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Evaluation of power system reliability levels for (n-1) outage contingency

Badr M. Alshammari *

Electrical Department, College of Engineering, University of Ha'il, Saudi Arabia

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ABSTRACT

Throughout the world, power utilities have been struggling relentlessly with the delicate balance between cost and security/reliability. The experience gained by the power utilities at the Kingdom of Saudi Arabia has been similar to that of many public and private utilities around the world. In conjunction with energy conservation, power system security and reliability evaluation has grown to constitute a subject of prime interest. This paper presents, illustrative practical applications to evaluate power System reliability based on the (n-1) contingency. Therefore, the methodology is demonstrated in this paper, is based on combined between the evaluation of the reliability indices and contingency analysis. The methodology has been successfully applied to portions of a practical power system representing the Saudi electricity grid, where composite system performance reliability indices have been evaluated. The model System which is used contains hundreds of buses and tens of complex stations and analyzed using advanced and numerically effective large-scale computer scheme.

1. Introduction

A reliability index is a numerical measure of the performance level of a component or a system. A generalized form of the reliability definition, takes into consideration the effect of repair or replacement after a failure (Billinton, 1970; Endrenyi, 1978). In general, a component in a power system may exist in one of two states, namely "operation" or "failure". In some cases extra states may be considered to indicate partial operation, derated functioning or repair and maintenance. A system is said to be secure if it is able to tolerate the outage of components without interrupting the demand supply. Given an electric power system on N components, the N − k criterion is used to evaluate the outage of k components (Li et al., 2017).

Reliability indices for a power system are calculable from either its performance history or from component data utilizing mathematical models which express the system reliability indices in terms of the component indices included in the ICR (1966, 1968).

The construction of these mathematical models depends to a great extent on the system size and structure.

The contingency analysis applied to analysis process is the most time consuming stage (Gomez-Exposit et al., 2018), since there are many components to simulate outages. Availability of vast and accurate component performance data is a vital requirement for the calculation of reliability indices. Such data would facilitate firm and stable evaluation of the reliability indices which are of a probabilistic nature. The collection of such data for power systems is not a simple task because of the large number of components and the long history required. In general, the reliability indices described fit both components and systems. An event may be the operation, the failure of a component or interruption of power at a load point or any other performance criteria of interest to the system planner or operator. In this regards, in evaluation stage, it is needed to identify which contingencies change the system operation state, and to send the necessary information to the control center to ensure reliability to power system operation (Grijalva and Roy, 2013). Some of approaches for solving together the ranking and the evaluating contingencies processes can be found in de Jong et al. (2018), Pérez-Londoño et al. (2017), Daram et al. (2016), and Sunitha et al. (2013). These approaches seek to help the system operator in decision making, ensuring a secure operating system. In general, most of recently researches for failure analysis have been

* Corresponding Author.
Email Address: bms.alshammari@uoh.edu.sa
https://doi.org/10.21833/ijaas.2019.11.009
Corresponding author's ORCID profile:
https://orcid.org/0000-0001-6819-3695

classified to two methods. The first method, evaluates cascading outages based on deterministic criteria (Hardiman et al., 2004; Makarov et al., 2011; Ciapessoni et al., 2011; Miller, 2008; Henneaux et al., 2013; Koenig et al., 2010). The second method evaluates and predicts cascading outages in the probabilistic criteria (Dobson, 2012; Lee, 2008; Chen et al., 2006).

An electric power network containing generation and transmission facilities could be divided into several states in terms of the degree to which adequacy and security constraints were satisfied in a reliability evaluation of the composite system. The power system reliability evaluations had concentrated on the analysis of system adequacy, the ability to supply all loads within performance requirements. In addition, the electric power utilities have a key mandate to maintain a continuous and sufficient power supply to the customers at a reasonable cost (Pandzic et al., 2016). Power system cost-effectiveness, security, adequacy and reliability analyses have evolved over the years from mere theoretical topics of limited interest, during the era of generous economy and abundant supply and facilities, to a vital branch in today's highly-competitive business environment of power utility planning and operations (Torre et al., 2008; El-Kady et al., 1985; 1986; Chen et al., 2007; Poudel et al., 2018). The investigated reliability indices are not only useful for design of flexible power supply reliability for various customers but also beneficial to long-term system capacity expansion planning of electric power systems (Choi et al., 2006).

The methodology presented in this paper has been implemented in an efficient computerized algorithm which analyzes the network structure, generation and load balance and evaluates various composite system performance reliability indices and applied to the system under normal operation or subject to contingencies with certain or random occurrences. Practical application to apportion of the Saudi power grid is also presented in this paper for demonstration purposes.

2. Problem formulation

The reliability of a power system depends on the reliability of its individual components as well as the size and structure of the system. Various factors should be considered when evaluating the reliability of the system. Examples of these factors are the operation and failure time distributions, failure modes, operation practices and load priorities.

2.1. Reliability evaluation processes

The reliability analysis of a power system can be described by a six-step process as shown in Fig. 1. Step I represents the component constants and capabilities. Steps II and III represent the possible component outages and the definition of possible system failure modes resulting from single or multiple component outages. Step IV represents possible realizations of the component performance which may be actual or simulated. Step V describes the system model, where the system performance is obtained (power Sow analysis). The techniques used for such analysis are selected based on their accuracy and speed to suit either planning or operation studies. At step VI the system model results are analyzed to evaluate the system reliability.

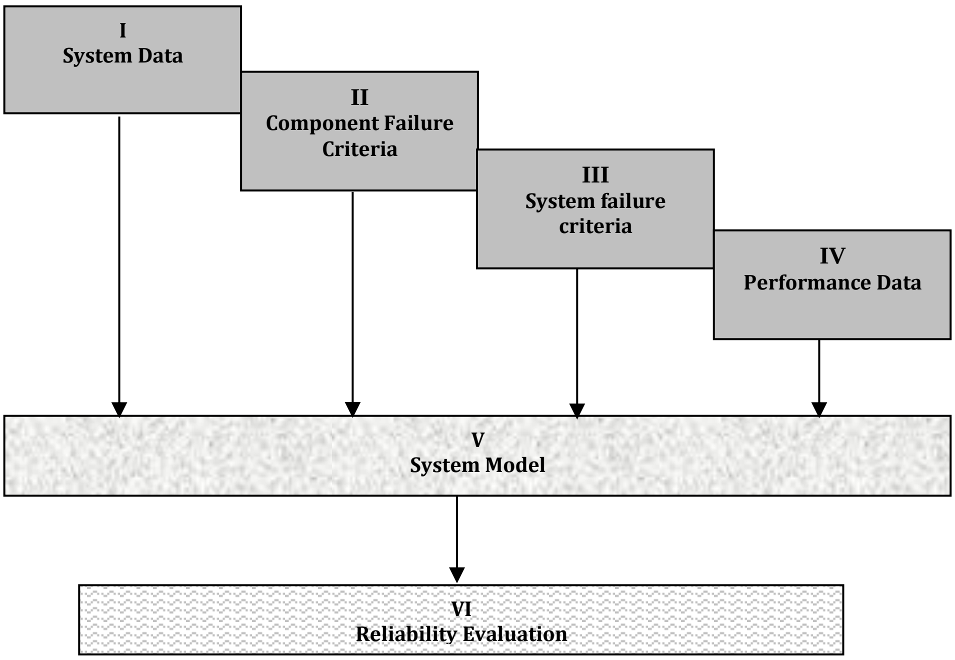

Fig. 1: Reliability evaluation processes (van Casteren et al., 2000)

2.2. Conditional probabilities of system failure

In almost all probability applications in reliability evaluation, component failures within a fixed environment are assumed to be independent events. It is entirely possible that component failure can result in system failure in a conditional sense. This can occur in parallel facilities that are not completely redundant. If the load can be considered as a random variable and described by a probability distribution, the failure at any point due to component outage is conditional upon the load exceeding some value at which a satisfactory voltage level at the load point can be maintained.

If two events designated A and B are considered to be independent, then

$$P\,(A \cap B\,) = P(A) \cdot P(B). \quad (1)$$

If the occurrence of A is dependent upon N number of events B_i, which are mutually exclusive, then

$$P(A) = \sum_{i=1}^{N} P\big((A|B_i \cdot P(B_i)\big). \quad (2)$$

If the occurrence of A is dependent upon only two mutually exclusive events for component B, success and failure, designated B_x and B_y, respectively, then

$$P\,(A) = P(A|B_x)\ \cdot P(B_x) + P\big(A|B_y\big) \cdot P\big(B_y\big) \quad (3)$$

With respect to reliability, this can be expressed in a simpler form:

$$\begin{aligned} &P(system\ failure) \\ &= P(system\ failure\ if\ B\ is\ good)P(B_x) \\ &+ P(system\ failure\ if\ B\ is\ bad)P\big(B_y\big). \end{aligned}$$

The complementary form is similar as:

$$\begin{aligned} &P(system\ success) \\ &= P(system\ success\ if\ B\ is\ good)P(B_x) \\ &+ P(system\ success\ if\ B\ is\ bad)P\big(B_y\big). \end{aligned}$$

2.3. Large-scale reliability modeling

The practical power system is large-scale in nature. It consists of numerous elements, which are characterized by forced outage rates representing their tendency to be off-service due to malfunctions. A suitable technique would implement an efficient partitioning scheme based on Ward equivalence, in order to retain only the parts of the system affected by a contingency, while the rest of the system is modeled by network equivalents. The use of the partitioning scheme permits a faster contingency analysis for large systems. In order to accurately simulate practical operator's response to power network outages, a maximum load-supply optimization scheme should be employed prior to the evaluation of various system reliability measures. The optimization algorithm evaluates the post-outage generation-load pattern based on real-time emergency dispatch procedures, which try to maximize the amount of system load supplied during the system outage. The generation and transmission reserve capacities of the retained network represent the optimization variables, which are manipulated to maximize the load supplied during the outage situation. The system reliability indices are determined based on the optimized post-outage generation-load pattern. These reliability indices can then be evaluated and displayed for both individual and groups of loads of interest associated with various system outages and according to their probability of occurrence.

2.4. Power system reliability indices

In general, a set of system-wide outage-based reliability indices can be defined. These reliability indices, which can easily be coded into computer programs, are sufficient to describe a range of practical reliability measures in large-scale power systems. This section summarizes the most widely-used indices for measuring the levels of power system reliability under outage conditions.

For a contingency m, the values of the network variables will be the solution of the maximum load-supply optimization problem. Also, let fm be the probability of contingency scenario m (the sum of fm for all m, including base-case contingency-free scenario is 1). Then the following three system-wide contingency-based reliability indices may be defined.

2.4.1. System-wide loss of load probability

Loss of load probability (LOLP), which indicates the probability (chance) that a system load would be lost, fully or partially, due to randomly occurring single or multiple contingencies (outages) in the system. The random nature of the outages is simulated using actual historical outage data of various system elements. The loss of load probability can be expressed in the Eq. 4,

$$LOLP = \sum_{m=1}^{M_c} LOLP^{(m)} \quad (4)$$

where

$$LOLP^{(m)} = Max_l\{Y_l\ LOLP_l^{(m)}\} \quad (5)$$

represents the system loss of load probability for any assumed contingency m (loss of generation and/or transmission) in the power grid,

$$LOLP_l^{(m)} = \lambda_l^m\ f_m \quad (6)$$

represents the loss of load probability at bus ℓ for contingency m,

$$\lambda_l^{(m)} = \begin{cases} 0 & if \quad P_\ell^{(m)} \le P_\ell^o \\ 1 & if \quad P_\ell^{(m)} > P_\ell^o \end{cases} \quad (7)$$

where, P_ℓ^o denotes the scheduled demand at load bus ℓ. Also, M_c denotes the number of contingencies considered and Y_ℓ is a 0 or 1 factor to indicate subsystems (if desired).

2.4.2. System-wide expected value of demand not served

Expected value of demand not served (EDNS) reliability index can be shown with following equations.

$$\varepsilon(DNS) = \sum_{\ell=1}^{n_L} Y_\ell \varepsilon(DNS_\ell) \tag{8}$$

where n_L is the number of load buses in the system,

$$\varepsilon(DNS_l) = \sum_{m=1}^{M_c} \varepsilon(DNS_\ell^{(m)}) \tag{9}$$

represents the expected value of demand not served at bus ℓ,

$$\varepsilon(DNS_l^m) = f_m DNS_\ell^{(m)} \tag{10}$$

represents the expected value of demand not served at bus ℓ for the contingency m and

$$DNS_l^m = Demand\ not\ served\ at\ bus\ l\ for\ contingency\ m \tag{11}$$

2.4.3. System-wide expected value of energy not served

Expected energy not served (EENS), which indicates the amount of TWh of energy per year that is likely not to be supplied to a system load center due to randomly occurring single or multiple contingencies (outages) in the system. Therefor can be expressed the Expected energy not served (EENS) in the Eqs. 12 to 15 as following:

$$\varepsilon(ENS) = \sum_{\ell=1}^{n_L} Y_\ell \varepsilon(ENS_\ell) \tag{12}$$

where

$$\varepsilon(ENS_l) = \sum_{m=1}^{M_c} \varepsilon(ENS_\ell^{(m)}) \tag{13}$$

represents the expected value of energy not served at a bus ℓ,

$$\varepsilon(ENS_l^m) = f_m ENS_\ell^{(m)} \tag{14}$$

represents the expected value of energy not served at bus ℓ for contingency m,

$$ENS_l^m = T^{(m)} DNS_\ell^{(m)} \tag{15}$$

represents the energy not served at bus ℓ for contingency m and $T^{(m)}$ denotes the time duration of contingency m.

3. Large-system reliability indices

The overall program structure which is used in this paper revolves around three major tasks during normal program execution. The first major task is the preparation of several database blocks, which contain system node and element data, area and zone definitions, outage history data, station element data, station configuration data and flow pattern data. The second major task includes validation of all database entries using a comprehensive 3-level data-checking routine. In the third major task, various station and system reliability indices is evaluated (including loss-of-load probability, bottled generation, surplus capacity and unutilized transmission).

4. Application of performance reliability evaluation

The system reliability performance has been applied to a practical power system comprising a portion of the interconnected Saudi power grid, where overall system reliability indices are evaluated and assessed. The power system consists of two main regions, namely the Central region and the Eastern region. The two systems are interconnected through two 380 kV and one 230 kV double-circuit lines. The system model used in the current application comprises 119 buses (19 generators, 100 loads), 334 lines and 122 transformers, as shown in Fig. 2.

5. System reliability results for (n-1) contingency scenario

The detailed system results show the impact of individual system (including all stations) component outages on various system reliability measures. It should be noted that, in order to maximize insight and knowledge gained from the reliability assessment, the (n-1) results include outages of all simulated system-wide station components (generators, transformers, breakers and input/output transmission links).

5.1. Maximum station flow for (n-1) contingencies

Table 1 summarizes the impact of the worst single contingency (including breaker outages) on maximum station flow for some examples of the network stations analyzed. The results of this table are important in measuring the relative robustness of various station designs. For example, a large drop in maximum station flow when the worst-case single contingency occurs would indicate a vulnerable station configuration design, while a small (or no) drop in maximum station flow when the worst-case single contingency occurs would indicate a robust and resilient station configuration design. For easy reference and comparison, the stations are ordered in accordance with the percentage drop in maximum flow. From the detailed station output report of station #8001, the 132KV transmission link between stations #8001 and #8091 was out one time for a total of 1396 hours during its in-service period. This has caused its outage occurrence probability to jump to about 0.04. Its outage, however, did not affect the total station load supply capability of 202.1 MVA. Comparing the outage of this element with that of the breaker #220 in the same station, which has no reported historical outages, we clearly see that the maximum station flow would drop to about 117.6 MVA. On the other hand, in station #8009, a heavy drop of 127.7 MVA (30%) in the maximum station flow would occur subject to outages in any of the breaker, transformer, or breaker.

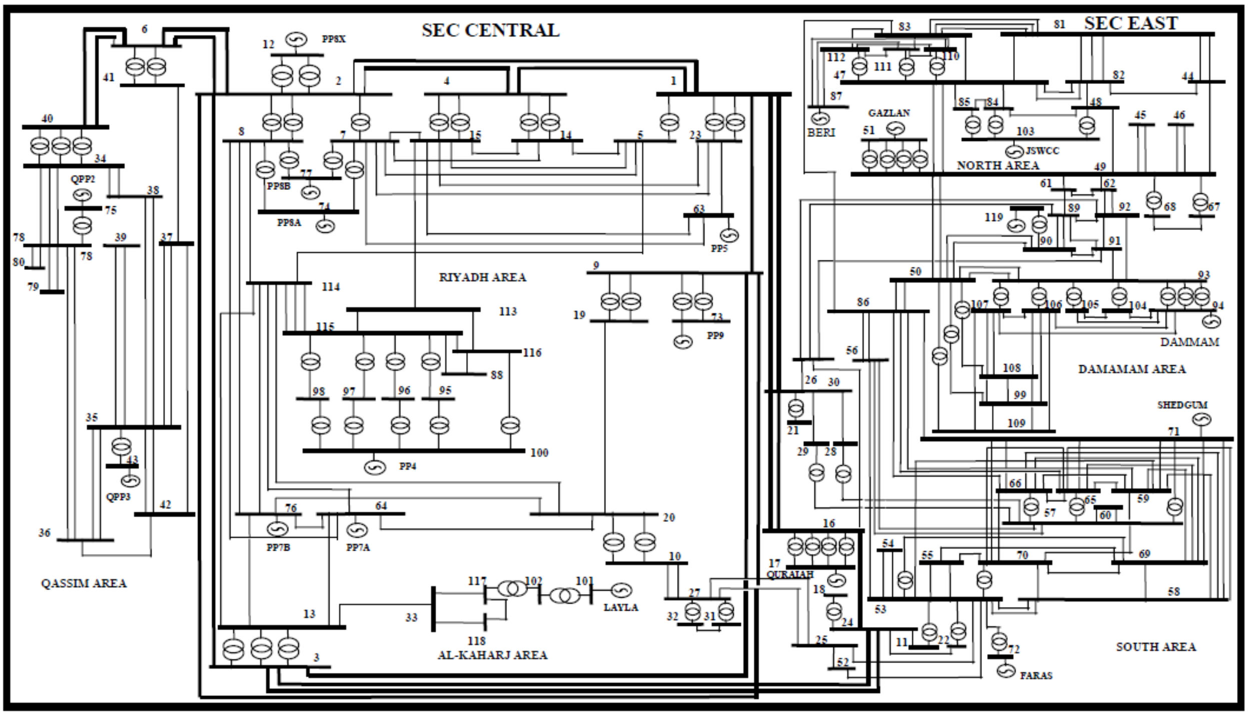

Fig. 2: Single-line diagram of the power system model used

Table 1: Impact of worst-case single contingency on station maximum flow for (n-1) contingencies

Station Number	Station Maximum Flow Nominal (MVA)	Station Maximum Flow Minimum (MVA)	Percentage Change (%)
8009	182.6	127.7	30
8762	2.9	2	31
8064	100.9	67.2	33
8091	137.1	91.4	33
8601	40.5	27.1	33
8800	339	226	33
8813	102.9	68.6	33.3
9010	339	226	33.3
8501	36.1	24	34
8058	147.4	93.8	36
8006	345.6	211.9	38.7
8760	106.8	63.8	40
8077	33.8	20	40
8001	202.1	117.6	41.8
8020	213.1	113.1	47
8034	196.6	100	49

5.2. Station load loss for (n-1) contingencies

Table 2 summarizes the impact of the worst single contingency (including breaker outages) on station load loss for some examples of the network stations analyzed. The results of this table are important in measuring the relative strength of various station designs. For example, a large drop in supplied station load when the worst-case single contingency occurs would indicate a weak station configuration design, while a small (or no) drop in the supplied load when the worst-case single contingency occurs would indicate a strong station configuration design. For easy reference and comparison, the stations are ordered in accordance with the percentage drop in the supplied load. The outage of breaker #220 in station #8014 would cause a maximum load loss of 235.7 MVA to occur. In station #8036, none of the elements has reported historical outages. The maximum load loss of 20 MVA is caused by the outage of breaker and transformer, in station #8039. In station #8041, none of the elements has reported historical outages. However, the outage of the transmission, transmission and breaker would cause about 2.6 MVA of load loss. In station #8076, a total load loss of 4.2 MVA represent the worst case scenario and it occurs for the outage of the transmission link between stations #8777 and #8076.

5.3. Station surplus capacity for (n-1) contingencies

Table 3 summarizes the impact of the worst single contingency on station surplus capacity for all network stations analyzed. The results of this table are important in measuring the relative abundance of station capacity for various station designs. From the reliability point of view, a large drop in capacity surplus when the worst-case single contingency occurs would indicate a less-reliable station. That is, a relatively large capacity surplus indicates better reliability.

Table 2: Impact of worst-case single contingency on station load loss for (n-1) contingencies

Station Number	Maximum Load Loss (MVA)	Total Station Nominal Load (MVA)	Percentage Change (%)
8040	0.8	40.8	2
8041	2.6	42.6	6.1
8108	2.8	42.8	6.5
8106	4.3	64.1	6.7
8059	28.8	111.3	25.9
8068	6.6	25.5	25.9
8076	4.2	14.2	29.6
8009	61.3	189	32.4
8034	96.6	196.6	49
8039	20	40	50
8069	6.3	12.6	50
8708	2.2	18.8	11.7
8091	113.9	205.3	55.5
8012	7.9	8.7	90.8
8036	30	30	100
8037	8.5	8.5	100

From the quality point of view, however, such relatively large capacity surplus would indicate poor quality, because of the excess station transfer capability paid for, but not actually being used. For easy reference and comparison, the stations are ordered in accordance with the percentage change in station capacity surplus. In station #8441, a minimum capacity surplus of 0 MVA is caused by an outage of breaker or generator. In station #8760, a minimum capacity surplus 45.7 MVA is caused by the outage of breaker and transformer. On the other hand, element outages in station #8761 would not cause any capacity surplus or load loss.

Table 3: Impact of worst-case single contingency on station surplus capacity for (n-1) contingencies

Station Number	Maximum Capacity Surplus		Maximum Nominal Station Flow (MVA)	Percentage Change (%)
	Nominal (MVA)	Maximum (MVA)		
8764	0	2	8.8	22.7
8801	23.6	23.6	81.3	29
8763	0	0.7	2.3	30.4
8761	0	0.9	2.9	31
8762	0	0.9	2.9	31
8006	117.4	117.4	345.6	34
8760	88.7	88.7	106.8	83
8012	58.2	58.2	62.3	93.4

5.4. Station unutilized capacity for (n-1) contingencies

Table 4 summarizes the impact of the worst single contingency on generating station's unutilized capacity for all SEC-C stations analyzed. The results of this table are important in measuring the relative abundance of available generating power for various station designs. From the reliability point of view, a large drop in generation unutilized when the worst-case single contingency occurs would indicate a less-reliable station. That is, a relatively large generation unutilized capacity indicates better reliability. From the quality point of view, however, such relatively large generation unutilized capacity would indicate poor quality, because of the excess generation available and paid for but not actually being used. For easy reference and comparison, the stations are ordered in accordance with the percentage change in generating unutilized capacity. In station #8013, a maximum non-utilized capacity of 88.3 MVA occurs due to outages in any of the three breakers. In station #8020, however, a maximum non-utilized capacity of 215.9 MVA occurs for the outage of transformer. In stations #8068 and #8070, a maximum non-utilized capacity of 25.5 MVA and 55.1 MVA, respectively, occurs for the outage of breakers.

Table 4: Impact of worst-case single contingency on station unutilized capacity for (n-1) contingencies

Station number	Maximum capacity unutilized		Maximum nominal station Flow (MVA)	Percentage change (%)
	Nominal (MVA)	Maximum (MVA)		
8813	0	38.3	102.9	37.2
8058	98.2	98.2	147.4	66.6
9001	1450	1800	2500	72

6. Conclusion

Reliability is very important measure of the performance of power system; the reliability is mainly concerned with the inability of the system to fulfill its load-supply commitments. The costs associated with low service reliability is enormous, and can be largely avoided if enhances system planning simulation models and appropriate computer-sided solution tools. Systems with hundreds of buses and tens of complex stations can only be analyzed using advanced and numerically effective large-scale algorithms for reliability evaluation, as has been demonstrated in this paper. The solution of the reliability evaluation problem in power systems; by evaluate key reliability indices, including System reliability indices, loss-of-load probability, bottled generation, surplus capacity and unutilized transmission under (n-1) contingency, is presented in this paper with real-life power systems with practical large-scale sizes.

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Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

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