IET Energy Systems Integration

Research Article

eISSN 2516-8401
Received on 28th July 2019
Revised 9th February 2020
Accepted on 23rd February 2020
E-First on 13th March 2020
doi: 10.1049/iet-esi.2019.0080
www.ietdl.org

Fault detection method in subsea power distribution systems using statistical optimisation

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Abstract: Developing automation solutions that enable remote communications, monitoring and control for subsea applications are key steps in designing subsea power distribution systems. These systems require fast local control to protect the multiple electrical loads and the capability of transferring prompt real-time trip signals. This study introduces a data-driven distributed fault detection and identification algorithm to monitor multiple subsea loads. The proposed scheme is divided into three steps. First, a stochastic hidden-Markov model (HMM) is developed to model the dynamic evolution of different potential conditions of multiple subsea loads. Simultaneously, the second step computes a model of the transition probability between the current operating condition and the potential response of an individual load. In the third step, using real-time measurements, the HMM is updated to predict an unobserved degradation of the load's current condition. This is achieved through an integrated perturbation analysis and sequential quadratic programming method. An assessment of case studies on subsea AC power system is presented, which includes different subsea motor loads for compressors and pumps. Results show robustness against uncertainty in measurement noise and changes in equipment mean time between failures, providing enhanced reliability.

1 Introduction

For subsea applications, power from shore technology presents the lower capital investments along with several practical benefits when compared with the existing installations with local generation. In addition, the importance of reduced environmental emissions (both CO_2 and NO_x) is receiving increasing attention in recent years. One alternative for subsea power applications to address these concerns is the implementation of the concept of subsea factory, which brings subsea processing and production. This concept brings substantial demands on the reliability and built-in redundancy, uptime and safety of the technology for distributing, delivery and control of subsea power systems. However, there are substantial challenges that oil/energy companies and main technology suppliers need to overcome [1–3]. Potential solutions need to find adequate trade-offs because: (a) cost efficiency (capital and operational expenditures) and recovery rates, (b) sustainability and risk and (c) reliability and flexibility.

A typical subsea electrical installation consists of subsea loads for pumping, gas compression and pipeline direct-electrical heating (DEH) applications [3, 4]. In this kind of power system, the main goal is to keep the subsea power distribution stable by isolating only faulted components while keeping the rest of the equipment in operation. To do so, one of the main functions of the condition monitoring system is to detect faults in a timely manner and with reasonable accuracy, even in the presence of system uncertainty and noisy measurements.

There is a risk for failures among controllers and the power components, for example, between controller and power switching devices (insulated-gate bipolar transistors, thyristors, integrated gate-commutated thyristors etc.). These kinds of risks are common and relatively acceptable in many industrial applications; however, they can be devastating in standard subsea power equipment.

1.1 Literature review

In [5], randomised algorithm is proposed to be integrated with the data-driven optimisation-based monitoring strategy for local faults detection in multiunit chemical processes. Multivariate statistical methods for data-driven process monitoring have gained significant attention, especially for decentralised monitoring purposes [6–8]. Concurrently, study of latest methods based on machine-learning techniques to distinguish actual system state changes from false changes is presented in [9]; however, this has not been applied to power systems. These techniques and other methods are unable to be effectively applied for non-linear fault detection because of their limitation to cover up the status of an original process variables. Thus, deployment of these concepts in real practical applications is questionable due to requirement of substantial computation efforts.

Predictive equipment maintenance is the core for high-power supply systems in industrial and oil and gas applications, to mitigate service loss in case of occurring a failure, especially in subsea environment, where the device accessibility is hard. The existing technology is heavily dependent on static fault detection algorithms and there are great demands for such schemes to leverage the understanding of the failure dynamics, e.g. cascaded failures in the subsea power distribution network. Consequently, there is a great interest for prognosis techniques in predicting the evolution of a fault that leads to major failures in subsea systems. This makes it possible to predict impending faults and their duration.

The existing fault detection methods heavily depend on thresholds and residual trace analysis. In practice, threshold (ratio) methods impose conservative limits or can be easily deteriorated by possible errors leading to improper system assessment that does not correspond to the failure condition [10–12]. However, these techniques are inefficient and cause practical issues in the fail-safe operating system, for example, in terms of motor faults and smart grid faulty condition. The remaining gap for most of the proposed solutions is the current state of the device/equipment is assessed, in which ignoring their history operation information.

These issues are addressed in published literature with emphasis on subsea power grid, e.g. in [13] a control system for subsea wells detects ground faults for isolating the affected subsea power lines. This method includes four relays operatively connected to the positive/negative voltage power bus bars. In [14], a mixed power transmission line comprising two or more sections with at least one overhead section and at least one underground section uses activation an auto-recloser relay integrated within an intelligent electronic device (IED) located at a substation, a junction. The IED is connected to the measurement equipment that may be current/ voltage or other electrical parameter sensed from mixed line. Similar concepts are also introduced for an offshore gas production proving the feasibility of utilising IED-based numerical relay for overcurrent detection [15]. These methods detect a travelling wave (peak width of the travelling wave, rise time and a discharge time of the first peak) from the signal received from measurement equipment. The travelling wave is created due to the fault in a section/or more sections of the mixed power transmission line. In [16], the fault location is determined through distributing fibre optic sensor along the path of power cable, especially to detect the current discharge location. The operating principles of this solution are based on the expected propagation speed of pulses in the power cable. The submarine power cable for, e.g. wind turbine power generation is the focus of what is claimed for.

In [17, 18], a good overview on the state-of-the-art methodologies considering the fault detection in subsea applications is reported. Note that the invention in [17] deals with faults occurring at the subsea cable used in the DEH; however, this solution is equally applicable to other types of subsea power cables.

The evaluation of current practice associated with fault detection and identification strategies with focus on subsea control modules is patented in [19], where asset conditions are continuously monitored to provide a substantial reduction of production downtime as a result of equipment failures and health and safety risks. In this work, a new method that monitors collected sensor data from subsea control system is discussed to identify an impending equipment abnormality.

In [20], a hidden-Markov model (HMM) is utilised to determine a transformer fault model. The model is utilised to determine the dissolved gas concentration. The current health state of the transformer fault model is then tested in health state data. However, this publication does not address its use in transformers within subsea applications.

For the application of interest, there have not yet been reported solutions in the literature based on the proposed HMM.

1.2 Contributions of this paper

This paper addresses statistical analysis based on a HMM for investigation of dynamic characteristics of multiple loads for powering electric machinery on the seabed. It gives an approach for predicting the condition monitoring status of key components placed in pressurised, submerged subsea power grid. In various subsea power loads, when an incorrect diagnosis happens, the devastating effects lead to considerable expense because of inspection, repair or forced outage.

Many control and protection solutions rely on running state of the subsea loads and have low tolerance against early alarm dynamic functionality of them or even from subsea loads service/ maintenance standpoint. Therefore, the knowledge of the states (current and future) of the subsea loads, e.g. motor pump/ compressor is a valuable asset for safe operation and to reduce maintenance efforts.

It is necessary to develop a methodology that enables capturing of a ‘complete picture’ of the subsea load condition for the sake of reliability improvement, which laying out the main contribution of the present paper in the following consecutive sections.

1.3 Paper organisation

This paper is organised by five sections as follows: a brief overview of the subsea power systems, its requirements and demands for advanced fault detection methods are discussed in Section 2. Section 3 presents the detailed proposed fault detection algorithm for typical subsea AC power transmission and distribution system. The effect of unobserved system states on fault monitoring and protection applications is also discussed in Section 3. An exemplary case studies including different subsea loads with degraded operation modes are analysed in Section 4 along with an impact of phasor measurement units (PMUs) measurement errors. Finally, the outcome and findings of the proposed method are drawn in Section 5.

2 Background

To meet the challenges listed above, Joint-Industry Project (JIP) including ASEA Brown Boveri (ABB) [21–23], *Equinor ASA* (formerly *Statoil*), *Total S.A* and *Chevron Corp.* was established to develop subsea power transmission, distribution and conversion technologies at greater distances, in deeper waters and in harsher environments. The technology is being designed to operate in water depths up to 3000 m, transmission distances up to 600 km and power levels up to 100 MW. These new technologies will enable subsea processing that requires large amounts of power for applications such as subsea compression, subsea oil boosting etc. These technologies are an enabler for oil companies’ vision of the subsea factory and are key elements in the all-electric subsea processing facility distributing power on the seabed. It would provide the flexibility to take power from shore when feasible, freeing up the often-limited space on topside installations or ultimately giving the alternative to produce oil and gas without any topside installation.

A high-level objective for subsea applications is to design the equipment so as to minimise production downtime and number of retrievals for subsea processing, possibly powering the subsea grids vision (see Equinor ASA vision [24]).

3 Mathematical modelling of a fault detection configuration

3.1 Problem statement and subsea AC power transmission and distribution structure

The current focus of the next generation of subsea power systems is with 50/60 Hz AC transmission and distribution system. A typical single-line diagram of ABB subsea power distribution AC system as shown in Fig. 1, where the power can be supplied from either any available topside installation or from shore.

The subsea power system shall supply three-phase electric power from shore/topside to a subsea distribution and power conversion system with multiple subsea power consumers. The system consists of two subsea switchgears (A and B), in which each switchgear supplies four different subsea loads/consumers: one motor compressor (with variable-speed-drive and input transformer), one motor pump (with variable-speed-drive and input transformer), one subsea uninterruptible power supply (UPS) and one cable oil pipeline for DEH. For the sake of simplicity, this paper excludes the UPS and DEH loads. Table 1 specifies the parameters and ratings for the system of interest.

In the present time, variable-speed-drive units for offshore compressor and pump applications are located at atmospheric pressures either onshore or on a platform with long variable-frequency step-out cables feeding the loads. These technologies are essentially limited to few numbers of dedicated loads, determined by, e.g. available space and riser slots on a platform. Electric and power electronic components will be placed in a harsh environment with dielectric liquid and pressurised to ambient pressure at the seabed. Consequently, in case of loss of power to subsea loads or loss of production, continuous health monitoring of the subsea loads is of great importance to predict the next state ahead of equipment as well as loads.

There is no known concept for a reliable and robust detection method of failures, particularly cascaded failures based on their physical dynamics in multiple subsea loads in existing condition process monitoring. To overcome the lack of technology, the intention of the proposed scheme is to suggest a novel failure detection concept with inclusion of three main characteristics.

Sensitive: With the help of this method, potentially some of the missing info/data for equipment states is compensated through measurements sequence, in which characterises the cascaded failures/abnormalities. This technique is, therefore, resilient to the measurement errors/noise unlike conventional readings performed by PMUs.

Robust: Integrating temporary and spatial information on interactions among multiple loads connected to the same switchgear. Thus, an indistinguishable status of the equipment state

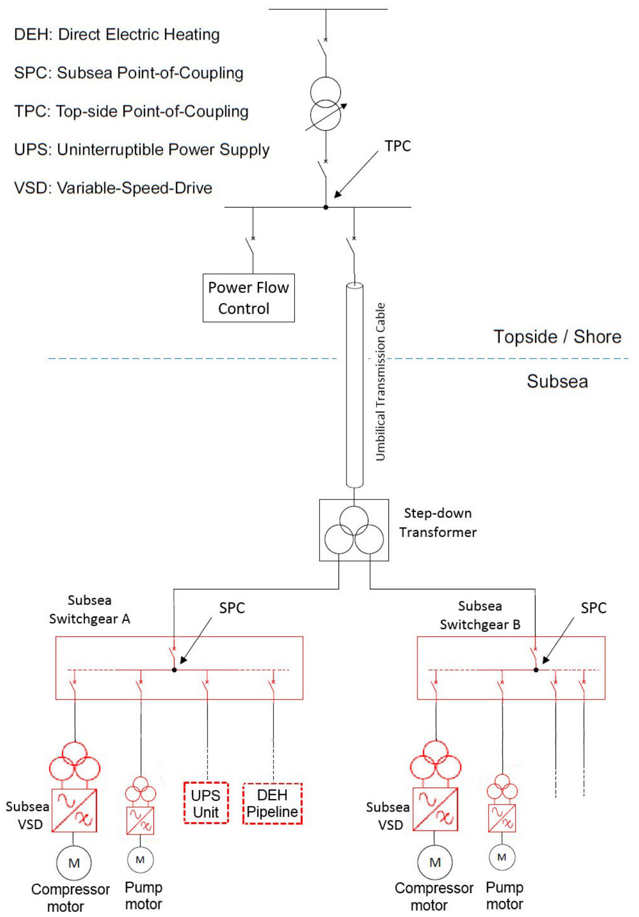

Fig. 1 *Schematic representation of conceptual subsea power distribution AC system with multiple loads*

Table 1 Technical specifications of the studied subsea power grid

Parameters	Value	Parameters	Value
onshore/grid voltage	132 kV	nominal system frequency	50 Hz
subsea transmission cable voltage/length	110 V/140 km	VSD output frequency	150 Hz
switchgear rated voltage	30 kV	VSD output voltage/ rated power	6.6 kV/15 MVA
switchgear to VSD step-out distance	150 m	VSD to subsea load distance	50 m
VSD system probability of 5 year in service	≥80%	circuit-breaker probability after 2500 open/close cycles in no load	90%

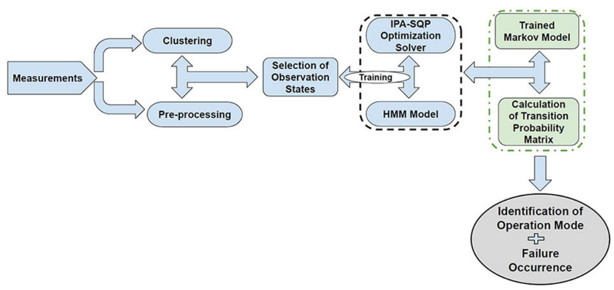

Fig. 2 *Overall architecture of the proposed HMM for operation mode/ failure detection*

is being identified, whereas it is not possible by means of static measurements such as PMUs.

Flexible: To be functioned effectively in early diagnosis and pre-warning stage when the subsea loads are in potential risks.

3.2 Principles of the proposed fault detection and prediction scheme based on Markov model

As a solution to the existing issues, this work explores feasibility of a HMM which is a stochastic modelling approach that is widely employed in industrial applications. HMM is often utilised for expressing dynamic evolution of processes between multiple potential states [25]. The running state of an individual subsea load is split into three stages so as healthy state, dynamic pre-failure state and faulty situation. At the same time, the calculation model is constructed by including the transition probability in the recursive condition between dynamic evolution processes of failure for an individual load.

This paper proposes to determine a fault location and timing of the loads outages by already placed/available data acquisition system or voltage/current measurement devices. Fig. 2 illustrates overview of the proposed HMM for operation mode and failure detection purposes. Henceforth, the Markov-based chain is developed for modelling the unobservable evolution of the subsea load equipment status. The obtained subsea power system measurements from load side are then derived an output process of the HMM. It implies that unobserved states of the load devices are estimated according to the identified output process of the HMM model. However, other prevalent approximation algorithms such as particle filtering as explained in [26] can be used to estimate an unobserved status state, depending on the physical characteristics of failure dynamics.

This work uses solution according to an integrated perturbation analysis and sequential quadratic programming (IPA-SQP) method for the validation analysis purpose.

In this section, the modelling steps to establish the intended HMM is described. In general, the HMM is formed by the following principles as:

(i) Number of states in the model denoted by N.

The individual states are noted by $\{1, 2, \ldots, N\}$, and the specific state at time instant t is noted as q_t.

(ii) A sequence of observations or measures for each state, M that is stated via

$$\boldsymbol{V} = \{v_1, v_2, \ldots, v_M\} \tag{1}$$

A state transition probability matrix denoted by $\boldsymbol{A} = \{a_{ij}\}$, where a_{ij} is interpreted as the conditional probability for transition of individual state at time instant t to one-step-ahead state at time $t + 1$

$$a_{ij} = P(q_{t+1} = j | q_t = i), \quad 1 \le i, j \le N$$

where $0 \le a_{ij}$ and $\sum_{j=1}^{N} a_{ij} = 1$.

(iii) An observation probability distribution matrix is represented by $\boldsymbol{B} = \{b_i(k)\}$, where $1 \le k \le M$ and $b_j(k) = P(o_t = v_k, | q_t = j)$.

(iv) An initial row vector for expression of the distribution of different states is determined by $\pi = \{\pi_i\}$

$$\pi_i = P(q_1 = i), \quad 1 \le i \le N \tag{2}$$

At this stage, to establish the HMM model, the following parameters are defined as follows: N, M together with the probability matrices/vectors of $\boldsymbol{A}$, $\boldsymbol{B}$ and π. To find these parameters, we use the notation of λ, where we have

$$\lambda = \text{function}(\boldsymbol{A}, \boldsymbol{B}, \pi) \tag{3}$$

For computing the $P(O|\lambda)$, implying the probabilities summation to identify the state sequences up to the last observation state, we have

$$P(O|\lambda) = \sum_{\substack{i=1 \\ t=1}}^{\substack{N \\ T-1}} \pi_i \, b_i(o_t) \tag{4}$$

where the IPA-SQP algorithm provided in flowchart in Fig. 3, which is utilised to maximise the observation probability of the load status. Here, O_t is representing the given set of observation sequences until time instant t. At the present time, the method requires to determine the highest probability quantity as

$$\delta_t(i) = \max P(q_t = i | O_t = \lambda) \tag{5}$$

with some mathematical efforts we can define the following expression to find the state $q_t$among N-hidden states for maximising (5), thus:

$$\arg\max P(q_t = i | O_t = \lambda) = \arg\max \left(\sum_{\substack{j=1 \\ t=1}}^{\substack{N \\ T-1}} \delta_t(i) \, a_{ij} \, b_j(O_{t+1}) \right) \tag{6}$$

Furthermore, to obtain the reliable values of state sequences along with the argument tracking that maximise (6) per each interval t and j, the iterative procedure based on IPA-SQP is implemented.

The final step of the entire process is devoted to the learning of the developed Markov model including unobserved states. To do so, we need to develop an approximated model for state i at time instant t as well as state j at one-step ahead, $t + 1$ according to the available model in the previous state and the measurements sequence. This probability is denoted by $\varphi_t(i, \ j)$ and formulated as

$$\varphi_t(i, \ j) = P(q_t = i, \ q_{t+1} = j | O_{\mathrm{T}} = \lambda) \tag{7}$$

The expansion of (7) can be rewritten as follows:

$$\varphi_t(i, \ j) = \frac{P(O_t, \ \ q_t = i|\lambda) \, a_{ij} \, b_j(O_{t+1}) P(O_{\mathrm{T}+1}|q_{t+1} = j, \ \lambda)}{P(O_{\mathrm{T}}|\lambda)} \tag{8}$$

Considering the original model

$$\text{model}\ \lambda = (\boldsymbol{A}, \ \boldsymbol{B}, \ \pi)$$

At the end of the described procedures, the estimated HMM after training process, in which includes an unobserved load states with finite measurement sequence can be given as below. This is accomplished by IPA-SQP numerical algorithm as shown in Fig. 3

$$\text{estimated model}\ \hat{\lambda} = \left(\hat{A}, \ \hat{B}, \ \hat{\pi}\right) \tag{9}$$

In which

$$\hat{\pi}_i = \sum_{j=1}^{N} \varphi_1(i, \ j)$$

$$\hat{a}_{ij} = \frac{\sum_{t=1}^{T-1} \varphi_t(i, \ j)}{\sum_{t=1}^{T-1} \sum_{j=1}^{N} \varphi_t(i, \ j)}$$

$$\hat{b}_j(k) = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} \varphi_t(i, \ j)}{\sum_{t=1}^{T} \sum_{i=1}^{N} \varphi_t(i, \ j)}$$

For the further analysis, the procedure can be continued to discriminate the failure with respect to how it is deteriorating the operation of the affected load. Therefore, all the degradation states are categorised into three-boundary limits as shown in Fig. 4: (i) healthy state (green), (ii) reduced state (yellow) and (iii) severe state (red).

From common practice, certain PMU or other measurements may not contain rich enough information for this monitoring purposes; in other words, they may lack the needed observability of the system's behaviour. This is even more severe in subsea power distribution comprising multiple loads, while their status configuration might provide similar measurements as other loads. In many already existing solutions, where the traditional detection schemes based on the instantaneous measurement are deployed, and their weaknesses are more obvious during this situation to distinguish the two states. From mathematical representation, it means that even for two different hidden-states sequences, the observation sequence gives the same values for both.

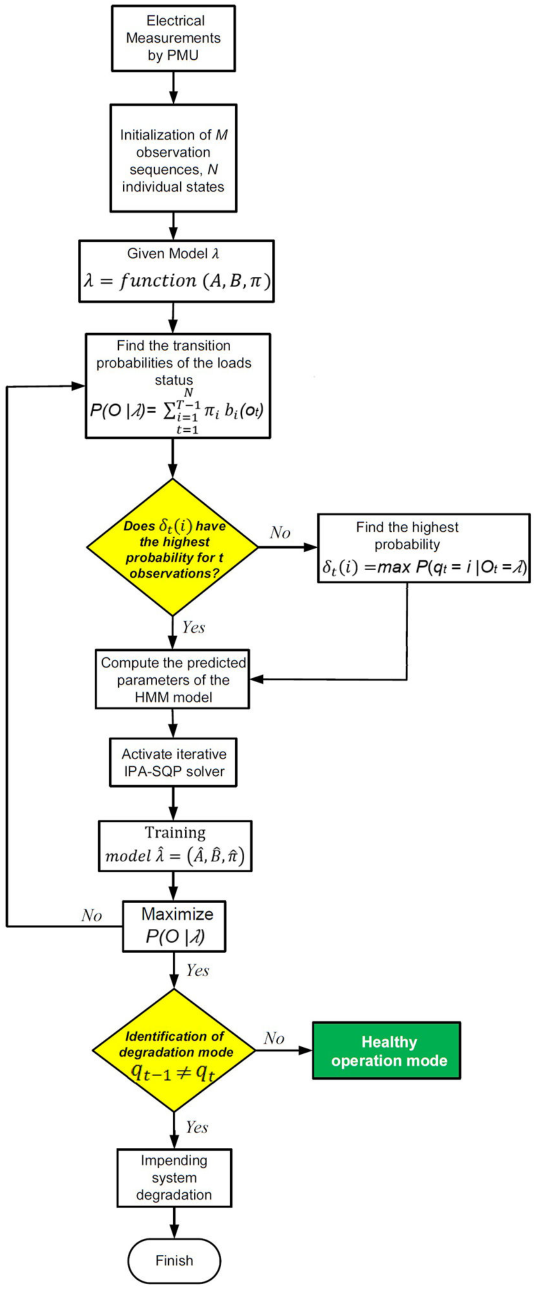

Fig. 3 *Iterative procedure to estimate the HMM through initial and unobserved states*

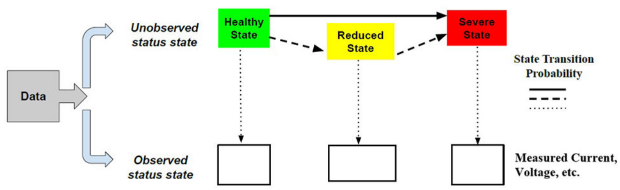

Fig. 4 *Graphical map of three-boundary modes versus measured system variables for HMM model training*

Table 2 Probability computation of the observation sequences in load train 1 connected to switchgear A

Operation mode Subsea load 1	Healthy state	Reduced state	Severe state
boundary condition 1	0.4462	0.4534	0
boundary condition 2	0	0.3216	0.4903

Table 3 Probability computation of the observation sequences in load train 1 connected to switchgear A including 10% measurement errors

Operation mode Subsea load 1	Healthy state	Reduced state	Severe state
boundary condition 1	0.5307	0.5418	0.0003
boundary condition 2	0.00008	0.6631	0.6680

In the flowchart shown in Fig. 3, the method uses the physical dynamics of the failures instead to the transition probabilities expression to overcome lack of observability. On the other hand, to complete an estimated HMM, three steps need to be fulfilled as:

(i) Problem assessment.
(ii) Identification of state sequence matrix $\boldsymbol{Q}$.
(iii) Learning process of HMM-derived model.

First step in the procedure is the investigation formulation, in which deals with the generating probability of the observed state sequences through used model. Second step is dealt with an unveiled hidden (unobserved) state to adjust the observation sequences. The final step is considering the parameters optimisation for the model to provide robustness against noises or errors in PMU readings; henceforth, enhancing the computational burden as well.

The discussed solution proposes a direct optimisation-based function fitting approach that uses an IPA-SQP solver to estimate the unknown/unobserved states as part of HMM learning step (to approximate the probability distribution effectively). However, from the available literature such as [27], it is found out that the other techniques such as particle filtering, expectation–maximisation method, which is so-called Baum–Welch and so on have been employed. With the help of integrating the dynamic states of the loads into the HMM formulation, it provides the handling of irregular and unobserved dynamic states. The iterative algorithm of IPA-SQP helps training the HMM through exploiting 80% of data processed. To get more insight and details about IPA-SQP solver, we see [28, 29].

4 Simulation of exemplary case studies

For simplicity, it is presumed that for the subsea power system shown in Fig. 1, there are four different subsea loads containing two compressors and two pumps that are supplied from subsea switchgears A and B. The simulation study was performed with subsea transmission cable of 110 kV, switchgear operation voltage level of 30 kV and two pumping-compression trains with voltage level of 6.6 kV and power 15 MW per each production train connected to the switchgears A and B.

The measurement data sets include the normal operation and the faulty condition obtained via testing scenarios of the subsea load trains. The shallow-water tests conducted by ABB in 2017–2018 with the operating conditions as outlined in [30]. The developed model was trained and executed using those simulation measurements to validate the theoretical findings. The measurements are used as health indicators; henceforth, 900,000 acquired measurement data per each load device within an hour considered. In total, 86,400,000 observations during 24 h operation for all four load devices are obtained. On the one hand, with 21,600,000 observations per each connected load device corresponding to the acquired measurements during full day operation. All the current and voltage measurements obtained from PMUs are normalised within range of [0, 1] for magnitudes and $[-\pi, \pi]$ related to phase readings.

The assessment is further continued by assuming the recorded data for the subsea load train 1 is deteriorated due to degradation compared with the remaining consumers. As a result, the sum of degradation profiles for other three load devices is an input to categorise all these measurements into N-degradation states that will be the main source for learning/training of the developed Markov model. In the next step, all observations related to the affected load train 1, of which are different from the above-mentioned training source, will be used as far as model verification step is proceeded.

It is worth noting that the peak magnitude of the measurements does not provide valuable index for identifying a degradation mode. The iterative steps are now used at each time interval to detect fault and categorise the fault happened in load train 1 associated with mode of degradation as we discussed before.

To get valid approximation of model λ_1, we supposed to have observation sequence of first load train to develop the new model parameters as

$$\boldsymbol{V}^1 = \{v_{t-3}\, v_{t-2},\, v_{t-1},\, v_t,\, v_{t+1}\}$$

where the v_{t+1} is not known.

Based on the derived probability expression above, the probability for V^1 to remain in healthy mode at one-step-ahead of the current time instant, $P\left(\boldsymbol{V}^1, q_{t+1} = j \middle| \hat{\lambda}_1\right)$, which is called boundary condition 1, is presented in Table 2 for first subsea load train connected to the Switchgear A.

It is confirmed that since the value for the Green boundary (0.4462) is smaller than the second degradation mode, yellow boundary, in which has the probability of 0.4534, the system status state is predicted to be in healthy state. The assessment is continued to figure out the probability of the observation sequence of V^1 to be kept in reduced-state mode, entitled boundary condition 2, for intended time $t+1$, which has the probability value of 0.3216 for the same load train 1 connected to the switchgear A. Considering the given values in Table 2, there is a large gap between second degradation mode and the severe degradation, implying the system remains in reduced state as it was desired.

Robustness analysis of the proposed approach has been performed with respect to the measurement noise. To this end, Gaussian noise was added to the observation states and probability values are recalculated to obtain the maximum likelihood of the currents/voltages. The results listed in Table 3 confirm an acceptable accuracy for the estimation of the multiple subsea loads' status under 10% measurement errors.

Emerging subsea production systems are vulnerable to hidden failures of some components interfering with subsea control systems that can influence plant output production. These hidden failures are not easy to detect, even during steady-state operation and system disturbances can lead to protection relays unnecessary disconnect equipment from service in response [31, 32]. Therefore, to end the simulation study, the hidden failure probabilities are accounted as an optimisation constraint to suppress its impacts on the failure diagnosis to comply with manageable probability bands. The consequences of hidden failures are thus embedded in the data obtained from cascading outage scenario to produce such data for simulation purpose. An illustrative case study is simulated, where the reliability indices of probability, frequency/year and duration in hours/year of the loss-of-load event are computed. To do so, in both operating scenarios, with and without the contingency inclusion resulting from hidden failures, outage happened due to energisation of circuit-breaker trip mechanism of each load. In the case of hidden failure contingency consideration, there are two assumptions for circuit-breaker trip mechanism failure probability as follows: case $1 = 4.22 \times 10^{-4}$ and failure probability of case $2 = 4.22 \times 10^{-3}$.

Obtained results are provided in Table 4 indicating that the protection system is deteriorated because of neglecting hidden failures effect. As shown in Table 4, reliability indices decrease when the failure probability of the circuit-breaker trip mechanism

Table 4 Effects of hidden failure probability of load circuit breaker on the protection system

Reliability index	Without hidden failure contingency	With hidden failure contingency	
		Case 1	Case 2
calculated probability	1.106×10^{-3}	1.1117×10^{-3}	1.1605×10^{-3}
frequency, per year	0.4322	0.4341	0.4479
duration, year	21.88	21.91	22.15

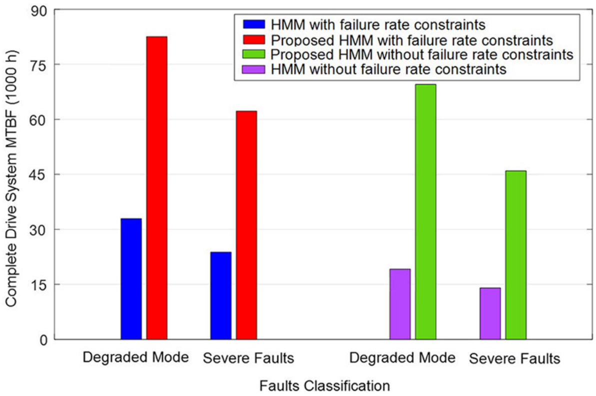

Fig. 5 *Calculated MTBF for a complete motor drive system as a function of the operation mode: comparison of the traditional HMM and the proposed HMM with/without equipment failure rate variations*

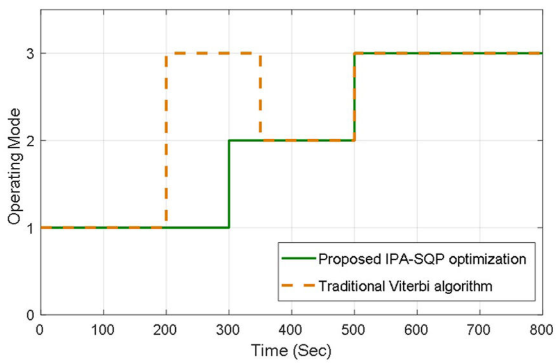

Fig. 6 *Influence of hidden states in the trained HMM model during fault in subsea load train at t = 300 s: performance comparison of the proposed IPA-SQP algorithm and traditional Viterbi algorithm*

increased, case 2. To address this, hidden failure effects included in the protection system design. Outcome confirms that the protection system performance is enhanced by suppressing the hidden failures resulting in more robust subsea condition monitoring system.

On the basis of best available reliability estimates for the equipment under development and with the known knowledge, e.g. in [33], that Variable-Speed-Drive (VSD) failures attributed to nearly 33% of entire subsea power system production unavailability. Henceforth, primarily focus of reliability enhancement is related to VSD system as one of the key components to achieve the system availability target. It is assumed that in the case of severe or critical failures, 0% production is achieved, whereas in degraded mode 60% production capacity is fulfilled. To perform this analysis, the drive system is broken up into its components and the failure rates of these components are defined based on available data from the manufactures and/or field tests. Afterwards, the component failure rates are aggregated to calculate the expected system failure rate and the overall system reliability targets.

It is also beneficial to assess reliability improvement using developed model by adding an extra equipment constraint on the mean-time-between-failure (MTBF) values for a complete drive system. The results from this analysis is very important to identify critical equipment (in this example VSD) and provide input for further reliability growth considering the equipment reliability constraints such as failure rates variations. The comparative results from traditional Markov model and the proposed one including the effects of equipment reliability constraints for VSDs are provided in Fig. 5.

Degraded operation mode is primarily due to the thermal protection or drive control system malfunctions. To name examples leading to severe faults; short-circuit phenomena in power semiconductor switches or DC-link capacitors inside inverter part are most common. Analysis of degraded operation mode excluding failure rate constraints in Fig. 5 shows that the traditional HMM predicts drive system to fail on average twice per year. In the case of severe failures, traditional HMM model estimates shut down of a drive system once per year. Obviously, such an MTBF values are too low for many applications including the studied system in this work.

To better understand the effectiveness of the HMM-based strategy to detect operating modes, performances of both the proposed IPA-SQP optimisation and the widely used Viterbi algorithm are compared, as shown in Fig. 6. In this evaluation, the system operates in healthy state (mode 1) until complete failure (mode 3) happens at $t = 500$ s. Since the failure occurred in the single load train, the system must initially transfer to the degraded state (mode 2) at $t = 300$ s prior to mode 3. This is the desired operation profile. As a result of introducing the hidden state at $t = 200$ s for duration of 150 s, the protection system perceived a severe failure mode immediately utilising the HMM model based on the Viterbi algorithm, showing poor robustness against system uncertainty. From this study, it is seen that the proposed IPA-SQP optimisation can mitigate the effect of the uncertainty in the form of hidden states to detect the actual operation mode at $t = 300$ s. Conversely, the Viterbi algorithm wrongly draws the power system to mode 3 on introducing constraints into the load train of interest.

In early design process of condition monitoring system, it is important to pay close attention to hidden failure contingency of the protection mechanisms to enhance overall power outage statistics. As a result, operational costs are reduced while profitability and flexibility are increased.

5 Conclusion

The proposed method in this paper provides a robust condition monitoring solution made possible through a statistical methodology based on HMMs for identification of failure and degradation status of individual loads. A typical subsea power AC transmission and distribution system, comprised of four different loads, was simulated to evaluate the proposed detection method. Simulation results show that the proposed method enables a better understanding of asset risks and improving the prediction probability of the imminent fault in subsea load equipment to prevent equipment failure propagation. This solution offers robustness against uncertainty in measurement noise and changes in equipment MTBFs, providing enhanced reliability. In addition, it is briefly illustrated how the use of this method can extend the need of maintenance by early load degradation prediction, making the method suitable for condition-based maintenance applications. This can provide valuable information to be utilised for asset management and/or performance assessment as specified in different international organization for standardizations.

6 Acknowledgment

The authors thank ABB partners in the Joint-Industry Project (Subsea Power JIP): *Equinor ASA* (formerly *Statoil*), *Total S.A.* and *Chevron Corporation*.

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