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Design and configuration of a computerized maintenance management system for improving the availability performance of the national ICT broadband backbone: A case of the DAR ES SALAAM–KIMANZICHANA ROUTE, TANZANIA

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ABSTRACT

The Dar es Salaam–Kimanzichana route of Tanzania's National ICT Broadband Backbone (NICTBB) has repeatedly fallen short of the 99.999% availability target, with monthly values as low as 73.29% (December 2023) and 86.454% (March 2026). This study identifies the factors behind the shortfalls, examines how logged outage causes relate to monthly availability, and configures a Computerised Maintenance Management System (CMMS) for the route.

A mixed-methods design combined a questionnaire given to all 50-route staff (43 returned, 86.0%), 41 months of Tanzania Telecommunications Corporation Limited (TTCL) records and optical time domain reflectometer (OTDR) tests on 40 of 48 fibre cores. Staff perceptions were ranked with the Relative Importance Index (RII), and fibre cuts ranked highest among the technical factors (RII = 0.916). In a regression on 33 months, logged fibre-cut and power-outage hours explained 96.1% of the variation in availability, at about 0.25 points per hour. A model with these two terms predicted eight unseen months with a mean absolute error of 0.24 points. Because both predictors are downtime hours, this result reflects how availability is recorded as much as it explains it. The power-outage estimate rests for one month, and the configuration-resolution effect, which rests for two months, did not hold up and is not used. A CMMS was configured on the Fiix platform with work-order, scheduling, asset, inventory, notification and reporting functions. Network Management System integration and OTDR fault location are planned, and the system has not yet been tested in live use. We recommend completing the integration, backing up power at the nodes, protecting the route and recording outage causes in more detail.

Key words: National ICT Broadband Backbone, Computerised Maintenance Management System, Availability Performance, Fibre Cuts, Multiple Linear Regression, TTCL.

1. INTRODUCTION

The Dar es Salaam–Kimanzichana route is one of the busiest parts of Tanzania's National ICT Broadband Backbone (NICTBB). It links the commercial capital, home to roughly 5.4 million people [1], with long-haul transmission towards Pwani, Lindi, Mtwara and Ruvuma. Government systems, banks, mobile operators and households depend on it. The NICTBB is a strategic national asset for e-government, digital trade and mobile backhaul [2]. It is run by the Tanzania Telecommunications Corporation Limited (TTCL) under the oversight of the Tanzania Communications Regulatory Authority (TCRA), which expects licensed providers to deliver reliable service [3].

Backbone availability targets are usually set between 99.9% and 99.999%. ITU-T G.827 defines availability parameters for digital paths [4], ITU-T G.911 gives calculation methods for fibre optic systems [5], and operators still differ in how they define and count an outage [6]. Five nines allow about 26 seconds of downtime a month, which is a hard target for a single fibre route. We use it because it is TTCL's stated benchmark, not because we expect it to be easy to reach. The link for Dar-es Salaam Kimanzichana route is protected by using a ring. Fibre cuts and slow fault response are among the main causes of unplanned outage [7]. Many operators therefore use a Computerised Maintenance Management System (CMMS), which brings asset registers, work orders, preventive schedules and indicators such as Mean Time to Repair (MTTR) into one platform [8]. In Africa, many operators still rely on fragmented records and manual coordination, which prolongs outages [9].

TTCL's records show the scale of the problem. The route has had breakdowns every year since 2014, rising from one in 2014 to 13 in 2021, 18 in 2022 and 19 in 2023, then easing to eight in 2024 and ten in 2025. Here a breakdown means a service-affecting fault event in the Network Operations Centre (NOC) log. Average monthly availability was 88.6% in 2023, 96.8% in 2024, 97.1% in 2025, and 93.1% for January to May 2026. Eight of the 41 months reached 99.999%, and eight fell below 90%, the lowest being 73.29% (December 2023) and 86.454% (March 2026). Logged fibre-cut downtime was 464 h in 2023, 154 h in 2024 and 128 h in 2025. If every breakdown was a fibre cut, that is about 24, 19, and 13 hours per breakdown, so the yearly breakdown counts and the monthly downtime hours are consistent. In our survey, only 11.6% of maintenance records were in a formal digital system and only 14.0% of faults were reported through system tools. No purpose-built CMMS exists for a national backbone route in Tanzania, and little published work links measured availability factors to a model that a CMMS could use.

1.1 Research Objectives

The main objective is to design and configure a CMMS that supports better availability on the Dar es Salaam–Kimanzichana route. The specific objectives are (i) to identify the factors that affect availability on the route; (ii) to develop a regression model that describes and predicts monthly availability from logged outage causes, and to test it against simpler baselines; and (iii) to configure a CMMS whose functions trace back to the findings, stating clearly what is implemented and what is planned.

2. LITERATURE REVIEW

2.1 Maintenance and Availability

Corrective maintenance follows failure, preventive maintenance follows a schedule, and predictive maintenance acts on monitored condition. Relying mostly on corrective work is easy to start with but usually brings unplanned downtime and higher long-term cost, and the literature recommends a move towards proactive approaches [10], [11]. Availability is the probability that a system is operating at a

given moment under stated conditions [12]. In steady state it is given by Equation (1):

$$A = \frac{MTBF}{MTBF + MTTR} \tag{1}$$

where A is steady-state availability, MTBF is the mean time between failures and MTTR is the mean time to repair. Operators do not report the steady state value, however. A monthly figure is worked out from logged outage time, as in Equation (2):

$$A_m = 100\ \frac{(T - D)}{T} \tag{2}$$

Where A_m is monthly availability (%), T is the number of hours in the month, and D is the downtime logged in it. If a month has n failures, then $D = n \times$ MTTR and $T - D = n \times$ MTBF, so Equation (2) is Equation (1) applied to one month. Reliability theory matters through n, how often the fibre fails. Maintainability matters through MTTR, how fast it is restored. Systems theory matters through the CMMS, which has to join people, procedures and data.

2.2 Factors Affecting Availability

Studies of fibre backbones point first to fibre cuts [13], and an analysis of an operational IP backbone found that cuts, maintenance activity and equipment faults account for most failures [14]. Power supply is the next common cause where the grid is unreliable [15], and a documentary study of laboratories in Kinshasa linked chronic power instability to equipment damage and data loss [16]. On the NICTBB itself, Chingumbe and Mahabi [17] linked long restoration times to fault location and accessibility, the readiness of restoration teams and weak preventive maintenance. Environmental effects are less clear: flooding damaged aerial cables in Rio Grande do Sul, while the underground network held up well [18]. Latency, congestion, interoperability and cyber-security incidents are often listed as threats, but they usually degrade service quality rather than switch a link off, so none of them can be assumed to matter on this route.

2.3 Models and Forecast Accuracy

Multiple linear regression (MLR) models a continuous outcome, here monthly availability, as a linear function of several predictors [19]. Influence on the fit is checked with Cook's distance [20]. Machine learning has been used to predict network failures [21], and a neural network model has been compared with finite element methods for predicting the mechanical properties of bio-composites [22]. We chose regression because a maintenance engineer can read its coefficients. A MAPE below 10% is often called highly accurate forecasting [23], but that says little here: availability only moves between about 73% and 100%, and a model that always predicts the training means would score a MAPE of about 4% on our holdout months. We therefore compare errors with naive baselines [24] and with the identity in Equation (2).

2.4 Computerized Maintenance Management Systems

A CMMS automates work orders, keeps an asset register and maintenance history, and produces performance reports [25]. A properly installed system has been reported to cut direct maintenance costs by 5% to 10% within three years [8]. Most products were built for plants, utilities and transport rather than optical networks [9], and work on the NICTBB confirms reliance on manual records and informal communication [17]. Fibre monitoring is a separate field. OTDR-based fault measurement is well established [26], remote fibre test systems (RFTS) apply it continuously and are sold as products, ITU-T L.25 covers optical cable maintenance [27], and a related MEng study developed a maintenance management system for mobile network availability [28]. We found little that joins these strands for a national fibre route. Redundancy, the duplication of an element essential to normal operation so that its failure does not stop a vital function, is a standard way to remove single points of failure in networks [29], and GIS-based automated mapping and facilities management (AM/FM) ties asset records to maps and work orders for utility networks, including telecommunications [30].

2.5 Research Gap and Conceptual Framework

Four gaps stand out. Many routes still keep fibre assets on paper, in spreadsheets or on old AutoCAD maps. Most CMMS products are not tailored to optical backbones, and none exists for this route. Teams follow different procedures, so reporting is inconsistent. And work orders are raised by phone, messaging apps and handwritten job cards, with no automatic trigger from alarms or OTDR readings. The conceptual framework (Figure 1) follows an input–process–output logic. The inputs are the candidate factors, including fibre cuts. The process has three parts: ranking of staff perceptions with the Relative Importance Index (RII), regression on telemetry with holdout validation, and CMMS design. The output is availability performance, supported by the model and the CMMS.

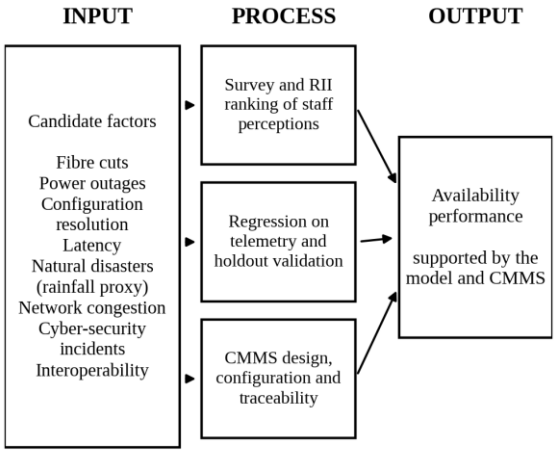


Figure 1: Conceptual framework of the study

3. MATERIALS AND METHODS

3.1 Design and Study Area

The study used a mixed-methods design: questionnaire ratings, telemetry and regression, together with staff input on current practice. The CMMS was configured following the waterfall model [31]. The work covers the Dar es Salaam–Kimanzichana route, about 81 km through Dar es Salaam and Pwani regions. The cable has 48 cores in four loose tubes of 12, and eight cores carry traffic.The exact length when the cable is buried plus slacks for coil is 85,05km, but when it is aerial installed in consist of 83.0km The Kimanzichana equipment is recorded as having a throughput of two terabytes, which we read as 2 Tbit/s. The transmission system type is DWDM equipment operating at 1650nm wavelenghts. The questionnaire, raw data and OTDR traces are in the dissertation behind this paper [32].

3.2 Population and Sampling

The target population was the 50 people who worked directly on the route: seven fleet supervisors, 13 NOC engineers, 12 field engineers, eight field technicians and ten casual labourers. With a population this small a census is the natural design, and all 50 were given the questionnaire. Yamane's formula [33] gives a minimum of 44 for $N = 50$ and a 5% margin of error, so inviting everyone exceeded it. Forty-three questionnaires came back, a response rate of 43/50 = 86.0% (Table 1). The technical data cover 41 months of NMS and NOC records, January 2023 to May 2026. The first 33 months (to September 2025) were used to build the models and the last eight (October 2025 to May 2026) were kept for validation.

Table 1: Respondents and response rate by stakeholder group

Stakeholder group	Invited	Returned	Response (%)
Fleet supervisors	7	6	85.7
NOC engineers	13	11	84.6
Field engineers	12	10	83.3
Field technicians	8	7	87.5
Casual labourers	10	9	90.0
Total	50	43	86.0

Group totals are taken as the number invited, which matches the 50 questionnaires distributed.

3.3 Data Collection and Factor Ranking

The questionnaire had 52 questions: seven on demographics and current practice, 43 five-point Likert items (5 = strongly agree, 1 = strongly disagree) in seven themes, and two open-ended questions. Secondary data came from TTCL maintenance logs, NMS history and outage reports. Monthly availability is the figure reported by the TTCL NOC. TTCL computes its availability on NICTBB link by taking the average of service availability and network availability. Fibre-cut hours (FC) and power-outage hours (PO) are the logged durations of service-affecting events with that cause; the files do not say whether overlapping events or several systems were added together. Configuration-resolution hours (CR) are logged hours of configuration work. Latency came from TCRA quarterly reports and rainfall from the Tanzania Meteorological Authority. The cable was tested at the optical distribution frame in Dar es Salaam with a Yokogawa AQ7280 OTDR at 1550 nm. Forty of the 48 cores were tested, and one trace from each tube is reported here. Staff ratings were ranked with the Relative Importance Index [34], given by Equation (3):

$$RII = \frac{\Sigma W}{(A \times N)} \qquad (3)$$

Where W is the weight given by a respondent (1 to 5), A is the highest weight (5) and N is the number of respondents (43). An RII of 0.80 or more was classed as high and 0.60 to 0.79

as moderate-high [35]; items of 0.60 or more were treated as significant. Positively worded items (for example, systems integrate effectively) were also scored in reverse, because agreement with them means the factor is not a problem.

3.4 Model Development and Validation

The starting model was an MLR with monthly availability as the outcome, as in Equation (4):

$$A = \beta_0 + \beta_1 FC + \beta_2 PO + \beta_3 AvrgL + \beta_4 R + \beta_5 CR + \varepsilon \quad (4)$$

where A is monthly availability (%), FC, PO and CR are in hours, L is average latency (ms), R is rainfall (mm), β_0 is the intercept and ε is the error term. Eight candidate predictors were entered first. Cyber-security downtime, interoperability downtime and network congestion were zero in all 33 months and were dropped, leaving the five in Equation (4). Fitting was done in Jamovi 2.6.44.0 and checked with R^2, adjusted R^2, RMSE, the F-test, the Durbin–Watson test and variance inflation factors (VIF). We then checked Cook's distance [20]; refitted without the influential months and without CR; and compared the models with three baselines: the identity in Equation (2) with T = 730 h, the training mean, and the previous month's value. Holdout predictions were scored with the mean absolute error (MAE) [36], root mean squared error (RMSE) and mean absolute percentage error (MAPE) [37], given by Equations (5), (6) and (7):

$$MAE = \left(\frac{1}{n}\right)\sum |A_i - P_i| \quad (5)$$

$$RMSE = \sqrt{\left[\frac{\sum (A_i - P_i)^2}{n}\right]} \quad (6)$$

$$MAPE = \frac{1OO}{n}\sum \left|\frac{|(A_i - P_i)}{A_i}\right| \quad (7)$$

Where A_i is the actual value, P_i the predicted value and n the number of holdout months. Availability is capped at 99.999%, so a linear prediction above the cap is set to 99.999%.

3.5 CMMS Configuration

The CMMS followed the waterfall stages of requirements analysis, design, implementation, testing, and deployment with feedback. Requirements came from the survey, the telemetry findings and the gaps in current practice. The system was configured on Fiix, a commercial cloud platform, so the work is configuration and customisation, not new software development. Section 4.5 says which functions are in place, and which are planned.

4. RESULTS AND DISCUSSION

4.1 Factors Affecting Availability: Staff Perceptions

The 43 respondents were NOC engineers (25.6%), field engineers (23.3%), casual labourers (20.9%), technicians (16.3%) and fleet supervisors (14.0%). About 42% had more than ten years of experience. Only 11.6% of records were in a digital system, against 32.6% on paper, 32.6% in Excel and 23.3% with no consistent method. Of the 43 items, 32 had an RII of 0.60 or more. Table 2 lists the items that match the factors tested later against the telemetry, with a note on how each can be checked in the records. Fibre cuts ranked first among them (RII = 0.916; 38 of 43 agreed or strongly agreed, none disagreed), followed by natural disasters and delayed fault reporting (0.842). Latency, congestion, configuration resolution and power outages fell between 0.809 and 0.819.

Table 2: RII of the main technical and operational factors (N = 43)

Questionnaire item	Rank	RII	Check against records
Fibre cuts affect availability	3	0.916	FC logged, mean 20.7 h/month
Natural disasters cause failures	17	0.842	Rainfall unverified
Delayed fault reporting adds downtime	16	0.842	Not measured
Latency affects availability	19	0.819	Not a route-level measure
Network congestion affects availability	20	0.809	Zero downtime logged

Questionnaire item	Rank	RII	Check against records
Configuration resolutions affect availability	21	0.809	Non-zero in 2 months
Power outages affect availability	22	0.809	Non-zero in 3 months
Systems integrate effectively (interoperability)	23	0.805 (0.395 reversed)	Zero downtime logged
Equipment failures add downtime	27	0.781	Not measured
Cyber-security incidents affect availability	28	0.781	Zero downtime logged

Rank is among all 43 items. The full table is in the supplementary file.

The interoperability item is worded positively. Agreement means staff see no interoperability problem, and once it is reverse-scored its RII is 0.395, below the cut-off, so we no longer list interoperability as a perceived factor. Most other factor items read “X affects availability”, a wording that invites agreement [38]. That may be part of why congestion (0.809) and cyber-security (0.781) scored high when no downtime from either was logged in 33 months. These results are perceptions, and we keep them apart from the telemetry findings: the records decide what goes into the model, and the survey informs the CMMS requirements.

By theme, CMMS adoption scored highest (mean RII 0.908, all eight items above 0.87) and infrastructure protection and maintenance practice lowest (0.606). Staff agreed that preventive maintenance reduces recurring failures (0.888) but not that MTTR is kept within acceptable limits (0.465) or that fault response is satisfactory (0.493). They know what good practice looks like and do not believe it is happening yet. Cronbach's alpha was 0.912 over all 43 items, which shows the instrument holds together as a whole but not that each of the seven themes is a single scale [39]. Casual labourers were 20.9% of respondents, and we did not compute RII by group.

4.2 OTDR Measurements

Table 3 gives the four traces reported here. On core 1, fibre loss at 0.15 to 0.19 dB/km over 53.19 km should be about 8 to 10 dB, yet the total was 16.049 dB. The extra 6 to 8 dB must come from events along the trace, and only one, a 1.502 dB loss at 43.20 km, is itemised here. It was measured in one direction, and a one-way splice loss can be a gainer/loser artefact, so it should be averaged over both directions before it is called high [40]. The core 1 trace ends at 53.19 km, short of the 81 km route. We cannot yet say whether this is a break or a limit of the pulse setting, and a retest would settle it.

Table 3: OTDR results at 1550 nm for the four reported cores

Core (tube)	End (km)	Loss (dB)	Remark
1 (1)	53.19	16.049	0.15–0.19 dB/km; 1.502 dB event at 43.20 km, one direction
13 (2)	8.44	–	Break or open connector at 8.44 km
31 (3)	5.91	0.698	0.149 dB/km; end reflectance 43.2 dB
42 (4)	32.23	–	Clean end at 32.23 km; reflectance 56.9 dB

Cores 13, 31 and 42 end between 6 and 32 km from Dar es Salaam. These cores are among the `40 spare cores of the cable installed. A break in a dark core does not affect availability, so these findings show cable condition and a risk to spare capacity. They do not support the availability model. A summary of four cores out of all 40 cores is in the supplementary file.

4.3 Availability Data and the Regression Model

Figure 2 shows all 41 months. Over the 33 model-building months availability averaged 94.1% (median 96.4%, SD 6.44) and fibre-cut downtime averaged 20.7 h a month, reaching 78.6 h. Three variables need a closer look before any coefficient is read. Power outages were logged in only three months and total 88.0 h, of which 83.5 h (95%) fall in December 2023. Configuration resolution totals 15.4 h and comes from two months, April 2023 and April 2024, each with exactly 7.7 h. Two identical entries look like a standard value, not a measurement, and should be checked against the NOC log.

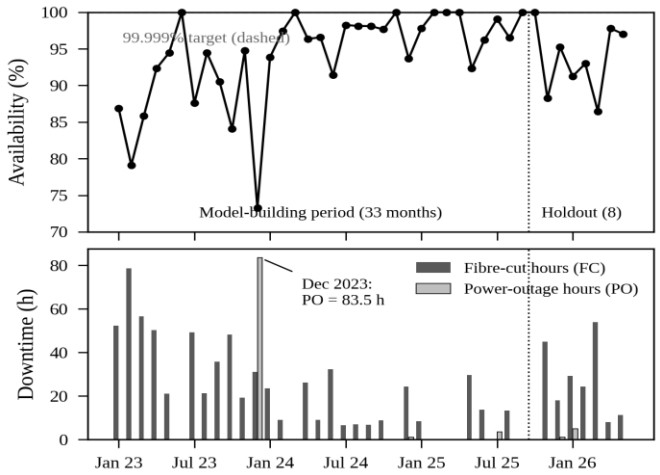


Figure 2: Monthly availability, fibre-cut hours and power-outage hours, January 2023 to May 2026

Rainfall and latency do not look valid for this route. The monthly rainfall values add up to 6,360 mm for 2023 and 7,230 mm for 2024, five to six times the roughly 1,000 to 1,200 mm a year expected for Dar es Salaam, and 55% of the values are multiples of 50 mm. They may be cumulative, multi-station or mis-scaled. Latency takes only six distinct values in 33 months, each repeated for several months, because it comes from TCRA quarterly reports. These describe what users experience, not an 81 km fibre segment, where propagation delay is about 0.4 ms. We keep both variables in the starting model for transparency, leave them out of the preferred model, and do not read their non-significance as evidence about their effect on this route.

The five-predictor model fitted well: $R^2 = 0.989$, adjusted $R^2 = 0.986$, RMSE = 0.677 and $F(5, 27) = 467$ ($p < 0.001$), with a Durbin–Watson statistic of 1.69 ($p = 0.166$) and VIF of 1.07 to 1.43. Table 4 gives the coefficients and Equation (8) the fitted model with rounded values:

Table 4: Coefficients of the five-predictor model (N = 33)

Predictor	Estimate	SE	p	Std. β	Partial η^2
Intercept	99.79	0.288	< 0.001	–	–
FC (h)	−0.2654	0.0073	< 0.001	−0.843	0.980
PO (h)	−0.2198	0.0094	< 0.001	−0.496	0.953
Latency (ms)	0.00103	0.00116	0.381	0.022	0.029
Rainfall (mm)	2.63×10^{-5}	3.71×10^{-4}	0.944	0.002	0.000
CR (h)	0.6044	0.0769	< 0.001	0.175	0.696

$$A = 99.79 - 0.265FC - 0.220PO + 0.001L + 0.00003R + 0.604CR \quad (8)$$

This result is close to an accounting relationship, and R^2 should be read that way. FC and PO are downtime hours, and Equation (2) already makes availability a function of downtime. In all eight months with no logged downtime, availability was 99.999%, and the intercept sits at that ceiling. The slope is less obvious. In a 730-hour month one hour of outage should cost 0.137 points, but the fitted slope is about 0.25, roughly 1.8 times larger, as if the effective month were about 400 hours long. One explanation is that the availability figure adds up several affected systems or directions while an outage hour is logged once. The coefficients are best read as empirical conversion factors between logged hours and reported availability.

4.4 Influence, Sensitivity and Validation

Cook's distance, computed in Jamovi, had a mean of 0.110, a median of 0.00135 and a standard deviation of 0.285, and ranged from 2.36×10^{-6} to 0.997. The median is far below the usual guide of $4/n = 0.121$, so most months have almost no influence on the fit, and the mean is raised by a few months. The largest values belong to December 2023, which carries most of the power-outage hours (0.780), and to the two April months, the only ones with configuration-resolution hours (0.997 each). October 2023 is a different kind of outlier: it is 3.8 points below what FC and PO predict, which points to downtime that was not logged under either cause. Table 5

shows what happens to the coefficients when these months or terms are removed.

Table 5: Coefficient sensitivity to influential months and to CR

Fit	n	FC	PO	CR
Five-predictor model	33	−0.265	−0.220	0.604
Without CR	33	−0.248	−0.229	–
Without December 2023	32	−0.265	−0.200 (p = 0.38)	0.604
FC + PO	33	−0.251	−0.226	–
FC + PO, without December 2023	32	−0.251	−0.242 (p = 0.53)	–
FC + PO, without the two April months	31	−0.265	−0.220	–
FC + PO, without all three months	30	−0.265	−0.216 (p = 0.29)	–

Estimates are in percentage points per hour. Unless a p value is shown, $p < 0.001$.

The FC coefficient is stable, between −0.25 and −0.27 in every fit. The PO estimate is also stable in size (−0.20 to −0.24) but is significant only because of December 2023; without that month p is 0.38 to 0.53, and in the FC + PO fit the month is reproduced almost exactly (predicted 73.29, actual 73.29), so that single month largely determines the PO estimate. The second month supports the size of the effect: July 2025 had 3.47 h of power outage, no fibre cut, and availability of 99.07%, a loss of 0.27 points per hour. The power-outage effect is therefore plausible but poorly estimated.

The CR term is different. Its estimate comes from two months, and the term in effect gives each of them its own parameter. Both sit above what FC alone would predict, by 5.0 points (April 2023) and 3.0 points (April 2024). The most likely reason is double counting, with part of the 7.7 h of configuration work also logged as fibre-cut time, or planned April work that was not counted as an outage. CR was zero in all eight holdout months, so it was never tested on new data. We do not use it for any recommendation. The preferred model has FC and PO only, given by Equation (9):

$$A = 99.93 - 0.251FC - 0.226PO \qquad (9)$$

Where the symbols are as in Equation (8). For this model R^2 = 0.961, adjusted R^2 = 0.958, RMSE = 1.25, the 95% confidence intervals exclude zero (FC −0.274 to −0.227; PO −0.258 to −0.193) and the Durbin–Watson statistic is 2.00.

Table 6 compares the models on the eight holdout months. The FC + PO model had an MAE of 0.241 points, an RMSE of 0.345 and a MAPE of 0.262%. The five-predictor model scored 0.321, 0.410 and 0.353%, so adding latency, rainfall and CR made out-of-sample accuracy worse. The identity baseline from Equation (2) had an MAE of 3.02 points, because its slope is about half the observed one, and the training mean and the previous month did worse still (Figure 3).

Table 6: Holdout accuracy of the models and baselines (8 months)

Model	R^2 (train)	MAE	RMSE	MAPE (%)
Identity, Equation (2), 730 h	–	3.02	3.66	3.34
Training mean	–	3.89	4.48	4.22
Previous month	–	5.39	6.88	5.86
FC only	0.704	0.496	0.565	0.540
FC + PO (preferred)	0.961	0.241	0.345	0.262
FC + PO + CR	0.988	0.256	0.350	0.281
Five predictors	0.989	0.321	0.410	0.353

MAE and RMSE are in percentage points.

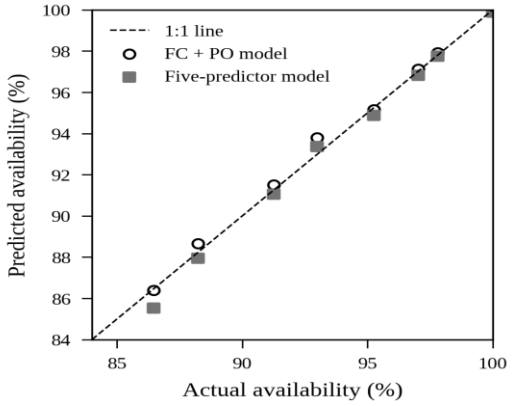


Figure 3: Actual versus predicted availability for the eight holdout months, with the 1:1 line

The residuals of the FC + PO model are mixed in sign (three positive, five negatives, mean −0.19). The five-predictor model under-predicted in seven of eight months (mean +0.22), so its extra terms shift the level, possibly alongside a change in logging practice after September 2025. Two cautions apply. The holdout was an easier test than the training period: it has no extreme power-outage month, CR is zero throughout, and FC reaches only 54 h against 78.6 h in training. That is why the five-predictor holdout RMSE (0.41) is below its in-sample value (0.677). And eight points is a small test.

4.5 CMMS Configuration

The CMMS was configured on Fiix with secure login, user management, role-based dashboards, a mobile app for field crews, work orders, preventive schedules, an asset register, spare-parts inventory, SMS and e-mail notification, and reporting of downtime trends, fault frequency and MTTR. Table 7 traces each finding to a function and states its status, and Figure 4 shows the architecture, with planned links dashed.

Table 7: Findings, CMMS functions and implementation status

Finding	CMMS function	Status
Fibre cuts, largest logged loss (about 0.25 points per hour)	Work orders, crew alerts by SMS and e-mail, MTTR tracking	Configured
Alarm-triggered work orders	NMS alarms into the Fiix integration hub through SNMP	Planned
Fault location on the route	OTDR distance matched to the asset register, corrected for slack	Planned
Power outages	Preventive schedules for generators and UPS	Configured
Configuration work not logged apart from outage time	Separate work-order category for configuration tasks	Configured
Scattered records, manual reporting	Asset register, reporting module	Configured
Waiting for spares	Spare-parts inventory	Configured
Model output	Predicted availability on the dashboard	Planned

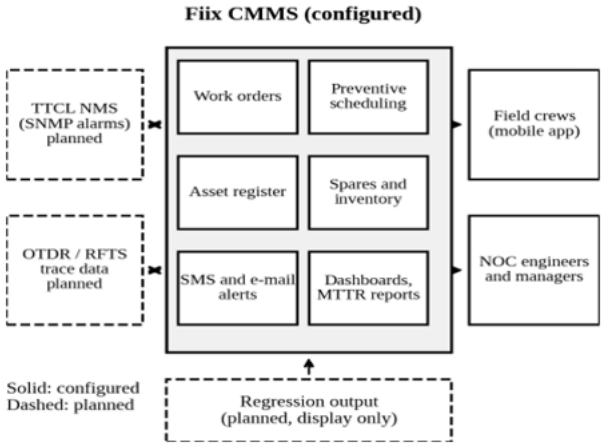


Figure 4: CMMS architecture. Solid boxes are configured, dashed boxes are planned

The intended response to a fibre cut has four steps: a loss-of-signal alarm raises a work order, the OTDR distance is matched to the asset register to estimate the fault position, crews are alerted with the kilometre marker, and a ticket tracks MTTR until the fibre is spliced. Only the work order, the alerts and the MTTR ticket exist now. OTDR distance is optical length, so it has to be corrected for cable slack and helix factor before it becomes a route kilometre or GPS point, and RFTS products already do this. The regression model is not embedded in the CMMS; for now, it is a planning aid outside the system. According to TTCL internal reports, the system raises an escalation alert when a repair passes two hours. This is a trigger for management attention, not a repair-time target, since mean fibre-cut downtime was about 24, 19 and 13 hours per breakdown in 2023 to 2025. This paper presents no test

records or user feedback, so the system is a configured prototype. A System Usability Scale study [41] with TTCL staff is the next step, and its effect on availability, MTTR and cost has not been measured.

4.6 Discussion

The regression says that in TTCL's logs, availability falls by about a quarter of a point for every logged hour of fibre-cut or power-outage downtime. That is largely a statement of how availability is recorded. It does not explain why cuts happen or why repairs take as long as they do. What it gives is a practical conversion: at the 2025 level of about ten breakdowns a year, cutting one hour from each repair saves about ten logged hours a year, worth roughly 0.2 points of average monthly availability. That figure is indicative and not costed, because TTCL cost data were not available to us.

Staff and records are consistent on fibre cuts, which staff endorsed most strongly, and which are the largest logged source of lost availability, in line with earlier work [13], [14]. Consistent is not confirmed, though, because FC is by definition the downtime recorded under that label. Power outages are rare and the estimate rests mainly on one month, but another month agrees in size and weak grids are well documented [15], so the case for reliable backup power stands on evidence. The positive CR coefficient is not supported: it depends on two identical entries, is probably double counting and did not improve holdout accuracy.

Latency and rainfall were not significant, but neither measures this route, so this says little about their effect. If the cable is buried or ducted, rainfall may matter little [18], but that is a hypothesis and the rainfall data are extracted. The next step is a model of what drives downtime, not downtime itself: the number of cut events, the parts of MTTR (detection, dispatch, travel, splicing, and waiting for spares), the cause of each cut and its location. These are the levers a CMMS can change, and its work orders will record them once in use. The limits are plain. The model rests on 33 monthly observations tested on eight, the study covers one 81 km segment, staff ratings are perceptions, and theme-level reliability was not assessed.

CONCLUSION

This study configured a CMMS for the Dar es Salaam–Kimanzichana route and examined what the available data say about availability. First, staff perceive fibre cuts as the leading cause of low availability, followed by natural disasters and delayed fault reporting, with latency, congestion, configuration resolution and power outages also rated highly. These are perceived factors, and the telemetry can check only some of them. Second, in 33 months of TTCL records, logged fibre-cut and power-outage hours explain 96.1% of the variation in monthly availability at about 0.25 points per hour, and a model with these two terms predicted eight unseen months with a mean absolute error of 0.24 points. Because the predictors are downtime hours, this describes how availability is recorded as much as it explains it. The power-outage estimate rests on one month, the configuration-resolution effect is not supported, and rainfall and latency could not be tested validly. Third, a Fiix-based CMMS was configured with work-order, scheduling, asset, inventory, notification and reporting functions. NMS integration, alarm-triggered work orders and OTDR fault location are planned, and the system has not been tested in live use.

6. RECOMMENDATIONS

TTCL management should: (i) use the CMMS in the daily work of the NOC, complete the planned NMS and OTDR integration, and train staff to use it consistently; (ii) make reliable backup power at the route's nodes a priority, with generators and UPS units on a maintenance schedule; (iii) protect the fibre route through closer coordination with road and utility works, and verify the cores that the OTDR showed ending short of the full route; (iv) record configuration work separately from outage time, and record event counts and the parts of MTTR for every fibre cut, so that the effect of configuration work and of repair stages can be tested properly; (v) run OTDR testing on a regular schedule with bidirectional splice-loss measurement, and use the model to guide spare-parts stocking and staffing; and (vi) document how monthly availability is calculated, and refit the model as more months are collected. Future work should compare availability, MTTR and cost before and after deployment, model the drivers of downtime, repeat the study on other NICTBB segments with verified route-level rainfall and latency data, and compare regression with time-series and machine-learning methods.

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DECLARATIONS

Ethics. Participation was voluntary and respondents gave consent before data collection. Thanks to DIT for writing to TTCL presenting the first author, Godfrey Nyarwango in request for permission for data collection and thanks to TTCL for allowing the same author to collect data from NOC to be used for research purposes. Conflict of interest. The first author is employed by TTCL, the operator of the route studied. TTCL did not direct the analysis or conclusions. *Funding, there was no funding source to undertake this research, Data availability.* The anonymised monthly dataset and questionnaire are in the supplementary file; further data are available from the corresponding author on reasonable request, subject to TTCL's approval. *Author contributions.* G. Nyarwango: investigation, data curation, formal analysis, software, original draft. M.E. Mkiramweni: supervision, methodology, review and editing. F.M. Sanga: supervision, review and editing. J.N. Mkilania: review and editing.

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