Tampere University

Viljami Hakkarainen

# A MACHINE LEARNING MODEL FOR DYNAMIC PAYLOAD ESTIMATION OF A WHEEL LOADER

Bachelor's thesis
Faculty of Information Technology and Communication Sciences
Examiners: Prof. Okko Räsänen
April 2025

# ABSTRACT

Viljami Hakkarainen: A Machine Learning Model for Dynamic Payload Estimation of a Wheel Loader
Bachelor's thesis
Tampere University
Bachelor's Degree in Computing and Electrical Engineering
April 2025

Wheel loader scales require high accuracy under challenging operating conditions. Many of the current industry solutions rely on proximity switches placed at specific positions along the boom path to determine when weight measurements should be taken. This is not ideal because proximity switches are difficult to install and induce more possible breakpoints. This thesis presents a more robust solution that is not dependent on proximity switches while also delivering superior accuracy. This thesis was done in collaboration with Tamtron, a manufacturer of industrial scales and weighing solutions.

Sensor data was collected from a Volvo L220 wheel loader using pressure sensors and inertial measurement unit (IMU) sensors. The sensors were connected to a controller area network (CAN) interface. The captured data includes boom cylinder pressure, boom angle, and boom acceleration. Data was collected during lifting operations with known payloads in the range of $0\,\mathrm{kg}$ – $15\,000\,\mathrm{kg}$. Two different models for payload estimation were developed: a neural network approach and a novel angle-interval sampling technique that uses LASSO regression. The angle-interval method collects sensor data from a specific boom angle range at $1.25°$ intervals, transforming the otherwise non-linear relationship between the sensor data and payload into an approximately linear one.

The angle-interval regression model significantly outperformed the neural network model, achieving a mean absolute error of $17.9\,\mathrm{kg}$ and a root mean square error of $24.6\,\mathrm{kg}$. This accuracy exceeds the industry requirements, which require a maximum permissible error of $25\,\mathrm{kg}$ – $75\,\mathrm{kg}$, depending on the payload [1, Table 6]. The model is computationally efficient for microcontroller implementation and can be easily calibrated across different wheel loader models. These things make the regression model a potential solution for Tamtron's next-generation, manufacturer-agnostic wheel loader scales.

Keywords: machine learning, payload estimation, CAN, IMU, neural network, linear regression model

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

# TIIVISTELMÄ

Viljami Hakkarainen: Koneoppimismalli Pyöräkuormaajan Dynaamisen Kuorman Ennustamiseksi
Kandidaatintyö
Tampereen yliopisto
Tieto- ja sähkötekniikan kandidaattiohjelma
Huhtikuu 2025

---

Pyöräkuormaajavaaoilta vaaditaan korkeaa punnitustarkkuutta vaikeissa mittausolosuhteissa. Monet tämänhetkiset vaakaratkaisut käyttävät puomin kulkuradalle asennettuja rajakytkimiä mittausalueen määrittämiseen. Rajakytkimien käyttö ei kuitenkaan välttämättä ole optimaalinen ratkaisu, sillä niiden asennus on työlästä ja rajakytkimet lisäävät mahdollisesti vaurioituvien komponenttien määrää. Tämä opinnäytetyö esittelee luotettavamman ratkaisun, joka ei ole riippuvainen rajakytkimistä ja saavuttaa samalla paremman tarkkuuden. Opinnäytetyö on tehty yhteistyössä Tamtronin kanssa, joka on kansainvälinen teollisten vaakojen toimittaja.

Työssä kerättiin sensoridataa Volvo L220 -pyöräkuoramaajasta käyttämällä paine- ja kulma-antureita, jotka oli kytketty CAN-rajapintaan. Kerätty data sisältää nostosylinterin paineen, nostopuomin kulman ja nostopuomin kiihtyvyyden. Data kerättiin nosto-operaatioiden aikana, joissa käytettiin $0\,\mathrm{kg}$ – $15\,000\,\mathrm{kg}$ kalibroituja punnuksia. Kuorman ennustamiseen kehitettiin kaksi erilaista mallia: neuroverkkomalli ja nostopuomin kulmavälin näytteistystä hyödyntävä LASSO-regressiomalli. Jälkimmäinen malli kerää sensoridataa puomikulman ollessa tietyllä välillä $1.25°$:n välein, muuttaen muuten epälineaarisen suhteen sensoridatan ja kuorman välillä lineaarista approksimoivaksi.

Nostopuomin kulmavälin näytteistystä käyttävä malli saavutti huomattavasti paremman mittaustarkkuuden kuin neuroverkkomalli. Regressiomallin keskimääräinen absoluuttinen virhe oli $17.9\,\mathrm{kg}$ ja keskineliövirheen neliöjuuri oli puolestaan $24.6\,\mathrm{kg}$. Tämä tarkkuus täyttää pyöräkuormaajavaa'an lailliset vaatimukset, joiden mukaan absoluuttinen virhe saa olla korkeintaan $25\,\mathrm{kg}$ – $75\,\mathrm{kg}$ riippuen punnuksen kuormasta [1, Taulukko 6]. Tämä regressiomalli on laskennallisesti tehokas, mahdollistaen sen toteuttamisen mikrokontrollerilla. Regressiomalli on myös helposti kalibroitavissa eri valmistajien pyöräkuormaajille. Nämä ominaisuudet tekevät regressiomallista potentiaalisen ratkaisun Tamtronin uuden sukupolven pyöräkuormaajavaa'aksi.

Avainsanat: koneoppiminen, kuorman ennustaminen, CAN, IMU, lineaarinen regressiomalli

# PREFACE

I would like to thank Tamtron for the opportunity to work on this challenging and relevant industrial problem. I am also very grateful to my supervisor, Jouni Gustafsson, not only for suggesting this interesting thesis topic, but also for his consistent support and helpful feedback during the research process.

Tampere, 10th April 2025

Viljami Hakkarainen

The AI tools utilized in my thesis and their purposes are described below.

**Claude 3.7 Sonnet:** Claude 3.7 Sonnet was used to get grammar feedback to ensure that the text is easy to understand.

I acknowledge that I am fully responsible for the entire content of my thesis, including the parts generated by AI, and accept accountability for any violations of ethical standards in publications.

# CONTENTS

# LIST OF SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| Adam | Adaptive Moment Estimation |
| $\Delta\theta_{\text{boom}}$ | boom angle interval for data collection |
| $P_{\text{body}}$ | wheel loader body pressure |
| $\theta_{\text{boom,max}}$ | maximum boom angle for data collection |
| $\theta_{\text{boom,min}}$ | minimum boom angle for data collection |
| $\theta_{\text{boom}}$ | boom angle |
| $\dot{\theta}_{\text{boom}}$ | rate of change in boom angle |
| $\dot{P}_{\text{boom}}$ | rate of change in boom cylinder pressure |
| $P_{\text{boom}}$ | boom cylinder pressure |
| CAN | Controller Area Network |
| $\ell_2$ | euclidean norm |
| EWMA | Exponentially Weighted Moving Average |
| IMU | Inertial Measurement Unit |
| LASSO | Least Absolute Shrinkage and Selection Operator |
| $\ell_1$ | manhattan distance |
| MLP | Multilayer Perceptron |
| MSE | Mean Squared Error |
| ReLU | Rectified Linear Unit |
| RMSProp | Root Mean Square Propagation |
| RSS | Residual Sum of Squares |

# 1. INTRODUCTION

Accurate dynamic payload estimation in wheel loaders is an important requirement across numerous industrial applications, from construction and mining to agriculture and waste management.

Traditional wheel loader weighing systems often rely on proximity switches installed at specific positions along the boom path [2][3][4]. However, this has some limitations: proximity switches are difficult to install and prone to mechanical failures.

This thesis presents a novel mathematical model for dynamic payload estimation using data from pressure sensors and inertial measurement unit (IMU) sensors, while not being dependent on proximity sensors. The research is done in collaboration with Tamtron, a manufacturer of industrial scales and weighing solutions. The proposed model aims to build the foundation for Tamtron's next-generation wheel loader scale, which has the following requirements:

1. Manufacturer agnosticism: The solution should work with different wheel loader models and manufacturers through appropriate sensor installation and calibration.
2. Computational efficiency: The algorithm must be feasible for implementation on microcontrollers with limited computational capabilities.
3. High accuracy: A maximum permissible error of $25\,\mathrm{kg}$ – $75\,\mathrm{kg}$, depending on the load [1, Table 6].
4. Improved reliability: The solution should not depend on proximity switches.

The methodology involves capturing calibrated ground truth measurements across a range of loads ($0\,\mathrm{kg}$ – $15\,000\,\mathrm{kg}$) while recording boom cylinder pressure, boom angle, and other relevant parameters via the controller area network (CAN) bus interface. The data was recorded from a stationary vehicle position and the boom was lifted upward and downward at two different velocities. For our purposes, we want to estimate the payload from the upward movement of the boom while the boom is in motion.

This thesis entails the development process, mathematical foundations, and performance evaluation of the proposed dynamic payload estimation algorithm. The ultimate goal is to develop a robust, accurate, and versatile weighing system that overcomes the limitations of current solutions while meeting the requirements of industrial applications.

# 2. RELATED WORK

Various methods have been studied for determining the payload of a front-end loader. [5][6][7][8][9][10][11]. The methods can be roughly divided into physics-based approaches, machine learning based approaches, and empirical approaches. The physics-based methods model physical properties, such as the forces, torques and motion dynamics of the wheel loader to determine the payload [7][10]. Machine learning based methods use sensor information such as boom angle, pressure, and inclination angle from known measurements to estimate the payload. [5][8] A combination of different methods can also be used [6][8][9].

## 2.1 Physics-Based Modeling Approaches

Madau et al. [7] developed a force estimation algorithm for a 14-ton wheel loader. The payload was estimated while the vehicle was in a stationary position. Static and dynamic lifting operations were included, the latter making this study relevant to our interests. Their approach divided the system modeling into two components: a kinematic model and a dynamic model. The kinematic model was used to determine the location of the linear and rotational joints. These joints connect the different elements of the wheel loader together. The dynamic model was used to calculate the horizontal and vertical forces acting on the bucket. Inertia and friction were estimated by collecting data at different loads and angular velocities, which led to improved model accuracy. This approach was relatively effective in both static and dynamic lifting operations with varying boom angles, resulting in a maximum error of 3%.

Ballaire et al. [10] developed a physics-based model for dynamic payload estimation on a tractor front-loader. Two models were developed. A static model was used to calculate the joint torques at the boom and bucket pivots. These torques are caused by the hydraulic cylinder forces and are directly influenced by the payload mass, which affects both joint torques. A dynamic multi-body-system was used as the second model with the purpose of calculating the acceleration of each component. Unlike with the static model, the payload does not influence the joint torques in the dynamic model. The difference between the joint torques is used to estimate the payload. Both models require the inertial parameters of the equipment. To obtain these inertial parameters, the researchers completely disassembled the machine and weighed each individual component separately. This meticulous approach was proven to be effective. The payload was estimated within 1% of full-scale accuracy, regardless of the boom position or the position of the payload (center of gravity). Although the model delivered accurate results in various lifting conditions, this approach is not suitable for vehicle-agnostic commercial solutions due to its complexity.

Although physics-based approaches can be effective for payload estimation, there are some clear limitations for commercial usage. Physics-based approaches require detailed knowledge of the system properties, such as kinematics and mass, which vary from manufacturer to manufacturer. If the system properties cannot be obtained from the manufacturer, this either requires an accurate simulation model, which in itself is not an easy task to do, or each component of the system must be weighed manually, which is very time-consuming. For these reasons, physics-based modeling approaches may not be optimal for vehicle-agnostic commercial solutions, but may work very well for manufacturer-specific weighing solutions, where the system properties remain constant.

## 2.2 Machine Learning Based Approaches

Savia M. et al. [5] used a neural network to predict the payload of a moving LHD (Load-Haul-Dump) machine where the inputs were pre-processed using a Kalman filter. Data was collected from nearly 600 weighings. The neural network consisted of 1 layer of 9 neurons. Boom cylinder pressure, boom position, and inclination angle were used as input for the best-performing model. Some additional parameters, such as hydraulic oil temperature and driving speed, were also tried, but including them resulted in worse performance. With this approach, a mean relative error of 1.68% was achieved. However, only measurements with static boom positions were collected, limiting the practicality of the results for our goal of dynamic payload estimation.

Hindman et al. [8, p.34-41] used a 4-layer artificial neural network with a 5x10x10 neuron architecture. The pressure differential (difference between the pressure on the extension side and the retraction side) and the cylinder lengths were used as input to the network. The network was tested with a payload of $3436\,\mathrm{kg}$ in both moving and stationary machine conditions, and the boom was lifted up and down throughout the testing phase. In the stationary condition, a mean error of $91.1\,\mathrm{kg}$ (2.65%) and a standard deviation of $236.3\,\mathrm{kg}$ were achieved. However, in the moving condition the mean error was $255.0\,\mathrm{kg}$ (7.42%) with a standard deviation of $552.7\,\mathrm{kg}$. Although the results of this paper are not very promising, the accuracy in the stationary condition shows some promise, especially considering that only 3 input parameters were used for training the network.

While the research is very limited on pure machine learning based approaches, they show some potential. Machine learning based approaches could work well in commercial applications because they do not require detailed mechanical knowledge of each specific machine. Less sensors may also be needed compared to dynamic models that generally require more comprehensive data. However, computational complexity and large data requirements may be a concern when considering machine learning based approaches [8, p.34-41][5].

## 2.3 Hybrid Approaches

Hindman et al. [8, p.45-51] combined a kinematic linkage model and an artificial neural network to form a hybrid model for dynamic payload estimation for a moving wheel loader. Both static and dynamic boom positions were used to train the network. Payloads of $0\,\mathrm{kg}$, $3945\,\mathrm{kg}$ and $5563\,\mathrm{kg}$ were used to train and test the model. The first half of the recorded data was used for model training, the second half was used for testing. A small and computationally simple 5x10x10 network was used because the algorithm had to be implemented on a microcontroller. The input of the network consisted of the estimate produced by the kinematic linkage model and some additional inputs, such as the boom pressure, the velocity of the boom cylinder and the acceleration of the vehicle. The algorithm predicts the payload mass with an overall full-scale error of 1.96%. Although the model is not sufficiently accurate for industrial applications, this study provides valuable insight into how vehicle acceleration data can be used to improve accuracy when the loader is in motion.

Feng J. et al. [6] developed a multi-stage model for dynamic payload estimation. The multi-stage model combines a dynamic model, optimized least squares method, and a neural network, where each model is used at a different phase of the machine cycle. Various working conditions with varying boom angles, driving speeds, inclination angles, and payloads were tested. Despite challenging test conditions, this multi-stage approach resulted in an average relative error of 0.51%.

Hybrid approaches can clearly provide very high accuracies. However, hybrid approaches are likely the least suitable approach for commercial vehicle-agnostic solutions due to their complexity. Hybrid approaches may be optimal for manufacturer-specific implementations, where the complexity is reduced since the weighing solution is made for a specific vehicle.

## 2.4 Empirical Approaches

Empirical approaches use direct measurement data rather than theoretical models [9, p. 33-36][11]. The system is calibrated by recording the cylinder pressures while lifting known payloads (including an empty bucket) in constant motion. These pressures are measured only during upward boom movement within a specified boom angle range determined by proximity sensors. These recorded measurements create a "calibration space", which is used to estimate new unknown payloads. A new payload is estimated by interpolating the measured pressure value in the calibration space. The payload is estimated once the boom exceeds the calibration range. Velocity compensation can be implemented by recording each calibration payload with more than one velocity, resulting in a multidimensional calibration space. The empirical approach can be effective, but its accuracy depends on measurement conditions that are similar to those of the calibration conditions. Empirical approaches were not discussed in much detail in this study because there is limited research on them. Out of all the different payload estimation methods we have discussed, the empirical approach is most similar to Tamtron's current solution and is commonly used in commercial applications.

Clearly, many different approaches can be used for accurate payload estimation. However, each approach has their limitations when it comes to their suitability for commercial applications. Methods that require detailed knowledge of the system's physical properties are not ideal for commercial use due to the difficulty of implementation. Empirical approaches are likely the most suitable for commercial applications due to their ease of implementation, but their working conditions are more limited since the measurements need to be taken close to calibration conditions. While machine learning based approaches can have high demands in terms of data quantity and data quality, they are certainly more vehicle-agnostic, which makes them a potential option for commercial solutions. Despite the possible advantages of the machine learning based methods, there is not much research on them for dynamic payload estimation. This thesis aims to address this gap by developing a model for dynamic payload estimation that meets the given accuracy requirements, is computationally efficient, does not require massive amounts of data, and can be used across different wheel loader models.

# 3. METHODOLOGY

This chapter presents the methods used in this study. Section 3.1 discusses the hardware setup and the methods used to collect the data. Section 3.2 discusses the data processing and feature engineering methods. The models developed for payload estimation are discussed in sections 3.3 and 3.4, respectively.

## 3.1 Hardware and Data Collection Setup

Two pressure sensors and two IMU sensors were used for data collection. The sensors were installed on a Volvo L220 wheel loader (Figure 3.1), which has a maximum capacity of $15\,000\,\mathrm{kg}$. The data was recorded by connecting the sensors to a controller area network (CAN) interface and saving the raw CAN messages into CSV files. The CSV files were then parsed with a Python script to convert the data into a suitable format, where each column corresponds to measurements of one measurement parameter.


***Figure 3.1.*** *Volvo L220 wheel loader used for data collection*

The measurement parameters of the inertial measurement unit (IMU) and the pressure sensors are listed in Table 3.1. A sample rate of $100\,\mathrm{Hz}$ was used in all sensors.

***Table 3.1.*** *Sensor Measurements*

| IMU Sensor | Pressure Sensor |
|---|---|
| Angle | Pressure |
| Orientation | Temperature |
| Acceleration | |

The following payloads were measured: $0\,\mathrm{kg}$, $1000\,\mathrm{kg}$, $2000\,\mathrm{kg}$, $5000\,\mathrm{kg}$, $7000\,\mathrm{kg}$, $10\,000\,\mathrm{kg}$, $13\,000\,\mathrm{kg}$, and $15\,000\,\mathrm{kg}$. Each weight was lifted upward and downward for a total of 5 up and down movements at two different velocities: once at maximum speed and once at a slower pace. Thus, 10 complete lifting cycles per payload were recorded. Every measurement was recorded while the vehicle remained stationary.

### 3.1.1 IMU Sensors

Two IMU sensors were installed on the wheel loader. One sensor was installed to the body of the wheel loader to measure the inclination angle relative to the ground (Figure 3.2). This is an important measurement because the inclination angle impacts the gravitational force placed on the boom and thus, it impacts the measured pressure as well. Another IMU sensor was installed on the wheel loader's boom (see illustration in Figure 3.3), which measures the boom angle and acceleration during lifting operations. These measurements are important for tracking the boom's position and movement dynamics since they directly influence the forces acting on the payload.

***Figure 3.2.*** *IMU sensor attached to the body of the wheel loader*

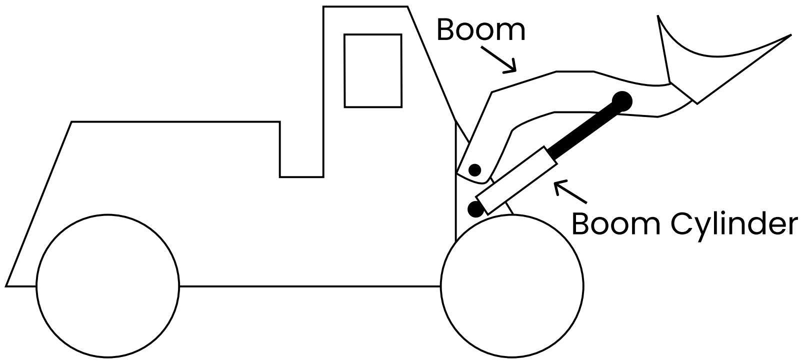


***Figure 3.3.*** *Simplified illustration of a wheel loader showing the boom and boom cylinder*

### 3.1.2 Pressure Sensors

Two pressure sensors were installed on the wheel loader to measure pressure and sensor temperature. The primary sensor was connected to the boom lift cylinder to directly measure the hydraulic pressure during lifting and lowering operations, which is directly related to the payload. The secondary pressure sensor was installed in the main hydraulic system manifold to monitor the overall pressure of the system, which provides insight into the machine's operational state.

## 3.2 Data Processing and Feature Engineering

### 3.2.1 Low-Pass Filtering

A second-order Butterworth [12] low-pass filter was used to filter the sensor data from IMU and pressure sensors. The Butterworth filter is a digital signal processing filter designed to have a flat frequency response in the passband and a roll-off rate determined by its order. For an $n$th order low-pass Butterworth filter, the magnitude response is given by:

$$|H(j\omega)|^2 = \frac{1}{1 + \left(\frac{\omega}{\omega_c}\right)^{2n}} \tag{3.1}$$

where $\omega_c$ is the cutoff frequency and $n$ is the filter order.

For our purposes, a second-order implementation (n = 2) with a cutoff frequency of $2\,\mathrm{Hz}$ was chosen. The second-order filter provides a good balance between filtering performance and computational complexity. The cutoff frequency was chosen by analyzing the signals in the FFT domain and seeing that most of the signal energy is concentrated below $2\,\mathrm{Hz}$. This configuration effectively removes high-frequency noise components from the data while preserving the important information of the signal.

### 3.2.2 Feature Scaling

The input features and target variables were scaled for numerical stability. For the input features, the data was normalized in the following way:

$$x_{scaled} = \frac{x - \mu}{\sigma} \tag{3.2}$$

where $\mu$ is the mean of the feature and $\sigma$ represents its standard deviation. This centers the features around zero and ensures that each feature contributes equally to the model's learning process and prevents features of larger magnitudes from essentially dominating the training. The same scaling procedure was used for the target variable.

### 3.2.3 Derived Feature Calculation

Angular velocity was not measured directly from the IMU sensors. Instead, angular velocity was estimated by calculating the difference between consecutive angular measurements and multiplying them by the sample rate. This was done on filtered data to avoid noisy results.

The rate of change in boom cylinder pressure was also derived from the filtered pressure sensor data using a similar approach. Using both derived features turned out to be useful in all of the tested payload estimation methods.

### 3.2.4 Data Segmentation

Each recording captured 5 complete lifting cycles, where one cycle consists of both the upward and downward movement of the boom. We were only interested in the upward motion phase of the cycle. The data was manually segmented by identifying the start and end points of each upward motion based on boom angle measurements. Each segment was saved as a separate file, so one file represents one upward lifting motion from a single cycle.

### 3.2.5 Training and Validation Data Split

The data was split into training data and validation data as described in Table 3.2. The selected training and validation data split was designed to evaluate the model's ability to accurately estimate payload across the full operating range. The training data contains measurements from the entire operating range. The validation data consists of measurements that were not included in the training data. Using completely different payloads between training and validation datasets prevents data leakage that could artificially inflate performance metrics. Using only 5 payloads for training rather than all eight reduces the time spent on the calibration procedure, making this solution more practical for field deployment.

***Table 3.2.*** *Training and Validation Data Split*

| Training Data | Validation Data |
|---|---|
| $0\,\mathrm{kg}$ | $2000\,\mathrm{kg}$ |
| $1000\,\mathrm{kg}$ | $7000\,\mathrm{kg}$ |
| $5000\,\mathrm{kg}$ | $13\,000\,\mathrm{kg}$ |
| $10\,000\,\mathrm{kg}$ | |
| $15\,000\,\mathrm{kg}$ | |

## 3.3 Neural Network-Based Payload Estimation Model

An artificial neural network is a machine learning model inspired by the behavior of the brain [13]. The network consists of layers of artificial neurons that are connected to each other and used to process information. Neural networks have shown remarkable effectiveness across many fields, such as computer vision and natural language processing [14]. For our payload estimation task, neural networks seemed like a promising approach due to their ability to model complex non-linear relationships between sensor inputs (boom cylinder pressure, boom angle, angular velocity) without requiring complex physical modeling of the system. The multilayer perceptron (MLP) was selected due to its computational efficiency, making it suitable for implementation on embedded systems with limited resources.

### 3.3.1 Model Architecture

A multilayer perceptron (MLP) model with 1 hidden layer of 8 nodes was chosen for the final model by trial and error on the validation set. Models with more complex configurations (more layers, more nodes) were also tested, but the results were worse. The model consists of 5 inputs: boom cylinder pressure, body pressure, rate of change in boom cylinder pressure, angular velocity, and boom angle. The model architecture is illustrated in Figure 3.4.

A rectified linear unit (ReLU) was used as the activation function. ReLU can be mathematically represented in the following way:

$$f(x) = \max(0, x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{3.3}$$

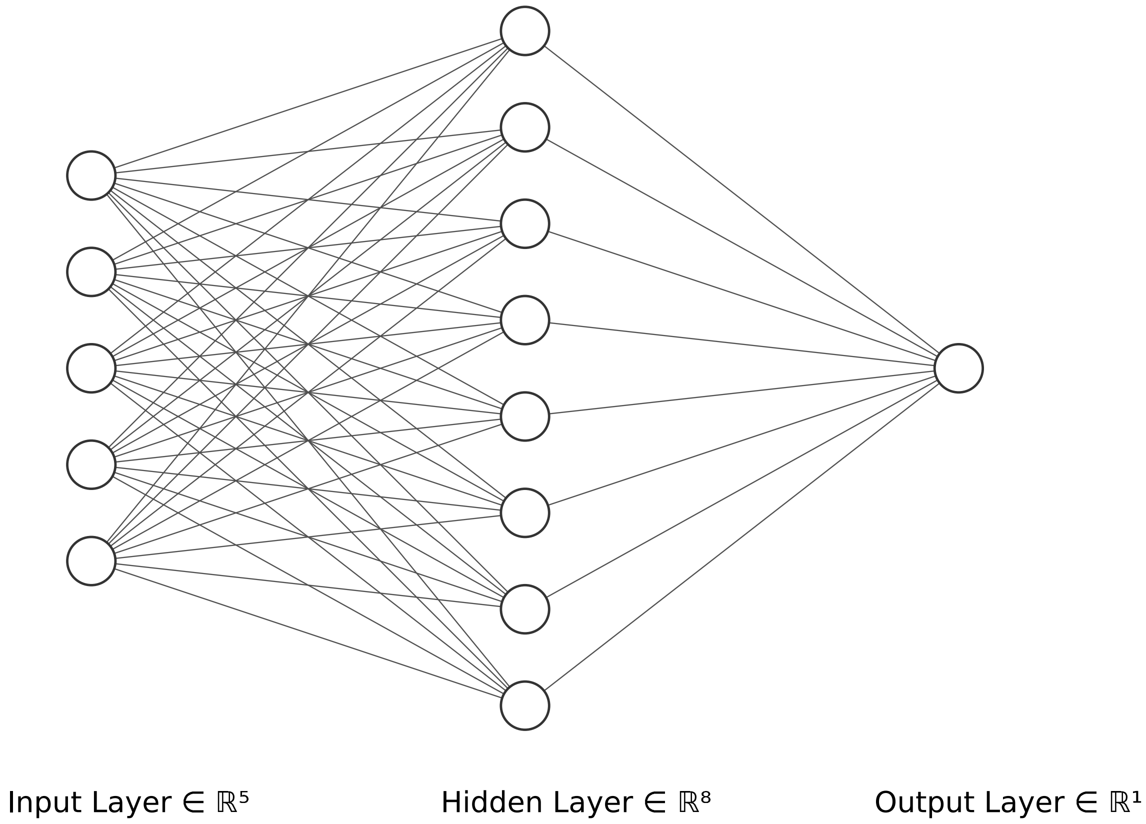


***Figure 3.4.*** *Architecture of the neural network used in this study*

where $x$ is the input to a neuron.

ReLU is currently the most widely used activation function in neural networks [15]. ReLU mitigates the vanishing gradient problem [16] and is computationally simple, allowing for fast training of neural networks. Several activation functions were tested for this study, but ReLU resulted in the best performance. Hyperparameter tuning will be discussed in more detail in the next chapter.

### 3.3.2 Hyperparameter Tuning

Mean squared error (MSE) was chosen as the loss function because of its heavy penalization of large errors. In our case, we were more concerned with the maximum deviation of the payload rather than with the mean deviation. MSE measures the average squared difference between the estimated values and the true values. MSE can be mathematically represented as follows:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{3.4}$$

where $n$ is the number of data points, $Y$ is the vector of observed values and $\hat{Y}$ is a vector of the predicted values.

The Adam optimizer with a learning rate of $0.001$ was chosen. Adam was selected for its efficiency and robust performance with noisy data [17]. Adam builds on two other optimization algorithms: adaptive gradient (AdaGrad) [18] and root mean squared propagation (RMSProp) [19].

AdaGrad dynamically adjusts the learning rate for each parameter based on its gradient history. The learning rate is reduced for parameters with high gradients, while higher learning rate is maintained for parameters with low gradients. This makes AdaGrad suitable for sparse data, but the increasingly diminishing learning rate leads to minimal updates and slow convergence over time.

RMSProp addresses AdaGrad's limitation by tracking the exponentially weighted moving average (EWMA) of squared gradients, giving more weight to recent updates. This effectively prevents the learning rate from becoming excessively small, allowing the algorithm to adapt more quickly.

Using the techniques of AdaGrad and RMSProp, Adam maintains the benefits of the adaptive learning rate of AdaGrad while avoiding its convergence issues by using RMSProp's recency weighting system. Additionally, Adam uses a separate momentum mechanism that tracks the EWMA of the gradients themselves (not squared gradients as in RMSProp). This momentum mechanism allows the optimizer to build up speed in consistent gradient directions and smooth out oscillations, making the optimizer more robust against getting stuck in poor local minima or saddle points. These properties make Adam well-suited for our noisy sensor data.

Batch size refers to the number of samples used in one forward and backward pass of the neural network. A high batch size generally means that the gradient updates are more stable and less noisy, but the convergence can be slow and more memory is required. The opposite is true for small batch sizes. Small batch sizes also tend to generalize better, possibly due to the noise they add. [13, Chapter 8] A batch size of 64 was determined to be optimal through trial and error.

The hyperparameter configuration is summarized in Table 3.3. The optimal hyperparameters were determined through an iterative approach. Standard values from the literature were used as a starting point for each hyperparameter. Each hyperparameter was adjusted while monitoring the model's performance on the validation set.

***Table 3.3.*** *Neural Network Hyperparameters*

| Training Parameter | Configuration |
|---|---|
| Optimizer | Adam (Adaptive Moment Estimation) |
| Learning Rate | 0.001 |
| Loss Function | Mean Squared Error (MSE) |
| Maximum Epochs | 100 |
| Batch Size | 64 samples |
| Validation Split | 20% of training data |

## 3.4 Angle-Interval Sampling and Regression Modeling for Payload Estimation

While regression models are widely established in machine learning, no studies have been published on their use for dynamic payload estimation of wheel loaders or other front-end loaders. This study presents a novel approach that combines a linear regression model with angle-interval sampling.

### 3.4.1 Sampling Methodology

This approach works by collecting data when $\theta_{\text{boom}} \in [\theta_{\text{boom,min}}, \theta_{\text{boom,max}}]$. The data is collected at fixed angle intervals ($\Delta\theta_{\text{boom}}$) of $1.25°$. At each measurement point, we collect the boom cylinder pressure ($P_{\text{boom}}$), body pressure ($P_{\text{body}}$), rate of change in boom cylinder pressure ($\dot{P}_{\text{boom}}$), and rate of change in boom angle ($\dot{\theta}_{\text{boom}}$). Then, a linear regression model is fit to the measured points.

The optimal sampling interval $[\theta_{\text{boom,min}}, \theta_{\text{boom,max}}]$=$[20°, 32.5°]$ was determined by analyzing how the input variables correlate with the payload across different boom angle ranges. The lower limit ($20°$) allows different starting positions of the lifting cycle, such as when material is collected from an elevated pile. The upper limit ($32.5°$) allows for payload estimation within the typical lifting range and avoids unnecessarily lifting the boom to its maximum height. The values of the optimal sampling parameters are shown in Table 3.4.

***Table 3.4.*** *Optimal Parameter Values for Data Sampling*

| Parameter | Value |
|---|---|
| $\theta_{\text{boom,min}}$ | $20°$ |
| $\theta_{\text{boom,max}}$ | $32.5°$ |
| $\Delta\theta_{\text{boom}}$ | $1.25°$ |

The payload is estimated using the collected data once the boom angle exceeds the upper limit of our sampling interval ($\theta_{\text{boom,max}}$). This means that there is no continuous payload estimation throughout the entire lifting cycle, but this was not a requirement for the model. In fact, Tamtron's current wheel loader scale works in a comparable way, i.e. the payload is estimated once the boom has moved past two proximity sensors.

### 3.4.2 Regression Model Formulation

Linear regression is a machine learning technique that assumes a linear relationship between the dependent variable $y$ and the regressors $\mathbf{X}$. In its simplest form with only one input variable $\mathbf{x}$, the model can be expressed as:

$$\hat{y} = \beta_0 + \beta_1 x + \varepsilon_i \tag{3.5}$$

where $\hat{y}$ is the predicted value, $\beta_0$ is the line intercept, $\beta_1$ is the slope coefficient, $x$ is the input variable and $\varepsilon_i$ represents the error term. This equation represents a straight line in two-dimensional space.

For a dataset with $n$ samples, this can be expressed in vector form as:

$$\hat{\mathbf{y}} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{3.6}$$

where $\hat{\mathbf{y}} = [\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n]^T$, $\boldsymbol{\beta} = [\beta_0, \beta_1]^T$, $\mathbf{X} = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix}$, and $\boldsymbol{\varepsilon} = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n]^T$.

For multiple input variables, this formula can be extended by adding more columns to $\mathbf{X}$. The regressor matrix $\mathbf{X}$ for our data would look like this:

$$\mathbf{X} = \begin{bmatrix} 1 & P_{boom,1} & P_{\text{body},1} & \dot{P}_{\text{boom},1} & \dot{\theta}_{\text{boom},1} \\ 1 & P_{boom,2} & P_{\text{body},2} & \dot{P}_{\text{boom},2} & \dot{\theta}_{\text{boom},2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & P_{boom,n} & P_{\text{body},n} & \dot{P}_{\text{boom},n} & \dot{\theta}_{\text{boom},n} \end{bmatrix} \tag{3.7}$$

LASSO (Least Absolute Shrinkage and Selection Operator) regression is a modified regression technique that performs both feature selection and regularization [20]. This is achieved by adding a penalty term $L_1$ to the objective function of a regular linear regression model based on the absolute value of the coefficients. The addition of the penalty term means that some of the coefficients will be shrank towards 0. The penalty term $L_1$ for a dataset with $p$ features can be formulated mathematically as follows:

$$L_1 = \lambda \sum_{i=1}^{p} |\beta_i| = \lambda \|\boldsymbol{\beta}\|_1 \tag{3.8}$$

where $\lambda$ is the regularization parameter that controls the amount of regularization, $\beta_i$ is the $i$th coefficient, $p$ is the number of features, and $\|\cdot\|_1$ denotes the $\ell_1$ norm (Manhattan distance).

The objective function of the LASSO regression is to minimize the sum of the residual sum of squares (RSS) and the regularization term $L_1$. The objective function can be described mathematically as follows:

$$\min_{\boldsymbol{\beta}, \beta_0} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta} - \beta_0\|_2^2 + \lambda \|\boldsymbol{\beta}\|_1. \tag{3.9}$$

where $\mathbf{y}$ is the vector of the actual payloads in the training data, $\boldsymbol{\beta}$ is the coefficient vector, $\boldsymbol{\beta_0}$ is the intercept term, and $\|\cdot\|_2$ denotes the $\ell_2$ norm (Euclidean norm).

Lasso regression was chosen for this study due to its ability to prevent overfitting. By selecting the most important features and reducing the complexity of the model, it is able to estimate the payloads with high accuracy. The optimal value for $\lambda$ was determined via cross-validation on the training set.

### 3.4.3 Intuition

Although the relationship between the measured variables and payload is generally not linear, things change when a small boom angle range is observed. When the boom angle range is small enough, the relationship becomes approximately linear. This is likely due to only small changes in the moment arms and the lifting velocity. Thus, a linear regression model can be used in such circumstances.

There are several reasons for collecting samples with fixed intervals, as opposed to collecting all samples from the desired boom angle range. First, this approach effectively acts as a form of downsampling, which reduces the influence of sensor noise. Second, this sampling approach creates a more uniform representation of the data, since each portion of the boom angle range contributes equally to the model. In this way, slower movements do not dominate certain angle regions. Lastly, this approach is computationally efficient and can be easily implemented on microcontrollers with limited computational capabilities.

It should be noted that this approach does not work well in the end ranges of the boom. However, this is irrelevant for our purposes since we are only concerned with estimating the payload at one singular point during the lifting cycle. There is no realistic scenario in which we want to measure the payload at either end point of the boom range.

# 4. RESULTS

Detailed performance metrics of each individual model are presented in Tables 4.1 and 4.2, respectively. Table 4.3 contains a side-by-side comparison of the performance of both models, where the mean absolute error and the root mean square error (RMSE) are calculated across all samples of the test data.

***Table 4.1.*** *Performance of the Neural Network Model*

| **Payload (kg)** | **Mean Absolute Error (kg)** | **Maximum Absolute Error (kg)** | **Target Absolute Error (kg)** |
|---|---|---|---|
| 2000 | 58.6 | 631.8 | $\leq 25$ |
| 7000 | 76.7 | 384.7 | $\leq 50$ |
| 13000 | 137.0 | 1142.1 | $\leq 75$ |

The accuracy of the neural network model was not sufficient for our needs. The neural network model failed to estimate the payload with sufficient accuracy for all test samples.

***Table 4.2.*** *Performance of the Angle-Interval Regression Model*

| **Payload (kg)** | **Mean Absolute Error (kg)** | **Maximum Absolute Error (kg)** | **Target Absolute Error (kg)** |
|---|---|---|---|
| 2000 | 10.5 | 18.9 | $\leq 25$ |
| 7000 | 13.1 | 23.5 | $\leq 50$ |
| 13000 | 31.4 | 67.5 | $\leq 75$ |

The angle-interval regression model estimated the payload with very high accuracy. The absolute error for each test sample is less than the maximum permissible error, making it a suitable model for future development.

***Table 4.3.*** *Overall Performance Comparison of Payload Estimation Models*

| **Model** | **MAE (kg)** | **RMSE (kg)** |
|---|---|---|
| Neural Network Model | 91.3 | 134.6 |
| Angle-Interval Regression Model | 17.9 | 24.6 |

# 5. CONCLUSION

This thesis proposed a novel approach for estimating the dynamic payload of wheel loaders using fixed-interval angle sampling and regression modeling techniques. With a mean absolute error of $17.9\,\mathrm{kg}$, the model's accuracy exceeds the specified accuracy requirements [1, Table 6]. This solution eliminates the need for proximity switches while also maintaining computational efficiency, making it a suitable candidate for future development.

While direct comparison with the current literature is complicated due to different conditions such as vehicle movement and ground inclination, our model's performance appears highly competitive. For example, the accuracy we achieved significantly surpasses the $91.1\,\mathrm{kg}$ MAE reported by Hindman et al. [8, p.41] for their neural network approach under similar stationary conditions. However, it must be emphasized that the current validation was performed under specific conditions (stationary vehicle, level ground). Thus, further validation across more diverse operational conditions is needed before drawing strong conclusions about the model's performance in real-world settings.

The accuracy of our neural network model was not sufficient and the model failed to exceed its accuracy requirements with all test samples [1, Table 6]. This can likely be attributed to several factors. The model tried to continuously estimate the payload at all points of the lift cycle, instead of estimating the payload once at one specific angle, making the prediction task more challenging. The training data was limited not only because of its small size, but also because the sensor data is inherently noisy, further amplifying the problems associated with a small sample size.

The research demonstrates that simple regression models can outperform complex neural networks for dynamic payload estimation when the model is properly constrained to relevant boom angle ranges, and an effective sampling methodology is used.

Future work should include the collection of training data from different inclination angles and evaluating the model's performance on a moving wheel loader. The inclination data can be used as an input to the model, making the model more robust for real-life scenarios where the ground is not always level. Different terrain inclinations alter the gravitational forces acting on the boom, which affects pressure readings and payload estimation.

# REFERENCES


[1] International Organization of Legal Metrology. *Automatic catchweighing instruments. Part 1: Metrological and technical requirements - Tests*. International Recommendation R 51-1. Edition 2006 (E), Erratum (2010.08.09). Organisation Internationale de Métrologie Légale, 2006. URL: https://www.oiml.org/en/files/pdf_r/r051-1-e06.pdf (visited on 03/18/2025).

[2] PFREUNDT GmbH. *The WK60 wheel loader scale*. Brochure. 2025. URL: https://www.pfreundt.de/fileadmin/images/produkte/Produktbl%C3%A4tter-PDF/Produktbl%C3%A4tter_2025/PFREUNDT_Produktblatt_2025_02_RAD_EN.pdf (visited on 03/24/2025).

[3] PTE Scales. *Wheel loader scale*. Dynamic weighing ensures more accurate and reliable weighing in larger machines. PTE Scales. 2025. URL: https://www.ptescales.fi/en/wheel-loader-scale/ (visited on 03/24/2025).

[4] Scale and Control Inc. *WLS555 Weigh On The Move Wheel Loader Scale*. PTE Scales. 2025. URL: https://www.scaleandcontrol.com/uploads/1/1/3/1/113114037/sci_wls555_weigh_on_the_move_wheel_loader_scale_brochure_02_02_24.pdf (visited on 03/24/2025).

[5] Savia, M. and Koivo, H. N. Neural-network-based payload determination of a moving loader. *Control Engineering Practice* 12.5 (2004). Fuzzy System Applications in Control, pp. 555–561. ISSN: 0967-0661. DOI: 10.1016/S0967-0661(03)00136-9.

[6] Feng, J.-y., Chen, W., Wang, T.-j., Tan, P. and Li, C.-s. Online prediction of loader payload based on a multi-stage progressive model. *Automation in Construction* 144 (2022), p. 104621. ISSN: 0926-5805. DOI: 10.1016/j.autcon.2022.104621.

[7] Madau, R., Colombara, D., Alexander, A., Vacca, A. and Mazza, L. An online estimation algorithm to predict external forces acting on a front-end loader. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering* 235.9 (2021), pp. 1678–1697. DOI: 10.1177/09596518211005583.

[8] Hindman, J. J. Dynamic payload estimation in four wheel drive loaders. PhD thesis. University of Saskatchewan, 2008.

[9] Walawalkar, A. and Verlag, A. *A Method for Dynamic Payload Estimation in Hydraulic Excavators:* Schriftenreihe Schienenfahrzeuge und Transportsysteme. Aprimus Verlag, 2022. ISBN: 9783985551293.

[10] Ballaire, F. Dynamic, Continuous, and Center of Gravity Independent Weighing with a Loader. doctoralthesis. Technische Universität Kaiserslautern, 2015, XXIII, 130, A 31.

[11] Bennett, N., Walawalkar, A. and Schindler, C. Payload Estimation in Excavators: Model-Based Evaluation of Current Payload Estimation Systems. *3rd Commercial Vehicle Technology Symposium (CVT2014)*. Vol. 3. Kaiserslautern, Germany, Mar. 2014.

[12] Butterworth, S. On the Theory of Filter Amplifiers. *Experimental Wireless & the Wireless Engineer* 7 (Oct. 1930), pp. 536–541.

[13] Goodfellow, I., Bengio, Y. and Courville, A. *Deep Learning*. http://www.deeplearningbook.org. MIT Press, 2016.

[14] LeCun, Y., Bengio, Y. and Hinton, G. Deep Learning. *Nature* 521 (May 2015), pp. 436–44. DOI: 10.1038/nature14539.

[15] Ramachandran, P., Zoph, B. and Le, Q. V. Searching for Activation Functions. *CoRR* abs/1710.05941 (2017). arXiv: 1710.05941.

[16] Glorot, X., Bordes, A. and Bengio, Y. Deep Sparse Rectifier Neural Networks. *Proceedings of the 14th International Conference on Artificial Intelligence and Statistics (AISTATS)*. Vol. 15. Jan. 2010.

[17] Kingma, D. P. and Ba, J. *Adam: A Method for Stochastic Optimization*. 2017. arXiv: 1412.6980 [cs.LG].

[18] Duchi, J., Hazan, E. and Singer, Y. Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research* 12.Jul (2011), pp. 2121–2159.

[19] Hinton, G. *Overview of mini-batch gradient descent*. Lecture 6 of Neural Networks for Machine Learning. Slide 27. 2014. URL: https://www.cs.toronto.edu/~tijmen/csc321/slides/lecture_slides_lec6.pdf (visited on 03/21/2025).

[20] Tibshirani, R. Regression Shrinkage and Selection Via the Lasso. *Journal of the Royal Statistical Society: Series B (Methodological)* 58.1 (1996), pp. 267–288. DOI: 10.1111/j.2517-6161.1996.tb02080.x.