Intelligent Agent Meets with TSO and DSO for a Stable Energy Market: Towards a Grid Intelligence

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Abstract

In this work, we solve the problem of energy market instability that is caused by unstable energy generation and consumption of the smart grid. In particular, we propose an intelligent agent that can co-ordinate between transmission system operator (TSO) and distribution system operator (DSO) to capture the bidirectional nature of grid stability for energy generator and consumer. To do this, we design a Markov decision process for enabling an intelligent TSO-DSO agent while this agent can autonomously manage energy market clearance when the behavior of the grid becomes stable. Then we solve this decision problem by designing a tailored neural advantage actor-critic (A2C) model. Finally, we perform our experiment using the state-of-the-art grid stability analysis dataset and the results show that the proposed scheme can detect more than 15% market unsuitability than the individual TSO and DSO approaches.

1. Introduction

One of the core goals of the smart grid framework 4.0 [1] is to efficiently manage the distributed energy resources (DER) by coordinating between transmission system operator (TSO) and distribution system operator (DSO). In particular, to enhance the energy market stability and mitigating the issue of instability for energy supply and demand, detecting the instability of grid health is essential. Additionally, the stability coefficient of energy generator and consumer is proportional to energy market elasticity [2], [3]. Therefore, it is imperative to design a mechanism for the decentral smart grid control (DSGC) infrastructure by considering a bidirectional nature of grid energy generator and consumer. Thus, in this work, our goal is to provide an efficient energy market clearance mechanism by capturing grid behavior (i.e., generator and consumer), which not only detects the grid instability but also take an action for market clearance.

The summary of key contributions as follows:

- First, we propose an intelligent TSO-DSO agent for coordinating between TSO and DSO to cope with the dynamics of bidirectional energy generator and consumer.
- Second, we develop a Markov decision process to capture the behavior of response delay and energy market stability of the considered grid to decide the market clearance action.
- Third, we design a tailored neural A2C-based algorithm for the proposed intelligent TSO-DSO agent.
- Finally, our experimental results show that the proposed intelligent TSO-DSO agent can achieve a performance gain of around 15% more than the individual approach of TSO and DSO.

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning(KETEP) and the Ministry of Trade, Industry & Energy(MOTIE) of the Republic of Korea (No. 70300038). *Dr. CS Hong is the corresponding author.

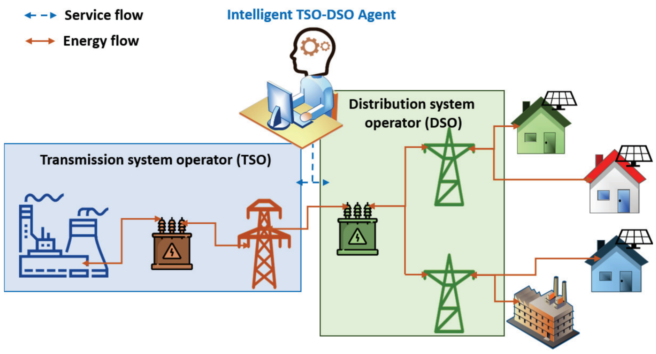

Figure 1: A system model for coordinating between TSO and DSO by an intelligent agent for a stable energy market.

2. System Model and Intelligent TSO-DSO Agent Design

A. System Model

Considering a decentral smart grid control (DSGC) infrastructure (as seen in Figure 1), where TSO is responsible for transporting energy from the energy generation sources to DSO. Consequently, the DSO can distribute that energy to consumer/prosumer. To ensure a stable energy market that relies on energy generation and demand, a co-ordination between TSO and DSO is performing by a newly introduced intelligent TSO-DSO agent. Let us consider a set $\mathcal{N} = \{1, 2, \dots, N\}$ of N energy generators and consumers, where each $i \in \mathcal{N}$ power generation and consumption is denoted by $P_i(t)$ (i.e., (+ve) for generator, and (-ve) for consumer). Thus, the dynamics of generator/consumer can determine by using an oscillator model [2],

$$\frac{d^2\phi_i}{dt^2} = P_i - \alpha_i \frac{d\phi_i}{dt} + \sum_{j=1, j\neq i}^{N} \Upsilon_{ij} \sin(\phi_j - \phi_i), \quad (1)$$

where $\phi_i(t)$ denotes rotor angle, a damping constant is represented by α_i, and Υ_{ij} is a coupling strength between i and j. Now, to represent oscillator model (1) in a form of frequency deviation, we denote consumed and produced power as $\hat{P}_i$ and utilizes the well established frequency deviation model [3] as follows:

$$\hat{P}_i(t) = P_i - \gamma_i \frac{d\phi_i}{dt}(t), \tag{2}$$

where γ_i represents elasticity of each energy source and consumer $i \in \mathcal{N}$, and γ_i is proportional to the market price elasticity [3] of each $i \in \mathcal{N}$. Additionally, $\frac{d\phi_i}{dt}$ is an angular frequency deviation for power grid reference rotation $2\pi \times 50$ Hz or $2\pi \times 60$ Hz (i.e., depends on grid architecture). Hence, the risk of instability induces by a certain response delay τ_i from each energy generator and consumer $i \in \mathcal{N}$. Thus, we consider a finite time domain T (i.e., time intervals lengths) and $\hat{P}_i(t)$ is represented as $\hat{P}_i(t-\tau)$ by considering response delay τ. Therefore, using (1) and (2), we can rewrite the oscillator model [2] as follows:

$$\frac{d^2\phi_i}{dt^2} = P_i - \alpha_i \frac{d\phi_i}{dt} + \sum_{j=1}^{N} \Upsilon_{ij} \sin(\phi_j - \phi_i) - \gamma_i \frac{d\phi_i}{dt}(t-\tau). \tag{3}$$

The stability $r_i(t) \approx \frac{d^2\phi_i}{dt^2}$ of energy market relies on the the stability of grid generation and consumption. Therefore, averaged frequency measurements of (3) over the finite lengths T time intervals can capable of measuring the grid stability,

$$\begin{aligned} r_i(t) \approx \frac{d^2\phi_i}{dt^2} = P_i - \alpha_i \frac{d\phi_i}{dt} + \sum_{j=1}^{N} \Upsilon_{ij} \sin(\phi_j - \phi_i) - \\ \frac{\gamma_i}{T} \int_{t-T}^{t} \frac{d\phi_i}{dt}(t' - \tau) dt'. \end{aligned} \tag{4}$$

Thus, we can write the grid stability $r_i(t)$ as follows:

$$\begin{aligned} r_i(t) = P_i - \alpha_i \frac{d\phi_i}{dt} + \sum_{j=1}^{N} \Upsilon_{ij} \sin(\phi_j - \phi_i) \\ - \frac{\gamma_i}{T} [\phi_i(t-\tau) - \phi_i(t-\tau-T)]. \end{aligned} \tag{5}$$

Negative value of (5) determines a stable energy market while positive value represent instability of the considered energy market. Therefore, it is imperative to co-ordinate between TSO and DSO for assuring a stable energy market, since the generation source are controlled by TSO while consumer/prosumer are controlled by DSO. Therefore, we design a decision support system by considering Markov decision process [4] that not only detects the grid stability but also can take decision for market clearance. Thus, we denote the market clearance indication as follows:

$$a_t = \begin{cases} 1, & \text{if } r_i(t) \geq 0, \\ 0, & \text{otherwise,} \end{cases} \tag{6}$$

where $a_t = 1$ if $r_i(t)$ is positive (i.e., no clearance), and 0 otherwise.

B. Intelligent TSO-DSO Agent Design

In this section, we design an *intelligent TSO-DSO agent* for the considered DSGC. Considering a set $\mathcal{S} = \{1, 2, \ldots, S\}$ of S states, where each state s_t is a tuple of $3 \times N$ elements, $\boldsymbol{s}_t : (\tau_1, P_1, \gamma_1 \ldots \tau_N, P_N, \gamma_N) \forall i \in \mathcal{N}, \boldsymbol{s}_t \in \mathcal{S}$. Thus, using (5), we can formulate a state value function of Markov decision process [5] as follows:

$$v_{\pi_\theta}(\boldsymbol{s}_t) = \mathbb{E}_{\pi_\theta}\big[\sum_{t=0}^{T-1} \beta^t r_i(t)_{t+1} | \boldsymbol{s}_t\big], \forall \boldsymbol{s}_t \in \mathcal{S}, \tag{7}$$

where $\beta \in (0,1)$ is a discount factor that helps to convergence. We need to design the intelligent TSO-DSO agent in a way so that it can capture the dynamics of energy generator/consumer over time since these dynamics is random over time. Therefore, we design to propose a model-free deep reinforcement using actor-critic method. Thus, the advantage function of the intelligent TSO-DSO agent is as follows:

$$\Lambda(\boldsymbol{s}_t, a_t) = [r_i(t)_{t+1} + \beta v_{\pi_\theta}(\boldsymbol{s}_{t+1})] - v_{\pi_\theta}(\boldsymbol{s}_t). \tag{8}$$

(8) has to use one neural network for estimating $v_{\pi_\theta}(\boldsymbol{s}_t)$ parameterized by θ for a policy π_θ. Therefore, the updates of neural network using policy gradient [5] is defined as follows:

$$\nabla_\theta L(\theta) = \mathbb{E}\big[\nabla_\theta \log \pi_\theta(a_t|\boldsymbol{s}_t) \Lambda(\boldsymbol{s}_t, a_t)\big]. \tag{9}$$

Algorithm 1: Intelligent TSO-DSO Agent for Stable Energy Market Clearance based on a Tailored Neural A2C

Input: $\boldsymbol{s}_t : (\tau_1, P_1, \gamma_1 \ldots \tau_i, P_i, \gamma_i) \forall i \in \mathcal{N}, \boldsymbol{s}_t \in \mathcal{S}$
Output: π_θ, a_{t+1}
Initialization: $P_i(t)$, $\phi_i(t)$, α_i, Υ_{ij}, θ, β, π_θ, *neural network*
while $t \leq T$ **do**
  Calculate: $r_i(t), \forall i \in \mathcal{N}$ using eq. (5)
  if (*Training* $==$ *true*) **then**
    for $\forall \boldsymbol{s}_t \in \mathcal{S}$ **do**
      Take action: $\pi_\theta(a_t|s_t, \theta)$
      Estimate: $v_{\pi_\theta}(\boldsymbol{s}_t)$ using eq. (7)
      Evaluate: $\Lambda(\boldsymbol{s}_t, a_t)$ using eq. (8)
      Execute policy gradient: $\nabla_\theta L(\theta)$ using eq. (9)
      Determine policy and neural parameters: π_θ and θ
    end for
  else
    Execution of intelligent TSO-DSO agent
    Load current policy: π_θ
    Find clearance decision: $\pi_\theta(a_{t+1}|s_t, \theta)$
  end if
  Send market clearance decision a_{t+1} to TSO and DSO
end while
return

3. Solution Approach of Intelligent TSO-DSO Agent

We propose Algorithm 1 to solve energy market stability problem by an intelligent TSO-DSO agent. The Algorithm

1 runs by a psychically deployed edge server at grid communication infrastructure. Line 2 in Algorithm 1 calculates grid stability for all generators and consumers of DSGC infrastructure. The training procedure is taken place from lines 3 to 10 in Algorithm 1. In particular, line 5 chooses a market clearance action while based on that action, a state value function (7) is estimated in line 6. Further, advantage function (8) of the intelligent TSO-DSO agent is evaluated in line 7; meanwhile, policy gradient (9) is calculated in line 8 by the considered neural network (in Algorithm 1). Policy π_θ of energy market clearance is determined at line 9 in Algorithm 1. The execution procedure of the intelligent TSO-DSO agent is presented from lines 11 to 15. Lines 13 and 14 are responsible for loading the already train policy and energy market clearance decision of the intelligent TSO-DSO agent (in Algorithm 1), respectively. Finally, market clearance decision is send by the intelligent TSO-DSO agent to TSO and DSO for ensuring the stability of the energy market. Additionally, the computational complexity for executing the market clearance decision for TSO and DSO of Algorithm 1 leads to $\mathcal{O}(|\mathcal{N}| \times |\mathcal{S}|)$ whereas the training procedure of the proposed Algorithm 1 does not affect this execution complexity due to off-line training.

4. Experimental Result

We have performed our experiment using the state-of-the-art grid stability dataset [6] by implementing the proposed intelligent TSO-DSO agent (i.e., Algorithm 1) on the python platform. Then we have compared our results with two usual cases: 1) only TSO, 2) only DSO, using similar neural network settings. We illustrate the important parameters of our experiment setup in Table I while other parameters are considered the same as [6].

First, we compare the training rewards of the proposed intelligent TSO-DSO agent with only TSO, and only DSO in Figure 2. The intelligent TSO-DSO agent has achieved higher rewards due to the capability of coordinating between TSO and TSO for analyzing response delay parameters τ and grid elasticity γ of each producer and consumer. Second, we illustrate the energy market clearance decisions based on grid stability analysis by the proposed intelligent TSO-DSO agent in Figure 3 during the testing. In Figure 3, we can see the proposed tailored A2C-based intelligent TSO-DSO agent can significantly achieve the performance with respect to market instability detection for energy market clearance than the traditional approaches. In particular, the proposed intelligent TSO-DSO agent can detect the market unstable situation at least 15% more than the individual TSO and DSO. Thus, coordination between TSO and DSO can provide a guarantee for establishing a stable energy market clearance scheme.

5. Conclusion

In this paper, we have introduced a new intelligent TSO-DSO agent for a stable energy market clearance scheme by coordinating between TSO and DSO. We have proposed a tailored neural A2C-based intelligent TSO-DSO agent by formulating a Markov decision process to cope with the dynamics of grid energy generation and consumption. The proposed intelligent TSO-DSO agent can detect energy market stability/instability, as well as, capable of taking energy market clearance decision for the smart grid users. Finally, our experiment results show the efficacy of the proposed scheme over the traditional approaches, which brings one step ahead to establish an efficient way to manage the distributed energy resources for the smart grid.

Table I: Summary of Experimental Setup

Description	Value
No. states $\|\mathcal{S}\|$ for training	8000
Learning rate	0.001
Discount factor	0.99
No. of episode	400
Fully connected layer, neurons, and activation	2, 300, ReLU
Optimizer, Loss	Adam, Cross entropy

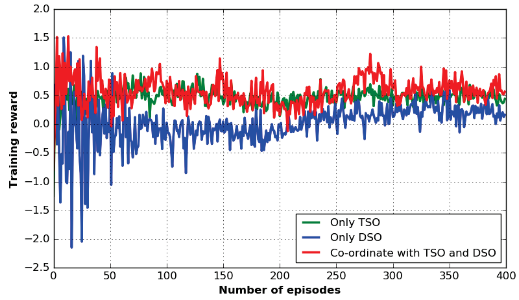

Figure 2: A comparison of cumulated training reward achieved by intelligent TSO-DSO agent over individual TSO and DSO for energy market stability.

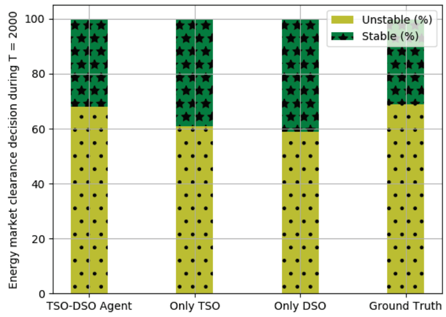

Figure 3: Grid stability detection for energy market clearance during the execution of intelligent TSO-DSO agent.

References

[1] NIST, "Smart Grid Framework", *[Online]: https://www.nist.gov/el/smart-grid/smart-grid-framework*, Release 4.0, 2017 (Visited on October 25, 2020).

[2] B. Schäfer, C. Grabow, S. Auer, J. Kurths, D. Witthaut, and M.Timme, "Taming instabilities in power grid networks by decentralized control," *European Physical Journal: Special Topics*, vol. 225, no. 3, pp. 569–582, 2016.

[3] B. Schäfer, M. Matthiae, M. Timme, and D. Witthaut, "Decentral smart grid control," *New Journal of Physics*, vol. 17, no. 1, 2015.

[4] M. S. Munir, S. F. Abedin, D. H. Kim, N. H. Tran, Z. Han and C. S. Hong, "A Multi-Agent System toward the Green Edge Computing with Microgrid," *2019 IEEE Global Communications Conference (GLOBECOM)*, Waikoloa, HI, USA, 2019, pp. 1-7.

[5] M. S. Munir, S. F. Abedin, N. H. Tran and C. S. Hong, "When Edge Computing Meets Microgrid: A Deep Reinforcement Learning Approach," *in IEEE Internet of Things Journal*, vol. 6, no. 5, pp. 7360-7374, October 2019.

[6] UCI Machine Learning Repository, "Electrical Grid Stability Simulated Data Data Set", *[Online]: https://archive.ics.uci.edu/ml/datasets/Electrical+Grid+Stability+Simulated+Data+*, November, 2018 (Visited on October 25, 2020).