# Improved control of compressed air networks using machine learning


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# ABSTRACT

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Mining companies in South Africa are under financial strain and so need to minimise expenses to stay profitable. Improving the efficiency of compressed air networks could lead to a significant reduction in electricity costs, which will benefit mines. Some mines rely on a central control room that monitors and controls compressed air networks remotely. Due to the complexity of compressed air networks, some software-based solutions have been used to assist with improved supply control.

The Dynamic Compressor Selector (DCS) controller is an existing compressor control system that has been used to achieve electricity cost savings. This controller relies on accurate matching of compressed air supply and demand to improve control of a compressed air network. Simulation software has also been applied to evaluate and implement energy-saving initiatives on mining compressed air networks.

The current software-based solutions are based on fundamental principles and physical relationships. These solutions rely on real-time instrumentation availability and accuracy to function properly, which is problematic on mines. Furthermore, due to the complexity of some mining compressed air networks, expert knowledge is often required for the setup of existing solutions. These challenges could delay or hinder the implementation of existing solutions.

From the literature, machine learning models such as artificial neural networks (ANNs) have been applied for the prediction of parameters in complex systems. A need was identified to investigate the feasibility of applying a machine learning model for the prediction of parameters in a mining compressed air network. A need was also identified to apply a machine learning model for real-time prediction to improve compressed air network control.

A platinum mining complex with a large compressed air network was identified as a suitable case study. A method, based on common steps in research, was applied to develop an ANN for predicting pressures on the mining compressed air network. The developed ANN achieved a mean absolute percentage error (MAPE) of 4.20% for all predicted parameters, thus verifying it to be accurate. This application of machine learning was combined with a real-time energy management system (EMS) to develop a compressed air network control solution that could improve the compressed air network supply. This was achieved by implementing the EMS to trigger the start and stop commands of compressors and machine learning to predict pressures and verify whether suggested compressor combinations would work.

The developed compressed air network control solution was implemented at the case study mining complex. An accurate simulation model was developed and applied to assist in validating that the solution could improve compressed air network control. The simulation software helped to identify some shortcomings of the solution, which were addressed by updating the solution. A real-time test was performed which indicated a potential electricity cost saving of R 1.6 million per annum.

The application of an ANN to predict pressures in a mining compressed air network successfully mitigated issues faced regarding instrumentation and complexity. Implementing this system to aid control room operators managed to achieve electricity cost savings whilst delivering the required pressure to critical demand points. This validates the possibility of applying a machine learning model for real-time prediction to improve compressed air network control.

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# NOMENCLATURE

| Symbol | Description | Units |
|---|---|---|
| $D$ | Diameter | $m$ |
| $f$ | Darcy friction factor | - |
| $g$ | Gravitational acceleration | $m/s^2$ |
| $K$ | Loss coefficient | - |
| $L$ | Length | $m$ |
| $m$ | Mass flow | $kg/s$ |
| $P$ | Pressure | $kPa$ |
| $R$ | Gas constant | $J.K^{-1}kg^{-1}$ |
| $Re$ | Reynolds number | - |
| $T$ | Temperature | $K$ |
| $y$ | Actual value | - |
| $\bar{y}$ | Average of actual value | - |
| $\hat{y}$ | Predicted value | - |
| $v$ | Velocity | $m/s$ |

**Greek**

| | | |
|---|---|---|
| $\Delta$ | Difference | - |
| $\varepsilon$ | Error value | - |
| $\epsilon$ | Pipe roughness | $\mu m$ |
| $\mu$ | Viscosity | $kg/s.m$ |
| $\rho$ | Fluid density | $kg/m^3$ |

# LIST OF ABBREVIATIONS

| Abbreviation | Description |
|---|---|
| AI | Artificial intelligence |
| ANN | Artificial neural network |
| CV(RMSE) | Coefficient of variation of root mean square error |
| DCS | Dynamic compressor selector |
| EMS | Energy management system |
| ESCO | Energy savings company |
| GDP | Gross domestic product |
| GUI | Graphical user interface |
| IGV | Inlet guide vane |
| KNN | *k*-Nearest neighbours |
| LR | Linear regression |
| MAPE | Mean absolute percentage error |
| NMBE | Normalised mean bias error |
| OPC | Open platform communication |
| PLC | Programmable logic controller |
| PTB™ | Process Toolbox™ |
| RMSE | Root mean square error |
| SCADA | Supervisory control and data acquisition |
| SVM | Support vector machine |

# CHAPTER 1 BACKGROUND AND LITERATURE

## 1.1 Introduction

### 1.1.1 Mining in South Africa

Eskom confirmed a declining electricity sales trend on 31 March 2019, with the largest decline being that in large power users in the mining industry. Factors including low economic growth, commodity market volatility, load-shedding and increasing electricity costs have led to a downscaling of operations [1].

Mining companies in South Africa are under financial strain, and there have been continuous efforts to minimise expenses to remain profitable [2]. Several mining operations in South Africa had to shut down production due to the Coronavirus 2019 (Covid-19) global pandemic. Additional capital costs required to open mine sites will put further strain on the mining sector [3]. The mining sector contributed R351 billion to the South African gross domestic product (GDP) in 2018 [4] and R360.9 billion, equal to 8.1% of the GPD, in 2019 [5].

Input costs and the price of a commodity are the main factors affecting the profit margin of mining groups [6]. If the price of a commodity decreases below a certain point and the mining group is not able to produce profit, it becomes less viable to sustain the mining operations. According to Bredenkamp [6], some mining groups can continue their mining operations when surplus capital is available. Reduction of the wage bill, the closing of shafts, halting of projects and selling of capital-intensive shafts are some alternative options that mining groups should investigate when continued mining operations become economically unviable, according to Bredenkamp. Mining groups do not have control over commodity prices and must therefore position themselves with a profit margin that is as large as possible. This could be done by reducing the input costs associated with the mining operations.

Wages, consumable material (explosives and other chemicals), transportation, electricity, and fuel are the main contributing factors to the daily operational costs of the platinum group metals (PGM) sector [7]. These operational costs are mainly associated with the production and processing of the commodity. Reducing the operational costs could lead to increased profitability for PGM companies.

The Minerals Council of South Africa estimates that input cost inflation in the mining sector was 3.5% above the national average production inflation, at a total of 8.4% in 2019 [5]. The rise in the cost of electricity, gas, and water was estimated at 10.9%, largely due to Eskom electricity tariffs [5]. Increased electricity tariffs over time have opened an opportunity for electrical energy management. Bredenkamp [6] found that the capital expenditure of gold mine operations could be reduced by implementing effective energy management. This reduction in capital expenditure would increase profit margin and help mines to remain operational. Understanding how mines in South Africa work is key to identifying areas where operational costs could be reduced.

Production and services are two of the main categories associated with underground mining [8]. Production includes all processes associated with mining the ore-rich reefs underground, such as drilling, blasting, and sweeping of material. Services are the elements that are required to enable production, such as compressed air, hoisting, refrigeration, dewatering, and ventilation [9].

All the services associated with production require electricity. Applying effective energy management in these services might reduce energy usage and increase the profitability of mines.

### 1.1.2 Energy consumption of mining systems

To understand the energy consumption of different mining systems, electricity consumption is evaluated. The data in Figure 1 shows a breakdown of the electricity consumption on a typical underground mine.

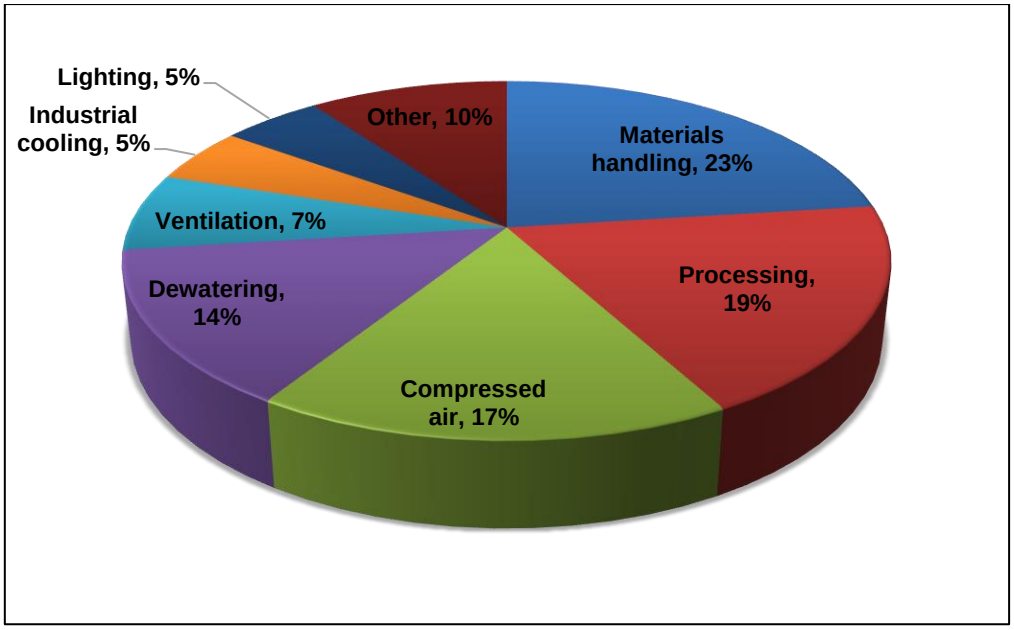


**Figure 1:** Electricity consumption in mining [10]

Compressed air, dewatering, and ventilation are services that consume the most electricity. Significant electricity cost savings could be achieved by improving efficiency or applying effective energy management of these electricity-intensive services.

Different energy management strategies have been implemented successfully in the underground mining sector to reduce electricity costs. Some of these strategies include load shifting, peak clipping, and energy efficiency projects on large energy consumers [11]. These type of projects are typically a result of demand-side management (DSM) initiatives implemented by energy savings companies (ESCOs) to reduce electricity usage [12].

Load shifting strategies are implemented to shift power usage from peak electricity billing periods. The total energy consumed during a day remains constant, although electricity consumption during peak periods is reduced. Mine dewatering systems usually provide the scope for load shifting projects due to the available storage of underground dams [13]–[15]. Water is stored in these dams during peak billing periods and pumped during off-peak billing periods. The same amount of water is pumped, although the cost of pumping is reduced due to the different tariffs during the day [16].

Another control strategy that can be implemented to reduce electricity costs is peak clipping. Peak clipping focuses on reducing electricity consumption during peak billing periods. These type of projects obtain energy efficiency, as total energy consumption is reduced [17]. Compressed air systems and cooling systems are targeted mainly with peak clipping projects by reducing energy consumption during a specific period of the day, which is usually done in peak billing periods. This can be achieved by reducing pressure setpoints or closing sections on a compressed air system or stopping a fridge plant [11].

Energy efficiency projects is another control strategy commonly implemented to reduce energy consumption. The largest impact on total energy consumption is achieved by energy efficiency projects. These projects are implemented to reduce energy consumption throughout the day. Energy efficiency projects have successfully been applied to compressed air and mine dewatering systems [18]–[21]. Complete system control is often required to obtain these energy savings [16].

Implementing one of these strategies in the compressed air system of a typical underground mine could lead to significant electricity cost savings. Peak clipping and energy efficiency projects are more feasible than load shifting projects on compressed air [16]. The implementing of compressed air energy storage (CAES) has shown that it is possible to implement load shifting on compressed air systems but, due to challenges and safety concerns, these experiments were discontinued on mines [17], [22].

The literature has shown that implementing these energy management strategies for compressed air is an effective way to reduce costs. To implement an energy management strategy for a compressed air network, more detail is provided to understand the system.

## 1.2 Mining compressed air networks

### 1.2.1 Preamble

Large compressed air networks are installed in the South African mining industry. The main reason for the industry-wide use of these systems is that compressed air systems are reliable, versatile, and easy to use [23]. Compressed air is used to operate a range of pneumatic equipment, including rock drills, loaders, agitators, venturi blowers, pumps, saws, and loading boxes [24]. Compressed air systems, therefore, form an integral part of mining operations.

Compressed air networks consist of multiple compressors connected to working areas with pipes, with some of the pipe sections spanning up to 40 kilometres [24]. These large compressed air networks are complex, which adds to the possibility of significant energy losses [17], [24]–[32].

Usually, compressed air networks are monitored from a central control room [33]. This central monitoring ensures integrated control of the network, including supply and demand control. Compressors and air-treatment systems are part of the supply side. Distribution, storage systems and end-user equipment form part of the demand side [18]. Supply and demand control is crucial for energy management and production. The dynamic nature and complexity of these compressed air networks add to the difficulty of applying the most efficient supply control.

### 1.2.2 Compressed air network supply

In the South African mining environment, compressed air is commonly supplied by multi-stage centrifugal compressors [26]. These compressors are chosen for their reliability and ability to deliver a large quantity of compressed air at a stable discharge pressure [34].

Multistage centrifugal compressors consist of more than one impeller in series to form different stages within a compressor. Air enters the compressor and is compressed through each stage to increase the overall compression ratio of the compressor [34]. A compressor station, also referred to as a compressor house, can house one or more compressors [24]. Compressors supply compressed air to large networks of pipelines to surface and underground consumers [35].

Insufficient compressed air supply could lead to production losses [18], [19], [26], [36]. Mines therefore often oversupply compressed air networks [19], [36], [37]; however, this is inefficient because it often leads to unnecessary energy losses [24], [36].

### 1.2.3 Compressed air network demand

The compressed air demand will vary between different mines, although most mines make use of the following equipment [18]:

- Rock drills (pneumatic drills);
- Mechanical ore loaders;
- Loading boxes;
- Refuge bays;
- Pneumatic control systems;
- Instrument air;
- Agitation; and
- Pneumatic conveying.

Refuge bays are an example of an end user with a low-pressure requirement. Rock drills, on the other hand, have a high-pressure requirement to function properly. The requirement for these users is generally between 50 kPa, for low-pressure users, and 700 kPa for high-pressure users [38]. The pressure requirement during the day will therefore vary based on the requirement of the equipment that is used throughout the day.

Demand pressure can be controlled by surface compressed air valves located in the compressed air pipeline before entering the mine shaft. These valves are used to control pressure according to the requirement of the shaft at a specific time. Underground control valves operate on a similar principle as surface control valves but are used to control compressed air usage of underground levels or sections [18]. This form of demand control allows for more accurate control of compressed air usage on a compressed air ring [18].

Compressed air is regularly classified as the most expensive form of energy, with only 5% of the energy required to generate compressed air that is converted into useful compressed air energy. Compressed air application or demand should be kept to a minimum due to its expensive cost [39].

Inefficient compressed air consumption is caused by factors such as compressed air leaks, unnecessary wastage, and pressure drops caused by network characteristics. These factors

negatively impact on electricity costs as well as service delivery, or pressure delivery, to working areas [40]. The pressure delivered to working areas is directly related to the drilling rate of rock drills, which ultimately affects the amount of ore produced [36], [40], [41]. Wastage of compressed air, therefore, harms the profitability of the production process due to increased generation costs as well as a reduction in production rates. To ensure that the production rate is not impacted negatively, the pressure requirements of pneumatic equipment for it to function properly must be met.

In addition, leaks and wastage must be kept to a minimum to increase network efficiency. Leaks and inefficient control of air and compressors are detrimental to the efficiency of a compressed air system [42]. Matching supply and demand is crucial for network efficiency, which is achieved through effective control.

### 1.2.4 Compressed air network control

One of the main control parameters in a compressed air network is network pressure. Network pressure should be maintained at a level that matches the consumer with the highest pressure requirement. This will ensure that this consumer is not affected negatively by low pressure. Not all consumers are high-pressure consumers, however, which will result in an oversupply of pressure to low-pressure consumers. This mismatch between pressure requirement and pressure supply leads to inefficiencies in the compressed air network, which could be reduced by effective control on the supply and demand side [26].

Compressed air consumption of specific consumers can be maintained by installing a control valve to a consumer [43]. Control valves are one of the main forms of control on the demand side [27], [31]. Further control of the compressed air network is performed on the supply side.

Supply control is the control of supply flow to match the required demand flow. As mentioned in previous sections, if the demand flow is not met, production could be impacted negatively. The oversupply of compressed air, on the other hand, leads to energy wastage. To ensure that the supply flow matches the demand adequately, supply or capacity control is implemented to control the compressed air supply flow [26].

Compressor supply flow can be controlled with the following methods:

**Compressor scheduling** [44]

The simplest method of supply control is to start and stop compressors to match the supply and demand throughout the day. When a compressor is stopped, the electric motor is switched off

completely. To maintain the reliability of a compressor, it should not be started for a certain time – which differs for compressors – once it has been stopped. Compressors should therefore only be stopped when the demand no longer justifies an additional running compressor.

**Unloading and loading of compressors** [26]

Unloading and loading a compressor is a method of controlling the supply to the compressed air network. When a compressor is in a loaded state, it can supply to its full capacity. Unloading is, however, the same as isolating the compressor from the system. To isolate the compressor, a blow-off valve is opened, and the compressed air is blown into the atmosphere. By blowing air into the atmosphere and not into the system, the compressor can operate at a reduced load and power consumption due to the lack of compression.

**Inlet throttling control** [45]

Inlet throttling control changes the operating point of a compressor. This is achieved by increasing the losses at the inlet of the compressor, thereby modifying the inlet pressure to the compressor. This method of control reduces the efficiency of the compressor.

**Inlet guide vane (IGV) control** [45]

Inlet guide vanes are another method to alter the operating point of a compressor. This is done by changing the angle of the inlet guide vanes that, as a result, change the mass flow rate entering the compressor. Velocity, angle of velocity, and the volume of air entering the compressor are affected by the angle of the inlet guide vane. The angle of the inlet guide vane is altered using an actuator that is connected to the compressor. A controller, such as a programmable logic controller (PLC), typically controls the actuator, depending on the compressor's operating point and compressed air network conditions [46].

**Blow-off valve control** [47]

Blow-off control can be used as a method of supply control but this is, however, inefficient, as air is blown into the atmosphere and is thus a waste of energy and considered as bad practice. Blow-off control is, however, used to unload a compressor and to prevent compressors from surging.

Compressor surge is described as the point where a compressor is no longer able to maintain peak head and the system becomes unstable [48]. Surge conditions are damaging to compressors and could lead to increased repair costs [48]. Surge control is therefore often applied to compressors to avoid surges from happening.

**Speed control** [30]

The speed of an electric motor can be regulated by using a variable speed drive (VSD). Actual load conditions can be met by regulating the speed of the electric motor driving the compressor, which can reduce the energy consumption of that motor. However, the costs of installing VSDs are high.

Compressors are scheduled by operators according to the required demand pressure. The best practice is for operators to monitor the compressed air network from a central control room [17], [31]. According to the literature, a central control room is a critical component to monitoring and controlling a compressed air system and realising compressed air network improvements.

The demand side is often prioritised when network efficiency is of concern, although compressor control is crucial to realising energy savings from network improvements. Several energy management strategies have been implemented to achieve energy savings, which is discussed in the following section.

## 1.3 Existing energy management strategies on compressed air systems

### 1.3.1 Preamble

Several strategies have been implemented to improve the energy efficiency of compressed air networks. Typical strategies to reduce demand include:

- Leak repairs [41];
- Pressure scheduling [9];
- Replacement of pneumatic equipment with hydraulic, mechanical, or electrical equipment [24], [49]; and
- Splitting compressed air rings into high- and low-pressure sides [50].

Compressor supply has to adjust to improvements in compressed air network efficiency or demand to obtain energy savings. Typical strategies to improve compressor supply control include [26]:

- Centralising compressor control;
- Automating compressor operation;
- Operator training; and
- Implementing compressor controllers.

Compressed air supply control is discussed further in the next section due to the importance of supply control to realise energy savings.

### 1.3.2 Centralising compressor control

Supervisory control and data acquisition (SCADA) systems are used for remote logging and control of on-site mine equipment. The SCADA system retrieves data through communication with PLCs. PLCs are used to communicate directly to field equipment and receive information from instrumentation [26], [27], [43].

A central control room will usually house a SCADA system to monitor and control all equipment and instrumentation connected to the communication network relevant to the compressed air network [43]. Using SCADA-to-PLC communication, operators can monitor and control the compressed air network from a central location. This central control philosophy allows for a holistic approach to monitoring and control of the compressed air network. It is beneficial for decision making and reacting to changes in a dynamic system [31].

### 1.3.3 Automating compressor operation

Compressor controllers can control the operation of a compressor automatically [26], [46], [51]. Control of a compressor is established by communication with the controller directly to the compressor's PLC. These controllers are used to control the inlet guide vane angle and blow-off valve position of compressors. A typical control parameter is the discharge pressure setpoint [26], [46], [51]. The controller will adjust the inlet guide vane depending on the current discharge pressure to match the specified setpoint. These controllers are not only capable of regulating supply pressure but are also used for surge protection [52]. The controller will use the inlet guide vane position of a compressor to control the discharge pressure and will open the blow-off valve before a compressor reaches surge conditions. The compressor is thus controlled automatically according to the pressure setpoint.

One such controller has been developed by Moore Industries International. The Moore controller can control the compressor as stated above. An additional feature of this controller is advanced monitoring by sending feedback from different compressor components to the SCADA system. The inlet guide vane angle and blow-off valve position are the main control parameters [9], [12], [26], [46].

### 1.3.4 Operator training

Literature indicates that compressors are not controlled optimally when they are controlled manually. Behaviour such as incorrect compressor selection or starting and stopping of compressors according to a schedule, instead of monitoring demand and matching the supply, leads to inefficient operation of a compressed air network [46].

Several studies have shown that operator training is an effective method to improve compressor control [2], [20], [26], [53]. Increased understanding and knowledge of the compressed air system can have a positive effect on compressor control.

### 1.3.5 Implementing compressor controllers

Controllers can be implemented to control the operation of a single compressor, such as mentioned in Section 1.3.3. and to control a network of compressors. A controller such as the dynamic compressor selector (DCS) controller has been implemented on compressed air networks to control a network of compressors dynamically. This controller can determine the required compressor selection and pressure setpoint of compressors to match the required demand. This type of controller is a software-based solution and is investigated further to determine its abilities and limitations.

## 1.4 Literature of existing software-based strategies

### 1.4.1 Preamble

Compressors can be controlled automatically using controllers such as the Moore controller. These controllers can automatically adjust compressor supply characteristics to improve compressor supply and avoid surges. Most mining complexes in South Africa have some form of automatic compressor control [17], [25], [27]. In this study, compressor controllers are investigated with the focus on compressed air network control rather than automatic compressor control.

The DCS controller can dynamically determine the most efficient compressor combination and compressor discharge setpoint of compressors. This controller was developed by Van Heerden [51] based on work done by Venter [54] and has been implemented on several mining complexes to realise energy savings [26], [27], [46]. The DCS controller is a real-time solution that is investigated further in the next section.

Other existing software-based solutions that have been used to obtain operational efficiency are simulations. Simulations can be used to predict changes in a compressed air network and to evaluate the feasibility of operational improvements [19]. Simulations can also be used as a verification tool to prove that operational improvements could lead to energy savings [55]–[57].

### 1.4.2 Dynamic compressor selection

Van Heerden [51] developed a dynamic compressor selector controller (DCS controller) based on work done by Venter [54] to dynamically control compressed air network supply. The information discussed regarding the DCS controller in this section is based on the studies performed by Van Heerden and Venter. The information regarding the implementation of the DCS controller is based on the studies [25]–[27], [46], [51], and [54]. By monitoring compressed air demand continuously, the software can determine the most efficient compressor combination. To determine this, calculations are performed based on compressor and compressed air network characteristics.

The DCS controller receives shaft pressure profiles and demand flow. Using these parameters and accounting for pipe friction losses and leaks, a total compressed air demand is predicted. By using this predicted total demand, the DCS controller can prioritise compressors and compressor setpoints to ensure that end-point pressures will meet the required setpoint [25], [51]. Using this controller, it is possible to achieve improved supply and demand matching, which could lead to energy savings [26].

The core objective of the DCS controller is to control compressed air supply efficiently to reduce energy wastage while ensuring demand pressure requirements are met. The core capabilities of DCS include [25], [51]:

- Dynamic compressor prioritisation;
- Dynamic supply setpoint calculation; and
- Automatic starting and stopping of compressors.

The DCS controller as originally designed by van Heerden [51] was not able to prioritise compressors based on their location. As a result, there was a possibility of selecting a compressor combination that is not feasible due to the network layout (pipe diameter, distance, etc.). Other shortcomings such as platform stability and efficiency curves of compressors were addressed in a further study conducted by van Heerden [25], and the controller hence evolved into the dynamic compressor controller (DCC). The complete details of the shortcomings and improvements to the old version are not discussed in this section. For this study, the latest version of this controller is

discussed and is henceforth referred to as the DCS controller. The operating principles of the DCS controller is discussed next.

The DCS controller can access data from instrumentation through open platform communication (OPC) to the SCADA in real-time. OPC is an industry-standard method that is used to enable communication between different devices from different manufacturers. The DCS controller is thus able to receive data from instrumentation in real-time and send commands to the relevant equipment [25], [51].

Information required to implement DCS includes the following [26], [46]:

- Compressor discharge pressure setpoint;
- Compressor discharge mass flow;
- Compressor delivery pressure;
- Compressor inlet guide vane position;
- Compressor blow-off valve position;
- Compressor running status;
- Compressor power;
- End-user pressure set point;
- End-user pressure downstream of the valve;
- End-user mass flow;
- Pipe lengths and pipe diameters for entire compressed air network; and
- Pipe geometry for the entire compressed air network.

Without the information above, it is not possible to implement the DCS controller [36]. Additional information that is not required but that could benefit the implementation of the DCS controller includes [46]:

- End-user pressure upstream of the valve;
- Existing compressor priorities;
- Existing compressor pressure set points;
- Valve open/close positions; and
- Other additional control or site-specific constraints.

With the information mentioned above, the DCS controller simulates the entire compressed air network on the surface. The simulation comprises two calculation sections. Required compressor discharge pressure setpoints and the required supply flow is calculated in the first section. The other section determines the most energy-efficient solution (in terms of compressor combination)

that will deliver the required supply flow. Network characteristics and inefficiencies such as pressure drop and frictional losses are taken into account to improve the accuracy of results [26].

The simulations performed by the DCS controller were based on work done by Venter [54]. Venter made the following assumptions to perform the compressed air network calculations mentioned above:

- The flow of compressed air in the network is at a steady state;
- The flow of compressed air is one dimensional, incompressible and isothermal;
- Pipe roughness is constant throughout the entire compressed air network;
- Historical data is correct;
- Losses due to leaks are negligible;
- The entire compressed air network is at the same height; and
- The viscosity of air at 316 K is constant at $3.0134 \times 10^{-5}$ kg/m·s.

The thermodynamic equations required to calculate the theoretical results for the compressed air network that are used by the DCS controller are listed in Appendix A.

The DCS controller was developed by incorporating the assumptions, thermodynamic equations, and mathematical modelling [25], [51], [54]. This controller can simulate compressed air flow dynamically. Actual system parameters such as pressure and flow are used as inputs to obtain results from the simulation. The flow required from each compressor, or compressor house, is then determined for current and future conditions with the results obtained from the simulation. In previous studies, additional simulation software tools were used to verify the results from the simulation of the DCS controller [25], [26], [46], [51].

The method of the theoretical compressor controller was integrated into a user-friendly interface platform by Van Heerden [25], [51]. This platform has a graphical user interface (GUI) which improves its practicality for mine personnel. The platform can thus be applied to display control outputs.

The DCS controller has the ability to [25]–[27]:

- Receive data in real time;
- Simulate an optimal compressed air network, taking into account future conditions;
- Dynamically determine setpoints for discharge pressure of individual compressors;
- Prioritise compressors according to predicted requirements;
- Control discharge pressure setpoint, start, stop, load and unload commands;

- Control pressure setpoints of surface control valves;
- Split compressed air ring into a high- and low-pressure network;
- Take compressor location into account; and
- Account for leakage and pressure losses in the system.

For the DCS controller to function, accurate real-time data is required [46]. The DCS controller uses filtered real-time data to simulate the optimal compressed air network conditions. Filtering is done to ensure the stability and accuracy of calculations. Further adjustments that are made to the real-time data accounts for flow loss through leaks in the network. This adjustment is made to the measured demand flow for consumers; therefore, the total loss is added to the total demand at the consumer end, ensuring that the simulated network is in an ideal state. The simulation is thus based on the ideal network state and not necessarily the instantaneous network state [26].

According to Van Heerden [25], demand flow for each consumer should be adjusted to account for network losses. This is an example of a shortcoming that was addressed from the original (older version) DCS controller [51]. Van Heerden [25] and Jonker [26] applied the formula below successfully.

$$m_{Adjusted} = m_{Measured} \times \left(1 + \frac{m_{Total\ supply}}{m_{Total\ demand}}\right) \quad (1)$$

$$m_{Adjusted} : Scaled\ mass\ flow\ for\ specific\ consumer\ [kg/s]$$

$$m_{Measured} : Measured\ mass\ flow\ for\ specific\ consumer\ [kg/s]$$

$$m_{Total\ supply} : Total\ measured\ supply\ flow\ [kg/s]$$

$$m_{Total\ demand} : Total\ measured\ demand\ flow\ [kg/s]$$

This formula is used to adjust the demand flow of each specific consumer by a factor of total supply and demand. Flow loss in the network that is not measured, such as leaks, is thus accounted for. Jonker [26] then further compared this adjusted demand flow to a calculated future demand flow for each consumer. The difference between the current measured flow and interpolated baseline flow is calculated. This value is added to the baseline flow at a future period to calculate the predicted future demand flow. Figure 2 shows how future demand flow in 30 minutes is determined.

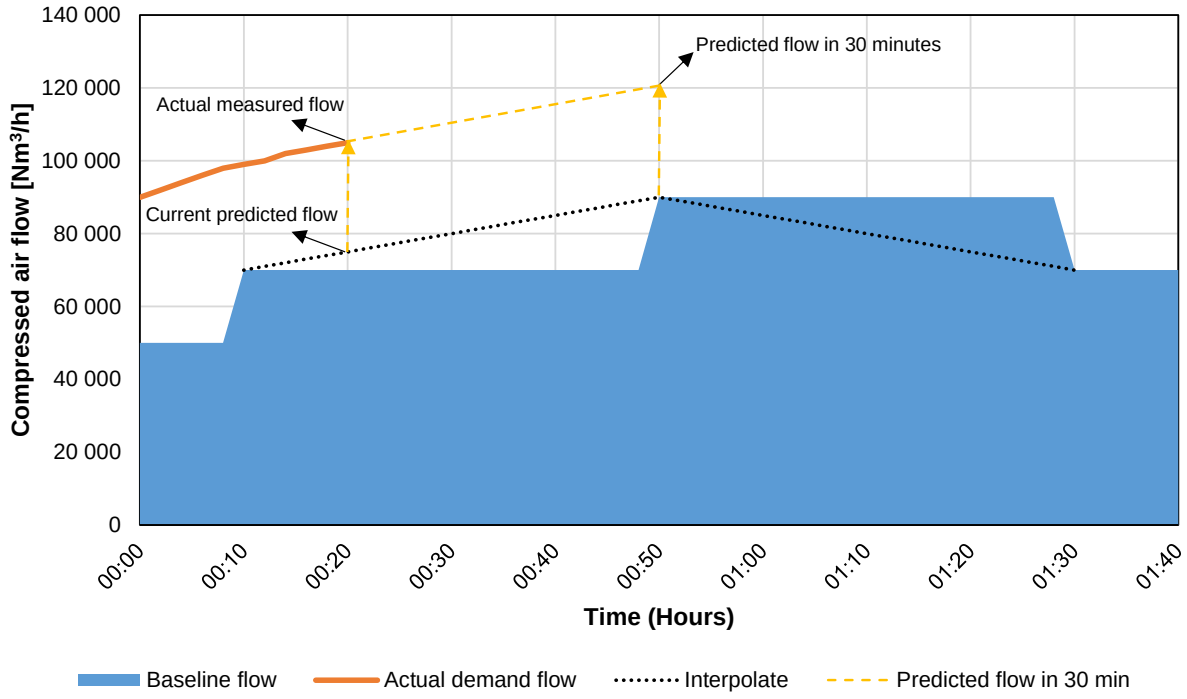


**Figure 2:** Predicted demand flow adjustment

The current adjusted flow is compared to the predicted future flow value in 30 minutes and 60 minutes. The highest value is used for the specific consumer. This is done to ensure that the total demand flow, including losses in the network, will be matched by the supply flow in calculations [26]. This new required demand is then used by an air solver (which is a part of the simulation), in the DCS controller to simulate the virtual network.

The air solver (or air simulator [25], [51]) simulates the compressed air network through mathematical modelling. The solver uses real-time data and the new required demand, as calculated above, to simulate the compressed air network. The network is set up as shown in Figure 3 (adapted from [25], [51], [54]):

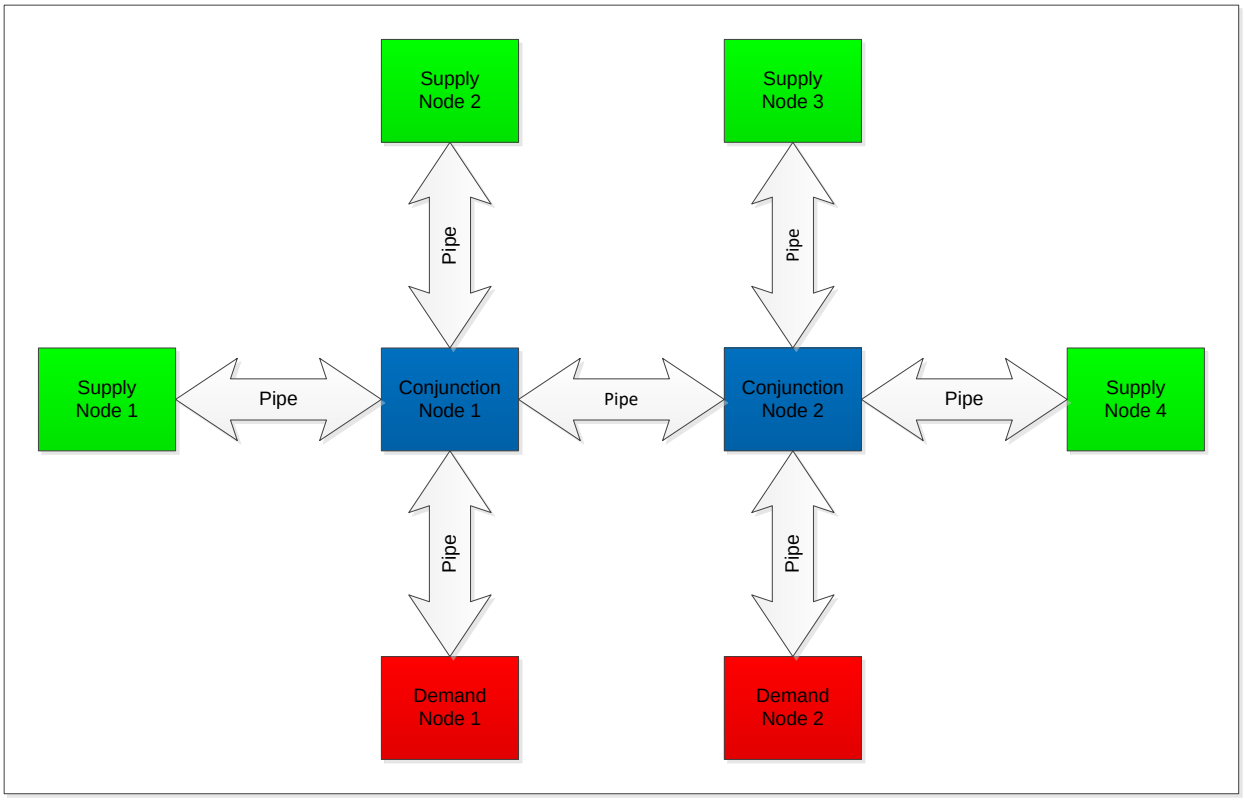


**Figure 3:** DCS simulation network example

Supply, demand, and conjunction points are depicted by nodes, while pipes form connections, similar to a typical mining complex [25], [51]. In Figure 3, the outer nodes represent the supply nodes (compressors) and demand nodes (shafts, plants, etc.). Flow and pressure are required for these supply and demand nodes. The air solver estimates the flow and pressure for the conjunction nodes in the middle, which represent the different conjunctions on the network [25], [51].

Determining the mass airflow balance is the first step in the air solver simulation [25], [51], [54]. The total mass of air flowing into a node equals the mass of air flowing out of the node. It is assumed that air flowing out of the nodes is negative, and air flowing into the nodes is positive. The solver simulates the balance of the mass flow through each node. Bernoulli's principle (equation in Appendix A) is then used to calculate the mass flow through the pipes to the following node. The flow balance in the conjunction nodes is calculated continuously.

After mass balance through the network has been established, the pressures of the conjunction nodes are calculated [25], [51], [54]. The solver iterates different pressures for a specific conjunction node to minimise (as close to zero as possible) the sum of the mass flow through the node. This ensures that there is a mass balance between the total calculated supply flow and the total adjusted demand flow. This process of iteration is repeated to establish the pressure for all

the conjunction nodes. Several studies applied commercial simulation software tools to prove the accuracy of this simulation technique [25], [26], [46], [51].

The calculated pressure requirement at demand nodes should be higher than or equal to the consumer's set point pressure. In the event where this is not the case, the simulation is restarted. This process is repeated until this condition is met for each consumer [25], [51]. When this is completed, all pressure and flow requirements are known.

The following results are thus available from the simulation:

- Mass flow balance through the network;
- Required upstream pressure for each consumer;
- Adjusted demand flow for each consumer; and
- Required supply flow.

Using the calculated pressure and flow requirements, the discharge setpoints of the compressors are then calculated. This is done by using the consumer with the highest upstream pressure requirement as the driving node [25]. If the system can maintain the pressure of the driving node, all other consumers will receive sufficient air pressure. In the case that the air solver is not able to calculate a suitable solution, the system can revert to a backup setpoint [25], [26]. The backup setpoint acts as a safety measure for such a scenario and can be specified as an input. Another feature of the DCS controller is its ability to determine compressor combinations.

The DCS controller simulates different compressor combinations in order of priority [25]–[27]. The user can specify the compressors with the highest priorities. Factors such as availability can influence priority and can be added to the input data of the DCS controller. This would enable it to exclude a compressor automatically if required, for example when maintenance is performed [26].

The DCS controller determines the characteristics of each compressor by logging power and the flow range at 20-kPa pressure intervals [26]. This characteristic is thus captured in terms of performance and power efficiency. The DCS controller can determine the minimum and maximum discharge flow capability at different pressures within a specified minimum and maximum guide vane angle. Figure 4 shows an example of the flow and guide vane characteristics of a compressor characterised by the DCS controller in the study performed by Jonker [26]:

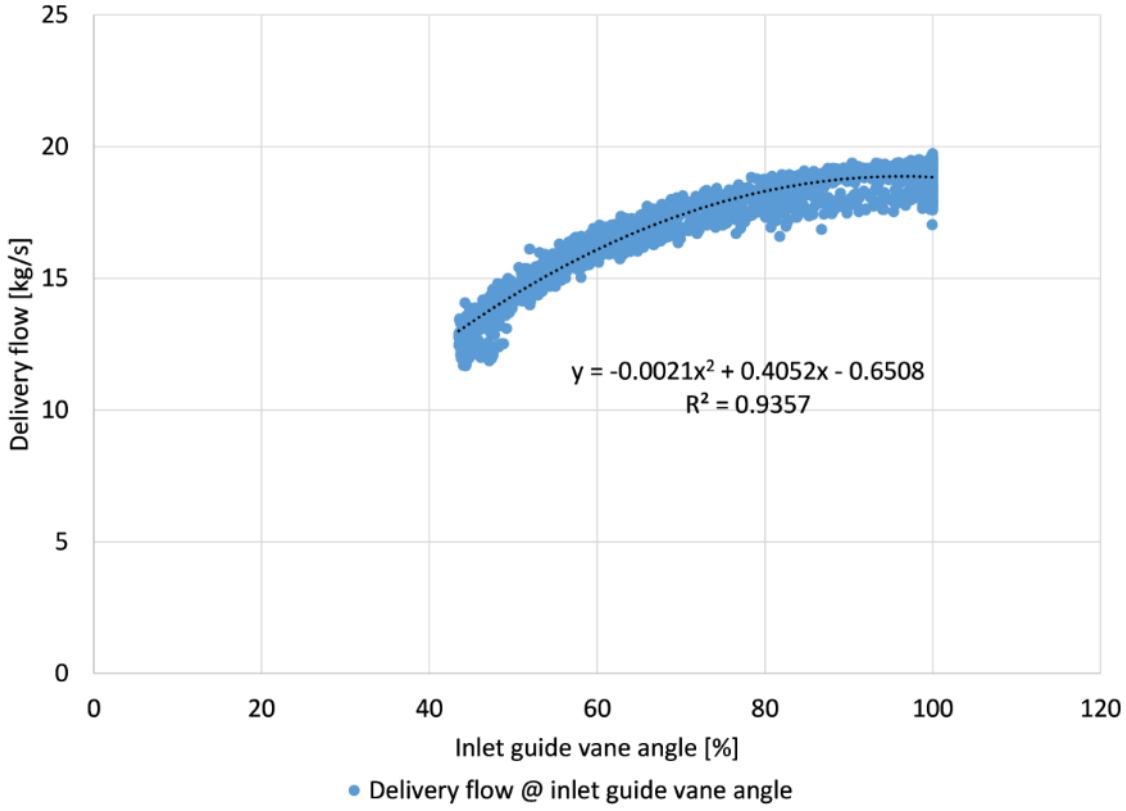


**Figure 4:** Compressor characteristic curve for guide vane angle and delivery flow [26]

These characteristics of the compressors are updated continuously, although the user can edit or delete logged values if errors occur. The most effective compressor combination is determined in the second phase of simulation by using the compressor characteristics as determined in this process.

In the second phase of the simulation, the best suitable compressor combination is determined. The adjusted flow values and pressure requirements, as determined in the first phase of simulation, are used to determine the most effective compressor combination that will meet these requirements. This second phase of the simulation is also performed by the air solver component in the DCS controller [25].

Multiple solutions are simulated in the ideal compressed air network state, with each solution using a different compressor combination. In this way, the most efficient compressor combination can be determined for supplying the required flow. The simulation is iterated, each time either adding or removing a different compressor from the actual running compressors. Figure 5 shows the method in which the compressor selection is altered for each iteration in a network with four compressors (adapted from [25], [26]). A running compressor is represented by a “1” and a compressor that is stopped is represented by a “0”.

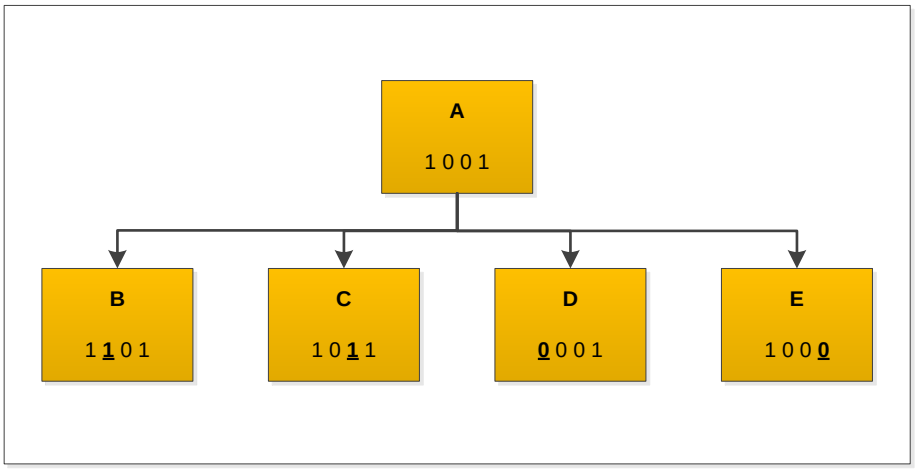


**Figure 5:** Simulated compressor combinations

From the compressor combinations shown in Figure 5:

- A is the current compressor combination. Compressor 1 and 4 are running;
- In B, compressor 2 is started;
- In C, compressor 3 is started;
- In D, compressor 1 is stopped; and
- In E, compressor 4 is stopped.

In the ideal situation, only one compressor selection change will be made. The simulation will, however, calculate additional possibilities for each of the initial solutions if required [25]. In this scenario, each solution has two changes to the compressor selection, which is not preferred.

Solutions are filtered before they are accepted to ensure that the predetermined criteria are met. These criteria or conditions can be specified, which include but are not limited to the following [26]:

- The required supply flow must be more than the minimum supply flow;
- The required supply flow must be less than the maximum supply flow; and
- All the proposed compressors must be available and ready to start.

All solutions that do not meet the criteria in the filtering process are disregarded as solutions. To determine the most efficient compressor combination, the delivery flow of each compressor must be determined. When the delivery flow of each compressor in the solution is known, the power can be determined by using the efficiency curves captured by the DCS controller for each compressor. Using the adjusted flow and pressure requirements from the first phase of the

simulation, the delivery flow for each compressor in each solution can be determined using the method described by Van Heerden [25] as illustrated in Figure 6.

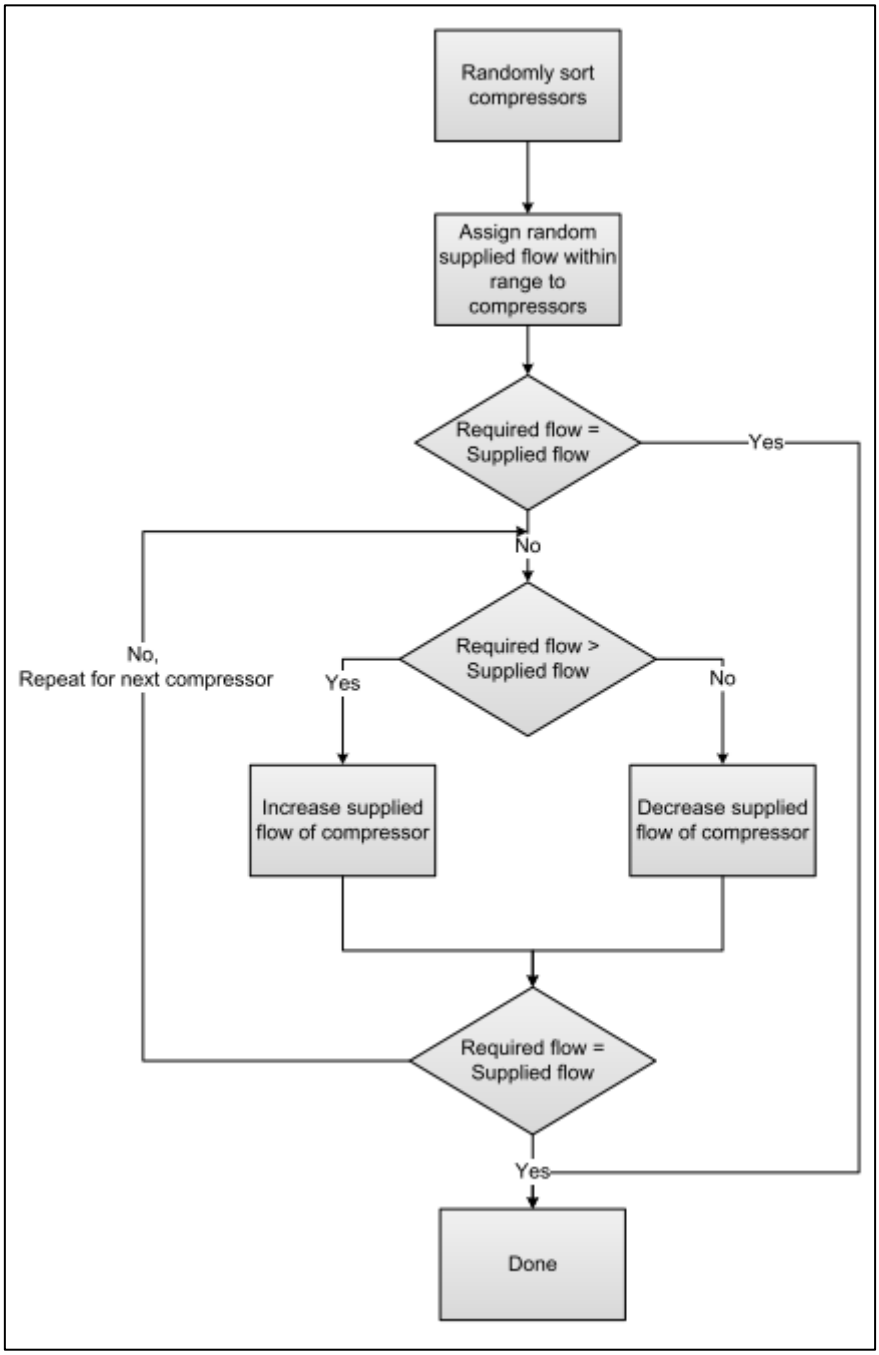


**Figure 6:** Compressor flow delivery calculation process [25]

The process of flow delivery calculation, as shown in Figure 6, is as discussed by Van Heerden [25]. In the process of determining the flow of each compressor, a different delivery flow expectancy is assigned to each compressor in the simulated solution. This delivery flow is a random value that is within the flow range of the specific compressor. The total random delivery

flow is compared to the required flow and adjusted (increased) in the order of compressor priority until the required flow is met. This entails increasing the compressor's delivery flow with the highest priority until the required flow is matched or this compressor is at maximum delivery capacity. If the first compressor is at maximum delivery capacity, the delivery flow of the compressor with the second-highest priority is increased. This process is repeated until the total delivery flow is equal to the required supply flow. The delivery flow of each compressor is now known.

All the solutions that passed the criteria which can match the required supply flow are now considered. The delivery flow and pressure of each compressor are known and therefore the power consumption of each compressor can be determined using the characteristic curves. Using this method to determine the power consumption, the solution with the most energy-efficient combination is selected [25].

The DCS controller can communicate output commands to the compressors as determined in the simulation. These output commands include:

- Stop and start command;
- Unload and load command; and
- Discharge pressure setpoint.

Before any command is transmitted to any compressor, a last check is performed to ensure that compressors are not cycled unnecessarily. This is done by comparing the current actual power consumption to the simulated power consumption to determine whether the difference is within a certain adjustable range [26]. This will prevent the unnecessary changing of compressors.

The total demand can thus be matched efficiently by using the DCS controller. To implement the DCS controller, the following infrastructure is required [26]:

- Pressure control valves at consumers;
- Compressed air leak management and demand reduction initiatives;
- Automated compressors with capacity control techniques;
- Field instrumentation, such as pressure transmitters and flow meters; and
- A centralised control room.

According to Jonker [26], it is not possible to implement the DCS controller without the infrastructure mentioned above. This controller has been proven to work on mining complexes to achieve electricity cost savings. It is, however, clear that is not possible to implement this

controller without the correct infrastructure, such as accurate field instrumentation of various types. A lack of instruments or of accuracy of available instruments have been shown to have caused delay in implementation or hindered implementation viability [19], [23], [40], [46], [51], [58].

The complexity and dynamic nature of compressed air networks can also hinder the application of this controller [17], [24]–[32]. This controller was designed originally for compressed air networks that only consist of one compressor house and one or two consumers close by. The DCS controller was later adapted to be implemented in more complex networks, though with no guarantee that it would be able to capture all the characteristics and dynamic nature of compressors and the compressed air network.

This controller considers factors such as auto compression, flow loss, pressure drop, and friction loss to improve the accuracy of calculations. This can, however, become a tedious process in a large and complex compressed air network. To implement the DCS controller, the supply side, compressed air network, and demand side must be characterised. Data collected from instruments that is unavailable or inaccurate could delay implementation or hinder the accuracy of the solutions proposed by the controller. Even in the case where all the information is available, the complexity of a compressed air network can hinder simulation accuracy. Venter [54] and Van Heerden [25], [51] both mention that a 10% loss in accuracy can be expected in simulations of fluid dynamics due to all the assumptions made before the simulation process.

The solutions that the controller provides are site-specific and cannot easily be duplicated at different sites. Although the DCS controller has a GUI to improve the design and implementation of this solution at a site, its implementation is time-consuming and requires many site-specific assumptions [25]–[27]. It is therefore not necessarily possible to take an existing implemented DCS controller and copy it to another site without completely rebuilding the platform.

The DCS controller is designed to match compressed air supply with demand as efficiently as possible. The focus is thus on compressed airflow while ensuring that the pressure is maintained above certain desired levels during the day. Other software solutions like simulations are not necessarily focused on the matching of supply and demand flow and can simulate a range of different parameters of a compressed air network. Simulation software has been used to verify the results obtained from the DCS controller [25], [26], [46], [51] and is thus discussed in Section 1.4.3.

### 1.4.3 Simulation software

When an energy-saving project or strategy is identified, it is necessary to determine the feasibility and potential electricity cost saving of this project. Friedenstein [23] states that first-principle calculations, simplified mathematical models, and practical tests are some of the methods used in this process. Software technology has seen major improvements due to advancements in computing hardware. As a result of these improvements, simulations have now become a valuable tool in many industries [59].

The main advantage of using simulations is the ability to test new policies, procedures, and methods without disrupting the actual system [56]. Simulations can therefore be used to test and identify energy and operational improvement opportunities in mining compressed air systems.

Simulations have been used in several studies for energy-saving projects on compressed air networks in the mining environment. These simulations are used as a tool to determine the feasibility of projects as well as to quantify or give more accurate estimates of the possible savings of projects before they are implemented [19], [23], [60]–[62].

Different simulation software packages exist that can be used for a variety of flow simulations. These technologies aim to simulate various flow scenarios as accurately as possible. Nell [62] developed a methodology to identify, evaluate, and addresses compressed air network inefficiencies in which simulations were a key part. The simulation packages considered by Nell are discussed below.

**SolidWorks flow simulator** [63]

This simulation requires part modelling before flow simulation can be done. Flow characteristics are calculated using the Navier-Stokes equation. This simulation software is only available as an add-in to Solidworks and not as standalone simulation software. Figure 7 shows a typical simulation using the SolidWorks flow simulator.

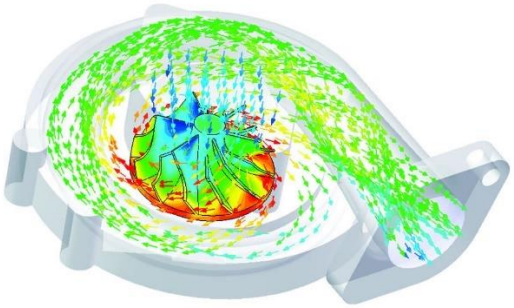

**Figure 7:** SolidWorks flow simulator illustration[1]

From Figure 7, it is evident that part modelling is important for the simulation to function. Complex problems can, however, be solved at a detailed level when part modelling is done in high detail. With large compressed air networks, part modelling may be difficult and time-consuming, as all individual components have to be modelled to simulate the network.

**KYPipe** [64]

This software is aimed at solving steady-state flows and pressures for pipe network systems for liquid flow and gas applications where the density is constant. Mass continuity and energy equations are used to solve different parameters. KYPipe is suited for applications where liquid density is or can be used as a constant. This simulation is thus not suitable for compressible fluids.

[1] https://www.javelin-tech.com/blog/2015/09/every-design-engineer-needs-solidworks-flow-simulation/

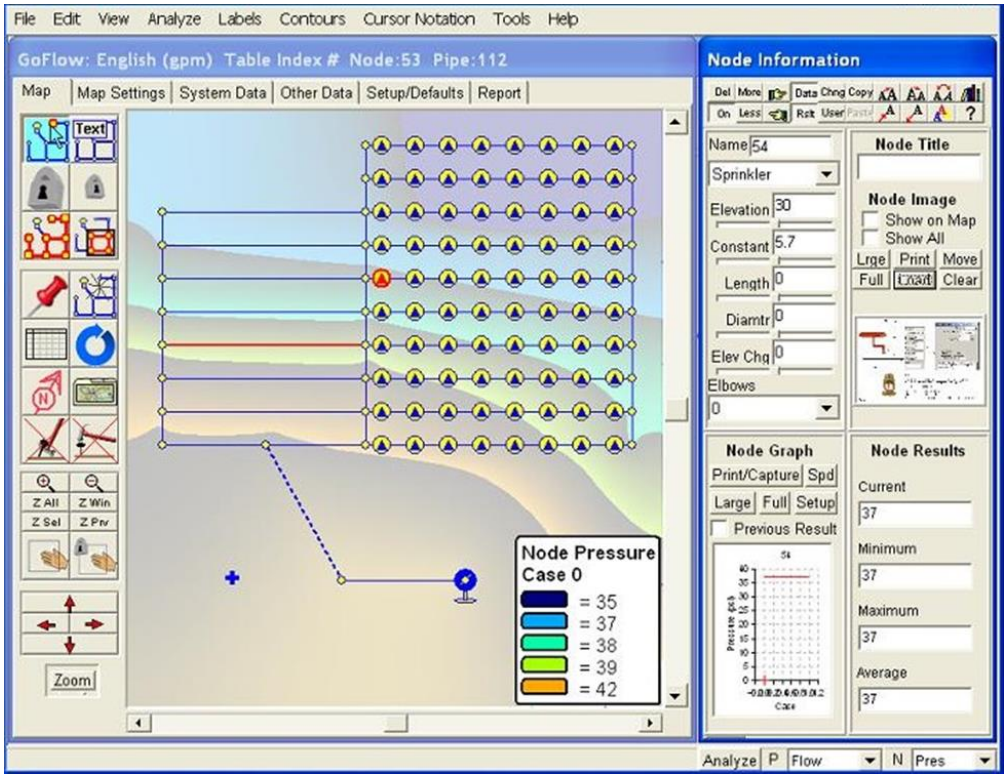


**Figure 8:** KYPipe simulation illustration[2]

**Flownex** [54], [62]

Flownex can be used to simulate both compressible and incompressible fluids. This simulation software can be used for a wide variety of mining applications. The demo version, however, only allows a limited number of pipes and nodes to be used, while the full version comes at a costly price.

[2] https://kypipe.com/goflow/

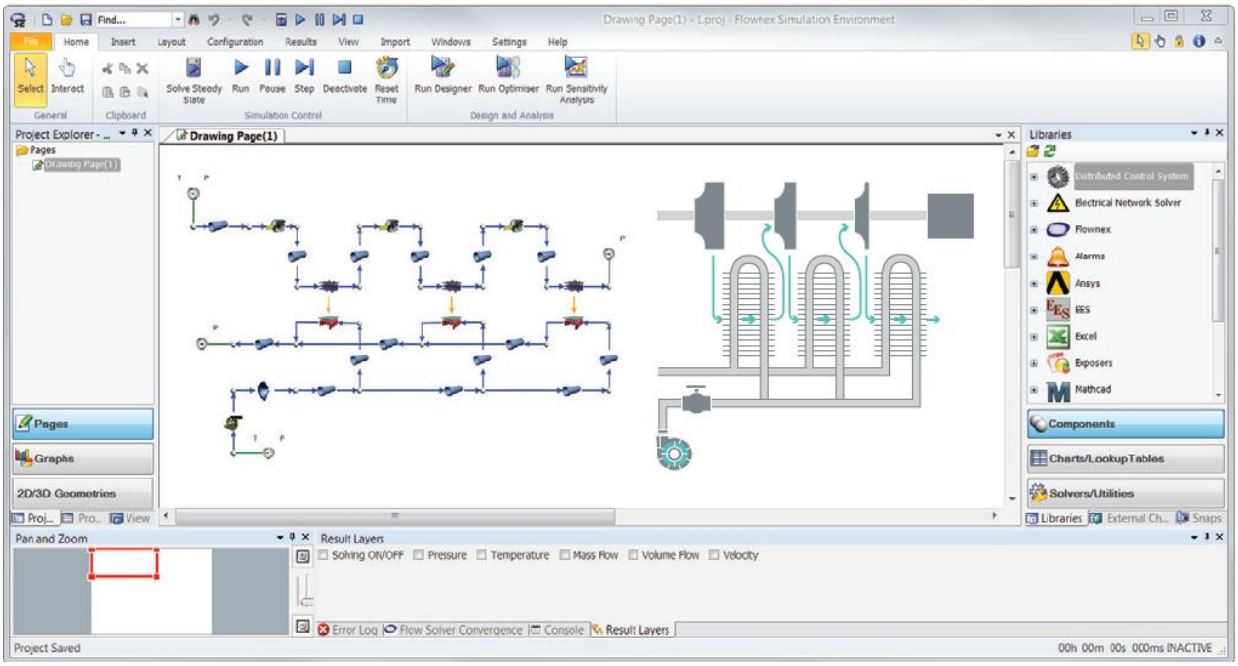


**Figure 9:** Flownex simulation illustration[3]

**Process Toolbox™ (PTB™)** [2], [9], [20], [23], [36], [53], [55], [62]

This hydraulic simulation flow solver can be used to simulate mine systems such as compressed air networks, water reticulation, and refrigeration systems. All the components of a compressed air network can be incorporated into a single simulation model to easily evaluate proposed scenarios or identify network inefficiencies.

This simulation software uses an empirical approach to modelling components. Input data for every component is thus required in the simulation model.

**Simulation package comparison**

The table below shows the advantages and disadvantages of each simulation software package.

[3] https://www.flownex.com/download/mining-brochure/?wpdmdl=3964&masterkey=5eeb811f3319b

**Table 1:** Simulation package comparison

| Simulation package | Advantages | Disadvantages |
|---|---|---|
| SolidWorks flow simulator | • Accurate simulation software<br>• High-detail solutions | • Part modelling required, which may be time consuming<br>• Requires full SolidWorks simulation package |
| KYPipe | • Accurate<br>• Can be applied for liquid flow and gas applications | • Not suitable for compressible fluids |
| Flownex | • Simulation of compressible and incompressible fluids<br>• Mining applications | • Demo version limited<br>• Full version expensive |
| Process Toolbox ™ (PTB™) | • Mining applications<br>• Accurate<br>• Ease of use (user friendly) | • Input data required for each component |

PTB™ has been used in various mining-related studies and proved to be accurate in the evaluation of projects before implementation [2], [9], [20], [23], [36], [53], [55], [62]. PTB™ is best suited for mining compressed air simulations. Friedenstein [23] developed a simulation methodology to conduct investigations on mining compressed air systems. The three main steps to implementing a simulation model, according to Friedenstein [23], are:

Step 1: Investigate the system;

Step 2: Develop and verify the simulation model; and

Step 3: Implement simulation and execute simulation scenarios.

These steps are discussed in Appendix B to provide additional information to the reader. The process explained in Appendix B is based on work done using PTB™ and could be replicated for other simulation software [23].

From the information provided in this section, it is clear that there are some shortcomings or factors that influence the feasibility of using simulations with regards to energy savings projects.

A wide variety of data is required to create a simulation. If data is not available or the data cannot be acquired, the simulation cannot be developed, which could delay the simulation process significantly. Data that is available should be accurate to be useful for the simulation.

Accuracy of data is crucial, as most simulation software rely on thermodynamic calculations to determine solutions. Inaccurate data could lead to the simulation generating inaccurate results. Therefore, time must be invested to ensure that all the data used in the simulation is reliable and accurate to ensure the usability of the simulation for the testing of scenarios.

The development and implementation of a simulation model have been found to be time- and resource-intensive [19], mainly due to the gathering of missing data, verifying of existing data accuracy, and understanding the complex nature and layout of some compressed air networks [40]. Due to this time-consuming nature, if time is constrained, creating a simulation model for a wide variety of accurate results is not always the best option. When a simulation model is available, however, it can be an effective tool for evaluating projects.

When it comes to determining the feasibility of projects and the effect of system changes, simulations are effective. One strategy of improving compressed air network efficiency is to improve compressed air network supply control to match the demand, as is the goal of a DCS controller. This can be simulated using software such as PTB™, although no real-time implementation of this has been observed in the studies observed [2], [9], [20], [23], [36], [53], [55], [62]. This strategy provides the benefit of testing other supply combinations or schedules to improve the knowledge of the system, which can be used to train operators. This will, however, only be helpful in hindsight and will not provide real-time assistance or control to the operators to control the system.

The complexity of compressed air networks has been observed and mentioned in the literature [17], [24]–[32]. One study focused on reducing the complexity of compressed air networks [61], thereby increasing the viability to create accurate simulation models while not consuming too many resources. It is therefore clear that the complex and dynamic nature of compressed air networks proves to be a challenge for software-based solutions such as simulations and the DCS controller.

There is a need to address the issue of the complex nature and the time required to determine values in such a system accurately. Booysen [17] implemented a compressor control strategy on a South African mining complex to achieve energy savings. Booysen used simulation software to verify results before implementing computerised pressure control of compressors. From this study, Booysen recommended implementing artificial intelligence (AI), such as an artificial neural

network (ANN), to improve control of the system. Technology such as AI has been used to predict parameters in complex systems, including some mining applications [28], [65]–[67]. Hyder et al. [66] reviewed the use of AI, machine learning, and autonomous technologies in the mining industry. Hyder et al. [66] found an increase in the application of these technologies in the following mining sectors:

- Prospecting and exploration;
- Exploratory and production drilling;
- Mining operations; and
- Autonomous vehicles.

From their study, Hyder et al. [66] further identified potential applications of AI in the mining industry, which included autonomous support systems. Machine learning or AI could therefore potentially address the shortcomings of software-based strategies and so, it is discussed in Section 1.5.

## 1.5 Review of AI and machine learning solutions

### 1.5.1 Preamble

Approximating and predicting values in complex processes have become an important part of many industries. To address the complex nature of compressed air networks, different types of models can be considered for parameter prediction. The following main model categories exist for parameter prediction in complex processes [65], [68]–[71]:

- White box (engineering) methods;
- Black box (statistical or AI) methods; and
- Grey box (combination or hybrid) methods.

White box models use fundamental principles and known physical relationships to determine system parameters [65], [72], [73]. The DCS controller and simulation software discussed in section 1.4 would be categorised as white-box models. The complexity of flow dynamics in compressed air systems have led to the search for alternative compressor models to predict parameters. Inaccurate results obtained from mechanistic models were the motivation for this search [28]. Some of the advantages and disadvantages of these models are listed in Table 1 and discussed in Section 1.4.3. The main disadvantages include the cost, accuracy, and expertise required to set up the models [65], [73]–[76]. These types of models are a good option for

evaluating new projects when there is a lack of historical data, especially where design specifications of facilities are available [69], [71].

Black box models use statistical learning from historical data to predict parameters. The relationship between parameters is approximated through a process of regression [77]. A mathematical equation or model is used to express the relationship between parameters, although the actual relationship is unknown [65], [77]. Advantages of these models include calculation speed and simplicity of models when compared to other models [78]. These models are trained by using historical data instead of traditional engineering or programming methods, thus not requiring expert knowledge [78].

Grey box models use a combination of physical simulations and regression to determine parameters [79]–[81]. These models are used in cases where the approximation of relationships between variables is poor or cannot be approximated through physical laws [81]. Black-box models are used to determine these relationships, while others are determined using fundamental physical principles. These types of models have shown good accuracy in some instances [28], [71]. These models can, however, suffer from computational inefficiencies [79], while disadvantages associated with white-box models, such as expert knowledge and cost, can apply to grey box models to a certain extent [65].

### 1.5.2 Statistical regression models

Statistical regression is a technique used to approximate how a set of variables (dependant variables) are affected by changing a set of independent variables [82], [83]. A statistical regression model (SRM) can be any function or mathematical equation that models the relationship between variables. In terms of mathematics, this process can be expressed as follows:

$$y = f(x; w) + \varepsilon \tag{2}$$

$$y : independant\ variable$$

$$x : dependant\ variable$$

$$w : parameter\ or\ weight\ that\ is\ changed\ during\ process\ of\ regression$$

$$\varepsilon : error$$

Figure 10 shows four types of SRM which are discussed in further detail.

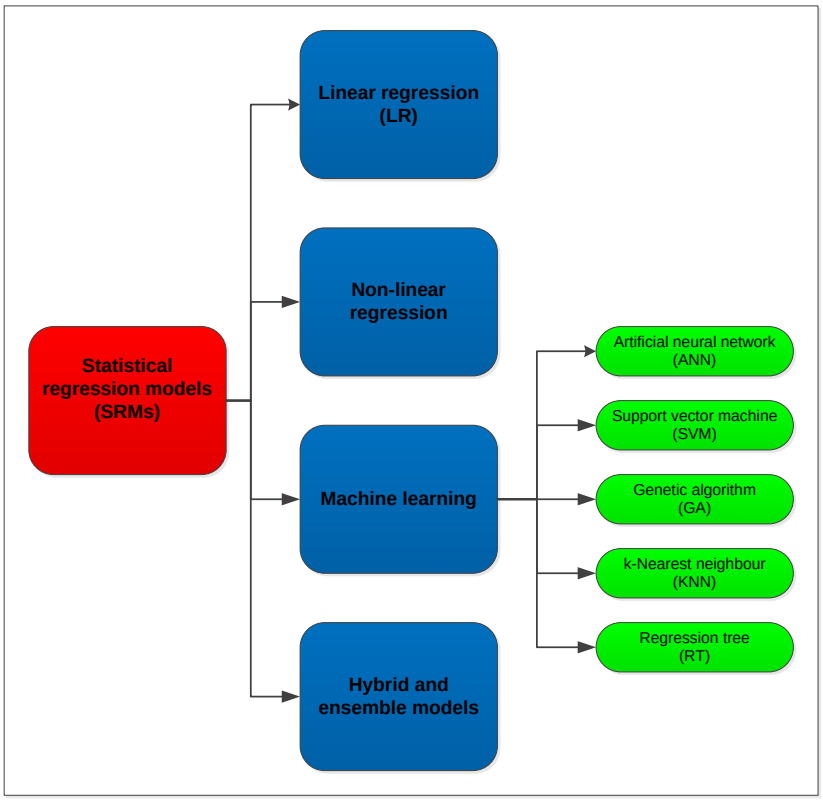


**Figure 10:** Types of statistical regression models

Linear regression (LR) has been applied in several fields of study [84]–[87]. Most regression methods are elaborations or modifications of LR modelling [88]. LR is based on the assumption of a linear relationship between two or more variables [88], [89]. In the same way, non-LR assumes that this relationship is non-linear.

Machine learning models have become a frequently used tool in recent times [82]. The increase in the use of machine learning models can to some extent be attributed to advances in computer technology [90]. Open-source machine learning packages have become easier to access in programming languages like Python and R, which have eased the setup and use of more complex models [69], [91]–[93]. Some of the models in this category that have been applied for prediction in the mining industry include [68], [94]:

- Artificial neural networks (ANN);
- Support vector machines (SVM);
- Genetic algorithms (GA);
- k-Nearest neighbours (KNN); and
- Regression trees (RT).

The use of machine learning models in the mining industry started about a decade ago, with many potential economic benefits through cost reduction, productivity improvement, continuous production, and improved safety [66]. The use of ANNs to model complex systems has become popular due to their ability to account for non-linear dependencies on multiple independent variables, [71], [73], [79], [95]. Hybrid or ensemble models comprise a combination of any of the models in the different categories [65].

### 1.5.3 Machine learning models

The different types of machine learning models can be used for a range of applications. Due to the complexity of the models, a brief overview is given of each model to highlight the main concepts of each model.

#### Linear regression (LR)

LR is a common technique that is used to determine a linear relationship between dependent and independent variables through regression [89]. Figure 11 illustrates the fitting of a linear model to a set of variables. The independent variable is displayed on the x-axis while the dependent variable is displayed on the y-axis.

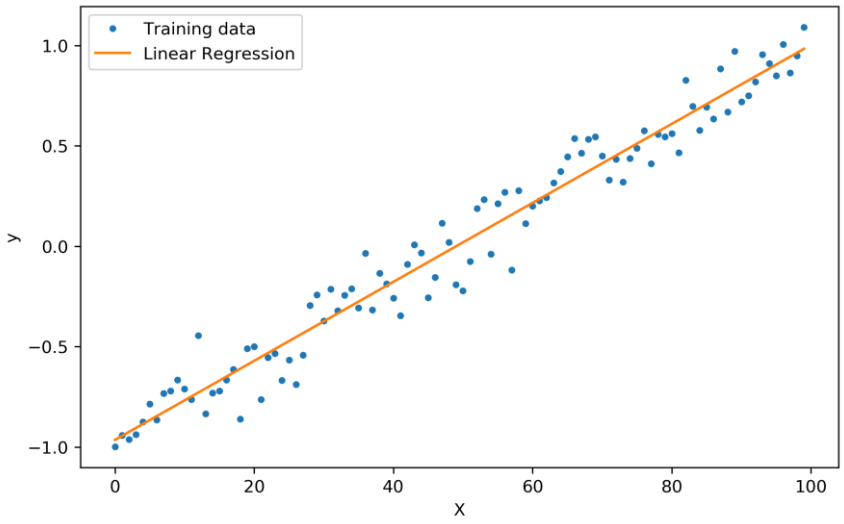


**Figure 11:** Linear regression fitting example[4]

Simple LR refers to an LR model with a single independent variable, whereas multiple linear regression has multiple independent variables [77], [96]. Different algorithms can be applied but

[4] https://mlfromscratch.com/machine-learning-introduction-8-linear-regression-and-logistic-regression/#/

remain applicable to both linear regression types [88], [89]. These algorithms differ, although they all focus on the even distribution of residuals between positive and negative values [89]. The difference between the true and predicted values for data points in a training set is referred to as a residual. The residuals can be calculated as follows:

$$Residual = y_i - \hat{y}_i \tag{3}$$

$$y_i: i^{th}\ true\ value$$

$$\hat{y}_i: i^{th}\ predicted\ value$$

**Artificial neural networks (ANNs)**

An ANN consists of nodes that are grouped together to form layers [65], [73], [93], [97]. The nodes in each layer are connected to all the nodes of the adjacent layers. The basic structure of an ANN consists of three layer types:

- Input layer;
- Hidden layer(s) (single or multiple); and
- Output layer.

The structure of a basic ANN is shown in Figure 12.

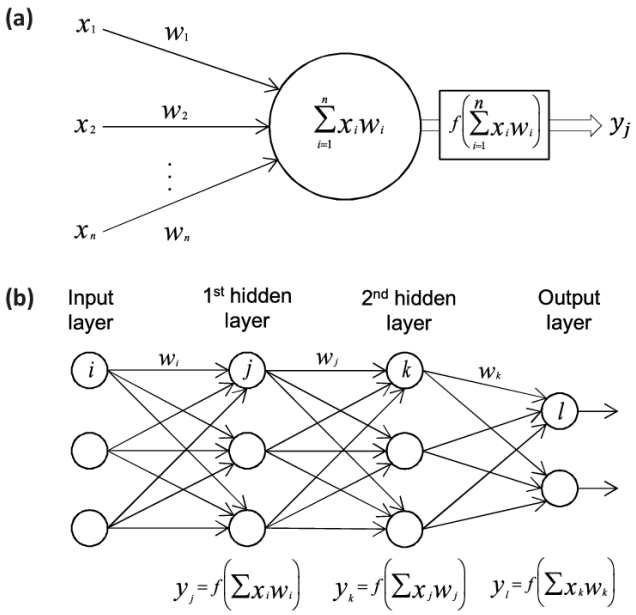


**Figure 12:** Structure of a basic ANN [98]

Figure 12 (a) displays the basic structure of a node. In this figure, input variables ($x_n$) are connected to nodes, with each connection assigned a specific weight ($w_n$). Weights are assigned to connections to quantify the influence of each variable [93]. The number of independent variables determines the number of inputs to the ANN. Mathematical functions and activation functions are represented by each node [65]. The output of the ANN is represented by $y_j$.

Figure 12 (b) provides an overview of the structure of an ANN. Here, the structure of the different layers and connections between nodes are shown. From Figure 12 (b), the output of a layer is used as the input value to the consecutive layer. Each layer functions as shown in Figure 12 (a) is discussed above. More information regarding the mathematics of an ANN is discussed in Appendix C.

**Support vector machines (SVMs)**

In SVMs, a potential non-LR problem can be transformed into a linear problem through a function known as a kernel [99]. In Figure 13, variables $\boldsymbol{x_1}$ and $\boldsymbol{x_2}$ are transformed to new variables $\boldsymbol{\phi(x_1)}$ and $\boldsymbol{\phi(x_2)}$ respectively [68].

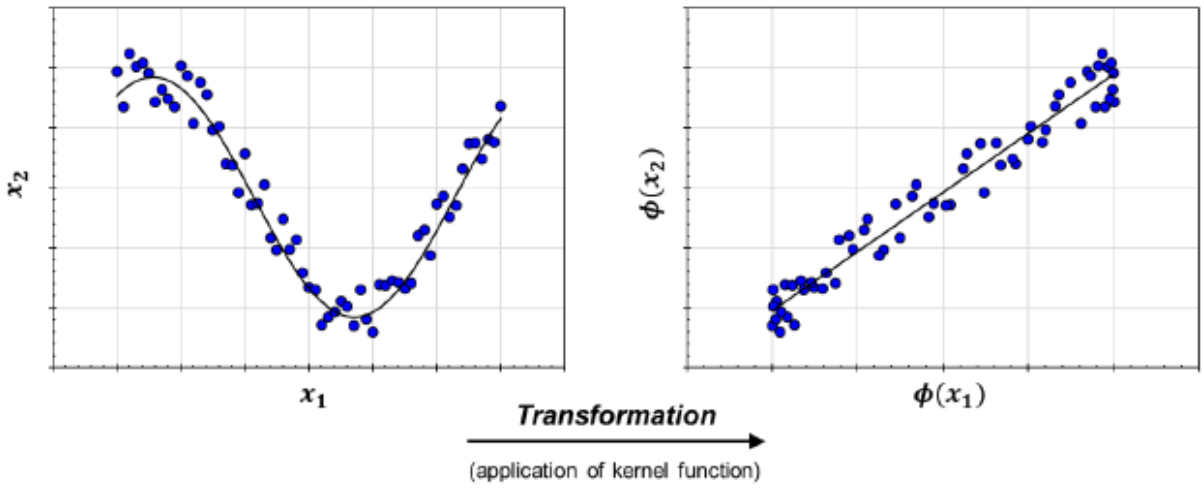


**Figure 13:** Non linear SVM transformation [68].

The problem becomes an LR problem after transformation. The non-linear two-dimensional variables ($\boldsymbol{x_1}$ and $\boldsymbol{x_2}$) can also be transformed into a linear three-dimensional problem. This can be achieved through the application of a multivariable function.

**k-Nearest neighbours (KNNs)**

An example where a KNN algorithm is applied is shown in Figure 14.

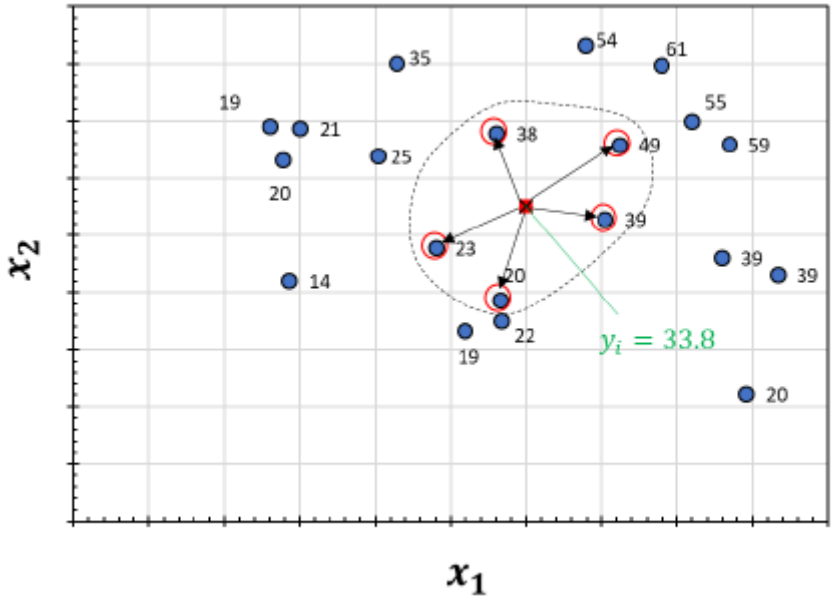


**Figure 14:** Illustration of KNN for k = 5 [68]

All outputs are calculated, using the algorithm, directly from the provided training data [100]. The output is calculated by averaging the $k$-data points nearest to the desired point [82], [101]–[103] Figure 14 shows an example where the five nearest data points were used (because $k$ is equal to 5) to calculate a new output of 33.8 [68]. Averaging can be done on a weighted base using a kernel function, which increases the complexity of the algorithm [103].

Parameters known as hyperparameters are not calculated by the regression process and must be selected. Examples of hyperparameters include the number of hidden layers for an ANN, the application (or absence) of a constant or intercept term in LR models, and the kernel function for SVM and KNN models [68], [92].

From the literature, it was found that none of the models outperformed other models in every application [68], [79]. Factors such as the size of datasets, variables selected, model parameters, etc., had a greater effect on the outcome of model accuracy than the type of model [68]. According to the literature, no model is implicated as the best-performing model. Wang et al. [65], however, mentioned the possibility of applying an ANN for real-time monitoring, given the ability to capture complex non-linear relationships between variables. The number of input data required for an ANN suggests that it could provide a simple accurate alternative to simulation software [78]. Compared to other approaches, such as simulation software, less expertise and effort are required for setup [78]. An ANN has therefore been selected to address the need for the study.

## 1.6 Need for the study and research objectives

### 1.6.1 Summary of literature

Throughout this chapter, the improvement of compressed air networks in the mining environment to achieve energy savings was a main focus. Several studies focused on implementing software-based solutions, such as the DCS controller (real-time solution) or simulations, to improve supply control. These solutions were proven to be successful, although challenges such as instrumentation availability, accuracy, and complexity of these networks hindered implementation.

Studies mentioned that machine learning models could be applied for the prediction of parameters in complex systems. One study ([17]) recommended testing a machine learning model, such as an ANN, to improve compressor supply control. Table 2 provides a summary of the literature and the relevance to the topics of this study. An “x” represents that a study addressed the field of study, whereas an “o” indicates that the field of study was partially addressed.

**Table 2:** Summary of literature

| | Field of study | | | | | | |
|---|---|---|---|---|---|---|---|
| **Reference** | **Mining** | **Energy saving** | **Compressed air** | **Real-time solution** | **Simulation software** | **Data availability and accuracy** | **Machine learning / AI** |
| [1], [3]–[5] | x | | | | | | |
| [7], [10], [104] | x | x | | | | | |
| [2], [8], [15], [20] | x | x | | | x | | |
| [6], [11], [12], [30], [33], [50] | x | x | x | | | | |
| [9], [16], [29], [35], [38], [41], [54], [57], [58], [105] | x | x | x | | x | | |

| | Field of study | | | | | | |
|---|---|---|---|---|---|---|---|
| **Reference** | **Mining** | **Energy saving** | **Compressed air** | **Real-time solution** | **Simulation software** | **Data availability and accuracy** | **Machine learning / AI** |
| [13], [14], [55], [106], [107] | x | x | | x | x | | |
| [19], [23], [24], [62] | x | x | x | | x | o | |
| [17], [18], [27], [46] | x | x | x | x | x | o | |
| [21], [53] | x | x | | x | x | o | |
| [22] | | x | x | x | | | |
| [25], [26], [31], [51], [61] | x | x | x | x | x | | |
| [28] | | | x | | | | x |
| [32] | | x | x | | | | |
| [34] | | | x | | | | |
| [36] | x | x | x | x | | x | |
| [37], [43] | x | x | x | x | | | |
| [39] | | x | x | | | | x |
| [40], [49], [108] | x | x | x | | | o | |
| [42], [60] | | x | x | | x | | |
| [44], [45] | | x | x | | | | x |
| [47], [48] | | | x | | x | | |
| [52] | x | x | x | x | | o | |

| | Field of study | | | | | | |
|---|---|---|---|---|---|---|---|
| **Reference** | **Mining** | **Energy saving** | **Compressed air** | **Real-time solution** | **Simulation software** | **Data availability and accuracy** | **Machine learning / AI** |
| [56] | | | | x | x | | |
| [59] | x | x | | | x | | |
| [63], [64] | | | | | x | | |
| [67] | | x | x | x | x | | x |
| [66], [68] | x | x | | | | | x |
| [69], [72], [96], [97], [109] | | x | | | | | x |
| [65], [70], [71], [79], [80] | | x | | | x | | x |
| [73], [76], [78], [82], [83], [90] | | | | | x | | x |
| [74], [75], [77], [84]–[89], [92], [93], [95], [98], [99], [102], [103], [110]–[112] | | | | | | | x |
| [81] | | | | x | x | o | x |
| [91] | | x | x | | | o | x |
| [94] | x | | | | | | x |
| [100] | | | | x | | | x |
| [101] | | | | x | x | o | |
| [113] | | x | | | x | o | x |
| [114] | | | | | x | o | x |
| [115] | | x | | | | o | |

From Table 2 it is evident that several studies have been performed with regards to energy savings in conjunction with compressed air in the mining industry. Studies include the implementation of real-time solutions (such as a DCS controller), simulation software approaches, or a combination of both to achieve energy savings. These studies did, however, not use machine learning models or address issues with instrumentation availability and accuracy. In many cases, this challenge led to a delay or hindrance in project implementation.

A large group of studies was reviewed with regards to machine learning models. Several of these studies evaluated the application of a machine learning model on energy modelling and prediction of energy usage. These studies were, however, not focused on the mining industry.

Several studies partially addressed real-time instrumentation (data) availability and accuracy. These studies mentioned the challenges, with most recommendations including one of the following solutions:

- Installation of required instruments [17], [18], [21], [27], [46], [49], [91];
- Estimation of missing or inaccurate data [23], [24], [81];
- Simulation of required data [101], [113], [114];
- Using portable instrumentation for spot checks [19], [23], [40], [62];
- Adjusting boundary conditions of the project to avoid problem areas [52];
- Instrumentation inspection and maintenance procedures [53]; and
- Implementation of outlier detection [101], [108], [115].

Only one study addressed the issue of real-time availability and accuracy by developing and implementing a compressor control and scheduling strategy [36]. To implement this strategy, a thorough understanding of the compressed air network was required, thus not addressing the complexity of compressed air networks [36]. Software-based solutions have been proven to be effective for improving compressed air network control. From the literature, however, several shortcomings were identified, which are summarised in Section 1.6.2.

### 1.6.2 Shortcomings of existing research

Shortcomings of the existing software-based solutions (as discussed in Section 1.4) have been proven to be problematic. These shortcomings could impact the potential energy cost savings significantly in terms of the time that these projects are delayed or cannot be implemented successfully.

Shortcomings of the DCS controller include:

- Infrastructure required (centralised control room, SCADA, variety of field instrumentation);
- Accurate field instrumentation of various types required;
- The complexity and dynamic nature of compressed air networks can be difficult to capture;
- Characterisation of a compressed air network is manual and can be tedious; and
- The implementation of a controller is site-specific and not easily replicated at other sites.

Shortcomings of simulations include:

- Simulation packages can be expensive;
- Resource intensive and time-consuming, especially when modelling of individual components is required;
- Accurate field instrumentation of various types required (more than DCS controller);
- Do not provide real-time solutions or assistance to operators; and
- The complex and dynamic nature of compressed air networks can be difficult to duplicate.

### 1.6.3 Research problem

Mining companies in South Africa have to reduce costs to stay profitable. From the literature, it is apparent that improving compressed air supply control is an effective method of reducing energy costs. Software-based solutions, such as the DCS controller (real-time solution) and simulation software, have been implemented to achieve energy savings. However, these software-based solutions have shortcomings that could hinder implementation.

All the shortcomings of these software-based solutions cannot necessarily be overcome. One of the shortcomings observed to be problematic in both instances (i.e., simulations and the DCS controller) is the need for a wide variety of accurate instrumentation. Another issue arising in both instances is the complex nature of compressed air networks. Expert knowledge could be required to address these issues in the implementation of a DCS controller or simulation model. It has, however, been shown that machine learning models such as ANNs could be used to predict parameters in a complex system. The need thus arises to implement a solution that can overcome the challenges of instrumentation accuracy and the complexity of compressed air networks without delaying or hindering the implementation of a solution.

There is a need to investigate the feasibility of applying a machine learning model for the prediction of parameters in a mining compressed air network. Furthermore, there is a need to apply a machine learning model for real-time prediction to improve compressed air network control.

### 1.6.4 Research objectives

The research problem will be addressed by defining and addressing research objectives. To address the feasibility of applying a machine learning model in this context, it is required to define and capture parameters to build a machine learning model. Therefore, an energy management system (EMS) would need to be implemented on a site to capture the available data of a mining compressed air network. Once the data is captured, a machine learning model, specifically an ANN, can be developed to address the first part of the research problem.

After addressing the first part of the research problem, the developed model should be applied to improve compressed air network control. This could be done by developing a compressed air network control solution to assist control room operators to improve supply control, which has been shown to be effective from the literature. After the development of the solution, it has to be validated that the research problem was addressed.

To address the research problem and shortcomings from the existing research the following objectives will be considered:

- **Research objective 1**: Set up an energy management system (EMS) for real-time monitoring and data logging of compressed air network parameters;
- **Research objective 2**: Develop and determine the feasibility of applying an ANN for the prediction of parameters in a compressed air network;
- **Research objective 3**: Develop and implement an ANN driven compressed air network control solution to assist control room operators with compressor scheduling and selection; and
- **Research objective 4**: Validate that the proposed solution addressed in the research problem.

## 1.7 Dissertation layout

**Chapter 1** discussed the background of mining in South Africa and the energy consumption of mining systems. Compressed air systems were identified as a large energy consumer and some

energy management strategies were discussed. Software-based solutions to improve compressed air network control was discussed through extensive literature. To address the shortcomings of these solutions, AI and machine learning were identified as a potential field of study. The chapter concludes by summarising the literature, identifying shortcomings of existing research, and providing a research problem and objectives.

**Chapter 2** provides a methodology to address the research problem and objectives. The method discusses the processes derived from literature to implement an EMS and develop a machine learning model. The specifications and development of a compressed air network control solution to assist control room operators with compressor scheduling and selection will be discussed. This chapter concludes with the verification process that will be followed.

**Chapter 3** implements the developed methodology at a South African platinum mining complex. The case study background is discussed as well as the details of an existing simulation model. The results obtained from implementing an EMS, developing an ANN, and implementing the developed compressed air network control solution is discussed. In this chapter, the relevant objectives are verified and validated through simulation and actual implementation.

**Chapter 4** concludes the study by providing a summary of the dissertation. The main results are highlighted followed by some recommendations for future work to conclude the chapter.

## 1.8 Conclusion

Mining companies in South Africa are under pressure to reduce costs to stay profitable. Research has shown that compressed air systems are one of the most expensive utilities in the underground mining environment. There are various methods to reduce energy costs in compressed air networks, which could be beneficial for profitability.

Effective compressor scheduling and selection are some of the most effective strategies to improve compressed air energy efficiency. Most South African mines have been found to monitor compressed air networks from a centralised control room by control room operators. Operators are thus responsible for compressor selection and compressor discharge pressure set points. Software-based solutions can be applied to aid control room operators in compressor selection decision making to improve the compressed air supply.

Software-based solutions such as the DCS controller have been implemented successfully on mines to improve compressed air supply control through compressor scheduling and setpoint control improvements. The DCS controller is focused mainly on providing a real-time solution for the most efficient compressor selection and compressor supply setpoint. This controller has been

implemented to operate fully automated or to be used as an aid for control room operators. The base of the DCS controller relies on mass flow balancing and simulation of pressure in the compressed air network, which can only be achieved by characterising the compressed air network.

Another software-based approach that has been used to improve compressed air network supply is simulations. Simulations have been used to simulate possible scenarios or changes in system parameters to prove that certain energy-saving strategies, such as a new control philosophy, would be feasible. Simulation software offers in-depth solutions but are not real-time and does not necessarily benefit operators in real-time to make compressor selection decisions.

Shortcomings of the existing software-based solutions that have been discussed in the previous sections have been proven to be problematic. These shortcomings could impact the potential energy cost saving significantly in terms of delayed or hindrance of successful implementation. AI or machine learning was identified as a potential field of study which could address the identified challenges. Different machine learning models were discussed in Section 1.5.3. Based on the literature reviewed, there was no specific model which outperformed other models in every application. Some studies did, however, highlight the potential of implementing an ANN for real-time applications. Based on the reviewed literature, an ANN was selected for the investigations in this study.

Section 1.6.1 provided a summary of the literature reviewed, where the shortcomings were highlighted for the existing research. From the literature and shortcomings, a research problem was formulated. The problem included the need to investigate the feasibility of applying a machine learning model for the prediction of parameters in a mining compressed air network. A further need was identified to apply a machine learning model for real-time prediction to improve compressed air network control.

To address the problem, research objectives were specified. The first objective is to set up an EMS for real-time monitoring and data logging of compressed air network parameters. The second objective is to develop and determine the feasibility of applying an ANN for the prediction of parameters in a compressed air network. An ANN driven compressed air network control solution should be developed and implemented to assist control room operators with compressor scheduling and selection. The last objective is to validate that the proposed solution has addressed the research problem. The chapter concluded with an overview of the dissertation layout.

# CHAPTER 2 METHODOLOGY

## 2.1 Introduction

From the background and literature in Chapter 1, a research problem was identified, as discussed in Section 1.6.3. A need was determined to investigate the feasibility of applying a machine learning model for the prediction of parameters in a mining compressed air network. A machine learning model is applied to determine the feasibility of overcoming some challenges regarding instrumentation and to address the complexity of compressed air networks. An artificial neural network (ANN) is applied for parameter prediction instead of characterising the network manually as is done in the DCS controller or with simulation software.

After this need has been addressed, it is further determined whether a machine learning model can be applied for real-time prediction to improve compressed air network control. The methodology set out in this chapter follows the order of the research objectives, as specified in Section 1.6.4. The methodology thus addresses each objective and includes the following:

- Real-time monitoring and data logging energy management system;
- Machine learning model development;
- Compressed air network control solution development and implementation; and
- Verification methodology.

Each step discusses the relevant process (derived from literature), which is followed to successfully implement and address each of the research objectives. Verification specifications are also discussed for steps where necessary, which are ultimately addressed in Step 4.

## 2.2 Real-time monitoring and data logging energy management system

### 2.2.1 Preamble

In this section, a method is discussed to address research objective 1, which is to set up an EMS. The DCS controller is a real-time solution based on an EMS [25]. The DCS controller is not implemented in this study, although a similar approach is followed to set up the EMS for monitoring and data logging purposes. This solution uses the same approach to evaluate the

network characteristics, to determine whether changes are required to the current compressor combination, and to log network data in real time. These elements form an integral part of DCS implementation methodologies [25]–[27].

The following process steps are followed to set up an EMS, which is adapted from the process implemented by Jonker [26] whilst implementing DCS:

- Step 1.1: Process parameters identification;
- Step 1.2: Communication specification;
- Step 1.3: Existing infrastructure; and
- Step 1.4: Data logging and calculations.

By implementing the steps mentioned above, an EMS is set up to perform calculations and log data required for the solution. When implementing the DCS platform, next is to complete a simulation [26], [46], [51]. When key instrumentation is not available, this step cannot be implemented. An ANN is thus used to address this challenge, which is discussed in Section 2.3. Some calculations and network parameter evaluation are, however, performed on the platform before the ANN is utilised (discussed in Section 2.2.5).

Calculations are performed on the logging platform to determine the compressed air network status (or compressor selection effectiveness). This includes start and stop triggers for compressors as discussed in Section 1.4.2. These triggers are determined based on current network conditions and are explained in detail. All monitored data is logged which could be utilised for the ANN. The identification of process parameters is the first step in the implementation setup of an EMS.

### 2.2.2 Step 1.1: Process parameters identification

The first step in the implementation of a DCS controller is to ensure that specific process parameters are available and accurate [25], [26]. If these parameters are unavailable or inaccurate, the DCS controller will not be able to simulate the compressed air network and send control commands to equipment [25], [26], [36]. This issue forms part of the challenges associated with the implementation of the DCS controller.

As found in Section 1.2.4, pressure is one of the main control parameters. To ensure the operation of pneumatic equipment, sufficient supply pressure is required. Supply pressure is therefore identified as one of the main parameters required for this solution. Other parameters include consumer consumption, compressor running, and load statuses. Knowledge is required on whether compressors are actively supplying compressed air, and a metric of the consumer side consumption is also required.

Table 3 compares the minimum requirements for parameters to implement a DCS controller (as discussed in Section 1.4.2) compared to an ANN as a solution for real-time parameter prediction:

**Table 3:** Required parameters for different solutions

| Process variable description | DCS controller | ANN as a solution |
|---|---|---|
| Compressor discharge mass flow [kg/s] | x | |
| Compressor discharge pressure [kPa] | x | |
| Compressor inlet guide vane position [%] | x | |
| Compressor running status [0/1] | x | x |
| Compressor loaded status [0/1] | x | x |
| Compressor electrical power consumption [kW] | x | x (or at least rated power) |
| Consumer pressure requirement [kPa] | x | x |
| Consumer pressure downstream of valve [kPa] | x | |
| Consumer compressed air consumption [kg/s] | x | x |
| Consumer pressure upstream of valve [kPa] | | x |

According to Table 3, significantly less information is required for the ANN as a solution compared to the information required for a DCS controller. This is consistent with the literature, which indicates that machine learning models like ANNs require a small number of parameters to adequately represent a system compared to traditional simulation approaches [65]. Upstream consumer pressure is the only parameter required additionally for the ANN solution when compared to the DCS controller. On the other hand, multiple additional parameters are required to install a DCS controller successfully. However, Jonker [26] noted that this information would be beneficial for a DCS controller as it could be used to improve the accuracy of simulation results.

Field instrumentation is used to relay measured process parameters through PLCs to the SCADA, as discussed in Section 1.4.2. These values are then communicated to the DCS controller through the OPC connection from the SCADA. This communication information is discussed in Section 2.2.3.

### 2.2.3 Step 1.2: Communication specification

The DCS controller can communicate commands to field instrumentation via the SCADA and PLCs. This is, however, not discussed in detail as this study does not include automatic control of field instrumentation through a controller. Instead, this study only displays output parameters to assist control room operators. Figure 15 displays how communication is established to all the different elements of the solution. This is based on the literature of communication specifications of the DCS controller, as discussed in Section 1.4.2.

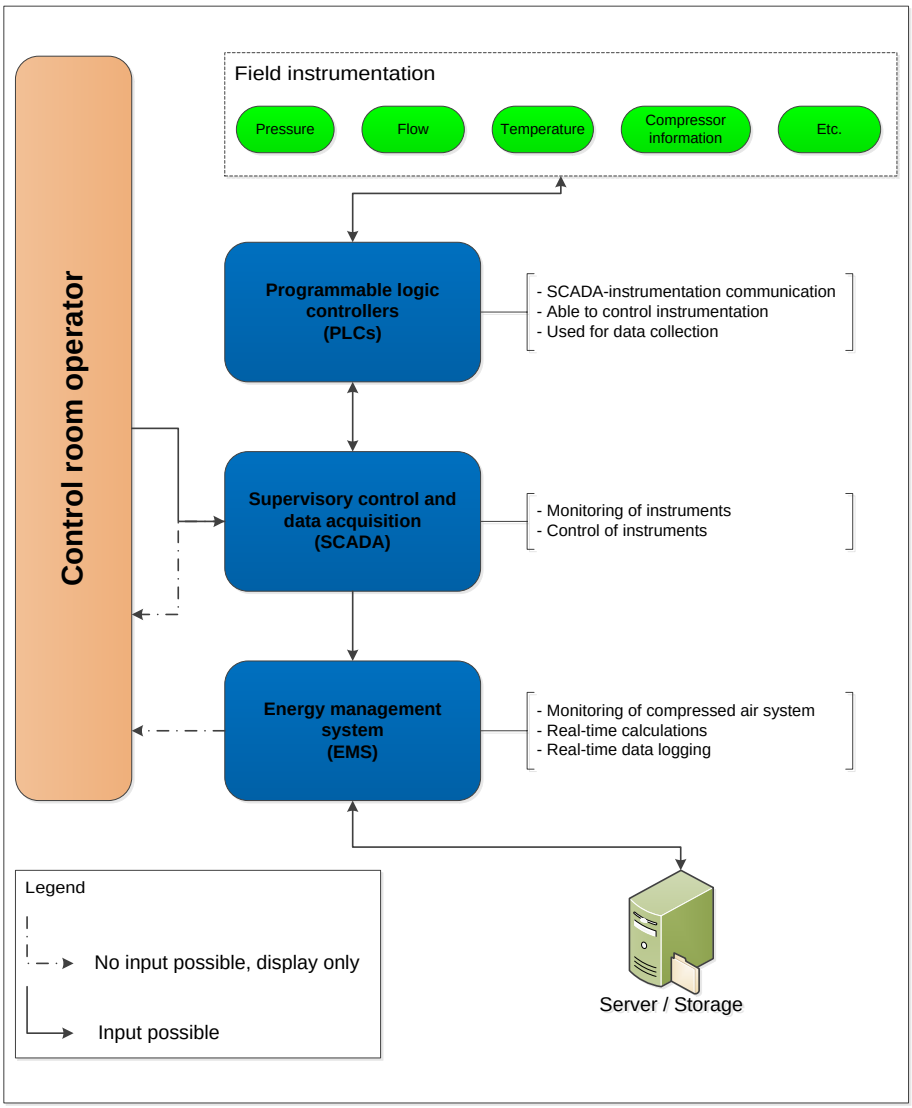


**Figure 15:** The EMS, SCADA, and instrumentation communication link

Process parameters are measured by using field instrumentation. These parameters are then communicated to the SCADA via PLCs, as previously discussed in Section 1.4.2. An EMS, with similar monitoring functionality to a DCS controller, is implemented. This platform is used to perform calculations and save data. This ensures that there is a form of historical and real-time data available to be accessed by another program or the ANN.

All the relevant information can be linked in the EMS to be logged and monitored and to perform calculations in real time. Once communication between the components has been established, the next step can commence. This includes identifying existing infrastructure on the compressed air network to link the correct information to the EMS.

### 2.2.4 Step 1.3: Existing infrastructure

The next phase is to identify all existing infrastructure and relevant information relating to the compressed air network [26]. For the DCS controller, a detailed surface layout must be obtained, which is used to build a virtual compressed air network into the controller. This layout should include the length, diameter, and bends of each pipe section [25], [51]. This has been proven to be challenging, as detailed layouts are not usually available [26]. Some studies have, therefore, used other techniques, for example Google Earth, to approximate pipe lengths and bends [26], [27], [36], [46], [54], [105]. When using a DCS controller, these layouts are required. However, when an ANN is applied, it is not required, as ANNs can approximate relationships through mathematical modelling, although the actual relationships are unknown [65]. It could, however, be beneficial to have such a layout to provide an overview of the system.

A detailed layout is not required; however, it is necessary to ensure that all supply (compressors), demand (shafts, plants, workshops, etc.) and site-specific details are known. Site-specific details include process parameters (discussed in Section 2.2.2), priorities between different compressors, operating constraints from a technical perspective, and any other information that will affect control [26]. Details from the demand side include process parameters and other details such as operating schedule.

For a DCS controller, thorough knowledge of the compressed air network is required to construct an accurate simulation [26], [27] given the manual characterisation and setup of the compressed air network in the controller. When using an ANN, the characterisation of the compressed air network is done automatically through machine learning [28], [76]. This would simplify this process of characterisation as it is not done manually. It would also not necessarily require thorough knowledge to construct an accurate representation of the compressed air network, unlike a DCS controller.

The next step in configuring the solution is to set up the EMS to enable data logging, monitoring and real-time calculations [26]. This solution tests an alternative method for predicting parameters in the system to the built-in simulation of a DCS controller in order to mitigate issues faced in the implementation of the DCS controller. The simulation step is thus not discussed in detail, as this is replaced by another method as explained in Section 2.3. In the following section, some calculations are discussed for which the EMS platform is used.

### 2.2.5 Step 1.4: Data logging and calculations

With the establishment of communication, together with data that was gathered as discussed in the previous sections, data logging and real-time calculations can now be set up [26], [27]. All relevant data is logged through the EMS. Once the EMS is set up, calculations are performed on the logging data to form real-time virtual parameters [25], [26], [36]. These virtual parameters can be set up to provide additional information regarding the compressed air network. Virtual parameters are used to determine when a compressor can be started or stopped, depending on the network conditions.

Jonker [26] developed a strategy to evaluate when a compressor is required to start and stop. A similar procedure is implemented in this study. Jonker, however, developed the strategy for a specific site, and it was based on the operating principles of a DCS controller. The procedure in this study is thus adapted to be used as a generic solution. Figure 16 describes the start procedure as implemented by Jonker [26]:

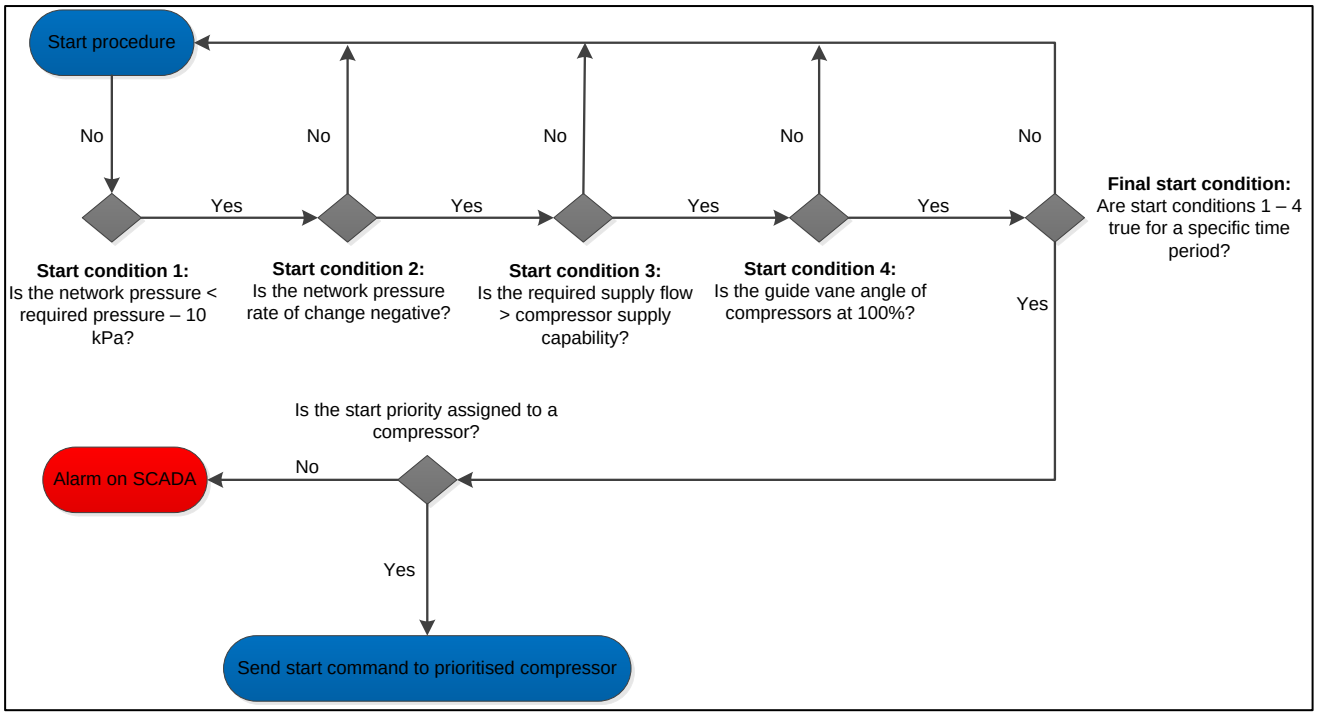


**Figure 16:** Start trigger procedure for DCS controller

Figure 16 illustrates the conditions that are evaluated before a compressor is started. The conditions are discussed below:

Start condition 1 - If the network pressure is more than a predetermined pressure difference (Jonker used 10 kPa) below the required pressure, the condition is satisfied, and the start procedure continues to the following step.

Start condition 2 - If the pressure rate of change is constant or decreasing, the process continues.

Start condition 3 - The total flow capacity of compressors is evaluated and compared to the total required supply flow. If the capacity of current running compressors is not able to match the demand, the condition is satisfied. This step is not required in this study given the proven inaccuracy and unavailability of instrumentation such as compressed air supply flow meters.

Start condition 4 - The guide vane angles of all running compressors should be above a predetermined limit or at a maximum position. This would indicate that all compressors are at or close to maximum delivery and an additional compressor might be required to sustain or increase pressure. If this is the case, the process continues.

All the previously mentioned conditions should be active for a predetermined time before the final start command is sent to the prioritised compressor to ensure the stability of the system and avoid the unnecessary starting of a compressor. The DCS controller then continues to assign a start command to the compressor that is currently set to the highest priority. Priorities of compressors are set based on site-specific details and the efficiency of compressors. To ensure that the proposed compressor selection would satisfy demand, DCS controllers use flow balancing.

It is assumed that if the total flow capacity of the compressors is greater than the required demand, the pressure requirements will be met. DCS controllers use flow balancing; however, flow balancing is not possible with known issues in availability and accuracy of instrumentation such as compressor discharge flow meters. For this reason, an ANN is used to solve the problem. This procedure is thus altered by removing Start condition 3 and replacing the priority checker with a method that involves an ANN model.

An ANN is used to predict pressure based on the current network conditions and the proposed compressor combination. This ensures that pressure requirements are met. After a specific solution is determined that is able to satisfy pressure requirements, power consumption is considered. In this way, the proposed solution is ensured to satisfy the pressure requirement while being the most energy-efficient option. If the solution does not satisfy the pressure requirement,

an additional compressor will then have to be started, which could be less efficient than starting another compressor correctly the first time.

The updated procedure, adapted from the processes implemented by Jonker [26] and Taljaard [36], is displayed in Figure 17.

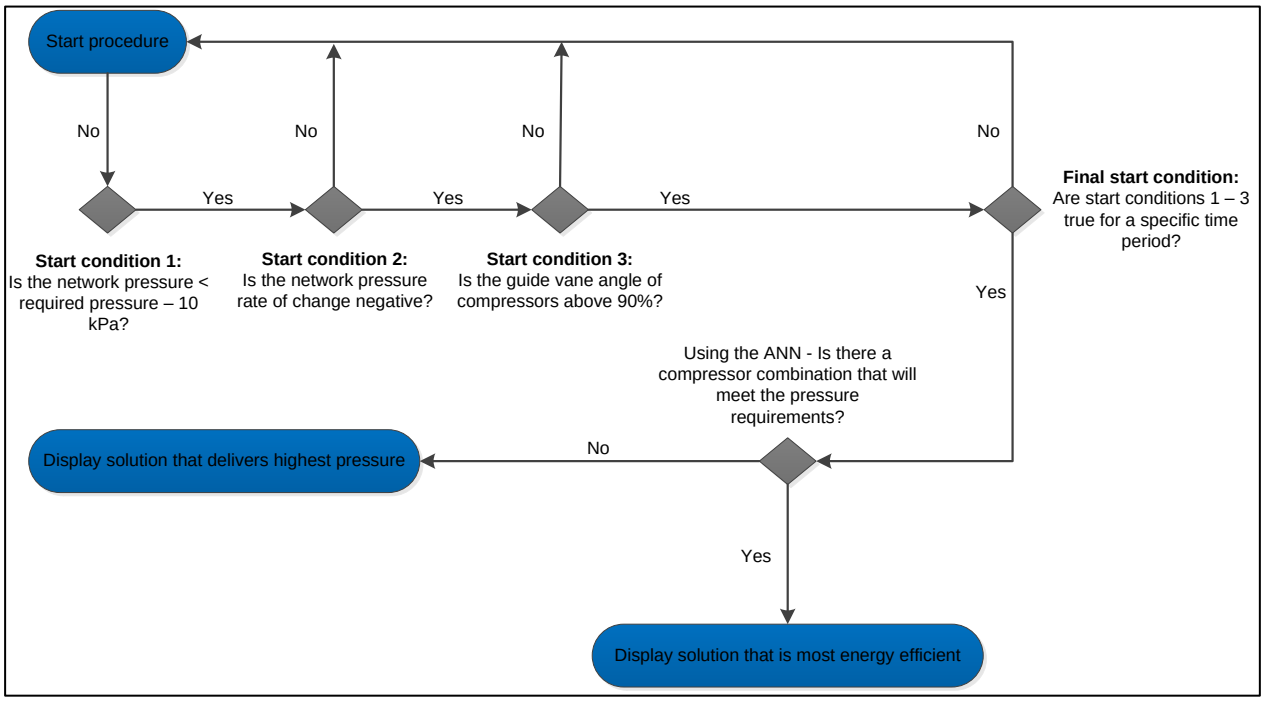


**Figure 17:** Start trigger procedure for the compressed air network control solution

The main difference between the original procedure and the adapted procedure is the removal of the supply flow condition. The supply flow condition has been removed to reduce the amount of information required from flow instruments that could be inaccurate. The updated procedure uses the ANN to verify whether a solution can satisfy the pressure requirements. If there is a solution, the most energy-efficient solution is displayed, otherwise, the solution that delivers the highest pressure is displayed.

The updated stop procedure entails a similar logic and is shown in Figure 18.

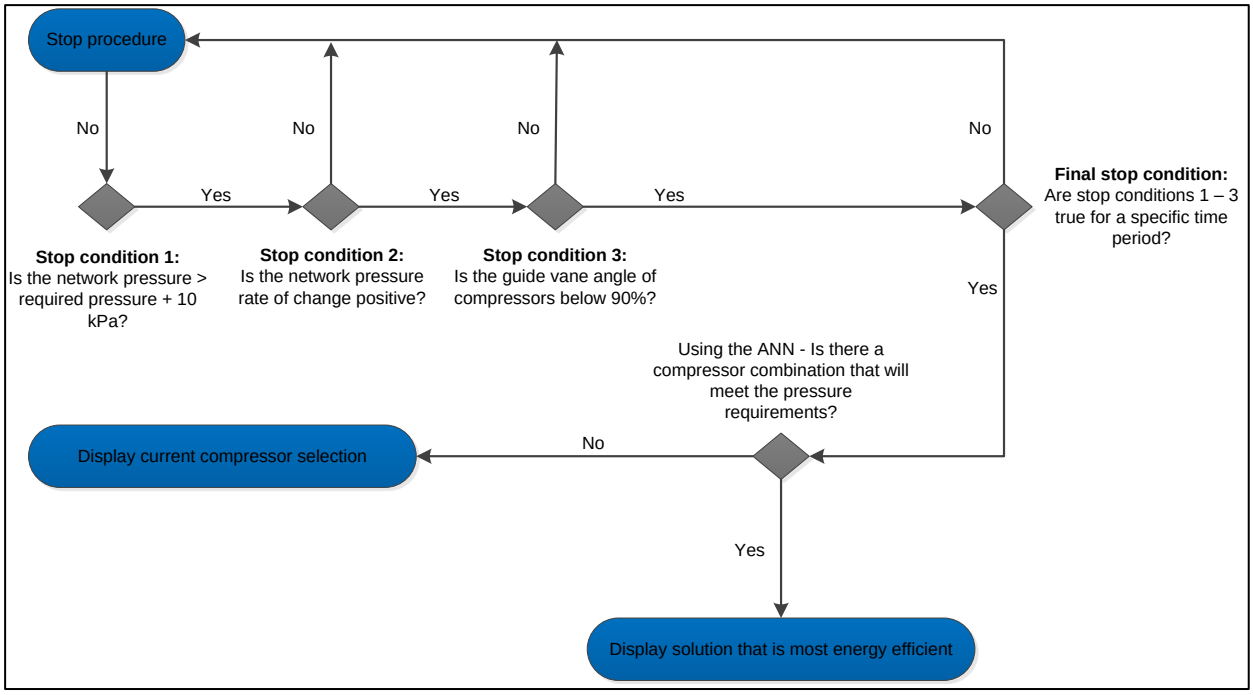


**Figure 18:** Stop trigger procedure for the compressed air network r control solution

From Figure 18, the stop conditions that are evaluated are as follows:

Stop condition 1 - If the network pressure is more than a predetermined pressure difference (Jonker used 10 kPa) above the required pressure, the condition is satisfied, and the stop procedure continues to the following step.

Stop condition 2 - If the pressure rate of change is constant or increasing, the process continues.

Stop condition 3 - The guide vane angles of all running compressors should be below a predetermined limit or cutting back. This would indicate that all compressors are not at maximum delivery and a compressor might be stopped. If this is the case, the process continues.

The process followed after these conditions are satisfied is similar to the adapted start procedure. The most energy-efficient combination is displayed in the case of a viable solution. Where no solution exists that will satisfy pressure requirements, the current compressor combination is shown as the suggested combination.

From the discussed start and stop trigger procedures, an ANN is used to evaluate whether proposed solutions meet the network requirements. This is discussed thoroughly in the following

section. After all the steps discussed in Section 2.2 have been implemented, Objective 1 of the research objectives (discussed in Section 1.6.4) will have been completed.

## 2.3 Machine learning model development

### 2.3.1 Preamble

The method to develop a machine learning model, an ANN, is discussed in this section, which addresses research objective 2. Based on studies reviewed in the literature, there are common steps followed in the development and evaluation of machine learning models. Procedures for implementing the DCS controller and the development of simulation models in the context of this study have also been considered. The following methodology has been derived from these common steps and is used to develop an ANN:

- **Step 2.1**: Project scope [19], [62], [68], [69], [91];
- **Step 2.2**: Data gathering [36], [65], [68], [69], [86], [100], [104];
- **Step 2.3**: Feature selection [68], [69], [86], [111];
- **Step 2.4**: Data treatment [65], [68], [69], [100], [109];
- **Step 2.5:** Model development [65], [68], [69], [73], [91], [92], [114]; and
- **Step 2.6:** Model implementation [65], [69], [71], [76].

Having trained the ANN successfully, the next step in the methodology is discussed. The next step includes using the trained ANN to predict values in a compressed air network in real time.

### 2.3.2 Step 2.1: Project scope

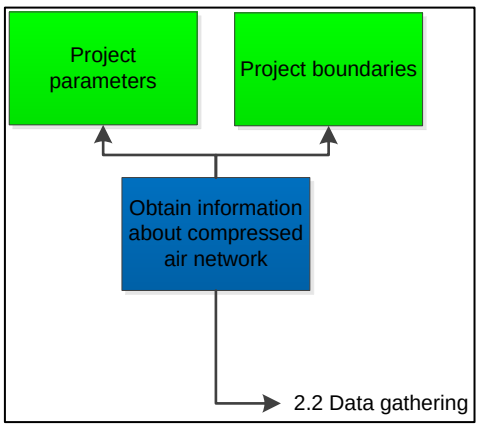


**Figure 19:** Machine learning model development project scope

The parameters and boundaries of the project must be defined before further steps are taken [19]. The objectives and requirements for the model need to be defined to ensure that the model

solves a specific problem and to avoid problems such as scope creep [62]. From Section 1.6.3, it is known that this machine learning model is applied to evaluate whether proposed compressor combinations would satisfy pressure requirements, given the current network conditions. To do this, an ANN is used to predict the pressure delivered to consumers on a compressed air network, given the current conditions (depending on available data), and proposed compressor combinations. This model should therefore be able to predict pressure at consumers to determine whether proposed compressor combinations will be effective.

The boundaries of the project are kept to surface supply and demand details. This study discards the prediction of parameters in the underground network due to the application of the model. This is similar to the boundaries of studies where DCS controllers were implemented [25]–[27]. The model is implemented in real time to assist with solution verification. The data required for the model should thus be available in real time, which should be kept in mind when available data is evaluated.

### 2.3.3 Step 2.2: Data gathering

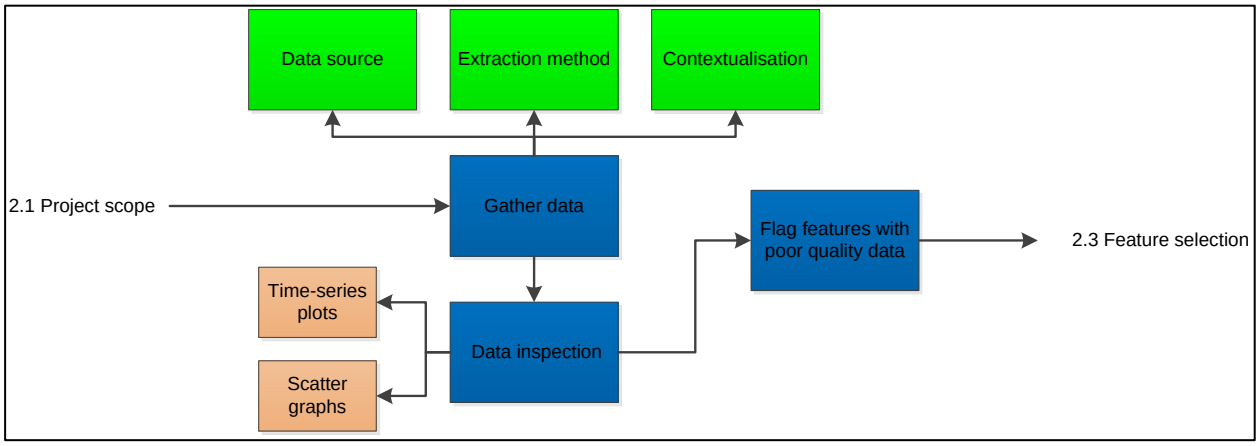


**Figure 20:** Illustration of the data gathering process.

Data is sourced from the implemented EMS where data is stored. This step is therefore reliant on the successful completion of research objective 1 (discussed in Section 1.6.4), which will have been achieved through the process discussed in Section 2.2. The type of data, frequency of measurement, storage method and access method should be selected [68], [69]. This information is required to outline the process of data extraction to the model. Historical data is used for the development of the model, although the model should be able to retrieve data with the same characteristics in real time. All data that cannot be gathered through the EMS in real time should be discarded for training purposes. This ensures that the data is available from a single source when the model is implemented.

When access to historical and real-time data is available for the model, context must be applied to the data [69]. Context is added in the form of identifying the type and unit of measurements captured in the data. Data that is not relevant to the context of the system where the model is applied is disregarded. This step is important for the identification of parameters that are used for prediction purposes [69], [86], [111].

Having identified the relevant data, it can be inspected. Inspections are done to assess data quality [68], [69]. Data inspections allow for informed decisions to identify features that will be suitable for further analysis, based on data quality and integrity. Features should be omitted if possible when one or more of the following conditions are present: when a large number of outliers exist or periods of missing data or unreliable measurements are noticed [68], [100], [110]. Visualisation of data can be done to gain an understanding of the data at hand and to further identify possible issues. Plots such as time-series plots are used to evaluate typical daily operations. Scatter graphs are useful to identify typical operating ranges and outliers. This process ensures that data quality and integrity are maintained.

Poor quality data will reduce the accuracy of the model [115]. During data gathering, poor quality data is therefore disregarded. In this way, the features with higher quality data are identified. The next step is to select the features to be used in the ANN model from the gathered high-quality data.

### 2.3.4 Step 2.3: Feature selection

The available data, after data gathering and filtering has been done as discussed in Section 2.3.3, can often contain multiple variables. To reduce the time spent on the process of implementing the machine learning model, data treatment is thus only done after the main drivers of the system are identified [111]. Main drivers are variables that could have a direct impact on the predicted parameters of the machine learning model [65], [68].

All the available data types are evaluated from which the most important features are selected [65]. Due to the application of this model and actual real-time data, there is no process to determine the most important variables. In the context of this study, there is only a limited amount of supply and demand variables available. The feature selection process for this study thus does not investigate issues such as multicollinearity. Methods such as principal component analysis to produce additional driver sets as done in some other studies are not implemented [68]. Measured values and combinations of the measured values, as mentioned in Section 2.2.2, are selected as inputs. Measured values consist of demand and supply data as listed in Table 3.

Some benefits of feature selection include reducing measurement and storage requirements, reducing model training time and improved prediction performance by avoiding high dimensionality [111]. Dimensionality refers to the number of features in a dataset. A lower dimensionality can reduce the expense of creating, storing and processing measurements [111]. Having completed the feature selection, a list of possible inputs to the model is known that are used to predict some output variables. In this case, the pressure at consumers is the desired output variables. Data treatment can now be performed for the training of the model. This is important to ensure the accuracy and stability of the model.

### 2.3.5 Step 2.4: Data treatment

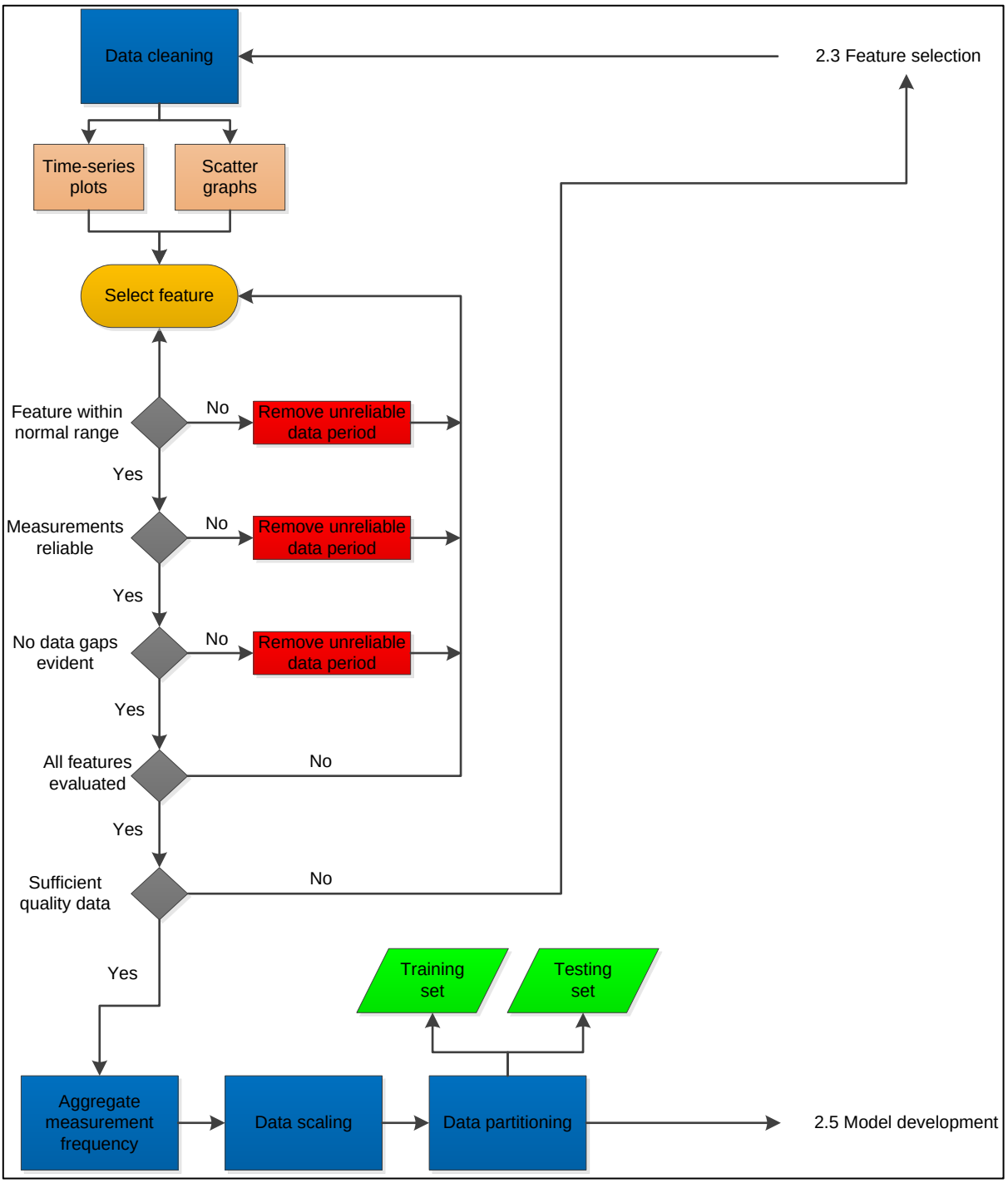


**Figure 21:** Illustration of the data treatment process.

Now that data has been gathered, initial inspections have been done and features have been selected, data treatment can be done. In most procedures, this process includes data cleaning and data scaling. This step is done to improve model training by improving the quality of data [68], [69].

Data cleaning refers to the process of detecting and removing inaccuracies in a data set [69], [100]. According to Gous [115], high-quality data is required for accurate models and removing abnormalities ensures consistency. For this study, data cleaning consists mostly of identifying poor quality data and removing it. No form of data approximation or backfilling is thus used to fill gaps in data. Poor quality data is identified similarly as explained in Section 2.3.3 regarding data inspection. Inspection plots and logic tests are used to determine whether data is within expected normal ranges.

If ANNs do not have sufficient data, it could harm prediction accuracy [97], [112]. Features that provide too little usable data should therefore be removed, and, if required, feature selection should be re-evaluated. Once feature selection is re-evaluated, the process of data treatment is then re-applied and repeated until a data set is available with reliable data of high quality. Reliable data with high quality will have no gaps, spikes or outliers present [115]. After having cleaned the raw data, the data is aggregated to a lower measurement frequency. This is done by averaging data for each of the data points in a selected period. Guisasola et al. [110] noticed that a lower measurement frequency tended to yield more accurate and reliable results.

Before the model development is complete, data is scaled or normalised to improve model performance [69], [109]. During this process, variables are scaled to have the same minimum and maximum values. In this way, the effect of variables with greater numerical values does not dominate those with smaller numeric values [109]. Scaling values between zero and one is a popular method used in studies [68], [109], [112]. This is done using the equation below:

$$z_{i_{scaled}} = \frac{z_i - z_{min}}{z_{max} - z_{min}} \tag{4}$$

The scaling parameters of each feature in the data set are stored for the implementation of scaling in real time. It is important to store this information for the complete training set to ensure the variables are scaled correctly.

The last step in data treatment is data partitioning, which entails splitting the data into a training and testing set. The model is trained using the training set and tested with unseen data from the testing set. A standard calculation technique is used to calculate the error. This is done to avoid the overfitting of a model. Overfitting is when a model predicts training data very well but fails or is inaccurate when applied to unseen or new data [82], [98], [114].

A shuffled split is performed where data is first shuffled randomly before being split. A common training-testing split of 70%-30% is implemented for this study [68], [113]. Having treated and split the data into training and testing sets, the model development is now discussed.

### 2.3.6 Step 2.5: Model development

Section 1.5.2 mentioned that Python and the R-programming languages have become popular in the development of machine learning models. This is because of the number of external statistical packages available to ease the development of these models. Similar to the approach of Manobei et al. [93], the Keras[5] Python package in conjunction with Tensorflow[6] is applied to develop and implement an ANN. Scikit-learn[7] tools were used to perform data scaling and partitioning as mentioned in the previous section.

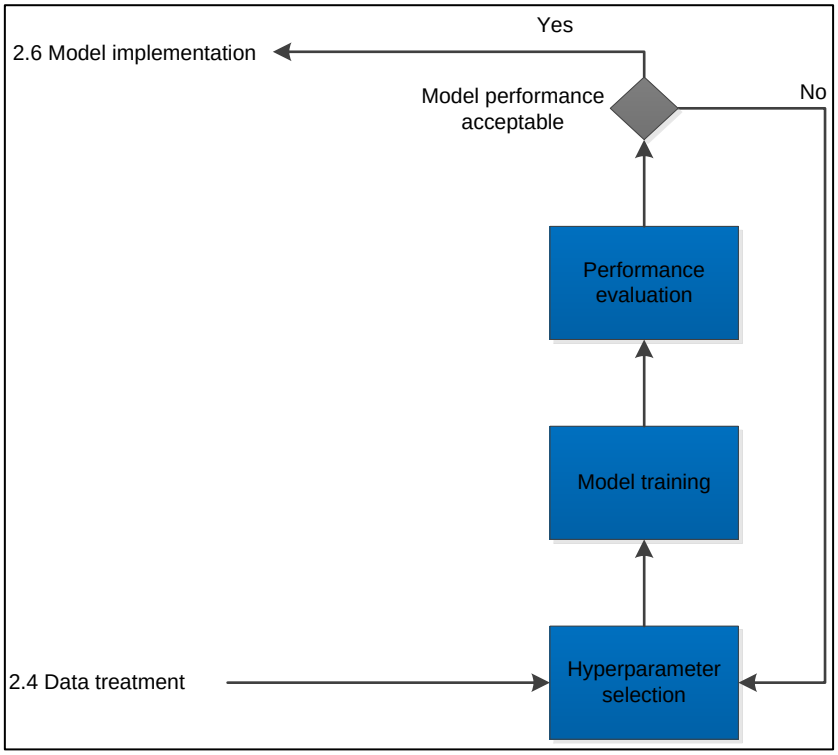


**Figure 22:** Illustration of the model development process

[5] https://keras.io/

[6] https://www.tensorflow.org/

[7] https://scikit-learn.org/stable/

The first step to creating the model is to select hyperparameters (discussed in Section 1.5.3). These parameters influence the form of the model. These parameters are set beforehand and are not influenced by the training process; they do, however, influence the total number of parameters [92]. These parameters influence model accuracy; therefore; complete studies are done to select the best possible hyperparameters for a model. Most selection techniques are based on a form of “trial-and-error” [28], [92]. Some common techniques for selecting hyperparameters include manual search, grid search, random search, and Bayesian optimisation [68], [92]. This study is not focused on selecting the best possible hyperparameters to optimise the model for accuracy. Instead, the focus is to prove the feasibility of using a machine learning model, such as an ANN, to predict values in a complex system to replace traditional first-principle methods in this context. Hyperparameters are thus altered manually until an acceptable level of accuracy is achieved to continue with the implementation. Acceptable levels of accuracy are discussed at the end of this section. Once the feasibility is proved, further studies can be performed to improve the specific model in this application.

The following hyperparameters are specified for the ANN [65], [68]:

- Number of hidden layers and units;
- Activation function – a function used to transform neuron input;
- Learning rate – affects the size of change to the model in response to estimated error when model weights are updated;
- Number of epochs – number of times the training data is shown to the network during training; and
- Batch size – number of samples given to the network before parameters updates happen.

Having set these parameters, model training can commence. Model training is done with training data, while testing accuracy with the testing data set. This is done to avoid overfitting of the ANN [68], [82], [98]. After the model is trained, as determined by the hyperparameters, it is evaluated for accuracy and consistency.

To quantify the prediction performance of the model, accuracy and consistency attributes are evaluated. Although these attributes can be evaluated in different ways, the root mean square error (RMSE), coefficient of variation for root mean square error (CV(RMSE)), and the normalised mean bias error (NMBE) can be used. RMSE is a measure of the difference between actual and predicted values. CV(RMSE) is the measure of variability between actual and predicted values. This coefficient gives context to the size of the error relative to the quantity being modelled and indicates the uncertainty in the model [69], [97]. A lower CV(RMSE) is desired, as this will mean

a lower uncertainty. NMBE, on the other hand, is an indication of bias in a regression model by quantifying the tendency of the model to under- or overestimate values in a series. A positive value would indicate that a model tends to overestimate the actual value, while a negative value could indicate the underestimation of the actual value. NMBE is also used to gain insight into model performance. These metrics can be calculated using the formulas below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{5}$$

$$CV(RMSE) = \frac{RMSE}{\bar{y}} \times 100 \tag{6}$$

$$NMBE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n \times \bar{y}} \times 100 \tag{7}$$

where $y_i$ is the actual value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the average of the actual value, and $n$ is the number of predictions in the period of analysis.

These parameters discussed are used to track model accuracy and bias through the development process. There are not specified requirements that have to be met for the model to be accepted, although ASHRAE guideline 14 is considered. ASHRAE guidelines for energy modelling requires that baseline models meet the requirements listed in the table below:

**Table 4:** Baseline model required values from ASHRAE Guideline 14 [97].

| | **Monthly** | **Daily** | **Hourly** |
|---|---|---|---|
| CV-RMSE | 15% | 22% | 30% |
| NMBE | 5% | 7% | 10% |

From Table 4 there are different minimum levels of accuracy and bias required depending on the data interval of predictions. This is, however, just for reference, as these guidelines are for energy modelling, and are not a determining factor in the model development process. Another parameter that could be used is the mean absolute percentage error (MAPE), as mentioned in Section 1.4.3. MAPE has been used in several studies to determine the accuracy of prediction and simulation

models [65], [78], [87], [95], [113]. A value as close to zero is desirable, although, for this study a value below 10% is considered accurate. This value is based on literature [106], [107].

Hyperparameters are adjusted through trial-and-error, and the model is retrained to the point where accuracy is acceptable. This process is repeated until the model is deemed accurate. Having established accuracy, research objective 2 (as discussed in Section 1.6.4) will have been verified and the model can be prepared for implementation.

### 2.3.7 Step 2.6: Model implementation

The model is now trained and capable of taking inputs and predicting outputs. The model is thus ready for implementation. To use the model, some form of data pre-processing is required to ensure that new data (for the implementation period) is in the correct format, i.e. the correct features in the correct frequency and scaled using the known scaling parameters [69]. The data can now be fed into the model to predict real-time outputs.

The implementation is a real-time prediction, which is discussed in Section 2.4. For this model to be used, it has to be saved or exported in a format that can be loaded at a later stage. In this way, the model can be trained and developed on an independent system from where it is implemented. The model can thus be updated or retrained at a later stage without interrupting the current system where it is implemented.

The trained model as well as the scaling information for the input and output parameters are saved to be used when the model is implemented. Periodic updates can be performed to the model if there are significant changes in the system or the performance of the model declines. These updates can be performed by repeating the machine learning process described in Section 2.3.

The next section explains how this model is applied to solve the problem of evaluating compressor combination feasibility. The reason for the use of this model is that a DCS controller relies on flow balancing to prove that pressure will be sufficient, which is affected by instrumentation availability and accuracy. The ANN is therefore used to predict pressure at consumers to prove whether proposed compressor combinations will be effective or not.

At this stage, research objective 1 and 2 (as discussed in Section 1.6.4) will have been addressed. This addresses the first part of the research problem regarding the feasibility of applying a machine learning model for the prediction of parameters in a mining compressed air network, as discussed in Section 1.6.3.

### 2.3.8 ANN model development overview

Figure 23 gives an overview of the process followed that was described in Section 2.3 to develop the ANN model.

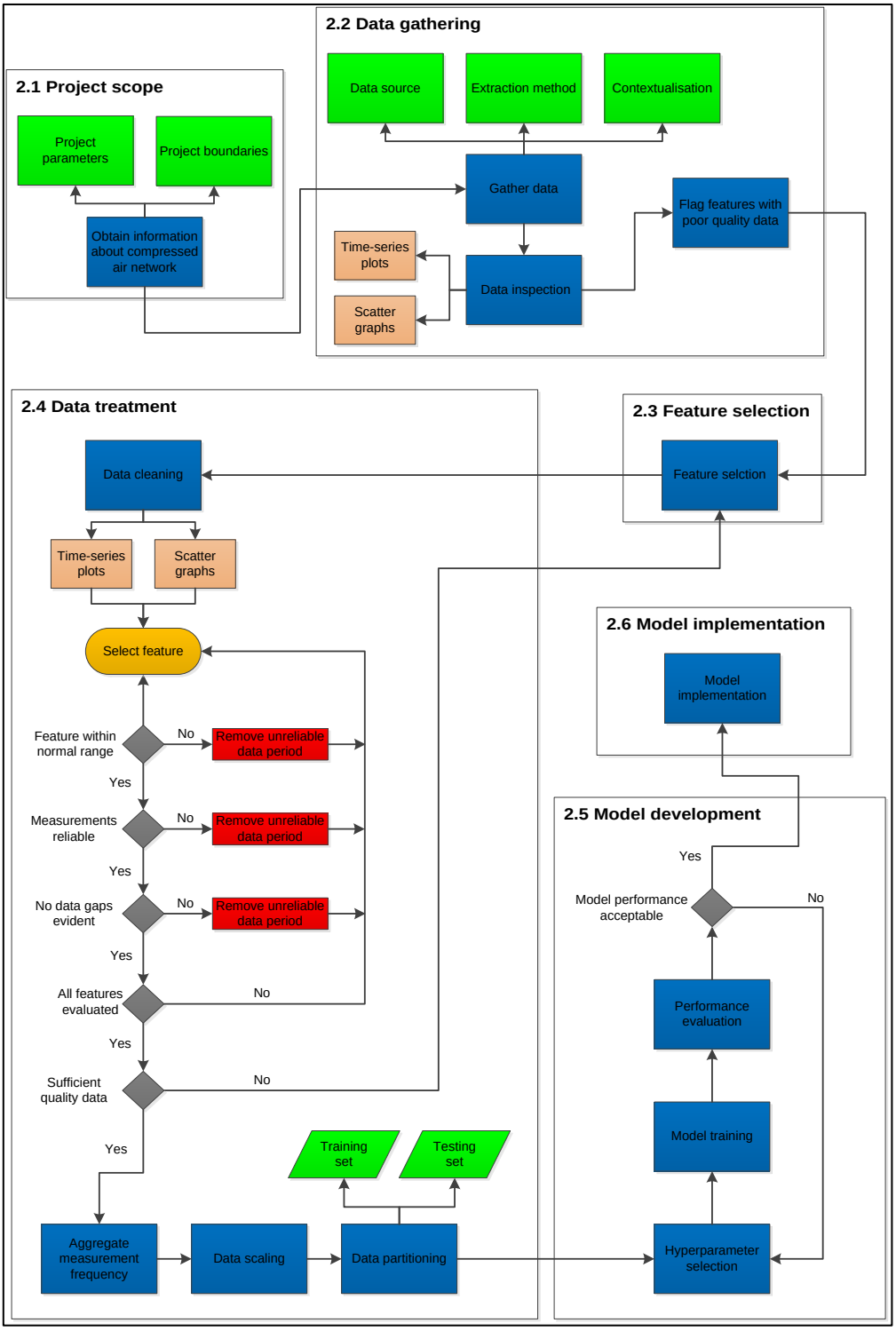


**Figure 23:** Machine learning model development process overview

The first step is to define the project scope, which was discussed in Section 2.3.2. After the scope is defined and boundaries have been set for the model, data gathering can be performed. Data gathering is discussed in Section 2.3.3. From the gathered data, the next step is feature selection, as discussed in Section 2.3.4. The selected features potentially reduce the size of the dataset, which is then used in the data treatment process. Data treatment is performed to improve data quality, which was discussed in Section 2.3.5. Treated data can be used for model development through the process discussed in Section 2.3.6. After the model is developed, it can be exported and implemented. Implementation of the developed ANN is discussed next.

## 2.4 Compressed air network control solution development and implementation

### 2.4.1 Preamble

This section discusses the application of a machine learning model for real-time prediction to improve compressed air network control. This method addresses research objective 3, as discussed in Section 1.6.4, which ultimately addresses the second part of the research problem, as discussed in Section 1.6.3.

After data gathering and logging, as discussed in Section 2.2, data manipulation and how the trained ANN (Section 2.3) is applied to deliver a solution that will assist control room operators to improve supply control is discussed. Figure 24 shows an overview of the key elements of the compressed air network control solution.

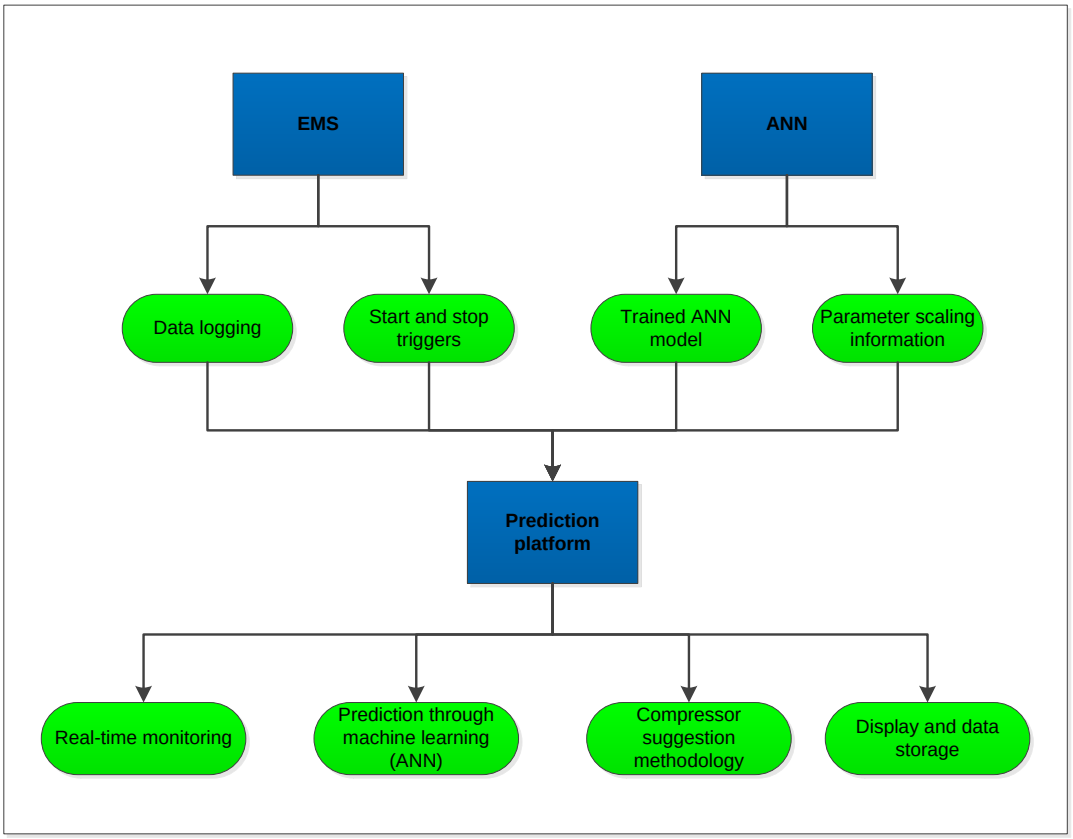


**Figure 24:** Overview of solution implementation

Figure 24 shows how the real-time implemented system will function. Data is firstly captured with the various available field instruments (such as pressure transmitters, flow meters, etc.). This data is then conveyed to the SCADA via PLCs to be accessed by the EMS. The data is logged and calculations are performed, as discussed in Section 2.2.5, which addresses research objective 1 (discussed in Section 1.6.4). This data is stored in a generic format. Section 2.4 focused on the next steps and discussed how the data is used and handled to provide real-time assistance to control room operators. This included process steps that involve the utilisation of the trained ANN model (discussed in Section 2.3, which addressed research objective 2 and was discussed in Section 1.6.4) and the communication to control room operators to assist with supply control.

Research objective 3 is to develop and implement an ANN driven compressed air network control solution to assist control room operators with compressor scheduling and selection. To achieve this objective, design specifications are set up, thus creating measurable outcomes. According to the literature, the real-time DCS controller has been effectively applied for assisting control room operators with compressor scheduling and selection [25]–[27], [46], [51], [54]. However, due to the shortcomings as discussed in Section 1.6.2, an ANN is applied for background calculations and predictions. To improve compressor scheduling and selection, a compressor suggestion

methodology must be developed. This compressor methodology should follow a process of iteration to test different combinations (like the DCS controller), although applying the ANN to verify solutions. To communicate and capture information, the design of a GUI and data logging are included in the requirements in the development of the DCS controller [25], [51]. From this information, the verification specifications of the proposed compressed air network control solution are thus derived:

- Specification 1: Real-time monitoring;
- Specification 2: Prediction through machine learning;
- Specification 3: Compressor suggestion methodology; and
- Specification 4: Display and data storage.

Section 2.4 provided an overview of the method that is implemented to address each specification. The background processes are discussed in detail. These processes utilise the tools discussed previously in Section 2.2 and Section 2.3 in real time.

The main functionality of the program is only to display. No input or other functionality is added, as the purpose is to test the feasibility of using an ANN model to predict pressure, which is used to assist in compressor selection. All displayed data is stored for reporting and verification processes. Before this solution is implemented fully, a “soft-implementation” is performed. This entails implementing the program without displaying outputs to control room operators [26]. This is done to gather data and to verify the results before implementing the system.

Figure 25 shows the process followed by the developed compressed air network control solution in detail. This figure is discussed throughout the subsections of Section 2.4 as each design specification is addressed.

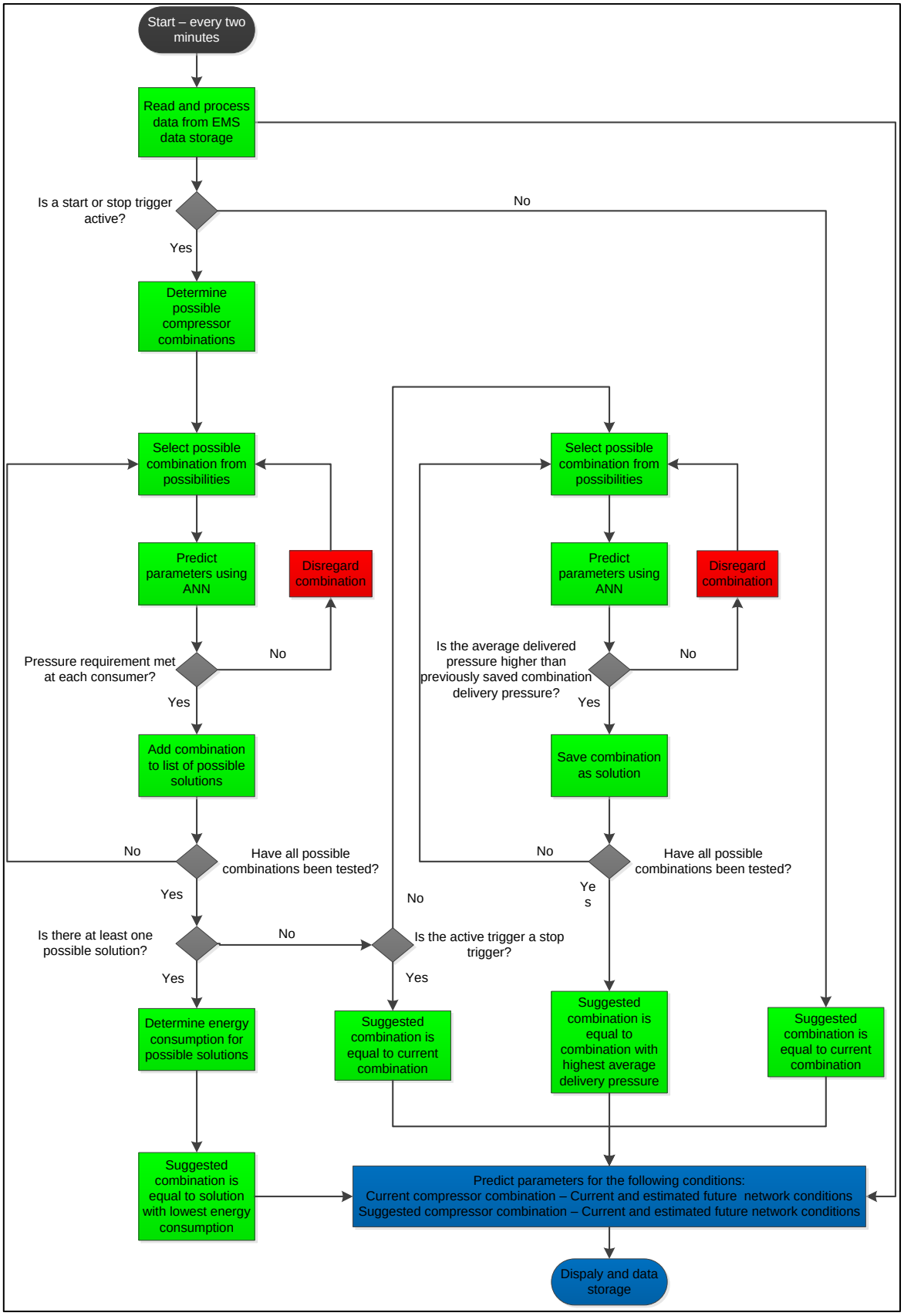


**Figure 25:** Compressed air network control solution prediction process

### 2.4.2 Specification 1: Real-time monitoring

Once the prediction program is started, it is important to note that the scaling information of the training dataset and the trained model details of the program should be loaded, as determined in Section 2.3.5 and 2.3.6. After this is done the program can start with the monitoring process.

Section 2.2 discussed how data is monitored and saved by the EMS. The EMS stores data in two-minute intervals to ensure that the latest data is available to the compressed air network r control solution. All available data, such as the necessary inputs (or features) for the ANN model, is processed to be utilised at a later stage. Other information also crucial for the compressed air network control solution includes the start and stop triggers that are set up and calculated on the EMS, as discussed in Section 2.2.5.

While the triggers are not active, the compressed air network control solution will not perform calculations to determine another suggested compressor combination; instead, it will only use the current compressor combination, as shown in Figure 25. When any trigger becomes active, the compressed air network control solution will start a process of testing different compressor combinations by using the ANN model as a tool to predict whether the proposed compressor combinations will provide sufficient pressure. This process is discussed in Section 2.4.3.

### 2.4.3 Specification 2: Prediction through machine learning

After data is read by the prediction program, it must be processed before it is sent to the trained ANN model [69]. The relevant input features, the same as used in training, are first extracted. The data is then processed into the correct measurement frequency and format to match that of the training data.

With the data in the correct format and the loaded scaling information, the data is now scaled and sent to the ANN model. The ANN model is utilised in different ways, depending on the start and stop trigger statuses that are calculated by the EMS.

As seen in Figure 25, when a start or stop trigger is not active, the program will only use the ANN to predict pressure upstream of consumers with the current compressor combination. This prediction is made for both the current network conditions and estimated future conditions. This is done to show control room operators what the current network conditions are supposed to be as well as give an idea of what the expected conditions will be in a specified amount of time. To estimate future conditions, a similar approach to Jonker [26], as discussed in Section 1.4.2, is used, which is illustrated in Figure 26. Jonker [26] selected 30 minutes, which has also been selected for this study.

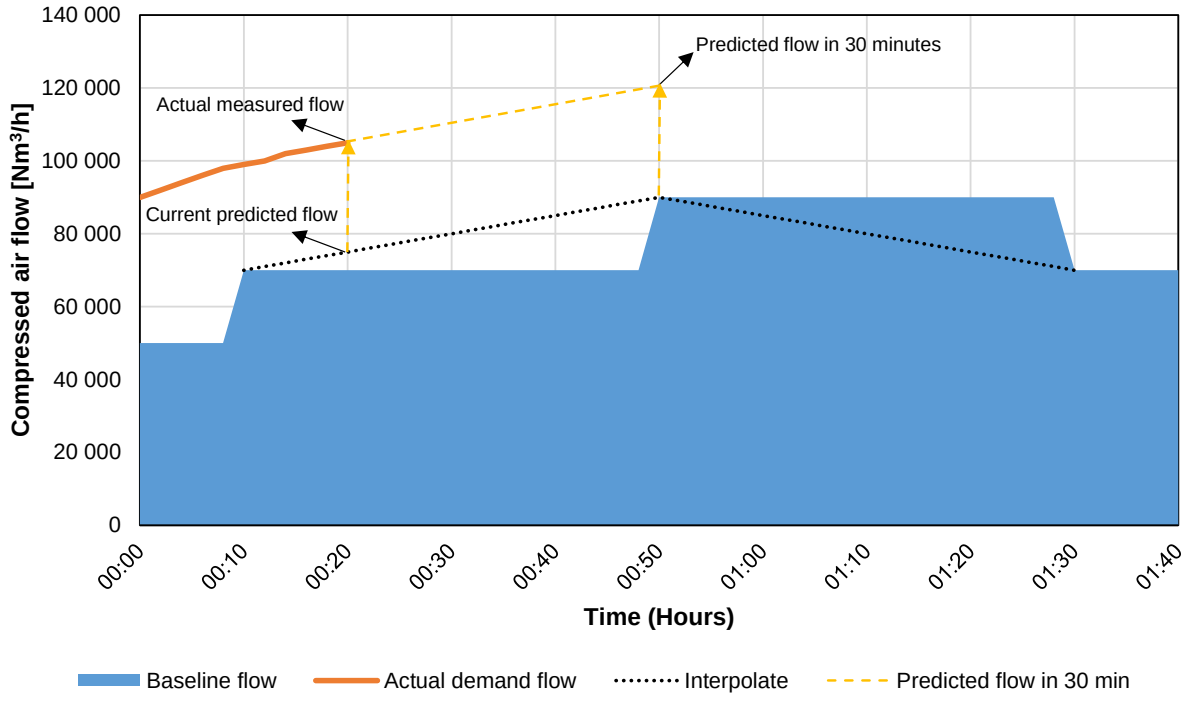


**Figure 26:** Predicted demand flow adjustment

From Figure 25, when a start or stop trigger is active, the program will perform similar predictions to when the triggers are not active, but with additional information. This additional information includes the prediction of the same parameters for current and expected future conditions, but using a suggested compressor combination. The process of selecting the best possible compressor combination, specifically in terms of energy consumption, while delivering sufficient air pressure for the current demand is discussed in Section 2.4.4.

### 2.4.4 Specification 3: Compressor suggestion methodology

This process will only be followed in the event that a start or stop trigger is active, as seen in Figure 25. When a trigger is active, a process of iteration is followed for the different compressor combinations allowed. This process is similar to the process of DCS controller simulation [25], [51]. The possible combinations are determined by the number of compressors that can be started at a single time (selection freedom) and the availability of compressors [26]. When this has been established, all available combinations are determined. Figure 27 illustrates the process of iteration to determine the available compressor combinations for a network with four compressors where it is allowed to change the status of one compressor at a time.

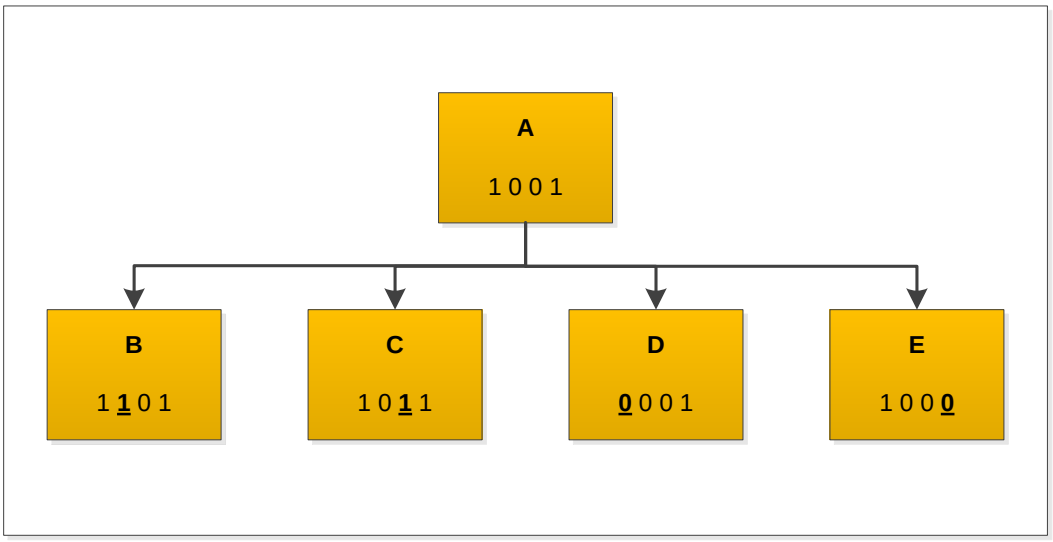


**Figure 27:** Simulated compressor combinations

From the compressor combinations shown in Figure 27:

- A is the current compressor combination. Compressor 1 and 4 are running;
- In B, compressor 2 is started;
- In C, compressor 3 is started;
- In D, compressor 1 is stopped; and
- In E, compressor 4 is stopped.

When a start signal is received, all options where an additional compressor is started are considered, i.e., only the two possible combinations on the left (B and C). Similarly, for a stop signal, only the two combinations indicated on the right (D and E) are considered. Using the current network conditions and iterating through all possible compressor combinations (as seen in Figure 25) determined in the previous step, a prediction is performed. All viable solutions are now determined by using the known required demand conditions as a measure of viability. If the proposed compressor combination can meet the demand requirement at the current network condition, the proposed combination is accepted as a possible solution.

It should be noted that the suggested methodology does not consider running compressors in an unloaded state. Compressors are either regarded as running and loaded or not running. This is to ensure that the supply is efficient and that energy is not wasted or lost through compressor blow-off (as discussed in Section 1.2.4).

From Figure 25, if there is no possible solution, the compressed air network control solution will suggest a compressor combination based on the active trigger. If a stop trigger is active, the

compressed air network control solution will suggest that the current compressor combination stays unchanged, thus not stopping a compressor. In the event where a start trigger is active, the compressed air network control solution will iterate through all available compressor combinations again and select the combination with the highest predicted average pressure. This is, however, not the case when there are possible solutions.

If there are possible solutions, they are evaluated in terms of predicted power consumption. This is done by summating the average power consumption for all running compressors in the proposed combination for each of the possible solutions. The solution with the lowest power consumption is selected. The selected solution would thus be the compressor combination that consumes the least power while still satisfying the compressed air demand requirement.

To summarise, the following data is predicted when a trigger is active:

- Predicted consumer pressure with current compressor combination and current network conditions;
- Predicted consumer pressure with current compressor combination and expected future network conditions;
- Predicted consumer pressure with suggested compressor combination and current network conditions; and
- Predicted consumer pressure with suggested compressor combination and expected future network conditions.

To relay and capture the predicted values to the necessary parties, data display and storage are set up.

### 2.4.5 Specification 4: Display and data storage

A simple display is developed to assist control room operators with supply control to display the following information:

- Current compressor combination;
- Suggested compressor combination;
- Current network conditions;
- Expected future network conditions;
- All predicted values as discussed in the previous section; and
- Additional platform-specific information.

To display this information, a GUI is developed with a similar format as shown in Figure 28.

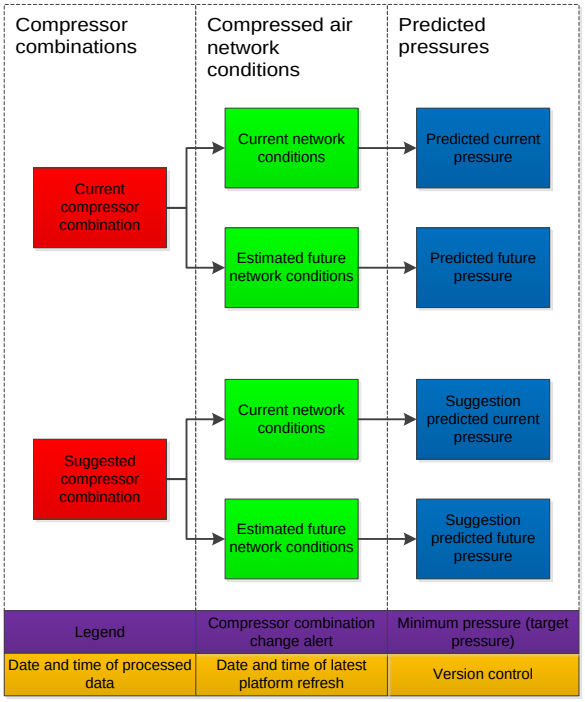


**Figure 28:** Display design for the compressed air network control solution

An alert also appears when a change in compressor selection is required. This alert is added to attract the attention of the control operators. Some other additional information includes a legend for the display, the pressure target required at the time, the date and time of the processed data, the time of the most recent platform refresh, and what version of the program is running. This data is not necessarily required for the control but is important to ensure that the most recent data and compressed air network control solution is currently implemented.

All displayed data is logged in a format similar to that of the EMS. This is done for ease of data analysis. Additional processes such as daily reporting can be set up to evaluate the compressed air network control solution performance [25], [108], although this is not in the scope of this study.

## 2.5 Verification methodology

The development of the solution comprises various aspects. Every section addresses a specific research objective, which was determined in Section 1.6.4. In this section, the research objectives are re-evaluated to verify that the specifications have been met.

Research objective 1, to set up an EMS for monitoring and data logging, is addressed by applying the method discussed in Section 2.2. Research objective 2, to determine the feasibility of applying an ANN for the prediction of parameters in a compressed air network, is addressed by applying the method discussed in Section 2.3. Research objective 3, to develop and implement an ANN

driven compressed air network control solution to assist control room operators with compressor scheduling and selection, is addressed through the implementation of the method discussed in Section 2.4. After the successful development and implementation, specifications are verified to ensure that the compressed air network control solution is operating as intended.

To verify research objective 3, the specifications determined in Section 2.4 are evaluated. These specifications include the following:

- Specification 1: Real-time monitoring;
- Specification 2: Prediction through machine learning;
- Specification 3: Compressor suggestion methodology; and
- Specification 4: Display and data storage.

Once all specifications are verified, the solution is able to perform the task as designed. These individual specifications thus also form the basis of investigation when the compressed air network control solution is not working or is to be improved.

This section described the verification process. The result of implementing the method is discussed in Chapter 3. Section 3.3 discusses the verification of the research objectives as set out in this section.

Once all specifications are verified, the solution is ready for soft implementation. Soft implementation is done where the compressed air network r control solution is implemented in the background and data is gathered, which is used to validate whether the compressed air network control solution can solve the research problem as defined in Section 1.6.3. Simulation software is used to validate that the solutions provided by the compressed air network control solution is suitable to assist control room operators with the supply control of a compressed air network. After validation has been performed using simulation software, the compressed air network control solution is implemented in full. Control room operators will be allowed to see the compressed air network control solution and follow the suggestions, which forms part of the validation process which is discussed in Section 3.4.

## 2.6 Conclusion

Chapter 2 discussed the methodology that is applied to address each of the research objectives and research problem. The processes discussed throughout the methodology was derived from literature, where a similar process was implemented successfully. The first element of the methodology was to set up a real-time monitoring and data logging EMS. This process was mainly

derived from studies where EMSs were implemented as part of setting up DCS controllers. The main steps regarding EMS setup included process parameter identification, communication specification, existing infrastructure, data logging, and calculations. These steps were discussed in Section 2.2 and is implemented to address research objective 1.

The second research objective was to develop and determine the feasibility of applying an ANN for the prediction of parameters in a compressed air network. From the literature, it was found that common steps were followed during the development of machine learning models. A method was developed from these steps and discussed in Section 2.3. The steps included project scope, data gathering, feature selection, data treatment, model development, and model implementation. These steps are generic and can be applied to develop any machine learning model, although in this case an ANN was selected.

The method presented in Section 2.3 included accuracy metrics to use during the development process. Where CV(RMSE) is used to evaluate variability and uncertainty in the model, a lower CV(RMSE) is desired. NMBE was the metric selected to indicate bias, where a positive value indicates the tendency of a model to overestimate and negative to underestimate. These parameters were selected to evaluate the model through the development process. Due to a lack of relevant research regarding the minimum required values for these metrics, for the application intention of this model, MAPE was also included. Based on the literature, a MAPE of 10% was selected to be the threshold to determine whether a model is accurate. During the model development step, hyperparameters are adjusted through trial-and-error and model training is performed. This process of hyperparameter adjustment and model training is repeated until the model is deemed accurate. Model training is thus performed until a MAPE of at least 10% is achieved for all predicted parameters. Section 2.3, therefore addressed research objective 2 as well as the first part of the research problem.

The third research objective was to develop and implement an ANN driven compressed air network control solution to assist control room operators with compressor scheduling and selection. From the literature, several elements were identified from existing software-based strategies, which could be implemented to improve compressor scheduling and selection. Based on the existing strategies and shortcomings, specifications of a compressed air network r control solution were determined. These specifications were discussed in Section 2.4 and included real-time monitoring, prediction through machine learning, a compressor suggestion methodology, and display and data storage.

Through the implementation of the method discussed in Section 2.4, a compressed air network control solution could be developed. This solution can assist control room operators to improve compressor selection and scheduling. This is achieved through real-time monitoring, the application of a machine learning model to verify suggested compressor combinations, and the display and storage of data. The successful implementation is verified by evaluating each of the specifications specified for the solution. The implementation of this compressed air network control solution addressed research objective 3.

Lastly, in Section 2.5 the verification methodology was discussed. Each of the main elements in the methodology addressed a specific research objective. Upon successful verification of each element, a soft implementation of the compressed air network control solution can be performed. Results from the soft implementation are used to validate the compressed air network control solution using simulation software. After this, a real-time implementation test is performed as part of the validation process.

# CHAPTER 3 RESULTS AND DISCUSSION

## 3.1 Introduction

### 3.1.1 Preamble

The purpose of this chapter is to illustrate and evaluate the results of the proposed solution to improve compressed air network supply. This chapter discusses the results obtained by applying the method discussed in Chapter 2 to a case study. The results show how effectively the solution addressed each of the objectives (Section 1.6.4) and the research problem statement of the study (Section 1.6.3). Each research objective is addressed and verified. Simulation software was used as a tool to validate the solutions proposed by the developed compressed air network control solution. After the solutions were validated using simulation software, the compressed air network control solution was implemented in full. A test was performed, and the results are discussed to validate that the compressed air network control solution was able to assist operators to improve supply control.

### 3.1.2 Case study background information

This section addresses the first research objective, as discussed in Section 1.6.4.

**Research objective 1**: Setup an energy management system (EMS) for real-time monitoring and data logging of compressed air network parameters

To address this objective, the method discussed in Section 2.2 was applied to implement an EMS for real-time monitoring and data logging.

An underground platinum mining complex was identified as a suitable case study for the implementation of the methodology discussed in Chapter 2. This mining group has a complex compressed air network spanning several kilometres on the surface. The steps followed to implement an EMS included identifying process parameters (Section 2.2.2), identifying communication specifications (Section 2.2.3), identifying existing infrastructure (Section

2.2.42.2.2) and the setup data logging and calculations (Section 2.2.52.2.3). Figure 29 shows the layout of the compressed air network at the mining complex:

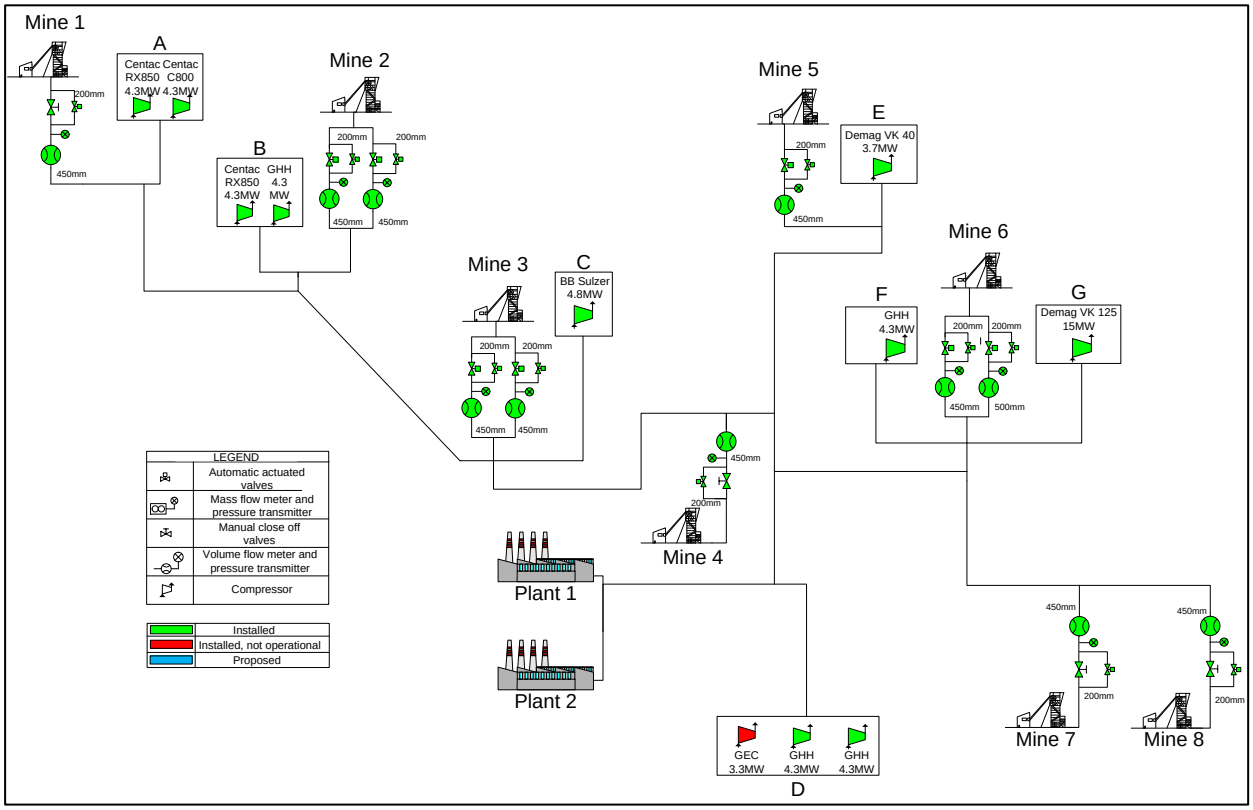


**Figure 29:** Case study surface compressed air network layout

From Figure 29 it is evident that there are 11 compressors, eight mine shafts and two plants connected to the surface compressed air network. From Figure 29 it is also evident that the GEC compressor located at compressor house D is not operational. Only Mine 2, Mine 3 and Mine 6 are operational. The other connected mines are disconnected or in care and maintenance and do not consume compressed air. The details of the compressors and their power ratings are listed in Table 5.

**Table 5:** Case study compressor specifications

| Compressor | Rated power (kW) | Compressor house |
|---|---|---|
| 1. Centac C800 | 4.3 | A |
| 2. Centac RX850 | 4.3 | A |
| 3. GHH | 4.3 | B |
| 4. Centac RX850 | 4.3 | B |
| 5. BB Sulzer | 4.8 | C |
| 6. GEC | 3.3 | D |
| 7. GHH | 4.3 | D |
| 8. GHH | 4.3 | D |
| 9. Demag VK40 | 3.7 | E |
| 10. GHH | 4.3 | F |
| 11. Demag VK125 | 12.5 | G |

All compressors listed are multistage centrifugal compressors with automatic guide vane and blow-off control. The available process parameters, with regards to that mentioned in Section 2.2.2, are listed below for all the available compressors:

- Compressor discharge pressure [kPa];
- Compressor inlet guide vane position [%];
- Compressor running status [0/1];
- Compressor load status [0/1]; and
- Compressor power consumption [kW].

Process parameters were measured through field instrumentation which is similar to the communication specification discussed in Section 2.2.3. The compressor discharge mass flows were not available for all compressors, which hindered the possibility of implementing a DCS controller. The following process parameters were available for all active consumers (Mine 2, Mine 3, Mine 6, Plant 1 and Plant 2):

- Consumer pressure requirement [kPa];

- Consumer pressure downstream of valve [kPa];
- Consumer compressed air consumption [Nm$^3$/h]; and
- Consumer pressure upstream of valve [kPa].

From the available data, it is evident that it would not be possible to implement a DCS controller due to the lack of compressor discharge flow instruments. As mentioned, however, even if all data is available, the accuracy of the various measurements and the complexity of the compressed air network remains a challenge. This case study had a large surface compressed air network, which increased the difficulty to characterise the network. The need, therefore, existed to use alternative solutions for the characterisation of the compressed air network.

The layout provided in Figure 29 as well as the process parameters and communication specifications added to the investigation of existing infrastructure (discussed in Section 2.2.4). Additionally, a normal weekday that represents the typical demand profile for all consumers is presented in Figure 30.

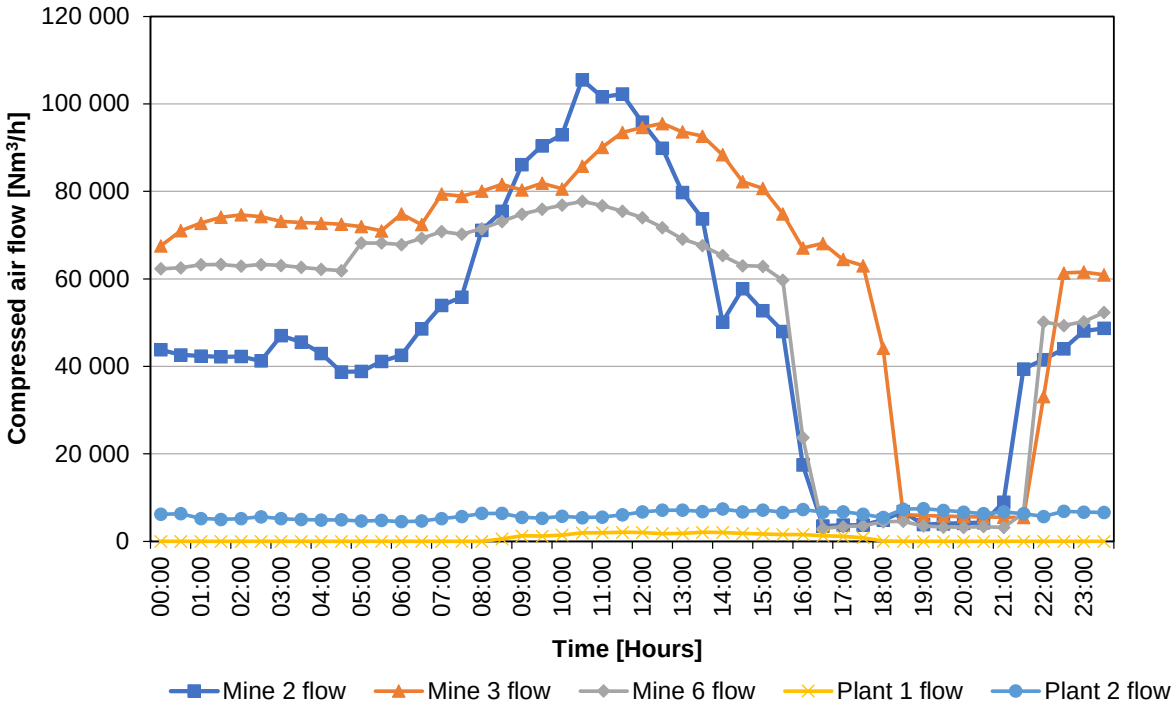


**Figure 30:** Typical demand profile for case study consumers

As seen in Figure 30, the compressed air demand of the shafts is much higher than the consumption of the two plants. The different mining operations, as mentioned in Section 1.1, include drilling, blasting, and sweeping of material. For this mining complex, blasting is performed between 16:00 and 21:00, sweeping between 21:00 and 06:00, and drilling between 06:00 and

16:00. These times might differ slightly between the different mines on the compressed air network.

An existing EMS was available at the mining complex. This EMS was used to implement monitoring and data logging. The EMS functions are explained in various parts of this document with regards to communication from the EMS to all available instrumentation (Section 1.4.2 and Section 2.2.3). This EMS was utilised to gather the data and to perform the calculations with regards to start and stop triggers. This data was logged in real time in two-minute intervals. Using raw data to monitor the current system status, start and stop triggers were set up to signal when a compressor is required to start or stop. The triggers were set up, as discussed in Section 2.2.5, and the results are reported in Section 3.3.2. An EMS was set up for real-time monitoring and data logging. This section, therefore, verifies that research objective 1 was addressed.

### 3.1.3 Evaluating simulation model accuracy

The PTB™ simulation software package was used to create a simulation model of the surface compressed air network case study mining complex. This simulation model was used as a tool in this study to evaluate results from the implemented solution as part of the validation.

Calibration of the model was done using a 24-hour profile of a typical production day. The results for compressor power obtained from the baseline simulation are shown in Figure 31. The mean absolute percentage error (MAPE) was the metric used to determine the accuracy of the simulation model as mentioned in Section 1.4.3 and Section 2.3.6.

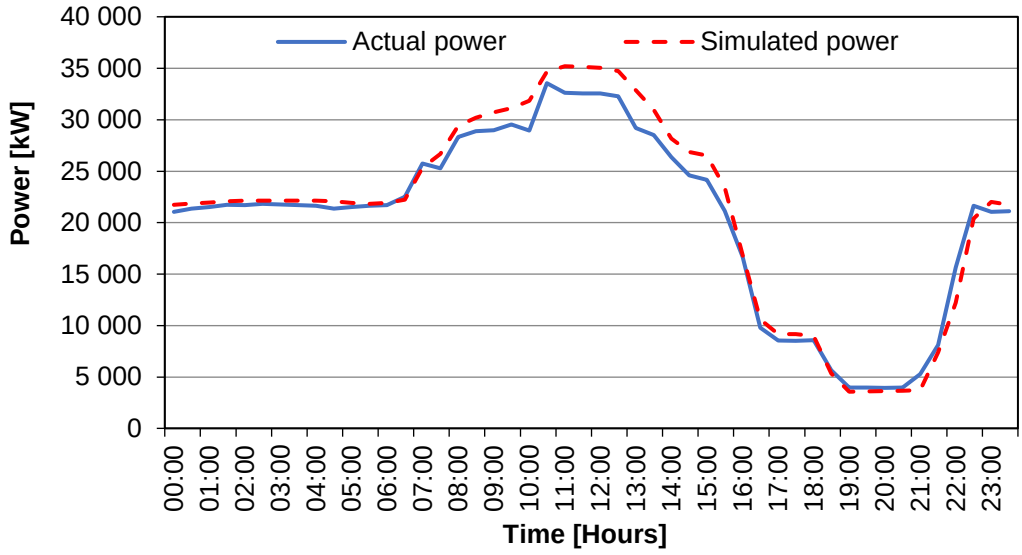


**Figure 31:** Total simulated vs. actual compressor power

Figure 31 shows the actual power consumption profile of the compressors on a typical production day plotted against the simulated power. A MAPE of 6.24% was achieved, which is below the desired 10%, and in terms of power consumption, the simulation model is thus considered accurate. To determine whether the simulation could accurately capture demand characteristics, including surface valve control on the consumer side, the surface shaft pressure and flows were evaluated.

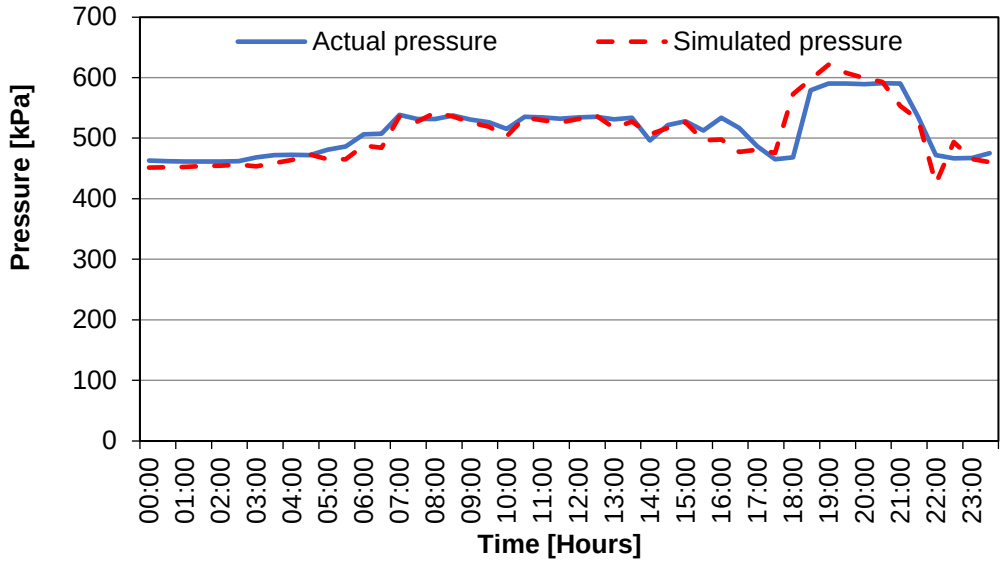


**Figure 32:** Average simulated vs. actual surface shaft pressure

Figure 32 compares the actual average shaft pressure and the simulated average shaft pressure for all the mines on the compressed air network. A MAPE of 2.84% was achieved for the average surface shaft pressures. Table 6 shows the calculated errors for all simulated pressure of consumers.

**Table 6:** Calculated errors for simulated pressure of consumers

| Consumer | MAPE (%) |
|---|---|
| Mine 2 | 4.28 |
| Mine 3 | 3.03 |
| Mine 6 | 2.86 |
| Plant 1 | 2.77 |
| Plant 2 | 2.77 |

As seen in Table 6, the calculated MAPE of each consumer is below 5%. This indicates that the pressure of consumers could be simulated accurately. The other important metric that was crucial in the simulation is consumer flow. Figure 33 shows the simulated consumer compressed airflow.

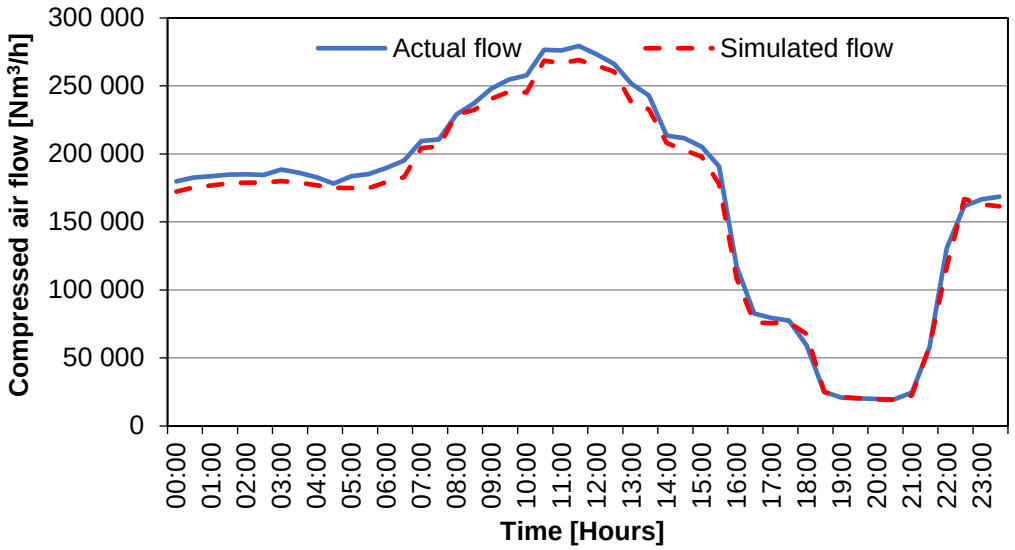


**Figure 33:** Total simulated vs. actual consumer compressed airflow

Figure 33 shows the total actual consumer flow plotted against the total simulated consumer flow. The MAPE for the figure was calculated to be 3.96%, which indicates that the simulation model could accurately represent the compressed air consumed. Table 7 shows the calculated errors for the simulated compressed airflow of all consumers.

**Table 7:** Calculated errors for simulated consumer flow

| Consumer | MAPE (%) |
|---|---|
| Mine 2 | 5.07 |
| Mine 3 | 4.07 |
| Mine 6 | 3.54 |
| Plant 1 | N/A |
| Plant 2 | 3.18 |

From Table 6, the calculated MAPE of each consumer is below 6%. Plant 1 did not consume any flow on this day and therefore achieved a MAPE of 0%. These results indicate that the

compressed air flow of consumers could be simulated accurately. Additional simulation results are provided in Appendix D. The simulation could achieve a level of accuracy which met the requirements to verify that this simulation model is an accurate representation of the compressed air network. This verified simulation model could therefore be used as a tool to evaluate changes to the compressed air network. This verified simulation model was used as an additional validation step to prove that the implemented compressed air network control solution provided feasible solutions for compressed air supply.

## 3.2 Development of case study machine learning model

### 3.2.1 Preamble

This section addresses the second research objective, as discussed in Section 1.6.4.

> **Research objective 2**: Develop and determine the feasibility of applying an ANN for the prediction of parameters in a compressed air network

To address this objective, the method discussed in Section 2.3 was applied to develop an ANN for the prediction of parameters in a compressed air network. An overview of the method is shown in Figure 23. The results of applying this method are discussed in this section.

### 3.2.2 Step 2.1: Project scope

The first step was to determine the scope of the model, as discussed in Section 2.3.2. The scope of the ANN is to predict pressure delivered to consumers on the compressed air network of mining complex A. The delivered pressure refers to the compressed air network pressure upstream of the consumer. The boundaries of the model are limited to the network on the surface, similar to studies regarding the DCS controller [26], [27]. It is assumed that underground pressure requirements would be met if the surface pressure targets (as set out by the mining complex) are met. The pressure was predicted in real time using the available process parameters as logged by the EMS for current compressed air network conditions.

### 3.2.3 Step 2.2: Data gathering

The data gathering process is shown in Figure 20 and discussed in Section 2.3.3. This method was applied for the available process data, as listed in Section 3.1.2. The data was stored on a server in .csv format in a measurement frequency of two-minute intervals. All process parameters had been logging for six months at the time the machine learning model was trained. The historical

data for six months was thus used for this process. All captured historical data was available through the EMS in real time.

Data inspection was performed using time-series plots and scatter graphs to represent data graphically. Using this method, all features with a large number of outliers, periods of missing data and potential unreliable measurements were identified and removed. The figures below show examples of some of the outliers, missing data, and unreliable measurements that were observed in the data gathering process. Outliers were detected by evaluating the normal operating ranges of a given feature. Figure 34 shows an example of a scatter plot created for the #9 Demag VK40 compressor.

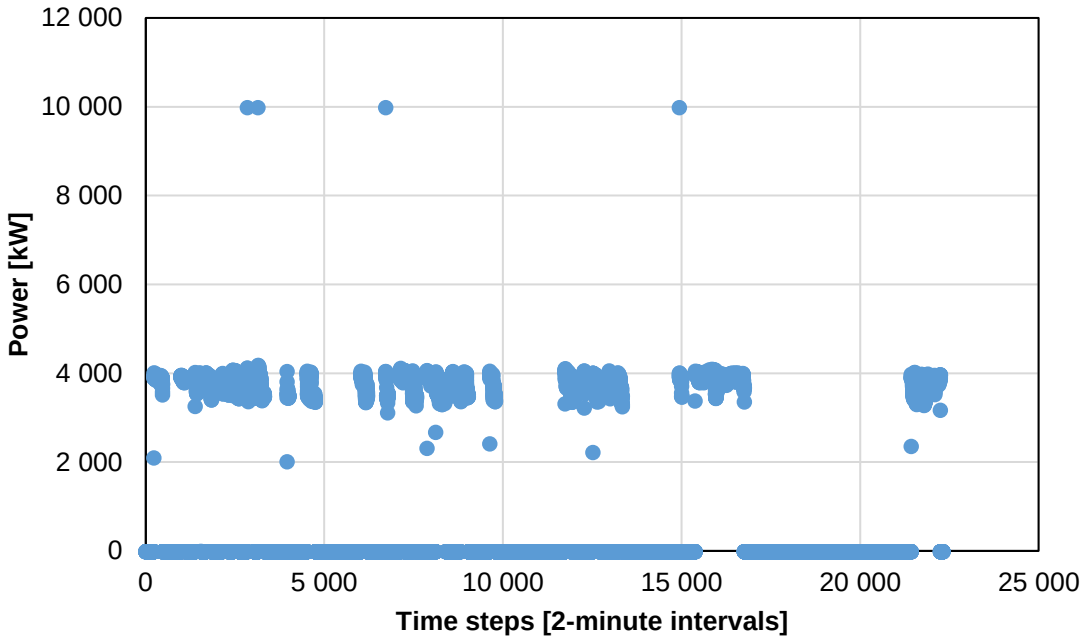


**Figure 34:** Scatter plot example of data outliers, Demag VK40 power consumption

From Figure 34, several outliers observed. From Table 5 it is known that the rated power for this compressor is 3 700 kW. The normal operating range of this parameter is between 0 kW and 4 100 kW as observed in the data. This range may be due to changes in operational efficiency or any number of reasons, although it is clear that values recorded near 10 000 kW are outliers. These values were found to be the same at each of the outlier points, indicating that the data is unreliable. Outliers can exist due to several reasons, for example, inaccurate instrumentation, communication issues, device failure, among others. The above is an example of outliers detected while performing spot checks during the data gathering step. The next type of data quality issue is missing data. An example of missing data is shown in Figure 35.

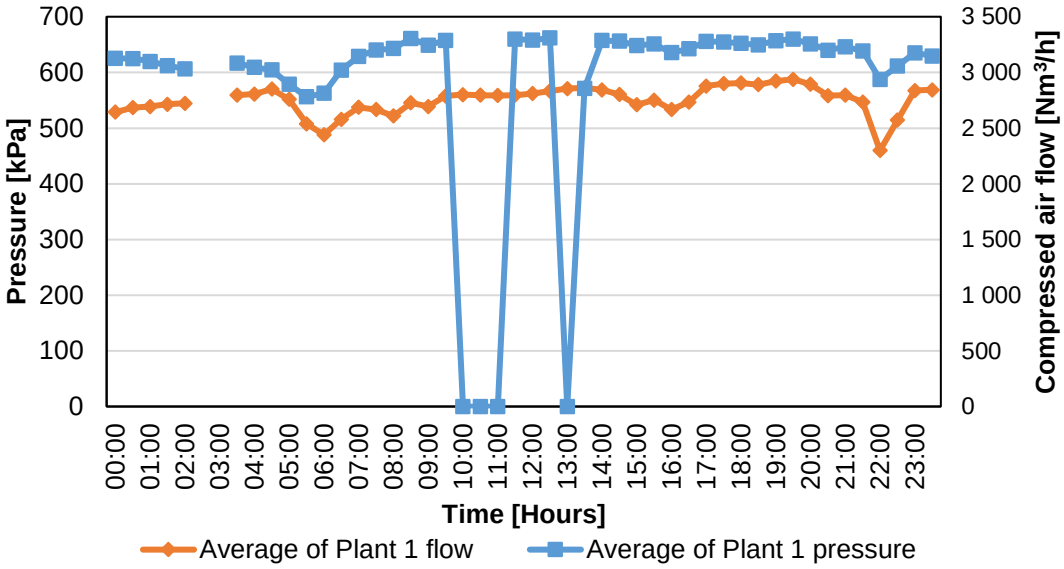


**Figure 35:** Time series plot example of missing data, Plant 1 pressure and flow

Figure 35 shows the compressed air pressure and flow for Plant 1 on the compressed air network for a typical production day. From Figure 35, it is evident that there is missing data for the pressure and flow between 02:00 and 03:30 and an issue with the plant pressure between 10:00 and 11:00 and at 13:00. Missing data is often a result of communication issues, power failure of devices in the communication chain from the instrument to the EMS, and issues with data logging on the EMS. The other example of data quality issues is when unreliable measurements are observed. An example of unreliable measurements is shown in Figure 36.

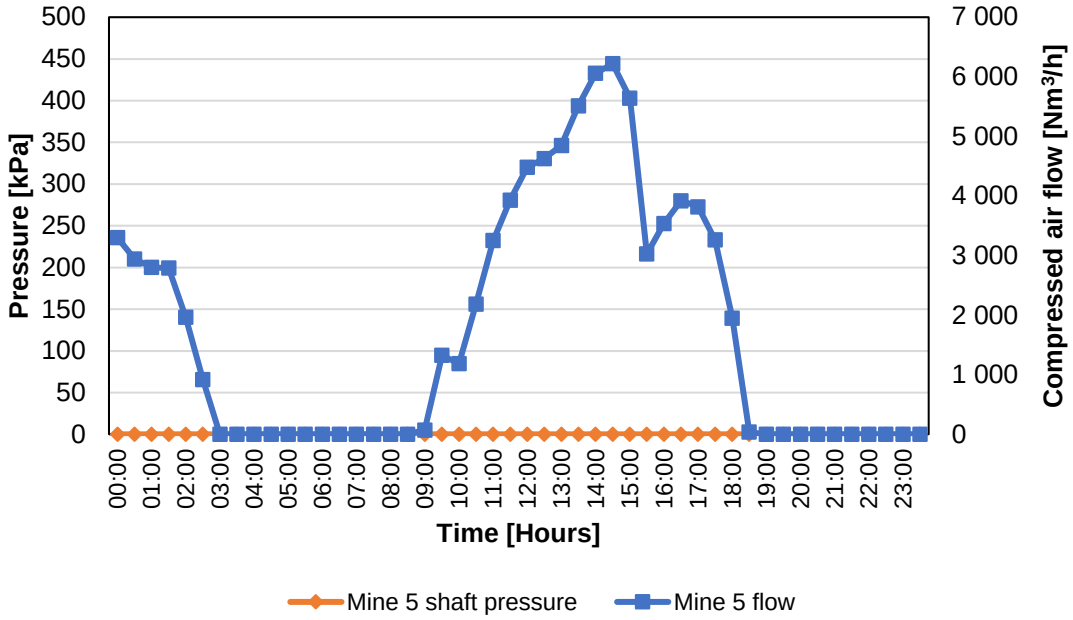


**Figure 36:** Time series plot example of unreliable measurements, Mine 5 pressure and flow

Figure 36 shows the shaft pressure and flow for Mine 5 on the compressed air network for a typical production day. From the data, there is no compressed air pressure supplied to the shaft, while at the same time, a flow consumption is observed. This indicates that there are unreliable measurements, as there cannot be any flow when a gauge pressure of 0 kPa is observed. This could indicate an issue with the pressure instrument or the flow instrument. It was confirmed with the mining complex that this shaft is no longer operational and is not consuming compressed air flow, thus the compressed air flow data is unreliable.

By performing scatter plots and time series plots for available data during the gathering process, the features with the most outliers, missing data and unreliable measurements were disregarded before the next step in model development. The features that were removed from the initial inspection include the following:

- Compressor discharge flows;
- Compressor power; and
- Mine 1, Mine 4, Mine 5, Mine 7 and Mine 8 pressure and flows;

The other features did have some issues, such as outliers and periods of missing data. However, this was removed in the data treatment phase, which was done after feature selection. This step in the process evaluated the data reliability and integrity. Data with the highest reliability should be used where possible.

### 3.2.4 Step 2.3 Feature selection

From the discussion in Section 2.3.4, once the relevant data is gathered, feature selection can be applied. The following features were identified that could be used in the prediction of upstream pressure:

- Compressor discharge pressure [kPa];
- Compressor inlet guide vane position [%];
- Compressor running status [0/1];
- Compressor loaded status [0/1];
- Compressor power consumption [kW];
- Consumer pressure requirement [kPa];
- Consumer pressure downstream of valve [kPa];
- Consumer compressed air consumption [$Nm^3/h$]; and
- Consumer pressure upstream of valve [kPa].

From the available data, the following features were selected to be used for the prediction of upstream pressure delivered to consumers.

- Compressor running status [0/1];
- Compressor loaded status [0/1]; and
- Consumer compressed air consumption [$Nm^3/h$].

These features were found to have good quality data. These values could also be manipulated to evaluate the impact on the compressed air network. For example, by altering the run or load status of a compressor, the effect on output can be evaluated. Compressed air consumption of consumers is relatively predictable for normal production days. This could create an opportunity to test how pressure is influenced as consumption changes throughout the day with a given compressor selection.

The following features were not selected:

- Compressor discharge pressure [kPa];
- Compressor inlet guide vane position [%];
- Compressor electrical power consumption [kW];
- Consumer pressure requirement [kPa];
- Consumer pressure downstream of valve [kPa]; and
- Consumer pressure upstream of valve [kPa].

These parameters were not selected due to poor quality data and their possibility of influencing the outcome of predicted pressure when estimating the input parameter. It was decided to follow the simplest approach with the least amount of input variables, as this would simplify the prediction model. If the accuracy of the model is not sufficient with this approach, and different input parameters such as those not selected for this iteration can be added to evaluate the influence on the accuracy of the model.

Data treatment is now only performed on the selected features. This saves time as only the selected features for the model are treated, instead of all the available data as mentioned in Section 2.3.4

### 3.2.5 Step 2.4: Data treatment

An illustration of the data treatment method is provided in Figure 21, in Section 2.3.5. The method of treatment included data cleaning and scaling and was applied in this section. Each of the selected features was investigated to remove poor quality data. In the data gathering step, data inspections were performed to identify features with a large number of outliers, missing data and unreliable measurements (as discussed in Section 2.3.3). Based on these inspections, entire features were removed from the process. In data cleaning, however, the selected features were inspected and the poor-quality data within the feature was removed. The data inspection was performed similarly to the process followed in data gathering, although by inspecting each feature for the entire data range and not just spot checks. The outliers, missing data, and unreliable measurement periods were removed from the data set.

Once the cleaning process had been completed, the data was of higher quality. The high-quality data was then aggregated to a lower measurement frequency. The measurement frequency of the current data was aggregated from two-minute intervals to 10-minute intervals. This was done to improve the stability of the system. Figure 37 below illustrates an example of the data aggregation performed.

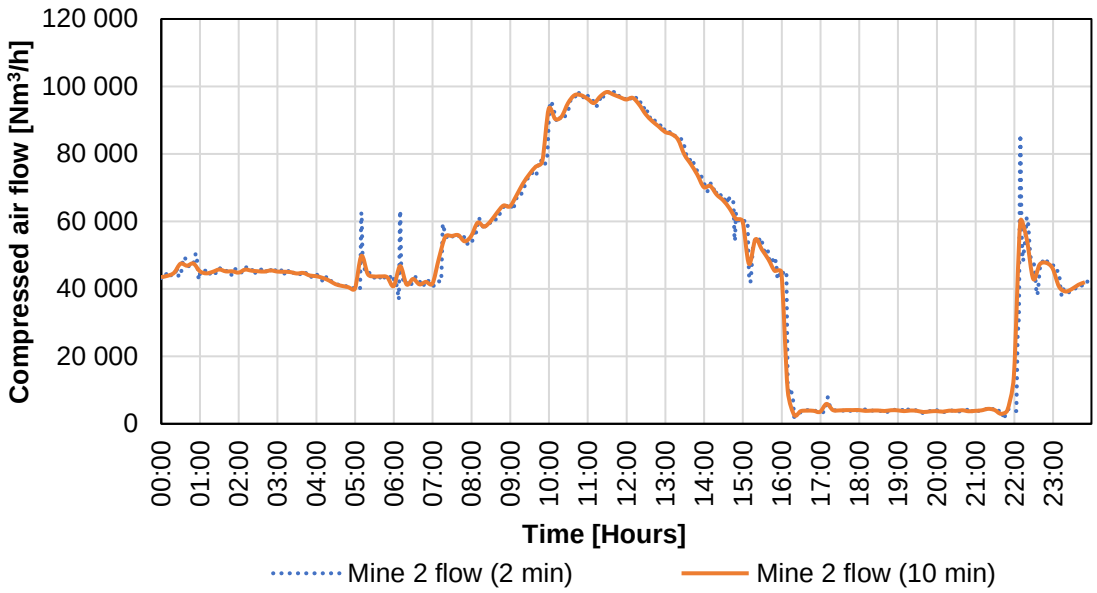


**Figure 37:** Example of data aggregation from a two-minute to 10-minute interval, Mine 2 flow consumption

From Figure 37, some spikes in data are filtered out due to the aggregation. The averaging of high-frequency data removes shorts spikes in data to generate a smooth line. This improved the stability of the predictions by filtering out rapid and instantaneous changes in the system that were not sustained.

The next step in data treatment was to scale the data. The data of each feature was scaled using equation (4) as explained in Section 2.3.5. The scaling information, namely the minimum and maximum values for the specific features were saved to be used at a later stage when the model would be implemented in real time. Figure 38 shows the unscaled data in 10-minute intervals after data aggregation had been done for the three mines on the compressed air network for the case study.

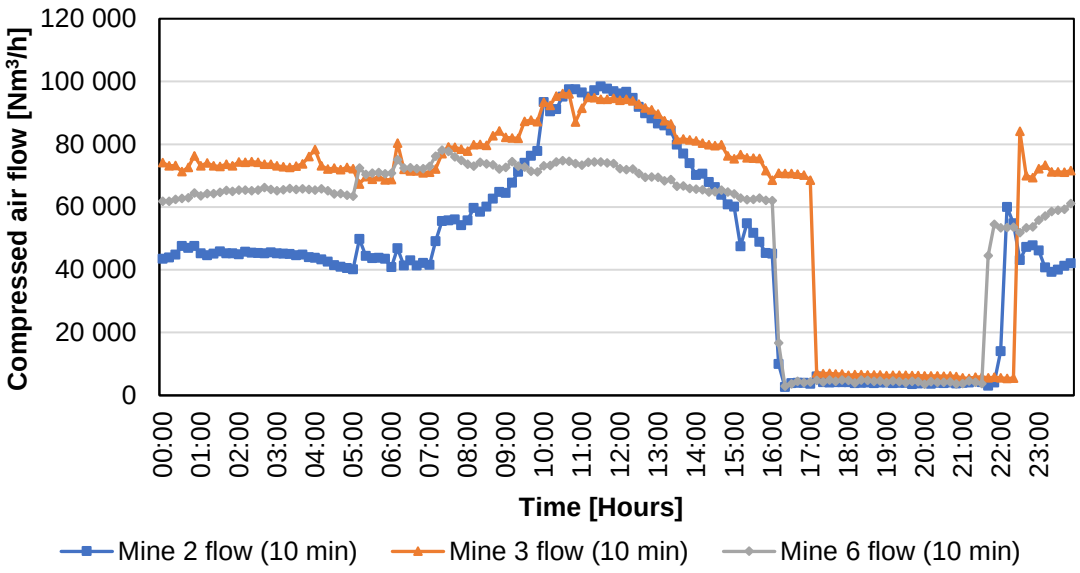


**Figure 38:** Aggregated consumer flow consumption

Figure 39 shows the scaled data which was used as input for the ANN. From Figure 39, it is apparent that consumers range between a minimum value of 0 and a maximum value of 1. This scaling could potentially improve the accuracy of the model by ensuring that the exact value of measured flow does not dwarf consumers with a lower measured flow. This was done, as previous studies (as discussed in Section 1.4.2) have shown that there are issues with the accuracy of instrumentation on mines. This would therefore address this issue of instrumentation accuracy to a certain extent. The instrument must be functioning and ranging normally, rather than being accurate to the exact flow value, as is required for the DCS controller and simulation models. The DCS controller and simulation models would calculate the change in pressure with an inaccurate value using traditional engineering methods, which would lead to inaccurate results. Conversely, the ANN could learn the effect of the change in input value on the pressure accurately, even if the measured flow is not correct.

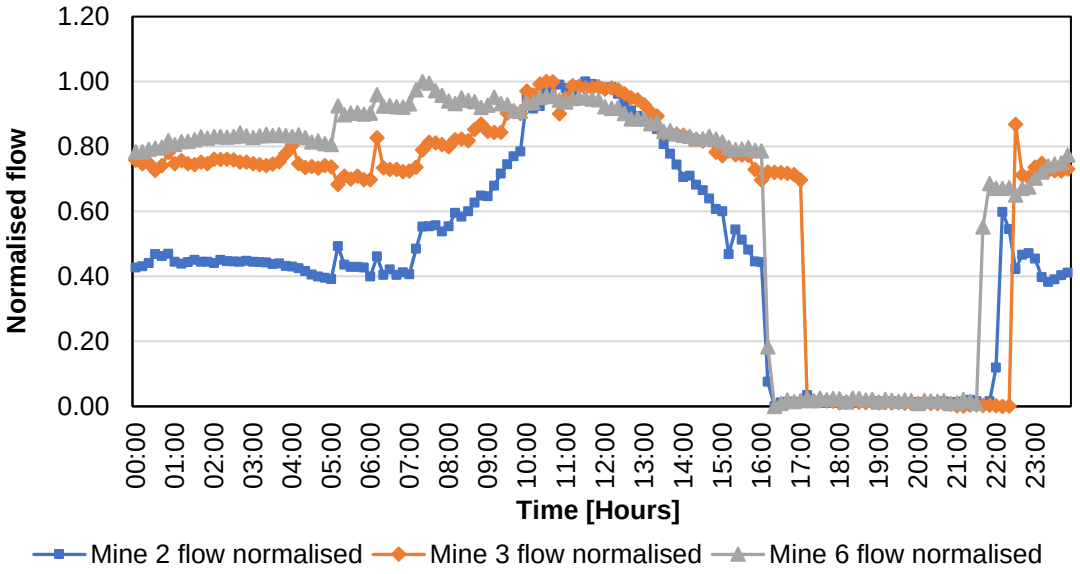


**Figure 39:** Scaled mine flow consumption

The treated data was randomly shuffled and divided into a training-testing split of 70%-30% as explained in Section 2.3.5. Model development was performed using the treated data.

### 3.2.6 Step 2.5: Model development

The first step in model development was hyperparameter selection, as explained in Section 2.3.6. The hyperparameters were selected before the model was trained and updated during model development by following the process discussed in Section 2.3.6. These hyperparameters were altered repeatedly through trial-and-error to improve the accuracy of the model throughout the model development phase. The final hyperparameter information is as follows:

- Number of hidden layers: 3;
- Activation function for hidden layers: Rectified Linear Unit (ReLU);
- Activation function for output layer: Linear (or no activation);
- Number of units: 15 (input), 64 (hidden 1), 32 (hidden 2), 16 (hidden 3) and 3 (output);
- Learning rate: 0.001;
- Number of epochs: 100; and
- Batch size: 32.

After these parameters had been set, model training could be performed. The training data was used to train the ANN model, while the testing data was used to verify the model accuracy. The figures in this section show the results obtained during the training process. Figure 40 shows the change in model accuracy achieved through the training process.

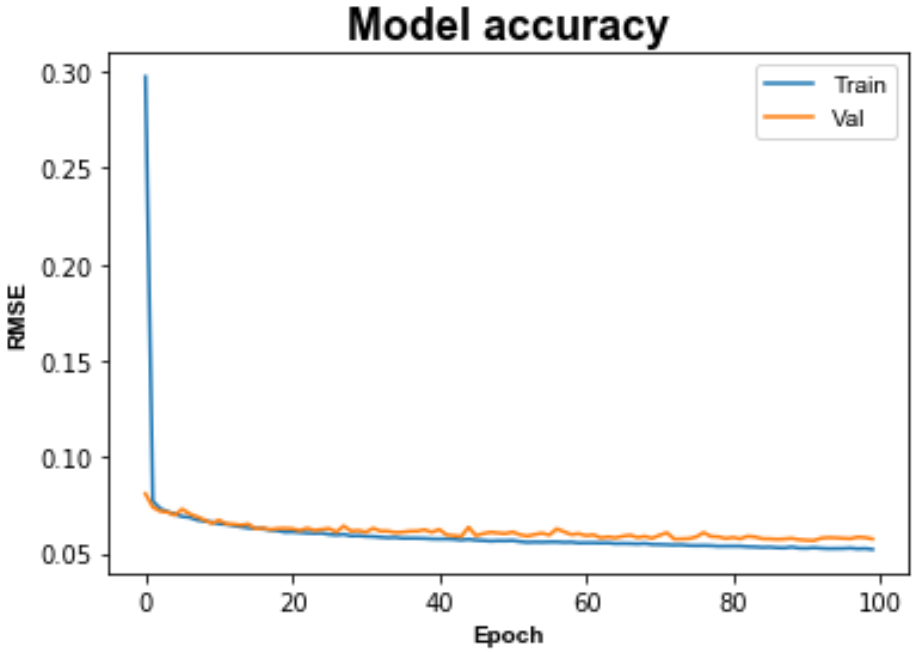


**Figure 40:** ANN root mean squared error through training and validation

In Figure 40, the accuracy (indicated by the RMSE) improves with each epoch or pass of the training dataset. The value of the RMSE is not as important as the fact that the value improves with each epoch. This indicates that the model accuracy improved throughout the training iterations. The value of RMSE can only be used to evaluate the difference between different iterations of training or where different models were used to predict the same parameters. This was done because the RMSE is not a dimensionless value. The values that were focused on instead are CV(RMSE) and NMBE, as explained in Section 2.3.6. Table 8 shows the calculated accuracy and bias metrics for the trained ANN model.

**Table 8:** Metrics calculated for the trained ANN model

| Parameter | Training set | Validation set |
|---|---|---|
| RMSE | 0.052 | 0.058 |
| CV(RMSE) | 6.085 | 6.784 |
| NMBE | 1.238 | 1.278 |

As seen in Table 8, the values for CV(RMSE) and NMBE are below the recommended values from ASHRAE Guideline 14 which was discussed in Section 2.3.6. The highest required accuracy for CV(RMSE) is 15% and NMBE is 5% according to this guideline, at a monthly prediction interval. According to the guideline, a lower accuracy is required as the prediction interval

increases. This model is thus considered accurate according to energy modelling standards. These standards are, however, not a determining factor in this study, as stated in Section 2.3.6.

A positive NMBE indicates that the model will tend to overestimate the predicted values. The accuracy indicator indicates that the model is accurate. To showcase the accuracy of the model, it was used to predict values in the validation set and is shown in the figures below. These figures show the normalised value for the actual pressure and predicted pressure for random samples from the validation data set. The validation set consisted of 4 346 samples, which is equivalent to the data of one month.

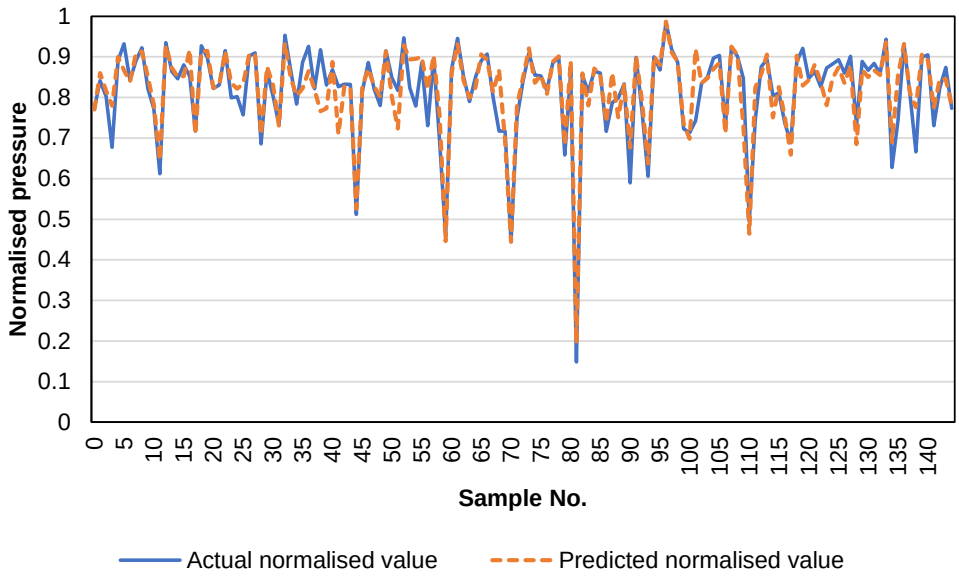


**Figure 41:** ANN model prediction output samples for Mine 2

Figure 41 shows the predicted pressure for Mine 2 compared to the actual pressure achieved. For the samples in the figure, a MAPE of 3.84% was achieved. A MAPE of 4.65% was achieved for the complete validation set. This value is below the desired 10% MAPE, which classifies the model as accurate. Figure 42 shows the predictions for Mine 3.

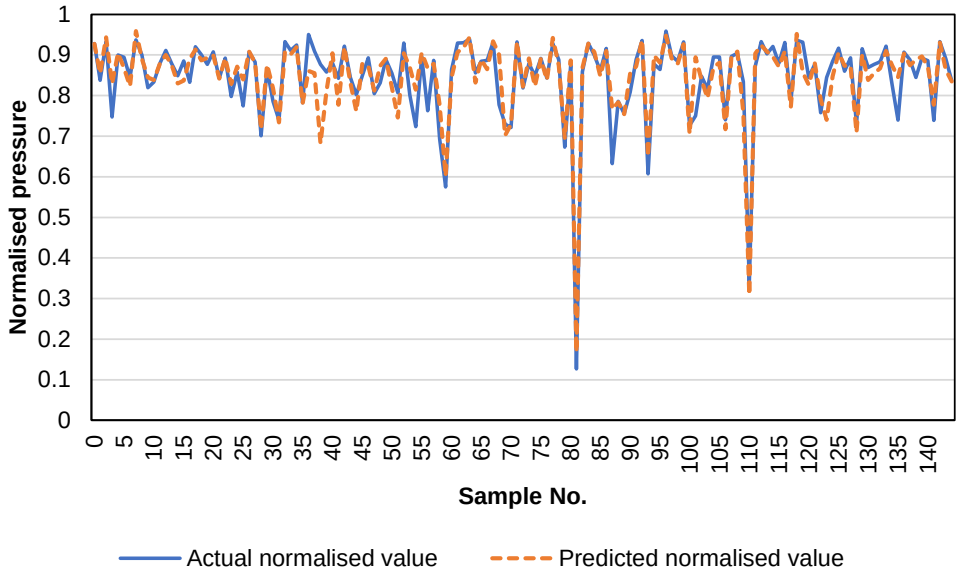


**Figure 42:** ANN model prediction output samples for Mine 3

Figure 42 shows the predicted pressure for Mine 3 compared to the actual pressure achieved. For the samples in the figure, a MAPE of 3.37% was achieved. A MAPE of 4.08% was achieved for the complete validation set. The achieved MAPE is similar to that of Mine 2, which is below the desired 10% MAPE. Figure 43 shows the predictions for Mine 6.

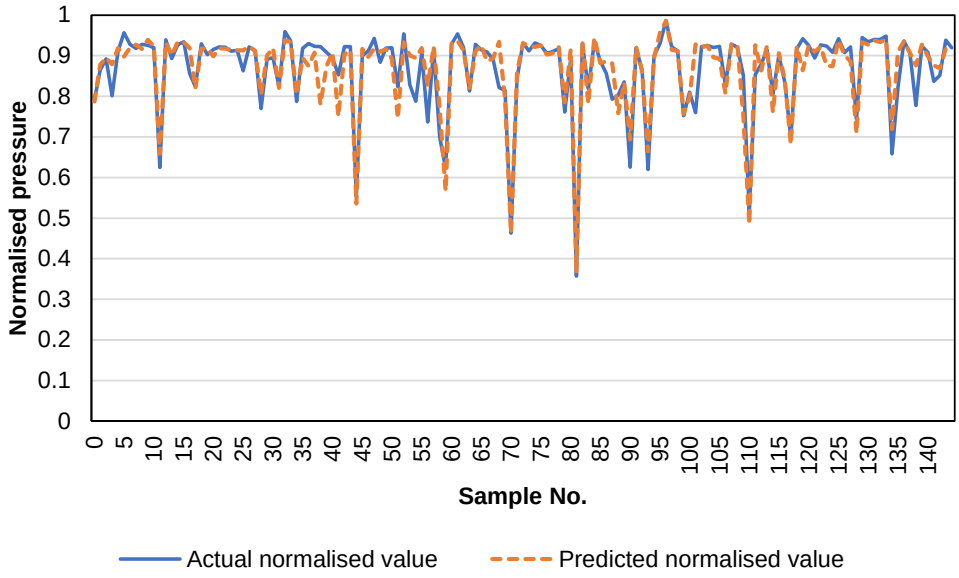


**Figure 43:** ANN model prediction output samples for Mine 6

Figure 43 shows the predicted pressure for Mine 6 compared to the actual pressure achieved. For the samples in the figure, a MAPE of 2.94% was achieved. A MAPE of 3.88% was achieved

for the complete validation set. The MAPE for this mine was the smallest, both in terms of the samples displayed and the complete validation set.

From the figures displaying the normalised results, the calculated MAPEs for all mines were below 5%. A MAPE of 4.20% was achieved for all predicted parameters in the validation set. This is below the desired 10%, which verifies that the model is accurate. From these results in the validation set, the ANN is therefore verified as accurate. It is further validated that it is feasible to use an ANN to predict compressed air pressure in a compressed air network. Although the error was determined to be small, it may be possible to reduce this error by repeating model training.

Model training can be performed again to increase the accuracy by altering hyperparameters and using the latest data available. This step can thus be repeated as required. The model implementation is discussed in the next section.

### 3.2.7 Step 2.6: Model implementation

The model was thus trained and ready to be implemented. The trained ANN can use the compressor run status, compressor load status, and consumer compressed air flow consumption to predict upstream pressure. This model was used as a tool to evaluate the compressed air network conditions in real-time by verifying whether a suggested compressor selection combination would provide sufficient pressure at the given compressed air flow consumption. Predictions were performed in real-time to assist control room operators with compressor selection. The following measures were put in place to make it possible to implement this ANN in real time.

The trained ANN and scaling information of the training data were saved. This information could now be loaded to the compressed air network control solution, as discussed in Section 2.4. This also created the opportunity to retrain and update the ANN if required, without interrupting the operation of the compressed air network control solution with the current version of the trained ANN.

Other important information required for the model implementation was the structure of input data and the frequency of input data (10-minute intervals). The next section discusses the implementation of the model in the compressed air network control solution, which was used to assist control room operators with compressor selection.

In Section 3.2, an ANN was developed to predict parameters in a compressed air network. It was determined that the model is accurate (in Section 3.2.6), thereby proving the feasibility of applying an ANN for the prediction of parameters in a compressed air network. This section, therefore,

verifies that research objective 2 was addressed. From the research problem, in Section 1.6.3, a need was identified to investigate the feasibility of applying a machine learning model for these purposes. Through the verification of research objective 2, it is thus validated that this part of the research problem was addressed.

## 3.3 Compressed air network control solution verification

### 3.3.1 Preamble

This section addresses the third and fourth research objectives, as discussed in Section 1.6.4.

**Research objective 3**: Develop and implement an ANN driven compressed air network control solution to assist control room operators with compressor scheduling and selection

To address these objectives, the method discussed in Section 2.4, was implemented to apply a machine learning model for real-time prediction to improve compressed air network control. An overview of the solution is provided in Figure 24. The verification specifications of the compressed air network control solution (as discussed in Section 2.4) are listed below and are addressed in this section.

- Specification 1: Real-time monitoring;
- Specification 2: Prediction through machine learning;
- Specification 3: Compressor suggestion methodology; and
- Specification 4: Display and data storage.

The results obtained from the real-time implementation of this compressed air network control solution are discussed. These results were obtained by implementing the compressed air network control solution at the case study mining complex. The compressed air network control solution was developed and implemented in real time to, firstly, verify the research objectives, which, secondly and ultimately would address the research problem. This section, therefore, discusses the implementation of the compressed air network control solution. The compressed air network control solution utilised the verified EMS (for monitoring and data storing, Section 3.1.2) and the verified ANN (as a tool to verify solutions generated by the suggestion methodology developed, Section 3.2) to improve compressor selection.

### 3.3.2 Specification 1: Real-time monitoring

Once the compressed air network control solution was started, the trained ANN and scaling information were loaded. Next, the compressed air network control solution loaded the latest available data, as stored by the EMS. This includes the relevant features required for the ANN as well as the developed start and stop triggers as set up in and calculated in the EMS. The figures below show the results of the triggers for a typical day at mining complex A.

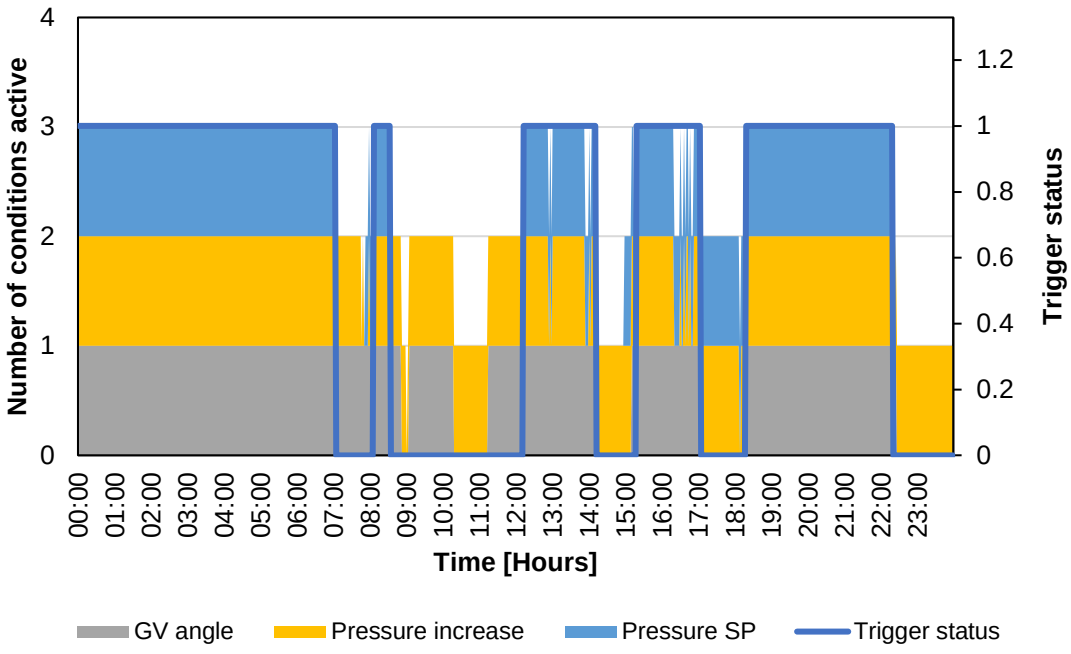


**Figure 44:** Implemented stop trigger results for a typical production day

Figure 44 shows the stop conditions and the trigger status. The different stop conditions were described in Section 2.2.5. From Figure 44, the three conditions should be active before the stop trigger is active. A filter was implemented to prevent the trigger from oscillating between the on (1) and off (0) status rapidly. For the trigger to change status, the instantaneous status would have to be equal to either the on or off condition for two minutes without interruption for the value to change. The result of this filtering is observed between 16:00 and 17:00 in Figure 44. The stop trigger became inactive only when the stop conditions were not met for two minutes. This filtering was implemented to improve the stability of the system. The same filter was implemented for the start procedure. The results for the start trigger are shown below.

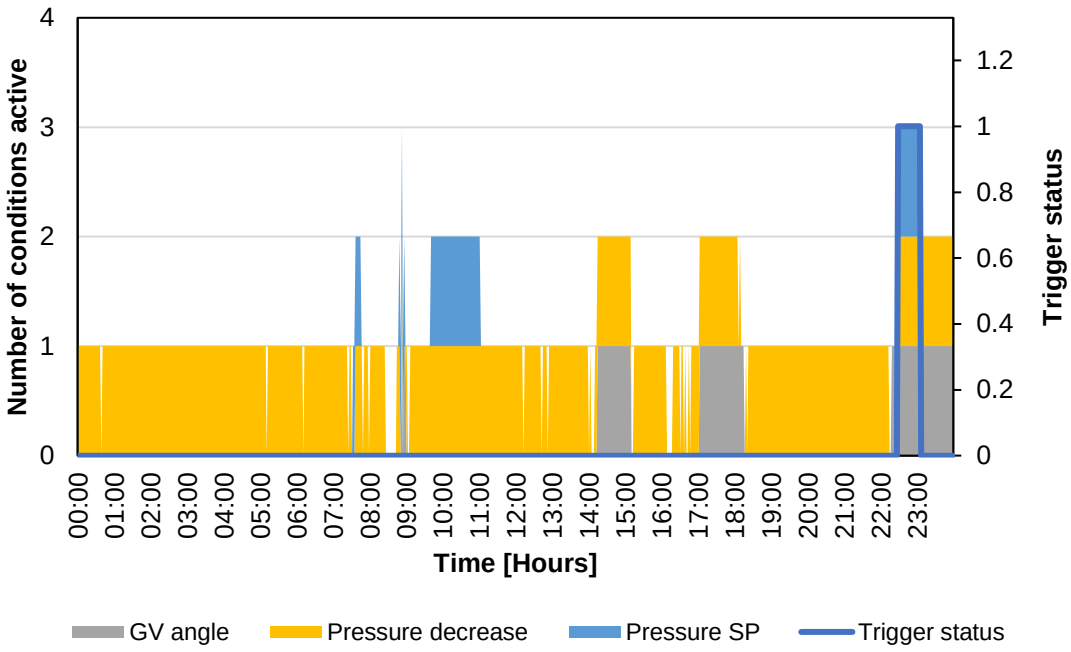


**Figure 45:** Implemented start trigger results for a typical production day

The start trigger was set up as explained in Section 2.2.5. In Figure 45, the trigger is active and functioning as expected. During the example day, the operators were not controlling according to the compressed air network control solution. The stop and start triggers were thus not followed, and by evaluating the results, it was found that the stop trigger was active for a greater duration compared to that of the start trigger. This could indicate that the compressed air grid was being oversupplied for the greater part of the day. If this was the case, a possible energy cost saving could be possible.

This concludes the real-time monitoring phase of the compressed air network control solution. The platform was updated every minute, thereby ensuring that the latest data was loaded. This verifies that Specification 1 of the compressed air network control solution was addressed. The data was then used to predict pressure on the compressed air network.

### 3.3.3 Specification 2: Prediction through machine learning

The loaded data was aggregated into the correct measurement frequency by averaging the two-minute interval data into 10-minute intervals. The data was scaled and processed into the correct order, which correlated with the format of the training data of the trained ANN. The formatted data could be utilised by the ANN to predict pressure in the compressed air network.

The pressure was predicted for the current network conditions as well as the expected network conditions in 30 minutes. This was done by calculating the expected flow, as discussed in Section 2.4.3, for each of the consumers. Figure 46, Figure 47 and Figure 48 show the actual results for real-time flow scaling from the implemented compressed air network control solution for three of the consumers.

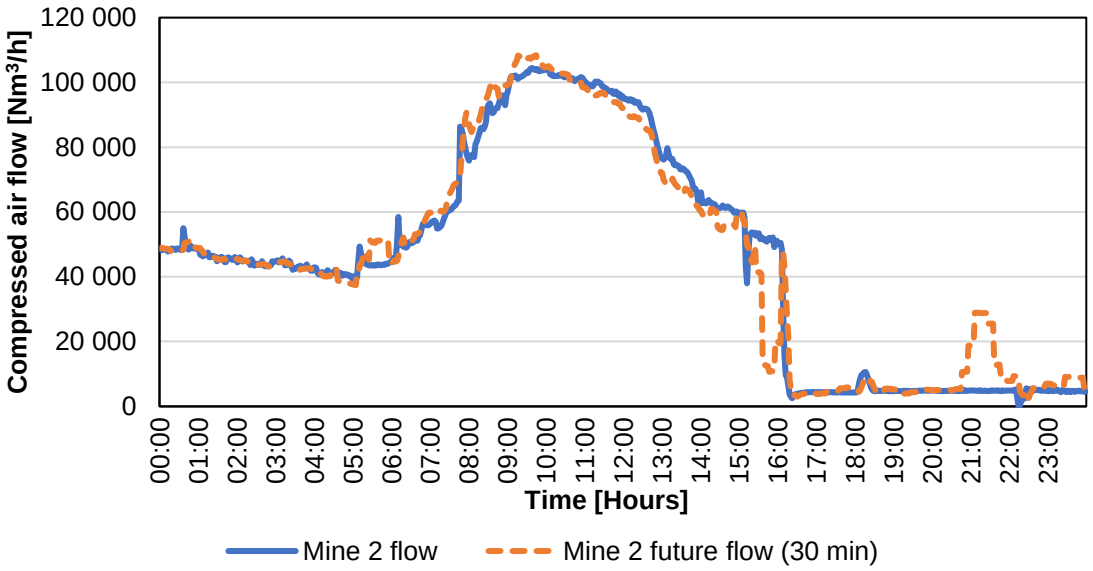


**Figure 46:** Implemented results of real-time future flow calculation for Mine 2

The result of the real-time flow calculation of Mine 2 is shown in Figure 46. From the figure, it is evident that flow is expected to increase from 05:00–10:00. From 11:00, the calculated future flow is below the actual flow, as the flow is expected to reduce. Figure 47 shows similar results for Mine 3.

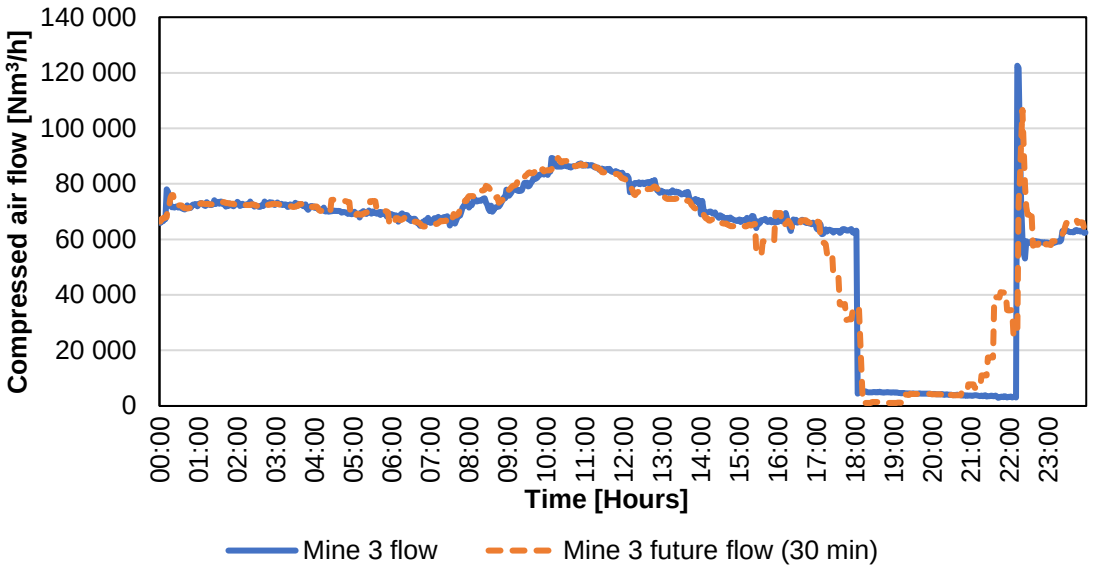


**Figure 47:** Implemented results of real-time future flow calculation for Mine 3

In Figure 47, the flow profile is steadier compared to the flow profile of Mine 2. A spike in data is observed where underground valves open, just after 22:00. This sudden increase in compressed airflow is due to the difference between the pressure on the grid and the unpressurised (or low pressure) underground network. Figure 48 shows the calculated future flow for Mine 6.

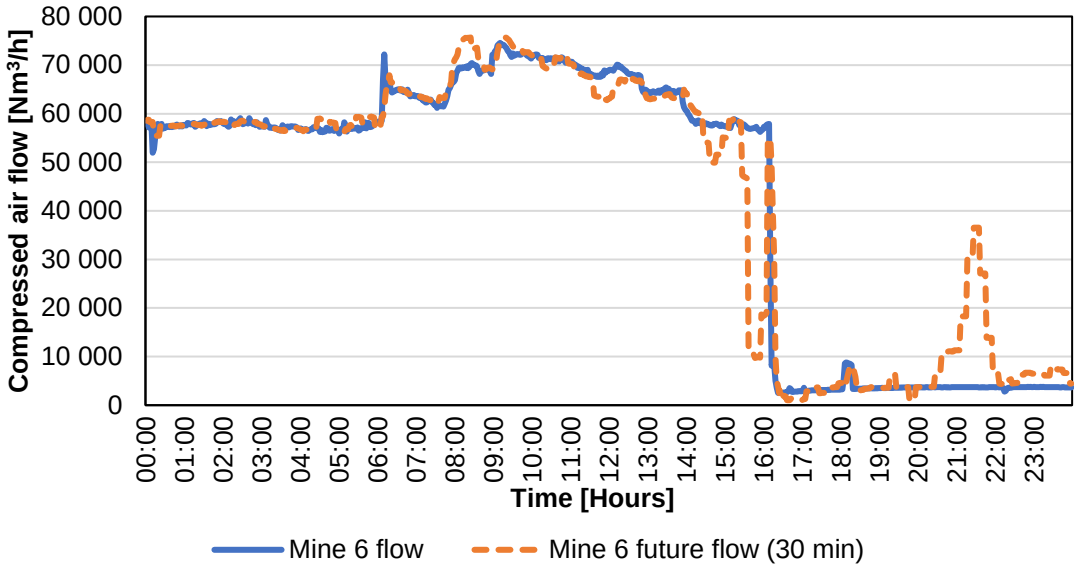


**Figure 48:** Implemented results of real-time future flow calculation for Mine 6

From the figures, it is evident that flow scaling functioned as expected. In Figure 46 and Figure 48 an increase in expected flow is evident, although there is no increase in actual flow. A day was

selected that led up to an “off” day where no mining was performed as usual. This day, therefore, showcases the expected conditions very well in the event that it had been a normal operating day. Using the flows shown in Figure 46, Figure 47 and Figure 48, predictions were made for the pressure as explained in Section 2.4.3 and Section 2.4.4.

As stated in Section 2.4.3, when a start or stop trigger is not active, the compressed air network control solution will only predict the upstream pressure for the current compressor combination. When a trigger is active the compressed air network control solution will predict upstream pressure for the suggested compressor combination as well. Details of the compressor suggestion methodology are discussed in Section 3.3.4. The figures below show the results obtained from the implemented model for each of the mines (main consumers) on the compressed air network. Figure 49 shows the actual pressure and predicted pressures for Mine 2, with the current compressor combination as implemented in real time.

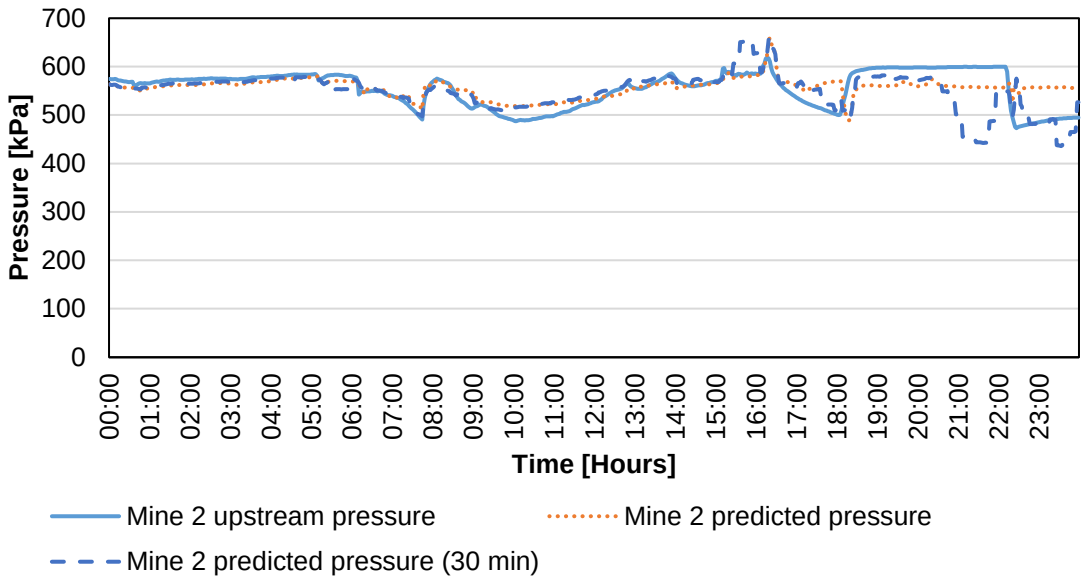


**Figure 49:** Result of implemented real-time pressure prediction of Mine 2 for the current compressor selection

A MAPE of 3.88% was achieved when comparing the actual pressure and the predicted pressure for the current combination, as shown in Figure 49; this is within the standards as discussed in Section 2.3.6. The accuracy of the model was acceptable from 00:00–16:00. After 16:00, the consumption of the compressed air network decreases drastically to a value close to zero. This harmed model accuracy, although it was still deemed sufficient. Figure 50 shows the result of the real-time pressure prediction of Mine 2 for the suggested compressor selection.

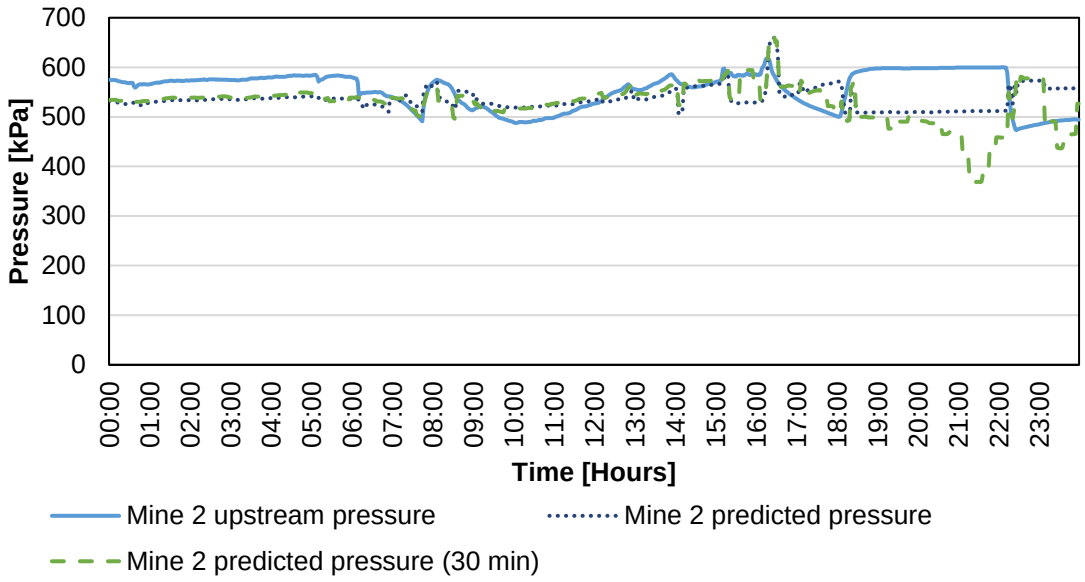


**Figure 50:** Result of implemented real-time pressure prediction of Mine 2 for the suggested compressor selection

As seen in Figure 50, a pressure below that of the actual pressure was predicted in the morning between 00:00 and 06:00. Nevertheless, this was still predicted to be above 500 kPa, which is the desired minimum for the mining complex. An issue, however, was noticed in the period from 18:00–22:00, where the pressure was predicted to be above 500 kPa only by a very small margin. This could prove to be an issue for operations since it is required to keep the pressure above 500 kPa. Based on this result, the compressed air network control solution was updated, before validation, to provide a margin of error of at least 20 kPa. Figure 51 shows the result of the real-time pressure prediction of Mine 3 for the current compressor selection.

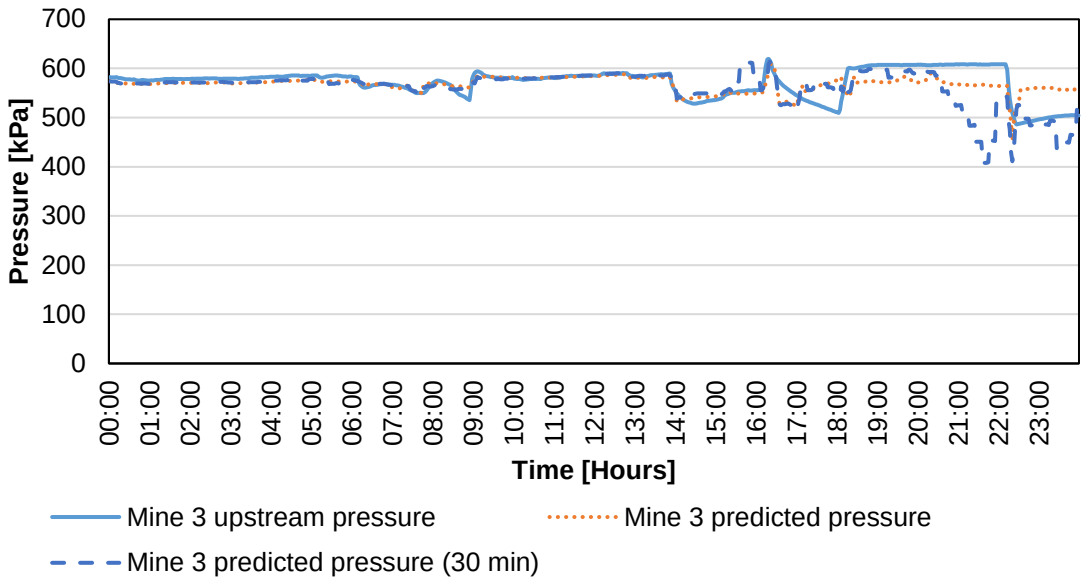


**Figure 51:** Result of implemented real-time pressure prediction of Mine 3 for the current compressor selection

In Figure 51, similar results are observed for Mine 3 compared to the results for Mine 2 in Figure 49. These results indicate that there is scope for possible improvement in operation, especially in the period of 00:00–06:00. In this period, the supplied pressure is high and could be reduced to a value closer to 500 kPa. To reduce supplied pressure, a compressor should be stopped (provided that pressure does not reduce below 500 kPa). This will lead to reduced energy consumption, which would be beneficial for the mine.

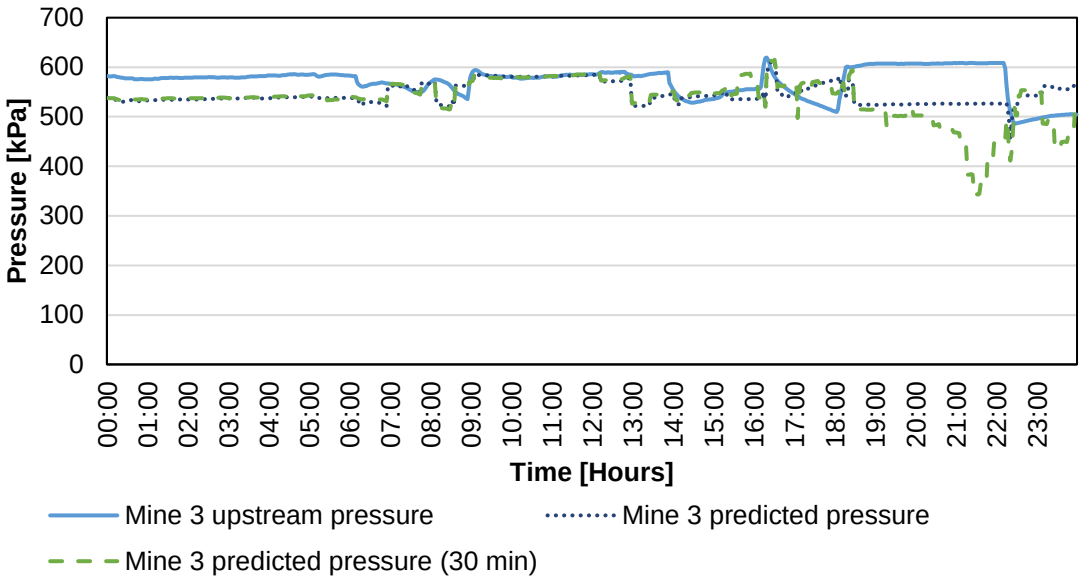


**Figure 52:** Result of implemented real-time pressure prediction of Mine 3 for the suggested compressor selection

The MAPE between the actual and predicted pressures (as shown in Figure 51) was calculated as 3.02%. Upon evaluating the suggested compressor combination predictions (as shown in Figure 52), the predicted pressure is only marginally above the 500 kPa setpoint. This could be troublesome given the small margin of error created with this operation. This was noted from the previous figures and was updated to prevent this from happening in the validation step. Figure 53 and Figure 54 shows the results obtained for Mine 6.

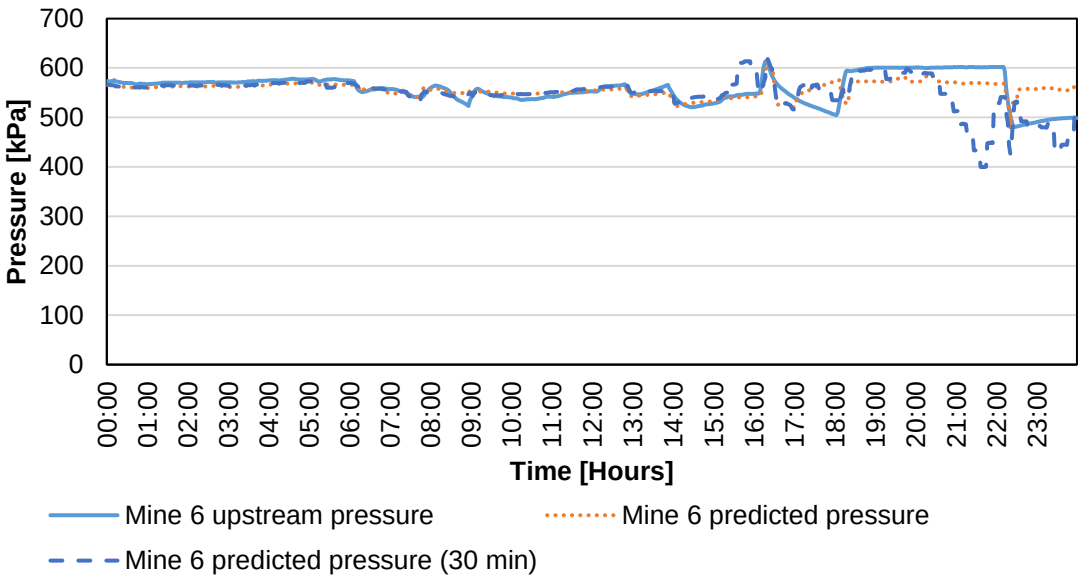


**Figure 53**: Result of implemented real-time pressure prediction of Mine 6 for the current compressor selection

In Figure 53, a MAPE of 3.05% is achieved, which is considered accurate. The results obtained for Mine 6 are similar to the results achieved for Mine 2 and 3. Figure 53 shows an accurate prediction, as well as a scope for possible improvement in supply operation between 00:00 and 06:00. Figure 54 shows the result of the real-time pressure prediction of Mine 6 for the suggested compressor selection.

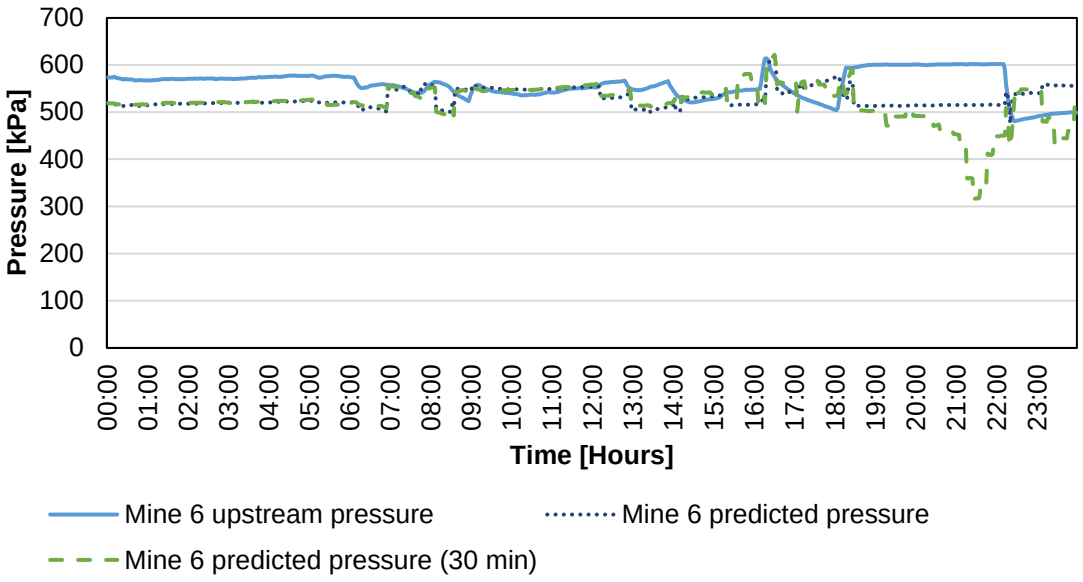


**Figure 54:** Result of implemented real-time pressure prediction of Mine 6 for the suggested compressor selection

The results, therefore, indicate that the ANN can predict pressure accurately and that there is possible scope for improvement in supply operation. The table below summarises the achieved errors for each of the mines from the discussed figures.

**Table 9:** Calculated errors for implemented real-time pressure prediction

| Consumer | MAPE (%) |
|---|---|
| Mine 2 | 3.88 |
| Mine 3 | 3.02 |
| Mine 6 | 3.05 |

Table 9 verifies that the implemented compressed air network control solution can predict pressure accurately in real time. This is an integral part of the solution and proves that it is feasible to predict the pressure of a compressed air network in real time. This model is thus regarded as having been successfully implemented and was used as a tool to verify the possibility of running different compressor combinations. This verifies that Specification 2 of the compressed air network control solution was addressed. The results of applying the compressor selection methodology as discussed in Section 2.4.4 is discussed in the following section.

### 3.3.4 Specification 3: Compressor suggestion methodology

When a start or stop trigger is active, the compressor suggestion methodology becomes active. The compressed air network control solution tests various compressor combinations through a process of iteration as discussed in Section 2.4.4. When a start trigger is active, the compressed air network control solution predicts pressure using all the different available combinations where a compressor is started. The predicted pressure for each of the compressor combination possibilities was evaluated and only combinations that delivered a pressure above the desired pressure setpoint was considered as a solution. The power consumption of each proposed solution was calculated by summing the rated power (or average power if available) of the active compressors. The solution which required the lowest calculated power while satisfying the pressure requirement was selected.

Table 10 shows the power matrix for the case study mining complex, as determined by calculating the average power consumption for each compressor:

**Table 10:** Compressor power matrix

| Compressor | Rated power (MW) | Average power consumption (kW) |
|---|---|---|
| 1. Centac C800 | 4.3 | 4 440 |
| 2. Centac RX850 | 4.3 | 4 125 |
| 3. GHH | 4.3 | 4 470 |
| 4. Centac RX850 | 4.3 | 4 330 |
| 5. BB Sulzer | 4.8 | 4 635 |
| 6. GEC | 3.3 | N/A |
| 7. GHH | 4.3 | 4 585 |
| 8. GHH | 4.3 | 4 760 |
| 9. Demag VK40 | 3.7 | 3 970 |
| 10. GHH | 4.3 | 4 380 |
| 11. Demag VK125 | 12.5 | 12 740 |

Figure 55 shows the actual run statuses of the compressors on the mining complex as collected through the EMS. The control room operators did not have access to the compressed air network control solution during this day and thus operated as normal without assistance.

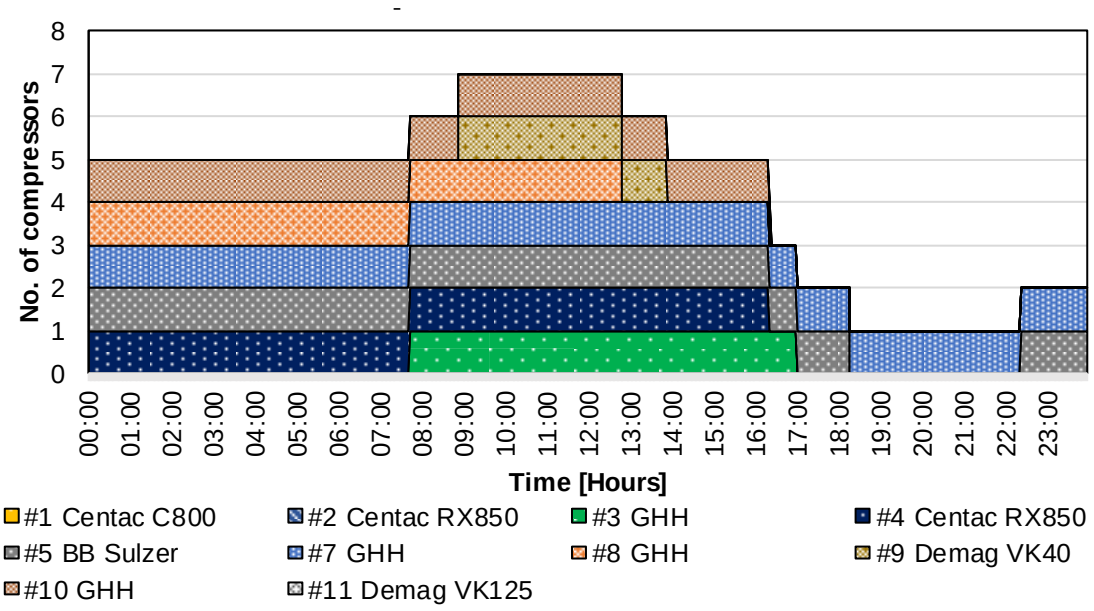


**Figure 55:** Compressor run statuses.

After applying the process of iteration and testing as discussed in Section 2.4.4, the following compressor combinations were suggested by the implemented compressed air network control solution in real time.

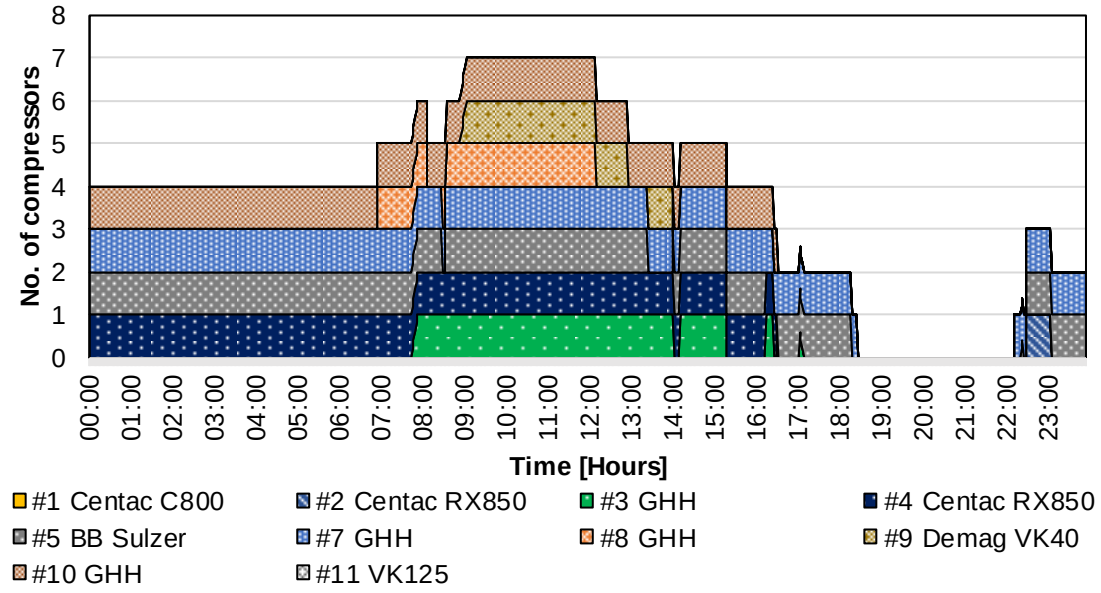


**Figure 56:** Implemented results for suggested compressor run status.

The results obtained shows that it could have been possible to run one fewer compressor from 00:00 to 07:00. At 07:00, the stop trigger was not active anymore and the compressed air network control solution followed the actual compressor combination. Just before 08:00, control room operators started an additional compressor, and the sudden increase in pressure due to the start-

up of the compressor activated the stop trigger once more. Due to this, the compressed air network control solution suggests stopping a compressor between 08:00 and 08:30. In the case where the control room operators were following the compressed air network control solution, this would not have happened. Instead, a compressor would not have been started before 08:00 due to the lack of a start trigger available, meaning that the stop trigger would not have been active in the period from 08:00 to 08:30.

Compressor selection remains constant throughout the peak consumption period (when compressed air usage is highest, during 09:00–12:00). The compressed air network control solution suggests that a compressor could be stopped earlier than stopped by the control room operators. This stopping of compressors continues to be the trend up until 16:00 with an average period of about an hour between the suggested stopping time and when the control room operators stop a compressor. If this was implemented, a significant saving could have been achieved.

From the results, an issue is, however, noted in the period between 18:00 and 23:00 where only one compressor was active. The compressed air network control solution suggests that all compressors could be switched off. If this is done, the pressure of the compressed air grid would drop to atmospheric pressure and pressure would not be sustained above the desired 500-kPa setpoint. The suspected reason for this behaviour is the drastic reduction in flow consumption, close to zero, from all consumers and the lack of training data where no compressors were running.

When the flow consumption reduces to this point close to zero, the compressed air grid is oversupplied by the large compressors, but this cannot be avoided due to the lack of smaller compressors on the compressed air grid. This issue was noted from the implemented results and the compressed air network control solution was updated to prevent a suggested solution where no compressors were active. Further development or retraining of the machine learning model can be performed where data is added where no compressor is running.

Between 22:00 and 23:00, the compressed air network control solution suggests that an additional compressor is started to increase the pressure of the compressed air network. At this stage, control room operators did not start a compressor and the pressure was below the desired 500-kPa setpoint. Had the control room operators been following the compressed air network control solution, there could have been an improvement in supply control. The compressed air grid pressure would have been above 500 kPa as required by the mine.

These results, therefore, verify that the compressed air network control solution can suggest compressor combinations that could improve the compressed air supply in real-time. This verifies that Specification 3 of the compressed air network control solution was addressed.

Next, it is verified that the data is displayed correctly and stored as required from the specifications. After this has been verified, control room operators will be allowed to view the verified solutions to validate that this compressed air network control solution can assist with the improvement of the compressed air supply. All calculated data is displayed and stored, which is discussed in the next section.

### 3.3.5 Specification 4: Display and data storage

One of the specifications is the display and data storage of all results that have been discussed. To display the information, an interface was designed to the framework described in Section 2.4.5. The interface displayed all information as discussed in Section 2.4.5, which includes all results discussed in Section 3.3. The interface updated every minute and displayed the 10-minute average for each of the data points displayed. Figure 57 shows the result of the designed and implemented interface.

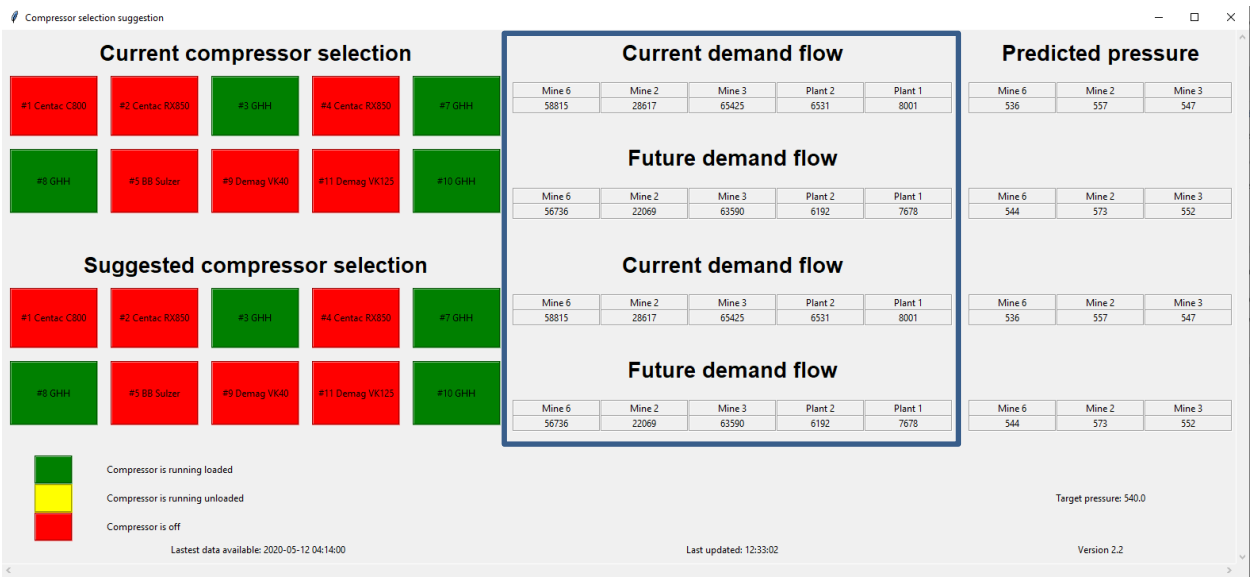


**Figure 57:** Implemented compressed air network control solution GUI.

In the example, no start or stop triggers are active. The suggested compressor selection is thus the same as the current compressor selection. From Figure 57, it is evident that the interface can display if a compressor is either running in a loaded state (green background), running in an unloaded state (yellow background), or not running (red background). This was done to enable control room operators to see the status of all the compressors and if a change is required. The

results of real-time flow scaling, as discussed in Section 3.3.3, is shown in the middle block of the interface.

The current demand flow and future demand flow was thus displayed for each consumer on the compressed air network. These flows are displayed horizontally next to the current compressor selection were repeated next to the suggested compressor selection blocks. This was done to easily differentiate between the different predicted pressures. The predicted pressures are displayed at the far right of the GUI and include the following, as discussed in Section 2.4.4, 2.4.5, 3.3.3 and 3.3.4.

- Predicted consumer pressure with current compressor combination and current network conditions;
- Predicted consumer pressure with current compressor combination and expected future network conditions;
- Predicted consumer pressure with suggested compressor combination and current network conditions; and
- Predicted consumer pressure with suggested compressor combination and expected future network conditions.

At the bottom, a legend is provided for the compressor statuses, the date of the last available data (to ensure that the latest data i.e., real-time data is being used), the time of previous interface update and the version of the compressed air network control solution currently implemented. The version was included to ease the tracking of updates that were made to the compressed air network control solution. In this way, it would be possible to roll back to previous versions in the case of bugs or issues experienced with the new version as development continues. It is therefore verified that the objective to display results in real-time was met. Figure 58 shows an example of an active start trigger.

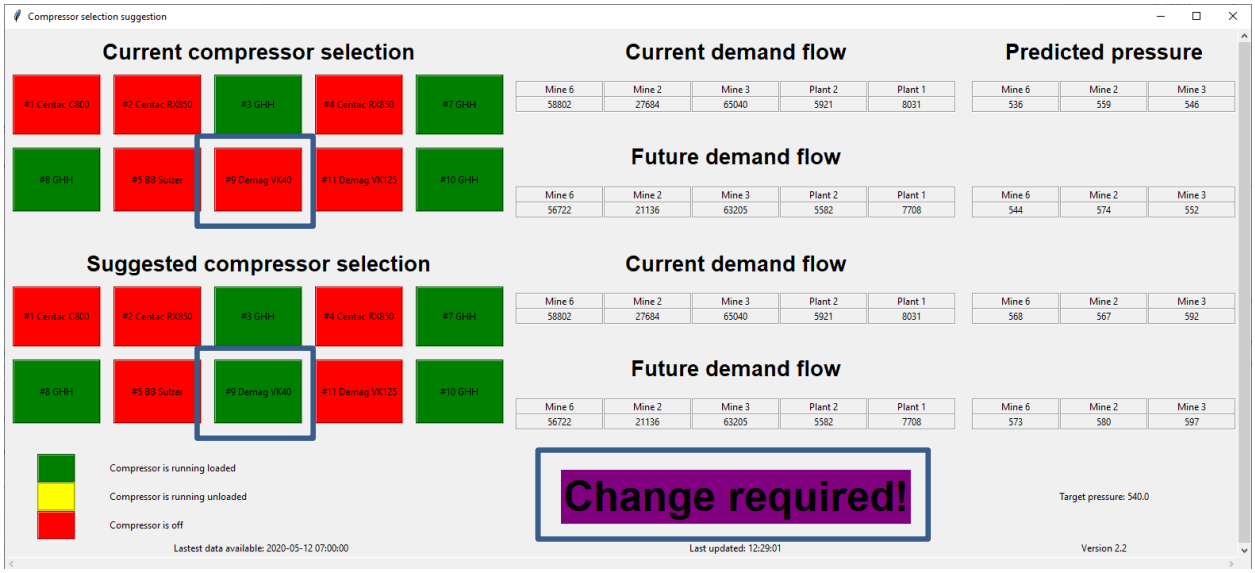


**Figure 58:** Implemented compressed air network control solution GUI with start trigger active.

Figure 58 is an example where a start trigger was active, as indicated with a square block. This is seen through the large purple banner that is displayed in the centre bottom of the screen which states, “Change required!”. This banner appears in the event that a start trigger is active and the compressed air network control solution has determined a suggested compressor combination that is different from the current combination. In Figure 58, four compressors were running, although the compressed air network control solution indicated that an additional compressor should be started. In this example, it can also be seen that there would be an expected increase in pressure when an additional compressor is started. Similar results are observed in Figure 59, where a stop trigger was active.

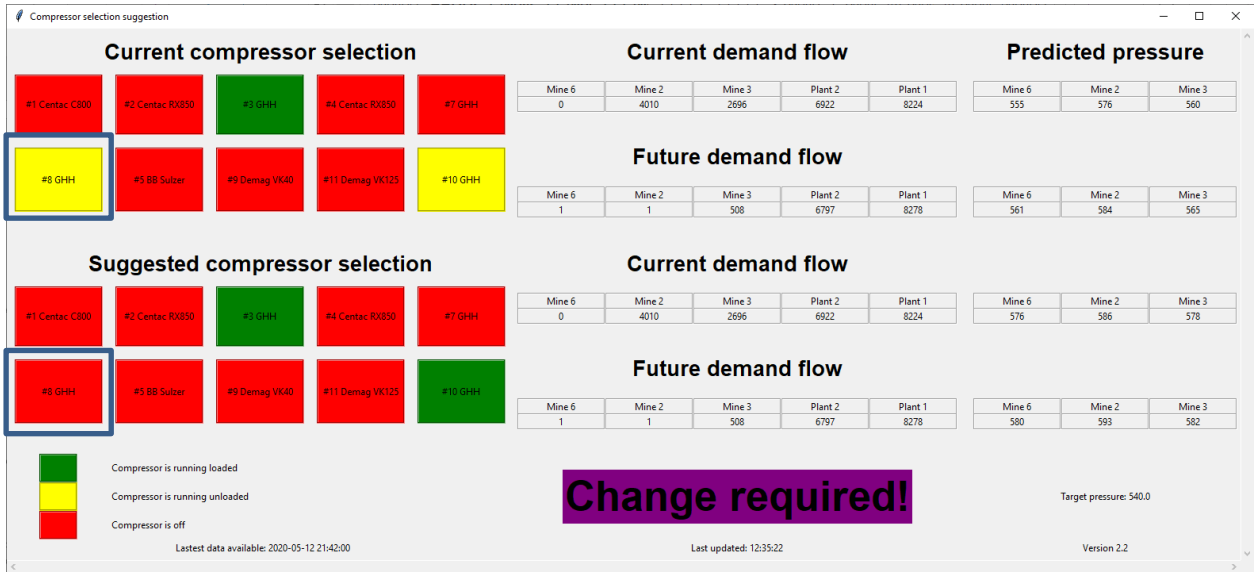


**Figure 59:** Implemented compressed air network control solution GUI with start trigger active.

In Figure 59, two compressors were being run in an unloaded state and a stop trigger was active. This is not recommended and regarded as an inefficient supply operation, as discussed in Section 1.2.4. From Figure 59, there is a difference in the current combination and suggested combination. As discussed in Section 2.4.4, the compressed air network control solution is not able to suggest that a compressor is run in an unloaded state, compressors can only be suggested to running in a loaded state or suggested to be inactive (off). In this example, a stop trigger is active and the “Change required!” banner is active, to alert the control room operator. It is also seen that the compressed air network control solution suggests switching off a compressor while running the other two compressors in a loaded state.

From the predicted pressures, this solution would increase the pressure even further. This is due to the loaded status of the compressors, which means that the supply efficiency would be improved significantly. The power consumption would thus be reduced significantly by stopping a compressor, and the pressure supplied would be increased at the same time. These examples, therefore, verify that the objectives for display, compressor suggestion and alerts were met. The display is an integral part, although without data capturing it would be difficult to evaluate and improve the compressed air network control solution.

All displayed data is captured and stored in a .csv format on the server running the compressed air network control solution. The data is saved by writing a new line for each tag in an existing .csv file for the current day, every minute when the platform refreshes. When the date changes to a new day, a new .csv file is generated. The layout of the data in the file is as follows:

“Date, Time, Tag, Value”

This data is therefore stored, which creates a historical database. This can be used for improving the compressor compressed air network control solution, evaluation of operator decisions and improving future operations. In the case of the mining complex used for the case study, the data was sent to a server daily and incorporated into automated daily reports to evaluate the operation of the previous day compared to the suggested or possible operation. All figures and results discussed in Section 3.3 regarding the compressed air network control solution were created using the data captured by this compressed air network control solution in real-time. From this section, it is therefore verified that Specification 4 of the compressed air network control solution was addressed.

All platform specifications were addressed in Section 3.3. This verifies that a compressed air network control solution was developed and implemented to assist control room operators with compressor scheduling and selection. It is therefore verified that research objective 3 was addressed. Validation is discussed next.

## 3.4 Validation of the proposed solution on a case study

### 3.4.1 Preamble

In Section 3.3, it was verified that the solution was developed and operated as intended. In this section, the last research objective is addressed.

| |
|---|
| **Research objective 4**: Validate that the proposed solution addressed the research problem |

To achieve the research object, this section, therefore, addresses the research problem that was identified in Section 1.6.3.

| |
|---|
| There is a need to investigate the feasibility of applying a machine learning model for the prediction of parameters in a mining compressed air network. Furthermore, there is a need to apply a machine learning model for real-time prediction to improve compressed air network |

In Section 3.2, it was validated that it is feasible to apply a machine learning model for the prediction of parameters in a mining compressed air. This section, therefore, addresses the need to improve compressed air network control through the application of a machine learning model for real-time prediction.

To validate that this verified compressed air network control solution could be applied to improve the compressed air network supply, simulation software is used as a tool in the validation process. The calibrated PTB™ model (Section 3.1.3) was used to validate the feasibility of the results obtained from the compressed air network control solution and to evaluate the ability to improve the supply control of a compressed air network. The compressed air network control solution was implemented, and a test was performed to evaluate the performance of the platform suggestions. Control room operators could make their own decisions regarding compressor selection, although they were requested to follow the suggestions if feasible. The results of this test are discussed in this section, which concludes the validation of the study.

### 3.4.2 Improved system operation

This compressed air network control solution was implemented and active at the mining complex. The results obtained were discussed in Chapter 3, and it was verified that all research objectives were met. During this period, continuous updates were performed to improve the display, prediction accuracy, and data storage capabilities. The compressed air network control solution was implemented in the background (operators could not see the display) during the main part of development before operators were allowed full access. Automated reporting was set up using the captured data from the compressed air network control solution, which provides an overview of the data created on the compressed air network control solution. This includes data such as:

- Suggested compressor selection;
- Future flow of each consumer; and
- Predicted pressures (for the current compressor selection and suggested compressor selection at the current and future flow conditions).

During the implemented period, the display was not shown to control room operators. This was done to allow the development of the compressed air network control solution to be completed and to prove the feasibility of the proposed solution. The compressed air network control solution was implemented for more than six months. During this period, continuous development was performed to the model in parallel. It was designed to allow for continual improvement while implemented on site.

To validate that this solution can improve the compressed air network supply, two tests were performed. The verified simulation model (Section 3.1.3) was first used to validate that the verified results, obtained from the implemented compressed air network control solution, would be feasible. After this validation, a real-time test was performed.

**Simulated validation**

The following figures show actual results that were obtained from the implemented compressed air network control solution. All figures contain actual data. The figures represent a 24-hour profile, where the compressed air network control solution was active, which represents an average working day at the case study mining complex. It should be noted that control room operators were not able to see the platform during this initial validation process. This was done to first validate that the compressed air network control solution could improve compressed air supply control using simulation software.

Using the calibrated simulation model, a baseline simulation was created. The actual data and consumer and supplier data was inserted into the simulation and the results from this simulation were saved. This saved baseline simulation data is regarded as the benchmark to which the results of the compressed air network control solution will be compared. By inserting the suggested compressor combinations throughout the day into the calibrated simulation model, the results can be compared to the baseline simulation. In Figure 60, the simulated compressor power is plotted for the selected production day.

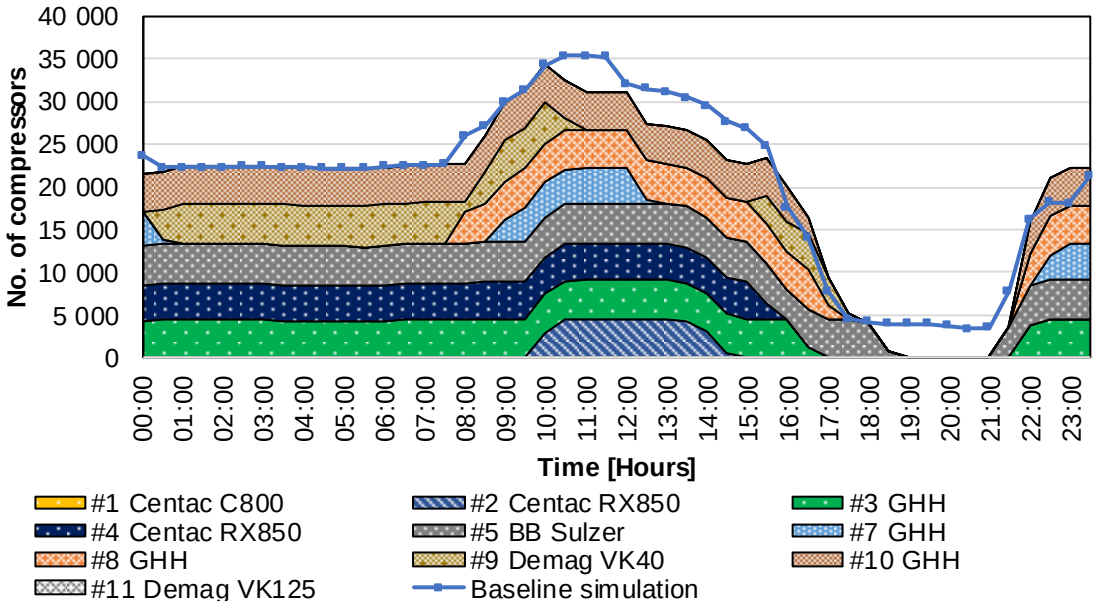


**Figure 60:** Simulated power consumption for simulated validation test

In Figure 60, the baseline simulation power consumption is represented by a line on the graph. The simulated power for each compressor is plotted on a stacked area graph to illustrate the simulated power for the suggested compressor combinations, as suggested by the compressed air network control solution. From these results, the compressed air network control solution suggested that one fewer compressor could have been run in the periods from 00:00–01:00,

07:30–08:30, 10:00–15:30 and 18:30–22:00. The results indicate that an additional compressor was required in the period from 16:00–17:00 and 22:00–24:00. These initial results indicate that energy cost saving is possible. To validate if this is the case, the pressure profile of consumers is first evaluated. If the pressure requirement is not met, it indicates that the suggested selection is not feasible. This would thus not result in an improvement of supply control. Figure 61 shows the average consumer upstream pressure as simulated for the baseline and suggested selections.

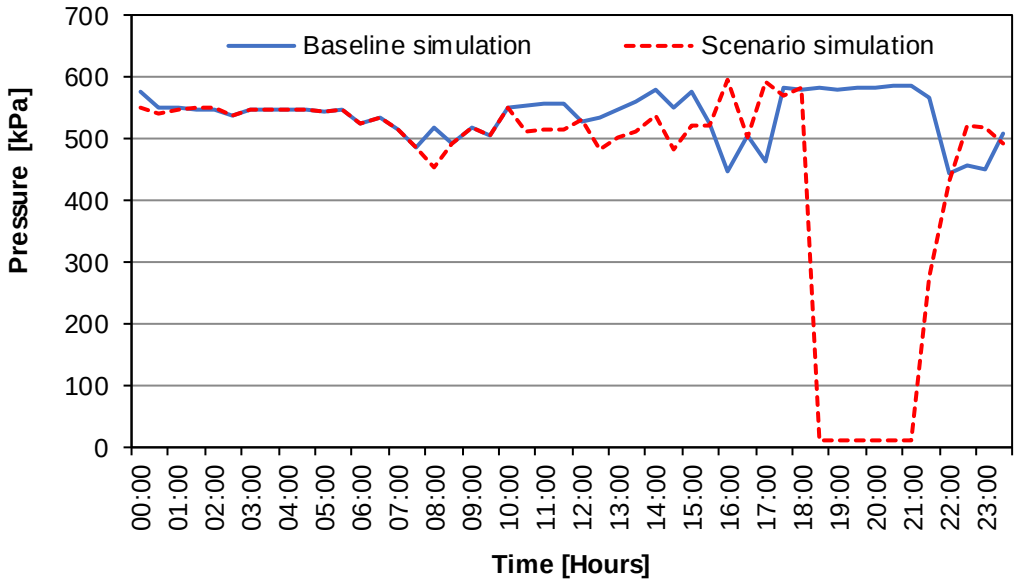


**Figure 61:** Simulated average consumer upstream pressure for simulated validation test

As can be seen in Figure 61, there are some points where the pressure do not meet the requirement. At 08:00 the pressure decreases to 453 kPa, which is 47 kPa below the desired pressure (500 kPa). This is not necessarily a true representation of the results that could have been obtained in the event where operators were allowed to see the compressed air network control solution. In this event, the operator started a compressor when a start trigger was not active yet. As a result, there was an immediate increase in pressure, which led to a stop trigger being generated and the compressed air network control solution suggesting that a compressor would be stopped. Simulating this stop led to a sudden and significant drop in pressure, which could have been much different if operators did not start when a trigger was not active.

At 12:30 and 14:30, the pressure decreases below 500 kPa to 485 kPa and 484 kPa respectively. These points are below the desired pressure, although only by 15 kPa and 16 kPa respectively. This can be due to the nature of the simulation being set up in 30-minute intervals. The values are simulated for each half hour, thus 48 intervals for a 24-hour profile. Where a change in compressor selection is suggested at a time like 14:42, the change would be implemented at 14:30 on the simulation, which could be a cause for these dips. This is therefore not of major

concern, although the pressure target within the drilling period (06:00–16:00) is of high importance. In this example, the target was set at 500 kPa during the day, although from the results, it is recommended that a variable target be set. This would allow for a higher pressure target during the drilling period a lower target during the non-drilling period, which could lead to additional energy savings.

A major concern, however, is noticed between 18:00 and 22:00. During this period the compressed air network control solution suggests that all compressors be switched off. This issue was discussed in Section 3.3.4 and addressed by updating the compressed air network control solution to block stop triggers when only one compressor is running. This could also be addressed by updating training information to include data points where no compressors are active.

As for the other periods during the day, it seems that there is an improvement in supply control. In the periods of 00:00–01:00 and 10:00–15:30, there was a reduction in power consumption, as seen in Figure 60, whilst pressure was kept above 500 kPa (excluding at 12:30 and 14:30 as discussed above). This indicates that energy saving could have been achieved, thereby improving compressed air supply control.

In the periods of 15:30–17:30 and 22:00–23:30, the opposite is observed where operators allowed pressure to reduce below the desired 500 kPa. In these periods, the compressed air network control solution suggested that an additional compressor should be started, which improved the supply pressure. This increase in pressure led to an increase in power consumption, although it is still considered an improvement in supply control due to the 500 kPa desired pressure. Figure 62 shows the effect of the altered supply flow on the consumer demand flow.

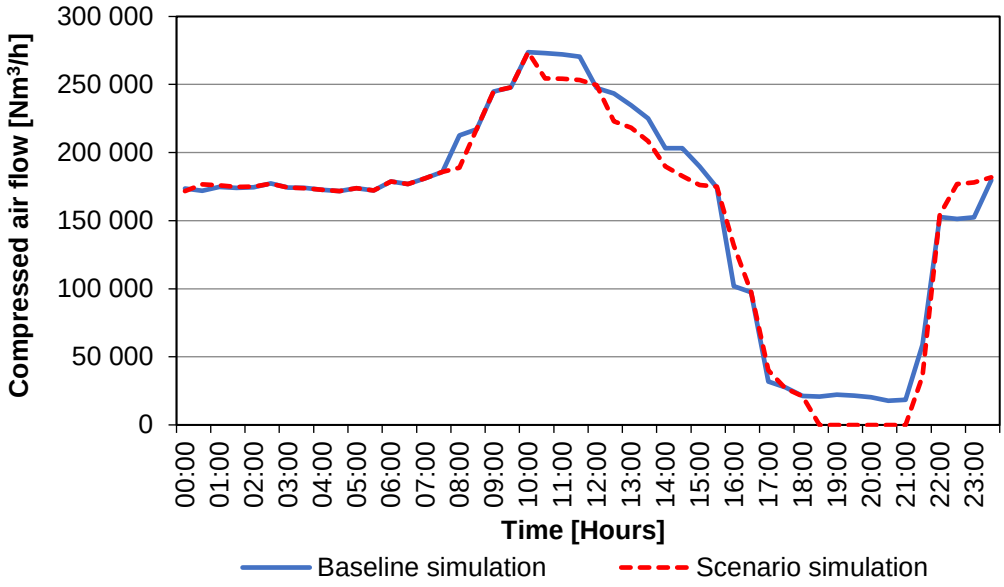


**Figure 62:** Simulated total consumer flow for simulated validation test

From Figure 62, it is apparent that total consumer flow follows a similar pattern as the average consumer upstream pressure. A decrease in supply pressure leads to a decrease in consumer demand flow, which leads to a saving in electricity costs. An increase in supply pressure leads to an increase in consumer demand flow, which will negatively affect energy consumption but could improve demand operations.

The results obtained from this test indicate that some issues need to be addressed; these issues include:

- Compressed air network control solution switches off all compressors (from 18:00 to 22:00);
- Minimum pressure set to 500 kPa should be increased during the drilling period; and
- Compressed air network control solution suggests stopping when operators start compressors; this is because the start signal was not active, thus switching off immediately.

The issues highlight where the compressed air network control solution needs to be updated, although they also indicate that the platform was able to improve compressed air supply control for the given control parameters. Through this test, it was validated that the compressed air network control solution was able to improve supply control for 75% of the day. The 25% where compressed air supply was not improved, however, required small adjustments.

The compressed air network control solution was updated to adjust for these observed issues. Updates include that a stop trigger cannot be generated if only one compressor is active. A variable pressure target was implemented to allow for a higher target during drilling periods, as this would prevent premature stopping of compressors. It is believed that the issue of suggesting stopping a compressor immediately after a start-up would not be an issue when operators are allowed to follow the platform. This is because operators would only start when the compressed air network control solution suggests rather than starting prematurely. This is, however, validated in the real-time test.

**Real-time validation test**

The updated compressed air network control solution was implemented and the mining complex agreed to a test. This compressed air network control solution was tested by following the suggestions for three days (from 06:00–18:00) and by following the guidelines below:

- The compressed air network control solution was displayed in the control room;
- The compressed air network control solution display was explained to the control room operators;
- The control room operator remained in full control; thus, responsible for compressor selection;
- The compressed air network control solution only provided suggestions; the operator decided if the suggested selection would be followed or not;
- An engineer was present in the control room to assist the operator, with regards to the compressed air network control solution from 06:00–18:00 (when most selection changes took place);
- The procedure of stopping a compressor was to put the compressor on unload for at least 10 minutes (possibly 20 minutes) after which the operator would decide whether to stop or load the compressor; and
- The control room operator had full authority over the compressor selection.

With the abovementioned guidelines, the test was performed. The results of the following key elements are discussed:

- Real-time monitoring – start and stop triggers;
- Compressor selection;
- Consumer upstream pressure; and
- Power consumption.

To validate that the solution can improve compressed air supply, two key factors are evaluated, namely power consumption and supplied upstream pressure. One way in which supply can be improved is by keeping supplied upstream pressure above the desired target pressure while a reduction in total power consumption is observed. Another way is by maintaining total power consumption at baseline level while an increased upstream pressure is observed. To validate that the proposed solution improved the compressed air supply of the mining complex, the results of the start and stop trigger statuses are evaluated first.

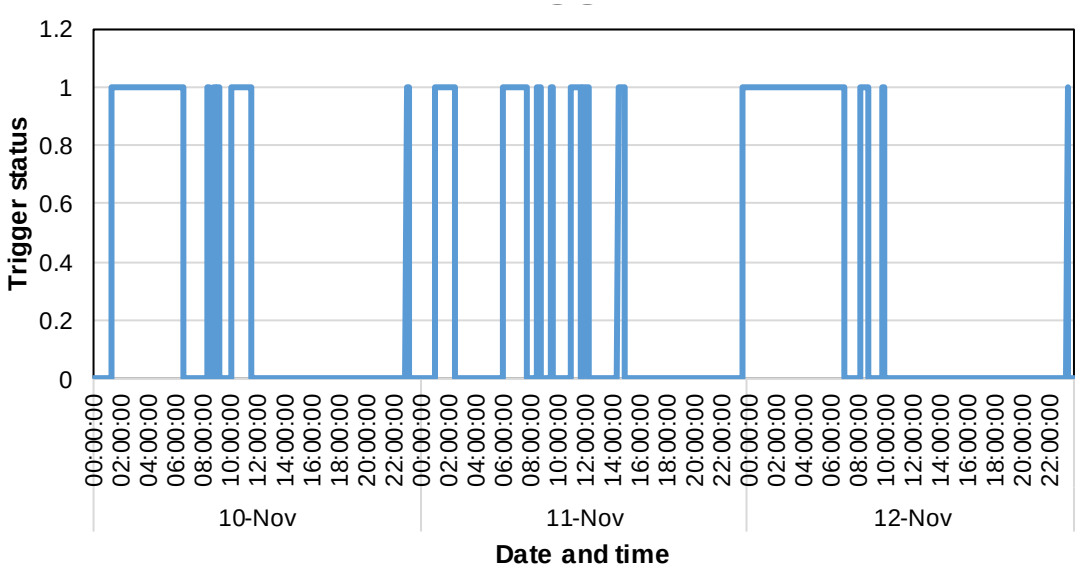


**Figure 63:** Real-time validation test start trigger results.

As seen in Figure 63, start triggers were only active for long periods of times from 00:00–06:00. During these periods, operators did not follow start or stop triggers, as the test was performed between 06:00 and 18:00. During the 06:00–18:00 time slot, start triggers were frequent; however, they were not active for long periods at a time. The average time that a start trigger was active (which includes the start-up time of the compressor) was 23 minutes. This indicates that operators followed the suggestions by the compressed air network control solution to start compressors. The largest number of triggers were observed between 06:00 and 12:00, which is when most compressors are typically started on this mining complex.

There were two instances during the test where operators indicated that they wanted to wait a few minutes before starting a compressor. These decisions were made based on experience, the fact that no complaints had yet been received and the fact that the operator had full authority regarding selection. These instances can be observed on 10 November between 10:00 and 11:30 and 11 November between 06:00 and 07:30. Figure 64 displays the results obtained from the stop triggers.

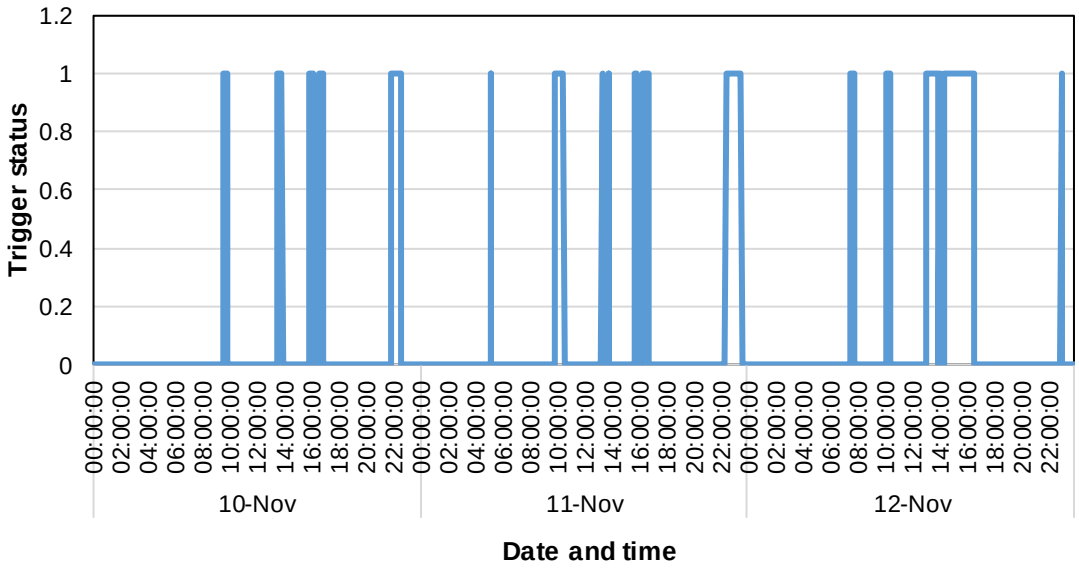


**Figure 64:** Real-time validation test stop trigger results

From Figure 64, the duration of stop triggers was not long during testing periods. The average time that a stop trigger was active (including the time of the stop-sequence) is 27 minutes. This indicates that operators adhered to the compressed air network control solution suggestions to stop compressors. Two compressors were maintained at the time of the testing (#5 BB Sulzer and #10 GHH). These compressors were thus not available to start; two such instances were observed where the compressed air network control solution suggested starting one of these compressors. Operators adhered to the suggested start-up although they selected a compressor of personal choice due to the unavailability of these compressors.

Figure 65 shows the actual compressor selections and power consumption compared to the baseline power consumption. The baseline was determined by using data from the production days of the two weeks leading up to the test. This baseline period was selected because it represented the actual average operation.

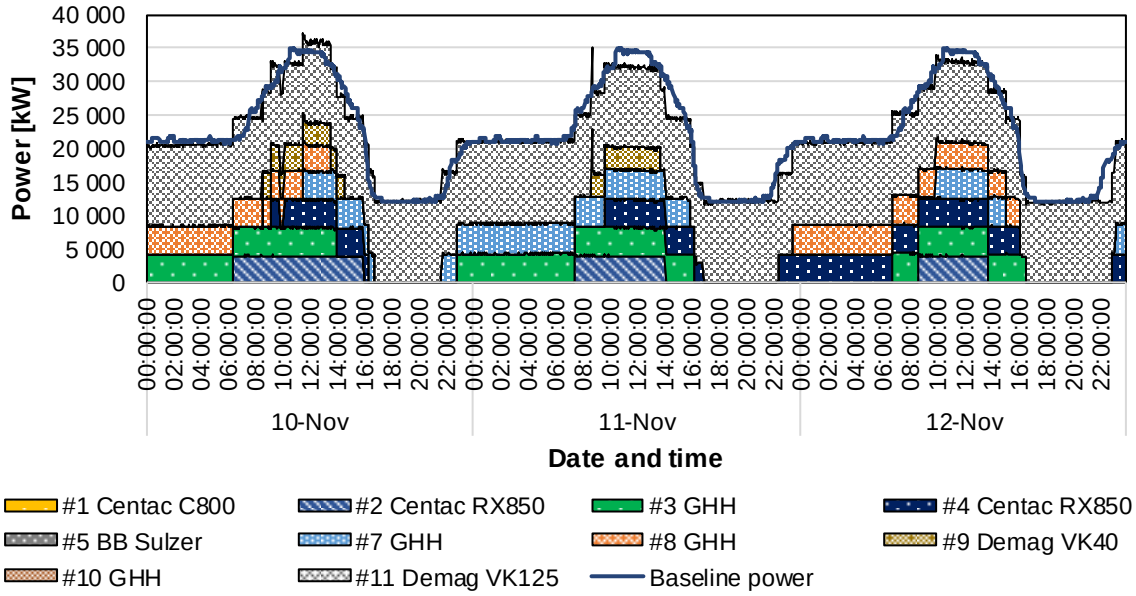


**Figure 65:** Real-time validation test compressor power consumption

Figure 65 shows the actual compressors that were active during the testing days. The compressor operation was similar outside of the testing period from 18:00 to 06:00. Therefore, the test was run for the period of 06:00 to 18:00. Between the three days, similar results are observed with compressors being started earlier than baseline power consumption from 06:00. Power consumption followed the baseline profile to the peak consumption, which was lower than the baseline profile. This is due to the specific compressor selection combination being more efficient than the average operation. This indicates that the compressed air network control solution succeeded in reducing power consumption. It is noted that the peak power consumption on the first day of testing did exceed the baseline, although the average power consumed during the peak consumption period was only 0.72% higher compared to the average baseline consumption.

From Figure 65, the compressed air network control solution tended to suggest stopping a compressor earlier compared to the baseline. This indicates that a possible energy saving (in the form of electricity costs) could be achieved by switching off compressors earlier compared to operations where the control room operators are not assisted by the compressed air network control solution. To validate that the solution did succeed in improving the compressed air supply, the upstream pressure must be evaluated as well. The upstream consumer pressure is shown in Figure 66.

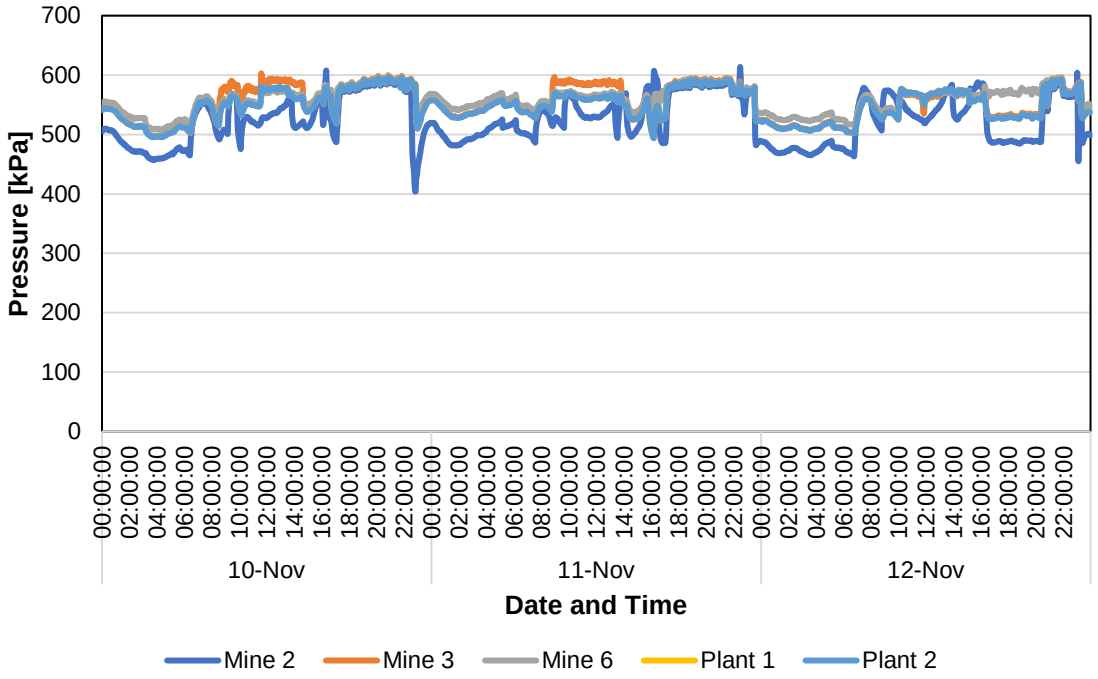


**Figure 66:** Real-time validation test consumer upstream pressure

From the consumer upstream pressure in Figure 66, the pressure remained stable and close to or above 500 kPa for the largest duration of time during the testing period. Pressures did reduce below the 500 kPa target pressure during non-testing times, although this is not of concern for the validation of the compressed air network control solution. The pressure was maintained above 500 kPa during the peak consumption periods (drilling), which is desired. There were some instances where the pressure reduced below 500 kPa during the test period, although not as severely as seen in the simulation validation. Table 11 shows the minimum upstream pressure for each of the consumers in the period of 07:00 to 18:00.

**Table 11:** Minimum upstream pressures during the testing period

| Test day | Mine 2 (kPa) | Mine 3 (kPa) | Mine 6 (kPa) | Plant 1 (kPa) | Plant 2 (kPa) |
|---|---|---|---|---|---|
| Day 1 | 487 | 504 | 515 | 503 | 503 |
| Day 2 | 485 | 496 | 513 | 494 | 494 |
| Day 3 | 486 | 503 | 519 | 503 | 502 |

Table 11 shows the minimum pressure from 07:00, although the official test started at 06:00. This is done to remove the false minimum created when operators did not follow the suggestions

mentioned previously. The lowest observed pressure was at Mine 2 on the second day of testing (485 kPa). From Figure 66, these minimum pressures occurred when pressure decreased suddenly and was not maintained. The compressed air network control solution reacted accordingly and the result thereof is observed in the average pressure for the testing period, as shown in Table 12.

**Table 12:** Average upstream pressures during the testing period

| Test day | Mine 2 (kPa) | Mine 3 (kPa) | Mine 6 (kPa) | Plant 1 (kPa) | Plant 2 (kPa) |
|---|---|---|---|---|---|
| Day 1 | 539 | 567 | 561 | 556 | 555 |
| Day 2 | 535 | 562 | 560 | 552 | 552 |
| Day 3 | 540 | 550 | 560 | 551 | 551 |

From Table 12, the average pressures maintained during the testing period was far above 500 kPa. To further validate that the compressed air network control solution succeeded in providing sufficient pressure to consumers, no complaints were received regarding low pressure from any of the consumers during testing periods. From these results, the compressed air pressure supply was sufficient. Improvement in compressor selection and sufficient supply of compressed air to consumers therefore validate improvement in compressed air supply control. The extent of electricity cost savings is calculated in the following section.

### 3.4.3 Electricity cost savings

To quantify the improvement in compressed air supply control, the electricity cost savings will be calculated. It is assumed that the upstream supply pressure of consumers was sufficient. The benefit can be calculated by quantifying the electricity cost saving. The electricity cost saving is first calculated for the example day where the simulation was used to validate that the compressed air network control solution was able to improve the compressed air supply. The period where the compressed air network control solution did not run any compressor was excluded from savings calculations, as this is not feasible. The calculated savings for the simulated profile equals a value of 14 900 kWh per day, which amounts to R 4.3 million per annum. The compressed air network control solution was updated to allow for higher pressure in the drilling period. This led to the stopping of compressors at a later stage, which is expected to reduce the savings potential. The actual savings achieved for the testing period will indicate what

the expected saving would be per annum. Figure 67 shows the average power consumption for the three testing days, as described in Section 3.4.2, compared to the calculated baseline power.

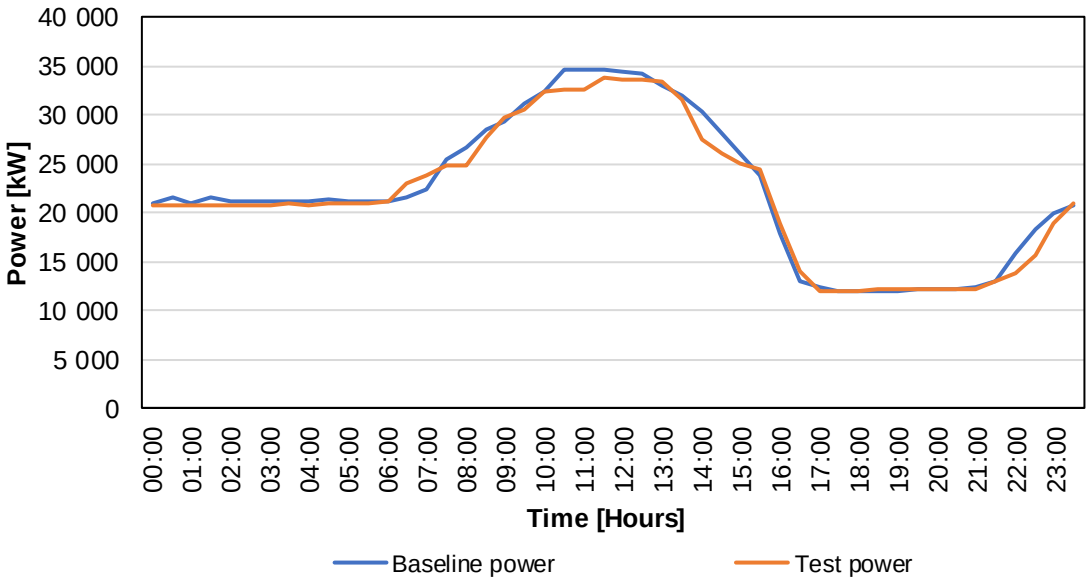


**Figure 67:** Real-time validation test power average power consumption

The power consumption between 06:00 and 18:00 was used to quantify the electricity cost savings. This cost-saving could thus be greater if the test were to run from 00:00–24:00, as there is additional potential for improving compressor selection timing and compressor combinations. The calculated average daily electricity cost saving for the three test days was 5 612 kWh, which amounts to R 5 750 per day. When extrapolating this value and accounting for winter electricity tariffs, it equals a potential electricity cost saving of R 1.6 million per annum. This cost saving validates that this solution improved the supply efficiency of the mining complex, thus solving the need for the study as described in Section 1.6.3.

The actual implemented test yielded a lower cost saving compared to the simulation validation. This is mainly due to the updates implemented on the compressed air network control solution to provide higher pressure during the peak consumption period. The fact that cost savings were achieved whilst providing sufficient pressure to the compressed air network validates that this solution can improve the compressed air network supply.

### 3.4.4 Discussion of validation findings

From the simulation results, a lower pressure was supplied to the compressed air network when comparing the suggested selection to the operator selection during the peak consumption period (as seen in Figure 61). This does not indicate an improvement in supply pressure, although it was

accompanied by lower power consumption. The compressed air network control solution was also updated to provide higher pressure during this period, as was achieved in the actual test. From Figure 61, the compressed air network control solution reacted immediately in the periods from 15:30 to 17:30 and 22:00 to 23:30 to avoid pressure from reducing below 500 kPa. This indicates an improvement in supply pressure and validates that the compressed air network control solution will be consistent in control operation. Operators allowed pressure to reduce below 500 kPa, this was not the case with the suggested combinations. The compressed air network control solution is programmed and operates using mathematics; thus, it will operate consistently and keep pressure above the desired target. This observed behaviour, therefore, validates that the solution improved compressed air supply control during the simulated test.

During the implemented test, it was not possible to compare the pressure provided by the operators to the expected results from the compressed air network control solution, as the operators were following the platform. During the implemented test, however, no complaints were received from consumers. It is further noted that there was only one instance where an operator started a compressor without the suggestion of the compressed air network control solution. This instance was done due to preference from the operator, although there was no need or issue with regards to the desired supply pressure. From the successful implementation and test results, it can thus be stated that supply operation delivered sufficient pressure. Since operators could see the platform, it is difficult to predict how they would have reacted unassisted. It is therefore difficult to compare and quantify the pressure benefit from the assistance provided by the compressed air network control solution.

It is thus concluded that pressure supply was sufficient and compared to the supply pressure of unassisted operations. When considering the energy cost saving achieved, it can be concluded that there was an improvement in supply control. From Section 3.4 it is validated that the research problem was addressed. This, therefore, also verifies that research objective 4 was addressed.

Throughout the implementation process, some shortcomings and challenges were evident. Issues that hindered the successful implementation, verification, or validation of the solution were addressed. This section however lists additional recommendations to address some shortcomings, which could improve the implemented solution.

- In Section 3.3.3, it is discussed how data is aggregated from two-minute intervals to 10-minute intervals. This step is performed to correctly format data for the implemented ANN. This data is, however, used for the GUI, discussed in Section 3.3.5, which leads to an issue where compressor combination changes only appear after at least five minutes have

passed. The display is set up to round the value for compressor status, where 1 is on and 0 is off (unload operation of a compressor overwrites the “on-off” status when active). A change in the status of a compressor is thus only displayed after a time of at least five minutes, as a result of data aggregation. It is recommended that the GUI evaluates the data in a two-minute interval to mitigate this behaviour. Data used for prediction purposes will remain the same due to the design specifications of the ANN.

- Start and stop trigger filters can be added to prevent unnecessary triggers directly after a compressor selection change has been implemented. A filter that prevents a trigger for 20 minutes is suggested to allow the network to stabilise before revaluation of triggers.
- Start and stop triggers can be improved by characterising compressors manually to potentially improve the timing of triggers.
- The GUI can be updated to improve elements such as layout, parameter visibility, and selected colours.
- Update the EMS to monitor compressor availability, if possible, to avoid suggestions where compressors are not available.
- Improve accuracy of the ANN by retraining with additional data sets or periodically (for example with changes in seasons).
- Implement real-time outlier detection to remove spikes or missing data in real time. This could potentially improve the real-time accuracy of predictions.
- The compressor suggestion methodology could be altered by determining compressor priority based on other characteristics instead of power. This method could be applied to test other possibilities, for example, priority based on reliability or total running hours. However, this study focused on improved compressed air network control to achieve energy cost savings.

These recommendations could be applied to potentially improve the implemented compressed air network control solution, although did not hinder successful implementation, verification, or validation. The implementation of this solution addressed the shortcomings of existing software-based strategies that were discussed in Section 1.6.2. This is significant and relevant to the mining industry, especially in terms of energy-saving strategies. This solution proved to be a viable option to implement at a South African mining complex to achieve energy savings.

This is significant as it has been shown from the literature discussed in Chapter 1 that the reduction in costs could improve the profitability of mines. From the summary of the literature in Table 2, it was seen that there is a lack of studies that addressed the use of AI and machine learning in the mining industry. This study proved the feasibility of applying technology such as

AI and machine learning to improve operations and efficiency of mining systems as was suggested by Booysen [17] and Hyder et al [66]. Hasan et al. [94] tested the use of AI or machine learning classifiers in the form of ensemble models (as discussed in Section 1.5.3) for the prediction of underground dam levels on a South African deep gold mine. Hasan et al. tested five different ensemble methods to reach a classification accuracy of 89% and concluded that the results indicated that AI could potentially be used to monitor and control mine de-watering systems. Hasan et al. concluded that similar investigations could be applied to other mining aspects such as compressed air networks. This conclusion further highlights the relevance of this study to the existing literature and the mining industry. The results of implementing the methodology discussed in Chapter 2 at a case study mining complex are concluded in Section 3.5.

## 3.5 Conclusion

In this chapter, the results of implementing the methodology developed in Chapter 2 on a case study platinum mining complex are discussed. The goal of the chapter was to implement the methodology to address each of the specified research objectives and the research problem. The selected case study featured a large compressed air network consisting of 11 compressors, eight mine shafts, and two plants.

The relevant background of the case study was discussed in Section 3.1; this included the setup of an EMS to monitor and log data. This was done through the application of the method discussed in Section 2.2, which addressed research objective 1. Insufficient data was available to implement a DCS controller. A simulation model was calibrated and verified to be accurate with MAPEs of 6.24% for compressor power, 2.84% for average surface shaft pressure, and 3.96% for total consumer compressed airflow. This simulation tool was used as part of the validation process.

Next, the development of an ANN was discussed for the case study compressed air network. This ANN was developed by applying the method discussed in Section 2.3. The boundaries of the model were set to predict only surface parameters, like some studies reviewed in the literature. Data was gathered from the data stored by the implemented EMS. Unreliable data features were removed following the data inspection process.

From the available features, the compressor running status, compressor load status, and consumer compressed air consumption were chosen as inputs to develop the ANN. Consumer upstream pressure was the selected output parameter. These features were selected based on data quality, reliability, and known relevance to the compressed air network. The simplicity of

altering inputs for the prediction of pressure in different scenarios was also considered as a reason for the selected input features.

Data treatment was performed according to the method, after which the model development process commenced. Hyperparameters were selected and altered through trial-and-error during the development process. The final hyperparameters were listed in Section 2.3.6. From the monitored accuracy and bias metrics, the model showed improvement in accuracy throughout the training. The CV(RMSE) values were determined to be 6.085 and 6.784, for the training and validations sets, respectively. This indicates a low level of variability between the actual and predicted values, from which it is concluded that there is a low level of uncertainty in the model. From the NMBE it was found that the model had a slight positive bias. The model would therefore tend to predict a value higher than actual, rather than lower. This bias was, however, small with a NMBE with a value of 1.238 and 1.278 for the training and validation sets, respectively.

A validation data set was used to validate the accuracy of the model. This data set included data that was not part of the training data. The MAPE for the predicted features were calculated to be 4.65% (Mine 2), 4.08% (Mine 3) and 3.88% (Mine 6). These values are below the desired 10%, which deemed the model accurate. The trained ANN was accurate and proved that it was feasible to apply an ANN for the prediction of parameters in a compressed air network. Through these results achieved in Section 3.2, research objective 2 was verified. This also validated that the first part of the research problem had been addressed.

Section 3.3 discussed the development and implementation of a compressed air network control solution by addressing each of the specifications set out in the methodology in Section 2.4. From the results in Section 3.3.2, the start and stop triggers were functioning in real time and the compressed air network control solution was updating as designed. Specification 1 of the solution was addressed, thereby verifying the real-time monitoring specification.

In Section 3.3.3, the results of real-time flow scaling and prediction of pressure were discussed. The MAPE of predictions for the selected day were 3.88% (Mine 2), 3.02% (Mine 3) and 3.05% (Mine 6), which indicated that the trained ANN model predicted pressures accurately in real time. These results verified the second speciation of the solution.

The third specification of the compressed air network control solution was verified in Section 3.3.4. The solution was able to suggest compressor combinations that could improve the compressed air supply in real time. Some issues were noted from the results, where the compressed air network control solution suggested switching off all compressors. This was, however, addressed before the real-time validation test in Section 3.4 was performed. The display and data storage

capabilities of the compressed air network control solution were discussed in Section 3.3.5. This verified that all the specifications as set out in the methodology in Section 2.4 were met. From Section 3.3, it is therefore verified that research objective 3 was addressed.

In Section 3.4.2, the verified simulation model was used as part of the validation that the implemented compressed air network control solution could improve compressed air network supply control. Suggestions from the implemented solution were tested in the simulation. Simulation results indicated that the compressed air network control solution was able to improve the compressed air supply for 75% of the day. The compressed air network control solution was updated because of issues noted during this validation test. Apart from the issues noted, less energy was required while keeping the pressure above the target set-point pressure or improving compared to actual operations.

The result of a real-time validation test is shown in Section 3.4.2. The test was performed over three days during the periods of 06:00–18:00 when most compressor selection changes took place. Compressor suggestions were followed, although an issue was observed where compressors were unavailable to start. The pressure was sufficient during the test, with no complaints received from any consumers. Not only was operation maintained by following the suggestions, but energy consumption was also reduced. This validates that the solution improved compressed air supply control.

From the simulation validation test, a potential electricity cost saving of R4.3 million per annum could be realised. Updates were performed to the solution to address issues and increase the target pressure. The implemented real-time test resulted in an achieved saving of R 5 750 per day, which equates to approximately R 1.6 million per annum. This saving was achieved for the period of 06:00–18:00, indicating that the potential savings could be higher. The improvement in energy consumption, while maintaining pressure supply, validates that this compressed air network control solution was able to improve compressed air supply control. Through this validation, it is concluded that the applied methodology addressed the research problem. This also verifies that research objective 4 was met.

Chapter 3, therefore, verified that all research objectives were met. From the results discussed in Chapter 3, it is confirmed that the research problem was addressed. This validates that the methodology, as discussed in Chapter 2, was successfully implemented to address the identified research problem. Some shortcomings and recommendations to improve the implemented solution were also discussed. Chapter 3 concluded by reiterating and highlighting the relevance of the study results to literature and the mining industry.

# CHAPTER 4 CONCLUSION

## 4.1 Summary

Mining companies in South Africa are under financial strain and there have been continuous efforts to remain profitable. One way in which the profit margin could be increased is to reduce input costs associated with mining operations. It has been shown that compressed air systems are one of the most expensive utilities in the underground mining environment.

In Chapter 1, several methods were discussed to improve compressed air network efficiency, which included strategies such as improved compressor supply control. In the literature, it was found that most mining complexes in South Africa has instrumentation in place that enables automatic control of individual compressors. This dissertation focused on compressed air network control rather than compressor control. To improve compressed air network control, software-based solutions were investigated. The two main software-based solutions that were considered were the DCS controller and simulation software.

The DCS controller can dynamically control the compressed air network supply. This controller was discussed in detail with the core capabilities including the dynamic prioritisation of compressors, dynamic calculation of compressor set-points, and automatically starting and stopping compressors. Several studies revealed that either a lack of available instrumentation or inaccurate instrumentation delayed or hindered the implementation of this controller. Another challenge identified was the complexity of accurately characterising compressed air networks.

In Chapter 1, it was found that simulations have been used in the process of implementing energy cost saving projects on compressed air networks in the mining environment. In several studies, this tool was specifically used to determine the feasibility of projects and to quantify the possible savings that could be achieved from these projects. To create and use simulations, however, expert knowledge is required. Due to the complexity of compressed air networks and the number of different and accurate measurements required, it can be challenging to develop such models. AI or machine learning was identified as a potential field of study which could address the identified challenges.

Prediction models can be classified into three types, namely white box, black box, and grey box models. The DCS controller and simulation software described form part of the white box group, which are based on fundamental principles and physical relationships between parameters. Some disadvantages of these models include that they can be expensive, less accurate than other models, and require expertise to set up. Black box models use statistical learning from historical data to predict parameters through the process of regression. These models include machine learning models. Grey box models use a combination of physical simulations and regression to determine parameters in a system. The advantages and disadvantages of each type of model were discussed and, owing to the potential of black-box models, statistical regression models were further researched.

The effect of changing a set of independent variables on dependant variables can be approximated using a technique called statistical regression. There are four types of SRMs namely LR, non-LR, machine learning, and hybrid and ensemble models. Different machine learning models were discussed in Section 1.5.3. Models such as ANNs have been implemented for several applications due to their ability to account for non-linear dependencies between multiple independent variables.

Based on the literature reviewed, there was no specific model which outperformed other models in every application. Some studies did, however, highlight the potential of implementing an ANN for real-time applications. Based on the reviewed literature, an ANN was selected for the investigations in this study.

From the background and literature reviewed in Chapter 1, a research problem was identified.

> There is a need to investigate the feasibility of applying a machine learning model for the prediction of parameters in a mining compressed air network. Furthermore, there is a need to apply a machine learning model for real-time prediction to improve compressed air network

To address the identified problem and shortcomings of existing research, the following objectives were specified:

- **Research objective 1**: Setup an energy management system (EMS) for real-time monitoring and data logging of compressed air network parameters;
- **Research objective 2**: Develop and determine the feasibility of applying an ANN for the prediction of parameters in a compressed air network;

- **Research objective 3**: Develop and implement an ANN driven compressed air network control solution to assist control room operators with compressor scheduling and selection; and
- **Research objective 4**: Validate that the proposed solution addressed the research problem.

Chapter 2 discussed the methodology that was developed to address each of the research objectives. The method of setting up real-time monitoring and data logging (through an EMS) was derived from the literature regarding the implementation of the DCS controller. This first step was developed to address research objective 1.

Next, a method comprising common steps in the literature to develop a machine learning model was discussed. This method included the project scope, data gathering, feature selection, data treatment, model development, and model implementation. CV(RMSE) and NMBE were used as indicators of model accuracy and bias during the development phase. It was, however, decided to use MAPE as the metric to verify whether a model is accurate. Based on the literature, a MAPE of 10% was selected to be the maximum allowed error for a model to be deemed accurate. An accurate model would address research objective 2, as well as the first part of the research problem.

The third research objective was addressed by applying the method discussed in Section 2.4. To verify that this objective was reached, design specifications were determined based on existing strategies and literature to address shortcomings. The specifications included real-time monitoring, prediction through machine learning, a compressor suggestion methodology, and display and data storage. After the successful implementation of these specifications, a compressed air network control solution was developed and could be implemented. This solution relied on the developed machine learning model to verify whether suggested solutions would meet pressure set-point targets. This could mitigate the shortcoming of the availability of instrumentation and the complexity of compressed air networks. This solution could also assist control room operators to improve compressed air network control. Objective 3 would thus be addressed once all specifications were implemented.

The last step of the methodology was to verify that all the main elements had been implemented to address the research objectives. After verification, a soft implementation could be used to validate the compressed air network control solution by using simulation software. After this, a real-time test could be performed to validate that the methodology was able to address the research problem, which would verify that the last research objective had been addressed.

The proposed methodology was implemented at an underground platinum mining complex. The implementation and results thereof were discussed in Chapter 3. The mining complex has a compressed air network consisting of 11 compressors, eight mine shafts and two plants. Different process parameters were available for the compressors and consumers, but they were found to be insufficient to implement the DCS controller. The complexity of the large compressed air network added to the challenge of implementing existing software-based solutions.

An EMS was set up using the method discussed in Section 2.2 to monitor and capture data in real-time, thereby verifying that research objective 1 had been addressed. A calibrated simulation model was evaluated, which would be used in the validation step. MAPEs were calculated for total compressor power (6.24%), average surface shaft pressure (2.84%), and total consumer compressed airflow (3.96%). Based on the calculated errors, it was verified that the simulation model was accurate.

The steps described in Section 2.3 were followed to develop an ANN for the prediction of parameters on the case study compressed air network. Data was gathered and examples were added of data inspection that was performed using the data visualisation techniques described in the methodology. During the feature selection phase, compressor running status, compressor load status, and consumer compressed air consumption were selected as inputs to the ANN. Consumer upstream pressures were the outputs of the ANN.

Data treatment was performed through the process described in Section 2.3.5. Treated data was then used to train the ANN model. The final hyperparameters of the model were listed in Section 3.2.6. The RMSE metric was tracked to ensure that the model accuracy was improving with each iteration. The CV(RMSE) values were determined to be 6.085 and 6.784 for the training and validations sets, respectively. This indicated a low level of variability between the actual and predicted values, which concluded that there was a low level of uncertainty in the model. From the NMBE it was found that the model had a slight positive bias. The model would therefore tend to predict a value higher than actual, rather than lower. This bias was, however, small with a NMBE with a value of 1.238 and 1.278 for the training and validation sets, respectively.

The MAPEs for the predicted features in the validation set were calculated to be 4.65% (Mine 2), 4.08% (Mine 3) and 3.88% (Mine 6) respectively. It was concluded that the ANN was accurate. This, therefore, verified that it is feasible to apply an ANN for the prediction of parameters in a compressed air network. Section 3.2 thus addressed research objective 2 and the first part of the research problem.

The results in Section 3.3 addressed the development and implementation of a compressed air network control solution. The compressed air network control solution was able to predict pressure in the compressed air network in real-time utilising the ANN. Some issues were highlighted with regards to compressor suggestion, although they were addressed. Results from the developed GUI were inserted, which functioned in real time. All the results that were discussed and displayed were stored on the server in a .csv format. It was verified that all compressed air network control solution specifications were met, thereby addressing the third research objective.

In Section 3.4, two methods were discussed to validate that the solution was able to improve compressed air supply control. The first method included the use of the verified simulation model to evaluate the effect of the suggested compressor combinations against actual operation.

A day that represented normal operating conditions was chosen for the simulation validation. The actual results of this day were inserted into the calibrated and verified simulation to create baseline simulation results. The suggested compressor combinations obtained from the implemented compressed air network control solution was then inserted into the simulation. These results were compared and reviewed in detail. From the results, some issues were noted, which were already noted during the verification phase of the implementation. These issues were addressed before the real-time validation test was performed.

The simulated validation test indicated that a potential electricity cost saving of R 4.3 million per annum was possible while maintaining the required pressure, and there were even instances where pressure supply was improved. It should however be noted that the compressed air network control solution was updated to provide a higher pressure to consumers, which led to a reduction in potential saving.

The real-time validation test was performed by allowing control room operators to see the display of the compressed air network control solution and instructing them to follow the suggestions. The test was performed over three days with guidelines as set out and agreed by the mining complex. During the test, it was noted that operators followed the suggested compressor combinations where possible. Some compressors could not be started due to maintenance, and in these cases, the operator started another compressor based on their preference.

A baseline for power consumption was constructed by using data of all production days in the two weeks immediately before the test. When comparing the average power consumption of the three test days to the baseline, it was evident that there was an improvement in power consumption. An average daily electricity cost saving of R 5 750 was calculated. When extrapolating this saving

and considering the Eskom tariff structure, a potential electricity cost saving of R 1.6 million could be achieved.

The results indicated that less power was consumed while upstream pressure was maintained without complaints. The results, therefore, validated that the implemented solution was able to improve compressed air supply control. This verified that research objective 4 was met by validating that the implemented solution improved compressed air network control. After the implementation, some shortcomings and addental recommendations were discussed which could be implemented to improve the solution.

In Chapter 3, the results of implementing the developed methodology were discussed. Each of the research objectives was addressed, thereby concluding the verification of the study. It was validated that it is feasible to apply a machine learning model for the prediction of parameters in a mining compressed air network. It was further also validated that a machine learning model could be applied for real-time prediction to improve compressed air network control. Chapter 3 concluded by reiterating and highlighting the relevance of the study results to literature and the mining industry.

## 4.2 Recommendations for future work

This study aimed to evaluate the feasibility of applying a machine learning model for the prediction of parameters in a mining compressed air network. Furthermore, a need was identified to apply a machine learning model for real-time prediction to improve compressed air network control. It was verified that the research objectives had been met, and it was validated that the research problem had been addressed. It can therefore be concluded that the study successfully addressed the identified research problem. Some possible shortcomings and improvements were identified, although not investigated, as they did not form part of the research objectives. It is recommended that these possible areas of improvement are addressed in future studies.

This methodology and developed solution have only been implemented on the mining complex used as a case study discussed in Chapter 3. From the literature and derived research problem, it is expected that other mining complexes face similar challenges. It is therefore recommended that this methodology be applied to other mining complexes with similar challenges. This could potentially benefit these mining complexes and add valuable research to a relatively unexplored application of machine learning models.

A potential future study could investigate the effects of feature selection, specifically in the context of applying a machine learning model on a mining compressed air network. This could potentially provide valuable information which could impact the accuracy of a model applied in this context.

The focus of this study was on the compressed air network. From Chapter 1, there are other energy-consuming services, such as de-watering and ventilation, where this technology could potentially be applied. A future study could investigate control systems of these services and whether similar implementations could provide a similar benefit to the application on a compressed air network.

From the literature in Chapter 1, the ANN model was chosen to be developed. It was, however, noted that several machine learning model types exist. It is recommended that a future study evaluates different machine learning models for the same application on a mining compressed air network. This could be beneficial and improve the suggestion provided by the developed compressed air network control solution, which could improve the results obtained in this study.

The developed compressed air network control solution provided compressor combination suggestions in real time. A potential feature that could be investigated in future studies is to update the GUI to include a live simulation function. This function could potentially allow control room operators to simulate compressor selection changes in real time to evaluate the effect on predicted pressures.

Machine learning models were specifically identified as a potential field of study to address the lack of available and accurate instrumentation on mining compressed air networks. For this application, it was proven to be successful. A real-time solution was implemented on a case study mining complex where insufficient instrumentation was available for a DCS controller.

The disadvantage of a machine learning model, however, is that historical data is required to perform model training. If a change is made to the compressed air network, for instance, a new compressor is installed. New data will be required to retrain the model, potentially rendering the solution inaccurate until sufficient historical data has been collected. In this regard, white-box models can be updated without much historical data. For this reason, it is recommended that a study be performed to compare implementations of white-box models (such as the DCS controller), black-box models (such as machine learning models), and grey-box (or hybrid) models to address the prediction of parameters in a mining compressed air network.

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# APPENDIX A – DCS CONTROLLER THERMODYNAMIC EQUATIONS

The formulas below form part of the thermodynamic equations applied by the DCS controller, as indicated by several studies from the literature [25]–[27], [46], [51], [54].

**Fluid density (ρ)**

The density of a fluid is a function of temperature and pressure and is expressed as kilograms per cubic meter. Fluid density can be calculated as follows:

$$\rho = \frac{P}{RT} \tag{A.1}$$

$$\rho : Fluid\ density\ [kg/m^3]$$

$$P : Pressure\ [kPa]$$

$$R : Gas\ constant\ [J.K^{-1}kg^{-1}]$$

$$T : Temperature\ [K]$$

**Reynolds number**

To determine whether fluid flow is turbulent or laminar, the Reynolds number is calculated. The Reynolds number is calculated with the following formula:

$$Re = \frac{\rho v D}{\mu} \tag{A.2}$$

$$Re : Reynolds\ number$$

$$\rho : Fluid\ density\ [kg/m^3]$$

$$v : Fluid\ velocity\ [m/s]$$

$$D : Pipe\ diameter\ [m]$$

$$\mu : Viscosity\ [kg/s.m]$$

**Pressure loss due to friction**

Pressure loss in a pipe due to friction can be determined using the friction factor in the equation as follows:

$$\Delta P_{friction} = f \frac{L}{D} \frac{\rho v^2}{2} \tag{A.3}$$

$$P_{friction} : Pressure\ loss\ due\ to\ friction\ [kPa]$$

$$f : Darcy\ friction\ factor$$

$$L : Length\ of\ pipe\ [m]$$

$$D : Diameter\ of\ pipe$$

$$\rho : Fluid\ density\ [kg/m^3]$$

Frictional losses in a pipe can be described by the Darcy friction factor, which is a dimensionless number. The Swamee-Jain approximation can be used to determine the Darcy friction factor:

$$f = \frac{0.25}{\left[\log\left(\frac{\epsilon}{3.7D} + \frac{5.74}{Re^{0.9}}\right)\right]^2} \tag{A.4}$$

$$f : Darcy\ friction\ factor$$

$$\epsilon : Pipe\ roughness\ [\mu m]$$

$$D : Pipe\ diameter\ [m]$$

$$Re : Reynolds\ number$$

$$v : Fluid\ velocity\ [m/s]$$

**Pressure loss due to geometry**

Changes in pipe geometry influence pressure. Pressure differences due to changes in pipe geometry can be calculated as follows:

$$\Delta P_{geometry} = K_L \frac{\rho v^2}{2} \tag{A.5}$$

$$P_{geometry} : Pressure\ loss\ due\ to\ geometry\ [kPa]$$

$$K_L : Loss\ coefficient\ due\ to\ geometry$$

$$\rho : Fluid\ density\ [kg/m^3]$$

$$v : Fluid\ velocity\ [m/s]$$

According to Venter [54], it is impossible to accurately assign a loss coefficient to the mine's complex compressed air network. A loss factor is therefore determined once-off using historical system pressures and flows.

**Bernoulli's principle**

Bernoulli's principle states that a fluid's velocity increases simultaneously with a decrease in static pressure or in the fluid's potential energy. The equation is described as follows:

$$\frac{\rho v^2}{2} + \rho g z + P = constant \tag{A.6}$$

$$\rho : Fluid\ density\ [kg/m^3]$$

$$v : Fluid\ velocity\ [m/s]$$

$$g : Gravitational\ acceleration\ [m/s^2]$$

$$z : Height\ [m]$$

$$P : Pressure\ [kPa]$$

This equation can be applied between two points in a pipe as follows:

$$\frac{\rho_1 v_1^2}{2} + \rho_1 g_1 z_1 + P_1 = \frac{\rho_2 v_2^2}{2} + \rho_2 g_2 z_2 + P_2 \quad \text{(A.7)}$$

From the assumptions made by Venter, the following is true:

$$\rho_1 g_1 z_1 = \rho_2 g_2 z_2$$

Bernoulli's principle can thus be simplified:

$$\frac{\rho_1 v_1^2}{2} + P_1 = \frac{\rho_2 v_2^2}{2} + P_2 \quad \text{(A.8)}$$

When pressure losses ($P_{loss}$) are accounted for, Bernoulli's principle can be written as follows:

$$\frac{\rho_1 v_1^2}{2} + P_1 = \frac{\rho_2 v_2^2}{2} + P_2 + P_{loss} \quad \text{(A.9)}$$

# APPENDIX B – SIMULATION IMPLEMENTATION METHODOLOGY

**Step 1: Investigate the system** [23]

Understanding what is required to model the system and acquiring data is the first step in the process of investigation. Data can be acquired through resources such as data storage systems, instrumentation, and communication with relevant site personnel. Site layouts play an important part in understanding the system and identifying the different parameters that will be required for the simulation model.

A baseline should be selected that will be used to test scenarios against. This period of the baseline should represent the typical operation of the mine. A simulation model can be calibrated sufficiently using 24 hours of normal operation. High quality and accurate data are required to ensure an accurate representation of the actual system [115].

Operation schedules of the mining system need to be understood. Different operations have different demand requirements. The operating schedule can be used to test different scenarios and to improve the compressed air efficiency throughout the day.

Where data is not available or missing, alternative sources or methods should be investigated to obtain the data. Spot inspections, estimations, or measurements using portable instrumentation are examples of methods that data can be gathered where there is a lack of instrumentation or data [62].

**Step 2: Develop and verify the simulation model** [23]

Simulation boundaries should be set in the development phase of the model. The boundaries are a determining factor in the level of detail and accuracy that can be obtained by the simulation model. Factors such as available input data, accuracy targets and available time and resources should be considered when process boundaries are selected.

The period and step size of simulation data are important to ensure that the effect of a scenario is fully captured. Previous studies have shown that a 24-hour period is sufficient thanks to the predictable operational nature of a typical working day [13], [62]. Changes in the compressed air system may take place in seconds or minutes. Step size should not be too high, otherwise replication of system control could become problematic and simulation accuracy could be reduced. Component modelling is the next step in the development of the simulation.

This step might vary for different simulation software. Some components that need to be characterised or modelled to create an accurate simulation include the following:

- Compressors (dynamic operating curve);
- Air pipes and network;
- Consumer demand profiles; and
- Air supply and demand controllers [12], [23].

The accuracy of the simulation model should then be determined to ensure that the model can be used to predict actual results when scenarios are simulated. Mean absolute error (MAE), mean absolute percentage error (MAPE) and coefficient of determination are some effective methods that can be used to measure model accuracy. These accuracy metrics should be determined for all major simulation outputs to ensure that the simulation is accurate.

Periodic simulation, or updating the simulation model periodically, can be used to verify the accuracy of the simulation model and to identify discrepancies. In this way the simulation model is kept up to date with the latest changes on the mine whilst ensuring the accuracy does not deteriorate.

**Step 3: Implement and execute simulation scenarios** [23]

The output data of the verified simulation is now used as a baseline for all parameters to measure the effect of any intervention. A scenario can be simulated, such as changing the operating schedule of compressors, to see what the effect would be on the compressed air network.

The effect of scenarios can be quantified by comparing data obtained from the simulated scenario with the baseline simulation. This comparison is made by analysing the differences of a parameter between the outputs of the two simulations. Energy cost savings can be quantified by comparing power consumption. Improvements in service delivery such as pressure can be measured by evaluating the difference in pressure delivered for a specific period.

Feedback is an important part of the implementation of the simulation model. Different scenarios should therefore be evaluated using the simulation model. The benefits of each scenario should be quantified and prioritised. All results and recommendations should then be communicated to the relevant mine personnel in the form of a report. The process of implementing projects can now be started.

# APPENDIX C – ADDITIONAL MACHINE LEARNING MODEL DETAILS

In this dissertation, an overview of different machine learning models was provided. The overview only included necessary details as it was mentioned in Section 2.3.6 that the Keras[8] Python package in conjunction with Tensorflow[9] is applied to develop and implement an ANN. Although not required, it could be beneficial to have a deeper understanding of the model types. An ANN was the selected model, therefore more details are provided on this type of model.

The mathematical structure of an ANN was designed to resemble the behaviour of biological neural networks [28], [79]. The basic structure of an ANN was discussed in Section 1.5.3, however, additional schematics are provided in Figure 68 and Figure 69.

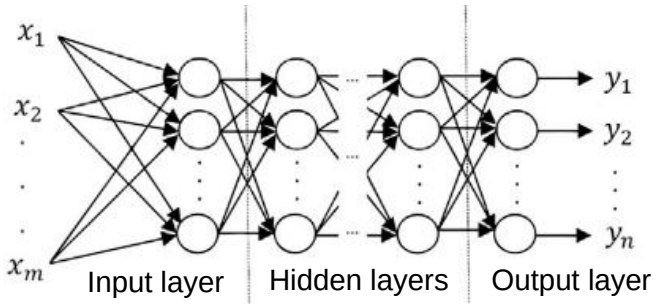


**Figure 68:** Schematic of an ANN [79]

Figure 68 shows the basic structure of one of the most popular types of ANNs, the multilayer neural network, also referred to as a multilayer perceptron [28], [68]. The different layers consist of interconnected neurons (process units). An example of a single process unit can be seen in Figure 69.

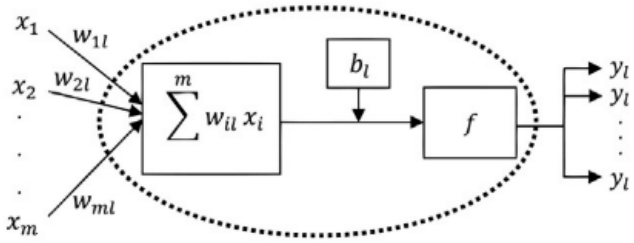


**Figure 69:** Schematic of a single process unit [79]

[8] https://keras.io/

[9] https://www.tensorflow.org/

In Figure 69 a processing unit, $l$, receives inputs, $x_{il}(i = 1,2, \dots, m)$, from other connected layers. These inputs, or signals, are multiplied with a weight, $w_{il}(i = 1,2, \dots, m)$, assigned to each connection from that input node. In the processing unit, two basic operations are performed to deliver an output, $y_l$. The first operation is the summation of the calculated input with a bias, $b_l$, which is specified for each processing unit, excluding input units [28], [68], [79]. Each node also has an activation function, $f$, assigned to it, which is responsible for the second operation in the unit. The process described is summarised with the following equation:

$$y_l = f\left(\sum_{i=1}^{m} w_{il} x_i + b_l\right) \tag{C.1}$$

Different activation functions are used with typical examples including hyperbolic tangent, logistic sigmoid, linear (or no activation) and rectified linear unit (ReLU) [68]. For this study, the ReLU function was applied. Compared to other activation functions, an advantage of ReLU includes the acceleration of convergence of the gradient descent algorithm [73]. The ReLU activation function can be expressed as follows:

$$\mathrm{f(x)} = \max\left[0, x\right] \tag{C.2}$$

From the formula, it can be seen that the application of this function will eliminate all negative input values. This and the linear non-saturating form of the formula form part of the advantage discussed above [73].

The result of the process unit output is then multiplied by the weight of the following connections, thus forming the input for the following layer. Each layer thus has its own set of weights and biases which can be adjusted to minimise the value of some error function [68]. The process of minimising this error is achieved through the application of some algorithm and a variant of a technique called backpropagation [68]. During the process, the algorithm adjusts the weights to decrease the calculated value of some error function through repeated steps (epochs) [68]. To avoid symmetry, weights are randomised at the initialisation of the training process [68].

# APPENDIX D – ADDITIONAL SIMULATION RESULTS

The simulation model that was used during the validation process is discussed in Section 3.1.3. The accuracy of the model was established, some additional results are however provided. Figure 70 shows a comparison of the simulated and actual surface shaft pressure for Mine 2.

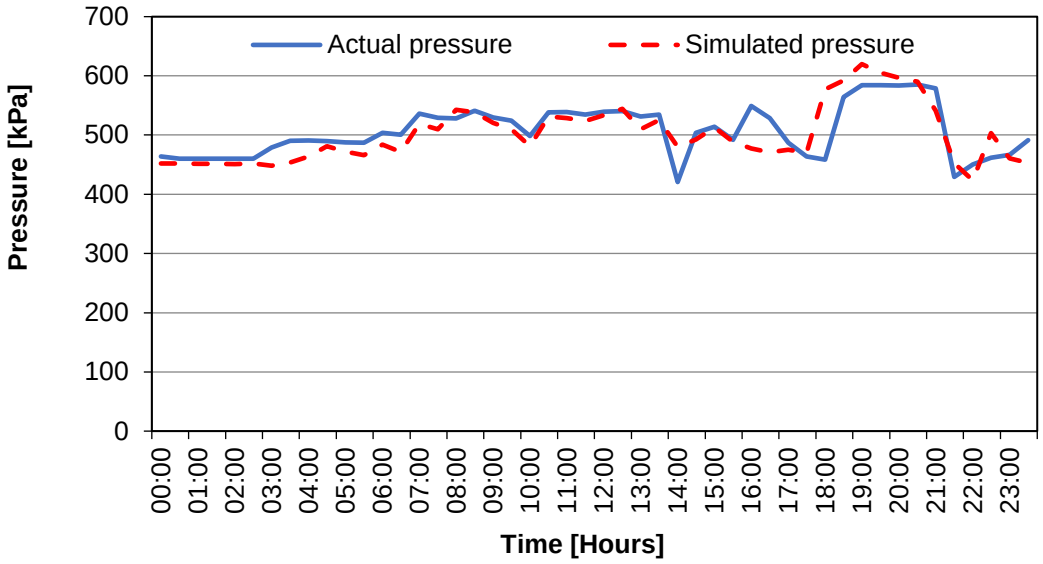


**Figure 70:** Mine 2 simulated vs. actual surface shaft pressure

From the simulated results for the surface shaft pressure of Mine 2, a MAPE of 4.28% was achieved. As discussed in Section 2.3.6, a MAPE of 10% will be regarded as accurate, therefore this value is well below the maximum allowed error. Figure 71 shows the simulated results of the compressed air flow consumption of Mine 2.

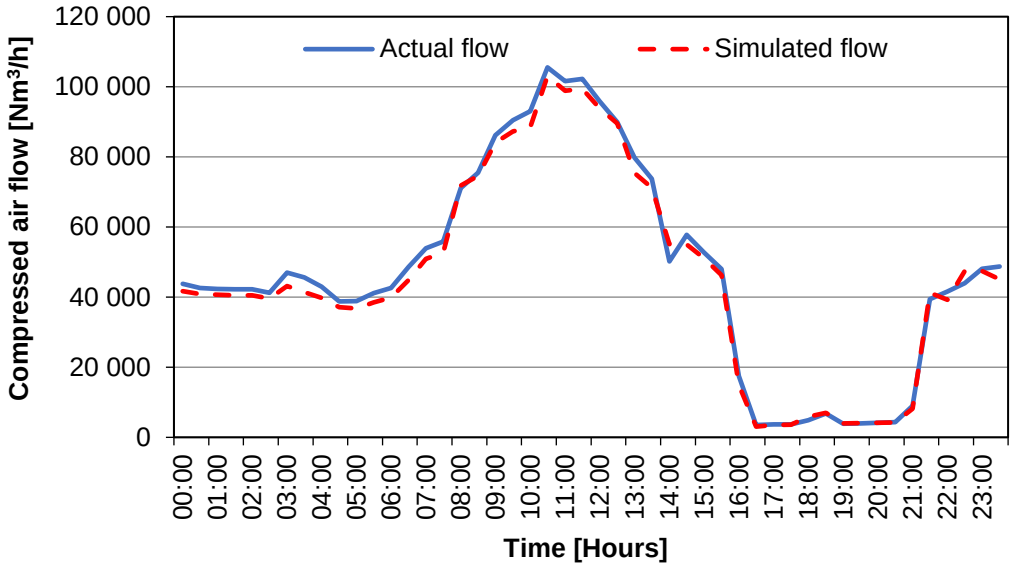


**Figure 71:** Mine 2 simulated vs. actual compressed air flow consumption

From Figure 71, the simulated flow profile for Mine 2 closely represents that actual flow. The calculated MAPE for this figure is 5.07%. Next, the simulated result for the surface shaft pressure of Mine 3 was evaluated.

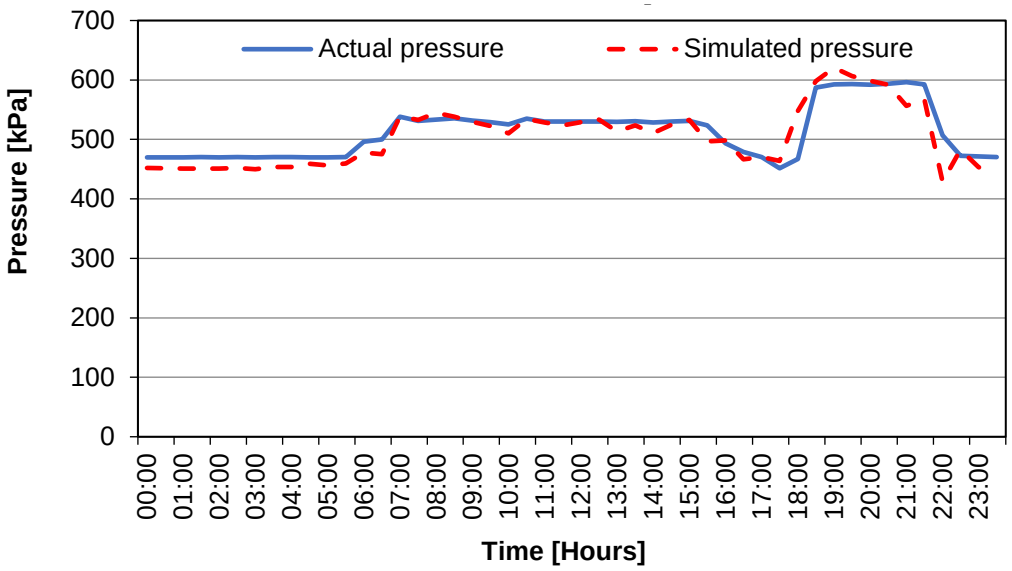


**Figure 72:** Mine 3 simulated vs. actual surface shaft pressure

From Figure 72, similar results are obtained from the surface shaft pressure of Mine 3, compared to Mine 2. A calculated MAPE of 3.03% was achieved, which complies with the desired level of accuracy. Figure 73 shows the result obtained for the simulated compressed air flow consumption of Mine 3.

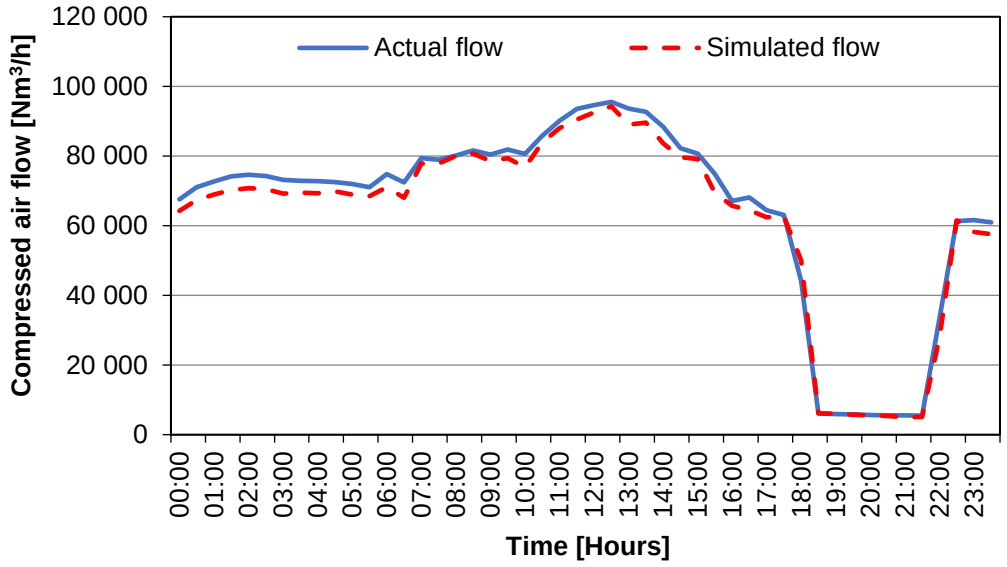


**Figure 73:** Mine 3 simulated vs. actual compressed air flow consumption

A MAPE of 4.07% was calculated for the results shown in Figure 73. The simulation was therefore able to accurately simulate the flow consumption of Mine 3. The results obtained for the simulation of parameters for Mine 6 are discussed next.

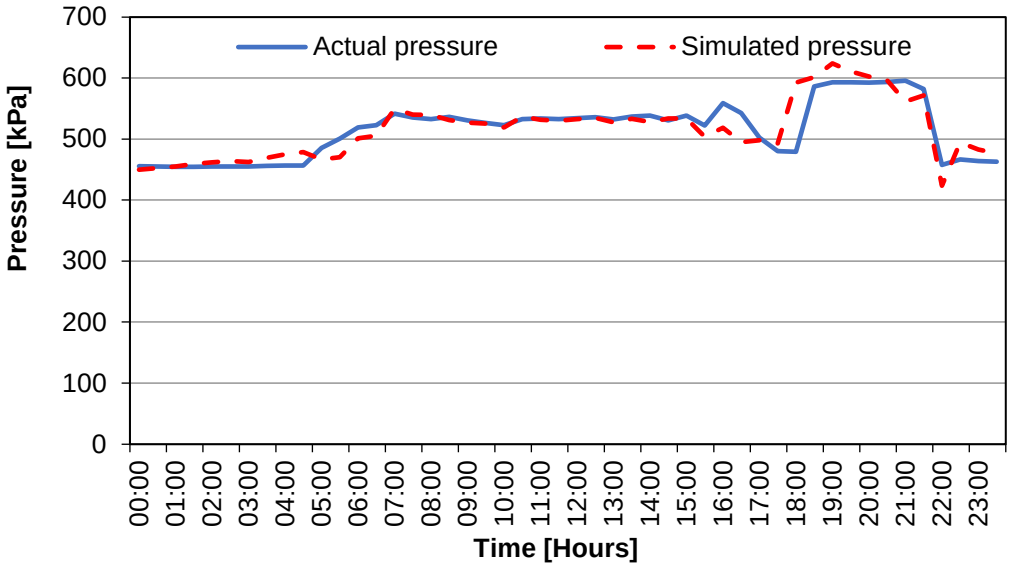


**Figure 74:** Mine 6 simulated vs. actual surface shaft pressure

From Figure 74, it can be seen that there is a small error between the simulated and actual values of the surface shaft pressure of Mine 6. This is supported by a calculated MAPE of 2.86%, which is the lowest MAPE that was achieved for the simulated results of the mines in the case study. Figure 75 shows the results obtained for the compressed air flow consumption of Mine 6.

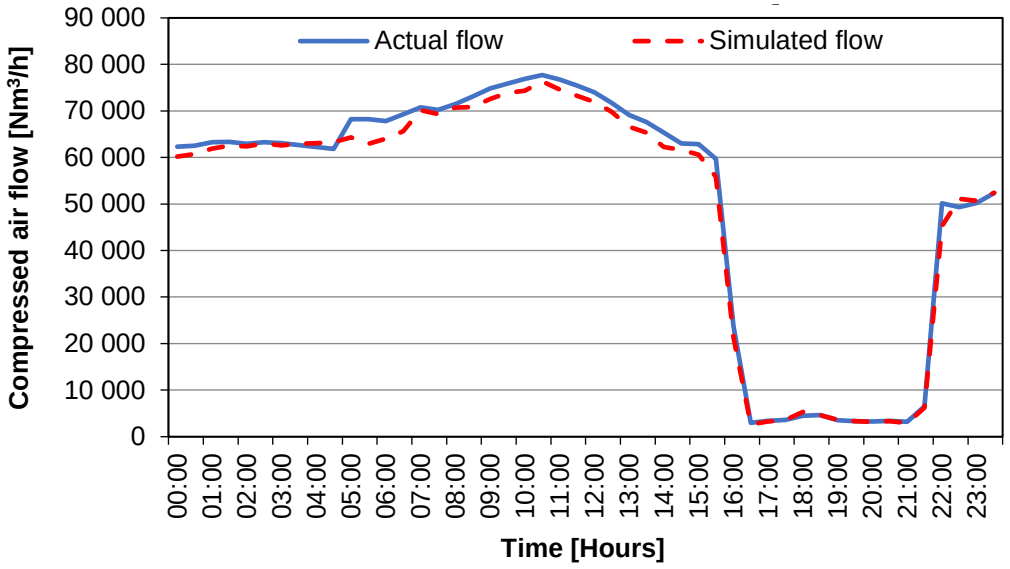


**Figure 75:** Mine 6 simulated vs. actual compressed air flow consumption

The MAPE achieved for the results shown in Figure 75 is 3.54%. This was the lowest calculated error for compressed air flow consumption of all the mines, similar to the results for the pressure of Mine 6. Lastly, the simulated results for Plant 2 are discussed.

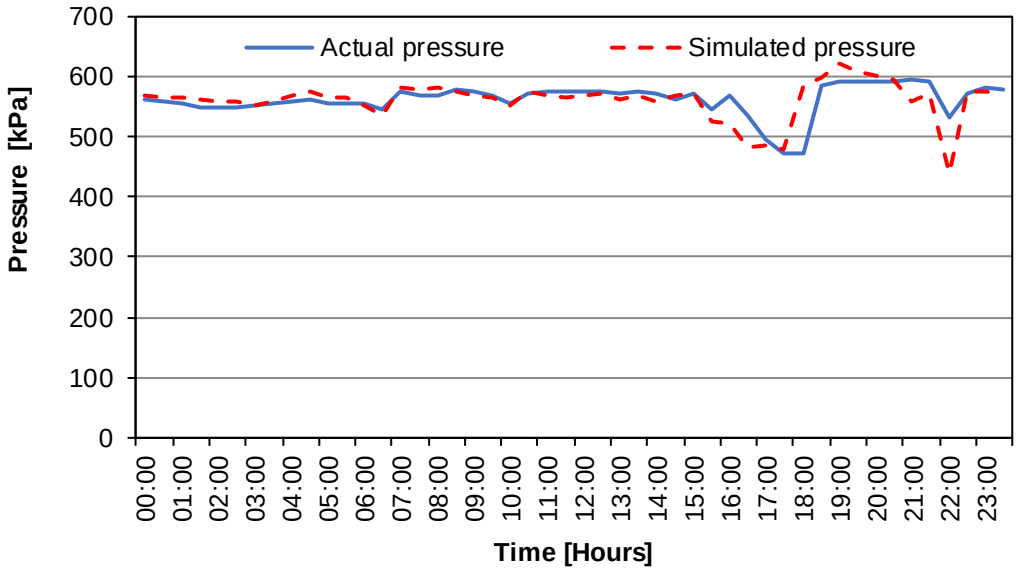


**Figure 76:** Plant 2 simulated vs. actual surface pressure

Simulated results for Plant 2 were within the specification to be deemed accurate. When comparing the simulated and actual pressure for Plant 2, as shown in Figure 76, a MAPE of 2.77% was achieved. A low level of error is also observed when evaluating the simulated compressed air flow against the actual flow, with a MAPE of 3.18%. The result of the compressed air flow consumption of Plant 2 is shown in Figure 77.

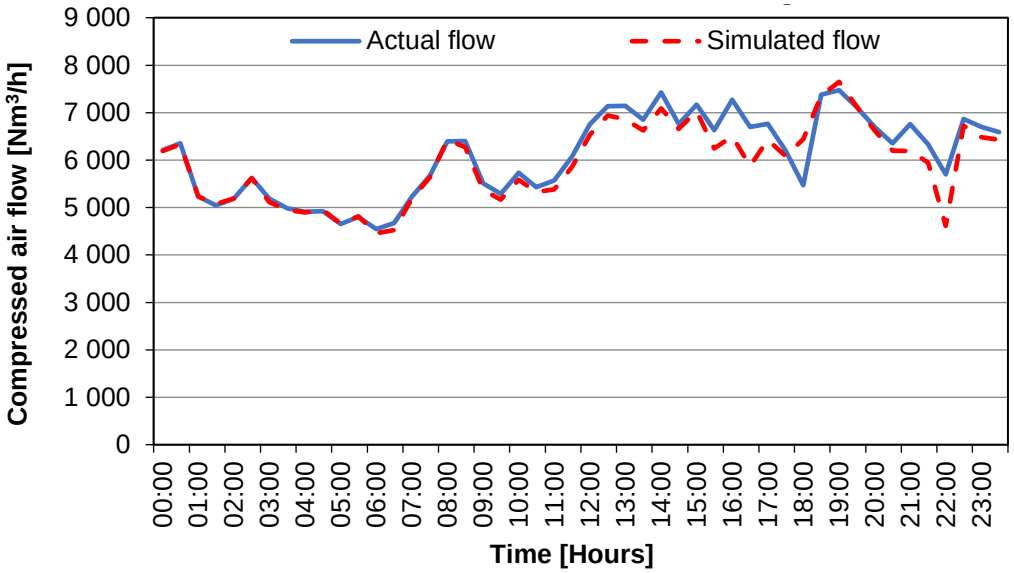


**Figure 77:** Plant 2 simulated vs. actual compressed air flow consumption

Each of the respective results discussed in this section had a calculated MAPE of below 6%. This is well below the desired standard of 10% that was specified in the study. The additional results provided in this section therefore supports the results in Section 3.1.3, where it was verified that the simulation model is accurate.