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WORK ORDER PRIORITIZATION USING NEURAL NETWORKS TO IMPROVE BUILDING OPERATION

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SUMMARY: *Current practices for prioritizing maintenance work orders are mainly user-driven and lack consistency in collecting, processing, and managing the large amount of data. While decision-making methods have been used to address some of the existing challenges such as inconsistency, they also have challenges including variation between comparison during the actual prioritization task as opposed to those outside of maintenance context. The data analytics and machine learning methods can help with extracting meaningful and valuable information, finding patterns, and drawing conclusions from the available data. Such methods have benefits including faster prioritization performance leading to less failure and downtimes, reduced impact of knowledge loss, decreased cognitive workload, identification of errors for adjusting the system, and determination of important factors impacting work order processing to support the development of data requirements. This paper summarizes the background on existing gaps in processing maintenance work orders and provides an overview of machine learning methods to support prioritizing work order. The paper then discusses the work order data of an educational facility as a case study, presents information on data exploration and data cleaning approach, and provides insights gained from their maintenance work order data. The insights gained present challenges such as submission of multiple work orders as one, missing data for certain criteria, long durations for addressing some of the work orders, and the correlation between criteria collected by the facility and the schedule. The paper continues by implementing artificial neural networks to benefit from work order data collected for automatically prioritizing the future work orders. The results present the optimum neural network structure based on mean squared error estimated and provides the best value for each parameter used for the development of the model. The accuracy and efficiency of the developed model was validated by the facility experts of the educational facility.*

KEYWORDS: *Facility Management, Maintenance Work Order, Prioritization, Artificial Neural Network.*

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1. INTRODUCTION

Facilities management (FM) is "a multidisciplinary or transdisciplinary profession drawing on theories and principles of engineering, architecture, design, accounting, finance, management, and behavioural science" (Teicholz, 2001, p.1.3). Prioritizing maintenance work orders is one of the challenges faced by facility managers as current practices lack consistency in collecting, processing, and managing the large amount of work orders and data. Based on previous extensive literature review, interviews, and surveys conducted in prior study (Ensafi et al., 2021, Ensafi et al., 2023, Ensafi et al., 2024), current practices heavily depend on user-driven approaches and the prioritization of work orders has been done manually or partially through management systems. This common approach used by many facility managers present many challenges.

The lack of information requirements has led to inconsistency in data collection and processing (Yang & Ergan, 2017; Lavy et al., 2019). Information requirements are needed to determine what data should be collected and how the data should be processed while also considering the organizational goals and avoiding generalization to all types of facilities (Besiktepe et al., 2020). Although some facilities collect information related to processing and performing maintenance tasks, not all of them benefit from the data collected. On the other hand, the information collected is not necessarily useful for future work order processing. The discontinuous data collection in different stages of work order processing hinders the opportunity to benefit from the collected data. Facilities need to understand the data overlap between different stages of work order processing to develop practical data requirements (Ensafi et al., 2023).

The traditional process of work order processing is impacted by individuals' knowledge, experience, workload, and some biases. There are variabilities across individuals' criteria selection and decision-making approaches leading to uncertainty, inconsistency within the input data, and poor performance (Ensafi et al., 2023). The extent of knowledge and experience of the staff who analyze the service requests can influence the work order processing (Cao et al., 2015; Tam et al., 2017). The lack of knowledge about asset performance will lead to errors and asset failure impacting the cost of O&M (Bayasteh et al., 2019; Salem & Elwakil, 2018) and occupants' safety and satisfaction (Cao et al., 2015). On the other hand, analyzing such large amount of information can lead to cognitive workload leading to different coping strategies including trading precision for speed and time, neglecting to process certain categories, stretching existing evidence to fit a new situation (Hollnagel & Woods, 2005). Furthermore, humans may be impacted by various cognitive biases such as focusing on limited objectives due to ambiguous nature of strategic decision making (Schwenk, 1985).

The existing processes require adequate staffing to fill the shifts for receiving work orders and there are mostly more work order requests than available staff for addressing them (Beauregard & Ayer, 2019). Making decisions and responding to many requests demand intensive labor hours (Chong et al., 2019). However, experienced individuals who have good knowledge of the facility are currently selected for processing work orders. At the same time, if the selected individuals leave the facility or retire, their expertise and knowledge will leave with them and may not be transferred to new individuals responsible for processing work orders (Ensafi et al., 2023).

While decision-making methods such as Analytical Hierarchy Process (AHP) (Saaty, 2008) have been used to improve the consistency of prioritization, they also represent challenges and gaps in their application. First, because of information overload resulting from processing multiple attributes for each alternative and because of limited human cognition capacity, humans are not able to compare multiple pairwise alternatives with different attributes at the same time. Such difficulty negatively impacts the decision-making process (Dixit, 2018; Hollnagel & Woods, 2005). Based on the results of prior study (Ensafi et al., 2023), the alternative comparison varies and is more realistic when performed during the actual work order prioritization task as opposed to outside of maintenance context. Third, pairwise comparison matrices are not assessed in a consistent manner by humans since they cover a combination of quantitative and qualitative analysis (Dixit, 2018). Lastly, the process and weights estimated are not evaluated, adjusted, and updated over time (Ensafi & Thabet, 2021).

The data analytics and machine learning methods can help with extracting meaningful and valuable information, finding patterns, and draw conclusions from the available data to support future decision-makings (Assaf et al., 2020; Jiang et al., 2020; Yang & Bayapu, 2019). Such methods allow faster prioritization performance leading to less failure and downtimes. They can capture the user knowledge removing the negative impact of staff leaving the facility while reducing the impact of lower level of experience and background knowledge on processing future work orders. Additionally, automating the work order processing can reduce the cognitive workload on facility staff allowing them to focus on critical thinking and emergency situations rather than routine tasks. Implementing machine learning will allow processing based on multiple inputs possibly reducing the impact of biases. Data analytics allows identifying important criteria by determining the relationship between different factors used for processing. This will also support the development of practical data requirements. Finally, an automated approach enabled by neural networks allows the automatic adjustment and update of the system based on new data and input providing a more practical solution over time. Neural networks are selected over other Machine Learning (ML) methods as they learn themselves and determine what is important without requiring a defined set of rules. Additionally, Artificial Neural Networks (ANNs) allow to consider more criteria (features) providing a more comprehensive solution as opposed to a human operator, and at the same time, it can determine the optimum number of criteria eliminating the collection of unbeneficial criteria.

The goal of this paper was to implement ANNs into work order data received from an academic facility in order to automatically prioritize their future work orders based on their historical work orders. This paper provides an overview of machine learning methods and especially neural networks for addressing some of the challenges with exiting practices for processing maintenance work orders. In order to conduct this research, the work order data of an educational facility was used. The received work order data was analyzed and preprocessed to automate the work order prioritization using neural network. The results present the optimum model configuration as well as optimum values for different hyperparameters for implementing neural networks to automatically process and prioritize future work orders.

2. LITERATURE REVIEW

Due to the rapid improvement of technologies used for facility management, more complicated and larger amount of data are created and are available to facility managers (Cao et al., 2015). Facility managers can use different tools and platforms to capture information, perform analysis, and draw conclusion on past performance while also anticipating future trends using Artificial Intelligence (AI) and Machine Learning (ML) (IFMA, 2021). Machine learning is "the process of training a computer model on a training dataset to perform a certain task so that it will be able to perform that exact task when given new data it had not encountered before" (Assaf et al., 2020, p.173).

Recently, an increasing number of studies are adopting AI techniques and ML algorithms to address design (Feng et al., 2019), construction (Ensafi et al., 2022), and facility management challenges (Awada et al., 2020; Feng et al., 2017; Tabrizi et al., 2012). Researchers have implemented AI and ML to address different aspects of building operation phase including air quality (Xie et al., 2020), energy consumption (Hajj-Hassan et al., 2020; Lu & Feng, 2020), and cost analysis (Liu et al., 2020; Gao et al., 2019).

Maintenance work orders can be prioritized by collecting and providing access to necessary information. Developing data requirements in strategic, management and operations levels (Chanter & Swallow, 2008) and implementing data-driven decision-making methods can support consistent and continuous data collection, storage, and analysis to support existing challenges with user-driven decision makings. Such approach can improve the quality of the work performed.

Researchers have considered data analytics and ML implementation for addressing challenges related to the work order processing. Assaf et al. (2020) used machine learning algorithms to address predictive maintenance by analyzing occupants' complaint data. They implemented text mining to identify the most frequent complains of the occupants. Based on their results, complains related to air conditioner were among the most frequent complains. They then used ML to develop a model to predict the future complains in order to help FM professionals to plan ahead. Cao et al. (2015) developed a framework using artificial intelligence to prioritize work orders based on both occupants' and facility managers' feedbacks. Considering occupants' satisfaction and safety is among the criteria considered when processing work orders. Being able to draw conclusions from previous work orders can help with developing better plans with addressing future work orders.

Besiktepe et al. (2019) used historical work order data in educational institutions to identify the frequency of maintenance activities and explore possible relationship between building age and type and maintenance activities. Their study identifies the systems with highest maintenance frequency and their results indicate no relationship between building age and type and the maintenance activities. Yang et al. (2018) developed a failure mode and effect analysis (FMEA) method using data mining to address the HVAC maintenance issues. They used the work order data from building energy management systems. Based on their results, the analysis of work order data can help with determining parameters for FMEA models while it can also help with determining the high impact failures. Furthermore, their results indicate that there is a relationship between frequency of faults and building type. Determining the frequency of maintenance activities of an asset can impact the FM approach in different aspects including priority of the asset or the maintenance type. Furthermore, data analytics allow other determining factors impacting the process of work orders such as building type in order to provide a more comprehensive and practical solution.

Kolokas et al. (2018) used the data collected from sensors and implemented artificial neural network for detecting and predicting faults in industrial equipment. Their results support predictive maintenance. The ML classifiers used in their study allowed them to predict equipment failures five to ten minutes before the breakdown using the changes from the data collected by the sensors. Canizo et al. (2017) implemented random forest to their workflow to predict wind turbines failures to address predictive maintenance. Although their results presented an overall success in predicting failures, they believe that there is a need for accuracy improvement. Current predictive maintenances are mainly scheduled based on the recommendation of the manufacturer. Updating the predictive schedule based on actual performance of the assets supports higher quality of services provided by the facility. Additionally, being able to predict failures ahead of time allows avoiding downtimes which leads to less facility cost.

Lempert et al. (2016) implemented machine learning for prioritizing road repair tasks according to optimal utilization of resources. Their proposed solution is based on defect recognition and classification methods and allows prioritizing the future repair tasks based on their historical data. Abdelrahim and George (2000) implemented the neural network into the process of prioritization and selection of pavement maintenance strategy based on the level of alligator cracks, traffic volume, condition of the pavement, distress type, and road class. Collecting and storing data in consistent and continuous matter allows benefiting from historical data to support processing future work orders. Such approach accelerates processing work orders while allowing the system to update over time.

Using the data from previously prioritized work orders and schedules and implementing data analytics to identify the associated weight of each criterion can assist with prioritization of future maintenance work orders. It can also help with defining data requirements and hence increasing consistency while reducing processing time. As discussed above, neural networks have been used in some fields such as road maintenance to prioritize a set of alternatives (Lempert et al., 2016). With defined framework, the neural network can be used to address the maintenance of building facilities by supporting the automation of maintenance work order processing. Among the different ML methods, neural network would be a better fit for addressing this problem because first, neural networks can be used with higher dimensional data corresponding to including more criteria. Such approach allows considering all influential criteria in decision-making leading to more accurate results. Second, neural network allows determining the right number of criteria based on the concept of overfitting/underfitting. Third, they can calculate the weights of the criteria based on the interaction between different criteria and the arrangement of neurons. Fourth, neural network can create the best arrangement itself to make accurate decisions without the need to specify the interaction by the modeler (defining rules in advance) while other ML algorithms require human intervention. fifth, neural network can be modified and adjusted based on new inputs. If the facility staff make any changes to the rankings and schedules created, the system can automatically learn from the changes occurred and implement that to the future prioritization. Such approach avoids manual changes providing a more practical solution over a longer time span while improving the performance of the system. Implementing data-driven decision-making using neural networks can therefore address human limited cognitive capacity and reduce cognitive workload by performing main part of prioritization task allowing FM staff to focus on abnormalities and emergency situation requiring higher decision-making skills. It can also reduce coping strategies. Additionally, processing work orders considering previous input from multiple users allows required adjustments and hence minimization of judgment and cognitive biases' influence. This paper aims to address the following research questions: 1) Can neural network prioritize work orders based on previous schedules created to support accuracy, efficiency, and consistency (in terms of criteria used)?; 2)What is the optimum neural network structure for prioritizing maintenance work orders based on the data received from an academic institution (case study)?

3. METHODOLOGY

To conduct this research, a case study approach was taken to investigate the implementation of neural network for prioritization of actual work order data. The operation and maintenance work order data from an educational facility was received, processed, and analyzed to develop the neural network model supporting the processing and prioritization of future work orders. Figure 1 presents the research steps taken to analyze and implement neural networks to the work order data received perform the educational facility and presents what has been addressed under each step. An application was submitted to the institutional review board (IRB) at Virginia Tech under the protocol number IRB- 20-879. According to the study objectives, IRB determined that the proposed activity is exempted for further review.

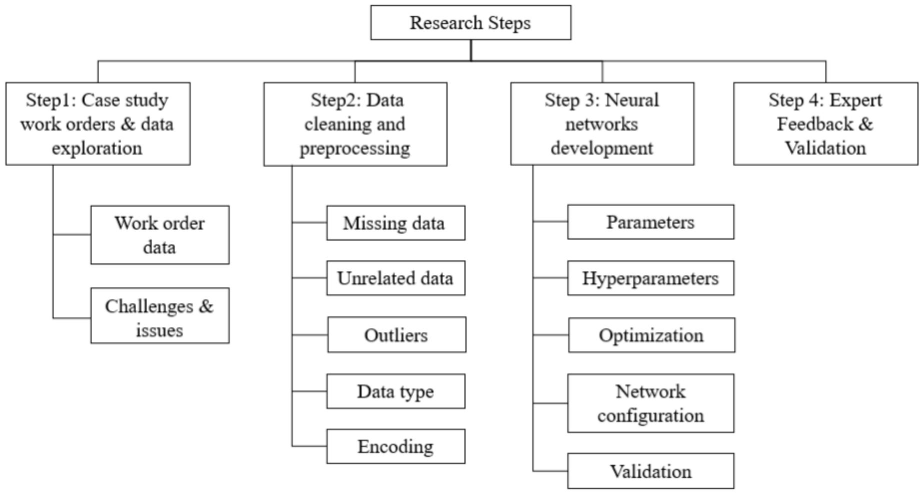

Figure 1: Research steps.

Step 1: The work order data collected during the past eight years by an educational facility was received for this research. The data included the work orders and 12 criteria (Table 1) mostly populated in the facility system to support the processing of their work orders. The data received was explored to understand the data and identify any challenges associated with their data such as missing data. Data exploration is a significant part of the process of developing machine learning solutions in terms of understanding the data, addressing the data quality challenges, and preparing the data for development (Kelleher et al., 2015). The accuracy and quality of data impacts the training process as well as the performance of the machine learning model and its outcome (El Naqa et al., 2018). Furthermore, since the data generated by the developed ML models feeds back into the models to further develop and train the models, small accuracy error can lead to extreme deviations from real outcomes over time (Polyzotis et al., 2019). This highlights the importance of data quality during different stages of data preprocessing including data analysis (Hellerstein, 2008). Researchers have indicated that poor data quality has cost businesses in the United Stated about $700 billion annually since problems raised from data quality issues can lead to project failure and revenue lost (Gudivada et al., 2017). Examples of data quality challenges include missing value, extreme high value or outliers, wrong value, false and/or inconsistent values, false data type, and new feature identified (Kelleher et al., 2015; Krishnan et al., 2016; Polyzotis et al., 2019).

Step 2: Data cleaning and preprocessing were carried out on the work order data of an educational facility to address the identified challenges and prepare the data for model training. As part of this step, a first meeting was conducted with the facility to receive their input and opinion about parts of the data cleaning processing (e.g., removing outliers). Data cleaning and preprocessing was performed using Python libraries including Pandas (McKinney, 2011), Numpy (Van Der Walt et al., 2011), scikit learn (Pedregosa et al., 2011). Data cleaning is "the process of detecting and correcting errors in data" (Chu et al., 2013, p.458). The importance of data cleaning has been highlighted by different researchers (Volkovs et al., 2014; Schelter et al., 2018; Gudivada et al., 2017) as inconsistent and incorrect data can negatively impact the results. Models developed with faulty data will lead to unreliable decisions taking away the benefits of data-driven decision-makings (Chu et al., 2016). Data preprocessing is the steps taken to transform the raw data to a format that can be used and analyzed by machine learning. Examples of such steps include encoding or the selection of the features to be used by the machine learning model (Gao, 2012).

Data cleaning techniques can be categorized into two groups: quantitative and qualitative (Chu et al., 2016). Qualitative techniques use constraints, rules, and patterns to identify the errors (duplicates, misclassification, misspelling and typos) (Hellerstein, 2008). Examples of setting constraints include specifying a one-way relationship between two attributes (Harrington, 2016), defining a set of values that are valid for a feature such as data type (Calı et al., 2003), or indicating that the primary key value which is the identifier cannot be null (Huang, 2017). This technique was used when working with contextual data such as using work description and building names to fill in the missing data for latitude and longitude. This technique was also used to search through work description and removed unrelated work orders, search through completion dates and remove rows with empty cells and change the user values with categories of years of experience. The quantitative techniques use statistical methods such as probabilities, mean, or distribution for identifying the outliers, errors (e.g., duplication, incorrect or missing values), and abnormalities (Hellerstein, 2008). This technique was used for dealing with numerical data such as filling the missing values for hours and number of crews using medians. The quantitative technique was also used for determining and removing outliers based on the duration taken to address maintenance tasks and was used to identify the correlations between criteria used and the schedules. To address the data quality challenges identified, data cleaning and preprocessing was performed using Python libraries including Pandas (McKinney, 2011), Numpy (Van Der Walt et al., 2011), scikit learn (Pedregosa et al., 2011) libraries.

Step 3: The cleaned data was used to implement neural networks, determine the best configuration, and automate the prioritization of work orders. Recently, Artificial Neural Networks (ANNs) have become popular and useful for problem-solving in various fields. The ANNs models can be used for addressing pattern recognition, natural language processing, classification, prediction, etc. (Abiodun et al., 2018). Artificial Neural Network is one type of machine learning models which reflects and mimics the behavior of the human brain to understand the relationship between a set of data allowing computer programs to solve complex data-driven problems (Abiodun et al., 2018; Wang, 2003). Neural networks can learn from modified inputs the need for redesigning the criteria and framework providing the most efficient and practical solution without manual modification (Abiodun et al., 2018).

First, 20 percent of the data was separated to be used for validation after training and testing the data. This approach is used to isolate a subset of the data on which model validation is performed with the same input condition (Duval, 1992). Using the Scikit learn library in Python, the remaining 80 percent of the cleaned data was randomly divided into training (64% of the total data) and test set (16% of the total data) in order to develop the neural networks model. An initial network architecture was chosen to start the training process. The TensorFlow (Abadi et al., 2016) and Keras (Chollet et al., 2015) libraries were used for developing the ANN model by determining the number of nodes for the hidden layers and changing the model hyperparameter (e.g., learning rate, distribution) to determine the best values for the model. As shown in Figure 2, neural network models consist of three sections: input, hidden, and output layers of neurons or nodes. The input layer represents the predictive features. The hidden layer represents an aggregation of information from input data. The more nodes included in the layers; the more interactions will be captured which finally impact the results (output layer). The connections between neurons are called edges and are associated with the numerical values of weights which indicate how strong a layer/node impacts the next layer/node.

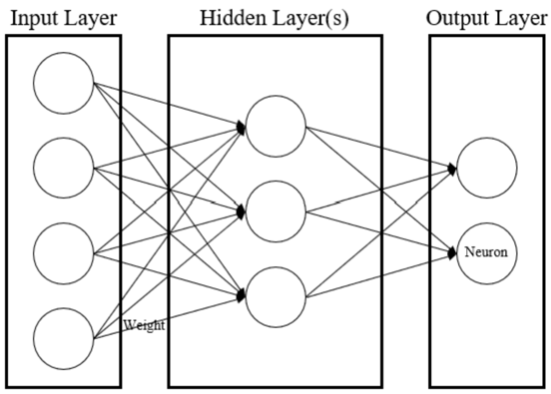

Figure 2: General neural network model.

For model training, the model takes the criteria (features) and their associated values as input and uses the duration taken from the date the work order is created until the date the maintenance task is completed as the output (expected result). Through the training, the model estimates the weight of each input in the hidden layer/s based on the outputs. Depending on the needs of the model, the hidden layer consists of one or more layers performing transformation on their input. The mean squared error was selected as the metric or loss function to obtain the best hyperparameters determining the best network configuration and supporting the performance of the model. The neural network starts with assigning random weights in the hidden layer to predict the output. Then the error indicating the difference between model's output (output layer) and previous recorded outcomes is calculated. The goal of the training model is to minimize that error by adjusting the weight of the edges connecting different neurons. To do so, backpropagation method is used to divide the error between the connections (Wang, 2003). The training of the neural network can be either based on the desired number of iterations or the desired error level.

After training the model, the test set would be given to the model and the output would be estimated by finding the sum of the weighted inputs. Through the test set, the accuracy of the model is estimated by comparing the results of the test and training sets. As this research only has access to one database, the 20 percent of the same database separated at the beginning was used as new data to validate the developed model using the results of mean squared error.

Step 4: A second meeting with three facility experts in the area of building operation and maintenance from the educational facility was conducted to first receive feedback regarding the insights gained from data exploration, cleaning, and preprocessing, and second validate the results of the developed neural networks model. This approach allows the facility expert to provide a shared opinion while providing feedback on a proposed model that deals with their daily practices adding to the insights of using ML models. The discussion was conducted through videoconferencing (zoom online meeting) and took about an hour. First, the results of data preprocessing, correlations determined, the parameters (features) used for this study, and the challenges with data preprocessing were discussed with the facility professionals to receive their opinion on the process and results. Second, the time that takes a facility staff to process 50 work orders (as they receive 50-70 work orders per day) was compared to processing time of the model and was discussed with the facility experts to measure the efficiency of the proposed approach. Third, the result of the 50 prioritized work orders performed by a facility staff was compared to the results of the model prioritization to determine the accuracy of the model. In the final step, the facility professionals were asked to provide feedback and discuss the advantages and disadvantages of using the model for prioritization.

4. WORK ORDERS AND DATA EXPLORATION (STEP 1)

The work order data of an educational facility was used to explore and process the work order data (Figure 3) and implement neural network for future work order processing. The educational facility has 213 buildings covering offices, classrooms, dining services, dormitories, laboratories, students' activity complexes. The buildings' area ranges from 685 sq ft to 418000 sq ft. The facility uses an in-house software for receiving the work orders and the work orders are processed and prioritized manually by the staff.

Total of 333436 work orders were received from the educational facility. The data collected from the facility covers the work order data from the past eight years (2014-2021). The facility receives approximately 50 to 70 maintenance requests per day on average (depending on the day and season). Based on the discussion with the facility as well as prior research (Ensafi et al., 2023, Ensafi et al., 2024), 12 criteria (Table 1), mostly used and populated in the facility system, were requested from the facility for the development of the neural network model. To consider the possible impact that years of experience had on the decision-making process, one of the selected criteria was the user who processed the work orders. Table 1 provides the description of the data received from the facility as well as the data type for each criterion.

Clerk	Date created	Order type	Category	Craft	Shop	Maintenance Type	Work Description	Building Type	Latitude	Longitude	Labor	Total hours	Date completed
ENTCLERK76	2014-09-29 7:35:10 AM	OP	PM	PM	PREVENTATIVE MAINTENANCE	4-SCHEDULED	SEMI ANNUAL SERVICE OF FUME HOOD EXHAUST FANS IN XXX	GENERAL PURPOSE BUILDING	Latitude 1	Longitude 1	1	7.82	2014-10-30 2:12:39 PM
ENTCLERK76	2014-09-29 7:35:11 AM	OP	PM	PM	PREVENTATIVE MAINTENANCE	4-SCHEDULED	SEMI-ANNUAL SERVICE OF EXHAUST FANS IN XXX BUILDINGS WITH PM COVERAGE	GENERAL PURPOSE BUILDING	Latitude 2	Longitude 2	2	0.44	2014-10-30 2:17:30 PM
ENTCLERK14	2014-10-15 7:48:15 AM	OP	CM	EL	ELECTRICAL	3-ROUTINE	XXX - NO POWER TO DOMESTIC HOT WATER PUMP	GENERAL PURPOSE BUILDING	Latitude 3	Longitude 3	3	6.64	2014-11-20 4:29:02 PM
ENTCLERK14	2014-10-15 7:54:36 AM	OP	CM	EL	PREVENTATIVE MAINTENANCE	3-ROUTINE	XXX 441A - LIGHT OUT IN MECHANICAL ROOM NEAR BOILERS	GENERAL PURPOSE BUILDING	Latitude 4	Longitude 4	3	4.35	2014-10-21 10:58:26 AM
ENTCLERK14	2014-10-15 8:05:41 AM	OP	CM	DOOR MAINTENANCE	PREVENTATIVE MAINTENANCE	3-ROUTINE	XXX - 3RD FLOOR DOOR NOT CLOSING PROPERLY, BOLTS CAME OUT OF CLOSER IN THE STAIRWELL.	GENERAL PURPOSE BUILDING	Latitude 5	Longitude 5			2014-10-16 6:48:00 AM
ENTCLERK39	2014-10-15 2:23:12 PM	OP	CM	GR	GROUNDS	3-ROUTINE	XXX- PLEASE REMOVE METAL POST WHERE TREE WAS CUT DOWN AT GRAVEL PARKING LOT ON LEFT IF COMING UP FROM DUCKPOND	AUXILIARY SERVICES	Latitude 6	Longitude 6	3	1.5	2014-10-20 8:57:58 AM
ENTCLERK39	2014-10-15 2:33:37 PM	OP	CM	HVAC	REFRIGERATION	3-ROUTINE	XXX-300 TOO HOT	GENERAL PURPOSE BUILDING	Latitude 7	Longitude 7	4	14.2	2014-10-24 2:32:51 PM
ENTCLERK14	2014-10-15 3:16:50 PM	OP	CM	ELEV	ELEVATOR	2-URGENT	ELEVATOR REPAIR - ELEVATOR IN FRONT LOBBY NOT WORKING.	GENERAL PURPOSE BUILDING	Latitude 8	Longitude 8			2014-10-17 2:13:14 PM
ENTCLERK88	2014-10-15 3:26:13 PM	OP	CM	RO	ROOFING	3-ROUTINE	XXX-OUTSIDE 3320--WATER CAME THRU THE PORT. SHOWS FRESH DISCOLORATION AND SOME BUBBLING.	GENERAL PURPOSE BUILDING	Latitude 9	Longitude 9	7	26.96	2015-01-06 1:44:46 PM

Figure 3: Example of data received

Table 1: Header's description

Header/criteria	Description	Data Type
Clerk	User who processed the work order. This column has later been transformed to years of experience of staff including small (below 2 yrs), medium (2-5 yrs), and high (over 5 yrs)	Categorical
Date created	The date and time the work order is entered into the system. Date and time when the work order is started is not known and is not tracked.	Date
Order type	Indicates the type of funding	Categorical
Category	Reflects a different categorization of maintenance type (e.g., corrective, preventative, renovations)	Categorical
Craft	Describes the shop responsible for addressing the work order (e.g., electrical, carpentry, elevator)	Categorical
Shop	The category of the work order (e.g., electrical, mechanical services, building trades, housekeeping)	Categorical
Maintenance Type	Describing the type of maintenance (e.g., scheduled, routine, urgent)	Categorical
Work Description	Short description of the work order	Textual
Building Type	The type of building (General Purpose Building, Academic/ Residence Building, Auxiliary Services, Physical Plant Building, Agriculture Services building, Single/Family Residence, Rental Property)	Categorical
Distance (Latitude/Longitude)	Distance from the main facility office (calculated using latitude and longitude)	Numerical
Labor	Number of labors for performing the maintenance task	Numerical
Total hours	The amount of time taken to perform the maintenance task	Numerical
Date completed	The date and time the work order (maintenance) is completed.	Date

The work order data received from the facility was further explored to understand the data and the features, determine irrelevant information, and identify challenges such as missing data and typos in order to address them. Data exploration was conducted by search through different columns to determine the empty cells, searching keywords in the work description column, and categorizing the rows based on a value for a specific column. Through exploring the work order data received, the following challenges were identified:

- Data included irrelevant work orders (e.g., work orders related to football fields, roads, bus stops) which needed to be removed.
- The "date completed" column had missing data. As this column covers the target for the machine learning model, the rows with missing data needed to be removed.
- The "Building Type", "Distance", "Labor", and "Total Hours" columns also had missing data.
- Some buildings had been demolished which needed to be removed from the list as they did not exist anymore.
- In some cases, instead of mentioning the location of the work order, the name of the facility staff which had the area assigned to them, was included in the descriptions. For instance, the requestor had entered "All my buildings" instead of the building name or the work order indicated "Inspect buildings in XXX's area".
- Some work orders included in the database were not actual work orders. They only covered discussions between facility staff such as pointing out an upcoming meeting.
- A few work orders included region number which was not discussed anywhere in the facility system.
- In few cases, multiple work orders were requested as one work order making it complicated to track resources, time, and labor.

5. DATA CLEANING AND PREPROCESSING (STEP 2)

The qualitative and quantitative methods were used to clean and prepare the data for implementation of neural networks. With reference to the third column in Table 1, the qualitative techniques were used when working with textual and categorical data and quantitative techniques were used for addressing numerical data. Both qualitative and quantitative techniques were used to prepare the data. Figure 4 presents the techniques used and steps taken to clean and pre-process the data.

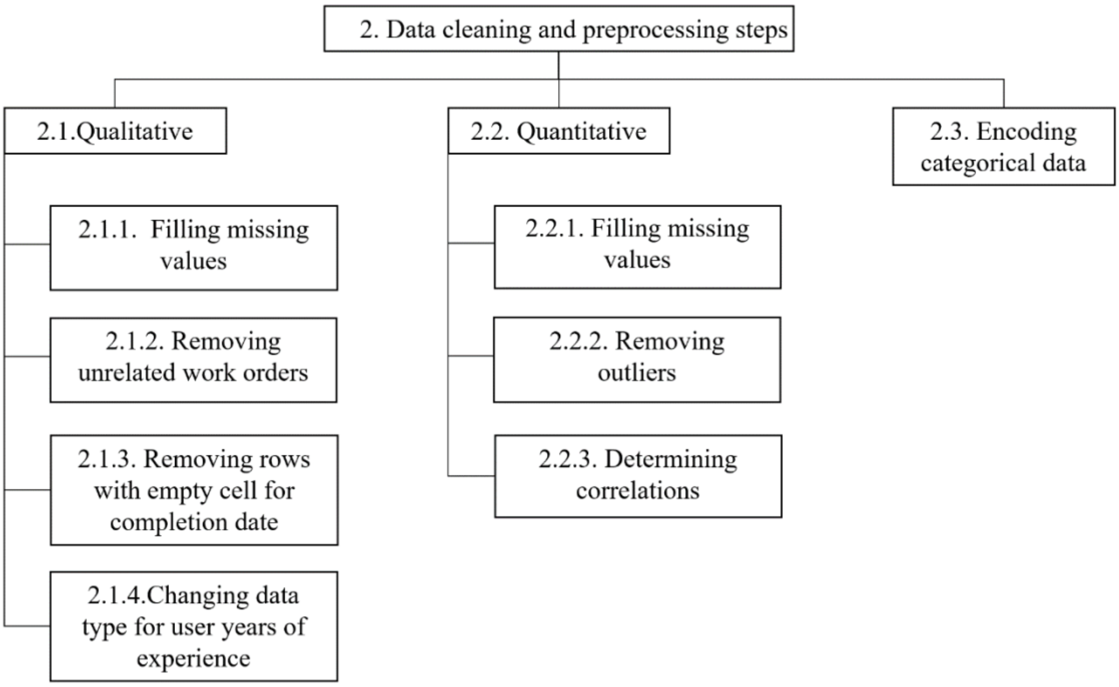

Figure 4: Steps taken for preparing the data.

For this research, the qualitative technique (Figure 4, step 2.1.) was first used to fill the missing values (Figure 4, step 2.1.1.) for "building type", "latitude", and "longitude" columns. To do so, the list of campus buildings was collected from the facility website which included the abbreviation and full name description for each building. The "Work Description" column in the work order database contained the building name or the building abbreviation. By using the exported list of building names and applying text mining code on the "Work Description" column, the building name or abbreviations were searched and identified in the description to fill in the missing values in building type, latitude, and longitude (distance) columns based on work orders associated with the same building which had a value for the mentioned columns (Pseudocode. 1).

```
List1 = [ Building ID, Latitude, Longitude] for all buildings
Object ID = [ Building ID | Non-Building-info]
Work Order Description = Object ID + Descriptive Information
List2 = [ Work Order Description] for all Work Orders
List3 = Work Orders containing Building ID in List2
For each "Building ID" in List3:
Do
Find the member containing the same "Building ID" in List1
        Get the associated Longitude and Latitude for that list member
        Append the extracted Longitude and Latitude to List2
Done
```

Pseudocode 1: Filling missing values.

The next step was to remove unrelated work orders (Figure 4, step 2.1.2.). Work orders containing the following keywords: purchase, road, bike rack, bus stop, seed, grass, sidewalk, and tree, were removed from the database as they were not addressing building operation and maintenance (Pseudocode. 2).

```
Object ID = [ Building ID | Non-Building-info]
Work Order Description = Object ID + Descriptive Information
List2 = [ Work Order Description] for all Work Orders

For each Work Order of List2:
Do
        If Work Order contains Non-Building-info:
                Delete Work Order
Done
```

Pseudocode 2: Removing unrelated work orders.

The “date completed” column was an important part of the database due to its significance in estimating the schedule and prioritization of the tasks performed which was used as the target column for the machine learning model. It was important to remove rows (Figure 4, step 2.1.3.) with missing value for this column. The qualitative method was then used to remove the rows with empty cells for this column.

The “clerk” column included the unique value for each facility staff processing work orders and needed to be changed to meaningful information (Figure 4, step 2.1.4.). The qualitative method was used to change the numerical values for the “clerk” to categorical values (Pseudocode. 3). The academic facility divides its staff into three categories based on their years of experience. After addressing all the missing data, the values for “clerk” column entered into the system was used to replace the values with one of the three categories (levels) of small (below 2 years), medium (2-5 years), and high (over 5 years) years of experience.

```
List1 = [ Clerk ID, The Range of Years of Experience] for all clerks
List2 = [ Clerk ID, Work Order Description, Other Work Order Info ] for all Work Orders
For each “Clerk ID” in List2:
Do
Find the member containing the same “Clerk ID” in List1
        Get the associated Years of Experience for that Clerk ID in List1
Replace Clerk ID in List2 with the extracted Years of Experience
Done
```

Pseudocode 3: Replacing clerk information.

The quantitative technique (Figure 4, step 2.2.) was implemented for further data cleaning. It was first used for addressing the remaining missing data (Figure 4, step 2.2.1.) and second, was used for removing the outliers based on the maintenance type (Figure 4, step 2.2.2.). Although some missing values were addressed using the qualitative method, the database still had missing values for “labor” and “total hours” which needed to be filled. The quantitative method was first used to simulate the missing data for “labor” (number of labors involved) and “total hours”. Using the rows filled with data, the data was grouped based on “Order Type”, “Category”, “Shop”, and “Maintenance Type” (Pseudocode. 4). These specific four factors were chosen based on the recommendation of the facility experts from the educational facility as they believed that rows with similar values for the four mentioned criteria can be used to simulate the labor and total hours. In other words, the values for labor and total can be almost similar when the values for the four parameters mentioned above are the same. About two percent of the data was removed as the entire category did not include any value for the labor and total hours columns. For the remaining data, the median value of each category was used for filling the missing cells. Using median instead of mean reduces the possible impact of any outliers.

After filling the missing data, the remaining data was explored as it is important to remove outliers from the database (Figure 4, step 2.2.). Outliers are datapoints that greatly differ from the rest of the data, and they can skew the final results. Based on the maintenance type (e.g., scheduled vs. emergency), the work order schedule estimated using the date created and date completed, was explored to identify outliers impacting the output column. Based on the recommendation of the facility experts, maintenance type was selected as a reference for determining the

```
List1 = [‘Work_order_Number’, 'Order_Type', 'Category', 'Shop', ‘Maintenance_TYPE’, ‘Number_of_Labors’] for all work orders
MetaData = Order_Type + Category + Shop + Maintenance_Type

List2 = [list of (GRP, MED) pairs] #Placeholder for Work Order Groups with similar MetaData (GRP), and associated Median number of Labors (MED).
For each work order in List1 that contains ‘Number_of_Labors’:
Do
Compare the MetaData for the current Work Order with the rest of the work orders in List1
MED = Median of the Number_of_Labors for all Work Orders with the same MetaData
GRP = [ list of Work Orders with the same MetaData]
Add (GRP, MED) to List1
Done

For each (GRP, Med) pair in List2:
Do
        For each work order in List1:
        Do
                If MetaData for GRP = MetaData for current work order in List1:
                        IF Number_of_Labors is empty:
                                Number_of_Labors = MED
        Done
Done
```

Pseudocode 4: Filling remaining missing data.

outliers as there should be a limitation in terms of how long the shops can take to address each maintenance type. The maintenance types were divided into four categories of emergency, urgent, routine, and scheduled. The following presents the definition of each category:

1. Emergency: immediate action required (e.g., security issue, life safety, life threating loss of research in a lab
2. Urgent: 24 to 48 hours response needed. (e.g., lights out, door not functioning, plumbing concerns)
3. Routine: one week response needed (e.g., replacement of ceiling tiles, HVAC filters)
4. Scheduled: should be addressed on specific date or month (e.g., fume hood)

The duration (number of days) taken for addressing each work order was calculated based on the date the work orders were submitted and the date on which the work orders were completely addressed. Given that the actual start date to perform each work order is not known (the educational facility does not track the date), it was assumed that the date and time the work order is entered into the system (Date Created) is the starting date/time of the work order. After determining the duration of the work orders in each category, the results were translated to Figure 4 and Table 2 and were discussed with the facility experts to determine the outliers based on the durations. Figure 5 and Table 2 summarizes work orders by maintenance type, duration to complete work orders divided into 5 duration categories and the number of work order in each duration category.

Based on the discussion with the educational facility and according to their practices, both 90 and 95 percentiles of each maintenance type were exported to be used for the machine learning model. Table 3 presents the maximum duration for each maintenance category. Work orders that took longer duration to be addressed were removed as they were counted as outliers by the facility. It is important to highlight that although a maintenance has been marked as urgent in the system, the time taken to address the maintenance may take longer than what is expected for such maintenance type depending on the issue identified and the resources needed for addressing the issue. The results of the 90 (283,325 rows) and 95 (299,065 rows) percentiles would be compared to select the best percentile in terms of model performance.

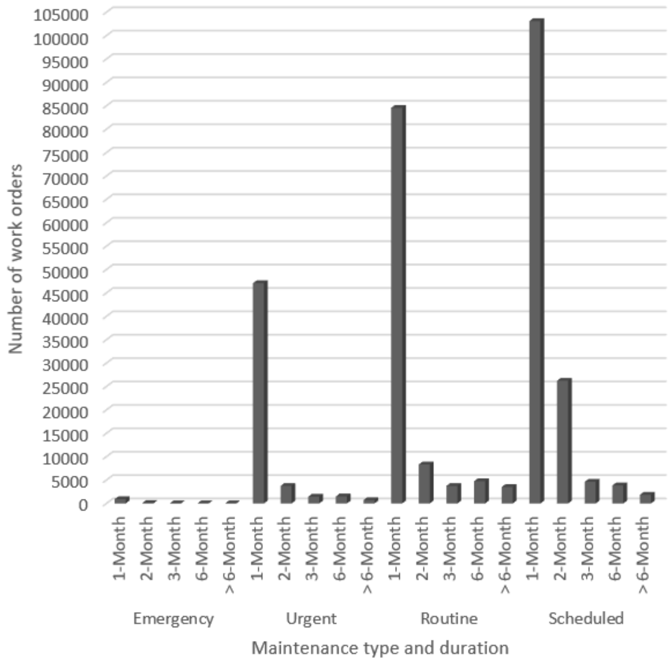

Figure 5: Number of work orders addressed for each maintenance type in the educational facility.

Table 2: Number of work orders addressed in each duration.

Maintenance type	Duration (Days)	Number of work orders
Emergency	<=30 Days	932
	30-60 Days	104
Total work orders: 1,131	60-90 Days	37
	90-180 days	42
	>180 days	16
Urgent	<=30 Days	47,083
	30-60 Days	3,748
Total work orders:54,493	60-90 Days	1,442
	90-180 days	1,502
	>180 days	718
Routine	<=30 Days	84,551
	30-60 Days	8,334
Total work orders:104,903	60-90 Days	3,744
	90-180 days	4,750
	>180 days	3,524
Scheduled	<=30 Days	103,107
	30-60 Days	26,229
Total work orders:139,663	60-90 Days	4,619
	90-180 days	3,848
	>180 days	1,860

In the final step of the data cleaning, the quantitative technique was used to understand the correlation between different parameters (features) in the database (Figure 4, step 2.3.). The correlation between different features included for the model was explored to make possible interpretations after the machine learning analysis. The correlations were estimated using the Dython library in Python (Dython, n.d.). Figure 6 presents the heat-map of correlations highlighting shop, craft, and category as parameters with the highest correlation with schedule (duration).

Table 3: Duration used for removing outliers.

Maintenance Type	Percentile kept	Duration (number of days)
Emergency	0.95	92
Urgent	0.95	77
Routine	0.95	140
Scheduled	0.95	79
Emergency	0.90	47
Urgent	0.90	42
Routine	0.90	76
Scheduled	0.90	57

After finalizing the database, "onehotcoding" from "sklearn" library was used to encode the categorical data (Figure 4, step 3). Onehotcoding turns the categorical data into multiple columns with each class being included in one column. It creates binary vector for each class removing the impact of numerical orders. For instance, if the building type has three types of A, B, and C, the building type column will be divided into three columns of Building A, Building B, and Building C. Value 1 indicates that the work order has that building type.

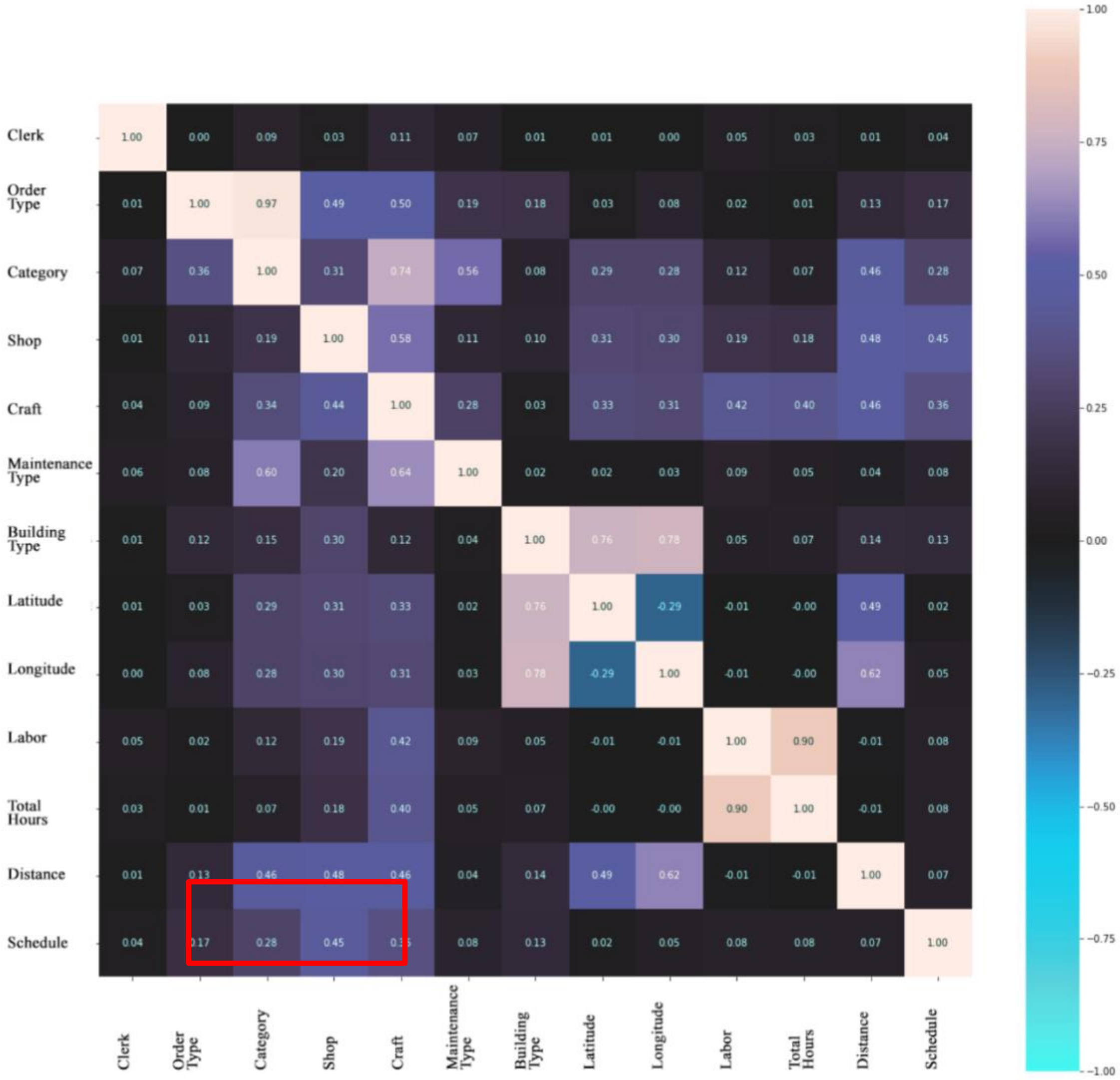

Figure 6: Correlation between different parameters.

Before using the data for neural networks, the dataset had to be normalized to create the same scale (ranging from 0 to 1) for all inputs and features. This technique helps when the database has features with different numbering scales. In this research, MinMaxScaler (sklearn library) was used to normalize the data.

6. ARTIFICIAL NEURAL NETWORK DEVELOPMENT (STEP 3)

After preprocessing and separating a set of data for validation, the remaining data was divided into a training set and a test set (train-test split). However, this method creates noisy results because of the randomness of the data and the stochastic nature of ANNs. In order to address the randomness of data (receiving different results when same model is trained on the same data) the same randomness (seed=7) was specified. Specifying a number for seed keeps the starting point the same and supports receiving consistent results when the model is trained on the same data again.

As discussed previously, the neural networks contain multiple layers including one input layer, one output layer, and one or more hidden layers. To perform the training, part of the criteria received from the facility (Figure 7, input) were used as features for the input layer of the model. The dates received from facility were used to estimate the duration by subtracting the two dates and times. The duration was used for the model output layer (Figure 7, output) for two main reasons. First, since the facility does not collect other dates associated with the work orders including the actual maintenance start date or the diagnostic duration. Second, based on previous discussions with the facility experts regarding their manual work order processing, it was identified that work orders with less distance or quick work orders were scheduled with higher priority as they could be addressed faster and be removed from the list. Therefore, it was assumed that the duration is the best feature that can be used considering what is collected by the facility and is stored in the database as well as considering their manual processing practices.

Input											Output
Clerk	Order Type	Category	Craft	Shop	Maintenance Type	Building Type	Latitude	Longitude	Labor	Total Hours	Work Order Duration

Figure 7: Input and outputs of the model.

Through the training process, the model uses the features (criteria) and their values to estimate the weight for each feature in the hidden layer/s and determine the significance of their impact on the duration/output (expected result). This is done by first assigning random weights to the neurons in the hidden layer and adjusting the weights using a loss function. A desired loss function, in this case mean squared error, is used through this process to adjust the estimated weights by minimizing the difference between estimated and actual output (duration). After training the model and determining the best network configuration, the test set is used to compare the results of the mean squared errors and ensure that the test set provides results that are close to results of the training model.

6.1 Development of the Neural Network Model

The TensorFlow (Abadi et al., 2016) and Keras (Chollet et al., 2015) libraries in Python were used to design and create the neural network model in order to train and test the data. Through creating the model, the number of nodes for hidden layers were determined, the values for hyperparameters were defined, and the activation function (relu and sigmoid) and optimizer (adam) were selected. After compiling the model, the KerasRegressor was used to convert the model to a scikit learn (Pedregosa et al., 2011) model to be able to optimize the model using GridSearchCV. The following sections provide the details of these steps (Figure 8).

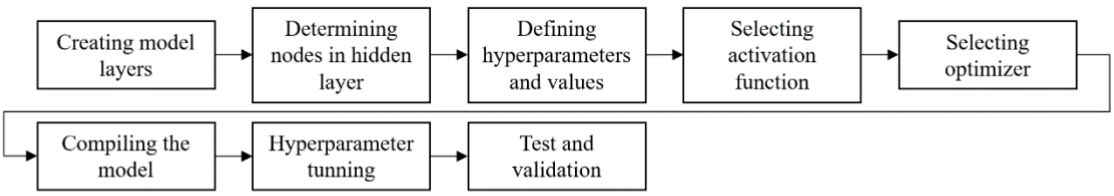

Figure 8: Steps taken to develop and test the model.

The size of the network depends on the number of nodes, the width depends on the number of nodes in a layer, and the depth describes the number of layers in the network. Although some literatures have counted one hidden layer as sufficient for approximation of most functions (Goodfellow et al., 2017), others have argued that one hidden layer is not sufficient or not as efficient as having multiple layers for all functions (Reed & MarksII, 1999). A sequential multiple-layer network or Multilayer Perceptron (MLP) was used as more than one layer was required for a multi-dimensional (multiple features) problem. The MLP constitutes a sequence of layers containing an input layer, one or more hidden layers, and an output layer. An important aspect when choosing a sequential MLP model is determining the number of hidden layers and the number of nodes in each layer.

First, the number of nodes for the hidden layers were determined using the number of nodes in the input and output layers. In the next step, a function was defined to vary the model hyperparameters in order to determine the best values for the model values as they control the training process. As opposed to parameters which are learned through the training process (e.g., weights), hyperparameters are the properties that should be determined and set prior to training as they are not learned through the process. The function defined changes the value for five hyperparameters of number of nodes in the first layer (number of features), number of samples per gradient update, learning rate (how quickly the parameters are updated by the network), distribution, and the total number of layers (input, hidden, and output layers). The following presents the values tested for each mentioned hyperparameter.

- First layer nodes' range: (55, 195, 10)
- Batch Size: [32, 64, 128, 256, 512]
- Learning rate: [0.005, 0.01, 0.1, 0.2, 0.3]
- Distribution: ['uniform', 'normal']
- Number of layers: [3, 4, 5, 6, 7]

In the next step, an activation function was selected. Activation functions determine how the weighted sum of the input is transformed into an output. The “Relu” activation function was used for input and hidden layers as it adds nonlinearity to the data allowing adaptation to a wide range of data. The “Sigmoid” activation was used for the output layer since this problem is dealing with regression and not classification.

There are multiple algorithms including gradient descent (Ruder, 2016) and adagrad (Lydia & Francis, 2019) that can be used for optimization of neural network training. Optimizers are used to reduce the losses of the machine learning models by changing attributes such as learning rate. The “Adam” optimizer was used for this research as it is more efficient in terms of memory use when working with large amount of data leading to more efficient training in less amount of time. “Adam” uses first and second gradient moments for estimating the individual adaptive rates of different parameters (Kingma & Ba, 2015). Adam optimizer combines two gradients of momentum and root mean square propagation. The momentum is based on exponentially weighted average of the gradients to increase the pace. Root means square prop is based on exponential moving average. The Adam optimizer benefits from the two gradients to be able to take big steps while maintaining minimum oscillation reaching the global minimum. Such approach positively impacts the time and training performance.

6.2 Model Optimization

Hyperparameter tuning or hyperparameter optimization was used to identify the optimal number and arrangement of hyperparameters discussed in the previous (e.g., learning rate and number of iterations for gradient descent, number of layers and neurons for the ANN) section to achieve the best performance. Such approach can increase model performance, maximize accuracy, and/or minimize errors. There are multiple algorithms that can be used for optimization, such as random, grid, and exhaustive search. Random search is good for identifying new hyperparameters values, but the processing takes more time. The random search uses random numbers to find the best score for a combination of hyperparameters. Exhaustive search tests all combinations and is therefore useful for small datasets as it has long processing time. For this model, the grid search (GridSearchCV imported from scikit-learn library in Python) which performs a systematic search using different number of layers and nodes per layer was selected. The grid search defines the space as a grid of hyperparameter values and every position in the grid is evaluated to identify the best vector in terms of model performance. The following are the arguments of the GridSearch:

1. Estimator which is the model instance
2. Scoring is the objective/metric/lost function which in this case was the negative mean squared error as it is the default loss function for regression models and is typically used for neural network models. This loss function calculates the average of squared difference ($\frac{1}{n}\sum_{i}^{n}(y_i - \hat{y}_i)^2$) between actual (duration in

the system) and predicted values (calculated duration). The goal of our model is to minimize the value for this hyperparameter and get the lowest score.

3. Cross validation (CV) was set to two as this research contained high amounts of data reducing the need for cross validation.
4. N-jobs for using the CPU cores in parallel which in this case the researchers selected 1 to use one CPU core.
5. Refit which refits the estimator based on a parameter.
6. Verbose is related to the messages presented.

6.3 Model Results

In order to determine the best configuration for the neural network, the development process tests different combinations of hyperparameters (Table 4) in terms of their values to achieve the least mean squared error supporting the accuracy and performance of the model. The best configuration was selected based on the value of the mean squared error estimated. There is no correct value for mean squared error, however, a lower value for mean squared error presents closer prediction to the actual value. As discussed in “Model Optimization” section, the mean squared error calculates the average of squared difference between actual and predicted values (actual and predicted duration) and the goal of the model is to get the minimum value to achieve the most accurate result through the model. Table 4 presents other combinations of the hyperparameters’ values. By comparing Table. 4 to Table 5, it is clear that different combinations of hyperparameter values had led to different mean squared error values. Through model training and by testing different combinations of the hyperparameter values, the model identified the optimum value for each hyperparameter in order to achieve the minimum mean squared error.

Table 4: Results of other combinations of hyperparameters.

batch_size	first_layer_nodes	init_mode	learning_rate	n_layers	mean_squared_error
32	105	uniform	0.1	4	0.415344
512	75	uniform	0.01	3	0.016354
32	55	uniform	0.1	4	0.034170
128	185	normal	0.01	3	0.015893
64	135	normal	0.1	6	0.415344
64	75	uniform	0.3	3	0.034170
64	185	normal	0.005	3	0.015938
128	185	normal	0.2	3	0.034170
128	75	normal	0.3	6	0.414476
256	55	normal	0.2	4	0.034170
512	145	normal	0.01	3	0.029696
32	85	normal	0.005	7	0.034170

Table 5 presents the results of the optimal model performance score (mean squared error) and best values for the hyperparameters. As mentioned above, both the 95 and 90 percentile data were tested to identify the best dataset to continue with. The following presents the results for both databases.

Table 5: Results of the ANN model.

Dataset	Mean squared error	Batch size	First layer nodes	Distribution	Learning rate	Number of layers
95 Percentile	0.016310	128	195	Normal	0.005	3
90 Percentile	0.025804	256	185	Normal	0.005	3

Based on the results, the 95-percentile database was selected for testing the model. The hyperparameters values of the 95 percentiles were used for the model to run the test set. The results of the test set presented the value of 0.01631 for the mean squared error which does not vary greatly from the training set result. As discussed previously, 20 percent of the data was separated before splitting the data for training and testing to be able to validate the model using new data. The mean squared error estimated from the validation dataset was 0.069147.

Figure 9 presents a comparison of the results of the developed model (ANN model) and actual data (processed and prioritized work orders received from the facility) in terms of work order prioritization. The comparison was made based on the rank of the work order in the processed list. As it is shown, a work order prioritized as first was prioritized as 13 by the model as it is based on multiple data entry over a long period of time.

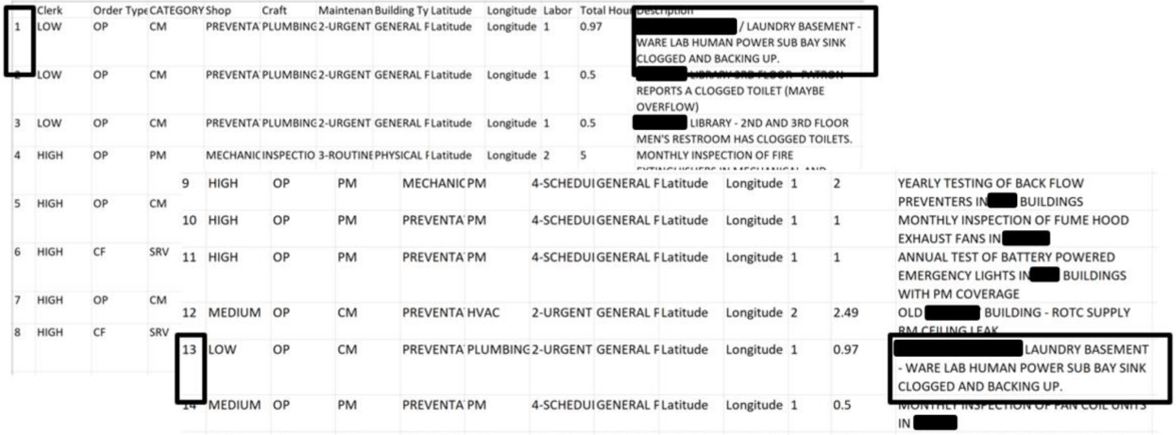

Figure 9: Comparison of actual and model prioritization.

To be able to further validate the developed model and adjust the parameters and hyperparameters if needed, the developed model should be validated using a completely new dataset.

7. EXPERT FEEDBACK & VALIDATION (STEP 4)

As discussed in the challenges associated with existing practices for processing and prioritizing work orders, the existing practices take long amount of time and are prone to errors. Additionally, the criteria and their associated ranking used for processing work orders vary among different individuals within the same facility as well as among individuals in different types of facility. Therefore, the objective of this study was to propose the implementation of neural networks to automate the process of prioritizing work orders in order to address the following goals. First, enhance efficiency of the work order prioritization in terms of the amount of time taken to process and prioritize them. Second, to improve the accuracy in terms of accuracy of the prioritization and ranking of the work orders. Third, to increase the consistency in terms of criteria used for prioritization of the work orders as well as their associated ranking.

In order to address the goals of the study, the final results were discussed with a group comprised of three facility experts (Two male and one female with 20-30 years of experience) working in the same facility that provided the work order data to receive their opinion and feedback on the practicality of the proposed approach and evaluate the accuracy and efficiency of the proposed model. The efficiency was measured by comparing the time taken by the model as opposed to time taken by a facility staff to process and prioritize the work orders. The accuracy of the proposed model was evaluated by comparing the results of 50 prioritized work order by the model as opposed to prioritization of the same set of work orders by the facility. Finally, the consistency in terms of criteria used for prioritization was discussed with the facility experts to confirm that using the same criteria by the proposed model will increase the consistency of their process.

In the first step, the facility experts were asked to provide feedback on insights gained from data exploration, correlations identified, and the challenges with data preprocessing which were related to how the data is being collected and stored by the facility. Using data exploration, multiple challenges including missing data for multiple columns, using facility staff name who have an assigned area instead of the location name, or submission of the discussion among facility staff as work orders were identified. Based on the discussion with the facility staff, lack of requirements and guidelines have led to inconsistency in terms of data collection and entry which hinders benefiting from the data collected in terms of data-driven decision-making methods. Based on their feedback, data exploration and analysis can assist them with monitoring procedures and can help them to address the challenges with future data collection by defining guidelines and requirements. For instance, based on the results of Figure 5, the facility experts believed that defining requirements and performing follow ups can help with addressing the maintenance tasks in an acceptable amount of time while ensuring that the maintenance tasks have been closed.

Such analysis can also help them to determine other criteria such as staff availability to better support their processing procedure. Furthermore, they believed that such analysis could help with redefining some criteria (e.g., changing a maintenance task category from urgent to routine) while evaluating the performance of the staff and any challenges faced by them in order to address them for future processes.

The facility experts indicated that work order data analysis can also assist them in determining what specific fields should be captured, what data should be collected through the description to better determine the type of the issues, and how and when to perform follow ups. Based on correlations determined in Figure 6, the facility experts believed that analyzing information used for processing work orders and determining their correlation and impact on prioritization and schedule can assist them in determining data requirements. In other word, if the facility is collecting data for a criterion such as distance which has little impact on the schedule as opposed to assigned shop, they should avoid spending resources to collect data for such criterion and replace the criterion with other beneficial criteria enhancing their practices. They also indicated that these types of analysis can help with determining better practices as well as providing an opportunity for adjusting existing requirements and workflows.

The time that takes the facility staff to process the daily work orders was discussed with the facility experts and was compared with the model processing time. This was done by comparing the amount of time taken by the model to prioritize 50 work orders as opposed to the amount of time taken by a facility staff to prioritize the same list. Based on the discussion among the facility experts, they believe that the proposed model can increase the processing speed and hence, positively impact the efficiency and productivity of the staff. However, they highlighted the importance of considering the learning curve of the staff in terms of working with automated systems when first being implemented.

The same list of 50 prioritized work orders by the facility was compared with the prioritization of the same work orders by the developed model. The results of the comparison were discussed with the facility experts to receive their feedback on the accuracy of the model. Based on the feedback received, the participants highlighted that the model is accurate and reasonable in its current version, and it only requires minor adjustments. They believed that analysis and implementation of such models greatly depend on the quality of the data used and therefore, they marked that the accuracy of the developed model can be improved by more comprehensive and consistent data collection by the facility.

In the final step, the facility experts were asked to discuss the advantages and disadvantages of the proposed model, the potential of the model for increasing efficiency, accuracy, and consistency, and provide feedback for enhancing the proposed model. Based on the discussion, the experts believe that because of the nature of the task and depending on the level of information provided when a work order is requested, there is still a need for human intervention. This also highlights the importance of investigating what data should be collected through service requests and in what format to collect comprehensive information and better support the processing and prioritization of work orders. Such approach can reduce the need for human interventions. The facility experts still believed that the proposed model in its current state and automation in general can help with improving consistency, accuracy, efficiency, and productivity of their staff supporting the operation of the facilities. The participants highlighted the significance of defining and developing standards and procedures for different stages of work order processing including receiving work order requests, processing work orders, and data related to the maintenance tasks performed to address the work order to better support data-driven approaches

8. DISCUSSION

This study used the work order data of an educational facility to develop a methodology in order to automate the process of prioritizing work orders. Such approach addresses the gap and challenges with user-driven and decision-making methods. Through the process of exploring, cleaning, and preprocessing work order data, insights regarding the current practices and data used by the facility were gained. Performing data exploration and preprocessing allowed the researchers to determine the challenges with the existing approach including data collected, data format, issues with data entry, and information missing. For example, the data cleaning presented the outliers in the database based on the maintenance type. Although the durations determined can be a good indicator of the need for adjustment of the existing practices such as changing maintenance types for some categories or addressing urgent maintenance in less time, the insight gained may also highlight the need for collecting more information such as availability of the staff. In other words, if staff are not available, a work order that has been scheduled may be delayed. Additionally, collecting data regarding the diagnosis process can help with more robust estimation of the duration taken for a work order to be addressed. The data preprocessing also allowed understanding the relationship between different criteria used for processing work orders. This would help with determining the impact of the existing criteria and data in the facility system on the prioritization process while identifying new criteria (e.g., availability of staff, maintenance start date). Identifying information needed for prioritization can help with development of data requirements and guideline while supporting the facilities by allocating resources to collecting data that have impact on their practices. Based on the feedback received from the facility lack of requirements and guidelines have led to inconsistency in terms of data collection and entry. They believed that the proposed methodology could help them with developing their data requirements as well as their guidelines in order to benefit from the data collected (e.g., determine the type of the issues, and how and when to perform follow ups). They also highlighted that the insight would allow them to adjust their existing user-driven practices.

In the next step, the preprocess data was used to investigate the implementation of neural networks for automating the prioritization of future work orders. Two assumptions were made to be able to develop the model. First, due to lack of precise data for start and finished dates and times of the maintenance tasks, the duration between scheduled and completion dates were used for schedule prediction. Second, due to limitations in accessing data of other facilities, the data used for validation process was from the same facility assuming that using new data from the same facility provides different database for validating the model. Out of the information received from the facility, ten criteria were used as input for the neural network model. The duration estimated from date created and date completion was used as the output for the model. Through the development of the model, number of neurons in hidden layer were determined, hyperparameters and their values for model training were defined, and the activation function and the optimizer were selected. Through training set, the weight and importance of each feature in terms of its impact on determining the duration was estimated by the model. Based on the selected loss function, in this case mean squared error, the results of the model training and test presented the optimum network configuration in terms of best parameter values including number of features (criteria) and number of layers. Such method can help facilities to determine the optimum amount of data that needs to be collected assisting with their data requirement development. Additionally, automating the process supports consistency in terms of what criteria is being used for processing work orders. The ML models can be used to benefit from the prior work order prioritization and schedules to prioritize future maintenance work orders. It can also help with defining data requirements and hence increasing consistency while reducing processing time. As discussed in this paper, neural networks have been used in various fields to prioritize a set of alternatives. With a defined framework, the neural networks can be used to address the maintenance of building facilities by supporting the automation of maintenance work order prioritization. Based on the discussion with a group consisting of three facility experts, the model can increase the efficiency in terms of processing time and accuracy of the existing practices and support the consistency in terms of data collected and criteria used for processing. The facility also highlighted the improved in staff productivity when implementing such methods. However, they highlighted the importance of developing guidelines and requirements to determine how the data should be collected, what data should be collected, and in what format in order to be able to perform analysis based on comprehensive data and receive a more accurate result.

9. CONCLUSION AND FUTURE RESEARCH

One of the critical aspects of facility management is the challenge of responding to the high number of work orders submitted daily with limited time and labor available. Existing practices for processing work orders are mainly user-driven and therefore are impacted by staff judgement, experience, knowledge, and biases leading to inconsistency in decision-making. Although decision-making methods (e.g., AHP) have been used to address some of the existing challenges such as inconsistency, they have other challenges including human limited cognitive ability for performing pairwise comparison or limitation of number of criteria used. Late responses or errors in processing can lead to asset failure increasing the cost of operation and maintenance. Data driven methods such as machine learning can benefit from historical data collected, to extract valuable information, find trends, and draw inferences and conclusions supporting and enhancing existing practices.

This study reviewed the challenges and gaps with user-driven methods for processing and prioritizing maintenance work orders. It proposed the implementation of machine learning techniques, in this case neural networks, to address the challenges with existing practices for processing work orders including efficiency in terms of performing the time-consuming task of manually processing work orders, accuracy in terms of minimizing errors and providing a practical prioritized list of work orders, and consistency in terms of using the same criteria for processing. The work order data of an educational facility with 213 buildings, and 333,436 work orders collected from 2014 to 2021 was used to explore work order data, gain insight, determine challenges with processing the data, and implement neural networks to automatically prioritize future work orders. The results of the model presented the optimum network configuration. Also based on the discussion with the facility experts, the proposed model and automation in general can assist with enhancing efficiency and accuracy of the existing practices for processing work orders as it allows faster processing with less errors. However, it is significant to determine and develop guidelines and requirements to collect consistent and useful data in order to be able to benefit from data analytics methods. The results of this study can help the facility to determine their best practices and address the challenges with their existing practices to better support the operation of their building facilities.

This paper contributes to the body of knowledge by developing a methodology to automate the work order prioritization using ANNs. Such approach can enhance the facility maintenance management and support the operation of the building facilities by reducing the processing time, increasing the consistency, and enhancing efficiency resulted from more accurate and updated results over time. Furthermore, this paper builds the foundation for supporting the operation of smart building. Automation is one of the aspects of smart buildings and this paper developed a methodology to automate the prioritization of work order.

This study had the following limitations. First, the criteria (features) used for the model were limited to the data collected by the educational facility. Future research will consider validating the results of this research by conducting more case studies. Additionally, conducting more case studies will allow validating the impact of other possible criteria on work order processing. Second, due to the data collection process of the work order data, the researcher did not have access to detailed description of the work orders. Future research will explore more detailed work order descriptions (e.g., equipment parts) and include those in the model to provide a more accurate model for processing future work orders. Third, as discussed in the literature, different facilities have different organizational goals. Additionally, facility type may impact the criteria used as well as their ranking. Future research will consider case studies of different facility types to increase the flexibility and applicability of the model to various facilities. Fourth, the output layer used for the study was based on the duration estimated from the existing two dates in the database. Future research will use databases with more accurate data such as prioritization numbering or more accurate dates including maintenance start date to achieve more robust results.

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