Computer Modeling in Engineering & Sciences

Tech Science Press

DOI: 10.32604/cmes.2023.029453

ARTICLE

Stochastic Programming for Hub Energy Management Considering Uncertainty Using Two-Point Estimate Method and Optimization Algorithm

Ali S. Alghamdi[1], Mohana Alanazi[2], Abdulaziz Alanazi[3], Yazeed Qasaymeh[1,*], Muhammad Zubair[1,4], Ahmed Bilal Awan[5] and M. G. B. Ashiq[6]

[1]Department of Electrical Engineering, College of Engineering, Majmaah University, Al-Majmaah, 11952, Saudi Arabia

[2]Department of Electrical Engineering, College of Engineering, Jouf University, Sakaka, 72341, Saudi Arabia

[3]Department of Electrical Engineering, College of Engineering, Northern Border University, Ar'Ar, 73222, Saudi Arabia

[4]Automation and Control Department, College of Engineering Technology, University of Doha for Science and Technology, Doha, 24449, Qatar

[5]Department of Electrical and Computer Engineering, College of Engineering and Information Technology, Ajman University, Ajman, 20550, United Arab Emirates

[6]Department of Physics, College of Science, Imam Abdulrahman Bin Faisal University, Dammam, 31441, Saudi Arabia

*Corresponding Author: Yazeed Qasaymeh. Email: y.qasaymeh@mu.edu.sa

Received: 20 February 2023 Accepted: 31 March 2023 Published: 03 August 2023

ABSTRACT

To maximize energy profit with the participation of electricity, natural gas, and district heating networks in the day-ahead market, stochastic scheduling of energy hubs taking into account the uncertainty of photovoltaic and wind resources, has been carried out. This has been done using a new meta-heuristic algorithm, improved artificial rabbits optimization (IARO). In this study, the uncertainty of solar and wind energy sources is modeled using Hang's two-point estimating method (TPEM). The IARO algorithm is applied to calculate the best capacity of hub energy equipment, such as solar and wind renewable energy sources, combined heat and power (CHP) systems, steam boilers, energy storage, and electric cars in the day-ahead market. The standard ARO algorithm is developed to mimic the foraging behavior of rabbits, and in this work, the algorithm's effectiveness in avoiding premature convergence is improved by using the dystudynamic inertia weight technique. The proposed IARO-based scheduling framework's performance is evaluated against that of traditional ARO, particle swarm optimization (PSO), and salp swarm algorithm (SSA). The findings show that, in comparison to previous approaches, the suggested meta-heuristic scheduling framework based on the IARO has increased energy profit in day-ahead electricity, gas, and heating markets by satisfying the operational and energy hub limitations. Additionally, the results show that TPEM approach dependability consideration decreased hub energy's profit by 8.995% as compared to deterministic planning.

KEYWORDS

Stochastic energy hub scheduling; energy profit; uncertainty; Hong's two-point estimate method; improved artificial rabbits optimization

1 Introduction

Consumers in the commercial, industrial, and residential sectors are all linked to energy networks [1] those that provide electricity, natural gas, and district heating or cooling. To this point, several studies have been conducted in connection with energy infrastructures. Combining these systems may profit from the combined and flexible qualities of these systems, and this combination has been the subject of different research. Natural gas distribution networks offer the potential to store energy straightforwardly and cost-effectively [2,3]. On the other side, the power system can transport energy from great distances with only a moderate amount of energy being lost in the process. Therefore, merging these two networks and making use of the assets of each will result in an improvement in the system's efficiency and reliability as well as optimum performance [2,3]. To understand the impact that the combination of different energy carriers has on the economic and technical indicators associated with energy systems, such structural and operational flexibility necessitates the existence of an all-encompassing framework. In recent years, a general framework known as a hub has been proposed in [4,5]. This framework, which combines a variety of energy carriers and performs conversion and storage in them to supply the required load on the consumer side, was developed as a result of research conducted in recent years. An energy hub is a unit that, upon receiving various energy carriers at its input and carrying out the required energy conversion or storage, provides, at its output, either the final energy required by the local consumer load or the input energy required by an independent energy distributor. This is accomplished by the energy hub receiving various energy carriers at its input and performing the necessary energy conversion or storage [6,7]. The combined heat and power (CHP) equipment, distributed generation, renewable energy sources, electrical and heating energy storage and boilers, and active loads are all components that might be included in an energy hub model. On the other hand, simultaneous and coordinated planning of all energy equipment at the point of use may increase network performance and system flexibility in conjunction with a variety of different kinds of electric, gas, and heating networks [8,9].

Several investigations on the concept of an energy center have been carried out. In [10], the energy hub has a variety of sources, such as cogeneration units, steam boilers, renewable resources, electric chiller, absorption chiller, and electric, heating, and cooling energy storage devices. The purpose of these varied sources is to increase the adaptability of energy hubs. The findings demonstrated that, in contrast to the balance-based methods, which do not guarantee the optimality of the response, the operation of a multi-carrier local distribution system had been done in the case of islands that are separated from the main grid because of significant incidents or faults [11]. The results of this study can be found here [11]. This network is made up of three energy hubs, each of which, while aiming to satisfy their demand as efficiently as possible, can keep their operational expenses to a minimum by exchanging energy with the other energy hubs in the network. Using electricity-to-gas converters, the reference [12] presented a framework for the optimal operation of interconnected energy hubs with the goals of lowering costs, meeting the energy requirements of consumers, cutting greenhouse gas emissions, and improving the interaction between electricity and gas networks. A framework for decentralized energy management has been established, and it is based on the interaction that permits coordination amongst energy hubs. This framework may be found in [13]. A trading platform that would assist the integrated energy hub system's self-organized trade has been developed as part of this study to enhance the economic performance of the integrated energy hub system. This was done to achieve the goal. In [14], a bi-level scheduling approach is presented for isolated microgrids considering multi-stakeholders to minimize the operational cost using Jaya-interior point method. In [15], a bi-level scheduling framework is developed to participate in electric vehicle battery swapping stations to regulate the isolated microgrid economic operation with the objective of net costs minimization and maximization of the profits.

A fresh paradigm for the efficient administration of energy hubs is described in reference [16]. As a result of this foundation, each energy hub is responsible for the management of its production resources to plan the supply and demand to lower the cost as well as the emission of pollutants. In [17], a hybrid robust energy management approach is presented for multi-energy microgrids including electric, heat, hydrogen and gas sub-networks considering uncertainties of renewable resources generation, and load demand. In [18], the linear approximation method is used to simplify the model of an interconnected system that includes three energy hubs, to reduce the computational costs; the study that was done in [19] provides a two-level optimization model of optimal planning. References [18,19] both aimed to reduce the costs associated with computation. An active distribution system can offer its excess power to the market and is used daily. This system is made up of DGs as well as various energy hubs. The hierarchical game approach is provided in reference [20], where it is used to discuss the development of an integrated energy system that includes the involvement of the customer in addition to electricity, gas, and several smart energy hubs. An ideal planning model that is based on dependability is described in [21] to link energy hubs employing multi-carrier energy infrastructures. This model is offered to connect energy hubs. In [22], an optimal and stochastic energy management framework for a energy hub plant is developed for solving the unit commitment problem considering for maximizing energy hub profit, minimizing the carbon emission, and mitigation of the uncertainties risk. In [23], a hierarchical energy management system is presented in the local network consisting of various residential energy hubs to minimize the cost and peak shaving of the upstream network. Both papers aim to minimize the cost of energy supply and greenhouse gas emissions. In [24], planning of energy hubs includes combined energy and heat sources, hydrogen storage systems, electric vehicles, and controllable loads is performed to minimize the cost of power generation as well as the spread of environmental pollution. An optimization strategy for energy hubs is provided in reference [25] in the context of the demand response energy market. The water wave optimization (WWO) algorithm is used to present the planning model for the performance of energy sources and energy storage by satisfying the constraints of the electricity and natural gas network while taking into consideration the responsive load. This is done by satisfying the requirements of the energy network. Quantum particle swarm optimization (QPSO) is used in [26] to investigate energy hub system planning using wind and photovoltaic sources with optimal interaction between different sources to supply different system loads. The overall goal of this investigation is to minimize the total system cost. Wind and photovoltaic sources are used as sources. Energy planning in a storage-based residential system is presented in reference [27] based on a multi-criteria optimization method with the participation of the demand side to minimize production costs and maximize the level of consumer satisfaction using the shuffled frog leaping algorithm. This was done to achieve both goals (SFLA). Using VlseKriterijumska Optimizacija I Kompromisno Resenje, Lu et al. [28] presented the optimization of the energy hub to minimize operating cost, carbon emission, and energy efficiency based on a multi-objective optimization model. The goal of this optimization is to maximize energy efficiency (VIKOR). Using an ant-lion optimizer and krill herd optimization (ALO-KHO) algorithm, AkbaiZadeh et al. [29] developed hub energy management with the participation of electricity, gas, and heating networks to minimize the cost of operation in the presence of energy and storage resources. This is done to achieve the goal of minimizing the cost of operation.

The review of previous studies has shown that the planning of energy hubs requires a stochastic approach that is implemented in terms of implementation and has a low computational cost. In addition, this presented a stochastic approach based on the market model for energy hubs should be able to maximize their revenue in day-ahead electricity, gas and heating markets. According to the literature evaluation, most of the stochastic programming is presented by the Monte Carlo simulation method. This method depends on the probability distribution function of the inputs and has a very high computational cost. On the other hand, efficient and coordinated planning of hub energy equipment in cooperation with all types of electricity, gas and heating networks requires a strong solver due to the non-linear and multi-dimensional nature of the problem. In addition, methods for one-dimensional and multi-dimensional approximations for the linearization of non-convex functions of natural gas transmission, generator cost and compressor performance are presented in the literature, these linearizations are not required when using meta-heuristic algorithms. Therefore, the review of the literature shows that there is a need for a stochastic energy hub planning framework with easy implementation and low computational cost in cooperation with day-ahead electricity, gas and heating markets for energy economic analysis with the aim of maximizing energy profit. This paper uses the two-point estimation method along with a meta-heuristic algorithm that has high computational power and optimization, and can provide the conditions to achieve maximum profit from an energy hub in the conditions of uncertainty of energy resources production.

In this article, the stochastic scheduling of the energy hub using an approach called Hang's two-point estimation method (TPEM) is presented. The goal of the paper is to achieve the maximum possible profit from the production of energy in the future market. Participants include networks for the distribution of electricity, natural gas, and district heating. According to NFL theory [30], a meta-heuristic algorithm may function well in addressing certain optimization issues, but the same algorithm cannot give an optimum solution in solving other problems. This is because some optimization problems are more complex than others. On the other hand, enhancing the performance of meta-heuristic algorithms by the use of specialized approaches might help avoid the algorithms' premature convergence and improve their capacity to arrive at the global optimum solution promptly. In light of this fact, the author of this research employs a brand-new meta-heuristic method known as artificial rabbits optimization (IARO) in order to tackle the issue of energy hub schedules. The behavior of rabbits as they search for food served as the basis for the artificial rabbit's optimization (ARO) algorithm [31]. The artificial rabbits optimization algorithm was developed because the traditional method suffers from premature convergence when applied to problems with high levels of complexity. In this work, the dynamic inertia weight technique [32] is used to increase the performance of standard ARO in dealing with these types of situations. In this investigation, a comparison is made between the effectiveness of the suggested IARO in resolving the stochastic energy hub scheduling issue and the performance of the classic ARO, PSO, and SSA approaches. The goal of this investigation is to maximize profits. The daily power and profit fluctuations for various energies in the markets for electricity, heating, and gas, as well as the influence of varying load levels, and also equipment exit rate, have all been analyzed for their impact on the profit from the sale of energy. The novelty of the paper is to present a combined approach of the two-point estimation method (PEM) and the meta-heuristic improved artificial rabbits optimization algorithm for the optimal planning of the energy hub. The two-point estimation method is applied for uncertainty modeling and the meta-heuristic algorithm is used to determine the optimal size of the hub energy equipment in the day-ahead market.

The major contributions of this paper are listed below:

1) Providing a stochastic scheduling framework including photovoltaic and wind energy sources, CHP, boiler, and energy storage based on Hang's two-point estimation method.
2) Maximization of energy profit due to participation in electricity, natural gas, and heating markets based on optimal scheduling framework of an energy hub.

3) Evaluation of changes in load levels and the forced output rate of renewable energy resources and CHP equipment in solving the problem of hub scheduling and energy profit.
4) A new meta-heuristic algorithm called the improved ARO algorithm based on dynamic inertia weight for solving energy hub schedules.
5) Comparing the performance of the optimal energy hub scheduling framework based on IARO with the traditional methods of ARO, PSO, and SSA.

The paper is organized in such a way that in Section 2, the formulation of the problem including the profit function and the operation and hub constraints are presented. In Section 3, Hang's two-point estimation method is described and the proposed meta-heuristic algorithm and how to solve the problem by it are described in Section 4. In Section 5, simulation results and Section 6, study findings are concluded.

2 Problem Formulation

The day-ahead market, with the aim function of maximizing energy profit, and with the restrictions of network operation and hubs are all taken into consideration in this section's stochastic scheduling presentation for participation in the electricity, natural gas, and district heating networks. The energy hub model and analytical approach are discussed in the paragraphs that follow.

2.1 Hub Energy System

Fig. 1 illustrates the stochastic scheduling framework for energy hub scheduling in the day-ahead market for electricity, gas, and heating. In order to increase the energy hub's profit in the electricity, gas, and district heating day-ahead markets, it is equipped with solar energy sources, wind sources, CHP, boilers, storage components, and electric parking lots based on electric vehicles (EVs).

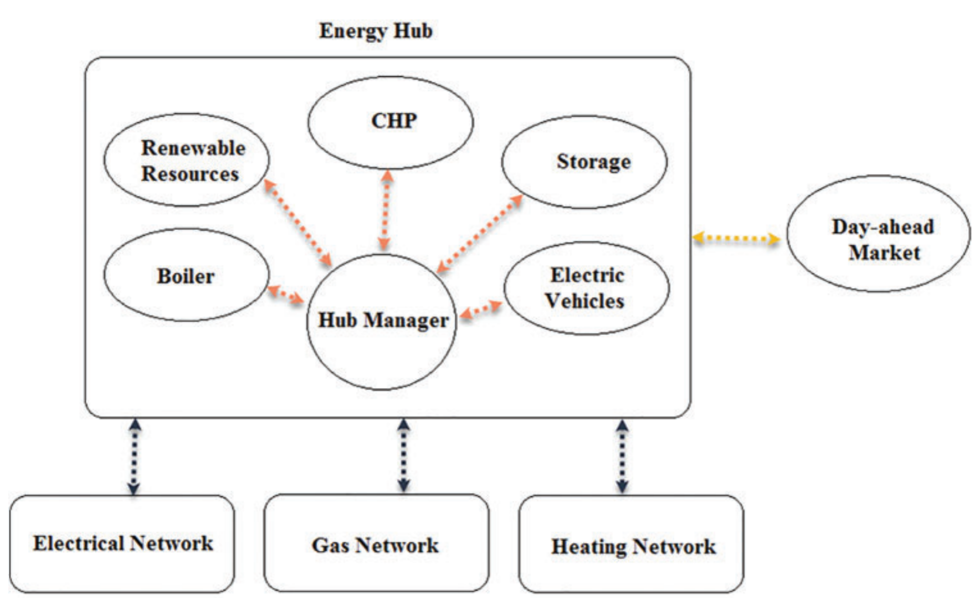

Figure 1: The presented framework of optimal energy scheduling of the energy hub

2.2 Objective Function

In this research, to maximize profits, hub energy stochastic scheduling utilizing Hang's two-point estimate method (TPEM) is given in the market confronting electricity, natural gas, and district heating. The sale of active and reactive power in the electricity market, as well as the revenue of the hub energy in the day-ahead natural gas and district heating markets, are all included in the goal function of profit maximization of the energy hub. This objective function is described as follows:

$$Max\ \mathrm{Pr}ofit = \sum_{t=\Omega_t} \sum_{m\in\Omega_{Hub}} \left\{ \lambda_t^e \left(H_{m,t}^p + k_q \left| H_{m,t}^q \right| \right) + \lambda_t^g H_{m,t}^g + \lambda_t^h H_{m,t}^{gh} \right\} \tag{1}$$

2.3 Limitations of the Problem

2.3.1 Power Flow Constraint

The power flow constraints in electricity, natural gas, and district heating networks are presented below [27–29]:

- The active and reactive power balance in different buses

$$DS_{e,t}^p - S_{e,t}^p + \sum_{m\in_{Hub}} AH_{e,m}^e H_{m,t}^p = \sum_{j\in\Omega_e} A_{e,j}^e F_{e,j,t}^p \quad \forall e, t \tag{2}$$

$$DS_{e,t}^q - S_{e,t}^q + \sum_{m\in_{Hub}} AH_{e,m}^e H_{m,t}^q = \sum_{j\in\Omega_e} A_{e,j}^e F_{e,j,t}^q \quad \forall e, t \tag{3}$$

- Active and reactive power flow of lines

$$F_{e,j,t}^p = G_{e,j}(V_{e,t})^2 - V_{e,t}V_{j,t} \left\{ G_{e,j}\cos(\delta_{e,t} - \delta_{j,t}) + B_{e,j}\sin(\delta_{e,t} - \delta_{j,t}) \right\} \quad \forall e, t \tag{4}$$

$$F_{e,j,t}^q = -B_{e,j}(V_{e,t})^2 + V_{e,t}V_{j,t} \left\{ B_{e,j}\cos(\delta_{e,t} - \delta_{j,t}) - G_{e,j}\sin(\delta_{e,t} - \delta_{j,t}) \right\} \quad \forall e, t \tag{5}$$

- Voltage angle in the base bus

  The voltage angle in the base buses are set at zero, i.e., $\delta_{e,t} = 0$, $\forall$ $e \in$Slackbus.

- Balance of gas power and flow

  The balance of gas power in different buses and gas flow through the pipeline at hour t are as follows:

$$GS_{g,t} - L_{g,t}^g + \sum_{m\in_{Hub}} AH_{g,m}^g H_{m,t}^g = \sum_{j\in\Omega_g} A_{g,j}^g F_{g,j,t}^g \quad \forall g, t \tag{6}$$

$$F_{g,j,t}^g = \kappa_{g,j}\mathrm{sign}\left(\pi_{g,t}, \pi_{j,t}\right) \sqrt{sign\left(\pi_{g,t}, \pi_{j,t}\right)\left(\pi_{g,t}^2, \pi_{j,t}^2\right)} \quad \forall g, j, t \tag{7}$$

- The heating power balance in buses

$$HS_{h,t} - L_{h,t}^h + \sum_{m\in_{Hub}} AH_{h,m}^h H_{m,t}^h = \sum_{j\in\Omega_g} A_{h,j}^h F_{h,j,t}^h \quad \forall h, t \tag{8}$$

- Heat power flow

  Heat power flow through a pipeline at time t is as follows:

$$F^{h}_{h,j,t} = c_{h,j}\dot{m}_{h,j}\left(T_{h,t} - T_{j,t}\right) \quad \forall h, j, t \tag{9}$$

DS^{p}, DS^{q}, G^{S}, and H^{S} represent the power of different stations assuming they are connected to the base bus or connected to a bus in different networks.

2.3.2 Network's Operation Constraints

The operating restrictions in the networks for electricity, natural gas, and district heating are discussed in this section. Eqs. (10)–(18) define these limitations.

- Voltage range of buses

$$V^{\min}_{e} \le V_{e,t} \le V^{\max}_{e} \quad \forall e, t \tag{10}$$

- Allowed capacity of lines and stations

$$\sqrt{\left(F^{p}_{e,j,t}\right)^{2} + \left(F^{q}_{e,j,t}\right)^{2}} \le F^{e,\max}_{e,j} \quad \forall e, j, t \tag{11}$$

$$\sqrt{\left(DS^{p}_{e,t}\right)^{2} + \left(DS^{q}_{e,t}\right)^{2}} \le DS^{\max}_{e} \quad \forall e, t \tag{12}$$

- Bus pressure limit

$$\pi^{\min}_{g} \le \pi_{g,t} \le \pi^{\max}_{g} \quad \forall g, t \tag{13}$$

- The capacity of gas pipes and station

$$-F^{g,\max}_{g,j} \le F^{g}_{g,j,t} \le F^{g,\max}_{g,j} \quad \forall g, j, t \tag{14}$$

$$-GS^{\max}_{g} \le GS_{g,t} \le GS^{\max}_{g} \quad \forall g, t \tag{15}$$

- The thermal limit of buses

$$T^{\min}_{h} \le T_{h,t} \le T^{\max}_{h} \quad \forall h, t \tag{16}$$

- The capacity of the station and heating pipeline

$$-F^{h,\max}_{h,j} \le F^{h}_{h,j,t} \le F^{h,\max}_{h,j} \quad \forall h, j, t \tag{17}$$

$$-HS^{\max}_{h} \le HS_{h,t} \le HS^{\max}_{h} \quad \forall h, t \tag{18}$$

2.3.3 Hub Energy Constraints

The hub energy in this research consists of solar and wind renewable energy sources, storage, electric parking, CHP, and a boiler, and it is linked to the regional heating network to deliver and receive energy. Eqs. (19)–(22) are used to compute the active gas production and hub heating powers

$$H^{p}_{m,t} = CHP^{p}_{m,t} + RES_{m,t} + \left(ST^{p,dch}_{m,t} - ST^{p,ch}_{m,t}\right) + \left(EV^{p,dch}_{m,t} - EV^{p,ch}_{m,t}\right) - HD^{p}_{m,t} \quad \forall m, t \tag{19}$$

$$H^{q}_{m,t} = CHP^{q}_{m,t} + ST^{q}_{m,t} + EV^{q}_{m,t} - HD^{q}_{m,t} \quad \forall m, t \tag{20}$$

$$H^{g}_{m,t} = -CHP^{g}_{m,t} + BO^{g}_{m,t} - HD^{g}_{m,t} \quad \forall m, t \tag{21}$$

$$H^{h}_{m,t} = CHP^{h}_{m,t} + BO^{h}_{m,t} - HD^{h}_{m,t} \quad \forall m, t \tag{22}$$

Eq. (23) presents the power balancing equation for CHP while taking into account the CHP power limit in the gas network, the electricity network, and the heating network.

$$CHP^{g}_{m,t} = \frac{(CHP^{g}_{m,t} + CHP^{h}_{m,t})}{\eta^{CHP}} \quad \forall m, t \tag{23}$$

$$0 \leq CHP^{h}_{m,t} \leq CHP^{h,\max}_{m} \quad \forall m, t \tag{24}$$

$$\sqrt{\left(CHP^{p}_{m,t}\right)^2 + \left(CHP^{q}_{m,t}\right)^2} \leq CHP^{e,\max}_{m} \quad \forall m, t \tag{25}$$

$$0 \leq CHP^{h}_{m,t} \leq CHP^{h,\max}_{m,t} \quad \forall m, t \tag{26}$$

Based on Eqs. (27)–(32), the storage system's limitations are stated. These limitations are based on the range of stored energy (Eq. (25)), the charge and discharge range (Eqs. (28) and (29)), the range of primary energy (Eq. (30)), the range of stored energy (Eq. (31)), and the charger's limit (Eq. (32)).

$$E^{ST}_{m,t+1} = E^{ST}_{m,t} + \eta^{ST,ch} ST^{p,ch}_{m,t} - \frac{1}{\eta^{ST,dch}} ST^{p,dch}_{m,t} \quad \forall m, t \tag{27}$$

$$0 \leq ST^{p,ch}_{m,t} \leq CR^{ST}_{m} st_{m,t} \quad \forall e, t \tag{28}$$

$$0 \leq ST^{p,dch}_{m,t} \leq DR^{ST}_{m} (1 - st_{m,t}) \quad \forall m, t \tag{29}$$

$$E^{ST}_{m,t} = E^{ini}_{m} \quad \forall m, t = 1 \tag{30}$$

$$E^{\min}_{m} \leq E^{ST}_{m,t} \leq E^{\max}_{m} \quad \forall m, t \tag{31}$$

$$\sqrt{\left(ST^{p,dch}_{m,t} - ST^{p,ch}_{m,t}\right)^2 + \left(ST^{q}_{m,t}\right)^2} \leq ST^{\max}_{m} \quad \forall m, t \tag{32}$$

Eqs. (33)–(38), which are stated as restrictions on EV parking, are given [27–30]. The equation is used to determine the amount of energy kept in EV batteries (33). Eqs. (34) and (35) define the charging and discharging capability of EVs. Eqs. (36) and (37) provide the energy value of the batteries at the time of arrival and departure, while Eq. (38) describes the capacity of the EV charger.

$$E^{EV}_{m,t+1} = E^{EV}_{m,t} + \eta^{EV,ch} E^{p,ch}_{m,t} - \frac{E^{p,dch}_{m,t}}{\eta^{EV,dch}} \quad \forall m, t \tag{33}$$

$$0 \le E_{m,t}^{EV,p,ch} \le CR_{m,t}^{EV} ev_{m,t} \quad \forall m, t \tag{34}$$

$$0 \le E_{m,t}^{EV,p,dch} \le DR_{m,t}^{EV} (1 - ev_{m,t}) \quad \forall m, t \tag{35}$$

$$E_{m,t}^{EV} = E_{m,t}^{arr} \quad \forall m, t = Arrival\, time \tag{36}$$

$$E_{m,t}^{EV} = E_{m,t}^{dep} \quad \forall m, t = Departure\, time \tag{37}$$

$$\sqrt{\left(EV_{m,t}^{p,dch} - EV_{m,t}^{p,ch}\right)^2 + \left(EV_{m,t}^{q}\right)^2} \le EV_{m,t}^{\max} \quad \forall m, t \tag{38}$$

Also, the boiler power balance equation and capacity constraints are defined based on Eqs. (39) and (40) [19].

$$BO_{m,t}^{g} = \frac{BO_{m,t}^{h}}{\eta^{BO}} \quad \forall m, t \tag{39}$$

$$0 \le BO_{m,t}^{g} \le BO_{m}^{\max} \quad \forall m, t \tag{40}$$

where CR^{EV}/DR^{EV} is equivalent to $\sum_{i=1}^{N_{1t}} CR_i^{ev} / \sum_{i=1}^{N_{1t}} DR_i^{ev}$ that DR^{ev}, CR^{ev} and N_{1t} are, respectively, the charging rate of the EVs, the discharging rate of the EVs, and the number of EVs in the parking lot at hour t. EV^{max} is equivalent to $\sum_{i=1}^{N_{1t}} CC_i^{ev}$ indicate CC^{ev} is the charging capacity of the EVs. E^{arr}/E^{dep} is equivalent to $\sum_{i=1}^{N_{2t}} SOC_i BC_i / \sum_{i=1}^{N_{3t}} BC_i$ which SOC expresses the state of charge and BC is the battery capacity of any EVs. N_{2t} and N_{3t} also refers to the arrival and departure times of EVs.

3 Two-Point Estimate Method and Implementation

Hong's two-point estimate method (TPEM), an approximation approach for calculating the uncertainty of solar and wind energy sources, is utilized in this article. Using the TPEM approach, certain representative points (s points for each variable) have been identified under the heading of concentrations based on the data supplied by the center of moments. Using the answers found for the representative points, these points were utilized to solve the model and the statistical data of the random output variable [33].

Consider that $X\{x_1, x_2, \ldots, x_l, \ldots, x_m\}$ represents a random variable with mean μ_{x_l} and standard deviation σ_{x_l} values. Also, Z is a random function of X ($Z = F(X)$). Each focus s of variables x_l can be defined as a pair consisting of a location $x_{l,s}$ and a weight $w_{l,s}$. The presented method is called Hong's two-point estimate method (HTPEM). According to the HTPEM method, the F function should be determined only s times for each random input variable x_l in the points created at the same place from the random input variable x_l and the average value of the remaining input variables (μ_{x_l}). Therefore, the total number of evaluations is 2 m. The location $x_{l,s}$ is defined as follows [33]:

$$x_{l,s} = \mu_{x_l} + \xi_{l,s} \times \sigma_{x_l} \tag{41}$$

where $\xi_{l,s}$ represents the standard location of the random variable x_l. Standard locations and weights of random variables x_l are defined as follows:

$$\xi_{l,1} = \frac{\lambda_{l,3}}{2} + \sqrt{m + \left(\frac{\lambda_{l,3}}{2}\right)^2} \tag{42}$$

$$w_{l,1} = -\frac{\xi_{l,2}}{m \times (\xi_{l,1} - \xi_{l,2})} \tag{43}$$

$$\xi_{l,2} = \frac{\lambda_{l,3}}{2} - \sqrt{m + \left(\frac{\lambda_{l,3}}{2}\right)^2} \tag{44}$$

$$w_{l,2} = -\frac{\xi_{l,1}}{m \times (\xi_{l,1} - \xi_{l,2})} \tag{45}$$

where $\lambda_{l,3}$ refers to the skewness of the random variable xl:

$$\lambda_{l,3} = \frac{E\left[\left(x_l - \mu_{x_l}\right)^3\right]}{\left(\sigma_{x_l}\right)^3} \tag{46}$$

The power of solar and wind renewable resources, in addition to loads, has been represented arbitrarily in the energy management issue. For each emphasis, the key element of energy management, the energy hub, must be used. The following is thought of as the problem's solution:

$$Z_{l,s} = F\left\{x_{1,1}, x_{l,2}, \ldots, x_{l,s}, \ldots, x_{m,s}\right\} \tag{47}$$

where $Z_{l,s}$ defines the vector of random output variables related to the concentration of the random input variable and refers to the non-linear relationship between input and output variables in the problem of energy hub management. The raw moments of the output random variables are defined as follows:

$$E(Z) \cong E(Z) + \sum_{s} w_{l,s} \times Z_{l,s} \tag{48}$$

The flowchart of the proposed stochastic methodology based on PEM and IARO is depicted in Fig. 2. Also, implementation steps to solve the problem are as follows:

Step 1) Setting the first and second moments of random output variables to 0: $E(Z) = 0$.

Step 2) In this step, the random input variable x_l is selected.

Step 3) $\lambda_{l,3}$, $\xi_{l,s}$ and $w_{l,s}$ values are computed using Eqs. (41)–(46).

Step 4) In this step, two estimated positions $x_{l,s}$ are determined.

Step 5) The hub energy management problem is solved for each focus.

Step 6) In this step, the raw moments of the output variables are updated.

Step 7) Steps 2 to 6 are repeated until all concentrations of input random variables are considered. If all concentrations and variables are considered, go to Step 8, and otherwise go to Step 2.

Step 8) Stop the algorithm and save the random output variables.

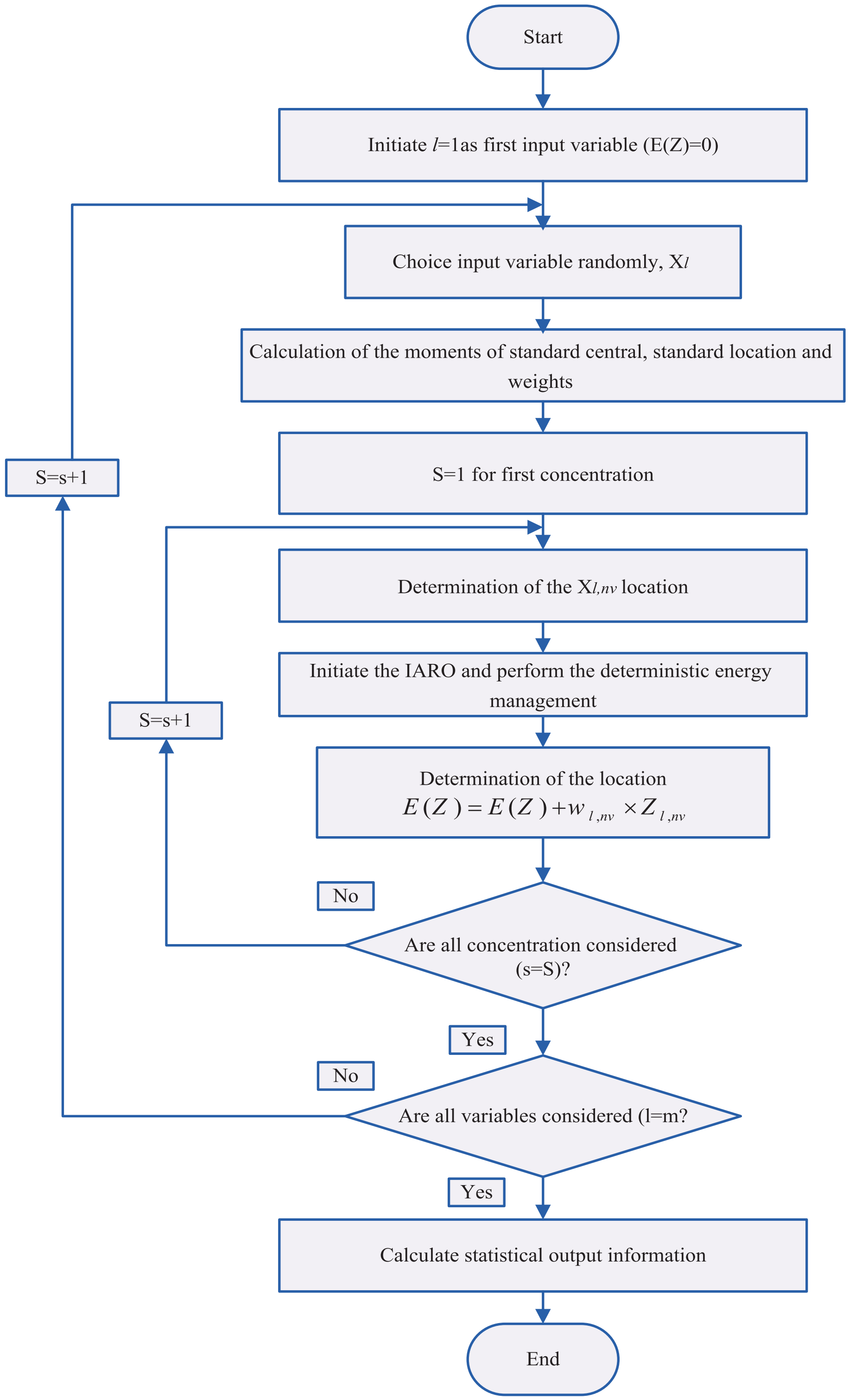

Figure 2: Flowchart of proposed stochastic methodology based on PEM and IARO

4 Proposed Optimization Method

In this study, an improved artificial rabbits optimization (IARO) is applied for optimal programming of the energy hub to maximize the energy profit in partnership with electricity, natural gas and district heating networks in the day-ahead market considering the uncertainty of photovoltaic and wind resource production. The role of the presented optimization algorithm is as a solver to determine the optimal capacity of hub energy equipment including photovoltaic and wind renewable energy sources, combined heat and power (CHP) system, boiler, energy storage and electric vehicles in the day-ahead market, as the profit of the system is maximized (Eq. (1)). Therefore, the presented meta-heuristic algorithm optimally determines the decision variables by considering the profit objective function and the constraints of network operation and hub energy in order to provide the best network performance. Providing an optimization algorithm with excellent exploration and exploitation power by achieving accurate scheduling of energy hub equipment as well as optimal energy management will lead to achieving more energy profit. Of course, the uncertainty of resources is also included in the presented stochastic planning.

4.1 Overview of the ARO

The ARO algorithm is based on rabbits' natural habitat survival techniques [31]. To tackle the optimization issue, the ARO algorithm employs foraging and hiding methods while minimizing the energy exchanged between these strategies.

4.1.1 Searching for Shortcut Food (Exploration)

In other words, they are not happy with the grass in their region and seek far afield, which is termed detour foraging. Rabbits tend to explore for food in far-off locations, therefore they have little interest in searching for food in their immediate surroundings. Within its territory, the ARO algorithm assigns each rabbit a certain number (d) of hiding spots. When searching for food, rabbits may sometimes take into account the location of other rabbits. In this technique, rabbits may receive enough food to eat while they are hunting for more food by congregating around a food source. Therefore, "detour foraging" refers to the practice of each searcher attempting to improve their position relative to the other searchers by introducing a disruption. The following is an explanation of how the detour foraging model is presented [31]:

$$\vec{v}_i(t+1) = \vec{x}_j(t) + R.\left(\vec{x}_i(t) - \vec{x}_j(t)\right) + round\,(0.5.\,(0.05 + r_1)).n_1,\quad i,j = 1,\ldots,n \text{ and } j \neq i \tag{49}$$

$$R = L.c \tag{50}$$

$$L = \left(e - e^{\left(\frac{t-1}{T}\right)^2}\right).\sin(2\pi r_2) \tag{51}$$

$$c(k) = \begin{cases} 1 & if\ k == g(l),\ \ k = 1,\ldots,d \text{ and } l = 1,\ldots,\lceil r_3.d \rceil \\ 0 & else \end{cases} \tag{52}$$

$$g = rand\,perm(d) \tag{53}$$

$$n_1 \sim N(0,1) \tag{54}$$

where $\vec{v}_i(t+1)$ denotes the ith candidate rabbit position at time $t+1$, $\vec{x}_i(t)$ designates the ith rabbit position at time t, n denotes the size of the rabbit population, d denotes the number of dimensions of the problem, T denotes the maximum number of iterations, $\lceil . \rceil$ denotes the ceiling function, and rand perm denotes the random order of integers 1 to d. Also, r_1 to r_3 denotes three random numbers in the range (1, 0).

4.1.2 Random Hiding (Exploitation)

A rabbit creates many hiding sites (d) around each dimension of the search area in each iteration and thinks about hiding in one of those locations. By doing this, it lessens the likelihood of hunting itself. The following definition applies to the ith rabbit's jth hiding spot [31]:

$$\vec{b}_{i,j}(t) = \vec{x}_i(t) + H.g.\vec{x}_i(t), \ \ i = 1, \ldots, n \ and \ j = 1, \ldots, d \tag{55}$$

$$H = \frac{T - t + 1}{T}.r_4 \tag{56}$$

$$n_2 \sim N(0, 1) \tag{57}$$

$$g(k) = \begin{cases} 1 & if \ k == j, \ \ k = 1, \ldots, d \\ 0 & else \end{cases} \tag{58}$$

A variety of hiding spots are created around a rabbit throughout each dimension d. H stands for the hidden parameter, which linearly changes from 1 to $1/T$ depending on a random disturbance occurring throughout the repetitions.

Rabbits are not interested in selecting one of the hiding locations at random in order to hide from the hunter and avoid being pursued. According to this definition of random concealing behavior [31]:

$$\vec{v}_i(t+1) = \vec{x}_i(t) + R.\left(r_4.\vec{b}_{i,r}(t) - \vec{x}_i(t)\right), \ \ i = 1, \ldots, n \tag{59}$$

$$g_r(k) = \begin{cases} 1 & if \ k == \lceil r_5.d \rceil, \ \ k = 1, \ldots, d \\ 0 & else \end{cases} \tag{60}$$

$$\vec{b}_{i,r}(t) = \vec{x}_i(t) + H.g_r.\vec{x}_i(t) \tag{61}$$

where $\vec{b}_{i,r}$ denotes hiding that is thought to be hidden from d hideouts at random, and r_4 and r_5 stand for integers between 0 and 1, again at random. The i-th searcher attempts to update his location with the random hideaway chosen from among the number of d hideouts following the equations above refers to a hideout considered randomly to hide from d number of hideouts and r_4 and r_5 represent numbers between 0 and 1, randomly. According to the above equations, the i-th searching person tries to update his position concerning the random hideout considered from the number of d hideouts.

The position of the i-th rabbit is updated as follows [31]:

$$\vec{x}_i(t+1) = \begin{cases} \vec{x}_i(t) & f\left(\vec{x}_i(t)\right) \leq f\left(\vec{v}_i(t+1)\right) \\ \vec{v}_i(t+1) f\left(\vec{x}_i(t)\right) > f\left(\vec{v}_i(t+1)\right) \end{cases} \tag{62}$$

4.1.3 Energy Reduction (Transition from Exploration to Exploitation)

In the ARO algorithm, rabbits often engage in detour foraging, but as iterations go on, they also engage in random hiding. As a result, the rabbit loses energy over time. The energy component is thus given as follows [31]:

$$A(t) = 4\left(1 - \frac{t}{T}\right)\ln\frac{1}{r} \tag{63}$$

r stands for a number between 0 and 1. The rabbit engages in random exploration and detours foraging when $A(t) > 1$. $A(t) \leq 1$ results in random hiding since the rabbit is not motivated to use its hiding sites at random. Fig. 3 depicts the search structure by factor A.

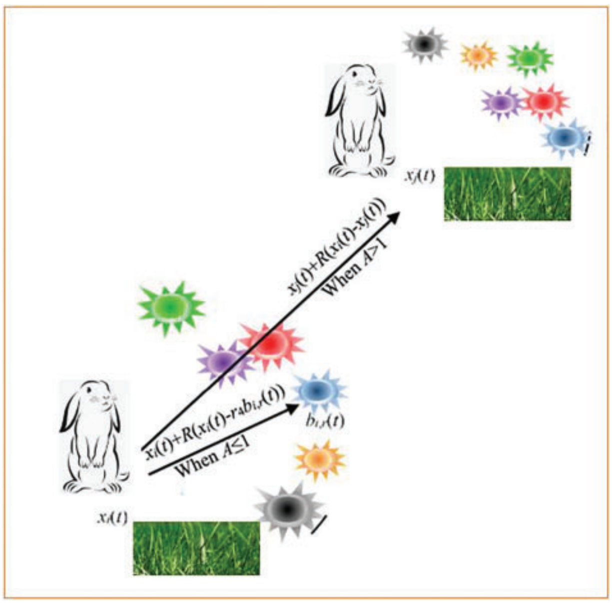

Figure 3: Search structure according to factor A

As a result, the ARO creates a population of rabbits at random to serve as candidate answers in the search space. The rabbit changes its location to a randomly selected rabbit from the population or a randomly selected rabbit drawn from the hides with each iteration. Factor A undergoes a declining process as the repetitions rise, forcing every rabbit in the population to carry out the transfer procedure. To get the best response from the algorithm, it has been modified until it meets the convergence condition. Fig. 4 displays the ARO algorithm's pseudo-code.

Initiate a rabbits set X_i and calculate the fitness (Fit_i) and X_{best}
While the convergence criteria is not met do
    For each individual X_i do
    Compute the A operator via Eq. (63)
    If A>1
        Select a rabbit from individuals randomly
        Compute R via Eqs. (51)-(54)
        Implement detour foraging using Eq. (49)
        Compute the Fit_i
        Update the present individual position via Eq. (62)
    Else
        Produce d burrows and pick hiding randomly via Eq. (61)
        Implement the hiding randomly via Eq. (59)
        Compute the Fit_i
        Update the individual position via Eq. (34)
    End If
    Update the best solution determined X_{best}
    End For
End While
Return X_{best}

Figure 4: Pseudo code of ARO

4.2 Overview of IARO

The non-linear dynamic weight inertia [32] equation is introduced in this paper in order to enhance dynamic control, achieve equilibrium between the phases of exploration and exploitation, as well as enhance the local search capacity of the algorithm against premature convergence. The definition of this inertia weight is as follows:

$$IW = IW_{\min} + (IW_{\max} - IW_{\min}) \times \frac{FV_{ave,good} - FV_1}{FV_{ave,good} - FV_{ave,bad}} \tag{64}$$

Rabbits are grouped according to their fitness function values into good and bad rabbits. $FV_{ave,good}$ represents the average fitness value of good rabbits, while $FV_{ave,bad}$ represents the average fitness value of bad rabbits. It demonstrates that rabbits have a lower average fitness value than they do on average. By balancing the exploration and exploitation phases, the suggested adaptive inertia weight may improve the algorithm's effectiveness and performance. Fig. 5 shows the IARO flowchart in action.

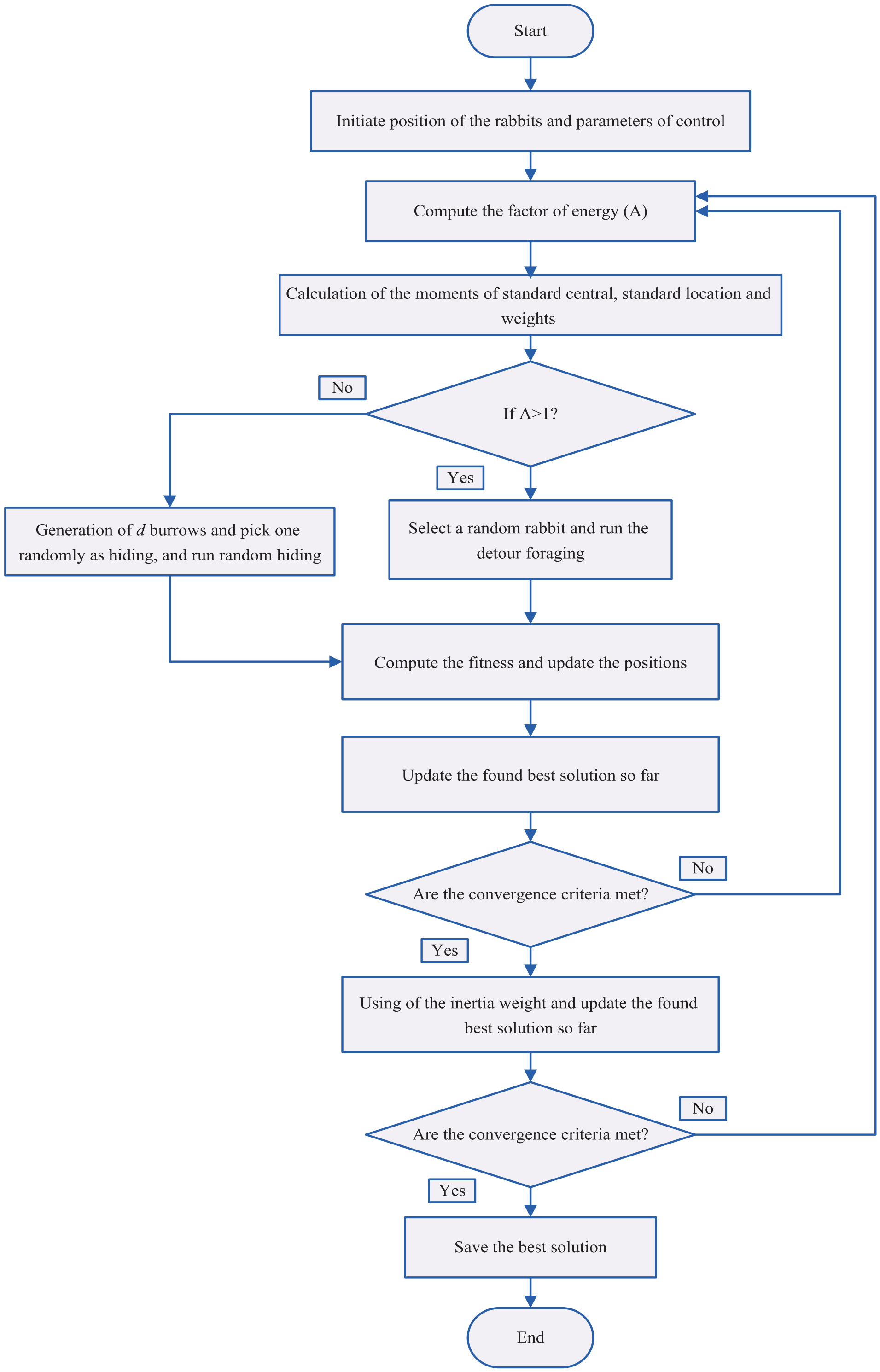

Figure 5: Flowchart of IARO

5 Simulation Results and Discussion

This section uses the HTPEM and IARO to demonstrate the results of stochastic hub energy scheduling and management in various networks that are exposed to electricity, gas, and district heating networks in day-ahead markets. In order to maximize hub profits, the hub energy scheduling issue is treated as an optimization problem. In this work, the optimization issue is solved using the IARO algorithm, and the performance of the algorithm is evaluated against that of the traditional ARO, PSO, and SSA approaches. Each algorithm's population, maximum iteration, and a number of independent executions are chosen as 100, 200, and 25 accordingly. Each algorithm is executed 25 times and the best solution among all executions is selected as the final solution. Also, the performance of the algorithms are evaluated using a statistical analysis including the Best, Mean and Worst, std indices. The proposed method is implemented in Matlab software on a personal computer with Intel Core i7-4510U, up to 3.1 GHz, 8 GB RAM, and Windows 10, 64-bit. Table 1 lists the control settings for several methods. It should be mentioned that the values given by their authors in reference articles serve as the control parameters for various approaches.

Table 1: Control parameters of different algorithms

Algorithm	Parameter	Value
ARO [31]	–	–
PSO [34]	C1, C2 (personal and social constants)	2
	Wmax and Wmin (maximum and minimum inertia weight)	0.9, 0.2
SSA [35]	c2, c3 (random numbers)	[0, 1]

5.1 System under Study and Data

The system under study consists of a 12-line electrical network with 9 buses, a gas network with 4 buses and 5 pipes, and an urban heating network with 9 buses and 9 pipelines (Fig. 6). Table 2 provides line/pipeline statistics using 1 MW as the base power, 1 kV as the base voltage, 10 bar as the basis pressure, and 100°C as the base temperature. The voltage, pressure, and temperature ranges are also [0.9, 1.1] p.u. Table 3 contains information on the system load during the electric load peak hour. During the other hours, the load percentage value is multiplied by the load value at 20:00. Fig. 7 depicts the load curve (peak load %) for the electric and heating networks. Fig. 8 also displays the daily energy pricing curve for electricity, gas, and district heating energy in the day-ahead market. Gas, electricity, and heating stations are rated at 7, 11, and 3 p.u, respectively. Seven hubs make up the suggested test system; their locations and details are shown in Fig. 6 and Table 4, respectively. Photovoltaic and wind energy are two of Hub's renewable energy sources; their estimated power is shown in Figs. 9 and 10, respectively [36]. Additionally, 60 EVs are thought to be present in hubs 1, 2, 3, 5, 6, and 7. Every hour, the information for battery SOC, BC, charge/discharge rate, EV efficiency, and the penetration rate is taken into account [30,37]. Charge/discharge rate and efficiency are estimated to be 0.3 and 0.88 for an electric storage system with a charger capacity of 0.5 p.u, and the minimum and the maximum capacity of 0.5 and 2 p.u, respectively. Additionally, the power, gas, and heating networks' CHP capacity is 2.5, 1, 1, with a combined efficiency of 0.8 [37]. The boiler system has a capacity and efficiency of 1 and 0.8, respectively.

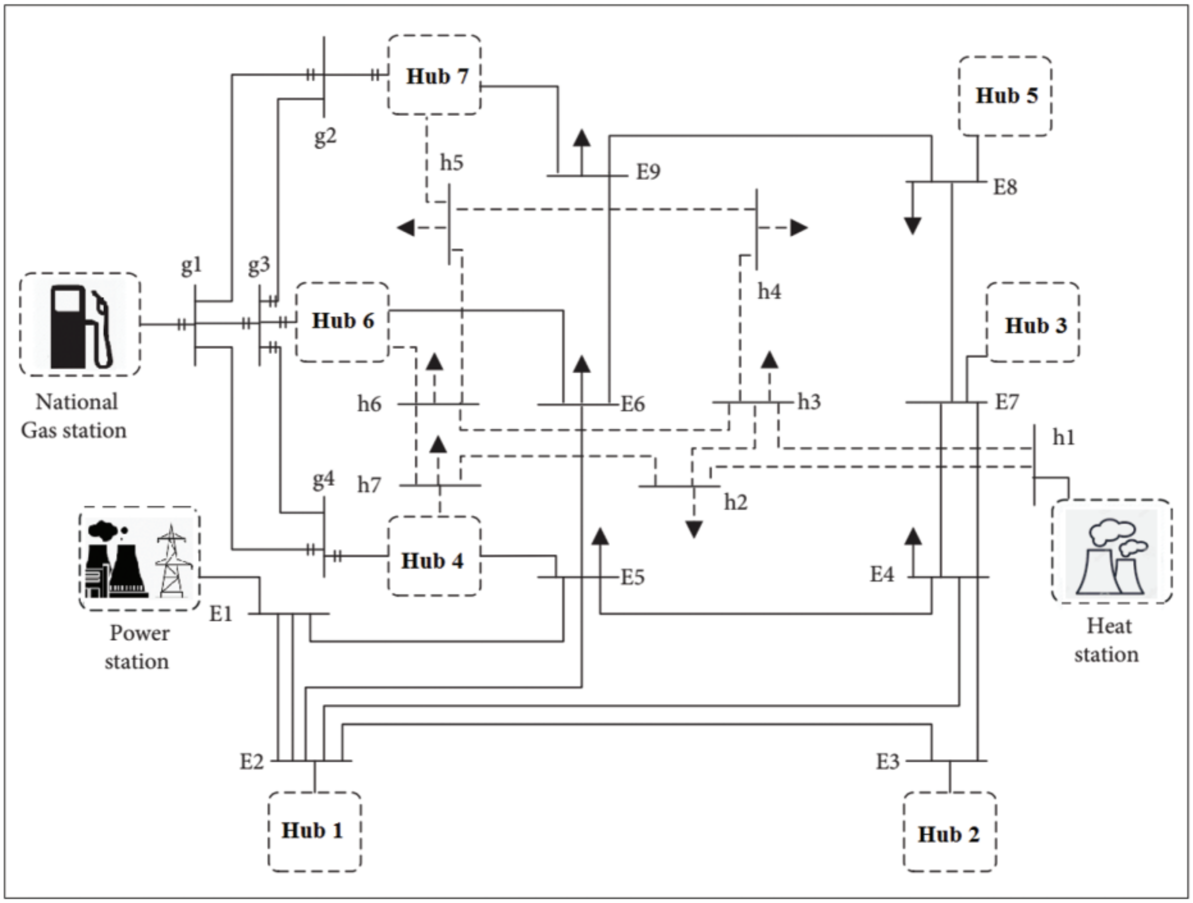

Figure 6: Schematic of the studied system

Table 2: Data of transmission lines, gas, and heating pipelines (p.u)

Electrical network				Natural gas network				District heating network		
Line	R	X	$F^{e,max}$	Pipeline	κ	sign	$F^{g,max}$	Pipeline	$c \times \dot{m}$	$F^{h,max}$
1-2	0.02	0.06	0.90	1-2	3	1	1.1	1-2	15	1.00
1-5	0.05	0.12	0.50	1-3	3.5	1	3.0	1-3	18.5	1.30
2-3	0.05	0.12	0.65	1-4	4	1	1.2	2-3	17.5	0.20
2-4	0.06	0.08	0.75	2-3	4.5	−1	0.6	2-7	18.5	0.50
2-5	0.06	0.11	0.80	3-4	4.5	1	0.8	3-4	19.5	0.65
3-4	0.07	0.11	1.20					3-6	19	0.20
4-5	0.01	0.04	0.65					4-5	15	0.35

(Continued)

Table 2 (continued)

Electrical network				Natural gas network				District heating network		
Line	R	X	$F^{e,max}$	Pipeline	κ	sign	$F^{g,max}$	Pipeline	$c \times \dot{m}$	$F^{h,max}$
4-7	0.01	0.03	0.90					5-6	19	0.10
5-6	0.02	0.05	1.10					6-7	19.5	0.20
6-9	0.10	0.09	0.30							
7-8	0.02	0.07	1.30							
8-9	0.08	0.12	0.35							

Table 3: Demand data for electricity, gas, and heating during peak hours (p.u)

Electrical network			Natural gas network		District heating network	
Bus	L^p	L^q	Node	L^h	Node	L^g
1	0	0	1	0	1	0
2	0	0	2	0.8	2	0
3	0	0	3	0.7	3	0
4	0.9	0.3	4	0.9	4	0
5	0.7	0.5	5	0.6		
6	1	0.2	6	0.5		
7	0	0	7	0.7		
8	0.5	0.5				
9	0.3	0.3				

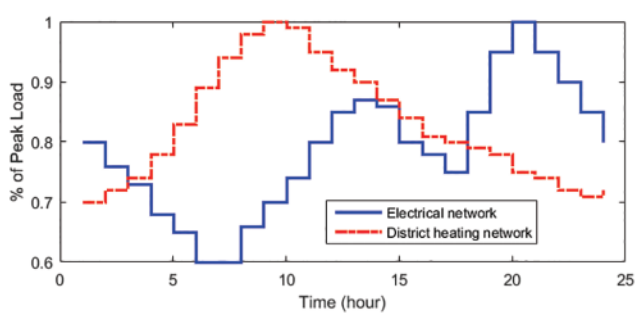

Figure 7: The daily curve of network load percentage

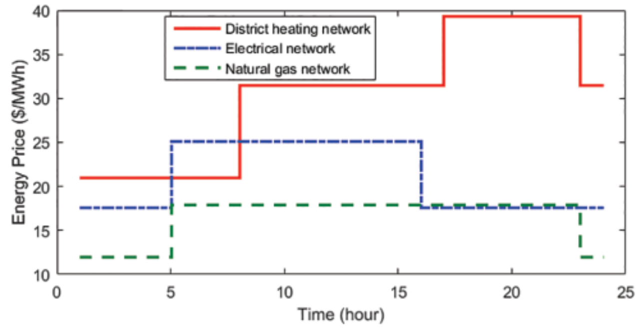

Figure 8: The daily curve of energy prices in the DA market

Table 4: Hub specifications

System	Location			RES	Storage	EVs	CHP	Boiler	Load (p.u)			
	E	G	h						HD^p	HD^q	HD^h	HD^g
Hub 1	2	-	-	✓	✓	✓			0.8	0.4	0	0
Hub 2	3	-	-	✓	✓	✓			0.5	0.3	0	0
Hub 3	7	-	-	✓	✓	✓			0.6	0.4	0	0
Hub 4	5	4	7				✓	✓	0.2	0.1	0.3	0
Hub 5	8	-	-	✓	✓	✓			0.4	0.2	0	0
Hub 6	6	3	6	✓	✓	✓	✓	✓	0.4	0.2	0.2	0
Hub 7	9	2	5	✓	✓	✓	✓	✓	0.4	0.2	0.2	0

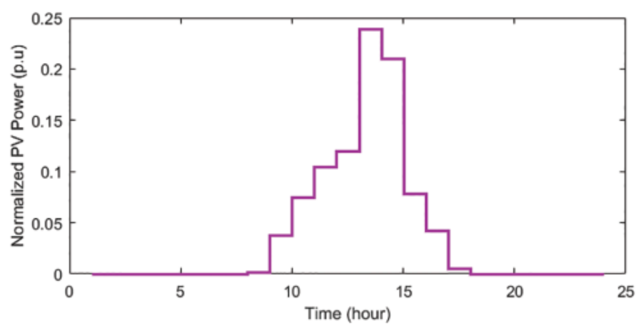

Figure 9: The daily curve of irradiance

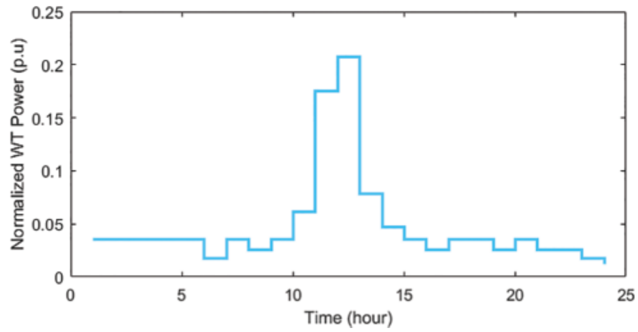

Figure 10: The daily curve of wind speed

5.2 Results of Deterministic Scheduling

The implementation of a new meta-heuristic algorithm called IARO allows for the optimal and deterministic scheduling of energy hubs without taking into account the unpredictability of renewable energy sources with the goal of maximizing profits in the day-ahead markets in various electricity, natural gas, and urban heating networks. The standard ARO, PSO, and SSA algorithms and the IARO algorithm have also been compared for their effectiveness in handling the energy hub scheduling issue. Fig. 11 depicts the convergence of several optimization techniques. It should be noticed that the objective function has a negative sign in order to meet the profit maximization target owing to the minimization in the Matlab program. It is clear that the suggested IARO approach outperformed other methods in terms of achieving the global solution or the highest profit with a greater convergence speed.

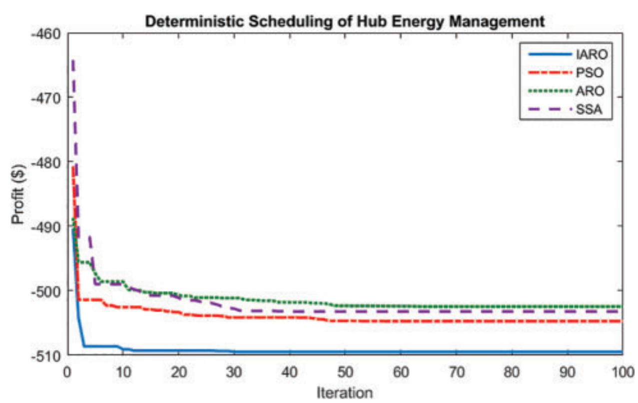

Figure 11: Convergence curve of different algorithms in solving the deterministic scheduling problem

Table 5 provides the numerical outcomes of hub energy scheduling based on the suggested technique. It is clear that in the 12th iteration, the IARO technique made a profit of \$509.40, but the other methods were unable to do so since they were trapped in the local optimum. Additionally, it is noted that although the conventional ARO technique's upgraded version experienced premature convergence with a profit value of \$502.11, the traditional ARO method did not due to the performance enhancement of the non-linear dynamic inertia weight approach. Also, the proposed method has a lower computational cost compared to the other methods. The greater capacity of the IARO algorithm has been validated in terms of attaining better statistical indicators, in addition to the statistical analysis carried out for various algorithms in Table 6. The findings demonstrated that by striking a balance between the algorithm's exploration and exploitation phases, energy hub scheduling based on IAR may avoid premature convergence and reach the global optimum more quickly. The findings demonstrate that by resolving the many operational and energy hub restrictions, a potent optimization technique can guarantee the energy hub's best economic performance.

Table 5: The numerical results of different methods in solving the deterministic scheduling problem

Algorithm/Item	Convergence iteration	Profit ($)	Solution time (s)	Algorithm status
IARO	12	509.40	152	Globally optimal
ARO	48	502.11	169	Locally optimal
PSO	47	504.74	158	Locally optimal
SSA	32	503.21	164	Locally optimal

Table 6: The statistical analysis results of different methods in solving the deterministic scheduling problem

Algorithm/Index	Best ($)	Worst ($)	Mean ($)	Std ($)
IARO	509.40	502.28	507.65	55.04
ARO	502.11	488.92	495.44	87.35
PSO	504.74	498.36	500.07	58.73
SSA	503.21	492.50	497.26	80.54

5.3 Results of Stochastic Scheduling

Using the HTPEM approach outlined in Section 3, the energy hub scheduling issue has been handled in this part by taking into account the power unpredictability of solar and wind energy sources. To put it another way, the impact of taking into account the power unpredictability of solar and wind sources on the amount of profit made by the energy hub has been assessed. The HTPEM approach and the IARO meta-heuristic algorithm have been used to compare the energy hub scheduling issue with the conventional ARO, PSO, and SSA methods. Fig. 12 depicts the convergence of several optimization techniques. The findings demonstrate that the IARO algorithm outperforms competing approaches with a lower convergence tolerance in fewer convergence repeats. As can be seen in Table 7, although the other techniques were unable to leave the local optimum and failed to make a profit of $463.59 after 33 iterations, the IARO approach did. It has been noted that although the classic ARO technique experienced early convergence with a profit value of $455.06, the performance enhancement of the traditional ARO method based on the non-linear dynamic inertia weight avoided the premature convergence of its enhanced counterpart. Also, the proposed method has a lower computational cost compared to the conventional ARO, PSO and SSA methods. Additionally, the effectiveness of the suggested technique during a statistical study carried out for various algorithms following Table 8 has shown the suggested algorithm's superiority. The findings of stochastic scheduling, like those of the deterministic technique, have shown that by figuring out the planned capacity of the energy hub equipment, a powerful optimization method may generate more profit.

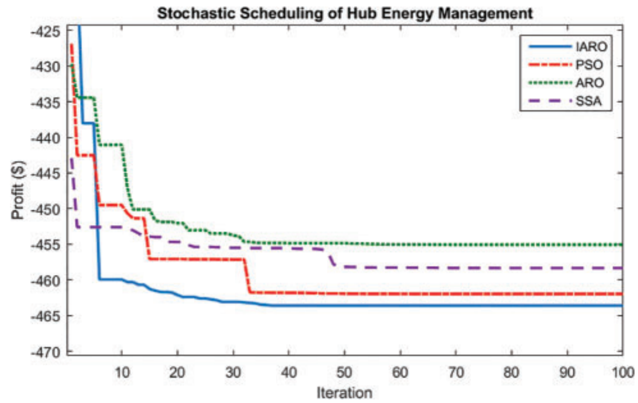

Figure 12: Convergence curve of different algorithms in solving the problem

Table 7: The numerical results of different methods in stochastic scheduling the hub energy

Algorithm/Item	Convergence iteration	Profit ($)	Solution time (s)	Algorithm status
IARO	33	463.59	174	Globally optimal
ARO	35	455.06	198	Locally optimal
PSO	33	461.95	181	Locally optimal
SSA	48	458.32	192	Locally optimal

Table 8: The statistical analysis results of different methods in stochastic scheduling the hub energy

Algorithm/Index	Best ($)	Worst ($)	Mean ($)	Std ($)
IARO	463.59	502.28	507.65	55.04
ARO	455.06	488.92	495.44	87.35
PSO	461.95	498.36	500.07	58.73
SSA	458.32	492.50	497.26	80.54

5.4 Results Comparison of Deterministic and Stochastic Scheduling

In this section, Table 1 compares the outcomes of the energy hub planning issue using two deterministic and random techniques. Table 9 shows that taking uncertainty into account has decreased Hub Energy's earnings. The system's profit is $509.40 in the deterministic state and $463.59 in the random state computed using the HTPEM approach, a fall of 8.99 percent. The results of comparing the suggested method's capacity with reference [38] also show its superiority in terms of generating more profit. The linearization of the issue and the complexity of its mathematical model are two drawbacks of MINLP programming as opposed to meta-heuristic approaches in reference [38], which use it to address the energy hub design problem.

Table 9: The results comparison of deterministic and stochastic scheduling of the hub energy

Algorithm/Item	Profit ($)
IARO (Deterministic)	509.40
IARO (Stochastic)	463.59
[38] (Deterministic)	504.74
[38] (Stochastic)	461.95

5.5 Comparison of the IARO with Some Well-Known Algorithms

In this section, the performance of the IARO in solving the problem is compared with the well-known GA [39], GWO [40] and circle search algorithm (CSA) [41]. It should be noted that the parameters of different algorithms are considered as the parameters provided by their authors. The performance comparison of different methods is presented in Table 10, respectively. As can be seen, among the presented methods, the GWO and the CSA have achieved the global optimal solution. It has been observed that the performance of the improved proposed method is better compared to other methods and has obtained more profit. On the other hand, the CSA has also provided a favorable and acceptable performance in solving the problem and maximizing energy profit.

Table 10: Comparison of different algorithms performance in stochastic scheduling the hub energy

Algorithm/Item	Convergence iteration	Solution time (s)	Profit ($)
IARO	33	174	463.59
GA	48	186	449.16
GWO	39	182	457.20
CSA	30	177	460.88

5.6 System Power and Profit in Deterministic and Stochastic Scheduling

The daily power and profit curves for various energies in deterministic and stochastic scheduling modes are shown in Figs. 13 and 14, respectively. The participation level of solar and wind sources has dropped in stochastic mode compared to deterministic mode, as seen by comparing the power curves in Fig. 13. Fig. 13 shows that from 1:00 to 7:00 during the early hours of the program, the active power of all Energy Hub equipment is negative. Due to the cheap price of power at this time, electric car charging and energy storage are taking place as a result of these circumstances. On the other hand, owing to low gas prices between the hours of 1:00 and 4:00, CHP has met the demand for hub equipment. On the other hand, Fig. 13 demonstrates that the power needed by the grid is provided by CHP equipment, renewable energy sources, storage systems, and electric cars as a result of the high cost of electricity between the hours of 8:00 and 24:00. The maximum permitted heating power, on the other hand, has been sent to the heating network throughout the day during these hours since heating energy is more expensive than gas. As a result, the power of the hub equipment is negative from 1:00 to 4:00 because the power supplied by the upstream network to the hub equipment is more than the power supplied by the CHP, solar, and wind energy sources combined. Additionally, the hub's equipment has a positive capacity between the hours of 8:00 and 24:00. As a result, in the aforementioned instances, energy management is carried out to optimize system profit, and because photovoltaic and wind generation are unpredictable in the stochastic scheduling mode, system profit is lower than in the deterministic scheduling mode.

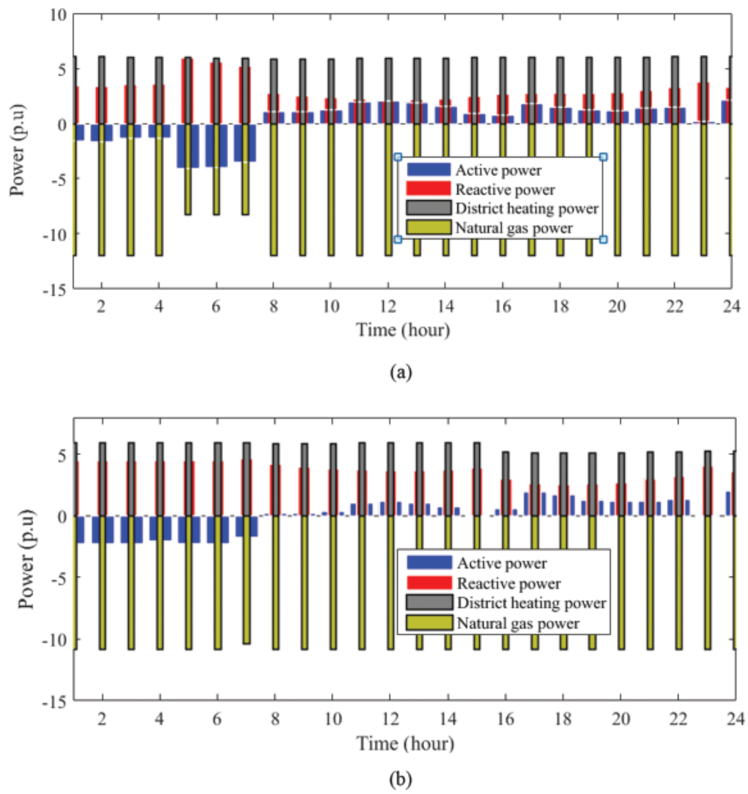

Figure 13: Daily changes of hub power for different energy equipment a) deterministic b) stochastic

Fig. 14 displays the profit hub's daily fluctuations. The findings show that the price of energy has an impact on the system's profit in the day-ahead market of various networks. Fig. 14 shows that the benefit of heating varies depending on the fluctuating cost of energy at various times. On the other hand, it can be seen from Fig. 14 that the profit of the power market is positive for the rest of the hours and negative from 1:00 to 7:00 owing to the energy storage provided by EVs. Additionally, the gas market's profit is negative since gas energy is used by CHP and steam boilers, and because the heating market consistently generates larger profits than the gas market does. The set of profits from all hubs in various forward markets is included in the profit from the future market in such a manner that the negative profit is equivalent to the positive cost.

The proposed method has optimal performance under changes in working conditions as well as changes in load demand. The purpose of evaluating the uncertainty of photovoltaic and wind renewable energy sources power as well as the load demand of the energy hub is the ability of the system in these conditions and to be robustness to the existing uncertainties. Hub energy system has maintained its performance level in achieving maximum energy profit in the conditions of uncertainty of renewable power generation and load demand. The proposed hub energy planning scheme has high scalability because it can be expanded to multiple and wider energy hubs. The proposed plan is practical and can provide the planners of energy hub systems in the energy industry with full knowledge of the economic evaluation of these types of systems and also the maximum revenue generation from them. Because in the proposed plan, a real approach to hub energy planning is included, taking into account the economic aspect of monetization as well as the technical aspect of generation and load demand uncertainties.

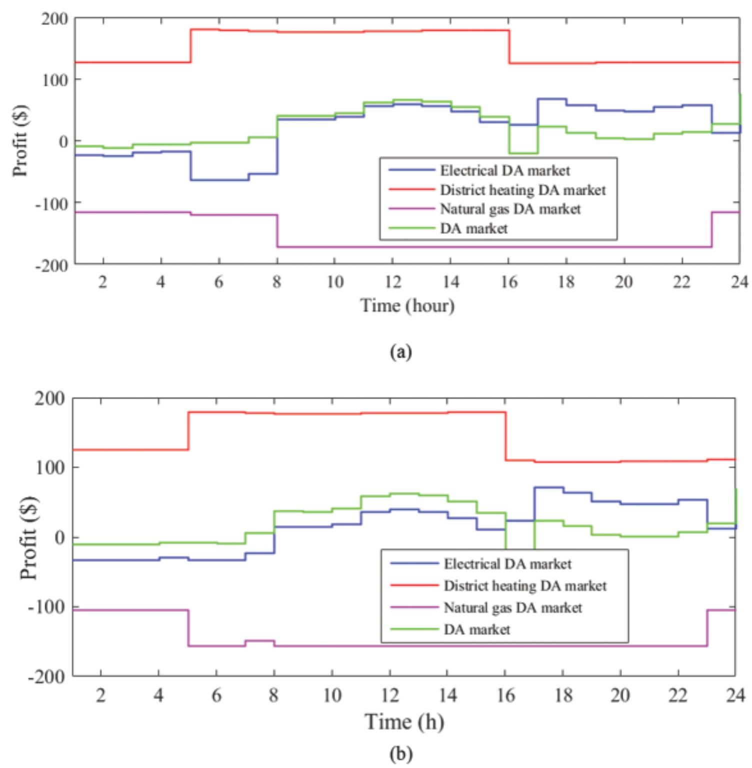

Figure 14: Daily changes of profit hub a) deterministic b) stochastic

6 Conclusion

To maximize the energy profit, this article uses stochastic scheduling of energy hubs to participate in the future energy market using electricity, natural gas, and urban heating networks while taking into account the unpredictability of solar and wind generation. IARO's new algorithm was introduced. In order to maximize the profit from the hub energy while fulfilling operational and hub restrictions, the optimum energy scheduling of the hub equipment was established, and the scheduling issue was put into practice. The study's conclusions are as follows:

- The results revealed that in the day-ahead market based on deterministic planning, the IARO, ARO, PSO, and SSA methods achieved energy profits of \$509.40, \$502.11, \$504.74, and \$503.21, respectively. This demonstrates the superior performance of the proposed framework based on IARO, which is the market leader in achieving the highest energy profits.
- Considering the uncertainty has decreased the system's profit by 8.99 percent based on the IARO method, according to the results of the stochastic scheduling of hub energy using the IARO, ARO, PSO, and SSA methods. Energy profit of 463.59 dollars, 455.06 dollars, 461.95 dollars, and 458.32 dollars was obtained in the future market.

- The findings demonstrated that the participation level of solar and wind power has dropped in stochastic planning as a consequence of the unpredictability of these sources, which has impacted system profit.
- The findings showed that the price of electricity, natural gas, and heating energy has a substantial impact on the system's profitability. The results also demonstrated that the next day's gas market profits are higher due to the reception of gas energy by CHP and steam boilers. The gas is fully negative the next day.

Access to accurate data of renewable energy sources and their uncertainty is one of the major limitations of the research. Robust hub energy planning based on the combined method of information gap decision theory and meta-heuristic algorithm is proposed for future work.

Acknowledgement: The authors extend their appreciation to the Deputyship for Research and Innovation, the Ministry of Education in Saudi Arabia for funding this research work through the Project Number (IFP-2022-35).

Funding Statement: This research is supported by the Deputyship for Research & Innovation, Ministry of Education in Saudi Arabia under Project Number (IFP-2022-35).

Author Contributions: Conceptualization, M.A., A.A., Y.Q., A.S.A., M.Z., A.B.A. and M.G.B.A.; methodology, M.A. and A.A.; software, M.A. and A.S.A.; validation, M.A., Y.Q. and A.A.; formal analysis, M.A., A.KA., Y.Q., A.S.A., M.Z., A.B.A. and M.G.B.A.; investigation, M.A., A.A., Y.Q., A.S.A., M.Z., A.B.A. and M.G.B.A.; resources, M.A., A.A., Y.Q., A.S.A., M.Z., A.B.A. and M.G.B.A.; data curation, M.A., A.A., Y.Q., A.S.A., M.Z., A.B.A. and M.G.B.A.; writing—original draft preparation, A.S.A., and A.A.; writing—review and editing, M.A., A.A., Y.Q., A.S.A., M.Z., A.B.A. and M.G.B.A.; visualization, M.A., A.A., Y.Q., A.S.A., M.Z., A.B.A. and M.G.B.A.; supervision, A.A., Y.Q., A.S.A., M.Z., A.B.A. and M.G.B.A.; project administration, M.A., A.A., Y.Q., A.S.A., E.S., M.Z., A.B.A. and M.G.B.A. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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