KTH ROYAL INSTITUTE
OF TECHNOLOGY

Mechatronics Capstone Course MF2121

Spring Term Report
Smooth Operator

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LIST OF FIGURES

ACRONYMS

AHRS Altitude and Heading Reference System

ARW Angle Random Walk

CAD Computer Aided Design

FMEA Faliure Mode Effects Analysis

IMU Inertial Measurement Units

I2C Inter-Integrated Circuit

LQR Linear Quadratic Regulator

MEMS Micro-Electro-Mechanical Systems

MIMO Multiple Input Multiple Output

ML Machine Learning

MLP Multi Layer Perception

MPC Model Predictive Control

NN Neural networks

PID Proportional-Integral-Derivative

RL Reinforcement Learning

SMC Sliding Mode Control

UART Universal Asynchronous Receiver/Transmitter

USB Universal Serial Bus

1 INTRODUCTION

This chapter will introduce the project and cover the background, project specifications and requirements amongst others to get an overview of the project.

1.1 Background

Excavators are used worldwide in multiple industries such as construction, mining, forestry, and agriculture. The market size was valued at slightly below 50 Billion USD by the end of 2024 [1]. The tasks of excavators involve digging, trenching, and grading different soils. These operations require high precision and depend heavily on the machine operator who, in traditional excavator operation, must manually coordinate the hydraulic actuators to achieve the desired outcome. High-precision task such as these become challenging and highly dependent on the seniority of the operator.

Current trends in construction equipment and construction machinery point towards more automation and operational support to meet the demands of the increasingly more complex modern construction tasks [2]. One main area where this is especially relevant is in the control of the excavator bucket. For the operator to maintain the bucket tip parallel to the ground during grading or lifting, they must control the boom and the arm at the same time, this movement requires both continuous adjustments and spatial awareness.

The foundation for the project was to simplify the inputs required from an excavator operator during the more high-precision tasks, such as grading and lifting. The current input system of two-lever controls are well established within senior operators but are quite advanced for junior operators. This creates a challenge to find a solution that satisfies both senior and junior operators. The prevalence and easy access to video game consoles for younger generations, with the current amount of console users across the world has reached an estimated 630 million people, ensures that more people each year are familiar with joystick inputs. [3]

This project aim to address this challenge, with support and collaboration from the stakeholders, by developing a control method that allows for the bucket tip of an excavator to move in parallel or perpendicular to the ground through a single control input. Bridging the required knowledge needed for the more advanced two-lever control mastered by senior operators and the junior operators through keeping the same input mechanism but lowering the amount of inputs.

The report will furthermore outline the requirements of the project, as well as a state of the art that shapes the theoretical background for the model.

1.2 Scope

The scope of this project is to design and implement a solution that makes it possible for a Volvo excavator of model EC20E to perform automatic grading and lifting. This includes replacing the two lever manual control that is the current steering mechanism of the excavator, with a single input system that coordinates and controls the movement of the three hydraulic actuators of the boom, arm, and bucket.

During the spring term, the project will focus on developing a complete simulation and control framework of the mode. Including building a dynamic model of the excavator in MATLAB simulink and simscape, selecting relevant sensors and determining sensor placement for accurate position estimation. As well as choosing and implementing control strategies such as PID or MPC to attain a precise trajectory planning.

1.3 Team structure

The team consists of nine members, all whom have the same responsibility to contribute equally to the project. At the beginning of the project the team created a code of conduct that every team member has to follow to ensure smooth teamwork that promotes inclusivity, openness, and patience. The code of conduct was derived unanimously and approved by each member in the group.

To further ensure efficient work flow, the team has divided into subgroups with different responsibilities. The three subgroups are divided according to the project areas. As of the beginning of the project, these subgroups were modelling, control, and implementation. Each subgroup has three team members working in it. The smaller teams are very flexible, meaning that the size of the subgroups can vary during the project depending on the workload for the task at hand in each subgroup.

For information keeping and sharing, a shared google drive is used, as well as discord channel for communication and a github for sharing code within the team. For each team meeting, members have different responsibilities such as creating the agenda, taking notes, and planning for when and where the next meeting should take place.

1.4 Stakeholders

The project stakeholders are KTH Royal Institute of Technology and Volvo Construction Equipment (Volvo CE). To fulfil KTH expectations we aim to deliver an academic project which meets the grade requirements. For Volvo CE, our aim is to provide a clear and realized solution.

1.5 Requirements

To be able to define the problems that will need to be solved to satisfy the expectations of the stakeholders, a set of requirements was derived.

Requirements

1. From a flat and level surface, the excavator bucket tip should be able to perform movements in the xy-plane.
    - Grading in x-direction
    - Lifting in y-direction
2. The precision should be within $\pm$ 5 mm in both directions (x and y).
3. To consistently achieve reliable results.
    - During continuous operation
    - While being subjected to disturbances
4. The code should be well written and easy to modify by the stakeholders.

2 STATE OF THE ART

This section summarizes the current state of the art (SOTA) in three clearly defined and relevant areas, with a focus on the scope of the project. Those areas are:

- Modelling of hydraulic arms/system.
- Control methods for hydraulic arms.
- Measured variables, sensors, and pose estimation for arms.

The objective is to understand what methods and viewpoints are commonly practised in relevant papers, understanding the modelling, analysing performance, trade-offs etc. The analysis also prevents the team from ”re-inventing the wheel” and pushing the technology forward.

2.1 Modelling of excavator

When developing a machine and its control software, it is important that the control methods can be tested and tuned on the machine during development to get an understanding of what methods are effective. During large parts of the twentieth century, this was done in real life on the real machine. In modern times however, modelling and simulations have become a crucial part of product development.

In this section multiple options are explored for constructing an accurate simulation model of the excavator. The parts that are relevant to model in this project are the hydraulic system and the mechanics of the boom, arm and bucket.

2.1.1 Modelling with Matlab Simulink

One popular way to model an excavator is to use Matlab Simulink. With Simulink, both a mechanical model and a hydraulics model can be made, describing the dynamics between the arm, boom and bucket, and simulating the behaviours of the three hydraulic actuators.

For the mechanical model, CAD parts can be imported to the Simscape Multibody environment, including dynamic properties of each part such as mass, center of mass, constraints and more. With dimensions and other properties from the data sheet of the real excavator, a model resembling the actual excavator can be created which should have similar dynamics. As for the hydraulics part, Simscape Fluids can be used for modelling the three actuators.

Parameters of the model can be optimized if they are inaccurate due to, for example, not being available in the data sheet. This is done by comparing data from operating the real excavator with the results from the model, when the same inputs are used. Simulink can then change the model parameters so that the results of the Simulink model match the measured results [4].

2.1.2 Modelling with Machine Learning

Recent research has explored data-driven modelling of hydraulic excavators using machine learning (ML), bypassing the need for complex physics-based simulations. Instead of relying solely on theoretical models, these approaches use real operational data to train ML models that predict excavator behaviour. Below, we analyze two key studies that employ supervised learning to model excavator dynamics.

One study in this field is "Towards RL-Based Hydraulic Excavator Automation" by Pascal Egli and Marco Hutter [5]. This research introduces a neural network-based approach to learn the relationship between operator inputs and machine behavior, utilizing real-world data.

Neural Networks (NNs) are a type of machine learning model inspired by how the human brain processes information. They consist of layers of simple units called neurons, which take inputs, apply weights and biases, and pass the result through an activation function to produce an output. These outputs are then passed to the next layer. During training, the network uses a process called back propagation to adjust its weights and biases. This involves comparing the network's prediction with the actual result and then working backwards through the layers to reduce the error. Over time, the network "learns" how to make better predictions from the data.

The core of Egli and Hutter's modeling approach is a three-layer MLP (Multi-Layer Perceptron), which is a widely adopted feedforward neural network. Each layer consists of 128 neurons with ReLU activation functions. The model takes as inputs the current joint positions, a history of joint velocities over the past 0.1 seconds, and a sequence of past valve commands (sampled at 30ms intervals over 0.99 seconds) to account for hydraulic system delays. The output predicts joint velocities for all four actuators (boom, dipper, telescopic arm, and shovel) at the next timestep (10ms ahead).

Kim and Kim [6] built upon Egli and Hutter's forward-dynamics modelling approach through three key modifications while maintaining the core MLP architecture. First, they transitioned from joint-space to cylinder-space velocity prediction, using the neural network to directly estimate hydraulic cylinder motions rather than joint movements. This reduced the complexity of what the neural network needed to learn. Second, they upgraded the model by using denser historical inputs (10ms resolution vs. Egli and Hutter's 30ms) while maintaining the same 0.99s lookback interval. Third, Egli and Hutter used semi-autonomous control with manual and automated joystick signals, under human supervision for safety. The engine speed and cabin position were fixed during two hours of 100 Hz recording to mimic real usage conditions. On the other hand, Kim and Kim fully automated data collection using randomized joystick patterns, reducing safety constraints and covering more hydraulic states, while keeping the same recording setup.

2.2 Control methods for hydraulic arms

During the SOTA analysis, two alternatives for controlling the excavator were identified. These are a fully automatic method and semi automatic method.

2.2.1 Fully automatic method

In this method all of the three degrees of freedom (boom, arm and bucket) are controlled by the computer to achieve the desired motion. This is the most conventional method for control of end effectors in the robot industry. The reference values for the angular velocities of the joints are usually calculated using a trajectory planning algorithm if a predetermined trajectory is desired. The trajectory algorithm uses inverse kinematics to calculate the references at every time step before the execution of the movement. If a live control is instead desired, a velocity controller is then used which calculates the inverse kinematics in real time at every time step. In both of these cases, a controller for each joint tries to follow an angular velocity reference.

The advantage of the fully automatic method is that the computer has control of all the degrees of freedom and thus there is no unpredictable input from the operator. The disadvantage is that needing to control all the degrees of freedom might make for a more complex controller.

2.2.2 Semi-automatic method

In this method the operator controls the arm of the excavator manually during grading and the boom during lifting. For the case of grading, the computer controls the boom- and bucket-actuators so that the bucket moves in a horizontal line. This reduces the control problem to two degrees of freedom instead of three. It is not an option to use a trajectory controller in this case due to the unpredictable nature of the operators input. During grading, the movement in the horizontal direction is largely achieved by the manual arm control.
The advantage of the semi automatic method is the potential of making the control problem less complex. The disadvantage is that the controller might not be able to keep up if the operator input is not smooth.

2.2.3 Joint control options

A controller is needed to make sure each joint angular velocity follows its reference. From the surveyed state-of-the-art analysis (SOTA), several control methods have been identified as potential candidates for achieving the goal, which are shown in Table 2.1. In this case, when using a feedback controller, it is desirable to use a feed-forward element to complement the feedback part. This feed-forward element can be constructed in several ways. The first method is to use a one-dimensional lookup table of known angular velocities and hydraulic valve openings to generate the control signal addition. However, due to the one-dimensional aspect, this lookup table will not be accurate at all times. Another alternative is using equations describing hydraulic dynamics [7]. This method requires precise knowledge about the workings of the hydraulic system. The method with the highest performance according to the SOTA analysis is a supervised learning method where a neural network learns the relationship between hydraulic cylinder velocity and hydraulic valve opening. In that case, kinematic relations are used to transform joint velocities to cylinder velocities. [6].

Table A.1 provides a detailed summary of relevant publications.

Methods	Advantages	Limitations
Machine learning (ML)	• Learns optimal control strategies based on data from operation of excavator. • Performs well in unstructured, dynamic environments. • Handles nonlinearities and model uncertainties.	• Safety and constraint satisfaction are difficult to guarantee. • Less interpretable and harder to tune [8]. • Transfer from simulation to real-world deployment is non-trivial.
PID (+ Split-Range)	• Simple and well-understood; quick to implement. • Reliable and commonly used in industrial settings. • Can be extended with feedforward or split-range control [9].	• Limited for multi-variable systems like X/Y axis coordination. • Performance degrades with system nonlinearities or varying loads. • In case of strong cross-couplings between inputs and outputs, decentralized control could not be used and another method would have to be used [10] p.219.
Model Predictive Control (MPC)	• Handles multi-input multi-output (MIMO) systems. • Easy to include constraints on the values [10]. • Provides predictive and optimized control performance.	• Requires a system model and greater computational power is needed if the sampling time is short [10] p.385. • Longer development and tuning time.
Linear Quadratic Regulator (LQR)	• Provides the simplest optimal control for linear systems [11]. • Minimizes control effort while achieving low error.	• Linearization of plant necessary. • Less flexible in handling constraints and robustness is not accounted for [12].
Lead/Lag control	• Increases phase margin, which typically results in faster response and reduced overshoot. • Conditionally proven robustness.	• Lead/lag controllers require a more precise plant model, which includes time delay for simulation performance to come close to real performance. • Limited low-frequency performance — not ideal for improving steady-state error or DC gain.

Table 2.1: Advantages and limitations of control methods.

2.2.4 Evaluation of joint Control Methods

Machine Learning (ML): ML has the highest performance potential. The challenges lie in that high quality data has to be collected from the real machine to train the model. Reinforcement learning has the disadvantage of needing a very accurate model of the system to perform well.

PID Control: PID is a strong baseline method for early prototyping and testing. It provides simplicity and quick deployment but might not meet full performance requirements alone. It could be hard to implement on a strongly coupled MIMO-system though[10]. Then MPC or similar optimization controllers could be used. Also, the methodology of the PID controller is familiar within our group.

MPC: MPC aligns well with the final project goals due to its capability to manage multiple actuators, predict disturbances, and ensure precision under constraints. One con is that it is not practiced by any of the group members but it is familiar to some. This could lead to the same problems encountered when using reinforcement learning (RL).

LQR: LQR is best suited for theoretical analysis or simplified test cases. Could not be ideal for full-scale implementation in this nonlinear hydraulic system. Could be improved if linearization is made.

Lead/Lag: Can be used in cascade with e.g. PID control to increase robustness in terms of phase margin.

2.3 Measured variables, sensors, and pose estimation for arms

Accurate sensor data and reliable pose estimation are essential for enabling assisted control of the excavator arm. This section outlines the key sensor requirements and the strategies used to estimate the pose of the excavator's moving parts.

2.3.1 Sensor Requirements for Excavator Pose Estimation

To enable the assisted movement of this project, it is crucial to precisely understand the excavator's position and motion. This is achieved through sensors that provide real-time data regarding the bucket's position, orientation, and movement. The collected data is then used as feedback to regulate motion and ensure high precision control. The system must deliver positional data with a precision of ± 5 mm, essential for accurate grading. Achieving this requires careful sensor selection that takes into account harsh environmental conditions, including dirt, vibrations, weather, friction and mechanical stress, while maintaining reliable performance over time.

Today, there are several established solutions where sensors are used to assist in bucket movements, automated grading control, and to perform tasks based on digital blueprints using advanced navigation technologies. A state of the art analysis of the sensors has been conducted regarding the available sensors and considerations for sensor selection, which is presented below. It is of interest to examine sensors used not only for excavators but also for heavy machinery to understand the requirements for sensors in similar machines and environments. In addition, exploring other fields where precision and control of an endpoint are key, such as robotic arms used in manufacturing, can provide valuable insight. However, it is important to note that many commercial solutions do not disclose detailed technical implementations, which limits our insight into the specific sensors used for excavator control.

One of the main challenges is measurement accuracy. Even small errors in the angle can significantly affect the bucket position estimate. Calibration and sensor noise are also critical issues. IMUs and other sensors suffer from drift and noise, which must be managed through techniques like Kalman filtering. Additionally, sensor placement can be tricky; some sensors may be difficult to mount, and it's important to avoid interference from vibrations or other movements that could affect accuracy.

2.3.2 Sensor Types

Relevant sensor types for this project are primarily inclinometers, rotary encoders, accelerometers, and gyroscopes. Many other projects with automated grading and leveling use lasers, LIDAR, or radar, which is not relevant here, as the project does not require automatic motion control, so environmental localization is unnecessary.

Accelerometer

Accelerometers measure acceleration that the sensor is subjected to, which can be categorized into changes of tilt, vibration, or impact, where different types of accelerometers have been developed to fit these categories accordingly. One of these sensor types is the capacitive accelerometer, which better fits low-acceleration measurements. Through the use of multiple accelerometers combined according to the 3-axis, a full understanding of the sensed object's orientation in 3D space can be extracted upon movement [13].

Inclinometer

Inclinometers are sensors that detect the angle at which they are positioned compared to the gravitational force. This sensor data, normally presented in degrees of the angle offset from the vertical or horizontal axis, is useful for determining the current tilt of the sensor or the object to which it is attached. Inclinometers utilize accelerometers to measure tilt and are calibrated to maintain accuracy within a specific measurement range. [14].

Rotary encoder

A rotary encoder is a device that measures the rotation or angle between two arms. It provides high accuracy in angle data and operates quickly. One of its key advantages is that it is not affected by changes in gravity or acceleration. However, it can be challenging to install, as it must be mounted at the rotation point of each arm, which could be particularly difficult for the bucket itself.

There are two main types of rotary encoders, incremental and absolute. Incremental encoders indicate changes in position by generating pulses per revolution, while absolute encoders allow for precise tracking without relying on a reference point by providing unique digital codes for each position [15].

Gyroscope

Gyroscopes use the earth's gravity to determine orientation. Gyro sensors sense the change in rotational angle per unit of time, or angular velocity. There are three main types of gyroscopes: mechanical, fiber-optical, and micro-electro-mechanical Systems (MEMS) gyroscopes.

Mechanical gyroscopes are simple and they utilise the angular momentum of a spinning rotor inside it to maintain its attitude. In a fiber optical gyroscope, there is a laser that sends two beams of light through an optical filter. The beams will return at the same time if there is no rotational change, if there was any change in rotation, the distance that the beams travel will change and thus, arrive at different times [16]. In comparison, micro-electro-mechanical systems (MEMS) or vibrational gyroscopes, measure the Coriolis acceleration of a vibrating element, which is proportional to angular velocity, and can be easily built smaller compared to other gyroscopes. When choosing and using a gyroscope, it is important to control its Angle Random Walk (ARW), bias offset and instability, as well as temperature, shock, and vibration sensitivity [17]

IMU

Inertial Measurement Units, or IMUs, are fundamental components in today's motion tracking and navigation systems. They combine accelerometers, gyroscopes, and sometimes magnetometers [18]. The combination of these sensors allows for accurate orientation tracking, which is particularly useful in environments where motion is complex and constantly changing. However, there are some limitations to using IMUs. The programming and data filtering required can be more challenging, as it often involves complex algorithms to handle sensor fusion and provide accurate output.

Additionally, during extended use, IMUs can experience "drift" in their data, especially due to the gyroscope, which affects long-term accuracy. However, this can be managed. The airline industry deals with this issue regularly, especially on longer flights. The solution to the problem is to reset the gyroscope during flight on a regular basis, meaning they are tuning during continuous operation [19]. Furthermore, the magnetometer within the IMU can be sensitive to interference from nearby motors, metal structures, or magnetic fields, which can distort the readings.

AHRS

Attitude and Heading Reference System (AHRS) is a sensor module that uses an IMU which consists of a MEMS to measure the angular rate, acceleration, and the Earth's magnetic field. An AHRS typically combines gyroscopes, accelerometers, and magnetometers to estimate the orientation in space. It is more advanced than a single IMU, they use measurements from the gyroscope, accelerometer, and magnetometer to provide an estimation of the orientation of a system, often using a Kalman filter. It is commonly used because it provides continuous orientation data without relying on external references and is more stable over time than a standalone IMU, thanks to built-in filtering and drift compensation from the Kalman filter. It is relatively easy to mount directly on individual links (boom, arm, bucket) without requiring mechanical connection to the joints. However it has lower angular accuracy compared to encoders when measuring joint angles between mechanical links and can suffer from long-term drift if not properly calibrated or fused with complementary sensors. High-precision AHRS units can also be very expensive, particularly when multiple sensors are needed for full system coverage [20].

A similar project used AHRS sensors with the goal of minimizing modifications to the original excavator. This made AHRS a well-suited solution. In their setup, the IMU was mounted on the body of the excavator to support operations on sloped terrain, while AHRS sensors were attached to the boom, arm, and bucket to measure joint angles. The sensors communicated via UART, I2C, and USB, and the data was processed using an ARM-based microprocessor running a Kalman filter to fuse information from the different sources. With this system, they achieved a bucket position accuracy within 50 mm [21].

2.3.3 Sensor Fusion

Sensor fusion is the process of combining data from multiple sensors to create more accurate and reliable information than what each sensor can individually provide. This technique is commonly used in systems where high precision, reliability, and stability are required in the results, such as in robotics, autonomous vehicles, and navigation systems [22]. This can be done either internally, for example, within the same device, like in IMUs and AHRSs, or externally, for example, in a separate processor or algorithm.

The main idea is that the sensor fusion reduces uncertainty in the final output compared to using individual sensors. Other benefits of sensor fusion are that it can also help compensate for things like sensor noise, limited accuracy, or lack of information regarding the environment where the sensor is operating. It can also be beneficial to use sensor fusion when the ideal sensor is very expensive [23].

However, even though there are many benefits to sensor fusion, there are also challenges. It can be difficult to differentiate between what is a true signal and what is noise, as well as handling different sampling rates that need to be synchronized. Furthermore, sensor fusion often involves complex computational processes and mathematical algorithms, especially when dealing with real-time applications that demand quick data processing. The complexity of the fusion algorithms increases with the number of sensors, as well as the computational demands [24].

2.3.4 Advantages and limitations of sensor types

A list of advantages and disadvantages was constructed for each researched sensor type to justify the selection of sensors for this project is presented in Table 2.2.

Sensor Type	Advantages	Limitations
Accelerometer	• Measures linear acceleration, can estimate tilt when stationary. • Simple and widely available.	• Sensitive to vibrations and impacts. • Requires sensor fusion to distinguish tilt vs acceleration.
Inclinometer	• Direct tilt measurement relative to gravity. • Simple installation per joint.	• Affected by vibrations and dynamic movements. • Slower response to fast changes.
Rotary Encoder	• High-accuracy rotational angle data. • Unaffected by gravity and acceleration.	• Requires precise mechanical mounting at joint axes.
Gyroscope	• Measures angular velocity with high dynamic response. • Ideal for fast rotational movements.	• Subject to long-term drift. • Does not provide absolute position, only changes.
IMU	• Combines accelerometer, gyroscope (and optionally magnetometer) for 3D orientation. • Suitable for dynamic motion tracking.	• Suffers from drift over time. • Requires advanced filtering. • Magnetometers sensitive to metal interference.
AHRS	• Combines IMU data with filtering and drift compensation. • Easier mounting compared to encoders. • Provides continuous orientation.	• Lower joint angle accuracy than encoders. • Can be expensive for multi-joint setups. • Requires proper calibration and fusion.

Table 2.2: Advantages and limitations of sensor types.

3 DESIGN CONCEPT

Based on the findings and conclusions from the SOTA analysis, we started discussing and developing design concepts for the excavator control system. The excavator system was divided into three main areas for the concept development: modelling method (including simulation environment), control method and sensor choice. Each of these components were thoroughly analysed with respect to stake holder- and functional- requirements. This section presents our selected design concept with motivations.

3.1 Modelling

To evaluate different algorithms and control methods efficiently and safely, it is beneficial to test them in simulation before applying them on the real excavator. This saves both time and money, as well as reducing the risk of damage. This was achieved by modelling the relevant parts for this project: the boom, stick and bucket - along with a simplified base to serve as a fixed reference. Two modelling approaches were considered, one using Simulink [25], which is a physics-based simulation environment, and one using a machine learning approach as seen in a former report in our SOTA analysis. The machine learning approach, such as the one presented by Egli and Hutter [5] and later extended by Kim and Kim [6], requires extensive real-world data collected directly from the excavator. This includes joint positions, valve commands, and sensor data sampled at high frequencies over long periods. Since we did not have continuous access to the excavator during this phase of the project, collecting such data was not feasible. In contrast, Simulink allows us to construct a physics-based model using known mechanical parameters and specifications provided by Volvo. This made Simulink a more practical and accessible modeling environment for our initial development phase, while keeping the option open to incorporate data-driven ML components in the future.

A high-fidelity model was modelled using Simulink's extension Simscape Multibody [26] and Simcape Fluids [4]. In order to work with Simscape Multibody a CAD-model of the relevant parts of the excavator was built using Autodesk Inventor [27]. This CAD-model was then imported into Simulink where a multidomain simulation of the excavator system was constructed. The parts were modelled so that the distance between the control arm mounts matches the Volvo Brochure. [28] This gives centimetre-precision. The mechanical structure was modeled in Simcape Multibody, while the hydraulic actuation system was represented using Simscape fluids.

3.1.1 Simulink & Simscape

In order to support collaboration and maintain an organized workflow within our group, the modelling and simulation work was done using Simulink's built-in project environment[29]. This allowed for consistent file management and the integration with GitHub[30] made the possibility for version control. This enabled for parallel contribution in a shared project, allowing for track changes over time as well as reducing the risk of conflict/data loss handling during development.

As mentioned in the introduction of section 3.1 a high-fidelity model was created to simulate a multidomain implementatoin of the excavator using Simscape- Multibody & Fluids. Simcape is a powerful Simscape toolbox that can be used in order simulate complex multidomain systems. The CAD-model of the excavator were imported to the Simulink workspace and was constructed using rigid transformations[31] between the rigid bodies as well as joints[32], to represent the relative degrees of freedom between the rigid bodies. Figure 3.1 illustrates the Simcape workspace while Figure 3.2 shows a snapshot of the excavator visualized using Simscape Multibody's Mechanics Explorer.

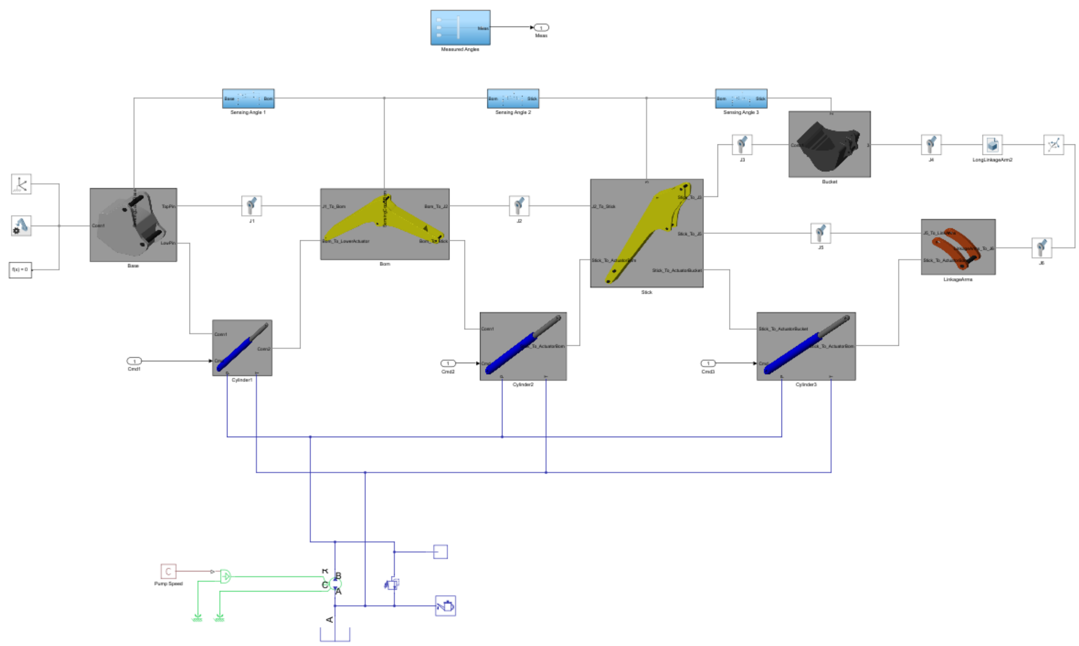

Figure 3.1: Multibody implementation of the excavator using Simscape- Multibody & Fluids.

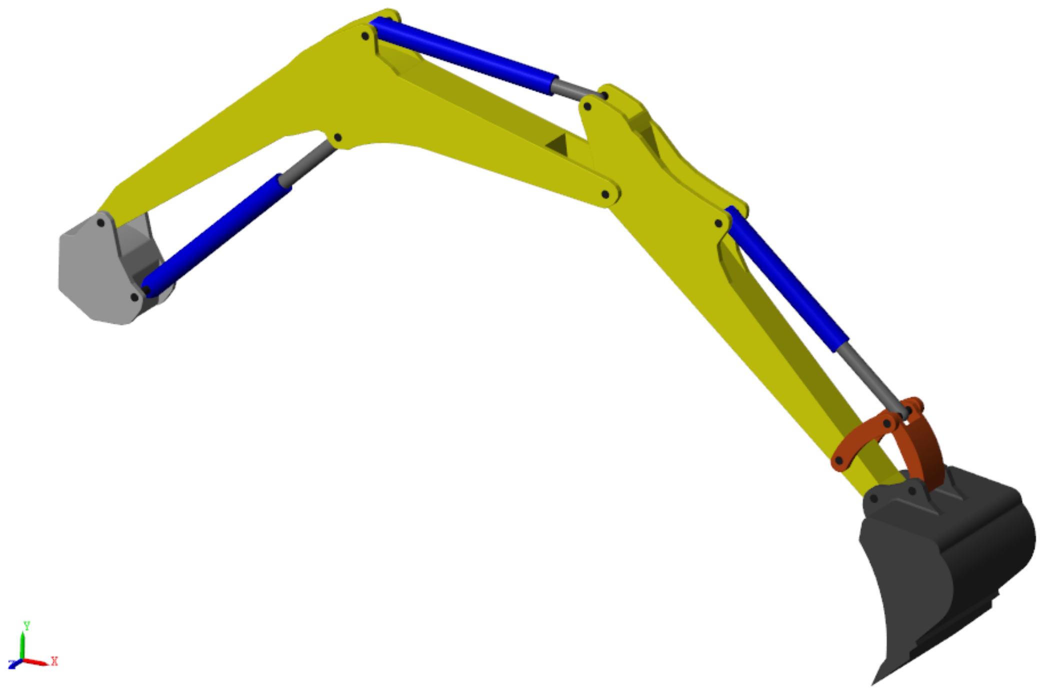

Figure 3.2: Model of the relevant bodies of the excavator visualized using Mechanics Explorer with Simscape Multibody.

3.2 Control methods

The design concept of the control method includes decisions about control setup, controlled variables and controllers.

3.2.1 Control setup

Based on the SOTA on control methods, a fully automatic method was chosen as the control method. This means that all three joints of the excavator are controlled by the computer, compared to the semi automatic solution where the operator controls the arm and the computer controls boom and bucket. This choice was made because of the higher versatility of the automatic method compared to the semi automatic. New grading functions, such as grading diagonal surfaces, should also be easier to implement using the automatic method.

3.2.2 Control variable

During grading and lifting, the bucket should move in a straight line. To achieve this motion, it was decided that velocity control of an end effector in Cartesian space was the best option due to much smoother operation compared to position control.

3.2.3 Kinematics

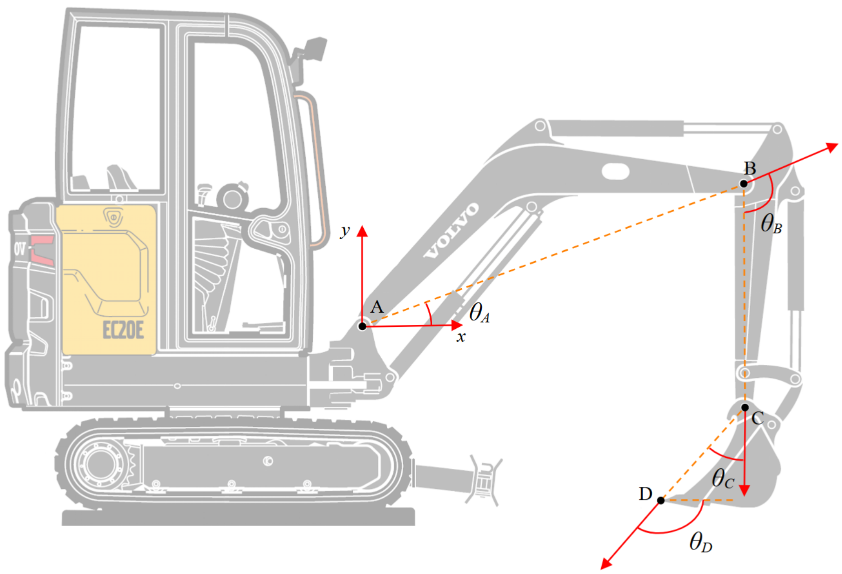

Figure 3.3: Symbols used for the kinematics equations

The reference velocity and orientation of the bucket in Cartesian space must be converted to reference angular velocities of the boom, arm and bucket joints, namely $\dot{\theta}_A$, $\dot{\theta}_B$ and $\dot{\theta}_C$ (see Figure 3.3 for reference). This is done with inverse kinematics through an inverse Jacobian matrix.

To calculate the inverse Jacobian, an expression for the forward kinematics is first stated. The forward kinematic expressions are then differentiated with respect to the joint angles, which form the Jacobian matrix. This matrix is then inverted in order to go from desired bucket velocity and orientation to desired joint angular velocities.

3.2.4 Joint Controllers

For controlling the joint angular velocities, it was decided that a reasonable starting point would be a PID controller. Due to the non linear nature of the hydraulic system and the linkages between hydraulic cylinders and joints, it is assumed that PID alone will not be sufficient. Therefore a feed forward element will also be used utilizing either a look up table, a physics relation method or even a neural network. It is deemed reasonable to start with a look up table and move up the ladder of complexity if time allows. The feed forward element will guess the required hydraulic valve opening required to achieve the desired joint angular velocity.

If time allows, a neural network will be tested as a controller. This network will be trained using data collected from the excavator. The network will initially have the same size as in Kim and Kim's automatic grading project [6], where three fully connected layers each having 128 nodes were used. As most of the highest performing automatic grading projects found during the SOTA all used neural networks, this would be the ideal solution.

3.2.5 Accounting for drift

Due to the velocity control, the bucket will drift in height when grading. This happens because only velocity is controlled, and not position, which means any disturbances in vertical position will be left uncorrected. To account for this drift, a method is proposed where, during grading, the height error of the bucket is calculated at each time step and used to change the Cartesian reference bucket velocity in the vertical direction as follows.

$$0 = (v_{ref} - v) + K(p_{ref} - p) \quad \rightarrow \quad v_{ref} = v - K(p_{ref} - p)$$

where K is a gain, v_{ref} is the improved reference velocity, v is the original reference velocity, p_{ref} is the improved reference position and p is the original reference position.

3.3 Sensors

The choice of sensors for the project had to be carefully selected and based on the research from the SOTA, there are a few things that need to be addressed. To enable such accurate control of the bucket tip, that the project requires, and to ensure that the motion stays parallel to the ground, the system will have to estimate the position of all moving parts in real time, with the required accuracy of ±5 mm and also take into consideration external disturbances such as vibration and dirt. This requires the sensor configuration to be very reliable and precise. To be able to reach this kind of accuracy a hybrid approach was chosen, combining IMUs together with cable pull rotary encoders. IMUs to measure the tilt of each segment of the excavator and rotary encoders to determine how much each joint has rotated.

The decision to move forward with the hybrid approach was based on the accuracy and reliability requirements. Even though IMUs alone offer a very flexible way of tracking orientation, they alone could not meet those requirements due to their tendency to pick up noise from vibrations and the possibility of drifting which is unwanted. To add cable pull rotary encoders, that, on the other hand, provide more stable and accurate measurements and are not too sensitive to noise due to vibrations, will make the configuration more robust, and can deliver high-precision position estimation in real time. Even though the conditions surrounding them are challenging. Although simple accelerometers could technically provide sufficient tilt information, the use of IMU can give better accuracy by also including gyroscopes, which improve orientation tracking through sensor fusion. Moreover, Volvo has previously used and validated IMUs in similar systems, making them available and supported.

Cable pull rotary encoders were chosen over rotary encoders mounted directly on the joints because they are significantly easier to install, especially when mounting on an existing machine. They do not require a direct connection to the axis of rotation, which simplifies integration. In addition, cable pull encoders are more robust in harsh environments since the main sensor unit can be placed in a protected area. They also experience less mechanical wear, since there is no direct rotational coupling.

3.3.1 Sensor Placement Strategy

The sensor placement plays a key part in the project. To try to minimize complexity while also maximizing accuracy, with a focus on choosing positions that would give a complete picture of the motion of the excavator, the following sensor configuration was chosen: four IMUs, mounted on the cabin, boom, arm, and bucket. As well as three cable pull rotaryencoders that will measure cylinder extension, see Figure 3.4.

While one of the IMUs is planned to be mounted on the bucket, we acknowledge that this is a challenging location. The bucket is highly exposed to dirt, impacts, and rapid movements, which can affect both the sensor's durability and the reliability of the data. Therefore, we intend to investigate the most protected possible placement on the bucket. Additionally, we remain cautious about relying too heavily on data from this IMU and instead consider it a supplementary source.

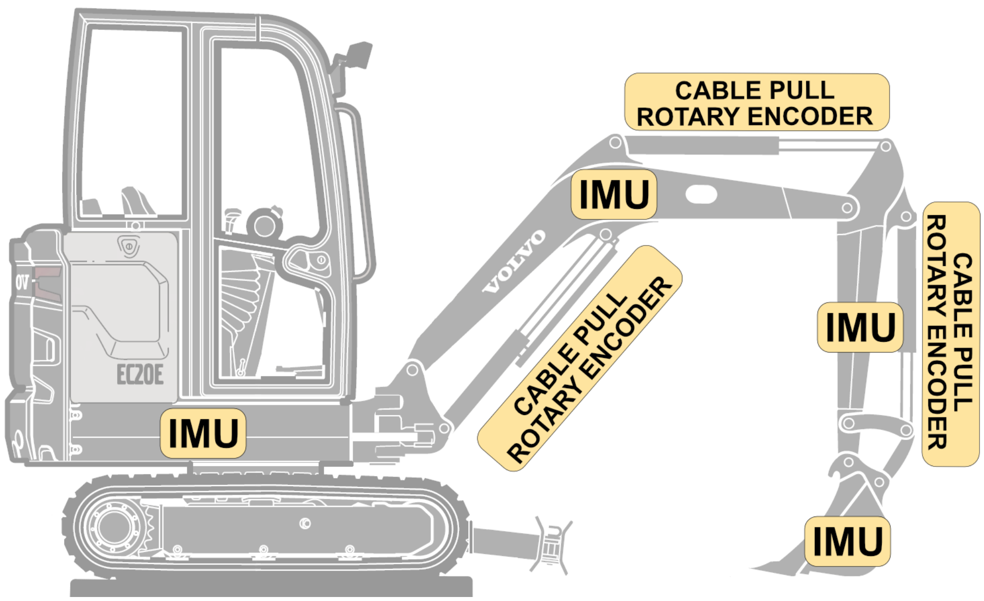

Figure 3.4: Sensor Placement

4 DISCUSSION AND CONCLUSION

In this section a further discussion about risks that could appear during the project and also the work that will be conducted during the fall term.

4.1 Risk analysis

During the course of the project, several risks have been identified. These risks could impact not only the development of the project, but also the final implementation and control of the system. It is crucial for the engineering process to conduct a risk analysis as it helps reveal different factors or hazards that can negatively impact the project. Therefore, a Failure Mode Effect Analysis (FMEA) was performed to help identify different risk factors and also to help evaluate these potential failure modes. The most significant risk that was identified was if someone got hit by the excavator. For more information please see Appendix B

4.2 HT25 plan

To reduce the risk of delaying the project when the fall term starts, it is crucial to order the sensors before the beginning of the general industrial holiday. Another aspect to consider is the system architecture before actually implementing on the real hardware. Figure 4.1 illustrates a simplified view of the system architecture. The operator inputs a signal into the microcontroller which in turn translates it into commands that control the hydraulic actuators. As shown in Figure 4.1, the operator uses a joystick — initially the SpaceMouse Enterprise[33] — to send motion commands to the microcontroller. Sensor data is also fed into the microcontroller to provide feedback. From the microcontroller, the signal is sent via a CAN interface — specifically the Kvaser USBcan Light 2xHS[34] — to a PLC unit. The PLC used in this project is the Parker IQAN-MC43[35], provided by Volvo CE, which generates PWM signals to control the hydraulic valves. This setup enables real-time control of the excavator's motion based on operator input and sensor feedback. A more detailed system description can be seen in Appendix C.

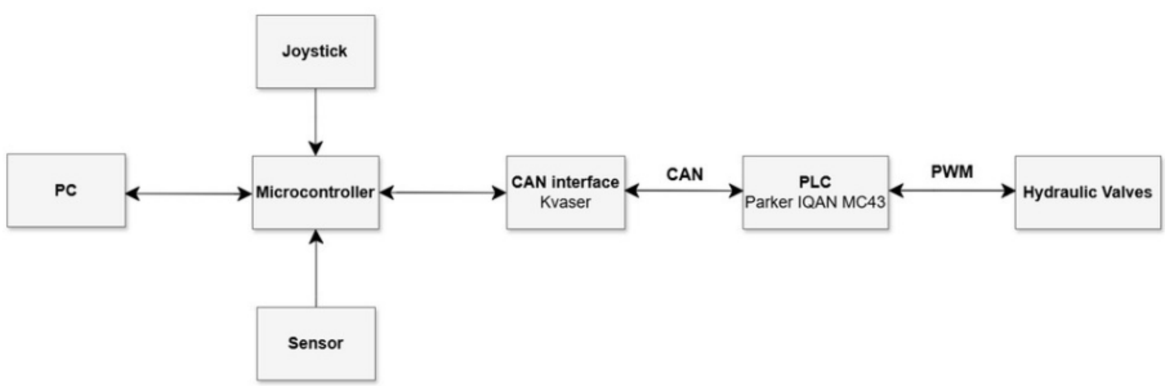

Figure 4.1: System architecture from PC to hydraulic actuators.

The project starts again at the end of August, in week 35, and continues until the middle of December. The project will begin with Volvo transporting the excavator to KTH. The team will then focus mainly on hardware implementation and tuning the controller in simulation. By the end of September, the group will be moving forward and working on sensor fusion. By mid-October, the aim is to test the control methods on the real machine.

All the tuning and software implementations aim to be finished by the end of November. Throughout the course, the group will be working on the report to make sure documentation is being done continuously.

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A Summary of Control Options

Paper	System	Method	Key Results	Notes
Kim, Kim (2025)	Hydraulic excavator	ML - velocity control	Achieved automated grading with an error of less than 1 cm. This was accomplished using a supervised learning neural network that approximated the hydraulic system. Feedback was done using errors in the jacobian matrix and feedback linearization.	Data was gathered from the real excavator but the controller was only tested in simulation on a neural network model that learned to mimic the real machine.
Pascal Egli (2022)	Hydraulic Excavator	ML - velocity control	Used 100min of data-collection, with minimal machine-specific data gave good results and even outperformed Leica in tracking accuracy.	A good result on the control performance with testing of several neural networks. Linear trajectory in the air as well as grading were chosen as evaluation scenarios.
Hannes Wind (2020)	Mini excavator (Simulation model)	P-controller + MPC	NMPC used to generate trajectories with actuator constraints taken into account. A simulation model were made in Simscape and was used along with a velocity and position controller. Mostly focuses on the trajectory generation for the excavator while building on previous publications when considering the dynamic model [36]. This author could be explored where he has a series of publications that is relevant for this project. Optimal control were implemented and achieved. Their next step is to implement that on a real excavator.	Not implemented on real hardware but works fine in simulation.
Liao, Haokai (2025)	Real & simulated Robot Arm	PID and Split-Range Control (nonlinear MIMO)	The AMRPID control method was effectively applied to the robotic arm's actuator, confirming practicality. Highlights need for further comparison with traditional PID.	Good schematics for system coherency and control schedule.
A. Frank (2017)	Mini toy Excavator (physical and simulation)	State-machin + MPC	MPC demonstrated effective and robust performance in tracking target positions, even with disturbances and modeling inaccuracies.	–
R. Malygin (2017) *"ROBOTICS CONTROLS FOR EXCAVATOR"*	Simulation of excavator	PID	Triangulation was most effective for solving Inverse Kinematics. PID was implemented, but not emphasized.	Good Simulink implementation and three IK methods tested. Modelling of hydraulics not confirmed. Useful comparison thesis.
Asif, Haleema (2017) *"Design and Comparison of Linear Feedback Control Laws for Inverse Kinematics based Robotic Arm"*	Robotic Arm	P, PID & LQR comparison	LQR gave best results with minimum motor torque.	Descriptive article with relevant results and clear discussions of methods.

Table A.1: Detailed summary of SOTA explorations studied for hydraulic and robotic systems.

B Failure Mode Effects Analysis

Step in the Process	Failure Mode (What could go wrong?)	Failure Causes (Why would the faliure happen?)	Failure Effects (What would be the consequences of faliure)	Likelihood of Occurrance (1-10) [10 = very likely to occur]	Likelihood of Detection (1-10) (10 = very unlikely to detect)	Severity (1-10) [10 = most severe effect]	Risk profile Number (RPN)	Actions to Reduce Occurance of Failure
Hardware implementation	Initial sensors not being able to meet project requirements.	Unrealistic demands or miscalculated inital choice	The need for new sensors	10	5	2	100	Being well prepared and ensuring that the sensor meet all requirements
Hardware implementation	Sensor falling off and getting damaged during operation.	Attaching sensors on excavators arm poorly.	The need for new sensors	1	5	6	30	Inspecting and calibrating sensors to detect unnatural behavior
Hardware implementation	Late delivery of system sensors delaying hardare implementation.	The need for new sensors	Project timeline delay	3	1	3	9	Volvo has a lot of sensors, also to order in time.
Electical implementation	Wiring the electrical components	Incorrect wiring or inputs.	The parts short circuts the existing hardware.	4	2	6	48	"Measure twice cut once"
Software implentation	Unwanted software behavior	Not enough edge case tests performed on software.	Unexpected behavior during edge cases	2	8	5	80	Implement as many edge case tests as possible, with priority on critical parts.
Controller implementation	Damage to the hydraulic system	Overloading of the hydralic system by having an input signal to the controller outside of the defined operating limits.	Time consuming repair because the parts may be hard to replace	4	2	7	56	Apply input saturation for the controller.
Operating Excavator	Someone gets hit by the excavator.	Not restricting movements of excavator or not having ensured enough saftey magin.	Physical injury or death.	2	10	10	200	Install a safety zone around excavator and have a kill switch for the excavator.
Operating Excavator	Excavator bucket damages the interior structure	Not restricting movements of excavator or not having ensured enough saftey magin.	Expensive for KTH to fix interior damages.	2	10	9	180	Place excavator far from walls.
Team communication	Duplicate or overlooked tasks.	No task structure in place.	Delayed Timeline and deteriorating team morale.	4	1	4	16	Assign tasks in a managment system
							Total RPN (sum of all RPNs):	719

C System Architecture

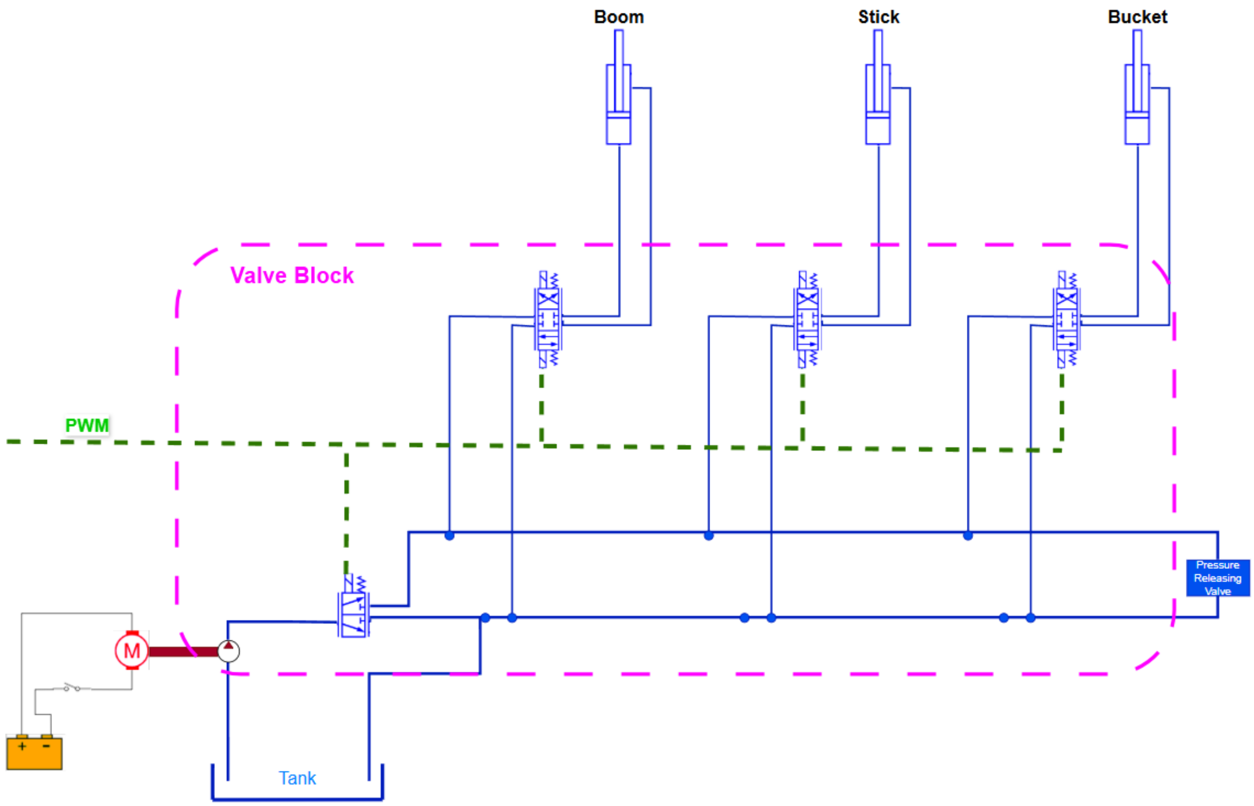

Figure C.1: Hydraulic circuit diagram for boom, stick, and bucket actuation using PWM-controlled valves. The PWM signal, which controls the valve block, is generated by the PLC as part of the control architecture illustrated in Figure 4.1.