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Case study line Brașov to Zărnești in Romania

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A condition-based maintenance methodology for rails in regional railway networks using evolutionary multiobjective optimization

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Abstract——**In this paper, we propose a methodology based on signal processing and evolutionary multiobjective optimization to facilitate the maintenance decision making of infra-managers in regional railways. Using a train in operation (with passengers onboard), we capture the condition of the rails using Axle Box Acceleration measurements. Then, using Hilbert-Huang Transform, the locations where the major risks are detected and assessed with a degradation model. Finally, evolutionary multiobjective optimization is employed to solve the maintenance decision problem, and to facilitate the visualization of the trade-offs between number of interventions and performance. Real-life measurements from the track from Braşov to Zărneşti in Romania are included to show the methodology.**

Keywords— Multiobjective optimization; acceleration measurements; Railway Engineering; KPIs; ARMOEA.

I. INTRODUCTION

Regional railway networks face many challenges for their daily operation. Two are the major affecting factors: (1) the low demand and (2) the dispersed population. As a consequence, often limited budget for operation and maintenance of the regional railway tracks is available. In this case, infra-managers must take well-informed decisions before performing inspections or maintenance, so to make the best out of the limited budget. Intelligent monitoring systems are widely used in the industry to control the degradation of the different railway assets. However, for regional railways, expensive equipment is usually unreachable due to the limited budget. Luckily, in recent years, sensor devices have become cheaper. Examples are in networking technologies, and different types of the cheap devices, like smart phones, accelerometers installed on trains and drones [1-6].

In this paper, the focus is on health condition monitoring of rails. The health condition should be kept controlled over time, to avoid defects and broken rails that might severely affect the safety of the operations. To decide which piece of rail requires maintenance and also which ones are the most critical pieces of rail, actual health condition of the rail should be collected. In this paper, we make use of Axle Box Acceleration (ABA) measurements that are able to detect the rail surface defects. By looking at the right features extracted from the acceleration data, location and severity of different types of defects can be obtained.

In some simple cases, the features can be acceleration values that exceed a predefined threshold. However, under the interference of measurement noises and normal vibrations of the wheel and rail, some defects might be difficult to observe directly from acceleration peaks in the time domain. Then, it is common in the literature that frequency domain methodologies are employed to focus on defect-induced vibration frequencies that can be easily observed from the signals, [7-15]. To circumvent the manual selection of method parameters, this paper employs the HHT to extract instantaneous frequency features. The first step of HHT, namely the empirical mode decomposition (EMD) can adaptively decompose a signal into several components with descending frequency bands. After the decomposition, the instantaneous frequency of each signal component, which can be essentially regarded as the reflection of local frequency variation, is computed by the Hilbert transform. This value can be used as the indicator that characterizes the health condition of rail, in a way similar to previous methods based on time-frequency analysis.

Based on performance indicators, we propose a methodology to use the rail degradation model for a multi-objective maintenance decision support system. A scenario-based approach is considered to include the stochasticity of the rail damage evolution. A set of KPIs is defined according to the degradation over time. Using evolutionary multi-objective optimization (EMO), the trade-offs between number of interventions and the effect on the performance is clearly observable. This will facilitate the decision making processes in regional railway, so that infra-manager can focus on those places with only the most relevant conditions. In Figure 1, a diagram of the methodology is presented, including the steps from monitoring to final decision making. In this paper, real-life measurements from the track Braşov to Zărneşti in Romania are included as case study to show the methodology.

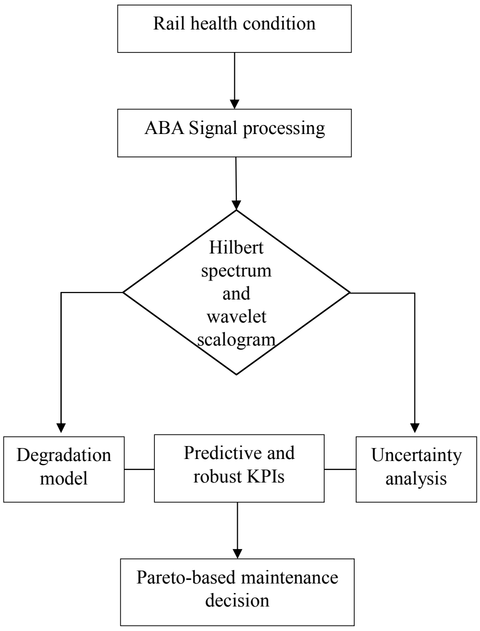

Fig. 1. A generic flowchart of the proposed methodology.

II. RAIL HEALTH MONITORING

In this paper, we use a regular train that is in operation (with passengers on board) to capture the vibration generated by the wheel-rail interaction (Fig. 2). When the wheel passes over a defect, the vibration is much different than when is passing through smooth rail. The differences between the responses can be employed to detect where the different sorts of defects are located and their severity. In the regional railway, damaged welds [16-19], and different types of rolling contact fatigue [20-21] can be found.

Fig. 2. On-board train measurement system in the Transylvanian area of Romania.

The principle of the ABA measurements is that the vibrations induced by a defect will be transmitted from the wheel-rail contact to the wheel and can be measure at the axle box. The location of the sensors is important, and to guarantee a good detection rate, many accelerometers are mounted on the axle boxes of the bogies. The magnitude of the ABA signal is dependent on train speed. In normal operation, the higher the speed, the higher the impact of the dynamic forces and thus the energy of the ABA signals. This also reflects the actual operational conditions over the defects. To consider this factor, multiple measurements are performed.

III. HILBERT SPECTRUM APPROACH

Hilbert spectrum is the result of the Hilbert-Huang transform (HHT) [22]. It first adaptively decomposes the original signal $\{\tau(t), t \in [0,T]\}$ into a number of intrinsic mode functions (IMFs) $\nu_\ell(t)$, $\ell = 1,2,...,N_{IMF}$ and a residual $r(t)$, using the empirical mode decomposition (EMD) algorithm. The resulting IMFs and residual meet the following equality:

$$\tau(t) = \sum_{i=1}^{N_{IMF}} \nu_\ell(t) + r(t) \tag{1}$$

In detail, the EMD algorithm can be described as follows:

Step 1: Obtain the upper and lower envelopes $e_u(t)$ and $e_l(t)$ of signal $\tau(t)$ by connecting all the signal maxima and minima, respectively, using spline interpolation. For the first iteration, this step starts with $i=1$, $\ell=1$ and $\nu_\ell^{(i)}(t) = \tau(t)$.

Step 2: Compute the function $e_m(t)$ that is the mean of signal envelopes $e_m(t) = [e_u(t) + e_l(t)]/2$.

Step 3: Let the estimated IMF $\nu_\ell^{(i+1)}(t) = \nu_\ell^{(i)}(t) - e_m(t)$ and the number of sifting iterations $i = i+1$.

Step 4: Check if the following stopping criterion is satisfied.

$$S(i) = \sum_{t=0}^{T} \frac{|\nu_\ell^{(i)}(t) - \nu_\ell^{(i-1)}(t)|^2}{|\nu_\ell^{(i-1)}(t)|^2} < \varepsilon \tag{2}$$

where ε is a positive number typically in the range from 0.2 to 0.3. If (2) is not satisfied, go to Step 1; otherwise, obtain the jth IMF $\nu_\ell(t) = \nu_\ell^{(i)}(t)$ and go to Step 5.

Step 5: Update $\ell = \ell + 1$, $i = 1$ and $\nu_\ell^{(1)}(t) = x(t) - \sum_{k=1}^{\ell-1} \nu_k(t)$.

Check if the signal $\nu_\ell^{(1)}(t)$ has only one pair of extrema. If not, go to Step 1; otherwise, obtain the residual $r(t) = u_\ell^{(1)}(t)$.

The extracted IMFs have descending frequency bands from $\nu_\ell(t)$ to $\nu_{N_{IMF}}(t)$ due to the iterative sifting process. They are regarded as intrinsic signal modes that have physical meanings.

This makes it possible to identify defect-induced signal features directly from the IMFs of ABA signals. Thus, the feature extraction of ABA signals can be done by using the IMF with the indicative frequency band.

Next, the instantaneous frequencies of the extracted IMFs are computed. The IMFs are first transformed to the analytic form using the Hilbert transform.

$$z_\ell(t) = v_\ell(t) + \mathrm{i} \cdot H[v_\ell(t)] = a_\ell(t)\mathrm{e}^{\mathrm{i}\cdot\theta_\ell(t)} \quad (3)$$

where $H[d_\ell(t)]$ denotes the Hilbert transform of IMF $d_\ell(t)$. The amplitude $a_\ell(t)$ and phase $\theta_\ell(t)$ of the analytic form are

$$\begin{cases} a_\ell(t) = \sqrt{v_\ell^{\,2}(t) + H[v_\ell(t)]^2} \\ \theta_\ell(t) = \arctan\left(\dfrac{H[v_\ell(t)]}{v_\ell(t)}\right) \end{cases} \quad (4)$$

Then the instantaneous frequency $\omega_\ell(t)$ of IMF $d_\ell(t)$ is defined as

$$\omega_\ell(t) = \frac{\mathrm{d}\theta_\ell(t)}{\mathrm{d}t} \quad (5)$$

Finally, the Hilbert spectrum of signal $\tau(t)$ can be obtained by:

$$S(\omega, t) = \mathrm{Re}\left[\sum_{\ell=1}^{N_{IMF}} a_\ell(t)\mathrm{e}^{\mathrm{i}\cdot\int\omega_\ell(t)dt}\right] \quad (6)$$

where Re is a real part operator. The Hilbert spectrum of a single IMF $v_\ell(t)$ is

$$S_\ell(\omega, t) = \mathrm{Re}[a_\ell(t)\mathrm{e}^{\mathrm{i}\cdot\int\omega_\ell(t)dt}] \quad (7)$$

The function in (7) represents the energy variation of instantaneous frequency with the change of time. The Hilbert spectrum has been successfully employed as KPIs for engineering applications [23] as a substitution for general power spectrum. In this paper, it is applied to ABA signals to quantify the health condition of rail and enable defect detections. A KPI for detection and assessment of a defect will have the form:

$$\gamma(t) = \mathrm{Re}[a_\ell(t)\mathrm{e}^{\mathrm{i}\cdot\int\omega_\ell(t)dt}] \quad (8)$$

where ℓ will be the selected IMF according to the ABA signals measured under different circumstances and for detecting the specific type of rail defect.

IV. Predictive and Robust KPIs

The real-life data coming from ABA sensors is subject to a set of different stochasticities. We define robust KPIs based on ABA and the Hilbert spectrum approach, which include these differences from different measurements over the same rail locations (with defects). The average of the measurement data is expressed as:

$$\gamma(k) = \frac{1}{M}\sum_{m=1}^{M}\gamma^m(k) \quad (9)$$

where $\gamma^m(k)$ is measurement m. For the worst and best severity scenarios, we consider

$$\gamma(k) = \max(\gamma^m(k)), \; m = 1,\ldots,M \quad (10)$$

$$\gamma(k) = \min(\gamma^m(k)), \; m = 1,\ldots,M \quad (11)$$

These values are fed into the degradation model. The generic degradation process of a rail infrastructure component contains stochastic dynamic as represented in Fig. 3.

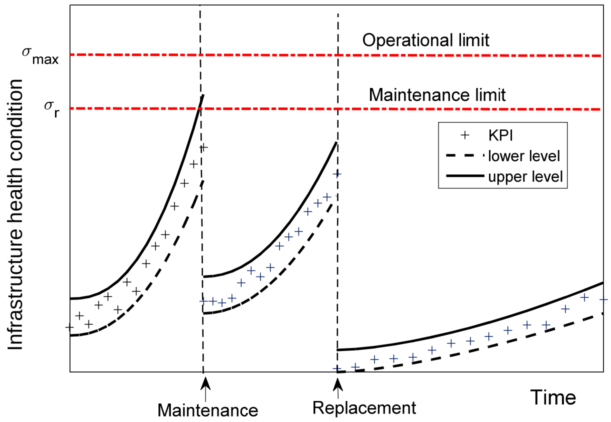

Fig. 3. Degradation process of a generic defect. A higher value indicates a worse condition. The initial condition is denoted by σ0, while σr and σmax represent the maintenance and operational limit, respectively.

Before the maintenance time, the defects could have grown to violate the maintenance limit (σ_r) potentially causing rail failure (σ_{max}). By replacing the degraded piece of the rail, the rail becomes healthy. Moreover, the growth rate of the defects at early stage is slightly slower that already severe defects.

Let's define *u(k)* as the maintenance action performed on rail surface defects at time step *k*. The following generic model is used to describe the degradation model based on degradation scenario *h*:

$$\gamma^h(k+1) = F^h(\gamma(k), u(k))$$

$$= \begin{cases} F_0^h(\gamma^h(k)) & \text{if no maintenance is applied} \\ F_1^h(\gamma^h(k)) & \text{if maintenance is applied} \\ F_2^h(k) & \text{if replacement is applied} \end{cases} \quad (12)$$

where $\gamma^h(k+1)$ is the prediction for scenario *h* and $\gamma(k)$ the measurement at instant *k*. The natural degradation function F_0^h only depends on the current condition and uncertainties. Maintenance function F_2^h recovers the rail condition, but replacement function F_2^h recovers the rail to an ‘‘as good as new” condition, regardless of the current condition or the history of maintenance interventions.

V. EMO FOR RAILWAY MAINTENANCE DECISIONS

Due to the conflicting nature between costs and track performance, there is not a single optimal solution that is able to optimize both objectives at the same time. Instead, a number of solutions can be obtained as trade-offs between different objectives. The solutions are known as the Pareto optimal. The multiobjective optimization problem can be formulated as follows:

$$\min\left\{J_1\left(u(k)\right), J_2\left(u(k)\right)\right\} \tag{13}$$

where $J_1\left(u(k)\right)$ is a function of the performance for the whole track, defined based on the predictive KPIs, and $J_2\left(u(k)\right)$ is the objective function that represents the number of interventions (related to maintenance cost). The first objective function is expressed as:

$$J_1\left(u(k)\right) = \sum_h \sum_t \sum_{defect} \alpha_{t,h} \gamma^h_{defect}(k+t) \tag{14}$$

where $\gamma^h_{defect}(k)$ is the KPI at the time step k for a *defect* and severity scenario h and $\alpha_{t,h}$ is a weight over the time predictions and scenarios.

The second objective function is simply considered as the number of interventions (maintenance or replacements). This is directly related to the budget of the infrastructure manager.

$$J_2\left(u(k)\right) = \sum_t \sum_{defect} \left(1 - u_{defect}(k+t)\right) \tag{15}$$

To solve the multiobjective optimization problem, different approaches are in the literature. Pareto dominance based MOEAs are approaches where Pareto dominance based mechanisms are adopted to distinguish and select candidate solutions e.g. non-dominated sorting genetic algorithm (NSGA-II) is of popular algorithms among others. Other approach is the indicator based MOEAs, where performance indicators of solution quality measurement are adopted as selection criteria in the environmental selection. In this paper an indicator-based MOEA is tested, called ARMOEA [29]. The algorithm takes advantage of a new proposed performance indicator of the solution named the enhanced inverted generational distance (IGD-NS) indicator which is able to distinguish solutions that have no contribution which can accelerate the evolution of a population towards the Pareto front. Further details of the algorithm can be found in [29].

Some MOEAs are more capable of dealing with regular Pareto fronts, whereas others are specifically tailored for problems with irregular Pareto fronts. For the maintenance optimization problem in this paper, a binary-based codification is used. The ARMOEA is selected in the current paper, due to: (1) compared to IGD, IGD-NS indicator can accelerate the evolution of a population towards the Pareto front (2) the proposed ARMOEA not only takes advantage of uniform, but also adaptively takes the adjustment of distribution of the reference points into account based on the contribution of candidate solutions. Therefore, the proposed optimization algorithm has better robustness in including different shapes of Pareto fronts. Moreover, in [29], the versatility of the algorithm was verified using different test problems considering various Pareto fronts.

There are four main solution sets in the ARMOEA. The sets include the population P, the archive A, the initial reference point set R, and the adapted reference point set R′. The population P is composed of the candidate solutions as final output, whereas the initial reference point set R is to keep the distribution of the candidate solutions in P uniform. Moreover, the archive A represents the Pareto front and rules the reference point adaptation. The candidate solutions are obtained according to the reference point adaptation method. In Algorithm 1, the main steps of ARMOEA are presented. Algorithm 2 depicts the mating selection in ARMOEA based on the IGD-NS.

Algorithm 1: general architecture of ARMOEA [29]

Input: *N (population size), N_R (number of reference points and archive size)*
Output: *P (final population)*
P ← Random Initialize (N);
R ← Uniform Reference Point(N_R);
A ← P;
R′ ← R;
while *termination criterion not fulfilled do*
  P′ ← Mating Selection (P,R’);
  O ← Variation (P’,N);
  [A,R′] ← Ref Point Adaption (A ∪O, R, P);
  P ← Environmental Selection (P ∪O, R, N);
return *P;*

Algorithm 2: Mating Selection(P,R′) [29]

Input: *P (population), R′ (set of adapted reference points)*
Output: *P′ (parents for variation)*
for *i=1 to M* **do**
  */*M denotes the number of objectives */*
  $f_i(p) \leftarrow f_i(p) - \min_{q \in P} f_i(q)$, $\forall p \in P$;
Calculate the fitness of each solution by (4);
P′ ← ∅;
for *i= 1 to |P|* **do**
  Randomly select p and q from P;
  if *$fitness_p > fitness_q$* **then**
    P′ ← P′ ∪{p};
  else
    P′ ← P′ ∪{q};
return P′;

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VI. Results for the line Bartolomeu-Zărnești

In this section, a real life case study is provided to show the capability of the proposed methodology. The track Bartolomeu-Zărnești in Romania is used as the case study. The track is situated in the Transylvanian region, among the Southern Carpathians, Romania and it connects Bartolomeu, a suburban area of the city Brașov, to the small town Zărnești [27]. Over the track, there are small towns containing railway stations as well. The railway service is important mostly in terms of (1) economy as the whole area is well known for high concentration of factories and also (2) tourism. Its attractions include natural reserves and national parks and historical and archaeological destinations [28]. To perform the proposed methodology on the full track Bartolomeu-Zărnești, the defect detection algorithm is run on the full track. Based on ABA, the location of the places where the ABA signal show largest energy variations can be highlighted as show in Fig. 4.

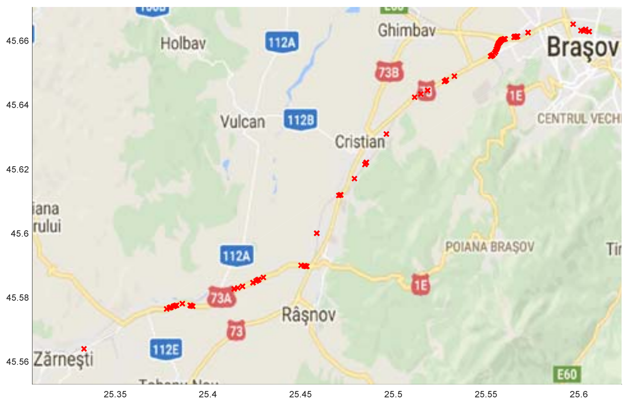

Fig. 4. Locations of the top 75 places where the ABA signal show largest energy variations.

Next, some examples of ABA signals, Hilbert spectrum and wavelet scalogram are presented for two types of defects. In Fig. 5 are the responses of ABA to corrugation, and in Fig. 6 to a welds.

The number of the intervention activities (number of replacements, maintenance, field monitoring) shall be defined by the infra-manager according to the budget and time constraint. Once the interventions are defined, if these works are located nearby, they can be grouped into a single maintenance task. The algorithm is run based on the default setting through 10 independent runs. Populations of 500 solutions and 50000 generations were carried out. The number of rail replacements is up to 70 for demonstrations (a reasonable number that should fit the capacities of the replacement operations and budget). The results shown in Fig. 7 and Fig. 8 are achieved using the platform called PlatEMO [29] on MATLAB 2017b at a desktop computer (2.60 GHz Intel Core i12, 32 GB of RAM). Considering the nature of a stochastic integer optimization problem, the performance of the used algorithm can be obtained in terms of (1) convergence, (2) diversity of the Pareto fronts, and (3) computational time. In this paper, as we challenge a real-life problem, simplicity and quickness are major indicators of the optimization algorithms to be used in practice. Therefore we compare the proposed ARMOEA performance in terms of required computational time with a widely used algorithm, i.e. NSGAII [29].

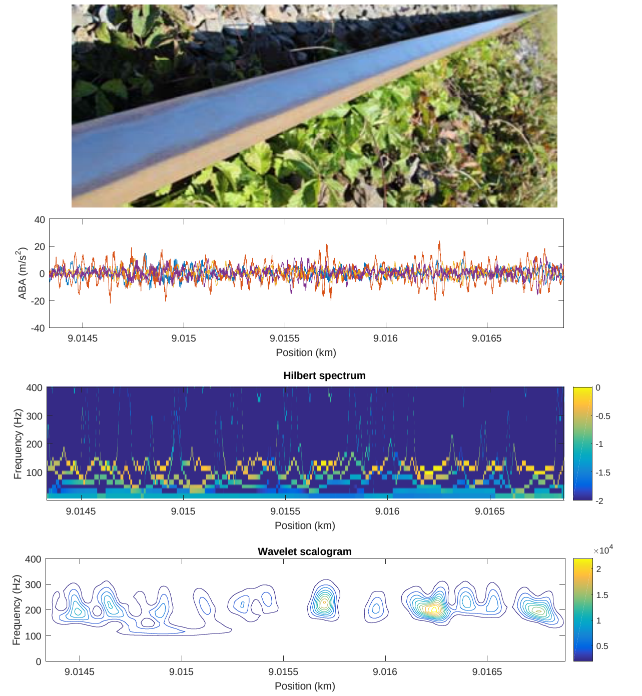

Fig. 5. Corrugation, ABA signals and their corresponding Hilbert spectrum and Wavelet scalogram.

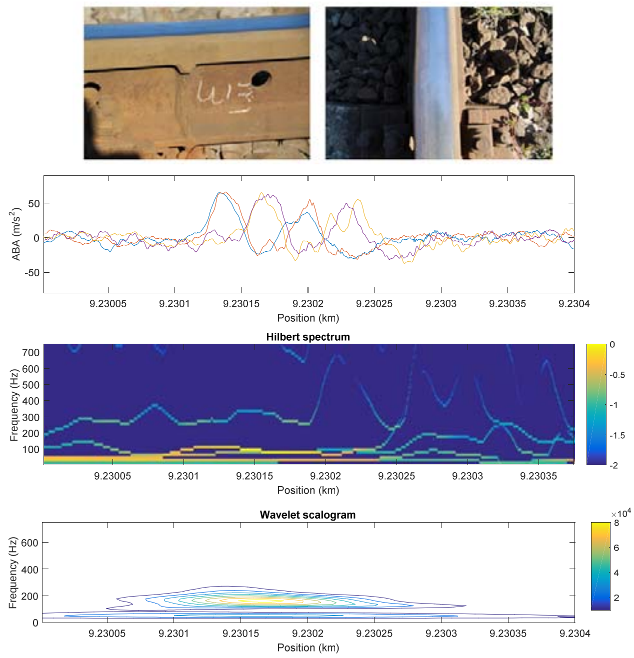

Fig. 6. Weld, ABA signals and their corresponding Hilbert spectrum and Wavelet scalogram.

For the same problem with same default setting, the ARMOEA algorithm performs faster (24.028 second on average with 0.083 second as standard deviation) compared to the NSGAII which has 25.722 second with 0.0988 second in standard deviation.

Fig. 7 shows the Pareto fronts using ARMOEA in four different numbers of replacement including $J_2=10$, $J_2=25$, $J_2=50$, $J_2=70$. Fig. 8 shows Pareto solutions for different levels of interventions. Infrastructure manager can decide the number of the replacements required according to the budget limits and maintenance free time slot which is available on the track.

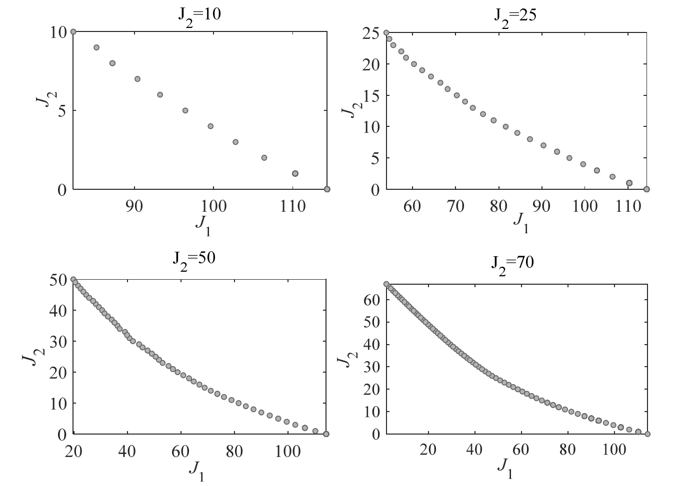

Fig. 7. Pareto front results for rail maintenance in the track Bartolomeu-Zărneşti for $J_2=10$, $J_2=25$, $J_2=50$, $J_2=70$.

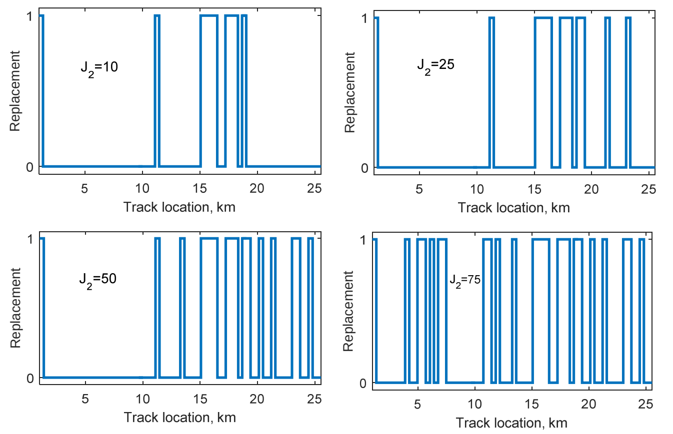

Fig. 8. Pareto solutions for different number of interventions. Value one is for those pieces with maintenance activities, otherwise zero.

VII. Conclusion

In this paper, we propose a maintenance decision system for regional railways based on signal processing and evolutionary multiobjective optimization. The proposed approach is applied to the condition-based maintenance of rail. A Hilbert spectrum approach is employed for detection of defects based on the axle box acceleration measurement. The condition of the rail is modelled including different degradation scenarios over time. The multiobjective optimization problem is formalized to find the trade-offs between the stochastic degradation scenarios and the number of interventions (replacements or maintenance). With the results, infrastructure manager can focus into the places where the highest increase of performance can be achieved, while keeping control of the limited budget for each intervention.

In future research, life cycle costs, social costs, CO_2 and emissions, among others, can be included so that the multiobjective optimization problem considers all the variables that are relevant for the regional railway line.

Acknowledgment

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