An Economic Risk Analysis in Wind and Pumped Hydro Energy Storage Integrated Power System Using Meta-Heuristic Algorithm

Nitesh Kumar Singh, Chaitali Koley, Sadhan Gope, Subhojit Dawn and Taha Selim Ustun

Abstract: Due to the restructuring of the power system, customers always try to obtain low-cost power efficiently and reliably. As a result, there is a chance to violate the system security limit, or the system may run in risk conditions. In this paper, an economic risk analysis of a power system considering wind and pumped hydroelectric storage (WPHS) hybrid system is presented with the help of meta-heuristic algorithms. The value-at-risk (VaR) and conditional value-at-risk (CVaR) are used as the economic risk analysis tool with two different confidence levels (i.e., 95% and 99%). The VaR and CVaR with higher negative values represent the system in a higher-risk condition. The value of VaR and CVaR on the lower negative side or towards a positive value side indicates a less risky system. The main objective of this work is to minimize the system risk as well as minimize the system generation cost by optimal placement of wind farm and pumped hydro storage systems in the power system. Sequential quadratic programming (SQP), artificial bee colony algorithms (ABC), and moth flame optimization algorithms (MFO) are used to solve optimal power flow problems. The novelty of this paper is that the MFO algorithm is used for the first time in this type of power risk curtailment problem. The IEEE 30 bus system is considered to analyze the system risk with the different confidence levels. The MVA flow of all transmission lines is considered here to calculate the value of VaR and CVaR. The hourly VaR and CVaR values of the hybrid system considering the WPHS system are reported here and the numerical case studies of the hybrid WPHS system demonstrate the effectiveness of the proposed approach. To validate the presented approach, the results obtained by using the MFO algorithm are compared with the SQP and ABC algorithms’ results.

Keywords: value at risk; conditional value at risk; wind energy; pumped hydroelectric storage system; moth flame optimization algorithm

1. Introduction

Today, wind energy is considered one of the leading renewable energy sources for electricity generation throughout the globe. This source may work with other conventional sources or energy storage systems depending on the energy demand situation. The development of any new technology can be significantly affected by its economic viabilities. Hence, economic risk computation is considered an essential aspect of the solution process to mitigate the economic risk. Risk in a wind-integrated system occurs due to its intermittent nature, and it may be of economic risk related to imbalance cost, or system security risk related to the operation of a power system in terms of voltage stability, frequency stability, etc. The system risk estimation is a chief phase of the power system to avoid any losses that occur in the system. The calculation also provides variations in the risk profiles as the system approaches complexity from its simple structure.
In the recent past, several researchers have performed their work in the field of system risk assessment. In ref. [1], CVaR and VaR are used as a tool to compute economic risk based on locational marginal pricing, and MVA flows in the system comprising wind energy and FACTS devices under several abnormalities in the system. CVaR can be used as a risk indicator for reserve capacity allocation in formulating robust risk constraints unit commitment in a day-ahead market [2]. Bathurst et al. [3] present the Markova probability approach for commercial risk through imbalance cost under advance contracting in the deregulated electricity market. A wind farm was used in this work for a substantial reduction in risk. A machine learning model has been presented by Bathurst et al. [4] to assess the economic risk in terms of imbalance cost for the wind integrated system. Paper [5] presents Nash and Rubinstein’s bargaining game models to mitigate system risk for the wind power provider through market risk exchange policy. In ref. [6], the CVaR index is utilized to measure EV aggregator’s risks due to some uncertainties, i.e., forecast errors of EV fleet characteristics, hourly loads, wind power generation, random outages of generating units, and transmission lines to fulfill the optimal bidding strategy. A conditional value-at-risk-based risk-averse optimal bidding strategy has been formulated in [7] in the day-ahead electricity market, considering uncertainties in renewable generation and electricity demand for the aggregators at the demand side. Ref. [8] presents a risk assessment approach based on risk index associated with system operation and components contingencies to analyze the power system security and planning under high penetration of wind power generation.

A risk assessment index for an adaptive ultra-short-term wind power prediction model is presented in [9]. In ref. [10], CVaR is used for measuring the risk associated with uncertainty in electricity market price forecasting and wind power forecasting in wind farm and energy storage integrated systems. An energy and risk management method for a microgrid comprising of a wind turbine, PV panels, Diesel generator, and various loads is presented by Shen et al. [11] for its active participation in the electricity pool to maximize its benefits by scheduling its controllable resources. A risk-based reserve optimization is proposed in [12] to evaluate the reserve requirement of large-scale wind energy systems working in co-operation with thermal power stations. The autoregressive integrated moving average method has been presented in [13] for risk management associated with demand forecast and battery management in PV-based microgrid. Risk measures in terms of CVaR and its management using mixed-integer linear programming are presented for an energy hub containing a fuel cell, wind power, and photovoltaic energy under an energy and reserve market environment in ref [14]. CVaR is used to analyze the risk in the stochastic decision-making model for the coordinated operation of renewable and virtual power plants taking part in the day-ahead market under the demand response program and in the presence of plug-in electric vehicles [15]. Optimal placement of wind generators based on CVaR values under different contingency conditions like line outage, generator outage, etc., are adopted for bi-level bidding strategy for a wind energy integrated system taking part in double auction competitive market in real-time [16]. An optimal dispatch model for the multi-source system containing wind, thermal and hydro storage in typhoon environment based on risk analysis with CVaR considering wind speed first and then identification of output scenario is presented in ref. [17]. CVaR is considered risk exposure due to the uncertainties present in the stochastic model for energy and reserve scheduling of renewable-based microgrid under an energy market environment, which is further solved by using multi-objective mixed-integer linear programming [18].

A bi-level robust game model incorporating uncertainties in power generation and consumption for a regionally integrated energy system containing a CCHP unit and virtual power plant is presented in ref. [19] in which CVaR is used as an energy risk measurement tool. CVaR is considered a risk evaluation method to avoid over-optimistic solutions in a two-layer adaptive stochastic model for an optimal multi-energy microgrid (wind, PV, thermal, Battery, and capacitor) under a voltage security constraint environment [20]. The CVaR model for time-varying economic risk with time-sequential security assessment in
Sustainability 2021, 13, 13542

a probabilistic model containing uncertainty in EV distribution and renewable energy of distribution system is presented in ref [21]. Risk due to reserve shortage while the optimal allocation of reserve capacity for islanded microgrid operation under intermittency of renewable and fluctuation in load is modeled using CVaR in [22]. Risks due to uncertainty associated with solar energy, price, load, and EV’s arriving and departing times in optimal scheduling of heating, power, and hydrogen-based microgrid incorporated with renewable energy sources (RES)–PV and plug-in electric vehicle (PEV) are modeled using CVaR in ref. [23]. The risk faced by the system operator in the daily scheduling of PV, wind power variation, real-time power market, load variation, and behavior of electric vehicle drivers is modeled using CVaR in a two-stage stochastic model for optimal scheduling of renewable-based microgrid integrated with PEV [24]. CVaR is used as a risk measuring tool while planning for an energy model hub containing renewable energy sources and an energy storage system for potential loss in different scenarios with different confidence levels and risk preferences [25]. Contagious VaR (CoVaR) and marginal CoVaR are used to construct the risk connection network of market participants taking part in the energy market under high renewable penetration [26].

In the past, a few works have been done on risk computation by several researchers, but some important points have not yet been addressed, which are discussed in this work.

• The effect of load demand on the line flow-based system risk.
• What is the scenario of economic risk variation after the integration of wind and a pumped hydroelectric storage (WPHS) hybrid system?
• What is the effect of different algorithms for optimal power flow solutions on the economic risk analysis?
• Comparative analysis of risk analysis parameters (VaR, CVaR) with different confidence levels.
• The main contributions of this work are as follows:
  • The risk assessment parameters (VaR and CVaR) are calculated with 95% and 99% confidence levels for different scenarios based on the MVA flows.
  • Minimizing economic system risk by optimal placement of a wind farm and a pumped hydroelectric storage hybrid system.
  • The MFO algorithm is used for the first time in this type of power risk curtailment problem.

To scrutinize the robustness of the proposed method over the considered objective functions, the problem is solved in three different stages with different optimization techniques. The first stage of the system comprises of base-load in the standard IEEE 30 bus system. The second stage of the system includes base-load and wind energy generation. In the third stage, the system comprises a base-load, wind power, and pumped hydroelectric storage (WPHS) hybrid system.

2. Mathematical Formulation

This section presents the mathematical modeling of the wind power generation, pump hydroelectric storage (PHS) system, value at risk (VaR), and conditional value at risk (CVaR).

2.1. Wind Power Generation

Wind power generation depends on wind speed and wind turbine specifications. In the power output characteristics of a wind turbine, $P_r$ is the rated output power. $v_{ci}$, $v_{r}$, $v_{co}$ are cut-in speed, rated speed, and cut-out speed of wind turbine, respectively.

The generated power from a wind turbine is as follows [27]:

$$P_v(w) = \begin{cases} 0 & 0 \leq v_{av} \leq v_{ci} \\ \frac{P_r - v_{av}}{v_r - v_{ci}} \left( \frac{v_{av} - v_{ci}}{v_r - v_{ci}} \right) & v_{ci} \leq v_{av} \leq v_r \\ P_r & v_r \leq v_{av} \leq v_{co} \\ 0 & v_{co} \leq v_{av} \end{cases}$$

(1)
Here, $v_{av}$ is the average wind speed and $P_r$ is the rated wind power.

2.2. Pumped Hydroelectric Storage System

The pumped hydroelectric storage (PHS) system can store or release electrical energy depending on the customer’s requirement. It can operate either in generating mode (when power demand is high) or in pumping mode (when power demand is low).

2.2.1. Generating Mode

This is also called the discharging mode of operation. It is used to fulfill the power demand during peak demand hours. The mathematical equation of generated energy of a pumped storage system is as follows:

$$E_g = \rho gh v_g n_g$$

(2)

2.2.2. Pumping Mode

This is also called the charging mode of operation. It is used to absorb energy during off-peak hours. The energy stored during the pumping mode is calculated as

$$E_p = (\rho gh v_p)/ n_p$$

(3)

Here, $\rho$ is the density of water, $g$ is the acceleration due to gravity, $v_g$ and $v_p$ are the volumetric water flow rate during generating and pumping mode, respectively. $n_g$, $n_p$ are the overall efficiencies of the pumped hydro storage system in generating and pumping operation, respectively [27].

2.3. Value at Risk (VaR) and Conditional Value at Risk (CVaR)

The VaR is computed as the maximum profit over a target time horizon such that the probability of the profit is less than or equal to $(1-\alpha)$ and CVaR is the expected value of the worst $(1-\alpha)$ cases of profit. $\alpha$ is the confidence level and $\alpha \in (0, 1)$ [10].

$$V_aR_\alpha (\text{profit}) = \max \{ t | P_r (\text{profit} \leq t) \leq 1 - \alpha \}$$

(4)

$$CV_aR_\alpha (\text{profit}) = E [\text{profit} | \text{profit} \leq V_aR_\alpha]$$

(5)

VaR and CVaR values are inversely proportional to the system risk, i.e., it gets a minimum (maximum negative) value when system risk is at maximum. Thus, it is required to minimize the system risk by moving from the left tail to the right tail in the graph shown in Figure 1 [1].

![Figure 1. Representation of CVaR and VaR.](image-url)
The VaR (with 95% confidence level) value represents the minimum percentage loss with a 5% chance on a given data in the portfolio chosen. Similarly, the VaR (with 99% confidence level) value represents the minimum percentage loss with a 1% chance on given data in the portfolio chosen. At the same time, CVaR (with 95% confidence level) represents the average loss percentage in the worst 5% return case for given data/values. Similarly, CVaR (with 99% confidence level) averages loss percentage value in the worst 1% return case in the given portfolio data.

2.4. Optimization Algorithms

The Nature-inspired Artificial Bee Colony algorithm (ABC) and the Moth Flame Optimization (MFO) algorithm are considered with conventional SQP optimization methods to solve the optimal power flow problem. The MFO method shows higher or superior convergence capabilities than the ABC algorithm, and both ABC and MFO offer more optimal solutions than the SQP.

2.4.1. Artificial Bee Colony Algorithm

It is a population-based search approach inspired by the intelligent behavior of honeybees with common control parameters, i.e., no. of employed bees, max cycle, colony size, etc. The main aim of artificial bees is to discover the places of food sources (fitness) with high nectar, which changes or is modified with time, and finally select the one with the highest nectar. Food sources were chosen randomly without using experience by scout bees.

\[
\text{Prop} = \left(0.9 \times \frac{fit_p}{\max(fit)}\right) + 0.1 \quad (6)
\]

Here, \(fit_p\) is the fitness value of the solution which is proportional to the nectar amount. The modification in position by onlooker bees and nectar amount of new sources are as follows:

\[
x_{pq} = x_{pq} + \varphi_{pq} (x_{pq} - x_{fq}) \quad (7)
\]

where \(f \in \{1, 2, 3 \ldots n_e\}\) and \(q \in \{1, 2, \ldots D\}\) are randomly chosen with D no. of parameters to be optimized. \(\varphi_{pq}\) is a random number generated between 0 and 1 in case of abandoned sources scout discover new force source as

\[
x_{pq} = x_{q \min} + \text{rand}(0, 1) \times (x_{q \max} - x_{q \min}) \quad (8)
\]

where \(x_{q \min}, x_{q \max}\) are the minimum and maximum limits of the parameters to be optimized.

The pseudo code for ABC algorithm is as follows [28]:

1. Begin.
2. Initial population.
3. While: the remaining iteration is done.
4. Select the site for the local search.
5. Employ bee for the particular chosen site and to evaluate fitness.
6. Select the bees with the best fitness and assign the remaining bees to look for randomly.
7. Examine the fitness of remaining bees and update optimum.
8. End while.
9. Return the best solution.
10. End.
2.4.2. Moth Flame Optimization Techniques

This is a nature-inspired algorithm based on the navigation method, a transverse orientation at a fixed angle towards the moon of moths. Moths utilize a single or multi-dimensional (hyper) space vector for flying. Set of moths are represented as

\[ MF = \begin{bmatrix}
    m_{f,1,1} & m_{f,1,2} & \ldots & m_{f,1,q} \\
    m_{f,2,1} & m_{f,2,2} & \ldots & m_{f,2,q} \\
    \vdots & \vdots & \ddots & \vdots \\
    m_{f,p,1} & m_{f,p,2} & \ldots & m_{f,p,q}
\end{bmatrix} \] (9)

where \( p \) is the no. of moths and \( q \) is no. of variables. The matrix containing the fitness value of moth is

\[ MFO = \begin{bmatrix}
    MFO_1 \\
    MFO_2 \\
    \vdots \\
    MFO_P
\end{bmatrix} \] (10)

Like the moth, the flame matrix and its corresponding fitness values are represented by the following matrices having the same order as moth matrices.

\[ OF = \begin{bmatrix}
    OF_{1,1} & OF_{1,2} & \ldots & OF_{1,q} \\
    OF_{2,1} & OF_{2,2} & \ldots & OF_{2,q} \\
    \vdots & \vdots & \ddots & \vdots \\
    OF_{p,1} & OF_{p,2} & \ldots & OF_{p,q}
\end{bmatrix} \] (11)

\[ MOF = \begin{bmatrix}
    MOF_1 \\
    MOF_2 \\
    \vdots \\
    MOF_P
\end{bmatrix} \] (12)

The moths are actual search agent that move around the search space, whereas flames are in the best position of moths that obtained so far. Therefore, each moth searches around a flame and updates it with the best solution.

3. Objective Function

The main objective of this work is to minimize the system generation cost in the wind and pumped hydroelectric storage (WPHS) system integrated power system. The system generation cost consists of the fuel cost of the thermal unit and the investment cost of WPHS. Suppose a network has ‘NB’ number of buses, ‘NG’ number of generators, ‘ND’ number of loads, and ‘NW’ number of wind turbines, then the mathematical expression of the objective function is as follows:

\[ \text{Min } F = \sum_{i=1}^{NG} C_i(P_{Gi}) + \sum_{n=1}^{NW} C_{WPHS} \] (13)

Here, \( C_i(P_{Gi}) \) is the cost-coefficient generation of the generator at bus ‘i’ and \( C_{WPHS} \) is the investment cost of the WPHS system. Some equality and inequality constraints must be considered to study the optimal power flow problem. The constraints for power flow solution are as follows:

**Equality constraints**

\[ \sum_{i=1}^{NG} P_{Gi} + P_W - P_{loss} - P_{di} = 0 \] (14)
where \( P_Gi \) is the power generation at the \( i \)th bus, \( P_W \) is power generated by wind turbines, \( P_{loss} \) is transmission loss and \( P_d \) is the power demand. \( G_j \) is the line conductance between buses \( i \) and \( j \). \( V_i \), \( V_j \) and \( V_k \) are the voltage magnitude at bus \( i \), \( j \), and \( k \). \( \delta_i \), \( \delta_j \), \( \delta_k \) and \( \theta_{ik} \) are the voltage angle at bus \( i \), \( j \), \( k \), and admittance angle of line connected between bus \( i \) and \( j \) with magnitude \( Y_{ik} \).

**Inequality constraints**

\[
V_{i}^{\text{min}} \leq V_i \leq V_{i}^{\text{max}} \quad \forall \ i = 1, 2, 3 \ldots \text{NB}
\]

\[
\varnothing_{i}^{\text{min}} \leq \varnothing_i \leq \varnothing_{i}^{\text{max}} \quad \forall \ i = 1, 2, 3 \ldots \text{NB}
\]

\[
P_{G_i}^{\text{min}} \leq P_Gi \leq P_{G_i}^{\text{max}} \quad \forall \ i = 1, 2, 3 \ldots \text{NB}
\]

\[
Q_{G_i}^{\text{min}} \leq Q_{G_i} \leq Q_{G_i}^{\text{max}} \quad \forall \ i = 1, 2, 3 \ldots \text{NB}
\]

\[
T_{L_i} \leq T_{L_i}^{\text{max}} \quad \forall \ i = 1, 2, 3 \ldots \text{NL}
\]

where \( V_{i}^{\text{min}}, V_{i}^{\text{max}}, \varnothing_{i}^{\text{min}}, \varnothing_{i}^{\text{max}}, P_{G_i}^{\text{min}}, P_{G_i}^{\text{max}}, Q_{G_i}^{\text{min}} \text{ and } Q_{G_i}^{\text{max}} \) are the lower and upper bounds of the voltage magnitude, phase angle, real power generated, and reactive power generated at \( i \)th bus respectively. \( T_{L_i}, T_{L_i}^{\text{max}} \) are the actual and maximum limit of MVA flows of the \( i \)th line.

**PHS operating constraints**

\[
P_{p}(t) = P_{W_pump}(t) + P_{g_pump}(t)
\]

\[
P_{p}^{\text{min}} \leq P_{p}(t) \leq P_{p}^{\text{max}}
\]

\[
k_{p}P_{p}^{\text{min}} \leq P_{p}(t) \leq k_{p}P_{p}^{\text{max}}
\]

\[
P_{s}^{\text{min}} \leq P_{s}(t) \leq P_{s}^{\text{max}}
\]

\[
k_{s}P_{s}^{\text{min}} \leq P_{s}(t) \leq k_{s}P_{s}^{\text{max}}
\]

\[
E_{|V|}(t+1) = E_{|V|}(t) + \left\{ (P_{p}(t) \cdot \eta_{p} - (P_{s}(t) \cdot \eta_{s})) \right\}
\]

\[
E_{\text{min}}^{\text{max}} \leq E_{|V|}(t) \leq E_{\text{max}}^{\text{max}}
\]

\[
k_{p} + k_{s} \leq 1
\]

Here, \( P_{p}(t), P_{W_pump}(t), P_{g_pump}(t) \) are the total pumping load, pumping from wind energy, and pumping from thermal generation. \( P_{p}^{\text{min}}, P_{p}^{\text{max}}, P_{s}^{\text{min}}, P_{s}^{\text{max}} \) are the lower and upper bound of pumping and generating power of the PHS system. \( E_{|V|}(t), E_{\text{min}}, E_{\text{max}}^{\text{max}} \) are the energy of PHS in MWhr at the time ‘\( t \)’, lower and upper bound of the energy capacity of the PHS system. \( k_{p}, k_{s} \) are the state variable \( \in (0, 1) \) for pumping and generating mode of operation which ensures that both pumping and generating cannot operate together [30].

4. Results and Discussions

In this work, the problem formulation and its solution are categorized into three stages. The optimal power flow problem has been solved in each stage with three optimization techniques, i.e., ABC, MFO, and SQP. MVA flows for each hour of operation, fuel cost, and system losses are collected, and the basis on which VaR and CVaR are calculated with 95% and 99% confidence levels. The flow chart of the proposed approach is given in Figure 2.
IEEE 30 bus test system is used here to analyze the economic risk of the system, and the test system data are taken from ref. [31]. The system was analyzed for a 24-h scheduling period with the help of a load scaling factor, as shown in Table 1 [30]. A wind generation of 15 MW rated capacity with variation in wind speed for 24 h [32] is considered to verify the impact of wind generation in economic risk analysis. The energy generated from wind is calculated as per formula [27] with cut in, cut out, and rated speed as 3 m/s, 15 m/s, and 26 m/s, respectively. The cost for wind energy generation is taken as 3.75 $/MW [32]. The PHS is considered here for mitigation of imbalance between the wind power generation and contracted power. The assumption made here is that the initial capacity of PHS is sufficient for mitigation of any worst imbalance which can occur during 24 h of operation.

To find the optimal location of the WPHS system; fuel cost and losses have been calculated by integrating 15 MW fixed WPHS generation in all the buses. Figure 3 shows the optimal cost and losses of the system after the integration of 15 MW WPHS generation. From Figure 3, it is observed that the fuel cost and losses are minimum at bus no. 4 compared to all other buses of the system. Therefore, the optimal location of WPHS generation is represented as bus no 4.

**Figure 2.** Flow chart of the proposed work.
To verify the impact of the WPHS system in economic risk analysis, the problem is solved in three different stages. The comparative analysis of risk coefficient VaR and CVaR is chosen with two different confidence levels, i.e., 95% and 99%.

To calculate the VaR and CVaR value, the MVA flow of the system is used here. To find the minimum cost and losses corresponding to the VaR and CVaR values, SQP, MFO, and ABC algorithms are used here.

Stage I: In this stage, the effect of load variations for a 24-h scheduling period is considered as per load scaling factor, and VaR and CVaR values are calculated for 95% and 99% confidence levels. The VaR and CVaR values for 95% confidence level are obtained using SQP, MFO, and ABC algorithm are shown in Figure 4.

From Figure 4a, it is observed that the economic risk coefficient VaR values for 95% confidence level are lower by using the MFO algorithm compared with SQP and ABC algorithms. From Figure 4a, it was detected that the VaR value using the MFO algorithm is minimum and the same in 11th and 12th-hour interval and its value is $−0.65782$. Similarly, the maximum VaR value using the MFO algorithm is $−0.78396$ in the 5th-hour interval. From Figure 4b, it can be observed that the CVaR value using the MFO algorithm is minimum in the 15th-hour interval, and its value is $−0.71235$. It is also observed that CVaR’s highest negative value, i.e., $−1.05263$, is obtained using SQP techniques, obtained in the fourth to the seventh-hour interval.

Figure 5 shows the VaR and CVaR values for 24 h scheduling period with 99% confidence level. From Figure 5a it is seen that VaR minimum negative value (i.e., $−0.7265$) is obtained in the fourth to the seventh-hour interval. From Figure 5b, it can be observed that the CVaR minimum negative value (i.e., $−1.80992$) is obtained in the 21st interval using the MFO algorithm.

| Hour | Load Scaling Factor | Hour | Load Scaling Factor | Hour | Load Scaling Factor |
|------|---------------------|------|---------------------|------|---------------------|
| 1    | 1                   | 9    | 1.1                 | 17   | 1.05                |
| 2    | 0.95                | 10   | 1.125               | 18   | 1.01                |
| 3    | 0.935               | 11   | 1.15                | 19   | 0.99                |
| 4    | 0.9                 | 12   | 1.15                | 20   | 1.035               |
| 5    | 0.875               | 13   | 1.149               | 21   | 1.02                |
| 6    | 0.865               | 14   | 1.14                | 22   | 1.065               |
| 7    | 0.925               | 15   | 1.125               | 23   | 1.04                |
| 8    | 1.05                | 16   | 1.075               | 24   | 1                |

Figure 3. Optimal cost and losses with wind power generation.
and the CVaR maximum negative value (i.e., −2.63158) is obtained with SQP technique in the fourth to seventh interval.

Figure 4. (a) VaR and (b) CVaR for 24 h scheduling period with 95% confidence level.

Figure 5. Cont.
Figure 5. (a) VaR and (b) CVaR for 24 h scheduling period with 99% confidence level.

Table 2 shows the optimal cost of the system for a 24-h scheduling period. From Table 2, it is observed that the MFO algorithm gives the minimum cost compared to the ABC algorithm and the SQP technique. From the table, it is also observed that if we reduce the load, then the system’s cost is also reduced. Table 2 also displays the optimal losses of the system for a 24-h scheduling period for the SQP, ABC, and MFO algorithms. It is observed that the MFO algorithm gives the minimum losses of the system compared to the ABC algorithm and the SQP technique. It can be concluded from the result that if we reduce the load, then losses of the system are also reduced.

Table 2. System optimal cost of the system for a 24-h scheduling period.

| Hour | SQP       | ABC       | MFO       |
|------|-----------|-----------|-----------|
|      | Cost ($/h) | Losses (MW) | Cost ($/h) | Losses (MW) | Cost ($/h) | Losses (MW) |
| 1    | 802.20    | 11.742    | 798.9258  | 9.0946      | 799.1074  | 9.1307      |
| 2    | 750.95    | 11.616    | 748.0734  | 8.3746      | 748.0321  | 8.3738      |
| 3    | 735.77    | 11.576    | 732.9526  | 8.1361      | 733.4201  | 8.2681      |
| 4    | 700.66    | 11.479    | 698.1734  | 7.6301      | 698.1724  | 7.6267      |
| 5    | 675.86    | 11.409    | 673.6562  | 7.2665      | 673.6466  | 7.2645      |
| 6    | 666.01    | 11.357    | 663.9615  | 7.1109      | 664.0429  | 7.1347      |
| 7    | 725.69    | 11.548    | 723.4554  | 8.1030      | 723.0055  | 8.0075      |
| 8    | 854.41    | 11.875    | 850.8142  | 9.8262      | 850.8096  | 9.8220      |
| 9    | 907.59    | 12.017    | 903.7043  | 10.5782     | 903.8688  | 10.6593     |
| 10   | 934.54    | 12.091    | 930.4833  | 10.9799     | 930.6083  | 11.0003     |
| 11   | 961.73    | 12.168    | 957.5228  | 11.3681     | 957.8674  | 11.2761     |
| 12   | 961.73    | 12.168    | 957.5182  | 11.3750     | 957.8674  | 11.2761     |
| 13   | 960.64    | 12.165    | 956.4369  | 11.3661     | 958.1420  | 11.6120     |
| 14   | 950.83    | 12.137    | 946.6842  | 11.2134     | 946.7261  | 11.2168     |
| 15   | 934.54    | 12.091    | 930.4850  | 10.9806     | 930.7390  | 11.0721     |
| 16   | 880.88    | 11.944    | 877.1282  | 10.1999     | 877.1274  | 10.1947     |
| 17   | 854.41    | 11.875    | 850.8098  | 9.8276      | 850.8096  | 9.8220      |
| 18   | 812.57    | 11.768    | 809.2118  | 9.2264      | 809.2047  | 9.2223      |
| 19   | 791.88    | 11.716    | 788.7540  | 8.9696      | 788.6463  | 8.9258      |
| 20   | 838.65    | 11.834    | 835.1518  | 9.6281      | 835.1327  | 9.6008      |
| 21   | 822.97    | 11.794    | 819.5496  | 9.3776      | 819.9296  | 9.4728      |
| 22   | 870.26    | 11.916    | 866.5741  | 10.0454     | 866.7185  | 10.0845     |
| 23   | 843.89    | 11.847    | 850.8098  | 9.8276      | 840.3490  | 9.6775      |
| 24   | 802.20    | 11.742    | 798.9258  | 9.0946      | 799.1074  | 9.1307      |
Stage II: In this stage, 24-h wind power generation is used with the variations of load, and VaR and CVaR values are calculated for two different confidence levels, i.e., 95% and 99%. Table 3 shows the 24-h wind power generation data [1]. The VaR and CVaR values considering wind power generations are obtained using SQP, MFO, and ABC algorithm for 95% confidence levels and shown in Figure 6.

Table 3. Wind power generation.

| Hour | Wind Power (MW) | Hour | Wind Power (MW) | Hour | Wind Power (MW) |
|------|-----------------|------|-----------------|------|-----------------|
| 1    | 12.75           | 9    | 7.5             | 17   | 12.5            |
| 2    | 11.875          | 10   | 12.5            | 18   | 9.375           |
| 3    | 9.375           | 11   | 12.75           | 19   | 8.375           |
| 4    | 10.25           | 12   | 6.25            | 20   | 11.5            |
| 5    | 11.5            | 13   | 12              | 21   | 5.25            |
| 6    | 8.875           | 14   | 10.25           | 22   | 11.875          |
| 7    | 10.75           | 15   | 12.5            | 23   | 9               |
| 8    | 11.75           | 16   | 8.875           | 24   | 11.75           |

Figure 6. (a) VaR and (b) CVaR with considering wind generation for 95% confidence level.
From Figure 6a, it is observed that the economic risk coefficient VaR values with considering wind generation for 95% confidence level are less by using the MFO algorithm compared to the SQP and ABC algorithms. From the Figure, it is observed that the minimum value of VaR using the MFO algorithm is \(-0.65065\) in (second-hour interval) and the maximum value of VaR using the MFO algorithm is \(-0.79964\) in (sixth-hour interval). In Figure 6b it can be observed that the CVaR minimum value using the MFO algorithm is \(-0.69659\) in the second-hour interval. From that figure, it is also observed that CVaR’s highest negative value, i.e., \(-1.85631\), is obtained using the SQP technique, and this value is obtained in the fourth- to the seventh-hour interval of the scheduling period.

Figure 7 shows the VaR and CVaR values considering wind generation for a 24-h scheduling period with a 99% confidence level. From Figure 7a, it can be seen that a minimum negative value of VaR (i.e., \(-0.74252\)) is obtained in second-hour interval using MFO algorithm and the VaR maximum negative value \(-1\) is obtained by using SQP techniques in almost all except the ninth- to 15th-hour interval. From Figure 7b, it is observed that a minimum negative value of CVaR (i.e., \(-1.85631\)) is obtained in the second-hour interval using the MFO algorithm and a maximum negative value of CVaR (i.e., \(-2.63158\)) is obtained by the SQP technique in the fourth to seventh interval.

![Figure 7. (a) VaR and (b) CVaR with considering wind generation for 99% confidence level.](image)

Figure 8 shows the cost and losses with considering wind generation for a 24-h scheduling period for three different techniques: SQP, ABC, and MFO algorithm. From Figure 8, it is observed that in the sixth-hour interval, cost and losses are lower in all three optimization techniques. The cost and losses values obtained are 667.7501 $/h
and 6.6877 MW, respectively, using the MFO algorithm. The almost same value, i.e., 667.7519 $/h and 6.6902 MW, is obtained using the ABC algorithm. The SQP technique gives a greater value, i.e., 668.61 $/h and 11.357 MW, than the MFO and ABC algorithms.

![Figure 8. Cost and losses with considering wind generation for 24 h scheduling period.](image)

**Stage III:** In this stage, VaR and CVaR values are calculated for two different confidence levels, (i.e., 95% and 99%), considering the WPHS system for a 24 h scheduling period. The WPHS system operation for a 24 h scheduling period is shown in Figure 9.

![Figure 9. WPHS system operation for 24 h scheduling period.](image)

It is assumed that PHS is only used to mitigate any imbalances between wind energy generation and contracted power. The operation of PHS is shown in Figure 9, where the positive value of power generation represents the generating stage and the negative power represents the pumping mode of the PHS operation.

The VaR and CVaR values considering the WPHS system are obtained using the SQP, MFO and ABC algorithms for 95% confidence levels and shown in Figure 10. From Figure 10a, it can be observed that the economic risk coefficient (VaR) values with considering WPHS for 95% confidence level are lower by using the MFO algorithm compared...
SQP and ABC algorithms. From the Figure, it is observed that the VaR minimum value using the MFO algorithm is $-0.66405$ in the seventh-hour interval and the maximum VaR value using the MFO algorithm is $-0.80356$ in the 20th-hour interval. From Figure 10a, it is observed that the CVaR minimum value using the MFO algorithm is $-0.75058$ in the first-hour interval. From the Figure, it is also observed that the CVaR highest negative value, i.e., $-0.86789$, is obtained by using SQP techniques in sixth-hour intervals.

![Figure 9. WPHS system operation for 24 h scheduling period.](image)

| Hour | SQP VaR | ABC VaR | MFO VaR | SQP CVaR | ABC CVaR | MFO CVaR |
|------|---------|---------|---------|----------|----------|----------|
| 1    | -0.9    | -0.86   | -0.82   | -0.78    | -0.74    | -0.7     |
| 3    | -0.85   | -0.81   | -0.77   | -0.73    | -0.7     | -0.65    |
| 5    | -0.8    | -0.76   | -0.73   | -0.7     | -0.65    | -0.6    |
| 7    | -0.75   | -0.72   | -0.69   | -0.68    | -0.64    | -0.62    |
| 9    | -0.7    | -0.67   | -0.65   | -0.64    | -0.62    | -0.6    |
| 11   | -0.65   | -0.63   | -0.61   | -0.6     | -0.6     | -0.6     |
| 13   | -0.6    | -0.59   | -0.58   | -0.57    | -0.56    | -0.55    |
| 15   | -0.57   | -0.56   | -0.55   | -0.54    | -0.53    | -0.52    |
| 17   | -0.55   | -0.54   | -0.53   | -0.52    | -0.51    | -0.51    |
| 19   | -0.53   | -0.52   | -0.51   | -0.5    | -0.5     | -0.5     |
| 21   | -0.51   | -0.5    | -0.5    | -0.49    | -0.48    | -0.47    |
| 23   | -0.5    | -0.49   | -0.48   | -0.47    | -0.46    | -0.45    |

Figure 10. VaR and CVaR with considering WPHS system with (a) 95% and (b) 99% confidence level.

The VaR and CVaR values considering the WPHS system are obtained using the SQP, MFO and ABC algorithms for 99% confidence levels and are shown in Figure 10b. From the figure, it can be observed that the VaR minimum value using the MFO algorithm is $-0.77441$ in the 11th hour interval, and the maximum VaR value using the MFO algorithm is $-0.9266$ in the sixth-hour interval. From Figure 10b, it is observed that the CVaR minimum value using the MFO algorithm is $-1.93602$ in the 11th hour interval. From this Figure it is also observed that the CVaR highest negative value, i.e., $-2.37051$, is obtained using SQP techniques in the sixth-hour interval.
Figure 11 shows the cost and losses with considering WPHS for a 24-h scheduling period for three different techniques: the SQP, ABC, and MFO algorithms. From Figure 11, it is observed that in the sixth-hour interval, cost and losses are lower in all the three optimization techniques. The minimum cost and losses values obtained are 668.1405 $/h and 6.5481 MW, respectively, using the MFO algorithm. Using the ABC algorithm, cost and losses values obtained are 668.4928 $/h and 6.5720 MW, respectively. The SQP technique gives a greater value, i.e., 669.37 $/h and 7.303 MW, than the MFO and ABC algorithms.

![Figure 11. Cost and losses with considering WPHS system for 24 h scheduling period.](image)

Figure 12a,b shows the comparative convergence characterized with ABC and MFO algorithms for the three different case studies. From Figure 12, it is observed that cost is lower in the base case condition compared to the wind power and WPHS integrated system. To find the economic risk of the system, optimal control parameters set for the initial interval with three different cases obtained are shown in Table 4.

![Figure 12. Comparative convergence plot using (a) ABC algorithm and (b) MFO algorithm.](image)
Table 4. Optimal setting of the control parameter for initial interval of the system.

| Control Variable | Normal System | With wind Power | With WPHS System |
|------------------|---------------|-----------------|-----------------|
|                  | SQP | ABC | MFO | SQP | ABC | MFO | SQP | ABC | MFO |
| PG₁              | 176.61 | 177.869 | 178.060 | 170.81 | 171.772 | 171.758 | 169.7 | 171.055 | 171.188 |
| PG₂              | 48.87 | 48.5084 | 48.4867 | 47.48 | 46.9748 | 46.9637 | 47.23 | 46.8821 | 45.5135 |
| PG₄ (WPH)        | — | — | — | 12.75 | 12.7500 | 12.7500 | 15.00 | 15.0000 | 15.00 |
| PG₅              | 21.52 | 21.3587 | 21.3301 | 21.10 | 20.8995 | 20.8900 | 21.02 | 20.8552 | 20.2404 |
| PG₈              | 22.23 | 20.9467 | 20.8686 | 18.99 | 17.1770 | 17.1896 | 18.47 | 16.6266 | 17.3108 |
| PG₁₁             | 12.27 | 11.8473 | 11.7485 | 11.13 | 10.5493 | 10.5584 | 10.95 | 10.0000 | 10.8859 |
| PG₁₃             | 11.36 | 12.0000 | 12.0000 | 10.18 | 12.0000 | 12.0000 | 9.99 | 12.0000 | 12.0000 |
| V₁               | 1.060 | 1.1000 | 1.1000 | 1.060 | 1.1000 | 1.1000 | 1.060 | 1.1000 | 1.0987 |
| V₂               | 1.042 | 1.0873 | 1.0843 | 1.041 | 1.0814 | 1.0810 | 1.043 | 1.1000 | 1.0740 |
| V₄ (WPHS)        | — | — | — | 1.025 | 1.0600 | 1.0600 | 1.020 | 1.0600 | 1.0600 |
| V₅               | 1.015 | 1.0594 | 1.0567 | 1.014 | 1.0497 | 1.0473 | 1.015 | 1.0603 | 1.0470 |
| V₈               | 1.020 | 1.0708 | 1.0660 | 1.023 | 1.0573 | 1.0567 | 1.021 | 1.0633 | 1.0565 |
| V₁₁              | 1.060 | 1.1000 | 1.1000 | 1.060 | 1.0903 | 1.1000 | 1.060 | 1.1000 | 1.0833 |
| V₁₃              | 1.060 | 1.1000 | 1.1000 | 1.060 | 1.0805 | 1.0820 | 1.060 | 1.1000 | 1.0455 |
| T₁₁              | 0.9968 | 0.9672 | 0.9513 | 0.9223 | 0.9000 | 0.9616 | 0.9789 | 0.9948 | 0.9966 |
| T₁₂              | 0.9020 | 0.9789 | 1.2000 | 0.9835 | 0.9252 | 0.9696 | 0.9225 | 1.0373 | 0.9387 |
| T₁₅              | 0.9673 | 0.9413 | 0.9000 | 1.0254 | 0.9000 | 0.9387 | 0.9096 | 0.9391 | 0.9282 |
| T₃₆              | 0.9693 | 0.9416 | 0.9000 | 0.9493 | 1.1000 | 0.9252 | 0.9616 | 0.9392 | 0.9543 |
| QC₁₀             | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 |
| QC₁₂             | 5.0000 | 3.9687 | 5.0000 | 5.0000 | 5.0000 | 4.9516 | 5.0000 | 4.4123 | 4.9516 |
| QC₁₅             | 4.9950 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 |
| QC₁₇             | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 |
| QC₂₀             | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 |
| QC₂₃             | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 |
| QC₂₅             | 5.0000 | 4.0413 | 5.0000 | 4.3920 | 4.8523 | 4.0862 | 5.0000 | 4.0035 | 5.0000 |
| QC₂₆             | 5.0000 | 5.0000 | 5.0000 | 4.9966 | 5.0000 | 5.0000 | 5.0000 | 5.0000 | 5.0000 |
| QC₂₉             | 4.5339 | 3.9970 | 0 | 3.5404 | 4.1497 | 3.9066 | 0 | 5.0000 | 5.0000 |
| Cost ($/h)       | 802.20 | 799.107 | 798.925 | 804.01 | 801.853 | 801.814 | 804.64 | 802.11 | 801.981 |
| Losses (MW)      | 11.742 | 9.1307 | 9.0946 | 11.742 | 8.7231 | 8.7106 | 9.043 | 8.9189 | 8.7390 |
| VaR(95%)         | −0.9227 | −0.74261 | −0.69056 | −0.9227 | 0.73907 | −0.72138 | −0.8220 | −0.6948 | −0.7655 |
| CVaR(95%)        | −0.9860 | −0.75849 | −0.72317 | 0.9860 | −0.79658 | −0.7803 | −0.8495 | −0.7505 | −0.7883 |

From Table 4, it is observed that the VaR and CVaR are lower with the integration of the WPHS system compared to the integrated system without and with wind generation. From the Table, it is observed that cost slightly increases with wind generation and the wind and PHS system because wind generation cost is considered here.

5. Conclusions

This paper presents a detailed economic risk analysis study of VaR and CVaR with confidences levels of 95% and 99% in the WPHS integrated system. The economic risk was calculated for three different stages based on the MVA flows of the system. Three different optimization techniques, i.e., ABC, MFO, and SQP, were used for optimal power flow solution in each stage. The MFO algorithm was used for the first time in this type of problem, which is the main novelty of this work. By comparing the results obtained after implementing algorithms like SQP, ABC, and MFO for both IEEE 30 bus test systems, it can be inferred that MFO gives a better performance in terms of the risk coefficient value. The risk associated based on MVA flows is lower in MFO than ABC and SQP. As the confidence level increases, the risk values increase. VaR values saturate as we move towards a higher confidence level, i.e., 99%, whereas CVaR values give more predictable differences towards a higher confidence level. Finally, it can be concluded that the integration of the WPHS in a power system using MFO is effective for minimizing the system risk. The system generation cost is also minimized after the incorporation of the wind farm and pumped energy storage system. The presented approach is a generalized one that can be implemented in any large, small as well as hybrid system.
Author Contributions: Conceptualization, N.K.S. and S.G.; methodology, C.K., S.D. and S.G.; software, N.K.S.; validation, C.K. and S.D.; formal analysis, T.S.U.; investigation, C.K. and S.G.; resources, N.K.S., C.K., S.G. and T.S.U.; data curation, T.S.U.; writing—original draft preparation, N.K.S.; writing review and editing, S.D. and T.S.U.; visualization, S.D. and S.G.; supervision, C.K.; project administration, C.K., S.G. and S.D.; funding acquisition, T.S.U. All authors have read and agreed to the published version of the manuscript.

Funding: Not Applicable.

Institutional Review Board Statement: Not Applicable.

Informed Consent Statement: Not Applicable.

Data Availability Statement: Not Applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Dawn, S.; Tiwari, P.K.; Goswami, A.K.; Panda, R. An Approach for System Risk Assessment and Mitigation by Optimal Operation of Wind Farm and FACTS Devices in a Centralized Competitive Power Market. *IEEE Trans. Sustain. Energy* 2019, 10, 1054–1065. [CrossRef]

2. Zhang, G.; Li, F.; Xie, C. Flexible Robust Risk-Constrained Unit Commitment of Power System Incorporating Large Scale Wind Generation and Energy Storage. *IEEE Access* 2020, 8, 209232–209241. [CrossRef]

3. Bathurst, G.; Weatherill, J.; Strbac, G. Trading wind generation in short term energy markets. *IEEE Trans. Power Syst.* 2002, 17, 782–789. [CrossRef]

4. Bathurst, G.N.; Weatherill, J.; Strbac, G. Optimal Dispatch of Wind Farms Facing Market Prices. In Proceedings of the 14th International Conference on the European Energy Market (EEM), Dresden, Germany, 6–9 June 2017.

5. Shin, H.; Baldick, R. Mitigating market risk for wind power providers via financial risk exchange. *Energy Econ.* 2018, 71, 344–358. [CrossRef]

6. Wu, H.; Shahidehpour, M.; Alabdulwahab, A.; Abusorrah, A. A Game Theoretic Approach to Risk-Based Optimal Bidding Strategies for Electric Vehicle Aggregators in Electricity Markets with Variable Wind Energy Resources. *IEEE Trans. Sustain. Energy* 2016, 7, 374–385. [CrossRef]

7. Xu, Z.; Hu, Z.; Song, Y.; Wang, J. Risk-Averse Optimal Bidding Strategy for Demand-Side Resource Aggregators in Day-Ahead Electricity Markets Under Uncertainty. *IEEE Trans. Smart Grid* 2017, 8, 96–105. [CrossRef]

8. Negnevitsky, M.; Nguyen, D.H.; Piekutowski, M. Risk Assessment for Power System Operation Planning with High Wind Power Penetration. *IEEE Trans. Power Syst.* 2015, 30, 1359–1368. [CrossRef]

9. Xue, Y.; Yu, C.; Li, K.; Wen, F.; Ding, Y.; Wu, Q.; Yang, G. Adaptive ultra-short-term wind power prediction based on risk assessment. *CSEE J. Power Energy Syst.* 2016, 2, 59–64. [CrossRef]

10. Thatte, A.; Xie, L.; Viassolo, D.E.; Singh, S. Risk Measure Based Robust Bidding Strategy for Arbitrage Use a Wind Farm and Energy Storage. *IEEE Trans. Smart Grid* 2013, 4, 2191–2199. [CrossRef]

11. Shen, J.; Jiang, C.; Liu, Y.; Wang, X. A Microgrid Energy Management System and Risk Management Under an Electricity Market Environment. *IEEE Access* 2016, 4, 2349–2356. [CrossRef]

12. Zhang, Y.; Han, X.; Xu, B.; Wang, Y.; Wang, M.; Ye, P. Risk-based Reserve Coordinative Unit Commitment for a Large-scale Wind-storage System. *Electr. Power Compon. Syst.* 2018, 46, 2004–2020. [CrossRef]

13. Tavakkoli, M.; Poursesamei, E.; Godina, R.; Vechiu, I.; Catalăo, J.P.S. Optimal Management of an Energy Storage Unit in a PV-Based Microgrid Integrating Uncertainty and Risk. *Appl. Sci.* 2019, 9, 169. [CrossRef]

14. Mokaramian, E.; Shayeghi, H.; Sedaghati, F.; Safari, A.; Alhelou, H.H. A CVaR-Robust- Based Multi-Objective Optimization Model for Energy Hub Considering Uncertainty and E-Fuel Energy Storage in Energy and Reserve Markets. *IEEE Access* 2021, 9, 109447–109464. [CrossRef]

15. Afzali, P.; Rashidinejad, M.; Abdollahi, A.; Bakhshai, A. Risk-Constrained Bidding Strategy for Demand Response, Green Energy Resources, and Plug-In Electric Vehicle in a Flexible Smart Grid. *IEEE Syst. J.* 2021, 15, 338–345. [CrossRef]

16. Panda, R.; Tiwari, P.K. Economic risk-based bidding strategy for profit maximisation of wind-integrated day-ahead and real-time double-auctioned competitive power markets. *IET Gener. Transm. Distrib.* 2019, 13, 209–218. [CrossRef]

17. Qian, M.; Chen, N.; Chen, Y.; Chen, C.; Qiu, W.; Zhao, D.; Lin, Z. Optimal Coordinated Dispatching Strategy of Multi-Sources Power System with Wind, Hydro and Thermal Power Based on CVaR in Typhoon Environment. *Energies* 2021, 14, 3735. [CrossRef]

18. Gazijahani, F.S.; Ajouladaci, A.; Ravanadegan, S.N.; Salehi, J. Joint energy and reserve scheduling of renewable powered microgrids accommodating price responsive demand by scenario: A risk-based augmented epsilon-constraint approach. *J. Clean. Prod.* 2020, 262, 121365. [CrossRef]

19. Li, X.; Wang, W.; Wang, H. A novel bi-level robust game model to optimize a regionally integrated energy system with large-scale centralized renewable-energy sources in Western China. *Energy* 2021, 228, 120513. [CrossRef]
20. Li, Z.; Wu, L.; Xu, Y. Risk-Averse Coordinated Operation of a Multi-Energy Microgrid Considering Voltage/Var Control and Thermal Flow: An Adaptive Stochastic Approach. *IEEE Trans. Smart Grid* 2021, 12, 3914–3927. [CrossRef]
21. Chen, L.; Liu, L.; Peng, Y.; Chen, W.; Huang, H.; Wu, T.; Xu, X. Distribution network operational risk assessment and early warning considering multi-risk factors. *IET Gener. Transm. Distrib.* 2020, 14, 3139–3149. [CrossRef]
22. Liu, Z.; Liu, S.; Li, Q.; Zhang, Y.; Deng, W.; Zhou, L. Optimal Day-ahead Scheduling of Islanded Microgrid Considering Risk-based Reserve Decision. *J. Mod. Power Syst. Clean Energy* 2021, 9, 1149–1160. [CrossRef]
23. Langeroudi, A.S.G.; Sedaghat, M.; Pirpoor, S.; Fotouhi, R.; Ghasemi, M.A. Risk-based optimal operation of power, heat and hydrogen-based microgrid considering a plug-in electric vehicle. *Int. J. Hydrog. Energy* 2021, 46, 30031–30047. [CrossRef]
24. Guo, Q.; Nojavan, S.; Lei, S.; Liang, X. Economic-environmental analysis of renewable-based microgrid under a CVaR-based two-stage stochastic model with efficient integration of plug-in electric vehicle and demand response. *Sustain. Cities Soc.* 2021, 75, 103276. [CrossRef]
25. Xuan, A.; Shen, X.; Guo, Q.; Sun, H. A conditional value-at-risk based planning model for integrated energy system with energy storage and renewables. *Appl. Energy* 2021, 294, 116971. [CrossRef]
26. Zhang, Q.; Li, F. From Systematic Risk to Systemic Risk: Analysis over Day-Ahead Market Operation under High Re-newable Penetration by CoVaR and Marginal CoVaR. *IEEE Trans. Sustain. Energy* 2021, 12, 761–771. [CrossRef]
27. Kalkhambkar, V.; Kumar, R.; Bhakar, R. Joint optimal allocation methodology for renewable distributed generation and energy storage for economic benefits. *IET Renew. Power Gener.* 2016, 10, 1422–1429. [CrossRef]
28. Karaboga, D.; Basturk, B. Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems. In Proceedings of the 12th international Fuzzy Systems Association World Congress on Foundations of Fuzzy Logic and Soft Computing, Cancun, Mexico, 18–21 June 2007; Springer: Berlin/Heidelberg, Germany, 2007; Volume 4529, pp. 789–798.
29. Mirjalili, S. Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. *Knowl. Based Syst.* 2015, 89, 228–249. [CrossRef]
30. Malakar, T.; Goswami, S.; Sinha, A. Optimum scheduling of micro grid connected wind-pumped storage hydro plant in a frequency based pricing environment. *Int. J. Electr. Power Energy Syst.* 2014, 54, 341–351. [CrossRef]
31. Abou El Ela, A.A.; Abido, M.A.; Spea, S.R. Optimal power flow using differential evolution algorithm. *Electr. Power Syst. Res.* 2010, 80, 878–885. [CrossRef]
32. Dawn, S.; Tiwari, P.K.; Goswami, A.K. A Joint Scheduling Optimization Strategy for Wind and Pumped Storage Systems Considering Imbalance Cost & Grid Frequency in Real-Time Competitive Power Market. *Int. J. Renew. Energy Res.* 2016, 6, 1248–1259.