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SMART_TC: an R&D Programme on uses of artificial intelligence techniques for tritium monitoring in complex ITER-like tritium plant systems

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ABSTRACT

The realization of nuclear fusion energy is nowadays based on the concept of tritium breeding and the success of the ITER experiment. The latter relies today on a static monitoring approach to fulfill the emission limits imposed by the regulatory institutions. Artificial intelligence applications for fault diagnosis and process monitoring anticipate potential for the dynamic management of tritium in complex plant systems. This paper explores the dynamic tritium inventory management issue in complex systems, reviews the diverse artificial intelligence techniques and discusses the most promising approaches for ITER-like plant system match balance monitoring.

1. Introduction

Tritium match balance monitoring is fundamental for ITER licensing and operation, as well as for future fusion commercial reactors. On the one hand, tritium is scarce and the fusion process needs to be self-sufficient [1]. On the other hand, tritium is a hard to track component that is radioactive and can permeate structural materials [2]. Its radioactivity nature makes it necessary to ensure the emissions do not overpass a certain limit. This is why the local authorities (ASN/IRSN in France) require to assess the total tritium inventory in the plant to guarantee that it is operating correctly.

The current strategy for tritium monitoring in ITER's Tritium Plant is conservatively based on a static procedure. This procedure consists of a two-step approach in which any effluent in the tritium plant susceptible to containing tritium traces must be derived to the Storage and Delivery System to assess the total tritium inventory. A calorimetry test performs this assessment and trapped tritium inventory both in the vacuum vessel and in the rest of the plant can be accounted for. Thus, a halt in the plant is needed, as it is well accepted that no plasma operation can take place while the tritium inventory assessment procedure is in progress [3].

This conservative static approach is constrained by the limitations of the current sensing monitoring solutions and the regulatory tritium emissions limits [4]. In this strategy, the flexibility of the plant operation is reduced and the tritium self-sufficiency, which is a key aspect to secure in a fusion reactor, is difficult to provide due to the mandatory periodic shutdown procedures. A dynamic monitoring approach could become an alternative to this scheme and boost the performance in the operation of tritium plants. This new kind of approach would need to rely on improvements in dynamic modeling, sensor solutions, and process monitoring algorithms.

Dynamic modeling codes for tritium plant components are under development [5,6] to support tritium balance matching. Dynamic modeling is particularly needed taking into account that in-vessel inventories remain uncertain and mass balance cannot be directly accounted for. There is no consensus among the scientific community concerning the models for trapped inventories in the torus [3]. This lack of agreement can heavily delay the achievement of the continuous and safe dynamic operation of a fusion power plant. In this context, tritium processing models may imply extra data for in-vessel assessments.

Tritium sensors are essential to perform tritium balance monitoring and assess the amount of tritium throughout the plant. However, there is no sensor solution able to provide a measurement accuracy over the 3–4 digits, and a sensor technology that can cover the whole range of concentration in which tritium can be found in a fusion reactor does not exist [4].

Special applications of artificial intelligence to process monitoring arise as a possible contribution to the problem of tritium monitoring in fusion power plants. This paper is designed to outline the research

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developed in the SMART_TC programme in which inprocess and FUS_ALIANZ collaborate with the Technical University of Catalonia to focus on proposing an advanced strategy for match balance dynamic monitoring in a tritium plant. Given the complexity of the task, the research will take advantage of the available computational capabilities and the advanced algorithmic approaches developed in the last years, combining several decision-making units in a *multi-agent* approach.

Artificial intelligence has already been proposed for the assistance in fault diagnosis for industry [7,8] and specifically in the nuclear field [9, 10]. Cases of success such as that shown by Yang and Mou [11] extend the interest of research in this field and manifests the promising derivations of their applications to new fields like tritium and fusion.

The document is organized as follows. Section 2 formalizes the tritium monitoring goal and outlines the motivation and the needs of a new perspective of the monitoring issue. Section 3 performs a review of the techniques prone to be used in a tritium monitoring environment from a fault diagnosis perspective. Finally, Section 4 drives a discussion in terms of further challenges in dynamic monitoring and suggestions in the ongoing developments.

2. Problem statement

A fault can be defined as an event in a system that causes a variable or property of the process to deviate from an allowed range [12]. Faults can be related to a change in a process parameter, a change in a disturbance parameter, failure in actuators or failure in sensors. Fault detection and isolation is a subfield in control engineering that studies how to find out, anticipate and warn about deviations of the plant performance from acceptable limits, even if the standard control strategy fails to this aim.

In tritium plants, faults can take the form of a gas chromatograph failing to function, the occurrence of glovebox overpressure or transducers yielding wrong values [13]. But a higher level fault to be taken care of is the tritium inventory mismatch that can turn into potential emissions and thus break the regulatory limits over the 0.1% of the total inventory [14].

The main tool to manage the fault state of a process is the use of measurements. Tritium concentration sensing solutions vary from a wide range of accuracy and applicability and different measurement techniques, such as liquid scintillation counters, ionization chambers, proportional counters, He-3 measurement with mass spectroscopy, RAMAN spectroscopy, gas chromatography and calorimetry [4]. Among them, calorimetry is one of the few able to measure tritium at high concentrations by accounting for the tritium decay heat, but it yields an accuracy of 2–3 digits only. Ionization chambers and proportional counters are suitable only for gas-phase tritium. Ionization chambers suffer from a trade-off between accuracy and time response, depending on their volume and need tight re-calibration strategies. Proportional counters are more sensitive to measurements but do not fit for online purposes. For liquid samples, liquid scintillation counters are the main solution available. Scintillators are based on absorbing energy from the tritium decay to convert its energy into photons and use a counter to measure the activity of the sample. They can also be used for gases if bubbled along the solvent sample [15].

The limitation of tritium sensors in terms of accuracy, response time and sampling frequency, as well as the small order of magnitude of allowable tritium balance mismatch, drove into the decision of a conservative static tritium inventory assessment in the design of the operation strategy of the ITER tritium plant [3]. In this monitoring approach, any process stream liable to contain tritium traces needs to be processed and milked down of tritium through the fourth column of the Isotopic Separation System. The tritium ends up located in the Storage and Delivery System, where it is present in a high concentration level that allows its measuring through in-bed calorimetry tests [3]. Plasma operation cannot take place during the inventory assessment procedure, which implies the periodic halt of the experiments to fulfill the tritium accountancy needs.

A static monitoring strategy is not efficient and would make the industrial production of electricity in future fusion reactors costly and harm its feasibility. If an uninterrupted operation is desired for industrial operation, an advanced dynamic monitoring approach is needed to allow the continuous operation of the plant while guaranteeing a correct operating range. This progress would represent a landmark in the history of fusion systems.

Such a dynamic approach can be conceived by taking advantage of both dynamic simulation and artificial intelligence data treatment as follows. The plant or system needs to be divided into several monitoring sections or mass balance areas (MBA) to separate the problem into several *assessment units*. A model of the plant or systems would work as a *digital twin* [16] that matches the inventories in the process and compares the measurements with those of the modeled plant. Depending on that comparison, the simulation shall issue an assessment or decision regarding the fault state of the system according to a model-based monitoring approach (see Section 3).

In parallel with the model-based reasoning, a set of data-driven intelligent units processes the data to complement the fault detection and diagnosis decision. These units, based on state-of-the-art techniques must have been previously trained with historical and simulation data and issue detection and/or isolation diagnostics depending on the state of the sensor data available from the process.

Each time step, the online fault diagnosis system concludes the fault-related global decision based on the assessment of the likelihood of each data-driven and model-based units. The process of weighting the different decisions is a critical point and must be studied further (see the discussion in Section 4). A possible monitoring scheme is shown in Fig. 1, where n data-driven approaches issue fault-related decisions alongside a mathematical model method to provide an improved plant assessment. The scheme shall also isolate the origin of the fault in order to recommend the plant engineers and operators the next action to solve or prevent the incoming fault.

Part of the difficulty in addressing tritium monitoring is caused by the low precision of tritium sensors. When the data-driven units are provided with a large enough data set for training, artificial intelligence can be used to narrow the uncertainty generated by tritium in the tritium plant. This way, the use of artificial intelligence together with sensor redundancy can help to tighten the gap of accuracy and allow for a dynamic monitoring strategy.

3. Review of monitoring approaches

Fault diagnosis can use from simple traditional techniques such as Shewhart graphs to advanced methods such as deep artificial neural networks. A broad classification separates data-driven methods, which derive models purely based on historical data, and model-based methods, which generate models that replicate the actual process based on first-principle mathematical modeling.

Regarding data-driven techniques, some of them are supervised machine learning techniques, meaning by this that they need labeled data (i.e. each training example is known to belong to normal operating conditions or a certain fault class) while others are unsupervised and able to find hidden patterns that can be useful for fault detection purposes.

Fault diagnosis mainly involves two separated steps: detection and isolation. Fault detection elaborates on detecting outlier data that imply non-normal operation conditions, while fault isolation focuses on identifying the precise location of the fault and the observed variables involved in it. This section will review the most interesting techniques prone to be applied in a tritium processing environment, some of them more suitable for isolation, detection, or both.

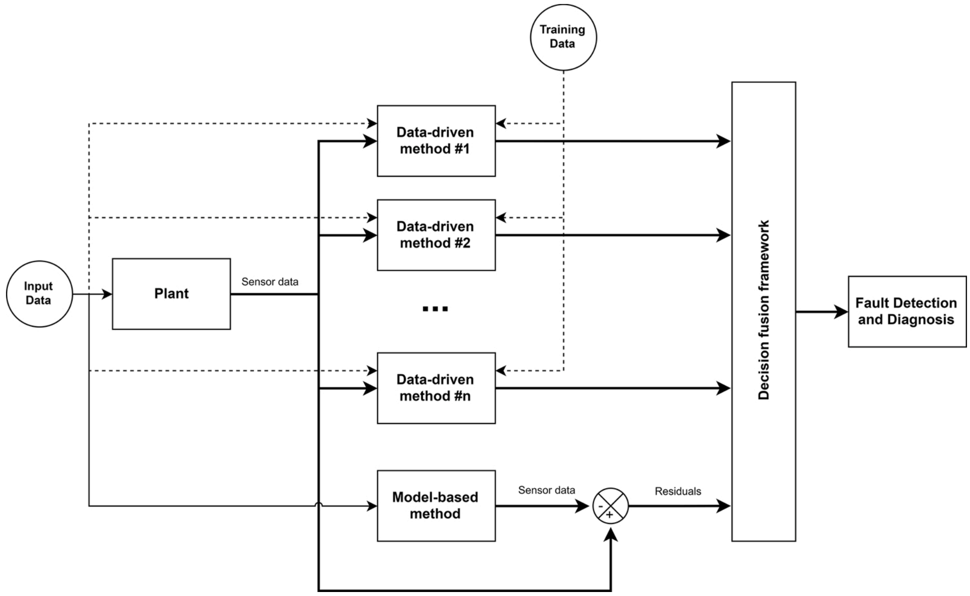

Fig. 1. Hybrid fault diagnosis architecture.

3.1. *Rigorous multivariate statistical approaches*

The need for improvement in monitoring techniques regarding spatial correlations (influence of the state of an observed variable in other variables) led to the development of fault detection techniques based on multivariate statistics. In this area, dimensionality reduction techniques such as principal component analysis (PCA), Fisher discriminant analysis (FDA) and partial least squares (PLS) were conceived.

PCA is a dimensionality reduction technique that projects the dataset into a lower dimension space while keeping the maximum degree of variance from the original dataset (see example in Fig. 2). This is done by performing an eigenvalue decomposition and projecting the data using the eigenvectors corresponding to the higher eigenvalues, the *principal components*. The principal components are orthogonal to each other and keep most of the variance from the original data set [17].

PCA is typically applied to the fault detection step, even though it can be also applied to the fault isolation step performing the appropriate discriminant analysis added as described so far.

FDA and PLS are also dimensionality reduction techniques. FDA performs the projection in a way that the scatter between observation corresponding to the same class (same fault) is minimized and the scatter between observations belonging to different classes is maximized, therefore directly serving as a fault isolation technique. PLS maximizes the covariance between the observation matrix and the class matrix [18], i.e. maximizes the scatter between data of the same class, by rotating the loading vectors iteratively until the regression is improved enough.

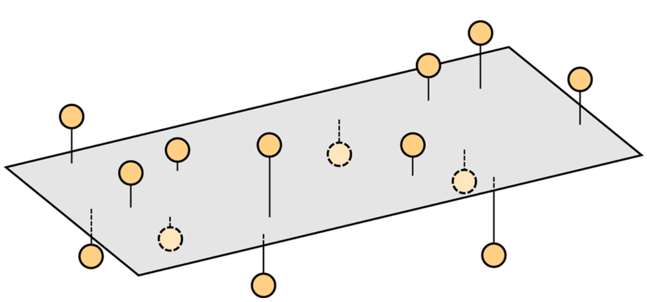

Fig. 2. Visualization of PCA dimensionality reduction from 3D to 2D. The PCA procedure finds the plane that minimizes the variability lost in the projection.

PCA, PLS and FDA do not account for dynamic behavior by themselves. In general, serial correlations (time-dependent) can be added by constructing an augmented input data matrix that includes lagged copies of the observed variables. The new matrix can be seen as a sliding window and the augmentation is parameterized by the lag parameter k and the embedding dimension M, such that the augmented matrix contains the vectors $\mathbf{x_i}(t)$, $\mathbf{x_i}(t-k)$, $\mathbf{x_i}(t-2k)$ and so on until $\mathbf{x_i}(t-(1-M)k)$ for all variables $i = 1, 2, \ldots, m$. The augmentation parameter k shall be determined satisfying that the new coordinates are as independent as possible but without losing information of the system. This task can be systematically approached by minimizing the autocorrelation function (ACF) or the average mutual information (AMI) [19]. On the other hand, the embedding dimension parameter M must comply with including the periodic responses of the system. When applying the data matrix augmentation approach to the methods outlined so far, their dynamic variants DPCA, DFDA and DPLS are obtained.

3.2. *Kernel approaches*

In contrast with the aforementioned techniques where the algorithm needs to generate a feature vector in order to perform the classification or clustering task, kernel-based methods rely on applying a kernel function on raw data.

Kernels are similarity functions whose output is a measure of how far two samples lie, i.e. how dissimilar they are. They help in building a cost function that, if minimized, separates the observation space in several regions representing each class, i.e. each fault class (see example in Fig. 3). There are various types of kernels, one of the most popular being the Gaussian kernel or radial basis function (RBF) kernel [20],

$$k(\boldsymbol{x}, \boldsymbol{x}^i) = \exp\left(-\left\|\boldsymbol{x} - \boldsymbol{x}^{(i)}\right\|^2 / 2\sigma\right)$$

where $k(\boldsymbol{x}, \boldsymbol{x}^i)$ is the similarity function for a test observation sample $\boldsymbol{x}$ and a landmark vector $\boldsymbol{x}^i$. The landmark corresponds to a training sample i of the same dimensions as $\boldsymbol{x}$ and σ is a hyperparameter related to the likelihood of the two samples belonging to the same class in the basis of a Gaussian distribution.

Support vector machines (SVM) are a widely used supervised technique based on kernels. SVM learn weights for similarity functions applied to all the training dataset by minimizing its cost function and doing a large margin separation of the data depending on their classes.

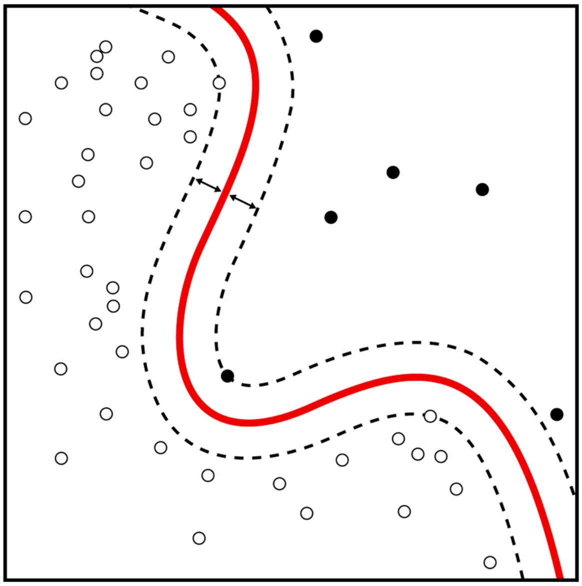

Fig. 3. Example of two-dimensional classification using SVM. Source: Alisneaky, CC0 1.0.

When using non-linear kernels such as RBF, they can learn complex classification functions like the one in Fig. 3.

3.3. Tree-based methods

Decision trees take the input dataset X and transform it into a response Y by breaking the input data into smaller subspaces, each one of them with a "purer" meaning in terms of information. In smaller regions, very simple local models can be fitted. The algorithm stops when further segmentation cannot improve the output above a specific threshold. The tree approach can then be seen as a set of IF-THEN statements where each conditional is applied inside the non-overlapping subspaces, which end up being a set of hyperrectangles.

When the output of a tree is discrete, it is called a classification tree, and when it has a continuous output, a regression tree. Decision trees differ from neural networks in that the latter has a fixed structure defined a priori by the user, while the former progressively grows according to optimum results in each region. On the other hand, the tree's computational complexity heavily increases with the dimensionality of the data.

The first automated decision tree was developed by [21] with the automatic interaction detection (AID). It managed to predict a value by averaging the input data at each partition and partitions were found by minimizing least-square deviations. After Morgan's success, many algorithms based on his were developed such as the MAID-M that allowed multiple variables, the THAID that could work for classification tasks, and the CHAID algorithm that added features to restrict overfitting, a direct consequence of the tree-based concepts [19]. Approaches still in use are the classification and regression tree (CART) algorithm [22] and the C4.5 [23]. CART combines classification and regression with a solution to overfitting, by programming a trade-off between model complexity and generalization of the model. C4.5 algorithm differs from CART in that it can provide multiple partitions per subspace, not only binary separation.

Between modern approaches arising from tree-based decision, random forests were created by Breiman [24]. Random forests add split randomization, which enhances the robustness of the model by averaging the behavior of different random trees. This feature also relates to resistance to overfitting issues. In general, tree-based approaches present themselves as flexible tools and have the potential of handling highly complex decision-making problems like fault diagnosis.

3.4. Artificial neural networks

An artificial neural network (ANN) is a computational model inspired by the connection between neurons in the human brain. The concept of *neural network* lumps a wide group of structures. Some types are multilayer perceptrons, radial basis function neural networks, Kohonen (self-organizing) neural networks and deep learning neural networks [19].

A typical neural network consists of a series of layers formed by nodes (see example in Fig. 4). The input layer represents the data fed to the system—for fault detection, mainly raw sensor measurements. Each of the input elements is fed to all nodes of the next layer, part of the *hidden layers*. The hidden layers nodes perform some calculations over the input values and output them to the last layer, the *output layer*. This layer acts in a similar way as the previous ones but its output will be the final result of the model and the one visible for the user, usually binary values that determine the membership of the input data to a certain class, e.g. a fault.

Any node in the hidden and output layers processes its input data in a linear part, $z^{[l]} = W^{[l]}a^{[l-1]} + b^{[l]}$ and a non-linear part or *activation*, $a^{[l]} = g^{[l]}\ z^{[l]}$. $W^{[l]}$ and $b^{[l]}$ are the trainable parameters of the network and represent the *weights* and the *bias*, respectively, of a generic layer l ($l \in [1, L]$). The activations are calculated applying a non-linear function to the linear values $z^{[l]}$. Many non-linear functions can be applied and some popular ones are the sigmoid $g(z) = \frac{1}{1+e^{z}}$, the hyperbolic tangent, $g(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$ or the rectified linear unit (ReLU) function, $g(z) = max(0, z)$.

The parameters (weights and biases) of an ANN are trained using known historical data to obtain a model able to predict the occurrence of faults upon new inputs. Unsupervised applications of ANN derive in the so-called self-organizing or Kohonen neural networks, which are able to train clustering models working with unlabelled data and using an ANN architecture.

3.5. Other data-driven techniques

Other approaches for fault diagnosis systems apply system identification and state-space representation to improve the effectiveness of data over different instants. One of the most used methods in this area is the canonicalvariate analysis (CVA).

CVA is a subspace algorithm that, in particular, shares common features with PCA, FDA and PLS and this makes it an interesting candidate for fault diagnosis. CVA is a dimensionality reduction technique based on multivariate statistical analysis but, in this case, it involves the selection of pairs input variable-output variable that maximizes a correlation measure [25]. Subspace algorithms assume that the augmented dynamic matrix (see Section 3.1) contains all the

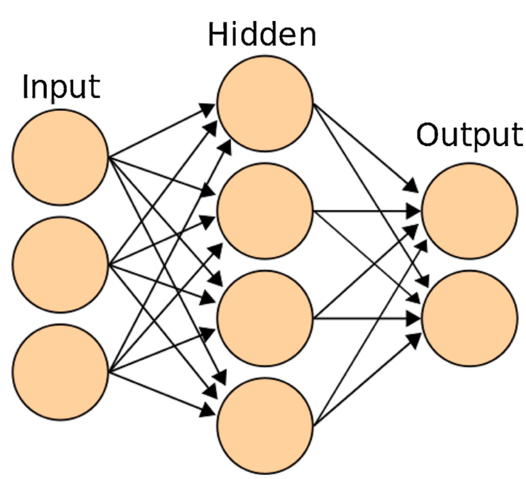

Fig. 4. Minimal ANN representation. Source: Cburnett, CC BY-SA 3.0.

dynamic information of the process, thus avoiding the need for a priori parameterization of models analogous to state-space representations.

3.6. Model-based methods

Model-based fault diagnosis relies on mathematical models to assess deviations in the behavior of the actual plant. These deviations are called *residuals* and can be obtained by several methods. Examples of them are state estimation and parity relations [26]; but also through a direct comparison between the simulated process and the actual plant. State-estimation uses the concept of observer to reconstruct the internal state of the system by measuring its outputs (sensor measurements) using the state space representation.

On the other hand, parity relations are capable of generating equations that only depend on the inputs and outputs of the system, thus managing to detect deviations in the residuals upon faulty behavior with less knowledge of the process.

Mathematical models, when available, are excellent tools to predict the behavior of the system, and are useful for fault isolation since their results are easy to physically interpret unlike data-driven methods, which sometimes can be seen as “black boxes”. But to be built, they need a lot of prior knowledge that is not always affordable for complex systems. However, simple model-based methods, even though not exact, can complement data-driven methods in those tasks they perform worse.

4. Discussion

4.1. The training of data-driven approaches

The topics faced in this document arise a new question: how to train the reasoning units since there is no data of highly intensive tritium processing systems such as ITER? The following ideas suggest new ways of exploiting data to this aim.

- Using the information available of failure in existing tritium systems such as TSTA, JET, TPL and TLK, as it appears in the compilations by Cadwallader [13] and Casey et al. [27]. However, the size of training sets in machine learning and pattern recognition is important, especially for complex and non-linear systems [28]. The available public literature regarding tritium systems does not provide for the massive amount of data that complex decision algorithms need.
- Simulation of tritium system faults through plant first-principle modeling could complete this lack of knowledge. Examples of this are the efforts made by Cristescu et al. [5] and the ongoing developments of Nougués et al. [6] in order to obtain new fault data.
- Also, useful ways to provide for additional data is exploring the use of other existing and well-known systems out of the tritium context as a test bench to study the different dynamic monitoring approaches (see Section 4.2).
- Transfer learning [29] can then be used as a tool to pre-train machine learning models for new uses based on previous trained and functional models.

4.2. The use of a test bench

Given the absence of large-scale tritium processes, actual historical data to train the fault diagnosis systems cannot be directly obtained. One of the possibilities to overcome this issue is to work on a system that does have historical data and/or allows to generate extra data through simulation, does already exist, and uses its learning process to pre-train the monitoring systems for tritium processes. A candidate that fits these expectations is the Tennessee-Eastman process.

The Tennessee Eastman process is a model of a chemical plant proposed by Downs and Vogel [30] and meant as a tool for validation at the control engineering field and to standardize the diverse results obtained along with the scientific literature.

This model is based on an actual plant owned by the Eastman Chemical Company and represents a complex, highly unstable system that is difficult to predict because of its internal recycle streams and the influence of the chemical reactions in the global pressure and temperature of the plant. This model allows access to a high variety of sensors, actuators, and the possibility to introduce disturbances and failures, making this model complete in terms of control and fault analysis and with a great background in the available literature, where efforts have been put into problems from classical control engineering [31] to fault diagnosis [32].

In addition to its interest for validation of the strategy itself, the Tennessee Eastman process can help set up a monitoring system such as that envisaged for tritium processes. The TE represents a relatively small system but complex enough to be of interest in the field of fault diagnosis.

4.3. Fusion of several data-driven and model-based decision units

As it can be seen from the review in Section 3, both model-based and data-driven approaches have complementary qualities. Mathematical models are normally more effective than data-driven models when enough information about the plant is available for its construction. However, in actual highly complex processes, accurate mathematical models are time-expensive. Data-driven techniques are powerful, relatively easy to implement, and more effective in detecting specific failures for which they have been trained, but they are less reliable in diagnosing unknown types of failure.

In the last years, a path of study has been initiated trying to combine both methods to solve the monitoring problem [12,33]. Some interesting approaches use fuzzy logic in order to combine different techniques such as that of Ruiz et al. [34], where simulation, artificial neural network and fuzzy logic based on IF-THEN rules are used. Fuzzy logic is reviewed by Chiang et al. [35] as a general tool to compose hybrid fault diagnosis approaches.

On the other hand, the first steps have been taken on applying a hybrid monitoring fault system using Bayesian networks as a generic tool for the integration of various fault diagnosis techniques [36,37]. This approach has not been applied to the monitoring of tritium in nuclear fusion and represents a promising path in future work.

5. Conclusions

The present document has stated the basis of the tritium monitoring problem in large tritium plants from the point of view of fault detection and isolation. The focus has been put on the need for a dynamic monitoring strategy to give nuclear fusion power plants the possibility to be feasible and how this goal is hard given the constraints of tritium sensing technology and emissions regulation. A review of advanced fault diagnosis techniques has been made in order to give a background for further challenges in the field. Such challenges are outlined in terms of training data management and collection, availability of models and hybrid approaches that can extract the best features for a global fault diagnosis approach. Further related work consists in how to address the correcting actions to be able to return to the normal operation of the plant in the event of the detection of a fault, therefore, avoiding a shutdown and reducing the impact of the correction in the normal operation of the complete system.AcronymsACFautocorrelation functionAIDautomatic interaction detectionAMIaverage mutual informationANNartificial neural networkCARTclassification and regression treeCVAcanonical variate analysisFDAFisher discriminant analysisMBAmass balance areasPCAprincipal component analysisPLSpartial least squaresRBFradial basis functionSVMsupport vector machines

Acronyms

ACF	autocorrelation function
AID	automatic interaction detection

AMI average mutual information
ANN artificial neural network
CART classification and regression tree
CVA canonical variate analysis
FDA Fisher discriminant analysis
MBA mass balance areas
PCA principal component analysis
PLS partial least squares
RBF radial basis function
SVM support vector machines

Author contribution

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Methodology: Eduardo Iraola, Luis Sedano
Software: Eduardo Iraola
Validation: Eduardo Iraola, Luis Sedano, José M. Nougués
Formal analysis: Eduardo Iraola, Luis Sedano
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Declaration of Competing Interest

The authors report no declarations of interest.

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References

[1] M. Abdou, N.B. Morley, S. Smolentsev, A. Ying, S. Malang, A. Rowcliffe, M. Ulrickson, Blanket/first wall challenges and required R&D on the pathway to DEMO, Fusion Eng. Des. 100 (2015) 2–43, https://doi.org/10.1016/j.fusengdes.2015.07.021.
[2] R. Causey, R. Karnesky, C. San Marchi, Tritium barriers and tritium diffusion in fusion reactors, Compr. Nucl. Mater. 4 (2012) 511–549, https://doi.org/10.1016/B978-0-08-056033-5.00116-6.
[3] I.-R. Cristescu, I. Cristescu, D. Murdoch, L. Dörr, M. Glugla, Tritium inventory assessment for ITER using TRIMO, Fusion Eng. Des. 81 (2006) 763–769, https://doi.org/10.1016/j.fusengdes.2005.06.367.
[4] M. Hara, Y. Kawamura, T. Tanabe, Tritium measurement I-tritium in gas, liquid, and solid, in: T. Tanabe (Ed.), Tritium: Fuel of Fusion Reactors, Springer Japan, Tokyo, 2017, pp. 137–164, https://doi.org/10.1007/978-4-431-56460-7_7.
[5] I.R. Cristescu, L. Dörr, A. Busigin, D. Murdoch, ITER dynamic tritium inventory modeling code, Fusion Sci. Technol. 48 (2005) 343–348, https://doi.org/10.13182/FST05-A939.
[6] J.M. Nougués, J.A. Feliu, G. Campanyà, E. Iraola, L. Batet, L. Sedano, Advanced tools for ITER tritium plant system modeling and design, Fusion Sci. Technol. 76 (2020) 649–652, https://doi.org/10.1080/15361055.2020.1741278.
[7] L. Ren, W. Lv, S. Jiang, Y. Xiao, Fault diagnosis using a joint model based on sparse representation and SVM, IEEE Trans. Instrum. Meas. 65 (2016) 2313–2320, https://doi.org/10.1109/TIM.2016.2575318.
[8] A. Eremeev, P. Varshavskiy, R. Alekhin, Case-based reasoning module for intelligent decision support systems, in: A. Abraham, S. Kovalev, V. Tarassov, V. Snášel (Eds.), Proceedings of the First International Scientific Conference "Intelligent Information Technologies for Industry" (IITI'16). Advances in Intelligent Systems and Computing, vol. 450, Springer International Publishing, 2016, pp. 207–216, https://doi.org/10.1007/978-3-319-33609-1_18.
[9] F. Caliva, F.S. De Ribeiro, A. Mylonakis, C. Demazirere, P. Vinai, G. Leontidis, S. Kollias, A deep learning approach to anomaly detection in nuclear reactors, 2018 International Joint Conference on Neural Networks (IJCNN) (2018) 1–8, https://doi.org/10.1109/IJCNN.2018.8489130.
[10] J. Liu, R. Seraoui, V. Vitelli, E. Zio, Nuclear power plant components condition monitoring by probabilistic support vector machine, Ann. Nucl. Energy 56 (2013) 23–33, https://doi.org/10.1016/j.anucene.2013.01.005.
[11] D.-L. Yang, W. Mou, An integrated decision support system in a Chinese chemical plant, Interfaces 23 (1993) 93–100, https://doi.org/10.1287/inte.23.6.93.
[12] R. Isermann, P. Ballé, Trends in the application of model based fault detection and diagnosis of technical processes, IFAC Proc. Vol. 29 (1996) 6325–6336, https://doi.org/10.1016/S1474-6670(17)58696-6.
[13] L.C. Cadwallader, Comparison of tritium component failure rate data, Fusion Sci. Technol. 47 (2005) 983–988, https://doi.org/10.13182/FST05-A816.
[14] T. Tanabe, Introduction of a nuclear fusion reactor. Tritium: Fuel of Fusion Reactors, Springer, Japan, Tokyo, 2017, pp. 3–25, https://doi.org/10.1007/978-4-431-56460-7_1.
[15] P. Fichet, A. Bultel, S. Markelj, C. Moreno, Review of the Different Techniques to Analyse Tritium, TRANSAT, 2018. Technical Report TRANSAT-D2.1.
[16] Inprocess Technology and Consulting Group, Digital Twins for Process Operations Enhancement, 2020, in: https://inprocessgroup.com/en/solution/digital-twins-for-process-operations-enhancement.
[17] L.H. Chiang, E.L. Russell, R.D. Braatz, Principal component analysis. Fault Detection and Diagnosis in Industrial Systems, Advanced Textbooks in Control and Signal Processing, Springer London, London, 2001, pp. 35–55, https://doi.org/10.1007/978-1-4471-0347-9_4.
[18] L.H. Chiang, E.L. Russell, R.D. Braatz, Partial least squares. Fault Detection and Diagnosis in Industrial Systems, Advanced Textbooks in Control and Signal Processing, Springer London, London, 2001, pp. 71–84, https://doi.org/10.1007/978-1-4471-0347-9_6.
[19] C. Aldrich, L. Auret, Unsupervised Process Monitoring and Fault Diagnosis With Machine Learning Methods, Springer London, London, 2013, https://doi.org/10.1007/978-1-4471-5185-2.
[20] G. Rätsch, A Brief Introduction Into Machine Learning, 21st Chaos Communication Congress, 2004, pp. 1–6. http://www.mva.me/educational/hci/read/ML_reading.pdf.
[21] J.N. Morgan, J.A. Sonquist, Problems in the analysis of survey data, and a proposal, J. Am. Stat. Assoc. 58 (1963) 415–434, https://doi.org/10.1080/01621459.1963.10500855.
[22] L. Breiman, J.H. Friedman, R.A. Olshen, C.J. Stone, Classification And Regression Trees, Routledge, 1984, https://doi.org/10.1201/9781315139470.
[23] S.L. Salzberg, C4.5: Programs for machine learning by J. Ross Quinlan. Morgan Kaufmann Publishers, Inc., 1993, Mach. Learn. 16 (1994) 235–240, https://doi.org/10.1007/BF00993309.
[24] L. Breiman, Random forests, Mach. Learn. 45 (2001) 5–32, https://doi.org/10.1201/9780367816377-11.
[25] T. Katayama, S. Sugimoto, Statistical Methods in Control & Signal Processing, CRC Press, McLean, Virginia, 2018, https://doi.org/10.1201/9781315214832.
[26] R.J. Patton, P.M. Frank, R.N. Clark, Issues of Fault Diagnosis for Dynamic Systems, Springer-Verlag, London, 2000.
[27] M. Casey, K. Gruetzmacher, J. Bartlit, L. Cadwallader, The Data Collection System for Failure/Maintenance at the Tritium Systems Test Assembly, Technical Report, Los Alamos National Laboratory, New Mexico, 1988. https://digital.library.unt.edu/ark:/67531/metadc1059876/.
[28] A. Jain, B. Chandrasekaran, Dimensionality and sample size considerations in pattern recognition practice, in: Handbook of Statistics, vol. 2, 1982, pp. 835–855, https://doi.org/10.1016/S0169-7161(82)02042-2.
[29] S. Bozinovski, Reminder of the first paper on transfer learning in neural networks, 1976, Informatica 44 (2020), https://doi.org/10.31449/inf.v44i3.2828.
[30] J. Downs, E. Vogel, A plant-wide industrial process control problem, Comput. Chem. Eng. 17 (1993) 245–255, https://doi.org/10.1016/0098-1354(93)80018-I.
[31] T. McAvoy, N. Ye, Base control for the Tennessee Eastman problem, Comput. Chem. Eng. 18 (1994) 383–413, https://doi.org/10.1016/0098-1354(94)88019-0.
[32] S. Yin, S.X. Ding, A. Haghani, H. Hao, P. Zhang, A comparison study of basic data-driven fault diagnosis and process monitoring methods on the benchmark Tennessee Eastman process, J. Process Control 22 (2012) 1567–1581, https://doi.org/10.1016/j.jprocont.2012.06.009.
[33] Y. Zhao, F. Xiao, S. Wang, An intelligent chiller fault detection and diagnosis methodology using Bayesian belief network, Energy Build. 57 (2013) 278–288, https://doi.org/10.1016/j.enbuild.2012.11.007.
[34] D. Ruiz, J.M. Nougués, L. Puigjaner, On-line process fault detection and diagnosis in plants with recycle, Comput. Chem. Eng. 23 (1999) S219–S222, https://doi.org/10.1016/S0098-1354(99)80054-4.
[35] L.H. Chiang, E.L. Russell, R.D. Braatz, Knowledge-based methods. Fault Detection and Diagnosis in Industrial Systems, Advanced Textbooks in Control and Signal Processing, Springer London, London, 2001, pp. 223–254, https://doi.org/10.1007/978-1-4471-0347-9_12.
[36] J. Siswantoro, A.S. Prabuwono, A. Abdullah, B. Idrus, A linear model based on Kalman filter for improving neural network classification performance, Expert Syst. Appl. 49 (2016) 112–122, https://doi.org/10.1016/j.eswa.2015.12.012.
[37] K. Tidriri, T. Tiplica, N. Chatti, S. Verron, A generic framework for decision fusion in fault detection and diagnosis, Eng. Appl. Artif. Intell. 71 (2018) 73–86, https://doi.org/10.1016/j.engappai.2018.02.014.