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PRODUCTIVITY ANALYSIS OF MANUAL CONDITION ASSESSMENT FOR SEWER PIPES BASED ON CCTV MONITORING

Yuan Chen[1,8], Xianfei Yin[2], Qin Zhang[3], Ahmed Bouferguene[4], Hamid Zaman[5], Mohamed Al-Hussein[4], Randy Russell[6], Luke Kurach[7]
[1] PhD Candidate, Department of Civil and Environmental Engineering, University of Alberta, Canada
[2] PhD Student, Department of Civil and Environmental Engineering, University of Alberta, Canada
[3] Undergraduate Student, Department of Computer Science, University of Alberta, Canada
[4] Professor, Department of Civil and Environmental Engineering, University of Alberta, Canada
[5] General Supervisor, Waste Management, City of Edmonton, Canada
[6] Engineering Technologist, EPCOR Drainage Services, Edmonton, Canada
[7] Senior Infrastructure Engineer, EPCOR Drainage Services, Edmonton, Canada
[8] ychen10@ualberta.ca

Abstract: Closed-circuit television (CCTV) monitoring has been widely employed in North America to assess the structural integrity of underground drainage infrastructure. This operation is usually conducted in two sequential phases. The first consists of dispatching operators to collect video of sections of pipes using remotely controlled robots equipped with specialized television cameras. In the second phase, the data collected in the field is delivered to the analysis facility, where technologists trained in defect classification can examine the video footage. In many municipalities the video-based assessment of the sewer pipes is conducted manually, and little is known about the productivity of this process. This knowledge gap, combined with the desire to implement better resource management solutions, forms the motivation for this research, in which the efficiency of the analysis of video footage of sewer pipe condition is explored. In fact, the duration of condition assessment of sewer pipes is influenced by multiple factors. Therefore, this paper conducts an assessment productivity analysis that uses statistical regression methods to investigate the specific factors influencing the duration of manual condition assessments for sewer pipes by each technologist using footage from CCTV monitoring. Finally, the proposed method is applied to the case of sewer infrastructure in the City of Edmonton, Canada, in order to facilitate productivity improvement for manual condition assessment and human resource allocation.

1 INTRODUCTION

The drainage system is one of the most important components of municipal infrastructure in a city, since it not only has the highest replacement value, but more importantly it plays a crucial role in improving the longevity of its citizens, especially in the context of highly populated areas where hygiene is a key factor for avoiding large-scale epidemics (Meeker 1971). As such, municipalities allocate substantial budget and other resources to carry out preventive maintenance work for sewer pipes in order to correct structural deterioration at the early stage of their occurrence so as to prevent wide disruptions in the level of service. One of the most effective means of inspecting underground sewer pipes relies on using closed-circuit television (CCTV) monitoring, a service generally performed by private companies or by municipalities' drainage departments (Iseley et al. 1997, Makar 1999). The inspection process is typically conducted by means of a remotely controlled robot equipped with a specialized television camera that accesses the drainage network through a service opening such as a manhole or a drain cleanout (Davis et al. 2001, Guo et al. 2009). In general, CCTV monitoring can be viewed as a two-phase operation in which the first part focuses on collecting the data, i.e., videos, by moving the robot along the pipe sections. Note that operators need to adhere to standards such as those described by the National Association of Sewer Service Companies (NASSCO) in order to obtain quality information that can be accurately analysed. In the second phase of CCTV monitoring, videos recorded in the field are delivered to the analysis facility where technologists (i.e., trained individuals) manually and visually examine the collected footage. During this process, defects are identified and classified into different categories (e.g., crack, fracture, or broken) using standardized nomenclature, i.e., NASSCO assessment document. Since maintenance can only begin when the technologists inspecting the videos have finalized their reports, it is important to ensure that the inspection step is completed as quickly as possible. Current researches on sewer pipes using CCTV monitoring primarily focus on application of innovative approaches and other artificial intelligence techniques in automated defect detection in order to replace human visual identification; by contrast, the productivity improvement of maintenance activities for sewer pipes from the management perspective attracts few attentions from the scholars (Moselhi and Shehab-Eldeen 2000, Sinha and Fieguth 2006, Yang and Su 2008, 2009). In fact, understanding the factors that can affect the productivity is essential for managers since this insight will allow them to more evenly distribute the workload between the members of the assessment team, not to mention the ability to improve their estimates of the duration needed to process a given batch of videos. As such, the objective of this research is to develop a regression model from which assessment times are estimated using the records collected from the industry partner. Statistical analyses are conducted on this model in order to determine the factors that affect the productivity of technologists. It is important to mention that effective corrective actions to improve productivity can only be taken after these factors are identified. To achieve this objective, this paper first introduces related data collection for manual condition assessment of sewer pipes. Then, assessment productivity analysis for each technologist is conducted using a linear regression model for the case of sewer infrastructure in the City of Edmonton, Canada, to determine the primary influencing factors. Furthermore, a series of assumption are verified for the developed models.

2 DATA COLLECTION

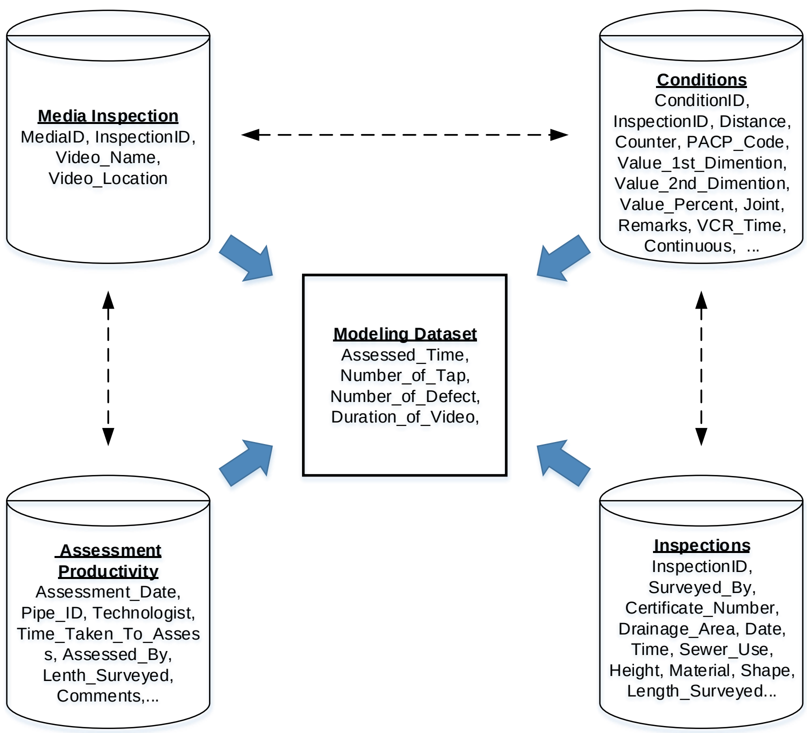


Figure 1: Data collection schematic

The dataset used in this study has been collected and merged from four databases maintained by EPCOR Drainage Services in Edmonton, Canada. The schematic of modelling the dataset can be seen in Figure 1. The database of media inspection provides the information for all videos recorded by CCTV monitoring in the field, while the conditions database describes the type of defects and their locations in the pipe examined by each technologist. The foreign key to link the two databases is InspectionID. The inspections database provides physical properties of the pipes such as height, slope, shape, material, length, the laid year, and location, which is linked with the conditions database through InspectionID. The time that technologists spend on the video-based assessment for each pipe is derived from the assessment productivity database, which is linked with the media inspection database through Pipe_ID and Video_Name.

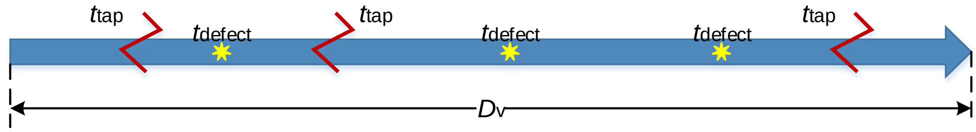


Figure 2: An illustration of assessment time

Based on rules of thumb and experience (see Figure 2), the total assessment time should theoretically be the sum of the inspection time spent on each defect (and the sewer taps) plus video duration for this pipe. In other words, the total assessment time can be written as,

[1] $T = D_v + \sum_{k \in F} n_k t_k$

where D_v is the duration of the video; n_k is the number of defects (or features) of type k ; and t_k is the time needed to inspect one such defect (or feature). Since EPCOR uses the NASSCO standard, four primary categories of pipe defects are listed based on pipeline assessment and certification program (PACP) (NASSCO 2015): structural defects, operation and maintenance defects, construction defects, and miscellaneous defects. In addition, each type of defect can have several subclasses. As for F , this study only considers the first-class defects and merges them as $F = \{tap, crack, deposit, ...\}$. As such, we assume the modelling dataset used in this study is composed of four variables listed in Figure 1. Of them, Number_of_Tap (n_{tap}) and Number_of_Defect of all types (n_{defect}) in each pipe are manually counted by filtering the data below the PACP_Code field, while other variables including Assessed_Time (T) and Duration_of_Video (D_v) are directly collected from the four databases. To be noted, the variable Duration_of_Video is the total time for each pipe recorded by CCTV monitoring. Although there are various types of defects, this study assumes technologists would spend approximately the same amount of time on each type of defect, with the exception of taps. In other words, tap and defect are treated differently.

The collected dataset contained observations of CCTV monitoring and pipe condition assessment for the year 2018 from various locations across the City of Edmonton. After necessary data cleaning, the final dataset contained 134 observations and the condition assessment for sewer pipes is conducted by three technologists. It guarantees that the number of observations for each technologist exceeds 30, which is the minimal amount for statistical analysis. The statistical description of all variables is presented by technologist in Table 1. The number in parentheses for each technologist refers to the total number of observations, while SD indicates the standard deviation.

Table 1: Statistical description of variables by technologist in the dataset

Technologist		Assessed_Time (second)	Number_of_Tap (No.)	Number_of_Defect (No.)	Duration_of_Video (second)
	Min.	600	0	4	10
#1	Max.	6,600	14	132	1,220
(58)	Mean	2,900.69	2.50	36.14	483.34

	SD	1,243.35	3.46	26.50	276.38
#2 (43)	Min.	900	0	14	194
	Max.	5,400	13	101	1,559
	Mean	2,183.72	5.42	42.84	569.95
	SD	1,070.37	3.61	23.37	290.18
#3 (33)	Min.	900	0	4	107
	Max.	7,200	30	100	1,541
	Mean	2,618.18	3.61	23.06	502.09
	SD	1,344.31	6.45	19.14	322.89

3 MODEL DEVELOPMENT

3.1 The Linear Regression Model

The multiple linear regression model, which is widely used in business, social science, engineering, and other disciplines, is a statistical approach to express the relationship between the dependent variable and more than one independent variable (Neter et al. 1989, Zaman et al. 2013). The general form of the multiple linear regression model is defined as (Neter et al. 1989):

[2] $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik} + \varepsilon_i$

where $i = 1,2,...,n$ with n is the number of observations; Y_i is the value of the dependent variable in observation i ; X_{ij} is the value of independent variable j in observation i ; β_j is the coefficient of independent variable j ; ε_i is the error term in observation i with a normal distribution $N(0,\delta)$, while ε_i and ε_j are independent for all $i, j = 1,2,...,n; i \neq j$.

Due to $E\{\varepsilon_i\} = 0$, the response function for regression model (i.e., Eq. (2)) can be transferred into Eq. (3). It means that the dependent variables Y_i satisfy normal distribution with mean $E\{Y\}$ and variance δ^2 .

[3] $E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$

A classical approach to estimate the coefficients β_j is the least squares method, which aims to find the values of β_j with the minimal value of the quadratic error S as Eq. (4). If we denote b_j as the estimator of β_j and b as the vector $(b_0, b_1, ..., b_k)$, the least squares estimators are described as Eq. (5).

[4] $S = \sum_{i=1}^{n} (Y_i - \beta_0 - \beta_1 X_{i1} - \beta_2 X_{i2} - \cdots - \beta_k X_{ik})^2$

[5] $b = (X^T X)^{-1} (X^T X) Y$, where $Y = [Y_1, Y_2, \ldots, Y_n]^T$ and $X = \begin{bmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1k} \\ 1 & X_{21} & X_{22} & \cdots & X_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{nk} \end{bmatrix}$.

In fact, the least squares method only reflects the parameter fitting. For uncertain models, stepwise regression is a helpful method, in a greedy fashion, to search the final optimal linear regression model among pre-listed independent variables (Neter et al. 1989). The Pearson test, meanwhile, is used to verify correlation coefficients among all independent variables as well as between the dependent variable and each independent variable (Pearson 1895). The above two functions can be realized by means of SPSS statistics software and the detailed introduction for the implementation process can be found in the SPSS documents (SPSS 2019a, 2019b).

3.2 Assessment Productivity Analysis

Since video-based assessment depends on the experience, expertise, and capability of the technologist to large extent (Meegoda et al. 2006), the multiple linear regression model for assessment productivity is conducted for each technologist separately. Using SPSS 24.0 software as the main tool and setting Assessed_Time in Table 1 as the dependent variable, the results for the three linear regression models, one for each technologist, are shown in Table 2. The Pearson test for all variables selected in the three built models is presented in Table 3.

Table 2: Linear regression models for assessment productivity

	Dependent Variable	Coefficient	T-test	R-square/ Adjusted R-square
Technologist #1	Constant	996.524	6.692***	83.2% / 82.5%
	Number_of_Defect	36.862	13.290***	
	Duration_of_Video	1.184	4.451***	
Technologist #2	Constant	137.671	0.862	84.4% / 83.6%
	Number_of_Defect	33.531	9.954***	
	Duration_of_Video	1.070	3.944***	
Technologist #3	Constant	960.676	4.766***	80.3% / 79.0%
	Number_of_Defect	50.597	6.537***	
	Duration_of_Video	0.977	2.130**	

Note: *** and ** are at the 0.01 and 0.05 significance level, respectively.

Table 3: The Pearson test for all variables

	Assessed_Time	Number_of_Defect	Duration_of_Video
Technologist #1:			
Assessed_Time	1.000	0.878***	0.539***
Number_of_Defect		1.000	0.351***
Duration_of_Video			1.000
Technologist #2:			
Assessed_Time	1.000	0.885***	0.677***
Number_of_Defect		1.000	0.528***
Duration_of_Video			1.000
Technologist #3:			
Assessed_Time	1.000	0.880***	0.723***
Number_of_Defect		1.000	0.678***

Duration_of_Video	1.000

Note: *** is at the 0.01 significance level.

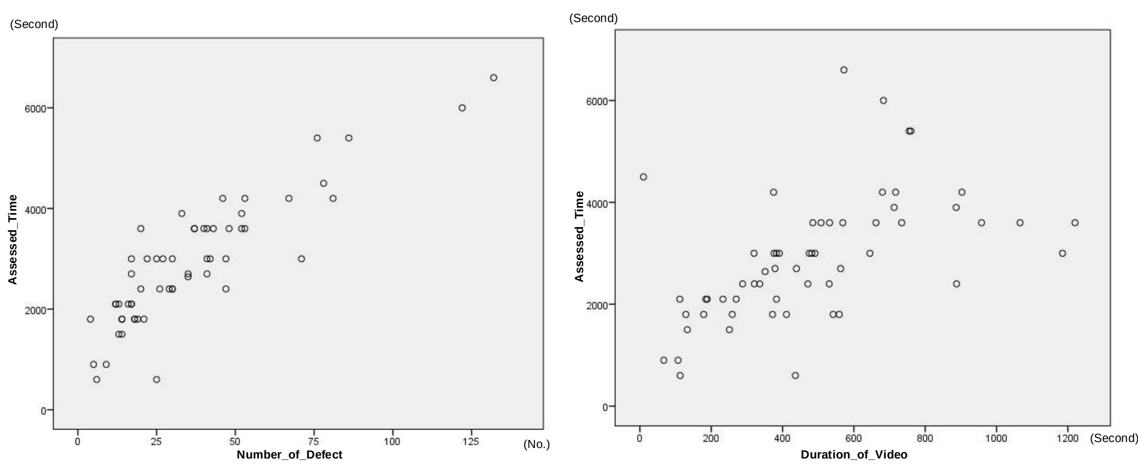
It can be seen that the fitness of the above three linear regression models is quite good, since in each case either R-square or adjusted R-square is close to or exceeds 80% (Zaman et al. 2013). Meanwhile, P-values for all the independent variables selected for the models show that all coefficients pass at least the 0.05 significance level. Also, we can find a variance in the influence degree of these factors on assessment productivity of different technologists, while there is a similarity in the coefficients of Duration_of_Video in the three linear regression models—all are around one. By contrast, the assessment productivity of all the technologists has a highly positive correlation with Number_of_Defect, which has a dominant performance in the case of Technologist #3. Furthermore, Number_of_Tap is excluded in the three linear regression models; this may be attributed to the values of this variable among these observations being too small (see the mean value from Table 1), further triggering a slight effect or no effects on individual assessment productivity. From the Pearson test, there is no high correlation between the independent variables (i.e., the coefficient is smaller than 0.7), which satisfies at least the 0.05 significance level. Meanwhile, the dependent variable, Assessed_Time, has a significantly good correlation with all selected independent variables.

Another interesting finding is that the constant value in each model is relatively large compared with other coefficients, while this performance is dominant among Technologist #1 and Technologist #3. A possible explanation of this result is that the manual video-based assessment for sewer pipes largely depends on the video quality (lighting, shooting angle, and other interferences) of the CCTV monitoring. Although Number_of_Defect is regarded as one of the independent variables, it cannot directly reflect the time the technologist spends on identification and classification of a specific defect. Sometimes, they need to use auxiliary tools to improve the frame quality after pausing the video playback. Moreover, the experience, expertise, and capability of the technologist and his or her operation habits during the entire process will also influence the assessment productivity. Hence, as seen from Table 2, the constant value of Technologist #2 is around 2.3 min, while Technologist #1 and Technologist #3 require more than 16 min.

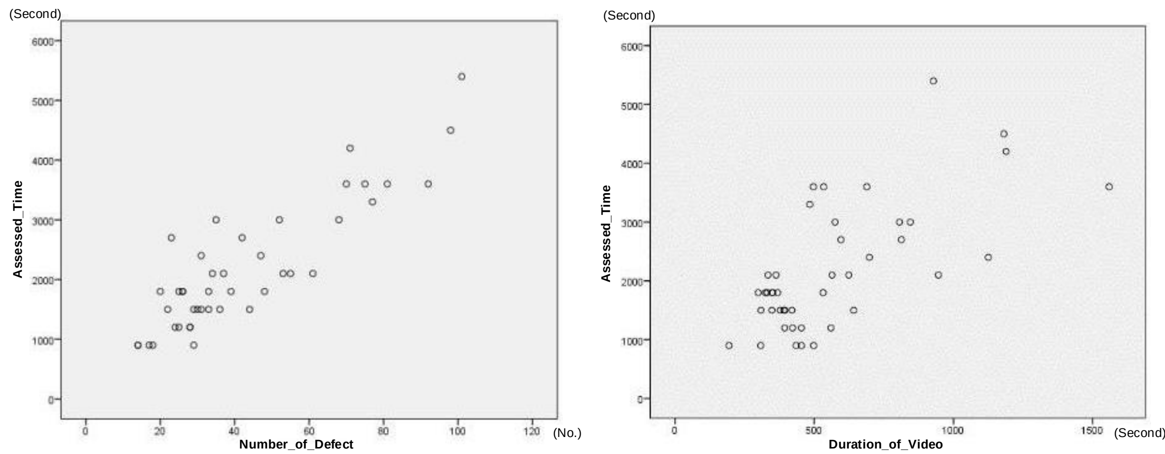
3.3 Assumption Verification for the Developed Models

- Linear relationship test

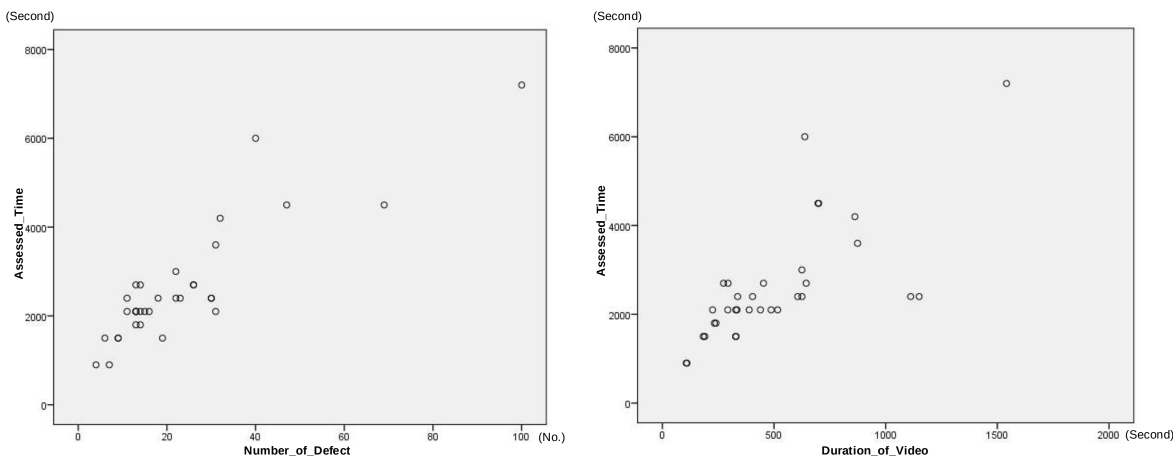
Before using the linear regression model, we assume there exists a linear relationship between the dependent variable and each independent variable selected in the developed models. To verify this point, the results are shown in Figure 3.



(a) Technologist #1



(b) Technologist #2



(c) Technologist #3

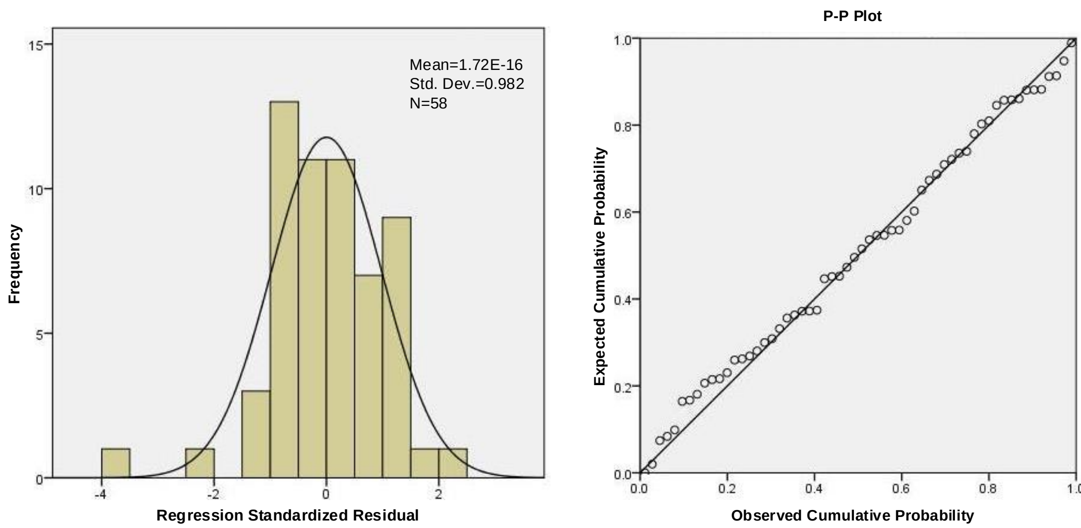
Figure 3: Linear relationship test for all variables

- Durbin-Watson test

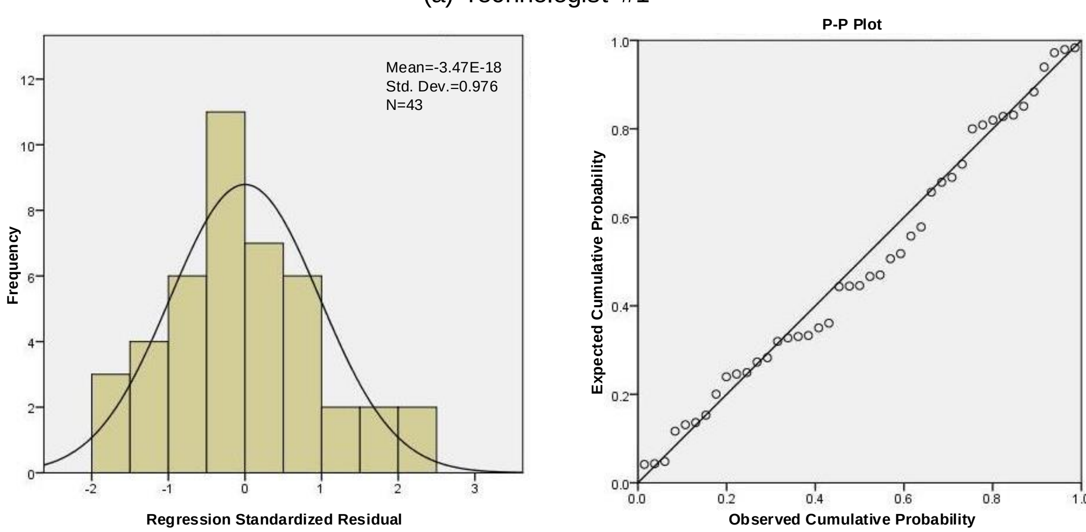
The Durbin-Watson test is used to verify whether there exists autocorrelation in residuals from the statistical regression model. Generally, if the range of the Durbin-Watson value is between 1.5 and 2.5, it indicates there is no autocorrelation among the residuals in the sample (Leung et al. 2000). As for the developed models, the Durbin-Watson values are 1.868, 1.466 (nearly 1.5), and 1.665 for Technologist #1, Technologist #2, and Technologist #3, separately. Hence, the developed models are found to satisfy this assumption for residuals.

- Histogram & P-P plot

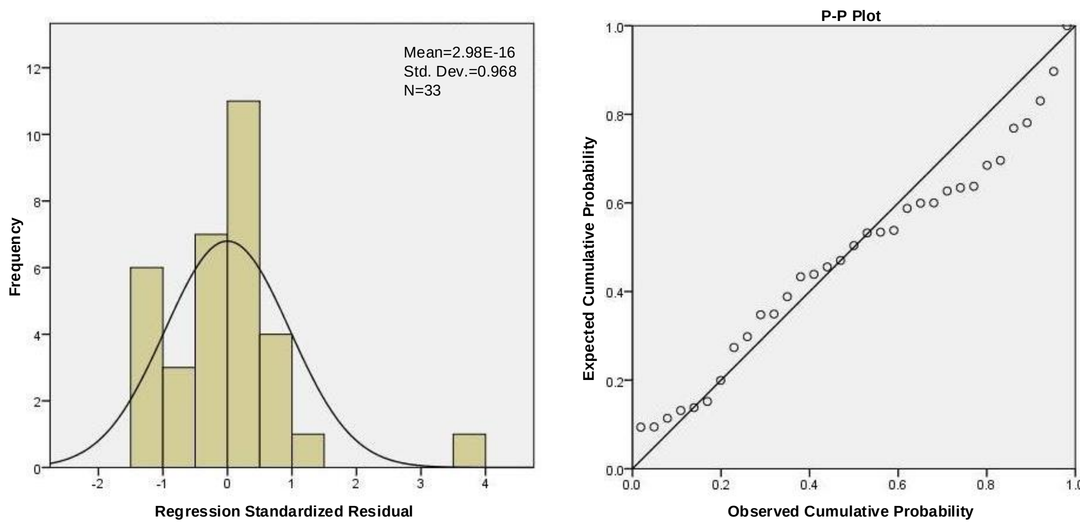
The histogram is used to display the distribution of regression standardized residuals, while the P-P plot is used to investigate the deviation between the observed cumulative probability of standardized residuals and their expected values. For instance, if the points in the P-P plot are distributed much closer to the diagonal, it indicates the greater normality. Hence, these two approaches help to verify whether the standardized residuals in the statistical regression model satisfy the normal distribution (see Figure 4).



(a) Technologist #1



(b) Technologist #2

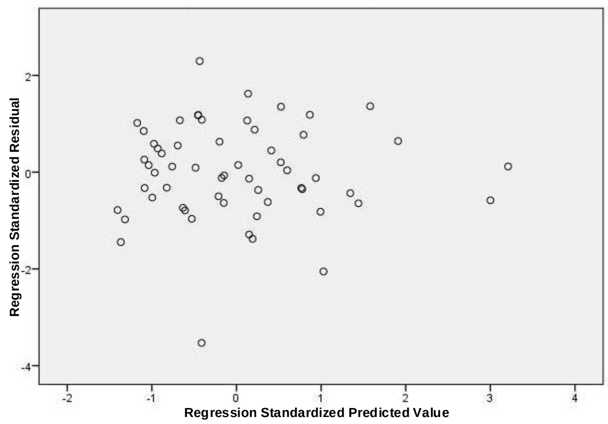


(c) Technologist #3

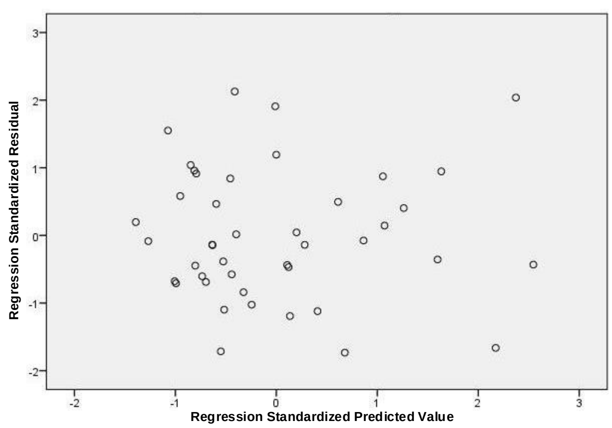
Figure 4: Histogram & P-P plot for regression residuals

- Scatter plot of the residuals

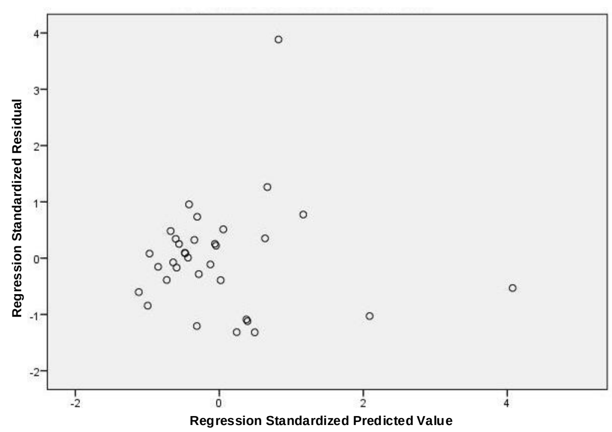
The scatter plot is used to verify whether the variance of standardized residuals is stable, meaning their distribution is scattered evenly around the value of 0. In this case, the linear regression model satisfies the assumption that the mean of the residuals is 0 and that its variance is constant (the results for the three developed models are shown in Figure 5).



(a) Technologist #1



(b) Technologist #2



(c) Technologist #3

Figure 5: Scatter plot for regression residuals

4 CONCLUSION

This paper develops a productivity analysis model for the manual condition assessment for sewer pipes based on CCTV monitoring. Using sewer networks in the City of Edmonton, Canada as a case study, three linear regression models are developed for the corresponding technologists in order to investigate the primary factors influencing assessment productivity individually. The overall goodness-of-fit values exceed 80%, indicating all the developed models can explain the assessment productivity with reasonable accuracy, although there is diversity in influencing factors of productivity. The common factors among the three technologists are the number of defects in the pipe and the video duration, which determine labour productivity to a varying degree. If the number of defects can be roughly estimated by some approaches/counting tools, this model is applicable to predict the total time a given technologist would spend on a certain workload of pipe assessment in order to reasonably schedule his/her task. Meanwhile, managers can allocate human resources more efficiently and adopt technical training in order to standardize assessment productivity of all technologists. Considering the large constant value for two of the three built models, future study may take other influencing factors into account to conduct a more reasonable linear regression model aiming at a specific technologist.

ACKNOWLEDGEMENTS

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