

Risk Assessment of Multi-area Interconnected Power System under Gas Station Network Attacked

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Abstract: This paper mainly investigates the risk assessment of multi-area interconnected power system with probabilistic optimal power flow (POPF) for charging load of plug-in hybrid electric vehicle (PHEV) under gas station network attacked. Firstly, the PHEV charging model is developed by analyzing the change of PHEV operation mode after running out of gasoline. Secondly, in a multi-region interconnected power system, a line overload risk index is established to evaluate the impact of PHEV charging on the tie-line powers with the gas station network unavailable, and POPF considering PHEVs, wind and photovoltaic generation is employed to reduce the risk of system operation. Finally, the method is tested on IEEE 118-bus system to analyze the impacts of PHEV charging on tie-line powers and the entire system under gas station network attacked, and the economy and safety of system operation are evaluated before and after optimization.

Keywords: Plug-in hybrid electric vehicle (PHEV), gas station network attacked, multi-area interconnected power system, risk analysis, line overload, probabilistic optimal power flow (POPF).

NOMENCLATURE

OS^i	operating status (OS) of the i^{th} PHEV	$f(Z_l)$	probability density function of Z_l
d^i	daily travel distance	S_G	set of the generators
O_r^i	remaining gasoline	a_{2i}, a_{1i} and a_{0i}	coefficients of cost function
O_p^i	consumed gasoline per kilometer	P_{Gi}, Q_{Gi}	active and reactive power of conventional generator
d_e^i	actual distance in the EV mode	P_{Wi}, Q_{Wi}	active and reactive power of wind generator
E_c^i	electric energy expenditure	P_{Si}, Q_{Si}	active and reactive power of photovoltaic generator
$e_{Traction}^i$	consumed electric energy per kilometer	P_{EVi}, Q_{EVi}	active and reactive power of PHEV charging load with gas station network attacked
AER^i	driving range in the EV mode	P_{Li}, Q_{Li}	active and reactive basic loads
C^i	battery capacity	P_i, Q_i	injection power
T_c^i	time duration of PHEV charging	$P_{Gi}^{max}, P_{Gi}^{min}$	maximum and minimum of active power generation
P_c^i	charging power	$Q_{Gi}^{max}, Q_{Gi}^{min}$	maximum and minimum of reactive power generation
η^i	charging efficiency	$(V_i^2)^{max}, (V_i^2)^{min}$	maximum and minimum of voltage magnitude
t_s^i	start charging time	$(I_{ij}^2)^{max}$	maximum of line current
P_t^i	charging load	S_B	set of nodes
Z_l	power flow of the l^{th} branch	S_L	set of lines
$Risk(Z_l)$	risk index of line overload		
$P(Z_l)$	probability of line overload		
$Se(Z_l)$	severity of line overload		
Z_{lmin}	lower limit of the l^{th} branch		
Z_{lmax}	upper limit of the l^{th} branch		
μ_{Z_l}	mean of branch power flow		
σ_{Z_l}	standard deviation of branch power flow		
F_l	cumulative distribution function of Z_l		

1. INTRODUCTION

Plug-in hybrid electric vehicles (PHEVs) are currently a promising solution to the increasingly severe environmen-

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tal pressure and energy depletion problems by reducing fuel consumption (Xiong et al. (2018)) and have two operation modes, i.e., electric motor or combustion engine (Shafiee et al. (2013)), which means that they obtain energy from the grid and gas stations. With the network and information technology extensively deployed in gas stations, the comprehensive automation management level of gas stations has been greatly improved, and an extensive gas station network has been formed. However, due to the openness of network, gas station network is found vulnerable to cyber attacks (Ding et al. (2018)), e.g., the WannaCry ransomware attack broke out on 12 May 2017 (Aaron et al. (2019)). PHEVs after running out gasoline cannot be refueled and can only be driven by electric under gas station network attacked, which would induce additional PHEV charging load and increase the operation risk of power system.

Furhermore, with the continuous scale expansion of the power system, complex interconnections among areas increase. Multi-area interconnected power system is an inexorable trend to the grid development (Lu et al. (2018)), and it helps to increase the reliability of the whole grid and optimize the resources in a large scale. However, it is also facing challenges due to high penetration of the volatile renewable energy and electric vehicles (EVs) (Khanabadi et al. (2018)). Especially, the PHEV charging load in these areas would increase with the gas station network of partial areas attacked, which leads to the increment of energy transmission from unattacked subarea to attacked subarea and the overload risk of tie-lines would grow up.

Therefore, this paper is with the purpose of evaluating the risk of tie-line overload caused by additional PHEV charging load in multi-region interconnected power system with gas station network attacked, and making POPF to reduce overload risk of tie-line. The main contributions of this paper include: (1) A model for risk assessment of tie-line overload is developed derived from probabilistic load flow (PLF) to evaluate the impacts of PHEV charging load on the multi-region power system under gas station network attacked. (2) Point estimate method (PEM) based probabilistic optimal power flow (POPF) is involved in optimizing the operation of multi-region interconnected power system and weakening the negative impacts on tie-line powers under gas station network attacked.

The rest of the paper is outlined as follows. Section 2 presents the model of PHEV charging load under gas station network attacked. Section 3 provides the formulation of risk indices of tie-line overload in multi-region interconnected power system. The POPF model is revealed in Section 4. Section 5 shows simulation results in detail. The conclusions is drawn in Section 6.

2. PHEV CHARGING LOAD

With gas station network attacked, PHEVs drained gasoline cannot be refueled and will work in electric mode. Hence, the remaining gasoline should be considered in modeling of PHEV charging load with gas station network attacked.

Firstly, for a vehicle (e.g., the i th PHEV), the daily travel distance can be modelled by a lognormal distribution

(Li et al. (2019), Pouladi et al. (2016)). Considering its gasoline remained in tank, the actual distance in the EV mode with gas station network unavailable can be calculated by

$$d_e^i = \begin{cases} OS^i \times d^i, & (1 - OS^i) \times d^i < O_r^i, \\ d^i - O_r^i/O_p^i, & (1 - OS^i) \times d^i \geq O_r^i \end{cases} \quad (1)$$

If the remaining gasoline can fulfill the required gasoline consumption, the actual distance in the EV mode d_e^i is acquired by daily travel distance and OS ; otherwise, it will be determined by daily travel distance and the range the remaining gasoline can support (Li et al. (2019)).

Then, the electric energy expenditure E_c^i can be obtained by

$$E_c^i = \begin{cases} d_e^i \times e_{Traction}^i, & d_e^i < AER^i, \\ C^i, & d_e^i \geq AER^i, \end{cases} \quad (2)$$

It is noted that $C^i = e_{Traction}^i \times AER^i$ (Pouladi et al. (2016)).

Next, the time duration of PHEV charging T_c^i can be determined by

$$T_c^i = \frac{E_c^i}{P_c^i \eta^i}. \quad (3)$$

Finally, combining the start time t_s^i (followed by normal distribution (Tan et al. (2014))) and time duration of PHEV charging, the charging load can be expressed by

$$P_t^i = \begin{cases} P_c^i, & t_s^i \leq t \leq t_s^i + T_c^i, \\ 0, & 1 \leq t < t_s^i, t_s^i + T_c^i < t \leq T, \end{cases} \quad (4)$$

where T is the charging period, and $T = 24$.

3. RISK ASSESSMENT MODEL OF LINE OVERLOAD

Based on the PHEV charging load, the PLF can be developed to obtain the branch power flows in multi-region interconnected power system, and on basis of the PLF results, risk indices of line overload can be quantified.

3.1 Risk index of line overload

According to the relationship of input variables X (including the basic load, photovoltaic and wind generation and PHEV charging load) and output variables Z (i.e., branch power flows), the PLF problem can be formulated as

$$Z = G(X). \quad (5)$$

Input variables X are decorrelated via integration of Nataf transformation and elementary transformation and sampled by point estimate method (Li et al. (2019)). Nataf transformation is employed to transform Variables in correlated non-normal distribution vector space into correlated standard normal distribution vector space with given marginal distribution function and correlation coefficient (Li et al. (2019)). And then, output variables Z is obtained by power flow calculation with each estimation point. On basis of the results of branch power flow, the risk index

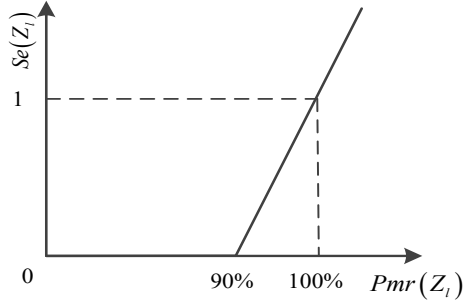


Fig. 1. The severity of line overload of the line overload can be quantified (Rocchetta et al. (2015), Wang et al. (2019)), i.e.,

$$Risk(Z_l) = \int_{-\infty}^{+\infty} P(Z_l)Se(Z_l) dZ_l. \quad (6)$$

3.2 Probability of line overload

The probability $P(Z_l)$ can be calculated according to the cumulative distribution function (CDF) of branch power flow (Li et al. (2017)), i.e.,

$$P(Z_l) = F_I(Z_l \notin [Z_{lmin}, Z_{lmax}]), I = |Z_l - \mu_{Z_l}| < 3\sigma_{Z_l}. \quad (7)$$

I is the confidence level when the samples of Z_l abide by 3σ principle. F_I is the CDF of Z_l , and it can be expressed as

$$F_I(Z_l \notin [Z_{lmin}, Z_{lmax}]) = \int_{Z_l \notin [Z_{lmin}, Z_{lmax}]} f(Z_l) dZ_l. \quad (8)$$

3.3 Severity of line overload

The severity of line overload $Se(Z_l)$ in Eq.(6) depends on the percentage of power flow to its rated values $Pmr(Z_l)$, which is related to the specified line characteristics and the power flow distribution in the power system. As shown in Fig.1, when $Pmr(Z_l)$ is lower than 90%, $Se(Z_l) = 0$. When $Pmr(Z_l)$ is more than 90%, $Se(Z_l)$ is a linear function of $Pmr(Z_l)$. When the branch flow is the rated, $Se(Z_l) = 1$ (Li et al. (2017), De Jong et al. (2018)).

When gas station network attacked, the risk indices of tie-line overload hereby can be quantified by multiplying the probability and severity of overload to investigate the impacts of PHEV charging on the multi-region interconnected power system.

4. POPF IN MULTI-REGION INTERCONNECTED POWER SYSTEM WITH PHEVS

Considering the potential risk increment caused by PHEV charging with gas station network attacked, the operation of multi-region interconnected power system is optimized based on POPF to improve the system security.

The POPF can be typically formulated as:

$$\min \sum_{i \in S_G} a_{2i} P_{G_i}^2 + a_{1i} P_{G_i} + a_{0i}. \quad (9)$$

a_{2i} , a_{1i} and a_{0i} are related to generation equipments and operating mode(Shargh et al. (2016)), subjected to the

power balance constraints (Xie et al. (2018)) and shown as:

$$\begin{cases} P_{G_i} + P_{W_i} + P_{S_i} - P_{EV_i} - P_{L_i} - P_i(e, f) = 0 \\ Q_{G_i} + Q_{W_i} + Q_{S_i} - P_{EV_i} - Q_{L_i} - Q_i(e, f) = 0 \end{cases} \quad (10)$$

The active and reactive power dispatch P_i and Q_i are the function of real and imaginary parts of nodal voltage e and f . The output power limits of generators, the voltage security limits, and the line flow limits (Aien et al. (2015)) are listed below(11):

$$\begin{cases} P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}, i \in S_G \\ Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max}, i \in S_G \\ (V_i^2)^{\min} \leq (e_i^2 + f_i^2) \leq (V_i^2)^{\max}, i \in S_B \\ I_{ij}^2 \leq (I_{ij}^2)^{\max}, (i, j) \in S_L \end{cases} \quad (11)$$

With path following interior point method (PFIP)(Du et al. (2019)) and 2m+1 PEM (Vahid-Pakdel et al. (2018)) integrated, the above POPF problem can be solved to obtain the fuel cost and branch power flows after optimization. The specific procedures are as follows:

- (1) According to data statistics on load and renewable energy generation, generate the correlated samples of basic load following the normal distribution, wind speeds following Weibull distribution (Morshed et al. (2018)) and light intensity following Beta distribution (Du et al. (2019)), and generate the PHEV charging load samples in different areas;
- (2) Using Nataf transformation, sample matrices of wind speed and light intensity are transformed to correlated standard normal distribution space. Combined with sample matrix of basic load, they are further transformed to independent standard normal distribution space by elementary transformation;
- (3) Based on sample matrices of basic load, wind speed, light intensity and PHEV charging load, calculate the locations and corresponding concentrations, and construct the sample points of 2m+1 scheme;
- (4) Run optimization power flow calculation for 2m+1 PEM, and obtain the fuel cost and branch power flows;
- (5) Analyze the security and economy of system operation before and after optimization to evaluate the optimization effects of POPF.

For the proposed method, the computational expense is dominated by computations of (5) – (9). Considering M input variables X and N sample values for each X , $2M + 1$ vectors are constructed according to 2m+1 scheme of PEM. For the iteration of optimization power flow K , each vector is employed to run optimization power flow for K times. The total number of loops is calculated as $K \times (2M + 1)$. After 2m+1 scheme of PEM, $2M + 1$ is usually much less than N and therefore the computational expense decreases.

5. CASE STUDY

The proposed method is tested on the modified IEEE 118-bus system. IEEE 118-bus system is firstly partitioned into three subareas based on K-means (Leou et al. (2018)) as shown in Fig.2. It is considered that there are 1770000 vehicles and the PHEV penetration level is 50% (Leou

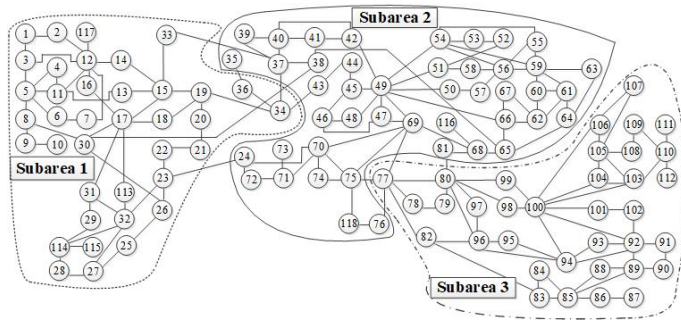


Fig. 2. Regional partition results of IEEE 118-bus system

et al. (2018)), which will be charged at nodes 16, 29, 33, 35, 41, 47, 75, 82, 88, 95, 106 and 115. The parameters of PHEVs are referenced as Li et al. (2019) and Pouladi et al. (2016). Two photovoltaic systems are connected to nodes 1 and 4. Nodes 62, 73, 87 and 111 are in connection with four wind farms.

Then, the impacts of PHEV charging on the risk of tie-line overload in multi-region power system can be investigated in gas station network attacked. The effects of operation optimization can be analyzed.

5.1 Impact of PHEV charging on risk indices of tie-line overload

With the subarea 1 and 3 of gas station network attacked, the charging load of PHEV in the attacked areas will continuously increase with the prolonged attacked time, which leads to the increment or decrement of tie-line power transmission between attacked subarea and unattacked subarea. Therefore, risk indices of tie-line overload before and after gas station network is attacked are compared to analyze the impacts of PHEV charging on the multi-region interconnected power system.

Figs.3 presents the risk indices of tie-line 22-24, 33-37, 30-38, and 34-43 between subarea 1 and 2 in period 15-22 with the normal operation and the prolonged attacked time of 24, 48 and 72 hours for gas station network. Because the power flows of these tie-lines flow from subarea 2 to 1, it can be seen from Figs.3-6 that the branch power flows increase after the gas station network in subarea 1 is attacked, and accordingly the risk indices of line overload get more severe.

Figs.7-10 present the risk indices of tie-line 76-77, 69-77, 75-77, and 81-80 between subarea 3 and 2 in period 15-22 with the normal operation and the prolonged attacked time of 24, 48 and 72 hours for gas station network.

Because the power flow of tie-line 76-77 and 75-77 is from subarea 3 to 2, it can be seen from Figs.7 and 9 that the branch power flow decreases after the gas station network in subarea 3 is attacked, and accordingly the risk of line overload weakens. On the contrary, the power flow of tie-line 69-77 and 81-80 is from subarea 2 to 3, it can be seen from Figs.8 and 10 that the branch power flow increases after the gas station network in subarea 3 is attacked, and the risk of line overload aggravates.

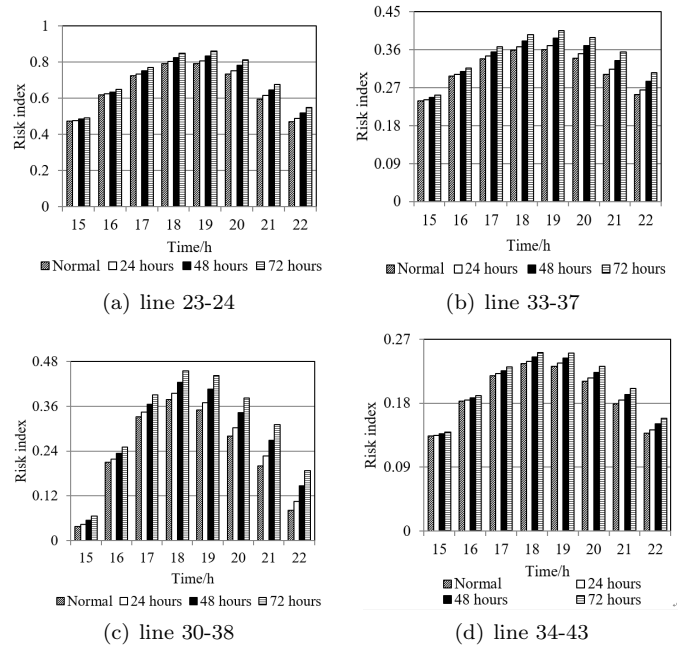


Fig. 3. Overload risk indices of line between subarea 1 and 2

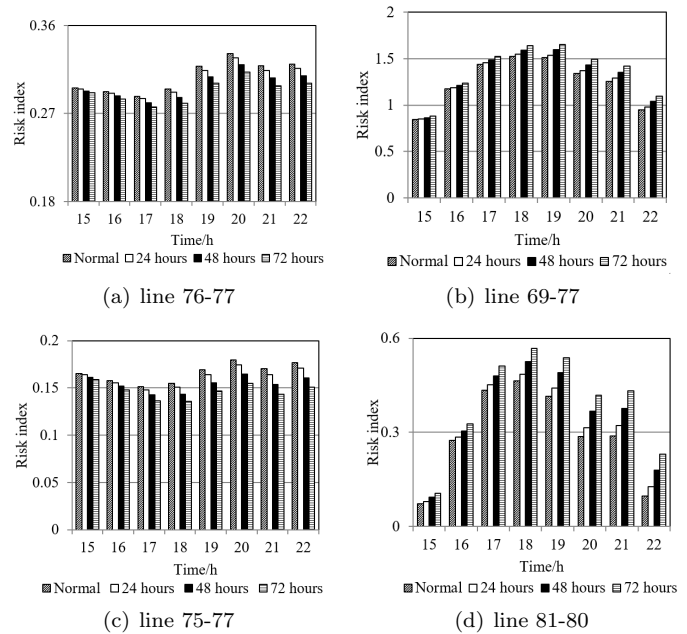


Fig. 4. Overload risk indices of line between subarea 3 and 2

5.2 Optimization analysis of multi-region interconnected power system with PHEVs

Based on the POPF, the operation of multi-region power system considering PHEV charging load under gas station network attacked is optimized. The optimization effects are analyzed from two aspects of economy and safety. Specifically, the fuel costs and risk indices of line overload before and after optimization are listed in Tab.1 and Figs.11-12.

From Tab.1 and Fig.4-5, it can be seen that with the prolonged attacked time, the fuel costs and risk indices

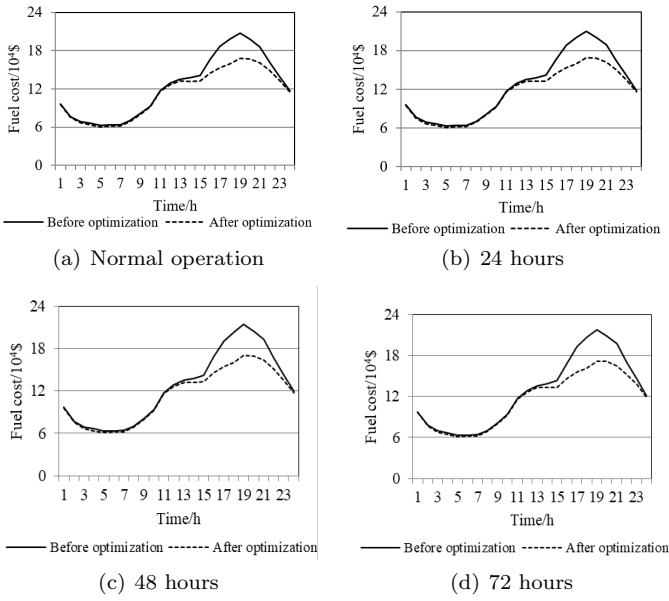


Fig. 5. Comparison of fuel cost

of line overload continuously increase. After optimization of power system, the fuel cost and risk indices of line overload reduce remarkably especially during peak load periods. Moreover, the incremental risk caused by PHEV charging weakens with the extension of gas station network attacked, which helps to improve the security of system operation.

Table 1. Overload risk indices before and after optimization

Attack time	Period	Fuel cost/ 10^4 \$		Risk index	
		Before optimization	After optimization	Before optimization	After optimization
Normal	15	14.137	13.210	60.140	48.939
	18	19.804	15.870	74.007	50.956
	21	18.610	16.067	70.422	49.141
	24	11.692	11.515	51.048	45.926
24hours	15	14.1705	13.229	60.257	48.971
	18	19.977	15.934	74.455	51.069
	21	18.851	16.169	71.101	49.333
	24	11.785	11.590	51.330	46.041
48hours	15	14.244	13.270	60.506	49.044
	18	20.312	16.049	75.288	51.292
	21	19.253	16.331	72.198	49.641
	24	11.931	11.703	51.766	46.198
72hours	15	14.320	13.312	60.762	49.118
	18	20.674	16.170	76.170	51.539
	21	19.674	16.496	73.318	49.948
	24	12.083	11.819	52.229	46.383

Fig.7 shows the risk indices of all tie-lines in different periods before and after optimization. It can be seen that, for most tie-lines especially line 69-77 and 23-24, the overload risk indices reduce. But the overload risk indices of some tie-lines, e.g. line 35-36 and 30-38, increase slightly.

6. CONCLUSIONS

This paper proposes a risk assessment method of multi-region interconnected power system with POPF for additional PHEV charging load under attacked. Firstly, the

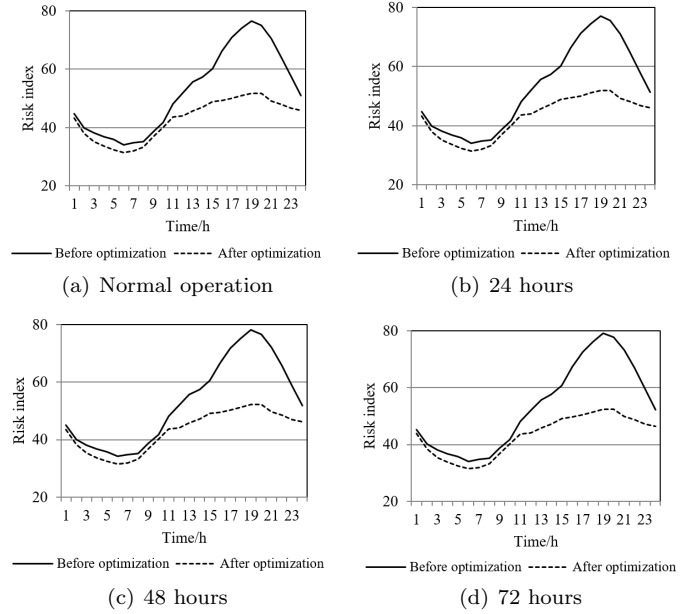


Fig. 6. Comparison of overload risk indices

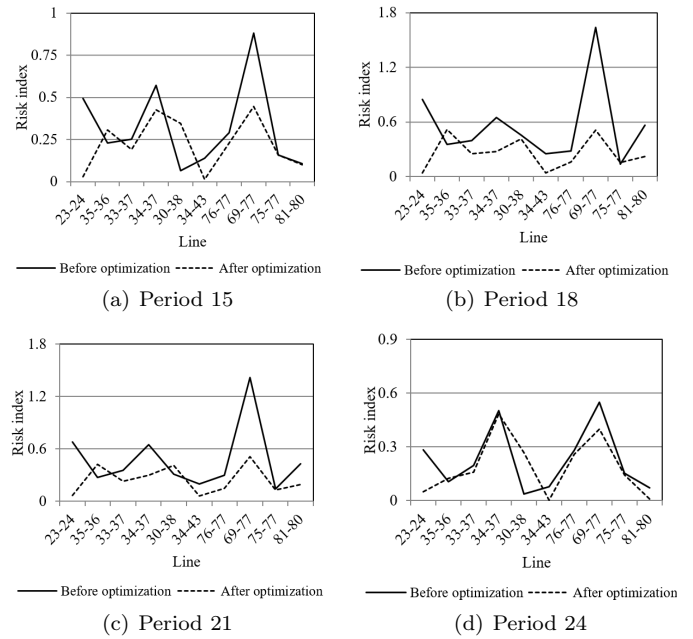


Fig. 7. Overload risk indices of tie-line before and after optimization (72 hours)

PHEV charging model is obtained with gas station network attacked. Then, with PEM based PLF to solve the problem, risk indices of tie-line overload are quantified based the PLF results to evaluate the impacts of PHEV charging on the multi-region interconnected power system. Furthermore, POPF considering PHEVs, wind and photovoltaic generation are employed to optimize the operation of multi-region interconnected system. The proposed method has been tested on the modified IEEE 118-bus system. The results show that the risk indices of line overload will increase with the prolonged attacked time when tie-line power flow streams from the an attacked area to the attacked area. On the contrary, the risk indices will reduce. Moreover, the fuel costs and risk indices of

the whole power system will decrease remarkably after optimization especially during the peak load periods.

REFERENCES

- R. Xiong, J. Cao, Q. Xu. Reinforcement learning-based real-time power management for hybrid energy storage system in the plug-in hybrid electric vehicle. *Applied Energy*, 211:538-548, 2018.
- D. Mao, Z. Gao, J. Wang. An integrated algorithm for evaluating plug-in electric vehicles impact on the state of power grid assets. *Electrical Power and Energy Systems*, 105:793-802, 2019.
- S. Shafiee, M. Fotuhi-Firuzabad, M. Rastegar. Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems. *IEEE Transactions on Smart Grid*, 4(3):1351-1360, 2013.
- D. Ding, Q. Han, Y. Xiang, X. Ge, X. Zhang. A survey on security control and attack detection for industrial cyber-physical systems. *Neurocomputing*, 275:1674-1683, 2018.
- Z. Aaron, Z. Wang, H. Chen, M. Mwenge. Recent advances in cryptovirology: State-of-the-art crypto mining and crypto ransomware attacks. *KSII Transactions on Internet and Information Systems*, 13(6): 3258-3279, 2019.
- W. Lu, M. Liu, S. Lin, L. Li. Fully decentralized optimal power flow of multi-area interconnected power systems based on distributed interior point method. *IEEE Transactions on Power System*, 33(1):901-910, 2018.
- M. Khanabadi, Y. Fu, L. Gong. A fully parallel stochastic multiarea power system operation considering large-scale wind power integration. *IEEE Transactions on Sustainable Energy*, 9(1):138-147, 2018.
- X. Li, J. Dong, D. Du, L. Wu, M. Fei. Impact of PHEV in active distribution network under gas station network attack. *ISA Transactions*, 2019.<https://doi.org/10.1016/j.isatra.2019.02.024>.
- J. Pouladi, M.B.B. Sharifian, S. Soleymani. Determining charging load of PHEVs considering HVAC system and analyzing its probabilistic impacts on residential distribution network. *Electric Power Systems Research*, 141:300C312, 2016.
- J. Tan, L. Wang. Integration of plug-in hybrid electric vehicles into residential distribution grid based on two-layer intelligent optimization. *IEEE Transactions on Smart Grid*, 5(4):1774-1784, 2014.
- R. Rocchetta, Y. Li, E. Zio. Risk assessment and risk-cost optimization of distributed power generation systems considering extreme weather conditions. *Reliability Engineering & System Safety*, 136:47-61, 2015.
- J. Wang, X. Xiong, J. Hu, X. Lu. Safety strategy of power transmission channel coordinated with transfer capability support for power system emergency. *International Journal of Electrical Power and Energy Systems*, 110: 232-245, 2019.
- X. Li, X. Zhang, L. Wu, P. Lu, S. Zhang. Transmission line overload risk assessment for power systems with wind and load-power generation correlation. *IEEE Transactions on Smart Grid*, 6(3):1233-1242, 2017.
- M. De Jong, G. Papaefthymiou, P. Palensky. A framework for incorporation of infeed uncertainty in power system risk-based security assessment. *IEEE Transactions on Power Systems*, 38(1):613-621, 2018.
- S. Shargh, B. Khorshid Ghazani, B. Mohammadi-Ivatloo, H. Seyedi, M. Abapour. Probabilistic multi-objective optimal power flow considering correlated wind power and load uncertainties. *Renewable Energy*, 94:10-21, 2016.
- Z. Xie, T. Ji, M. Li, Q. Wu. Quasi-Monte Carlo based probabilistic optimal power flow considering the correlation of wind speeds using Copula function. *IEEE Transactions on Power Systems*, 33(2):2239-2247, 2018.
- M. Aien, M. Rashidinejad, M.F. Firuz-Abad. Probabilistic optimal power flow in correlated hybrid wind-PV power systems: A review and a new approach. *Renewable and Sustainable Energy Reviews*, 41:1437-1446, 2015.
- D. Du, R. Chen, X. Li, L. Wu, P. Zhou, M. Fei. Malicious data deception attacks against power systems: a new case and its detection method. *Transactions of the Institute of Measurement and Control*, 41(6): 1590-1599, 2019.
- M.J. Vahid-Pakdel, B. Mohammadi-Ivatloo. Probabilistic assessment of wind turbine impact on distribution networks using linearized power flow formulation. *Electric Power Systems Research*, 162:109-117, 2018.
- M.J. Morshed, J.B. Hmida, A. Fekih. A probabilistic multi-objective approach for power flow optimization in hybrid wind-PV-PEV systems. *Applied Energy*, 211:1136-1149, 2018.
- D. Du, X. Li, W. Li, R. Chen, M. Fei, L. Wu. ADMM-based distributed state estimation of smart grid under data deception and denial of service attacks. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 49(8): 1698-1711, 2019.
- R.C. Leou, J.H. Teng, H. Lu, B. Lan, H. Chen, T.Y. Hsieh, C.L. Su. Stochastic analysis of electric transportation charging impacts on power quality of distribution systems. *IET Generation, Transmission & Distribution*, 12(11):2725-2734, 2018.