

Smart Predictive Chain and Sprocket Health Monitoring System for Two-Wheelers

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Abstract—The chain and sprocket assembly is a safety-relevant power-transmission subsystem in many two-wheelers, yet its degradation is normally assessed only through scheduled servicing, visual inspection and manual slack measurement. This paper presents the design and analytical evaluation of a low-cost, non-invasive, AI-enabled chain and sprocket health monitoring system for motorcycles, scooters and two-wheeler fleets. The architecture fuses vibration, acoustic, chain-tension and rotational-speed measurements with edge signal processing to classify drivetrain condition as healthy, warning or critical, and introduces a Chain–Sprocket Health Index (CSHI) and a degradation-trend model for remaining useful life (RUL). For a reference 428-pitch drivetrain (14/44 teeth, 94 links), the analysis shows that over 20–100 km/h the tooth-mesh frequency spans 130–648 Hz (5.0×) and the tight-span chain tension 364–1093 N (3.0×), so speed-referenced, order-normalised features are mandatory; that 16 kHz sampling with a 1.024 s window resolves the first ten mesh harmonics and at least one full chain revolution above 14.2 km/h; that on-board feature extraction cuts the data rate from 130.4 kB/s to 256 B/s (509-fold); that a 3 % chain elongation adds 35.8 mm of chain length that routine axle adjustment can conceal; and that a five-window persistence rule limits false alerts to 0.11 per 100 h with a mean detection latency of about 10 s under stated assumptions. Experimental classification accuracy and RUL error remain to be established through the staged validation protocol defined here.

Index Terms—Chain wear, sprocket health, predictive maintenance, condition monitoring, vibration analysis, acoustic sensing, machine learning, remaining useful life, two-wheelers, Internet of Things.

1. INTRODUCTION

Roller-chain drives remain widely used in motorcycles and other compact vehicles because they provide positive power transmission, a relatively simple construction and practical packaging. Their performance depends on the condition of interacting components, including pins, bushes, rollers, link plates and sprocket teeth. Wear at chain joints increases effective pitch and chain elongation; the resulting mismatch at the sprocket can alter engagement, increase dynamic loading and accelerate wear in the mating components [1]–[5]. In service, deterioration is affected by transmitted torque, speed, alignment, contamination, lubrication, temperature and maintenance practice.

For many two-wheelers, chain condition is checked during periodic service or by a rider or technician observing slack, noise and visible wear. Such checks are useful but intermittent and partly dependent on operator experience. A developing fault may therefore remain undetected between inspections. The consequences can include increased vibration and noise, reduced transmission efficiency, accelerated sprocket wear, chain derailment or failure, and unplanned vehicle downtime. These concerns are relevant not only to private users but also to delivery and shared-mobility fleets, where vehicle availability and maintenance consistency are important.

Condition-based maintenance (CBM) offers an alternative by scheduling inspection or replacement according to measured equipment condition. Prognostics and health management research has established workflows involving data acquisition, feature extraction, health-indicator construction, fault diagnosis and RUL estimation [8]–[12]. However, direct transfer of industrial monitoring systems to two-wheelers is constrained by cost, limited mounting

space, weather exposure, vibration from the engine and road, variable rider loads, and the need for a simple user interface.

This paper proposes a compact monitoring system that combines complementary sensing channels rather than relying on a single parameter. Vibration and acoustic signals capture dynamic signatures; a tension sensor tracks chain-span behaviour; a speed sensor provides operating context; and auxiliary operating variables help distinguish degradation from changes in load or speed. An embedded controller performs initial processing, while machine-learning algorithms classify condition and track degradation. The system is designed as a retrofit module and is intended to provide understandable alerts rather than requiring the rider to interpret raw sensor signals.

The aim of this work is to develop a compact, non-invasive monitoring framework capable of identifying chain-sprocket degradation and supporting condition-based maintenance for two-wheelers. The specific objectives are to:

- 1) design a retrofit sensor arrangement that acquires vibration, acoustic, chain-tension and rotational-speed data without dismantling the drivetrain;
- 2) develop a synchronised data-acquisition and preprocessing workflow that accounts for vehicle speed, load and operating state;
- 3) extract interpretable statistical, spectral and time–frequency features for drivetrain condition classification;
- 4) define a Chain–Sprocket Health Index (CSHI) and a three-level alert strategy (healthy, warning and critical);
- 5) establish a data-driven RUL estimation approach that is activated only after sufficient degradation history and validated end-of-life labels are available; and
- 6) define laboratory and field tests to quantify detection performance, repeatability, robustness and practical deployment constraints.

The principal contributions are: (i) an end-to-end framework linking multi-modal sensing to actionable maintenance information; (ii) a clear separation between condition classification, which can be developed from labelled condition snapshots, and RUL prediction, which requires longitudinal degradation data; and (iii) a quantitative analytical characterisation of a reference two-wheeler drivetrain that yields concrete design requirements for sampling, windowing, feature normalisation, edge processing and alert logic. The remainder of the paper is organised as follows. Section 2 reviews related work; Section 3 describes the system architecture; Section 4 details the methodology and analytical models; Section 5 presents and discusses the results; Section 6 states the limitations; and Section 7 concludes the paper.

2. RELATED WORK AND LITERATURE REVIEW

2.1 Chain wear, elongation and transmission dynamics

Research on roller-chain drives has examined wear mechanisms, tension, impact forces and the relationship between chain elongation and sprocket engagement. Sappok and Sauer [1] demonstrated component-level wear measurement using roundness metrology, illustrating that total chain-length measurement can conceal how wear is distributed across pins and bushes. Conwell and Johnson [2] developed an instrumented chain-drive test machine capable of measuring link tension and roller–sprocket impact during operation. Burgess et al. [3] presented a test rig that enabled continuous, in-situ wear measurement, reducing the need to dismantle the chain for inspection. These studies support the value of continuous or repeatable measurement, although their apparatus is not directly equivalent to a compact road-going motorcycle device.

More recent work has considered non-contact and condition-monitoring approaches. Nölcke [4] described camera-based monitoring of chain-span oscillation and a concept for direct, contactless elongation measurement. Dowd et al. [5] reported a precision in-situ chain-wear measurement tool and quantified measurement-system repeatability. Together, these works show that elongation is a meaningful degradation indicator and that measurement uncertainty must be considered when establishing maintenance thresholds.

2.2 Vibration and acoustic condition monitoring

Vibration is a widely used signal for detecting mechanical anomalies because changes in contact, impact, looseness and periodic excitation can alter signal amplitude and spectral content. Lee and Kim [6] demonstrated chain-sprocket-drive fault classification using an IoT vibration device and a convolutional neural network (CNN), transforming vibration signals into time–frequency representations. Their study supports the feasibility of embedded sensing and data-driven fault recognition in chain-drive systems. However, the fault cases focused on selected drivetrain components, and the results should not be interpreted as a validated chain-elongation estimator for road motorcycles.

Acoustic monitoring can complement vibration because impacts, friction and lubrication changes may affect sound emissions. Recent work on lubricated automotive chains has examined the relationship between friction, sound and vibration [7]. Acoustic measurements are nevertheless sensitive to ambient noise, microphone placement, engine sound and wind. Accordingly, this study treats acoustic information as a supporting feature and proposes sensor fusion to reduce dependence on any one signal.

2.3 Data-driven diagnostics and RUL estimation

Machine-learning methods are increasingly applied to fault classification and RUL prediction. Reviews by Jardine et al. [8], Lei et al. [9], Si et al. [10], Carvalho et al. [11] and Ferreira and Gonçalves [12] describe the progression from condition monitoring and feature engineering to data-driven and hybrid prognostics. Common approaches include support vector machines (SVM), decision trees, random forests, gradient-boosted models, artificial neural networks and deep-learning architectures. Deep models can learn complex temporal representations but may require larger labelled datasets and greater computational resources [13]–[15]. Surveys of fault diagnosis and predictive maintenance in rotating machinery further document the maturity of these methods for bearings and gearboxes [18], [20], and physics-informed hybrid approaches are emerging to compensate for scarce failure data [19].

A reliable RUL estimate depends on a meaningful degradation indicator, representative data across the operating envelope, a clearly defined end-of-life criterion and appropriate treatment of uncertainty. Studies have highlighted challenges associated with changing operating conditions, limited failure data, data imbalance, preprocessing and model interpretability [12], [16], [17]. For a two-wheeler chain, mileage alone is unlikely to represent degradation consistently because load, lubrication, contamination and riding style vary. A data-driven estimator should therefore use operating context and measured condition together.

2.4 Research gap

The reviewed literature establishes the feasibility of chain-drive sensing, quantitative wear measurement and machine-learning-based fault diagnosis. However, a practical gap remains between specialised test-rig investigations and a low-cost, integrated retrofit system for everyday two-wheelers. In particular, a unified approach is needed to: (i) combine vibration, sound, chain tension and rotational speed; (ii) separate changes caused by operating conditions from those caused by degradation; (iii) translate model outputs into an interpretable health index and maintenance alert; and (iv) establish a repeatable validation protocol using physical wear measurements as ground truth. The present work addresses this system-integration gap through a proposed architecture, a validation methodology and a quantitative analysis of the design constraints.

3. PROPOSED SYSTEM ARCHITECTURE

The system comprises five functional layers: (1) sensing, (2) signal conditioning and acquisition, (3) edge processing and inference, (4) communication and user interface, and (5) maintenance decision support. A vibration sensor is placed near the drivetrain, together with an acoustic sensor, a chain-tension sensor, a rotational-speed sensor, an electronic unit and a mobile application. The complete workflow, including sensing, signal processing, feature extraction, AI-based health assessment, RUL estimation and experimental validation, is presented in Fig. 1.

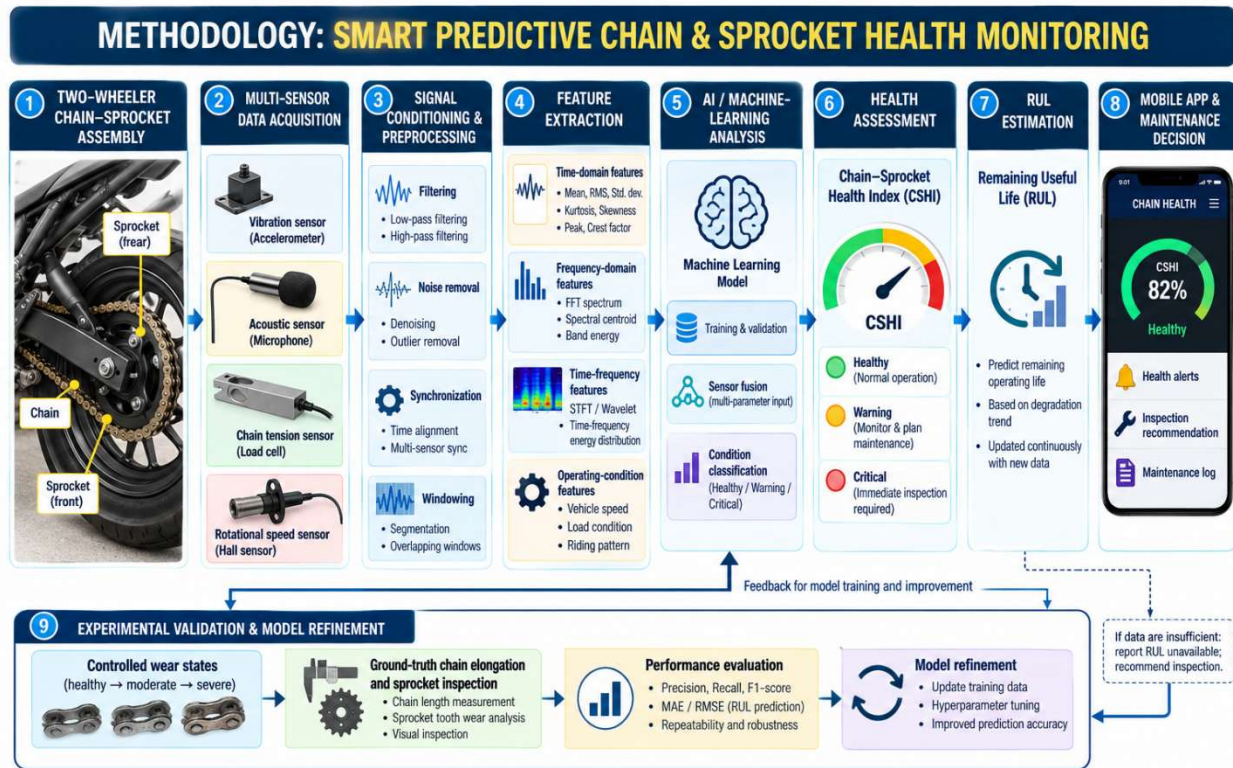


Fig. 1. Proposed methodology for the smart predictive chain and sprocket health monitoring system.

3.1 Sensor configuration

A triaxial MEMS accelerometer is mounted on a rigid, repeatable point on the swingarm or a suitable drivetrain-adjacent bracket. The location must be selected after preliminary transfer-path testing and must not interfere with wheel, chain or suspension movement. A microphone is positioned inside a protective enclosure with an acoustic port oriented toward the chain run. Chain tension may be measured using a suitably designed load-cell or displacement-based arrangement at a guarded chain span; the installation must not introduce excessive friction, alter chain alignment or compromise safety. A Hall-effect or optical sensor measures sprocket or wheel rotational speed. The controller also records operating context such as speed, throttle/load proxy, ambient temperature and test condition where available.

Sensor selection will be governed by measurement range, bandwidth, sampling rate, power consumption, environmental protection, mounting repeatability and cost. Sensor mounting and wiring must be secured away from the chain, tyre, exhaust and moving suspension components. The system should fail safely: sensor or communication failure must not affect the mechanical braking or propulsion systems.

3.2 Data acquisition and preprocessing

All channels are time-stamped by a common controller or synchronised clock. Data are divided into fixed-duration windows, with overlap selected to balance temporal resolution and computational load. Invalid samples, clipping, missing packets and sensor saturation are flagged before feature extraction. A low-pass or band-pass filter is applied only after the useful frequency range has been identified experimentally; filtering parameters must be documented to avoid suppressing fault-related content. Signals are normalised with parameters learned from the training set only.

Operating conditions are segmented into steady-speed, acceleration, deceleration and transient states. Comparisons are made within comparable operating regimes, or the operating state is included as a model input. This is important because speed and transmitted torque can change vibration and sound even when component health is unchanged (quantified in Section 5.1).

4. METHODOLOGY

4.1 Experimental design and ground truth

A staged test programme is proposed. Stage I characterises the healthy drivetrain over a matrix of speeds, loads and lubrication states. Stage II introduces or collects naturally worn chains and sprockets representing progressive degradation. Stage III evaluates the prototype under controlled laboratory conditions, followed by supervised road trials after safety review. Each test condition should be repeated to estimate variability.

Ground truth is established independently of the proposed model. Chain elongation is measured over a defined number of pitches n under a specified preload, using a calibrated gauge or length-measurement fixture, and expressed as $\varepsilon = (L_n - np)/(np)$, where L_n is the measured length and p the nominal pitch. Sprocket condition is documented through tooth-profile measurements, dimensional inspection and standardised photographs. Lubrication state, chain slack, alignment, mileage and maintenance history are recorded. Healthy, warning and critical labels must be defined before model training using manufacturer limits, engineering review and observed functional behaviour; universal thresholds should not be assumed across chain specifications. As a provisional, chain-independent convention, the warning label begins at 50 % of the replacement limit and the critical label at 100 % of that limit.

4.2 Feature extraction

For each vibration and acoustic window, candidate time-domain features include mean, standard deviation, root-mean-square (RMS), peak, peak-to-peak value, crest factor, kurtosis and skewness. Frequency-domain features include dominant frequencies, band power, spectral centroid and spectral entropy. Time–frequency features may be derived using the short-time Fourier transform or continuous wavelet transform. Tension features include mean tension, range, fluctuation RMS and speed-synchronous variation. Rotational speed is used to calculate order-related features and to normalise frequency components where appropriate.

The RMS value of a discrete signal $x[n]$ containing N samples is calculated as:

$$x_{RMS} = \sqrt{\frac{1}{N} \sum x[n]^2}, \quad n = 1, 2, \dots, N \quad (1)$$

The crest factor is defined as the ratio of peak magnitude to RMS magnitude. Kurtosis and spectral indicators are retained only if they demonstrate repeatability and discriminatory value in the collected data. Feature selection is performed within the training folds to prevent information leakage.

4.3 Chain–Sprocket Health Index

A normalised Chain–Sprocket Health Index (CSHI) is proposed to summarise the condition of the assembly. Let f_i denote a selected feature and $f_{i,ref}$ its healthy reference under a comparable operating state. A normalised deviation can be expressed as:

$$d_i = |f_i - f_{i,ref}| / (|f_{i,ref}| + \varepsilon_0) \quad (2)$$

A weighted index is then formulated as:

$$CSHI = 100 \times [1 - \sum w_i d_i^*] \quad (3)$$

where d_i^* is a bounded, calibrated deviation in $[0, 1]$ and the non-negative weights w_i sum to one. The index is therefore constrained to 0–100, with higher values representing healthier operation, and no single feature can move the index by more than $100w_i$ points. The weights and boundaries are not fixed a priori; they must be estimated using training data and reviewed for physical plausibility. A confidence or data-quality flag accompanies the index so that uncertain measurements are not presented as definitive health assessments.

4.4 Machine-learning models

Baseline models should include logistic regression, decision tree, random forest and support vector machine classifiers. These provide interpretable benchmarks and can operate on compact feature vectors. A gradient-boosted tree model may be evaluated where nonlinear feature interactions are important. A one-dimensional CNN or CNN–

LSTM model can be considered if the dataset is sufficiently large and the computational budget permits. Model selection should be based on grouped validation, inference latency, memory use, calibration and robustness—not accuracy alone.

Data must be split by physical chain or vehicle identity, rather than randomly splitting adjacent windows from the same test run across training and test sets. This prevents optimistic results caused by temporal correlation. Class imbalance can be addressed through class weighting or carefully controlled resampling. Hyperparameter tuning is confined to training/validation data, while a held-out test set is used once for final reporting.

4.5 Condition classification and maintenance alerts

The classifier returns class probabilities for healthy, warning and critical states. A warning is generated when the probability of degradation exceeds a validated threshold for k consecutive windows, reducing nuisance alerts from isolated transients. A critical alert should prompt inspection and should not be interpreted as an automatic declaration that the vehicle is unsafe or as a substitute for manufacturer maintenance instructions. The mobile interface displays the health index, alert category, recent trend, sensor status and recommended inspection action.

4.6 Remaining useful life estimation

RUL is defined as the remaining operating distance or time until a pre-established replacement criterion is reached. For a chain, the criterion may be a specified elongation limit or another manufacturer-approved condition threshold. The target variable must be measured longitudinally for each chain. Candidate estimators include regression models using health-index trends, survival analysis, state-space degradation models and recurrent neural networks. A simple baseline estimates the degradation rate from a robust slope fitted to recent health or elongation measurements:

$$RUL = (\varepsilon_{lim} - \varepsilon_{now}) / \dot{\varepsilon} \quad (4)$$

where ε_{lim} is the replacement limit, ε_{now} the current elongation estimate and $\dot{\varepsilon}$ the fitted degradation rate per unit distance. More complex models are justified only if they improve held-out performance. RUL should be reported with an uncertainty interval and an explicit unit (for example, kilometres under a stated duty cycle). If data are insufficient to support a defensible estimate, the system should report “RUL unavailable—inspection recommended” rather than generating a misleading numeric value.

4.7 Evaluation metrics

Classification performance is evaluated using the confusion matrix, accuracy, precision, recall, F1-score and macro-averaged F1. Recall for the critical class is particularly important because missed degradation may delay inspection; however, false alarms must also be quantified because they can reduce user trust. Receiver operating characteristic and precision–recall curves may be reported where class probabilities are available. For RUL regression, suitable metrics include mean absolute error (MAE), root mean square error (RMSE), and a prognostic score that penalises late predictions more heavily when appropriate. Calibration and interval coverage should be assessed if uncertainty bounds are provided.

System-level evaluation includes sensor uptime, packet loss, power consumption, inference latency, alert delay, mounting durability and user comprehension. Repeatability is assessed using repeated measurements under the same condition. Robustness tests vary speed, load, ambient noise, chain alignment and lubrication. Ablation experiments compare individual sensors with fused sensing to quantify the incremental value of each modality.

4.8 Reference drivetrain and analytical models

To obtain quantitative design requirements before hardware fabrication, the framework is analysed for a reference commuter-motorcycle drivetrain whose parameters are listed in Table I. The values are representative engineering assumptions and are not measurements of a specific vehicle; the chain linear mass, the road-load power and the replacement limit in particular must be replaced by vehicle-specific or manufacturer data during Stage I.

TABLE I. REFERENCE DRIVETRAIN PARAMETERS USED IN THE ANALYSIS

Parameter	Value	Basis
Chain pitch, p	12.7 mm (428-type)	Standard pitch
Front / rear sprocket teeth, Z_1 / Z_2	14 / 44	Assumed; ratio 3.143
Rear wheel rolling radius, r	0.300 m	Assumed
Sprocket centre distance, C	0.400 m	Assumed
Number of links, N_L	94 (calculated 92.7, rounded up to even)	Standard link-count formula
Chain length, $L = N_L p$	1.194 m	Calculated
Chain linear mass, μ	0.59 kg/m	Assumed
Design speed range	20–100 km/h	Urban to highway use
Road-load power at 20/40/60/80/100 km/h	0.6 / 1.6 / 3.0 / 5.5 / 9.0 kW	Assumed at the wheel
Illustrative replacement limit, ε_{lim}	3.0 % elongation	Assumed; use maker limit

Note: values marked “assumed” are inputs to the analytical model, not experimental data.

With rear-sprocket speed $n_2 = v/(2\pi r)$ for road speed v , the front-sprocket speed is $n_1 = n_2 Z_2 / Z_1$. The tooth-mesh (chain-link passage) frequency f_m , the chain speed v_c and the chain-revolution frequency f_c follow from

$$f_m = Z_1 n_1 = Z_2 n_2 \quad (5)$$

$$v_c = Z_2 p n_2, \quad f_c = v_c / L \quad (6)$$

Because a chain wraps a sprocket as a polygon, the instantaneous chain speed fluctuates (chordal action) by a fraction

$$\delta = 1 - \cos(\pi / Z) \quad (7)$$

When the chain has elongated by a fraction ε , its pitch becomes $p(1 + \varepsilon)$ while the sprocket tooth spacing is unchanged, so the rollers must seat on a larger pitch circle. The resulting pitch-radius rise on a sprocket with Z teeth is

$$\Delta r = p \varepsilon / [2 \sin(\pi / Z)] \quad (8)$$

This is a geometric upper bound that assumes the chain seats fully on the enlarged pitch circle. Treating the tight span as a taut string of free length $L_s \approx C$, its first transverse natural frequency and tension are estimated by

$$f_s = (1 / 2L_s) \sqrt{T / \mu}, \quad T = P / v_c \quad (9)$$

Finally, for the persistence rule of Section 4.5, let α be the per-window false-positive probability and q the per-window probability of correctly flagging a genuinely degraded state. Assuming independent windows, the probability that k consecutive windows are all false positives and the mean number of windows needed to obtain k consecutive detections (the standard waiting time for a run of successes) are

$$P_{FA} = \alpha^k \quad (10)$$

$$N_D = (1 - q^k) / [(1 - q) q^k] \quad (11)$$

5. RESULTS AND DISCUSSION

The results reported in this section are analytical: they are computed from the models in Section 4.8 for the reference drivetrain of Table I, and are exact under the stated assumptions. They are design results, not experimental measurements. They do not include measured classifier accuracy, RUL error or field reliability, which require the staged experiments of Section 4.1. Their purpose is to convert the proposed architecture into concrete, testable requirements and to identify which design choices are forced by the physics of the drivetrain.

5.1 Characteristic frequencies and operating-condition dependence

Table II and Fig. 2 give the characteristic quantities from (5), (6) and (9) over the design speed range. As road speed rises from 20 to 100 km/h, the rear sprocket turns at 177–884 rpm and the front sprocket at 556–2779 rpm; the chain speed increases from 1.65 to 8.23 m/s; and the tooth-mesh frequency increases from 130 to 648 Hz, a factor of 5.0.

Its 2nd and 3rd harmonics reach 1297 and 1945 Hz at 100 km/h. The chain-revolution frequency, at which a single stiff or elongated link would repeat, ranges from 1.38 to 6.90 Hz. The estimated tight-span tension rises from 364 to 1093 N (a factor of 3.0), and the span natural frequency from 31.1 to 53.8 Hz. The span mode remains 4.2 to 12.0 times below the mesh frequency across the range, so the two mechanisms are separable in the spectrum.

TABLE II. CHARACTERISTIC QUANTITIES OF THE REFERENCE DRIVETRAIN VERSUS ROAD SPEED

Speed (km/h)	Rear (rpm)	Front (rpm)	Chain speed (m/s)	Mesh f_m (Hz)	Chain rev. f_c (Hz)	Tension T (N)	Span f_s (Hz)
20	177	556	1.65	130	1.38	364	31.1
40	354	1112	3.29	259	2.76	486	35.9
60	531	1667	4.94	389	4.14	607	40.1
80	707	2223	6.59	519	5.52	835	47
100	884	2779	8.23	648	6.9	1093	53.8

Computed from Eqs. (5), (6) and (9) with the parameters of Table I. Tension is the tight-span estimate $T = P/v_c$ using the assumed road-load power.

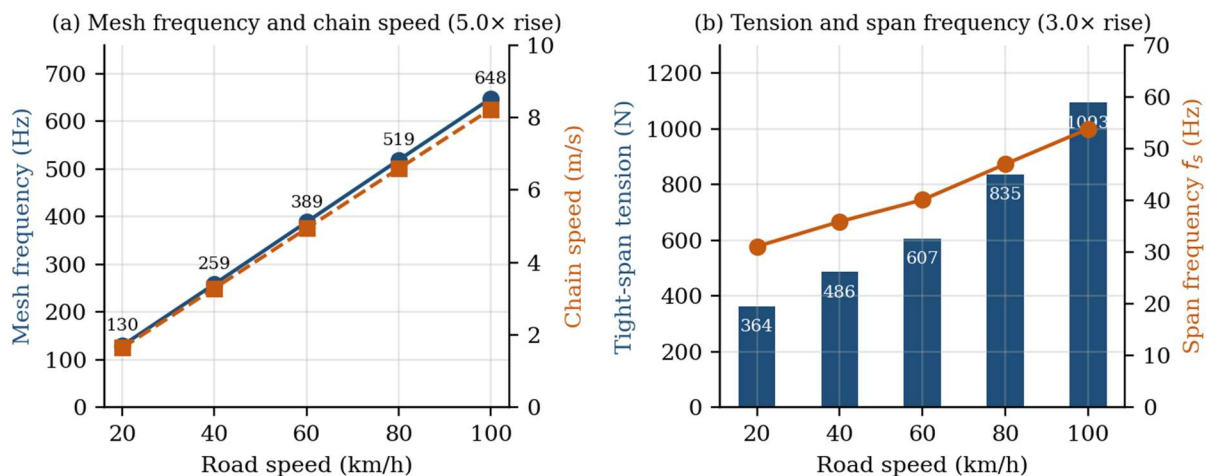


Fig. 2. Effect of road speed on mesh frequency, chain speed, tight-span tension and span natural frequency (data of Table II).

The practical consequence is that every dynamic signature of the chain drive moves with speed. A fixed-frequency band, or an amplitude threshold, that captures the mesh component at 20 km/h will miss it at 100 km/h, and amplitude and tension features change severalfold with no change in component health. Features must therefore be referenced to the shaft speed measured by the speed sensor: spectra are expressed in orders of the mesh frequency (f/f_m), tension fluctuations are normalised by the mean tension, and classification is performed within speed regimes or with speed as an explicit input. This quantifies why the speed sensor is a core measurement channel rather than an accessory, and supports the regime-based comparison adopted in Section 3.2.

Chordal action from (7) is 2.51 % of chain speed for the 14-tooth front sprocket but 0.25 % for the 44-tooth rear sprocket, a ratio of 9.8. The small sprocket is thus the dominant source of speed-synchronous excitation of the chain, which suggests, to be verified in transfer-path tests, that sensor positions close to the front sprocket and the tight span will carry the strongest mesh-related content.

5.2 Sampling bandwidth, windowing and edge data budget

The highest mesh frequency in the design range is 648 Hz, so its tenth harmonic lies at 6.48 kHz. A sampling rate of 16 kHz (Nyquist limit 8 kHz) resolves this harmonic with a 23 % margin ($8.00/6.48 = 1.23$) for the anti-alias filter transition. A window of 16 384 samples then lasts 1.024 s and gives a spectral resolution of 0.977 Hz, sufficient to separate the 31–54 Hz span mode from the harmonic series and the 1.4–6.9 Hz chain-revolution modulation sidebands. Such a window contains at least one full chain revolution whenever $f_c \geq 0.977$ Hz, that is above 14.2 km/h. Below

this speed, one-revolution features are unreliable and the system should report the state as “insufficient speed” instead of classifying. The tension channel needs far less bandwidth: 1 kHz sampling gives at least 18.6 samples per period of the highest span frequency (53.8 Hz).

TABLE III. DERIVED ACQUISITION AND EDGE-PROCESSING REQUIREMENTS

Quantity	Derived value	Basis
Highest mesh frequency (100 km/h)	648 Hz	Eq. (5)
10th mesh harmonic (100 km/h)	6.48 kHz	$10 f_m$
Vibration/acoustic sampling rate	16 kHz	Nyquist 8 kHz; 23 % margin
Analysis window / resolution	16 384 samples; 1.024 s; 0.977 Hz	N/f_s ; f_s/N
Minimum speed for one chain revolution per window	14.2 km/h	$f_c \geq 0.977 \text{ Hz}$
Raw data rate: 3-axis accelerometer (16-bit)	96.0 kB/s	$3 \times 16\,000 \times 2 \text{ B}$
Raw data rate: microphone (16-bit)	32.0 kB/s	$16\,000 \times 2 \text{ B}$
Raw data rate: tension (1 kHz) + speed/context (200 Hz)	2.4 kB/s	16-bit samples
Total raw data rate	130.4 kB/s (469 MB/h)	Sum
Feature stream (64 × float32 per 1 s window)	256 B/s (0.92 MB/h)	Edge extraction
Data reduction by edge processing	509 ×	$130.4 \text{ kB/s} \div 256 \text{ B/s}$

The channel counts, word lengths and feature-vector size are design assumptions.

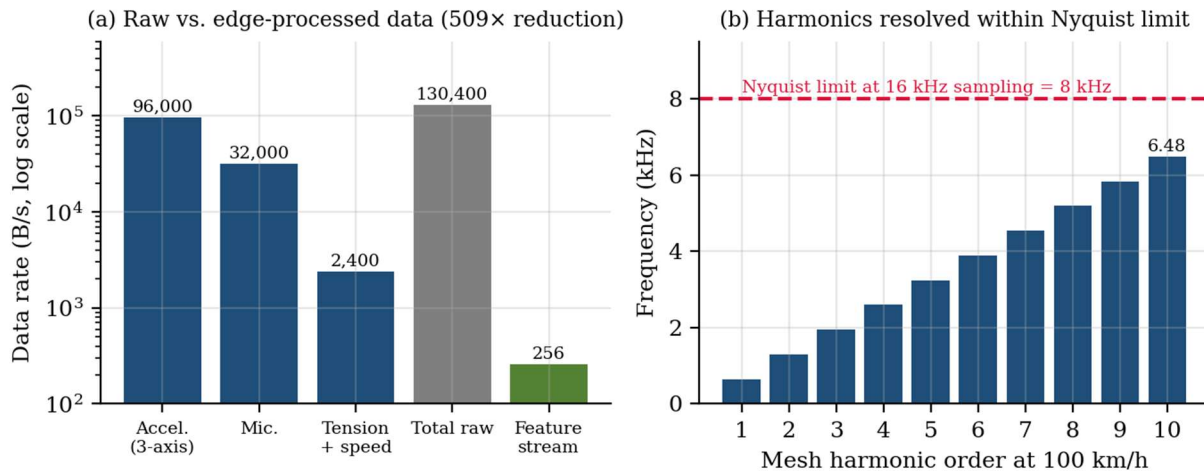


Fig. 3. (a) Raw and edge-processed data rates (log scale); (b) mesh harmonics at 100 km/h against the 8 kHz Nyquist limit of 16 kHz sampling.

As Fig. 3(a) shows, the unprocessed streams amount to 130.4 kB/s, or 469 MB per hour of riding, which is impractical to transmit over a low-power wireless link or to store on a retrofit module. Computing the features on the edge controller and sending only the feature vector reduces the data to 256 B/s (0.92 MB/h), a 509-fold reduction, while raw snippets can still be retained around alert events for later analysis. This result supports the edge-processing layer of the architecture on data-volume grounds independently of latency considerations.

5.3 Wear geometry, elongation and sprocket engagement

Table IV and Fig. 4 apply (8) and the chain geometry to elongations up to the illustrative 3 % limit. Each 1 % of elongation increases the pitch by 0.127 mm, the 20-pitch length by 2.54 mm and the total chain length by 11.94 mm. At 3 %, the pitch has grown by 0.381 mm, the chain is 35.8 mm longer, and the rollers must ride 2.67 mm higher on the rear sprocket (21.0 % of the pitch) and 0.86 mm higher on the front sprocket (6.7 % of the pitch). For the same elongation, the radial rise on the 44-tooth sprocket is 3.1 times that on the 14-tooth sprocket, in the ratio

$\sin(\pi/14)/\sin(\pi/44)$. The large sprocket therefore reaches the limit of tooth-flank engagement first, and the mismatch between elongated chain and sprocket is expected to be the mechanism that connects chain elongation to the sprocket-tooth loading discussed in [1]–[3].

TABLE IV. WEAR GEOMETRY OF THE REFERENCE DRIVETRAIN VERSUS CHAIN ELONGATION

ε (%)	Pitch growth Δp (mm)	20-pitch length (mm)	Total chain length gain (mm)	Axle travel to absorb (mm)	Rise Δr , front (mm)	Rise Δr , rear (mm)
0.5	0.064	255.27	5.97	2.98	0.14	0.45
1.0	0.127	256.54	11.94	5.97	0.29	0.89
1.5	0.191	257.81	17.91	8.95	0.43	1.34
2.0	0.254	259.08	23.88	11.94	0.57	1.78
3.0	0.381	261.62	35.81	17.91	0.86	2.67

Computed from $p = 12.7$ mm, a nominal 20-pitch length of 254.0 mm and $L = 1.194$ m. Axle travel is approximated as half the length gain for near-parallel spans; Δr from Eq. (8).

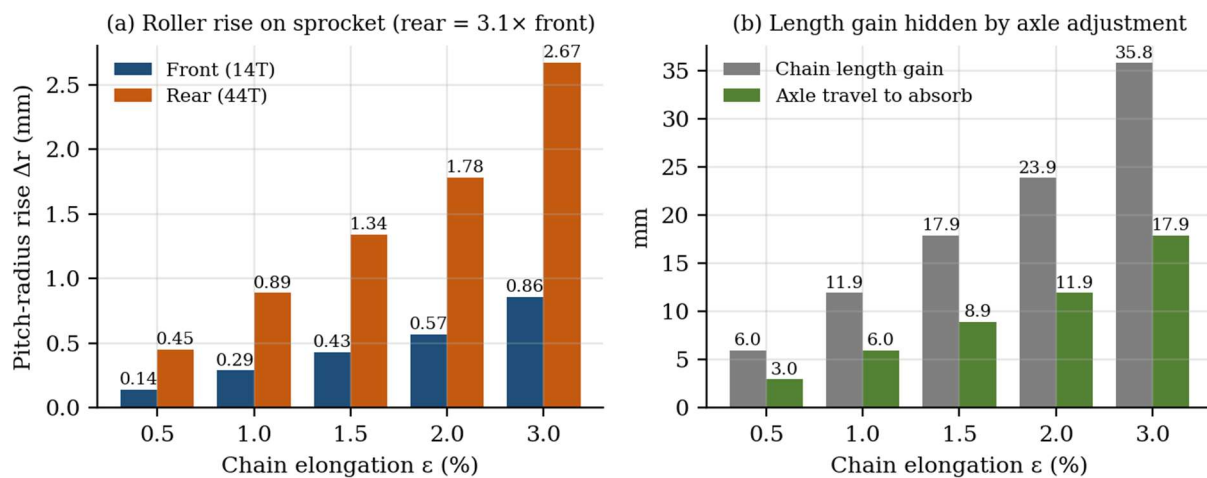


Fig. 4. (a) Pitch-radius rise on the front and rear sprockets versus chain elongation; (b) chain length gain and the axle travel needed to absorb it.

Two design implications follow. First, slack-based inspection is a weak indicator of elongation: since the chain length gain is absorbed by moving the rear axle, roughly 17.9 mm of adjustment at 3 % elongation (Table IV), a chain that is regularly re-tensioned shows near-constant slack while continuing to wear. The system should therefore record adjustment events, or infer them from a step change in static tension, and should not equate stable slack with stable condition. Second, the geometric changes to be detected are small: 0.127 mm of pitch mismatch at 1 % and 0.445 mm of radial rise at 0.5 % on the rear sprocket. Dynamic features must therefore be validated for sensitivity at the sub-millimetre level. The ground-truth gauge must be considerably finer: a 20-pitch measurement with 0.1 mm resolution resolves 0.039 % elongation, which is 1.3 % of the 3 % limit and is adequate as a reference. This is consistent with the emphasis on measurement repeatability in [5].

5.4 Complementarity of the sensing channels

Table V summarises what each channel measures and what confounds it, using the sensitivities identified in Sections 5.1–5.3 and the literature [4]–[7]. No channel is free of confounders, but the confounders differ between channels: acoustic content is corrupted by ambient noise, vibration by the mounting transfer path, and tension by load and by the axle adjustments described above. Speed is the only channel that serves as a reference for the others. Fusion is therefore justified as a means of cross-checking channels whose failure modes are independent, and the ablation experiments of Section 4.7 are the appropriate test of whether the added complexity produces measurable benefit. The magnitude of any such benefit is a hypothesis, not a result of this paper.

TABLE V. ROLE AND PRINCIPAL CONFOUNDERS OF EACH SENSING CHANNEL

Channel	Physical sensitivity	Principal confounders	Role in the framework
Vibration	Mesh impacts, pitch mismatch, looseness	Engine and road excitation; mounting transfer path	Primary condition feature (order domain)
Acoustic	Friction, impacts, lubrication state	Ambient, engine and wind noise; port position	Supporting feature; not used alone
Chain tension	Span dynamics, static tension, adjustment events	Load, speed, axle adjustment	Elongation proxy and adjustment logging
Rotational speed	Operating reference for f_m , f_c , T	Sensor alignment; missed pulses	Order normalisation and regime selection
Context (temperature, load proxy)	Operating state	Availability on retrofit	Regime segmentation; model input

Qualitative summary derived from Sections 3, 5.1–5.3 and [4]–[7].

5.5 Health-index behaviour

A worked example illustrates (2) and (3) (Fig. 6a). Take four features with calibrated deviations d^* of 0.12 (mesh-harmonic band power), 0.28 (RMS acceleration), 0.05 (tension fluctuation RMS) and 0.20 (acoustic band energy) and weights of 0.4, 0.3, 0.1 and 0.2. The weighted deviation is $0.4(0.12) + 0.3(0.28) + 0.1(0.05) + 0.2(0.20) = 0.177$, so $\text{CSHI} = 100(1 - 0.177) = 82.3$, which the proposed prototype presentation would show as “Healthy”. In this example the largest feature (mesh-harmonic power, $w = 0.4$) can lower the index by at most 40 points, so a single corrupted channel cannot by itself drive the index to the critical region. The acoustic feature, which is the most exposed to environmental noise, is limited to 20 points in the same way. This bounded-influence property is a direct consequence of the convex weighting and is the reason for constraining the weights to sum to one. The index does not remove the need for calibration: the weights, the mapping of index bands to alert states and the reference values $f_{i,\text{ref}}$ must be learned from Stage I and II data and checked against the ground-truth elongation, not tuned to maximise performance on a single dataset. The data-quality flag remains necessary so that missing channels lower the confidence of the index instead of silently reading as healthy.

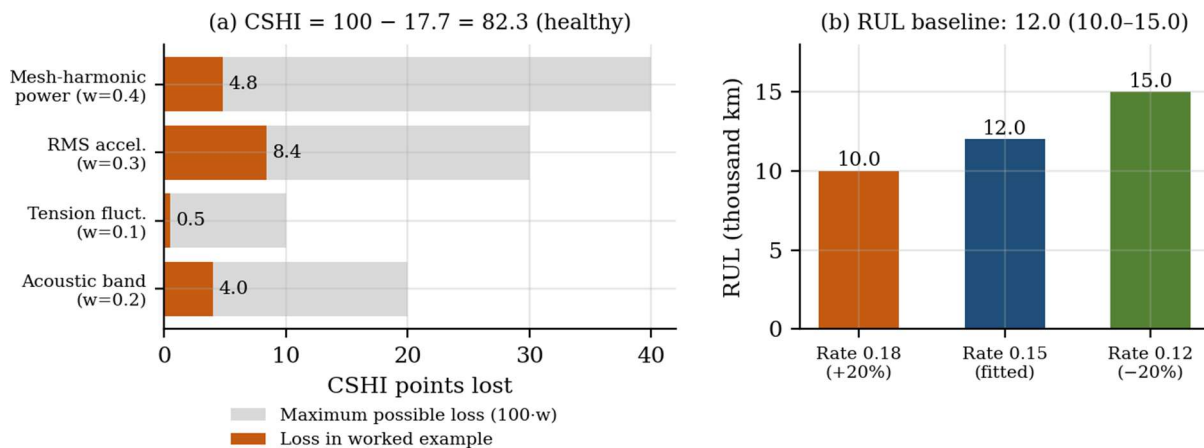


Fig. 6. (a) Contribution of each feature to the CSHI loss in the worked example against its maximum possible loss; (b) baseline RUL for the fitted degradation rate and $\pm 20\%$ rate uncertainty.

5.6 Alert logic: false-alarm burden and detection latency

Table VI and Fig. 5 evaluate the persistence rule with (10) and (11), taking one decision per second (360 000 windows per 100 h of operation). With a per-window false-positive probability $\alpha = 0.05$, alerting on a single window would produce 18 000 false alerts per 100 h, and requiring three consecutive windows still gives 45. Requiring five consecutive windows reduces the probability of a false alert to 3.1×10^{-7} per window, or 0.11 false alerts per 100 h, at the price of a mean detection latency of 10.3 windows (about 10 s) when 80 % of windows from a degraded chain

are flagged, and 6.9 windows when 90 % are flagged. Increasing to eight windows lengthens the latency to 24.8 s at 80 % without a meaningful further reduction in practical false-alarm burden. For chain wear, which develops over thousands of kilometres, latencies of seconds are operationally negligible, so a persistence of five windows or more is justified and a value of three or fewer is not.

TABLE VI. FALSE-ALERT BURDEN AND DETECTION LATENCY OF THE k-WINDOW PERSISTENCE RULE

k	$P_{FA} (\alpha = 0.05)$	False alerts / 100 h ($\alpha = 0.05$)	False alerts / 100 h ($\alpha = 0.02$)	Mean latency, $q = 0.8$ (windows)	Mean latency, $q = 0.9$ (windows)
1	5.0×10^{-2}	18 000	7 200	1.25	1.11
3	1.3×10^{-4}	45	2.9	4.77	3.72
5	3.1×10^{-7}	0.11	1.2×10^{-3}	10.26	6.94
8	3.9×10^{-11}	1.4×10^{-5}	9.2×10^{-9}	24.80	13.23

Computed from Eqs. (10) and (11) for 1 Hz decisions (360 000 windows per 100 h). Windows are assumed independent.

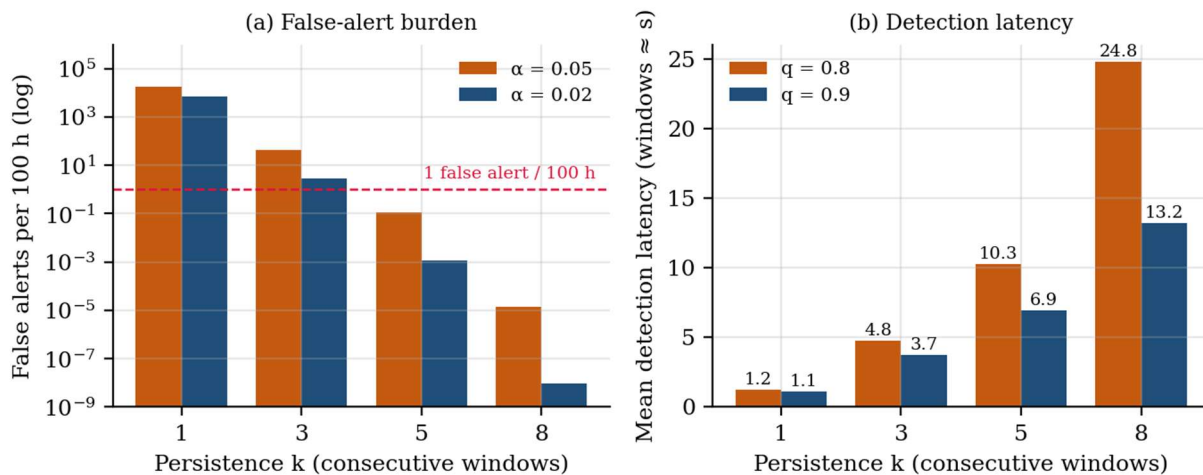


Fig. 5. (a) False alerts per 100 h and (b) mean detection latency of the k-window persistence rule (data of Table VI).

These figures are lower bounds on the true false-alert burden. Adjacent windows from the same road segment are positively correlated, so real false alerts cluster and the effective reduction from persistence is smaller than α^k suggests. The per-window rates α and q are properties of the trained classifier and can be established only in the experimental stage; the values in Table VI define the operating region to be targeted, and the analysis motivates reporting false-alert rate per 100 h alongside classification metrics, as proposed in Section 4.7.

5.7 Remaining useful life: baseline behaviour

For the baseline estimator (4) (Fig. 6b), consider a chain measured at $\varepsilon_{\text{now}} = 1.2\%$ with a fitted elongation rate of 0.15 %/1000 km and the 3.0 % limit of Table I. Then $RUL = (3.0 - 1.2)/0.15 = 12.0$ thousand km. A $\pm 20\%$ uncertainty in the fitted rate (0.12–0.18 %/1000 km) widens this to 10.0–15.0 thousand km, an asymmetric interval of -17% and $+25\%$ about the point estimate, because the rate appears in the denominator. This example is illustrative and not based on measured wear rates. It shows two properties that the final estimator must respect: uncertainty in the degradation rate produces a skewed RUL interval, and a late-biased error is more costly than an early one, which supports the prognostic score that penalises late predictions (Section 4.7). It also illustrates why RUL is withheld when the fitted slope is unreliable, as a near-zero rate would give an arbitrarily large and misleading RUL.

5.8 Discussion

The analysis refines the design of the proposed system in five respects. First, prior IoT- and CNN-based chain-drive fault classification [6] demonstrates that vibration-based recognition is feasible, but the speed dependence quantified in Table II indicates that such classifiers will need order-normalised inputs or explicit speed conditioning to be

transferable from a test rig at fixed speed to a road vehicle over a 5:1 speed range. Second, the edge-processing requirement follows from data volume as well as latency: a 509-fold reduction makes low-power wireless transfer feasible. Third, the elongation geometry (Table IV) explains why measured slack alone can be misleading and why tension and adjustment-event logging are included. Fourth, the persistence analysis (Table VI) sets a concrete target for the false-alert rate that the classifier must meet. Fifth, the CSHI construction bounds the influence of any single noisy channel.

Several implementation challenges remain. Engine and road noise may mask chain-related acoustic signatures; vibration transfer paths vary with sensor mounting, frame design and suspension configuration; the relationship between chain elongation and dynamic features may depend on speed, torque, lubrication and sprocket geometry; labelled failure data are difficult to obtain because chains are normally replaced before catastrophic failure; and a model trained on one motorcycle platform may not generalise to another without calibration or domain adaptation. The 3.0 % limit, the road-load powers and the chain mass are assumptions, and the reported frequencies, tensions and geometric quantities will shift for other chain sizes, sprocket combinations and vehicles, although the scaling relations (5)–(9) remain valid.

The proposed system should complement—not replace—routine inspection and manufacturer-recommended maintenance. Its practical value will depend on demonstrating that alerts are reliable, timely, interpretable and affordable under real operating conditions. Whether the approach reduces component wear, downtime or operating cost is an empirical question and should be reported only after comparative trials against conventional maintenance practice.

6. LIMITATIONS

This manuscript describes a proposed design, a validation methodology and an analytical characterisation for an assumed reference drivetrain. No experimental dataset, prototype test results, classifier accuracy, RUL error, cost breakdown or field reliability measurements are reported, and the paper does not claim validated performance or quantified improvements in maintenance outcomes. The analytical results depend on the assumptions of Table I. The CSHI weights and alert thresholds are proposed constructs requiring calibration; the false-alert analysis assumes independent windows; the sprocket-rise result is a geometric upper bound; and the taut-string model for span frequency neglects chain sag, bending stiffness and sprocket compliance. RUL prediction is contingent on collecting longitudinal degradation data and defining a defensible end-of-life criterion. These limitations should be addressed before the framework is presented as experimentally validated.

7. CONCLUSION AND FUTURE WORK

This paper proposed a multi-sensor, AI-enabled framework for monitoring chain and sprocket health in two-wheelers and characterised its design requirements analytically for a reference 428-pitch, 14/44-tooth, 94-link drivetrain. The specific findings are as follows.

- 1) **Speed dependence.** Over 20–100 km/h the tooth-mesh frequency rises from 130 to 648 Hz (5.0×), the chain speed from 1.65 to 8.23 m/s, the tight-span tension from 364 to 1093 N (3.0×), and the span natural frequency from 31.1 to 53.8 Hz, which stays 4.2–12.0 times below the mesh frequency. Speed-referenced, order-normalised features and regime-based classification are therefore required, and the speed sensor is a core channel.
- 2) **Acquisition design.** A 16 kHz sampling rate resolves the tenth mesh harmonic (6.48 kHz at 100 km/h) within the 8 kHz Nyquist limit, and a 16 384-sample window (1.024 s, 0.977 Hz resolution) contains at least one full chain revolution above 14.2 km/h; below this speed the system should report insufficient speed. Tension needs only 1 kHz sampling.
- 3) **Edge processing.** Raw sensing generates 130.4 kB/s (469 MB/h); transmitting a 64-feature vector per second reduces this to 256 B/s (0.92 MB/h), a 509-fold reduction.

- 4) **Wear geometry.** Each 1 % of chain elongation adds 0.127 mm of pitch and 11.94 mm of chain length; at the illustrative 3 % limit the values are 0.381 mm and 35.8 mm, and the rollers rise 2.67 mm (21.0 % of the pitch) on the rear sprocket versus 0.86 mm on the front sprocket, a ratio of 3.1. Because about 17.9 mm of axle adjustment can absorb this length at 3 %, slack alone can hide progressive wear, and adjustment events must be logged.
- 5) **Excitation source.** Chordal speed variation is 2.51 % for the 14-tooth front sprocket and 0.25 % for the 44-tooth rear sprocket (ratio 9.8), so the front sprocket and tight span are the priority locations for sensing.
- 6) **Health index.** The CSHI is bounded to 0–100 and limits the influence of any feature to $100w_i$ points; in the worked example, features with weights of 0.4, 0.3, 0.1 and 0.2 give CSHI = 82.3 (healthy).
- 7) **Alert logic.** With $\alpha = 0.05$, single-window alerts would produce 18 000 false alerts per 100 h and three-window persistence still 45, whereas five-window persistence gives 0.11 per 100 h (3.1×10^{-7} per window) at a mean latency of 10.3 s ($q = 0.8$), under an independence assumption that gives a lower bound.
- 8) **RUL.** In the worked baseline, 1.2 % elongation at 0.15 %/1000 km against a 3.0 % limit gives 12.0 thousand km, with a ± 20 % rate uncertainty producing an asymmetric 10.0–15.0 thousand km interval; RUL must be reported with an interval and withheld when data are insufficient.

These are analytical results under the stated assumptions. The classification accuracy, class-wise precision and recall, RUL error, sensor uptime and field reliability of the proposed system have not been measured and remain to be established experimentally. The framework should complement, not replace, manufacturer-recommended inspection and maintenance.

Future work will fabricate and calibrate the sensor module, establish controlled healthy-to-worn test states, collect repeated datasets across speeds, loads and lubrication conditions, replace the assumed parameters of Table I with measured values, and validate model generalisation across multiple vehicles. The next stage will report confusion matrices, class-wise precision and recall, per-window false-alert probability and false alerts per 100 h against the targets of Table VI, RUL MAE/RMSE with prediction intervals, sensor uptime, power consumption and inference latency.

Competing Interests

The authors of the study declare that they have no competing interests, either financial or non-financial. The study was conducted without any impact of commercial or personal interests.

Data Availability Statement

All data produced/generated during the current study included in this article.

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