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A non-cooperative multi-leader one-follower integrated generation maintenance scheduling problem under the risk of generation units' disruption and variation in demands

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Abstract

The generation maintenance scheduling deals with a time sequence of preventive maintenance outages for a given set of generation units in an electricity market subject to power system restrictions. Incorporating a leader-follower structure in generation maintenance scheduling models is essential because of the inherent conflict between the interests of an independent system operator (ISO) and generation companies (GENCOs). The present paper proposes a new preventive maintenance scheduling model for generation companies facing the risk of involving generation units' disruption and demand variations while ensuring the reliability of the power system. Each GENCO proposes the maintenance schedule of its generation units to the ISO in a non-cooperative manner intending to maximize its net profit. Then ISO reacts to the aggregated schedule according to the power system's reliability index. Thus, a new formula is developed to consider all the interactions between the power system's stakeholders. In this regard, a stochastic multi-leader one-follower approach is applied. The GENCOs are considered independent leaders at the upper-level and the ISO is considered a follower at the lower-level. Then an equivalent single-level counterpart model is presented for each leader. So, the whole problem is converted into multiple individual stochastic single-level models, and then the Nash Equilibrium concept is used to determine GENCO equilibrium strategies. The proposed methodology is evaluated using some modified IEEE reliability test systems. The numerical analysis confirms that the proposed model is more effective in cases with higher uncertainties. Moreover, the performed analysis demonstrated the importance of applying a bi-level approach to the problem. Finally, the superiority of the proposed approach compared to the existing one is confirmed.

Keywords:
Generation maintenance scheduling; non-cooperative game; multi-leader one-follower approach; power system's reliability; stochastic programming.

1. Introduction

An effective preventive maintenance scheduling allows the system to operate more reliable and achieve considerable savings (Zhu, 2021). Researchers have become increasingly interested in maintenance scheduling problems, and it has become one of the major research topics over the last decades (Bittar, Carpentier, Chancelier, & Lonchampt, 2022). Electricity is one of the most vital energies globally, and preventive maintenance plays a fundamental role in power system operations due to the ability to reduce the probability of failures. The generation maintenance scheduling (GMS) problem addresses an arrangement to take preventive maintenance actions on a set of generation units in an electricity market subject to power system restrictions (Charest & Ferland, 1993). Moreover, electricity consumption has grown over the years. For example, overall electricity sales in the United States in 2018 reached a peak of more than 4003000 GWh (Alves, 2021). Additionally, all types of electricity consumers expect electricity to be available at all times. Thus, the vast majority of electricity must be produced instantly as needed. Maintaining high reliability in generation units is essential to secure a long-term electricity supply. Therefore, determining optimal maintenance schedules can extend the lifetime of the equipment and avoid probable capital expenditures.

In a deregulated power system, a GMS problem relates to a conflict between two levels of stakeholders, generation companies (GENCOs) and an independent system operator (ISO). Each GENCO aims to maximize its profit, and the ISO strives to maintain the reliability of the power system. Two main indices almost measure the reliability of the power system; loss of load expectation (LOLE), and expected energy not supplied (EENS). LOLE represents the number of days per year, while EENS indicates the energy per year that is statistically expected to not meet demand. In this regard, a lower value of LOLE or EENS is more preferred. According to (Kim, Chang, Kim, & Kim, 2020), the Korean government has targeted the LOLE index to be 0.3 days/year. It implied that a three-day disruption might happen in the electricity supply for a ten years period. However, two main factors threaten the reliability of the power system. The first factor refers to the demand sides' uncertainty. In this regard, the reserve or standby capacities are employed to cope with the random deviations from the expected demand. Reports compiled by the Ministry of Trade, Industry, and Energy (MTIE) of Korea in 2017 state that the Korean government has made a long-term electricity supply plan and set the reservation target at 22% of the annual peak load, which is significantly higher than the typical reservation level of other countries that range between 12% and 15% (Kim et al., 2020). The available capacity shortage is the second factor that causes unreliability in the power system. In this case, the electricity shortage can occur even if the demand does not exceed the installed capacity but exceeds the available capacity level due to a disruption in the generation units. Scheduled maintenances and forced outages directly affect the available capacity level. For instance, a forced outage rate of 4–5% is reported by the North American Electric Reliability Corporation (NERC) (Kim et al., 2020). Thereby, the reliability of the power system can be threatened by a positive fluctuation on the demand side or some forced capacity outages. Positive fluctuations in the demand level and the risk of generation unit disruption, which could cause unreliable situations, are considered in this paper. Figure 1 illustrates how both uncertain situations need to be considered when solving a GMS problem. In this example, 300 MW is considered the annual peak load, and the installed capacity is 350 MW.

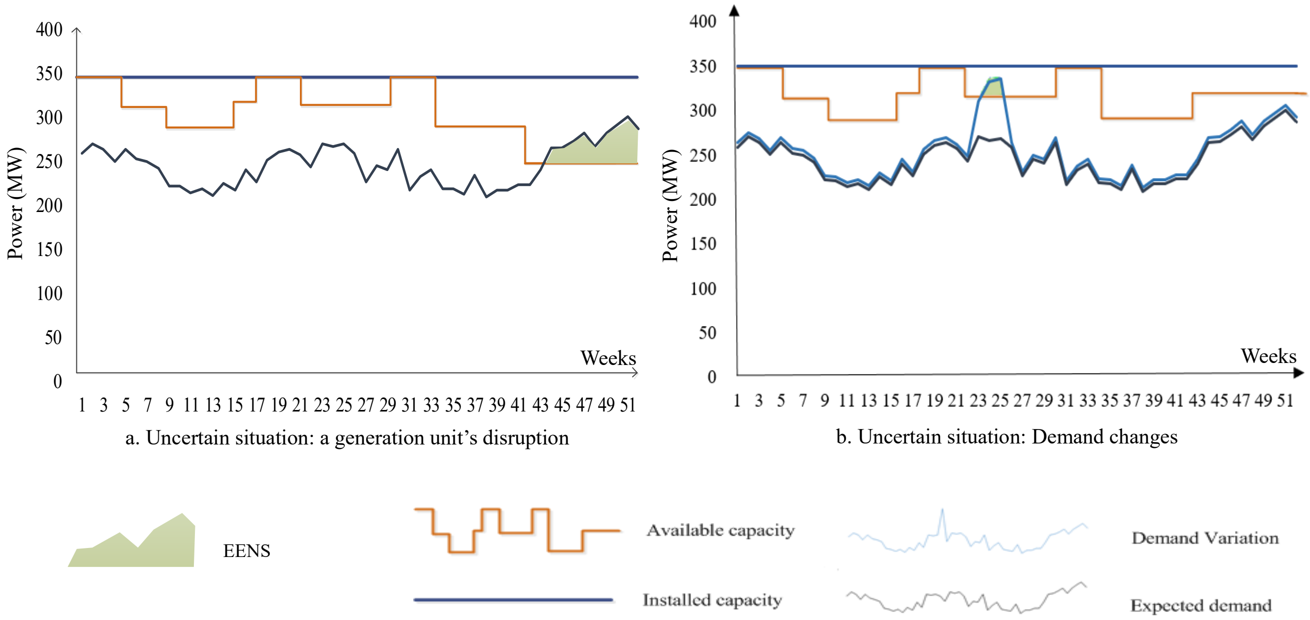


Figure 1: Example of unreliable situations due to the uncertainties in a. available capacity and b. demand side

Following the above remarks, three important issues are investigated in the present paper:

(1) How to design a suitable model for the GMS problem under disruptions of the generation units and variation in the demand?
(2) How to simultaneously ensure the power system's reliability and profitability of GENCOs?
(3) What are the significant impacts of ignoring the hierarchical structure in the power system?

Hence, a novel stochastic integrated GMS problem based on a multi-leader one-follower approach is presented to determine the best preventive maintenance schedules for generation units considering the ISO restrictions. In this regard, each GENCO proposes its maintenance schedule to the ISO in a non-cooperative manner at the upper level. Then ISO in the lower level decides about operational decisions and rescheduling signals to react to the GENCOs' schedules based on the power system reliability level. The conceptual framework of the proposed approach is shown in Figure 2. It is assumed that there are G number of GENCOs in the electricity market and each GENCO has predefined generation units ($\Xi(g)$). In the Figure 2, it is observed that $|\Xi(1)| = 2$, $|\Xi(2)| = 1$, and $|\Xi(G)| = 2$.

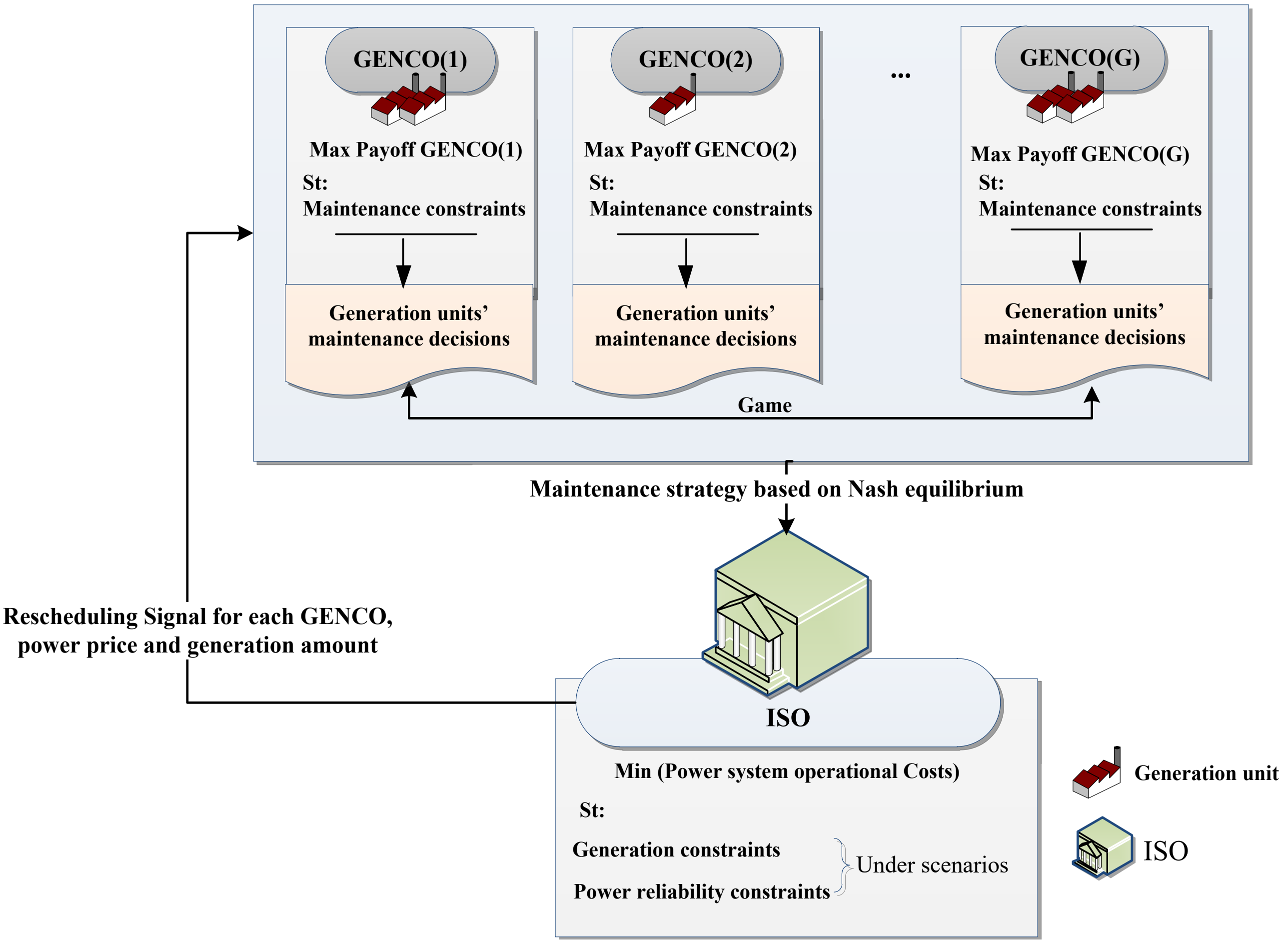


Figure 2: Overview of the leader-follower structure of the proposed GMS problem

Following is a breakdown of the content of this paper. The literature review is presented in Section 2. The stochastic bi-level GMS model definition and formulation are developed in Section 3. In Section 4, the solution methodology is discussed and in Section 5, the computational results are analyzed. Finally, conclusions and suggestions for the future research are presented in Section 6.

2. Literature review

Various aspects of the GMS problem and its stakeholder interactions have been investigated in recent years. (Yamayee, 1982), (Kralj & Petrović, 1988), (Dahal, 2004), (Khalid & Ioannis, 2012), and (Froger, Gendreau, Mendoza, Pinson, & Rousseau, 2016) published a literature review on the GMS studies from three main perspectives: mathematical modeling, power system features, and advanced solution methods. The latest review on the GMS problem provided a comprehensive overview of the GMS studies up to 2014 (Froger et al., 2016). Related research is clustered according to power system structure, objective function, solution methodology, uncertainty consideration, and other essential features. Moreover, they introduced some aspects of GMS that need to be further explored, such as the interaction between GENCOs and ISO and more uncertain parameters (Mazidi, Tohidi, Ramos, & Sanz-Bobi, 2018). However, game theory-based tools are needed when considering different stakeholder interactions. One of the most successful contributions of game theory in deregulated power systems is the application of optimization techniques to solve maintenance scheduling problems in a competitive environment. We review the literature on GMS problems in two subsections to cover recent studies. Section 2.1 provides a brief review of GMS problems in uncertain environments, while Section 2.2, overviews GMS problems using game theory-based approaches.

2.1. Uncertainty in GMS problems

Uncertainty in critical parameters of the GMS problem may lead to the infeasibility of solutions, sub-optimality, or both. Increasingly competitive, transparent, and agile electricity markets require generation unit maintenance managers to take into account uncertain parameters in the GMS problem. In the most recent GMS studies, an uncertain environment is considered and demand is the most common uncertain parameter ((Manshadi & Khodayar, 2018), (Kamali, Khazaei, Banizamani, & Saadatian, 2018), (Mazidi et al., 2018), (Bao, Gui, & Guo, 2018), (Ge, Xia, & Su, 2018), (Zhong, Pantelous, Goh, & Zhou, 2019), (Bagheri & Amjady, 2019), (Bozorgi, Pedram, & Yousefi, 2016), and (Yildirim, Gebraeel, & Sun, 2019)). However, uncertainty in energy sources ((Ji, Wu, & Zhang, 2016), (Kamali et al., 2018), (Ge et al., 2018), and (C. Wang, Wang, Zhou, & Ma, 2018)), energy price ((Kamali et al., 2018), (Shabanzadeh & Fattahi, 2015), (Ji et al., 2016), (Ge et al., 2018), (C. Wang et al., 2018), and (Sadeghian, Mohammadpour, & Mohammadi-ivatloo, 2019)), and the availability of generation units ((Bao et al., 2018), (Y. Wang et al., 2016), (Basçiftci, Ahmed, Gebraeel, & Yildirim, 2017), (Hassanpour & Roghanian, 2021), (Roghanian & Hassanpour, 2020), and (Bagheri & Amjady, 2018)) are considered as some of the other critical uncertainty sources in the related research. Different approaches including interval programming ((Manshadi & Khodayar, 2018)), stochastic programming ((Mazidi, Tohidi, Ramos & Sanz-Bobi, 2018), (Sadeghian et al., 2019), (Hassanpour & Roghanian, 2021), and (Roghanian & Hassanpour, 2020)), robust optimization ((Mazidi et al., 2018), (Ji et al., 2016), (Bagheri & Amjady, 2019), (Shabanzadeh & Fattahi, 2015)), and fuzzy programming ((Bao et al., 2018), (Ge et al., 2018)) are adopted to cope with uncertainties according to the problem characteristics. Hence, due to the inherent nature of strategic and operational decisions in GMS problems, scenario-based two-stage stochastic programming with known scenario occurrence probabilities is employed in the most relevant studies ((Mazidi et al., 2018), (Sadeghian et al., 2019), (Basçiftci et al., 2017; Manshadi & Khodayar, 2018), (Hassanpour & Roghanian, 2021), and (Roghanian & Hassanpour, 2020)). (Mazidi et al., 2018) proposed a bi-level stochastic programming GMS model under demand uncertainty. At the first stage, each GENCO makes the preventive maintenance decision to maximize its profit. Once the maintenance decisions have been set, and stochastic demand has been realized, ISO decides the total generated power and the clearing price for the market. (Sadeghian et al., 2019) developed a risk-based stochastic GMS model for a particular GENCO under uncertainty of the competitors' energy price and maintenance strategies. In this regard, maintenance decisions were considered the first-stage decisions, while total generated power was the second-stage decision. (Basçiftci et al., 2017) proposed a stochastic GMS model considering unexpected failure scenarios in the generation units. The failure scenarios were derived from the remaining lifetime distributions of the generation units and a chance constraint to ensure a reliable maintenance plan. They handled a large number of failure scenarios by the sample average approximation (SAA) method. (Hassanpour & Roghanian, 2021) developed a non-cooperative two-stage stochastic GMS model based on the risk of generation unit disruption. At first, GENCOs made their maintenance decisions in an uncooperative manner, and then ISO determined the total generated power after failure scenarios were realized. (Roghanian & Hassanpour, 2020) presented a stochastic GMS problem considering backup coverage for unexpected disruption in generation units. During the first stage, maintenance decisions and generation amounts were proposed, followed by backup generation unit selection in the second stage. As a result, uncertainty in critical parameters has become an integral part of the GMS formulation. This paper presents a bi-level two-stage stochastic GMS problem with variations in demands and risks of generation units' disruption.

2.2. Game theory approach in GMS problems

Over the past few decades, electricity markets in both developed and developing countries have been restructured and privatized. Therefore, the GMS problem has shifted from a centralized approach, which is used in regulated power systems with a single decision-maker, to a decentralized, multi-agent approach in deregulated power systems. In this regard, game theory approaches have increasingly gained attention due to the competition between electricity market stakeholders in deregulated power systems. Generally, GENCOs and ISO are the two main stakeholders with conflicts of interest in electricity markets. Each GENCO seeks to maximize its profit individually, while the ISO tends to ensure the desired level of the power system's reliability. Since GENCOs make their maintenance decisions in a non-cooperative manner, Nash equilibrium is practical to find an equilibrium strategy for all GENCOs ((Fotouhi Ghazvini & Moghaddas-Tafreshi, 2009), (Bozorgi et al., 2016), (Min, Kim, Park, & Yoon, 2013), (Mazidi et al., 2018) , (Sadeghian et al., 2019) , (Hassanpour & Roghanian, 2021), and (Moghbeli, Sharifi, Abdollahi, & Rashidinejad, 2020)).

A multi-leader one-follower approach is suggested to consider all interactions between GENCOs and GENCOs with ISO. A bi-level programming can be used to mathematically formulate a multi-leader one-follower configuration. In this approach, GENCOs are considered the leaders, while the ISO, an organization that makes decisions based on the GENCOs' strategies, is considered the follower. The decisions are taken independently and sequentially. Few studies applied a bi-level programming approach to formulate the GMS model ((Pandzic, Conejo, Kuzle, & Caro, 2012), (Pandzic, Conejo, & Kuzle, 2013), (A. Naebi Toutounchi, Seyed Shenava, Taheri, & Shayeghi, 2016), (Mazidi et al., 2018), (Rokhforoz, Gjorgiev, Sansavini, & Fink, 2021), and (Amir Naebi Toutounchi et al., 2019)). In all existing bi-level GMS studies, GENCOs are considered as the leaders and determine the maintenance of their generation units, individually. At the lower level, the ISO determines total generated power and market clearing prices. The strategic behavior of GENCOs in a non-cooperative manner makes the GMS problem a multi-individual bi-level stochastic programming problem. In this regard, the Nash Equilibrium concept is used to obtain a solution for the proposed model. In all relevant studies, once the Nash Equilibrium has been established for the multi bi-level models, ISO evaluates a reliability index such as EENS or LOLE to prepare appropriate penalties/incentives as rescheduling signals. Then, penalties are issued to GENCOs to change their maintenance decisions. The problem is solved in an iterative algorithm until desired reliability level for ISO is obtained. In contrast, the current study proposes a novel multi-leader one-follower two-stage stochastic approach for the GMS problem that omits the iterative procedure for ensuring the desired reliability by examining the rescheduling signals as a constraint in the lower-level model. This study addresses one of the important weaknesses of previous maintenance scheduling studies. A summary of the recent relevant studies on the GMS problem as well as the proposed model position compared to previous studies is presented in Table 1. Also, Figure 3 shows an overview of the GMS problem studies applying game theory to formulate interactions between GENCOs, and the interaction among GENCOs and ISO.

Table 1: A summary of recent related studies on the GMS problem

Reference	Schedule horizon	Schedule feature			Uncertainty		Bi-level programming		Rescheduling signal	Solution method		
		GENCO NCM	FOC	Reliability index	Parameter	approach	leader	follower		Nash equilibrium	KKT conditions	Iterative procedure for reliability
(Mazidi et al., 2018)	MT	✓	×	ENS & OC	Demand	TSSP	GENCOs	ISO	Penalty/ Incentive	✓	✓	✓
(Sadeghian et al., 2019)	ST & LT	✓	✓	Reserve level	Energy price & rival behavior	TSSP	×	×	Adjusted reserve level	✓	×	✓
(Basçiftci et al., 2017)	MT	×	×	Demand respond	Supply	TSSP	×	×	×	×	×	×
(Hassanpour & Roghanian, 2021)	MT	✓	✓	EENS	Supply	TSSP	×	×	Penalty/ Incentive	✓	×	✓
(Roghanian & Hassanpour, 2020)	MT	×	✓	EENS	Supply	TSSP	×	×	Penalty/ Incentive	×	×	✓
(Min et al., 2013)	MT	✓	×	Reserve level	×	×	×	×	Penalty/ Incentive	✓	×	✓
(Moghbeli et al., 2020)	MT	✓	×	Reserve level	×	×	×	×	Penalty/ Incentive	✓	×	✓
(Pandzic et al., 2013)	MT	✓	×	Reserve level	×	×	GENCOs	ISO	×	✓	✓	×
(Rokhforoz et al., 2021)	MT	✓	×	Demand respond	Failure behavior	stochastic	GENCOs	TSO	Incentive	✓	✓	✓
(Amir Naebi Toutounchi et al., 2019)	MT	✓	×	Reserve level	×	×	GENCOs	ISO	×	✓	✓	×
This study	MT	✓	✓	EENS	Demand & Supply	TSSP	GENCOs	ISO	Penalty/ Incentive	✓	✓	×

Items: NCM (Non-Cooperative Manner), FOC (Forced Outage Consideration), LT (Long-Term), MT (Mid-Term), ST (Short-Term), OC (Operational Cost), TSSP (Two-Stage Stochastic Programming), TSO (Transmission System Operator), ENS (Energy Not Supplied)

The review of previous relevant studies confirms that most studies have taken into account only one uncertainty source (as summarized in Table 1). Moreover, most researchers have used a single-level structure to formulate the GMS problem. So, in the current study, above mentioned gap is covered. Mentioned research gap is depicted in Figure 3, which illustrates how the proposed approach covers them. Therefore, the main characteristics of the proposed approach which have been considered in the current study can be summarized as follows:

- Static behavior of GENCOs in a non-cooperative manner.
- Market stakeholders' role through a bi-level programming approach.
- Generation units' disruption and demand variations as main sources of uncertainty.
- Adopting some modified IEEE reliability test systems to evaluate the effectiveness of the proposed model.

Developing a two-stage integrated model considering demand variations and generation units disruption as well as an efficient new solution algorithm are unique contributions of this study. As illustrated in Figure 3, three components in the GMS literature are the bi-level approach, static game of players, and uncertainty sources. The contribution of this study has been highlighted among those three components.

Addressing a multi-individual bi-level two-stage stochastic problem and obtaining Nash Equilibrium as the final solution without applying iterative procedure.

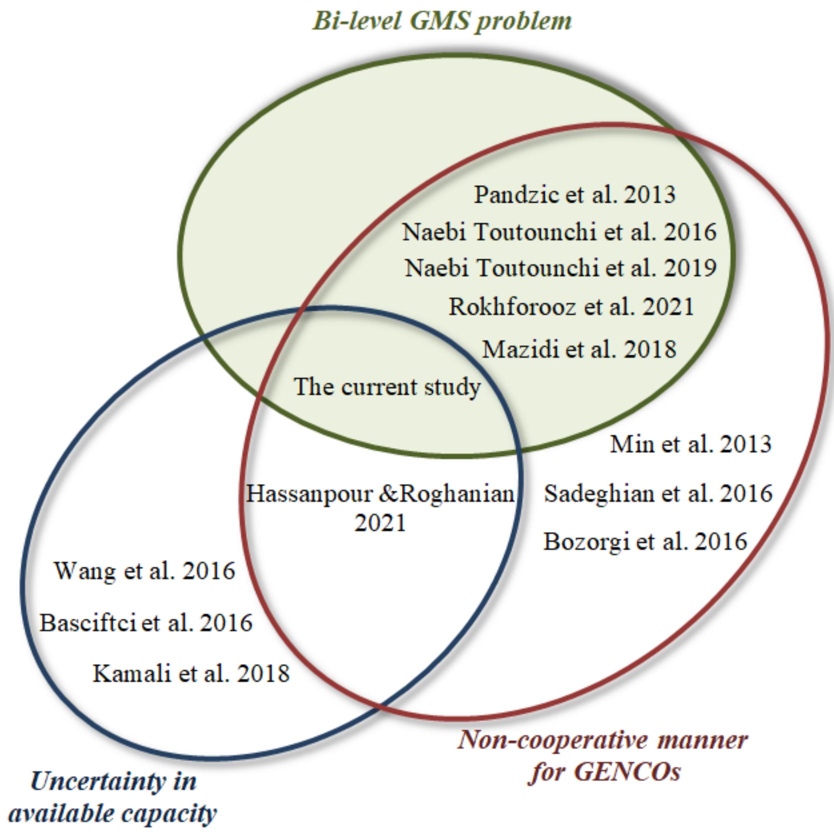


Figure 3: The overview of previous GMS studies with a competition structure

3. Problem description and model formulation

3.1. Problem description

ISO and GENCOs are the main actors with conflicting interests in deregulated power systems. Considering all the interactions between stakeholders becomes one of the most important issues for electricity market administrators and practitioners. In this study, we present a novel approach to stochastic GMS problems to determine which sequence of preventive maintenance outages is effective for a given set of generation units subject to ISO regulations. Thereupon, a multi-leader one-follower configuration is applied based on a bi-level programming approach to formulate the hierarchical structure of the GMS model. As independent leaders, GENCOs schedule the maintenance of the generation units at the upper level. At the same time, as a follower, the ISO decides about the system operation and rescheduling of signals in the lower level. A penalty/incentive mechanism is applied as the ISO signal to ensure the desired system reliability level, which is considered a constraint in the lower-level model to eliminate the iterative process between ISO and GENCOs. The following assumptions have been considered to formulate the problem.

- Demand can be met from multiple generation units
- An infinitive capacity dummy generation unit is considered to cover not supplied power hypothetically. This prevents the infeasibility of the mathematical model. Any usage of the dummy generation unit incurs a penalty, which can be interpreted as outsourcing cost or loss.
- Market clearing price is a parameter in the upper-level model that is obtained from the balance between generated power and electricity demand in the ISO model.
- Transmission and failure of the transmission lines and their influence on the GMS model are ignored in this study.

3.2. Mathematical formulation

In this section, a stochastic GMS problem is formulated using a bi-level two-stage stochastic programming approach. The model notations are provided in Table 2.

Table 2: Notations of the proposed model

Sets and Indices	
$\boldsymbol{\mathcal{R}}$	Set of available generation units, $\mathcal{R} = \{1, 2, \ldots R\}$
$\boldsymbol{\mathcal{K}}$	Set of disrupted generation units, $\mathcal{K} = \{1, 2, \ldots K\}$
$\boldsymbol{r}$	Index for available generation units ($r \in \mathcal{R}$)
$\boldsymbol{k}$	Index for disrupted generation units ($k \in \mathcal{K}$)
$\boldsymbol{I}$	Set of generation units ($I = \mathcal{R} \cup \mathcal{K}$)
$\boldsymbol{i, j}$	Indices for generation units ($i, j \in I$)
$\boldsymbol{\mathcal{G}}$	Set of GENCOs, $\mathcal{G} = \{1, 2, \ldots G\}$
$\boldsymbol{g}$	Index for GENCOs ($g \in \mathcal{G}$)
$\boldsymbol{\Xi(g)}$	Set of generation units owned by g
$\boldsymbol{\mathcal{T}}$	Set of time period, $\mathcal{T} = \{1, 2, \ldots T\}$
$\boldsymbol{t}$	Index for time period (week), ($t \in \mathcal{T}$)
$\boldsymbol{\mathcal{W}}$	Set of disruption scenario, $\mathcal{W} = \{1, 2, \ldots \Omega\}$
$\boldsymbol{\omega, \acute{\omega}}$	Indices for disruption scenario ($\omega, \acute{\omega} \in \mathcal{W}$)
$\boldsymbol{\mathcal{S}}$	Set of demand variation scenario, $\mathcal{S} = \{1, 2, \ldots S\}$
$\boldsymbol{s}$	Index for demand variation scenario ($s \in \mathcal{S}$)
Parameters:	
$\boldsymbol{N^g}$	Maximum simultaneous maintenance actions for GENCO g
$\boldsymbol{Load_t^s}$	Electricity demand at time period t under scenario s (MW)
$\boldsymbol{d_i}$	Required maintenance time for generation unit i which the maintenance must be performed within the considered time horizon (weeks)
$\boldsymbol{f_i}$	Fuel cost of generation unit i (\$/MBTU)
$\boldsymbol{\tau_i}$	Incremental term of fuel usage (Heat rate) of generation unit i (MBTU/ MW)
$\boldsymbol{O_i}$	Operational costs of generation unit i (\$/MW)
$\boldsymbol{M_i}$	Maintenance costs of generation unit i (\$/MW)
$\boldsymbol{q_i^{max}}$	Maximum capacity of the generation unit i (MW)
$\boldsymbol{q_i^{min}}$	Minimum capacity of the generation unit i (MW)
$\boldsymbol{q_{i\omega}^{max}}$	Maximum capacity of the generation unit i under scenario ω (MW)
$\boldsymbol{q_{i\omega}^{min}}$	Minimum capacity of the generation unit i under scenario ω (MW)
$\boldsymbol{FOR_i}$	Forced outage rate for the generation unit i
$\boldsymbol{K}$	A penalty of using dummy generation unit (\$/MW)

$\boldsymbol{\pi}$	Penalty/Incentive amount for each reliability deviation ($/MWh)
$\boldsymbol{\alpha}$	ISO coefficient to determine a reasonable reliability level
$\boldsymbol{up_i}$	Upward ramp of generation unit i (MW/h)
$\boldsymbol{down_i}$	Downward ramp of generation unit i (MW/h)
$\boldsymbol{p^s}$	The probability of scenario s occurrence
$\boldsymbol{p^\omega}$	The probability of scenario ω occurrence
$\boldsymbol{EL_t}$	Desired reliability level for ISO at time period t
$\boldsymbol{M}$	Large enough number
$\boldsymbol{H}$	Operational hours per week
$\boldsymbol{Peak_s}$	Peak load of scenario s (MW)
$\boldsymbol{X_0}$	Fixed maintenance plans for other GENCOs

Decision variables:

$\boldsymbol{Payoff_g}$	Payoff of GENCO g
$\boldsymbol{\Psi}$	Objective function of ISO
$\boldsymbol{X_{it}}$	Maintenance status of generation unit i at time period t, 1 if the generation unit is on maintenance, 0 otherwise
$\boldsymbol{q_{it}^{s\omega}}$	Average generated power of generation unit i at time period t under scenarios s and ω
$\boldsymbol{Q_t^{s\omega}}$	Average generated power of dummy generation unit at time period t under scenarios s and ω
$\boldsymbol{\mu_t^{s\omega}}$	Energy price at time period t under scenarios s and ω
$\boldsymbol{C_{it}}$	Contribution of generation unit i at time period t in reliability index deviation from the desired level
$\boldsymbol{\lambda_t^{s\omega}}$	Dual variable of Eq. 9
$\boldsymbol{\gamma_{its\omega}^1, \gamma_{its\omega}^2}$ $\boldsymbol{\gamma_{its\omega}^3, \gamma_{its\omega}^4}$ $\boldsymbol{\gamma_{it}^5, \gamma_{ts\omega}^6}$	Dual variable of Eq. 10, 11, 12, 13, 14, and 16, respectively

In terms of the notation, as mentioned earlier, the proposed bi-level integrated GMS (BLIGMS) model under the risk of generation units' disruption and demands variation is presented as follows:

$$Maximize \quad Payoff_g[X_{it}, \hat{q}_{it}^{s\omega}, \hat{C}_{it}] = \sum_{i\in\Xi(g),t,s,\omega} p^s p^\omega(\mu_t^{s\omega} - O_i - \tau_i f_i)\hat{q}_{it}^{s\omega} - \sum_{i\in\Xi(g),t} M_i q_i^{max} X_{it} - \sum_{i\in\Xi(g),t} \pi \hat{C}_{it} X_{it} \tag{1}$$

$$\mu_t^{s\omega} = \frac{\lambda_t^{s\omega}}{p^s p^\omega} \qquad \forall t, s, \omega \tag{2}$$

$$\sum_t X_{it} = d_i \qquad \forall i \in \Xi(g) \tag{3}$$

$$X_{it+1} - X_{it} - X_{it+d_i} \leq 0 \qquad \forall i \in \Xi(g), t \leq T - d_i \tag{4}$$

$$\sum_{i\in\Xi(g)} X_{it} \leq N^g \qquad \forall t \tag{5}$$

$$X_{it} = X_0 \qquad \forall i \notin \Xi(g), t \tag{6}$$

$$X_{it} \in \{0,1\} \qquad \forall i \in \Xi(g), t \tag{7}$$

$$\psi(\hat{X}_{it}, q_{it}^{s\omega}, C_{it}) = Min \sum_{i,t,s,\omega} p^s p^\omega (O_i + \tau_i f_i) q_{it}^{s\omega} + \sum_{t,s,\omega} p^s p^\omega K Q_t^{s\omega} \tag{8}$$

$$\sum_i q_{it}^{s\omega} + Q_t^{s\omega} = Load_t^s \qquad \forall t, s, \omega \quad : \lambda_t^{s\omega} \tag{9}$$

$$q_{it}^{s\omega} \leq (1 - \hat{X}_{it}) q_{i\omega}^{max} \qquad \forall i, t, s, \omega \ : \gamma_{its\omega}^1 \tag{10}$$

$$(1 - \hat{X}_{it}) q_{i\omega}^{min} \leq q_{it}^{s\omega} \qquad \forall i, t, s, \omega \ : \gamma_{its\omega}^2 \tag{11}$$

$$(q_{it+1}^{s\omega} - q_{it}^{s\omega})/H \leq up_i \qquad \forall i, t, s, \omega \ : \gamma_{its\omega}^3 \tag{12}$$

$$(q_{it}^{s\omega} - q_{it+1}^{s\omega})/H \leq down_i \qquad \forall i, t, s, \omega \ : \gamma_{its\omega}^4 \tag{13}$$

$$C_{it} = \frac{\sum_\omega p^\omega q_{i\omega}^{max} \hat{X}_{it}}{\sum_{i,\omega} p^\omega q_{i\omega}^{max} \hat{X}_{it}} (\sum_{s,\omega} H p^\omega p^s Q_t^{s\omega} - EL_t) \qquad \forall i, t \quad : \gamma_{it}^5 \tag{14}$$

$$C_{it}: free \qquad \forall i,t \qquad (15)$$

$$Q_t^{s\omega} \geq 0 \qquad \forall t,s,\omega \;\; : \gamma_{ts\omega}^{6} \qquad (16)$$

Eqs. (1)-(7) represent each GENCO model. Eq. (1) represents the payoff for the g^{th} GENCO. This equation displays the GENCO payoff, subtracting the cost from income values. The first term represents electric income; the second represents operation costs; the third refers to fuel costs; the fourth refers to maintenance costs, and the last represents an appropriate penalty/incentive based on the contribution generated by each generation unit in deviation from expected reliability index levels. Eq. (2) represents the marginal electricity price. The duration of maintenance for the generation unit is outlined in constraint (3). Constraint (4) ensures the continuity of the maintenance actions after maintenance starts and Constraint (5) limits the maximum generation units that can be on maintenance simultaneously. Also, in Eq. (6) the decisions of other GENCOs are considered fixed. Finally, constraint (7) expresses the maintenance decision as a binary variable. In the lower-level, the power system costs, i.e., operational, fuel, and shortage penalty costs are minimized according to Eq. (8). Constraint (9) describes the balance between generation amount and electricity demand. Constraints (10) and (11) restrict the upper and lower bounds of the generated power of each generation unit. Constraints (12) and (13) define the upward and downward ramping limits of each generation unit. Eq. (14) determines the contribution of each generation unit to the deviation of the reliability index from the desired level. In this equation, if GENCO i goes on maintenance ($\hat{X}_{it} = 1$) and the reliability criteria are violated ($\sum_{s,\omega} Hp^{\omega}p^{s}Q_t^{s\omega} - EL_t > 0$), the contribution of the i^{th} generation unit in the violation (MWh) is proportional to the potential maximum capacity outage to the sum of weighted maximum capacity outages. It is worth mentioning that $\sum_{s,\omega} Hp^{\omega}p^{s}Q_t^{s\omega}$ represents the expected energy not supplied in week t ($EENS_t$), and coefficient H is used to convert the obtained value to MWh. In this study, each week is considered 168 hours. Finally, lower-level variable types are declared in constraints (15) and (16).

3.3. Equivalent single-level GMS model for each GENCO

(Moore & Bard, 1990) proved that mixed-integer bi-level programming models are Np-hard due to the hierarchical structure. Here, Karush-Kuhn-Tucker (KKT) conditions are adopted to handle the proposed model by transforming the developed bi-level model into a single-level one. In this regard, KKT conditions of the lower-level model are obtained as follows:

$$p^{\omega}p^{s}(O_i + \tau_i f_i) - \lambda_t^{s\omega} + \gamma_{its\omega}^{1} - \gamma_{its\omega}^{2} - \gamma_{its\omega}^{3} + \gamma_{it-1s\omega}^{3} + \gamma_{its\omega}^{4} - \gamma_{it-1s\omega}^{4} = 0 \qquad \forall i,s,\omega,t \in (1,T) \qquad (17)$$

$$p^{\omega}p^{s}(O_i + \tau_i f_i) - \lambda_t^{s\omega} + \gamma_{its\omega}^{1} - \gamma_{its\omega}^{2} - \gamma_{its\omega}^{3} + \gamma_{its\omega}^{4} = 0 \qquad \forall i,s,\omega,t = 1 \qquad (18)$$

$$p^{\omega}p^{s}(O_i + \tau_i f_i) - \lambda_t^{s\omega} + \gamma_{its\omega}^{1} - \gamma_{its\omega}^{2} + \gamma_{it-1s\omega}^{3} - \gamma_{it-1s\omega}^{4} = 0 \qquad \forall i,s,\omega,t = T \qquad (19)$$

$$\gamma_{it}^{5}\Big(\sum_{i,\omega} p^{\omega} q_{i\omega}^{max} X_{it}\Big) = 0 \qquad \forall i,t \qquad (20)$$

$$Kp^{\omega}p^{s} - \lambda_t^{s\omega} - Hp^{\omega}p^{s}\left(\sum_{i,\acute{\omega}} X_{it}\gamma_{it}^{5}p^{\acute{\omega}}q_{i\acute{\omega}}^{max}\right) - \gamma_{ts\omega}^{6} = 0 \qquad \forall t,s,\omega \qquad (21)$$

$$[(1 - X_{it})q_{i\omega}^{max} - q_{it}^{s\omega}]\gamma_{its\omega}^{1} = 0 \qquad \forall i,t,s,\omega \qquad (22)$$

$$\left[q_{it}^{s\omega} - (1 - X_{it})q_{i\omega}^{min}\right]\gamma_{its\omega}^{2} = 0 \qquad \forall i,t,s,\omega \qquad (23)$$

$$[up_i - q_{it+1}^{s\omega} + q_{it}^{s\omega}]\gamma_{its\omega}^{3} = 0 \qquad \forall i,t,s,\omega \qquad (24)$$

$$[down_i - q_{it}^{s\omega} + q_{it+1}^{s\omega}]\gamma_{its\omega}^{4} = 0 \qquad \forall i,t,s,\omega \qquad (25)$$

$$Q_t^{s\omega}\gamma_{ts\omega}^{6} = 0 \qquad \forall t,s,\omega \qquad (26)$$

(9)-(16)

$$\lambda_t^{s\omega}, \gamma_{it}^{5}: free \qquad \forall i,t,s,\omega \qquad (27)$$

$$\gamma^1_{its\omega}, \gamma^2_{its\omega}, \gamma^3_{its\omega}, \gamma^4_{its\omega}, \gamma^6_{ts\omega} \geq 0 \qquad \forall i,t,s,\omega \qquad (28)$$

Eqs. (17)-(21) represent stationary conditions which are gradients of the Lagrangian function for the lower-level variables. Complementary slackness conditions are described in Eqs. (22)-(28). Eqs. (9)-(15) shows the primal constraints of the lower-level model. Finally, constraints (27) and (28) declare dual variable types. The single-level counterpart is obtained by adding the above constraints to the upper-level model. By transforming the bi-level model to the single-level counterpart, some nonlinearity terms have appeared. The model linearization steps are presented in Appendix. Nonlinear terms are replaced by some linear constraints to convert the obtained mixed-integer nonlinear programming (MINLP) model to a mixed-integer problem (MIP). Thus, the final integrated GMS model can be rewritten using predefined linearization constraints as follows:

$$Maximize \;\; Payoff_g = \sum_{i,t,s.\omega} [q^{max}_{i\omega}\gamma^1_{its\omega} - q^{max}_{i\omega}V_{its\omega} + \gamma^2_{its\omega}q^{min}_{i\omega} - q^{min}_{i\omega}F_{its\omega} - \gamma^3_{its\omega}up_i - \gamma^4_{its\omega}down_i] \\ - \sum_{i\in\Xi(g),t} M_i q^{max}_i X_{it} - \sum_{i,t} \pi Z_{it} \qquad (29)$$

(2)-(7)

(9)-(13)

$$\sum_{\omega,j} U_{ijt}p^{\omega}\, q^{max}_{j\omega} = H\sum_{\omega} p^{\omega}\, q^{max}_{i\omega} \sum_{s,\omega} D_{it\omega s} - \sum_{\omega} p^{\omega} q^{max}_{i\omega}\, X_{it}EL_t \qquad \forall i \in \Xi(g), t \qquad (30)$$

(15), (16), (17)-(19), (27), (28)

$$Kp^{\omega}p^{s} + \lambda^{s\omega}_t - Hp^{\omega}p^{s}\left(\sum_{i,\acute{\omega}} P_{it}p^{\acute{\omega}}q^{max}_{i\acute{\omega}}\right) - \gamma^6_{ts\omega} = 0 \qquad \forall t,s,\omega \qquad (31)$$

(A1)-(A13), (A16)-(A25), (A27)-(A37)

$$D_{it\omega s}, V_{its\omega}, F_{its\omega} \geq 0, Z_{it}, U_{ijt}, P_{it}: free,\; y^6_{ijt}, y^1_{its\omega}, y^2_{its\omega}, y^3_{its\omega}, y^4_{its\omega}, y^5_{ts\omega} \in \{0,1\} \qquad \forall i \in \Xi(g), t, s, \omega \qquad (32)$$

3.4. Scenario reduction

Maintaining the reliability of power systems is one of the main concerns of ISO. As illustrated in Figure 1, the reliability of the power system can be threatened by positive shifts in demand or shortages of available capacities. Therefore, in this paper, we focus on two types of uncertainty that can make unreliable situations: Fluctuations in demand and the disruption in the generation units.

To cope with demand uncertainty, some scenarios are generated. Fluctuations rarely occur at all demand points, so demand patterns with positive fluctuation on them which can lead to losing reliability, are recognized. Therefore, a demand scenario is considered as an event in which a positive change in demand occurs. Here, the number of scenarios (*S*) is related to the demand pattern and peak point features. Also, to consider uncertainty in available capacity, some failure scenarios are generated. Thus, a failure scenario is defined as an event in which some of the generation units go down due to disruption, while other generation units are accessible to provide service. Disruption of the generation unit k leads to a reduction of generation unit capacity to zero ($q^{max}_{k\omega} = q^{min}_{k\omega} = 0$). Generation unit failures are characterized by a Bernoulli distribution. The Bernoulli distribution is a discrete probability distribution of a random variable that takes the value "1" as a success with probability p and the value "0" as a failure with probability $q = 1 - p$ (Pishro-Nik, 2014). Therefore, the probability of the scenario ω is $p^{\omega} = \prod_{k=1}^{K} FOR_k \prod_{r=1}^{R}(1 - FOR_r)$, where FOR_k is the forced outage rate for the disrupted generation unit k and FOR_r is the forced outage rate of the available generation unit r.

Suppose N denotes the number of the generation units ($N = |I| = R + K$), then the total number of the possible failure scenarios is $\sum_{\iota=0}^{N}\binom{N}{\iota} = 2^N$, which grows exponentially with increasing N. Thus, if a power system has 20 generation units, the number of failure scenarios will be 1048576. In comparison, the number of generation units in the United States exceeds 22000 units.

Thus, considering both scenarios lead to having $S{\times}2^N$ number of scenarios in the proposed GMS model. A large number of scenarios render the underlying optimization problem intractable, especially in the presence of integer variables. Therefore, considering all the scenarios make the GMS model solve is complicated even for small power systems. In order to regain tractability, we need to trim down the number of scenarios while deteriorating the accuracy of the approximation as little as possible. In this paper, a new procedure based on the fuzzy clustering approach, which is named SRFC is introduced. One of the most widely used fuzzy clustering algorithms which is called Fuzzy C-means clustering (FCM) is applied to find a new scenario set with a fewer number of scenarios that can keep the solution close to that generated by the original scenario set. Fuzzy clustering is a class of algorithm for cluster analysis in which data elements allocate to classes or clusters. Here, attempts have been made to improve the weaknesses of the algorithm in determining the optimal number of clusters and the high randomness of the initial points to start the algorithm. These improvements can lead to increased robustness and improved clustering results. For this purpose, a two-objective mathematical model based on the p-median problem and the Elbow method is introduced to obtain a suitable C initial clusters' center. In this regard, the maximum amount of expected energy not supplied for each demand and failure scenarios are considered as objects ($EENS_t^{s,\omega} = p^\omega p^s(Peak_s - \sum_i q_{i\omega}^{max})$) which are defined just in situation$Peak_s > \sum_i q_{i\omega}^{max}$. Figure 4 shows a schematic view of the production of scenario objects in an example. In this example, 800 MW is considered as the annual peak load, and the installed capacity is 1000 MW.

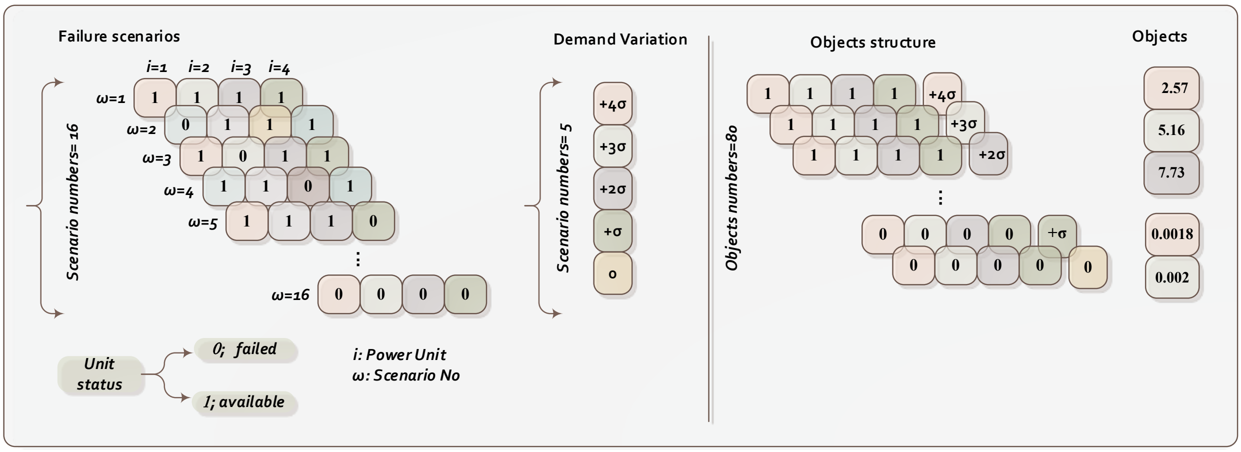


Figure 4: Schematic view of scenarios objects

Suppose a is an index that represents a scenario object and b is an index of the potential cluster center. Also, dis_{ab} represents the Euclidean distance between objects a and b, τ_{ab} represents a binary variable that takes "1" when object a is assigned to the cluster center b, and φ_b points to another binary variable to show if b is a cluster center. According to the aforementioned notations, the bi-objective initial clustering (BOIC) model for determining a suitable cluster number and initial points is represented as follow:

$$Min \sum_{a,b} dis_{ab}\tau_{ab} \tag{33}$$

$$Min \sum_{b} \varphi_b \tag{34}$$

$$\sum_{b} \tau_{ab} = 1 \tag{35}$$

$$\tau_{ab} \leq \varphi_b \tag{36}$$

$$\tau_{ab}, \varphi_b \in \{0,1\} \tag{37}$$

The bi-objective model presented above can be transformed into a single-objective model using the co-called ε-constraint method. The ε-constraint method is one of the most popular multi-objective optimization programming methods which was proposed by Haimes et al. (1971) for generating Pareto optimal solutions. In this method, all objectives except for one are converted into constraints and an upper bound limit is set for each of them. The method works by predefining a virtual grid in the objective space and solving different single-objective problems constrained to each grid cell. Thus, all Pareto-optimal solutions can be obtained if this grid is fine enough such that at most one Pareto-optimal solution is contained in each cell. This technique is used in several multi-objective studies ((Chamandoust et al. 2020), (Mazidi et al. 2014)).

Here, to obtain single-objective initial clustering (SOIC) model, we keep the first objective function (Eq. (33)) as the primary objective function and transform the second objective function (Eq. (34)) into a constraint $\sum_b \varphi_b \leq C$ with an upper bound *C*. In this regard, the initial solution and the reasonable number of clusters can be determined by defining an acceptable difference between the obtained objective function for *C* and *C-1* clusters. Then, the final clusters will be obtained using the FCM algorithm. Figure 5 presents the pseudocode of the proposed scenario reduction procedure.

Algorithm for reducing the number of scenarios by proposed SRFC approach

Input: FCM iteration $(iter)$, object (ENS_a), cluster number range $(C \in \Omega)$
Set objective function $(OBF(C) = \infty)$, cluster center $(c_j(iter) = \phi)$, membership values $(U_{aj}(iter) = \phi)$, acceptable difference (α)
Initialization Step
$iter = 0$
For $(C \in \Omega)$ **Do**
  Optimize the SOIC model
  Determine $OBF(C)$
  If $(OBF(C-1) - OBF(C) \leq \alpha)$ **Then**
  Break For
  End If
End For
Results C, τ_{ab}, and φ_b
$b = 1$
For $(j = 1{:}\,C)$ **Do**
  If $(\varphi_b = 1)$ **Then**
    $c_j(0) = ENS_b$
    For (a) **Do**
      $U_{aj}(0) = \tau_{ab}$
    End For
  End If
  $b = b + 1$
End For
Assignment Step
For $(iter = 1{:}\,\infty)$ **Do**
  For $(j = 1{:}\,C)$ **Do**
    While $(\left|c_j(iter-1) - c_j(iter)\right| \leq \varepsilon)$ **Do**
      Determine $U_{aj}(iter) = \frac{1}{\sum_k \left(\frac{dis_{aj}}{dis_{ak}}\right)^2} \quad \forall a,\ \forall j, k \in J$
      Update Step
      Determine $c_j(iter) = \frac{\sum_a U_{aj} ENS_a}{\sum_a U_{aj}}$
    End While
  End For
End For
Results c_j, U_{aj}

Figure 5: The pseudocode of the scenario reduction procedure using proposed modified FCM clustering

4. Solution methodology

GENCOs are supposed to propose their own maintenance schedules to the ISO, individually. Thus, due to the independent and simultaneous decision-making of GENCOs, we are facing a multi-individual single-level GMS model. In this regard, Nash Equilibrium (NE) concept is used to capture the solution of the proposed multi-leader one-follower game. A NE is defined as a set of GENCOs' maintenance strategies in which none of the GENCOs can increase its payoff individually by changing its maintenance strategy when the other GENCOs preserve their strategies. If $\theta^* = \{\theta_1^*, \theta_2^*, \dots, \theta_G^*\}$ indicates the NE strategy vector, the NE solution needs to satisfy Eq. (38).

$$Payoff_g(\theta_g^* | \theta_{-g}^*) \geq Payoff_g(\theta_g | \theta_{-g}^*) \qquad \forall g \tag{38}$$

An iterative procedure is introduced to obtain the NE solution mathematically. This heuristic algorithm is used in many previous papers to capture NE in static games ((Porter, Nudelman, & Shoham, 2008), (Pandzic et al., 2013), (A. Naebi Toutounchi et al., 2016), (Mazidi et al., 2018)). In this regard, each single-level GMS model is solved sequentially until none of the GENCOs can reach more payoffs by deviating from its strategy. Suppose that $\Gamma_1, \Gamma_2, \dots, \Gamma_G$ are the single-level GMS models and $\theta^1 = \{\theta_1^1, \theta_2^1, \dots, \theta_G^1\}$ are the initial feasible strategies for each GENCO. Each GENCO solves the profit-maximization problem by fixing the other GENCOs' strategies and saving its maintenance decisions. It is worth mentioning that one of the GENCOs is chosen randomly in each iteration. In this context, we suppose that the algorithm starts with the first GENCO. In this regard, Γ_1 is solved by fixing the decisions of the other GENCOs $(\theta_2^1, \theta_3^1, \dots, \theta_G^1)$, and the obtained maintenance decisions are considered as the first GECNO's new strategy (θ_1^2). Then Γ_2 is solved considering fixed decisions of the others $(\theta_1^1, \theta_3^1, \dots, \theta_G^1)$ and maintenance decisions (θ_2^2) are saved, and so on. Once all G problems have been solved, the current iteration is finished. All maintenance decisions are compared with starting points (or past maintenance decisions). If the maintenance decisions are the same as the past iteration strategy, the NE solution is obtained. Otherwise, an equilibrium point has not yet been acquired, and at least a GENCO could find a way to improve its objective function by changing its strategy. So, the maintenance decisions are saved as the next iteration strategy, and the iterative procedure continues. This iterative procedure will be repeated until the maintenance strategies become stable. In this approach, multiple NE points may exist while we considered the first found NE point. To find the other NEs, if there are any, the iterative procedure can be repeated by removing previously found NE and starting from a different initial point or a different GENCO. So, finding a NE strongly depends on a starting point. In this case, it is possible that iterations occur in a loop and NE could not be found. In this situation, we repeat the algorithm with another starting point. Figure 6 illustrates the Pseudocode of the aforementioned procedure.

Algorithm for finding the optimal solution of the proposed bi-level GMS model

Input: Parameters of the leader-follower GMS model, Iteration $(iter)$
Set $X_{it}(iter) = 0$
Rewrite the single level counterpart using SLGMS model
Phase 1: Initial maintenance strategy for each GENCO
$iter = 0$
For $(g \in \mathcal{G})$ **Do**
    Fix $\hat{X}_{i \notin \Xi(g),t}(0) = 0$
    Optimize the SLGMS model and determine $X_{i \in \Xi(g)t}(0)$
    Save $X_{i \in \Xi(g),t}(0)$
End For
Phase 2: Nash equilibrium
For $(iter = 1{:}\infty)$ **Do**
    For $(g \in \mathcal{G})$ **D**
        Solve the GMS model and determine the optimal $X_{i \in \Xi(g),t}(iter)$ by fixing $\hat{X}_{i \notin \Xi(g),t}(iter - 1)$
        Save $X_{i \in \Xi(g),t}(iter)$
    End For
            If $(X_{i \in \Xi(g),t}(iter) = X_{i \in \Xi(g),t}(iter - 1))$ **Then**
                $X_{i \in \Xi(g),t}(iter)$ is the Nash equilibrium
                Break For
            End If
End For
Result: $X_{i,t}(iter)$

Figure 6: The pseudocode of the proposed solution methodology for finding NE

Due to the complexity and MIP features of the investigated GMS model, commercial solvers cannot even handle small-size instances in a reasonable time. Previous related studies confirmed the high computational challenges of solving bi-level GMS models. For example, Mazidi et al. (2018) solved a bi-level GMS model with only six generation units. However, we face a more complicated GMS model in the current study due to penalty/incentive constraint consideration at the lower level. To cope with the complexity of the proposed model, some valid inequalities are introduced as follows. These inequalities can reduce the solution time of the GMS problem by adding some additional cuts in the proposed model feasibility space.

1) Number of maintenance weeks for all GENCOs

This constraint shows the total number of maintenance weeks for all GENCOs. In other words, the number of X_{it}s that will take 1 in the proposed model is equal to the total length of the maintenance durations of all GENCOs.

$$\sum_{i,t} X_{it} = \sum_{i} d_i \tag{39}$$

2) Limitation of the last possibility to start, and the first possibility to finish maintenance

For each generation unit, the starting point of the maintenance should happen between the first week and $(T - d_i)^{\text{th}}$ week. And also, one of the maintenance variables between $(d_i)^{\text{th}}$ week and the last week in the scheduling horizon should be 1 as the last week of the maintenance.

$$\sum_{t=1}^{T-d_i} X_{it} \geq 1 \qquad \forall i \tag{40}$$

$$\sum_{t=d_i}^{T} X_{it} \geq 1 \qquad \forall i \tag{41}$$

3) Maintenance sequence

Eq. (42) is defined to prepare all possible modes of the maintenance sequence requirement for each GENCO.

$$\sum_{m=0}^{d_i} X_{i(t+m)} \leq d_i \qquad \forall i, t < T \qquad (42)$$

4) Maintenance window selection

As mentioned above, Eq. (42) defines all possible modes of maintenance, while just one of these possibilities will occur. In this regard, we define a new binary variable (Υ_{it}) to formulate this limitation.

$$\sum_{m=0}^{d_i} X_{i(t+m)} \geq d_i \Upsilon_{it} \qquad \forall i, t < T \qquad (43)$$

$$\sum_{t=1}^{T-d_i+1} \Upsilon_{it} = 1 \qquad \forall i \qquad (44)$$

5) Maximum generation per week

According to constraints (9) and (10), the maximum amount of generation per week will be equal to the left of the limit (45), which is greater than the amount of demand in that week.

$$\sum_i (1 - X_{it}) q_{i\omega}^{max} + Q_t^{s\omega} \geq Load_t^s \qquad \forall t, s, \omega \qquad (45)$$

5. Simulation results

The developed GMS model efficiency is assessed on three modified reliability test systems. The first reliability test was extracted from the study (Hassanpour & Roghanian, 2021) with a 1023 MW installed capacity and 720 MW annual peak load. The second test system is extracted from (Mazidi et al., 2018) for a power system with 505 MW installed capacity and almost 440 MW peak load, and the third test which is presented by (Pandzic et al., 2013) was used in this analysis with 700 MW installed capacity and almost 610 MW peak load. For this purpose, the CPLEX solver on GAMS 23.5 is used on a computer with a 2.40 GHz core (TM) i5 CPU and 4.00 GB RAM. The data of the reliability test systems are presented in Table 3.

Table 3: Data for generation units in each IEEE reliability test system

Test system No.	GENCO No.	Unit No.	Type	Fuel	Unit size (MW)		Maintenance duration (week)	Cost			Heat rate (MBTU/ MW)	Upward/Down ward ramp (MW)		FOR
					$q_{i\omega}^{min}$	$q_{i\omega}^{max}$		Maintenance ($/MW)	Variable operation ($/MW)	Fuel ($/MBTU)		up_i	$down_i$	
1	1	1	Fossil steam	Coal	15.2	76	3	0.0100	0.0053	1.2	0.071	38	38	0.02
		2	Fossil steam	Oil#6	68.9	197	4	0.0050	0.0042	2.3	0.057	98	98	0.05
	2	3	Fossil steam	Coal	140.0	350	5	0.0044	0.0042	1.2	0.056	175	175	0.08
		4	Nuclear steam	LWR	100.0	400	6	0.0050	0.0018	0.6	0.059	200	200	0.12
2	1	1	Fossil steam	Coal	0.0	85	1	10.0000	1.0000	1.0	0.100	75	75	0.02
		2	Fossil steam	Coal	0.0	85	4	25.0000	7.0000	7.0	0.700	75	75	0.02
		3	Fossil steam	Coal	0.0	85	5	30.0000	9.0000	9.0	0.900	75	75	0.02
	2	4	Fossil steam	Coal	0.0	85	2	15.0000	3.0000	3.0	0.300	75	75	0.02
		5	Fossil steam	Coal	0.0	85	3	20.0000	5.0000	5.0	0.500	75	75	0.02
		6	Wind turbine	Wind	0.0	80	3	10.0000	9.0000	0.0	0.000	80	80	0.08
3	1	1-2	Fossil steam	Oil#6	2.4	12	2	0.0100	0.0300	2.3	0.071	12	12	0.02
		3	Fossil steam	Oil#2	4.0	20	2	0.0003	0.0300	3.0	0.086	20	20	0.10
		4	Fossil steam	Oil#6	25.0	100	3	0.0085	0.0050	2.3	0.059	50	50	0.04

	2	5	Fossil steam	Oil#6	2.4	12	2	0.0100	0.0300	2.3	0.071	12	12	0.02
		6-7	Fossil steam	Coal	15.2	76	3	0.0100	0.0050	1.2	0.071	38	38	0.02
		8	Fossil steam	Oil#2	4.0	20	2	0.0003	0.0300	3.0	0.086	20	20	0.10
		9	Fossil steam	Oil#6	25.0	100	3	0.0085	0.0050	2.3	0.059	50	50	0.04
	3	10	Fossil steam	Oil#2	4.0	20	2	0.0003	0.0300	3.0	0.086	20	20	0.10
		11-12	Fossil steam	Coal	15.2	76	3	0.0100	0.0050	1.2	0.071	38	38	0.02
		13	Fossil steam	Oil#6	25.0	100	3	0.0085	0.0050	2.3	0.059	50	50	0.04

All instances are considered a mid-term maintenance scheduling which is equivalent to 52 weeks. Also, in these cases, ISO parameters are considered as $\alpha = 2$ and $\pi = 25000$. It is worth mentioning that all of the reliability tests applied the same demand pattern that is published by (Shahidehpour & Mk, 2000). Also, in this study, the demand variation range is considered from 0 to +4 standard deviations through five load levels (S = 5) (Mazidi et al., 2018).

5.1. Scenario reduction analysis

In this section, the performance of the proposed SRFC method is evaluated in comparison with absolute enumeration, the solution of the BOIC model, and traditional FCM in payoff value, solution time, number of clusters, and the Davies-Bouldin Index. Davies-Bouldin Index is one of the well-known cluster evaluation metrics which can feature the intra-cluster distance and inter-cluster distance. The results of implementing four pre-mentioned methods on the first reliability test system are reported in Table 4.

Table 4: Evaluating the performance of the proposed SRFC method

Metric		Absolute Enumeration	BOIC	FCM	SRFC
Payoff	GENCO 1	-1125843.9	-8533078.2	-9203681.7	-9996350.7
	GENCO 2	-235711393.6	-208771365.9	-209691452.1	-215099524.4
solution time		02:39:07	0:13:09	0:21:31	0:15:12
Number of clusters		80	6	7	7
Davies-Bouldin Index		**0.00**	**0.63**	**0.28**	**0.07**

The suitable scenario reduction method keeps the final solution close to the solution which is obtained by the original scenario set. Table 4 shows the advantages and superiority of the SRFC method. It emphasizes that the proposed SRFC method could achieve a suitable scenario reduction in a reasonable solution time and accuracy. Applying the proposed scenario reduction method leads to reducing the second and third reliability test system scenarios to 12 and 38.

5.2. Valid inequalities performance

The performance of the proposed valid inequalities is examined among predefined reliability test systems. The results in terms of GENCOs' payoff and solution time are considered. The analysis is performed two times with different initial solutions, while the second run is done by the Nash Equilibrium point as the initial solution. This is done to properly analyze the effect of valid inequalities. For each reliability test system, to have a fair comparison regarding the accuracy and solution time of each added valid inequality set, the initial point and the order of solving GENCOs' models will be the same among runs between the valid inequality sets.

Table 5: Investigation computational time of the proposed valid inequalities effect

Test No.	None	First set [Eq. (39)]	Second set [VIs. (40) & (41)]	Third set [VI. (42)]	Fourth set [VIs. (43) & (44)]	Fifth set [VI. (45)]	All sets except fourth
1	0:15:12	0:12:03	0:13:37	0:13:46	0:18:12	0:14:51	0:12:17
	0:00:08	0:00:05	0:00:05	0:00:09	0:00:11	0:00:08	0:00:06
2	4:59:13	4:17:36	4:29:07	4:41:18	5:22:38	4:47:25	4:31:56
	0:08:05	0:07:13	0:07:30	0:07:52	0:08:53	0:07:16	0:07:13
3	9:17:04	8:22:34	8:27:43	8:46:12	8:59:47	11:06:19	8:28:55
	0:19:25	0:17:33	0:18:11	0:18:27	0:18:09	0:27:31	0:18:06

VI (Valid Inequality)

According to the reported results, GENCOs' profits are not changed among each set of inequalities, so it confirms the validity of the defined inequalities. Also, as reported in Table 5, it is confirmed that considering the first valid inequality set can almost improve the solution time, especially in large-size instances. Thus, the first set is recommended to be added to the GMS model.

5.3. Desired reliability level for ISO

Desired reliability level is a parameter that the ISO defines to compare with the obtained reliability index. In real cases, assuming no need for predicted maintenance, some not supplied energy might be happened due to the failures. Therefore, ISO cannot set the desired reliability level (EL_t) less than the inherent EENS of the electricity market. In this section, the EENS without considering preventive maintenance as the desired reliability level threshold ($EENS_t\_threshold$) is obtained according to Eq. (46). Coefficient H is used to convert the obtained value from MW to MWh. In this study, each week is considered 168 hours.

$$EENS_t\_threshold = \sum_{s,\omega,Load_t^s > \sum_i q_{i\omega}^{max}} Hp^{\omega} p^{s} (Load_t^s - \sum_i q_{i\omega}^{max}) \qquad \forall t \qquad (46)$$

$EENS_t\_threshold$ for each reliability test system is presented in Table 6.

Table 6: EENS threshold for the reliability test systems

Week No.	1	5	10	15	20	25	30	35	40	45	50	52
$EENS_t\_threshold$ RTS 1 (MWh)	878.6	1109.7	565.5	529.4	1109.7	1351.4	1109.7	540.7	536.2	1185.2	2748.6	2403.2
$EENS_t\_threshold$ RTS 2 (MWh)	82.5	97.5	4.6	4.1	97.5	110.7	97.5	4.3	4.2	101.6	290.9	162.5
$EENS_t\_threshold$ RTS 3 (MWh)	47.6	72.9	3.2	2.3	72.9	95.9	72.9	2.5	2.4	80.1	285.1	213.7

RTS (Reliability Test System)

Desired reliability level for ISO should never be less than the desired reliability level threshold obtained in Table 6. Therefore, the desired reliability levels for each week (EL_t) are determined as follows:

$$EL_t = \alpha[EENS_t\_threshold] \qquad \forall \alpha \geq 1, t \qquad (47)$$

5.4. Critical parameters sensitivity analyses

In this section, some sensitivity analyses among key parameters are explored to validate the proposed model and evaluate its performance. In this regard, the bi-level GMS model in deterministic and stochastic features are evaluated in terms of GENCOs' payoff, incentive participation, penalty participation, annual shortage, EENS, and energy price by changing parameters π, and α. Here, the reliability index "EENS" is obtained according to Eq. (48) and Eq. (49).

$$EENS_t = \sum_{\omega,s} Hp_{\omega} p_s Q_t^{s\omega} \qquad \forall t \qquad (48)$$

$$EENS = \sum_t \frac{1}{T}(EENS_t) \qquad (49)$$

The results of the deviation of each term with reference value are reported in Table 7. Reference values are obtained for π=25000 and α=2. It should be noted that since in this section validation of the proposed model is investigated, all the analyses are applied just on the first reliability test system.

Table 7: Proposed bi-level GMS model sensitivity analyses by changing of π and α

			Network performance measures' change due to deviation of π and α from their initial values							
Model	**π**	**α**	**GENCO1 payoff ($)**	**Incentive GENCO1 (MW)**	**Penalty GENCO1 (MW)**	**GENCO2 payoff ($)**	**Incentive GENCO2 (MW)**	**Penalty GENCO2 (MW)**	**Shortage (MW)**	**EENS (MWh)**
Deterministic environment	**25000**	**2**	**644164577.8**	**25657.3**	**0.0**	**532166115.1**	**21136.5**	**0.0**	**14.4**	**46.5**
	50000	1	-60919664.4	-5668.6	0.0	52543226.5	1261.5	0.0	-4.9	-15.9
		2	77759804.2	1424.3	0.0	159786213.3	9514.7	0.0	60.8	196.4
		3	167038983.9	6268.0	0.0	380575608.8	14673.6	0.0	112.0	361.8
		5	1047661756.3.0	9236.2	0.0	1891775526	27307.3	0.0	251.7	813.2
		10	1721607224.5	33464.1	0.0	5349200395.6	44392.7	0.0	409.2	1322.0
	25000	1	-120211908.3	-7094.4	0.0	-59773446.9	-1448.1	0.0	-10.7	-34.6
		3	14715311.0	479.5	0.0	250841792.0	9862.8	0.2	67.0	216.4
		5	337215451.9	13270.3	0.0	1173977807.2	46649.1	0.0	86.8	280.4
		10	1300452070.8	51690.5	0.0	3422692199.5	136457.7	0.0	188.6	609.3
	10000	1	-533766067.1	-16083.5	0.0	-404411133.5	-6310.0	0.0	-12.8	-41.4
		2	-489822287.7	-10496.1	0.0	-338897036.9	-2159.8	0.0	-0.4	-1.3
		3	-329970189.4	-6290.6	0.0	-283604913.8	5101.6	0.0	31.8	102.7
		5	-72357313.8	2505.9	0.0	156304141.0	31845.4	0.0	68.9	222.6
		10	59583976.1	23569.2	0.0	331451216.5	62579.7	0.0	150.5	486.2
Stochastic environment	**25000**	**2**	**-9996350.7**	**448.5**	**967.2**	**-215099524.4**	**0.0**	**8942.9**	**683.4**	**2207.9**
	50000	1	-92341751.7	-448.5	2794.4	-357876003.0	0.0	6.3	0.8	2.5
		2	105120261.8	-34.1	1243.2	216136990.7	119.6	-6464.1	18.9	61.0
		3	93894655.4	1417.7	116.9	654809263.9	1491.4	-7672.6	66.6	215.2
		5	117807965.9	2199.3	-364.6	300483034.6	2335.5	-7470.1	148.7	480.4
		10	662818361.3	12414.6	-967.2	1284112089.7	21119.6	-8942.9	230.6	745.0
	25000	1	-16876862.9	-448.5	582.9	-61053474.3	0.0	2508.3	-44.1	-142.5
		3	44940476.1	883.3	-610.7	248941317.8	472.8	-6656.1	80.4	259.7
		5	55807581.9	2489.7	-812.4	530743709.6	2182.1	-7839.0	145.8	471.0
		10	332466960.6	12058.3	-967.2	756301042.5	15034.4	-8942.9	229.5	741.4
	10000	1	-13339834.0	-448.5	8283.6	108761962.6	0.0	44533.0	19.0	61.3
		2	3457917.9	-448.5	4371.0	133783109.9	0.0	8568.5	69.1	223.2
		3	-2062728.2	489.6	636.3	207016337.1	97.7	-4223.6	112.5	363.4
		5	42846468.4	5991.7	-455.1	366889940.5	2161.6	-8237.5	112.8	364.4
		10	50723366.6	18983.9	-967.2	440046974.2	16144.7	-8942.9	117.9	380.9

According to Eq. (14), by increasing α and consequently increasing EL_t, ISO lets a higher EENS happen. Thus, in this situation, GENCOs tend to increase dummy generation unit usage up to EL_t to gain more incentives and payoffs. Therefore, they set their predictive maintenances in weeks, leading to higher dummy generation unit usage. According to the results, since installed capacity is always greater than loads in deterministic situations, GENCOs can set their maintenance decisions so that there is no EENS. Thus, they set maintenance weeks in peak loads to obtain more incentives. While in stochastic situations, smaller α can lead to a negative payoff for GENCOs because they cannot provide an EENS lower than EL_t. Hence, in this situation, lower π will lead to more profitability. But as α increases, incentive amounts and, consequently the profitability increase. Thus, ISO should determine a suitable α and π because they impose completely different strategies on the GENCOs. This case is more important when facing some operational level parameters uncertainties. Figure 7 shows each GENCO's incentive and penalty participation in different α in both deterministic and stochastic situations. As mentioned above, in a deterministic situation, EENS can be 0. GENCOs set EENS in [0, EL_t] to obtain more profit. Thus, the penalty never happens, and the incentive increases by increasing α. In a stochastic situation, a penalty may occur in a small α value, and by increasing the value of α, penalties will decrease while incentives are increasing.

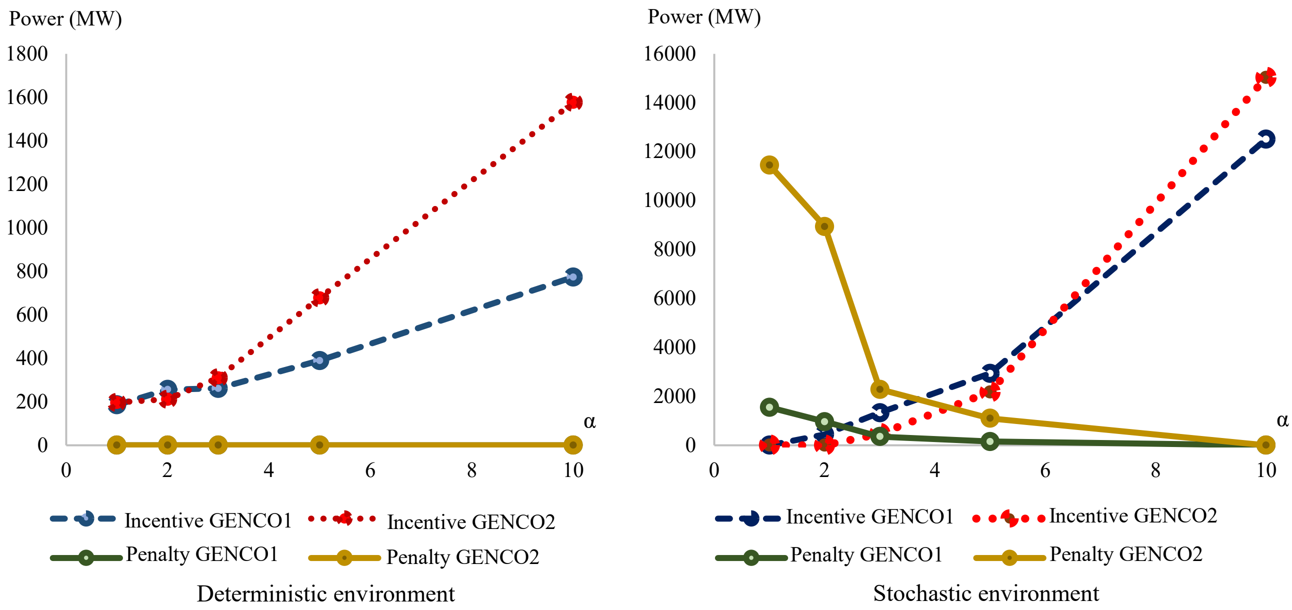


Figure 7: Incentive and penalty changes among different α

In economic theory, capacity constraints play a key role, and the price depends on the amount of available capacity. In maintenance scheduling problems, any reduction in available capacity leads to a reduction in the reservation level and will increase the electricity price. In the basic economic context, the essential drivers of price function are demand and supply, which in the electricity market concept refer to electricity load and the available capacity, respectively. In this regard, an increase in electricity load or a decrease in available capacity leads to an increase in the electricity price. Therefore, applying an appropriate electricity price function plays a fundamental role in GMS problems. In this study, due to the inherent features of the proposed GMS model, the dual variable of supply and demand balance constraint can be considered as the electricity price (Mazidi et al., 2018). The relation between electricity load, available capacity, and price for the deterministic GMS model is shown in Figure 8.

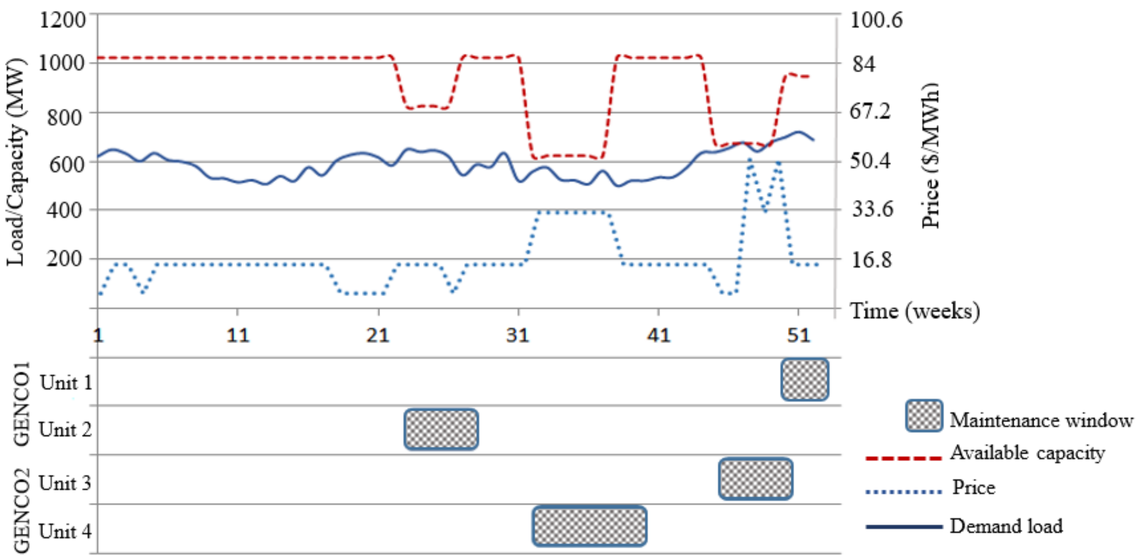


Figure 8: Electricity prices and maintenance schedules for deterministic model

According to the results, electricity price is affected due to the changes in available capacity and demand. As shown in Figure 8, available capacity decreases in maintenance weeks 23 to 26, 32 to 37, and 45 to 52, leading to increased electricity prices. Also, the highest electricity prices are observed in weeks 47 and 49, with a high risk of energy shortage.

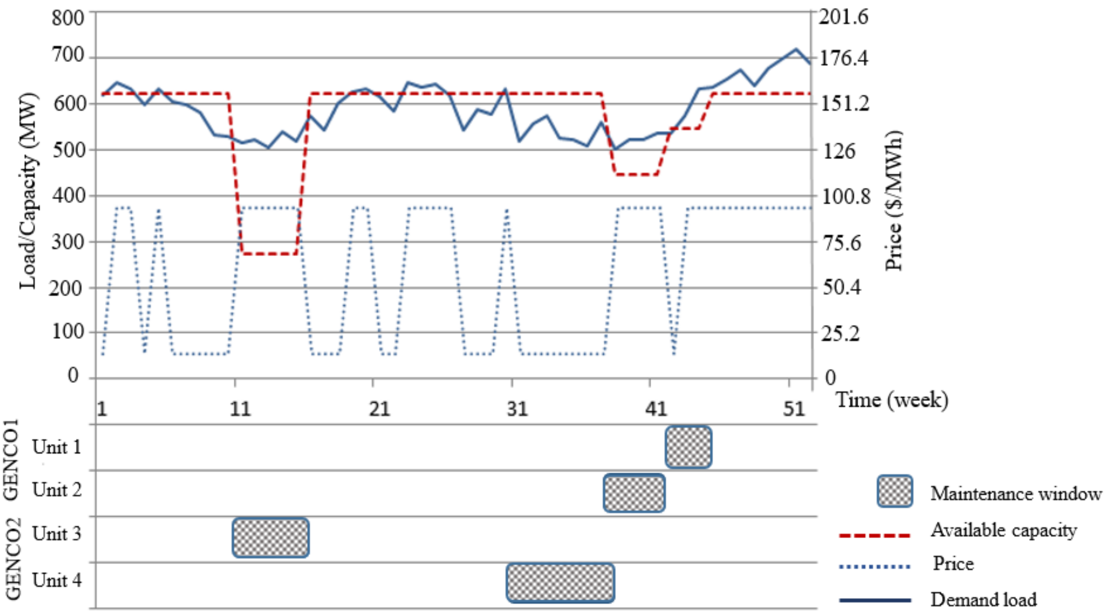


Figure 9: Electricity prices and maintenance schedules in the case of the 4th generation unit's failure

The stochastic situation, shown in Figure 9, also shows a decline in available capacity due to the failure of units or preventive maintenance. In the case of the failure of the 4th generation, the unit decreases the available capacity from 1023 MW to 623 MW. Thus, in weeks with demands more than available capacity, price increases to the highest amount of "price cap". Also, in maintenance weeks 12 to 16 and 39 to 42, and 43 to 45, electricity prices are increased due to the available capacity reduction. It is worth mentioning that, maintenance weeks of the 4th generation unit do not affect electricity price in the scenarios in which it is failed.

According to the results, energy price increases in the maintenance weeks due to the reduction of available capacity. Therefore, ISO especially in the real world, where the number of generation units is much more than the reliability test system under consideration should make sure that the schedules are not such that there is collusion between generation units to increase energy prices. The price reaches its maximum when generation units suggest their maintenance in specific weeks with higher demand. Therefore, the ISO must be very careful in determining α and π, because these are the only tools of the ISO that prevent these events by imposing completely different strategies on the GENCOs. Figure 10 shows how GENCOs' maintenance strategies are changed by changing ISO policies in various values of parameter α in the uncertain environment.

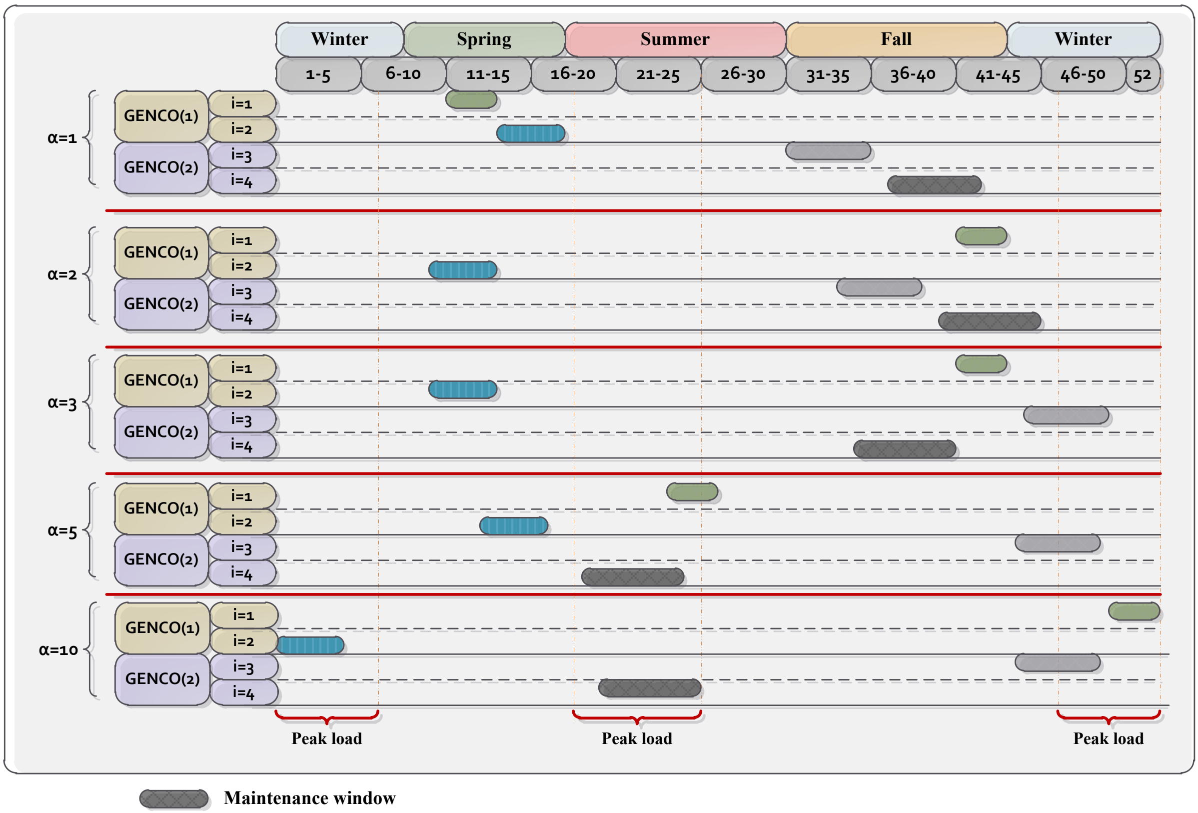


Figure 10: Maintenance scheduling of generation units in an uncertain environment

In the peak weeks of the year, electricity prices are expected to be higher. Also, decreasing the available capacity leads the electricity price reaches to its maximum. As shown in Figure 10, since increasing α allows more EENS, more incentives, and fewer penalties, the increase in α lead to a change in GENCOs' maintenance strategies from off-peak weeks to the mid-peak and peak weeks.

Figure 11 shows GENCOs' maintenance strategies in different π with α=2 and α=10. Results show that in smaller α, increasing the value of π leads to change in maintenance strategies to the off-peak weeks. However, in big α, increasing π leads to shifting maintenance strategies to the peak weeks due to the possibility of increasing EENS and increasing the incentive.

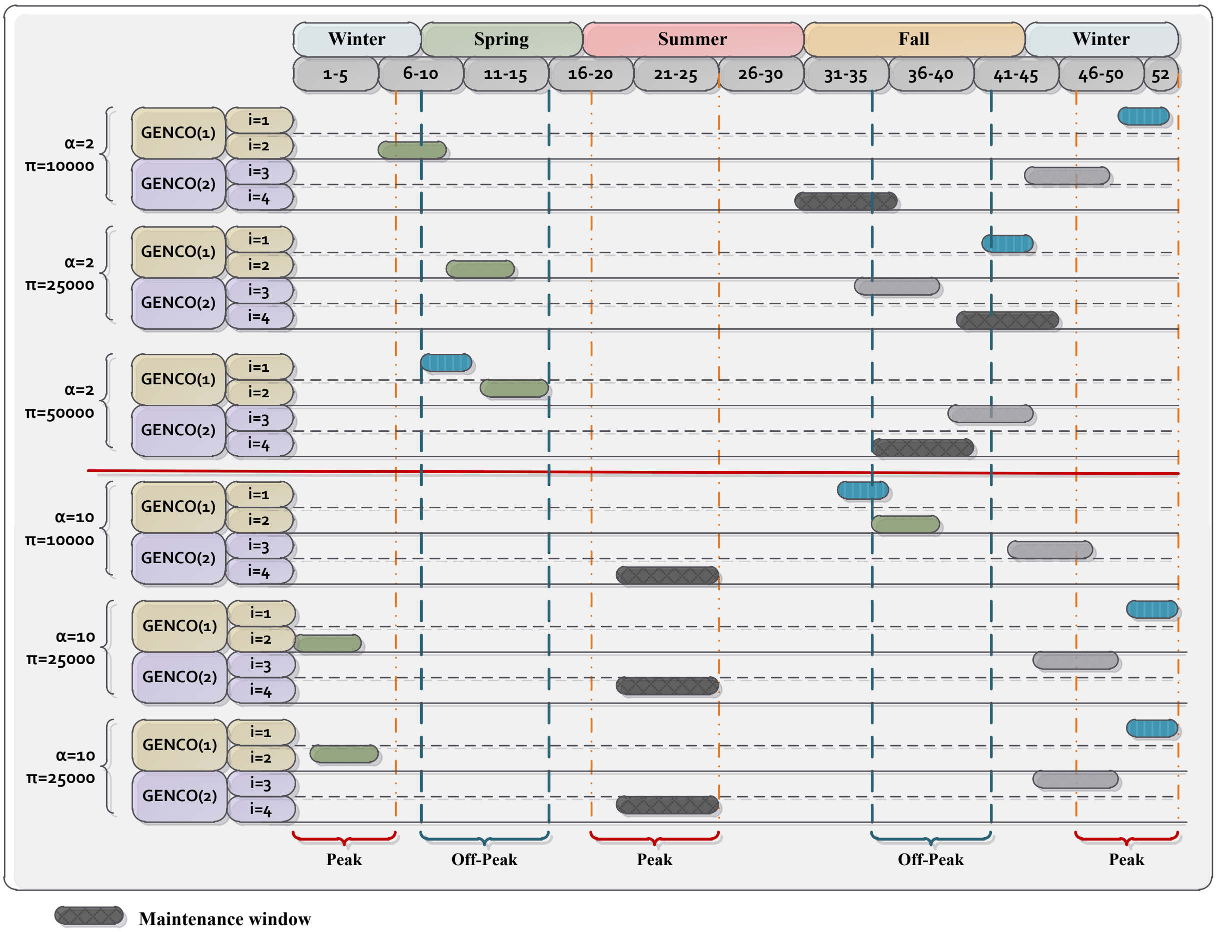


Figure 11: Maintenance scheduling of generation units under different π and α in stochastic situation

5.5. Stochastic measure of the GMS model

To consider the first pre-mentioned issue in Section 1, the necessity of applying uncertainties in the proposed GMS model is investigated by comparing the model results in both deterministic and stochastic environments. Table 8 shows a comparison between the deterministic and stochastic features in terms of reliability and profitability indices to investigate the impact of ignoring the risk of disruption in generation units and demand variations. To better illustrate the effects of ignoring uncertainties, ISO objective function and reliability index are also investigated when obtained maintenance decisions from the deterministic model are fixed in its model considering all possible scenarios.

Table 8: Effect of ignoring uncertain parameters in the proposed bi-level GMS model

α	Uncertainty approach	Objective function				Reliability		
		GENCO1	GENCO2	ISO	ISO (Det)/ ISO (St)	Respond demand (%)	EENS	EENS (Det)/ EENS (St)
1	Deterministic	523952669.5	472392668.2	4072108.1	1.30	99.9	2643.7	1.28
	Stochastic	-26873213.6	-276152998.7	**3109241.6**		97.9	**2065.4**	
2	Deterministic	644164577.8	532166115.1	4300070.7	1.27	99.9	2777.4	1.26
	Stochastic	-9996350.7	-215099524.4	**3380859**.4		97.8	**2207.9**	
3	Deterministic	658879888.8	783007907.1	4408582.6	1.25	99.7	3109.5	1.26
	Stochastic	34944125.4	33841793.4	**3507225.6**		97.8	**2467.6**	
5	Deterministic	981380029.7	1706143922.3	4898934.7	1.25	99.3	3371.0	1.25
	Stochastic	45811231.2	315644185.2	**3916731.6**		97.5	**2678.9**	
10	Deterministic	1944616648.6	3954858314.6	5710375.3	1.23	99.2	3688.6	1.25
	Stochastic	322470609.9	541201518.1	**4640889.8**		97.4	**2949.3**	

St (Stochastic), Det (Deterministic)

Considering the possibility of disruption to generation units and demand variations in the GMS model results in higher payoff for GENCOs and a better reliability index, but increases ISO objective function "network operational cost" and reliability index "EENS" if one of the scenarios happens. In fact, important information for the ISO that leads to rescheduling signals is missed. Generally, the solutions obtained from solving a deterministic model are always better than solving the stochastic model counterpart because in two-stage stochastic models, the worst-case scenario is considered, and the model is feasible even for the worst-case scenario. The deterministic solution in the proposed GMS model would be infeasible in some scenarios if the dummy generation unit was not taken into account. Here, non-considering possible uncertainties lead to an increase in blackouts and a decrease in the level of network reliability. Thus, a greater demand fluctuation or a greater generation units' failure probability, especially for high-capacity generation units, leads to increasing blackouts probability. Figure 12 shows the network operational costs and EENS changes through different α in stochastic and deterministic situations when a scenario happens.

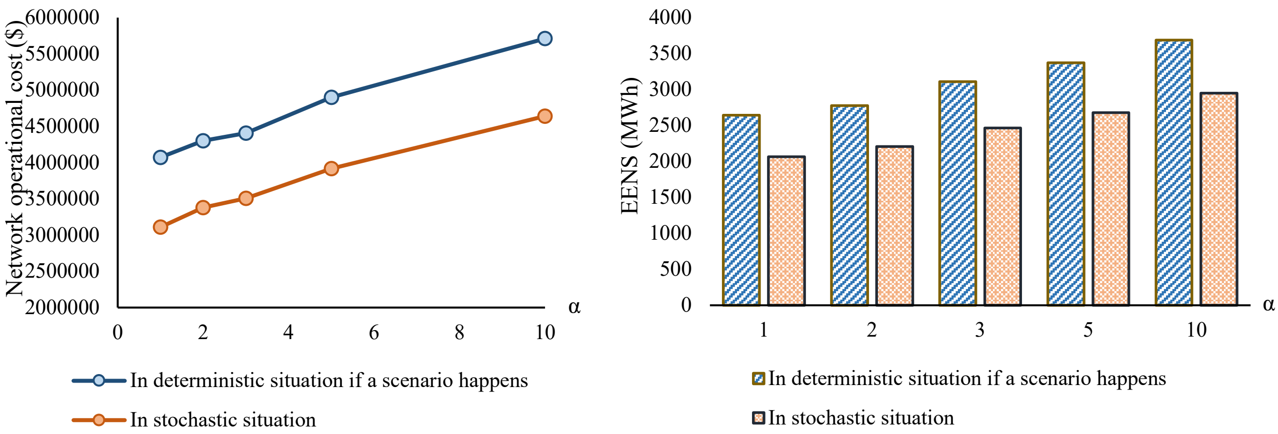


Figure 12: Network operational costs and EENS changes in deterministic and stochastic situation

To examine the potential benefit of considering the stochastic feature of the proposed GMS model over the deterministic counterpart, we evaluate two well-known concepts named value of the stochastic solution (VSS) and expected value of perfect information (EVPI). The VSS index is used to evaluate the difference between the objective function value of the stochastic solution and the expected of expected value (EEV). The EEV approach is applied as one of the simple stochastic approaches to determine the stochastic measures of the models. In this approach, first, each stochastic parameter is replaced by its corresponding expected value. Then the deterministic model is solved and evaluated for all scenarios. In the proposed model, the expected values of the available capacity and demand are determined by Eq. (50) and Eq. (51), respectively.

$$E[q_i^{max}] = q_i^{max} \times (1 - FOR_i) + 0 \times (FOR_i) = q_i^{max}(1 - FOR_i) \qquad \forall i \qquad (50)$$
$$E[q_i^{min}] = q_i^{min} \times (1 - FOR_i) + 0 \times (FOR_i) = q_i^{min}(1 - FOR_i)$$

$$E[Load_t^s] = \sum_s p_s(Load_t^s) \qquad \forall t \qquad (51)$$

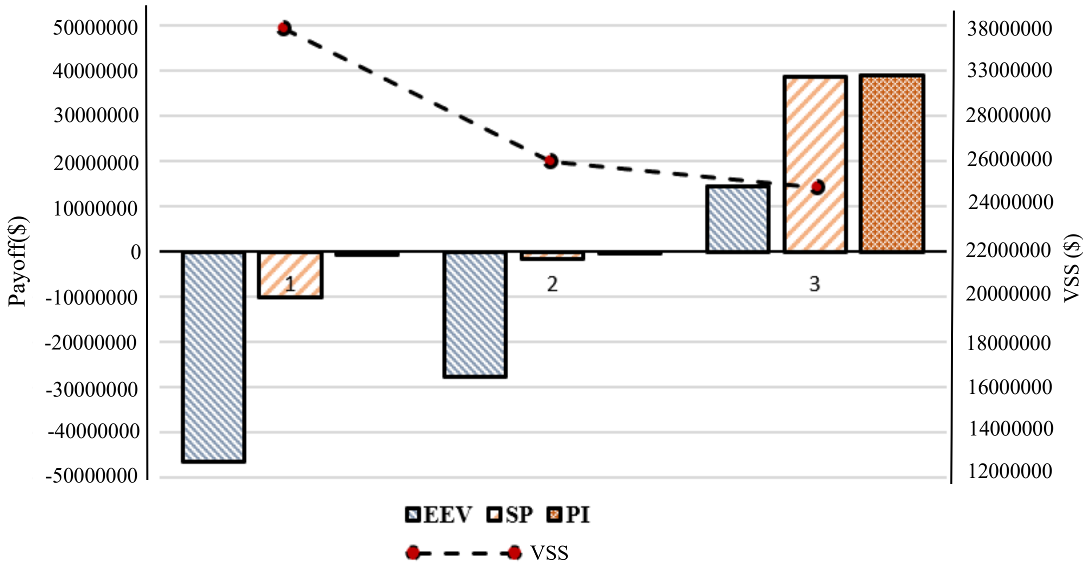
If $Payoff_g\left(E[q_i^{max}], E[q_i^{min}], E[Load_t^s]\right)$ presents the optimal decision in the first stage of the deterministic model, the EEV becomes, $E_{\omega,s}\left(Payoff_g\left(E[q_i^{max}], E[q_i^{min}], E[Load_t^s]\right)\right)$. Since this approach applies only an average of each uncertain parameter, the dummy generation unit's usage and consequently increasing the EENS is very probable. Perfect information (PI) value, called wait-and-see value, is obtained to determine the amount of reasonable investment in stochastic parameter prediction. The PI value is the expected value of all optimal values, which can evaluate the expected performance of complete information. In the wait-and-see approach, prior information on the generation unit's reliability status and demand amount is known. The EVPI is used to evaluate the difference between stochastic and perfect information solutions. This parameter measures how much is reasonable to pay to obtain perfect information about the future. As a result, this is an upper limit of the reasonable payment in return for complete information about the future. The performance analysis results of the stochastic programming solution (SP) using EEV and PI are reported in Table 9.

Table 9: Comparing of results achieved by the expected value, stochastic programming, and perfect information approaches

Uncertainty	RTS. No.	GENCO. No.	Payoff (Million)			VSS= (SP-EEV) (Million)	VSS/|EEV|	EVPI= (PI -SP) (Million)	EVPI/|SP|
			EEV	SP	PI				
Generation units' disruption & demand	1	1	-46.5	-10	-0.7	36.4	78%	9.3	92%
		2	-12476.6	-215.1	-134.1	122261.5	980%	81	37%
	2	1	-12797.2	1.8	2	12798.9	100%	0.2	11%
		2	-3016.2	8.8	9.2	3025.1	100%	0.4	5%
	3	1	-0.02	0.07	0.1	0.1	462%	0.01	14%
		2	-0.01	0.1	0.01	0.1	890%	0.04	38%
		3	-0.03	0.03	0.05	0.1	197%	0.02	48%
Demand	1	1	14.5	38.6	38.9	24.1	166%	0.3	1%
		2	18.4	25.4	27	6.9	37%	1.7	6%
	2	1	35.5	41	41.3	5.5	15%	0.3	1%
		2	13.3	30.8	31.8	17.5	131%	1.01	3%
	3	1	288.2	288.7	289.1	0.5	0%	0.37	0%
		2	472.5	473.6	482.5	1.07	0%	8.9	2%
		3	181.3	609.7	614	428.5	236%	4.3	1%
Generation units' disruption	1	1	-27.7	-1.6	-0.1	26.1	95%	1.8	95%
		2	-11710.1	-531.1	-45.9	11178.9	95%	485.2	91%
	2	1	-0.01	11.2	11.2	11.2	87311%	0.07	1%
		2	-0.3	9.4	9.6	9.7	3230%	0.15	2%
	3	1	0	0.2	0.2	0.2	2305%	0.01	7%
		2	0	0.3	0.3	0.3	12296%	0	1%
		3	-0.01	0.1	0.1	0.1	745%	0.01	19%

We investigated the VSS and EVPI measures in three stochastic situations. 1- Under both the risk of disruption in generation unit and demands variation, 2- Just under demands variation, and 3- Under the risk of disruption in generation unit.

Based on the results obtained in Table 9, VSS and EVPI parameters in the GMS model under uncertain parameters are higher than just considering one of the stochastic parameters. Figure 13 shows the EEV, SP, and PI objective function of unit 1 from GENCO 1 under the different stochastic situations.



1. Payoff under the risk of disruption and demands variation
2. Payoff under the demand's variation
3. Payoff under the risk of disruption

Figure 13: Payoff and its VSS changes under different stochastic situation

Also, comparing the VSS and EVPI parameters under different stochastic scenarios according to Table 9 is presented in Figure 14.

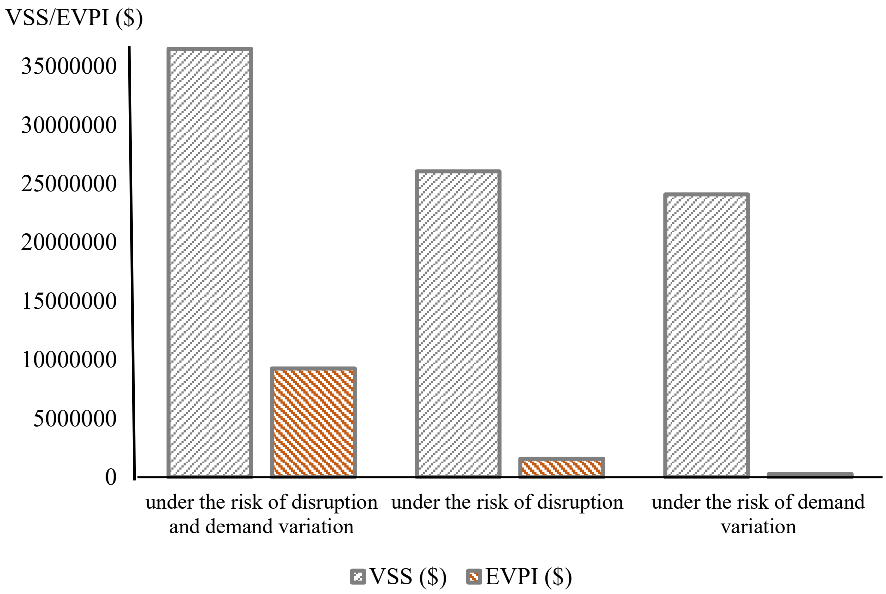


Figure 14: Comparison between VSS and EVPI under different stochastic scenarios

While VSS measures the value of using a stochastic model, EVPI measures the value of knowing more. So, for large EVPI, it is important to learn more. As reported in Table 9, VSS/|EEV| contains large values which indicate the usefulness and necessity of considering the stochastic model. Moreover, as illustrated in Figure 14, because of large values of VSS, it also confirms the usability of stochastic programming, however, the small values of EVPI confirm that having perfect information will not make a significant change in the decision compared with the stochastic programming model. Thus, the deterministic expected value of the second stage stochastic value is not enough to contain all the scenarios. Also, EVPI has taken a small value compared to VSS. Therefore, obtaining more information could not improve the objective value significantly.

5.6. Necessity of applying bi-level programming

In order to answer the second pre-mentioned issue in Section 1, the necessity of applying a leader-follower approach in the GMS problem is considered by comparing the results of the proposed BLIGMS model both with a GMS model without using a leader-follower structure which its formulation is introduced in (Hassanpour & Roghanian, 2021).
In order to achieve the necessity of applying the bi-level approach, the GMS model in the two mentioned formulations is evaluated in terms of “GENCOs payoff”, “reliability index”, and “solution time”. The obtained results are presented in Table 10.

Table 10: Comparing the proposed BLIGMS model and a GMS model without the bi-level structure

GMS model type	RTS. No	α	Payoff (Million $)			EENS (MWh)	Time	Number of the iteration
			GENCO1	GENCO2	GENCO3			
The proposed BLIGMS model	1	2	-10	-215.1	-	2207.9	0:15:12	1
		5	45.8	315.6	-	2678.9	0:13:46	1
		10	322.5	541.2	-	2949.3	0:12:23	1
	2	2	1.8	8.8	-	1109.7	4:59:13	1
		5	3.9	10.1	-	1453.4	4:37:06	1
		10	5.4	12.3	-	1657.1	4:12:55	1
	3	2	0.07	0.1	0.04	875.6	9:17:04	1
		5	0.1	0.2	0.05	1081.1	8:48:12	1
		10	0.2	0.3	0.07	1238.5	8:17:30	1
A GMS model without a leader-follower structure	1	2	-9.1	-194.4	-	2054.2	6:27:16	7
		5	37.2	243.2	-	2547.7	3:51:04	4
		10	299.5	496.4	-	2873.5	1:19:48	3
	2	2	1.6	8.4	-	1052.8	10:19:05	11
		5	3.3	9.6	-	1336.1	7:33:51	7
		10	5.3	11.9	-	1492.3	5:42:12	5
	3	2	0.07	0.09	0.03	823.6	16:28:31	16
		5	0.1	0.2	0.05	917.4	10:06:48	9
		10	0.2	0.3	0.07	1158.8	8:13:10	9

In the case of ignoring the bi-level structure, the total generated GENCOs determine power and maintenance decisions.

Thus, in this case, the Nash Equilibrium strategy includes a significant number of decision variables, and achieving equilibrium and convergence of decisions is very time-consuming and difficult. Also, the Lack of integration in players' decisions, ignoring the ISO decisions in the GENCOs model, and determining the amounts of incentives and penalties based on GENCO's previous iteration decisions lead to achieving local Nash Equilibrium and increasing the solution time. It is worth mentioning that incentives and penalties just force GENCOs to change their maintenance decisions in the next iteration with the hope of improving the reliability index. But actually, they make GENCOs change their strategy, not steer them to choose a strategy that leads to a better reliability level. The impact of not considering rescheduling decisions in an integrated model is discussed in the next section. Figure 15 illustrates a Solution time comparison between the proposed BLIGMS model and a GMS model without a leader-follower structure.

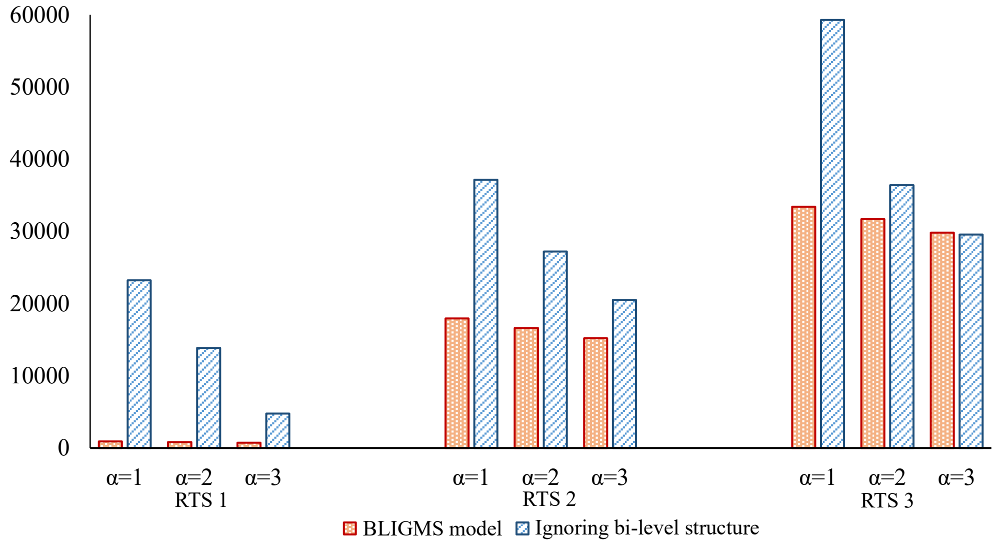


Figure 15: Solution time comparison between proposed BLIGMS model and ignoring bi-level structure

5.7. Superiority of the proposed mathematical model

In all related past bi-level GMS models, once the Nash Equilibrium strategy of the GENCOs is obtained, ISO evaluates a reliability index to prepare appropriate rescheduling signals such as incentives and penalties. In this regard, final maintenance schedules are obtained in an iterative procedure due to the consideration of the rescheduling signals. Signals forced GENCOs to change their maintenance decisions to improve the reliability index. In contrast, the current study proposes a novel leader-follower GMS model in that reliability signals instead of rescheduling signals are considered as the ISO decision variables and are determined in the lower-level model. Thus, each GENCO sets its maintenance schedule subject to the ISO decisions in just one iteration, and the GMS solution is obtained in an integrated decision-making approach. This will ensure achieving the global Nash Equilibrium strategy. Table 11 represents a comparison between the proposed BLIGMS model and a bi-level GMS model based on (Mazidi et al., 2018) study that reaches to desire reliability level by considering an iterative procedure for the ISO.

Table 11: Comparing the proposed BLIGMS model with a traditional iterative approach

GMS model type	RTS. No	α	Payoff (Million $) GENCO1	GENCO2	GENCO3	EENS (MWh)	Time	Number of the iteration
The proposed BLIGMS model	1	2	-10	-215.1	-	2207.9	00:15:12	1
		5	45.8	315.6	-	2678.9	00:13:46	1
		10	322.5	541.2	-	2949.3	00:12:23	1
	2	2	1.8	8.8	-	1109.7	04:59:13	1
		5	3.9	10.1	-	1453.4	04:37:06	1
		10	5.4	12.3	-	1657.1	04:12:55	1
	3	2	0.07	0.1	0.04	875.6	09:17:04	1
		5	0.1	0.2	0.05	1081.1	08:48:12	1
		10	0.2	0.3	0.07	1238.5	08:17:30	1
Traditional iterative approach	1	2	-9.3	-201.3	-	2178.2	02:52:38	5
		5	41.8	279.3	-	2413.1	01:14:43	3
		10	315.5	526.8	-	2910.7	00:43:57	3
	2	2	1.7	8.7	-	1085.4	06:39:19	7
		5	3.7	9.9	-	1319.1	05:57:24	4
		10	5.4	12.3	-	1601.7	05:18:06	3

		2	0.07	0.1	0.03	847.4	12:41:27	9
	3	5	0.1	0.2	0.05	984.3	10:33:12	6
		10	0.2	0.3	0.07	1077.5	09:48:32	4

From Table 11, it is observed that integration can have substantial effects on the solution time and quality of equilibrium strategies in the proposed GMS problem. The following reasons can be provided for improving the solution time and GENCOs' payoff of the proposed BLIGMS model in comparison with the traditional iterative approach counterparts:

- Low intelligence in iterative procedure in both GMS models with ignoring bi-level structure and traditional iterative approach in moving the maintenance strategies to the weeks which leads to higher reliability levels.

- Lack of effective communication between GENCOs and ISO in changing the maintenance strategies. In both GMS models with ignoring bi-level structure and traditional iterative approach, in each iteration, the Nash strategy is just affected by the incentives and penalties of the previous iteration decisions.

- Considering total generated power decisions with maintenance decisions as to the strategy of each GENCO in the GMS model with ignoring bi-level structure.

- Low accuracy in solving GMS model by ignoring bi-level structure due to guessing the total generation strategy of rival GENCOs in solving each GENCO model.

- In both GMS models with ignoring bi-level structure and traditional iterative approach, incentives and penalties of the last iteration are considered in the final solution instead of the final incentives and penalties.

Figure 16 illustrates the priority of the integrated GMS model compared to the other well-known models in the case of unit 1 of the first GENCO.

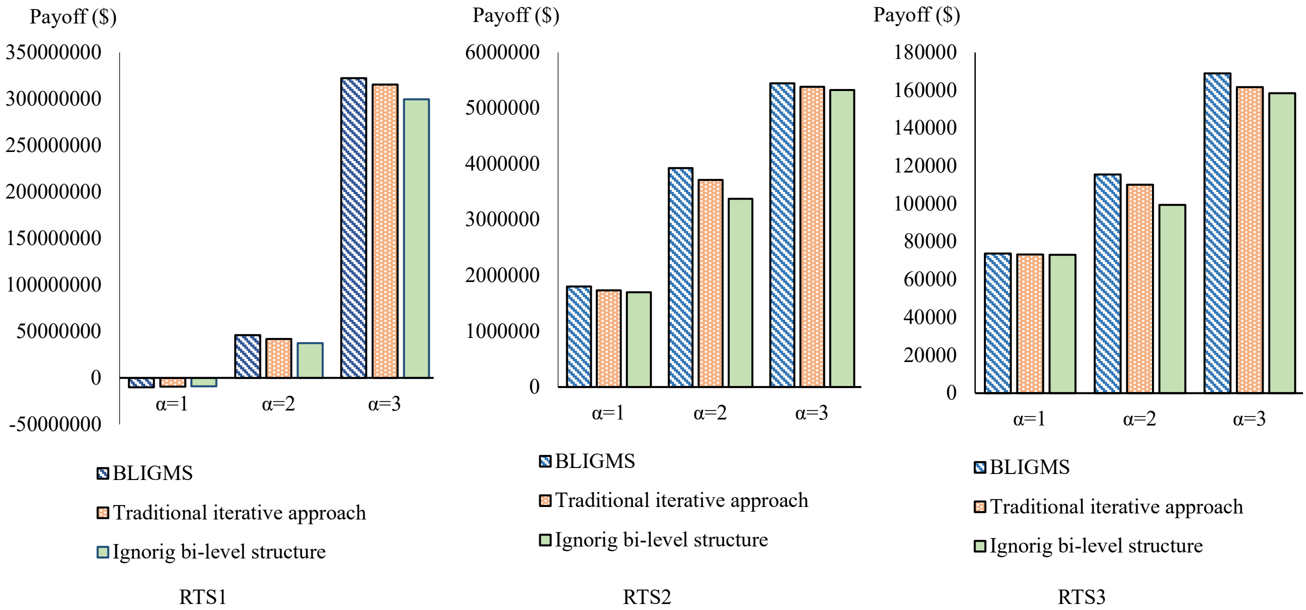


Figure 16: Payoff comparison between the BLIGMS model with ignoring bi-level structure and traditional iterative approach

As shown in Figure 16, the obtained Nash equilibriums in the GMS models ignoring bi-level structure and traditional iterative approach are local optimum most of the time. As a result, in the proposed mathematical framework GENCOs can gain more payoff while maintaining power system reliability.

5.8. Managerial insights

According to the findings of this study, there are remarkable suggestions for administrators and practitioners in the electricity market. In this sector, stakeholders perpetually compete in various aspects. Considering all the interactions between the main stakeholders has a significant impact on effective strategic and operational decisions. Therefore, a novel integrated GMS model based on the game theory concepts is developed in this study. The following managerial insights can be extracted from this study:

- Our results indicate that ISO should behave strictly in cases with high importance of system reliability while a lack of power generation may lead to high and irreparable costs. Therefore, ISO should consider a lower value for α and a higher value for π to ensure a high-reliability level of the power system.
- ISO should determine α and π precisely. A big value of α can cause GENCOs' high tendency to schedule their maintenance strategies in the mid-peak and peak weeks. Also, increasing π in a low value of α leads to having maintenance in the off-peak weeks, and increasing π in a high value of α leads to shifting maintenance strategies to the peak weeks.
- Considering an integrated GMS model ensures achieving the global optimum solution. Therefore, it is highly recommended to electricity market administrators use the proposed integrated approach instead of the traditional iterative procedure to ensure the GENCOs' payoff, power system's reliability level, and intelligent incentives and penalties while the maintenance scheduling time reduces significantly.

6. Conclusions and future insights

In this paper, we have formulated a novel integrated bi-level two-stage maintenance scheduling model for generation units in an electricity market under the risk of generation unit disruption and demand variations. This study explicitly strives to fill the gap in the relevant literature by:

- Introducing a novel integrated GMS model and omitting iterative procedure for solving the model while providing a global optimum solution in a reasonable time.
- Considering both reasons that threaten the power system reliability as uncertain parameters in the mathematical model and investigating the GMS problem under both deterministic and stochastic features.
- Employing a modified fuzzy clustering to reduce the number of scenarios and provide the ability to solve the model for large-size scales with appropriate solution accuracy.

Generation maintenance scheduling problems deal with a time sequence of maintenance for a given set of generation units in an electricity market considering the power system restrictions. Here, a non-cooperative manner between the GENCOs in offering the maintenance schedules to the ISO and also, ISO reaction to the aggregated schedule according to the power system's reliability are considered in an integrated non-cooperative bi-level model. In this regard, a multileader one-follower two-stage stochastic model is applied. The GENCOs are considered as independent leaders in the upper level and the ISO is considered as a follower in the lower level. Presenting an efficient mathematical framework for the GMS problem is extremely challenging. Because the formulation not only determines the solution in much less time but also leads to a more accurate equilibrium strategy.

The proposed methodology has been evaluated using some modified IEEE reliability test systems. The numerical analysis confirms that the proposed model is more effective in cases with higher uncertainties. And also, the necessity of applying the bi-level approach in the GMS problem and the superiority of the mathematical model in ignoring the iterative procedure compared to existing studies have been demonstrated in the performed analysis. Interesting directions for future research are investigating more realistic disruption scenarios and designing an intelligent algorithm to provide good scenarios. For example, preventive maintenance should lead to a lower forced outage rate for the related generation unit in periods after maintenance action. Thus, the failure rates could be considered different over the time horizon. Also, considering the startup/shutdown variable in the mathematical model to indicate On/Off modes is recommended. This variable is practical when the load is small and some generation units could stay Off. Another direction for future work is suggested to present more efficient algorithms based on metaheuristic algorithms to solve large-scale models.

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Appendix: The model linearization

In order to linearize complementary slackness constraints, new additional binary variables ($y^1_{its\omega}, y^2_{its\omega}, y^3_{its\omega}, y^4_{its\omega}, y^5_{ts\omega}$) are defined for Eqs. (22)-(26), respectively (Fortuny-Amat & McCarl, 1981). In this regard, Eq. (22) is replaced by constraints (A1) and (A2), Eq. (23) is replaced by constraints (A3) and (A4), Eq. (24) is displaced by constraints (A5) and (A6), Eq. (25) is changed by constraints (A7) and (A8), and finally, Eq. (26) is replaced by constraints (A9) and (A10).

$$\gamma^1_{its\omega} \leq My^1_{its\omega} \qquad \forall i,t,s,\omega \qquad \text{(A1)}$$

$$(1 - X_{it})q^{max}_{i\omega} - q^{s\omega}_{it} \leq M(1 - y^1_{its\omega}) \qquad \forall i,t,s,\omega \qquad \text{(A2)}$$

$$\gamma^2_{its\omega} \leq My^2_{its\omega} \qquad \forall i,t,s,\omega \qquad \text{(A3)}$$

$$q^{s\omega}_{it} - (1 - X_{it})q^{min}_{i\omega} \leq M(1 - y^2_{its\omega}) \qquad \forall i,t,s,\omega \qquad \text{(A4)}$$

$$\gamma^3_{its\omega} \leq My^3_{its\omega} \qquad \forall i,t,s,\omega \qquad \text{(A5)}$$

$$up_i - q^{s\omega}_{it+1} + q^{s\omega}_{it} \leq M(1 - y^3_{its\omega}) \qquad \forall i,t,s,\omega \qquad \text{(A6)}$$

$$\gamma^4_{its\omega} \leq My^4_{its\omega} \qquad \forall i,t,s,\omega \qquad \text{(A7)}$$

$$down_i - q_{it}^{s\omega} + q_{it+1}^{s\omega} \le M(1 - y_{its\omega}^4) \qquad \forall i,t,s,\omega \qquad \text{(A8)}$$

$$\gamma_{ts\omega}^6 \le M y_{ts\omega}^5 \qquad \forall t,s,\omega \qquad \text{(A9)}$$

$$Q_t^{s\omega} \le M(1 - y_{ts\omega}^5) \qquad \forall t,s,\omega \qquad \text{(A10)}$$

And also, for linearize Eq. (20) binary variable y_{it}^6 and constraints (A11) -(A13) are defined as below:

$$\gamma_{it}^5 \le M y_{it}^6 \qquad \forall i,t \qquad \text{(A11)}$$

$$\gamma_{it}^5 \ge -M y_{it}^6 \qquad \forall i,t \qquad \text{(A12)}$$

$$\sum_{j,\omega} p^\omega q_{j\omega}^{max} X_{jt} \le M(1 - y_{it}^6) \qquad \forall i,t \qquad \text{(A13)}$$

To linearize term $\sum_{i\in\Xi(g),t,s.\omega} p^s p^\omega \mu_t^{s\omega} q_{it}^{s\omega}$ in the objective function, the stationarity conditions (17)-(19) are multiplied by $q_{it}^{s\omega}$ and are summed for each defined interval. The result is presented in Eq. (A14).

$$\sum_{i,t,s,\omega} p^\omega p^s [\frac{\lambda_t^{s\omega}}{p^\omega p^s} - (O_i + \tau_i f_i)] q_{it}^{s\omega} = \sum_{i,s,\omega,t\in(1,T)} [\gamma_{its\omega}^1 q_{it}^{s\omega} - \gamma_{its\omega}^2 q_{it}^{s\omega} - \gamma_{its\omega}^3 q_{it}^{s\omega} + \gamma_{its\omega}^4 q_{it}^{s\omega} + \gamma_{it-1s\omega}^3 q_{it}^{s\omega}$$
$$-\gamma_{it-1s\omega}^4 q_{it}^{s\omega}] + \sum_{i,s,\omega} [\gamma_{i1s\omega}^1 q_{i1}^{s\omega} - \gamma_{i1s\omega}^2 q_{i1}^{s\omega} - \gamma_{i1s\omega}^3 q_{i1}^{s\omega} + \gamma_{i1s\omega}^4 q_{i1}^{s\omega} + \gamma_{iTs\omega}^1 q_{iT}^{s\omega} - \gamma_{iTs\omega}^2 q_{iT}^{s\omega} - \gamma_{iT-1s\omega}^4 q_{iT}^{s\omega} \qquad \text{(A14)}$$
$$+\gamma_{iT-1s\omega}^3 q_{iT}^{s\omega}]$$

The right-hand side of the above equation is a part of the objective function. So left side can be replaced in the final model objective function. Although new nonlinearities appear on the left side, they can be handled through the complementarity slackness conditions (22)-(25). Finally, Eq. (A15) re-written as follow:

$$\sum_{i,t,s,\omega} p^\omega p^s [\frac{\lambda_t^{s\omega}}{p^\omega p^s} - (O_i + \tau_i f_i)] q_{it}^{s\omega} = \sum_{i,s,\omega,t} [(1 - X_{it}) q_{i\omega}^{max} \gamma_{its\omega}^1 - \gamma_{its\omega}^2 (1 - X_{it}) q_{i\omega}^{min} + \gamma_{its\omega}^3 up_i \qquad \text{(A15)}$$
$$+\gamma_{its\omega}^4 down_i]$$

Two nonlinear term remains in the first and second statements of the left side. In order to linearize $X_{it}\gamma_{its\omega}^1$, new additional variable ($V_{its\omega} = X_{it}\gamma_{its\omega}^1$) and constraints (A16) -(A18) are defined. And to linearize $\gamma_{its\omega}^2 X_{it}$ new variable ($F_{its\omega} = \gamma_{its\omega}^2 X_{it}$) and constraints (A19) -(A21) are added to the model.

$$V_{its\omega} \le \gamma_{its\omega}^1 \qquad \forall i,t,s,\omega \qquad \text{(A16)}$$

$$V_{its\omega} \le M X_{it} \qquad \forall i,t,s,\omega \qquad \text{(A17)}$$

$$V_{its\omega} \ge \gamma_{its\omega}^1 - M(1 - X_{it}) \qquad \forall i,t,s,\omega \qquad \text{(A18)}$$

$$F_{its\omega} \le \gamma_{its\omega}^2 \qquad \forall i,t,s,\omega \qquad \text{(A19)}$$

$$F_{its\omega} \le M X_{it} \qquad \forall i,t,s,\omega \qquad \text{(A20)}$$

$$F_{its\omega} \ge \gamma_{its\omega}^2 - M(1 - X_{it}) \qquad \forall i,t,s,\omega \qquad \text{(A21)}$$

To cope with another nonlinear term $\sum_{i,t} \pi C_{it} X_{it}$ in the objective function, new variable ($Z_{it} = C_{it} X_{it}$) and constraints (A22)-(A25) are prepared.

$$Z_{it} \le C_{it} + M(1 - X_{it}) \qquad \forall i,t \qquad \text{(A22)}$$

$$Z_{it} \le M X_{it} \qquad \forall i,t \qquad \text{(A23)}$$

$$Z_{it} \ge C_{it} - M(1 - X_{it}) \qquad \forall i,t \qquad \text{(A24)}$$

$Z_{it} \geq -MX_{it}$ $\forall i, t$ (A25)

In order to cope with nonlinearity terms of the Eq. (14), it is transformed to the Eq. (A26).

$$C_{it} \sum_{i,\omega} p^{\omega} q_{i\omega}^{max} X_{it} = \sum_{\omega} p^{\omega} q_{i\omega}^{max} X_{it} \left(\sum_{s,\omega} H p^{\omega} p^{s} Q_{t}^{s\omega} - EL_{t}\right) \quad \forall i, t \quad \text{(A26)}$$

To linearize term $C_{it} \sum_{i,\omega} p^{\omega} q_{i\omega}^{max} X_{it}$, new variable ($U_{ijt} = C_{it} X_{jt}$) and constraints (A27)-(A30) are defined.

$$U_{ijt} \leq C_{it} + M(1 - X_{jt}) \quad \forall i, j, t \quad \text{(A27)}$$

$$U_{ijt} \leq MX_{jt} \quad \forall i, j, t \quad \text{(A28)}$$

$$U_{ijt} \geq C_{it} - M(1 - X_{jt}) \quad \forall i, j, t \quad \text{(A29)}$$

$$U_{ijt} \geq -MX_{jt} \quad \forall i, j, t \quad \text{(A30)}$$

And also, to linearize term $HX_{it} \sum_{\omega} p^{\omega} q_{i\omega}^{max} \sum_{s,\omega} p^{\omega} p^{s} Q_{t}^{s\omega}$, new variable ($D_{its\omega} = X_{it} p^{\omega} p^{s} Q_{t}^{s\omega}$) and constraints (A31)-(A33) are provided.

$$D_{its\omega} \leq p^{\omega} p^{s} Q_{t}^{s\omega} \quad \forall i, t, s, \omega \quad \text{(A31)}$$

$$D_{its\omega} \leq MX_{it} \quad \forall i, t, s, \omega \quad \text{(A32)}$$

$$D_{its\omega} \geq p^{\omega} p^{s} Q_{t}^{s\omega} - M(1 - X_{it}) \quad \forall i, t, s, \omega \quad \text{(A33)}$$

Finally, to linearize constraint (21) new variable ($P_{it} = X_{it} \gamma_{it}^{5}$) and constraints (A34)-(A37) are added to the model.

$$P_{it} \leq \gamma_{it}^{5} + M(1 - X_{it}) \quad \forall i, t \quad \text{(A34)}$$

$$P_{it} \leq MX_{it} \quad \forall i, t \quad \text{(A35)}$$

$$P_{it} \geq \gamma_{it}^{5} - M(1 - X_{it}) \quad \forall i, t \quad \text{(A36)}$$

$$P_{it} \geq -MX_{it} \quad \forall i, t \quad \text{(A37)}$$