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Exploiting Spatial and Temporal Dependencies to Enhance Fault Diagnosis: Application to Railway Track Circuits

K. Verbert, B. De Schutter, R. Babuška

Abstract— **In many practical applications, it is not feasible to measure a large number of variables. Therefore, strategies are required to enhance fault diagnosis, given the available monitoring signals. In this paper, we consider fault diagnosis in networks using a limited number of monitoring signals. We propose to use spatial dependencies between the monitoring data of the subsystems to discriminate between faults. Furthermore, the temporal properties of the monitoring signal are exploited. It is shown that, for a track circuit example, the spatial and temporal dependencies are valuable for diagnosis. Based on these features, an approach is proposed for fault diagnosis in the presence of environmental disturbances.**

I. Introduction

In this paper, we propose a model-based approach for fault diagnosis in networks in the presence of environmental influences. A *model-based* approach [1]–[3] is chosen over a *data-based approach* [4], [5] to ensure transparency. Furthermore, data-based approaches require a large and representative amount of labeled historical data, which is in general difficult to obtain [5]. Especially for our application in railways, due to preventive maintenance activities, usually few data samples are available that are characteristic of the natural degradation behavior.

As an application, we consider railway track circuits, which are used for train detection. Fault detection of railway track circuits has already been dealt with, e.g. in [4]–[7]. A distinction can be made regarding the way the monitoring data are obtained, e.g. using a measurement train [4], [5] or using track-side monitoring devices [6], [7]. In the current paper, track-side monitoring devices are considered because they continuously monitor the system state and are therefore suitable for the early detection and diagnosis of faults. The main difference compared to the approaches in [6], [7] is that in those works multiple monitoring signals are used, while in this paper, for each track circuit, only one measurement signal is available. Although the availability of a wide variety of measured quantities can be beneficial for model-based fault diagnosis [2], it is not realistic to assume that this will be realized for the whole rail infrastructure, as the related implementation and monitoring costs are high. Therefore, we restrict ourselves to one predefined monitoring signal, the current measured at the receiver, which is, in the Netherlands, already measured for a large number of railway sections.

To enhance diagnosis performance, we propose two new features that do not require additional measurements:

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1) Spatial dependencies within the network;
2) Temporal behavior of the considered subsystem.

The spatial dependencies are useful because they are different for different types of system faults, i.e. some faults only influence one subsystem, whereas other faults influence multiple subsystems. The temporal system behavior is valuable for diagnosis because various faults develop in different ways.

II. Fault diagnosis in networks

We consider the fault diagnosis of an arbitrary subsystem U within a network consisting of a number of similar subsystems and graphically represented by a, possibly unconnected, graph (see e.g. the graph in Figure 1). The black dots represent the subsystems and the edges represent connections between the different subsystems. We assume that for each subsystem i a monitoring signal M_i is available that characterizes system behavior.

Generally, the state X_i of each subsystem i can take $n \geq 1$ possible values v_1 till v_n. For each of these values, a different behavior of M_i is expected. For a system with more than one state value, i.e. $n > 1$, we can only infer system health from M_i when we know X_i. In this work, we assume that we know X_i (e.g. from additional analyses or sensors). So, it is assumed that at each moment we know what M_i would be in the healthy case. This signal is referred to as $M_{\text{healthy},i}$.

If M_U differs significantly from $M_{\text{healthy},U}$ there is some fault present in subsystem U. Then, our aim is to determine the type of the fault. To diagnose subsystem U, we propose to use the behavior of neighboring subsystems in the network. For this purpose, all potential system faults are classified in one of the following four fault categories (see Figure 1):

- I: Faults that influence all nearby subsystems,
- II: Faults that affect all connected subsystems in a close neighborhood,
- III: Faults that influence only one subsystem,
- IV: Faults that are related to an object o moving through the network on a specific path $\mathcal{P}_o$.

Because faults of category I also influence subsystems that are (from the network point of view) not connected with subsystem U, these faults can be considered as environmental influences (e.g. weather influences). We assume that (part of the) environmental influences are unavoidable, i.e. they are always present to some extent, and we aim to detect and diagnose other faults in the presence of these influences. Therefore, as a first step, we correct the monitoring signals for environmental influences. The effect of environmental influences on M_U, denoted as $M_{\text{env},U}$, can be determined

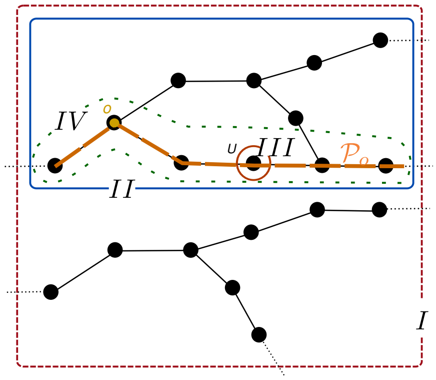

Fig. 1. Division of the subsystems in a network system.

from the monitoring signals of the subsystems in a close neighborhood of U, assuming that a sufficient number of the considered subsystems is healthy (apart from environmental influences). Optionally, additional information, e.g. weather reports, can be taken into account. The corrected monitoring signals M_i' are then used for fault detection and diagnosis. When a fault is detected, i.e. M_U' differs from its expected behavior $M_{\text{healthy},U}$, the spatial dependencies between the monitoring signals of the subsystems that are close to U are determined. Here, we distinguish between the following four types of spatial dependencies S:

D$_1$: No correlation with other subsystems,

D$_2$: Correlation with connected subsystems in a close neighborhood,

D$_3$: Correlation with subsystems on a specific path $\mathcal{P}_o$ for a specific object o passing through the network,

D$_4$: Correlation with all nearby subsystems.

When the spatial dependencies S are known, the fault can be classified:

if $S = \mathrm{D}_1$ **then** a fault of category III is present
if $S = \mathrm{D}_2$ **then** a fault of category II is present
if $S = \mathrm{D}_3$ **then** a fault of category IV is present
if $S = \mathrm{D}_4$ **then** a fault of category I is present

Note that in the case that all faults of category I are considered as environmental disturbance, dependencies of type D_4 are not expected to be present in the signals M_i'.

In general, multiple faults belong to each category. To discriminate between faults within one category, other features need to be considered, e.g. temporal system behavior (see Section IV-C).

III. Track Circuits

To illustrate the applicability of the method proposed in Section II, we consider the fault diagnosis of track circuits within a railway network. Double-rail, 75 Hz AC track circuits, as used in the Netherlands, are considered for this. However, note that the methods proposed in this paper can be easily applied to other track circuit variants.

A. Track circuit modeling

Throughout the world, track circuits are the most commonly used devices for train detection [6]. They operate by transmitting electric current to a receiver via the two rails. When the section (part of the track) is free, the transmitted signal reaches the far end of the section. When the section is occupied, the circuit is short-circuited by the wheel sets and the current does not reach the receiver (see Figure 2).

For this purpose, the railway track is divided into electrically separated sections, each having its own track circuit. At the side of the transmitter, a voltage, V_{rail} is applied between the two rails. At the opposite side, the current I_{c} flowing through the receiver is measured. The insulated joints between the different sections prevent current flow via the rails to neighboring sections, and the impedance bonds allow direct traction currents to flow to adjacent sections, while blocking the alternating currents used for train detection.

For a failure-free functioning of the track circuit, both the safety and the operational requirement must be satisfied [8]. The *safety requirement* states that the section must be reported as occupied when a train is present. The *operational requirement* states that the section must be reported as free when there is no train in the section.

To get insight into the system behavior and possible causes for the violation of one of these requirements, a track circuit model will be derived hereafter. To model the relation between the input voltage V_{rail} and the output current I_{c}, a good understanding of the electrical properties of the rails, ballast, and train shunts is required.

1) Rail impedance and ballast admittance: Here, with rail impedance the resistance is meant that 75 Hz current encounters when flowing in the longitudinal direction of the rail bars. The ballast admittance indicates how easily current can flow between the two rails and consists of the leakage between the rail fixings, sleepers, and earth [9].

To model rail and ballast impedance, the two-line transmission line model [6] is often used. This model assumes that the rail and ballast impedance are evenly distributed over the length of the track. For practical purposes, lumped parameter models, consisting of a finite number of (identical) cascaded subsections, are often considered to approximate the transmission line behavior. The number of subsections determines the accuracy of the model considered. For simplicity, we consider a model with only one subdivision (see Figure 3). A connection to an adjacent section is included to model insulated joint defects (see Section III-B.2).

2) Train shunt: When a train is present in a section, the wheels and axles create low-impedance connections between the two rails. Such a connection can be modeled by the resistor Z_{S} between the two rails, parallel to the ballast

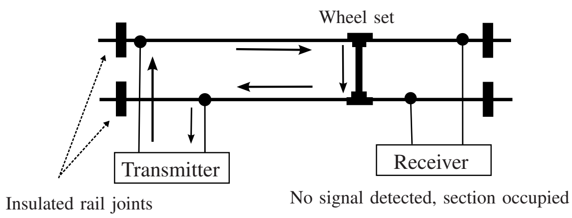

Fig. 2. Current flow in a track circuit.

impedance Z_{B}. Resistor Z_{S} is only connected when there is a train in the section. In Figure 3, a train shunt is realized by closing switch s and the shunt quality is modeled by the value of the resistor Z_{S}.

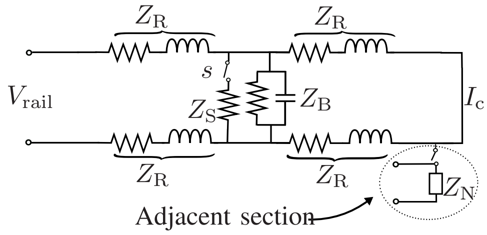

Fig. 3. Model of a track circuit.

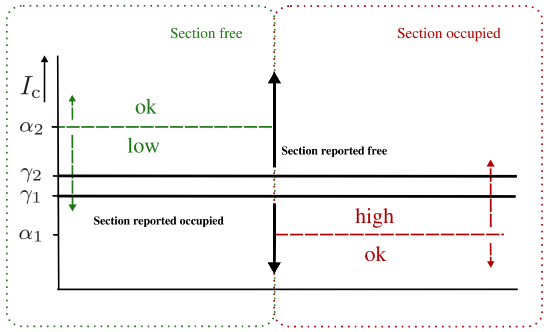

Fig. 4. Definition of the qualitative behaviors of I_{c}.

B. Fault types

Due to several causes, a track circuit can behave in an undesired way, e.g. due to an increased resistance of the rails, the current level at the receiver may be too low. In the worst case, this hinders the execution of the system task (train detection), resulting in a functional failure. To prevent functional failures, it is important to recognize system faults as early as possible. Therefore, in the sequel, fault types, related causes, and their effect on the system behavior are investigated. Note that here a fault is defined as a deviation in the system operation that does not hinder the execution of the system task (train detection), whereas a failure indicates that the system task can no longer be executed properly.

1) Train shunt imperfection: The proper functioning of a track circuit requires that every train short-circuits the section, meaning that the path "rail-wheels-axles-wheels-rail" should have a sufficiently low resistance for 75 Hz AC currents. A good train shunt can e.g. be hampered due to rail contamination or due to lightweight trains. In the case of a bad train shunt, the resistance of Z_{S} is relatively high, meaning that the path via the train is electrically less attractive and more current flows to the receiver. In the worst case, the safety requirement is violated.

2) Insulation imperfection: Insulated joints are used to prevent that 75 Hz AC currents can flow to neighboring sections. Problems can occur when insulated joints degrade or when conductive objects lie over the joints. Insulated joints are implemented in a way that they are fail-safe, meaning that a failure may affect the operational requirement, but will not affect the safety requirement. This is achieved by using phase-shifted currents in adjacent sections, so that a current signal of one section cannot energize the relay of an adjacent section. Insulated joint defects can be modeled by a connection to another circuit (see Figure 3). The impedance of this circuit determines the amount of inflow from or outflow to the adjacent section. In the case of an insulation problem, current flows out of the circuit and I_{c} is too low. This may lead to a violation of the operational requirement.

3) Rail conductance problems: The proper functioning of a track circuit relies on the conductance properties of the rails. The rail conductance is influenced by the quality of the rails themselves (e.g., damaged rail, broken rail), the quality of the bonds in jointed track, and electrical influences of disturbance currents (e.g. saturated track due to high traction currents). In the track circuit model, the quality of the rails is modeled by the value of the impedance Z_{R}. Problems occur when this resistance is too high; in that case, the path via the ballast Z_{B} becomes more attractive and the current level at the receiver decreases, which in the worst case results in a violation of the operational requirement.

4) Ballast condition: The condition of the ballast determines the resistance that currents encounter when flowing from one rail to the other rail or the ground. Because the effect of a decreasing ballast resistance is similar to that of a train shunt, it is important that the ballast resistance is sufficiently high and constant. Due to environmental influences (mainly weather) and aging, the ballast resistance will fluctuate over time. Some degree of fluctuation is acceptable, but when the ballast resistance becomes too low, the section will be reported as occupied, even if there is actually no train present (i.e. a violation of the operational requirement).

Table I(a) gives an overview of the faults considered together with their qualitative effect on I_{c}. Furthermore, the corresponding potential train detection error is listed. The effects on I_{c} are defined as follows (see Figure 4): "ok" means that the current is below the threshold α_1 when the section is occupied and above the threshold α_2 when the section is free; "high" means that the current is too high when the track is occupied, and "low" means that the current is too low when the track is free.

The track circuit is tuned such that even in the case of small current deviations, the presence and absence of a train are correctly reported, i.e.

if $I_{\mathrm{c}} > \gamma_2$ **then** section is reported as free,
if $I_{\mathrm{c}} < \gamma_1$ **then** section is reported as occupied,

with $\alpha_2 > \gamma_2 > \gamma_1 > \alpha_1$. So, α_1 and α_2 serve to define system health, whereas γ_1 and γ_2 are settings of the train detection system. For a free section, this means: When $I_{\mathrm{c}} > \alpha_2$, the system is healthy and the section is correctly reported as free. When $I_{\mathrm{c}} < \alpha_2$, the current is too low. However, when $\gamma_2 < I_{\mathrm{c}} < \alpha_2$ the section is still correctly reported as free and the corresponding system behavior is classified as faulty. Only when $I_{\mathrm{c}} < \gamma_2$, this fault results in a *false positive* (FP) detection result (i.e. a violation of the operational constraint). In this case, we no longer talk about a fault, but about a

TABLE I

FAULT CHARACTERISTICS

(a) Basic features

Fault (F)	Problem	Cause	Potential future failure	Current (I_c)
0	-	Healthy state	-	ok
1	Train shunt imperfection	Rail contamination	FN	high
2		Lightweight trains	FN	high
3	Insulation imperfection	Insulated joint defect	FP	low
4		Conductive objects	FP	low
5	Rail conductance impairment	Mechanical defect	FP	low
6		Electrical disturbances	FP	low
7	Ballast condition	Ballast degradation	FP	low
8		Ballast variation	FP	low $\vee$ ok $\vee$ high

(b) Dependencies

Spatial (S)	Temporal (T)
-	-
$D_1 \vee D_2 \vee D_4$	-
D_3	-
D_1	L $\vee$ E
D_1	A
D_1	E
D_2	I $\vee$ A
$D_1 \vee D_2$	L $\vee$ E
D_4	A $\vee$ L $\vee$ E $\vee$ I

failure. In the same way, for an occupied section, it holds that when $I_c < \alpha_1$ the system is healthy, when $\alpha_1 < I_c < \gamma_1$ the system is faulty (no train detection error), and when $I_c > \gamma_1$ the system fails, i.e. a *false negative* (FN) detection result and a violation of the safety constraint.

C. Overview

According to the approach proposed in Section II, a track circuit can be considered as a system for which the state X_i of each section i can take two possible values:

v_1 : Free section,
v_2 : Occupied section.

Furthermore, $M_i \equiv I_{c,i}$, and[1]:

$$M_{\text{healthy},i} = I_{\text{c,healthy},i} = \begin{cases} \alpha_2^+ & \text{if } X_i = v_1 \\ \alpha_1^- & \text{if } X_i = v_2 \end{cases}$$

Faults $1, 2$ are relevant to occupied track ($X_i = v_2$) and faults 3 till 7 (mainly) influence a free section ($X_i = v_1$).

Note that in this work, we only focus on the detection and diagnosis of faults (and not of failures). This way, the actual system state X_i can be inferred from M_i, so X_i and $M_{\text{healthy},i}$ are known at each moment.

IV. FEATURE EXTRACTION

This section focuses on feature selection for fault diagnosis. We first show that just actual system knowledge in combination with the measured signal I_c, is not sufficient to adequately distinguish between the different faults. Then, to enhance the diagnosis, we first consider what information can be gained from the measurements of neighboring sections (see Section II). Second, fault evolution characteristics are studied and accordingly the temporal dependencies of I_c are exploited.

A. System relations

Considering the track circuit example, it is observed that different types of faults have similar effects on I_c (e.g. both bad ballast condition, rail conductance impairment, and insulation problems result in a lower value of I_c). Hence, the discriminative power of only the instantaneous value of I_c is low, i.e. given the system state X (occupied or free), I_c only tells us whether the system is healthy or not. Considering our system knowledge (see Table I(a)), the available knowledge base is given by the following set of rules:

if $I_c = \text{ok}$ **then** $F \in \{0\}$
if $X = v_2$ and $I_c = \text{high}$ **then** $F \in \{1, 2\}$
if $X = v_1$ and $I_c = \text{low}$ **then** $F \in \{3, 4, 5, 6, 7, 8\}$

where F refers to the faults as given in Table I.

B. Spatial dependencies

For each section, only one monitoring signal (I_c) is available. However, this signal is measured for all sections. It is interesting to investigate whether the monitoring signals of other sections can provide additional information about the condition of the section under consideration. Additional information is contained in these data if there exist dependencies between the signals of neighboring sections that vary for different system faults. In the track circuit example, some faults are likely to influence all sections in a close neighborhood (e.g. ballast variation), other faults only influence sections of the same track (e.g. electrical disturbances), and still other faults are specific to one section (e.g. mechanical rail defects). Furthermore, a distinction can be made between faults that are train-specific (e.g. train shunt imperfection due to a lightweight train) and faults that are not train-specific. So, information from neighboring sections can enhance fault diagnosis. An overview of the spatial dependencies can be found in Table I(b), where the spatial dependencies S are defined, in agreement with Section II, as:

D_1: No correlation with other sections;
D_2: Correlation with sections on the same track;
D_3: Train-specific correlation;
D_4: Correlation with all nearby sections.

Note that all behaviors that are possible according to the available knowledge are listed. Now, our knowledge base can be extended with the following rules:

if $X = v_2$ and $S = D_3$ **then** $F \in \{1\}$
if $X = v_2$ and $S = D_3$ **then** $F \in \{2\}$
if $X = v_1$ and $S = D_1$ **then** $F \in \{3, 4, 5, 7\}$
if $X = v_1$ and $S = D_2$ **then** $F \in \{6, 7\}$

[1] α_2^+ includes all values larger than the threshold α_2 and α_1^- includes all values smaller than the threshold α_1.

if $X = v_1$ and $S = \mathrm{D}_4$ **then** $F \in \{8\}$

C. Temporal dependencies

In general, faults develop in a non-deterministic way and an exact quantitative description of fault evolution cannot be provided. However, often information is available regarding its qualitative time behavior, e.g. whether the time evolution of the fault is intermittent or approximately linear, which can be used to distinguish between the different faults. Here, we give a characterization of the time evolution of I_c for each of the faults. For simplicity, we restrict ourselves to the following four types of time behavior T: abrupt (A), linear (L), exponential (E), intermittent (I). The results are included in Table I(b). Note that the temporal dependencies T are considered to be only relevant for the diagnosis of a free section, i.e. $X = v_1$.

if $X = v_1$ and T = L **then** $F \in \{3, 7, 8\}$
if $X = v_1$ and T = E **then** $F \in \{3, 5, 7, 8\}$
if $X = v_1$ and T = A **then** $F \in \{4, 6, 8\}$
if $X = v_1$ and T = I **then** $F \in \{6, 8\}$

Considering Table I, it can be concluded that the two additional features clearly improve the discriminative power.

V. Fault diagnosis

This section deals with the fault detection and diagnosis of track circuits, so the detection of faulty behavior and the identification of its cause(s). First, the diagnosis problem is specified and assumptions are given. Second, the proposed diagnosis approach is described and finally, the approach is illustrated using an example.

A. Diagnosis task

Based on the features and knowledge discussed in Section IV and summarized in Table I, we aim to determine whether a particular section is healthy or not, and when it is not what the cause is of this behavior. Non-healthy system behavior can be due to a fault or due to a failure. Recall that in this work we focus on the diagnosis of faults, i.e. failure-free situations are considered. Furthermore, we assume that:

A_1: Ballast variations are considered as environmental influences, which are present in all sections (see Section II);
A_2: At most one of the faults 3 till 7 is present in the considered section (in addition to variations in the ballast resistance);
A_3: We have a closed world, i.e. Table I is complete;
A_4: A vast majority of the sections in each local neighborhood is healthy.

B. Diagnosis approach

The track circuit diagnosis task can be tackled according to the following steps:

1) Infer the system state X and the corresponding signal $I_{\mathrm{c,healthy}}$ from I_c:
   if $I_\mathrm{c} > \gamma_2$ **then** $X = v_1$ and $I_{\mathrm{c,healthy}} = \alpha_2^+$
   if $I_\mathrm{c} < \gamma_1$ **then** $X = v_2$ and $I_{\mathrm{c,healthy}} = \alpha_1^-$
2) Select the sections that are relevant for the diagnosis
3) If $X = v_1$, correct I_c for ballast variations
4) Check for faulty behavior:
   if $X = v_1$ **then** $(I_\mathrm{c} < \alpha_2 \implies F \neq 0)$
   if $X = v_2$ **then** $(I_\mathrm{c} > \alpha_1 \implies F \neq 0)$
5) If a fault is detected, determine features S (and T) and diagnose system behavior.

Steps $2-5$ are briefly worked out for the specific application.

1) If $X_i = v_1$: First, the current fluctuations due to natural ballast variation $I_{\mathrm{bal},i}$ need to be determined. This can be done based on the monitoring signals of healthy sections lying in a close neighborhood of the considered section i. The ballast variation can e.g. be computed as the (weighted) current fluctuations of the considered sections:

$$I_{\mathrm{bal},i} = \sum_{j \in \mathcal{K}_i} \frac{I_{\mathrm{c},j} - \bar{I}_{\mathrm{c},j}}{|\mathcal{K}_i|},$$

with $\mathcal{K}_i$ the set of sections in a close neighborhood of section i that are expected to be healthy and $\bar{I}_{\mathrm{c},j}$ the nominal value (i.e. long-term average) of $I_{\mathrm{c},j}$. The currents corrected for ballast $I'_{\mathrm{c},j}$ can then e.g. be computed as:

$$I'_{\mathrm{c},j} = I_{\mathrm{c},j} - I_{\mathrm{bal},i} \quad \forall j \in \mathcal{K}_i \cup \{i\},$$

and they can then be used for fault detection and diagnosis. When a fault is detected (i.e. $I'_{\mathrm{c},i} < \alpha_2$), the corresponding temporal (T) and the spatial (S) dependencies are determined. To determine the spatial dependencies S, the monitoring signals of neighboring section lying on the same track are analyzed. Based on T and S, the cause (or a set of possible causes) for the faulty behavior can be determined using Table I.

2) If $X_i = v_2$: Ballast variations play no significant role when $X_i = v_2$, so we can directly proceed with the detection of faulty behavior. When a fault is detected, i.e. $I_{\mathrm{c},i} > \alpha_1$, diagnosis is required. Then, it needs to be verified whether the problem is train-specific or not. For this purpose, the monitoring signals of sections lying on the train routes of several passing trains are analyzed. If the problem is train-specific, the faulty behavior is caused by a lightweight train and not due to rail contamination (i.e. fault 2 is present and fault 1 is absent). If the problem is not train-specific, rail contamination (among others) causes the faulty behavior, i.e. fault 1 is present. When rail contamination is present, problems with lightweight trains are no longer guaranteed to be identified in section i. However, defective trains will be detected in any other section without rail contamination.

C. Example

To illustrate the proposed method, we consider a simple fault diagnosis example. To this aim we assume that we have the monitoring data of three sections A, B, and C as depicted in Figure 5 available, with:

A: the section to be diagnosed,
B: a nearby preceding section,
C: a nearby section located on another track.

Furthermore, assumption A_4 is specified as:

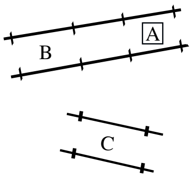

Fig. 5. Sections considered in the diagnosis example.

A'_4: Section B and C do not suffer from section-specific faults (i.e. faults for which $S = D_1$) and section C does not suffer from track-specific faults (i.e. faults for which $S = D_2$).

Assumption A'_4 is adopted here because (for simplicity) only two neighboring sections are considered. In the case that more sections are considered, the redundant information contained in these signals can be used to detect (and correct for) possible faults in neighboring sections.

Suppose that the monitoring signals shown in Figure 6 need to be analyzed. The gray areas indicate the time intervals in which the section is occupied by a train. As the behavior of healthy section C is as expected, ballast variation plays no significant role and we use the original signals for analysis. To diagnose section A, first the behavior of $I_{c,A}$ is analyzed. We conclude that till $t = t_1$, $I_{c,A} =$ "ok" (i.e. the current is above the threshold α_2 when the section is free and below the threshold α_1 when the section is occupied), which means that the system is healthy. At time t_1 the current level drops as a consequence of a train passage, but the current does not decrease below the threshold value α_1, so $I_{c,A} =$ "high", indicating that faults 1 and/or 2 are present. To determine which fault is present, we verify whether the problem is train-specific. This is done by checking whether the same problem occurred for other train passages. This is not the case, indicating that the fault is caused by a train shunt problem (e.g. a lightweight train). This conclusion is validated by the monitoring signal $I_{c,B}$ of preceding section B. Also from this monitoring signal, it can be concluded that one particular train suffered from shunt problems.

After the train passage at $t = t_1$ the behavior is normal again till $t = t_2$. Then, after $t = t_2$ some deviating behavior is observed: In some time intervals, the current level is below α_2 while the track is free, i.e $I_{c,A} =$ "low" indicating the presence of one of the faults $3-7$. To further specify which fault is present, we check whether there is a correlation with neighboring sections. Considering the monitoring signals $I_{c,B}$ and $I_{c,C}$, we observe a similar abnormal behavior in section B, but no deviating behavior in section C, from which we conclude that the disturbance is track-specific, i.e. S is of type D_2. So far, it can be concluded that $F = 6$ or $F = 7$. To make a further distinction, the time evolution of $I_{c,A}$ is studied. Based on the available part of the time signal, it seems reasonable to conclude that the temporal behavior T of $I_{c,A}$ is intermittent (I). Then it follows that $F = 6$.

In summary, from the signals in Figure 6, we can conclude that around $t = t_1$ a "defective" train passes through sections A and B and after $t = t_2$, sections A and B suffer from electrical disturbances.

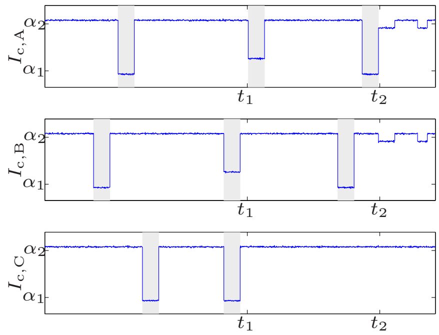

Fig. 6. Monitoring signals of sections A, B, and C.

VI. Conclusions

A new model-based approach has been proposed for fault diagnosis in networks in the presence of environmental disturbances. In this approach, besides system relations, temporal and spatial dependencies are used as features for the diagnosis. It is shown that, for the track circuit case, these features are valuable for diagnosis. Directions for further research are e.g., developing systematic methods to transform the measurement data to the feature space and the corresponding hypothesis space, exploiting additional system relations or system data to further improve diagnosis quality, and extending the method to handle situations where uncertainty plays a significant role.

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