Model based fault diagnosis in networked linear time invariant systems

THESIS BOOKLET

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1 Introduction

The complexity and the automation degree of technological processes are continuously growing in this modern era. Today, their standards pay close attention to issues regarding high availability, reliability, safe operation, and cost efficiency. Thus, every effort to enhance the reliability and robustness of individual components such as sensors, actuators, and controllers (or computers) is critical. However, a fault free situation can hardly be guaranteed. Hence, Fault Detection and Isolation (FDI) techniques are critical to ensure a reliable operation. Although Linear Time Invariant (LTI) systems form the known well investigated class of dynamic systems, their FDI methods still need improvements and refinements mostly in complex networked cases. Such advancements in the FDI methods may utilize the specialties of the application area of primary importance.

By using the minimum number of sensors placed cleverly, this present study aims to enrich the existing FDI literature specifically for model based fault diagnosis methods on networked LTI systems. Despite being limited to the LTI systems, this special class provides a mathematical framework to analyse and understand a wide range of phenomena in nature. Moreover, many nonlinearities can be approximated locally with linear models by defining a suitable domain or equilibrium point [1].

Two main classes of networked LTI systems are addressed in this study: robot platoons as an important part of modern transportation technologies, and Heat Exchange Networks (HENs) as one of the important processes of industries. The selection of robot platoons and HEN is based on their popularity in representing networked LTI systems over time in many literatures either in system or control theory. Some small examples where the robot or vehicle platoons are modelled by LTI systems for the sake of control purposes can be seen in the works of [2, 3, 4, 5]. In the case of HEN, the works by [6, 7, 8, 9] demonstrate the modelling of HEN as LTI system.

1.1 Model based FDI in networked LTI systems

Model based and data driven methods in FDI FDI mainly deals with monitoring processes to ensure the operation safety of control systems. There exist many different fault diagnosis techniques. Yet, the important main categories comprise model based and data driven methods. Data driven methods rely on data from system operations that are used to train machine learning (ML) or artificial intelligence (AI) data structures to detect and identify faults. Nowadays, these methods are gaining popularity because they are easier to implement due to the current development of digital computing technology. However, their reliability strictly depends on the availability and quality of the data.

Meanwhile, even though model based methods of FDI emerged in the early 70s, their performance has been proven in many successful implementations in the industrial processes. There are many different techniques and each of them is usually developed for different purposes. Mostly, these methods are based on dynamic system models. Model based methods often use models derived from first principles that rely heavily on the knowledge of basic physical and/or chemical principles. Model based fault diagnosis methods are also intimate with the modern control theory.

The importance and significance of FDI in networked systems On the other hand, nowadays, the modern society relies on networks, e.g., computer networks, transportation networks, social networks, electrical networks, etc. Although they could comprise simple elements, their large number and interconnections make them an important subclass of complex systems. As a dynamic system, a network presents many theoretical challenges during control or diagnosis method design.

Even though there is already abundant literature for fault diagnosis for networked systems, the number of works related to FDI in networked systems is advancing slowly compared to the rapid growth of the literature related to networked systems' complexity and communication techniques (protocols) development. There are still many various challenges because some approaches are effective only in handling some specific applications or faults. Nevertheless, the importance of network technologies in large scale control systems, as a powerful tool for data transfer, enforces the continuity of research in studying and developing fault diagnosis techniques for networked systems to ensure its reliability, availability, and security.

Generally, each subsystem in a networked system is designed with a specific function to accomplish a common goal in the network. A fault in a subsystem can propagate to others and will destroy or degrade the performance of the overall system. Thus, FDI is highly important to consider in the networked systems.

The sensor placement problem for FDI in networked systems It is preferred to install as few sensors as possible in the networked systems for either physical or financial reasons. On the other hand, there could be complex topologies in realistic networks (e.g. branching connections and loops). Thus, by considering the network topology, the sensor placement problem needs to be examined so that the existence of faults in the subsystems inside the network can be detected and isolated.

1.2 FDI in robot platoons

The importance of FDI in either robot or vehicle platoons can be seen from the large amount of existing literatures. [10] used parity equations to detect faulty sensors and actuators. [11] designed a fault detection technique and a sliding mode controller to compensate for the detected faults. A fault classification based on Machine Learning (ML) is also proposed by [12]. After devising an algorithm to detect and isolate the faults, [13] suggested using the model based approaches for vehicle platoons.

Most of the literature can be grouped into 2 categories. The first category is those who prioritize control objectives over fault identification (i.e., fault mitigation or the fault is treated as disturbances) such as in [14, 15, 11, 16]. Meanwhile, the second category is those who concentrate on fault isolation and estimation. This thesis tries to contribute to the second category in a networked environment. In this case, compared to the work of [13] which uses many sensors, and [10] which uses parity equations and nonlinear observers, model based fault diagnosis approaches that use conventional sensors and Unknown Input Observers (UIOs) are explored. UIO belongs to the group of linear observers. [17] and [18] have investigated the use of UIO to detect a faulty agent in the multi agent systems but have not gone into detail about the sources of the fault. [19] designed a centralized UIO for fault estimation purposes in a leader-follower linear multi agent systems. On the other hand, related to those previous works, this thesis explores how to design a bank of local UIOs in every subsystem to detect and isolate faulty sensors. Thus, it is more scalable compared to the global UIO. By considering simultaneous actuator fault and communication fault in the platoon's subsystems, actuator fault diagnosis is investigated that can be decoupled from communication faults.

1.3 FDI in heat exchanger network

Heat exchanger networks are a simple but important class of process systems. For FDI in process systems, much literature can be found. A number of possible neural network architectures for FDI in process systems are studied by [20]. Meanwhile, [21] proposed a hybrid technique by using the Principal Component Analysis (PCA) and a Bayesian network. A review about data driven methods for fault diagnosis in process systems has also been done by [22]. In addition, [23] did a literature review about data driven techniques that have been developed for chemical process systems. Recently, the interconnections among fault diagnosis, risk assessment, and abnormal situation management are analysed by [24].

As important as it is, many have researched parameter fault diagnosis in a heat exchange process, such as [25, 26, 27]. Moreover, the currently popular data driven methods have been exploited in much literature in handling parameter fault diagnosis in HEN [28, 29, 30]. However, in terms of network topology, splitting and joining connections are common to be found in the HEN. Combined with the sparsity of sensors and considering that it is not realistic to install sensors at every point or preferred place, it is important to investigate the sensor placement problem for fault diagnosis purposes in HEN. Yet, much literature neither includes the existence of these branching connections nor the sensor placement problem. Thus, this thesis tries to contribute by dealing first with investigating the sensor placement problem in correlation with branching connections' existence in the HEN. Then, by taking into account the obtained results, the parameter fault diagnosis using model based approach is explored.

Aside from joining and splitting connections, the existence of loops in networked LTI systems is also common as part of the network topology. In the case of HEN, the loop exists for energy or material efficiency and is a vital component in the control system. In a loop, a fault in a subsystem can propagate back to the subsystem where the fault first occurred. Here, fault estimation becomes more challenging as the fault's amplitude may become smaller [31]. Much of the literature discusses such problems using data driven approaches such as [32] and [33]. Therefore, this thesis tries to contribute to the same problem by proposing a model based approach as an alternative. Moreover, the approach considers that the proposed method uses the number of sensors as minimum as possible.

2 Basic notions

Fault modelling A fault is a phenomenon that changes the behaviour of the technological processes such that it no longer satisfies its original purpose. Generally, a fault induces considerable deviation from the normal behaviour of a system that is caused by some unexpected events [34] and it can be categorized into [35]:

1. Actuator faults (f_a): these faults cause changes in the actuator's behaviour.
2. Sensor faults (f_s): these faults directly affect the system's measurement.
3. Process faults (f_p): these faults directly affect the system's dynamic, for example a drastic change in system's parameter (parameter faults).

Consider the LTI systems with general state space representation as follows:

$$\begin{aligned} \dot{\boldsymbol{x}} &= A\boldsymbol{x} + B\boldsymbol{u} \ , \ \ \boldsymbol{x}(t_0) = \boldsymbol{x}_0 \\ \boldsymbol{y} &= C\boldsymbol{x} + D\boldsymbol{u} \end{aligned} \tag{1}$$

where $\boldsymbol{x}$ is the system's state, $\boldsymbol{u}$ is the system's input, and $\boldsymbol{y}$ is the system's measurement (output). A, B, C, and D are matrices with appropriate dimension.

Then, the actuator and sensor faults can be modelled by incorporating them into the general model in Eq (1) as:

$$\begin{aligned}\dot{\boldsymbol{x}} &= A\boldsymbol{x} + B(\boldsymbol{u} + \boldsymbol{f}_a)\\ \boldsymbol{y} &= C\boldsymbol{x} + D\boldsymbol{u} + \boldsymbol{f}_s\end{aligned} \tag{2}$$

Meanwhile, the parameter faults are modelled by changing the related matrix in the LTI model because they change the system's dynamic:

$$\begin{aligned}\dot{\boldsymbol{x}} &= A_f\boldsymbol{x} + B_f\boldsymbol{u}\\ \boldsymbol{y} &= C\boldsymbol{x} + D\boldsymbol{u}\end{aligned} \tag{3}$$

where A_f and B_f are matrices containing the changed parameters because of the faults.

Now, consider N interconnected subsystems by which the states of each subsystem in the network are also affected by the states of its neighbouring subsystems [36] as follows:

$$\begin{aligned}\dot{\boldsymbol{x}}^{(j)} &= A^{(j)}\boldsymbol{x}^{(j)} + B^{(j)}\boldsymbol{u}^{(j)} + I^{(j)}\boldsymbol{i}^{(j)}\\ \boldsymbol{y}^{(j)} &= C^{(j)}\boldsymbol{x}^{(j)} + D^{(j)}\boldsymbol{u}^{(j)}\end{aligned} \tag{4}$$

where $j = 1, 2, 3, ..., N$ represents the jth subsystem and $\boldsymbol{i}^{(j)}$ is the interconnection input which comes from the neighbouring subsystem's outputs. $I^{(j)}$ is an interconnection matrix with appropriate dimension.

By assuming static linear interconnections, the interconnection input $\boldsymbol{i}^{(j)}$ can be generally written as:

$$\boldsymbol{i}^{(j)} = L^{(jk)}\boldsymbol{y}^{(k)} \tag{5}$$

where $L^{(jk)}$ is called the adjacency matrix containing the relations between output measurements from the kth subsystem being connected as interconnection inputs to the jth subsystem.

Then, in the case of networked LTI systems subjected to actuator fault, sensor fault, and parameter fault, the dynamics of the jth subsystem can be written as:

$$\begin{aligned}\dot{\boldsymbol{x}}^{(j)} &= A_f^{(j)}\boldsymbol{x}^{(j)} + B_f^{(j)}(\boldsymbol{u}^{(j)} + \boldsymbol{f}_a^{(j)}) + I^{(j)}(\boldsymbol{i}^{(j)} + \delta\boldsymbol{i}^{(j)})\\ \boldsymbol{y}^{(j)} &= C^{(j)}\boldsymbol{x}^{(j)} + \boldsymbol{f}_s^{(j)} + D(\boldsymbol{u} + \boldsymbol{f}_a^{(j)})\end{aligned} \tag{6}$$

where $\delta\boldsymbol{i}^{(j)}$ is a term that describes the propagation of faults from other subsystems through the network.

Throughout this research, the fault is assumed to be an unknown vector that has zero value in fault free condition and it is a deterministic time function.

Fault detection, isolation, and estimation Here, some definitions and models related to the fault diagnosis process are presented [34, 35, 37]:

1. Fault detection: a binary decision about either there are some presences of any fault or the absence of all faults.
2. Fault isolation: the process to determine the occurrence location of the faults.
3. Weak fault isolation: fault isolation process where the faults are assumed to happen one at a time (no simultaneous faults).
4. Fault estimation: the process to determine the magnitude of the faults based on the available measurements.

Fault detection Consider a residual generator for system in Eq (2) that has the following model:

$$\begin{aligned} \dot{\boldsymbol{z}} &= A_z \boldsymbol{z} + B_{zu} \boldsymbol{u} + B_{zy} \boldsymbol{y} \ , \ \boldsymbol{z}(\boldsymbol{t_0}) = \boldsymbol{z_0} \\ \boldsymbol{r} &= C_z \boldsymbol{z} + D_{ru} \boldsymbol{u} + D_{ry} \boldsymbol{y} \end{aligned} \tag{7}$$

where $\boldsymbol{z}$ is the residual generator's states and $\boldsymbol{r}$ is the residual signal (or residues). A_z, B_{zu}, B_{zy}, C_z, D_{ru}, and D_{ry} are matrices with appropriate dimensions.

By taking the previous fault diagnosis definitions, the fault detection problem can be redefined as follows [35, 37]: given a system as in Eq (2), design a residual generator as in Eq (7) such that:

1. In the absence of fault (both $\boldsymbol{f_a} = \boldsymbol{0}$ and $\boldsymbol{f_s} = \boldsymbol{0}$), the residues should be asymptotically decays to zero ($\lim_{t\to\infty} \boldsymbol{r} = \boldsymbol{0}$).
2. The residues $\boldsymbol{r}$ should be affected by the fault (i.e. if $\boldsymbol{f_a} \neq \boldsymbol{0} \vee \boldsymbol{f_s} \neq \boldsymbol{0}$, then $\lim_{t\to\infty} \boldsymbol{r} \neq \boldsymbol{0}$).

Fault isolation In case of fault isolation, a bank of residual generators is designed in such a way that each residues is only affected by a specific fault [34, 35, 37]. Thus, by observing the produced residues, the fault can be isolated.

Fault estimation Fault estimation represents the next enhancement and is mostly done after the fault has been isolated. It is a challenging problem and some methods usually can only be applied to some specific type of faults [34, 35, 37]. Generally, the steady state value of the fault signal can be estimated and the estimation problem in case of a constant fault is formulated as follows: obtain the fault estimate $\hat{\boldsymbol{f}}$ such that $\lim_{t\to\infty} \|\boldsymbol{f} - \hat{\boldsymbol{f}}\| = \boldsymbol{0}$.

By assuming that the fault can be modelled as a constant signal, a common fault estimation method is to consider the fault as an additional state so that an observer can be designed to estimate it. The system model that is augmented by the fault is called an extended state space model and it can be written in the following general form:

$$\begin{aligned} \begin{bmatrix} \dot{\boldsymbol{x}} \\ \dot{\boldsymbol{f}} \end{bmatrix} &= \begin{bmatrix} A & F_x \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{f} \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} \boldsymbol{u} \\ \boldsymbol{y} &= \begin{bmatrix} C & F_y \end{bmatrix} \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{f} \end{bmatrix} \end{aligned} \tag{8}$$

where $\boldsymbol{f}$ is the considered fault, 0 is the zero matrix, F_x is the fault distribution matrix with respect to system's states, and F_y is the fault distribution matrix with respect to system's measurements.

3 The aims of the research

The aim of this research is to develop model based fault diagnosis methods for networked LTI systems, specifically robot platoons and heat exchange networks. The following goals are set:

1. To develop networked LTI system models that can meet the objectives of fault detection, isolation, and estimation purposes.

   As robot platoons and heat exchange networks are two important classes of networked systems, many previous works discuss their dynamical modelling. However, based on them, this study aims to construct suitable models that can be used for fault diagnosis. To do this, after the fault has been modelled (i.e. sensor fault, actuator fault, or parameter fault), a dynamical system model of the networked LTI systems will be constructed that includes the fault's model. This problem is challenging because, in addition to the model of the fault being included, the network's model should also be able to capture the fault's effect propagation from one subsystem to the others.

2. To solve the sensor placement problem that is necessary for fault diagnosis in the networked LTI systems.

   The sensor placement problem is the problem of selecting measurement variables (i.e. where to install sensors) to maximize some objectives while satisfying various design constraints. Here, the objective is that every possible fault should be able to be detected and isolated. Meanwhile, the constraints are related to physical and financial reasons, i.e., the number of sensors used is as minimum as possible and they are installed at realistic places, for example at the end of connections. This problem is challenging because, as the fault can propagate to the other subsystems, the source of the fault should still be able to be localized. Furthermore, as parameter fault is considered, suitable approaches that are independent of parameters should be explored. It should be noted that, by allowing sensors to be put only at some specific points, unmeasurable states will emerge.

3. To investigate the effect of network topology on fault diagnosis in networked LTI systems using the model based approach.

   This study also investigates the relationship between network topology and fault diagnosis by using the model based approaches. To make it similar to the real world environment, the features that are considered in the network topology are splitting connections, joining connections, and loops. This problem is challenging because, combined with the previously mentioned sensor placement problem, the presence of unmeasurable states could make the fault effect propagation difficult to track.

4 New scientific results

The new scientific results presented in this thesis are summarised in the following thesis points. For each thesis point, the corresponding author's publications are also listed.

4.1 Thesis I

The corresponding publications are [A1] and [A2].

In this thesis, a model based actuator and sensor fault diagnosis method for robot platoons that move in a leader-follower scheme is proposed. As a networked system with distributed control, the states of each robot are affected by the states of its preceding robot. Thus, to achieve reliable platoon control, network communication can be applied for the sake of information transmission. The sensor and actuator fault diagnosis method is studied separately because of their different goals. For actuator fault diagnosis, the goals are to detect, isolate, and estimate the fault. Meanwhile, for sensor fault diagnosis, the faulty sensor's detection and isolation are the goals. The considered sensors include a GPS-based sensor, a wheel-mounted velocity sensor, and a radar sensor for inter-vehicle distance measurement. No sensor fault is assumed in studying the actuator fault diagnosis and vice versa.

Sensor fault diagnosis related research results:

1. A model for robot platoons with network communication was proposed that can capture the effect of sensor fault propagation in the networked systems.

2. By using the networked system model as the basis, a bank of distributed Unknown Input Observers (UIO)s as residual generators was designed that isolate the faulty sensor in each robot.
3. A threshold computation was also proposed to prevent false alarms in the presence of measurement noise when there are no faulty sensors.
4. The extension of the UIO-based sensor fault isolation method for a more general class of networked LTI systems is also presented.

Actuator fault diagnosis related research results:

1. By exploiting the measurement redundancy, a filtering technique is proposed to eliminate the need for network communication so that the actuator fault and the communication fault can be decoupled from each other.
2. By using the filter, the model without network communication was derived that shows similar behaviour to the original model with network communication.
3. Based on the model without network communication, a PI observer was designed to estimate the magnitude of the actuator fault.
4. Two estimation filter gain design methods were examined. The pole placement design method results in a rapid fault estimation process but the measurement noise still influences the estimation result. Meanwhile, by using the Linear Quadratic Estimator (LQE), the measurement noise is eliminated but the estimation process needs a much longer time.

4.2 Thesis II

The corresponding publications are [A3] and [A4].

In this thesis, model based methods are proposed for fault detection, isolation, and estimation in heat exchange networks where the considered fault is the parameter change in the heat transfer coefficient that describes the effect of environmental temperature on the temperatures inside the heat exchange networks. In addition, the proposed model of the heat exchange networks includes splitting and joining connections that are common in real world applications.

The results of this research are:

1. By using Signed Directed Graph (SDG) to investigate the structural observability in solving the sensor placement problem, it is found that

- For splitting connections, it is enough to put sensors only at the end of each element after the split to detect, isolate, and estimate the fault that happens either before or after the split.
- For joining connections, it is necessary to put sensors at the end of each element both before and after the joint to detect, isolate, and estimate the fault that happens either before or after the joint.
- If the fault happens only at a certain location along the length of a specific tube, then putting a sensor only at the end of the considered tube is enough to detect and estimate the fault.

2. In the splitting connections, a bank of linear observers can detect and isolate whether the fault happens before or after the split.

3. As the parameter fault induces bilinear fault input terms in the model, a bank of nonlinear observers that is based on the parameter adaptation can estimate it.

4. By using sensitivity analysis, it is found that fault isolation can hardly be performed in the case of a single parameter fault in a certain location in a specific tube.

4.3 Thesis III

The corresponding publication is [A5].

In this thesis, a model based fault diagnosis method is proposed for the networked linear heat exchange systems that contain splitting and joining connections, and also loops. The considered fault enters into the subsystem as an additive linear input term.

The results of this research are:

1. By using steady state value analysis, a fault isolation algorithm requiring two sensors is proposed that can localize the fault in the loops inside the network.

2. After the fault has been isolated, a PI observer is proposed to estimate the magnitude of the fault.

3. The proposed method has good robustness against the heat transfer coefficient parameter uncertainty that is hard to estimate in practice.

4. The proposed method can also isolate and correctly estimate incipient faults (slowly developing faults).

5 Suggestions for future works

Here, possible future works for each thesis point are presented:

- For Thesis I, there is a possibility to explore other approaches to deal with the diagnosis of the communication faults in the network. In addition, the research results can further be used for designing a fault tolerant controller for such systems. Lastly, in this present study, actuator fault and sensor fault diagnosis are studied separately (i.e. no sensor fault is assumed during the actuator fault diagnosis study and vice versa). Thus, a further study to simultaneously integrate them can be considered.
- For Thesis II, it is shown that parameter fault at a certain location along the length of a tube in an element of heat exchange networks is hard to isolate. This leads to possible future work in finding other approaches to tackle this problem.
- For Thesis III, further studies can be carried out to generalize the proposed method to Multiple Input Multiple Output (MIMO) systems.

MTMT profile:
`https://m2.mtmt.hu/gui2/?type=authors&mode=browse&sel=10079504`

The author's publications

[A1] W. Kurniawan and L. Marton. "Sensor Faults Isolation in Networked Control Systems: Application to Mobile Robot Platoons". In: *Sensors* 21.20 (2021), p. 6702.

[A2] W. Kurniawan and L. Marton. "Actuator fault estimation in robot platoons". In: *Proceedings of the 11th International Conference on Systems and Control*. 2023, pp. 858–863.

[A3] W. Kurniawan, K. M. Hangos, and L. Márton. "Parameter fault diagnosis in heat exchange networks with distributed time delay". In: *IFAC-PapersOnLine* 55.18 (2022), pp. 39–44.

[A4] W. Kurniawan, K. M. Hangos, and L. Marton. "Parameter fault estimation in distributed heating/cooling systems". In: *Proceedings of the 7th International Conference on Sustainable Information Engineering and Technology*. 2022, pp. 111–118.

[A5] W. Kurniawan, K. M. Hangos, and L. Márton. "Fault Isolation and Estimation in Networks of Linear Process Systems". In: *Entropy* 25.6 (2023), p. 862.

References

[1] S. L. Brunton and J. N. Kutz. *Data-driven science and engineering: Machine learning, dynamical systems, and control*. Cambridge University Press, 2022.

[2] L. Zhang et al. "Internet connected vehicle platoon system modeling and linear stability analysis". In: *Computer Communications* 174 (2021), pp. 92–100.

[3] Y. Zhu and F. Zhu. "Distributed adaptive longitudinal control for uncertain third-order vehicle platoon in a networked environment". In: *IEEE Transactions on Vehicular Technology* 67.10 (2018), pp. 9183–9197.

[4] C. Latrech et al. "Integrated longitudinal and lateral networked control system design for vehicle platooning". In: *sensors* 18.9 (2018), p. 3085.

[5] S. Stüdli, M. M. Seron, and R. H. Middleton. "From vehicular platoons to general networked systems: String stability and related concepts". In: *Annual Reviews in Control* 44 (2017), pp. 157–172.

[6] S. K. Singh. *Process control: concepts dynamics and applications*. PHI Learning Pvt. Ltd., 2010.

[7] M. Bakošová and J. Oravec. "Robust model predictive control for heat exchanger network". In: *Applied Thermal Engineering* 73.1 (2014), pp. 924–930.

[8] A. Vasičkaninová et al. "Neural network predictive control of a heat exchanger". In: *Applied Thermal Engineering* 31.13 (2011), pp. 2094–2100.

[9] A. H. González, D. Odloak, and J. L. Marchetti. "Predictive control applied to heat-exchanger networks". In: *Chemical Engineering and Processing: Process Intensification* 45.8 (2006), pp. 661–671.

[10] R. Rajamani et al. "A complete fault diagnostic system for automated vehicles operating in a platoon". In: *IEEE transactions on control systems technology* 9.4 (2001), pp. 553–564.

[11] A. Khalil et al. "Output-only fault detection and mitigation of networks of autonomous vehicles". In: *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2020, pp. 2257–2264.

[12] A. Khalil and M. Al Janaideh. "On fault classification in connected autonomous vehicles using supervised machine learning". In: *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2021, pp. 1198–1204.

[13] G. Wang et al. "Two-level fault detection and isolation algorithm for vehicle platoon". In: *IEEE Access* 6 (2018), pp. 15106–15116.

[14] N. A. M. Subha and M. N. Mahyuddin. "Distributed adaptive cooperative control with fault compensation mechanism for heterogeneous multi-robot system". In: *IEEE Access* 9 (2021), pp. 128550–128563.

[15] A. Khalil et al. "Fault detection, localization, and mitigation of a network of connected autonomous vehicles using transmissibility identification". In: *2020 American Control Conference (ACC)*. IEEE. 2020, pp. 386–391.

[16] W. Wang et al. "Fault-tolerant platoon control of autonomous vehicles based on event-triggered control strategy". In: *IEEE Access* 8 (2020), pp. 25122–25134.

[17] X. Liu, X. Gao, and J. Han. "Robust unknown input observer based fault detection for high-order multi-agent systems with disturbances". In: *ISA Transactions* 61 (2016), pp. 15–28.

[18] I. Shames et al. "Distributed fault detection and isolation with imprecise network models". In: *2012 American Control Conference (ACC)*. IEEE. 2012, pp. 5906–5911.

[19] K. Zhang, G. Liu, and B. Jiang. "Robust unknown input observer-based fault estimation of leader–follower linear multi-agent systems". In: *Circuits, Systems, and Signal Processing* 36.2 (2017), pp. 525–542.

[20] T. Sorsa, H. N. Koivo, and H. Koivisto. "Neural networks in process fault diagnosis". In: *IEEE Transactions on systems, man, and cybernetics* 21.4 (1991), pp. 815–825.

[21] M. T. Amin, S. Imtiaz, and F. Khan. "Process system fault detection and diagnosis using a hybrid technique". In: *Chemical Engineering Science* 189 (2018), pp. 191–211.

[22] M. Alauddin et al. "A bibliometric review and analysis of data-driven fault detection and diagnosis methods for process systems". In: *Industrial & Engineering Chemistry Research* 57.32 (2018), pp. 10719–10735.

[23] N. Md Nor, C. R. Che Hassan, and M. A. Hussain. "A review of data-driven fault detection and diagnosis methods: Applications in chemical process systems". In: *Reviews in Chemical Engineering* 36.4 (2020), pp. 513–553.

[24] R. Arunthavanathan et al. "An analysis of process fault diagnosis methods from safety perspectives". In: *Computers & Chemical Engineering* 145 (2021), p. 107197.

[25] D. Dragan. “Fault detection of an industrial heat-exchanger: A model-based approach”. In: *Strojniški vestnik-Journal of Mechanical Engineering* 57.6 (2011), pp. 477–484.

[26] N. Khentout et al. “Fault monitoring and accommodation of the heat exchanger parameters of triga-mark II nuclear research reactor using model-based analytical redundancy”. In: *Progress in Nuclear Energy* 109 (2018), pp. 97–112.

[27] H. O. Njoku et al. “Combined pinch and exergy evaluation for fault analysis in a steam power plant heat exchanger network”. In: *Journal of Energy Resources Technology* 141.12 (2019), p. 122001.

[28] R. F. Garcia. “Improving heat exchanger supervision using neural networks and rule based techniques”. In: *Expert Systems with Applications* 39.3 (2012), pp. 3012–3021.

[29] M Mohanraj, S Jayaraj, and C Muraleedharan. “Applications of artificial neural networks for thermal analysis of heat exchangers–a review”. In: *International Journal of Thermal Sciences* 90 (2015), pp. 150–172.

[30] J. Huang et al. “An experimental study of clogging fault diagnosis in heat exchangers based on vibration signals”. In: *IEEE access* 4 (2016), pp. 1800–1809.

[31] S. M. M. Alavi, R. Izadi-Zamanabadi, and M. J. Hayes. “On the Generation of a Robust Residual for Closed-loop Control systems that Exhibit Sensor Faults”. In: *The IET Irish Signals and Systems Conference 2007*. 2007.

[32] S. Zhai, W. Wang, and H. Ye. “Fault diagnosis based on parameter estimation in closed-loop systems”. In: *IET Control Theory & Applications* 9.7 (2015), pp. 1146–1153.

[33] B. Sun et al. “Fault identification for a closed-loop control system based on an improved deep neural network”. In: *Sensors* 19.9 (2019), p. 2131.

[34] M. Blanke et al. *Diagnosis and fault-tolerant control*. Vol. 2. Springer, 2006.

[35] S. X. Ding. *Model-based fault diagnosis techniques: design schemes, algorithms, and tools*. Springer Science & Business Media, 2008.

[36] J. Lunze. *Feedback control of large-scale systems*. Prentice Hall New York, 1992.

[37] A. Varga. “Solving fault diagnosis problems”. In: *Studies in Systems, Decision and Control, 1st ed.; Springer International Publishing: Berlin, Germany* 84 (2017), pp. 8–9.