Auxiliary Frequency and Voltage Regulation in Microgrid via Intelligent Electric Vehicle Charging

Nan Zou, Lijun Qian
Department of ECE
Prairie View A&M University

Husheng Li
Department of EECS
University of Tennessee

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Reliability and power quality are most important factors while large-scale deployment of microgrid composed of diverse and intermittent sources (e.g., wind, solar) with uncertainty. 

EVs introduce significant impacts on the grid reliability. 

Take advantage of controllability of EV charging to provide faster auxiliary frequency and voltage regulation services, instead of treating as disturbance. 

Consider the secondary regulation services to overcome the volatility of uncertain supply and demand in microgrid.
Introduction --- Previous research

Frequency and voltage regulation services:
1. Automatic generation control (AGC) for large scale generator
2. Design or reschedule the droop controller of selected generators
3. Inverter based control: parallel inverter control; voltage source converter (VSC) based control.
4. Frequency and voltage control to accommodate the wind power fluctuation.
5. Primary frequency response.
6. Voltage regulation and peak shaving.
7. PEV-based reactive power compensation via stackelberg game.

Most of previous works may not consider charging/discharging profile together with charging constraints, and not consider EV for both frequency and voltage regulations.
Intelligent electric vehicle charging control for reduced cost and improved stability of microgrid is formulated as a constrained optimization problem.

To capture the uncertainty, a discrete-time Markov Decision Process (MDP) is adopted to model the system dynamics.

Value iteration and policy iteration for solving problem.

The simulation results indicate the resulted action policy made state transitions towards the stable states, thus scheduled EV to provide auxiliary regulation services to stabilize the system.
Real-time EV control system for stability enhancement:

- **Assumption:** 1) EV charger is bidirectional charger  
  2) System monitor frequency and voltage in real time

- **Scheme:**
  - **Idea:** by controlling the charger voltage and voltage phase angle, or control charging phase angle of current and voltage, it can control the magnitude and direction of active power and reactive power. Thus provide frequency and voltage regulation services.

\[
P = \frac{\hat{E}_S \hat{E}_L}{X_L} \sin \sigma
\]
\[
Q = \frac{\hat{E}_S^2 - \hat{E}_S \hat{E}_L \cos \sigma}{X_L}
\]
Operate EV charging/discharging/idle with inductor or capacitor in 9 modes: \((\text{power flow from grid} \rightarrow \text{EV}, P>0, Q>0)\)

- (a1) discharge active power \(P < 0\), consume reactive power by inductor \(Q > 0\);
- (a2) discharge active power only \(P < 0\);
- (a3) discharge active power \(P < 0\), compensate reactive power by capacitor \(Q < 0\);
- (a4) consume reactive power by inductor only \(Q > 0\);
- (a5) idle \(P = 0, Q = 0\);
- (a6) compensate reactive power by capacitor only \(Q < 0\);
- (a7) charge active power \(P > 0\), consume reactive power by inductor \(Q > 0\);
- (a8) charge active power only \(P > 0\);
- (a9) charge active power \(P > 0\), compensate reactive power by capacitor \(Q < 0\).
System Model --- Objectives and constraints

- Objectives: enhance the microgrid reliability modeled by system failure cost, and minimize the operation cost, including energy charging cost $C_i^c$, discharging life-cycle cost $C_i^d$ (function of battery price and percent of battery used), reward for energy injection into grid while discharging $C_i^r$, and the system failure cost $C_i^f$ for frequency deviation and voltage deviation.

$$Z = \min \left\{ \sum_{i=1}^{N} (C_i^c + C_i^d - C_i^r + C_i^f) \right\} \cdots (1)$$

- Constraints:
  - Grid reliable constraint: frequency & voltage deviation tolerance $|\Delta f| \leq f_\epsilon$, $|\Delta v| \leq V_\epsilon$
  - Charging/discharging rate constraint: $R_M^c \leq r_k \leq R_M^d$
  - Capacity and life-cycle constraints: $\eta_{k+1} = \eta_k + \gamma_k \frac{r_k}{EV_M} \quad 15% \leq \eta_k \leq 85$
    - Battery state-of-charge(SOC) next state depends on current state, charging rate, charging efficiency; To extend battery life-cycle, SOC should be bounded.
Model the EV control as Markov decision process because of the uncertainty.

- Define system state: \( s_k = (\Delta f_k, \Delta V_k) \in S \)
  - \( S \) is the state space of the MDP problem
  - \( \Delta f_k = f_k - f_{ref}, \Delta V_k = V_k - V_{ref} \), are frequency and voltage deviation.

- Define EV charging/discharging operation represent actions, the action space is \( A \), and action for time slot \( k \) is \( a_k \in A^{S_k} \), where the \( A^{S_k} \) represent the set of all possible actions.

*Possible actions in different states are different, and constrained by power quality, remain capacity of EV battery, charging rate, SoC, DoD(depth of discharge), etc.
Denote state transition probability as: \( P(s_{k+1} \mid s_k, a_k) \), where \( s_k \) and \( s_{k+1} \) are current and next states, \( a_k \in A^{s_k} \) is a possible action at state \( s_k \in S \), and satisfy \( \sum_{s_{k+1} \in S} P(s_{k+1} \mid s_k, a_k) = 1 \).

Example:

When state \( s_k = 5 \), take action \( a_2 \), totally 9 possible transitions, because of the uncertainty.

Assumption: once the system reach a failure state \( F \), it will keep failure, i.e.,

\[
P(s_{k+1} \in S \mid s_k = F, a_k \in A) = \begin{cases} 1, & s_{k+1} = F \\ 0, & otherwise \end{cases}
\]
EV Control via MDP

The value function:

\[ v^*(s_k) = \min_{a_k \in A^{s_k}} \left\{ l(s_k, a_k) + \sum_{s_{k+1} \in S} p(s_{k+1} | s_k, a_k) v(s_{k+1}) \right\} \cdots (2) \]

The policy function:

\[ \pi^*(s_k) = \arg \min_{a_k \in A^{s_k}} \left\{ l(s_k, a_k) + \sum_{s_{k+1} \in S} p(s_{k+1} | s_k, a_k) v(s_{k+1}) \right\} \cdots (3) \]
Solution Method --- Value Iteration & Policy Iteration

Equation (2) & (3) are typical formulation of Bellman equations, and it’s difficult to find policy only through Bellman equation. Treat them as consistency conditions and use value iteration and policy iteration to solve.

- Value iteration only use eqn.(2), start with a guess \( v^{(0)} \) of the optimal value, then construct a sequence to improve:
  \[
  v^{(i+1)}(s_k) = \min_{a_k \in A^{s_k}} \{ l(s_k, a_k) + v^{(i)}(\text{next}(s_k, a_k)) \} \cdots (4)
  \]

- Policy iteration use both eqn.(2)&(3), begin with a guess of optimal control policy, then improve it:
  \[
  v^{\pi(i)}(s_k) = \{ l(s_k, \pi^{(i)}(s_k)) + v^{\pi(i)}(\text{next}(s_k, \pi^{(i)}(s_k))) \} \cdots (5)
  \]
  \[
  \pi^{(i+1)}(s_k) = \arg \min_{a_k \in A^{s_k}} \{ l(s_k, a_k) + v^{\pi(i)}(\text{next}(s_k, a_k)) \} \cdots (6)
  \]
Simulation Setup:

- Frequency variation tolerance within $\pm 5\%$, is $\pm 3\text{Hz}$ for 60Hz.
- Voltage deviation tolerance within $\pm 10\%$, is $\pm 12\text{V}$ for 120V
- EV battery for Nissan Leaf, with (i) capacity: 24kWh (ii) cost: $12,000
- Level 2 charging mode (6~8 hour)
- Charging active power price: $0.08/\text{kWh}$
- Discharging active power price: $0.1/\text{kWh}$
- Battery degradation coefficient: $-2.71\times10^{-5}$
- State transition probability: most possible transition, 0.8; the rest 0.2 is uniformly distributed among other transitions.

Uncertainty from renewable sources and EVs in microgrid have significant influence on the state transition probability. The realistic value should be obtained through a learning procedure such as Q-learning algorithm. Here, the value used for simulation is assumed to be known.
Sample setup of 1-dimensional state transition probabilities shown below: (when $\Delta f=0$, $\Delta V \neq 0$, only action $a_4$, $a_5$, and $a_6$ are possible)

**TABLE I. 1-DIMENSIONAL STATE TRANSITION PROBABILITY (SAMPLE SETUP). $\downarrow$: $\Delta V$ DECREASE, $\rightarrow$: $\Delta V$ NOT CHANGE, $\uparrow$: $\Delta V$ INCREASE.**

| States | $a_4$ | | $a_5$ | | $a_6$ |
|--------|--------|--------|--------|--------|--------|--------|
|        | $\downarrow$ | $\uparrow$ | $\downarrow$ | $\uparrow$ | $\downarrow$ | $\uparrow$ |
| $F$    | 0      | 1      | 0      | 0      | 1      | 0      |
| $-12$  | 0.8    | 0.1    | 0.1    | 0.1    | 0.8    | 0.1    |
|        |        |        |        |        |        |        |
|        | 0.1    | 0.1    | 0.1    | 0.1    | 0.1    | 0.8    |
| $0$    | 0.8    | 0.1    | 0.1    | 0.1    | 0.8    | 0.1    |
|        |        |        |        |        |        |        |
| $12$   | 0.8    | 0.1    | 0.1    | 0.1    | 0.8    | 0.1    |
| $F$    | 0      | 1      | 0      | 0      | 1      | 0      |
Performance Evaluation

- Simulation results comparison: consider all cost function V.S. only consider failure cost function in the objective in eqn.(1).

  - **Common:**
    
    ✓ Both use value & policy iteration methods to solve MDP problem
    
    ✓ Program running time different for two type iterations, results of cost value and policy value are almost the same
    
    ✓ The optimal actions make the state transition toward the origin with zero frequency violation and voltage deviation. (Fig.1 & Fig.2)
    
    ✓ The system uncertainty and the constraints of EV charging/ discharging characteristics result in other diverse state transitions in different quadrants. (Fig.1 & Fig.2)
    
    ✓ All the value points constitute a likely concave surf which make the state transition towards to the central desired state that make the microgrid more stable. (Fig.3 & Fig.4)
Difference:

- In Fig. 1, a lot of states adopting reactive power control to complete voltage regulation first, then start frequency regulation after hitting zero voltage. (This is because reactive power control incurs less cost in the minimization objective than other actions.)

- In Fig. 2, only considering the grid stability in terms of frequency and voltage deviation, it has many states diagonally transit to the central part of the state space with less frequency and voltage deviation.

- The concave surf is more diversified at different states in Fig. 3 than that in Fig. 4.
Fig 1. Optimal Policy of the State Transition when considering all Costs
Fig 2. Optimal Policy of the State Transition when considering only Failure Cost
Fig 3. Total Cost of Optimal Control Policy when considering all Costs
Fig 4. Total Cost of Optimal Control Policy when considering only Failure Cost.
Conclusion and Future Work

- In summary, we studied the auxiliary frequency and voltage regulation to improve microgrid reliability by intelligent control of electric vehicle charging or discharging.
- The problem is formulated as a constrained optimization problem in order to find the optimal policy to reduce the failure cost and the EV operation cost.
- Because of the uncertainty in a microgrid, we adopted a discrete time MDP to model the system dynamics and used value iteration and policy iteration to solve the problem. Simulation results indicate the effectiveness of the proposed solution.
- It is important to model the uncertainties introduced in a microgrid. How to design effective learning algorithm for estimation of the transition probability that incorporating system uncertainty and SOC constraints is one of our future works.
Thanks !