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A Real-time Condition Monitoring-based Asset Management Model for Power Transformers in the Presence of Distributed Generation

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Abstract— *With the advent of advanced measurement and supervisory devices in power systems, wide area measurement systems and real-time monitoring of power systems have become viable. Accordingly, modeling techniques should be updated as well. This paper proposes a transformer asset management model based on real-time condition monitoring in the presence of distributed generation. The model is tested under different case studies and compared with the previous models in which constant failure rate model was used for asset management of transformers. The system cost includes operation, repair, and interruption costs. The objective is to determine the hourly loading of the transformer so that the cost of system is minimized. The long-term objective is to determine the loading pattern of the transformer which guaranties the most economical pattern among various options. Results showed that the proposed model is efficiently capable of returning more accurate responses if real-time monitoring data is used. A set of sensitivity analysis studies are also performed to highlight the impact of each factor separately. The contribution of distributed generators to supply the load is also investigated. Results showed that the use of distributed generators reduces the overall cost of the system by diminishing the risk-based element of the system cost.*

Keywords— Transformer asset management, Real-time condition monitoring, Risk, Distributed generation

NOMENCLATURE

Abbreviations and Acronyms

CDF	Customer Damage Function
DG	Distributed Generation
ENS	Energy Not Supplied
FOA	Forced-Oil-Air
HST	Hottest Spot Temperature
PD	Partial Discharge
WAMS	Wide Area Measurement Systems

Parameters

T_0	Reference temperature
$\bar{\lambda}$	Average failure rate for an indoor transformer
β	Shape parameter of the Weibull distribution associated with the failure probability of aging process
Δt	Duration of each time step in loss of life studies
ΔT_{HR}	Increase in the temperature of winding hottest-spot over top-oil temperature at nominal load
ΔT_{OR}	Top-oil temperature rise at rated load
ΔT_{WR}	Average increase in the winding temperature at nominal load
λ	Weather-dependent failure rate of an outdoor transformer
Pr_h	Hourly hybrid failure probability of transformer
ρ_h	Hourly electricity price
C_h^{DG}	Hourly cost function of DG
CDF	Customer Damage Function
$load_h$	Hourly demand
N	Expected duration of normal weather state
$P_{\max}^{DG}$	Maximum capacity of DG
$P_{\max}^{sub}$	Maximum capacity of transformer
S	Expected duration of adverse weather state
T_A	Ambient temperature
v	Weather condition; 0 for normal and 1 for adverse
F	Proportion of failures occurring in adverse weather
a, b	Proportional and constant coefficients for repair cost of power transformer
B, C	Empirical constants in calculation of HST-dependent failure probability of the transformer
n, m	Empirical constants depending on the winding sensors cooling
R	The loss ratio constant

Sets and Indices

h	Index of time in reliability-cost optimization
$t,\ T$	Index and set for time in loss of life studies, (t_1, t_2, ...t_i, ..,t_n)

Variables

ΔT_H	Winding hottest spot temperature rise over top-oil temperature
ΔT_O	Top-oil rise over the ambient temperature
C_h^{int}	Hourly interruption cost
C_h^{opr}	Hourly operation cost
C_h^{r}	Hourly repair cost
ENS_h	Energy not supplied
P_f	Hottest spot-dependent failure probability
P_h^{DG}	Hourly generation of DG
P_h^{sub}	Hourly transformer loading
P_w	Weather-related failure probability
Pr	Hybrid failure probability

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Research Paper

1. Introduction

Asset management is defined as an essential link between asset owners and the system operator in order to make a balance on cost, risk, and efficiency of assets [1]. The main objective is to choose spending strategies capable of returning the highest stakeholder value from the available budget [2].

Due to the substantial investments in power transformers, a significant attention is paid to transformers as one of the most important equipment in power system asset management [3–5]. Adverse operating and environmental conditions accelerate the aging process of power transformers. These include overloading, harmonic load currents, adverse weather, high ambient temperatures, physical damages, etc. The Hottest Spot Temperature (HST) increases due to overloading and high ambient temperatures. As a result of exposure to such conditions, the insulation performance is attenuated and different electrical/chemical phenomena may occur in the insulation including (but not limited to) dissolved gases in oil, Partial Discharge (PD) in the insulation, dielectric deterioration, and polymerization [6–9]. Accordingly, various testing methodologies could be used to diagnose upcoming faults originated from these phenomena in power transformers [10, 11]. Although testing methods help predict the repair/replacement schedule of equipment, they fail to give information on operational reliability of power transformers. In addition, environmental and weather conditions are not considered in testing methods for lifetime estimation and operational reliability calculation.

The total failure probability of a transformer is a function of different destroying phenomena. Therefore, the condition monitoring of power transformers is a major factor in reliability assessment of the overall system [6]. The majority of above-mentioned phenomena are measured or monitored through medium or long term periods in the present-day power systems. Therefore, the constant failure rate of transformers has been widely employed in the reliability assessment and planning of power systems reflecting the average condition of reliability indices. This kind of conventional reliability assessment is not capable of reflecting the real-time operating conditions including loading pattern, ambient temperature, aging, and weather status [6].

Historical data of transformer palys a key role in recognition of the transformer loss of life which is then employed to extract the failure probability of the asset. An estimation is required in order to complete the data history related to periods when no measurements were done. Machine learning [12–16] and fuzzy-base methods [17], [18] have been proposed in the literature to estimate the heath index of power transformers in case of absence or shortage of historical data. However, either underestimation or overestimation may occur in the estimation procedure resulting in inaccurate estimation of the transformer condition [6], [19]. Reference [15] presented a fuzzy failure rate model based on condition monitoring information. The results of the proposed model can be employed for reliability studies and maintenance scheduling in power systems. Since the condition monitoring data is expressed via a fuzzy normal distribution membership function, the model accuracy is endangered by the method approximations and expert knowledge interferences. Nonetheless, the lack of real-time condition monitoring in power systems has led researchers to apply constant failure rate models to investigate the transformer asset management. Reference [20] investigated the failure risk originated from the overloading in power transformers. The results indicate that loss of life and dielectric failure risks increase as HST rises under harmonics loads. Reference [21] analyzed the insulation response as a useful means for transformer risk assessment. A two-stage framework was suggested for power transformer asset maintenance in order to coordinate and schedule long-term and short-term maintenance actions [22], [23]. A delayed semi-Markov process is introduced in [24] to calculate time-varying or condition-based failure probabilities employing real-time data measured by advanced sensors. However, the system operator cannot use the results in a day-ahead scheduling of power system, since the time frame is over some minutes or hours. Also, no methodology was given to evaluate the historical aging and current health status of the transformer. A mathematical model is given in [25] capable of analyzing the characteristics of the dissolved gases in the transformer oil. The main outcome of this model is the filtration schedule for regulating the quality of transformer oil. Authors in [26] presented a comprehensive review on asset management methods extracted from industrial reports and academic studies. Additionally, a health index formulation is given for lifecycle prediction of power transformers. The procedures of various testing methodologies are described including dissolved gas analysis, oil-testing methods, partial discharge, dielectric dissipation factor, turns ratio test, transformer winding resistance, etc. However, no quantitative study is presented in [26]. A maintenance planning for in-service power transformers is presented in [27] using the health index approach. Weighting and scoring factors were assigned for each test to determine the actual condition of the power transformers relying on average historical data. Reference [6] presented a condition-dependent reliability model of a transformer and studied impacts of loading, HST-dependent aging, and weather condition on the failure probability. Using historical data, the long-term failure probability of a transformer was derived. Then, operating condition of the asset in a day-ahead study was applied to the model to extract the real-time failure probability. However, the long-term probability is resulted from average mid-term historical data. Unlike using real-time operating historical data, this method cannot represent the real health status of the asset. Reference [28] presents a methodology for estimating the health index of power transformers based on simple data obtained from oil sample analysis acquisition systems. The proposed method employs the history of the average daily load of power transformer to estimate the insulator degradation. Although using simple data is an advantage of the method presented in [28], the use of average data deviates the health index estimation from its real value in practice. Reference [29] used recent historical data from a two-year period of time to determine the insulation index of 10 power transformers. The historical data include average qualitative oil measurements for parameters such as furan, dissolved gas analysis, water content, breakdown voltage, interfacial tension, and acidity. The results can easily estimate the useful remnant lifetime of the transformer. Neglecting historical data prior to two years ago and utilizing average data are the main drawbacks of the proposed methodology in [29]. In another research [30], authors used average historical data on operation time, the load rate, and the pollution level to obtain helath index of the trandformer. The researches in the literature paid much attention to lifetime estimation of power transformers using historical data or testing methodologies. However, the application of asset management studies in transformer daily load scheduling has been disregarded. The failure probability of a power transformer affects the daily interruption and repair costs of the distribution system. Thus having known the hybrid age and weather dependent failure probabilities of power transfrmers, the daily load can be scheduled so as to minimize the total cost of system including operation, interruption, and repair costs.

Wide Area Measurement Systems (WAMS) provide time synchronized measurements across a power system in the future smart grid infrastructure. Thus, characterizing the power system state in its various operating points will be viable with a high resolution. This allows to enhance the information level necessary for supporting the system operator in daily scheduling of the power system. Real-time transformer condition monitoring is one practical benefit of integration and utilization of WAMS [31–33]. Employing WAMS data, many variables associated with transformers might be monitored online such as hottest spot temperature, dissolved gases, oil temperature, partial discharges, wall and winding vibration, and winding movement/deformation. Moreover, the weather data is available online. All data measured can then be collected and analyzed to provide accurate picture of the current situation and thus helping the operator with scheduling decisions.

The majority of published works in the literature, as reviewed above, paid attention to either testing methodologies or analytic methods for condition monitoring with long-term constant failure rates. In constant-rate condition monitoring, the HST-related remained lifetime of the power transformer is neglected. In addition, the correlation of weather data in total failure probability of power transformer is not considered in most of researches. Additionally, the impact of Distributed Generation (DG) units on daily transformer loading and total failure probability is still unknown. For instance, reference [34] proposed an asset management model for power transformers to decrease operation and maintenance costs relying on lifetime based failure probability of the equipment. However, the contribution of DG units in load scheduling is neglected. Thus, there is an undeniable need to a comprehensive research which considers: i) WAMS data employment to recognize the real-time health status or effective lifetime of power transformers, ii) weather data use for calculating total failure probability of power transformers, and iii) optimal daily loading of the transformer considering the contribution of DG units.

This paper proposes a transformer asset management using real-time historical data of the power transformer. In the smart grid concept, advanced meters and sensors play a significant role in gathering data from different assets. Therefore, the aging status of the transformer can be derived exactly. This will provide the system operator with a real picture of the transformer which in turn makes the scheduling results closer to real situation. The HST-dependent and the weather-dependent probability failure functions are calculated using the forecasted load, ambient temperature, and weather condition data. Then, the total failure probability of the transformer is derived. Using this function and electricity market prices, the operator evaluates a reliability-cost objective function to schedule the optimal 24-hour transformer loading in the presence of DG units. Moreover, the hourly loading of DG units will be determined.

The main contributions of this paper are listed as follows:

- Transformer asset management is viewed from a dynamic, real-time dependent perspective rather than the conventional static one,
- Unlike previous studies, this work applies a real-time condition-based failure rate model for reliability assessment of transformers using HST-dependent and the weather-dependent failure probability functions,
- The presented model considers the contribution of DG units in load supply and total failure probability in addition to calculating the optimal 24-hour loading for substation transformers and DG units.

The next sections are arranged as follows. In Section2, the model concepts are defined and the general methodology is described. In Section 3, the problem is formulated. Simulation results are presented in Section 4. Finally, conclusive remarks are given.

2. Problem Definition

Asset manager is responsible for preparing the long-term guideline for the system operator according to policies announced by the asset owner. The main purpose is to operate the system in a real-time operating period in a way that the long-term objectives and policies of the asset owner are satisfied. In this work, it is assumed that this task has been performed before and the output instructions are used by the system operator to schedule the day-ahead system operation. The main objective of the problem is to formulate a risk-based cost objective function which determines the hourly loading curves of the substation transformer and DGs.

Fig. 1 illustrates the framework of the proposed asset management model. The asset owner determines the corporate objectives and announces to the asset manager. These objectives originate from general policies set by policy makers considering benefits of stakeholders. The asset manager is responsible for making available a long-term asset plan for the system operator. In our model, it is assumed that the asset manager uses historical WAMS data to determine the real health status of the transformer. Therefore, the system operator is aware of the newest aging and failure probability of the transformer which reflects its real health status. Forecasting the load and receiving the forecasted ambient temperature data, the system operator is able to estimate the hourly HST. The weather condition forecast is also available for the day-ahead. The day-ahead market prices should be also predicted. The state of DGs and their availability for servicing is also checked. Finally, the system operator can calculate the total failure probability of the transformer in each hour. Here, the HST-dependent and weather-dependent failure probability functions are considered. It is worth saying that other probability failure functions such as that of dissolved gases or partial discharge can be modeled. However, the most important failure origin of a transformer is the HST aging. The weather-dependent failure probability is also modeled, since it can be important in adverse weather conditions. Finally, the problem is formulated as a reliability-cost objective function and the hourly loading patterns of transformer and DGs are derived.

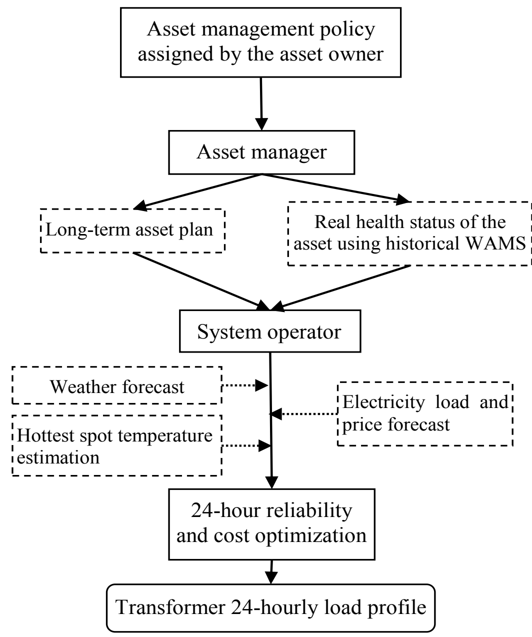

Fig. 1. The framework of the proposed asset management model

3. Problem Formulation

Transformer failures are divided in two categories: HST-dependent and weather-dependent failure models. These models are discussed in details in the following.

3.1. Hottest Spot Temperature Model

The majority of transformers used in power systems are insulated with mineral oil. The hottest spot is a major failure origin which is dependent on the ambient temperature and transformer loading. The transformer hottest spot is typically formed in the upper half of the windings [6]. The block diagram of the hottest-spot calculation is presented in Fig. 2 which is based on the heat transferring process [35]. The HST model in Fig. 2 is proposed by ANSI/IEEE C57.91 which is derived from average ratings and

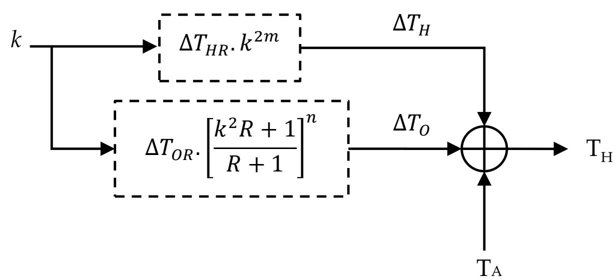

Fig. 2. HST model of a transformer

design models of different types of transformers [6]. It is assumed that there is no time constant for the temperature to go up or down. Therefore, the transient behavior of the temperature changing is neglected in the model, since the focus of the paper is not on the temperature accurate model and the simplified model will be adequately appropriate for our work.

According to Fig. 2, the HST model is composed of three main parts including the ambient temperature, the top-oil temperature rise over the ambient temperature, and the winding hottest spot temperature rise over the top-oil temperature. In this regard, the hottest spot temperature is calculated as:

$$T_H = T_A + \Delta T_O + \Delta T_H \tag{1}$$

Where $T_A$is the ambient temperature, ΔT_O is the top-oil rise over the ambient temperature, and ΔT_H is the winding hottest spot temperature rise over top-oil temperature. It is worth mentioning that the given formulation in the following is based on simplifying assumptions which are discussed in [35].

The top-oil temperature rise over the ambient temperature in steady-state condition is proportional to the per-unit loading as:

$$\Delta T_O = \Delta T_{OR} (\frac{k^2 R + 1}{R + 1})^n \tag{2}$$

Where ΔT_{OR} is the top-oil temperature rise at rated load, *k* is the per-unit loading and *R* is the loss ratio.

The increase in the temperature of winding hottest-spot over the top-oil temperature is given by:

$$\Delta T_H = \Delta T_{HR} (k^2)^m \tag{3}$$

In which ΔT_{HR} is the increase in the temperature of winding hottest-spot over top-oil temperature at nominal load,k^2 is the per-unit winding loss, *n* and *m* are empirical constants depending on the winding sensors cooling system. The winding hottest-spot temperature rise over top-oil temperature at rated load,ΔT_{HR}, can be calculated by adding a constant value over the average winding rise as:

$$\left\{ \begin{array}{l} \Delta T_{HR} = \text{Average increase of the winding temprature over top oil} + 15^{\circ} c \\ \\ \Delta T_{HR} = (\Delta T_{WR} - \Delta T_{OR}) + 15^{\circ} c \end{array} \right\} \tag{4}$$

In which ΔT_{WR} is the average increase in the winding temperature at nominal load. In fact, ΔT_{HR} is obtained from the average increase in the winding temperature over top-oil temperature plus 15 degrees Celsius corresponding to 65 degrees Celsius winding rise respectively. The HST is then derived by adding the ambient temperature to the top-oil rise and the hottest spot conductor rise over top-oil (See (1)).

A) HST-Dependent Aging Failure Model

Transformer aging failures are mostly originated from the insulation deterioration. The HST is the main reason of insulation depreciation; hence, it is investigated in this work. The Weibull distribution has been used in [6] to describe the aging failure probability of transformers. It is noted that the aging failure function is dependent on operating condition of the equipment. Therefore, we use the operating condition dependent function to model the failure probability of the transformer.

A transformer is under different operation conditions during a period *T*. The period can be divided into short sub-periods $t_1, t_2, ..., t_n$, and the HST temperature, $T_H(t_i)$ is considered constant in each sub-period. This assumption is suggested for simplicity. However, this assumption is close to the reality in our work, since the historical real-time WAMS data is available. The loss of insulation life tl_i in a sub-period t_i can be calculated as [36]:

$$tl_i = t_i e^{(\frac{15000}{T_0 + 273} - \frac{15000}{T_H(t_i) + 273})} \tag{5}$$

Thus, the overall loss of insulation life in period *T* is calculated as:

$$T_e = \sum_{i=1}^{n} t_i e^{(\frac{15000}{T_0 + 273} - \frac{15000}{T_H(t_i) + 273})} \tag{6}$$

As an equivalent expression, the total loss of insulation life T_e can be considered as the equivalent operation time under the reference temperatureT_0. Similarly, an equivalent operation time Δtl may be obtained for the sub-period durationΔt as well.

Provided that the transformer has survived for a period *T*, the HST-dependent failure probability of a transformer in a sub-period duration Δt can be expressed as [37]:

$$P_f = 1 - e^{\left(\frac{T_e}{C e^{\frac{B}{T_0 + 273}}}\right)^{\beta} - \left(\frac{T_e + \Delta tl}{C e^{\frac{B}{T_0 + 273}}}\right)^{\beta}} \tag{7}$$

Where *B, C* are empirical constants and β is the shape parameter of the Weibull distribution associated with the failure probability of aging process.

3.2. Weather-Dependent random failure model

Inherently stochastic events such as heavy lightning, heavy storms, typhoons, snow, ice, etc., can also lead to a transformer failure. The aforementioned events considerably increase the failure rate of an exposed transformer. For the sake of simplicity, a two-state model was proposed [38] to calculate the weather-dependent failure rate of an outdoor transformer:

$$\lambda(v) = \left\{ \begin{array}{ll} \bar{\lambda} \frac{N+S}{N} (1 - F), & v = 0 \\ \bar{\lambda} \frac{N+S}{N} F, & v = 1 \end{array} \right\} \tag{8}$$

Where *N* is the expected normal weather duration, *S* is the expected adverse weather duration, *F* is the proportion of failures occuring in adverse weather, *v* is the current weather condition (*v* is equal to 0 in normal weather and equals to 1 in adverse weather).

If the failure during Δt under the given weather condition v is constant, then the probability density function is mathematically an exponential function. The weather-related failure probability during Δt is:

$$P_w = 1 - e^{-\lambda(v)\Delta t} \tag{9}$$

3.3. Total Failure Probability Model

The structure of the two failure types is different and consequently the failure events are completely independent. Thus, the failure probability of a transformer in a sub-period duration Δt is calculated as follows provided that it has survived for a period *T* [37]:

$$\Pr_t = 1 - (1 - P_f(T, T_H, \Delta t))(1 - P_w(v, \Delta t)) \tag{10}$$

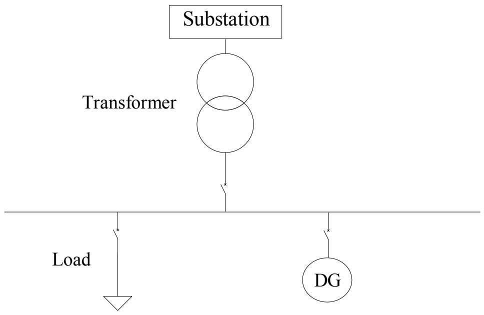

Fig. 3. The single-node model of the system under study

3.4. Reliability-Cost Operation Formulation

Fig. 3 illustrates the system under study. As shown, the substation transformer supplies the power for the distribution network from the upstream grid. To survey the impact of DGs on the hourly transformer loading and the asset management problem, DGs with typical supply functions are considered. For the simplicity, distribution network topology is neglected and the whole generation and demand are assumed to be at the same bus which is a common practice in asset management studies. The reliability-cost objective function is written as follows:

$$Min \sum_{h=1}^{24} C_h^{opr} + C_h^{int} + C_h^{r} \tag{11}$$

Where C_h^{opr} is the hourly operation cost, C_h^{int} is the hourly interruption cost, and C_h^{r} is the hourly repair cost imposed to the system. The operation cost is composed of two parts; cost of providing energy from the upstream and the generation cost of DGs:

$$C_h^{opr} = P_h^{sub} \times \rho_h + P_h^{DG} \times C_h^{DG},\ \forall \text{h} \tag{12}$$

Where P_h^{sub} is the hourly transformer loading, ρ_h is the hourly electricity price, P_h^{DG} shows the hourly power generation, and C_h^{DG} is the hourly cost function of DG. The interruption cost is calculated by multiplying the Energy Not Supplied (ENS) by Customer Damage Function (CDF) as shown in (13). The CDF is determined according to energy policies and customer type.

$$C_h^{int} = ENS_h \times CDF, \forall h \tag{13}$$

In which:

$$ENS_h = \Pr_h \times P_h^{sub} \tag{14}$$

The hourly repair cost of the transformer is expressed in (15). In fact, it calculates the cost of repair for a damage caused during hour h:

$$C_h^{r} = \Pr_h \times (a \times P_{\max}^{sub} + b) \tag{15}$$

A power balance constraint insures the generation and load match as:

$$P_h^{sub} + P_h^{DG} = load_h \tag{16}$$

Finally, power transformer and DG unit are restricted by their nominal capacities:

$$P_h^{sub} \leq P_{\max}^{sub} \tag{17}$$

$$P_h^{DG} \leq P_{\max}^{DG} \tag{18}$$

The aforementioned problem in (1)–(18) is solved by General Algebraic Modeling System (GAMS) software using a PC with Intel Core i7 CPU @3.20 GHz and 4 GB RAM.

Table 1. Parameters of the HST model

Parameter	Value
R (Degrees Celsius)	36
m	1
n	1

Table 2. Parameters of the failure models

	Parameter	Value
HST-dependent aging failure model	β	5.9
	B	15000
	C	$1.903*10^{-12}$
Weather-dependent failure model	*N (hour)*	200
	S (hour)	2
	F	0.6
	$\bar{\lambda}$ (year^{-1})	0.02

4. Results and Discussions

The proposed model is verified through numerical simulations in this section. The test transformer is a Forced-Oil-Air (FOA) cooled, 12 MVA substation transformer with 65 degrees Celsius average winding rise. The parameters of the HST model are shown in Table 1 [6]. The parameters of the transformer are listed in Table 2. The expected transformer life is considered 180000 hours by recommendations in [36]. It is worth noticing that historical data from the practical operation of a transformer can be used to achieve these parameters. The cost of DG supply is set to be 80 $/MWh.

The transformer aging failure rate under the reference HST (110 degrees Celsius) gives useful information on the health condition of the transformer. The aging failure rate of the transformer, which shows the normal operation and the wear-out stages on the transformer life span curve, has been taken from [6]. The hourly load, hourly ambient temperature, and hourly electricity price curves are also shown in Figs. 4-6.

The hourly failure probability model is examined under case studies shown in Table 3. In addition to average data, a set of recorded HST data by WAMS will be applied to show how real-time data can affect the results.

4.1. Applying estimated averaged historical data

In this subsection, it is assumed that averaged data from historical background of the transformer is applied. Thus, the average failure probabilities are calculated.

The failure probabilities for each case are shown in Figs. 7, 8, 9, 10, 11. As shown, for cases 1 and 3 (Fig. 7 and 9), HST-dependent failure probabilities are dominant and weather-dependent failure probabilities are small due to normal weather condition. As expected, the HST-dependent failure probabilities in Fig. 7 are greater than that of Fig. 10. Nonetheless, in cases 2

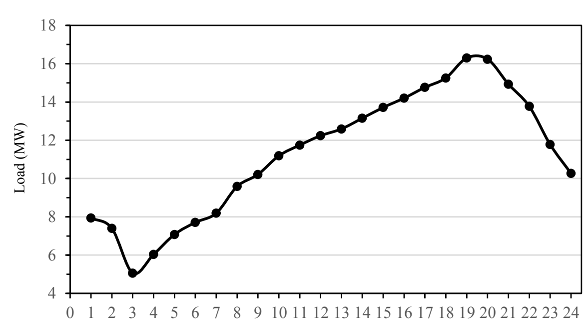

Fig. 4. Hourly load profile of the test system

Table 3. Description of case studies for numerical simulations

Case	Transformer aging condition	Weather condition
1	Survived for 5 years with equivalent reference HST (110)	Normal weather for 24 hours
2	Survived for 5 years with equivalent reference HST (110)	Adverse weather for 24 hours
3	Survived for 30 years with equivalent reference HST (110)	Normal weather for 24 hours
4	Survived for 30 years with equivalent reference HST (110)	Adverse weather for 24 hours

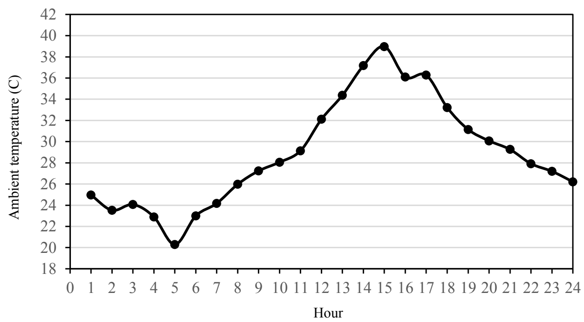

Fig. 5. Hourly ambient temperature

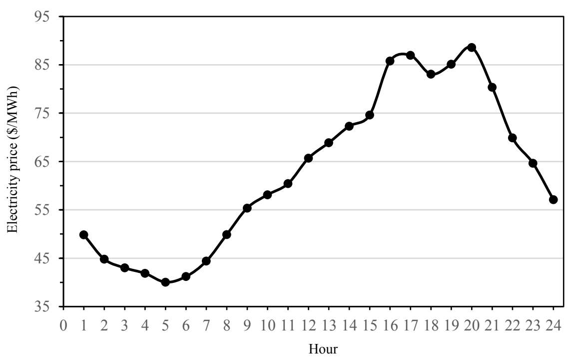

Fig. 6. Hourly electricity price

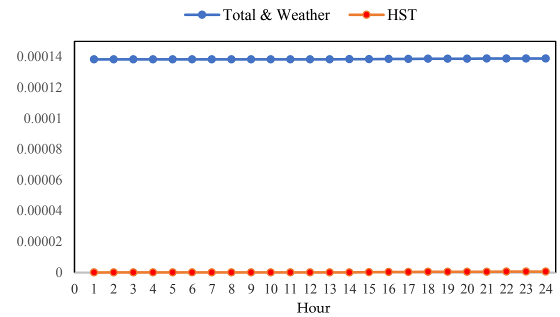

Fig. 8. Hourly failure probabilities for case 2

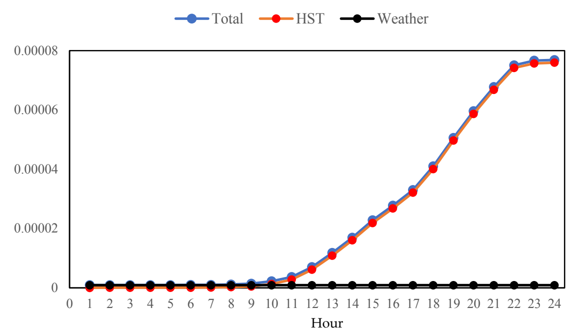

Fig. 9. Hourly failure probabilities for case 3

and 4 (Fig. 8 and 10), weather-dependent failure probabilities are dominant due to adverse weather condition. Also, HST-dependent probability values in case 4 are greater. It is mainly due to longer operation time of transformer in this case.

The hourly per-unit loading of the transformer is shown in Fig. 11 with supply cost of 80 $/MWh for DG. The transformer loading is dependent on failure probabilities illustrated in Figs. 7, 8, 9, 10,. As shown in Fig. 11, the transformer loading in case 1 is higher than other cases since the failure probability in this case is lower than others. In other words, lower failure probability indicates smaller interruption & repair cost of the transformer in the same level of loading.

The related hottest spot temperature profile is also shown in Fig. 12. As shown, the behavior of HST is like per-unit loading of the transformer, since it is dependent on transformer loading as discussed in section 3.1.

Hourly DG generation profile is shown in Fig. 13. Case 4 has the most participation of DG generation due to higher failure probabilities and higher risk of transformer overloading. DG generation profile is also shown for the case where the cost of DG supply is considered 115 $/MWh (See Fig. 14). As expected, the contribution of DG in supplying the load decreases for all cases as the cost of DG generation is enhanced. Due to the high price of DG generation, the output of DG is small or zero in many hours as shown in Fig. 14. However, it helps the system operator with supplying part of load during peak hours. A conclusive discussion is presented here to survey the trade-off between interruption & repair and DG generation costs. As failure probability of the

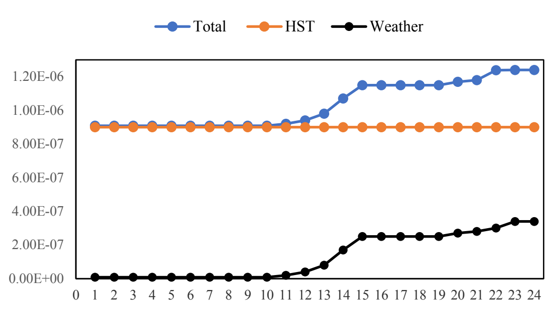

Fig. 7. Hourly failure probabilities for case 1

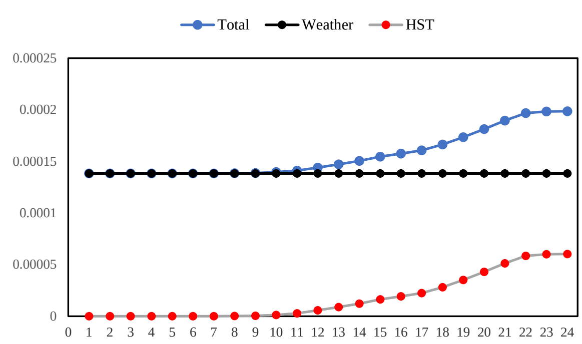

Fig. 10. Hourly failure probabilities for case 4

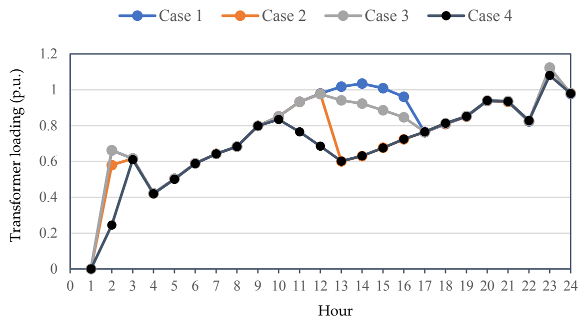

Fig. 11. Hourly per-unit loading of transformer with supply cost of 80 $/MWh for DG

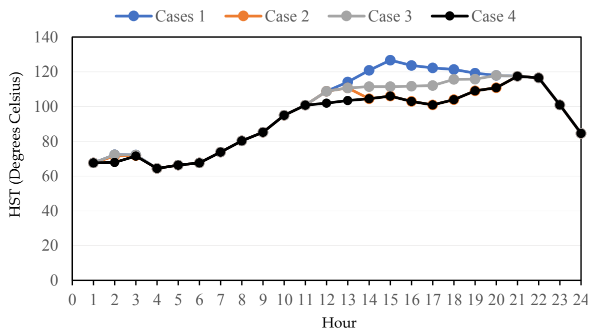

Fig. 12. Hottest spot temperature of the transformer with supply cost of 80 $/MWh for DG

transformer increases, the interruption & repair cost will become greater in the same loading pattern. Therefore, it will be more economical to decrease the transformer output and increase the DG generation to supply the load. The latter implication is valid as long as DG generation is affordable. However, as the supply cost of DG is enhanced from 80 $/MWh in Fig. 13 to 115 $/MWh in Fig. 14, DG generation becomes less affordable for all cases.

A cost summary is given in Table 4 with supply cost of 80 $/MWh for DG. As shown, results are close for cases 1 and 3 and also cases 2 and 4 pairwise. It shows that the weather condition is dominant and determines the major part of the risk imposed to

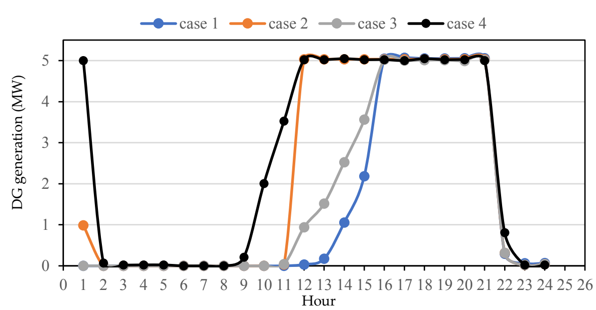

Fig. 13. Hourly DG generation with supply cost of 80 $/MWh

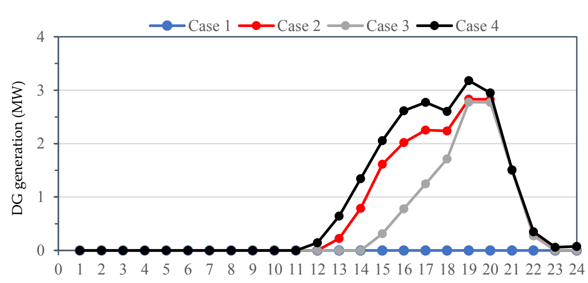

Fig. 14. Hourly DG generation with supply cost of 115 $/MWh

Table 4. Cost summary for case studies using average data with supply cost of 80 $/MWh for DG

Case study	Total cost, $	Operation cost, $	Interruption & repair cost, $
1	17921.80	17894.75	27.05
2	21570.03	18247.95	3322.08
3	17921.58	17894.17	27.41
4	21570.03	18247.95	3322.08

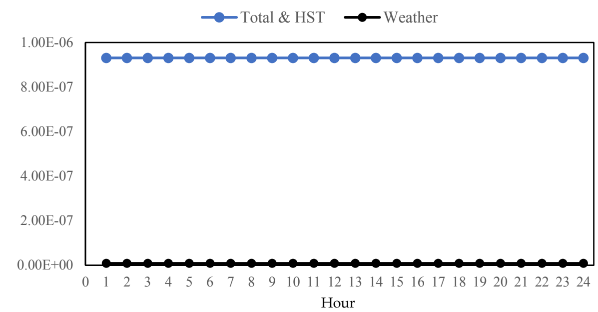

Fig. 15. Failure probabilities for case study 1 using WAMS data.

system.

4.2. Applying real-time historical WAMS data

In this scenario, the impact of using recorded data by WAMS will be investigated. Due to lack of recorded data, a set of HST data equal to 0.9 of average data was applied to the model as real-time data instead of average data in previous section.
Figs. 15, 16, 17, 18 show failure probabilities in case of using WAMS data. Comparing these curves with those of Figs. 7, 8, 9, and 10 verifies that the total failure probabilities are not as sensitive to real-time WAMS historical data as expected. However, HST-dependent failure probabilities have changed (decreased) as expected. Since the weather-dependent failure model was included in total failure probability, the overall result is not sensitive enough.

Table 5 shows the cost summary results with supply cost of 80 $/MWh for DG. Hourly loading of the transformer is also illustrated in Fig. 19. Comparing results of Table 5 with that of Table 4 and also Fig. 19 with Fig. 11 shows the close similarity of results with those of average data. This experience also confirms that the effect of weather is highly dominant in asset management studies of power transformers since the real-time WAMS data of HST does not significantly change the results.

4.3. Comparative study

In order to assess the proposed methodology, the main results are compared with the method proposed in [28]. The method adopted in [28] for extracting HST-dependent failure probability

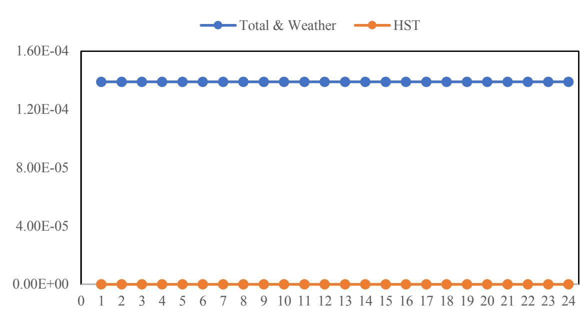

Fig. 16. Failure probabilities for case study 2 using WAMS data

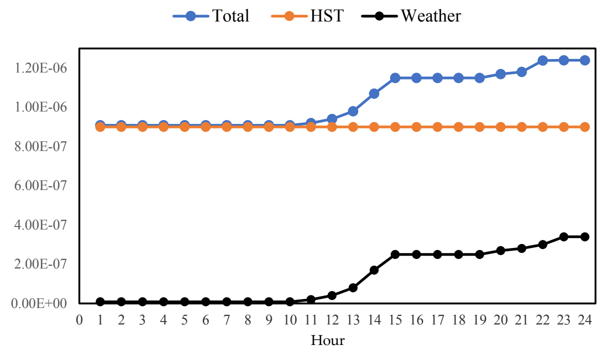

Fig. 17. Failure probabilities for case study 3 using WAMS data

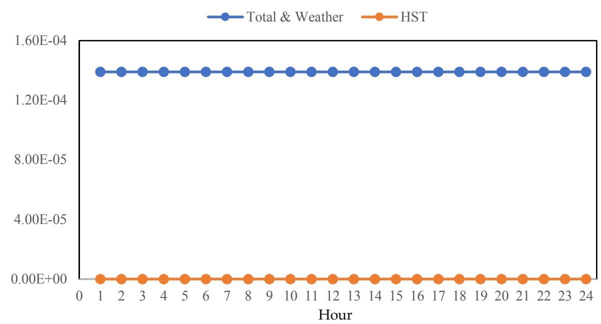

Fig. 18. Failure probabilities for case study 4 using WAMS data

function is similar to the approach taken in this work. However, the effect of weather condition in total failure probability function is not considered in [28]. The method presented in this work makes benefit of WAMS for HST data and [28] uses average data. In addition, this work presents a reliability-cost optimization to determine the daily scheduling of power transformer and DG unit while power transformers are proportionally loaded based on their nominal capacities in [28].

For the sake of brevity, the comparative results are only given for case 4 and the DG supply cost is set to 80 \$/MWh. Fig. 20 illustrates the comparative hourly loading of the transformer in the proposed method and the approach adopted in [28]. As shown in this figure, the transformer is overloaded during hours 11-23 in the method presented in [28]. This is due to the fact that there is no contribution of DG in the method of [28] which forces the

Table 5. Cost summary for each case study using WAMS data with supply cost of 80 \$/MWh for DG

Case	Total cost, \$	Operation cost, \$	Interruption & repair cost, \$
1	17916.11	17890.75	25.36
2	21563.03	18242.95	3320.08
3	17916.91	17889.50	27.41
4	21561.23	18239.15	3322.08

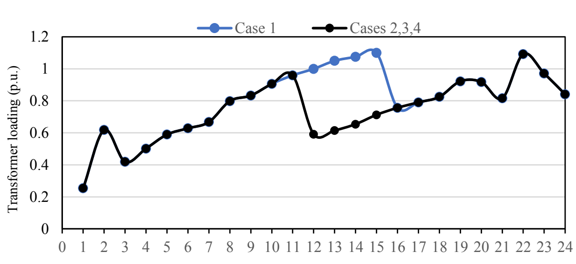

Fig. 19. Hourly per-unit loading of transformer using WAMS data

Table 6. Comparative cost summary

Method	Total cost, \$	Operation cost, \$	Interruption & repair cost, \$
Ref. [28]	22943.76	18956.25	3987.51
Proposed method	21563.03	18242.95	3320.08

Table 7. Cost summary comparison for case study 4 neglecting weather effect

	Total cost, \$	Operation cost, \$	Interruption & repair cost, \$
Average data	18053.12	17962.72	90.40
WAMS data	17896.81	17894.75	2.05

transformer to supply the entire load. In contrast, the transformer loading is moderated by the contribution of DG in the proposed method of this paper. Table 6 compares the cost summary results of the proposed method with that presented in [28]. Since the transformer is enviably overloaded, the interruption and repair cost is higher in the method of [28]. The operation cost is also greater in the method of [28] which is due to the fact that there is no contribution of DG to supply the load in peak hours when the grid electricity price is extremely high. Consequently, the total cost of system operation in the proposed method is lower than that of the method presented in [28].

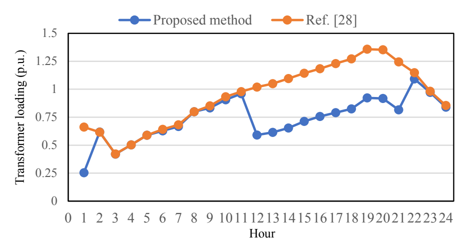

Fig. 20. Comparative hourly per-unit loading of transformer

4.4. Sensitivity analysis

A) Neglecting weather-dependent failure probability

In this scenario, the total failure probability function is calculated using only the HST-dependent failure probability function. For simplicity, the worst case in terms of risk (case 4) is studied. Table 7 gives a comparison between results of study when average and WAMS data are used. As seen, the total cost decreases if WAMS data is used. This observation implies that using average data imposes further costs leading to loss of optimal scheme for power transformer asset management. In other words, it confirms that the economic saving is meaningful as WAMS-based failure probabilities are employed. In the previous scenarios where both weather and HST dependent failure functions were considered, the dominant function was the weather-dependent function. Thus, the HST-dependent function did not play its role apparently (See Tables 4 and 5). Fig. 21 illustrates hourly per-unit loading of transformer for case 4. The system operator has overloaded the transformer during some hours in case of using WAMS data. It is mainly due to the fact that WAMS-based data for HST was considered 10% lower than average HST data. Lower HST data results in smaller failure probabilities of the transformer. Thus, the transformer overloading can occur with lower repair and interruption costs in case of using WAMS data. Accordingly, the DG contribution is lower during transformer overloading for WAMS data as shown in Fig. 22.

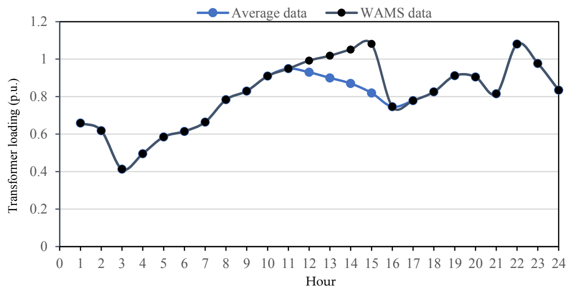

Fig. 21. Comparison of hourly per-unit loading of transformer for case study 4 neglecting the weather effect

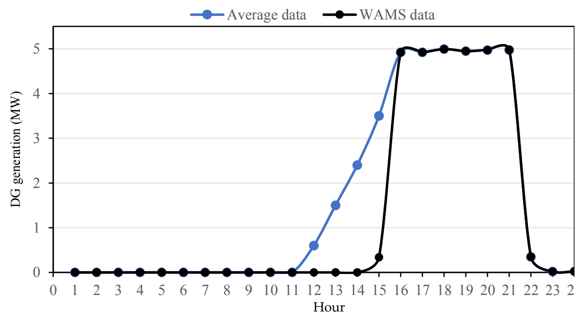

Fig. 22. Comparison of hourly DG generation for case study 4 neglecting the weather effect

B) *Neglecting HST-dependent failure probability*

In this scenario, the total failure probability function is calculated using only the weather-dependent failure probability function. For simplicity, the worst case in terms of risk (case 4) is studied. The weather-dependent failure probability function applies the 24-hour forecast data of weather condition. Results are compared with that of the hybrid function where both HST and weather failure probabilities were considered. Comparative results are presented using WAMS data.

As seen in Table 8, results are close to those of hybrid function. It is mainly due to the fact that the failure probability values are large for the weather-dependent failure function. Therefore, neglecting HST-dependent failure probability function will not affect the hybrid failure function. Fig. 23 confirms the latter claim as well. The per-unit loading of the transformer is fairy the same for both scenarios, except in peak load hours, i.e., 17-21, where a small difference can be observed.

C) *Neglecting DG contribution*

In order to investigate the impact of DG contribution on transformer asset management, the model was examined in the absence of DG units. In practical cases when no DG is available, distribution companies perform transformer asset management via planned maintenance measures. Moreover, load shedding during peak hours and demand response programs can help the system operator improve the transformer asset management. Like two previous sensitivity cases, the new study has been performed for case 4.

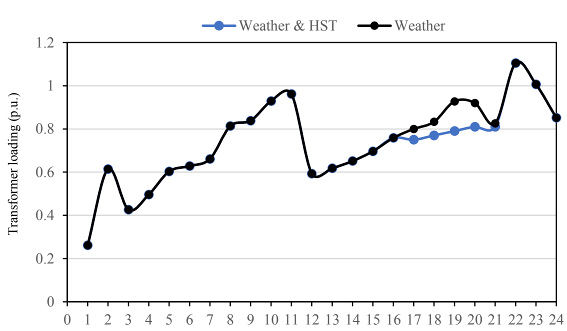

Fig. 23. Impact of HST on per-unit loading of the transformer in case study 4

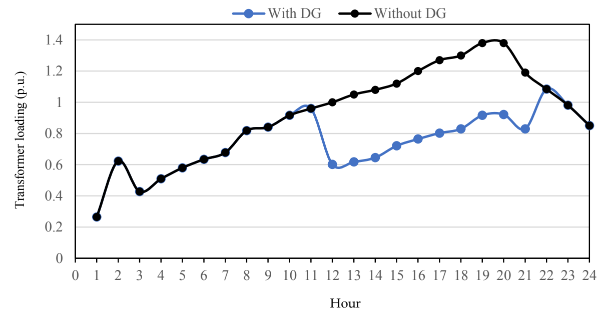

Fig. 24. Comparison of per-unit loading of the transformer for case study 4 with/without DG contribution using WAMS data

Table 9 and Fig. 24 present the results of model with and without DG contribution in case of using WAMS data. The total cost of the system decreases when there is a contribution by DG. The higher total cost in the lack of DG contribution refers to greater interruption and repair costs due to overloading of the transformer. In this comparison, the cost of DG generation was assumed to be 80$/MWh. It is expected that the cheaper the DG technology, the more beneficiary the DG contribution. As shown in Fig. 24, the transformer is overloaded during some hours of operation when DG is not used.

5. Conclusion

In this paper, a transformer asset management model based on real-time condition monitoring was presented. With the supervisory equipment in power systems, real-time monitoring of power systems has been viable. Accordingly, modeling techniques should be updated to use real-time data for condition monitoring and asset management of power system equipment.

Different aging phenomena occurring in a transformer were introduced and among them hottest spot temperature was modeled due to its dominant impact on the aging of transformer. Weather condition was also modeled as an important factor for calculating the failure probability of a transformer.

Features, advantages and disadvantages of the given model were discussed over the constant failure models used previously in the literature. The objective of the proposed model is to determine the hourly loading of the transformer with the contribution of distributed generators such that the total cost of system is minimized. Total cost of the system includes the operation cost and risk-based cost. Interruption and repair costs represent the risk-based cost in our model.

Results showed no significant sensitivity to real-time hottest spot temperature data provided by the wide area measurement system. The values of hottest spot temperature failure probability function are rather small while the weather-dependent one has greater values. Since the weather-dependent function is dominant in total failure probability function, neglecting the hottest spot temperature in total failure probability function did not change the results significantly.

A sensitivity analysis was also done to investigate the impact of DG contribution on the model output. Numerical simulations showed that the absence of DG imposes a high risk to the system due to transformer overloading resulting in an increase in the overall cost of the system. Surveys showed that if low and medium price technologies are used as distributed generators, the contribution of distributed technologies will be more beneficiary.

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Table 8. Cost summary comparison for case study 4 neglecting HST effect in case of using WAMS data

	Total cost, $	Operation cost, $	Interruption & repair cost, $
Neglecting HST effect	21519.01	18247.95	3271.06
Hybrid failure function	21561.23	18239.15	3322.08

Table 9. Cost summary comparison for case study 4 with/without DG contribution in case of using WAMS data

	Total cost, $	Operation cost, $	Interruption & repair cost, $
With DG	21561.23	18239.15	3322.08
Without DG	22135.16	18045.55	4089.61

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