisis and obtain the climate change goals. Some political implications drawn from extensive simulation results as: (i) for different levels of impact of hazardous events on the energy supply and demand, the government subsidy models play an important role in maintaining the profit of stakeholders in the SES network; (ii) when the government adopts a subsidy model, the sustainable benefits in terms on the economy, environment, and society are always higher than those in the baseline model without the government subsidy; (iii) for a high negative impact level of hazardous events on the supply side, the subsidy modes focusing on promoting the penetration of added capacity, such as RC and SS models, should be considered by the energy regulators and governments for the recovery of the RE market.

The COVID-19 pandemic has seriously affected not only the public health, education, and transportation sectors, but also sectors such as manufacturing, environment, and energy, mainly due to global logistics delays. Currently, the government subside models play an important role for recovering all aspects of the economy in the post-crisis. Thus, the proposed model can be applied to other countries in the energy sector or other sectors (e.g., manufacturing and transporting) in a sustainable manner. It can be used to provide a comprehensive analysis of the different level impacts of hazardous events on the government subsidy models for the sustainability of the distribution networks. This study focuses on the influence of COVID-19 on energy supply and demand. Incorporating other effects of COVID-19 on the RE sector, such as interest rate problems in global energy supply chains, could be a potential extension of this research. Also, changes in consumer behaviors due to COVID-19 are a great motivation for improving the demand response schemes of modern grids for meeting the UNSDGs. Finally, the proposed NSRF model depends on the expert experience for formulating uncertainties under the fuzzy membership function forms. Thus, it can be further enriched by collaborating with machine learning methods, such as deep learning, to express uncertainties based on the big data predictions and learning process.

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