A surrogate model to predict fault impacts under dynamic CCGT operation for fault detection and diagnosis

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Abstract:

The increase in renewable energy sources in power generation necessitates, in the short term, the use of flexible plants such as Combined Cycle Gas Turbines (CCGT), which will be operated more dynamically. Hence, it became crucial to maintain high efficiency and availability throughout all operation modes. This can be accomplished using physics-based faults detection and diagnostic (FDD) tools, which leverages the benefits of digital twins and instrumentation to automatically identify efficiency losses and identify potential causes of outages. In our previous work, a calibrated dynamic model of an industrial CCGT was developed and calibrated using industrial operating data. Typically, detected and anticipated faults were incorporated into the model, and their impacts on measured variables were simulated and analyzed. The results show that fault impacts strongly depend on plant load, and that transient responses do not follow a unique pattern. Physics-based FDD methods rely on prior knowledge of fault impacts across all operating conditions to explain discrepancies between digital-twin predictions and measured data. However, simulating faults for all possible operating conditions and fault combinations is computationally expensive and time-consuming. To address this limitation, this study proposes a simple surrogate model capable of providing fast and accurate representations of fault impacts using a limited number of input parameters. Under steady-state operations, the surrogate model takes the plant load as an input and provides the corresponding fault impacts. Transient operation periods are divided into two phases: a load-variation phase and a stabilization phase. During the load-variation phase, load ramp characteristics are used to estimate the slope of fault impact evolution, while the stabilization time is determined based on the load-ramp duration. The complete transient response is then approximated using two linear segments. The discrepancies between the surrogate model and the detailed dynamic simulations are quantified, demonstrating that the proposed approach reproduces fault impacts with acceptable accuracy. To further validate the methodology, a realistic dynamic operating scenario with combined synthetic faults is considered. The surrogate-generated fault impacts are then supplied to an FDD algorithm, which successfully detects all the faults with high accuracy. These results demonstrate that physics-based FDD remains effective despite the approximation of the surrogate model and can be used even under complex and highly dynamic operating conditions.

Keywords:

CCGT; Fault Detection and Diagnosis; Surrogate Model; Digital Twin; Dynamic Model.

1. Introduction

Since the 20th century, increasing automation and the critical need for reliability, safety, and quality in industrial processes have initiated a growing interest in fault detection and diagnosis (FDD) methodologies among researchers and industry professionals. In the meanwhile, the complexity of industrial processes continues to increase with technological advancements, making the occurrence of faults more critical and their detection more challenging [1]. In addition to the complexity, the variety of malfunctions that may occur, and the insufficiency and unreliability of the process measurements, made the reliance on human operators to deal with abnormalities and emergencies more difficult with high risk of erroneous decisions [2]. Therefore, the capacity to monitor, detect and assess the impact of malfunctions became a necessity for modern sophisticated technologies.

On the other hand, despite the accelerated installation of renewable energy capacities on the worldwide scale, conventional thermal power plants remain critical in ensuring grid stability and maintain energy security, especially combined cycle gas turbines (CCGT). In a technical report [3], the Joint Research Center (JRC) of the European Commission, the projections of flexibility requirements in Europe are published. Figure. 1 shows the expected increase in flexibility requirements across three different timescales (daily, weekly and monthly) across the European Union (EU). Depending on the timescale, different technologies are expected to meet the corresponding flexibility requirements. Interconnections and storage solutions, such as batteries, electrolysis, and pumped hydro, will play a crucial role in providing the flexibility needed for the grid. However, thermal units, whose production can be dispatched, continue to be an important part of the flexibility mix. Most of these power plants were initially built for base-load operations, are now operating more flexibly. This new operation mode might increase profits to some power plants, however, it causes a degradation of the lifetime due to fatigue, creep and corrosion [4]. Therefore, this study aims to extend the applicability of physics-based FDD methods to the dynamic operation of CCGT power plants, which offer high efficiency and flexibility among conventional thermal systems.

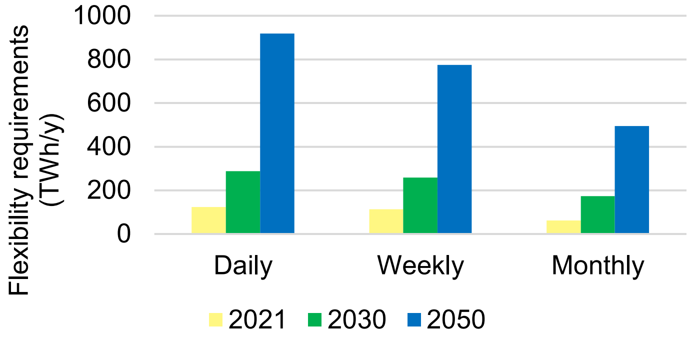


Figure. 1. *Daily, weekly and monthly flexibility requirements in the EU for 2021, 2030 and 2050 [3].*

Therefore, extending FDD methods to dynamic CCGT operation is essential to ensure high efficiency and availability. The following sections review model-based FDD methods, with a focus on their applications in the power generation industry, and present Metroscope's approach, which serves as the basis for this study. A calibrated dynamic model, developed in previous work, is then used to simulate and analyze fault impacts. To enable efficient access to this information, a surrogate model was introduced. Finally, the proposed methodology is evaluated through a realistic case study with synthetic fault injection, demonstrating accurate detection across a wide range of fault types and operating scenarios.

2. Model-based FDD methods

FDD methods helps power plants operator improve their assets efficiency and availability by providing them information about its health state. Undetected faults cause significant economic and operational consequences. Unscheduled outages cause losses that can range from hundreds of thousands to millions of dollars per day, depending on the power plant capacity and energy market [5]. These methods can be globally divided into two categories: model-based and data-driven approaches [6]. The first relies on a physical model to predict the behavior of the system while data-driven approaches use statistical and machine learning methods to model relationships between system measurements, relying on either supervised (labeled data) or unsupervised learning with feature extraction. Statistical techniques detect faults by comparing signal features to nominal baseline values to identify deviations [7]. Unlike model-based methods, these approaches depend primarily on historical data rather than prior system knowledge.

While both approaches present advantages and limitations, this study focuses on model-based methods due to their ability to embed expert knowledge through physical and empirical modeling. This provides deep insight into system behavior and enables causal root cause analysis [8], [9]. Their accurate representation of the process allows the detection of subtle deviations [7], including faults not previously observed, while offering adjustable trade-offs between false alarms and missed detections [10]. Furthermore, their limited reliance on historical data enables coverage of a wide range of modeled fault scenarios.

The following sections present the fundamentals and applications of model-based FDD methods. Subsequently, the Metroscope FDD algorithm, which serves as the basis for the proposed approach, is introduced.

2.1. Fundamentals and applications of model-based methods in the power generation industry

As it's name suggests, model-based methods rely on a mathematical model of the process under investigation, to predict its normal behavior. "Residuals" are the differences between the process and the model. Their presence indicates the presence of faults. For this reason, residuals can be called "symptoms". Under no fault condition, the residuals must be zero or close to zero. Figure. 2 illustrates a schematic description of the model-based fault diagnosis scheme as presented by [11]. The model runs in parallel and generates the same outputs as the process. The “residual generation” block computes the difference between the outputs of the process itself and model’s estimates. Several approaches of residual generation can be identified, as presented in [6], [11]: observer, parity space, parameter identification, fault detection filter and bond graph. Residual signals are influenced by uncertainties and disturbances, requiring a residual evaluation step to extract fault information through post-processing [11]. Common methods include fixed or adaptive thresholds, statistical feature analysis, and Bayesian approaches [7].

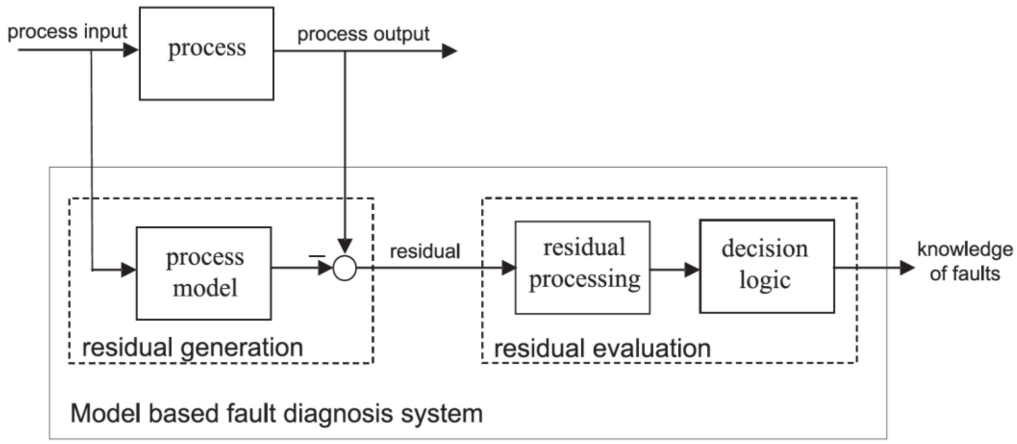


Figure. 2. *Schematic description of the model-based fault diagnosis scheme [11].*

Model-based approaches have been widely applied in the power generation industry to enhance power plant performance and reliability. For instance, In [12], a model-based approach is applied to fault diagnosis in distributed photovoltaic systems using a physics-based digital twin. Residuals are generated by comparing measured and estimated signals, with fault detection based on thresholding and identification achieved through residual direction analysis using a fault signature library. In [13], a model-based diagnostic framework is applied to a nuclear power plant feedwater system using first-principles models and virtual sensors to overcome limited instrumentation. Residuals are generated from analytical redundancy relations, with fault detection based on consistency checks and isolation performed through reasoning-based diagnosis supported by fault signatures. In [14], a model-based approach is applied to boiler leak detection using a mass-balance model combined with a recursive least-squares estimator with a forgetting factor. Residuals are generated from flow imbalances, enabling adaptive fault detection under time-varying conditions and improving early leak detection compared to conventional methods. Other applications for condenser fouling detection [15] and gas turbine gas path analysis [16] can also be found in the literature.

A major research gap can be identified in existing FDD applications, which predominantly focus on individual components and are often limited to steady-state operation. Such approaches fail to capture fault propagation across interconnected systems and their impact on overall plant performance. This limitation is particularly critical under modern operating conditions, where frequent load variations introduce significant dynamics. To address this gap, the steady-state method developed by the industrial partner, Metroscope, is extended to dynamic operation without modifying the original algorithm, by providing instantaneous inputs that reflect the current state of the power plant.

3. Metroscope FDD methodology

The Metroscope software, embedding a model-based FDD approach, is deployed at a large number of nuclear and CCGT power plants. However, the solution offered only covers steady-state operations. Therefore, transient and unstable periods are filtered out before conducting any simulation or diagnosis. The global methodology is show in Figure. 3:

- For each power plant, a specific steady-state digital twin is developed using Modelica [17]. A dedicated open source modeling library called Metroscope Modeling Library (MML) [18] is developed for this purpose. It contains all the necessary components needed to model CCGTs and the secondary cycle of nuclear power plants. The main goal of the digital twin is to set a performance reference depending on the boundary conditions, such as ambient conditions and load, which will be referred to as the “healthy” state. This is achieved by a dedicated calibration methodology.

- The values provided by the digital twin are compared to the real measures from the installed instrumentation and the difference is calculated. Each difference is considered as a "symptom" of potential occurring faults.
- The digital twin is also used to explicitly model and simulate all the potential faults that may occur on the system. The set of impacts of each fault on the measured quantities of the system is called the "fault's signature", allowing its detection and isolation from other faults. The signatures of the modeled faults are encapsulated in a "fault matrix".
- To allow the automatic detection of the faults, an inferential engine is developed. Using the computed symptoms and the fault matrix, the associated FDD algorithm explores a large number of fault combinations and magnitudes and delivers the most probable one as a diagnosis. The measured variables for which symptoms are computed and used by the FDD algorithm as indicators are called "observables".

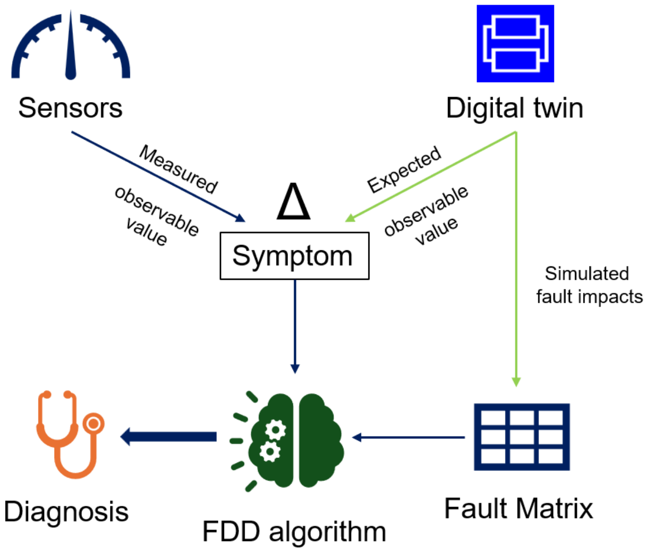


Figure. 3. *Metroscope's model-based FDD methodology.*

Applying this approach only for steady-state operations was considered sufficient for power plants operating mainly in steady state, like nuclear power plant. This enables a simpler modeling approach and allows the application of some assumptions related to the fault matrix. Therefore, the data is filtered to meet stability criteria for both model calibration and diagnosis. Moreover, the model's equations exclude the time derivatives and the control system. The control setpoints are assumed to be met, considering that the control system achieved a stable response.

The Metroscope FDD algorithm automates the detection of faults and estimates their magnitudes, based on three key inputs:

- Symptom vector $\bar{\Delta}$: It consists of the list symptoms of each observable at each measurement point.
- Diagnosis parameter vector $\bar{\sigma}$: A list of normalization parameters assigned to each observable, which encapsulates both the measures and model's uncertainties. Symptoms are considered significant when they exceed 2σ.
- Fault matrix $\bar{\bar{M}}$: Faults signatures encapsulated in a table (will be detailed later).

By analyzing these three inputs at each measurement point, the algorithm generates a list of potential faults that best explain the observed gaps. It should be noted that in the current steady-state approach, from one measurement point to another, only the symptom vector changes. The diagnosis parameter vector and the fault matrix are assumed to remain constant.

3.1.1. Fault matrix

The main objective of the fault matrix is to provide the algorithm with accurate information on how each fault impacts the system, enabling it to explain the observed symptoms. Power plants operate under a wide range of conditions, and faults may occur with varying levels of intensity. Therefore, to supply the algorithm with the most precise information about fault impacts, one could consider simulating all possible faults at each measurement point under the exact operating conditions and for different magnitudes. In a standard CCGT, around 40 faults are modeled in the current Metroscope methodology. If such an approach is adopted, at least

40 simulations would need to be performed at each measurement point, each with different fault magnitudes. This would result in a significant computational cost and introduce additional challenges related to simulation convergence. Moreover, such an approach prevents real-time application, as the computational time would exceed the available time for online processing. Therefore, a simplified fault representation is introduced to avoid performing simulations at each measurement point. This representation takes the form of the fault matrix described earlier and is established after assessing and adopting several simplifying assumptions. In the current implementation of the software, the diagnosis is limited to full-load and steady-state operating conditions. This restricted operating range reduces the variability of fault signatures and makes these simplifications acceptable. As a result, three main assumptions are considered:

- Fault impacts are independent of variations in boundary conditions, such as ambient temperature or pressure. For example, a tube leak of 5 kg/s causing a 2 bar pressure drop at an ambient temperature of 25 °C will produce the same 2 bar drop under any other ambient temperature.
- Fault impacts vary linearly with respect to fault magnitude. For example, a tube leak of 5 kg/s causing 2 bar pressure drop, will cause 4 bar pressure drop at 10 kg/s.
- Fault impacts are mutually independent, meaning that the effects of multiple faults can be superimposed (added or subtracted) without interaction. For example, a tube leak of 5 kg/s causing a 2 bar pressure drop and a heat exchanger fouling resulting in a 4 bar pressure drop on the same line will together produce a total pressure drop of 6 bar if they occur simultaneously with these magnitudes.

Table 2.1.1 shows a simple example of a fault matrix. The impacts are calculated as the difference between the values of the observable simulated by the healthy model and those obtained when the corresponding fault is activated. The magnitudes shown in the table correspond to the values given to each fault to calculate its signature. For example, at a 5% fouling of a certain heat exchanger, the measurable temperature will decrease by 2 K, the pressure by 2 bar and the mass flow rate will increase by 6 kg/s. The linearity assumption between the impact and the magnitude gives the algorithm the possibility to easily extrapolate to guess the intensity of each detected fault.

Table 2.1.1. *Example of a fault matrix.*

Fault name	Magnitude	Impact on measured quantities		
		Temperature (K)	Pressure (bar)	Flow (kg/s)
Leakage	10 kg/s	- 10	+ 3	+ 5
Fouling	5%	- 2	- 2	+ 6

Extending the methodology to cover dynamic operations introduces significant challenges to the use of a constant fault matrix. First, the load range becomes wider, introducing an additional variable that strongly influences the plant response to fault occurrences. Moreover, this approach completely neglects transient periods, which are significantly affected by the thermal inertia of components and the actions of control loops.

3.1.2. Metroscope FDD algorithm

The choice of the suitable algorithm is heavily influenced by industrial and physical constraints. For instance, the list of faults proposed by the algorithm must remain physically meaningful and easily interpretable. In other words, the algorithm should not identify all possible faults simultaneously simply because of numerical feasibility. Instead, it must filter the results and retain only the most significant faults. Furthermore, it must avoid detecting faults with non-physical magnitudes, such as negative flows or unrealistically large flows in small pipes. To address this issue, specific bounds are defined for each fault type. The chosen approach is a heuristic based on the Conjugate Gradient algorithm [19]. Its flow chart is shown in Figure. 4.

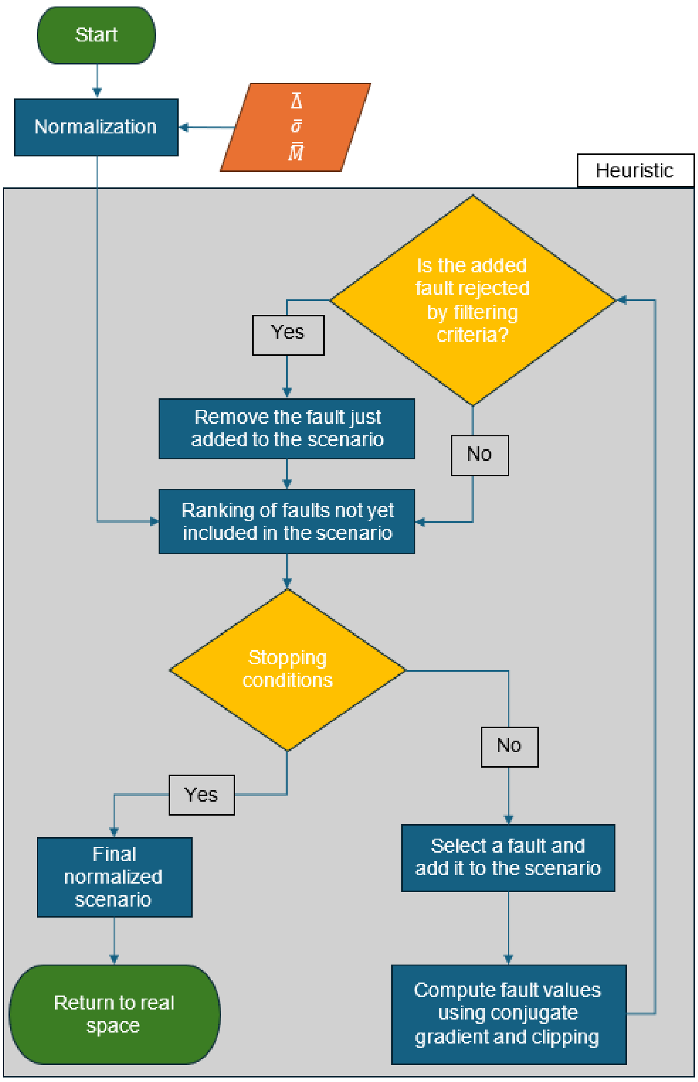


Figure. 4. *Metroscope FDD algorithm flow chart.*

Here is a step-by-step explanation:

- As mentioned earlier, for a given measurement point, the symptom vector is computed. $\bar{\Delta}$, $\bar{\sigma}$ and $\bar{\bar{M}}$ are given as inputs.
- Normalization block: the diagnosis parameter vector $\bar{\sigma}$ is used to normalize both $\bar{\Delta}$ and $\bar{\bar{M}}$. From now on, the algorithm will only be reasoned in the normalized space. This allows the comparison of variables with different units.
- In the heuristic block:
    - In the first iteration, the diagnosis scenario is empty, meaning that no faults are yet selected. The faults are therefore ranked by applying an orthogonal projection of the impacts generated by each fault individually and computing the residual with respect to the symptom vector. Faults with lower residuals have greater potential, as they better explain the observed symptoms, and are therefore ranked higher. All faults contained in $\bar{\bar{M}}$ are evaluated in this step.
    - Starting from the second iteration, the residual used to rank the faults is computed with respect to the residual obtained in the previous iteration. In this way, each step evaluates whether adding a new fault improves the explanation of the symptom vector.
    - Stopping conditions are then applied. The first occurs when no additional faults remain to be explored, and the second corresponds to reaching a predefined maximum number of faults to be suggested. Once one of these two conditions is satisfied, the final diagnosis scenario is projected back into the real space using the diagnosis parameter vector $\bar{\sigma}$.

- If none of the stopping conditions are satisfied, the next highest ranked fault is added to the scenario. To compute the selected faults magnitudes, the conjugate gradient and clipping method is applied. The objective is to ensure that these faults explain the observed symptoms as accurately as possible by minimizing the residuals. The main advantage of selecting this method is its computational efficiency.
- A second set of filters is then applied to determine whether the added fault should be retained or removed from the diagnosis scenario. These filters are numerous, and some are confidential. They are mainly based on extensive industrial experience and aim to eliminate false detections as much as possible. Some filters are simple, such as applying a minimum threshold on the fault normalized magnitude to ensure that its impact is significant. Others are more complex, for example identifying faults that appear only to compensate for each other.
- If the filters are satisfied, the added fault is retained, and a new ranking is performed with this fault included in the scenario. Otherwise, the fault is permanently removed from the list of potential faults, and the ranking is recomputed without it.

The algorithm relies on two key assumptions: linearity of fault impacts with respect to their magnitudes and the absence of interactions between faults. Relaxing these assumptions would require modifications to the algorithm and is left for future work. Extending the approach to dynamic operation therefore focuses on validating its main inputs, the symptom vector and the fault matrix, while keeping uncertainty parameters unchanged. The accuracy of the symptom vector depends on the digital twin's ability to reproduce system dynamics, whereas the fault matrix must be efficiently generated using a surrogate model adapted to operating conditions.

4. Surrogate modeling of fault impacts

Using the simplified modelling approach presented in a previous study [20], the dynamic model of the steam cycle of a CCGT is developed. This model was then calibrated and validated on real data, resulting in an accurate simulation of the dynamic behavior of the power plant. This ensures the validity of the symptom vector during dynamic operations. To assess the impact of faults on the observables of system, each fault is explicitly modeled and activated, and the difference between the healthy and faulty results are computed. In a previous study [21], this same model was used to simulate the dynamic impact of three faults: preheater fouling, high pressure (HP) steam drum drain leak, and intermediate pressure (IP) desuperheater valve leakage, during a ramp up dynamic scenario. The results show that the impact of these faults depend on the operating conditions, most importantly the power plant's load, with complex trends during load variations.

As explained in the previous section, the FDD algorithm requires a fault matrix to perform the diagnosis. In varying operating conditions, the unique fault matrix accuracy is limited. In principle, one could simulate all faults under the exact operating conditions of each measurement point using the full dynamic model. However, this approach is computationally unreasonable and impractical for real-time applications. Therefore, a surrogate model capable of generating fault matrices as a function of operating conditions is required.

In [22], the validity of the three assumptions related to the fault matrix is assessed. The results show that the assumption of linear fault impacts with respect to fault magnitude is generally valid within the typical detection range, despite some localized non-linearities caused by control system activation or saturation. As these effects affect only a limited number of fault-observable pairs and the method relies on many observables, the linearity assumption remains acceptable. Similarly, fault interactions are minimal and mainly linked to control system behavior, justifying the assumption of no interaction. Addressing these limitations would require modifications to the diagnosis algorithm and is left for future work. In contrast, fault impacts strongly depend on load conditions.

A simplified approach to predict the fault impacts is therefore proposed. It consists of dividing the impact evolution into three segments: steady-state, load variation and settling time. Figure. 5 illustrates the example of the preheater fouling impact of its water outlet temperature during a load ramp up. The transition between operating modes is considered as linear. Therefore, predicting the delimiting points of each regime and connecting them with straight lines is considered sufficient to reproduce the overall impact evolution. Here, three points predicted by the surrogate model:

- **Point A:** It marks the end of the first steady state period. During steady-state operation, fault impacts are assumed to depend only on the load. Therefore, the surrogate model generates the fault matrix based on the Inlet Guide Vanes (IGV) angle, which controls the mass flow rate through the gas turbine, and represents the load of the power plant. The same fault matrix is applied throughout the steady-state period preceding Point A.

- **Point B:** It marks the end of the ramp-up phase. During load variation, the surrogate model predicts the slope governing the transition of the impact from its initial steady-state value to the value corresponding to the end of the load ramp. To estimate this slope, the surrogate model uses the initial IGV angle and the ramp slope as inputs. Knowing Point A and the predicted impact slope, the linear segment connecting A to B can then be defined. At Point B, the instantaneous derivative of the IGV angle becomes zero, indicating the start of the settling phase.
- **Point C:** It marks the end of the settling period. Since the final steady-state IGV angle is already known at Point B, the impact value at Point C (ordinate) can be directly determined using the same steady-state approach applied at Point A. The remaining unknown is the time coordinate (abscissa). The surrogate model therefore predicts the settling time based on the IGV step achieved during the ramp and the ramp duration. It can be seen that Point C does not lie exactly on the impact curve; the discrepancy corresponds to the relative tolerance used to define the final steady-state impact value used to compute the settling time [23].

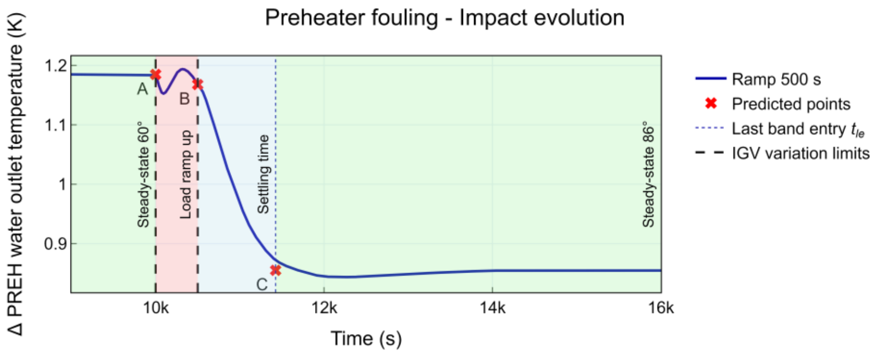


Figure. 5. *Operation segmentation example with predicted points.*

In order to train the model, a preprocessing phase is required. It consists of simulating the faults in various conditions:

- Steady state: The load range is therefore discretized, and faults are simulated at different IGV angles, with results stored in fault matrices.
- Load variation: Following a similar approach, multiple load ramp scenarios are simulated by performing transitions between IGV angles with varying ramp durations, providing impact profiles under diverse transient conditions. During load variation, the surrogate model uses precomputed impact slope matrices defined for each initial IGV angle and ramp rate. It then applies bilinear interpolation based on the actual starting IGV angle and load ramp slope to predict impact evolution.
- Settling time: At this stage, the load profile is fully defined by the initial IGV angle, ramp slope, and duration. Settling times, computed under various conditions, are stored in matrices indexed by these parameters. The surrogate model then applies trilinear interpolation to generate the fault matrix corresponding to the actual load profile.

To assess its validity, the surrogate model is applied to a simple dynamic scenario consisting of a steady-state part-load operation followed by a ramp-up to a new steady-state load. **Figure. 6** shows an example of fault impact prediction by the surrogate model compared to the full model during this scenario. It illustrates the impact of an HP steam turbine bypass fault on the outlet temperature, showing a significant deviation exceeding 20σ, which makes this observable a strong fault indicator. The surrogate model prediction closely follows the dynamic model response, as seen in the upper plot, while the lower plot confirms that the error remains very small at a maximum of 0.5σ during the settling phase. In steady-state conditions, the surrogate model achieves negligible errors at the two load levels, demonstrating the high accuracy and reliability of the proposed surrogate model for steady-state part-load operations.

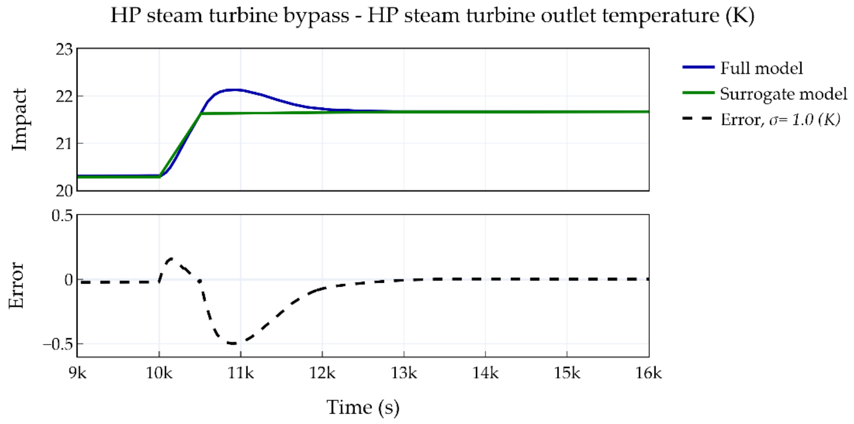


Figure. 6. *Full model vs surrogate model impact of the HP steam turbine bypass on the HP turbine outlet temperature.*

Similar results are obtained for other fault-observable pairs, where the highest errors occur during the settling phases, and no errors during steady-state operations. For some observables that are strongly influenced by nearby control systems, the largest errors may occur during the ramp itself. Nevertheless, in all cases, the errors remain within the 2σ threshold used by the FDD algorithm.

This initial application indicates that the proposed surrogate modeling approach can predict fault impacts with acceptable accuracy. However, additional realistic conditions must be considered, including incomplete settling between ramps, the presence of multiple faults affecting the same observable, and the occurrence of sudden faults during operation. Addressing these aspects requires a more comprehensive use case with realistic operating conditions and an actual diagnosis procedure, which is the objective of the next section of this work.

5. Evaluation of the surrogate model approach to diagnose multiple faults

Building on the surrogate modeling approach developed previously, this section evaluates its performance within a complete FDD framework under realistic conditions. A representative load profile from a CCGT power plant is used, with various fault scenarios simulated to generate synthetic data. This approach enables controlled and reproducible assessment of fault impacts, overcoming the limitations of scarce and poorly characterized industrial datasets. The surrogate model is used to dynamically generate fault matrices, which are then integrated into the FDD process to evaluate both fault prediction accuracy and overall diagnosis performance. For this purpose, a synthetic dataset is generated using a representative load profile and predefined fault scenarios. The selected profile, based on real CCGT operating conditions, consists of a seven-hour sequence of load ramps with varying slopes and directions, as show in Figure. 7. Several ramps occur in close succession, preventing fault impacts from fully reaching steady state.

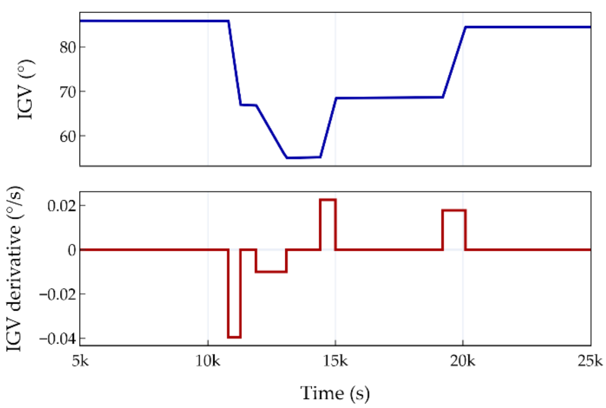


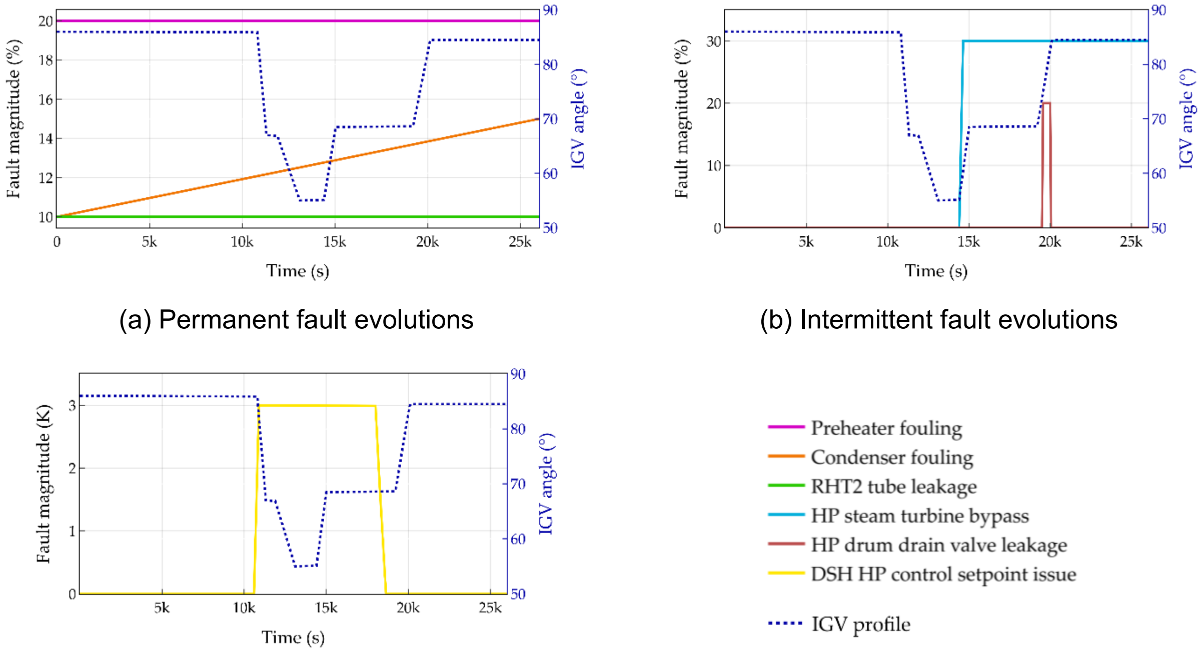
Figure. 7. *IGV angle profile (top), IGV angle instantaneous derivative (bottom).*

Five different faults of three types are activated in different scenarios as shown in Figure. 8:

a) Three permanent faults are considered: preheater, reheater 2, and condenser fouling. Fouling is modeled as a decrease in the heat transfer coefficient of the heat exchanger. The first two correspond to slow-evolving faults with constant magnitudes over the analysis period, whereas condenser fouling is treated as a fast-evolving fault.

b) Two intermittent faults are considered: HP turbine bypass and HP drum drain valve leakage. The turbine bypass opens to 30% at t = 14,400 s and remains open, while the drain valve leakage occurs at t = 19,500 s and closes after 500 s. These abrupt faults generate strong perturbations in the signals, challenging the surrogate model’s prediction accuracy.

c) A control-related intermittent fault is also considered: a 3 K bias in the HP desuperheater setpoint measurement, occurring during the transient period.



(a) Permanent fault evolutions

(b) Intermittent fault evolutions

(c) Control fault evolution

Figure. 8. *Evolutions of induced (a) permanent faults, (b) intermittent faults, and (c) control fault.*

The synthetic dataset is generated using two simulations of the dynamic model: one representing healthy operation and another including the defined faults. Symptoms are obtained as the difference between faulty and healthy behaviors. For numerical stability, some faults are introduced gradually, and analysis begins after signal stabilization. The surrogate model is then applied to estimate the fault impact and generate instantaneous fault matrices to be injected into the FDD algorithm. Figure. 9 compares the estimated and actual magnitudes of each fault:

a) For the preheater fouling fault , the average estimation error is about 1.15 pp. Larger deviations occur during the activation of sudden faults (−4.5 pp during turbine bypass opening and +10 pp during drain valve opening), reflecting limitations of the surrogate model in capturing abrupt dynamics. Nevertheless, detection remains continuous and overall accurate.

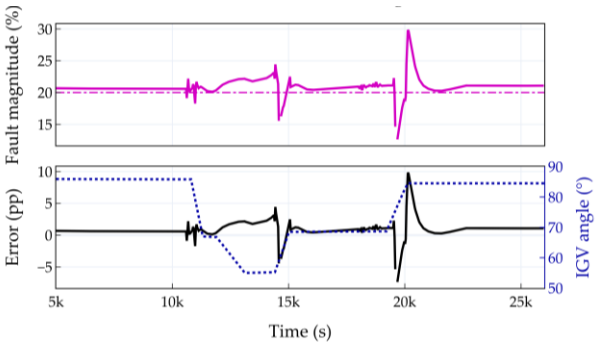
b) The Reheater 2 tube leak shows improved accuracy, with an average error of 0.35 pp. However, detection temporarily disappears during the turbine bypass activation and later recovers with a transient deviation before stabilizing.

c) The condenser fouling fault exhibits the most stable behavior, with a mean error of −1.91 pp. Its strong impact on condenser pressure enables robust detection despite load and magnitude variations.

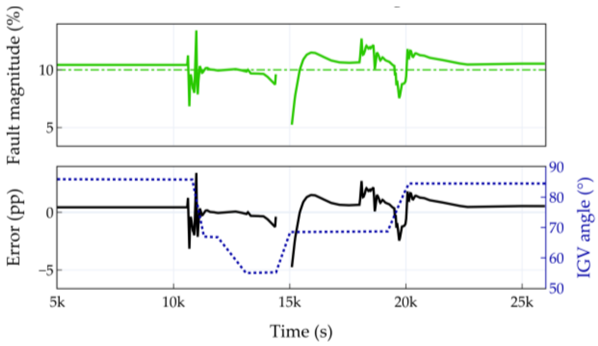
d) For intermittent faults, the HP turbine bypass is detected almost instantaneously. During activation, the estimated magnitude follows a transient exponential behavior due to unmodeled dynamics but converges to zero error once steady state is reached.

e) The HP drum drain valve leakage shows a brief 90 s false detection following the bypass activation, likely due to similar symptom signatures. The fault is then correctly detected within about one minute, with an average error of −5 pp, and persists slightly after disappearance due to dynamic effects.

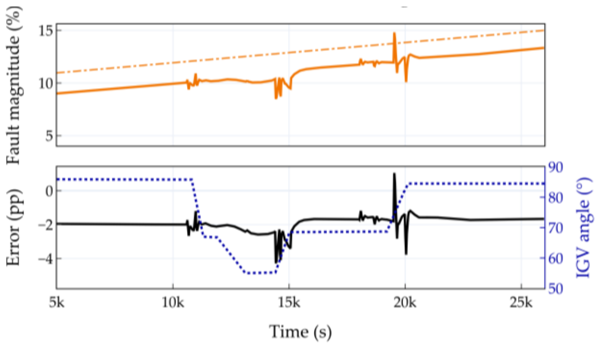
f) Finally, the HP desuperheater setpoint bias is accurately detected with near-zero average error. Its progressive nature avoids strong transients, facilitating quantification, although minor perturbations remain due to interactions with other faults and load changes.



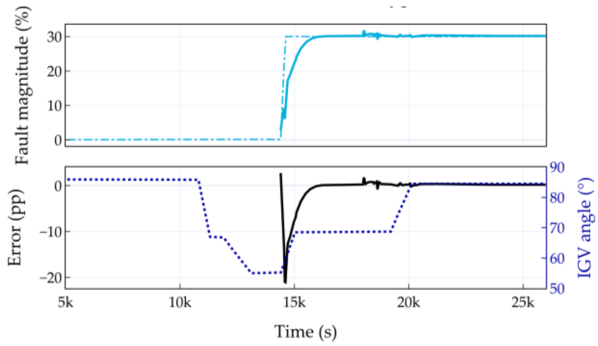
(a) Preheater fouling



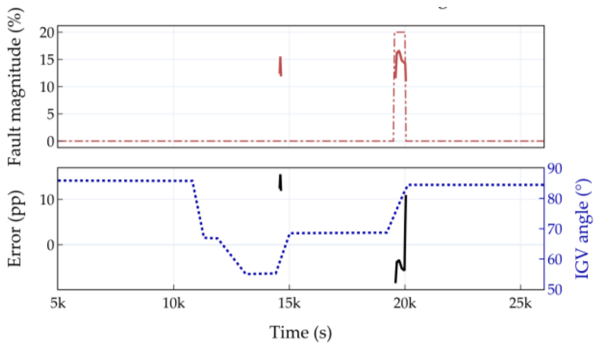
(b) Reheater 2 tube leakage



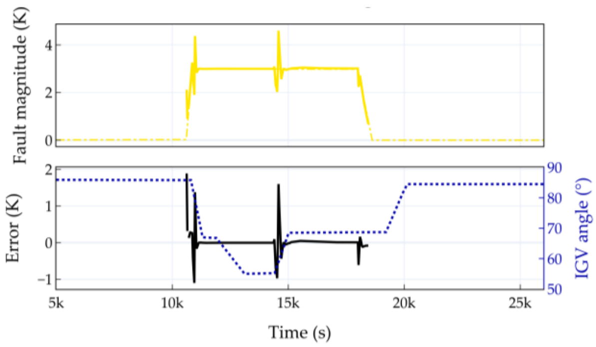
(c) Condenser fouling



(d) HP steam turbine bypass



(e) HP drum drain valve leakage



(f) HP desuperheater control issue

Figure. 9. *Fault detections using the surrogate fault model and Metroscope's FDD algorithm.*

The application of the FDD algorithm using the proposed surrogate model shows that the detection of multiple faults occurring during complex dynamic operating periods is possible and accurate throughout a complex dynamic scenario. However, it also highlights several limitations associated with the simplicity of the method, most notably the neglect of the dynamic effects induced by the sudden activation of faults.

6. Conclusions and perspectives

This study demonstrates the potential of extending model-based FDD methods to dynamic, system-level operation in CCGT power plants. By combining a physics-based digital twin with a surrogate modeling approach, fault impacts can be efficiently predicted under varying operating conditions. The results show that the methodology enables accurate fault detection and quantification across a range of fault types, including transient and interacting scenarios, while maintaining robustness to dynamic effects. These findings highlight the relevance of the proposed approach for improving monitoring and diagnosis in modern, flexible power plant operation. As a next step, the proposed method should be validated using real operational data instead of synthetic symptoms to assess its robustness under practical conditions. In addition, improving accuracy during transient periods could be achieved by implementing a finer discretization of operating conditions.

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