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An Evolving Fuzzy Neural Network for Characterizing and Predicting Asymmetric-Information Risk Causes in Road Maintenance Projects: A Kenyan Case Study

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Abstract

Asymmetric information, meaning the uneven spread of project-relevant knowledge among clients, contractors and consultants, is a persistent but weakly quantified source of construction risk, and it matters a great deal for publicly funded road maintenance in developing economies. This paper characterises the asymmetric-information risk causes of a Kenyan urban road maintenance project, the Periodic Maintenance and Spot Improvement of Kinoo Shopping Centre Loop (Tender No. KURA/DEV/HQ/311/2024-2025), and develops an evolving fuzzy neural network (EFuNN) that tracks them while remaining interpretable. Ten risk indicators covering the contractor, client, consultant and external domains were read off the tender document, the conditions of contract and its data sheet, the bills of quantities, the Form 7 schedule of construction material basic prices and the environmental management plan. Each indicator was given an explicit scoring rule tied to a named clause and fuzzified into three Gaussian linguistic granules. Because the weekly progress records for the case lot were not released, the indicator stream was reconstructed rather than observed: the clause-derived scores set the level of each trajectory, contract provisions set its shape over the project lifecycle, and bounded random variation was added to give 208 weekly samples across the case lot and seven comparable KURA maintenance lots. A five-layer evolving Takagi-Sugeno-Kang network with novelty-based rule creation, utility pruning and recursive-least-squares adaptation was trained prequentially on this stream. It grew a compact seven-rule base and recovered the specified composite risk index with a root-mean-square error of 0.031, a mean absolute error of 0.024 and a coefficient of determination of 0.83. These figures measure how closely the network reproduces a reference index that this paper defines in Equations (2) and (3); they are not a test against realised claims, delays or cost growth, and they should be read as evidence of online structural identification rather than empirical validation. The fuzzy categorisation points to market volatility, time pressure and liquidated-damages exposure as the most adverse causes, each traceable to a specific clause of the contract. The study contributes a documented and auditable route from contract clauses to a continuous, time-varying risk signal, together with evidence that an evolving neuro-fuzzy predictor can follow such a signal while staying small enough to read.

Keywords

Asymmetric Information, Construction Risk, Evolving Fuzzy Neural Network, Takagi-Sugeno-Kang, Road Maintenance, Kenya

1. Introduction

Construction is a principal engine of economic development, yet it remains among the most risk-exposed of all industries because every project is a customised, temporary undertaking delivered by a shifting coalition of stakeholders under fluctuating market conditions [1] [2]. In developing economies such as Kenya, road-improvement and periodic-maintenance works are especially consequential for mobility and regional productivity, but their delivery is frequently undermined by cost overruns, disputes and delays [3]. A structural and often overlooked driver of these outcomes is asymmetric information: the condition in which one party to a transaction holds more, or better, information than another [4] [5].

Unlike the symmetric-information premise that underlies most conventional risk tools, asymmetric settings generate behavioural hazards—moral hazard, adverse selection and opportunistic claiming—because stakeholders act on different, and sometimes strategically withheld, subsets of project knowledge [6] [7]. Contractors may understate capacity limitations or price essential inputs opaquely during tendering, while clients may disclose scope, financial or regulatory constraints only partially [5]. These asymmetries are amplified where contractual roles are ambiguously defined [8], and they are difficult to capture with static, deterministic models that neither represent vagueness nor adapt as the project evolves. The problem is therefore twofold: the risk causes must first be characterized in a way that is auditable against the contract, and they must then be predicted with a model that tracks their evolution over the project lifecycle.

Fuzzy logic and neural networks offer complementary tools for this problem: fuzzy logic reasons under vagueness and incompleteness, while neural learning discovers patterns in complex data [9] [10]. Their integration as fuzzy neural networks has been used to model subjective construction risks, but conventional formulations such as the adaptive neuro-fuzzy inference system are static—calibrated once and unable to respond to emerging, context-specific risks [11] [12]. Evolving fuzzy systems overcome this limitation by creating, adapting and pruning rules online as data stream in, making them well suited to the non-stationary risk environment of a live construction project [13]-[15]. All of these formulations rest on the graded notion of membership introduced by Zadeh [16], which is what allows a partially disclosed contractual state to be represented as a degree rather than forced into a binary category.

This paper addresses the first two objectives of a larger study by 1) characterising the asymmetric-information risk causes of a representative Kenyan road maintenance project directly from its contractual documentation, and 2) developing an evolving fuzzy neural network (EFuNN) that tracks these risks while remaining interpretable to project managers. Three contributions follow. The first is a document-grounded characterisation built on ten indicators, each traceable to a named contract clause and each given an explicit scoring rule, so that a reader can reproduce any value from the tender document itself. The second is a transparent fuzzy categorisation of the indicator data across linguistic granules, which locates the adverse mass of the risk profile in particular contractual provisions rather than in general categories. The third is a compact evolving neuro-fuzzy predictor whose formulation, learning rules and performance are reported in full, together with an explicit account of what its accuracy figures do and do not establish. On that last point the paper is deliberate: the weekly records needed to drive the model were not released, so the indicator stream is reconstructed from documentary parameters and the prediction target is an aggregation scheme specified in this paper rather than an observed project outcome. The reported accuracy therefore measures recovery of that specification, and the paper separates documentary from assumed material throughout so that the boundary stays visible. The remainder is organised as follows. Section 2 reviews asymmetric-information risk and evolving fuzzy systems. Section 3 describes the case project, the selection of comparable lots, the scoring rules and the construction of the indicator stream. Section 4 formulates the fuzzification, the composite index and the evolving model. Section 5 reports and discusses the results and sets out the limitations, and Section 6 concludes.

2. Related Work

2.1. Asymmetric-Information Risk in Construction

Systematic reviews establish that information asymmetry pervades every phase of construction procurement and execution, and that it originates on all three sides of the client-contractor-consultant triangle [4] [5]. On heavy-civil projects, contractors and owners identify markedly different deficiencies in the same information set, a direct empirical signature of asymmetry [17]. Contract ambiguity has been shown to be a leading antecedent of conflict [8], and asymmetric trust degrades management performance through impaired knowledge sharing [18]. Proposed mitigations range from relational contracting and building-information modelling [19] to blockchain-based disclosure [20] and optimally structured time- and cost-based contracts [7]. Despite this breadth, the literature remains largely qualitative or single-snapshot: few studies express asymmetric-information risk as a quantitative, time-varying signal that can be predicted and acted upon during delivery.

2.2. Fuzzy Neural and Evolving Fuzzy Systems

Fuzzy set theory provides a natural language for the partial, vague disclosure states that characterise asymmetry, while neuro-fuzzy systems such as the adaptive neuro-fuzzy inference system combine this expressiveness with data-driven learning [11] [21]. Interval type-2 fuzzy methods have improved expert-judgment aggregation for risk prioritisation [22], and machine-learning and neuro-fuzzy models have been applied to mega-project risk prediction [23] [24]. However, most such models are static: they are calibrated once and cannot track the drift in risk relationships that occurs as a project moves from tender to completion. Evolving fuzzy systems are explicitly designed for such non-stationary streams, adding and removing rules online while preserving interpretability [13] [15], and multi-layer evolving fuzzy neural networks have recently demonstrated strong online-learning performance [14]. The present study brings this evolving paradigm to bear on asymmetric-information risk in Kenyan road maintenance, a combination not previously reported.

3. Case Project and Risk-Indicator Data

3.1. Case Project and Data Sources

The case project is the Periodic Maintenance and Spot Improvement of Kinoo Shopping Centre Loop, Lot 1 (Tender No. KURA/DEV/HQ/311/2024-2025), in Kikuyu Constituency, Kiambu County, procured by the Kenya Urban Roads Authority (KURA). The works cover drainage rehabilitation, earthworks, natural-material base and sub-base, bituminous surfacing and road furniture. The contract runs for six months from the commencement date under Sub-Clause 8.2 and carries a three-month defects liability period under Sub-Clause 11.1. Working capital of KShs 7 million is required and stated in the tender as 20 per cent of the Engineer's Estimate, which places the estimate at approximately KShs 35 million.

The evidence base for this study is the tender document itself, which runs to 317 pages. It contains the instructions to tenderers, the qualification and post-qualification criteria, the general and special conditions of contract, the contract data sheet, the special specifications, the bills of quantities and their preamble, the Form 7 schedule of construction material basic prices, and the environmental and social management plan set out in Section 2500. Everything used to build the indicators comes from these parts, so any value in the analysis can be checked against a named clause, bill or schedule.

It is equally important to state what was not available. KURA released the pre-award documentary record but not the executed contract, the interim payment certificates, the monthly progress reports, the correspondence file or the claims register for Lot 1. The study therefore works from the documents that fix the rules of the exchange. Those rules are the proper subject of an asymmetric-information analysis, since they determine who is obliged to disclose what and on what terms, but they do not record how the parties actually behaved week by week. Section 3.4 explains how that gap was handled and Section 5.5 sets out what it costs the argument.

3.2. Selection of Comparable Maintenance Lots

A single lot yields only 26 weekly points, which is too short a stream to exercise the rule-creation and pruning mechanisms of an evolving model in any meaningful way. Seven further KURA periodic-maintenance and spot-improvement lots were therefore brought in from the same procurement cycle. A lot was admitted only if it satisfied every one of the criteria in Table 1. The criteria were fixed before any indicator values were computed, so the comparison set cannot have been tuned to produce a particular result.

Table 1. Criteria applied in selecting the seven comparable KURA maintenance lots.

Criterion	Requirement applied	Reason for inclusion
Procuring entity	Kenya Urban Roads Authority, urban roads development directorate	Common employer and common disclosure practice
Contract form	KURA standard works contract with the same general conditions and data sheet structure	Ensures Sub-Clauses 8.2, 8.7, 13.8, 14.6 and 14.7 carry identical meaning
Work category	Periodic maintenance and/or spot improvement of urban roads	Same scope families: drainage, base and sub-base, surfacing, road furniture
Contract duration	Four to eight months; case lot is six months under Sub-Clause 8.2	Comparable schedule compression, so x9 is measured on a like basis
Contract value	KShs 20 million to 60 million; case lot Engineer's Estimate approximately KShs 35 million	Same qualification thresholds and the same KShs 3 million interim certificate floor
Procurement cycle	2023/2024 or 2024/2025 financial year	Same market and index conditions under Sub-Clause 13.8
Price adjustment	Weightings, KNBS indices, one-month adjustment period	Makes the market volatility indicator x8 comparable across lots
Delay damages	0.01 per cent of the contract price per day, capped at 10 per cent	Makes the liquidated-damages exposure indicator x10 comparable across lots

The screen is deliberately narrow. Holding the procuring entity, the contract form, the duration band and the price-adjustment regime constant means that the eight lots share a single contractual environment and differ mainly in scale and site conditions. This matters for the indicators: a clause reference such as Sub-Clause 8.7 or 13.8 only carries the same meaning across lots if the underlying form is the same, and a score built on that clause is only comparable if the threshold behind it is the same. Lots outside the KURA urban maintenance programme, lots let under a different standard form, and lots whose duration exceeded twelve months were excluded on those grounds. Trunk road contracts under other authorities were excluded for the same reason, since their disclosure obligations and penalty regimes are not equivalent.

3.3. Operationalising the Ten Risk Indicators

Ten risk indicators, x1 to x10, were defined across four domains, namely contractor, client, consultant and external. Each is scaled to the unit interval, where 1 denotes a favourable disclosure state (clear, transparent, on time or stable) and 0 an adverse one (hidden, opaque, delayed or volatile). Table 2 names the indicators, their domain and the governing contractual anchor.

Table 2. The ten asymmetric-information risk indicators and their governing contractual anchors.

Indicator	Domain	Governing contractual anchor (clause)
x1 Experience/capacity disclosure	Contractor	Key-personnel and similar-contracts criteria; turnover
x2 Financial transparency	Contractor	Turnover KShs 32M; working capital KShs 7M; Form 7 prices
x3 Payment timeliness	Client	Interim cert. KShs 3M (14.6); 90-day payment (14.7.1); advance (14.2.1)
x4 Scope/change disclosure	Client	Engineer variation authority 25% (3.1.2); BOQ bills; provisional sums
x5 Information-flow efficiency	Consultant	Language clause (1.4); reporting and correspondence with Engineer
x6 Documentation clarity	Consultant	Blank BOQ rates and Form 7 prices; special specifications; drawings
x7 Regulatory/environmental compliance	External	EMP Section 2500; insurance (18.1); statutory approvals
x8 Market volatility (stability)	External	Price-adjustment weightings, Table A; KNBS indices (13.8)
x9 Time-to-completion pressure	External	6-month completion (8.2); commencement (8.1); programme (8.3)
x10 LD-exposure proxy	External	Delay damages 0.01%/day (8.7); cap 10% (8.7.1); deductions

Naming a clause is not by itself enough to make a score reproducible, so Table 3 goes further. For each indicator it states the specific documentary quantity that was scored, the rule used to map that quantity onto the unit interval, and the two anchor points that fix the ends of the scale. The rules were written before any scoring took place and applied uniformly to all eight lots. A reader with the tender document in hand can therefore recompute any indicator level and arrive at the same number.

Three scoring patterns cover the ten indicators. Ratio rules apply where the contract states a numeric threshold and the document supplies a value to compare against it, as with the Engineer's variation authority of 25 per cent under Sub-Clause 3.1.2 (b) (ii). Completeness rules apply where the obligation is that a schedule, form or report be supplied in full, as with the Form 7 basic price schedule or the reporting duties under Sub-Clause 14.3. Proximity rules apply where risk grows as the project approaches a contractual trigger, as with the completion date under Sub-Clause 8.2 or the delay-damages cap under Sub-Clause 8.7.1. In every case the direction of the scale is fixed so that 1 is the favourable end.

Two features of the tender show why the documentation and transparency indicators score below the mid-point rather than at the favourable end, and both

Table 3. Scoring rules used to operationalise each indicator from the contract documents.

Indicator	Documentary quantity scored	Scoring rule	Anchors (0 and 1)
x1 Experience/capacity disclosure	Key personnel posts evidenced against those required (4.3, 6.9); similar contracts evidenced against the three required	Ratio: mean of (posts evidenced/posts required) and (similar contracts evidenced/3)	0 = no verifiable evidence; 1 = all key posts and three similar contracts fully evidenced
x2 Financial transparency	Form 7 items priced with attached supplier confirmation; BOQ items carrying a rate	Completeness: mean of the priced-and-confirmed fraction of the ten Form 7 items and the rated fraction of BOQ items	0 = schedule returned blank; 1 = every item priced and confirmed
x3 Payment timeliness	Days elapsed to payment against the 90-day period (14.7.1(b)); certificate value against the KShs 3 million floor (14.6)	Proximity: 1 minus (days elapsed/90), floored at 0, reduced where certified value falls below the interim floor	0 = payment at or beyond 90 days; 1 = payment within the month of certification
x4 Scope/change disclosure	Cumulative variation value against the Engineer's 25 per cent authority (3.1.2(b)(ii)); provisional and prime cost sums as a share of Bill 1	Ratio: 1 minus (cumulative variation/25 per cent of contract price), reduced by the unexpended provisional sum share	0 = variation authority exhausted; 1 = no variation and no unexpended provisional sums
x5 Information-flow efficiency	Monthly statements in the required three copies (14.3); correspondence in the language of the contract (1.4); cash flow estimate within 21 days (14.4.2)	Completeness: fraction of the reporting obligations met within their stated periods in the reporting month	0 = no reporting obligation met; 1 = all met on time
x6 Documentation clarity	Internal consistency of the stated qualification thresholds; contiguity of BOQ numbering; presence of a rate against every non-provisional item (BOQ preamble, item 9)	Completeness less an inconsistency penalty: fully specified fraction, reduced by one increment for each documented internal contradiction	0 = specification unusable without clarification; 1 = fully specified and internally consistent
x7 Regulatory/environmental compliance	EMP Section 2500 compliance reports filed with the Engineer; evidence of insurance within 30 days of signature (18.1); third-party cover at KShs 10 million (18.3)	Completeness: fraction of EMP matrix obligations reported and statutory cover evidenced	0 = no compliance report and no evidence of cover; 1 = periodic reports filed and all cover evidenced
x8 Market volatility (stability)	Movement in the KNBS civil engineering cost indices for the Table A cost heads against base values 28 days before tender	Volatility: 1 minus normalised absolute index movement over the one-month adjustment period (13.8.3), weighted by the Table A shares	0 = movement at or above the highest observed in the cycle; 1 = indices at base value
x9 Time-to-completion pressure	Weeks remaining to the Sub-Clause 8.2 completion date, net of the commencement and programme periods (8.1, 8.3)	Proximity: remaining float divided by the total contract period	0 = at the completion date with work outstanding; 1 = full period remaining at commencement
x10 LD-exposure proxy	Accrued delay damages at 0.01 per cent of the contract price per day (8.7) against the 10 per cent cap (8.7.1)	Proximity: 1 minus (accrued exposure/cap)	0 = cap reached; 1 = no accrued exposure

are visible in the source rather than assumed. First, the qualification requirements contradict themselves. The post-qualification conditions in the instructions to tenderers call for a minimum average annual construction turnover of KShs 32 million and three similar contracts of at least KShs 15 million each, while the summary of post-qualification criteria a few pages later states KShs 35 million and three road projects of KShs 17.5 million. A tenderer reading the document cannot tell which threshold governs. Second, the bills of quantities are numbered 1, 4, 8, 9, 12, 15, 16 and 20, so the numbering carries gaps that the document nowhere explains, and the rate column is left blank for the tenderer to complete while the preamble forbids nil, included or lump-sum entries. Neither feature is unusual in Kenyan road procurement, but both are precisely the partial and inconsistent disclosure that x6 is meant to register, and both are recorded in the scoring rather than inferred from it.

3.4. Reconstruction of the Weekly Indicator Stream

Applying the rules in **Table 3** to the tender documents yields one scored value per indicator per lot. That is a static picture taken at award, and an evolving model needs a stream. Because the weekly records that would supply such a stream were not released, the stream was reconstructed rather than observed. The reconstruction is set out here in full so that a reader can judge exactly which parts of the analysis rest on documentary evidence and which rest on assumption.

Reconstruction proceeded in three steps. First, the clause-derived score from **Table 3** sets the level of each indicator, that is, the value its trajectory takes at the reference point. Second, the shape of each trajectory over normalised project time t in [0, 1] is taken from the contract rather than fitted to any outcome. The disclosure and documentation indicators rise linearly as the record accumulates, at rates of 0.35 for x1, 0.30 for x2, 0.25 for x5 and 0.20 for x6 over the full period. Payment timeliness x3 carries a Gaussian trough centred at mid-contract, because Sub-Clause 14.2.4(a) begins recovering the advance once certified interim payments pass 20 per cent of the accepted contract amount and completes recovery at 80 per cent, which squeezes net certified cash across that band. Schedule float x9 and distance from the delay-damages trigger x10 decline linearly towards the completion date, by 0.70 and 0.55 respectively, since both are defined as proximity to a fixed contractual date. Regulatory compliance x7 and market stability x8 carry sinusoidal components on top of their trend, representing the periodic inspection cycle in the EMP matrix and the monthly index revision under Sub-Clause 13.8.3; x8 additionally trends downward by 0.25 across the cycle. Third, independent Gaussian variation was added at each weekly step, with a standard deviation set per indicator between 0.06 and 0.10 according to how much week-to-week movement the underlying record would plausibly show, and the result clipped to [0, 1].

Sampling 26 weekly steps for each of the eight lots gives a time-stamped stream of 208 observations of the ten indicators. Each lot is generated from its own random stream, so the eight series are independent draws around the same contract-derived shapes rather than replicates of one another. **Table 4** states, element by element, whether the material is documentary or assumed. The distinction governs how the results in Section 5 should be read. The indicator definitions, their clause anchors, their scoring rules and their levels are documentary. The direction of each lifecycle shape follows from a clause; its magnitude and curvature do not. The week-to-week variation is assumed outright. No part of the stream is an observed weekly project record, and the paper makes no claim that it is.

Table 4. Provenance of each element of the indicator stream, separating documentary material from assumed material.

Element of the data construction	Status	Source or assumption
Indicator definitions and domains	Documentary	Contract clauses listed in Table 2
Scoring rules and anchor points	Documentary	Table 3, applied to the tender document
Indicator level at the reference point	Documentary	Scores read from the tender, conditions of contract, bills of quantities, Form 7 and EMP Section 2500
Comparability of the seven further lots	Documentary	Criteria in Table 1, applied to KURA procurement records
Direction of each lifecycle trajectory	Documentary	Implied by Sub-Clauses 14.2.4(a), 8.2, 8.7 and 13.8
Magnitude and curvature of each trajectory	Assumed	Chosen by the authors to be consistent with the clause direction; not calibrated to any outcome
Week-to-week variation	Assumed	Independent Gaussian per indicator, standard deviation 0.06 to 0.10, clipped to [0, 1]
Weekly sampling interval and 26-step horizon	Assumed	Chosen to correspond to the six-month period in Sub-Clause 8.2
Composite index weights and interaction terms	Assumed	Author-specified from contract materiality and prior literature; values and reasoning in Table 5
Realised claims, delays and cost outcomes	Not available	Not released by KURA for the case lot; discussed in Section 5.5

4. Model Formulation and Learning

4.1. Gaussian Fuzzification

Each indicator value was fuzzified into three Gaussian membership functions representing the linguistic granules ADVERSE, MODERATE and FAVOURABLE based on fuzzy set theory [16] and plotted in Figure 1(a), centred at 0, 0.5 and 1 with a common width $\sigma = 0.22$. The membership of a value x to term m with centre c_m is

$$\mu_m(x) = \exp\left[-(x-c_m)^2/(2\sigma^2)\right], c_m \in \{0, 0.5, 1\} \quad (1)$$

These granules give the model an interpretable vocabulary: any indicator observation is expressed as simultaneous, graded membership in the three terms rather than a single crisp label, which is essential where disclosure states are partial rather than binary.

4.2. Composite Asymmetric-Information Risk Index

The prediction target is a composite risk index that aggregates the adverse component of each indicator with pairwise interactions that reflect how asymmetries compound. Writing the adverse level of indicator j as $a_j = 1 - x_j$ and letting $g = t$ denote normalised project time, the latent risk is

$$z = 1.15\sum_j w_j a_j + \sum \lambda_k(g) \cdot a_p a_q \tag{2}$$

where the linear weights w place more emphasis on financial, scope and schedule disclosure than on procedural obligations, and the time-varying coefficients lambda weight the schedule and liquidated-damages interaction more heavily late in the project and the opacity and scope interaction more heavily early, so that the risk regime is non-stationary by construction. The risk score is then obtained by squashing the latent risk onto the unit interval with a logistic link,

$$y(t) = 1\Big/\Big(1 + \exp\big[-4.2(z - 0.62)\big]\Big) + \varepsilon(t) \tag{3}$$

with epsilon(t) a small zero-mean disturbance. Equation (3) supplies the continuous reference signal that the EFuNN is trained to reproduce online. Because that signal is nonlinear and non-stationary, it rewards a predictor able to adapt its structure over a predictor whose structure is fixed in advance.

The weights and interaction coefficients are specified by the authors rather than estimated from outcome data, and **Table 5** gives their values alongside the reasoning behind each. Three considerations set the linear weights. Contract materiality carries the most force, so financial transparency takes the largest single weight at 0.16, followed by payment timeliness and scope disclosure at 0.13 each, since these three sit closest to the clauses that convert an information gap into money: the Form 7 price schedule, the 90-day payment period under Sub-Clause 14.7.1, and the Engineer's 25 per cent variation authority under Sub-Clause 3.1.2. Prior evidence supplies the second consideration, since systematic reviews place financial and scope disclosure among the strongest antecedents of dispute and cost growth [4] [5], contract ambiguity has been shown to be a leading route to conflict [8], and contract structure governs how asymmetry translates into outcomes [7]. Restraint supplies the third. The weights span only 0.05 to 0.16 and sum to unity, so no indicator dominates the index, and the four procedural indicators x5, x6, x7 and x1 retain non-trivial weight rather than being written out of the aggregation.

Five pairwise interactions enter the index, and three of the five vary with project time because the contract makes them do so. The schedule and delay-damages pair strengthens as g approaches 1, rising from 0.12 to 0.32, since exposure under Sub-Clause 8.7 accrues only as the completion date nears and is meaningless at commencement. The market and financial pair also strengthens, from 0.10 to 0.20, because index movement under Sub-Clause 13.8 compounds with pricing opacity as more of the adjustable cost is certified. Two pairs weaken over the same span: financial opacity with scope disclosure falls from 0.30 to 0.18, and experience disclosure with financial transparency falls from 0.22 to 0.12, because both do their damage early, while rates are being fixed and variations authorised, and are largely spent by the closing weeks. The payment and scope pair is held constant at 0.16, since neither side of it has a contractual reason to strengthen or

Table 5. Coefficients of the composite risk index in Equations (2) and (3), with the basis for each. Values are those implemented in the model.

Term	Coefficient	Value	Basis
a1 Experience disclosure	w1	0.10	Qualification evidence under 4.3 and 6.9; bears on capacity but carries no automatic financial trigger
a2 Financial transparency	w2	0.16	Largest weight. Form 7 prices and BOQ rates govern valuation, price adjustment and claims [4] [5]
a3 Payment timeliness	w3	0.13	The 90-day payment period (14.7.1) and advance recovery (14.2.4) drive cash exposure directly
a4 Scope/change disclosure	w4	0.13	Engineer's 25 per cent variation authority (3.1.2) and unexpended provisional sums [8]
a5 Information-flow efficiency	w5	0.05	Procedural. Reporting obligations under 14.3 and the language clause 1.4
a6 Documentation clarity	w6	0.06	Procedural, weighted slightly above x5 for the documented internal inconsistency in the qualification thresholds
a7 Regulatory/env. compliance	w7	0.05	Procedural. Sanction risk under EMP Section 2500 is contingent rather than automatic
a8 Market volatility	w8	0.11	Table A weightings expose the majority of adjustable cost to KNBS index movement (13.8)
a9 Time-to-completion pressure	w9	0.10	Fixed six-month period (8.2) with no float allowance in the data sheet
a10 LD-exposure proxy	w10	0.11	Automatic accrual at 0.01 per cent of the contract price per day to a 10 per cent cap (8.7, 8.7.1)
a2 x a4 opacity and scope	lambda1(g)	0.30 − 0.12 g	Weakens across the period; rate and scope ambiguity bites while rates are being fixed
a1 x a2 experience and finance	lambda2(g)	0.22 − 0.10 g	Weakens across the period; undisclosed capacity matters most at tender and early mobilisation
a3 x a4 payment and scope	lambda3	0.16	Constant. Delayed certification and unstable scope compound at any stage of the works
a9 x a10 schedule and damages	lambda4(g)	0.12 + 0.20 g	Strengthens towards completion, since exposure accrues only as the 8.2 date nears
a8 x a2 market and finance	lambda5(g)	0.10 + 0.10 g	Strengthens across the period as more adjustable cost is certified under 13.8
Scaling constant on the linear term	-	1.15	Places z near the logistic inflexion across the observed range of adverse levels
Logistic gain and offset	-	4.2, 0.62	Keeps y in the interior of [0, 1]; the realised stream spans 0.372 to 0.753
Output disturbance	epsilon(t)	sd 0.02	Zero-mean Gaussian, clipped to [0, 1]; represents residual measurement noise in the index

weaken across the period. The interaction structure is therefore not symmetric decoration: it encodes a claim that the risk regime early in a maintenance contract is a pricing and scope regime, and late in the contract a schedule and penalty regime.

Two points deserve stating plainly. First, this index is a specified aggregation scheme in the sense that a design-code formula is specified. It encodes one defensible reading of the contract and the literature, and a different reading would yield different coefficients. Second, it is not an observed outcome. Nothing in Equations (2) and (3) was fitted to claims, extensions of time or cost growth, because no such record was available. Section 5.3 states what the resulting accuracy figures establish and Section 5.5 states what they do not.

4.3. Evolving Takagi-Sugeno-Kang Architecture

The predictor is a five-layer evolving Takagi-Sugeno-Kang fuzzy neural network (Figure 2). Layer 1 receives the ten indicators $x(t)$. Layer 2 fuzzifies them. Layer 3 holds an evolving base of rules, each rule i being an input-space prototype (centre) c_i whose firing strength for an incoming sample is a Gaussian receptive field

$$f_i(x) = \exp\left[-\|x - c_i\|^2 \big/ \left(2\sigma_r^2\right)\right], \sigma_r = 0.42 \tag{4}$$

Layer 4 normalises the firing strengths so that they form a partition of unity,

$$w_i = f_i \big/ \sum\nolimits_j f_j \tag{5}$$

and Layer 5 forms the output as the normalised, firing-weighted sum of first-order Takagi-Sugeno consequents. Each rule carries a linear consequent vector θ_i acting on the augmented input $\tilde{x} = \left[x \quad 1\right]$, giving the risk prediction

$$\hat{y}(t) = \text{clip}\left[\sum\nolimits_i w_i\left(\theta_i \cdot \tilde{x}\right), 0, 1\right] \tag{6}$$

The rule base is not fixed: its size and parameters evolve online as described next, which is what distinguishes the model from a static neuro-fuzzy system with a pre-set grid of rules.

4.4. Online Learning: Rule Creation, RLS Adaptation and Pruning

Learning follows a prequential (predict-then-learn) protocol with three online mechanisms. First, a new rule is created whenever an incoming sample is not adequately covered by the existing base, that is, when the maximum firing strength falls below a novelty threshold $r = 0.42$:

$$\text{if } \max\nolimits_i f_i(x) < r \Rightarrow \text{add rule with } c_{\text{new}} = x, \theta_{\text{new}} = 0, P_{\text{new}} = 10^3 I \tag{7}$$

Second, the consequents of all firing rules are updated by weighted recursive least squares (RLS) with a forgetting factor $\lambda = 0.985$ that lets the model track drift. For each rule the gain, prediction error and covariance update are

$$g_i = P_i \tilde{x}^{\mathrm{T}} w_i \big/ \left(\lambda + w_i \tilde{x} P_i \tilde{x}^{\mathrm{T}}\right), e = y - \theta_i \tilde{x}^{\mathrm{T}} \tag{8}$$

$$\theta_i \leftarrow \theta_i + \left(g_i e\right)^{\mathrm{T}}, P_i \leftarrow \left(P_i - g_i \tilde{x} P_i\right) \big/ \lambda \tag{9}$$

Third, every 26 samples the base is pruned by utility: the accumulated normalised firing of each rule is divided by its age, and rules whose mean utility falls below $u_{\min} = 0.010$ are removed, provided at least three rules remain. This keeps the structure compact and interpretable. Table 6 collects the hyperparameters governing these three mechanisms together with the values used throughout, and Algorithm 1 summarises the complete online procedure, which mirrors the MATLAB implementation used to produce the results.

Table 6. Hyperparameters of the evolving fuzzy neural network.

Parameter	Symbol	Value
Membership-function width	σ	0.22
Rule receptive-field width	σ_r	0.42
Novelty threshold (rule creation)	r	0.42
RLS forgetting factor	λ	0.985
Pruning interval	—	26 samples
Minimum rule utility	$u_{\min}$	0.010
Warm-up (seed) window	—	26 samples

Algorithm 1. Prequential online learning of the EFuNN.

```
input : stream {x(t), y(t)},    hyperparameters (r, sigma_r, lambda, u_min)
init    : empty rule base
for each time step t = 1..T
f    <- exp(-||x(t) - C||^2/(2*sigma_r^2))           % firing strengths
w    <- f/sum(f)                                                   % normalise
yhat(t) <- clip( sum_i w_i * (theta_i * [x 1]'), 0, 1 )      % PREDICT
record squared error (y(t) - yhat(t))^2
if isempty(f) or max(f) < r                                   % rule creation
add rule: C <- [C; x],    theta <- 0,    P <- 1e3*I
for each rule i (weighted RLS)                              % LEARN
g <- (w_i * P_i x')/(lambda + w_i * x P_i x')
theta_i <- theta_i + (g * (y - theta_i x'))'
P_i         <- (P_i - g x P_i)/lambda
every 26 steps: prune rules with utility/age < u_min (keep >= 3)
end
```

4.5. Prequential Evaluation and Metrics

Because the model learns online, it was evaluated prequentially: at each step the current model predicts the incoming sample before that sample is used to update it, so the reported error is genuine one-step-ahead generalisation. The first 26 samples (one contract cycle) seed the rule base and are excluded from scoring, leaving 182 scored observations. Continuous accuracy is measured by the root-mean-square error, the mean absolute error and the coefficient of determination.

These three statistics measure agreement between the EFuNN output and the reference index $y(t)$ defined by Equations (2) and (3). They quantify how closely the network recovers a specified aggregation from the indicator stream alone. They are not a measure of agreement with realised project outcomes such as claims lodged, extensions of time granted or cost growth incurred, and no claim of that kind is made from them anywhere in this paper.

$$\begin{aligned} &\text{RMSE} = \sqrt{(1/N)\sum(y-\hat{y})^2}, \\ &\text{MAE} = (1/N)\sum|y-\hat{y}|, \\ &R^2 = 1-\sum(y-\hat{y})^2 \Big/ \sum(y-\bar{y})^2 \end{aligned} \tag{10}$$

5. Results and Discussion

5.1. Characterization of the Risk Causes

Table 7 reports the descriptive statistics of the Kinoo lot indicator data together with the fuzzy membership share of each indicator across the three linguistic granules, obtained by evaluating Equation (1) on the scored values. Three indicators carry the bulk of the adverse mass: market volatility (x8, 19.7 per cent adverse), time-to-completion pressure (x9, 18.0 per cent) and liquidated-damages exposure (x10, 11.4 per cent). The pattern is that of a maintenance programme compressed into a six-month window, exposed to volatile input prices through the price-adjustment mechanism, and running under a penalty regime that accrues automatically. Market volatility and schedule pressure are close enough that their ordering should not be over-read; what separates them jointly from the rest is a gap of more than six percentage points to the next indicator. The contractor and consultant disclosure indicators occupy an intermediate range with adverse shares between 3.5 and 7.9 per cent, consistent with partial rather than complete disclosure, and regulatory compliance (x7, 1.6 per cent) is the least adverse of the ten. Figure 1 shows the categorisation directly: panel (a) places the observed data against the three membership functions, and panel (b) gives the per-indicator membership share, which makes the concentration of adverse mass in the market and schedule channels immediately legible.

Table 7. Descriptive statistics and fuzzy membership share of the Kinoo lot indicator data (n = 26 weekly observations).

Indicator	Mean	Std	Adverse	% ADV	% MOD	% FAV
x1 Experience disclosure	0.637	0.134	0.363	3.5	67.9	28.7
x2 Financial transparency	0.562	0.147	0.438	7.9	73.4	18.7
x3 Payment timeliness	0.643	0.160	0.357	5.3	62.3	32.4
x4 Scope/change disclosure	0.551	0.105	0.449	5.9	79.3	14.8
x5 Information-flow efficiency	0.599	0.109	0.401	4.3	74.4	21.3
x6 Documentation clarity	0.596	0.118	0.404	4.3	74.7	20.9
x7 Regulatory/env. compliance	0.665	0.091	0.335	1.6	67.4	31.1
x8 Market volatility	0.460	0.185	0.540	19.7	68.9	11.4
x9 Time-to-completion pressure	0.510	0.222	0.490	18.0	61.8	20.2
x10 LD-exposure proxy	0.544	0.193	0.456	11.4	68.0	20.6

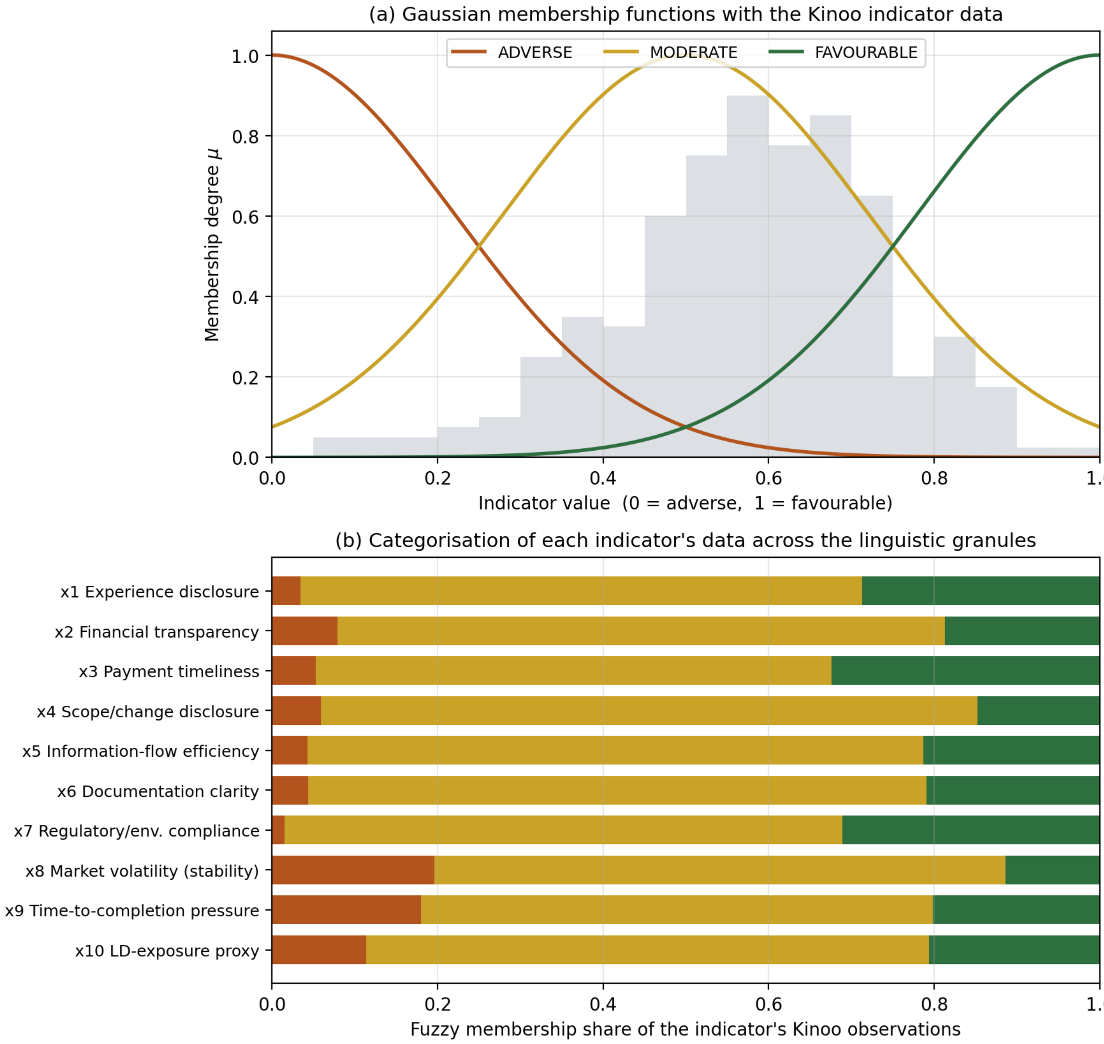

Figure 1. Categorisation of the Kinoo indicator data on the Gaussian membership functions: (a) the three membership functions with the observed data; (b) the fuzzy membership share of each indicator across the ADVERSE, MODERATE and FAVOURABLE granules.

5.2. Architecture and Rule-Base Evolution

Figure 2 shows the five-layer architecture and its online-adaptation loop. Trained prequentially, the EFuNN grew its rule base from one rule to seven over the 208-sample stream, and Figure 3 shows that the growth was incremental rather than front-loaded. Four rules were in place by sample 22, part-way through the first lot, and the remaining three arrived at samples 65, 156 and 183. The utility-based pruning mechanism never fired. At the end of the stream the mean normalised firing of the seven rules ranged from 0.114 to 0.307, every one of them an order of magnitude above the pruning threshold u_min of 0.010, so no rule ever became a candidate for removal and the rule count is monotone increasing throughout. The pruning mechanism is therefore part of the specified architecture but is untested by this stream, and the compactness of the final base is due to the novelty threshold governing rule creation rather than to any subsequent removal.

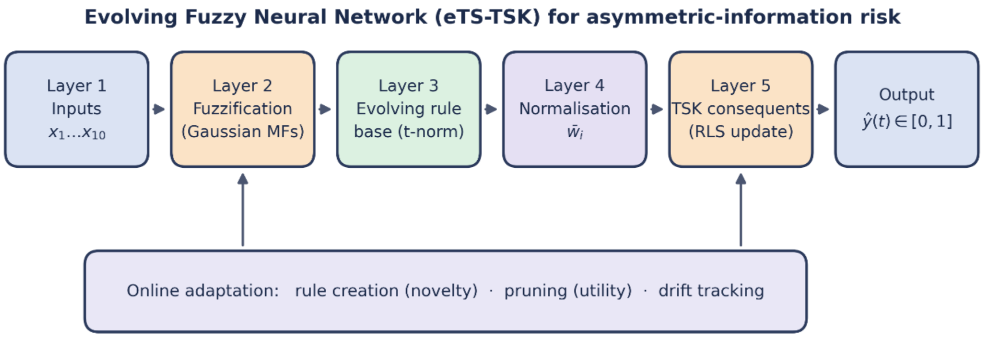

Figure 2. Five-layer evolving Takagi-Sugeno-Kang architecture with the online-adaptation loop (rule creation, pruning and drift tracking).

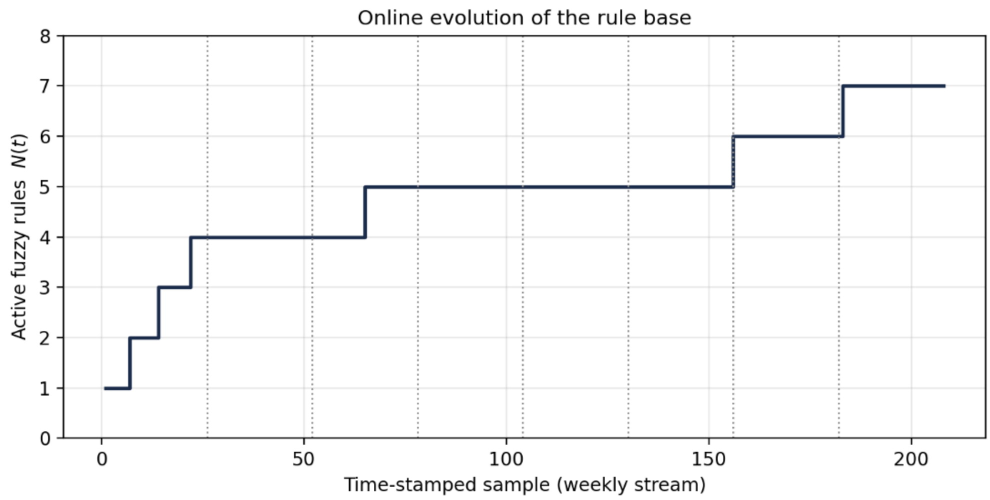

Figure 3. Online evolution of the active rule count, which grows monotonically from one rule to seven; dotted lines mark contract (lot) boundaries. No pruning event occurred at the utility threshold used.

Two things follow. The first is that seven rules over a ten-dimensional input space is a severe compression, which suggests the asymmetric-information space is organised around a small number of recurring risk archetypes rather than a long tail of special cases. The second is that the model had not finished learning when the stream ended. A rule created at sample 183 has only 26 samples of experience behind it, and the steady arrival of new rules late in the stream indicates the input space was still presenting configurations the existing base did not cover. This is what one expects from an evolving system meeting genuinely new lots, but it also means the final structure should be read as the state at the end of eight contracts, not as a converged rule base. Learning was otherwise stable, with no divergence of the RLS covariance and predictions bounded in [0, 1] throughout.

5.3. Predictive Performance

On the 182 scored observations the EFuNN reproduced the reference indexwith an RMSE of 0.031, an MAE of 0.024 and an R2 of 0.83, an average deviation of about 2.4 percentage points on the [0, 1] risk scale, against a reference signal spanning 0.372 to 0.753. Figure 4 shows the predicted trajectory following both the short-term fluctuations and the gradual upward drift towards the completion deadlines, which is the non-stationary behaviour a static model cannot follow.

What this establishes is bounded, and worth stating precisely. The network was never given the functional form of Equations (2) and (3). It did not know the weights, the interaction pairs, the time-varying coefficients or the logistic link. Working only from the ten indicators and a one-step-ahead error signal, it assembled a seven-rule structure that tracks an aggregation whose form changes as g moves from 0 to 1. That is a result about online structural identification, and it is the property that matters if the same architecture is later driven by observed rather than reconstructed indicators.

What it does not establish is predictive accuracy against project reality. The reference index is a construction of this paper, so a sufficiently flexible online learner would be expected to recover it to some degree, and the exercise would carry little information were the recovery not achieved under a strict prequential protocol with a rule base small enough to remain readable. The accuracy figures should therefore be read as verification that the learning machinery behaves as specified, not as validation of the risk model against claims, delays or cost growth. Section 5.5 sets out what a validation study would require.

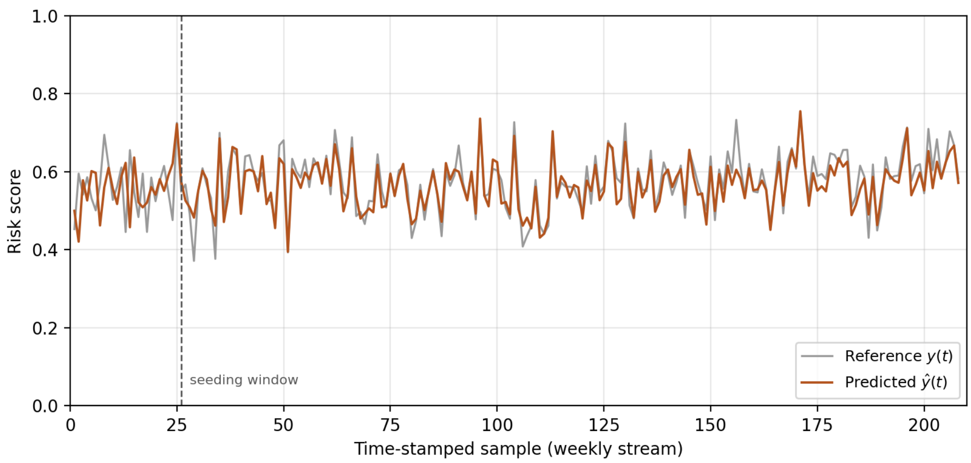

Figure 4. Reference composite risk index y(t) from Equations (2) and (3) versus the EFuNN one-step-ahead prediction over the 208-sample reconstructed weekly stream. The dashed line marks the end of the 26-sample seeding window, before which predictions are not scored.

5.4. Discussion

Two findings carry practical weight, and both depend on the chain running from the source documents through the scoring rules to the model output.

The first is auditability. Because every indicator is anchored to a clause, bill or schedule in Table 2 and scored by an explicit rule in Table 3, a high adverse share can be traced back to a specific contractual provision rather than to a general category of risk. The adverse mass in x8, at 19.7 per cent the largest of the ten, follows from the price-adjustment weightings, which expose the fuel, equipment, cement, steel and bitumen cost heads to KNBS index movement on a one-month cycle under Sub-Clause 13.8; between them those heads carry the majority of the adjustable cost. The adverse mass in x9, at 18.0 per cent, follows from the six-month period in Sub-Clause 8.2 read together with the commencement and programme periods in 8.1 and 8.3, which between them consume the first four weeks before physical work is measured. The adverse mass in x10, at 11.4 per cent, follows from Sub-Clause 8.7, where exposure accrues automatically at 0.01 per cent of the contract price per day to a 10 per cent cap, so the indicator declines as an arithmetic consequence of elapsed time rather than of any behavioural judgement. A project team can act on each of these without accepting the model.

The three indicators that dominate the categorisation in Section 5.1 are also the ones the specification loads most heavily late in the stream, since the schedule and damages interaction gains weight as g grows, which is exactly the span over which x9 and x10 decline. This consistency should be read for what it is. The categorisation and the model behaviour are two readings of the same contractual structure passed through the same scoring rules, so their agreement confirms that the pipeline is coherent. It is not independent corroboration, and treating it as such would repeat the error the accuracy figures already invite.

The second finding is that compactness buys interpretability. Seven rules over a ten-dimensional input space is a severe compression, yet the model tracks the reference signal closely across the whole stream, which suggests the space is organised around a small number of recurring risk archetypes rather than a long tail of special cases. For a project team this is the difference between a prediction and a reason: a rising risk score can be attributed to identifiable drivers and acted on before it materialises, whether by requiring fuller financial disclosure under the Form 7 schedule, tightening change-order procedure against the 25 per cent variation authority, or reappraising schedule exposure ahead of the delay-damages threshold. A model that predicted equally well through a hundred opaque rules would support none of those moves.

5.5. Limitations and the Validation That Remains

Three limitations bound what has been shown, and they compound rather than sit independently.

The indicator stream is reconstructed. **Table 4** separates the documentary material from the assumed material, and the assumed part, meaning the magnitude and curvature of each lifecycle trajectory together with the week-to-week variation, does real work in generating the observations the model consumes. A different but equally defensible reading of the same clauses would produce a different stream, and the paper offers no evidence about how far the results would move under such a reading.

The reference index is specified rather than measured. The weights and interaction terms in **Table 5** rest on contract materiality and prior literature, not on calibration against outcomes, and the accuracy statistics in Section 5.3 measure recovery of that specification. This is the circularity a reader should keep in view: the model is asked to rediscover a rule the authors wrote down, and it succeeds at that. Nothing in the results speaks to whether the specification itself predicts what happens on site.

Realised outcomes were not available. KURA released the pre-award documentary record but not the payment certificates, progress reports, correspondence or claims register for the case lot, so this study contains no outcome variable against which the index could be tested even in principle.

Closing the gap requires three things. The first is an outcome series, meaning dated records of claims lodged, extensions of time granted and variation orders issued, against which the index can be scored as a predictor rather than as a target. The second is comparison against static baselines, since the value of the evolving formulation over a fixed-grid ANFIS or a linear model on the same stream has not been quantified here and cannot be inferred from a single set of accuracy figures. The third is a sensitivity analysis over the coefficients in **Table 5**, to establish how far the characterisation in Section 5.1 depends on the particular weights chosen and whether the ordering of the three most adverse causes survives plausible alternatives. The companion evaluation study addresses the first of these on a portfolio of completed KURA maintenance contracts.

6. Conclusions

This paper characterised the asymmetric-information risk causes of a Kenyan urban road maintenance project from its contractual documentation and developed an interpretable evolving fuzzy neural network to track them. Ten clause-anchored indicators were defined, each given an explicit scoring rule tied to a named provision and each fuzzified into three Gaussian granules. The fuzzy categorisation identified market volatility, time pressure and liquidated-damages exposure as the most adverse causes, and each of the three traces to a specific clause: the price-adjustment weightings under Sub-Clause 13.8, the six-month period in Sub-Clause 8.2, and the delay-damages regime in Sub-Clause 8.7.

Because the weekly records needed to drive the model were not released, the indicator stream was reconstructed from those clause-derived scores using contract-informed lifecycle shapes and bounded random variation, and **Table 4** states which elements are documentary and which assumed. A five-layer evolving Takagi-Sugeno-Kang network with novelty-based rule creation, utility pruning and recursive-least-squares adaptation grew a seven-rule base and recovered the specified composite index with an RMSE of 0.031, an MAE of 0.024 and an R2 of 0.83 under a strict prequential protocol. Since that index is defined by the authors in Equations (2) and (3), these figures verify that the learning machinery identifies a non-stationary aggregation online without being told its form. They are not a validation against realised claims, delays or cost growth, and none is claimed.

What the study contributes, then, is a documented and auditable route from contract clauses to a continuous, time-varying risk signal, together with evidence that an evolving neuro-fuzzy predictor can follow such a signal while staying small enough for a project team to read. Future work will drive the same architecture with observed indicator series from completed contracts, test the index against realised claim and delay outcomes, and sweep the aggregation weights to establish how far the characterisation depends on them.

Author Contribution

Joseph Maina Kaberenge conceived the study, assembled the contract documentation, defined and scored the ten risk indicators, implemented the evolving fuzzy neural network in MATLAB, carried out the analysis and wrote the original draft. Cyrus Babu supervised the research design, advised on the construction-management framing of the asymmetric-information indicators and their contractual anchors, and reviewed and edited the manuscript. Isaac Fundi supervised the modelling and evaluation, advised on the fuzzification scheme and the online learning protocol, and reviewed and edited the manuscript. All authors read and approved the final version.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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