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Investigating equipment productivity in feeder road maintenance in Uganda

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ABSTRACT

Rural roads form the largest part of Uganda's road network (approximately 50.2%) and is therefore a critical part of economic growth in an agriculturally dependent country like Uganda. With Uganda's rural population standing at approximately 76% of the total population and agriculture still employing approximately 72% of Uganda's population, this underscores the need to fix loopholes in road maintenance strategies in Uganda with emphasis on rural roads. This study sought to conduct a detailed cost analysis with a view to determining whether productivity is at an optimum for specific road maintenance equipment in Uganda, with emphasis on mechanized agricultural plantation access road maintenance works. Two descriptive research methods were used: observations and case study approach. Control parameters affecting machine production were identified as machine repair costs, maintenance costs, machine depreciation costs, worker's salaries, machine insurance costs, and machine fuel costs. Machine downtime was mainly affected by delays in procuring spares. The total hourly machine production costs were calculated to be 699,602 Ugx (185.84USD). This cost calculation can be improved upon in subsequent studies. The study recommends the need for an effective centralised electronic database where all feeder road maintenance data is collected, analysed, and recorded.

Introduction

Most African countries annually spend approximately 2% of their GDP on roads and tend to spend more on capital investments than maintenance. Lack of maintenance deteriorates overall quality of roads and increases the road rehabilitation costs, which usually cannot be adequately covered (World Bank, 2010). The approved road maintenance budget for FY 2019/20 (UGX 448.833bn) constituted 0.36% of Uganda's GDP (UGX 126,258bn), well below the minimum recommended of 0.85%. Only 2.9% of the annual maintenance budget was allocated to Community Access Roads (CARs), (MoWT, 2020).

With the significant impact of rural roads on national development, they are no longer considered a feature of agricultural policy, but have become a critical headline indicator of development at global level (World Highways, 2015). Considering Community Access Roads account for approximately 50.2% (79,947 km) of the road network in Uganda (MoWT, 2020), and with Uganda's rural population standing at approximately 76%, this underscores the need to fix loopholes in road maintenance strategies in Uganda with emphasis on rural roads. Agriculture has and continues to be one of Uganda's most crucial sectors of the economy employing over 72 percent of the population, majority of them women and youth and contributing over 23.5 percent of GDP over the years (MAAIF, 2018).

1.1. Problem statement

Muhwezi et al. (2020) identified material and machinery related factors as the most important factors affecting cost performance of unpaved road maintenance work in Uganda and concluded that critical attention be paid to the problems under each of these factors when planning and implementing road maintenance budgets. Low machine availability indicates redundancy (downtime), which Schaufelberger and Migliaccio (2019) identified as having a substantial impact on equipment productivity and organizational performance. With rural feeder roads being a critical driver of economic growth coupled with the fact that agriculture still employs approximately 72% of Uganda's population and considering that 76% of Uganda's population is rural based, the need to maintain community access roads is therefore paramount. A focus on large, commercial private sector led plantation agriculture ventures, with multiple community synergies creates an

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interesting study environment for a mechanized rural community access road maintenance model.

In light of this, this research sought to conduct a detailed cost analysis with a view to determining whether productivity is at an optimum for specific road maintenance equipment in Uganda with emphasis on large scale mechanized plantation access road maintenance works. Close attention was paid to the less tangible costs of downtime, that are not normally considered while monitoring equipment performance since they are assumed to be somehow offset by other costs.

2. Literature review

2.1. Equipment downtime

Downtime is the time when an equipment is not operational due to repairs or mechanical adjustments (Nwanya et al., 2017). Downtime tends to increase as equipment usage increases. Availability refers to the portion of the time when equipment is in actual production or is available for production, which is the opposite of downtime. Santo et al., (2019) identified equipment misuse for heavier duties than their intended design, inadequate staffing, poorly trained operators and mechanics, failure to adhere to equipment Standard Operating Procedures (SOPs), as some of the factors for premature failures of road construction equipment in Uganda. Marinelli et al., (2014) used an Artificial Neural Network (ANN) based model, with a 94% accuracy, for predicting condition levels of earthmoving trucks. The model identified an almost exclusive connection of the condition level with the kilometres travelled and the maintenance level. The impact of machine age and capacity was found to be negligible.

Edwards et al., (2002) used a regression model to predict downtime costs of tracked hydraulic excavators operating in the UK opencast mining industry. Machine weight was used as a predictor for both cycle time and hire cost. The type of work under execution was seen to have significant impact on costs and production. Two research gaps were identified; the first one, being the need to incorporate cost per hour of consumables to perfect the model. The second being the incorporation of a broader range of equipment types operating in different work environments to create multiple downtime cost functions. Downtime data analysed by Nepal and Park, (2004) were found to represent an average of 6 per cent of planned working time for equipment. They went on to point out that, "Research on construction equipment downtime is limited" and that the downtime data they observed were, "chaotic".

Edwards et al., (2000) found that downtime is chaotic and not necessarily a function of machine size. The study conducted, concluded that downtime does not increase with machine weight. Percentage direct maintenance cost on parts was also found to increase with machine weight. The research also found that, approximately-four days and nine hours per annum were lost to machine downtime in the quarrying and mining industry accounting for about 1.8% of total production time. Yang et al., 2003, meanwhile, employed a fuzzy model to derive an "acceptable" result that might be improved given more independent variables while Seung and Sinha, (2006), used an artificial neural network in attempting to account for modelling the complexity and changeable nature of excavating environments in the construction sector.

Downtime data for heavy mining dump trucks in Eritrea, was analysed by Dyson, (2018) and he found that the total downtime from body and frame breakdowns approximated 50.83hours of downtime per machine per month. This accounted for about 25% of the production time per machine. Factoring in other component breakdowns indicated fleet availability of 64% and downtime of 36%. Downtime could also be exasperated by inadequate labour, placing many damaged machines on a waiting mode since most of the labour will be committed to planned maintenance and other breakdowns. Non-availability of an effective component replacement plan and equipment mid-life refurbishment, also increases the risk of machine failure and downtime. The Caterpillar performance handbook indicates that the total number of actual operation hours on a machine along with the ownership period is a key factor in determining operating and owning costs (Caterpillar, 2017). With recent advances in engine idle reduction systems (EIRS), idle time, for even short periods, can be reduced up to 60 percent. Cat, 2020 cites excessive idle time as jeopardizing component life, accelerating wear of Tier 4 technologies, requiring unnecessary fluid and filter changes, burning through warranty hours, and sacrificing resale value.

2.2. Equipment productivity

Neely et al., (1995) describes performance measurement as the process of quantifying action, where measurement is the process of quantification and action correlates with performance. Performance Measurement System (PMS) is defined as the set of metrics used to quantify the efficiency and effectiveness of action. Within a broad context, there are three diverse techniques to measure productivity: Index measurement, linear programming, and econometric models (Singh et al., 2000). In this research, OEE (Overall Equipment Effectiveness) and TEEP (Total Equipment Effectiveness Performance) were selected due to their wide usage as productivity measurement tools in equipment asset utilisation.

Though various maintenance activities have been adopted to ensure high equipment reliability, unplanned breakdowns usually occur as explained by Tanwari et al., (2006) with equipment of whatever type no matter how complex or simple, however cheap or expensive, being liable to breakdown. Therefore, not only procedures should be considered for equipment maintenance, but also the possibility of breakdowns and disruption of operation must be considered during capacity planning and activity scheduling. As such, to achieve better results, the main aspects of equipment reliability must be considered.

The aim of every mechanized feeder road maintenance operation is to produce at a lower unit cost, where production performance depends on the availability and utilisation of the equipment. Therefore, equipment must operate efficiently and when a breakdown occurs, the repair reaction time, Mean Time To Repair (MTTR) must be minimal and recorded for further analysis. Downtime, however small it may be, has significant implications on productivity. On the other hand, Jula et al., (2006) explains that there are a lot of reasons why difficulties arise in equipment operations, and this includes selection of equipment, the way the equipment is used or applied, maintenance practices, inadequacies in technical skills, lack of mid-life equipment rebuild, quality of equipment and component refurbishment, quality of replacement parts as well as the maintenance organization structure.

Furthermore, the impact and frequency of equipment downtime has a negative effect on an organization's productivity and profitability. Barabady and Kumar (2008) found that a 36% down-time factor cost a mining company 2,821,616 tonnes of ore in a period of 6 months due to breakdown of equipment components. More often, breakdown of equipment is only viewed as mere downtime to operations, however, this has a triple cost implication on the organization, production cost in not meeting the output target and associated maintenance costs. The more breakdowns are experienced, the more parts will be required to repair broken down equipment as well as maintenance labour cost which usually arises from un-planned work. This greatly affects production costs (Barabady et al., 2017). It is therefore prudent that equipment failure is prevented or kept to a certain minimum threshold. This can be achieved by building and developing a workplace culture that focusses on careful machine handling and understanding that maintenance activities undertaken before failure are less disruptive to production and easy to correct.

Sessions et al., (2021) indicated that, maintenance cost is a key part of production costs, and that logistics and spare parts management should be considered in the organisation's maintenance plans. Also, the operational phase and reliability characteristic of a piece of equipment can be used to effectively determine spare part prediction (SPP) to avoid run outs. Machine utilisation refers to the percentage of available production time during a selected time period that a machine operates to process materials. Machine production depends upon job efficiency, which can be defined as machine utilisation on a time usage basis (Caterpillar, 2017), with an 83% job efficiency being fairly robust.

All the reviewed literature focused mainly on production and downtime cost factors, equipment usage methods, equipment condition prediction models, dump truck down-time calculations, excavation environments, and equipment reliability in mining and road maintenance situations. Two research gaps were identified; the first one, being the need to incorporate cost per hour of consumables to perfect the model. The second being the incorporation of a broader range of equipment types operating in different work environments to create multiple downtime cost functions. Therefore, having noted the above information gap, this research was therefore carried out to address the factors leading to machine downtime and provide a cost per hour rate for machine non-productivity, as part of a cost model solution.

3. Methodology

The study adopted a case study design to investigate in detail the variables under study in feeder road maintenance equipment. The case study approach allows the use of both quantitative and qualitative data analysis (Zainal, 2007). The selected case study area was Kakira Sugar Limited (KSL) in Jinja, Uganda. The selected case study design was a single case (holistic) design with quantitative techniques used in data collection and analysis. The quantitative approach was adopted because the study intended to establish the factors that affect equipment down time in feeder road maintenance at the case study site (Kakira Sugar Ltd). The quantitative approach was thought to be best suited for this study because it allows for collecting numeric data on observable individual behaviour of samples, then subjecting this data to statistical analysis (Amin, 2005).

The case study location was selected because of its large well-established mechanized feeder road maintenance department and availability of well documented equipment usage and maintenance records. The KSL sugar estate has over 400 km of feeder roads under mechanized maintenance. Field observations and archival documents were used. The level of observer participation varied from wholly participant to non-participant. The researcher collected data through field notes and static photographs.

3.1. Data collection

The selected case study design was a single case (holistic) design with quantitative techniques used in data collection and analysis. Primary Sources included data collection by use of field observation of ongoing road maintenance works. Secondary sources involved review of archival records in the form of textbooks, journals and organisational annual reports alongside the KSL road maintenance and equipment records.

3.2. Validity of the data

Care was also taken to ensure case study design quality tests of internal validity, construct validity, and external validity were adhered to. Since the key issue in internal validity is the causal relationship between variables, the solution lay in establishing key conditions/parameters to be met prior to establishing these causal effects.

For construct validity, three tactics were used. The first was the use of various sources of proof, so as to arrive at a certain conclusion through many thought processes. The second tactic was to establish a chain of evidence and the third tactic was to have the draft case study report reviewed by key experienced technical persons.

3.3. Reliability of the data

The reliability issues were solved by use of case study protocols to improve on documentation and the development of a simple database to store data in an organised format. Field data input in SPSS software was tested using; 1-correlation analysis to determine the relationship between different variables, 2-Normality analysis where a histogram of residuals was plotted for the dependent variable, 3-Equality of variance where a plot of residuals against the predicted values was generated.

3.4. Data analysis

As mentioned before, the data collected was analysed using IBM SPSS Statistics version 26, because this is the most recommendable package for analysing research data (Sekaran and Bougie, 2016). The analysis relied on both descriptive and inferential statistics. Field data input in SPSS software was tested using; 1-correlation analysis to determine the relationship between different variables, 2-Normality analysis where a histogram of residuals was plotted for the dependent variable, 3-Equality of variance where a plot of residuals against the predicted values was generated. These were in turn used to develop linear regression models for various equipment cost models.

4. Results and analysis

A total of 6 machines were considered for observation during the feeder road maintenance works at KSL. These included the TATA 2516C lorry trucks, the INGERSOL RAND vibrator, the JCB 3CX excavator, the CAT 950H FRONT END LOADER, the CAT 120H MOTORGRADER, and the CAT D6H EARTHMOVER/BULLDOZER. KSL also had lots of equipment records relating to these machines spanning over 10 years, which made the data more accurate and representative.

4.1. Factors influencing cost of machine production and downtime

The key objective while analysing cost of machine pro-duction was to develop a cost per km rate for feeder road maintenance. This involved analysing different facets of feeder road maintenance operations and their associated costs.

4.1.1. Common machine repairs, maintenance, and servicing operations

Common machine repairs included items such as; Tyre punctures, starting failures, bolt terminal replacements, tilt cylinder hose/hydraulic hose replacements; segment bolt, ripper mounting bolts, under carriage cop bolts, and discharged bolt replacements, clutch rod replacements. Leakages were also a common feature.

Minor field repairs such as broken bolts, hoses and terminals were usually solved on site since spares for these were mostly available at the satellite station. Therefore, the researcher sourced for reported and recorded incidences of machine breakdown in the field, and their associated spares for repairs, whose costs were known in the market. This therefore helped to plot a rough cost estimate for the minor repairs per machine, per month. This was later converted into a cost per hour rate by ratioing the monthly rate with an 8 hour workday, 25 days a month. The selected work time is however ideal, since work times greatly vary and are not necessarily 8 hours a day and 25 days a month.

Major repairs were carried out at the main garage workshop. Based on information provided by the main garage manager, major repair costs were heavily determined by the damaged part, the associated costs of sourcing and delivering spares (whether nationally from local dealers or internationally) and the installation costs (sometimes done by expatriate machine repair specialists). These major repairs were highly unpredictable and random. They were also varying even on machines of the same type. With recorded data highly unavailable, the researcher was not able to acquire insightful data on these major repairs besides getting a view of the ongoing major repairs. Machine servicing data was, however, readily available with various equipment being serviced after different hours of operations or km covered.

The main observed challenge at the main garage was the long lead time it took to obtain major machine components. Many of the heavy equipment (especially CAT machines), were on breakdown awaiting importation of critical spares which had delayed. There was therefore a gap in KSL's major component replacement plan.

Repair labour costs were calculated as constants with or without a machine failure, since the mechanics were paid monthly salaries which were not necessarily tied to equipment failures. The mechanics were grouped into Class I and II mechanics with Class I mechanics earning about 350,000 Ugx while Class II mechanics earn about 450,000 Ugx monthly. This can be converted into approximately 1,750Ugx and 2,250 Ugx per hour, for the Class I and II mechanics respectively, taking into consideration a daily 8 hour working schedule and a 25 days working month.

4.1.2. Machine utilisation

The Ingersoll rand compactor had the highest utilisation at 85.7%, followed by the JCB 3CX excavator and CAT D6H earthmover at 85.4%; the FEL CAT 950H and Motor grader CAT 120H averaged about 84%, with the TATA 2516C coming in last at 83.1%. Average Machine Utilisation was 84.7%.

4.1.3. Machine availability

Machine Availability, also known as uptime, refers to the percentage of time a machine is in operation. The Ingersoll rand compactor had the highest utilisation at 98.2%, followed by the JCB 3CX excavator and CAT D6H earthmover at 98%; the FEL CAT 950H at 97%, the Motor grader CAT 120H averaged about 96.7%, with the TATA 2516C coming in last at 95.8%. Average Machine Availability was 97.3%.

4.1.4. Machine depreciation costs

Declining balance method was adopted in this research due to its advantages over the other methods of calculating depreciation. The machine salvage values are shown in Table 1, with machine useful life estimated at a maximum of 25 years.

The earthmover D6R had the highest depreciation at 25% (3,900,000Ugx) of the total monthly depreciation, followed by the front-end wheel loader at 23% (3,600,000Ugx), the motor grader CAT 120H at 21% (3,300,000Ugx), the roller compactor at 16% (2,400,000Ugx), the backhoe excavator at 12% (1,800,000Ugx), the TATA lorry at 3% (450,000Ugx) of the total depreciation respectively.

4.1.5. Total Machine production costs

Basing on the different cost parameters that were identified, Table 2 below, was generated with the various cost aspects assigned to each machine.

The CAT D6 earthmover had the highest daily machine production cost, accounting for 24% of the total; followed by the CAT 120H Motor grader at 20%; CAT 950H front end loader at 17% with the JCB 3X excavator, TATA 2516C truck, and Ingersoll rand roller compactor all at 13% respectively. The daily fleet production cost can be converted to an hourly cost by dividing the daily production cost by the number of machine hours worked.

Table 2
Daily Fleet operation cost at KSL

Equipment	Daily Production cost (Ugx)
CAT D6	2,069,921
IR COMP ROLLER	1,156,818
CAT 950H FEL	1,468,586
MGRADER CAT 120H	1,678,444
TATA 2516C	1,079,215
JCB 3CX	1,160,936
TOTAL (Ugx)	8,613,920

4.1.6. Summary of hourly machine production costs at KSL

Basing on all the above machine production cost parameters, different aspects of machine production cost per hour have been summarized as indicated in Table 3.

From Table 3, total hourly machine production costs were 699,602 Ugx. The average km of road maintained at KSL was approximately 2.33 km of feeder road.

Therefore: The hourly machine production cost per km = (699,602 /2.33 km) = approx. 300,258.37Ugx per hour/km.

4.2. Machine days to next failure and downtime

The machine days to next failure comprised of Mean Time Before Failure (MTBF) and the Mean Time To Repair (MTTR).

These calculated MTTR and MTBF values for the different machines have been indicated in Table 4.

The Ingersoll Rand Compactor had the highest MTTR at 73 hours followed by the JCB 3CX at 72, CAT D6 at 60, the CAT 950H and 120H at 44 and 43 respectively, then the TATA with the lowest at 38. Average MTTR was calculated to be 1.333 which corresponds to the average machine downtime and is approximately 16.7% of the total machine operational time. Downtime data analysed by Nepal and Park (2004) were found to represent an average of 6% of planned working time for equipment. Dyson (2018) found a downtime of 36% for mining dump trucks. Edwards et al., (2000) found downtime to be 1.8% of total production time for equipment operating in the quarrying and mining industry. The downtime data observed is midway both observations and supports the findings of Nepal and Park (2004), and Edwards et al., (2000) who indicated that downtime data is usually "chaotic".

Table 3
Cost aspects of Fleet operation costs per hour at KSL

	Operation cost aspects	Nature of cost	Cost (Ugx)/hr
1	Machinery repair and maintenance cost	Direct	262,353
2	Machine fuel costs/expenses	Direct	235,148
3	Machine insurance costs	Indirect	67,851
4	Operators' salaries	Direct	57,000
5	Machine depreciation costs	Indirect	77,250
TOTAL HOURLY OPERATIONAL COSTS (Ugx)			**699,602**

Table 1
Machine purchase, salvage, and depreciation costs

SNo.	Equipment	Machine purchase cost		Salvage Value (UGX)	Machine Depreciation Rate (Annually-UGX)	Machine Depreciation Rate (Monthly-UGX)
		UGX	USD			
1	lorry-TATA 2516C	150,000,000	41,667	15,000,000	5,400,000	450,000
2	backhoe excavator-JCB 3CX	600,000,000	120,000	60,000,000	21,600,000	1,800,000
3	road compactor/roller-INGERSOL RAND vibrator	800,000,000	175,000	80,000,000	28,800,000	2,400,000
4	front end wheel loader-CAT 950H	1,200,000,000	320,000	120,000,000	43,200,000	3,600,000
5	motor grader-CAT140G	1,100,000,000	300,000	110,000,000	39,600,000	3,300,000
6	earthmover (bulldozer)-CAT D6H	1,300,000,000	300,000	130,000,000	46,800,000	3,900,000

Table 4
MTTR and MTBF for various equipment at KSL

SNo.	Equipment	MTBF (hrs)	MTTR (hrs)
1	CAT D6	60	1
2	IR COMP ROLLER	73	1
3	CAT 950H FEL	44	1
4	MGRADER CAT 120H	43	1
5	TATA 2516C	38	2
6	JCB 3CX	72	2

4.2.1. Machine cumulative hours and MTBF

As indicated in Table 5, the two variables of Machine cumulative hours and MTBF of 5No. sampled machines in feeder road maintenance works, were considered to examine their relationship. The scatter diagrams indicated a linear relationship between the two variables. Pearson's bivariate correlation coefficient showed a strong negative linear relationship between the two variables ($r = -0.847$) that is insignificantly different from zero ($p < 0.070$).

This implies that an increase in machine cumulative hours (age) leads to a decrease in MTBF, thus frequent breakdowns. This agrees with the findings of Nwanya et al., (2017). This however disagrees with Marinelli et al. (2014), whose model found the impact of machine age on equipment condition levels to be negligible.

4.2.2. Machine weight and MTBF

As indicated in Table 6, the two variables of Machine Weight (kg) and MTBF of 6No. sampled machines in feeder road maintenance works, were considered to examine their relationship. The scatter diagrams indicated a linear relationship between the two variables. Pearson's bivariate correlation coefficient showed a moderate negative linear relationship between the two variables ($r = -0.597$) that is insignificantly different from zero ($p < 0.211$).

4.2.3. Machine weight and MTTR

As shown in Table 7, the two variables of Machine Weight (kg) and MTTR (hours) of 6No. sampled machines in feeder road maintenance works, were considered to examine their relationship. The scatter diagrams indicated a linear relationship between the two variables. Pearson's bivariate correlation coefficient showed a low positive linear relationship between the two variables ($r = 0.042$) that is insignificantly different from zero ($p < 0.937$). This agrees with Edwards et al., (2000) who found that downtime does not increase with machine weight.

4.2.4. Machine weight and Daily production cost

As shown in Table 8, the two variables of Machine Weight (kg) and Daily production cost (Ugx) of 6No. sampled machines in feeder road maintenance works, were considered to examine their relationship. The scatter diagrams indicate a linear relationship between the two variables. Pearson's bivariate correlation coefficient showed a low positive linear relationship between the two variables ($r = 0.250$) that is insignificantly different from zero ($p < 0.633$). This implies that an increase/decrease in machine weight had a negligible effect of daily production costs. This disagrees with Edwards et al., (2002) whose regression model for tracked hydraulic excavators operating in the UK opencast mining industry found machine weight a key predictor of maintenance cost, which is a key component of daily production cost.

Table 5
Correlation analysis for Machine cumulative hours and MTBF *TATA 2516C excluded.

Correlations		Cumulative hours worked	MTBF
Cumulative hours worked	Pearson Correlation	1	-0.847
	Sig. (2-tailed)		0.070
	N	5	5
MTBF	Pearson Correlation	-0.847	1
	Sig. (2-tailed)	0.070	
	N	5	5

Table 6
Correlation analysis for Machine Weight and MTBF

Correlations		Machine weight (kg)	MTBF
Machine weight (kg)	Pearson Correlation	1	-0.597
	Sig. (2-tailed)		0.211
	N	6	6
MTBF	Pearson Correlation	-0.597	1
	Sig. (2-tailed)	0.211	
	N	6	6

Table 7
Correlation analysis for Machine Weight and MTTR

Correlations		Machine weight	MTTR
Machine weight	Pearson Correlation	1	0.042
	Sig. (2-tailed)		0.937
	N	6	6
MTTR	Pearson Correlation	0.042	1
	Sig. (2-tailed)	0.937	
	N	6	6

Table 8
Correlation analysis for Machine Weight and Daily production cost

Correlations		Machine weight (kg)	Daily production Cost (Ugx)
Machine weight (kg)	Pearson Correlation	1	0.250
	Sig. (2-tailed)		0.633
	N	6	6
Daily production Cost (Ugx)	Pearson Correlation	0.250	1
	Sig. (2-tailed)	0.633	
	N	6	6

4.2.5. MTTR and Daily production cost

As shown in Table 9, the two variables of MTTR (hours) and Daily production cost (Ugx) of 6No. sampled machines in feeder road maintenance works, were considered to examine their relationship. The scatter diagrams indicated a linear relationship between the two variables. Pearson's bivariate correlation coefficient showed a moderate negative linear relationship between the two variables ($r = -0.634$) that is insignificantly different from zero ($p < 0.176$).

Table 9
Correlation analysis for MTTR and Daily production cost

Correlations		MTTR	Daily production Cost (Ugx)
MTTR	Pearson Correlation	1	-0.634
	Sig. (2-tailed)		0.176
	N	6	6
Daily production Cost (Ugx)	Pearson Correlation	-0.634	1
	Sig. (2-tailed)	0.176	
	N	6	6

4.2.6. *MTTR and Cumulative Machine hours*

As shown in Table 10, the two variables of MTTR (hours) and Cumulative machine hours of 5No. sampled machines in feeder road maintenance works, were considered to examine their relationship. The scatter diagrams indicated a linear relationship between the two variables. Pearson's bivariate correlation coefficient showed a moderate negative linear relationship between the two variables (r = -0.674) that is insignificantly different from zero ($p < 0.212$).

4.2.7. *Daily production costs (Ugx) and Cumulative Machine hours*

As shown in Table 11, the two variables of Daily machine production costs (Ugx) and Cumulative machine hours of 6No. sampled machines in feeder road maintenance works, were considered to examine their relationship. The scatter diagrams indicated a linear relationship between the two variables. Pearson's bivariate correlation coefficient showed a low negative linear relationship between the two variables (r = -0.427) that is insignificantly different from zero ($p < 0.399$).

4.3. *Development of a cost model for parameters identified.*

4.3.1. *Cost modelling parameters*

The deterministic cost model predicting daily machine production costs considered Repair cost, Maintenance costs, Machine tyre costs/ undercarriage costs, Fuel expenses/costs, Operator costs, and Insurance costs alongside costs due to machine depreciation as research parameters. The relationship between different factors/parameters and the daily machine production cost were developed as Linear Regression Cost models in SPSS. Different linear regression models were developed for different machinery since each was unique and had its own data sets that would influence machine performance. Model fit was tested through collinearity (using data correlations) and normality (using histograms of residual data sets).

4.3.2. *TATA 2516C data cost model*

From the regression data in Table 12, the following output model was generated.

Multiple linear regression was used to test if the km covered [predictor variable 1], fuel consumed [predictor variable 2], significantly predicted the Daily machine production cost [response variable].

The fitted regression model was:

Daily Production Cost (Ugx) = 841569.566 + 59.803(km covered) + 4499.998 fuel consumed(1)

Since $p < 0.05$, therefore, all b-coefficients in our table are highly statistically significant. The strongest predictors in our coefficients table are: Fuel consumed ($\beta = 0.970$) and then followed by machine km covered ($\beta = 0.033$).

4.3.3. *JCB 3CX data cost model*

From the regression data in Table 13, the following output model was generated.

Table 10
Correlation analysis for MTTR and Cumulative machine hours

Correlations		MTTR	Cumulative machine hours
MTTR	Pearson Correlation	1	-0.674
	Sig. (2-tailed)		0.212
	N	5	5
Cumulative machine hours	Pearson Correlation	-0.674	1
	Sig. (2-tailed)	0.212	
	N	5	5

Table 11
Correlation analysis for MTTR and Cumulative machine hours

Correlations		Cumulative machine hours	Daily production Cost (Ugx)
Cumulative machine hours	Pearson Correlation	1	-0.427
	Sig. (2-tailed)		0.399
	N	6	6
Daily production Cost (Ugx)	Pearson Correlation	-0.427	1
	Sig. (2-tailed)	0.399	
	N	6	6

Multiple linear regression was used to test if the Machine Hours Worked [predictor variable 1], fuel consumed [predictor variable 2], significantly predicted the Daily machine production cost [response variable].

The fitted regression model was:

Daily Production Cost (Ugx) = 940969.976 + 1153.344 (machine hours covered) + 4531.694 fuel consumed (2)

Since $p < 0.05$, therefore, all b-coefficients in our table are highly statistically significant. The strongest predictors in our coefficients table are: Fuel consumed ($\beta = 0.944$) and then followed by machine Hours worked ($\beta = 0.058$).

4.3.4. *Ingersoll rand compactor data cost model*

From the regression data in Table 14, the following output model was generated.

Multiple linear regression was used to test if the Machine Hours Worked [predictor variable 1], fuel consumed [predictor variable 2], significantly predicted the Daily machine production cost [response variable].

The fitted regression model generated was:

Daily Production Cost (Ugx) = 889527.934 + 208.239(machine hours covered) + 4508.778 fuel consumed. (3)

Since $p < 0.05$, therefore, all b-coefficients in our table are highly statistically significant. The strongest predictors in our coefficients table are: Fuel consumed ($\beta = 0.995$) and then followed by machine Hours worked ($\beta = 0.005$).

4.3.5. *CAT 950H front end loader machine data cost model*

From the regression data in Table 15, the following output model was generated.

Multiple linear regression was used to test if the Machine Hours Worked [predictor variable 1], fuel consumed [predictor variable 2], significantly predicted the Daily machine production cost [response variable].

The fitted regression model was:

Daily Production Cost (Ugx) = 889527.934 + 208.239(machine hours covered) + 4508.778fuel consumed (4)

Since $p < 0.05$, therefore, all b-coefficients in our table are highly statistically significant. The strongest predictors in our coefficients table are: Fuel consumed ($\beta = 0.995$) and then followed by machine Hours worked ($\beta = 0.005$).

4.3.6. *CAT 120H Motor grader machine data cost model*

From the regression data in Table 16, the following output model was generated.

Multiple linear regression was used to test if the Machine Hours Worked [predictor variable 1], fuel consumed [predictor variable 2], significantly predicted the Daily machine production cost [response

Table 12
Regression analysis for km covered, and fuel consumed and Daily machine production cost for TATA 2516C

Coefficients[a]										
TATA 2516C Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	841569.566	0.139		6052636.410	0.000	841569.284	841569.847		
	km	59.803	0.003	0.033	23251.140	0.000	59.798	59.808	0.149	6.714
	fuel consumed (ltrs)	4499.998	0.006	0.970	692748.466	0.000	4499.985	4500.011	0.149	6.714

a. Dependent Variable: Daily Production Cost (Ugx)

Table 13
Regression analysis for Machine Hours worked, fuel consumed, and Daily machine production cost for JCB3CX.

Coefficients[a]										
JCB 3CX Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	940969.976	244.453		3849.295	0.000	940470.014	941469.937		
	Hours worked	1153.344	77.409	0.058	14.899	0.000	995.024	1311.663	0.078	12.862
	Fuel consumed (ltrs)	4531.694	18.585	0.944	243.839	0.000	4493.684	4569.704	0.078	12.862

a. Dependent Variable: Daily production cost (Ugx)

Table 14
Regression analysis for Machine Hours worked, fuel consumed and Daily machine production cost for IR COMP.

Coefficients[a]										
IR COMP Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	889527.934	94.352		9427.789	0.000	889336.759	889719.109		
	Hours worked	208.239	28.482	0.005	7.311	0.000	150.530	265.949	0.148	6.763
	Fuel consumed (ltrs)	4508.778	3.293	0.995	1369.180	0.000	4502.106	4515.451	0.148	6.763

a. Dependent Variable: Daily production cost (Ugx)

Table 15
Regression analysis for Machine Hours worked, fuel consumed and Daily machine production cost for CAT950H FEL.

Coefficients[a]										
CAT 950H FEL Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	889527.934	94.352		9427.789	0.000	889336.759	889719.109		
	Hours worked	208.239	28.482	0.005	7.311	0.000	150.530	265.949	0.148	6.763
	Fuel consumed (ltrs)	4508.778	3.293	0.995	1369.180	0.000	4502.106	4515.451	0.148	6.763

a. Dependent Variable: Daily production cost (Ugx)

Table 16
Regression analysis for Machine Hours worked, fuel consumed and Daily machine production cost for CAT 120H M. GRADER.

Coefficients[a]										
CAT 120H MG Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	1023142.072	322.086		3176.614	0.000	1022490.592	1023793.552		
	Hours worked	922.714	148.407	0.015	6.217	0.000	622.533	1222.895	0.080	12.555
	Fuel consumed (ltrs)	4543.602	11.042	0.986	411.465	0.000	4521.267	4565.938	0.080	12.555

a. Dependent Variable: Daily production cost (Ugx)

variable].

The fitted regression model was:

$$\text{Daily Production Cost (Ugx)} = 1023142.072 + 922.714(\text{machine hours covered}) + 4543.602 \text{ fuel consumed.} \quad (5)$$

Since $p < 0.05$, therefore, all b-coefficients in our table are highly statistically significant. The strongest predictors in our coefficients table are: Fuel consumed ($\beta = 0.968$) and then followed by machine Hours worked ($\beta = 0.015$).

4.3.7. CAT D6H earthmover machine data cost model

From the regression data in Table 17, the following output model was generated.

Multiple linear regression was used to test if the Machine Hours Worked [predictor variable 1], fuel consumed [predictor variable 2], significantly predicted the Daily machine production cost [response

Table 17
Regression analysis for Machine Hours worked, fuel consumed, and Daily machine production cost for CATD6H E. Mover.

Coefficients[a]										
CAT D6H E. Mover Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	986204.343	0.181		5449534.804	0.000	986203.969	986204.717		
	Hours worked	24545.627	0.050	0.208	488124.255	0.000	24545.523	24545.731	0.149	6.694
	Fuel consumed (ltrs)	4500.010	0.002	0.805	1893256.053	0.000	4500.006	4500.015	0.149	6.694

a. Dependent Variable: Daily production cost (Ugx)

variable].

The fitted regression model was:

Daily Production Cost (Ugx) = 986204.343 + 24545.627machine hours worked + 4500.010 fuel consumed. (6)

Since $p < 0.05$, therefore, all b-coefficients in our table are highly statistically significant. The strongest predictors in our coefficients table are: Fuel consumed ($\beta = 0.805$) and then followed by Calculated Daily Undercarriage cost ($\beta = 0.208$).

5. Conclusions and recommendations

5.1. Conclusions

Overall, the following are the researcher's conclusions:

The control parameters affecting machine production were identified by the researcher as; machine repair costs, maintenance costs, machine depreciation costs, worker's salaries, machine insurance costs, and machine fuel costs. Machine downtime was mainly affected by delays in procuring spares. This was mainly a planning and procurement challenge when it came to spare parts.

The total hourly machine production costs was calculated to be 699,602 Ugx(185.84USD). This can be improved upon in subsequent studies.

Daily machine production cost models, for different machines involved in feeder road maintenance were formulated. These can also be refined through subsequent studies while factoring in major equipment repairs.

5.2. Recommendations

There is need for road maintenance companies to create a centralised electronic database where all feeder road maintenance data is collected, analysed, and recorded. Most data accessed is in hardcopy format and risks getting damaged/destroyed. This will also reduce on unnecessary movements between the satellite stations and the main garage.

Road maintenance companies need to collect more machine data on cycle times, MTTR, MTBF, and onsite field machine repairs. This will improve on management planning decisions regarding spare parts stockpiling and procurement.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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