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# Fault diagnosis in track circuits based on *fuzzy* models

# *Diagnóstico de fallo para circuitos de vía basado en modelos fuzzy*

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**Resumen**

*La gran importancia del transporte de personas y mercancías a través del sistema ferroviario está condicionada a factores como velocidad, seguridad, economía y medio ambiente.*

*Los trenes son detectados/"localizados" por circuitos eléctricos (llamados circuitos de vía) usando los raíles como medio de transmisión, su funcionamiento es afectado por cambios en la impedancia de la vía, dando lugar a gran susceptibilidad de operación y altas tasas de averías.*

*Considerando que el método de diagnóstico de fallo es basado en modelo, se utilizarán modelos fuzzy en este enfoque. Cuando no se conocen todos los parámetros del proceso, el uso de modelos fuzzy puede ser una buena opción para el modelado. El diagnóstico de fallo en los circuitos de vía utilizando conceptos fuzzy puede contribuir a mejorar los índices de rendimiento del ferrocarril, lo que permite la detección temprana de fallos.*

*Palabras clave: modelado fuzzy, diagnóstico de fallo, algoritmo, control, modelo, circuito de vía, señalización, ferrocarril, vía, fiabilidad, disponibilidad, seguridad.*

**Abstract**

The vast importance of people and goods transportation through the railway system is due to factors such as speed, safety, economic and environmental.

Being trains detected/"located" by electrical circuits (called track circuits) using the rails as transmission medium, its operation is affected by changes in track impedance, imposing great susceptibility of operation and high failure rates.

Considering that the fault diagnosis method is model-based, fuzzy models will be used in this approach. When all process parameters are not known, the use of fuzzy models can be a good choice for modeling. The fault diagnosis in track circuits using fuzzy concepts can contribute to improve the performance indexes of railways, enabling early detection of faults.

keywords: fuzzy modeling, fault diagnosis, algorithm, control, model, track circuit, signalling, railway, track, reliability, availability, safety.

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## 1. Introduction

The signalling systems regulate the movement of trains and for this reason are governed by high levels of safety, ensuring the necessary spacing between trains running in same direction, preventing head-on collision and avoiding the flank impact at conflict points. For this reasons it is necessary to know, in a safe way, the effective position of trains. The availability criteria is also a major factor in railway operation, due to the fulfillment of operational schedule in order to achieve an efficient usage of infrastructure and a high reliability of signalling systems.

In order to promote the safety and availability of railway system artificial intelligence techniques can be used to diagnose faults in signalling systems and especially in track circuits, as these are elements of great importance in railway operations. In this point of view the *fuzzy* logic adoption has advantages in cases wherein the uncertainties about the system are significant, as in track modeling, which leads to adopt *fuzzy* concepts to fault diagnosis in track circuits. The main advantage of this approach lies in no need of the use of precise and accurate analytical models of real system, allowing to obtain the relation of input-output data by *fuzzy* models of TS (Takagi-Sugeno) type. The ability of representing nonlinear systems by aggregation of several local linear models implies a good performance of TS techniques on systems modeling.

### 1.1. Specifics of railways

From the signalling point of view, the detection of trains position, associated with the emission of electrical signals by rails, is technically designated by “track circuit”. This device consists in a transmission module and a reception module, using the track as physical transmission medium. Track circuits were created in the United States about a century ago and later used throughout the world. Currently, the Portuguese railway network is using thousands of these devices, implying that these are critical elements to ensure the availability of railway infrastructure and consequently of this transportation mode.

Track circuits are the main method to detect the position of trains worldwide, used both in “heavy” systems (conventional and high speed) and in mass transit networks (namely commuter lines and underground lines).

The several components comprising the track circuit are subject to fault modes (due to aging, weather conditions and track maintenance) which must be detected as early as possible in order to keep the system operating according the required levels of safety and availability. To achieve this aim, automatic processes are used for monitoring and diagnosis, leading to more efficient maintenance policies[1]. For these reasons, the potential benefits of monitoring and diagnosis in track circuits include:

- Possibility of a post analysis of incidents by improving the fault detection capability through processes of fault location and classification;
- Maintenance cycles reduction, whereby the cycle of periodic on-site inspection may be wider;
- Track circuits availability improvement, by reducing the failure periods during operational hours and by decreasing the trains delays;

[1] The fault diagnosis has strong appeal in the engineering of preventive maintenance.

- Costs reduction of preventive and corrective maintenance, as track circuits components can be replaced and repaired in time to prevent failures;

- Improving the performance of track circuits, optimizing the signalling system operation, reducing penalties costs and increasing the quality of provided railway services.

A track circuit is made with an electrical signal emission module at one end of a section of rails and a reception module at the opposite end of the defined section (separated by the track), both being in permanent communication during the train absence[2], which comprises the operating state called free track circuit, as illustrated in figure 1.


**Figure 1:** Track circuit principle operation (free steady-state).

The information transmitted through the rails is associated to trains positioning system, which is affected automatically by the presence of train in a track circuit, as illustrated in figure 2, wherein the communication between the emission and the reception modules is interrupted (absence of electrical current at track circuit reception point). This track circuit occupation is then "transmitted" to the train that circulates in rear, ensuring a minimum safe distance between trains and avoiding collision. The transmission track circuits states to the drivers is materialized, optically, by lineside signals, showing different light aspects according to safety conditions and the current exploitation status.

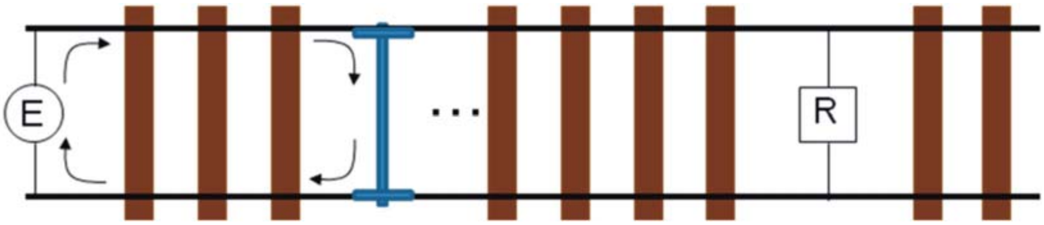


**Figure 2:** Track circuit principle operation (occupation by train).

Additionally to track circuits application in train detection, there are (not in the Portuguese railway network) inductive sensors (coils) installed on trains in a front position of head wheels, used to capture the driving information transmitted continuously on rails. This information is processed on-board and displayed on driver's panel. The information transmitted includes safety functions, ATP (Automatic Train Protection), and also non-vital information, ATO (Automatic Train Operation) and ATS (Automatic Train Supervision) [2].

[2] This principle reflects the intrinsic safety (fail safe) state, using the negative logic as operation basis.

Currently, in the Portuguese railway network, there are many types of track circuits and the more recent are based on electrical signals with frequency modulation of FSK (Frequency Shift Keying) type. This latest track circuits generation is supported by electronic circuits operating in audio-frequencies, so called audio-frequency track circuits. These is sophisticated equipment, included some of them (those of more recent design) internal processing capabilities. These are track circuits with high-level of complexity because they are designed to allow external monitoring and some kind of remote configuration and electronic adjustment.

Depending on track characteristics, the technology used and mounting typology of track circuits, the maximum range of one track section can reach up to about 1.5 km length.

All the safety critical systems are based on a negative logic operation, e.g., have as normal state the less restrictive situation in order that the system changes (fall) immediately to the safe state if a fault, a failure, a malfunction or a processing discrepancy occur. However, this safety premise, in case of failure on train detection system (which will consider in case of failure that a train it's occupying the section), carries very significant delays in train movements, which justifies the adoption of automatic mechanisms for fault detection and isolation.

### 1.2. Fault detection and isolation

Complex industrial systems, which include railway transportation system, need to be monitored continuously in order to early detection of faults (operation discontinuities) so that they can ensure high safety levels, providing a good quality of service and reduce the economic burden.

FDI (Fault Detection and Isolation) techniques can be used for real time monitoring of critical systems and operate based on following principles:

- Detection, which verifies the existence of faults;
- Isolation, that determines the fault type occurred, through the location (actuators, process, sensors, etc.) and the temporal behavior of fault – this stage occurs after the detection phase;
- Identification[3], which resolves the intensity and extent of faults.

Several approaches can be adopted to implement an automatic FDI system, depending on the available knowledge about the system under study. The FDI methods allow a model-based approach.

In many cases, the data collected during on-site inspection actions is analyzed empirically (without automation) by maintenance technicians, with the aim of identifying any anomalies. Thus, it becomes necessary an automatic data evaluation (provided by FDI mechanisms) to reduce the time spent in data analysis phase and to improve the performance of diagnostic tasks, allowing the maintenance technicians to have a rigorous and systematic analysis of data to optimize the preventive maintenance plans – in an intelligent maintenance paradigm.

[3] The identification phase is often confused with fault insulation, which are closely linked and interdependent tasks.

To ensure a good coverage, the FDI model-based approach requires some system knowledge to enable the extraction of relevant technical features, as well as a large and cataloged database, covering most of operational situations that may occur in real environment.

The analytical redundancy is presented as a versatile FDI approach. It uses the process model for checking the consistency of signals by comparing the measured signals and their estimation by model. However, the models definition for nonlinear complex systems is very difficult, because in general some of the parameters to use in mathematical equations that are part of models aren't accessible [1]. Given the *fuzzy* modeling characteristics, it is assumed that is an effective tool under the conditions mentioned above.

Addressing the signalling systems and particularly the track circuits may be noted that the systems diagnosis purpose is to provide accurate information to the maintenance technicians about the fault patterns in track circuits operation, thus ensuring high quality of provided information.

Track circuits use a scheduled regular maintenance regime being this kind of maintenance very costly. The ability to diagnose faults in track circuits allows a quick and timely response to malfunctions, which bring significant economic advantages. However, sudden failures can occur between scheduled inspections. In this context, only the urgent maintenance can be performed during the higher traffic density hours, which imply high costs due to preventive maintenance be performed only at nighttime without trains.

There are a significant number of faults in track circuits which, after analysis on-site, are classified as "undetected failure" or "normalized without action", situations that can be and should be evaluated through fault diagnosis systems and remote monitoring, condition that will reduce the maintenance burden and the operational costs.

### 1.3. Fault diagnosis based on fuzzy models

When the processes characteristics and the operating conditions aren't entirely known to use *fuzzy* models is a very attractive option, allowing to describe the processes without the use of complex techniques for modeling nonlinear systems.

There has been a growing trend in the interest of obtaining *fuzzy* models using data acquired by measurement. If there is no knowledge about the processes characteristics, rules and membership functions of *fuzzy* models can be obtained based on process measurement data. This methodology allows an easy model achievement and the possibility to insert additional rules based on expert's experience, usually in areas that weren't covered by process measures. *Fuzzy* logic can integrate information from different sources, such as physical laws, numerical data or heuristics. The *fuzzy* modeling has some advantages compared with other modeling methods such as mathematical modeling and neural networks. When the *fuzzy* modeling is used it is possible to obtain a more clear process representation under study and also a linguistic interpretation in the form of rules.

The proposed approach for fault detection in track circuits uses a *fuzzy* model operating without faults. The data used to obtain this *fuzzy* model were achieved through a simulated model of process because weren't available real data. Fault detection occurs when the residuals amount exceeds a predetermined value. The residuals are result from comparison the *fuzzy* model outputs with the real data of process outputs, as depicted in figure 3. Thus, the residuals are processed using *fuzzy* decision techniques and thereby the faults are detected and isolated.

The residual signal contains information about faults as well as the uncertainty effect in the model, requiring to establish residual limits to avoid false alarms (if the residual signal exceeds the range defined by the limits the alarm is activated, otherwise the system operates in a fault-free mode).

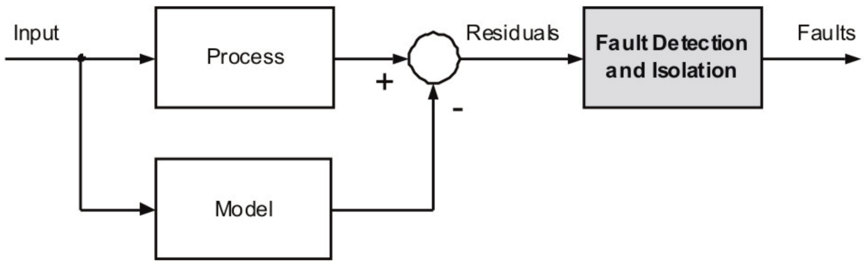


**Figure 3:** Structure type of model-based FDI.

The model-based residuals generation is obtained by residual evaluating for each of *n* models, one for each fault type. Thus, at time instant *k*, the residual is calculated for each fault in accordance with:

$$r_i(k) = y_i - \hat{y}_i \qquad (1)$$

In which $y_i$ represents the process output and $\hat{y}_i$ the observer output of fault with index $i$, wherein $i$=1, ..., $n$. The fault isolation is the phase that follows the fault detection (after activated). This stage uses as many *fuzzy* models as faults to isolate, as shown in figure 4.

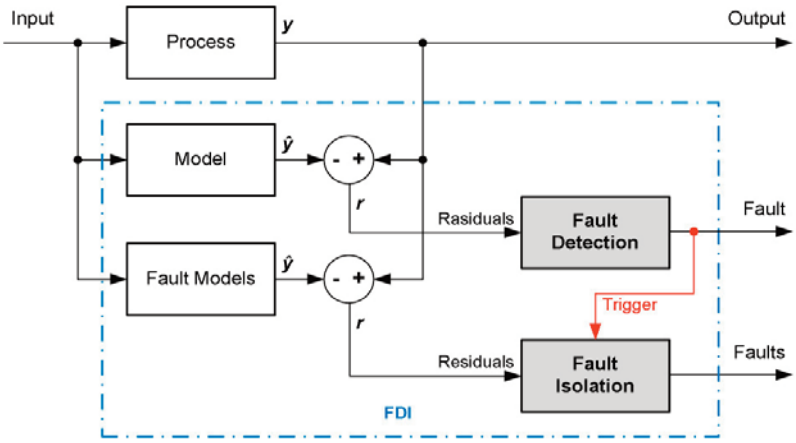


**Figure 4:** Fault isolation activation by fault detection stage.

The comparison between the outputs of each *fuzzy* model of faulty process and the process data originates several residuals, one for each fault model, allowing investigate the fault occurred. This investigation occurs when the residual value is close to zero. In this context, it becomes necessary to have knowledge of several kinds of faults, so as to create *fuzzy* models for each of possible faults.

## 2. Process Modeling

In projects involving railway safety and simultaneously the rails usage as transmission medium of electrical signals for command and control, the most difficult obstacle to overcome is related to track electrical characterization.

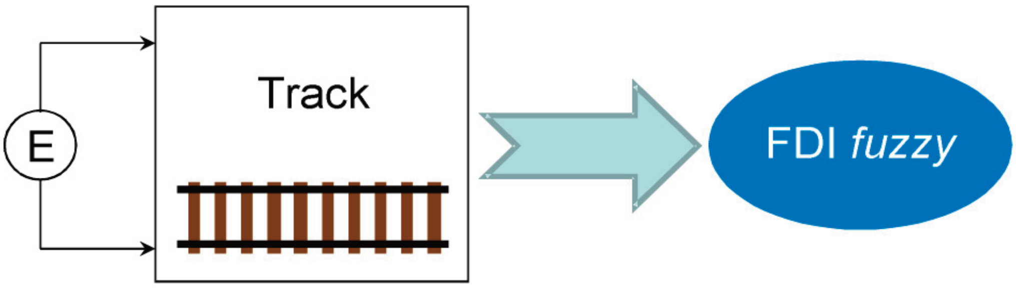


**Figure 5:** Measuring the track parameters.

In order to evaluate the track characteristics as appropriate physical transmission medium for track circuits operation it becomes necessary to develop the proper equivalent electrical model. This model will be used to generate process data and thus obtain the *fuzzy* models for use in fault diagnosis.

*Fuzzy* models of TS type usually have better performance in systems modeling than other structures. This capability is due to the ability representation of nonlinear systems by aggregation of several local linear models/approximations [6], as shown in figure 6. Therefore, the TS *fuzzy* models will be used in FDI architectures for track circuits, as illustrated in figure 5.

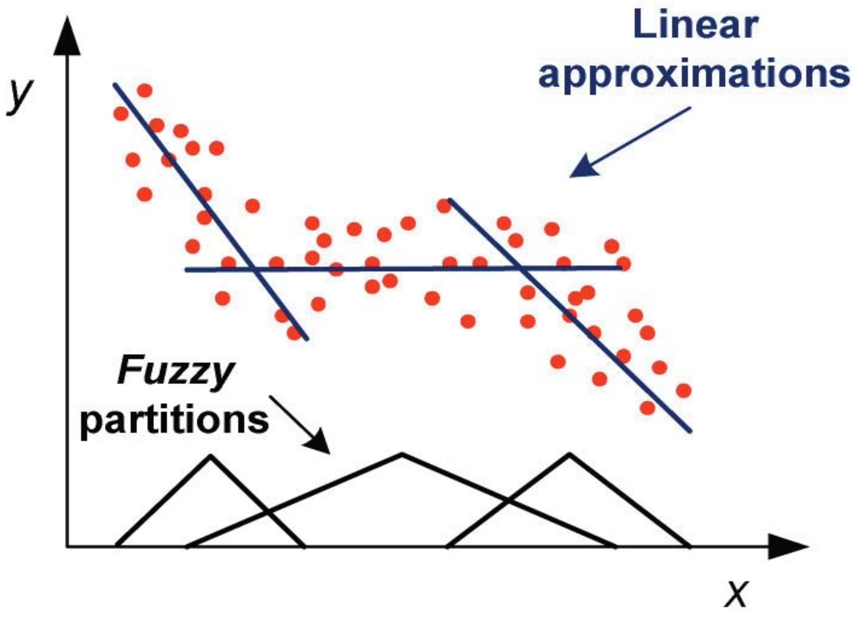


**Figure 6:** Local linear approximations of a nonlinear system.

The local linear approximations are obtained by dividing the input space into several subspaces (clusters), one for each linear relationship between input and output, using the aggregation (clustering) algorithm Gustafson-Kessel [3]. The *fuzzy* clustering algorithm Gustafson-Kessel presents generally as the most widely used in solving problems of modeling and identification for dynamic processes. This algorithm served as basis for modeling the track and subsequently the track circuit.

### 2.1. Track model

The reference values for electrical track characteristics, then presented, have as main study focus the UIC60 standard rail and the European gauge, with the assumption of an ideal track insulation (both rails are electrically insulated from ground).

A first approximation to the track impedance was achieved by the definition of biquadratic cells [5], whose quadripole is illustrated in figure 7.

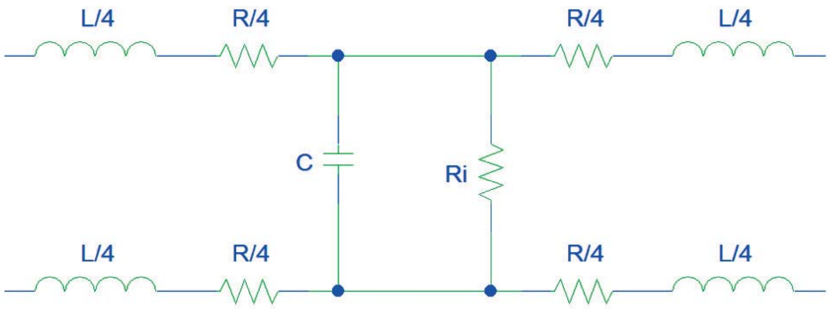


**Figure 7:** Equivalent electrical model of track.

The typical values used in model characterization are obtained from experimental abacuses [4] with a dynamic measurement range between 1 Hz and 25 kHz, being the spectrum band which better ensures:

- The propagation of electrical signals through the track in audio-frequencies range (limited bandwidth);

- The signal encoding usage in order to ensure immunity to interferences associated with electrical traction systems (with relevant harmonic contents located up to 20 kHz);

- The frequency band with higher occupancy rate is between 0 and 10 kHz, whereby the band more favorable is between 10 and 20 kHz, recommending a central frequency value around 15 kHz.

Each quadripole is built based on knowledge acquired about the track physical behavior, presenting as fundamental parameters the following electrical quantities:

*L*: Longitudinal inductance of rails (typical value between 1 and 2 mH/km) – is a physical quantity that varies proportionally with the electrical traction current that flows through the rails;

*R*: Longitudinal resistance of rails (typical value around dozen Ω/km), which completes the rails inductive effect and that also varies in proportion to electrical current of return traction;

*C*: Cross capacitance between the rails and with the ground (typical value of dozens of nF/km) – at track circuit working frequency the value of capacitive component in track impedance is negligible compared to insulation resistance;

$R_i$: Insulation resistance between rails (minimum value of 1.5 Ω.km and may go up to 10 Ω.km under ideal conditions) – physical quantity very dependent of track conditions, particularly in accordance to ballast quality and of atmospheric conditions.

The track insulation is a very important factor in track circuits operation, this insulation being guaranteed in the way that is shown in figure 8.

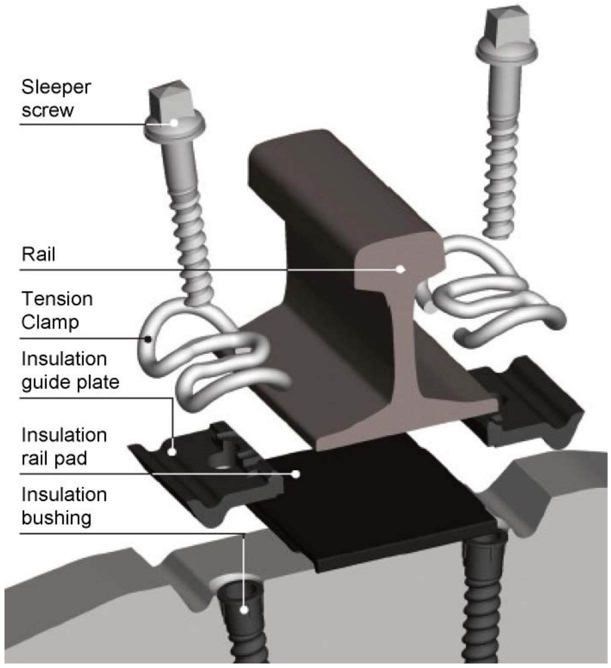


**Figure 8:** Rail fastening (track insulation).

Note that when the variation of track characteristics around the nominal values is significant, implies a seasonal adjustment of track circuits regulation parameters and constituent components (example summer and winter) in order to ensure a proper and safe operation of the equipment. This principle underlies the preventive maintenance theory, which can be achieved efficiently using fault diagnosis techniques employing *fuzzy* concepts.

Typical values of track parameters to be applied to process model are, as can be seen in figures 9 to 12 (for 1 km length):

1.3 mH for longitudinal inductance of rails;

12 Ω for longitudinal resistance of rails;

80 nF for cross capacitance between rails;

5.7 S for conductance of the track.

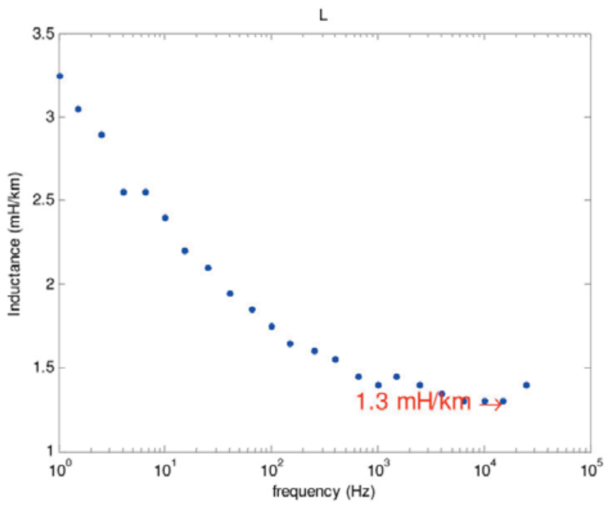


**Figure 9:** Model parameters of track (longitudinal inductance).

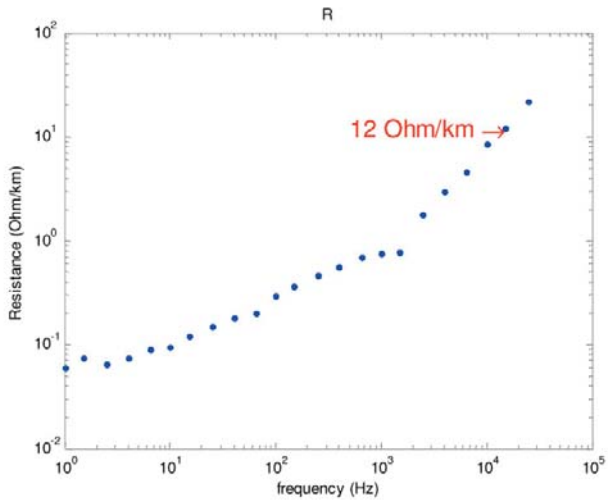


**Figure 10:** Model parameters of track (longitudinal resistance).

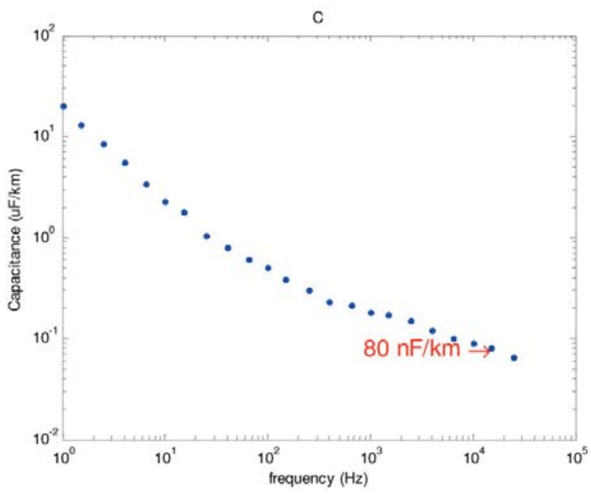


**Figure 11:** Model parameters of track (cross capacitance).

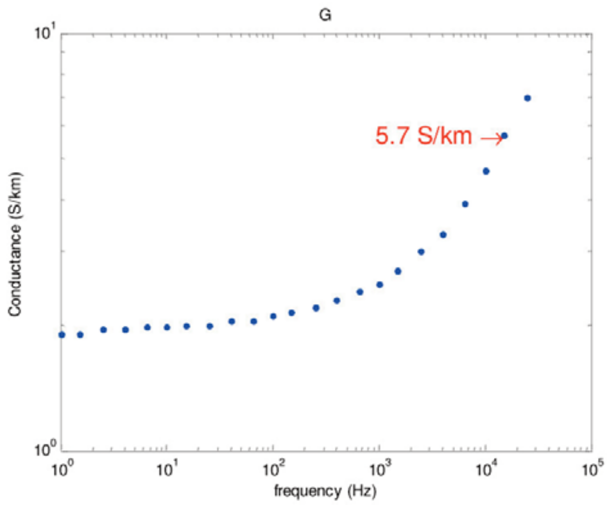


**Figure 12:** Model parameters of track (cross conductance).

In practice, the parameters of resistance *R* and inductance *L* vary slightly with the type of rail used and with the track construction elements (sleepers, ballast, etc.). However, the parameters of capacitance *C* and conductance *G* vary strongly with local environmental conditions and geological track assembly.

The relationship between the transfer function of track electrical model and the corresponding parameters of simulation module (see figure 13) is then presented in order to illustrate the simulation performed.

$$H(S) = \frac{\frac{1}{L \times C}}{S^2 + S\left(\frac{R}{L} + \frac{G}{C}\right) + \left(\frac{1}{L \times C} + \frac{R \times G}{L \times C}\right)} = \\ = \frac{9{,}6154 \times 10^9}{S^2 + 7{,}1259 \times 10^7 S + 6{,}6731 \times 10^{11}} = \\ = \frac{nn0}{S^2 + dn1 \times S + dn0} \qquad (2)$$

In the model gain function, when it increases the complex frequency *S* verifies that the gain decreases and the attenuation value becomes consequently very high, which difficult the signal propagation. This effect summarizes the low-pass filter behavior.

## 2.2. Track circuit model

The emission voltage of audio-frequency track circuits typically ranges between 1 and 10 volts depending on technology and manufacturer. The voltage applied to rails requires the fulfillment of specific requirements regarding the safety of people who interact with the track, these are railway staff or ordinary citizens.

Coded track circuits, because of its bigger immunity to interference present in railway environment, have the advantage of reducing the signal magnitude injected into the track as well as increasing the reception module sensitivity, thus enabling the discrimination of electrical signals with much smaller amplitudes, conferring robustness to the track circuit.

Typical values of reception module sensitivity for audio-frequency track circuits are between 10 and 200 mV,whose premises are related to transmitting signal level by emission module and the distance to overcome by electrical signal. However, the magnitude of encoded signal at reception point must be such that has a margin in light of receiver module sensitivity – FSK track circuits used in the Portuguese railway network are regulated to 900 mV (at reception point).

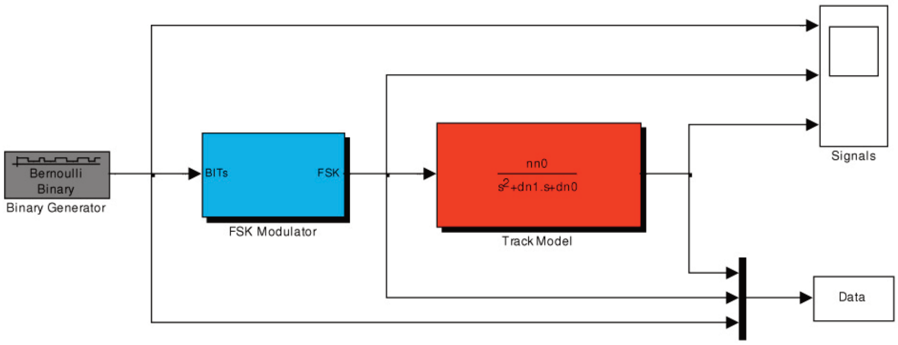


**Figure 13:** Track circuit block diagram.

The track circuit simulation structure is based in two fundamental parts, being the first composed by the track circuit components (integrating the binary code block generator and the FSK modulator block) and the second composing the characteristic electrical model of the track (modeled by quadratic function in complex frequency *S* domain) as illustrated in figure 13.

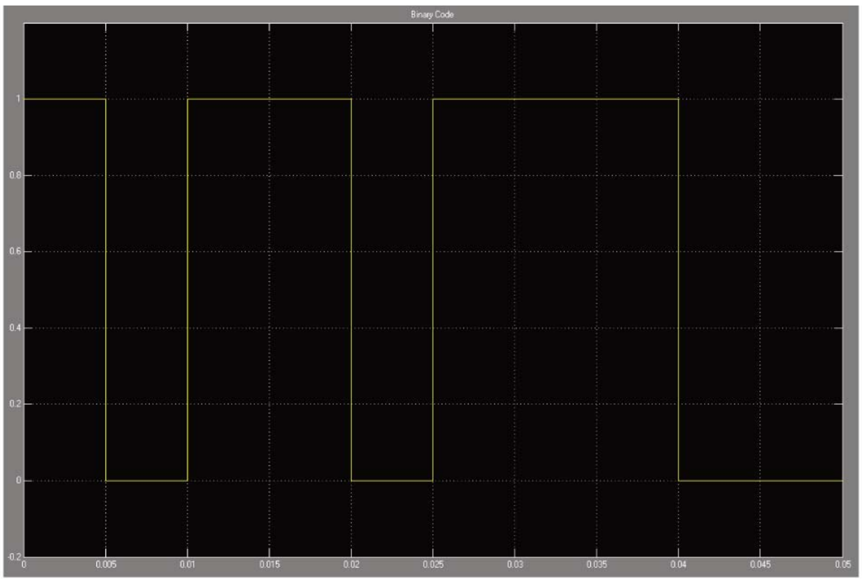


**Figure 14:** Track circuit encoding signal.

The binary code used in track circuit modeling, simulated by Bernoulli[4] series, shows a bit 0 occurrence probability of 0.4, thereby obtaining a 0.6 value for bit 1 probability, as can be seen by examining figure 14.

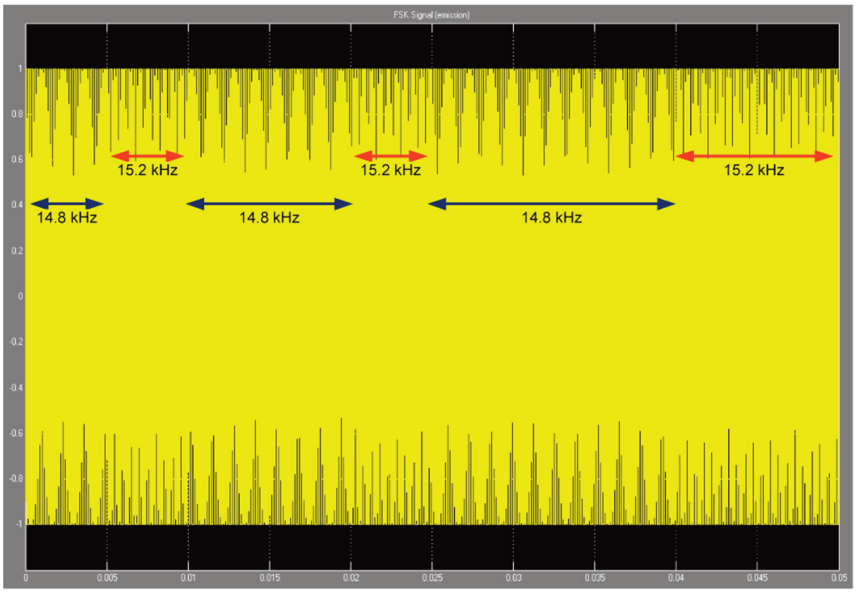


**Figure 15:** Track circuit emission signal.

Looking at figure 15 it is possible to match the two logical levels of BFSK (Binary Frequency Shift Keying) modulated signal at upper and lower frequencies for emission and reception track circuit signals, which are illustrated in greater detail in figure 17.

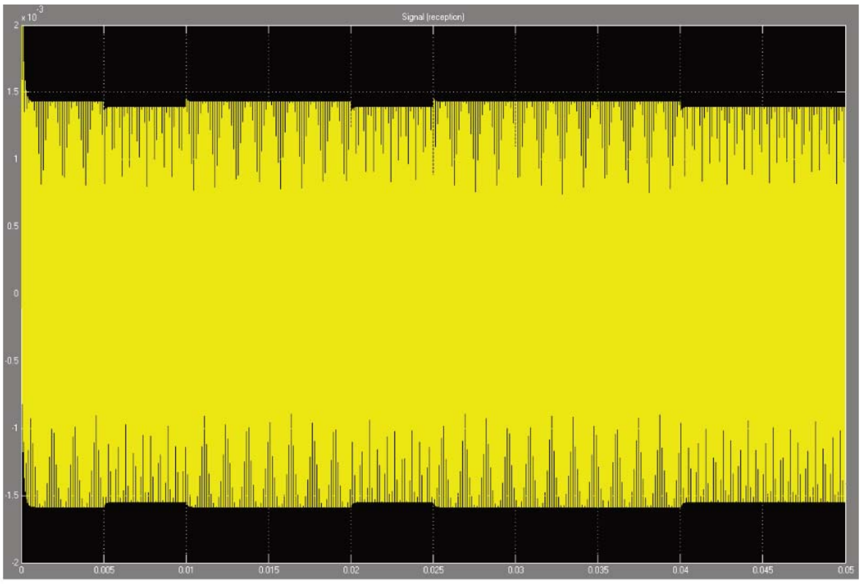


**Figure 16:** Track circuit reception signal.

The effect of different attenuation levels to lower and upper frequencies of BFSK reception signal is checked on output signal variable envelope of simulation chain (see figure 16), summarizing the low-pass filter behavior, with higher attenuation at upper frequency of BFSK signal, of 15.2 kHz ($f_0$ + 200 Hz), which corresponds to modeling the logical level 0 of track circuit binary code.

[4] The Bernoulli distribution is a discrete distribution in the sample space {0, 1} with probabilities P(0)=1–p and P(1)=p. The distribution name is allusive to the Swiss scientist Jakob Bernoulli, mentor of theory..

The frequency shift of BFSK modulation is confirmed visually by counting the cycles number when it is active the logical value 0 (slightly more than 3 cycles of sinusoid in the considered extract of data– see figure 17) compared to homologous analysis to the extract representing the logical value 1 (less than 3 cycles), which corresponds to a higher frequency associated to logical level 0, as expected.

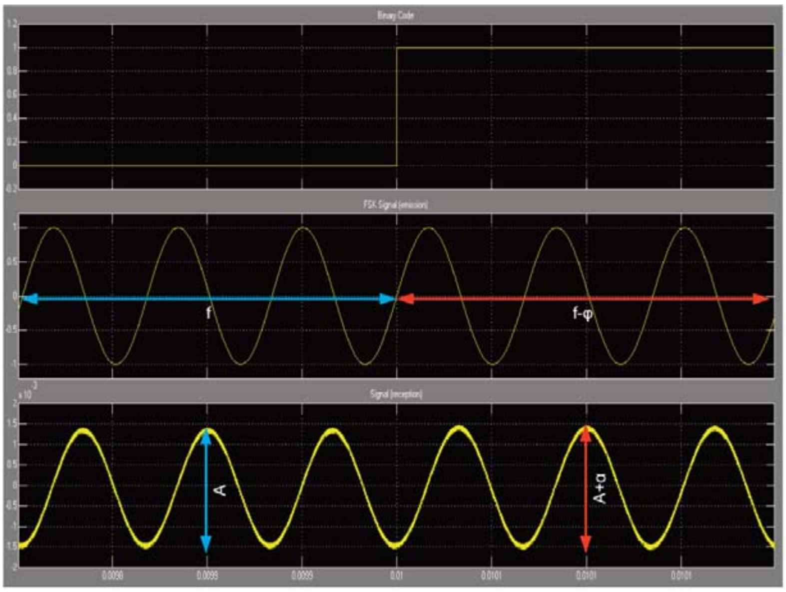


**Figure 17:** Details of track circuit emission and reception signals.

The data thus generated (associated to FSK track circuit operation with 1 km length) and that above were characterized in detail, provide the basis for experimentation of model-based fault diagnosis techniques, whose results are presented in next section.

## 3. Results of *fuzzy* FDI

The proper adjustment of models to reality, for processes with and without faults, is proved by performance results obtained for the faulty and fault-free models of process, allowing thus to evaluate the TS *fuzzy* models performance in performing tasks of fault detection and isolation in track circuits.

To measure the performance of *fuzzy* models obtained for the process to operate faultlessly and under the influence and faults is used, as a normalized residual measure, the calculation method of variance accounted for, VAF (Variance Accounted For performance index for the model), mathematically defined as it follows:

$$VAF = \left[1 - \frac{cov(y_i - \hat{y}_i)}{cov(y_i)}\right] \times 100\% \qquad (3)$$

Where $y_i$ represents the process output and $\hat{y}_i$ the *fuzzy* model output.

To ensure the duality of analysis was used another performance index by calculating the mean square error RMS (Root Mean Squared error) between the process output data and the *fuzzy* model outputs, whose expression is presented below:

$$RMS = \sqrt{\frac{\sum_N (y_i - \hat{y}_i)^2}{N}} \qquad (4)$$

Where $N$ represents the number of data used.

Through analysis of expressions 3 and 4 it turns out that the VAF and RMS performance indexes are normalized residual measurements, presenting the residual evaluation terms $y - \hat{y}$, as indicated in (1).

### *3.1. Residual generation*

The VAF and RMS performance indexes are a numerical translation of generated residuals, allowing thus a rapid evaluation of achieved performance in fault-free and faulty models generation.

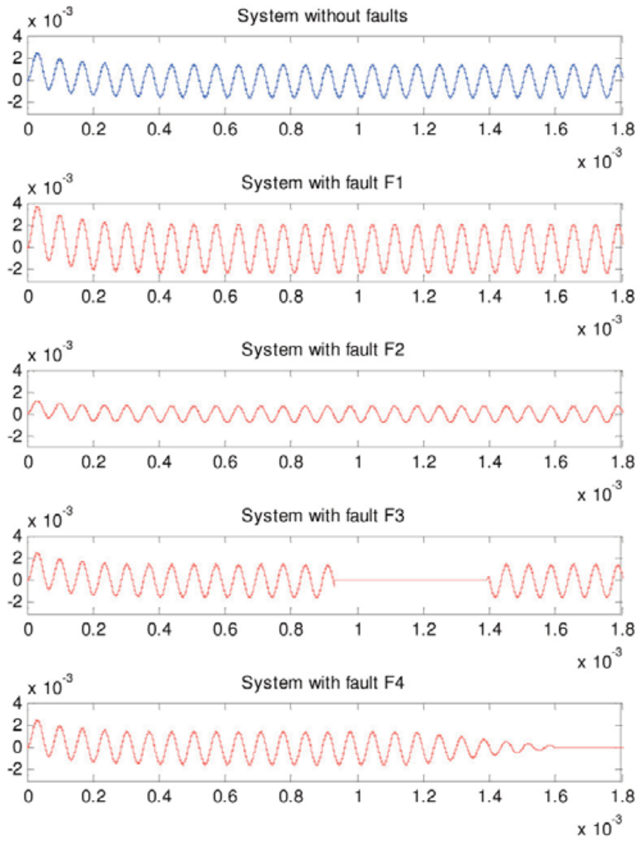


**Figure 18:** Fault modes of process output signals.

The approach used in establishing the most appropriate *fuzzy* parameters, supported on trial and error method, revealed that fault types $F_1$ and $F_2$ have the same results as for system to operate faultlessly, because they follow the same sinusoidal temporal pattern (same operating frequency, but with different magnitudes, according to fault type), as can be verified in figure 18. However, despite the differences in magnitude compared to process output signal to operate faultlessly, the modulation of fault types $F_1$ and $F_2$ have VAF values of approximately 99.75%. The results obtained for the performance indexes of the latter two fault patterns aren't satisfactory (see *fuzzy* modeling result in figures 19 and 20), materializing lower values for VAF, between 75% and 80%, and high RMS values, between $400\times10^{-6}$ and $450\times10^{-6}$.

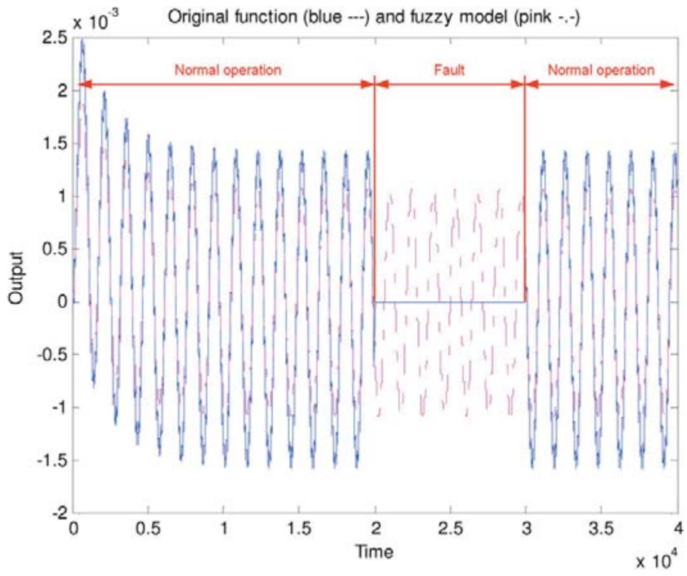


**Figure 19:** Signals corresponding to fault mode $F_3$.

Once the *fuzzy* models determination for fault types $F_3$ and $F_4$ based on data comprising states of normal operation, transient state and steady-state (see figures 19 and 20) the achievement of a credible model isn't successful. Thus, *fuzzy* models were calculated only based on fault steady-states, e.g., in the zone corresponding to effective fault data (ignoring the normal operation and transient states) and in which learning for model building isn't negatively affected.

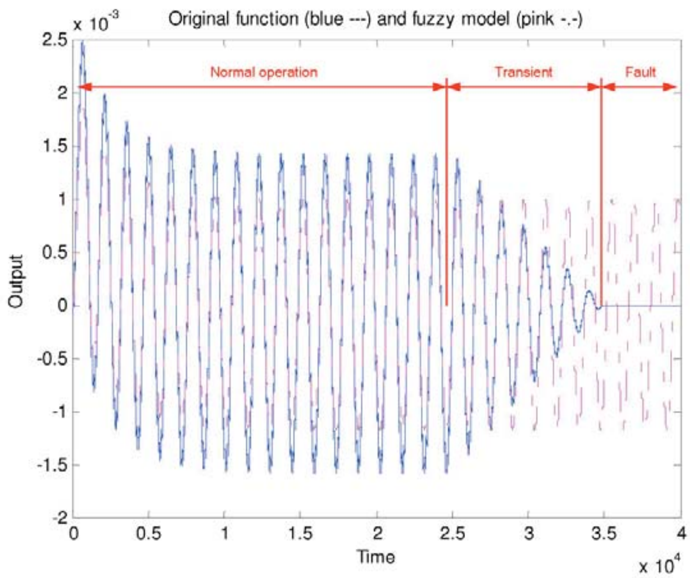


**Figure 20:** Signals corresponding to $F_4$ fault mode.

Following what has been described above concerning to several states that decompose the faults, we chose to characterize a single failure state (null signal zone $F_{3\_4}$) for fault patterns $F_3$ and $F_4$, confirming that the process output signal was approached perfectly by the *fuzzy* model, which corresponds to a VAF performance index of 100% and RMS of zero.

Obtained the *fuzzy* models for the process to operate faultlessly and operating under influence of faults $F_1$, $F_2$, $F_3$ and $F_4$ ($F_{3\_4}$), it is necessary to evaluate the fault detection and fault isolation stages.

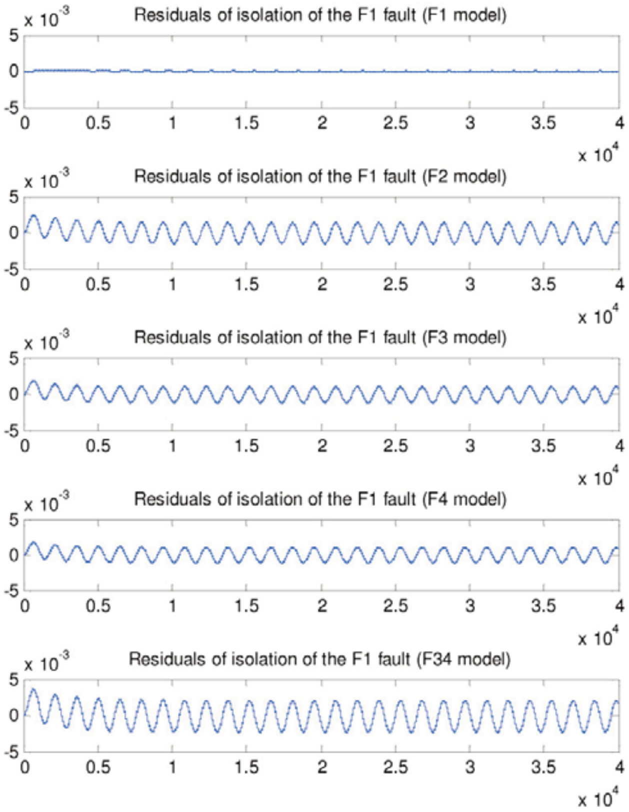


**Figure 21:** Residual representation of $F_1$ fault isolation.

As illustrative summary of generated residuals at fault isolation stage are shown in figure 21 the residual signals for each fault type, which translates visually (residual signal tending to zero) if a fault is or not correctly isolated.

### 3.2. Fault detection

In obtaining the *fuzzy* model for the FSK transition cycle with frequency $f_0$ – 200 Hz were used three clusters. In figure 22 it can be seen, as expected in view of good performance, that the achieved approximation by *fuzzy* model closely overlaps the process output data (excluding the Gaussian noise observed in output signal).

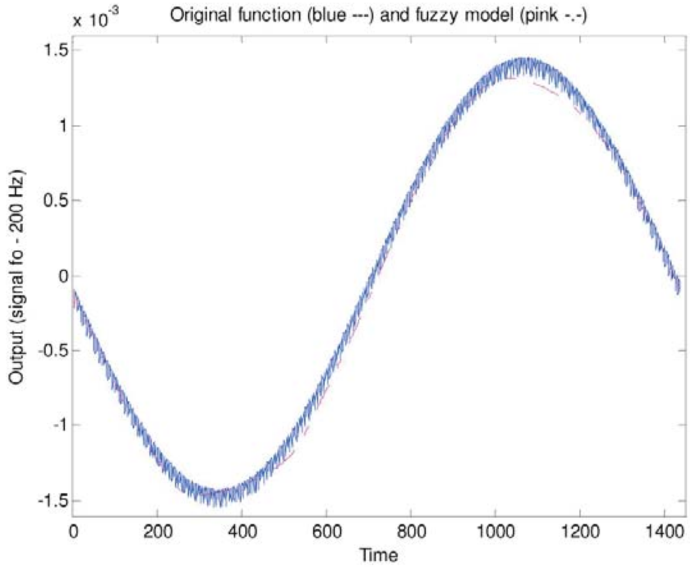


Figure 22: Process output signals ($f_0$ – 200 Hz frequency component).

Given the results obtained for RMS performance indexes, which follow the same behavior of VAF as can be seen by table 1 analysis, it is confirmed that fault detection performs coherent (detects all data sets with faults). In this perspective and in light of RMS threshold concept for fault detection, may define the $100\times10^{-6}$ value as a fault detector criterion (error accounting value above which the fault is detected).

| | Data $F_0$ | Data $F_1$ | Data $F_2$ | Data $F_3$ | Data $F_4$ | Data $F_{3\_4}$ |
|---|---|---|---|---|---|---|
| **VAF** | 99.75 | 88.59 | 0.63 | 67.90 | 71.88 | 0.00 |
| **RMS** ($\times10^{-6}$) | 51.78 | 531.07 | 522.45 | 516.67 | 471.15 | 1000.00 |

**Table 1:** VAF and RMS performances on fault detection.

In particular, highlights that the VAF and RMS results for the data $F_{3\_4}$ (fault data corresponding to common area of fault types $F_3$ and $F_4$) have extreme values, as corresponding to electrical signal absence at track circuit reception point.

### 3.3. Fault isolation

After fault detection stage follows, in processing chain, the fault isolation stage, which presents a data combination quite different from previous because all fault data are combined with all fault models (see figure 23 diagram).

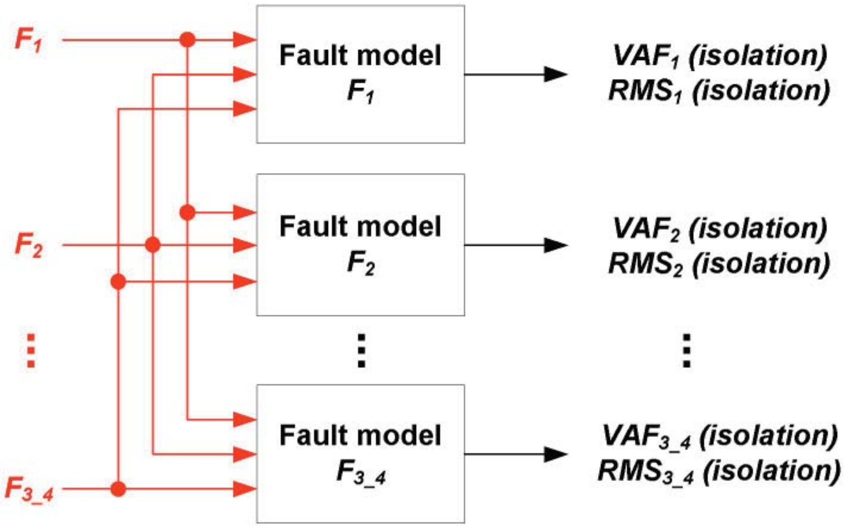


**Figure 23:** Fault isolation scheme.

The threshold values used for fault isolation (also used in fault detection stage) were obtained through experimentation and are limited by:

VAF > 95%;

RMS < $100 \times 10^{-6}$.

It is thus, by analysis of table 2 results, the data that make up the fault type $F_1$ only combine in VAF performance with the model $F_1$, the data that correspond to fault type $F_2$ only match in VAF performance with the model $F_2$ and the data that aggregate the steady-state of fault types $F_3$ and $F_4$ only correspond to model $F_{3\_4}$.

| VAF | Model $F_1$ | Model $F_2$ | Model $F_3$ | Model $F_4$ | Model $F_{3\_4}$ |
|---|---|---|---|---|---|
| Data $F_1$ | 99.75 | 55.32 | 74.71 | 75.23 | 0.00 |
| Data $F_2$ | 0.00 | 99.75 | 75.23 | 73.44 | 0.00 |
| Data $F_3$ | 3.36 | 66.76 | 75.77 | 75.88 | 0.00 |
| Data $F_4$ | 4.10 | 70.49 | 80.09 | 80.22 | 0.00 |
| Data $F_{3\_4}$ | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 |

**Table 2:** VAF performances on fault isolation.

Also noted that the data-model correspondence for $F_3$ and $F_4$ don't have acceptable VAF performance. These results are due to the fact that there have generated models (learning phase) with ranges of data that includes three distinct operation zones, as already mentioned above.

In a checking viewpoint of fault isolation stage behavior, now in view of RMS performance index, it shows that the result is consistent with what is obtained by analysis with VAF criteria, as can be seen by comparing tables 2 and 3.

| RMS ($\times 10^{-6}$) | Model $F_1$ | Model $F_2$ | Model $F_3$ | Model $F_4$ | Model $F_{3\_4}$ |
|---|---|---|---|---|---|
| **Data $F_1$** | 77.66 | 1100.00 | 790.52 | 784.16 | 1600.00 |
| **Data $F_2$** | 1000.00 | 25.89 | 264.73 | 271.29 | 524.10 |
| **Data $F_3$** | 896.24 | 526.39 | 449.04 | 451.20 | 912.75 |
| **Data $F_4$** | 870.02 | 483.19 | 396.90 | 398.50 | 889.30 |
| **Data $F_{3\_4}$** | 1600.00 | 522.70 | 785.60 | 792.12 | 0.00 |

**Table 3:** RMS performances on fault isolation.

As shown for fault detection, also at isolation stage the data comprising the $F_{3\_4}$ vector assume extreme valuesfor VAF (100%) and RMS (with 0.00) performance indexes, which is due to perfect correspondence between model and process output signals – the electrical signal absence at track circuit reception point implies a stationarity of fault pattern and so a coherent *fuzzy* modeling and *fuzzy* identification.

## 4. Conclusions

The use of approaches to fault diagnosis has greatly contributed to technical incidents restriction and therefore accidents reduction in different areas as industry, in oil, chemical, nuclear, aerospace, railway, etc., thus minimizing human and materials losses.

The main difficulties arising from model-based fault diagnosis implementation underlie in obtaining models with good performance and in high complexity of processes. However, when there isn't sufficient information (complete) about processes and these are nonlinear, the use of *fuzzy* models improves the fault diagnosis capability. For all of these reasons was materialized the fault diagnosis approach based on model, using *fuzzy* models of Takagi-Sugeno type obtained through data generated by simulated process of a hypothetical track circuit. Applying the fault diagnosis approach based on *fuzzy* models (of Takagi-Sugeno type) to track circuits has proven its potential in FDI stages, with appropriate performance indexes and reaching VAF values close to 100% and RMS results with low values (about $50\times10^{-6}$), representing an approximation at all similar to the relationship of input-output data.

In summary, *fuzzy* logic is a theory that fits fully in FDI techniques implementation, particularly when knowledge about processes is approximate and limited such as the track electrical model, whose characteristic electrical parameters are very variable (function of physical properties and of influence that environmental changes lead), and therefore with the track circuits operation mode.

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