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Robust Self-Scheduling of PVs-Wind-Diesel Power Generation Units in a Standalone Microgrid under Uncertain Electricity Prices

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Abstract— *In the semi-autonomous regions and remote islands, the multiple diesel units are usually used for supplying demand and exchanging power with other adjacent zones. In the risk-aware generation companies consisting of diesel engines, photovoltaic panels (PVs), and wind turbines, the uncertain electricity market prices affect the optimum operating points of these units, the total revenue gained from selling energy to neighbor microgrids, and the daily fuel cost of the diesel generators. Moreover, the output power of the diesel engines is a nonlinear function of their specific fuel consumption at discrete loading intervals. Therefore, this paper aims to present a risk-aware mixed integer nonlinear optimization problem for finding the best generation schedules of the diesel units involving the energy price fluctuations. The total fuel costs of the diesel engines minus the total revenue achieved from procuring power for nearby regions is minimized as a cost objective function satisfying the lower and upper generation bounds in each loading subinterval, the load-generation balance criterion, and the nominal capacities of generating units. The cubic spline interpolation is used for accurately fitting the fuel-power curves of the diesel generators at successive loading subintervals because of its zero norm of residual in comparison with* 5^{th} *degree and quadratic polynomials. A benchmark microgrid with six diesel generators, PVs and wind turbines is robustly scheduled using the budget of uncertainty with no need to probability distribution and membership functions of energy prices. It is revealed that this strategy is practical for each price-taker generation company, which desires the risk-aversion production patterns of the diesel power production units against the energy market price uncertainty in a specific operating horizon.*

Keywords—Diesel generators, robust non-linear programming (RNLP) problem, specific fuel consumption (SFC), uncertainty budget, uncertain electricity prices.

NOMENCLATURE

Symbols

F_j^t	Fuel consumption of the diesel generator *j* at time *t*
F_j	The fuel requirement of the diesel generator *j* (g)
j	in time *t* (g/kWh)
N_w	The number of the wind turbines
P_j^t	The power product of the diesel engine *j* in time *t* (per unit)
P_w^t	The generated power of the wind turbines farm (kW)
P_j^{max}	The power generation capacity of the diesel generator *j* (kW)
P_{PVs}^t	The power output of a photovoltaic panel (W)
S_j^t	The SFC of the diesel engine
T_t^a	The ambient temperature at time *t*
N_{PVs}	The number of the photovoltaic panels
P_r^w	The wind turbine rated power (kW)
A_w	Scale factor
k_w	Shape factor
s_w	The wind speed (m/s)
s_{in}	The wind turbine cut-in speed (m/s)
s_{out}	The wind turbine cut-out speed (m/s)
s_r	The wind turbine rated speed (m/s)

Indices

j	Index of diesel generators
t	Operating time interval (hour)

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Greek letters

α	Typical uncertain variable
β	Typical known variable
χ_t	The solar irradiance (W/m^2)
η	The conversion coefficient of a photovoltaic panel
γ	Typical objective function
Ψ	The budget of uncertainty
$\overline{\lambda}_P^t$	The predicted electricity rate in operating period *t* (\$/kWh)
λ_P^t	Electricity market price at hour *t*
λ_F	The diesel fuel price (\$/g)
$\overline{\alpha}_t$	The predicted decision value at hour *t*
δ, ξ_t	The dual variables of the robust optimization method
$\widehat{\lambda}_P^t$	Maximum deviation of the actual energy rate from its predicted value in time *t* (\$/kWh)
$\lambda_{P,min}^t$, $\lambda_{P,max}^t$	The lower and upper bounds of the electricity market price at hour *t* (\$/kWh)

1. INTRODUCTION

In the remote regions such as Masirah Island in Oman, a central power station with a number of diesel units is used to generate electricity for local consumers or adjacent zones [1, 2]. Uninterrupted fuel transportation for power production in thes{Bukar, 2019 #21}e zones poses a great challenge in economic dispatch of diesel engines and their integration with renewable energies [3]. Meanwhile, optimal operation of multiple diesel engines in semi-autonomous microgrids reduces their fuel costs and emitted pollutants [4, 5]. The specific fuel consumption (SFC) of the diesel producer is a non-linear function of its power product in successive discrete operating intervals, which are defined by minimum and maximum per unit loading capacity [6]. In other words, a non-linear problem is solved over a 1-day study period to find how much fuel is utilized by each diesel unit to supply a given level of demand [7]. In the standalone networks, the total fuel requirement of the diesel engines is minimized, while the load-generation balance constraint and the power production limit of these units are fulfilled [8]. But, if a price-taker generation company desires to maximize its profit, the daily revenue obtained from selling energy to near load centers minus the total fuel cost of the diesel generation units should be maximized [9].

In [4], a multi-objective demand side management including economic and environmental indices has been investigated for a smart microgrid to improve load variations. The microgrid consists of diesel generator, photovoltaic, wind turbine, micro turbine, energy storage system, and fuel cell. Additionally, the energy exchange with upstream network is also considered. The ant lion optimization algorithm is proposed to solve the optimization problem. In [6], multiple marine diesel generators are economically dispatched by harmony search optimization (HSO) algorithm [10] for powering a semi-submersible oil drilling rig platform. Various electrical load levels, demand-generation balance criterion and generation capacity constraint are considered in optimal hour-ahead scheduling problem. Numerical results achieved from optimal scheduling of diesel units with unequal ratings are compared with those found by GA, PSO, MinCon, and MinMax solvers to reveal its capability in discovering high quality and more reliable scenarios. In [8], a wind turbine, diesel engines, and compressed air energy storage (CAES) integrated microgrid is optimally scheduled using a quantum particle swarm optimization (QPSO) and sequential quadratic programming (SQP) based bi-level optimization process. In the outer layer, the sum of investment and operation costs is minimized, to find the optimum size of each component, while the generation and emission costs of the diesel units is minimized in the lower level to obtain the best operating point of the system. The demand response program and the uncertainties on load demand and wind power output are also modeled. Several recently published works have focused on optimal short-term scheduling of diesel generators in renewables assisted energy systems [11, 12]. The optimal utilization and economic management of diesel generators and energy storage systems in islanded microgrids has been investigated in [11]. To this aim, the optimization problem is formulated as a linear programming (LP) problem and the maximum utilization of renewable energy and the reduction of the fuel cost of diesel units are targeted as much as possible. The demand side management programs are also used as a solution to deal with the variation in efficiency of diesel generators with production level. Liu et al. [13] solved a multi-objective mixed-integer nonlinear programming problem using a prediction optimization algorithm to minimize the total fuel consumption of the diesel engines in the presence of a battery. The state of charge (SoC), battery charge and discharge power, as well as the fuel consumption and power product of the diesel units are selected as the decision variables. The demand uncertainty should be considered to guarantee the flexibility and resiliency of the hybrid power generation system against the unexpected load values. Authors of [14] presented a photovoltaic (PV)-diesel-battery hybrid system to generate energy in a rural district of Gobi Desert, China. A meta-heuristic algorithm called Elephant Herding optimizer is introduced, which minimizes the greenhouse gas emissions, annualized system cost, and the loss of load probability. Numerical analysis demonstrates that PVs has a prominent impact by 97% of costs and 1735 kg carbon reduction in 1-year period. In all PV integrated power generation facilities, the uncertainty associated with the solar irradiations should be studied using all-sky images and irradiance forecasts in less than 10-minute forecasting time intervals [15]. Moreover, a dual-axis sun tracking system with four-quadrant photo detectors, a pyrheliometer, small DC servo motors, and programmable logic controller, which allowed the automatic measurement of the direct solar radiations, can be linked with solar systems to increase their power products and reliability [16]. Authors of [17] evaluated a 5kW PV-battery-wind-diesel grid, which can be used in residential sector of Turkey. It is found that the diesel fuel consumption, energy procurement cost and the annual carbon emissions are less than those of diesel only systems. Uncertainty of wind power and PV product should be considered in robust and risk-seeker modes of info-gap decision theory and robust optimization models [18, 19]. Implementation of demand response programs on electrical loads and machine learning techniques based wind/solar power generation forecasting algorithms can also overcome this issue [20].

In [21], a model is presented for a standalone hybrid system consisting of photovoltaic, diesel generator, wind turbine, and stationary (battery) and mobile (electric vehicles) energy storage systems. The authors have proposed a multi-objective optimization problem to minimize the total cost of investment, maintenance and operation of the available resources as well as the emission level of the system. In addition, the limitations of planning and operation of resources and storage devices are also considered. The nonlinear form of different uncertainties including load, renewable energy and energy demand of electric vehicles are modeled. Rongjie in [22] uses a fuzzy artificial bee colony optimization method to plan a hybrid diesel energy system. Experimental results for different configurations of photovoltaic, diesel, wind power, and energy storage are presented and their pollution emissions are compared. In. Some governing factors such as wind potential, capital investment cost, oil price, and battery cost should be considered in decision making process [23, 24]. Initial investment cost, annual energy saving, efficiency and payback period of a solar dish Stirling heat engine-battery-wind turbine based power generation system should be compared with PV assisted one [25, 26]. In [27], a crow search algorithm (CSA) is introduced which minimizes the total fuel requirement of the diesel generation units and finds the best charge/discharge pattern of the pumped hydro storage (PHS) in PVs included systems. The CSA finds more economic operating scenarios for PHS-PVs-diesel connected networks with less fuel requirement and lower computational burden than GA and PSO. Integration of diesel producers with renewable energy resources based power generation infrastructure has more benefits than single renewable grids [28]. In this context, the authors of [19, 29, 30] combined PVs, battery and diesel generators for electrification of rural or small communities geographically located far away from power grids. In [31], economic and environmental benefits of micro-hydro, solar and wave energy in off-grid small villages, that are reliant on diesel power producers, is proved defining two targets "*allowable-cost*" and "*levelized cost of energy (LCOE)*". Remote community optimization model (RCOM) of Canadian Hot Springs Cove results in LCOE of \$0.76/kWh for diesel only operating mode. By adding a 225 kW hydro turbine to this project, \$5.2 M is saved considering a 30-years lifetime. According to "allowable-cost" analysis, wave energy is more cost-effective and eco-friendly option if it is delivered in less than \$0.59/kWh resulting in 40% diesel fuel consumption and returning \$23,206/kW installed. Similarly, solar power causes 12% fuel saving and a return of \$6844/kW installed. In [32], the main objective is the economic and environmental evaluation of a PV/diesel /biogas/battery system to supply the load demand of a village in China. The proposed system results in an annual reduction of 1300 tons of carbon dioxide (CO_2) compared to the diesel generator. In addition, the results of the sensitivity analysis show that the cost reductions of biogas generators and batteries can effectively decrease the total costs of the system. Alzahrani, et al. [33] review the most important optimization methods of hybrid systems in order to reduce the operation costs and total network losses. This review paper focuses on the hybrid energy system consisting of photovoltaic, diesel generator and energy storage and examines the proposed methods in the literature from various aspects. In the developing countries such as Iran, the power transmission from national grid to remote rural communities is not an economically viable proposition. Hence, diesel engines with significant fuel requirement are mainly utilized for electrification

Table 1. The main characteristics of the previous works

Ref.	System Architecture	Off-grid/On-grid	Methodology	Performance Parameters
[1]	Diesel, PV, WT, Natural gas generator	Off-grid	HOMER	NPC, COE, pollutant emission
[3]	Diesel, PV, PHS, FC	Off-grid	MOCSA	NPC, LPSP
[5]	Diesel, PV, PHS, Battery	Off-grid	HOMER	NPC, COE, CO_2 emission
[7]	Diesel, PV	Off-grid	MATLAB	LCOE, loading factor, total fuel consumption
[9]	Diesel, PV, WT, FC, Battery	Both	NSGA-II	configuration, size
[12]	Diesel, PV, Battery	Off-grid	HOMER	NPC, LCOE, operating cost
[15]	Diesel, PV, Battery	Off-grid	MATLAB/ HOMER	NPC, CO_2 emission
[19]	Diesel, PV, WT, Battery	Both	HOMER	NPC, COE, pollutant emission, grid tariff
[21]	Diesel, PV, WT, Battery	Off-grid	SCA, CSA	cost of construction, maintenance, operation, emission level
[22]	Diesel, PV, WT, Battery	Off-grid	Fuzzy artificial bee colony	cost, load shortages, pollutant emission
[24]	Diesel, PV, WT, Battery	Off-grid	Monte Carlo	total annual costs, reliability
[26]	Diesel, PV, WT, Battery, Reverse osmosis	On-grid	DRL	operating cost, cost of battery, pollution cost
[28]	Diesel, PV, WT	Off-grid	HOMER	CO_2 emission, cost of energy
[30]	Diesel, PV, Battery	Off-grid	PSO/ HOMER	LPSP, CO_2 emission, annualized cost
[32]	Diesel, PV, Battery, Biogas	Off-grid	HOMER	NPC, COE, CO_2 emission
Present research	Diesel, PVs, Wind turbine	Off-grid	Robust Optimization, electricity price uncertainty	Diesel fuel cost, Revenue, Net operation cost

of these microgrids. Capacity of diesel generators conventionally prepared twice greater than maximum demand to avoid from load spike. Aggregator of these units within a remote area, that exchanges power with other adjacent zones, can solve an optimal short-term self-scheduling problem for maximization of its profit obtained from selling energy to geographically close off-grid networks, which has not been studied in the reviewed works. Moreover, the uncertainty of the electricity market prices is not considered in the optimal energy trading of the wind-diesel-PVs hybrid GenCo. The novelties of this paper are stated as follows:

- An aggregator of multiple diesel generators, PVs and wind turbines in a remote area such as small rural communities, which exchanges power with near off-grid zones, desires higher revenue and lower fuel cost. A cost minimization approach is mathematically presented for optimal self-scheduling of diesel power production units. The SFC of each diesel engine is modelled as a 3^{rd} degree polynomial function of its power output, which is limited by minimum and maximum per unit loading capacities at discrete successive intervals. The total fuel cost of the diesel generators minus the daily revenue obtained from selling power to adjacent microgrids is minimized as the main objective function under the various budget of electricity market price uncertainty.
- The electricity price fluctuations affect the operating pattern of the diesel generators and the aggregator's profit obtained from selling the power outputs of diesel engines, PVs, and wind farms. A robust non-linear programing (RNLP) problem is developed to minimize the total fuel cost of diesel units minus the total revenue gained from selling electricity production of diesel generators, PVs and wind turbines to neighbor semi-autonomous regions against the variation of uncertain energy rates. Firstly, the forecasted electricity prices are involved in risk-neutral or deterministic decision making process before modelling uncertainty. Then, the uncertainty budget changes from 0 to 100% to determine the robust or risk-aversion fuel utilization and energy production patterns of the diesel generators in 1-day operating period.
- The sensitivity of the decision variables (such as the SFC and power products of the diesel generators as well as the aggregator's fuel cost and revenue) to the uncertainty budget is analyzed. For instance, when the uncertainty budget is set out as 0.25, the actual electricity prices in 25% of the whole study horizon (hours 19 to 24) differ from the predicted values. At other hours, it is known or determined without uncertainty. The diesel generation company (GenCo) maximizes its revenue achieved from selling electricity produced by the diesel generators, PVs and wind turbines and minimizes the total diesel fuel cost under various budgets of uncertainty.

The mathematical models of the wind, PVs, and diesel engines power generations are presented in Section 2. The robust optimization based self-scheduling of the diesel power production units is provided in Section 3. Numerical results and discussions is presented in Section 4. Finally, concluding remarks and future trends are stated in Section 5.

2. Mathematical power generation models of wind turbine, diesel engines and photovoltaic panels

It is supposed that a generation company (GenCo) with a number of solar photovoltaic (PVs) panels, wind turbines, and multiple diesel engines aims to supply the total electricity demand of a microgrid while selling energy to other adjacent areas. Hence, the daily diesel fuel cost minus the total revenue obtained from selling electricity generation of PVs, wind turbines, and diesel engines to these microgrids should be minimized as the net-cost objective function presented in Eq. (1). where, P_j^t and F_j^t are the output electrical power and fuel consumption of the diesel generator j at time t, respectively. Moreover, P_j^{max} refers the maximum power product or generation capacity of the diesel engine j. The electricity market rate at hour t and the diesel fuel price are indicated by λ_P^t and λ_F, respectively. The PVs and wind products are indicated by P_{PVs}^t and P_w^t, respectively.

$$\underset{P_j^t, F_j^t}{Minimize} \sum_{t=1}^{T=24} \sum_{j=1}^{N} \lambda_F \times F_j^t - \left\{ \lambda_P^t \times \left(P_j^t \times P_j^{max} + P_{PVs}^t + P_w^t \right) \right\} \tag{1}$$

The value of the wind speed (s_w) is modeled using the Weibull probability density function as formulated by Eq. (2). Moreover, the value of the wind farm power product (P_w^t) is approximated as Eq. (3). The scale factor and the shape factor are two constant parameters related to the wind turbine structure, which are denoted by A_w and k_w, respectively. Moreover, s_{in}, s_{out}, and s_r refer the wind turbine cut-in, cut-out, and rated speeds, respectively. The rated power of each wind turbine is given by P_r^w [34].

$$f(s_w) = \frac{k_w}{A_w} \left(\frac{s_w}{A_w} \right)^{k_w - 1} \exp\left(- \left(\frac{s_w}{A_w} \right)^{k_w} \right) \tag{2}$$

Table 2. The SFC of Wärtsilä 16V26A diesel generator [37].

Loading power (p.u.)	Fuel requirement (g/kWh)
0.25	233.12
0.5	201
0.75	192.98
0.85	195.2
0.9	195.51
1	196.55
1.1	199.11

$$P_w^t = \begin{cases} 0 & s_w < s_{in};\ s_{out} \le s_w \\ N_w P_r^w \frac{s_w - s_{in}}{s_r - s_{in}} & s_{in} \le s_w < s_r \\ N_w P_r^w & s_r \le s_w < s_{out} \end{cases} \tag{3}$$

Eq. (4) formulates the power output of a photovoltaic panel [35]. where, N_{PVs} is the number of the photovoltaic panels; P_{PVs}^t refers the power output of photovoltaic panels. The conversion coefficient of the photovoltaic panels is shown with η. A is the array area of the photovoltaic module. Finally, χ_t and T_t^ashow the solar irradiation and the ambient air temperature, respectively.

$$P_{PVs}^t = N_{PVs} \eta A \chi_t \left\{1 - 0.005 \times (T_t^a - 25)\right\} \tag{4}$$

According to Eq. (5), the fuel consumption of the diesel power production unit *j* at hour *t* is calculated using its power generation and specific fuel consumption (SFC). According to Table 2, the SFC of the diesel generators is calculated based on exponential and polynomial functions. Table 3 demonstrates that a cubic spline interpolation function is more accurate than higher-order polynomial models. Obviously, there is no data at starting these units. Therefore, the 2^{nd} and 5^{th} order polynomial functions and the cubic spline model are used for finding the initial fuel consumption at starting point of the diesel engines. Using the 5^{th} polynomial function, the extrapolated amount is equal to 233.12 g/kWh, which is not accepted because it should be higher than that at 0.25 per unit loading condition. This is resulted from this fact that maximum SFC of a diesel unit corresponds to its starting point. Hence, the cubic spline model is used for estimating the initial SFC at starting stage as 289 g/kWh [36].

$$F_j^t = S_j^t \times P_j^t \times P_j^{max} \tag{5}$$

The SFC of the diesel power production unit *j* in time *t* is denoted by S_j^t and can be obtained from Eqs. (6)–(12) [36].
For $0 \le P_j^t < 0.25$:

$$S_j^t = 2.951\left(P_j^t\right)^3 + 187.8\left(P_j^t\right)^2 + 270.67 P_j^t + 289 \tag{6}$$

For $0.25 \le P_j^t < 0.5$:

$$\begin{aligned} S_j^t =& 2.9512\left(P_j^t - 0.25\right)^3 + 190.08\left(P_j^t - 0.25\right)^2 \\ &- 176.184\left(P_j^t - 0.25\right) + 233.12 \end{aligned} \tag{7}$$

For $0.5 \le P_j^t < 0.75$:

$$\begin{aligned} S_j^t =& 7.0041\left(P_j^t - 0.5\right)^3 + 192.293\left(P_j^t - 0.5\right)^2 \\ &- 80.591\left(P_j^t - 0.5\right) + 201 \end{aligned} \tag{8}$$

For $0.75 \le P_j^t < 0.85$:

$$\begin{aligned} S_j^t =& -1442.4\left(P_j^t - 0.75\right)^3 + 197.546\left(P_j^t - 0.75\right)^2 \\ &+ 16.869\left(P_j^t - 0.75\right) + 192.98 \end{aligned} \tag{9}$$

For $0.85 \le P_j^t < 0.9$:

$$\begin{aligned} S_j^t =& 1940.1\left(P_j^t - 0.85\right)^3 + 235.158\left(P_j^t - 0.85\right)^2 \\ &+ 13.1\left(P_j^t - 0.85\right) + 195.2 \end{aligned} \tag{10}$$

Table 3. Residuals in 5^{th}-degree and quadratic polynomial models and cubic spline curve fitting approach [37]

Curve fitting method	Norms of residuals
Cubic spline interpolation	0
5^{th} degree polynomial	0.316
Quadratic polynomial	6.011

For $0.9 \le P_j^t < 1$:

$$\begin{aligned} S_j^t =& 67.134\left(P_j^t - 0.9\right)^3 + 55.8598\left(P_j^t - 0.9\right)^2 \\ &+ 4.1427\left(P_j^t - 0.9\right) + 195.51 \end{aligned} \tag{11}$$

For $P_j^t = 1$:

$$\begin{aligned} S_j^t =& 67.134\left(P_j^t - 1\right)^3 + 76\left(P_j^t - 1\right)^2 \\ &+ 17.328\left(P_j^t - 1\right) + 196.55 \end{aligned} \tag{12}$$

As restricted by inequality constraint (13), the per unit loading power changes between 0 and 1 [36].

$$0 \le P_j^t \le 1; \quad \forall t = 1, \ldots, T \ and \ j = 1, \ldots, N \tag{13}$$

3. Robust self-scheduling problem

In the robust optimization technique, which was introduced by Soyster in 1973 [38], the uncertainty is handled with no need for any information about the uncertain variable. The flowchart of the proposed robust optimization algorithm is shown in Fig. 1. As stated in Eq. (14), it is supposed that $\gamma = f(\alpha, \beta)$ is a linear function of the uncertain vasriable α and changes nonlinearly by the known variable β. In Eq. (15), any positive or negative deviation of the uncertain variable (α) from the predicted value $(\overline{\alpha})$ is limited by $\widehat{\alpha}$.

$$\min_{\beta} \gamma = f(\alpha, \beta) \tag{14}$$

$$|\alpha - \overline{\alpha}| \le \widehat{\alpha} \tag{15}$$

As mentioned, the objective function γ varies linearly by the uncertain variable α. Hence, the nonlinear optimization problem should be modeled as Eqs. (15)–(17). where, the matrix $A(\beta)$ with components $a_t(\beta)$ indicates the coefficients of the uncertain variable α. Similarly, the matrix $B(\beta)$ consists of the known variables β. It is obvious from Eqs. (16) and (17) that the total cost γ can be minimized by reducing the linear function $f(\alpha, \beta)$ as much as possible.

$$\gamma \ge f(\alpha, \beta) \tag{16}$$

$$f(\alpha, \beta) = A(\beta) \times \alpha + B(\beta) \tag{17}$$

In the risk-aware optimization problem, a robust optimal solution should be find that ensures the global optimality of the objective function γ allowing a specific prediction error. Considering the forecast error in estimating α, the global optimal scenario will be found with great probability by involving the robust counter term ω_i in Eq. (14). In other words, Eqs. (18)–(20) are used for minimizing the cost objective function γ using the auxiliary function $f(\alpha, \beta)$ under the uncertain operating condition.

$$\begin{aligned} f(\alpha, \beta) =& \min_{\omega_t} \sum_t a_t(\beta) \times \widehat{\alpha} \times \omega_t \\ &- A(\beta) \times \overline{\alpha} - B(\beta) \end{aligned} \tag{18}$$

$$\sum_t \omega_t \ge \Psi \tag{19}$$

Table 4. The technical characteristics of the wind turbines [34] and photovoltaic panels [35]

Parameter	Value	Parameter	Value
Shape factor	5	Rated power of each wind turbine (kW)	100
Scale factor	25	Number of wind turbines	10
Cut-in speed (m/s)	5	Conversion coefficient of a photovoltaic panel	0.187
Cut-out speed (m/s)	70	Array area of a photovoltaic module	2.5
Rated speed (m/s)	35	Number of PV panels	1000

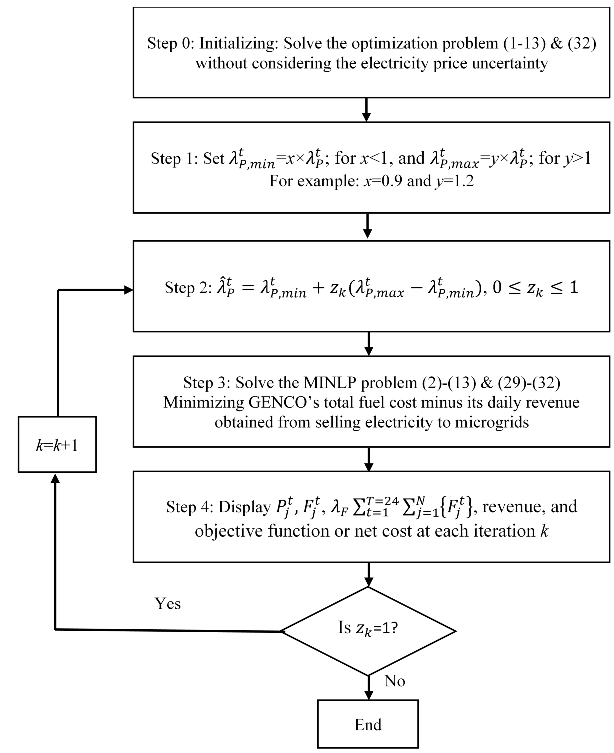


Fig. 1. The flowchart of the proposed robust self-scheduling algorithm

$$0 \le \omega_t \le 1 \tag{20}$$

Hence, the cost objective function (14) with quality and inequality constraints (18)–(20) can be rewritten as Eq. (21) and inequality constraint (22). It should be mentioned that $\overline{\alpha}_t$ is the predicted decision value at hour t. As obvious, the matrix form of the 3^{rd} term of Eq. (18), which is defined as $min_{\omega_t}\sum_t a_t(\beta)\times\widehat{\alpha}\times\omega_t$, is presented in relation (21). Moreover, constraints (19) and (20) are merged as inequality constraint (22).

$$\min_{\omega_t}\left[\begin{array}{cccc} a_1(\beta)\times\widehat{\alpha}_1, & a_2(\beta)\times\widehat{\alpha}_2, & \ldots & a_n(\beta)\times\widehat{\alpha}_n \end{array}\right]\begin{pmatrix}\omega_1\\ \omega_2\\ \vdots\\ \omega_n\end{pmatrix} \tag{21}$$

$$\begin{pmatrix} 1 & 1 & \ldots & 1\\ 1 & 0 & \ldots & 0\\ 0 & 1 & \ldots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \ldots & 1\end{pmatrix}\begin{pmatrix}\omega_1\\ \omega_2\\ \vdots\\ \omega_n\end{pmatrix} \ge \begin{pmatrix}\Psi\\ 1\\ \vdots\\ 1\end{pmatrix} \tag{22}$$

Therefore, the dual maximization problem (18)–(20) can be given by Eqs. (23) and (24):

$$\max_{\xi_i,\delta}\ \Psi\delta+\sum_t\xi_t \tag{23}$$

$$\delta+\xi_t \le a_t(\beta)\times\widehat{\alpha}_t \tag{24}$$

By adding Eq. (23) to optimization approach, minimization of γ is carried out so that maximum value of auxiliary function $f(\alpha,\beta)$ equals to γ. According to Eqs. (20), (23) and (24), the maximum cost value of the function $f(\alpha,\beta)$ is found by maximizing the robustness cost $\Psi\delta+\sum_t\xi_t$ and minimizing the revenue term $A(\beta)\times\overline{\alpha}+B(\beta)$, to minimize the net cost γ under the worst case with maximum cost function $\Psi\delta+\sum_t\xi_t$ and minimum revenue term $A(\beta)\times\overline{\alpha}+B(\beta)$. Meanwhile, the expected profit should be greater than the threshold value $\delta+\xi_t$.

$$\min_{\beta,\xi_t,\delta}\ \gamma \tag{25}$$

$$\gamma \ge f(\alpha,\beta) \tag{26}$$

$$f(\alpha,\beta)=\Psi\delta+\sum_t\xi_t-A(\beta)\times\overline{\alpha}-B(\beta) \tag{27}$$

$$\delta+\xi_t \le A(\beta_t)\times\widehat{\alpha}_t \tag{28}$$

As stated in the objective function (1), the price-taker producer desires the minimum cost and maximum revenue attained from selling the diesel generators, PVs, and wind turbines power products to other semi-autonomous regions. Supposing that λ^t_P is the uncertain electricity price in time t and the energy market rates are unknown at Ψ% of the whole operating period, the risk-constrained robust optimal self-scheduling of the diesel generators can be modeled as Eqs. (29)–(31). The total power generation of the diesel generators, PVs, and wind turbines should be larger than the total electrical demand, as formulated by Eq. (32). where, P^t_D represents the total electricity consumption of the main and adjacent microgrids. In other words, the main objective of the GenCo is to minimize the fuel cost and maximize the total revenue from selling power to all microgrids.

$$\min_{\substack{\xi_t,\delta,P^t_j\\ F^t_j,S^t_j}}\ \gamma \tag{29}$$

Subject to: Constraints (2)–(13)

$$\begin{aligned}\gamma \ge &\sum_{t\in T}\sum_{j=1}^{N}\left(\lambda_F\times F^t_j\right)+\Psi\delta+\sum_{t\in T}\xi_t\\ &-\sum_{t\in T}\overline{\lambda}^t_P\times\left\{P^t_{PVs}+P^t_w+\sum_{j=1}^{N}\left(P^t_j\times P^{max}_j\right)\right\}\end{aligned} \tag{30}$$

$$\delta+\xi_t \le \sum_{j=1}^{N}\left(P^t_j\times P^{max}_j+P^t_{PVs}+P^t_w\right)\times\widehat{\lambda}^t_P \tag{31}$$

$$\sum_{j=1}^{N}\left(P^t_j\times P^{max}_j+P^t_{PVs}+P^t_w\right)\ge P^t_D \tag{32}$$

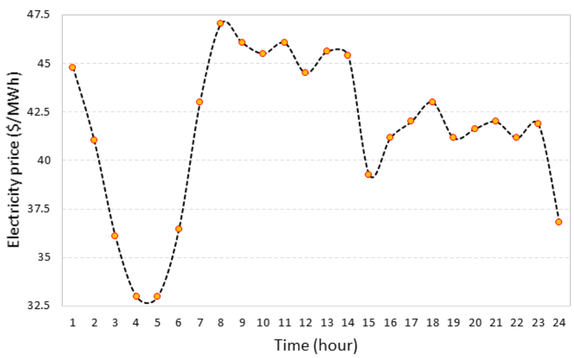


Fig. 2. The forecasted electricity prices

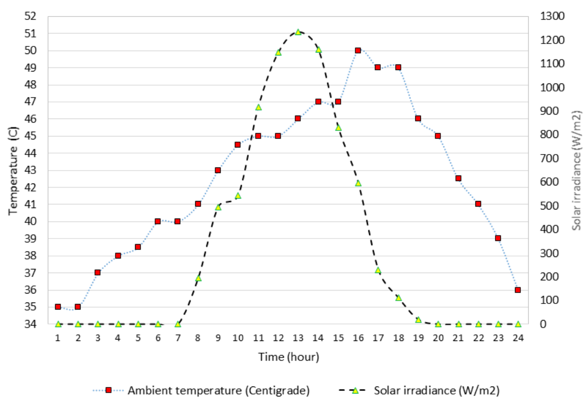


Fig. 3. The ambient air temperature and the solar irradiance over the sample day

4. CASE STUDIES, NUMERICAL RESULTS, AND DISCUSSIONS

As stated in Sections 2 and 3, it is supposed that there are a number of semi-autonomous communities, which isolated from the national power system. In one of them, an aggregator of diesel generators desires to minimize the total diesel fuel cost and maximize the daily revenue by selling energy to others. A benchmark microgrid composed of 6.25, 5, 4, 3.75, 2.5, and 1.5 MW diesel engines, PVs and wind farms with characteristics reported in Table 4, is studied over a 24-h time period to demonstrate the robust performance of the proposed model in finding the best generation schedules under the uncertain electricity prices. The SFC-power characteristic of the diesel engines is considered as Eqs. (3)–(9) [37]. It should be mentioned that the proposed robust self-scheduling strategy can be applied to each rural or small network geographically located far away from the regional electricity grid that only exchanges power with other adjacent zones. The robust nonlinear optimization problem modeled as Eqs. (26)–(28) and (2)–(10) is developed under the general algebraic modeling system (GAMS) [39] and solved using the branch-and-reduce optimization navigator (BARON [40].The forecasted electricity market prices [41] are shown in Fig. 2. These values are obtained from the price forecasting approaches [42]. The diesel fuel rate is considered as 1.5 $/g [43]. The ambient air temperature and the solar irradiance over the sample day are considered as Fig. 3. Figure 4 illustrates the hourly variations of the electrical demand. Different cases have been studied to prove the robustness and effectiveness of the proposed algorithm in finding the optimum operating point of the power generation units. In case 1, it is supposed that there are only diesel engines

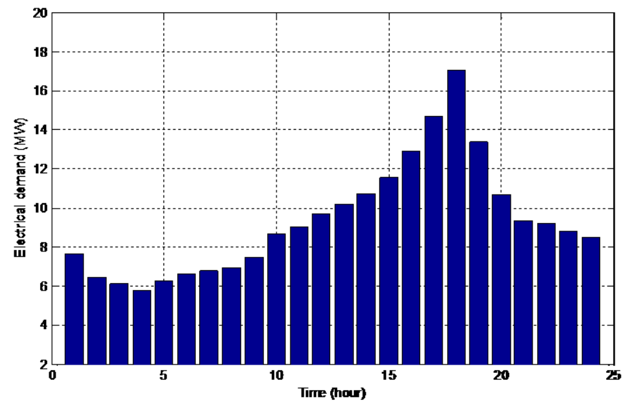


Fig. 4. The hourly changes of the electricity demand

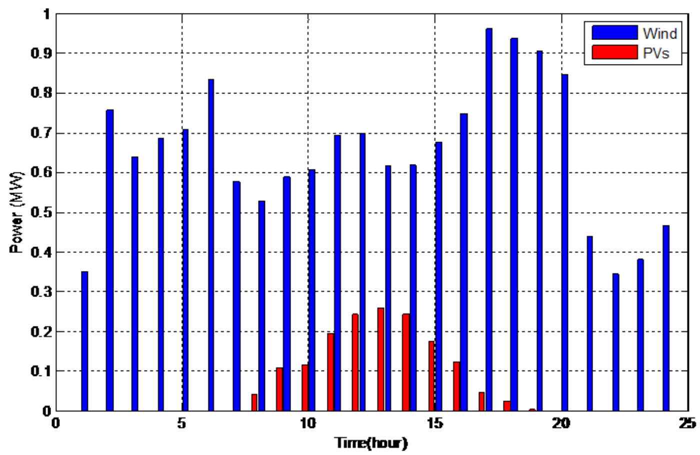
for supplying the electricity loads without considering the energy price uncertainty. In the second scenario, PVs and wind farms are also contributed to load procurement process under deterministic energy rates (without considering uncertainty of electricity prices). To model the budget of energy price uncertainty described in Fig. 1, it is supposed that the minimum and maximum values of the electricity prices are respectively equal to 0.9 and 1.2 times of the deterministic electricity rates shown in Fig. 2. Then, four robust optimization scenario are applied to diesel-PVs-wind hybrid power generation strategy with the uncertainty budget weight (z_k) equal to 0.25, 0.5, 0.75, and 1, respectively. At each robust optimization iteration, the value of uncertain electricity price ($\overline{\lambda}_P^t$) involved in Eq. (30), is obtained using z_k, $\lambda_{P,min}^t$ and $\lambda_{P,max}^t$ as shown in Fig. 1. Moreover, the maximum deviation of the hourly electricity prices from the forecasted values ($\widehat{\lambda}_P^t$) is calculated as the difference between the values shown in Fig. 2 and the uncertain electricity price $\overline{\lambda}_P^t$. The budget of uncertainty is interpreted as follows: For the last Γ% of the whole study period, the actual electricity rates may be different from the predicted ones. It is obvious that Γ changes from 0 to 1. Zero value of Γ represents a deterministic optimal day-ahead scheduling strategy for the multiple diesel engines without considering uncertainty. When it equals to 1, the energy market prices at each hour from $t = 1$ to $t = 24$ are uncertain or unknown within a predefined limited interval, which is modeled by maximum allowed deviation, $\widehat{\lambda}_P^t$.

The power generation of wind, PVs and diesel units in cases 1 and 2 without considering the uncertainty of electricity prices are obtained as Fig. 5. The total fuel cost of the diesel engines, the daily revenue obtained from selling the power products of the PVs, wind farm and diesel generators, and the cost objective function are compared in Table 5. Although the daily revenue achieved from selling electricity to other microgrids reduces (almost 491$ reduction in revenue), the total fuel cost of the diesel engines also reduces significantly (6780$), which results in 6289$ cost saving due to the penetration of wind turbines and solar PV panels.

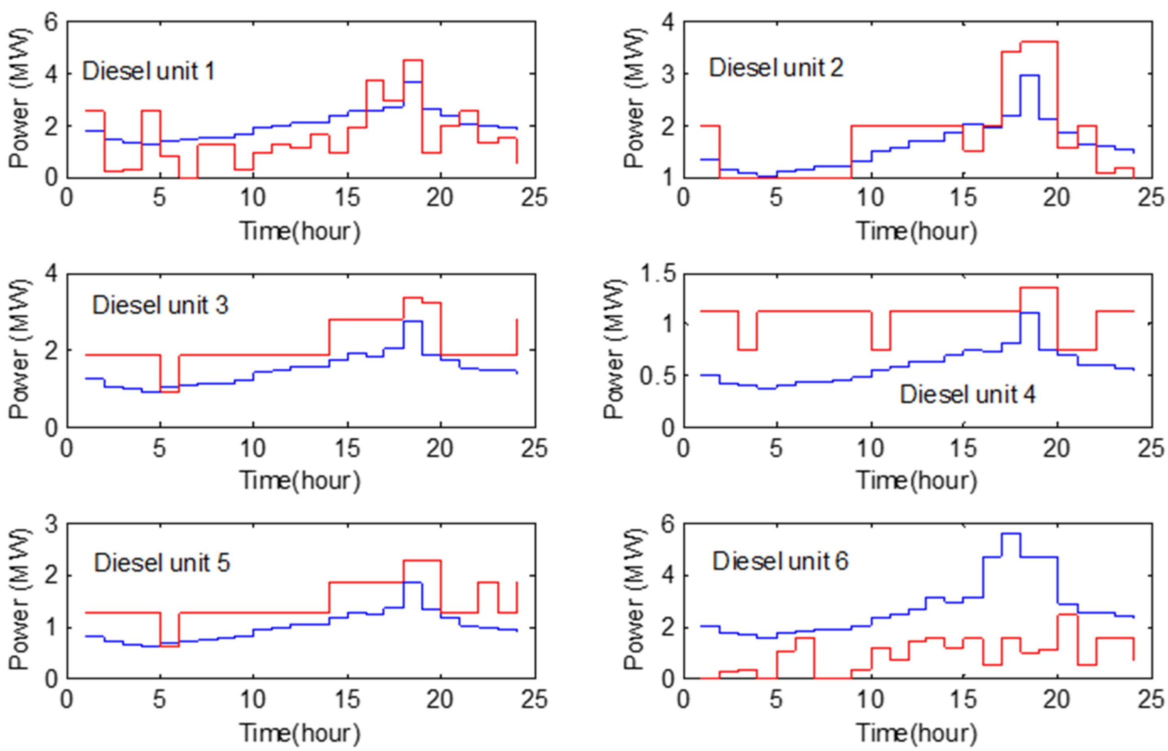
To demonstrate the cost-effectiveness of the proposed algorithm against the electricity market price uncertainty, five scenarios are studied with various budgets of uncertainty from 0 to 1. In other words, the value of uncertainty budget is considered to be 0, 0.25, 0.5, 0.75 and 1 with the steps of 0.25. The net-cost objective function is depicted as Fig. 6. It is obvious from this figure that if the uncertainty budget is considered to be 0.5, the risk-constrained optimal economic dispatch problem is solved for finding the robust generation patterns of the diesel units against the known electricity rates from $t = 1$ to $t = 12$ and the uncertain price quantities from $t = 13$ to $t = 24$. The aggregator's daily operation cost is minimized in risk-neutral ($\Gamma = 0$) and risk-seeker ($0 < \Gamma \leq 1$) decision making process (29)–(32) subject to equality and inequality constraints (2)–(13). As illustrated in Fig. 6, the

Table 5. The fuel cost, revenue and net-cost function of the PVs-wind-diesel hybrid power generation strategy in cases 1 and 2 without considering uncertainty of electricity prices

Case study	Power generation units	Diesel fuel cost ($)	Revenue ($)	Net cost ($)
1	Diesel engines	474,414	9,412	465,002
2	PVs-wind-diesel	467,634	8,921	458,713



(a) PVs and wind power products



(b) Diesel engines outputs

Fig. 5. The power generation of PVs, wind farm and diesel engines in cases 1 (blue) and 2 (red)

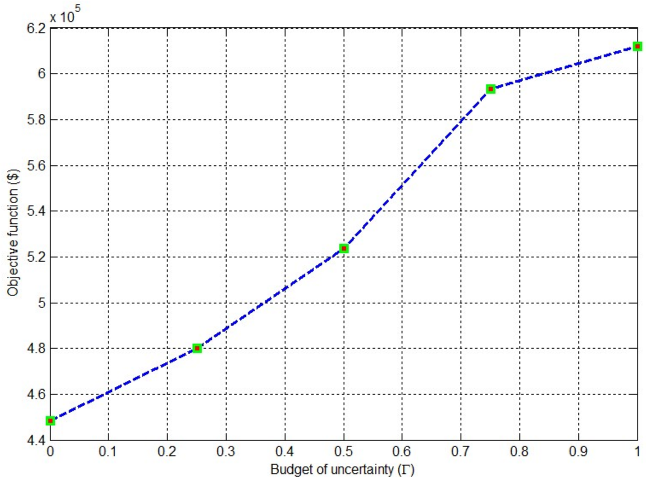


Fig. 6. The net-cost objective function values in five scenarios under the various degrees of conservatism

degree of conservatism, Γ, affects the total revenue achieved from selling energy to adjacent rural grids and the daily diesel fuel cost. It is wrong to expect each diesel unit operates with its maximum capacity to minimize the total fuel cost and maximize the daily revenue attained from trading energy with nearby customer networks. Because of two reasons as follows: First, their fuel costs are also considered in optimization problem as (30), and (5)–(12). Secondly, uncertain energy prices, which is added to robust decision making strategy as $\Psi\delta + \sum_{t\in T} \xi_t$ in (30) and constraint (31), changes the best generation patterns of the diesel units to immune from the lower or under-estimated electricity rates. Figure 7 enables the aggregator of the diesel engines-PVs-wind farms to decide how co-operate these units and guarantee a specific value of revenue against uncertainty in risk-neutral or deterministic and risk-seeker or robust power trading scenarios. As expected from (5)–(12) and (30), the total revenue achieved from selling electricity and the daily diesel fuel cost changes nonlinearly with uncertain electricity prices or budget of uncertainty. The electricity market prices affect the power outputs of the diesel engines, that nonlinearly affect their fuel consumptions as expected from (5)–(12) and Table 1. In the 1^{st} optimization approach, it is supposed that the energy price is known for each 1-hour time interval and Γ is zero. The deterministic or risk-neutral economic dispatching of the diesel generators results in \$448415 cost under the forecasted energy prices. The budget of uncertainty is then increased with steps of 0.25 in robust or risk-seeker decisions. The total fuel cost minus the daily revenue gained from selling power to other load zones, increases while the degree of conservatism, Γ, increases and vice versa. Because, the GenCo's owner wants to be immune against the risk of lower energy prices by imposing the robust cost $\left(\Psi\delta + \sum_{t\in T} \xi_t\right)$, which increases its operation cost as fulfilled by (30). In other words, when the aggregator of the diesel power production units desires lower costs, the degree of robustness or conservatism will reduce. There is a tradeoff between the optimality of solutions (expected cost) and the budget of uncertainty (degree of conservatism). Hence, the distance of the best solution of the risk-taker robust scheduling strategy from the optimal operating points of the diesel engines in base optimization approach (lower cost in $\Gamma = 0$) will increase, as proved in Fig. 7. In different sections of this figure, the optimum power generation curves of the diesel engines are compared for five values of Γ. For example, if Γ is 0.75, the actual electricity rates may be different from the predicted ones in the last 75% of the whole operating time interval. In the first 25% of this period, the prediction error is zero and the actual energy prices are as same as the forecasted values. Therefore, the operation cost increases from \$448415 in the risk-free optimization scheme to \$593271 in robust technique with $\Gamma = 0.75$. Similar analysis can be considered for $\Gamma = 1$ or 100% robustness against the uncertain electricity market prices with the predefined maximum deviations of the actual energy rates from the predicted values. In the worst operating condition with $\Gamma = 1$, the cost increases to \$612152. Obviously, if the aggregator desires to be conserved from the risk of the under-estimated electricity rates, higher budget should be allocated for uncertainty. The numerical results obtained from the presented approach with the existing ones are summarized in Table 6. All simulations are carried out using a Lenovo with 2.10 GHz CPU, 4 GB RAM. As obvious from Table 6, the calculation time of the existing algorithms have not been reported. Meanwhile, the maximum calculation time for running a risk-constrained self-scheduling of the multiple diesel units-PVs-wind farms is almost 20 minutes. Moreover, it is revealed that the total fuel cost of the diesel engines in the risk-aware optimization techniques presented in [44] and [45] are greater than that found by the interval robust optimization algorithm of the current research. In addition, the daily revenue obtained from selling electricity to adjacent microgrids in [44] and [45] are less than that achieved from solving the worst-case scenario (with 100% degree of conservatism) using the proposed robust optimization method.

5. Conclusions and Future Trends

Electrification of remote areas such as islands and isolated villages is usually based on diesel generators, photovoltaic panels, and wind turbines. Hence, this paper presented a robust model for optimal short-term self-scheduling of these units. A generation company composed of diesel engines, PVs and wind farms aims to obtain higher revenue from selling energy to small communities, and pay lower diesel fuel cost in daily operating period. Meanwhile, the electricity market price uncertainty affects the total revenue gained from selling electricity production of diesel engines, PVs and wind farms and the optimal fuel consumption and power generation pattern of the diesel units. Because of the nonlinear relation of the specific fuel consumption and power outputs of the diesel generators, daily fuel cost of these producers will change as a result of changing their power productions. Meanwhile, the electricity price uncertainty affects the total revenue results from selling power products of the diesel engines, PVs and wind farms to neighbor microgrids, the specific fuel consumption of diesel units, and their daily fuel cost. Hence, a robust nonlinear programming problem was solved to find a good scenario for operating six diesel generators and minimize the net operation cost over a 24-hour time horizon. The net operation cost is defined as the total fuel cost of the diesel generators minus the daily revenue obtained from selling energy procured by the diesel generating units, PVs, and wind turbines to adjacent zones. Both deterministic or risk-free and probabilistic or risk-seeker optimization approaches were implemented on test system by increasing the budget of uncertainty (Γ). The key findings of the present work are summarized as follows: If the uncertainty budget of the electricity price increases, the generation company will pay more to be immune from the risk of the lower energy rates and attain less profit. When the aggregator of the diesel generators, PVs and wind turbines desires higher profits and lower costs, it is recommended to reduce the degree of conservatism or robustness against the under-estimated electricity rates. The presented method enables the GenCos to find the best fuel consumption and power production schedules of the diesel generators with minimum fuel cost and maximum revenue under the various budgets of electricity price uncertainty. As the future trends, the uncertainties associated with the wind speed and solar irradiations will be applied to robust scheduling problem using info-gap decision theory method to make both risk-averse and risk-seeker decisions in under-estimated (shortfall) and over-estimated (surplus) power products, respectively. Moreover, the emission footprints of the diesel generators should be minimized as the taxes on greenhouse

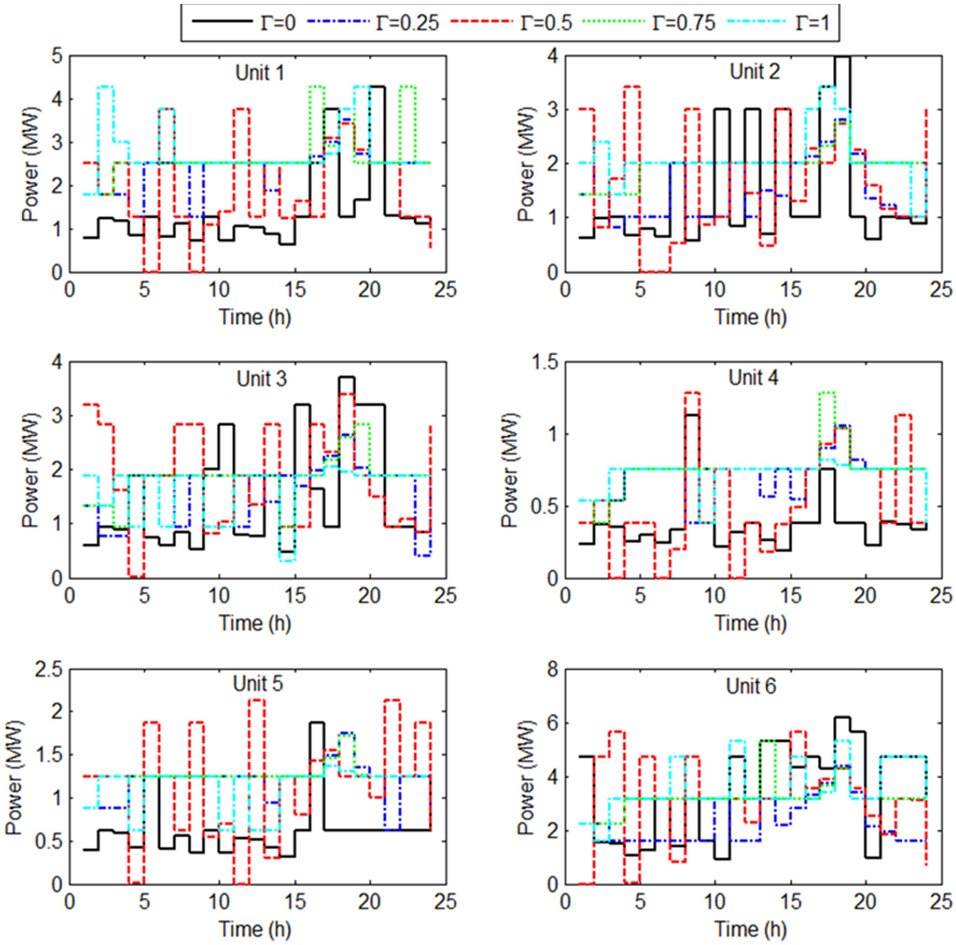


Fig. 7. The risk-neutral and risk-aware generation schedules of the diesel engines under the uncertain electrical power prices

Table 6. The comparison between the proposed algorithm and the existing methods

Refs.	Risk-constrained	Risk-neutral	Fuel cost ($)	Revenue ($)	Net operation cost ($)	Calculation time
[46]	-	✓	456886	8715	448171	Not reported
[37]	-	✓	442705	8620	434085	Not reported
[36, 47]	-	✓	450362	8590	441772	Not reported
[45]	✓	-	635087	10890	624197	Not reported
[44]	✓	-	630428	11076	619352	Not reported
Proposed approach	✓	-	623806	11835	611971	20 min.

gases emitted from the internal combustion engines such as diesel units. It should be mentioned that there are some limitations in the proposed model. As an instance, although diesel generators, wind turbines, and photovoltaic units are modeled in this paper with the aim of maximizing the total revenue and minimizing the diesel fuel cost, still there are other alternatives, such as storage devices that could have effective roles in the scheduling of these resources, but are not considered in the proposed model. As another example, the load uncertainties are not focused here. However, it should be noted that taking into account the main aims and novelties of the paper, such assumptions would not affect the main findings of the paper and for the sake of simplicity such considerations are not modeled. Hence, to continue this study for the future applications, stochastic load models could be developed. Also, other novel technologies, such as the hydrogen-fueled gas turbines, could be modeled as the new generation of turbines to explore the importance of these types of resources in the future power systems.

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