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Fatigue-Constrained Energy-Efficient Speed Advisory for Rolling Stock: From Frame Strain Measurements to an AI-Based Framework for Electric Locomotives

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Abstract

Energy-efficient train control usually optimises speed for traction energy and running time alone, while the structural fatigue of the vehicle frame is treated as a fixed design property. This paper argues that speed also drives fatigue damage and should enter the same optimisation. The argument is built on full-scale strain-gauge tests of the frame of an ADM-1 special self-propelled railcar operated in Uzbekistan. Sixteen measuring channels were recorded at 10, 30, 55 and 60 km/h; finite element results agreed with the measurements within 5–10%. Maximum stress grows almost linearly with speed (median $R^2 = 0.92$). In the most loaded zone, under the diesel-engine beam, the stress gradient is 2.73 MPa per km/h and the permissible stress of 152.75 MPa under GOST 31846-2012 is reached at about 54 km/h. A combined cost of traction energy, Miner-type fatigue damage and running time is formulated, and an illustrative calculation shows that the optimal cruising speed lies well below the strength limit. On this basis, a machine-learning driver advisory framework is proposed for UzEL electric locomotives.

Keywords

rolling stock, frame fatigue, strain-gauge measurement, finite element method, energy-efficient train control, driver advisory system, machine learning.

1. Introduction

The railway fleet of Uzbekistan is ageing: of more than 180 special self-propelled rolling stock (SSRS) units in service, about 64% have exceeded a 20-year service life [1]. Extending the life of such vehicles through diagnostics, strength assessment and targeted reinforcement is cheaper than replacement, and it has been shown to be feasible for the ADM-1 railcar [1, 2]. Service-life extension, however, holds only if the vehicle is then operated within the loads it was assessed for. Strain-gauge tests showed that

frame stress rises steadily with running speed and exceeds the normative limit in the most loaded zones at 50–60 km/h [1]. Speed is therefore not only an operational choice but also a fatigue-loading parameter.

Speed is, at the same time, the main control variable of energy-efficient train operation. Optimal control theory selects the speed profile that minimises traction energy for a given running time [3–5], and driver advisory systems (DAS) show such profiles on the cab display. Data-driven and machine-learning methods are increasingly applied to railway operations data [6]. These methods rarely treat structural fatigue of the frame and running gear as an objective or a constraint. This paper links the two problems. Its contributions are: (i) a regression analysis of measured frame stress versus speed for 16 strain-gauge channels of the ADM-1 frame, with the speed at which each zone reaches its permissible stress; (ii) a combined cost function of traction energy, fatigue damage and running time, with an illustrative trade-off calculation; (iii) a machine-learning framework that carries this approach to UzEL electric locomotives.

2. Materials and methods

2.1. Test object and measurements. The object is the load-bearing frame of ADM-1 railcar No. 609, total mass 34.5 t, made of steel with a yield strength of 235 MPa and an elastic modulus of $2 \cdot 10^{11}$ N/m². Ultrasonic thickness gauging at 64 points confirmed design plate thicknesses with no critical corrosion [1]. A finite element (FE) model of the frame was built in SolidWorks Simulation from the measured geometry. Strain gauges (BF350-10AA) were placed at the stress-concentration zones predicted by the FE model, following GOST 31846-2012 [7]. Running tests were carried out on the Uzbekiston–Chinoz line section on straight track and in curves of 600 and 900 m radius. The maximum stress was recorded at 10, 30, 55 and 60 km/h for 16 channels in seven frame zones (I–VII). Equivalent stresses were obtained by the von Mises criterion:

$$\sigma_{eq} = \sqrt{(\sigma_x^2 + \sigma_y^2 - \sigma_x \cdot \sigma_y + 3\tau_{xy}^2)} \qquad (1)$$

The permissible stress for the working, traction and design-speed modes is $[\sigma]$ = 152.75 MPa, and 211.5 MPa for the transport mode [1, 7].

2.2. Stress–speed regression. For each channel k, the maximum stress was fitted by least squares as a linear function of speed v (km/h), and the speed at which the channel

reaches [σ] was found from the model. As a check, v* was also found by linear interpolation between the two measured speeds that bracket [σ]:

$$\sigma_k(v) = a_k + b_k \cdot v, \quad v_k^* = ([\sigma] - a_k) / b_k \qquad (2)$$

2.3. Fatigue damage as a function of speed. Residual life of the frame follows the Miner linear damage rule with the fatigue curve of GOST 31846-2012 [7, 8]:

$$N\Sigma = N_G \cdot \sigma_{-1}d^m / \Sigma\, t_i \cdot \sigma_{ai}^m, \quad \sigma_{ai} \geq \sigma_{-1}d \qquad (3)$$

where N_G is the number of cycles at the knee of the fatigue curve, m its slope exponent, $\sigma_{-1}d$ the endurance limit of the part, σ_{ai} the amplitude of the i-th load level and t_i its share of cycles. The yearly number of cycles is taken from rail-joint passages, and residual life is the ratio of NΣ to the yearly number of cycles [1]. To bring speed into this rule, stress amplitudes are assumed to scale with the measured stress–speed relation of the critical channel, so that the relative damage per kilometre is

$$D(v) = (\sigma(v) / [\sigma])^m \qquad (4)$$

2.4. Traction energy and combined cost. Traction energy over a section of length L with n stops is estimated from the running resistance $w_0(v) = A + Bv + Cv^2$ and the kinetic energy lost in braking. The recommended cruising speed minimises a weighted, normalised cost subject to the strength constraint:

$$E(v) = [w_0(v) \cdot M \cdot g \cdot L + n \cdot M \cdot v^2/2] / \eta \qquad (5)$$

$$J(v) = w_E \cdot E/E_{max} + w_D \cdot D/D_{max} + w_T \cdot T/T_{max}, \quad \sigma(v) \leq [\sigma] \qquad (6)$$

where M is vehicle mass and T(v) = L/v the running time. The illustrative case uses L = 20 km, n = 2, M = 34.5 t, η = 0.85, A = 1.0, B = 0.01, C = 0.0003 (w_0 in N/kN) and fatigue exponent m = 4. These resistance and fatigue coefficients are assumed for demonstration and are not measured values for the ADM-1.

3. Results

3.1. Frame stress grows linearly with speed. All 16 channels show stress rising with speed; the linear model explains 79–99% of the variance (median $R^2 = 0.92$). Zones I–IV stay at 10–61 MPa up to 60 km/h, while zones V–VII carry 89–161 MPa at 60 km/h (Fig. 1).

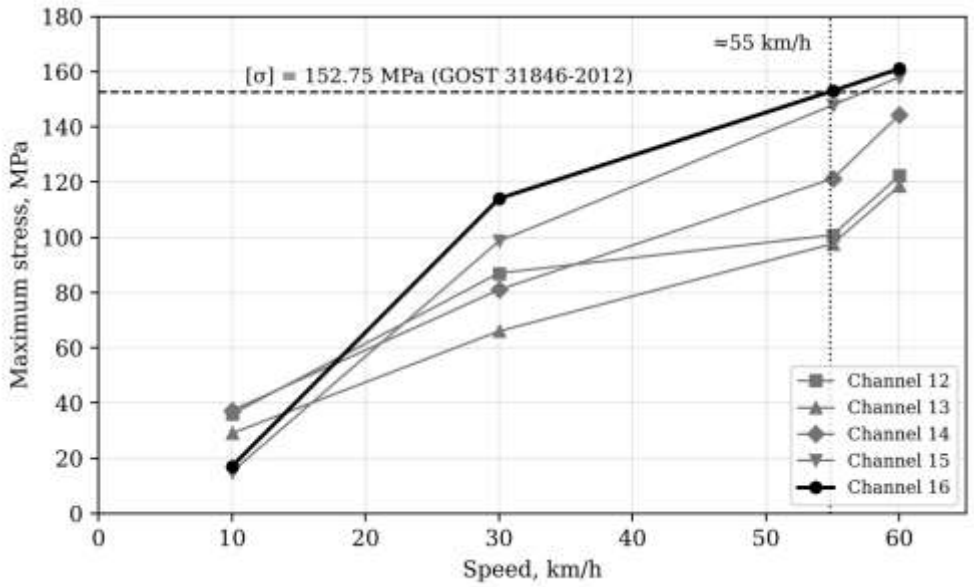


Fig. 1. Measured maximum stress in frame zones VI and VII versus running speed

Table 1. Linear stress–speed models for the most loaded channels and the speed at which each reach [σ] = 152.75 MPa

Zone	**Channel**	**a, MPa**	**b, MPa per km/h**	**R^2**	**v*(regression), km/h**	**v*(interpolation), km/h**
VII	16	5.5	2.73	0.92	53.9	54.8
VII	15	−2.0	2.76	0.96	56.1	57.4
VI	14	18.0	2.01	0.99	67.0	not reached
VI	13	13.3	1.67	0.98	83.8	not reached
VI	12	28.1	1.51	0.91	82.7	not reached
V	10	−1.9	1.23	0.79	126.0	not reached

The critical zone is VII, under the diesel-engine beam, where inspection also found fatigue cracks [1]. Both estimates place its limit at 54–55 km/h; the regression gives the lower, safer value because the measured curve flattens slightly between 55 and 60 km/h. Reinforcing the longitudinal beams with welded cover plates lowered the FE maximum stress from 159.4 to 143.3 MPa (−10.1%) and raised the safety factor from 1.57 to 1.76 [1]. This margin would move the limit speed of zone VII upward, which needs confirming by a repeat running test.

3.2. Energy, damage and time trade off against each other.

In the illustrative case, moving from 30 to 50 km/h saves 40% of running time but costs 68% more traction energy and about seven times more fatigue damage per kilometre (Table 2). Damage grows fastest because it follows the fourth power of stress.

Table 2. Illustrative cost components for a 20 km section with two stops

Speed, km/h	**σ in zone VII, MPa**	**Energy, kWh**	**Running time, min**	**Relative damage D**
30	87.4	4.26	40.0	0.11
40	114.7	5.55	30.0	0.32
45	128.3	6.31	26.7	0.50
50	142.0	7.15	24.0	0.75
55	155.6	8.07	21.8	1.08

With weights $w_E = 0.4$, $w_D = 0.3$ and $w_T = 0.3$, the minimum of J lies at 29 km/h; when time dominates ($w_T = 0.6$), it moves to 40 km/h. In every case tested the optimum stays below the 54 km/h strength limit, so the limit acts as a hard bound and the weights choose the operating point inside it.

4. Discussion: an AI-based advisory framework for UzEL electric locomotives

The ADM-1 results show that one variable, speed, links frame fatigue and traction energy, and that a strength limit can be found from a few measured points. On an electric locomotive fleet these relations can be learned continuously, because the vehicles already record the signals needed. The proposed framework has four layers (Fig. 2).

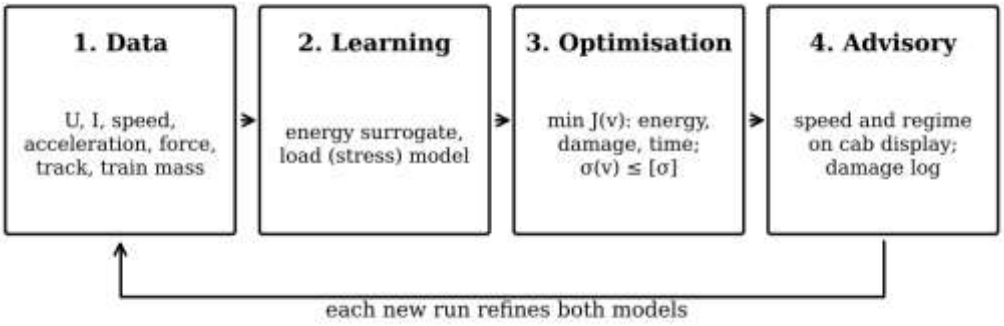


Fig. 2. Proposed fatigue-aware energy-efficient driver advisory framework

Data layer. On-board signals of UzEL locomotives (catenary voltage, traction current, speed, acceleration, traction and braking force) are combined with the track

profile, train mass and timetable. **Learning layer.** An energy model predicts traction energy per section, and a load model predicts frame or bogie stress from speed and track features. The load model is first fitted on dedicated strain-gauge runs, as was done for the ADM-1, and then extended through vibration and acceleration signals recorded routinely. Gradient-boosted trees suit both tasks, since the data are tabular and the relations smooth [9]. **Optimisation layer.** For each section ahead, the system minimises J(v) under the strength limit, the line speed limit and the timetable; regenerative braking is added to the energy term. **Advisory layer.** The recommended speed and driving regime are shown to the driver, and accumulated damage per locomotive is logged, so that maintenance intervals can follow actual loading. This extends earlier work on condition-based repair intervals for SSRS electrical equipment [10].

The study has three limits. The stress–speed relation rests on four speeds and one vehicle, so the linear form should be checked with more speed steps. The energy and fatigue coefficients of Section 3.2 are assumed, so the optimal speeds there demonstrate the method rather than values for operation. Finally, stresses in an electric locomotive frame and bogie differ from those of a diesel railcar, so the load model must be recalibrated on UzEL test runs before any advice reaches a driver.

5. Conclusions

1. Strain-gauge tests of the ADM-1 frame show that maximum stress grows almost linearly with speed in all 16 channels (median $R^2 = 0.92$), at up to 2.76 MPa per km/h in the most loaded zone.

2. The zone under the diesel-engine beam reaches the permissible stress of 152.75 MPa at 54–55 km/h, which sets a strength-based speed limit for this vehicle before reinforcement.

3. Because fatigue damage follows a power of stress, it rises faster with speed than traction energy does. A cost function that weighs energy, damage and running time places the optimal cruising speed below the strength limit for all weightings tested.

4. The approach can be transferred to UzEL electric locomotives as a machine-learning driver advisory system that learns energy and load surrogates from on-board data and recommends fatigue-aware, energy-efficient speed profiles.

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