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Retired Electric Vehicle Battery for Optimal Dynamic Economic Dispatch Against the Intermittent of Photovoltaic Power Output

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Abstract: Recently, electric vehicles (EVs) have surged in demand to reduce greenhouse gas emissions produced by gasoline cars. However, most EV batteries could not be utilized for traction purposes when they have reached 80% of their normal capacity. This has led to the waste disposal of EV batteries, which has caused ever increasing severe damages to the environment. To handle this issue, we propose the use of retired batteries from electric vehicles (REVB) for coping with the dynamic economic dispatch (DED) problem. In this study, the REVB was employed to reduce the impact of the intermittent output power of photovoltaic (PV). To examine the efficacy of the proposed technique, the IEEE 30 and 118 buses were utilized as a test system. The objective of this study was to minimize the fuel cost of thermal generation. The DED optimization problem was approached and solved by implementing General Algebraic Modelling System (GAMS) Software and quadratically-constrained programming (QCP) method based on CONOPT solver. From the simulation results, it was found that the application of REVB could minimize the fuel cost of thermal power generation for the DED problem including PV compared to other techniques provided in this paper. The REVB could reduce the total fuel cost by 10.78 % compared to the standard DED problem for IEEE 30 Bus. For IEEE 118 bus, the lowest best total fuel cost produced by REVB reached the amount of 11.75 % compared to conventional DED problem.

Keywords: Electric vehicles (EV), Retired electric vehicle battery (REVB), Dynamic economic dispatch (DED), Photovoltaic (PV).

1. Introduction

Nowadays, the rapid development of renewable energy technology has merit as a solution to the world energy problem [1]. In Indonesia, photovoltaic (PV) as a type of renewable energy source rapidly grows because this country lies in the equator path and gets solar irradiation over years [2]. Nevertheless, the spread out and expansion of PV trigger a severe problem for electric power system operations. The treatment of PV output is the main subject in power system operation [3].

The dynamic economic dispatch (DED) problem has been studied for a long time as an important subject in power system operation which has a function to reduce the total thermal generation costs by optimal dispatching of generation output. Due to the high level of intermittent and unpredictable PV output, the DED study faces a new challenge to maintain the power system operation in secure, stable, and reliable [4]. In [4], the authors proposed the DED problem considering the emission and valve point effect. In this study, the mathematical model of the DED problem with wind-solar-thermal integrated energy was developed. Furthermore, an enhanced moth-flame optimization algorithm has been proposed to solve the multi-objective DED problem. While a DED model considering the uncertainty of wind generation was proposed in [5]. In [5], the authors developed a special technique based on the decomposition algorithm to facilitate real-time application. The optimization model was constructed as a two-stage stochastic optimization problem. In [6], the intermittent of the wind power output was studied for the DED problem and solved using a robust optimization model. Artificial intelligence method has been successfully applied for solving economic load dispatch problems such as chaotic social group optimization (CSGO) [7], squirrel search optimizer (SSO) [8], orthogonal particle swarm optimization [9], and water wave optimization algorithm (WWOA) [10].

In [7], CSGO has been applied to solve the economic dispatch problem with multiple fuel sources. The efficacy of this technique is examined by using four tested systems (10-units, 20-units, 30-units, and 40-units). In [8], the SSO algorithm was utilized to solve various types of economic load dispatch problems by minimizing the total generation cost of units while satisfying various constraints such as power balance constraints, prohibited operating zones, ramp rate constraints, and operating limits of generators. In [9], the effect of load demand management for the DED problem was analyzed. An orthogonal PSO algorithm was utilized to minimize cost and emission. In [10], WWOA was utilized for solving economic dispatch problems with generator constraints. In this study, the generator such as ramp-rate limits, prohibited operating zones including the system transmission losses are considered to examine the efficacy of the proposed approach. In [11], robust optimization was proposed to increase the level of renewable energy sources while minimizing the total operating cost and respecting the spinning reserves required to maintain continuity of supply. In this study, the optimization problem was constructed as a multi-objective DED problem with renewable obligation requirements. In [12], the authors proposed modified teaching-learning-based optimization to solve the DED issue including thermal generations and wind power. In this study, the planning issue comprises the total fuel cost function with valve-point loading effect and the transmission power losses. All proposed techniques [5-10] have shown sophisticated results in solving the DED problem. Moreover, the methods above require more experiments and statistical analysis to obtain their best performance due to being stochastically solved.

Since PV generation is categorized as a non-dispatchable generation unit and depends on the change of weather conditions, the battery is utilized to compensate for the effect of PV output in the grid. Nowadays, battery plays a key role in the power system grid and electric vehicle. Nevertheless, the battery in an electric vehicle is only utilized up to 80% of its nominal state of charge [13]. In the future, the waste of retired electric vehicle batteries (REVB) will affect the environment. A REVB simultaneously reduces the waste of difficult-to-recycle batteries by being applied to the power system grid to accommodate for the effect of PV output power. In [13], the REVB was utilized for park-level integrated energy systems. In this study, the optimization problem was constructed as a bi-level optimization model. While the REVB was utilized to maintain the stability in the microgrid as in [14].

Considering the potential of REVB as a promising energy storage system to utilize in power system operation, this paper proposed the use of REVB as an energy storage system to solve the DED problem. In addition, the high penetration of PV generation is included in the DED problem to

Table 1. List of notations used in this paper

Symbol		Meaning
a_i, b_i, c_i	:	The cost coefficients of the i-th thermal generation unit
C_T	:	Total fuel cost of thermal generation units
N_g	:	The number of thermal generation units
$P_{Gi,t}$	:	Output of the i-th thermal unit at t-th time step
T	:	Total time interval
N_d	:	The number of loads
N_{pv}	:	The number of installed PVs
$P_{di,t}$	:	The demand of t-th hour
$P_{PVi,t}$	:	PV output power at t-th hour
$P_{ch\text{-}i,t}$	:	Power charge to REVB at t-th hour
$P_{disch\text{-}i,t}$	:	Power discharge of REVB at t-th hour
RU, RD	:	Ramp-up and ramp-down of thermal generator units
P_{Gi}^{min}, P_{Gi}^{max}	:	Minimum and maximum of thermal power outputs
P_{ch-i}^{min}, P_{ch-i}^{max}	:	Minimum and maximum of power charge of REVB
$P_{disch-i}^{min}$, $P_{disch-i}^{max}$	:	Minimum and maximum of power discharge of REVB
SOC_i^{min}, SOC_i^{max}	:	Minimum and maximum of state of charge of REVB
$SOC_{i,t}$	:	State of charge of REVB at t-th hour
η_{ch}	:	REVB charge efficiency
η_{disch}	:	REVB discharge efficiency
B_{NB}	:	The number of batteries
φ_{bc}	:	An available capacity of REVB
ρ_c	:	A battery capacity in new condition
γ_p	:	The needs of injected active power from battery
SOC_{max}	:	The maximum of state of charge of R-EVB where we assume it as 80% of nominal battery capacity

examine the efficacy of REVB for handling the intermittent PV output power. The DED problem is constructed as a quadratic optimization problem in GAMS software. The DED problem is constructed as a quadratic optimization problem and implemented using GAMS software. This DED problem is solved using a numerical optimization technique namely quadratically constrained programming (QCP) based on CONOPT solver in GAMS software. The objective of this study is to minimize the total cost of thermal generator units while maximizing the thermal output power affected by intermittent PV output power and REVB.

The rest of the paper is described as follows: Section 2 describes the problem formulation of DED including PV and REVB. The implementation of the proposed method is shown in Section 3. Section 4 shows the simulation results of the proposed idea and its analysis. Section 5 highlighted the conclusions of the research.

2. Problem formulation

Dynamic economic dispatch (DED) becomes high random due to the high integration of photovoltaic (PV) generation compared to conventional DED. The approach considered in this paper assumes that a retired electric vehicle battery (REVB) is utilized to overcome the problem caused by intermittent PV output power. PV output power is affected by weather conditions and is classified as the most often non-dispatchable generation source. Therefore, the goal of DED in this study is to obtain the minimum fuel cost of thermal generation output affected by intermittent PV output with considering power system balance, power output limits, ramp-rate bounds, and battery capacity limits. The notations utilized in this paper are provided in Table 1.

2.1 Fuel cost function for thermal generation units

In this paper, it was considered a power supply system composed by N_g number of thermal and N_{pv} number of PV generating units to supply N_d number of loads for 24 hours power system operation. The fuel cost of thermal generation units in \$/h Eq. (1) utilized as the objective function [15] is formulated as a quadratic function.

$$\min C_T = \sum_{t=1}^{T}\left(\sum_{i=1}^{Ng} C_i(P_{Gi}, t) = \sum_{i=1}^{Ng} c_i + b_i P_{Gi,t} + a_i P_{Gi,t}^2\right) \quad (1)$$

The coefficient of thermal generator a_i, b_i, c_i are in \$/MW^{2}h, \$/MWh, and \$/h, respectively.

2.2 Equality constraints

Power balance as representative of equality constraint considering the effect of PV power output and REVB is defined in Eq. (2).

$$\sum_{i=1}^{Ng} P_{Gi,t} = \sum_{i=1}^{Nd} P_{di,t} - \sum_{i=1}^{Npv} P_{PVi,t} + \sum_{i=1}^{Npc} P_{ch-i,t} - \sum_{i=1}^{Npd} P_{disch-i,t} \quad (2)$$

2.3 Inequality constraint

Inequality constraints in this DED problem are represented by thermal generator limits Eq. (3), ramp-rate limits Eqs. (4a) and 4(b), power charge limits of REVB Eq. (5), power discharge limits of REVB Eq. (6), and state of charge (SOC) of REVB Eqs. (7a) and (7b).

2.3.1. Upper and lower bounds of thermal generator

Each thermal generator has a different output power capacity to supply the electrical load demands. The upper and lower thermal generator are given by Eq. (3).

$$P_{Gi}^{min} \leq P_{Gi,t} \leq P_{Gi}^{max} \quad (3)$$

2.3.2. Ramp-up and ramp-down of thermal generator

Power system requires flexibility for their dynamic operating. Therefore, a dynamic constraint for each thermal generator is very important to increase or decrease the thermal generator output power to supply the sudden change of electrical load demands on interval time *T*. The dynamic constraints of thermal generator units are provided in Eqs. (4a) and (4b).

$$P_{Gi,t} - P_{Gi,t-1} \leq RU \quad (4a)$$

$$P_{Gi,t-1} - P_{Gi,t} \leq RD \quad (4b)$$

2.3.3. Lower and upper limits of charge and discharge power of REVB

To ensure the normal use and guarantee the cycle life of the retired electrical vehicle battery (REVB), it is important to give limitations for the charge or discharge power of REVB.

$$P_{ch-i}^{min} \leq P_{ch-i,t} \leq P_{ch-i}^{max} \quad (5)$$

$$P_{disch-i}^{min} \leq P_{ch-i,t} \leq P_{disch-i}^{max} \quad (6)$$

2.3.4. Lower and upper limits of SOC of REVB and SOC computation

To ensure the level of charge of REVB relative to its capacity, it is important to give limitations for the SOC of REVB.

$$SOC_i^{min} \leq SOC_{i,t} \leq SOC_i^{max} \tag{7a}$$

$$SOC_{i,t} = SOC_{i,t-1} + \left(P_{ch-i,t} \times \eta_{ch} - \frac{P_{disch-i,t}}{\eta_{disch}}\right) \tag{7b}$$

2.4 Retired electric vehicle battery calculation

In this study, we use a retired electric vehicle battery from Tesla electric vehicle with a nominal capacity in new condition as of 100kWh. The availability of REVB capacity (φ_{bc}) is computed by Eq. (9) where the injected active power (γ_p) divided by the SOC_{max} of REVB. The number of REVB that are required in solving DED problem affected by PV generation unit is formulated as in Eq. (9) where the availability of REVB capacity is divided by a REVB capacity in its new condition.

$$B_{NB} = \frac{\varphi_{bc}}{\rho_c} \tag{8}$$

$$\varphi_{bc} = \frac{\gamma_p}{SOC_{max}} \tag{9}$$

3. Implementation of the proposed approach

In this section, a brief overview of a mathematical modelling language called GAMS for solving DED problems is described.

3.1 GAMS language

GAMS language is the most powerful tool based on a high-level language to overcome mathematical optimization problems with abbreviate algebraic representations. Many optimization solvers are included in GAMS language such as CPLEX, KNITRO, CONOPT, DICOPT, etc [16]. These solvers are employed to solve different types of optimization problems such as linear, non-linear, and mixed-integer optimization problems. GAMS language is commonly utilized to overcome a large and complex problem that may involve much improvement to build a precise model. Models can be constructed, tackled, and recorded simultaneously by preserving the same GAMS model file. The framework of a mathematical optimization model implemented in GAMS has the portions including sets, data, variable, equation, model, and output.

3.2 Solving DED problems using GAMS language

In this section, the procedures to solve the DED problem are provided where the GAMS code is inspired from [17]. The procedures of DED optimization process considering the effect of PV generating unit are shown as follow,

1. Define the GAMS model indicating number of thermal generating units, time interval *t*, etc.
   a. Set the time interval for 24 hours power system operation. GAMS code is shown as follow,
   ```
   Set
   t hours /t1*t24/
   ```
   b. Set number of thermal generating units. GAMS code for IEEE 30 bus with 6 thermal generating units is written as follows,
   ```
   i thermal units /p1*p6/
   ```
2. Define the input of GAMS model in the form of parameters, scalars, and tables i.e. generator limits, fuel cost generator, ramp-rate, SOC battery, etc.
   a. Set the charge (η_{ch} or eta_c) and discharge (η_{disch}or eta_d) efficiencies of REVB, SOC maximum, initial SOC of REVB. The charge (η_{ch}) and discharge (η_{disch}) efficiencies of REVB are set as 0.95. SOC maximum of REVB is 30 MW. The amount of initial SOC of REVB is 6 MW (20% of SOC maximum). GAMS code is shown as follows,
   ```
   Scalar
   eta_c  /0.95/
   eta_d  /0.95/
   SOCMax /30/;
   SOC0 = 0.2*SOCMax;
   ```
   b. Set the coefficient of thermal generator (a_i, b_i, and c_i), the maximum and minimum of thermal generating units (P_{max} and P_{min}), and ramp-rate thermal generator (RU and RD). GAMS code is shown as follows,
   ```
   Table gendata(i,*)
   P1 a       b c Pmin Pmax RU
   RD
      0.00375 2 0 50   200  50
   50
   *  *       * * *    *    *  *
   *  *       * * *    *    *  *
   p6 0.02500 3 0 12   40   10 10;
   ```
   c. Set the load and PV output power for 24 hours. GAMS code is written as follows,
   ```
   Table RE(t,*)
       PV Load
   t1  0  166
   *   *  *
   *   *  *
   ```

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```
t24 0  196;
```

3. Set the decision variable such as thermal fuel cost [`costThermal`], thermal generation output at time *t* [`p(i,t)`], charge power of REVB at time *t* [`pcbat(t)`], discharge power of REVB at time *t* [`pdbat(t)`], SOC of REVB at time *t* [`SOC(t)`] as in (7b), minimum and maximum thermal generating output at time *t* [`p.lo(i,t)`, `p.up(i,t)`] as in Eq. (3), maximum and minimum charge power of REVB at time *t* [`pcbat.up(t)`, `pcbat.lo(t)`] as in (5), minimum and maximum discharge power of REVB at time *t* [`pdbat.up(t)`, [`pdbat.lo(t)`] as in Eq. (6), and the limits of SOC at time *t* [`SOC.up(t)`, `SOC.lo(t)`] as in Eq. (7a). The maximum values of charge power, discharge power, and SOC at time *t* are set to 80% of SOC maximum. While the lower limit of SOC at time *t* is set to 20% of SOC maximum. The minimum values of charge and discharge power of REVB are set to 0. Furthermore, initial SOC of REVB [`SOC0`] is set to 20% of SOC maximum at 24 o'clock. GAMS code is described in below,
```
Variable
costThermal
p(i,t)
pdbat(t)
pcbat(t)
SOC(t)
p.up(i,t)= gendata(i,'Pmax');
p.lo(i,t)= gendata(i,'Pmin');
SOC.up(t)      = 0.8*SOCmax;
SOC.lo(t)      = 0.2*SOCmax;
SOC.fx('t24') = SOC0;
pcbat.up(t)    = 0.8*SOCmax;
pcbat.lo(t)    = 0;
pdbat.up(t)    = 0.8*SOCmax;
pdbat.lo(t)    = 0;
```
4. Define the equations that construct the connections between data and variables i.e. thermal fuel cost, ramp-rate constraints, power balance constraints, state of charge battery, etc.
    a. Set the thermal cost function as in Eq. (1). GAMS code is written in below,
    ```
    Equation Ramp-Up, Ramp-
    Down, ObjFunc, balance,
    SOC_Bat,
    ObjFunc..costThermal=e=sum(
    (t,i),gendata(i,'a')*power(
    p(i,t),2)+gendata(i,'b')*p(
    i,t)+gendata(i,'c'));
    ```
    b. Set the power balance of DED problem as in Eq. (2). GAMS code is written in below,
    ```
    balance(t)..sum(i,
    p(i,t))=g= (RE(t,'Load'))-
    (RE(t,'PV'))+(pcbat(t)-
    pdbat(t))$SOCMax;
    ```
    c. Set the ramp-rate of thermal generating unit as in Eqs. (4a)-(4b). GAMS code is written in below,
    ```
    Ramp-Up(i,t)..p(i,t+1)-
    p(i,t)=l=gendata(i,'RU');
    Ramp-Down(i,t)..p(i,t-1)-
    p(i,t)=l=gendata(i,'RD');
    ```
    d. Set the SOC of REVB as in Eq. (7b). GAMS code is written in below,
    ```
    SOC_Bat(t)$SOCMax..SOC(t)
    =e= SOC0$(ord(t)=1)+SOC(t-
    1)$(ord(t)>1)+pcbat(t)*eta_
    c - pdbat(t)/eta_d;
    ```
5. Solve DED problem using QCP method by minimizing the total thermal cost. The GAMS code for this part is described as follows,
```
model DEED /all/;
solve DEED using qcp
minimizing costThermal;
```
6. Print out the solution of DED model such as optimal thermal generating output power, optimal total thermal generating cost, charge and discharge power of REVB, and SOC of REVB. The GAMS code is provided as follows,
```
display  p.l,  costThermal.l,
pcbat.l, pdbat.l, SOC.l;
```

4. Results and analysis

This section provides the data of generator characteristics such as fuel cost and ramp-rate for IEEE 30 and 118 buses, the simulation result, and the result analysis.

4.1 Simulation results and analysis for IEEE 30 bus

We have conducted all the simulations in this study using Core i7 with 2.80 GHz and 8 GB of RAM. The proposed technique has been implemented and validated using GAMS language [16] and solved by a CONOPT solver. The data of thermal generator fuel cost, upper and lower limits of thermal generator output power, and ramp-rate are shown in Table 2 and 3, respectively. The load and PV output power

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patterns are shown in Fig. 1, respectively. All data of IEEE 30 bus are depicted from [18, 19]. For Fig. 1, the abscissa is the time point t at 1, 2, ..., 24 o'clock, where t = 1 is the current time at which the load and PV output predictions are carried out for 24 hours. The peak load as seen in Fig. 1 is 283.4 MW [19-21]. The installed PV power capacity is set to 126 MW (44.46% of load peak) [18]. Furthermore, the installed REVB required by the system is set to 30 MW (10.59% of load peak). In this study, R-EVB is prepared to maintain the power needs for 24 hours of power system operation. By using Eqs. (8) and (9), we require 375 of REVB to supply the power system operation as of 30MW with the SOC maximum around 80% of its nominal value in new condition (100kWh). The comparison of total generator output and its fuel cost generated by conventional DED, DED with PV, and DED with PV and REVB is illustrated in Fig. 2 and 3. To examine and validate the efficacy and accuracy of the proposed method (QCP), we firstly utilize QCP method to solve static economic dispatch problem affected by PV and REVB to fulfill the load demand as of 283.4 MW [19-21]. The simulation result and its comparison to other techniques are shown in Table 4. It could be seen from Table 4 that the thermal generating cost of the proposed method is less when compared to other algorithms. The value of the cost minimization objective of proposed method is 721.345 $, ESCA is 796.345 $, FPA is 799.696 $, IPSO is 801.978 $, SGA is 803.699 $, MOPSO is 802.39 $, and FPSO is 800.72 $. Hence from the comparison of other algorithms it can be said that proposed method in

Table 2. Thermal generator fuel cost

No Bus	Fuel cost coefficient		
	a_i	b_i	c_i
1	0.00375	2.0	0
2	0.01750	1.75	0
5	0.06250	1.0	0
8	0.00834	3.25	0
11	0.02500	3	0
13	0.02500	3	0

Table 3. Thermal generator limit and ramp-rate

No Bus	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)	Generator ramp-rate (MW)	
			RU	*RD*
1	50	200	50	50
2	20	80	20	20
5	15	50	13	13
8	10	35	9	9
11	10	30	8	8
13	12	40	10	10

Table 4. Comparison of different methods for solving static economic dispatch problem

Approach	Fuel Cost ($)
Fuzzy Particle Swarm Optimization (FPSO) [19]	800.72
Multi-Objective Particle Swarm Optimization (MOPSO) [20]	802.39
Simple Genetic Algorithm (SGA) [21]	803.699
Improved Particle Swarm Optimization (IPSO) [21]	801.978
Flower Pollination Algorithm (FPA) [21]	799.696
Enhanced Sine Cosine Algorithm (ESCA) [21]	796.345
Proposed Method (ED-PV-REVB optimized by QCP)	721.373

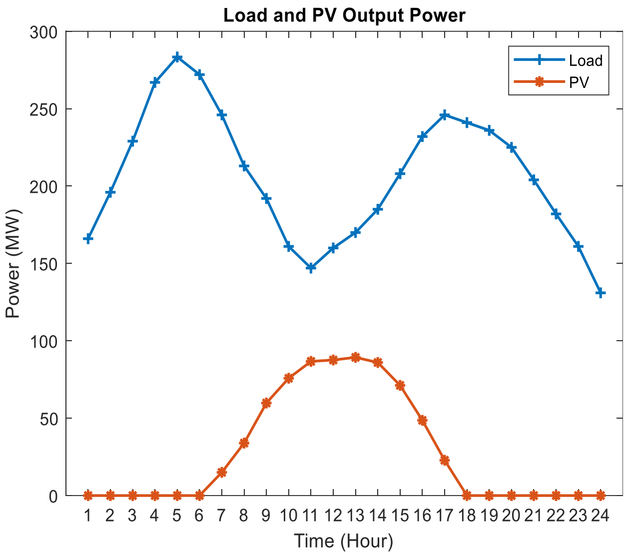

Figure. 1 Load and PV output power

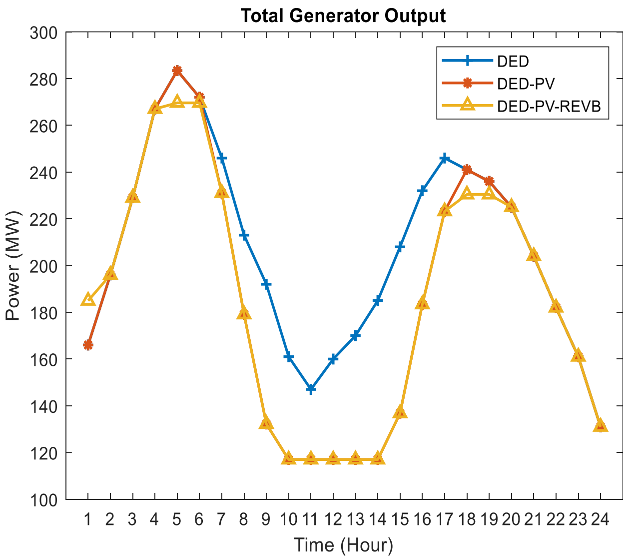

Figure. 2 The comparison of total thermal generator output

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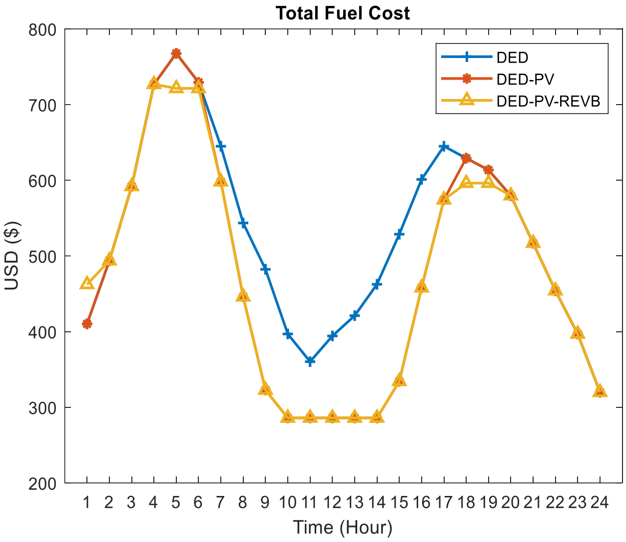


Figure. 3 The comparison of total fuel cost

Table 5. Comparison different methods for solving DED problem

Method	Total Fuel Cost ($)
Genetic Algorithm (GA) [22, 23]	13135
Particle Swarm Optimization (PSO) [22, 24]	13155
Artificial Bee Colony Algorithm (ABCA) [22, 25]	13121
Artificial Immune System (AIS) [22, 26]	13111
Gravitational Search Algorithm (GSA) [22]	13100
DED (QCP)	12710
DED-PV (QCP)	11392
DED-PV-REVB (QCP)	11340

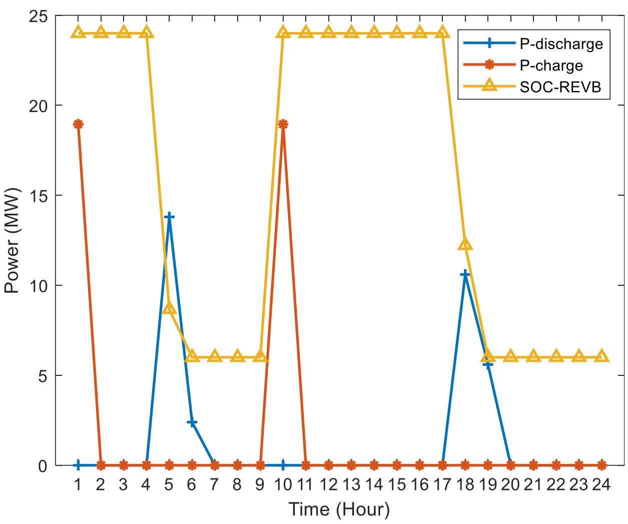


Figure. 4 The comparison of power charge, discharge, and SOC-REVB

this study is the best in minimization of cost objective. Therefore, the study in this paper is extended to being a dynamic economic dispatch (DED) problem for 24 hours power system operation. The total thermal generator output power and its fuel cost in 24 hours are shown in Table 5. Then, Fig. 4 shows the comparison of power charge, discharge, and SOC-REVB.

Fig. 2 shows the comparison results of total power supply for 24 hours. This condition can directly measure the flexibility of the total power supply. The result corresponds to the use of REVB for DED including PV where it could reduce the total power supply at 15:00, 18:00, and 20:00. Fig. 3 shows the same computation with the total fuel cost setting. This setting can directly measure the total fuel cost of power supply resulted from optimization process. Note that the employment of REVB can decrease fuel cost of power supply three times around 15:00, 18:00, and 20:00. Table 4 shows the value of the cost minimization objective of proposed method is 11340 $, DED-PV (QCP) is 11392 $, DED (QCP) is 12710 $, GA is 13135 $, PSO is 13155 $, ABCA is 13121 $, AIS is 13111 $, and GSA is 13100 $. It can be seen from Table 4 and Fig. 2 and 3 that the proposed method produced the lowest best total cost of 11340 $ and total power supply of 4451 MW. The second lowest best total cost of 11392 $ and total power supply of 4464 MW obtained by DED including PV based on QCP. The proposed method could compress the fuel cost around 10.78 % of fuel cost produced by standard DED. Meanwhile, DED with PV can reduce the fuel cost by 10.36% from fuel cost resulted by conventional DED. As shown in Fig. 4, the REVB was discharged of their power two times at 05:00 and 18:00 while the REVB was charged at 02:00 and 10:00. Both the REVB charge and discharge power were within their SOC.

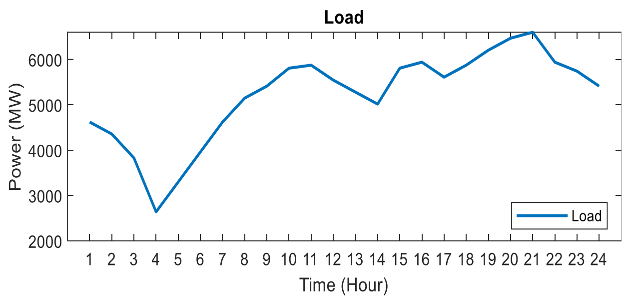
4.2 Simulation Results and Analysis for IEEE 118 bus

An IEEE 118 bus test system is used in this section to demonstrate 24-hour DED based on the proposed method. The system data, generator fuel cost data, thermal generating unit output power limits, are cited from [1], including ramp-rate data. The daily total load and PV data collected from [1, 29] are given in Fig. 5. The peak load in this power system model is 6600 MW and occurred at 21:00 o'clock. We assume the total installed PV capacity of five PV modules is 2110 MW (31.97% of load peak) [1, 30] as given in Fig. 5. Furthermore, the total installed REVB capacity for three REVBs is 660 MW (10% of load peak). In this work, REVB is employed to keep the power needs for 24 hours. We require 2750 of REVB corresponding to Eqs. (8) and (9) to supply the power system grid as of 660MW. The SOC maximum is set to 80% from its nominal value (100kWh). The total generator output and its fuel cost produced by conventional DED, DED incorporating PV, and proposed technique are illustrated in Fig. 6 and 7. To ensure the robustness and accurateness of the proposed method, the proposed method is applied to static economic dispatch problem considering the PV generation unit and REVB to supply the load demand as of 6600 MW. The comparison methods for solving static economic dispatch problem are shown in Table 6. It can be said from Table 6 that the thermal generator fuel cost produced by the proposed method is less compared to other algorithms. The value of the cost minimization objective of proposed method is 103064 \$, IPSOIW is 130033 \$, PSOCFA is 130001 \$, BBO is 129735 \$, and ALC PSO is 129546 \$. Hence from the comparison of other algorithms, it can be said that the proposed method in this study is the best for minimizing of cost objective. Moreover, the study in this paper is extended to being a dynamic economic dispatch (DED) problem for 24 hours power system operation. The total thermal fuel cost for 24 hours of power system operation are shown in Table 7. Fig. 8 shows the comparison of power charge, discharge, and SOC for three REVBs utilized in this system power model.

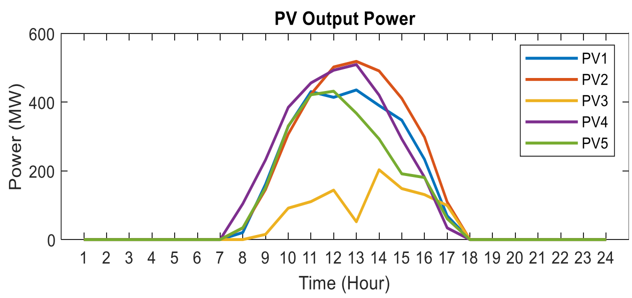
From Fig. 6, the proposed approach can reduce the total generator output at 07:00, 08:00, 14:00, 15:00, and 21:00. The use of REVB can affect the generator units to produce their output power more flexible under the uncertainty of PV output. The result corresponds to the use of REVB for DED including PV where it could reduce the total power supply at 15:00, 18:00, and 20:00. Fig. 3 shows the same computation with the total fuel cost setting. This setting can directly measure the total fuel cost of power supply resulted from the optimization process.

Table 6. Comparison of different methods for solving static economic dispatch problem

Approach	Fuel Cost (\$)
Improved Particle Swarm Optimizer with Inertia Weight (IPSOIW) [27]	130033
Particle Swarm Optimization with Constriction Factor Approach (PSOCFA) [27]	130001
Biogeography Based Optimization (BBO) Algorithm [27]	129735
Particle Swarm Optimization with An Aging Leader and Challengers Algorithm (ALC PSO) [28]	129546
Proposed Method (ED-PV-REVB optimized by QCP)	103064



(a)



(b)

Figure. 5: (a) Load and (b) PV output power

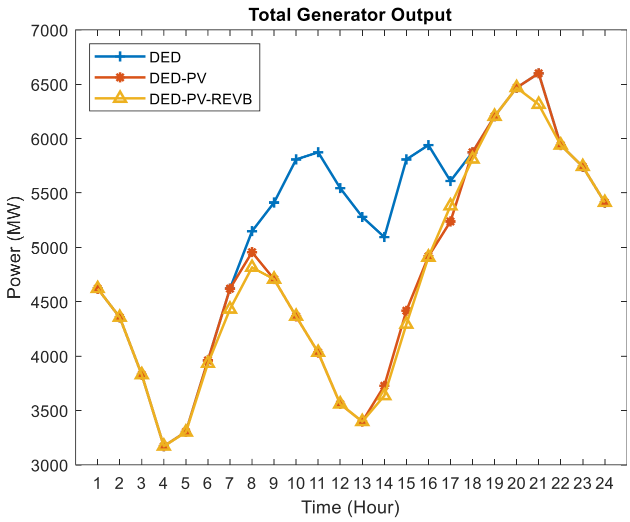


Figure. 6 The comparison of total generator output

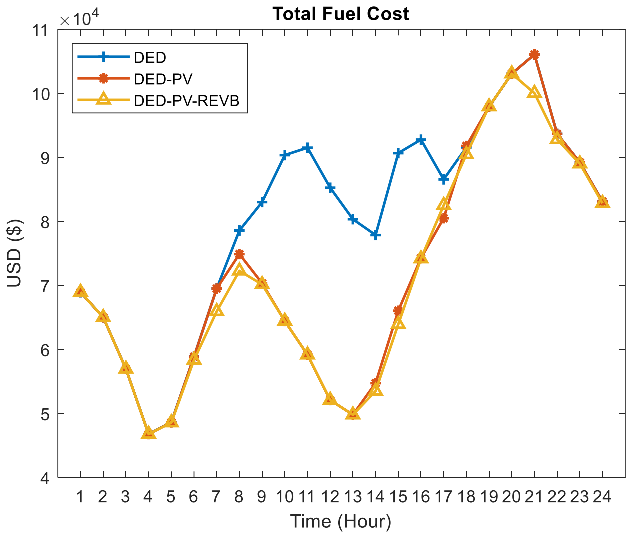


Figure. 7 The comparison of total fuel cost

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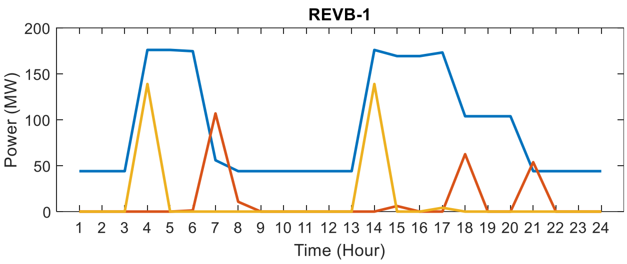
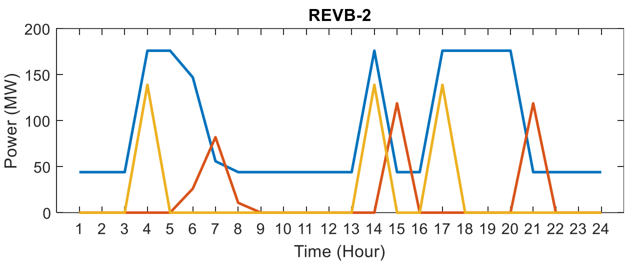
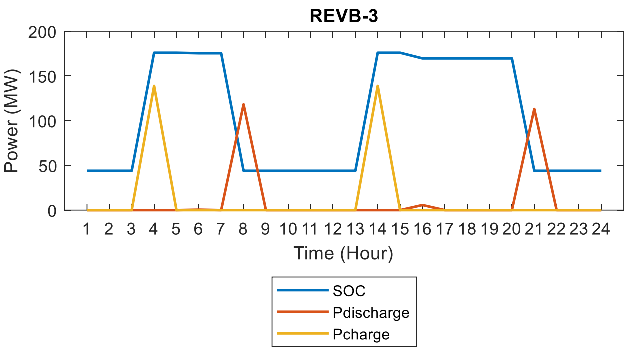


(a)



(b)



(c)

Figure. 8 The comparison of (a) Power charge, (b) Discharge, and (c) SOC-REVB

Table 7. Total generator output power and its fuel cost in 24 hours

Methods	Total Fuel Cost ($)
Genetic Algorithm (GA) [22, 23]	5733318
Particle Swarm Optimization (PSO) [22, 24]	5800886
Artificial Bee Colony Algorithm (ABCA) [22, 25]	5912620
Artificial Immune System (AIS) [22, 26]	5609163
Gravitational Search Algorithm (GSA)[22]	5576667
DED (QCP)	1936200
DED-PV (QCP)	1725800
DED-PV-REVB (QCP)	1708700

Note that the employment of REVB can decrease the fuel cost of power supply three times around 15:00, 18:00, and 20:00. Table 7 shows the value of the cost minimization objective of proposed method is 1708700 $, DED-PV (QCP) is 1725800 $, DED (QCP) is 1936200 $, GA is 5733318 $, PSO is 5800886 $, ABCA is 5912620 $, AIS is 5609163 $, and GSA is 5576667 $. It can be seen from Table 7 and Fig. 6 that the proposed method produced the lowest best total cost of 1708700 $ and a total power supply of 112620 MW. The second lowest best total cost of 1725800 $ and total power supply of 113410 MW obtained by DED including PV. The lowest worst total cost of 193620 $ and total power supply of 125616 MW for conventional DED.

The proposed method could compress the fuel cost around 11.75 % of fuel cost produced by standard DED solved by QCP. Meanwhile, DED with PV can reduce the fuel cost as 10.87% from fuel cost resulted from conventional DED. As shown in Fig. 8, Both charge and discharge power for three REVB were within their SOC. From Fig. 5 to 8 and Table 6 and 7, it is figured out that the employment of REVB can produce conventional generators more economical cost compared to only conventional generator optimization and integrated PV unit.

5. Conclusion

This paper has been proposed the application of REVB to solve the DED problem affected by the intermittent PV power output. The REVB could reduce the total fuel cost by around 10.78 % compared to the conventional DED problem for IEEE 30 Bus. For IEEE 118 bus, the lowest best total fuel cost is yielded by REVB around 11.75 % from standard DED problem. The REVB is a very promising energy storage utilized to manage and distribute the power flow in power system operation considering the PV generation unit. In the future, the study of the DED problem could be extended by including the N-1 security criterion, congestion management, etc.

Conflicts of Interest

The authors declare no conflict interest.

Author Contributions

Conceptualization, Mardlijah and Muhammad Abdillah; methodology, Muhammad Abdillah and Mardlijah; software, Muhammad Abdillah and Sovia Prabaningtyas; validation, Muhammad Abdillah and Mardlijah; formal analysis, Qori Afiata Fiddina and Mardlijah; investigation, Mardlijah and Sovia Prabaningtyas; resources, Muhammad Abdillah; data curation, Muhammad; writing—original draft preparation, Mardlijah and Muhammad Abdillah; writing—review and editing, Mardlijah and Qori Afiata Fiddina; visualization, Qori Afiata Fiddina and Sovia Prabaningtyas. All authors have read and agreed to the published version of the manuscript.

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