

Optimising mining refrigeration systems through artificial intelligence

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ABSTRACT

Title: Optimising mining refrigeration systems through artificial intelligence

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The deep-level mining industry needs to overcome large operating costs to remain profitable. One of the largest contributors to operating costs is a mine's refrigeration and ventilation system, which consumes up to 28% of a mine's total energy cost. As a result, reducing the operating cost of the refrigeration system will have a large impact on a mine's profitability.

Refrigeration optimisation is often done by applying static optimisation techniques. Although some optimisations use simulation to reduce operating costs, optimisations are not robust enough when subject to varying inlet temperatures, flows and demands. Other optimisations use efficient plant selection, but do not consider varying tariff periods, such as peak, standard and off-peak periods. This study attempts to address these shortcomings by considering varying tariff structures and using artificial intelligence (AI) to determine operating conditions.

The individual refrigeration plants were characterised using historical data to obtain realistic models for each plant as well as the entire system. AI optimisation techniques were used as a solution model and applied to the characteristic model to determine the optimal operating conditions. The use of AI allowed the solution model to be implemented in dynamically automated control refrigeration systems.

Manual implementation was done to validate the optimisation model as the infrastructure did not allow for automated implementation. The operation did not use the storage facilities in the system and most savings were the result of water storage utilisation during peak periods. Efficient plant selection further increased the savings, which resulted in an annual saving of R9.5 million due to the reduced energy consumption during peak tariff periods.

The optimisation model requires little maintenance. The system has been operational for more than two months with no need to maintain the models. Only models and varying system limitations need to be updated according to plant maintenance or downtime. Furthermore, the savings can be maintained by implementing an automated system. The automated system will prevent a loss in savings due to human error or lack of manual implementation by operators.

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ABBREVIATIONS

3-D	Three-dimensional
4-D	Four-dimensional
AI	Artificial Intelligence
BAC	Bulk Air Cooler
DIKW	Data-Information-Knowledge-Wisdom
FSP	First-stage Plant
KPI	Key Performance Indicator
MCU	Mobile Cooling Unit
PLC	Programmable Logic Controller
SCADA	Supervisory Control and Data Acquisition
SI	Système Internationale
SSP	Second-stage Plant
TOU	Time-of-use
VSD	Variable Speed Drive

CHAPTER 1 – INTRODUCTION

1.1 Background

The South African deep-level mining industry has been crippled by increasing electricity costs [1]. The expanding nature of mines results in larger operating costs. Furthermore, the year-on-year decrease in production seen in the industry requires that systems become more efficient [2]. Energy savings and optimisation are essential to maintain the profitability of mines.

Electricity costs are the second-largest cost incurred by a mine [3]. The largest energy consumers are the ventilation, refrigeration, compressed air and dewatering systems [3]. The vast and complex nature of the various systems leaves opportunity for optimisation through new techniques. With the progress into Industry 4.0, new optimisation techniques have been developed to optimise vast and complex systems faster and more accurately than before.

Although artificial intelligence (AI) has proven to be a useful optimisation tool, it has failed to be used in the South African deep-level mining industry. However, the ability of AI to characterise and solve a system through semi-empirical methods makes it ideal for the mining industry that tends to operate machinery or systems outside of the designed ideal conditions [4].

1.1.1 South African gold mining industry

South Africa produced 210 tonnes of gold in 2010, seating third in the world for gold production.¹ In 2018, the gold production had decreased year by year to only 130 tonnes of gold seating, thereby placing South Africa ninth in the world for gold production.¹ Figure 1 shows the steady decline in production for the gold industry [5].

¹ F. Els, "Top 20 gold producing countries," *Mining.com*, 9 Jul. 2019. [Online]. Available: <https://www.mining.com/featured-article/top-20-gold-producing-countries/> [Accessed: 01-Jun-2020].

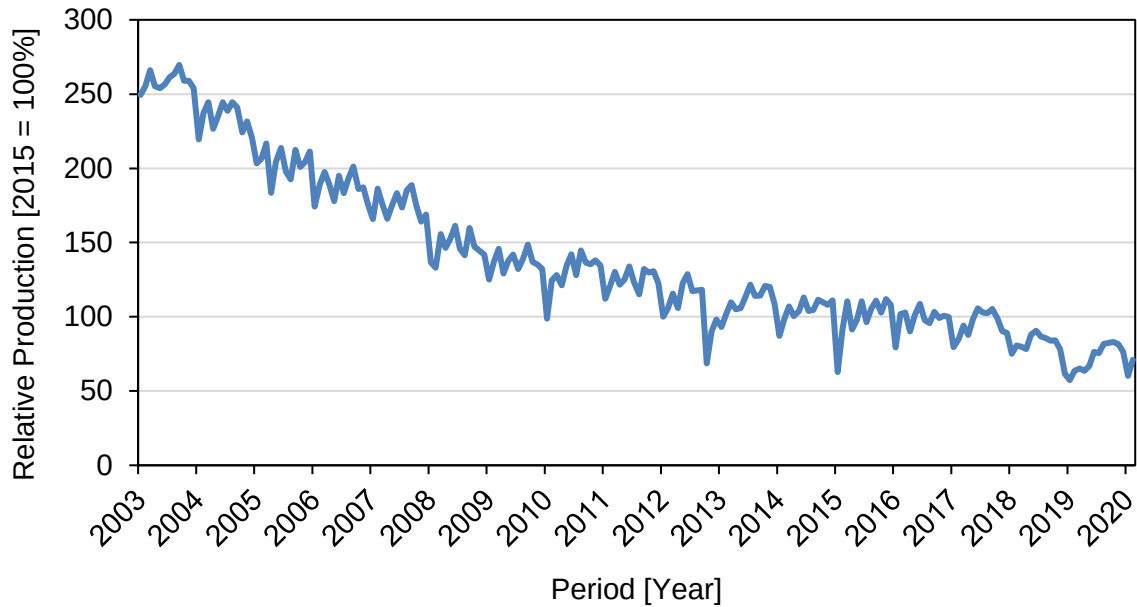


Figure 1: South African gold mining relative historical production values

The curve appears to have plateaued in 2017 but large strike actions crippled the industry in 2018, causing a steep decline in production [2]. Although the South African gold mining industry boasted a workforce of 339 000 individuals in 1997, the workforce consisted of a mere 112 000 individuals by the end of 2017 [2]. The industry continues to decrease in size and production due to ongoing obstacles such as [1], [6]:

- Recessive state of health in the workforce.
- Mining expanding away from the shaft infrastructure.
- Continuous production stoppages due to the Department of Mineral Resources.²
- Increasing electricity costs.
- Infrastructure being operated for much longer than its design lifetime.

The gold price along with the currency exchange rate have assisted several mines in remaining profitable, which allowed marginally profitable mines to remain operational. However, the ever-increasing electricity costs counteract the effects of the gold price and currency conversion rate.

² D. McKay, "Section 54s cost SA mines R4.8bn in 2015, and 2016 may be worse," *MiningMX*, 19 Aug. 2016. [Online]. Available: <https://www.miningmx.com/opinion/columnists/27866-stoppages-lop-r4-8bn-off-2015-revenue-2016-worse/> [Accessed: 22-Jun-2020].

1.1.2 Energy cost trend

South Africa has experienced large increases in electricity costs over the last 15 years. The largest annual increase in price occurred in the 2010/2011 period with an increase of 31.5%. Figure 2 shows the yearly increase in electricity cost and the average cost of electricity [7].

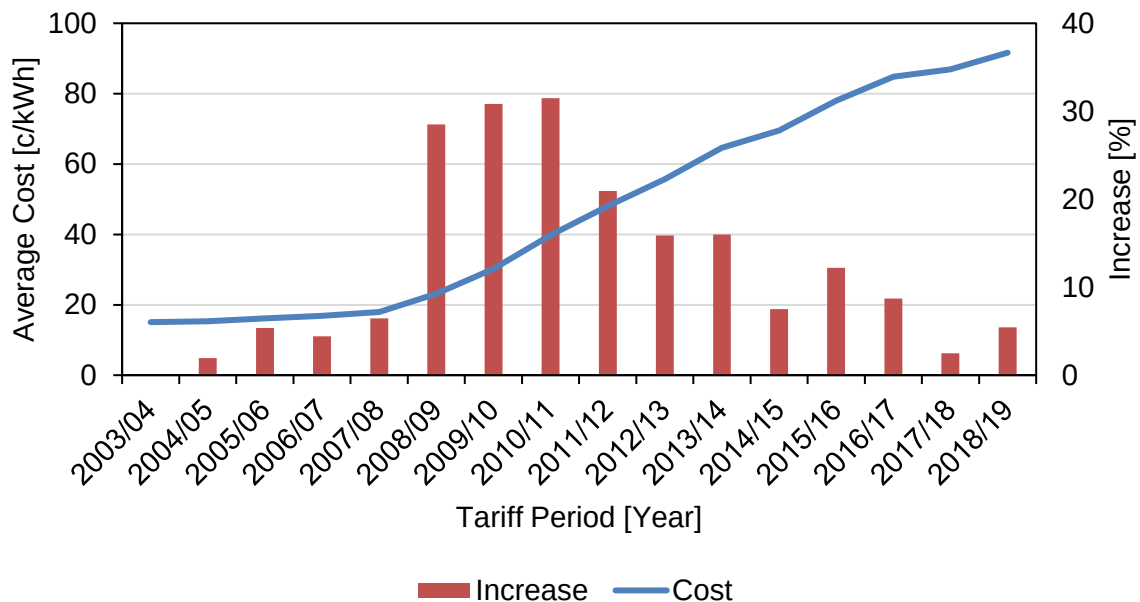


Figure 2: South African electricity price trend

The energy cost increases, as shown in Figure 2, are further accompanied by a restrained power network that occasionally requires large consumers to reduce usage during prescribed times. The reduction is necessary to free up capacity and prevent nationwide blackouts. The reduction resulted in several mines and processing facilities losing production and processing opportunities [8]. The South African deep-level mining industry is subjected to harsh labour environments that further limit the capacity to produce. The industry is riddled with strikes, politics and health issues that all contribute to further downtime experienced by the mine and, ultimately, production losses [6]. As a result, efficiency and optimisation projects continue to be vital to the industry's productivity.

1.1.3 Typical mine energy cost distribution

The South African deep-level mining industry is characterised by large operating costs, comprising predominantly of labour and electricity [3]. The large energy consumers of a deep-level mine are:

- **Ventilation and refrigeration:** large surface fans (up to 3 MW) induce airflow through the mine, providing cooling and oxygen to the underground workers and environment. These fans are not sufficient for mines in excess of 2 km below the surface, in which case refrigeration is required to cool the air entering the mine and workplaces [9].
- **Compressed air:** large centrifugal compressors (up to 15 MW) supply compressed air that is used during the drilling, tramming and cleaning shifts of the mining cycle. Occasionally, compressed air is used as a temporary localised cooling method [10].
- **Pumping:** water is used in mines for production, cooling and safety purposes. Underground water sources also result in water entering the underground environment. This water is pumped to surface, where it is treated and disposed of to prevent the underground area from flooding [11]. The dewatering pumps are dependent on the depth of the mine (up to 2 MW).

There are other consumers that contribute to the total electricity bill. These are loading and lighting systems, and offices and hostels. Figure 3 shows the typical energy cost breakdown for a deep-level mine c.

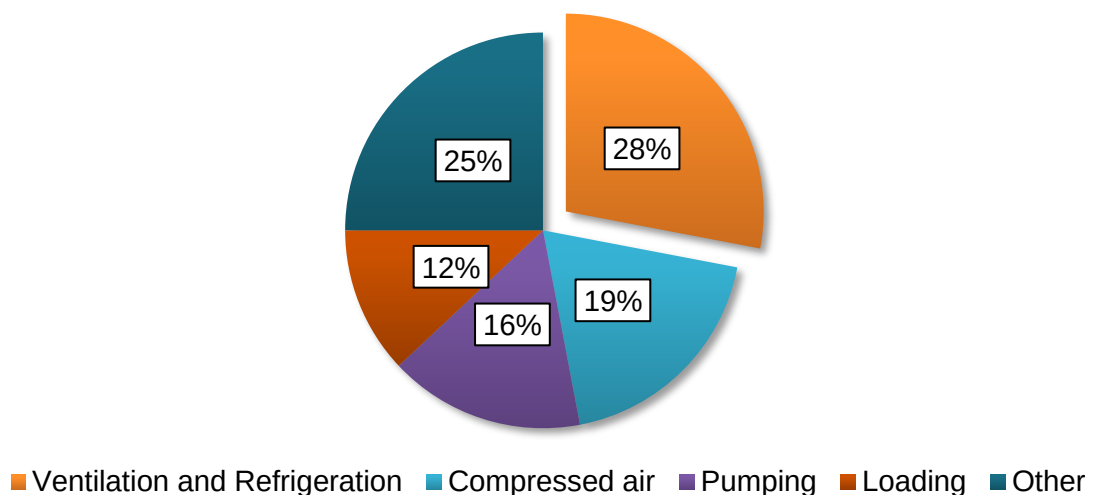


Figure 3: Typical mine energy cost distribution

As a whole, the ventilation and refrigeration system contributes 28% to the total energy bill for a typical deep-level mine, as shown in Figure 3. The ventilation system consists of primary, secondary and tertiary components to ensure airflow through the mine. Similarly, the refrigeration system consists of primary, secondary and tertiary components to ensure adequate cooling is supplied [12].

The ventilation and refrigeration systems are integrated because the main purpose for the cooling system is to cool the air going underground and into workplaces. Water is used as a medium for heat transfer. The heat from the air going underground and to the workplaces is transferred to the water, causing a reduction in air temperature. The heat is extracted from the water into the environment through the refrigeration system and the cycle starts again [9].

1.2 Refrigeration system

Underground, mines experience virgin rock temperatures of up to 60 °C, resulting in the need for effective refrigeration systems [13]. These refrigeration systems supply working areas with ventilation to prevent temperatures exceeding 32.5 °C wet bulb and 37 °C dry bulb [14]. Refrigeration systems provide cold water to the bulk air coolers (BACs) to help supply cool inlet ventilation.

Deep-level mining consists of three tiers of cooling. The amount of cooling provided decreases with each tier, but becomes more focused. The first tier consists of surface BACs. The surface BACs cool a large portion of the air that enters the mine to overcome heat increases due to auto-compression [9]. The secondary tier of cooling consists of underground BACs used to cool air to a group of workplaces or an entire level. Although the secondary cooling tier provides less cooling, it is more focused than the primary tier. The tertiary tier consists of mobile cooling units (MCUs) that are used occasionally to cool air entering specific workplaces [15]. Figure 4 depicts the typical cooling configuration of a deep-level mine's cooling infrastructure.

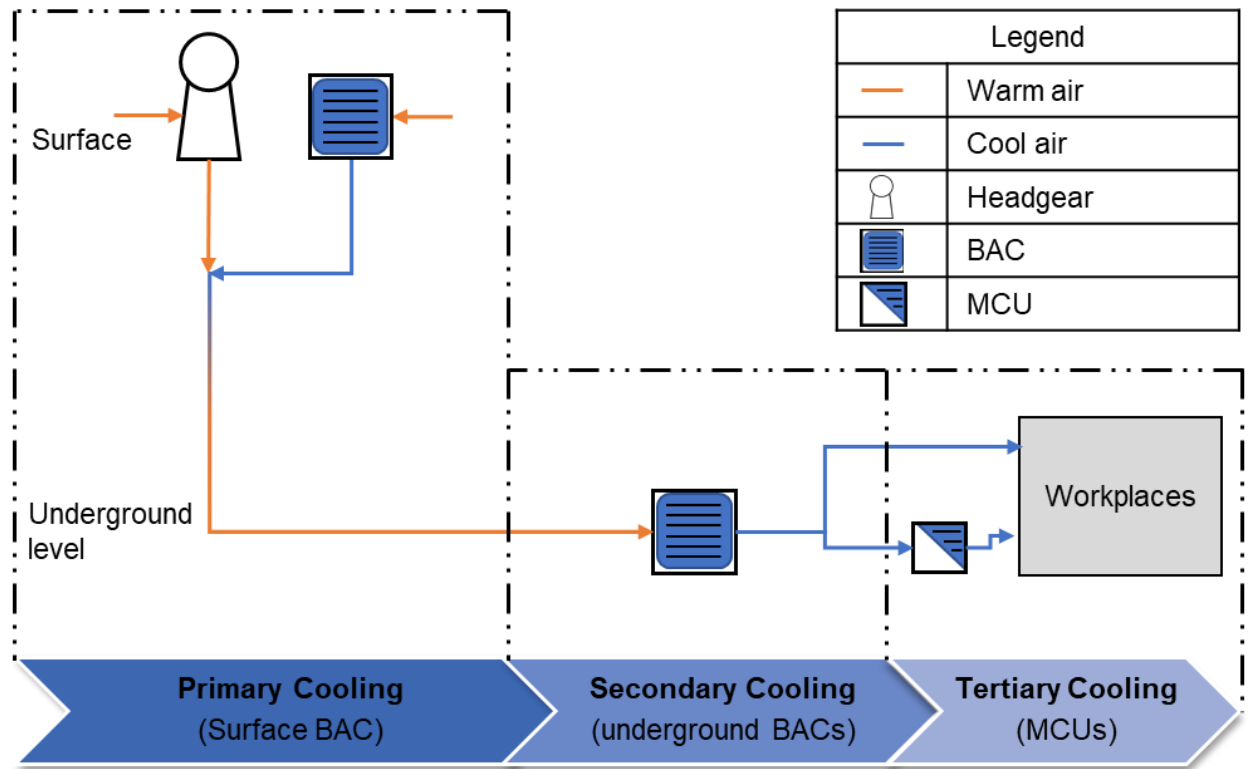


Figure 4: Typical deep-level mine cooling configuration

Water is circulated to each cooling tier, which acts as a medium for heat transfer. The heat is extracted from the water, into the environment, and is circulated to the cooling components, thereby completing the closed-loop cycle. Refrigeration plants, which are either located on surface or underground, extract the heat from the water [16]. The power consumers in the ventilation and refrigeration system are described in Table 1.

Table 1: Ventilation and refrigeration system power consumers

Power consumer	Description
Fans	Fans are responsible for the ventilation circulation in the mine and through the cooling components.
Pumps	Pumps are responsible for the circulation of the heat transfer medium (water) in the mine and through the cooling components.
Refrigeration plants	Refrigeration plants remove heat from the system through the principles of the refrigeration cycle.

The ventilation and refrigeration system can be split into two circuits, namely the water circuit and the ventilation circuit. The water circuit consists of dams, refrigeration plants and pumps whereas the ventilation circuit consists of fans. The respective cooling components (i.e. BACs and MCUs) are the interface between the two circuits that are responsible for the heat transfer between the two circuits [17].

The fans of the ventilation and refrigeration system operate continuously to supply adequate ventilation to the workplaces. The result is that the directly associated cooling components, such as BACs or MCUs, operate similarly [12]. The cooling components require water flow, which is supplied by pumps that ensure the water flow to the cooling components operate continuously.

The water cycle has storage capacity through dams, which allows a level of independent operation. The dams create opportunities to reduce the operating costs of the refrigeration system through dam management. Dam management in the refrigeration system is more complex than in the dewatering system due to temperature and level requirements that need to be satisfied, as opposed to only level requirements. This study focuses on the water cycle of operations.

1.2.1 Present operation and infrastructure

Mine refrigeration infrastructure was installed for designs that were developed, on average, 25 years ago, with some systems operating for more than 35 years [18]. The designed cooling requirements have since changed due to the constant expanding nature of deep-level mines. Production areas have either become deeper or further away from shaft infrastructure [6].

The economic circumstances currently challenging the mining industry prevent newly designed refrigeration infrastructure from being installed [19]. Even with adequate maintenance, the aged refrigeration plants do not operate according to the design specifications anymore and are occasionally relocated to operate in conditions outside of the design [19].

The typical mine refrigeration plants consist of two tube-in-shell vessels: the condenser and evaporator [17], [20]. The evaporator transfers heat from the warm circulation water to the refrigerant. The condenser transfers the heat from the refrigerant to the condenser water, whereafter the condenser cooling tower transfers the heat from the condenser water to the environment. Figure 5 depicts a typical refrigeration plant on a deep-level mine.

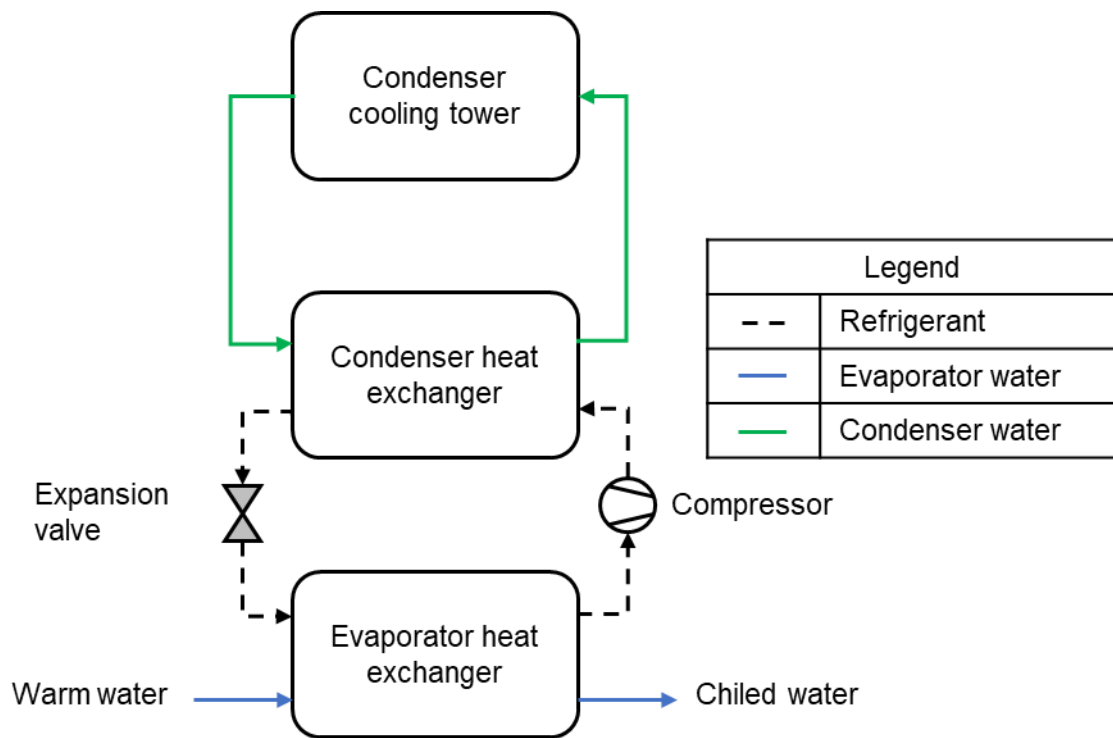


Figure 5: Typical refrigeration plant in deep-level mines

The cooling duty achieved by the refrigeration plants is affected by the following external factors [20]:

- **Condenser inlet temperature:** the capacity for heat transfer in the condenser cycle is affected by the inlet temperature. A higher temperature limits the capacity, which decreases the cooling duty achieved.
- **Condenser mass flow rate:** similar to the condenser inlet temperature, the condenser flow affects the heat transfer capacity. A lower flow rate limits the capacity, which decreases the cooling duty achieved.
- **Evaporator inlet temperature:** the source of heat transfer in the refrigeration plant is the evaporator water. A decrease in the evaporator inlet temperature limits the amount of heat to be transferred, which decreases the cooling duty achieved.
- **Evaporator mass flow rate:** similar to the evaporator inlet temperature, the evaporator flow determines the amount of heat to be transferred. A lower flow rate limits the amount of heat to be transferred, which decreases the cooling duty achieved.

- **Guide vane position:** guide vanes control the refrigerant mass flow rate. Closing the guide vanes restricts the flow of refrigerant, limiting the heat transfer capacity of the refrigerant, which decreases the cooling duty achieved.

Mine refrigeration systems consist of more than one refrigeration plant, as depicted in Figure 5. Cooling requirements are mine-specific, which results in each plant being configured uniquely. The various configurations further complicate finding the correct operations for the ever-changing cooling requirements [21].

1.2.2 Present control strategy

Mine refrigeration systems are designed in step responses to varying cooling requirements. A large (generally 2 MW) refrigeration plant is started to satisfy the instantaneous water demand or to satisfy temperature requirements. As a result, excess cooling is often applied to meet either water demands or temperature requirements [12].

Variable speed drives (VSDs) are used on pumps in an attempt to reduce the step size during the start-up of refrigeration plants [22]–[24]. VSDs allow motors to operate at a lower power consumption by decreasing the speed of the motor [25]. The reduction in speed reduces the evaporator mass flow rate, which reduces the cooling duty achieved and power consumption of the refrigeration plant. Figure 6 shows the basic operation of a VSD.

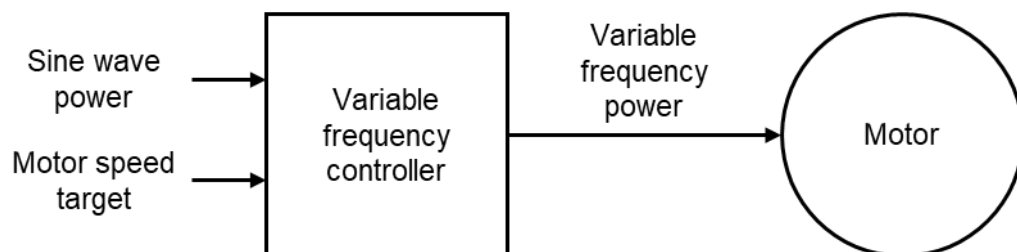


Figure 6: Schematic of VSD operation

The VSDs reduce the response step size allowing for finer, more efficient control. The control of a system aims to find the balance between service delivery requirements and operating efficiency (which results in cost savings). The service delivery requirements for a refrigeration system are typically the water temperature and dam levels [17].

In the mining industry, refrigeration plants are controlled manually. The decision-making is done by a control room operator with the assistance of live data. Control room operators prioritise service delivery over optimisation and cost savings, thus further contributing to excess cooling supplied. An automated system can consistently prioritise service delivery without neglecting optimisation and cost savings [26].

A supervisory control and data acquisition (SCADA) system acts as an interface between control room operators and automated machinery. A SCADA provides a live interface that alerts control room operators to various issues that need to be addressed, such as dam levels or water temperatures. SCADAs assist in system efficiency through condition monitoring [27]. Figure 7 shows an example of a SCADA interface. The alarms can be seen at the top of the window.

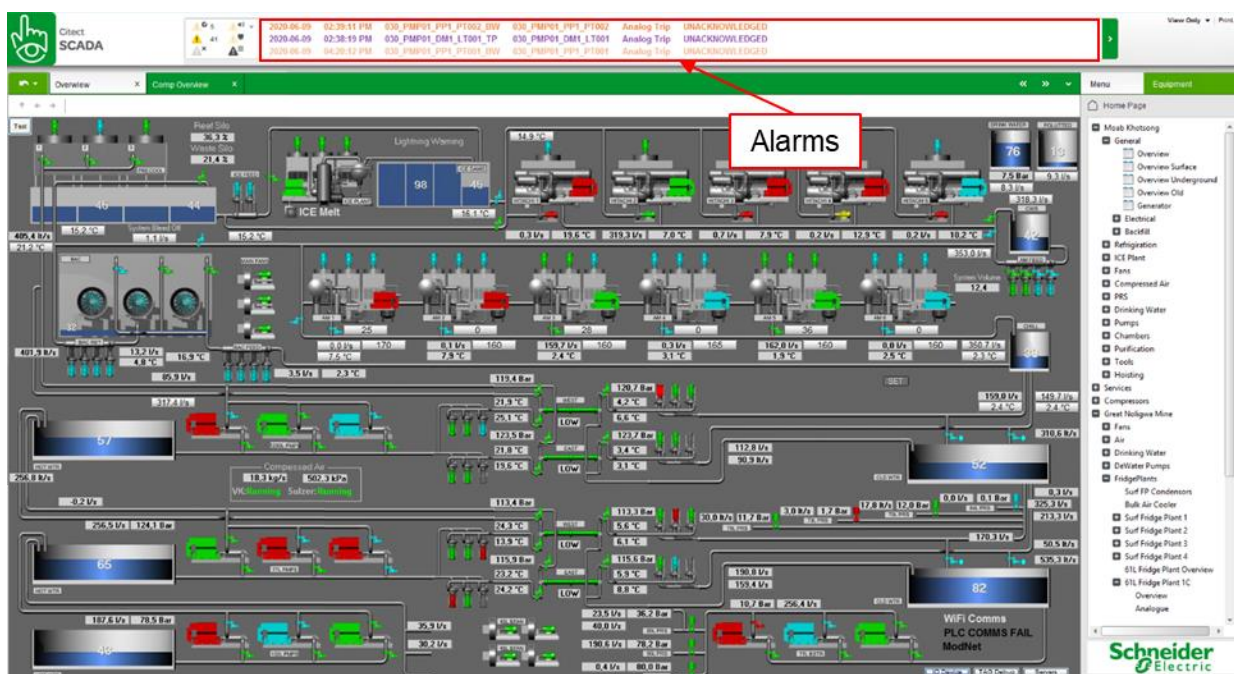


Figure 7: Example of a SCADA interface

1.2.3 Set-point control

Mine refrigeration systems are typically controlled according to a set-point corresponding to the time of day [28]. The set-point dictates the target for the respective component or key performance indicator (KPI) of the system [29]. Feedback is implemented through sensors measuring the output. The difference between the set-point and the measured value determines the response necessary to meet the set-point. The necessary response is sent to the controller to be implemented either automatically or manually. Figure 8 shows the control flow in a set-point control model.

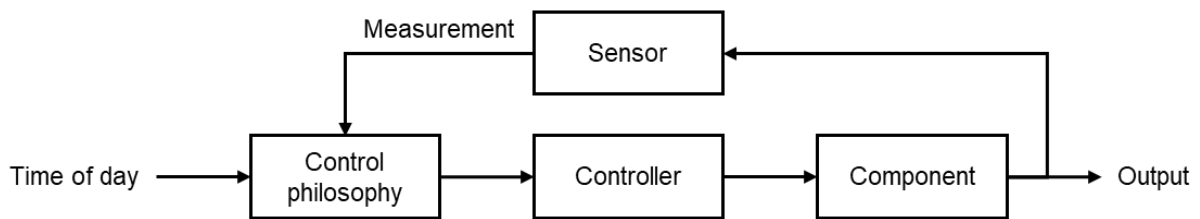


Figure 8: Set-point control flow diagram

Set-point control models are simplistic to implement and maintain, but have the following disadvantages [29]:

- Prone to becoming outdated in developing systems and system requirements.
- Unable to result in stable energy efficiencies or load shifts due to variations in system requirements or operating conditions.

1.2.4 Dynamic control

Dynamic control is more complex than set-point control, but follows a similar control flow, as shown in Figure 8. The difference between the two control methods is the control philosophy. Set-point control only requires the output measurement and time of day to determine the appropriate response in system components.

Dynamic control consists of two states, namely the baseline state and the present operating state. The output measurement, along with numerous other measurements, is used to determine the difference between the two states and the target is adjusted accordingly [29]. Thereafter, the output measurement is compared with the adjusted target and the appropriate response is determined. Figure 9 shows a typical control flow in a dynamic control model.

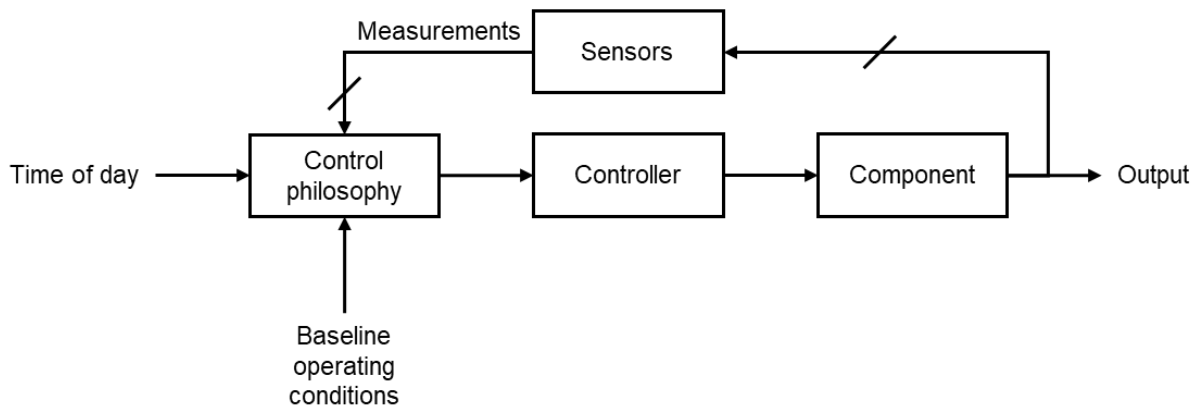


Figure 9: Dynamic control flow diagram

Dynamic control models address stability issues for variations in system requirements or operating conditions, but have the following disadvantages [29]:

- The complexity of the control philosophies is exponentially dependent on the complexity of the system.
- Complex control philosophies result in large computational requirements and computational times.

1.3 Artificial intelligence

AI can be used to improve the optimisation process by decreasing the computational times for larger, more complex characteristic models without affecting the solution accuracy. ‘Artificial intelligence’ is an umbrella term that encompasses various characterisation and optimisation methods. Some benefits of AI are, but are not limited to:

- **Characterisation:** AI is able to characterise a system based on historic data to a certain level of accuracy. This characterisation requires less time and computational requirements compared to classical techniques, such as simulation digital twins [30].
- **Optimisation:** Various AI algorithms exist to determine the most financially viable operating conditions for a system. These techniques are able to solve real-time, due to the improved computational performance, and can thus provide live insights in control [31].
- **Automation:** Through the live insight provided from AI optimisation techniques, systems can be operated autonomously, with little to no human intervention [31].

The global AI industry was valued at R665.9 billion (\$39.9 billion)³ in 2019 and the value is expected to increase by 42.2% a year to R12.2 trillion (\$733.7 billion)³ in 2027 [32]. The expected growth in the industry is projected from the previous growth rates and is summarised by the following influences:

- **Solution:** Software solutions, such as libraries and programs, for designing and implementing AI applications in various industries contributed to the growth of AI. The addition of maintenance and support to software solutions has contributed to the overall growth [32].
- **Technology:** The incorporation of AI capabilities into consumer electronic devices and the investment in cloud services and data storage solutions have contributed to growth of data analysis through AI. This further contributed to the growth of the global AI industry [32].
- **End use:** The advertising and media industry is the largest contributor to the use of AI, at 20% of the market, but is expected to be surpassed by the healthcare industry by 2027. The drive to analyse data has led to the adoption of AI in the majority of industries. The most used AI application is a conversational application, namely a 'chatbot' [32].
- **Region:** The influence of the governing authorities affects the growth and adoption of AI applications. An example of this is the American AI Initiative that cultivates public trust in AI. North America is responsible for 42% of the global AI industry [32].
- **Key companies:** Large companies (such as Google, NVIDIA, Microsoft and IBM) are continuously investing in AI to ensure a customer base. The result is the development of AI applications and solutions, which further contribute to the growth of the global AI industry [32].

The mining industry is not in the top seven industries utilising AI in their processes⁴. The lack of AI applications in the mining industry leaves a gap in data analysis and system optimisation. AI applications are generally used in data mining, analytics and system optimisation due to the effective computer performance [32].

³ \$1 = R16.69 on 18 July 2020.

⁴ [Goldhub, "Gold mine production," 30 June 2020. <https://www.gold.org/goldhub/data/historical-mine-production> [accessed 03-Feb-2021].

The mining industry develops data through sensors. Sensors monitor various components of the numerous systems required in the mining process. The result is that large amounts of data are available to be analysed to determine further opportunities for improvement and optimisation [16]. In the analysis, AI assists in determining correlations between different systems and responses to different system inputs.

Some AI characteristic techniques include machine learning and deep learning which provide improved computational performance in mimicking real-life systems to make informed decisions [31]. However, these techniques are used for characterisation and different AI techniques are required for optimisation purposes. AI further provides optimisation techniques that have improved computational performance, which allows for the optimisation to operate continuously in dynamically controlled systems. Two AI techniques used in optimisation are particle swarm optimisation and genetic algorithms [31].

1.3.1 Genetic algorithm

Genetic algorithms are a form of AI, specifically a population-based optimisation technique [33], which are used to optimise non-linear systems with parametric constraints [34]. Genetic algorithms survey the constraint area for the most feasible solution through various generations of population. The genetic algorithm begins with a population of possible solutions, which are evaluated according to the fitness function. The stop criteria are checked to determine convergence: if the solution converges, the output is provided. The stop criteria consist of the number of generations and function tolerance. The number of generations restricts the number of iterations and the function tolerance tests for convergence by determining the average relative change in fitness value.

If the stop criteria are not met, the population undergoes selection. The best solutions, based on the fitness function and constraints, are selected to create a part of the new population. The rest of the new population is created by a combination of crossover and mutation. Crossover combines pairs of solutions in the population to form a fraction of the new population. The final solutions of the new population are created through mutation, which randomly changes the solutions (according to a Gaussian distribution). The new population is evaluated and the process continues until the stop criteria are met. Figure 10 summarises the structure of a genetic algorithm in a flow chart.

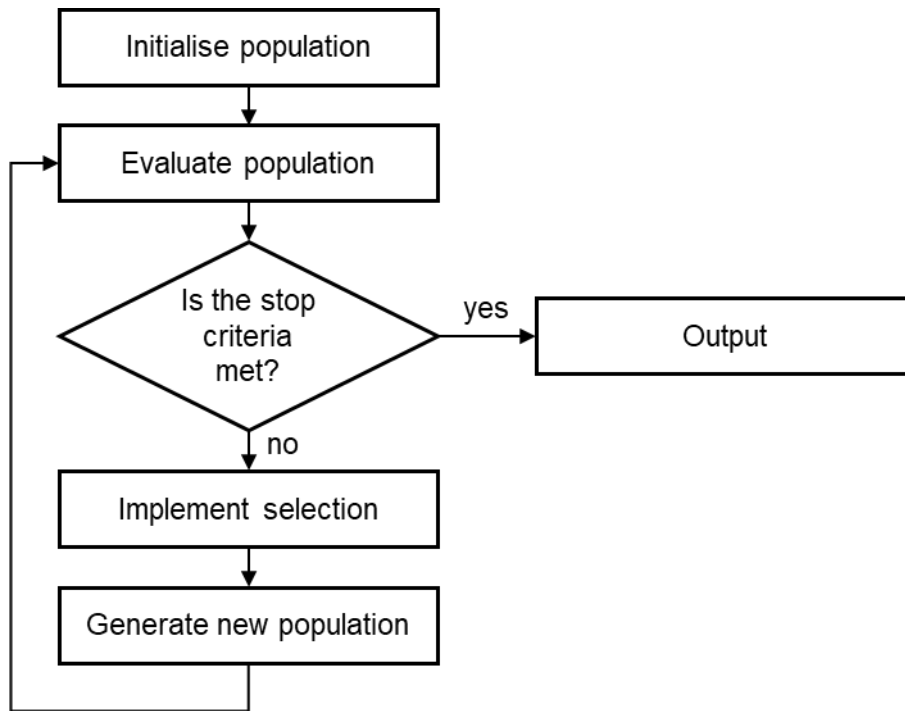


Figure 10: Basic structure of a genetic algorithm⁵

Although a genetic algorithm is a widely used optimisation technique, the following parameters have to be considered carefully:

- Objective function development.
- Population size.
- Rate of mutation or crossover.
- Selection criteria.

Choosing inappropriate values or methods for the above-mentioned parameters inhibits convergence or results in meaningless results [35].

⁵ D. Guitierrez-Navarro and S. Lopez-Aguayo, "Solving ordinary differential equations using genetic algorithms and the Taylor series matrix method," *Journal of Physics Communication*, p. 3, 2018.

1.3.2 Particle swarm optimisation

Particle swarm optimisation is another population-based optimisation form of AI that is used to solve complex non-linear systems with parametric constraints [33]. Particle swarm optimisation uses particles, which have influence on one another, to survey a constraint area for the most feasible solution [35]. Particle swarm optimisation begins with particles in random locations within the constraint area. The fitness value of each particle is determined and stored. Each particle has a personal best location that results in the lowest fitness value. The personal best locations are compared to obtain the global best position that results in the lowest fitness value.

Thereafter, the particles move across the constraint area, affected by the personal and global best locations. New locations for the particles are determined and the stop criteria are evaluated. If the stop criteria have not been met, the particles' fitness values are determined and the personal and global best values are updated. Once the stop criteria have been met, the global best value is returned as the solution. Figure 11 summarises the structure of particle swarm optimisation in a flow chart.

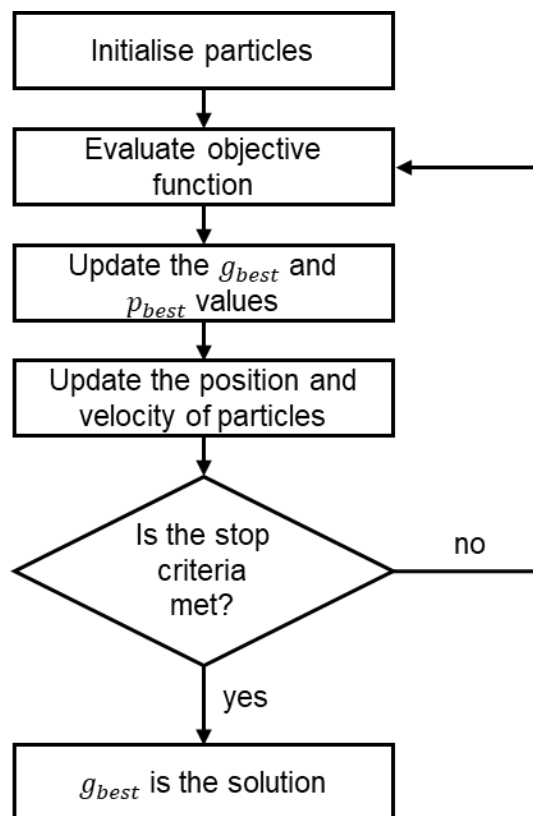


Figure 11: Basic structure of particle swarm optimisation [33]

Particle swarm optimisation has the ability to scan a constrained area to determine the most feasible solution but, similar to genetic algorithms, the following parameters have to be considered carefully:

- Swarm size.
- Acceleration coefficients.
- Inertia weight.
- Cognitive and social component scale values.

If selected inappropriately, the above-mentioned parameters will either result in the convergence of an infeasible point or the convergence of a local minimum and not the most feasible solution of the system [35], [36].

1.3.3 Optimisation comparison

Generally, particle swarm optimisation results in a higher solution quality and a better computational performance than the conventional genetic algorithm [33]. Particle swarm optimisation returned the a result with an error 10 orders of magnitude smaller than the result of the conventional genetic algorithm in 2.7 times less time [33]. Therefore, particle swarm optimisation is more appropriate for a dynamic optimisation control system due to its improved performance and computational performance.

1.4 Literature study

Refrigeration systems contribute significantly to the operating costs of a deep-level mine [13]. With the decline in production rates and the increase in electricity costs, continuous optimisation is necessary to assist the profitability of the deep-level mining industry [1]. Previous research has been able to assist in this regard but there is room for improvement. Previous studies can be categorised according the following criteria, which are subsequently discussed:

- **Data-Information-Knowledge-Wisdom (DIKW) model:** the DIKW model is used to determine the KPIs of a system and ensure that the service delivery requirements are met.
- **Energy management:** cost savings can be achieved through energy management and monitoring. Energy management focuses on preventing oversupply and unnecessary supply to achieve energy cost savings.

- **Energy efficiency and load shifting:** cost savings can be achieved through either using the power consumed more efficiently or using storage capabilities to reduce peak-period energy consumption.
- **System characterisation:** cost savings techniques can be identified and validated through system characterisation techniques; for example, the response surface method.
- **Design optimisation:** reconfiguring present infrastructure or installing new technology can result in energy efficiency and energy cost savings.
- **Static simulation optimisation:** financially beneficial projects can be determined through characteristic simulation and human identification.
- **Mathematical optimisation:** financially beneficial projects can be determined through the mathematical characteristic model and the mathematical analysis thereof.
- **Semi-empirical optimisation:** financially beneficial projects can be determined through characteristic models developed through historical data and the mathematical analysis thereof.

1.4.1 DIKW model

Most optimisation techniques use the DIKW model. The DIKW model is based on the concept of increasing the context and understanding pertaining to data, which enables decision-making in automated or dynamic systems [16], [37]. The basis of the DIKW model is portrayed in Figure 12 [38].

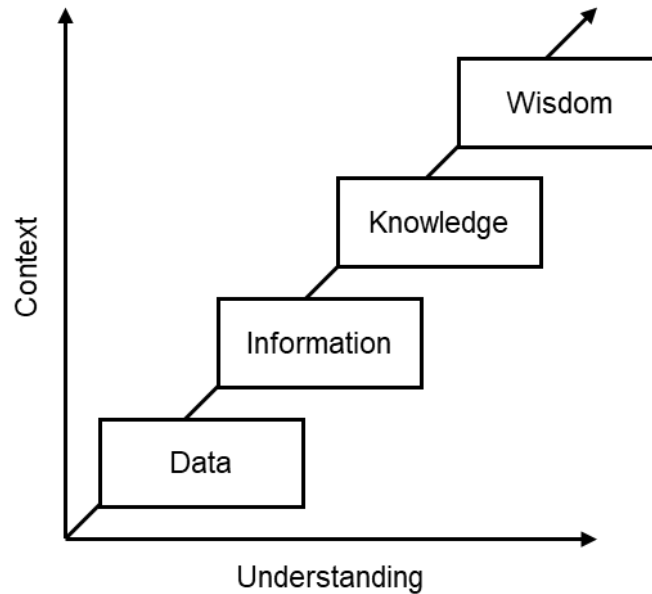


Figure 12: DIKW model

Data refers to the raw data measured by sensors, which is read by SCADAs and stored by historians. The raw data has no context and merely represents a point in a two-dimensional plane. The plane has the axes time, that the measurement was taken, and the variable being measured. Actions cannot be determined from the raw data as there is no context behind it.

Information refers to the structured merge of raw data [39]. The structured merge of raw data adds context to the raw data, thus resulting in useful data. Due to the structured merge, relationships in the data are revealed in the information tier of the DIKW model. For example, the operating profiles of refrigeration plants or profiles of water temperature.

Knowledge refers to the cognitive structuring of information [40]. In the knowledge tier, patterns are determined from the information and generally answer the 'how' question. An example is determining whether refrigeration plants are improving or deteriorating in performance or whether variants in water temperatures are attributed to ambient conditions.

The data, information and knowledge tiers are based on past events and measurements. The wisdom tier is based on future events in response to the knowledge obtained [40]. Wisdom can be seen as actionable knowledge by implementing measures to optimise systems or overcome the obstacles encountered, as noticed in the knowledge tier of the DIKW model. Wisdom is the decision-making tier in a control philosophy.

Previous implementations of the DIKW model on a deep-level mining refrigeration system resulted in improved service delivery [16]. The continuous monitoring of KPIs through automated reporting ensured that the refrigeration system ran according to design and that any issues were noticed and addressed within days. The implementation of the DIKW model, however, did not consider electricity cost and time-of-use (TOU) tariffs. As a result, the model improved service delivery, but at the expense of energy savings.

1.4.2 Energy management

Energy management satisfies the instantaneous demand without oversupply. Cost savings are achieved by preventing oversupply. The implementation of an energy management system requires that the instantaneous demand requirements be determined. The demand requirements are often split by working shifts (such as the cleaning, drilling and blasting shift), thereby allowing for future improvements in the prevention of oversupply.

The installation of an energy management system requires continuous maintenance to prevent the loss of savings due to system deterioration [41]. Improved strategies were implemented on an existing energy management system to ensure sustainable energy savings. The implementation, however, installed new technology (namely VSDs) to satisfy the demand more accurately to produce the savings. Further cost savings can be achieved using a control strategy to optimise energy usage according to the applicable TOU tariffs.

Other energy management system implementations used set-point control on dam levels and hierarchical control of refrigeration plants to achieve cost savings according to the TOU tariff [28]. Set-point control allowed refrigeration plant energy consumption to be moved out of the evening peak period, but the optimal system configuration was not determined to achieve the set-point. The hierarchical control started plants according to individual performance, but neglected combined system performance. Further optimisation can be achieved through refrigeration plant and system characterisation.

A study that implemented an energy management system implemented set-point control along with hierarchical control to achieve cost savings by avoiding energy usage in peak periods [28]. However, variations in the demand and operating conditions resulted in deteriorating savings and energy inefficiencies. The need exists for an energy management system that achieves cost savings through energy efficiency and load shifting.

1.4.3 Energy efficiency and load shifting

The financial benefit of optimising refrigeration systems is derived from either energy efficiency or load shifting [42]. Energy efficiency projects are based on reducing the amount of energy a system uses while maintaining an acceptable system outcome. Load shifting projects rely on using similar amounts of energy throughout the day but shifting the energy requirements between various periods. Figure 13 depicts the difference between energy efficiency and load shifting.

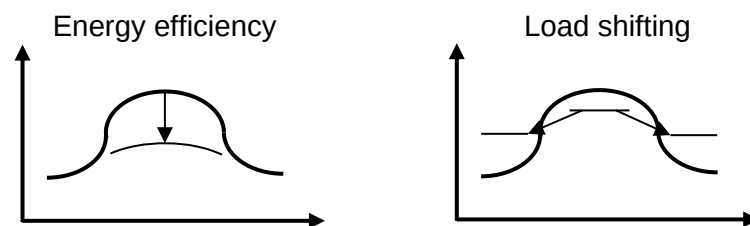


Figure 13: Energy efficiency and load shifting comparison⁶

Energy efficiency projects improve system efficiencies by using less energy for the same or similar outcome. In refrigeration systems, energy efficiency is typically obtained through:

- Energy management projects, typically demand-side management [16], [43].
- Control philosophy adjustments [3], [41].
- Installation of new technology [22], [24].

Load shifting projects are dependent on the TOU tariff structure of the electricity supplier. In the South African deep-level mining industry, the electricity supplier is the South African electricity public utility, namely Eskom. Eskom's TOU tariff structure divides weekdays into 5 hours of peak periods, split into a morning and evening peak, 11 hours of standard periods, and 8 hours of off-peak periods [44]. Figure 14 shows the detailed TOU schedule for the low- and high-demand seasons as well as weekdays, Saturdays and Sundays.

⁶ L. Kreuder and C. Spataru, "Assessing demand response with heat pumps for efficient grid operation in smart grids," *Sustainable Cities and Society*, vol. 19, no. Oct., p. 137, 2015.

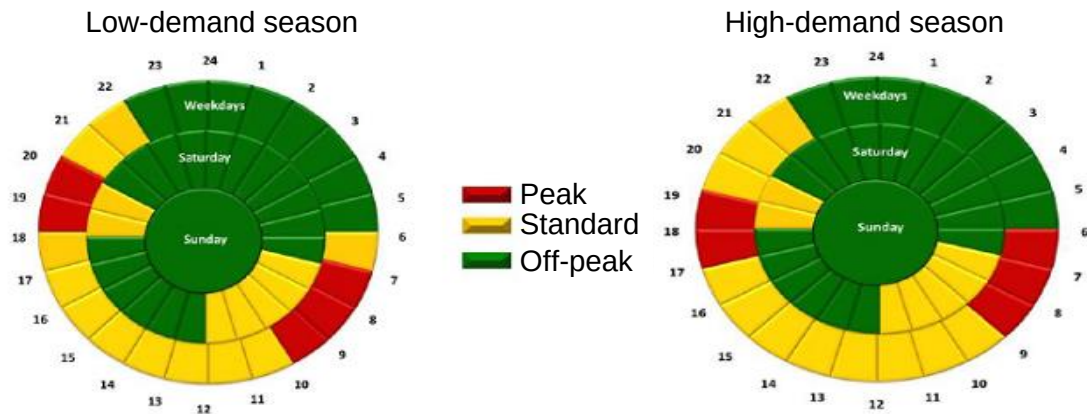


Figure 14: Eskom TOU schedule⁷

Load shifting projects use storage facilities, such as dams in the refrigeration system, to move energy consumption from the peak periods to the standard and off-peak periods. This is due to the tariff for the peak period being 45% more than the tariff for the standard period in the low-demand season and 230% more in the high-demand season [44].

For adequate load shifting to be implemented, the cooling requirements need to be determined. A previous study has implemented dynamic set-points to allow for variations in cooling requirements [12]. The control implemented load shifting based on dynamically determined set-points, which led to cost savings. However, refrigeration plants were operated according to a hierarchical control, resulting in a system inefficiency.

Other studies implemented dynamic control on a mine refrigeration and ventilation system [3], [13], [45]. The control predicted the cooling requirements for the day and the appropriate control response was determined. The control was automated through an energy management system. However, system inefficiencies occurred due to the hierarchical selection of refrigeration plants to operate to meet requirements.

⁷ Eskom Holdings SOC Ltd, "Tariffs & Charges Booklet 2020/2021," no. April, p. 39, 2020.

Another study that has implemented load shifting on refrigeration systems use a form of prediction to determine the cooling requirements that need to be met [28]. Hierarchical selection was implemented to satisfy the cooling requirements, which resulted in system inefficiency. The need exists for a computational control method to achieve cost savings through both energy efficiency and load shifting. A computational control method will allow for energy efficiency and load shifting to occur dynamically.

A study done on the heating, ventilation and air conditioning system of building implemented AI, specifically an artificial neural network, to characterise the system and enhance system operation through multi-objective optimisation [46]. Cost savings were achieved through energy efficiency. The system did not have any storage capabilities and, as a result, TOU optimisation was not possible. The need exists for a similar optimisation process to be followed in the mining industry to achieve cost savings through dynamic energy efficiency and load shifting.

1.4.4 System characterisation

A characteristic model is developed to provide a digital representation of the system. The digital representation is required to validate results and, in some methods (such as mathematical and semi-empirical optimisation), it is necessary in the optimisation technique. The characteristic model is typically done through curve-fitting techniques or simulation.

Curve fitting refers to the process of finding an equation to represent a set of data points to form the characteristic model. There are various curve-fitting computational methods and the use of each is dependent on the nature of the relationship in the data [47]. Figure 15 shows the curve-fitting process.

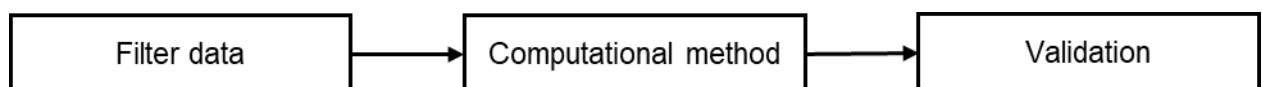


Figure 15: Curve-fitting process

The first step in the process is to validate the raw data. The validation process is necessary to remove data generated during system downtime, network downtime or system maintenance. Using this data will result in an inaccurate representation of the system. Some validation methods include limit checks, range checks and presence checks.

The next step in the process is to use a computational method to develop the representative curve. The representative equation determines the computational method to be used. The representative equation should neither result in an overfit nor an underfit. An overfit curve will result in a perfect fit to the data set, which is representative of the system. An underfit curve does not mimic trends seen in the data.

The final step in the process is to validate the representative equation. A visual representation will assist in identifying either an overfit or underfit curve. Some validation methods involve using the coefficient of determination (R^2) and doing graphic residual analysis. The coefficient of determination quantifies how well the model fits the data, but does not guarantee a good fit [48]. A graphic residual analysis that shows random residuals is indicative of a good fit [48].

Improving existing infrastructure by installing new technology requires the characterisation of the system to determine expected results. A previous study characterised the refrigeration system through simulation [49]. Although simulation was able to determine optimised operations, further optimisation can be achieved through TOU tariff optimisation.

System characterisation through simulation has been shown to assist in energy management [43]. The simulation model was used to optimise system operations by preventing oversupply while maintaining the targets for the respective KPIs. This static simulation optimisation is prone to deterioration due to variations in the system demand or operating conditions.

Simulation-based characterisation was used in another study to assess electrical energy cost savings [50]. The study developed a site-specific simulation model, opposed to a generic model, to accurately determine the potential cost savings achievable by optimisation. The simulation served as the solution validation in the optimisation process.

Energy audits can also be done by using simulation [51]. Simulation models allow for high-level system inefficiencies to be determined and addressed. The simulation model further provided a form of system documentation that can be used in further optimisation or design processes.

The mining industry predominantly uses simulation in system characterisation. The benefit of simulation is the ease of use but it lacks the ability to characterise a deteriorated system, which leads to inaccurate optimisation. Historical data can be used to characterise a deteriorated system, thus improving optimisation accuracy. AI provides the opportunity to characterise a system based on historical data [52], [53]. Previous studies used AI to predict dam levels, however, the accuracy of characterisation still needs to be improved [52], [53].

1.4.5 Design optimisation

Overall system optimisation can be achieved by installing new technology. The installation of MCUs in a system resulted in cost savings by preventing oversupply and unnecessary supply of cooling [15]. Although the MCUs improved the overall system efficiency, further cost savings can be achieved through TOU control strategies on the primary cooling components.

Energy efficiency was further achieved by installing VSDs [22], [24], which led to a financial benefit. Although the VSDs allowed for adequate cooling to be supplied, which prevented oversupply, the control of the refrigeration system did not incorporate storage capabilities to move energy consumption out of peak periods.

Mining refrigeration systems have been optimised by installing MCUs and VSDs [15]. The installations improved the overall system efficiency, thereby achieving a financial benefit. However, implementing improved control strategies that use storage capabilities to move energy consumption out of peak periods will further increase the financial benefit achieved.

1.4.6 Static simulation optimisation

Optimisation strives to achieve financial benefits due to energy efficiency and load shifting. Optimisation techniques have similar methods [54], which are depicted in Figure 16.

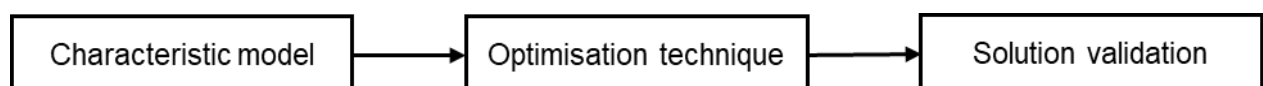


Figure 16: Optimisation process

Simulation proves to be a useful tool by not only obtaining efficient operating profiles for the refrigeration system, but also validating the result [43]. Simulation is often used to validate the results of other optimisation techniques [50]. Various simulation packages, such as Process Toolbox [43], [55] and Flownex [51] have been used to optimise mine refrigeration systems.

Static simulation optimisation entails obtaining operating conditions and the respective outputs of the system, whereafter the system is modelled through simulation. Identified operational improvements are simulated to determine the impact. The benefit of using a simulation is that the results will be within operational constraints, thereby contributing to the validation process. Table 2 summarises the optimisation components, shown in Figure 16, for static simulation optimisation.

Table 2: Static simulation optimisation components

Characteristic model	Optimisation technique	Solution validation
A simulation model is used as the digital representation of the system.	Human identification of changing component configurations and new component installations is used to obtain a financial benefit.	The simulation model is used to validate the optimisation solution.

Although static simulation optimisation requires little effort if the characteristic model has already been developed, it has the following disadvantages:

- A significant level of effort is required to set up the characteristic model.
- The optimisation is applicable to the obtained operating conditions and subject to variations in the operating conditions.
- Human identification is required, which may not always result in the optimal solution.
- Human identification may not always result in a financial benefit.

1.4.7 Mathematical optimisation

Mathematical optimisation uses theory and equations to create a characteristic model [56], [57]. Using theory and equations results in a characteristic model that is developed in less time than a simulation-based model. Various algorithms, such as non-linear programming, quadratic programming and mixed-integer linear programming, can be applied to the characteristic model. The type of algorithm is dependent on the characteristic model.

The results from the optimisation are validated through analysis or simulation before implementation. Simulation requires that the characteristic model also be simulation-based. Table 3 summarises the optimisation components, shown in Figure 16, for mathematical optimisation.

Table 3: Mathematical optimisation components

Characteristic model	Optimisation technique	Solution validation
Theory and equations are used to develop the digital representation of the system.	Numerous optimisation algorithms are used to determine the optimal solution.	Either analysis or simulation is used to validate the solution.

Mathematical optimisation will result in the optimal solution for the system due to the algorithms resulting in the minimum operating costs. However, the disadvantages are:

- Complex systems result in large computational requirements and computational times.
- Using theory and equations results in a solution for ideal components and not components that have deteriorated from the design.
- Validation requires an additional model to be developed, whether it be simulation- or analysis-based.

1.4.8 Semi-empirical optimisation

Semi-empirical optimisation is similar to mathematical optimisation with the difference being the development of the characteristic model. Semi-empirical optimisation uses historical data and curve-fitting techniques to develop a digital representation of the system [58]. Algorithms are applied to the characteristic model to determine the optimal solution.

Either analysis or simulation is used to validate the solution. Simulation requires that the characteristic model needs to be simulation-based and adjusted to the historical data. Table 4 summarises the optimisation components, shown in Figure 16, for semi-empirical optimisation.

Table 4: Semi-empirical optimisation components

Characteristic model	Optimisation technique	Solution validation
Historical data and curve fitting techniques are used to develop the digital representation of the system.	Numerous optimisation algorithms are used to determine the optimal solution.	Either analysis or simulation is used to validate the solution.

Similarly, semi-empirical optimisation will result in the optimal solution for the system due to the use of algorithms. Characterisation through historical data and curve-fitting techniques results in a more accurate solution by accounting for the deterioration in system components. However, semi-empirical optimisation does have the following disadvantages:

- Complex systems result in large computational requirements and computational times.
- Validation requires an additional model to be developed.
- Simulation-based validation requires a complex simulation model to be developed to account for the component variation from design, as seen in the historical data.

The above-mentioned optimisation techniques vary in complexity and accuracy. The increase in accuracy is proportional to the increase in computational requirements and times. Longer computing times result in dynamic control limitations. The optimisation techniques can be ordered as follows from the least accurate to the most accurate:

1. Static simulation optimisation.
2. Mathematical optimisation.
3. Semi-empirical optimisation.

1.4.9 Literature study summary

Table 5 summarises the related research that has been discussed in the previous sections and indicates the current gaps. Green indicates that the condition has been met and red indicates a gap in the study. The following conditions have often been mentioned in the literature study and are the basis of the comparison amongst the studies:

- **Deep-level mining industry:** Does the study take place in the deep-level mining industry? The deep-level mining industry is unique in operation due to the various system requirements and operations.
- **Refrigeration system:** Does the system focus on a refrigeration system? Refrigeration systems provide unique control variables and operating conditions. The optimisation of refrigeration systems relies on multi-variable optimisation.
- **Characterisation:** Does the study use characterisation techniques in optimisation? Theoretical optimisation lacks accuracy due to the true operating capability of infrastructure not being accurately represented.
- **Optimisation:** Does the study perform optimisation of a system? Further, is the optimisation limited to the present installation of infrastructure?
- **Artificial intelligence:** Does the study use a form of AI in the optimisation process? Complex systems result in the need for improved computational performance in the optimisation process.
- **Financial benefit:** Does the study result in a financially feasible solution?

Table 5: State-of-the-art matrix indicating gaps in previous research

Sources	Deep-level mining industry	Refrigeration system	Characterisation	Optimisation	Artificial intelligence	Financial benefit	Comments
[3], [12], [13], [45]							Dynamic control was implemented to prevent overcooling.
[43], [49]–[51]							Simulation was used for plant characterisation.
[16], [28], [41]							Refrigeration KPIs were monitored to maintain energy savings measures or improve service delivery.
[15], [22], [24], [37]							Simulation was used for plant characterisation. New technology was installed leading to the financial benefit.
[46]							An artificial neural network was used for system characterisation.
[52], [53]							Characterisation techniques were compared for dewatering systems.

1.5 Need for the study

A need for AI technologies is evident for the optimisation of deep-level mine refrigeration systems, as shown in

Table 5. As detailed earlier in the chapter, AI provides more opportunities for reducing operating costs through efficient control. This has however not been seen in the mining industry for financial benefit. Thus, this study aims to address this need by satisfying the following objectives:

- Characterise individual refrigeration plants through historical data.
- Reduce operating costs of the refrigeration system.
- Use an AI-based optimisation technique with improved computational performance so that the optimisation can be used in dynamically controlled systems.

1.6 Summary

The chapter explained that the South African deep-level mining industry is characterised by large energy-intensive systems. Refrigeration and ventilation systems are amongst these large systems, which account for 28% of a mine's total energy consumption. Rising energy costs necessitate reduced operating costs for the mines to remain profitable.

The underground environment is exposed to high virgin rock temperatures of up to 60 °C. Refrigeration systems assist the ventilation system by supplying work areas with ventilation that does not exceed the legal requirements of 32.5 °C wet-bulb and 37 °C dry-bulb temperature. It is necessary to optimise refrigeration systems due to mines developing beyond their original operational designs.

In the South African deep-level mining industry, refrigeration systems are controlled manually to obtain a specific chilled water temperature. Manual control, which is implemented by control room operators, prioritise service delivery (water temperature) over system efficiency. Energy management is necessary to decrease the operating costs while ensuring service delivery requirements are satisfied.

Various optimisation techniques have been used to identify operating profiles that result in a financial benefit. However, these techniques have long computational times that prevent them from being used in dynamic control systems. Using AI improves the computational performance of optimisation, thus making the optimisation viable in dynamically controlled systems.

This study addresses the need to improve computational performance when optimising refrigeration systems. This study uses AI optimisation techniques along with system characterisation (to account for design variance) to identify operating profiles that result in a financial benefit.

1.7 Dissertation overview

Chapter 1 detailed the problem this study aims to address. An overview of present research and technology was described, thereby identifying the need for this study. A brief background of the industry of the study was described to assist in the understanding of the problem.

Chapter 2 describes the methodology used to address and solve the problem described in Chapter 1. The implementation of the described methodology fulfils the gap identified in the present research.

Chapter 3 depicts the results obtained from implementing the methodology on a specific mine through simulation and physical implementation. The results are compared with the present operation to determine the financial benefits obtained.

Chapter 4 provides a conclusion to this study. Recommendations are identified for further improvement to address the identified problem and gap in research.

CHAPTER 2 – METHODOLOGY

2.1 Introduction

This chapter describes the methodology applied to develop a solution to the problem discussed in Section 1.5. Figure 17 depicts the simplified layout of the methodology applied.

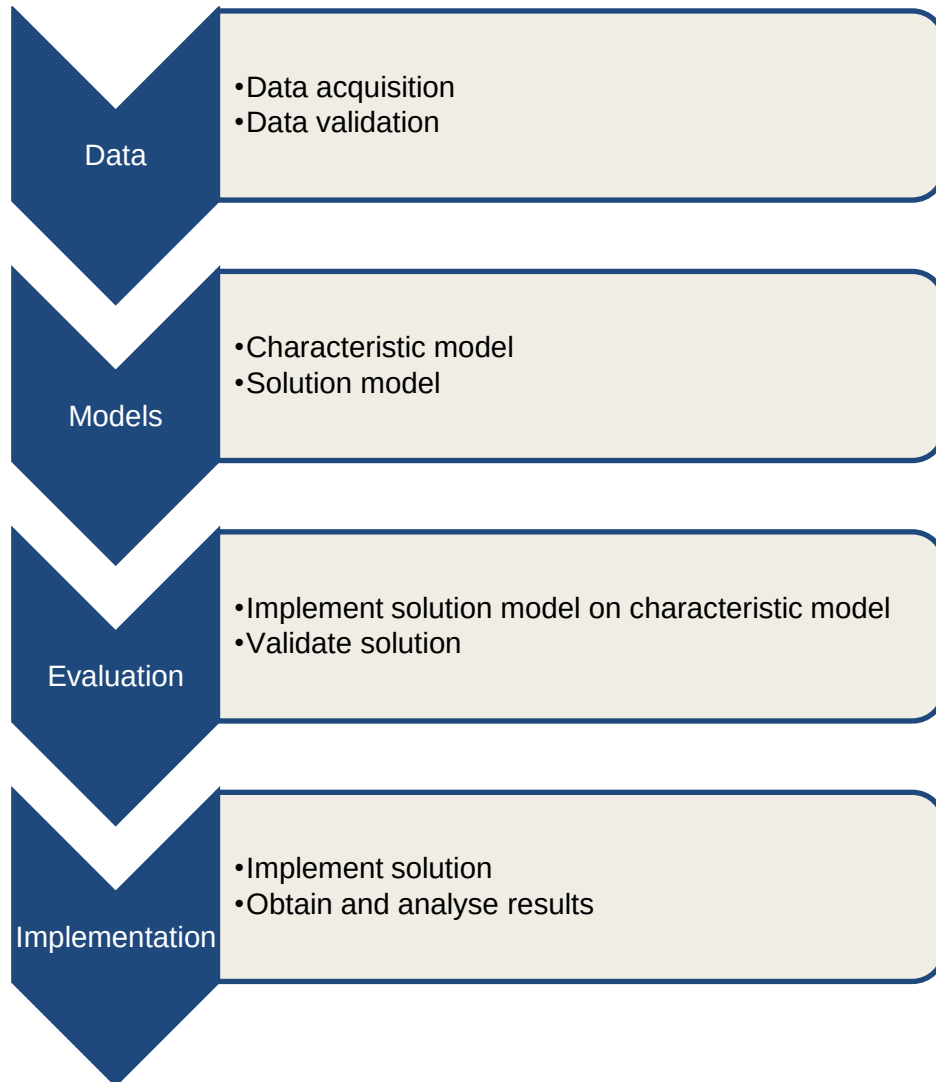


Figure 17: Simplified methodology layout

The first step in addressing the problem, as depicted in Figure 17, is acquiring and validating data for the specific refrigeration system. The data is used to develop a characteristic model. A solution model is developed and implemented on the characteristic model to obtain a solution. The solution is validated and implemented before the results are obtained and analysed for further improvement. The methodology was developed for two-stage refrigeration systems, as portrayed in Figure 18, but can be adjusted for single-stage refrigeration systems.

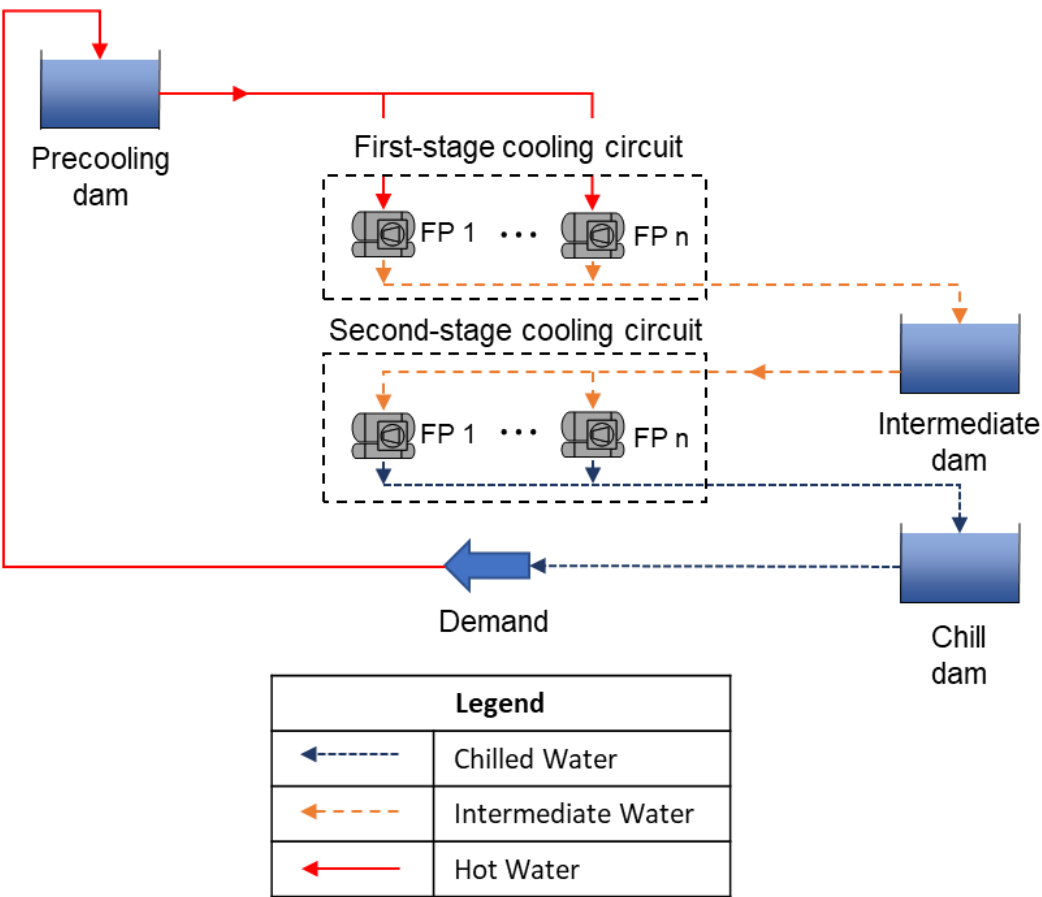


Figure 18: Typical two-stage refrigeration system layout

Two-stage refrigeration systems use an intermediate dam between the two cooling circuits. The intermediate dam allows for variations in water flow between the two cooling stages, thus improving the versatility of the system. The first-stage cooling circuit receives water from the precooling dam. Heat is extracted from the water, which is sent to the intermediate dam.

The second-stage cooling circuit receives water from the intermediate dam. Heat is further extracted from the water and sent to the chill dam before supplying the BAC and underground operations. The water gains heat from the BAC and underground operations and is sent to the precooling dam.

2.2 Data

2.2.1 Data sources

The refrigeration system creates large amounts of data. The data comes from sensors that continuously measure parameters, system infrastructure limitations and properties (such as dam capacities). Refrigeration plants are responsible for most of the generated data. Table 6 identifies the data sources for a refrigeration plant.

Table 6: Refrigeration plant data sources

Sensor data	Infrastructure properties
• Evaporator flow rate • Evaporator inlet temperature • Evaporator outlet temperature • Condenser flow rate • Condenser inlet temperature • Condenser outlet temperature • Guide vane angle • Power consumption	• Installed motor power capacity • Evaporator flow limitation • Condenser flow limitation • Guide vane angle limitation

Dams are largely responsible for the remaining generated data. Table 7 identifies the data sources for dams.

Table 7: Dam data sources

Sensor data	Infrastructure properties
• Inlet flow rate • Outlet flow rate • Dam level • Dam temperature	• Dam capacity

2.2.2 Data acquisition

Data from infrastructure limitations and properties is attained from design reports, drawings and layouts. The generated sensor data of the refrigeration system needs to be stored to allow for analysis and modelling. Figure 19 depicts the flow of sensor data from generation at the sensor to storage.

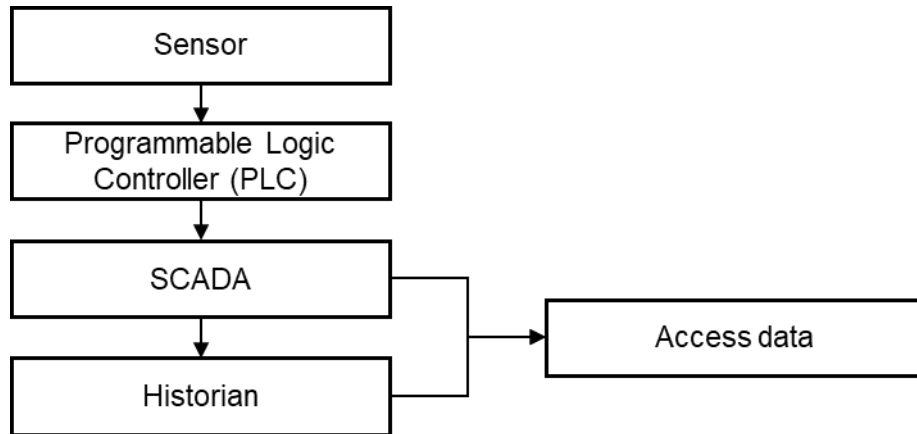


Figure 19: Data flow diagram

Data is generated by sensors that continuously measure parameters. The measured data is transferred from the sensor to the programmable logic controller (PLC). The PLC acts as an interface for the SCADA to access the data from the sensors. The SCADA further provides a user interface to display the live data and stores the data for a limited period. A historian is used to store the data for extended periods. The data is attainable through either the SCADA or the historian.

2.2.3 Data validation

Data validation is necessary to ensure trustworthy and accurate data. Zero value, flat line detection, and boundary detection are the main considerations for data validation in automatic data collection systems [59]. The following tests are implemented on the acquired data set to ensure data integrity:

1. **Constant value check:** A measurement that has been constant for a prolonged period is an erroneous measurement. Erroneous data is omitted from the data set.

2. **Measurement unit check:** The units of the data need to be consistent to prevent inaccurate comparisons. The units are converted to Système Internationale (SI) units to ensure consistency, for example l/h is converted to l/s.
3. **Sensor range check:** The measured data needs to coincide with the sensor measurement range. A flow rate of 10 l/s for a sensor that can only measure up to 5 l/s is considered an erroneous measurement. Erroneous data is omitted from the data set.
4. **Boundary check:** Data values beyond the minimum and maximum realistic values for certain parameter are regarded as erroneous measurements. A 35 °C temperature measurement for a parameter that usually lies between 10 °C and 20 °C is regarded as an erroneous measurement. Erroneous data is omitted from the data set.
5. **Redundancy check:** Redundant sensors allow for comparisons between two data points. A comparison resulting in a large discrepancy indicates that one of the measurements is erroneous. The two points are subjected to data validation checks to identify the erroneous measurement. Erroneous data is omitted from the data set.
6. **Correlation check:** The measurements of a refrigeration plant need to correlate with one another. A measurement indicating that a cooling duty has been achieved when a plant is not operational is regarded as an erroneous measurement.
7. **Mass balance check:** The sum of the mass flow rate rates entering a point must be equivalent to the sum of the mass flow rates leaving the point. A discrepancy between the two values indicates that a mass flow rate has been measured erroneously.
8. **Energy balance check:** The sum of the cooling duty achieved by the evaporator of a refrigeration plant and the power consumption of the compressor must be equivalent to the cooling duty achieved by the condenser cycle of the refrigeration plant.

The data validation procedure assists in identifying faulty and broken instrumentation. The remaining data set is trustworthy and can be used in further analysis and modelling. The data set is an accurate representation of the system and the operations of the system.

2.3 Characteristic model

2.3.1 Background

A characteristic model can be developed from the trustworthy data set. The purpose of a characteristic model is to mimic a system to obtain outputs with varying inputs. A characteristic model of a refrigeration system requires that the following components be characterised individually (as shown in Figure 18):

- Inlet.
- Demand.
- Storage facilities (dams).
- Cooling components (refrigeration plants).
- Electricity cost tariff structure.

2.3.2 Inlet

The refrigeration system receives water from the BAC and underground operations. The parameters characterising the inlet water are depicted in Figure 20 and described in Table 8.

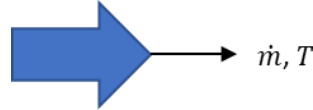


Figure 20: Inlet characteristic parameters

Table 8: Inlet characteristic parameters

Parameter	Symbol	Unit
Flow rate	$\dot{m}$	l/s
Temperature	T	°C

The flow rate is dependent on the BAC and underground operations, which are both time-of-day dependent. The inlet flow rate is modelled by a matrix that contains all the inlet flow rates for the various time periods of the day, as shown in Equation (1).

$$\overline{\dot{m}_{in}} = \begin{bmatrix} \dot{m}_{in,1} \\ \vdots \\ \dot{m}_{in,48} \end{bmatrix} \quad (1)$$

Here, $\overline{\dot{m}_{in}}$ is the matrix containing all the inlet flow rates for the various time periods in l/s, $\dot{m}_{in,1}$ is the inlet flow rate for time period 1 of the day (00:00) in l/s and, similarly, $\dot{m}_{in,48}$ is the inlet flow rate in l/s for time period 48 of the day (23:30). Similarly, the inlet temperature is characterised by a matrix, as shown in Equation (2).

$$\overline{T_{in}} = \begin{bmatrix} T_{in,1} \\ \vdots \\ T_{in,48} \end{bmatrix} \quad (2)$$

Here, $\overline{T_{in}}$ is the matrix containing all the inlet temperatures for the various time periods in °C, $T_{in,1}$ is the inlet temperature for time period 1 of the day (00:00) in °C, and similarly $T_{in,48}$ is the inlet temperature in °C for time period 48 of the day (23:30).

2.3.3 Demand

The demand of a refrigeration system typically includes the surface BAC and the underground operations. The parameters required to characterise the demand are depicted in Figure 21 and described in Table 9.

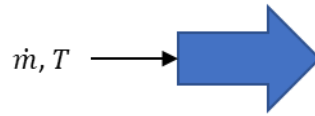


Figure 21: Demand characterisation parameters

Table 9: Demand characteristic parameters

Parameter	Symbol	Unit
Flow rate	$\dot{m}$	l/s
Temperature requirement	T	°C

The flow rate is time-of-day dependent. Although the temperature requirement can be time-of-day dependent, it is typically a fixed set-point for all times of the day. As a result, the demand is modelled by a matrix that consists of the flow rate for each time period of the day, as shown in Equation (3).

$$\overline{\dot{m}_{demand}} = \begin{bmatrix} \dot{m}_{demand,1} \\ \vdots \\ \dot{m}_{demand,48} \end{bmatrix} \quad (3)$$

Here, $\overline{\dot{m}_{demand}}$ is the matrix containing all the demand flow rates for the various time periods in l/s, $\dot{m}_{demand,1}$ is the demand flow rate for time period 1 of the day (00:00) in l/s, and similarly $\dot{m}_{demand,48}$ is the demand flow rate for time period 48 of the day (23:30) in l/s.

2.3.4 Dams

Dams are responsible for the storage capabilities of a refrigeration system. The parameters required to characterise the dams are depicted in Figure 22 and the internal parameters are listed in Table 10.

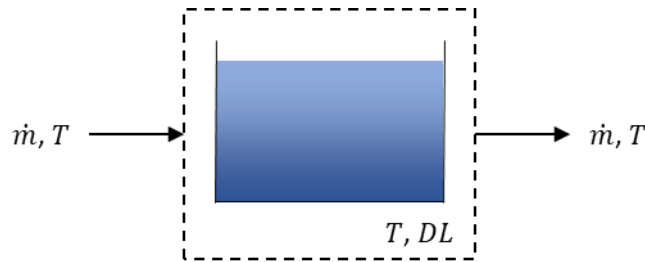


Figure 22: Dam characterisation parameters

Table 10: Dam characteristic parameters

Parameter	Symbol	Unit
Level	DL	%
Temperature	T	°C

The level of the dam is a ratio comparing the mass of water in the dam with the mass capacity of the dam, as shown in Equation (4).

$$DL = \frac{m}{m_{cap}} \quad (4)$$

Here, DL is the dam level as a percentage, m is the mass of water in the dam in l , and m_{cap} is the mass capacity of the dam in l . The mass of water in the dam is calculated by adding the mass of water into the dam to the present mass of water in the dam and subtracting the mass of water out of the dam, as shown in Equation (5).

$$m(i) = m(i-1) + \sum_{j=1}^n m_{in,j}(i-1) - \sum_{j=1}^k m_{out,j}(i-1) \quad (5)$$

Here, $m(i)$ is the mass of water in the dam at time period i in l , $m_{in,j}(i)$ is the mass of water into the dam for inlet flow j and time period i in l , n is the number of inlet flows, $m_{out,j}(i)$ is the mass of water out of the dam for outlet flow j and time period i in l , and k is the number of outlet flows. Dams have upper and lower limits that can be modelled through Equation (6).

$$m_{min} \leq m \leq m_{max} \quad (6)$$

Here, $m(i)$ is the mass of water in the dam in l , m_{min} is the minimum mass capacity of the dam in l , and m_{max} is the maximum mass capacity of the dam in l .

The mass of water for the precooling dam, intermediate dam and chill dam are shown in Equations (7) to (9), respectively.

$$m_{pre}(i) = m_{pre}(i-1) + m_{in}(i-1) - \sum_{j=1}^n m_{first,j}(i-1) \quad (7)$$

$$m_{int}(i) = m_{int}(i-1) + \sum_{j=1}^n m_{first,j}(i-1) - \sum_{j=1}^k m_{second,j}(i-1) \quad (8)$$

$$m_{chill}(i) = m_{chill}(i-1) + \sum_{j=1}^k m_{second,j}(i-1) - m_{demand}(i-1) \quad (9)$$

Here, $m_{pre}(i)$ is the mass of water in the precooling dam for time period i in l , $m_{int}(i)$ is the mass of water in the intermediate dam for time period i in l , $m_{chill}(i)$ is the mass of water in the chill dam for time period i in l , $m_{first,j}(i)$ is the mass of water through the first-stage refrigeration plant j for time period i in l , and $m_{second,j}(i)$ is the mass of water through the second-stage refrigeration plant j for time period i in l .

The temperature of the water in the dam is calculated as a function of the present dam temperature, the temperature of the water entering the dam, and the mass of water in the dam and entering the dam respectively, as shown in Equation (10).

$$T(i) = \frac{m(i-1)T(i-1) + \sum_{j=1}^n m_{in,j}(i-1)T_{in,j}(i-1)}{m(i-1) + \sum_{j=1}^n m_{in,j}(i-1)} \quad (10)$$

Here, $T(i)$ is the temperature of water in the dam for time period i in °C, $m(i)$ is the mass of water in the dam for time period i in l, $m_{in,j}(i)$ is the mass of water into the dam for inlet flow j and time period i in l, and $T_{in,j}(i)$ is the temperature of water for inlet flow j and time period i in °C.

The temperature of water for the precooling dam, intermediate dam and chill dam are shown in Equations (11) to (13), respectively.

$$T_{pre}(i) = \frac{m_{pre}(i-1)T_{pre}(i-1) + m_{in}(i-1)T_{in}(i-1)}{m_{pre}(i-1) + m_{in}(i-1)} \quad (11)$$

$$T_{int}(i) = \frac{m_{int}(i-1)T_{int}(i-1) + \sum_{j=1}^n m_{first,j}(i-1)[T_{pre}(i-1) - \Delta T_{first,j}(i-1)]}{m_{int}(i-1) + \sum_{j=1}^n m_{first,j}(i-1)} \quad (12)$$

$$T_{chill}(i) = \frac{m_{chill}(i-1)T_{chill}(i-1) + \sum_{j=1}^k m_{second,j}(i-1)[T_{int}(i-1) - \Delta T_{second,j}(i-1)]}{m_{chill}(i-1) + \sum_{j=1}^k m_{second,j}(i-1)} \quad (13)$$

Here, $T_{pre}(i)$ is the temperature of water in the precooling dam for time period i in °C, $T_{int}(i)$ is the temperature of water in the intermediate dam for time period i in °C, $T_{chill}(i)$ is the mass of water in the chill dam for time period i in °C, $\Delta T_{first,j}(i)$ is the temperature change of water over the first-stage refrigeration plant j for time period i in °C, and $\Delta T_{second,j}(i)$ is the temperature change of water over the second-stage refrigeration plant j for time period i in °C.

2.3.5 Refrigeration plants

Refrigeration plants are responsible for the cooling provided in a refrigeration system. Continuous exposure to the operating conditions and water quality results in the plant performance deteriorating from the design. As a result, characterisation based on historical data is necessary to determine the cooling performance of the individual refrigeration plants accurately. The outcome of the refrigeration plants is a change in temperature over the evaporator, which is characterised by the parameters depicted in Figure 23 and listed in Table 11.

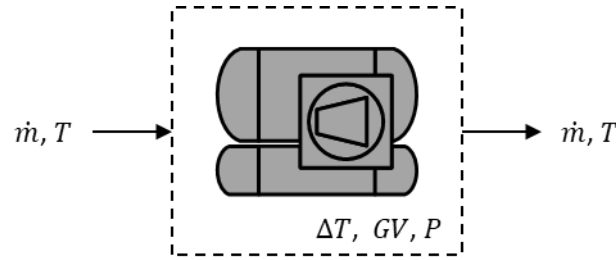


Figure 23: Refrigeration plant characteristic parameters

Table 11: Refrigeration plant characteristic parameters

Parameter	Symbol	Unit
Evaporator change in temperature	ΔT	°C
Evaporator inlet temperature	T	°C
Evaporator flow rate	$\dot{m}$	l/s
Guide vane angle	GV	%
Power consumption	P	kW

The largest determining factor of performance amongst the parameters is guide vane position [60]. The change in temperature can be estimated as a function of guide vane position, inlet evaporator temperature and evaporator flow rate. Equation (14) was found to be the most reliable characteristic equation for refrigeration plants.

$$\Delta T_{plant,i}(GV, T_{inlet}, \dot{m}) = x_{1,i}T_{inlet}GV + x_{2,i}GV\dot{m} + x_{3,i}T_{inlet}GV\dot{m} + x_{4,i}GV^2 + x_{5,i}GV \quad (14)$$

Here, $\Delta T_{plant,i}$ is the change in evaporator temperature over the evaporator of plant i in °C, GV is the guide vane angle as a percentage, T_{inlet} is the inlet evaporator temperature in °C, and $\dot{m}$ is the evaporator flow rate in l/s. The constants $x_{1,i}$, $x_{2,i}$, $x_{3,i}$, $x_{4,i}$ and $x_{5,i}$ are refrigeration plant specific (i).

Response surface methodology is used to characterise the respective plants. The constants $x_{1,i}$, $x_{2,i}$, $x_{3,i}$, $x_{4,i}$ and $x_{5,i}$ are calculated to ensure that Equation (14) is representative of the selected and filtered data set for each refrigeration plant, i . The coefficient of determination (R^2) alongside graphic residual analysis determine the quality of fit.

The power consumption of the refrigeration plants is dependent on the guide vane angle and is estimated by Equation (15).

$$P_i(GV) = y_{1,i}GV^2 + y_{2,i}GV + y_{3,i} \quad (15)$$

Here, P_i is the power consumption of plant i in kW and GV is the guide vane angle as a percentage. The constants $y_{1,i}$, $y_{2,i}$ and $y_{3,i}$ are determined similarly to the constants $x_{1,i}$, $x_{2,i}$, $x_{3,i}$, $x_{4,i}$ and $x_{5,i}$ from Equation (14). The R^2 and the graphic residual analysis determine the quality of fit for Equation (15). Refrigeration plants are subject to upper and lower operating limits, which are modelled by Equations (16) and (17).

$$0 \leq GV \leq 100 \quad (16)$$

$$0 \leq \dot{m} \leq \dot{m}_{max} \quad (17)$$

Here, GV is the guide vane angle as a percentage, $\dot{m}$ is the mass flow rate for the refrigeration plant evaporator in l/s, and $\dot{m}_{max}$ is the maximum capacity mass flow rate for the refrigeration plant evaporator in l/s.

2.3.6 Electricity cost tariff structure

The refrigeration system electricity cost is determined by the energy consumption and the tariff applicable to the time of consumption. The tariff structure is characterised as a matrix that contains the tariff for each time period, as shown in Equation (18).

$$\overline{tariff} = \begin{bmatrix} tariff_1 \\ \vdots \\ tariff_{48} \end{bmatrix} \quad (18)$$

Here, $\overline{tariff}$ is the matrix containing the tariff for the various time periods in c/kWh, $tariff_1$ is the tariff applicable to time period 1 of the day (00:00) in c/kWh and, similarly, $tariff_{48}$ is the tariff applicable to time period 48 of the day (23:30) in c/kWh. The electricity cost is calculated by multiplying the tariff matrix by the energy consumption matrix, as shown in Equation (19).

$$Cost = \bar{E} \cdot \overline{tariff} \quad (19)$$

Here, $Cost$ is the electricity cost in c, $\bar{E}$ is the energy consumption matrix in kWh, and $\overline{tariff}$ is the tariff matrix in c/kWh.

2.4 Solution model

2.4.1 Background

The solution model is implemented on the characteristic model to determine the efficient operating conditions. The solution model uses particle swarm optimisation to determine the minimum of an objective function within the defined constraints. The objective function is the power consumption of the system whereas the constraints are the operating and physical limitations of the various system components (dams and refrigeration plants). Particle swarm optimisation was selected due to its solution quality and computational performance being better than that of genetic algorithms (as discussed in Section 1.3.3).

2.4.2 Particle swarm optimisation

Particle swarm optimisation consists of particles dispersed randomly across the constraint area for the defined problem. The particles navigate through the constraint area via information exchange to find the global minimum of the defined problem. Table 12 lists the parameters used in particle swarm optimisation.

Table 12: Particle swarm optimisation parameters

Parameter	Symbol
Position for particle j	X_j
Velocity for particle j	V_j
Personal best for particle j	$p_{best,j}$
Global best	g_{best}

A particle's initial position is determined randomly and thereafter the particle's position is determined based on its velocity and present position. The new position of the particle is determined through Equation (20).

$$X_j(i + 1) = X_j(i) + V_j(i + 1) \quad (20)$$

Here, $X_j(i + 1)$ is the new position particle j for iteration $(i + 1)$, $X_j(i)$ is the position for particle j for iteration i , and $V_j(i + 1)$ is the velocity for particle j for iteration $(i + 1)$. The velocity of the particle is determined through the following three components:

- **Inertia:** The influence of the present particle's velocity on the next iteration particle's velocity.
- **Cognitive component:** The influence of the particle's personal best position on the next iteration particle velocity.
- **Social component:** The influence of the swarm's (all the particles) best position on the next iteration particle velocity.

The velocity of the particle is determined before the position is updated. The velocity is determined through the sum of the inertia ($\omega V_j(i)$), cognitive component ($\varphi_1 r_1 [p_{best,j} - X_j(i)]$), and social component ($\varphi_2 r_2 [g_{best} - X_j(i)]$), as shown in Equation (21).

$$V_j(i + 1) = \omega V_j(i) + \varphi_1 r_1 [p_{best,j} - X_j(i)] + \varphi_2 r_2 [g_{best} - X_j(i)] \quad (21)$$

Here, $V_j(i + 1)$ is the velocity for particle j for iteration $(i + 1)$, ω is the inertia constant, $V_j(i)$ is the velocity for particle j for iteration i , φ_1 is the cognitive acceleration constant, r_1 and r_2 are random numbers, $p_{best,j}$ is the personal best position for particle j , $X_j(i)$ is the position for particle j for iteration i , φ_2 is the social acceleration constant, and g_{best} is the best position for the swarm. The ranges for the constants are depicted in Table 13 [61].

Table 13: Particle swarm optimisation constants ranges

Constant	Minimum	Maximum
ω	0.4	0.9
φ_1 and φ_2	1.2	2
r_1 and r_2	0	1

The stop criteria are evaluated before the objective function is evaluated again for each particle using the updated position. The stop criteria prevent unnecessary iterations if the solution has converged on a feasible point and prevents an infinite loop occurring from a convergence on an infeasible point. The stop criteria consist of [62]:

- **Iteration count:** A limit is set on the number of iterations to prevent the solution model from being caught in an infinite loop due to a convergence on an infeasible point.
- **Improvement:** No change or changes in the global and personal best values below a threshold will stop the solution model to prevent the solution model from diverging from a minimum point.
- **Convergence:** If a percentage of the particles converges on a point, the solution model is stopped and the converged point is presented as the solution.

A solution that results in the convergence criterium being met, is the solution to the problem and optimisation model. In that case, the global best position is the point in the constraint area that results in a minimum value for the objective function. The particle swarm optimisation algorithm is summarised in Figure 24.

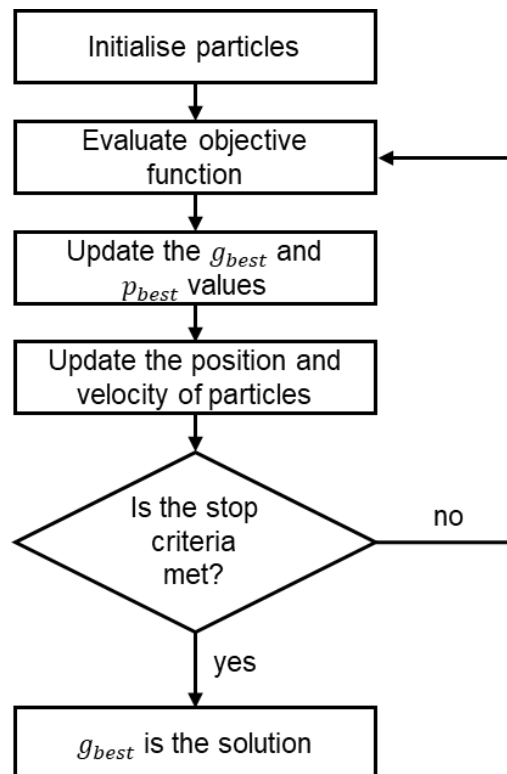


Figure 24: Particle swarm optimisation algorithm [33]

2.4.3 Objective function

The objective function is the function that represents the cost of operating the system, and a minimum value for the objective function is the minimum operating cost for the system. The energy cost for the refrigeration system is used as the objective function, which is represented in Equation (22).

$$f = 0.5 \sum_{i=1}^{48} \sum_{j=1}^{n+k} P_{plant,j} (GV_j(i)) tariff(i) \quad (22)$$

Here, n is the number of refrigeration plants in the first cooling stage, k is the number of refrigeration plants in the second cooling stage, $P_{plant,j}$ is the power consumption for plant j in kW as a function of guide vane angle, $GV_j(i)$ is the guide vane angle for plant j at time period i as a percentage, and $tariff(i)$ is the tariff applicable at time period i .

Equation (22) sums the product of the applicable tariff and the power consumptions for all the plants and for all the time periods of the day. The 0.5 factor is necessary to convert the power consumption into energy consumption as the day is divided into 48 half-hour time periods as opposed to 24 one-hour time periods.

2.4.4 Objective variable

The objective variable is what the solution model optimises to determine a minimum value in the objective function. The objective variable is a matrix containing all the guide vane angles and flow rates for the refrigeration plants for each time period of the day. The guide vane angle matrix and flow rate matrix are combined to make the objective variable matrix, as shown in Equation (23).

$$\bar{x} = \begin{bmatrix} \overline{GV} \\ \bar{m} \end{bmatrix} \quad (23)$$

Here, $\bar{x}$ is the objective function matrix, $\overline{GV}$ is the guide vane angle matrix, and $\bar{m}$ is the flow rate matrix. The guide vane angle matrix and the flow rate matrix are shown in Equations (24) and (25), respectively. The guide vane angle matrix and flow rate matrix are divided primarily by the refrigeration plant and secondary by the time period.

$$\overline{GV} = \begin{bmatrix} GV_1(1) \\ \vdots \\ GV_1(48) \\ \vdots \\ GV_{n+k}(1) \\ \vdots \\ GV_{n+k}(48) \end{bmatrix} \quad (24)$$

Here, $\overline{GV}$ is the guide vane angle matrix, $GV_1(1)$ is the guide vane angle for refrigeration plant 1 for the time period 1 as a percentage, $GV_1(48)$ is the guide vane angle for refrigeration plant 1 for the time period 48 as a percentage, $GV_{n+k}(1)$ is the guide vane angle for refrigeration plant $n + k$ for the time period 1 as a percentage, $GV_{n+k}(1)$ is the guide vane angle for refrigeration plant $n + k$ for the time period 1 as a percentage, and $GV_{n+k}(48)$ is the guide vane angle for refrigeration plant $n + k$ for the time period 48 as a percentage. Similarly, the flow rate matrix is found in Equation (27).

$$\overline{m} = \begin{bmatrix} \dot{m}_1(1) \\ \vdots \\ \dot{m}_1(48) \\ \vdots \\ \dot{m}_{n+k}(1) \\ \vdots \\ \dot{m}_{n+k}(48) \end{bmatrix} \quad (25)$$

Here, $\overline{m}$ is the flow rate matrix, $\dot{m}_1(1)$ is the flow rate for refrigeration plant 1 for the time period 1 in l/s, $\dot{m}_1(48)$ is the flow rate for refrigeration plant 1 for the time period 48 in l/s, $\dot{m}_{n+k}(1)$ is the flow rate for refrigeration plant $n + k$ for the time period 1 in l/s, and $\dot{m}_{n+k}(48)$ is the flow rate for refrigeration plant $n + k$ for the time period 48 in l/s. The solution model varies the objective variable within the constraints.

2.4.5 Constraints

The constraints for the solution model are determined from the system configuration as well as the operating and physical limitations of the system components. Following the flow of water in the refrigeration system, the first component is the precooling dam. The precooling dam has limit constraints, depicted in Equation (26).

$$m_{pre,min} \leq m_{pre}(i) \leq m_{pre,max} \quad (26)$$

Here, $m_{pre,min}$ is the minimum precooling dam capacity in l, $m_{pre}(i)$ is the mass of water in the precooling dam for time period i in l, and $m_{pre,max}$ is the maximum precooling dam capacity in l. The mass of water in the precooling dam is calculated through Equation (7). The mass in the dam for every time period is evaluated to ensure that the constraints are not exceeded. The precooling dam is the first dam in the system, which is unaffected by cooling components. As a result, it has no temperature requirements.

The next component in the cooling system is the first-stage cooling circuit. The first-stage cooling circuit has guide vane angle and flow rate restrictions. The guide vane angle should be between 0% and 100% open. This restriction is characterised by Equation (27).

$$0 \leq GV_j(i) \leq 100 \quad (27)$$

Here, $GV_j(i)$ is the guide vane angle for plant j for time period i as a percentage. The guide vane angle constraint is evaluated for all time periods. The flow rate of a refrigeration plant is limited between 0 and the maximum flow rate design for the specific refrigeration plant. This constraint is depicted in Equation (28).

$$0 \leq \dot{m}_{plant,j}(i) \leq \dot{m}_{plant,j,max} \quad (28)$$

Here, $\dot{m}_{plant,j}(i)$ is the flow rate for plant j for time period i in l/s and $\dot{m}_{plant,j,max}$ is the maximum flow rate for plant j in l/s. Although the refrigeration plants have power consumption constraints, these are not necessary in the solution model as the characteristic equations for the respective plants ensure that the power limitations are not exceeded.

The intermediate dam follows the first-stage cooling circuit in a two-stage cooling system. In single-stage cooling systems, the chill dam follows the first-stage cooling circuit and does not have constraints for an intermediate dam or for the second-stage cooling circuit. Similar to the precooling dam, the intermediate dam has capacity limitations, depicted in Equation (29).

$$m_{int,min} \leq m_{int}(i) \leq m_{int,max} \quad (29)$$

Here, $m_{int,min}$ is the minimum intermediate dam capacity in l, $m_{int}(i)$ is the mass of water in the intermediate dam for time period i in l, and $m_{int,max}$ is the maximum intermediate dam capacity in l. The mass of water in the intermediate dam is calculated through Equation (8). The intermediate dam has a maximum temperature requirement, as depicted in Equation (30).

$$T_{int}(i) \leq T_{int,max} \quad (30)$$

Here, $T_{int}(i)$ is the temperature of the intermediate dam for time period i in °C and $T_{int,max}$ is the maximum temperature requirement for the intermediate dam in °C. The intermediate dam temperature (T_{int}) is calculated through Equation (12). The maximum temperature requirement is necessary to prevent the inlet conditions of the second-stage cooling circuit exceeding design and operating limitations.

The second-stage cooling circuit follows the intermediate dam and precedes the chill dam in the refrigeration system. Similar to the first-stage cooling circuit, the second-stage cooling circuit has guide vane angle and flow rate restrictions. These restrictions are covered in Equations (27) and (28).

The chill dam follows the second-stage cooling circuit and has capacity limitations and a maximum temperature requirement that are similar to the intermediate dam. The capacity limitations are depicted in Equation (31).

$$m_{chill,min} \leq m_{chill}(i) \leq m_{chill,max} \quad (31)$$

Here, $m_{chill,min}$ is the minimum chill dam capacity in l, $m_{chill}(i)$ is the mass of water in the chill dam for time period i in l, and $m_{chill,max}$ is the maximum chill dam capacity in l. The mass of water in the chill dam is calculated through Equation (9). The demand of the refrigeration system requires that the temperature of the chill dam remains below the temperature target, as depicted in Equation (32).

$$T_{chill}(i) \leq T_{target} \quad (32)$$

Here, $T_{chill}(i)$ is the chill dam temperature for time period i in °C and T_{target} is the target temperature for the chill dam in °C. The chill dam temperature (T_{chill}) is calculated through Equation (13). The chill dam does not have a minimum temperature requirement, which ensures that the full storage capability of the dam can be used to ensure operating cost savings.

The refrigeration system is largely a closed-loop system. To prevent dam level issues from occurring, the total flow of water into the refrigeration system must be equivalent to the total flow of water out of the system for the period of a day. Similarly, the total flow of water through the two cooling stages must be equivalent for a period of a day. These relationships are characterised in Equation (33).

$$\sum_{i=1}^{48} m_{in}(i) = \sum_{i=1}^{48} \sum_{j=1}^n m_{first,j}(i) = \sum_{i=1}^{48} \sum_{j=1}^k m_{second,j}(i) = \sum_{i=1}^{48} m_{demand}(i) \quad (33)$$

Here, $m_{in}(i)$ is the total mass flow of water into the refrigeration system for time period i in I , n is the number of refrigeration plants in the first-stage cooling circuit, $m_{first,j}(i)$ is the total mass flow of water through plant j of the first-stage cooling circuit for time period i in I , k is the number of refrigeration plants in the second-stage cooling circuit, $m_{second,j}(i)$ is the total mass flow of water through plant j of the second-stage cooling circuit for time period i in I , and $m_{demand}(i)$ is the total mass flow of water out of the refrigeration system for time period i in I .

The initial and final dam levels need to be equivalent to ensure the repeatability of the optimised solution from day to day as well as being a redundancy check to ensure that the flows of water into and out of the refrigeration system are equivalent. This relationship is characterised in Equations (34) to (36).

$$m_{pre,init} = m_{pre,final} \quad (34)$$

$$m_{int,init} = m_{int,final} \quad (35)$$

$$m_{chill,init} = m_{chill,final} \quad (36)$$

Here, $m_{pre,init}$ is the mass of water in the precooling dam at the start of the day in I , $m_{pre,final}$ is the mass of water in the precooling dam at the end of the day in I , $m_{int,init}$ is the mass of water in the intermediate dam at the start of the day in I , $m_{int,final}$ is the mass of water in the intermediate dam at the end of the day in I , $m_{chill,init}$ is the mass of water in the chill dam at the start of the day in I , and $m_{chill,final}$ is the mass of water in the chill dam at the end of the day in I .

2.5 Implementation

The result of the solution model is optimised guide vane angles and refrigeration plant evaporator flow rates. These values need to be implemented to achieve operating cost savings. A manual implementation is necessary to ensure that the system operates automatically without the influence of control room operators.

The solution model requires that the inlet variable (water into the refrigeration system) and demand be known for each time period of the day. This requires a form of prediction to ensure that the operating profiles can be adjusted to ensure that operating cost savings are still achieved. The prediction method used is a simple scaling method that compares the instantaneous measured values for the inlet water temperature and flow with the determined average temperature and flow for the specific season. The percentage difference between the values is applied to the remaining inlet parameters.

The scaled inlet variable is used and the solution model is implemented on the characteristic model to determine the optimised operating profiles for the guide vane angles and refrigeration plant evaporator flow rates. These profiles are implemented manually on the system as verification before an automated system can be used to implement these profiles. For verification, the system is monitored closely and the following parameters are measured and recorded for evaluation and analysis:

- Dam temperatures.
- Dam levels.
- Refrigeration plant power consumptions.

The measurements are done by preinstalled sensors. The recorded values are used to determine the practicality of the optimised system and the financial benefit. The implementation is necessary for low-demand and high-demand tariff periods to account for discrepancies in demand and tariffs between the two periods of the year. The summarised implementation process is depicted in Figure 25.

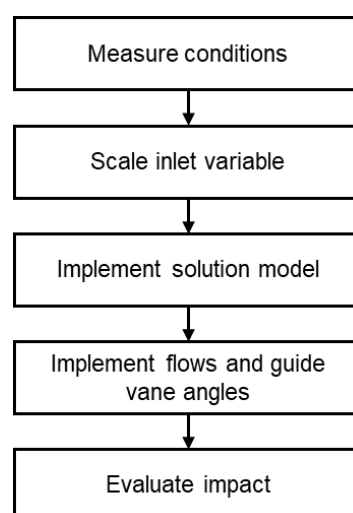


Figure 25: Manual and automated implementation process

2.6 Solution model summary

The respective characterisation equations are shown in Equations (14) and (15).

$$\begin{aligned} \Delta T_{plant,i}(GV, T_{inlet}, \dot{m}) \\ = x_{1,i}T_{inlet}GV + x_{2,i}GV\dot{m} + x_{3,i}T_{inlet}GV\dot{m} + x_{4,i}GV^2 \\ + x_{5,i}GV \end{aligned} \quad (14)$$

$$P_i(GV) = y_{1,i}GV^2 + y_{2,i}GV + y_{3,i} \quad (15)$$

A solution model, in the form of a particle swarm optimisation algorithm, is implemented on the characteristic equations to determine the most financially viable operating profiles. The results of the solution model are the guide vane angles and evaporator flow rate profiles for each refrigeration plant. The solution model aims to determine a minimum value for the objective function, as shown in Equation (22).

$$f = 0.5 \sum_{i=1}^{48} \sum_{j=1}^{n+k} P_{plant,j}(GV_j(i)) tariff(i) \quad (22)$$

The optimised solution determined by the solution model is subject to the constraints shown in Equations (26) to (36).

$$m_{pre,min} \leq m_{pre}(i) \leq m_{pre,max} \quad (26)$$

$$0 \leq GV_j(i) \leq 100 \quad (27)$$

$$0 \leq \dot{m}_{plant,j}(i) \leq \dot{m}_{plant,j,max} \quad (28)$$

$$m_{int,min} \leq m_{int}(i) \leq m_{int,max} \quad (29)$$

$$T_{int}(i) \leq T_{int,max} \quad (30)$$

$$m_{chill,min} \leq m_{chill}(i) \leq m_{chill,max} \quad (31)$$

$$T_{chill}(i) \leq T_{target} \quad (32)$$

$$\sum_{i=1}^{48} m_{in}(i) = \sum_{i=1}^{48} \sum_{j=1}^n m_{first,j}(i) = \sum_{i=1}^{48} \sum_{j=1}^k m_{second,j}(i) = \sum_{i=1}^{48} m_{demand}(i) \quad (33)$$

$$m_{pre,init} = m_{pre,final} \quad (34)$$

$$m_{int,init} = m_{int,final} \quad (35)$$

$$m_{chill,init} = m_{chill,final} \quad (36)$$

Finally, the results of the solution model are implemented to achieve the financial benefit. An initial manual implementation is required to verify the characteristic and solution models before automated implementation. This process is, however, identical for both automated and manual implementation.

2.7 Conclusion

The chapter discussed how historical data was obtained for the refrigeration plants. The data was validated, through numerous checks, to ensure that it represents the system and the operation of the system accurately. The validated data was used to characterise the refrigeration plants to determine accurate temperature changes over the evaporator and the respective power consumptions for various inlet parameters. Mathematical equations were used to further characterise refrigeration system components as well as characterise the system.

The chapter explained how an AI algorithm was used as a solution model and implemented on the characteristic model to determine the most cost-effective operating conditions. Particle swarm optimisation was selected as the algorithm because it had a better solution quality and computational performance than genetic algorithms, detailed in Section 1.3.3. The solution model provided operating profiles for the refrigeration plants as an output.

Chapter 3 discusses the implementation process of the solution model from characterisation to implementation. Further, the results of the implementation are portrayed and discussed in Chapter 3 and compared with the results from the solution model.

CHAPTER 3 – RESULTS

3.1 Introduction

This chapter describes the results pertaining to a case study of the methodology described in the previous chapter. The case study consisted of a two-stage cooling system with three dams and 11 refrigeration plants, as shown in Figure 26.

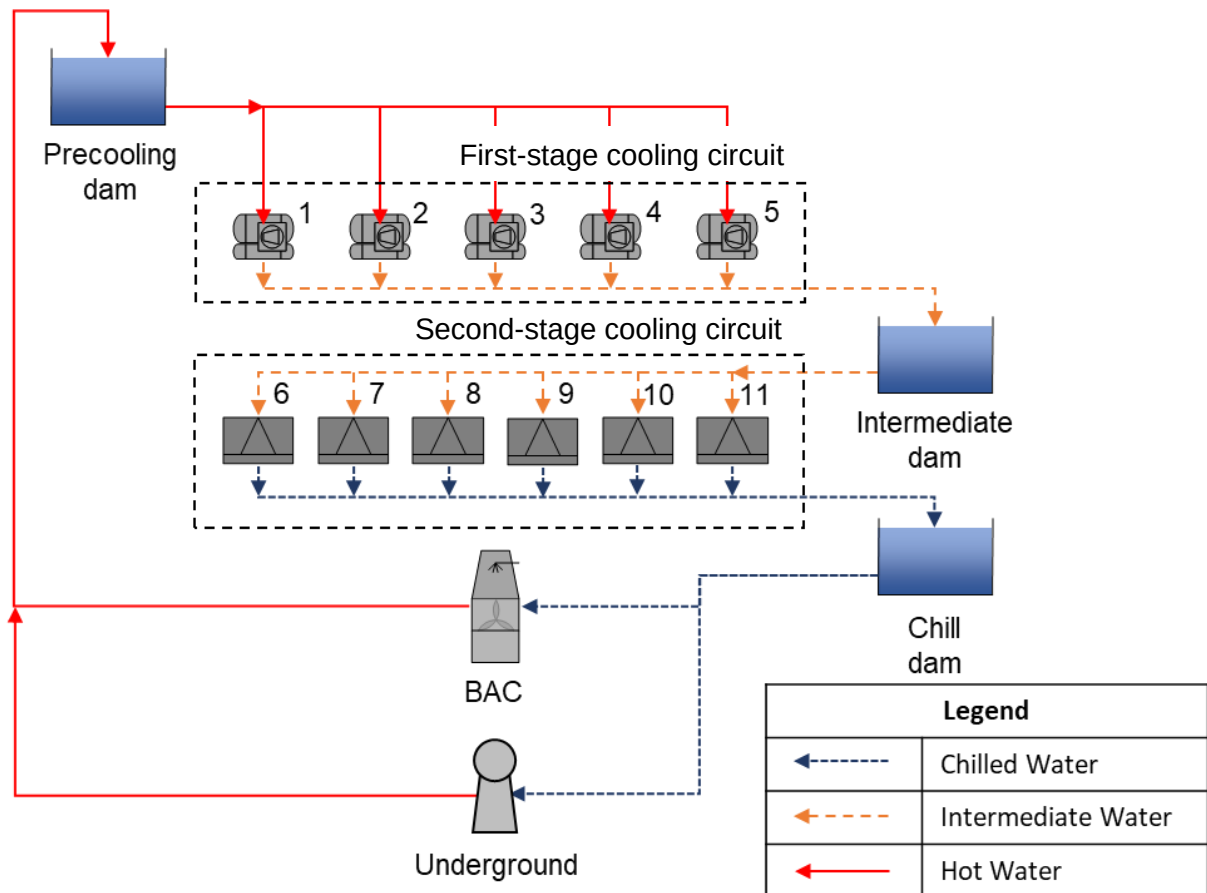


Figure 26: Case study system layout

The BAC did not have storage capabilities and, as a result, the water entering the BAC left the BAC. The water network down the shaft to the underground working areas consisted of a three-chamber pipe feeder system, thus the water entering the underground environment and the water leaving the underground environment were equivalent. The fissure water was pumped up separately and not sent through the cooling circuit.

The system consisted of three dams, namely a precooling dam, an intermediate dam and a chill dam. The precooling dam received water from the BAC and the underground operations, which fed the first-stage cooling circuit. The intermediate dam received water from the first-stage cooling circuit and fed the second-stage cooling circuit. The chill dam received water from the second-stage cooling circuit and fed the BAC as well as the underground operations. The dam capacities are shown in Table 14.

Table 14: Case study dam capacities

Dam	Capacity [MI]
Precooling dam	9
Intermediate dam	5
Chill dam	5

The total surface storage capability was 19 MI. The two stages of the refrigeration system consisted of two variations of refrigeration plants. All the plants in the second-stage cooling circuit were the same and all the plants in the first-stage cooling circuit were the same, except for refrigeration plant 5 that had a smaller motor installed. The refrigeration plant design specifications are shown in Table 15.

Table 15: Case study refrigeration plant design specification

Refrigeration plant	Evaporator flow [l/s]	Evaporator inlet temperature [°C]	Evaporator outlet temperature [°C]	Installed motor power [kW]
1, 2, 3, 4	250	16	6	2 000
5	250	16	6	1 600
6, 7, 8, 9, 10, 11	180	6	1.5	1 200

3.2 Characterisation results

3.2.1 Data collection

A year's operating data, in half-hour intervals, was obtained for each plant. The respective validation processes were implemented on the data to ensure that the data was an accurate representation of the system. The validated data set was used along with the characteristic equations to determine the characteristic models for the refrigeration plants. The two characteristic models developed for the refrigeration plants were performance [Equation (14)] and power consumption [Equation (15)]. An example of the validated data set is shown in Appendix B.

3.2.2 Refrigeration plant performance characterisation

The refrigeration plant performance equation, as shown in Equation (14), was used to determine the change in temperature over the evaporator for the respective inlet conditions.

$$\begin{aligned}\Delta T_{plant,i}(GV, T_{inlet}, \dot{m}) \\ &= x_{1,i}T_{inlet}GV + x_{2,i}GV\dot{m} + x_{3,i}T_{inlet}GV\dot{m} + x_{4,i}GV^2 \\ &\quad + x_{5,i}GV\end{aligned}\quad (14)$$

The refrigeration plants, however, did not operate below 30% guide vane angle and, as a result, the characteristic equation was adjusted to a split-wise function, as shown in Equation (37).

$$\begin{aligned}\Delta T_{plant,i}(GV, T_{inlet}, \dot{m}) \\ &= \begin{cases} x_{1,i}T_{inlet}GV + x_{2,i}GV\dot{m} + x_{3,i}T_{inlet}GV\dot{m} + x_{4,i}GV^2 + x_{5,i}GV & \text{for } GV \geq 30 \\ 0 & \text{for } GV < 30 \end{cases}\end{aligned}\quad (37)$$

The characteristic equation, consequently, provided an operating curve for the specific refrigeration plant. The equation resulted in a four-dimensional (4-D) function. For visualisation purposes, a dimension was kept constant to allow for a three-dimensional (3-D) representation. Figure 27 shows the characteristic model for a second-stage refrigeration plant. The flow dimension was kept constant in this figure.

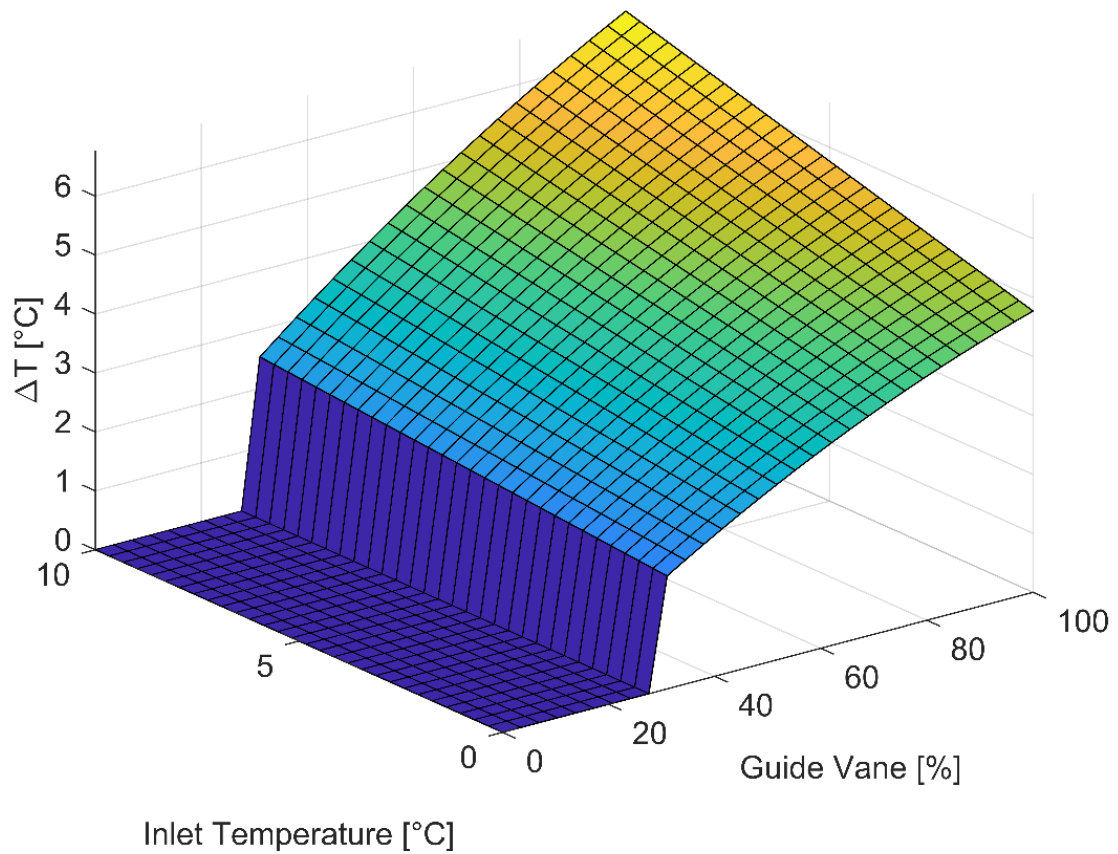


Figure 27: Second-stage refrigeration plant 3-D surface curve of the characteristic model (constant flow dimension)

An increase in inlet temperature was seen to increase the ΔT (as shown in Figure 27) due to larger temperature differentials between the water in the evaporator and the refrigerant inside the evaporator. This facilitated a larger heat transfer, which resulted in an increased ΔT . A similar trend was seen in the first-stage refrigeration plants, shown in Figure 28.

Figure 29 shows the characteristic model for a second-stage refrigeration plant (the same refrigeration plant as Figure 27). The temperature dimension was kept constant in these figures to allow for a 3-D representation. Figure 27 and Figure 29 together show the characteristic model for the refrigeration plant according to Equation (37).

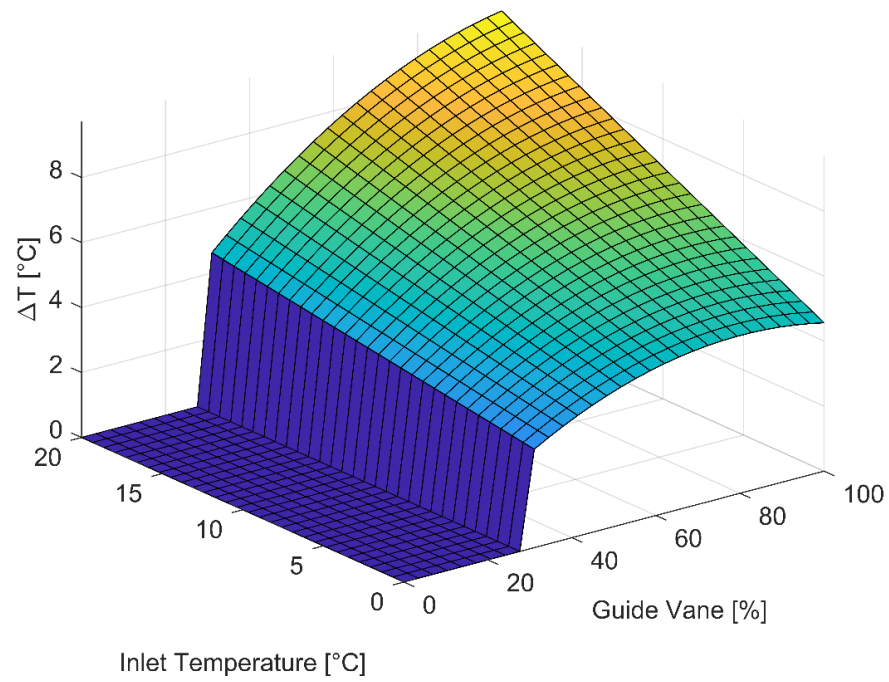


Figure 28: First-stage refrigeration plant 3-D surface curve of the characteristic model (constant flow dimension)

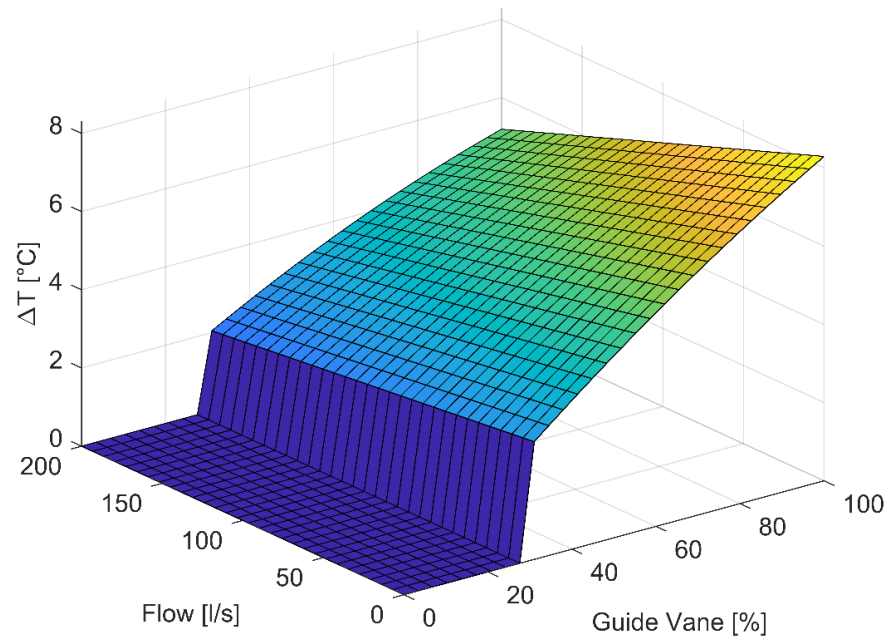


Figure 29: Second-stage refrigeration plant 3-D surface curve of the characteristic model (constant temperature dimension)

An increase in flow was expected to decrease the ΔT due to a similar duty being achieved as shown in Figure 29. A similar trend was noticed in the first-stage refrigeration plants, as shown in Figure 30. Figure 30 represents the characteristic curve for the same refrigeration plant as Figure 28, where the temperature dimension was kept constant.

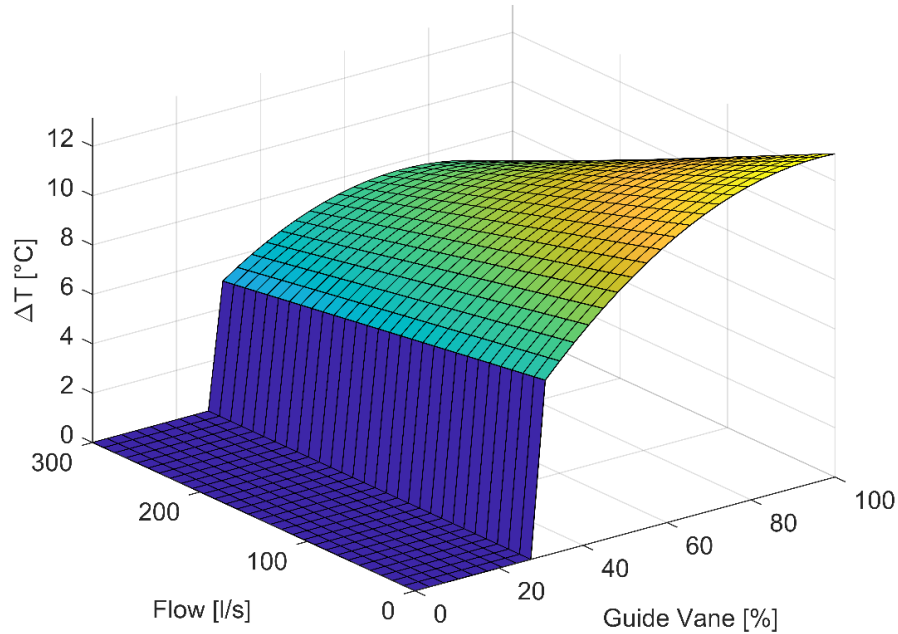


Figure 30: First-stage refrigeration plant 3-D surface curve of the characteristic model (constant temperature dimension)

The coefficient of determination (R^2) for the characteristic model, as shown in Figure 27 and Figure 29, was found to be 0.7482. The constants x_1 , x_2 , x_3 , x_4 and x_5 were specific to the refrigeration plant to ensure that the operation of the respective plant was emulated in the optimisation. Table 16 indicates the constants and the coefficients of determination for each plant in the system.

Table 16: Refrigeration plant performance characteristic equation variables

Refrigeration plant	x_1	x_2	x_3	x_4	x_5	R^2
1	-0.0010	-0.0003	0.0000	-0.0003	0.1176	0.9021
2	-0.0007	-0.0003	0.0000	-0.0002	0.1072	0.8910
3	-0.0487	-0.0018	0.0003	-0.0003	0.3734	0.8581
4	-0.0052	-0.0005	0.0001	-0.0004	0.1535	0.8551
5	-0.0336	-0.0014	0.0002	-0.0010	0.3237	0.5894
6	-0.0053	-0.0005	0.0001	-0.0010	0.1644	0.7092
7	-0.0036	-0.0006	0.0000	-0.0014	0.3265	0.7482
8	0.0017	-0.0003	0.0000	-0.0013	0.2341	0.7531
9	-0.0021	-0.0005	0.0000	-0.0008	0.2392	0.7511
10	0.0027	-0.0001	0.0000	-0.0016	0.2067	0.2781
11	0.0044	0.0001	0.0000	-0.0011	0.1405	0.3630

Some refrigeration plants had coefficients of determination less than 0.7 (plants 5, 10 and 11) due to low operating times within similar operating conditions. This resulted in a lack of data for developing an accurate characteristic system. The average characteristic equations of the respective plants (first- and second-stage plants) were used for these plants.

3.2.3 Refrigeration plant power consumption characterisation

Similarly, the refrigeration plant power equation, as shown in Equation (15), was used to determine the power consumption of the refrigeration plant for the respective inlet conditions.

$$P_i(GV) = y_{1,i}GV^2 + y_{2,i}GV + y_{3,i} \quad (15)$$

The equation was adjusted to ensure that minimum operating conditions were also characterised, as shown in Equation (38).

$$P_i(GV) = \begin{cases} y_{1,i}GV^2 + y_{2,i}GV + y_{3,i} & \text{for } GV \geq 30 \\ 0 & \text{for } GV < 30 \end{cases} \quad (38)$$

Figure 31 compares the power consumption data and the characteristic equation of a first-stage refrigeration plant. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

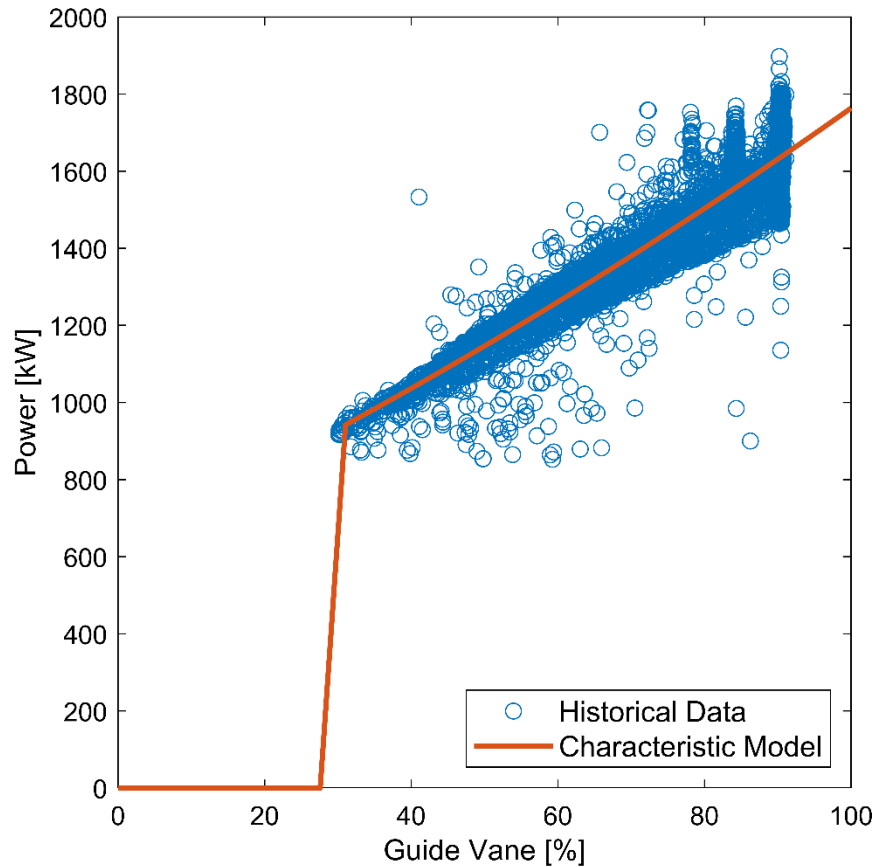


Figure 31: Refrigeration plant power characteristic model

The coefficient of determination (R^2) for the characteristic model was found to be 0.8932. The constants y_1 and y_2 were specific to the refrigeration plant to ensure that the power consumption of the specific plant was emulated in the optimisation process. Table 17 indicates the constants and the coefficients of determination for each plant in the system.

Table 17: Refrigeration plant power characteristic equation variables

Refrigeration plant	y_1	y_2	y_3	R^2
1	-0.0225	13.2140	661.0086	0.8358
2	0.0226	8.9604	641.9457	0.8932
3	0.0085	9.3773	673.3298	–
4	0.0165	8.3692	748.6262	0.7452
5	0.0173	6.9656	641.7386	0.7817
6	0.0919	-4.7382	691.9141	–
7	0.0919	-4.7382	691.9141	–
8	0.0919	-4.7382	691.9141	–
9	0.0919	-4.7382	691.9141	–
10	0.1043	-6.1027	731.8386	0.9202
11	0.0795	-3.3736	651.9896	0.9134

The power meters for refrigeration plants 3, 6, 7, 8 and 9 were either faulty or inaccurate and required calibration. As a result, the average characteristic equation constants (y_1 , y_2 and y_3) for the first-stage cooling circuit plants were used for refrigeration plant 3. Similarly, the average characteristic equation constants for the second-stage cooling plants were used for refrigeration plants 6, 7, 8 and 9. The characteristic plots of all the refrigeration plants can be found in Appendix A.

3.2.4 Inlet characterisation

A year's operating data was obtained to determine the average inlet parameters to the refrigeration system. Weekends were excluded from the operating average as normal operations occurred from Monday to Friday. Further, the data was divided between the two Eskom seasons:

- Low-demand season (from September to May).
- High-demand season (from June to August).

The inlet parameters, namely the inlet water temperature and flow rates, were averaged to determine a daily operating profile for the various Eskom seasons. Figure 32 and Figure 33 show the average daily operating profiles of the inlet parameters for the low- and high-demand season, respectively.

The inlet water flow was higher in the low-demand season due to the need to cool the air going down the shaft to the workplaces. This cooling was not required in the high-demand season due to colder ambient conditions. The inlet water temperature was also higher in the low-demand season due to the warmer ambient conditions. As a result, optimised operating profiles were determined separately for the low- and high-demand season.

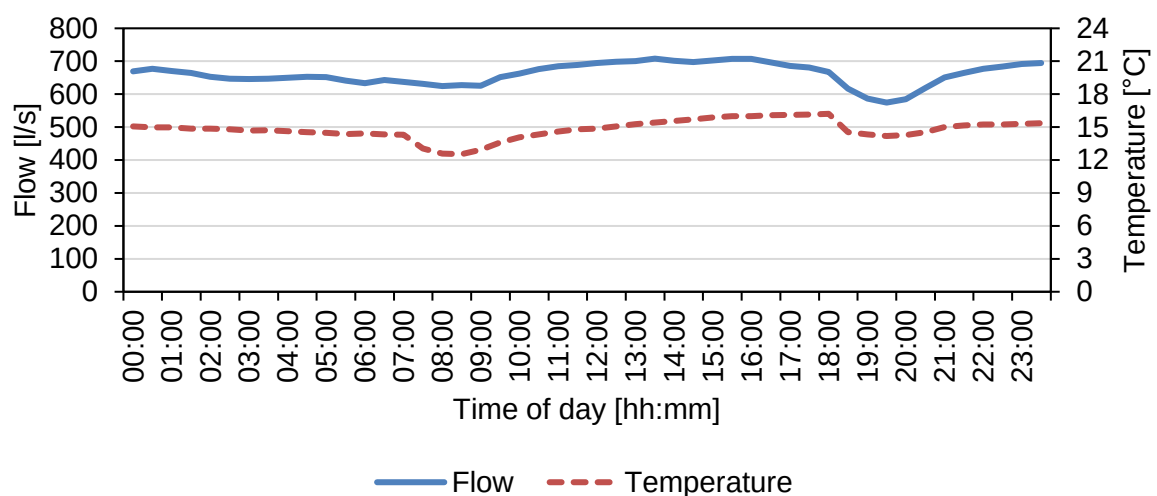


Figure 32: Low-demand season conditions inlet water parameters

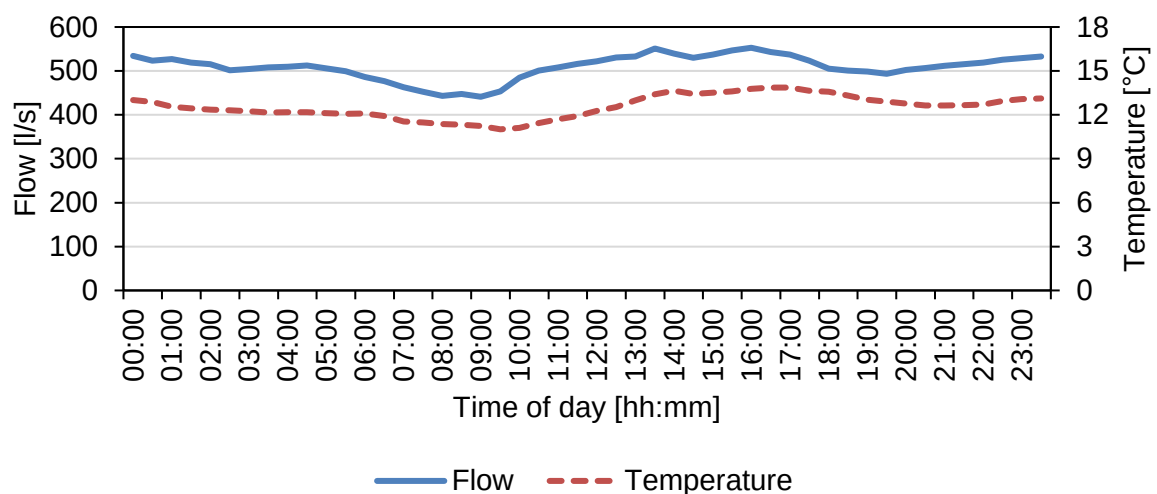


Figure 33: High-demand season conditions inlet water parameters

3.3 Solution model results

The solution model minimised the objective function for the refrigeration system, depicted in Equation (22). The *tariff* matrix is a function of the applicable Eskom season (low-demand and high-demand season). Figure 34 shows the tariff structure for both the low- and high-demand season that were applicable to the mine.

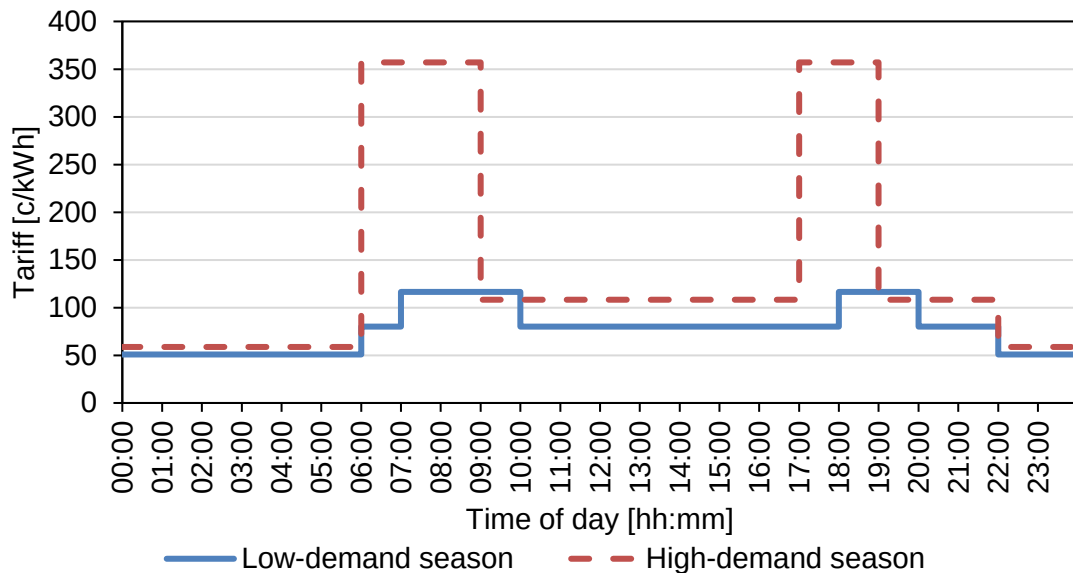


Figure 34: Tariff structure for low and high-demand season

The high-demand season tariff structure varied between 58.74 c/kWh and 357.04 c/kWh depending on the specific time period [44]. This was considerably higher than the low-demand season tariff structure that varied between 50.86 c/kWh and 116.45 c/kWh. The high-demand season further had fees for excessive reactive power usage, but this cost was neglected in this study. The solution model results were divided between the two Eskom seasons.

3.3.1 Low-demand season

The solution model achieved cost savings primarily through load shifting. The benefit of using particle swarm optimisation in the process was its ability to determine the best operating profiles instantaneously and dynamically, as opposed to set-point control. Water was chilled outside of peak periods, using dam capacities, to achieve the load shift. Figure 35 depicts the water flow through the first-stage refrigeration plants for a period of one day.

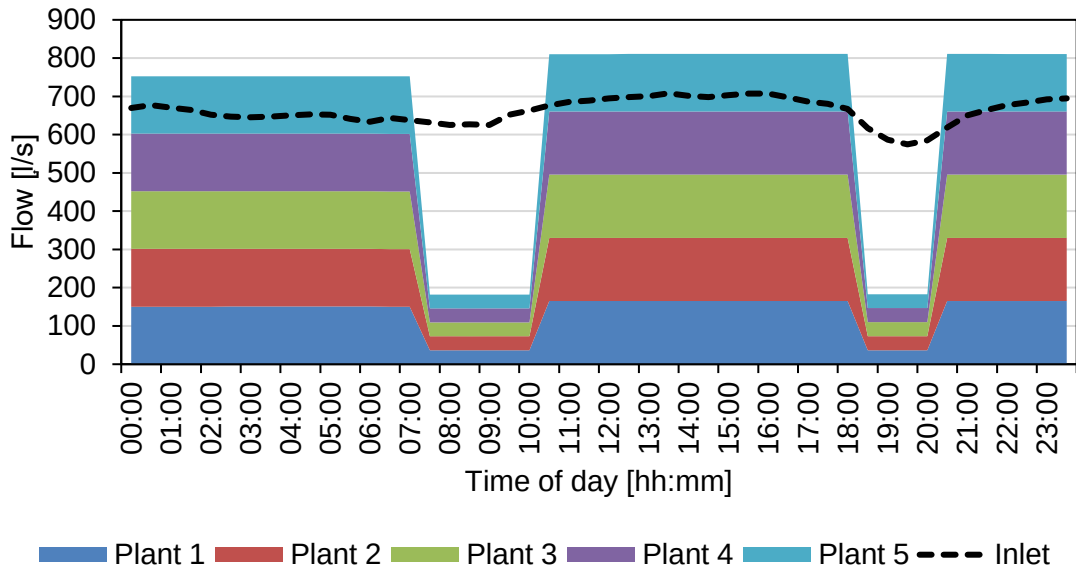


Figure 35: First-stage refrigeration plants flows

The water flows through the first-stage refrigeration plants were more than the inlet during standard and off-peak periods so that minimal flow was required during the peak period, shown in Figure 35. The flow during the peak period could not be zero as the dam capacities could not solely supply the demand for the duration of the peak periods. This trend was similar in the second-stage refrigeration plants, as shown in Figure 36.

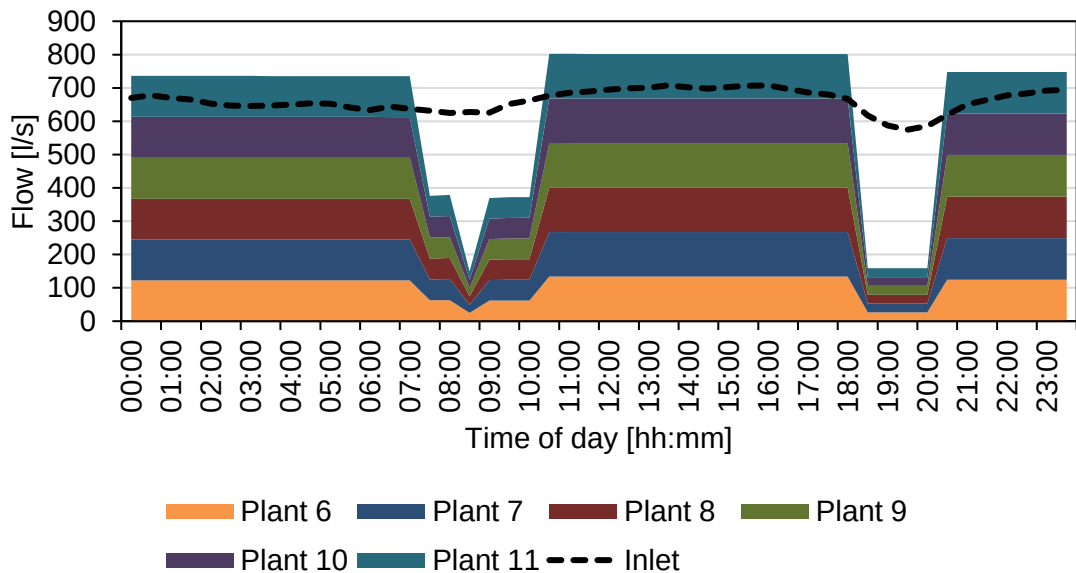


Figure 36: Second-stage refrigeration plants flows

The flow during the morning peak period was higher through the second-stage refrigeration plants than the first-stage refrigeration plants. This was due to the intermediate dam acting as a buffer between the two stages, compensating for the difference in flows between the two stages. The effect of the varying flow rates on the dam levels is shown in Figure 37.

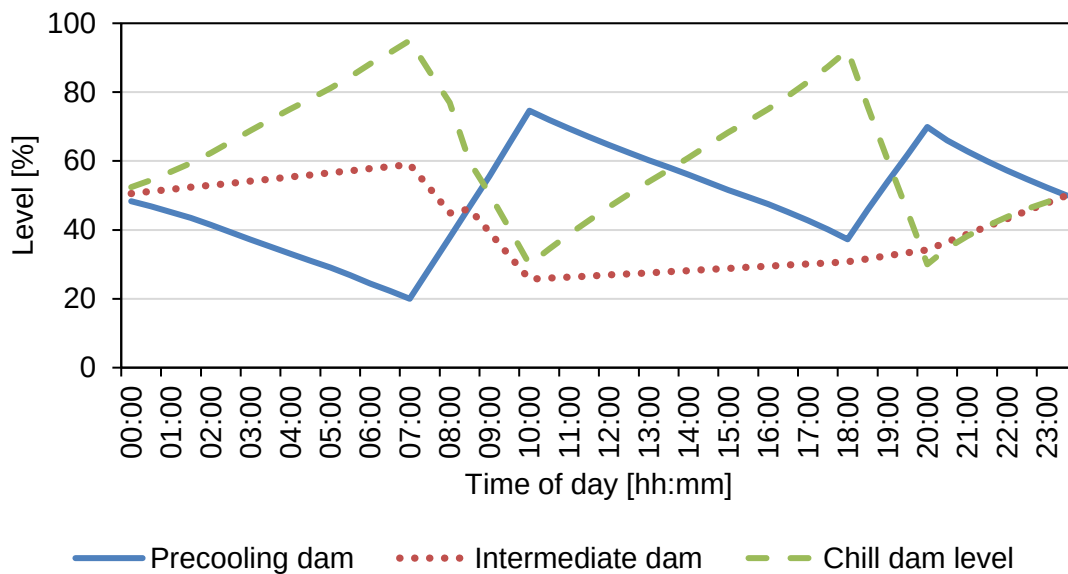


Figure 37: Dam levels

The precooling dam reached a minimum before the peak period, as seen in Figure 37, to accommodate the inlet water entering the dam during the peak period. A minimal amount of water was passed through the first-stage refrigeration plants, resulting in a maximum dam level at the end of the peak period.

The chill dam reached a maximum before the peak period to accommodate the flow of water down the shaft and to the surface BAC during the peak period. The dam capacity was the limiting factor in determining the water flows for the second-stage refrigeration plants during the peak periods. Insufficient chill dam storage required that water be circulated through the second stage.

The intermediate dam reached a maximum before the morning peak period. The dam level remained low to achieve savings in the standard tariff period. The dam level increased again during the off-peak tariff period. The shorter evening peak allowed for minimal water to be circulated through the second stage, resulting in no buffer being required from the intermediate dam.

The flow rates and power consumption through the refrigeration plants were also influenced by the dam temperatures. Using the thermal storage properties of the dams further allowed for cost savings opportunities. Particle swarm optimisation determined the optimal operating profiles to use this property dynamically, unlike conventional set-point control. The dam temperatures for the solution are depicted in Figure 38.

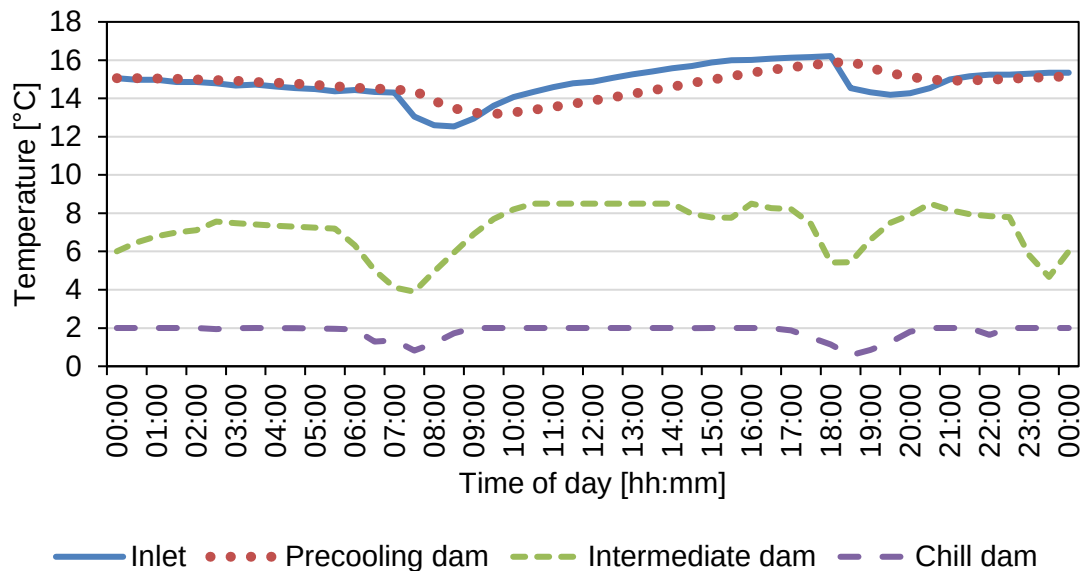


Figure 38: Dam temperatures

The precooling dam temperature was affected solely by the inlet water. The intermediate dam reached a minimum temperature at the start of the peak period to allow for water to be circulated through the first-stage refrigeration plants without the plants operating. This warm water from the precooling dam increased the temperature of the intermediate dam during the peak periods.

The chill dam temperature followed a similar trend to the intermediate dam temperature. The warmer water circulating from the intermediate dam through the non-operational second-stage refrigeration plants increased the chill dam temperature during the peak periods. However, the chill dam temperature did not oscillate as much as the intermediate dam due to the 2 °C temperature requirement.

The energy consumption was thus shifted from the peak period to other tariff periods. This resulted in cost savings due to the peak-period tariff being higher than the tariffs for off-peak periods. The total power consumption for all the refrigeration plants is shown in Figure 39. The power consumption for both the cooling stages were added to achieve the power consumption curve.

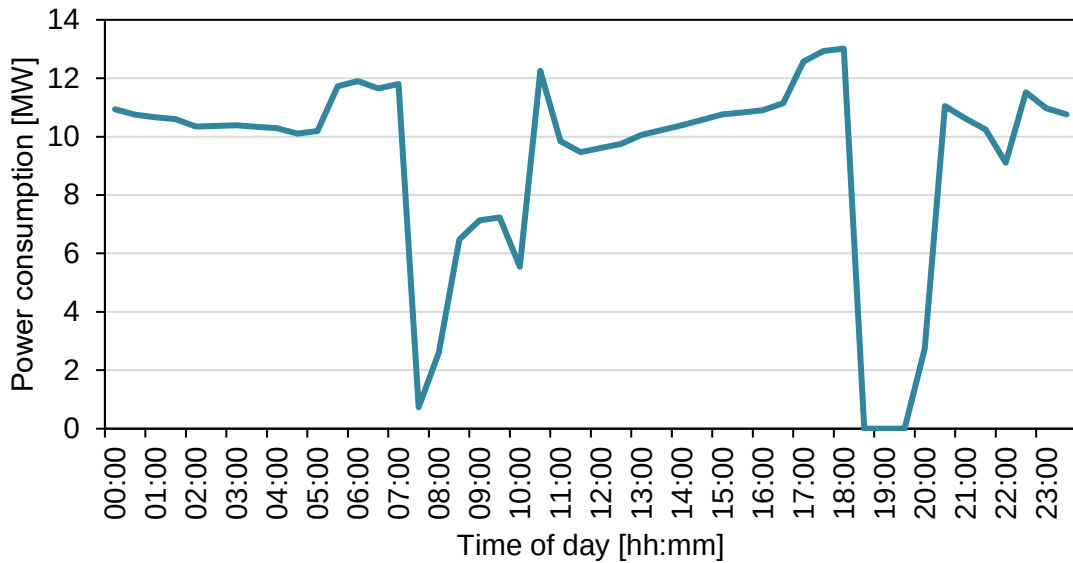


Figure 39: Total refrigeration plant power consumption

The morning peak period, being an hour longer than the evening peak period, required some cooling to compensate for the limited storage capacity in the chill dam. The chill dam was able to sustain the demand in the evening peak period without the need for additional cooling. The varying nature of the profile was to ensure that the chill dam temperature target was maintained and varied according to the operating conditions.

Although set-point control could achieve load shifting with a smoother profile than the profile shown in Figure 39, the operating profiles would not be robust. The profiles would be set based on the average inlet parameters but variations in the demand would hinder the performance of the set-point control strategy. Furthermore, set-point control was not able to determine the most efficient operating combination of the refrigeration plants.

Particle swarm optimisation, however, could be used to determine the most efficient operating profiles for variations in the demand as well as inlet parameters. The profiles were optimised to obtain a financial benefit by using the most efficient combination of refrigeration plants and shifting the power consumption out of peak periods (load shift).

3.3.2 High-demand season

The peak tariff period for the high-demand season was one hour earlier in the morning and evening than in the low-demand season. There were more opportunities for cost savings in the high-demand season due to the higher peak period tariff rate. The inlet parameters for the high-

demand season, depicted in Figure 33, were used in the solution model to determine the optimised operating profiles. Figure 40 depicts the water flow through the first-stage refrigeration plants for a period of one day.

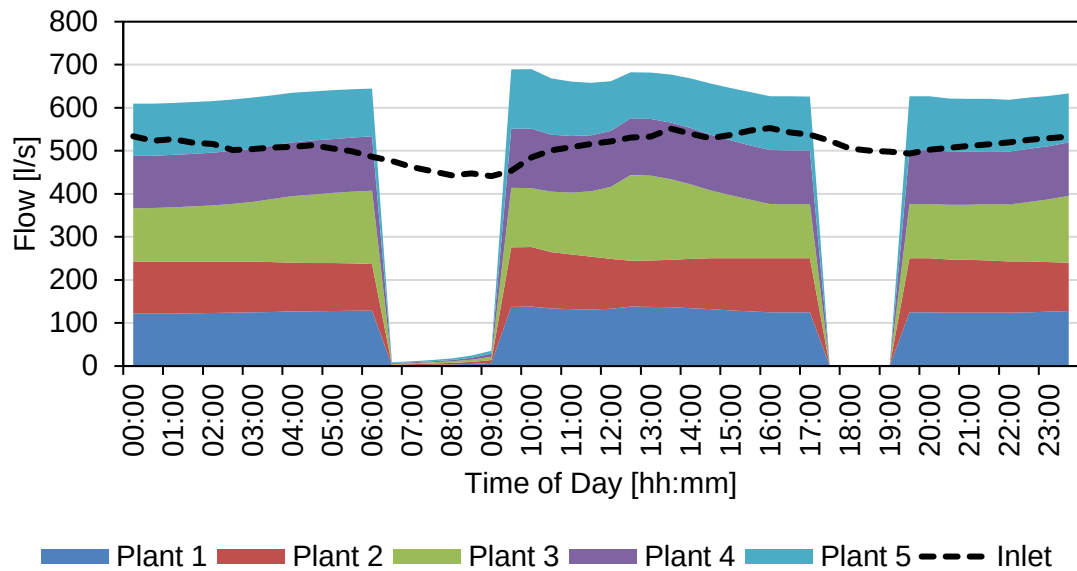


Figure 40: First-stage refrigeration plants flows

Similar to the low-demand season, the water flow through the first-stage refrigeration plants was reduced in the peak periods and shifted to the standard and off-peak tariff periods. The shift resulted in a more cost-effective power consumption by the refrigeration plants. This trend was further seen in the second-stage refrigeration plant flows, as depicted in Figure 41.

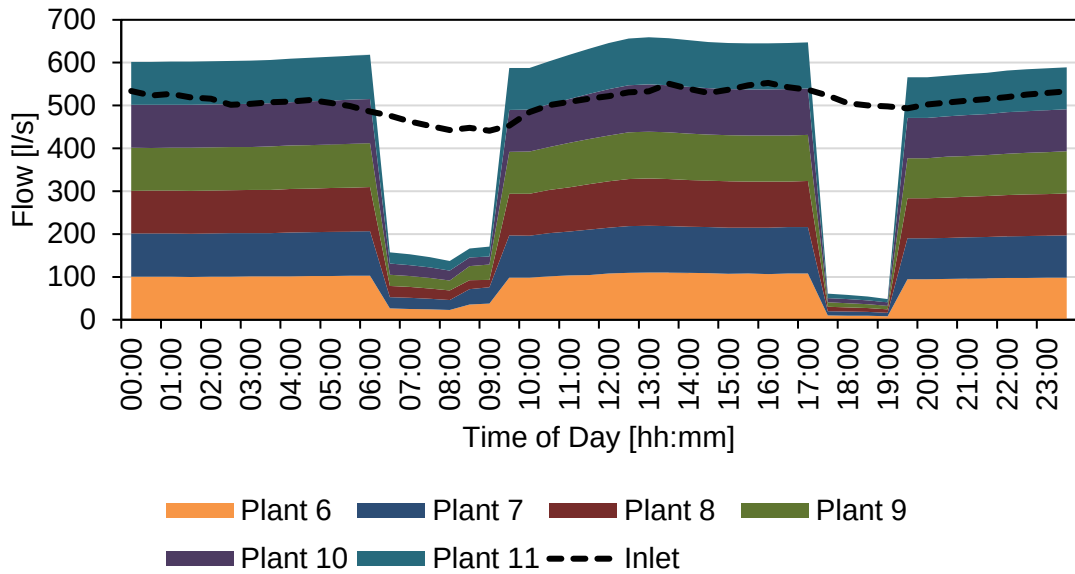


Figure 41: Second-stage refrigeration plants flows

The inlet and demand water flows were less in the high-demand season than the low-demand season. This resulted in a reduced flow through the second-stage refrigeration plants during peak periods as the dam capacities managed to sustain the demand for a longer period of time. This is seen by comparing the peak period flow rates in Figure 36 and Figure 41. The dam levels as a result of the plant flows are shown in Figure 42.

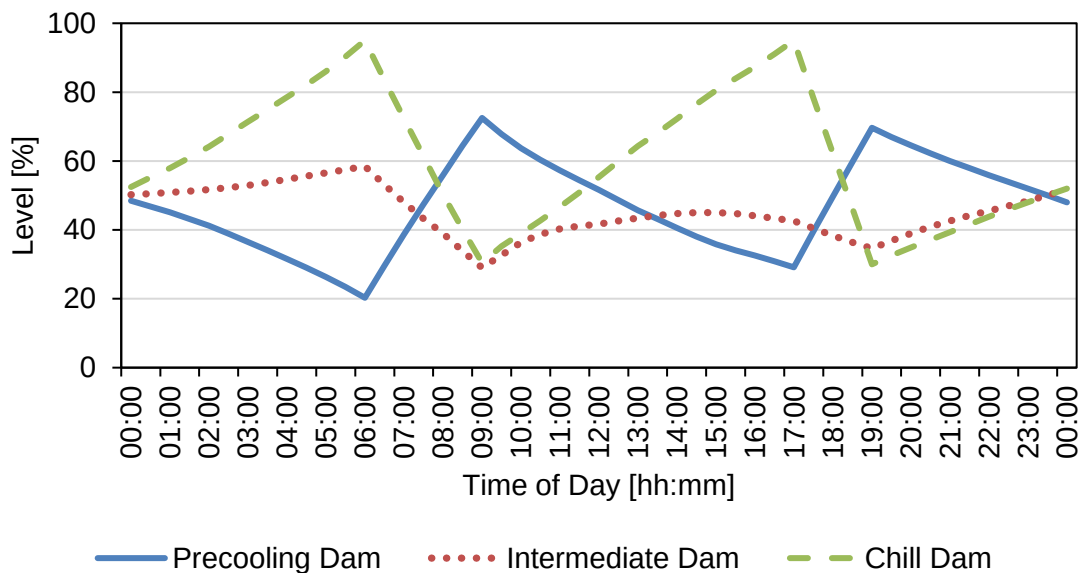


Figure 42: Dam levels

The precooling dam reached a minimum before the peak period to accommodate for the inlet water during the peak period. For the duration of the peak period, the flows through the first-stage refrigeration plants were reduced, which caused an increase in the precooling dam level. The dam level subsequently reached a maximum at the end of the peak period. The flow through the first stage was more than the inlet water during non-peak periods, which resulted in a decreasing dam level.

Contrastingly, the chill dam reached a maximum before the peak period. The dam level decreased during the peak period as the flow through the second stage was less than the demand flow, which resulted in a minimum dam level at the end of the peak periods. During the non-peak periods, the flow through the second stage was more than the demand, which increased the dam level.

The intermediate dam acted as a buffer between the two stages. A maximum dam level was reached at the start of the peak period to accommodate for a difference in flow rates between the two stages. The level remained low during the standard tariff period to ensure cost-effective operations. The dam level subsequently increased during the off-peak period to the initial dam level.

The dam levels and refrigeration plant flows were affected by the dam temperatures in the solution model. The solution model required that the temperature and the level requirements were met in the optimised solution. The dam temperatures for the low-demand season solution are shown in Figure 43.

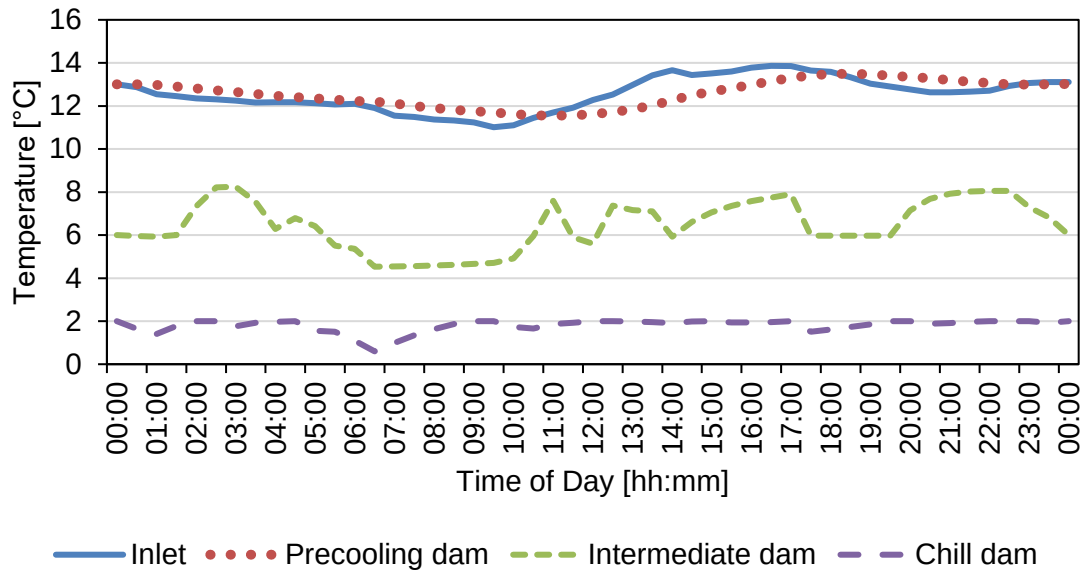


Figure 43: Dam temperatures

The precooling dam temperature emulated a moving average of the inlet water temperature because the only water entering the dam was the inlet water. The intermediate dam temperature remained constant in the peak periods due to the minimal, close to zero, flow through the first-stage refrigeration plants. In non-peak periods, the intermediate dam temperature varied without reaching a temperature that prevented the chill dam temperature from meeting the 2 °C requirement.

The chill dam temperature decreased before increasing in the morning peak period due to the warmer water circulating through the second-stage refrigeration plants. The chill dam temperature stabilised at the 2 °C temperature requirement outside of the peak periods to ensure cost-effective plant operations.

Similar to the low-demand season, the energy power consumption of the refrigeration plants was shifted from the peak tariff period to the standard and off-peak tariff periods. The effect was load shifting that was adjusted dynamically to the inlet parameters. The total power consumption for all the refrigeration plants is shown in Figure 44.

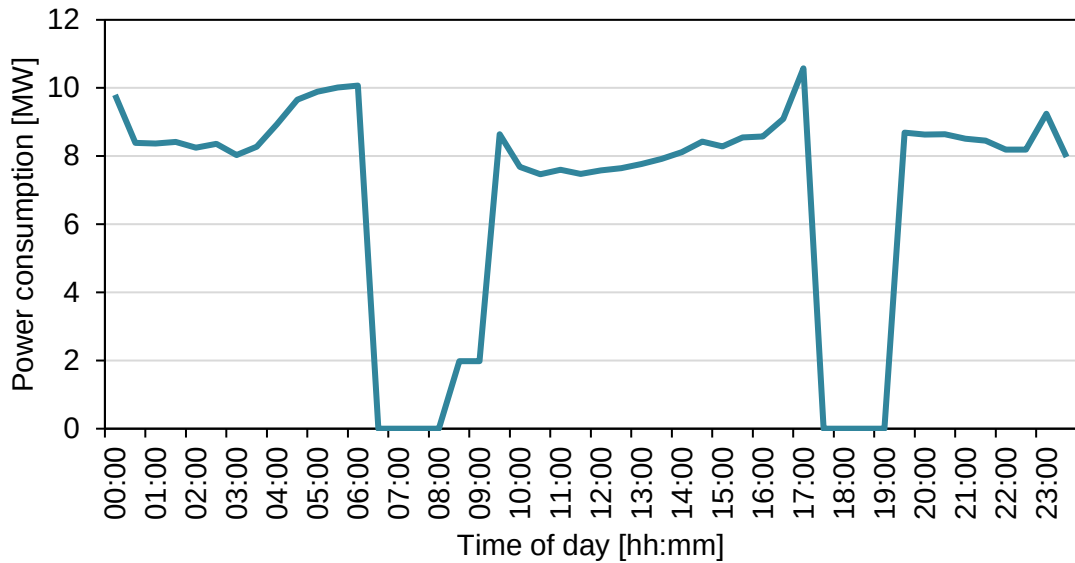


Figure 44: Total refrigeration plant power consumption

The inlet and demand flows for the high-demand season were lower than in the low-demand season. As a result, only 2 MW of refrigeration plants was required for a half hour in the morning peak period to ensure that demand was satisfied. No further cooling was required in the peak periods for the optimised solution.

The solution model results depict cost savings opportunities through utilising dam capacities. The optimised solution can be achieved dynamically by using particle swarm optimisation in the control method. The results from the solution model are validated through simulation before an implementation validation can be done.

3.4 Simulation results

Simulation was used to determine the accuracy of the solution model. A simulation was built and calibrated in Process Toolbox, which is a software package used in the mining industry to model and simulate thermohydraulic systems [43], [63], [64]. Figure 45 shows the model used to validate the solution model results.

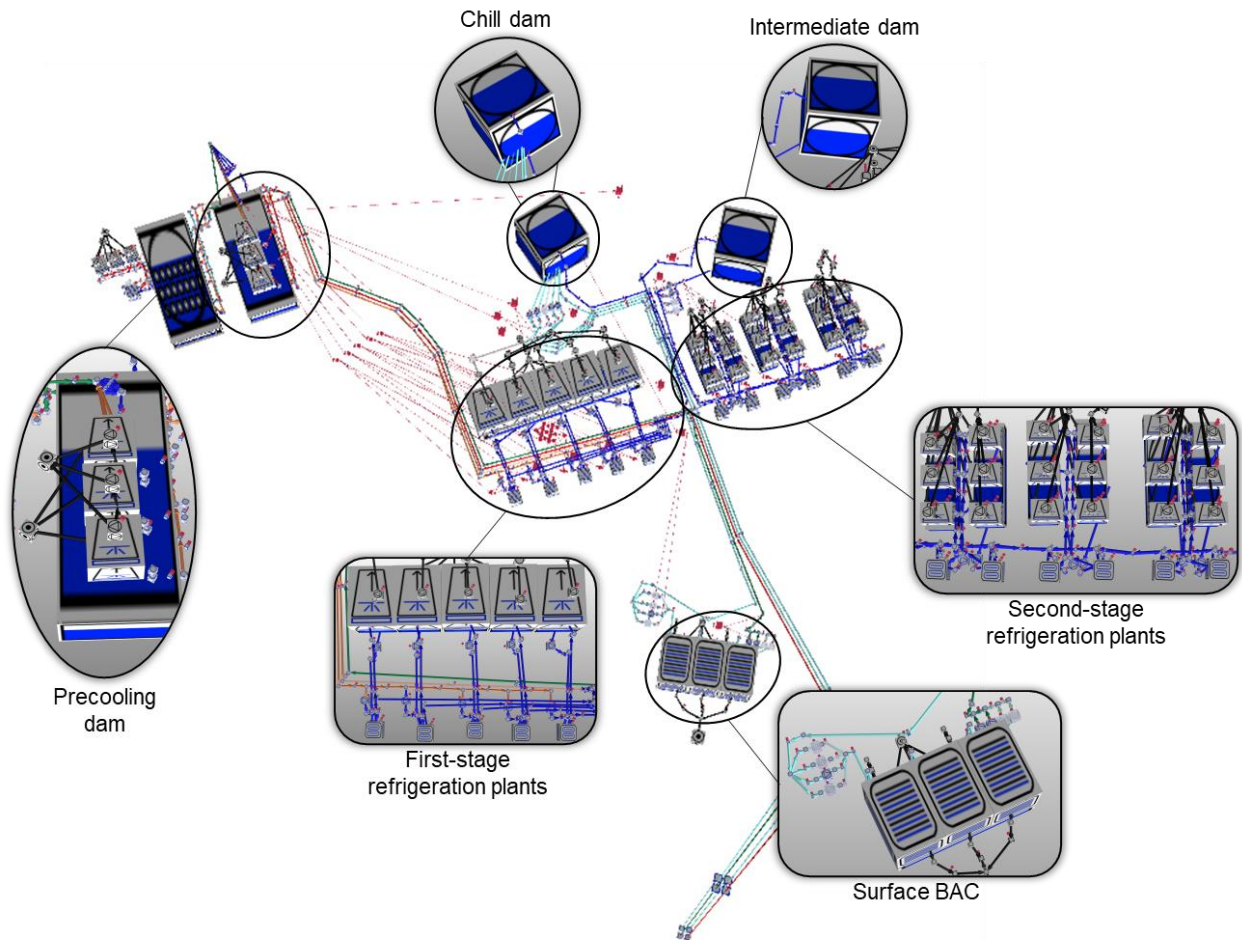


Figure 45: Refrigeration system simulation model

The simulation model was developed according to the physical infrastructure and the design specifications of the individual components. The same inlet parameters and operating profiles for the solution model were used as for the low-demand season and the total power consumption was compared. Figure 46 compares the power consumption for the solution model and the simulation.

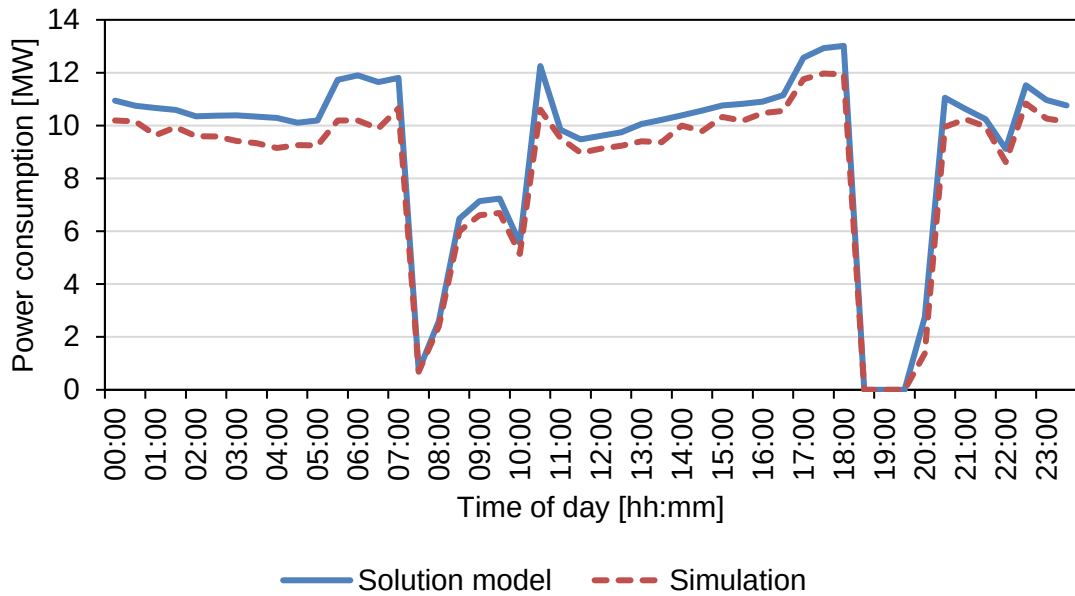


Figure 46: Power consumption comparison between solution model results and simulation

The solution model's power consumption was on average 7.4% higher than the simulated power consumption. This was mainly due to the following two factors:

- The simulation used the design specifications for the refrigeration plants and did not account for the inefficiencies due to age and operating outside of design conditions.
- The simulation did not incorporate the refrigerant in the heat exchange and assumed that the refrigerant could absorb infinite heat. The effect of the water temperature nearing the refrigerant temperature was not simulated.

The exclusion of the refrigerant in the simulation resulted in the dam temperatures being lower than the solution model and below the system capabilities; for example, the chill dam temperature being below 0 °C. However, the higher power consumption from the solution model acted as a conservative buffer to allow for inaccuracies.

3.5 Implementation results

A manual implementation was necessary due to the lack of automated infrastructure. The implementation procedure was signed off by the site engineer to ensure that all system and legal requirements were satisfied. The following refrigeration system parameters were controlled manually by the control room operators:

- Refrigeration plant evaporator flow.
- Refrigeration plant guide vane angle.
- Refrigeration plant status (starting or stopping a plant).

The inlet parameters (water flow and temperature into the refrigeration system) were inserted into the solution model. The solution model solved for the optimal operating profiles based on the present inlet parameters. The results of the solution model were displayed to the control room operators who implemented the values for the evaporator flows and the guide vane angles. Figure 47 depicts the described process.

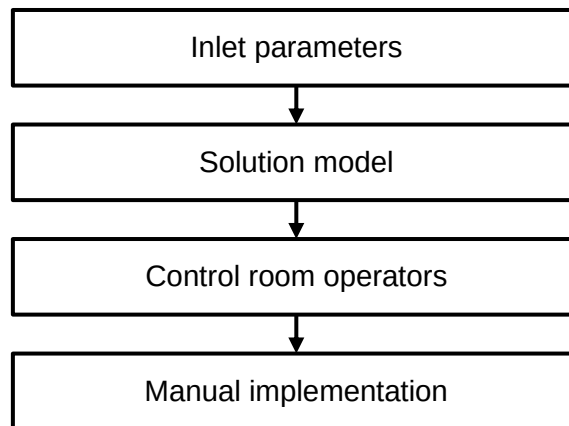


Figure 47: Implementation process

Figure 48 depicts the solution model results that were presented to the control room operators. FSP refers to the first-stage plants and SSP refers to the second-stage plants. For example, FSP1 refers to first-stage refrigeration 1 and SSP1 to second-stage refrigeration plant 1.

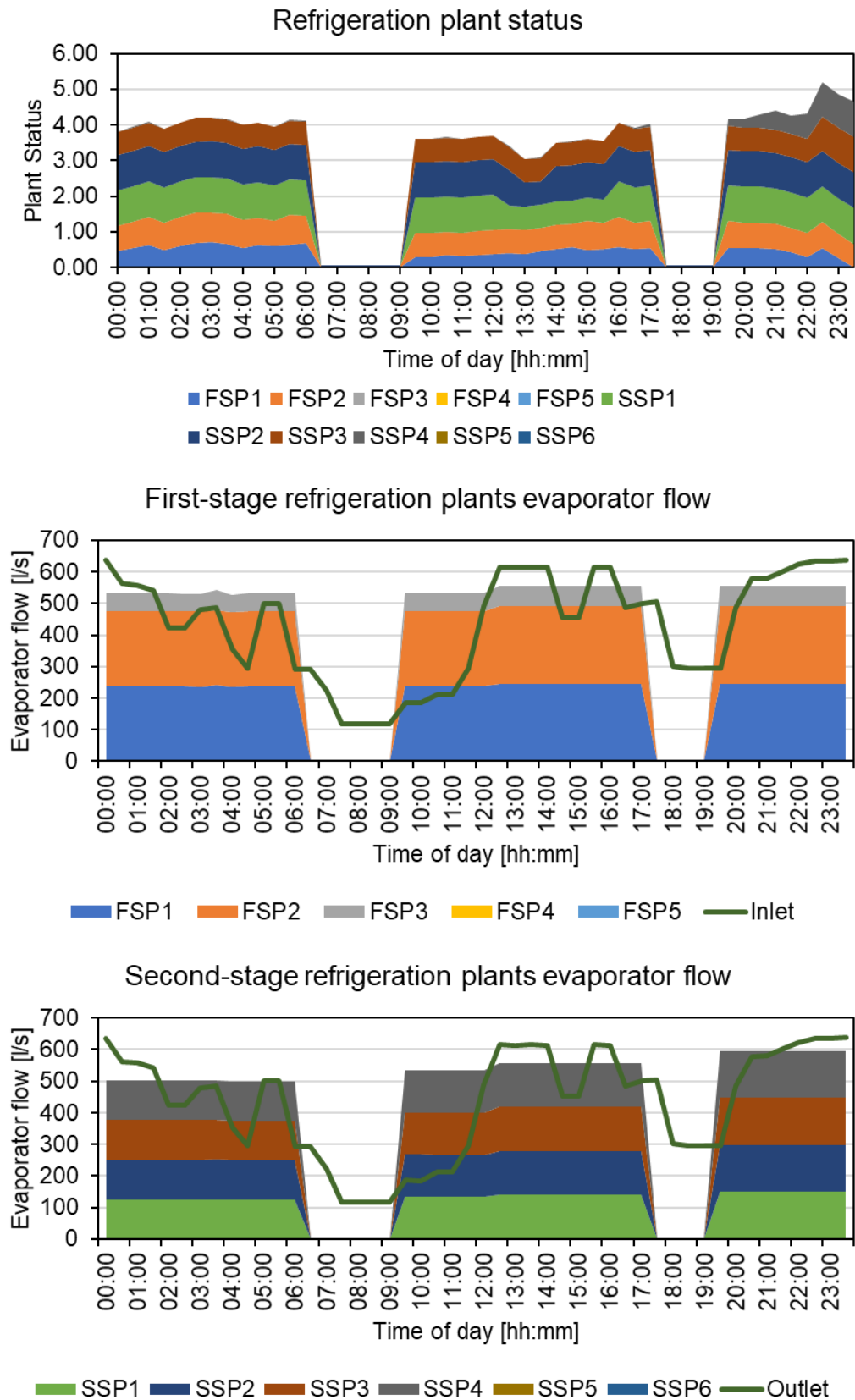


Figure 48: Dynamically determined operating profile

The key outputs of the refrigeration system for the manual implementation and the solution model were compared to validate the model. The key outputs were divided between service delivery requirements and cost savings. The specific outputs for the refrigeration system are listed in Table 18.

Table 18: Key output parameters for implementation comparison

Group	Output parameter
Service delivery	Chill dam temperature
Cost savings	Refrigeration system power consumption

3.5.1 Chill dam temperature

The implementation took place in the high-demand season (winter season). The chill dam temperature target was adjusted to 4 °C due to the surface BACs not operating and the mine experiencing lower ambient temperatures than previous years. Figure 49 compares the chill dam temperature expected for the solution model with the actual chill dam temperature. The actual chill dam temperature was a result of the manual implementation.

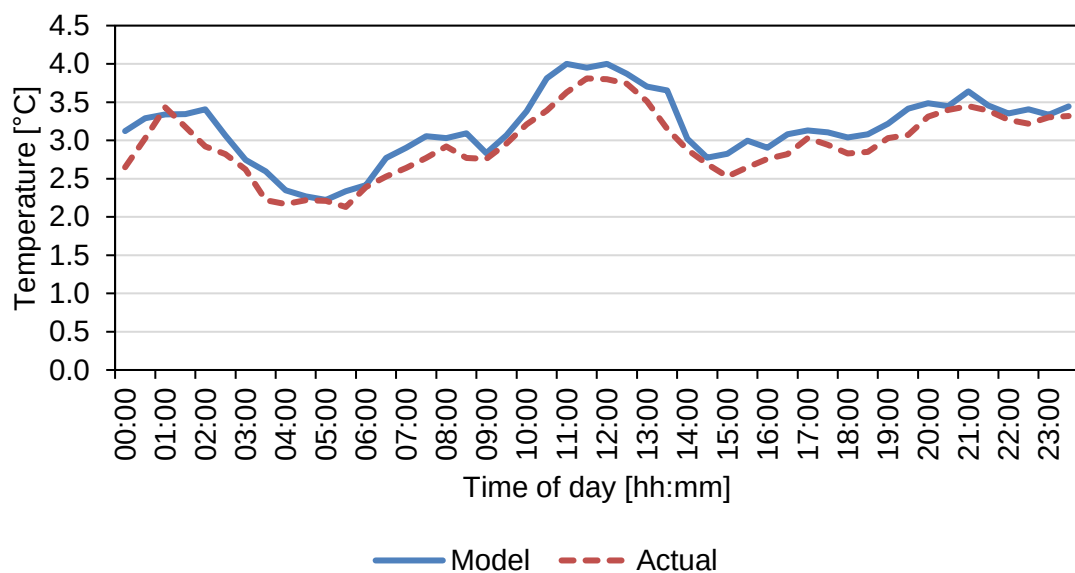


Figure 49: Chill dam temperature implementation comparison

The largest temperature difference was 0.5 °C, as shown in Figure 49. The model was largely seen to be conservative in the expected chill dam temperature. The actual chill dam temperature remained below the target of 4 °C. This validated that the model could control the refrigeration system accurately without having a negative effect on the outlet water temperature.

3.5.2 Refrigeration system power consumption

The power consumption of the refrigeration system was a factor of the number of operational refrigeration plants and the specific plants guide vane angles. The solution model dictated both these factors. Figure 50 compares the expected power consumption of the solution model with the actual implementation power consumption.

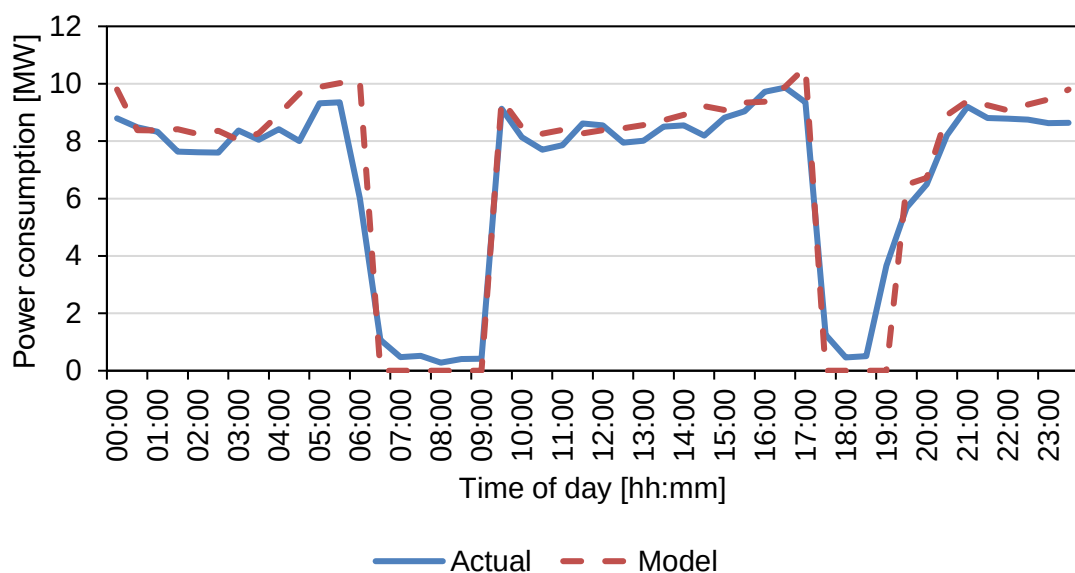


Figure 50: Power consumption implementation comparison

The actual implementation began the morning peak period early and ended the same period late. The result was that more energy was required in the middle of the day to compensate for this, as shown in Figure 50. Similar behaviour can be seen in the evening peak period, which was the result of manual control. These issues will be alleviated with automated control and implementation.

During the period when the implementation followed the correct profiles, the expected power consumption had an average absolute error of 6.44% compared with the actual power consumption. The actual power consumption further included minimal power consumption from the pumps required to circulate the water, since power meters were either not reliable or not available. This was also noticed in the peak periods when pumps were operational to ensure sufficient water circulated in the system.

The implementation validated that the power consumption expected was accurate and conservative, noting that the actual power consumption contained pump power consumption. As a result, the model was able to control the refrigeration system without having negative effects on the service delivery of the system while ensuring cost savings were achieved.

3.5.3 Financial benefit

The implementation of the solution model resulted in cost savings due the dynamic shift of energy consumption out of the peak. The shift was dynamic due to the use of particle swarm optimisation, which allowed for the optimised profiles to be determined in the control while service delivery requirements were maintained. Figure 51 and Figure 52 compare the baseline operation profile with the optimised profile for the high-demand and low-demand seasons, respectively.

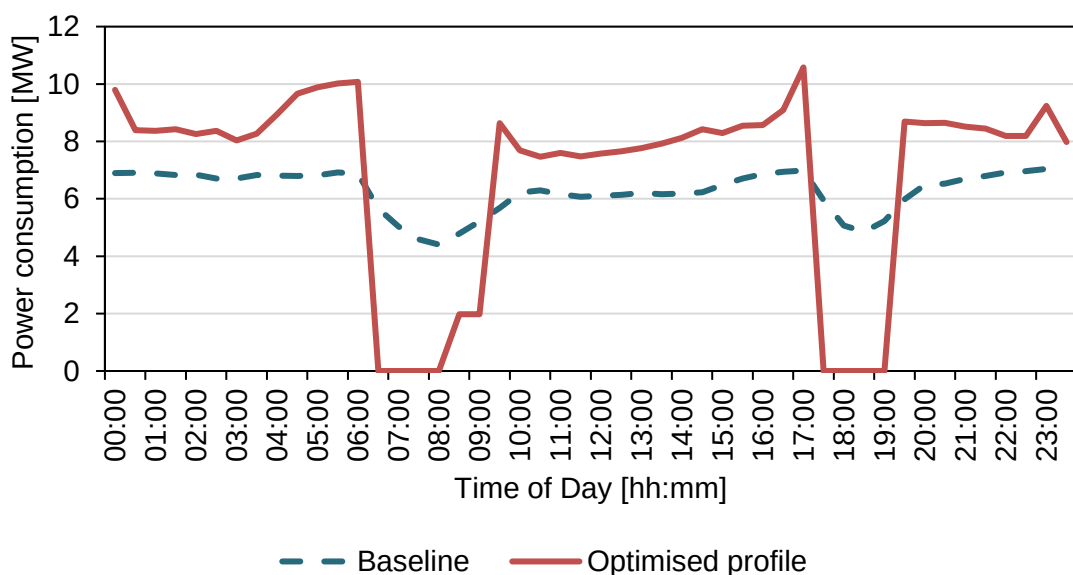


Figure 51: Optimised profile compared with the baseline profile for high-demand season

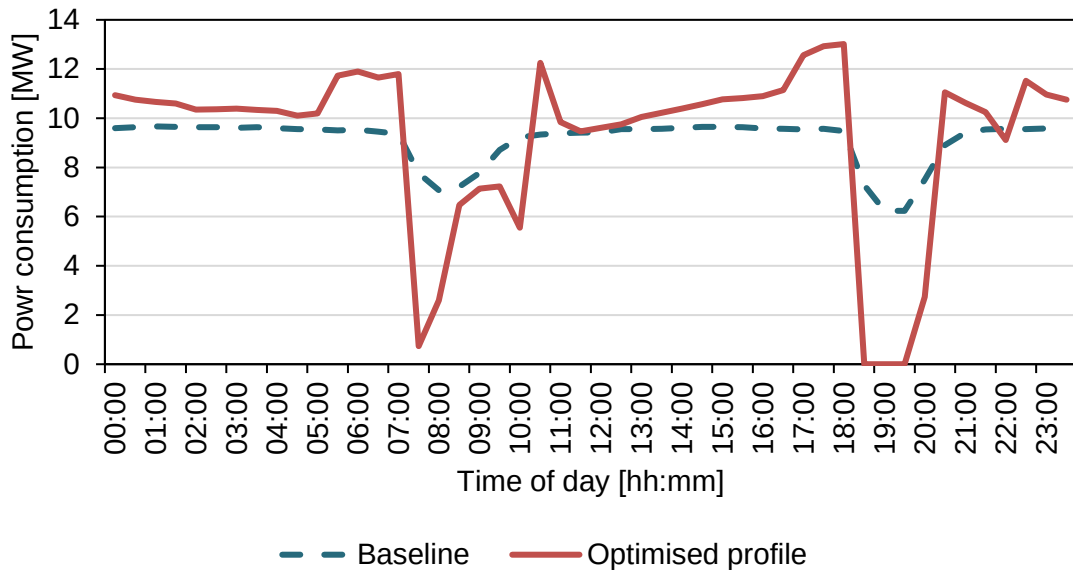


Figure 52: Optimised profile compared with the baseline profile for low-demand season

The implementation of the dynamic load shifting resulted in a daily savings to date of R2.23 million.⁸ Using the average parameters for the high-demand (winter) and low-demand (summer) seasons, an expected saving of R9.5 million per annum could be achieved due to dynamic load shifting. The load shifting dictated by the solution model was able to maintain the service delivery requirements. A more detailed cost savings comparison is given in Appendix B.

The system has been implemented for 2.5 months with no additional system maintenance being required. The initial setup of the manual system required that the control room operators be trained to ensure that the system was well understood and usable. For the duration of the implementation (2.5 months), no additional maintenance was required; therefore, there was no gap in the implementation duration.

3.6 Optimisation and control comparison

The optimisation resulted in cost savings achieved through load shifting. Similar results can be achieved through classical optimisation methods, such as optimisation through practical experience and simulation [12], [65]. However, the use of particle swarm optimisation in optimisation and control has numerous advantages, which are compared in the following subsections.

⁸ As at 18 October 2020.

3.6.1 Characterisation

Classical methods typically use simulation to characterise a system as opposed to using historical data. Developing a characteristic simulation is time-consuming and tedious [66]. Many resources are required to determine the fine details of the system (such as pipe sizes and dam elevations). Furthermore, a characteristic simulation requires a capital investment to obtain the simulation package.

Using historical data reduces the time required to develop a characteristic model while achieving a higher characteristic accuracy. The higher accuracy is due to the ability to incorporate component inefficiencies in the characteristic model. No additional cost is required as the characterisation can be done in numerous open source coding languages (such as Python™).

3.6.2 Optimisation process

Classical optimisation methods typically use a combination of practical experience and trial and error to determine more feasible operating conditions, which is a time-consuming and tedious process. A large possibility exists that the most feasible operating conditions are not determined. Due to the large time requirements, classical optimisation techniques result in static optimisation of systems (not accounting for variations in system conditions).

A typical refrigeration system requires five simulation iterations to obtain an optimised profile. The numerous iterations are required to ensure that the service delivery requirements are satisfied. Each iteration typically requires 3–5 minutes to solve for all the required time periods in the simulation model. This was measured on the simulation model on the same mine as in this study.

However, particle swarm optimisation requires a single iteration to determine the most feasible operating conditions, with the iteration providing a solution within 5 minutes. This was measured on the solution model on the same mine in this study using the same computer as the simulation model. Consequently, classical optimisation methods provide a solution within 15–25 minutes compared with the 5 minutes of particle swarm optimisation.

Particle swarm optimisation is able to determine the most feasible operating conditions in a shorter time period. Although there is a possibility of not determining the most feasible conditions, it is less than that of the classical optimisation method. The reduced time required to determine the operating conditions allows for dynamic optimisation to occur for a system (accounting for variations in system conditions).

3.6.3 Control implementation

The use of particle swarm optimisation in control philosophies has several benefits compared with classical control methods. Classical control methods involve set-point control and priority plant selection to mimic an optimised profile. However, due to the improved computational performance of particle swarm optimisation, the present conditions can be used to determine the dynamic operating profile.

The largest advantage of using particle swarm optimisation is the reduced time required to determine the most feasible operating conditions. This allows for dynamic control of systems while maintaining service delivery requirements. A summary of the comparison between classical optimisation and particle swarm optimisation is shown in Table 19.

Table 19: Optimisation technique comparison summary

	Classical optimisation	Particle swarm optimisation
Characterisation	• Often simulation based • Time-consuming and tedious	• Based on historical data • Reduced time required to develop
Optimisation process	• Results in a static optimisation • Time-consuming and tedious	• Results in a dynamic optimisation • Reduced time required to obtain a solution
Control implementation	• Often set-point and priority control	• Dynamic component selection based on present conditions • Robust to variations in system conditions

3.7 Conclusion

A two-stage mining refrigeration system was modelled using semi-empirical methods and optimised using particle swarm optimisation. The refrigeration plants were modelled to emulate historical data to account for inefficiencies and deviations from design specifications. Each

component was modelled individually and combined in a system model to achieve the characteristic model.

The solution model, using particle swarm optimisation, was applied to the mine-specific characteristic model to achieve the optimised operating profiles for the refrigeration plants. It was necessary to implement the solution model manually due to a lack of automated infrastructure.

The manual implementation validated that the solution model was able to maintain service delivery requirements by ensuring that the chill dam temperature remained below the target. The power consumption expected from the refrigeration plants was within an average absolute error of 6.44% compared with the actual power consumption, noting that the actual power consumption contained pump power consumptions.

The solution model altered the operating profiles based on the present conditions. The use of particle swarm optimisation made it possible to implement the solution model in a real-time automated control system. The resulting control system would be more robust to variations in conditions than standard set-point control strategies.

The manual implementation resulted in cost savings to date of R2.23 million due to the achieved load shifting over a period of 2.5 months. Sustainable implementation was achieved as there was no gap in the implementation period. Using the average inlet water parameters for the two Eskom seasons (high-demand and low-demand season), a financial benefit of R9.5 million per annum is achievable. This cost saving is only based on weekdays as weekends provide no load shifting opportunities.

Further, the optimisation process and control philosophy were completed in less time than other optimisation processes (such as simulation optimisation [12], [65]) due to the use of particle swarm optimisation. Due to the reduced computing time, the developed control philosophy was able to adjust operating profiles dynamically to ensure the maximum cost savings for the day were achieved without affecting the service delivery requirements.

CHAPTER 4 – CONCLUSION

4.1 Summary

There are numerous marginally profitable mines in the South African deep-level mining industry due to increasing electricity costs and decreasing production rates. Decreasing the electrical operating costs of a mine will result in a larger profit margin in instances where refrigeration systems are responsible for 28% of the entire electricity bill of a mine.

Refrigeration systems are necessary to supply adequate ventilations conditions, which are the legal limits, to the working areas. Underground environments are constantly developing, thus resulting in the refrigeration system no longer operating according to its design. Continuous optimisation is necessary to ensure that the refrigeration system is operating efficiently.

Manual control is typically implemented on South African deep-level mining refrigeration systems with a target temperature for chilled water. Control room operators implement the control and prioritise service delivery (water temperature) over system efficiency. The need exists for energy management systems that satisfies the service delivery requirements while achieving cost savings through system efficiency.

Previous optimisation techniques used on the refrigeration system had long computational times and resulted in static target profiles. AI optimisation techniques reduce the computational time, thereby allowing for target profiles to be determined dynamically and that vary according to the present system requirements.

This study addressed the need for the optimisation of refrigeration systems with improved computational performance. AI optimisation techniques were used with system characterisation to provide dynamic targets for the control room operators. The dynamic optimisation was able to compensate for present infrastructure availability and varying present system requirements.

The following objectives were identified to provide a solution to the above-mentioned need:

- Characterise individual refrigeration plants.
- Reduce the operating costs of the refrigeration system.
- Use an optimisation technique with improved computational performance to allow for the optimisation to be used in dynamically controlled systems.

The refrigeration plants were characterised individually using historical data and the response curve method. The individual characterisation was required to emulate the performance of the refrigeration plants at different operating conditions. This ensured that the optimisation model accounted for design variances, such as inefficiencies occurred over years of use.

The plants were characterised with an average coefficient of determination of 0.8. Some plants had an average coefficient of determination below 0.7 due to a lack of operating data and similar operating conditions. The specific average characteristic equation was used for these refrigeration plants.

The refrigeration system was optimised using particle swarm optimisation. The algorithm determined the target profile for each refrigeration plant's evaporator flow and guide vane based on the present infrastructure and present requirements. The optimisation resulted in a daily cost savings of R80 000 and an expected annual cost savings of R9.5 million while satisfying the service delivery requirements (chill dam temperature below 2 °C).

Particle swarm optimisation is an AI optimisation technique that has a better computational performance than classical methods used in the South African deep-level mining industry. The result is that the optimisation can be implemented on dynamically controlled systems to achieve cost savings while maintaining the service delivery requirements for variations in the system requirements.

The methodology can be applied to various mining refrigeration systems to obtain cost savings while maintaining service delivery requirements. The methodology is adjustable and can be used on multi-stage refrigeration systems (including single-stage refrigeration systems). The implementation of the methodology on different refrigeration systems will result in cost savings due to the lack of dynamic optimisation in mining control systems.

4.2 Limitations and recommendations

Although AI is widely used in optimisation processes, research indicates that it is seldomly found in the deep-level mining industry. The result is a gap in research for the mining industry and further research is required to fulfil the gap and understand the benefit that AI can provide. The following recommendations are made to fill this gap in current research:

- Modelling the basic ventilation system of the BAC will allow the optimisation to further prevent overcooling occurring on the ventilation circuit. The water temperature demand and water flow demand will adjust according to the ambient air conditions.

- Further characterisation of the demand (such as underground water consumers and their respective instantaneous requirements) will allow the optimisation model to prevent overcooling occurred due to the control not knowing the specific demand requirements. Further research into the characterisation of underground consumers is required to achieve cost savings through preventing the overcooling.
- The condenser circuits of the refrigeration plants have an impact on the cooling duty achieved by the plant. As a result, including the condenser circuit parameters in the model will result in a more accurate characteristic model, which will allow the optimisation model to solve to a more accurate and cost-effective operation.
- AI can further be used to characterise refrigeration plants more accurately. Using an artificial neural network, a refrigeration plant can be characterised with minimal data and a high level of accuracy. Having the artificial neural network structure may result in minimal effort required to update the characteristic model to account for maintenance and changes to refrigeration plants. An artificial neural network may further be able to provide simpler characterisation for refrigeration plants with more parameters (such as condenser circuit parameters).
- The incorporation of power factor analysis and characterisation to determine the most cost-effective operation, including reactive power charges. This is not an essential on mines with power factor correction solutions, but will provide a more complete solution for mines lacking power factor correction services.
- A lack in the automated implementation infrastructure exists in mining industry due to the age of the present infrastructure. Research is required to determine the sustainability of the implementation of the methodology on an automated control system.

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APPENDIX A REFRIGERATION PLANT CHARACTERISATION

A.1 Characteristic model summary

The refrigeration plant power consumption was characterised by Equation (38).

$$P_i(GV) = \begin{cases} y_{1,i}GV^2 + y_{2,i}GV + y_{3,i} & \text{for } GV \geq 30 \\ 0 & \text{for } GV < 30 \end{cases} \quad (38)$$

Here, P_i is the power consumption of plant i in kW and GV is the guide vane angle as a percentage. The constants $y_{1,i}$, $y_{2,i}$ and $y_{3,i}$ are refrigeration plant specific constants. Table 20 indicates the constants for all the plants and the coefficients of determination.

Table 20: Refrigeration plant power characteristic equation variables

Refrigeration plant	y_1	y_2	y_3	R^2
1	-0.0225	13.2140	661.0086	0.8358
2	0.0226	8.9604	641.9457	0.8932
3	0.0085	9.3773	673.3298	–
4	0.0165	8.3692	748.6262	0.7452
5	0.0173	6.9656	641.7386	0.7817
6	0.0919	-4.7382	691.9141	–
7	0.0919	-4.7382	691.9141	–
8	0.0919	-4.7382	691.9141	–
9	0.0919	-4.7382	691.9141	–
10	0.1043	-6.1027	731.8386	0.9202
11	0.0795	-3.3736	651.9896	0.9134

Refrigeration plants 3, 6, 7, 8 and 9 had faulty power meters and, as a result, no data was available. The average characteristic equations of the respective plants (first- and second-stage plants) were used for these plants. Similarly, the refrigeration plant performance was characterised using Equation (37).

$$\Delta T_{plant,i}(GV, T_{inlet}, \dot{m}) = \begin{cases} x_{1,i}T_{inlet}GV + x_{2,i}GV\dot{m} + x_{3,i}T_{inlet}GV\dot{m} + x_{4,i}GV^2 + x_{5,i}GV & \text{for } GV \geq 30 \\ 0 & \text{for } GV < 30 \end{cases} \quad (37)$$

Here, $\Delta T_{plant,i}$ is the change in evaporator temperature over the evaporator of plant i in °C, GV is the guide vane angle as a percentage, T_{inlet} is the inlet evaporator temperature in °C, and $\dot{m}$ is the evaporator flow rate in l/s. The constants $x_{1,i}$, $x_{2,i}$, $x_{3,i}$, $x_{4,i}$ and $x_{5,i}$ are refrigeration plant specific constants (i). Table 21 lists the constants for all the plants and the coefficients of determination.

Table 21: Refrigeration plant performance characteristic equation variables

Refrigeration plant	x_1	x_2	x_3	x_4	x_5	R^2
1	-0.0010	-0.0003	0.0000	-0.0003	0.1176	0.9021
2	-0.0007	-0.0003	0.0000	-0.0002	0.1072	0.8910
3	-0.0487	-0.0018	0.0003	-0.0003	0.3734	0.8581
4	-0.0052	-0.0005	0.0001	-0.0004	0.1535	0.8551
5	-0.0336	-0.0014	0.0002	-0.0010	0.3237	0.5894
6	-0.0053	-0.0005	0.0001	-0.0010	0.1644	0.7092
7	-0.0036	-0.0006	0.0000	-0.0014	0.3265	0.7482
8	0.0017	-0.0003	0.0000	-0.0013	0.2341	0.7531
9	-0.0021	-0.0005	0.0000	-0.0008	0.2392	0.7511
10	0.0027	-0.0001	0.0000	-0.0016	0.2067	0.2781
11	0.0044	0.0001	0.0000	-0.0011	0.1405	0.3630

The average characteristic equations of the respective plants (first- and second-stage plants) were used for plants with coefficients of determination less than 0.7 (refrigeration plants 5, 10 and 11).

A.2 Refrigeration plant 1

Figure 53 compares the power consumption operating data and the characteristic equation for refrigeration plant 1. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

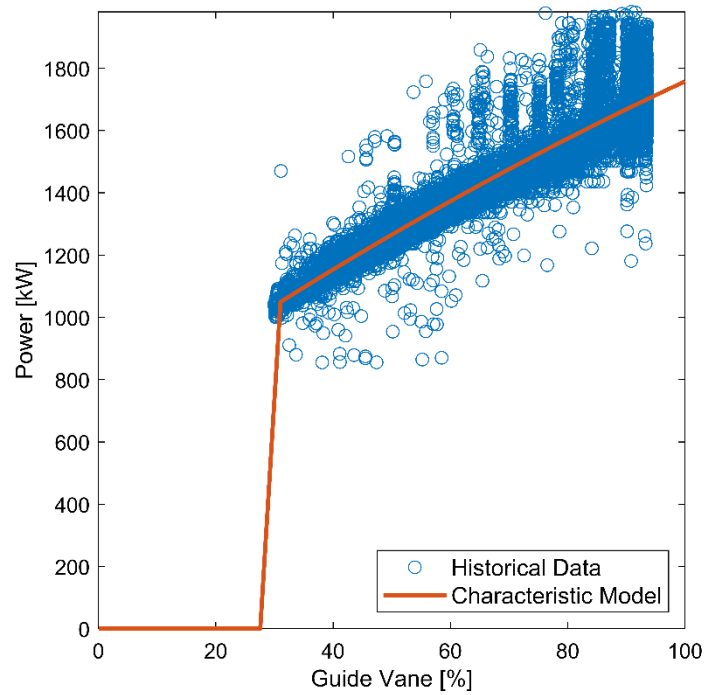


Figure 53: Refrigeration plant 1: power characteristic model

The operating data for refrigeration plant is shown in Figure 54 and Figure 56. The difference between the two graphs is the axes since the operating data exists in a 4-D plane but the figures provide a 3-D depiction of the data. The operating data was used to obtain the constants for the characteristic equation. Figure 55 and Figure 57 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

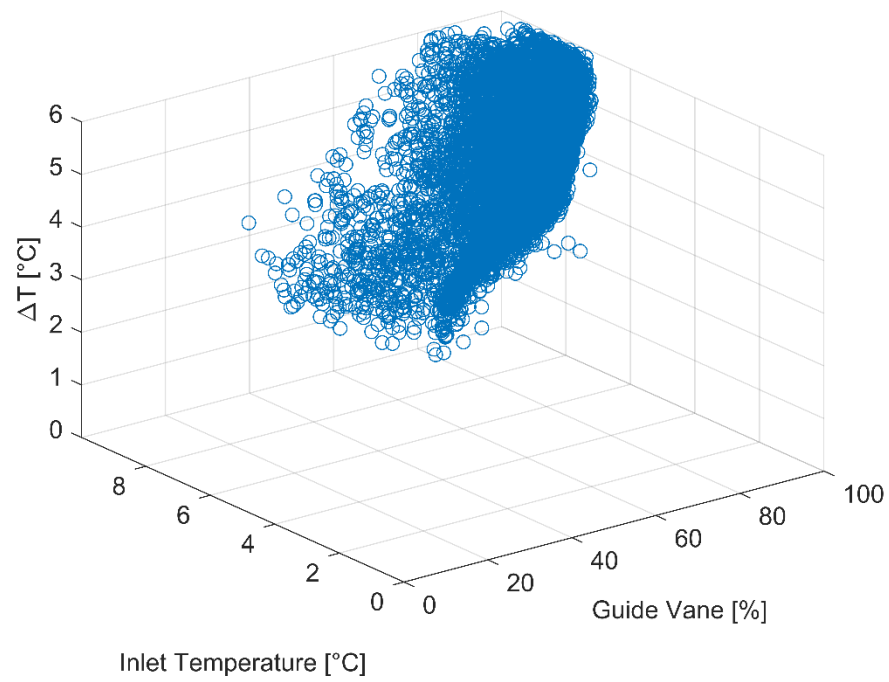


Figure 54: Refrigeration plant 1: 3-D scatter plot of operating data

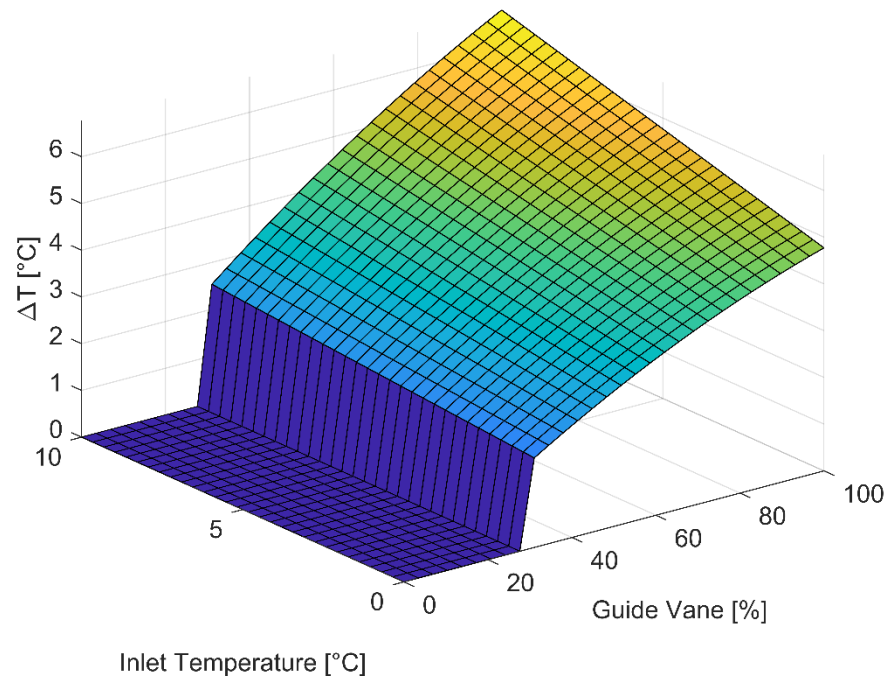


Figure 55: Refrigeration plant 1: 3-D surface curve of characteristic model (constant flow)

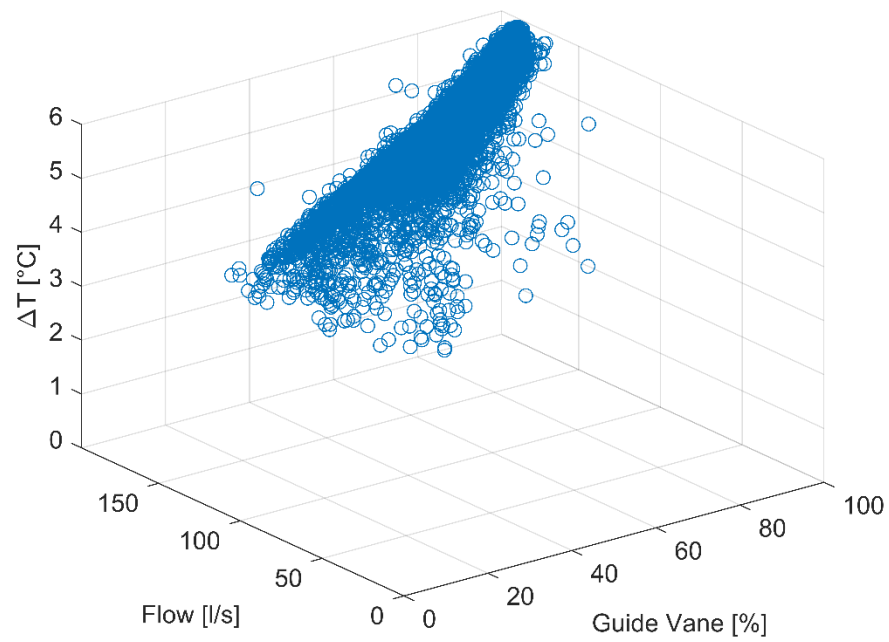


Figure 56: Refrigeration plant 1: 3-D scatter plot of operating data

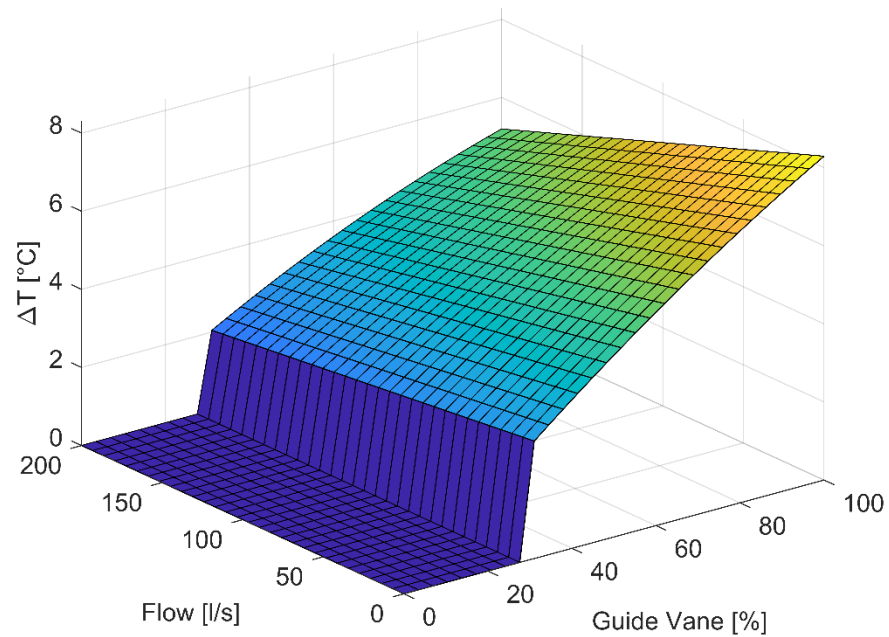


Figure 57: Refrigeration plant 1: 3-D surface curve of characteristic model (constant inlet temperature)

A.3 Refrigeration plant 2

Figure 58 compares the power consumption operating data and the characteristic equation for refrigeration plant 2. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

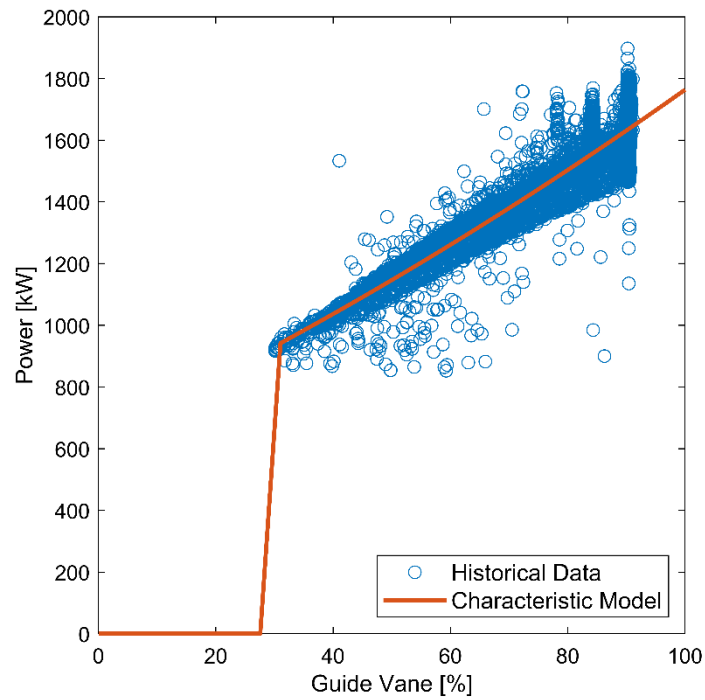


Figure 58: Refrigeration plant 2: power characteristic model

The operating data for refrigeration plant 2 is shown in Figure 59 and Figure 61. The operating data was used to obtain the constants for the characteristic equation. Figure 60 and Figure 62 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

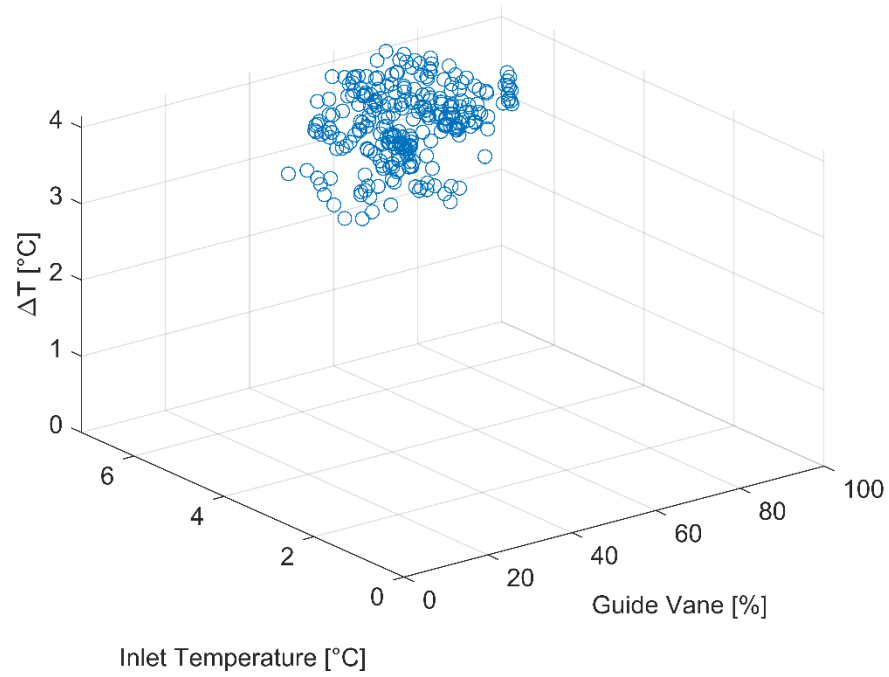


Figure 59: Refrigeration plant 2: 3-D scatter plot of operating data

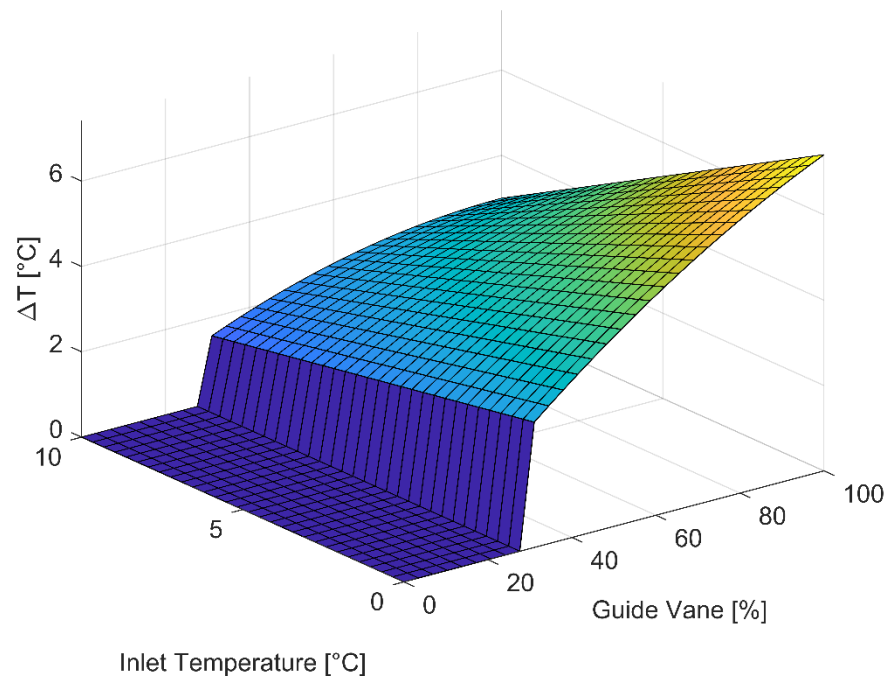


Figure 60: Refrigeration plant 2: 3-D surface curve of characteristic model (constant flow)

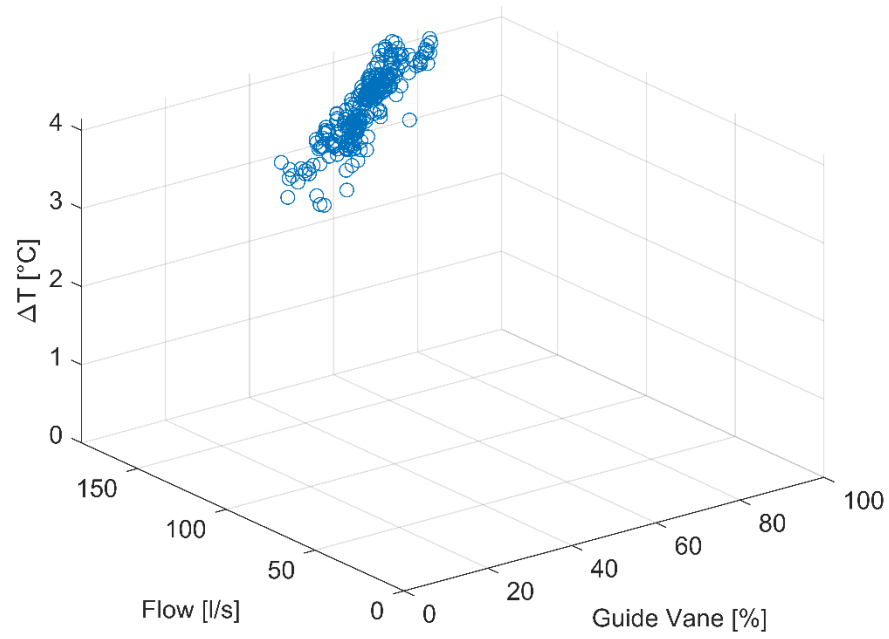


Figure 61: Refrigeration plant 2: 3-D scatter plot of operating data

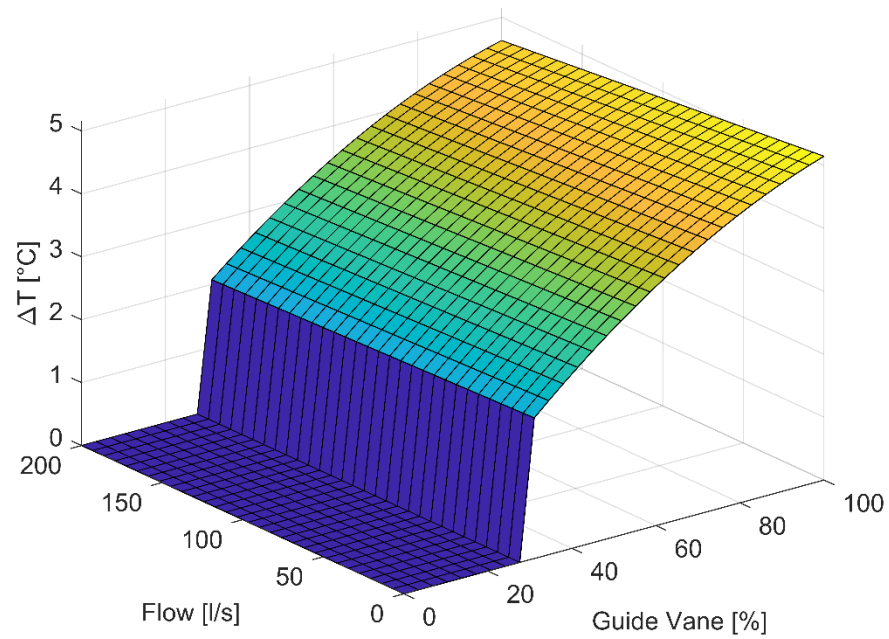


Figure 62: Refrigeration plant 2: 3-D surface curve of characteristic model (constant inlet temperature)

A.4 Refrigeration plant 3

Figure 63 compares the power consumption operating data and the characteristic equation for refrigeration plant 3. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

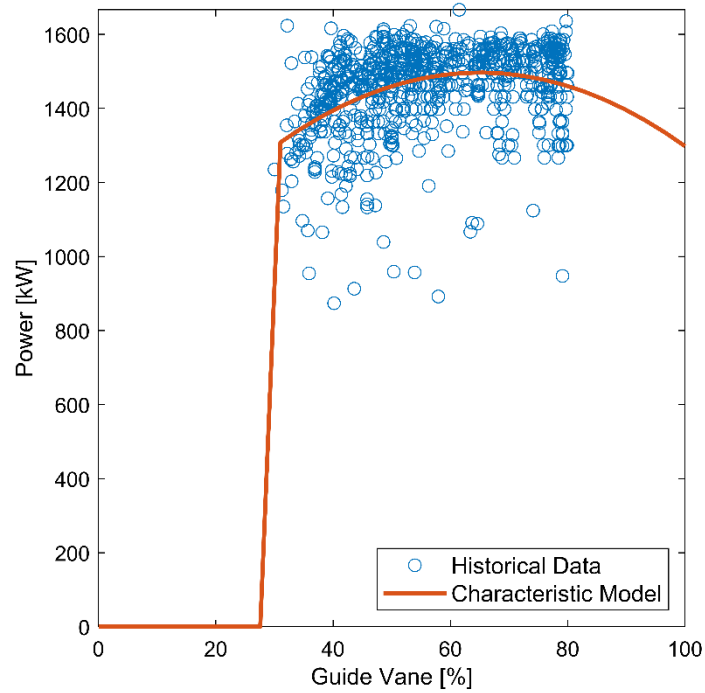


Figure 63: Refrigeration plant 3: power characteristic model

The operating data for refrigeration plant 3 is shown in Figure 64 and Figure 66. The operating data was used to obtain the constants for the characteristic equation. Figure 65 and Figure 67 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

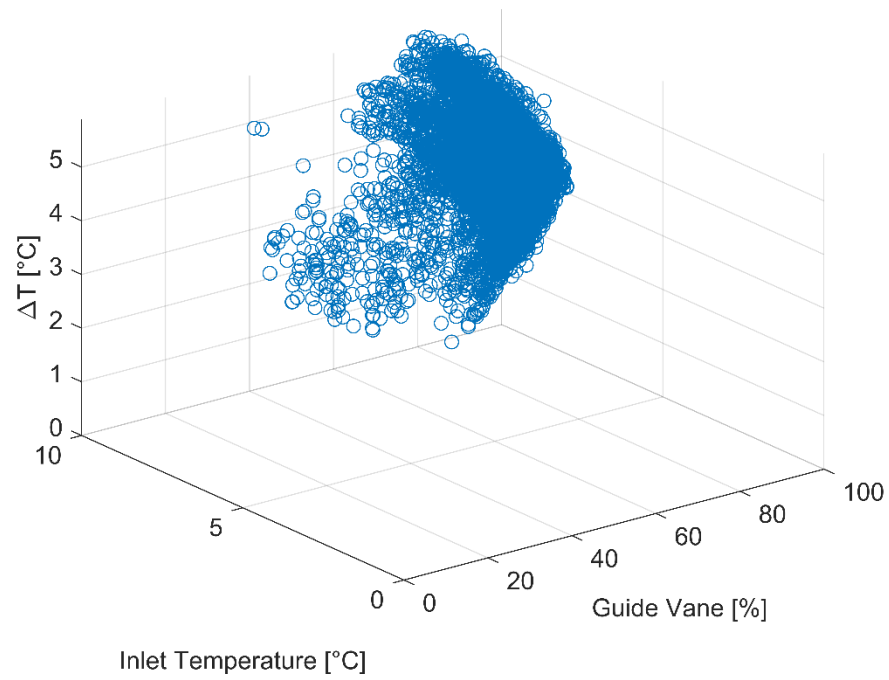


Figure 64: Refrigeration plant 3: 3-D scatter plot of operating data

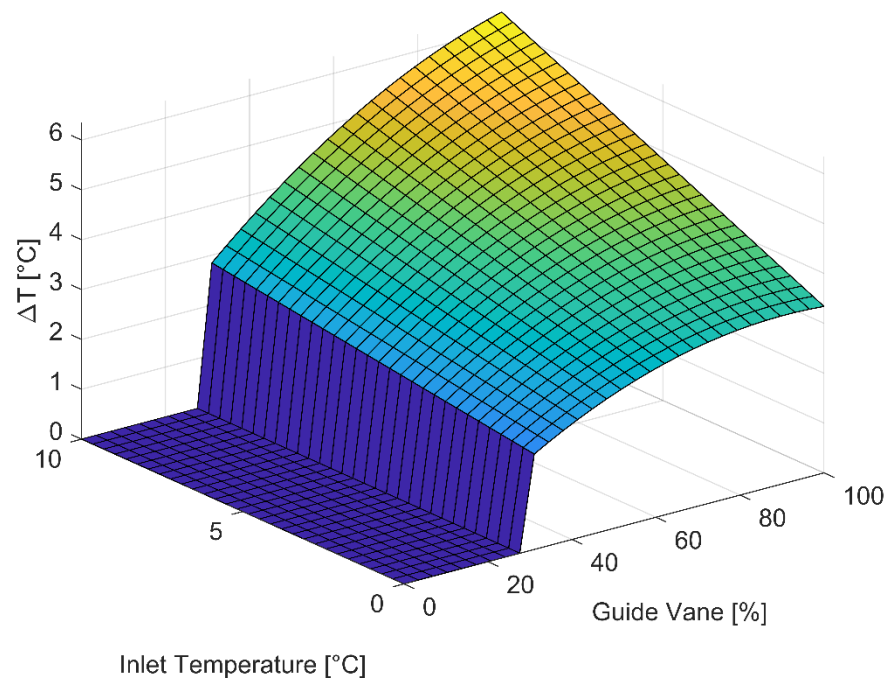


Figure 65: Refrigeration plant 3: 3-D surface curve of characteristic model (constant flow)

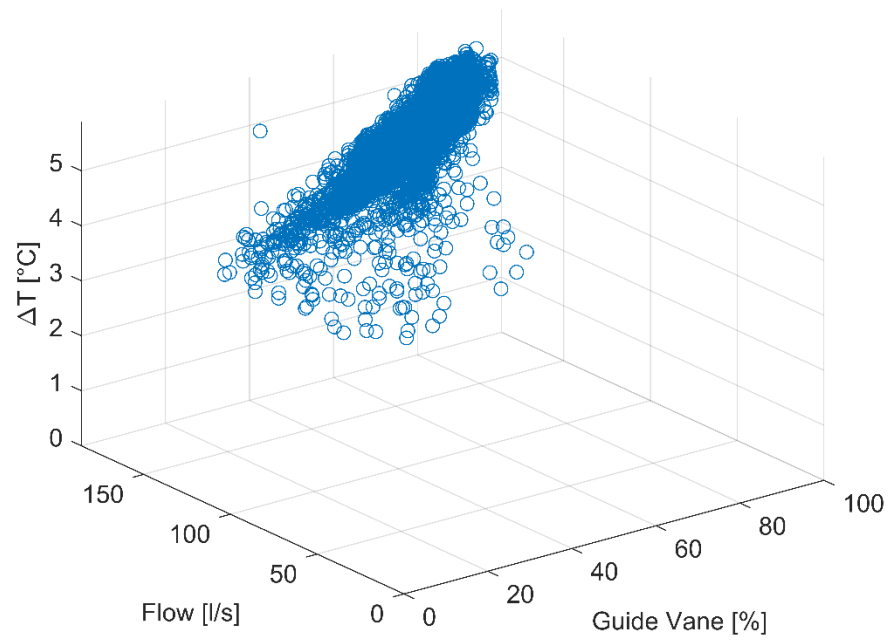


Figure 66: Refrigeration plant 3: 3-D scatter plot of operating data

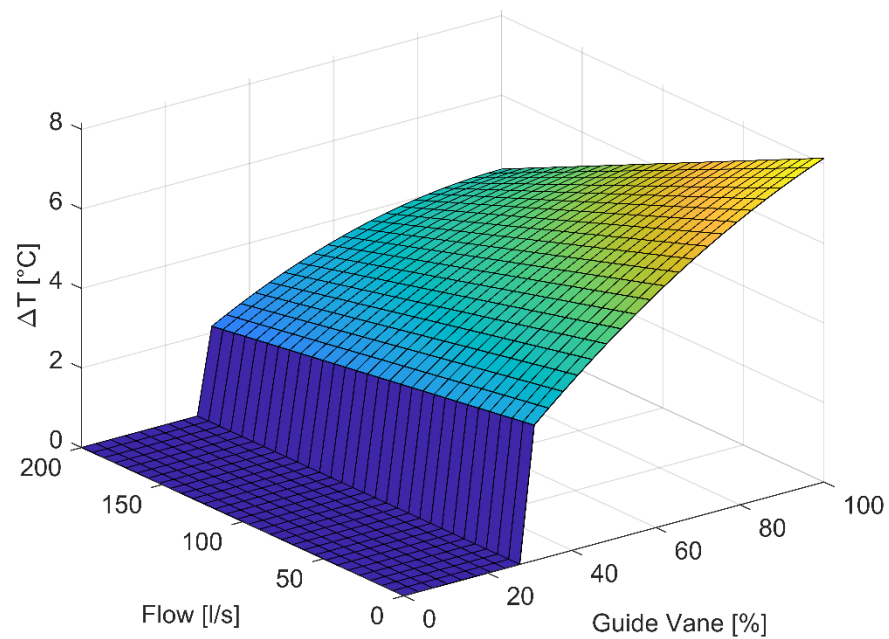


Figure 67: Refrigeration plant 3: 3-D surface curve of characteristic model (constant inlet temperature)

A.5 Refrigeration plant 4

Figure 68 compares the power consumption operating data and the characteristic equation for refrigeration plant 4. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

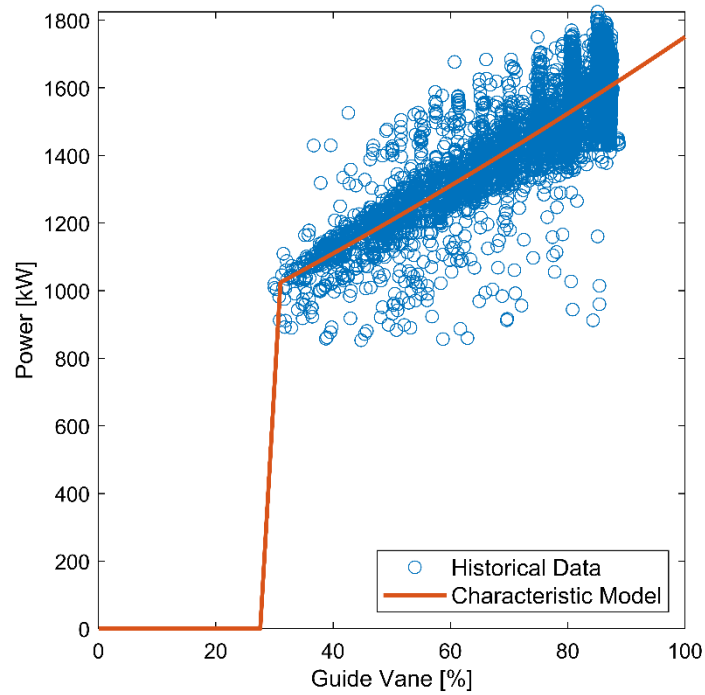


Figure 68: Refrigeration plant 4: power characteristic model

The operating data for refrigeration plant 4 is shown in Figure 69 and Figure 71. The operating data was used to obtain the constants for the characteristic equation. Figure 70 and Figure 72 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

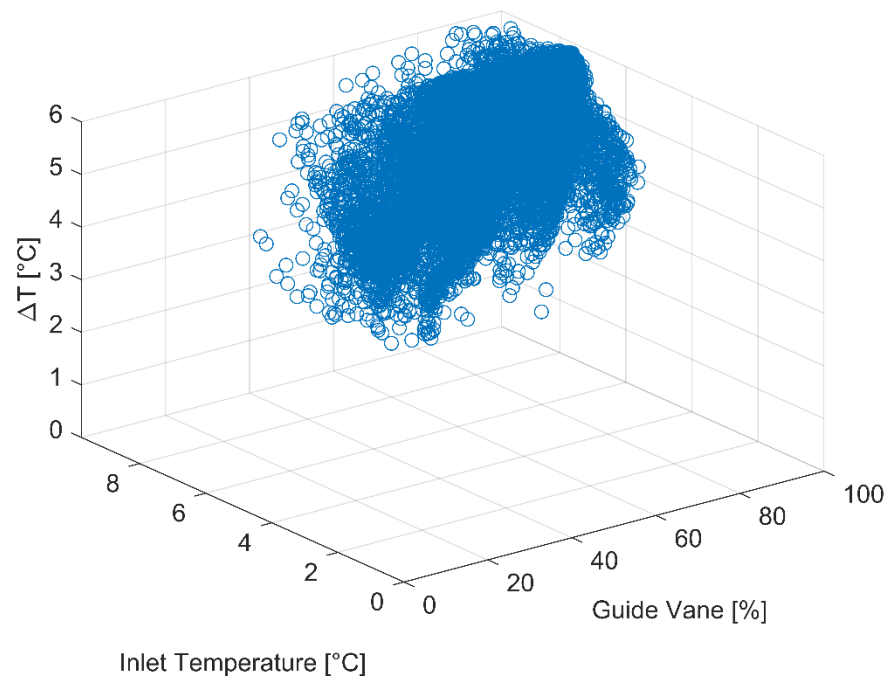


Figure 69: Refrigeration plant 4: 3-D scatter plot of operating data

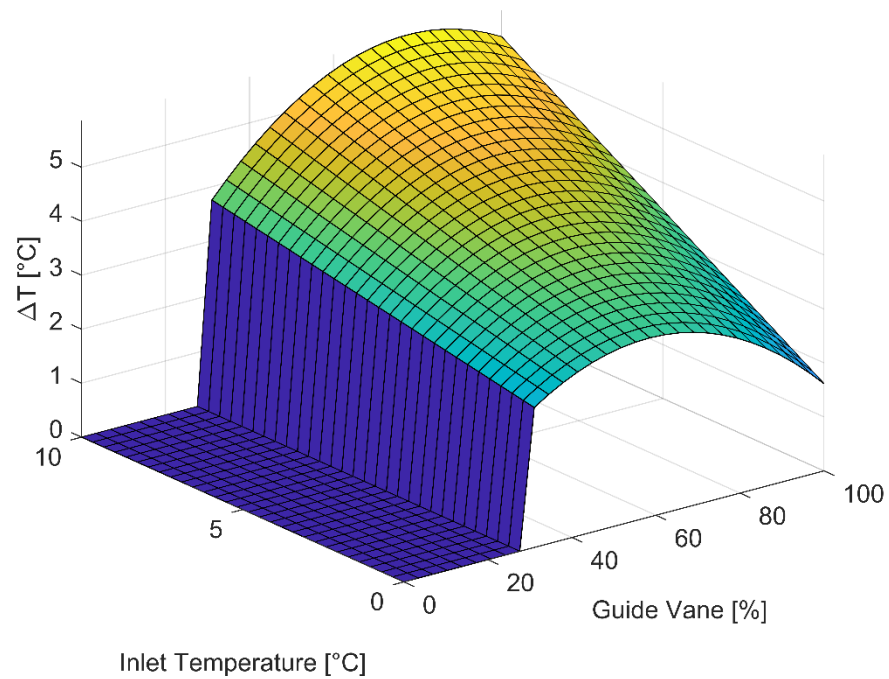


Figure 70: Refrigeration plant 4: 3-D surface curve of characteristic model (constant flow)

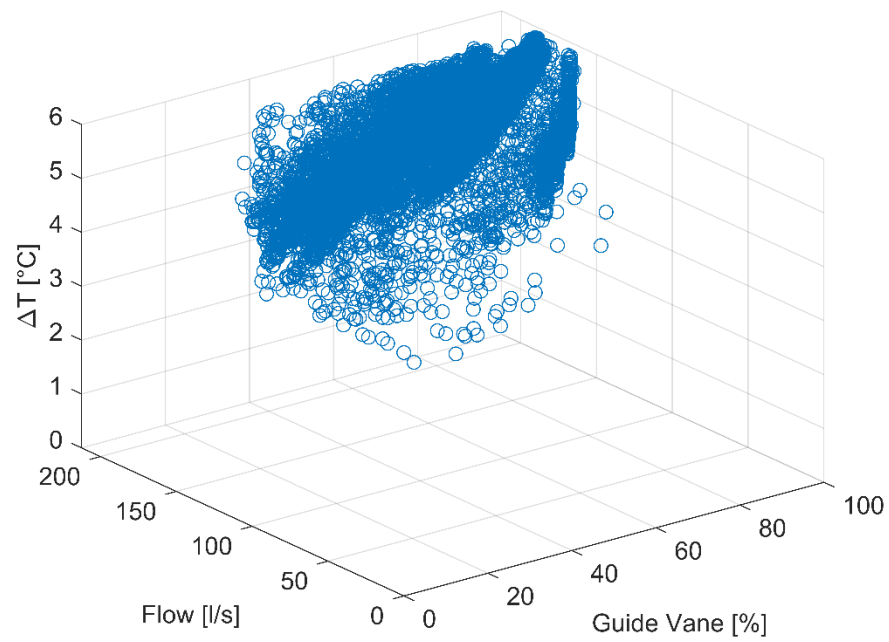


Figure 71: Refrigeration plant 4: 3-D scatter plot of operating data

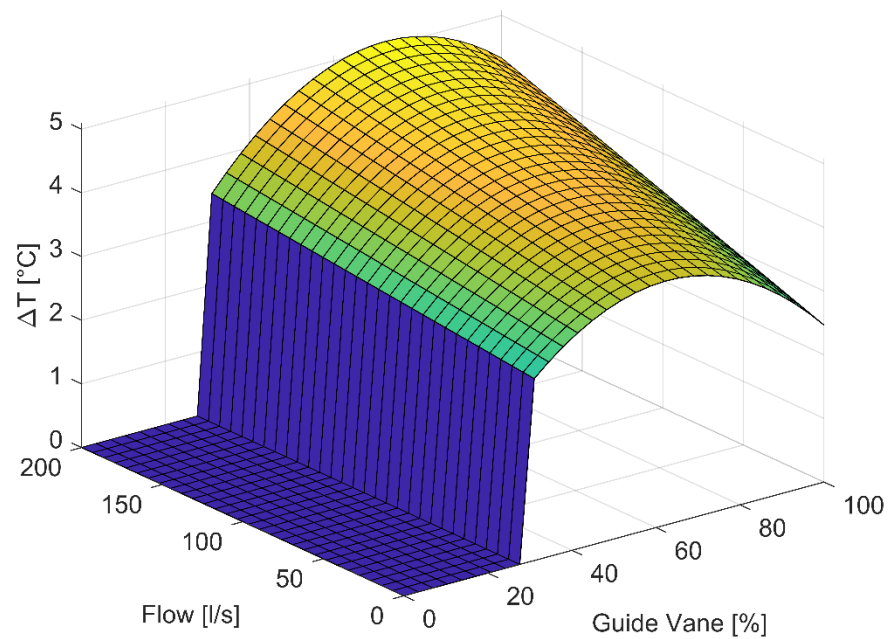


Figure 72: Refrigeration plant 4: 3-D surface curve of characteristic model (constant inlet temperature)

A.6 Refrigeration plant 5

Figure 73 compares the power consumption operating data and the characteristic equation for refrigeration plant 5. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

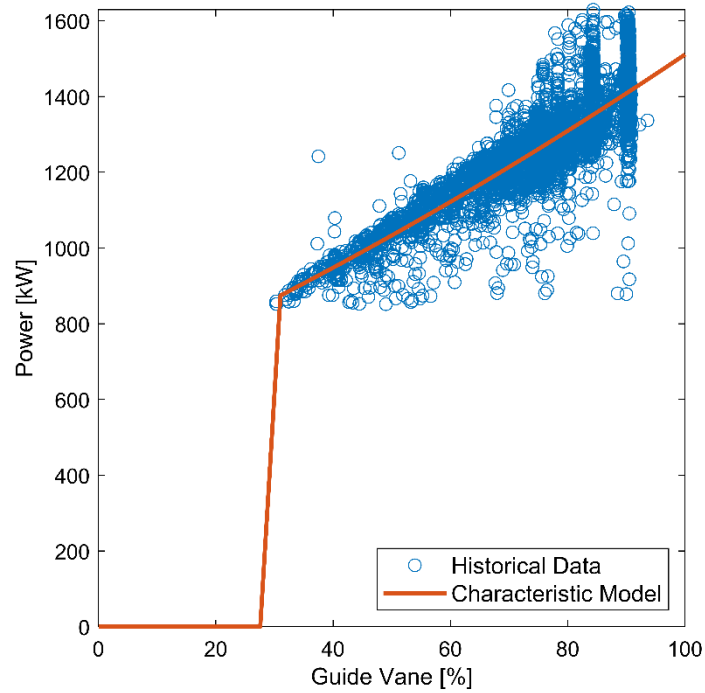


Figure 73: Refrigeration plant 5: power characteristic model

The operating data for refrigeration plant 5 is shown in Figure 74 and Figure 76. The operating data was used to obtain the constants for the characteristic equation. Figure 75 and Figure 77 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

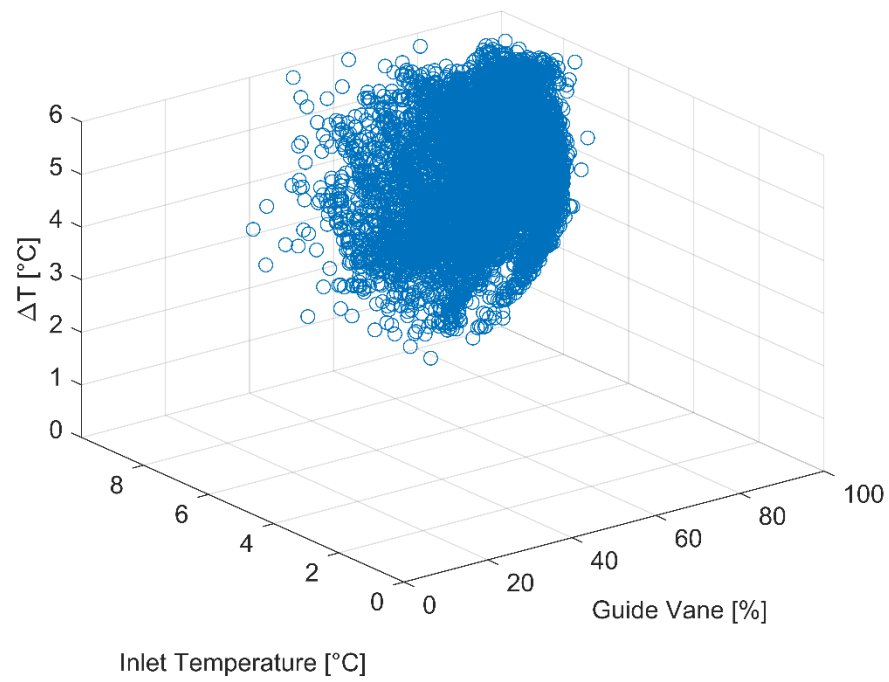


Figure 74: Refrigeration plant 5: 3-D scatter plot of operating data

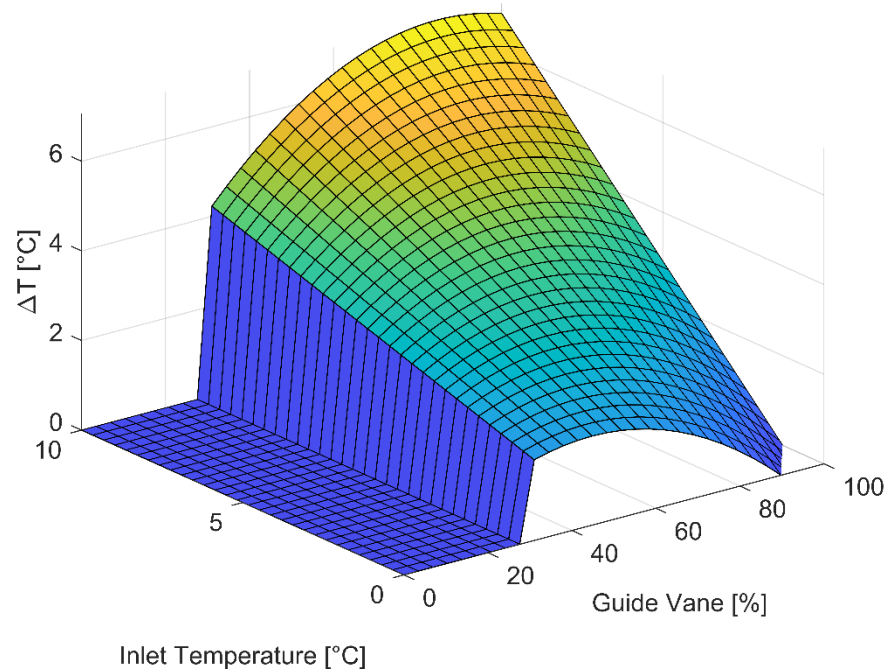


Figure 75: Refrigeration plant 5: 3-D surface curve of characteristic model (constant flow)

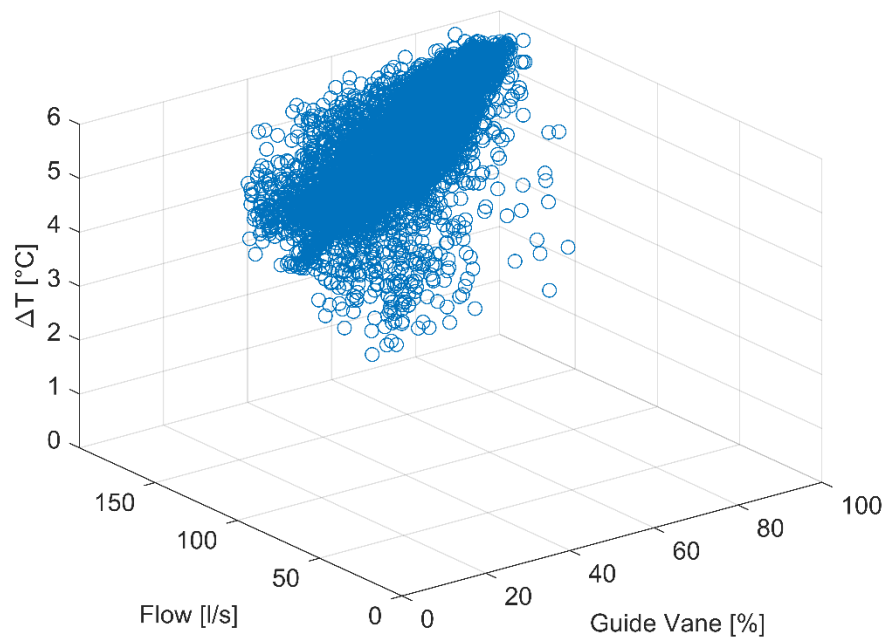


Figure 76: Refrigeration plant 5: 3-D scatter plot of operating data

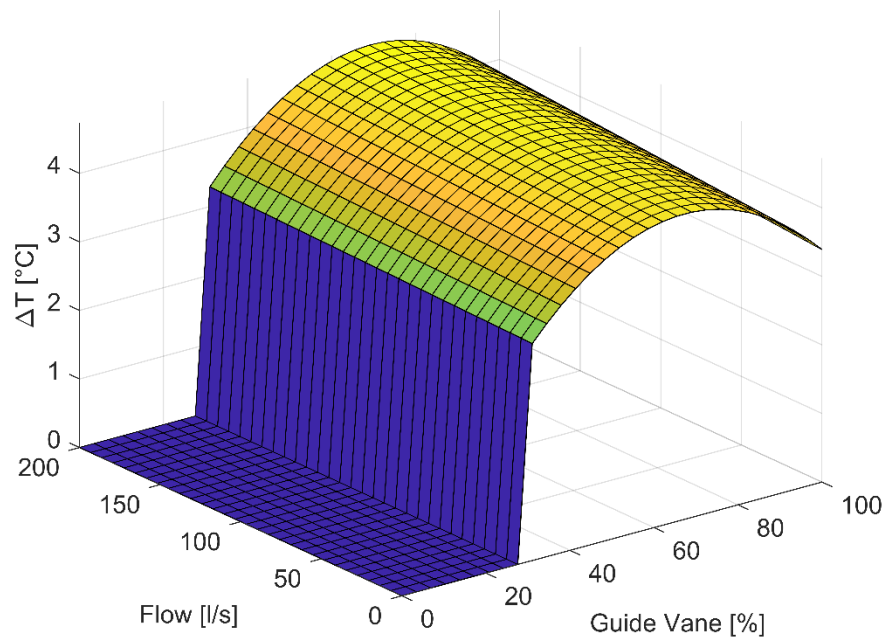


Figure 77: Refrigeration plant 5: 3-D surface curve of characteristic model (constant inlet temperature)

A.7 Refrigeration plant 6

Figure 78 compares the power consumption operating data and the characteristic equation for refrigeration plant 6. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

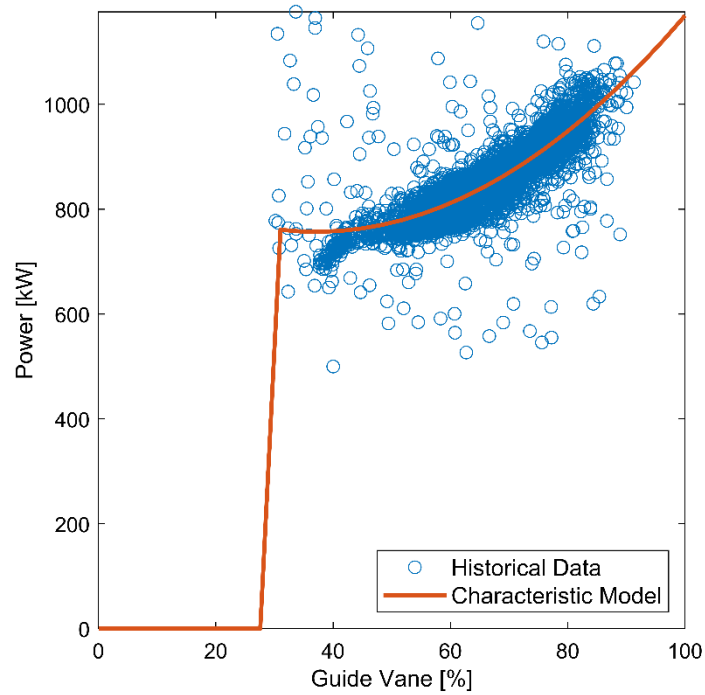


Figure 78: Refrigeration plant 6: power characteristic model

The operating data for refrigeration plant 6 is shown in Figure 79 and Figure 81. The operating data was used to obtain the constants for the characteristic equation. Figure 80 and Figure 82 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

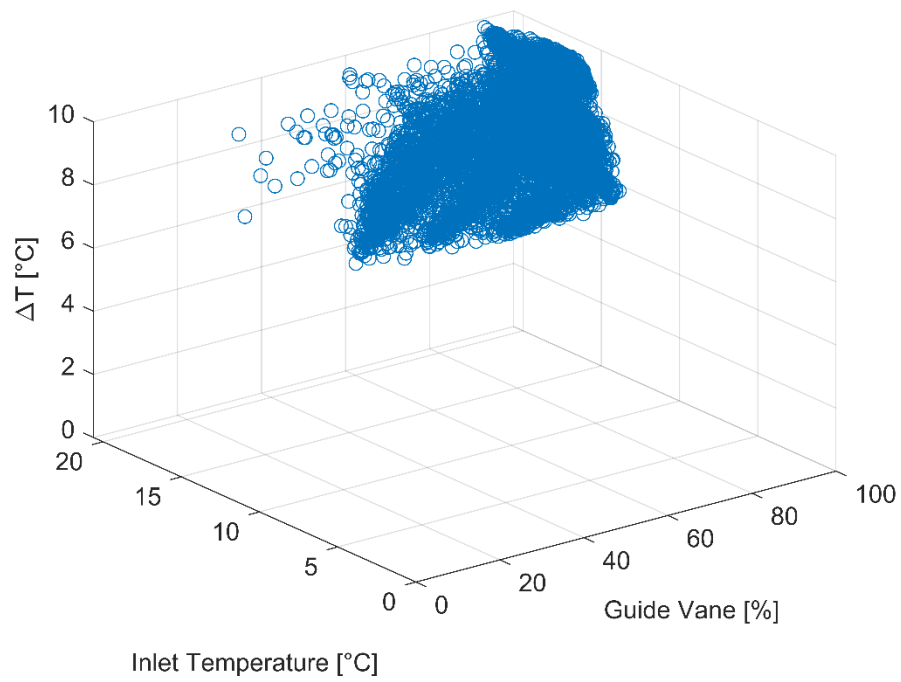


Figure 79: Refrigeration plant 6: 3-D scatter plot of operating data

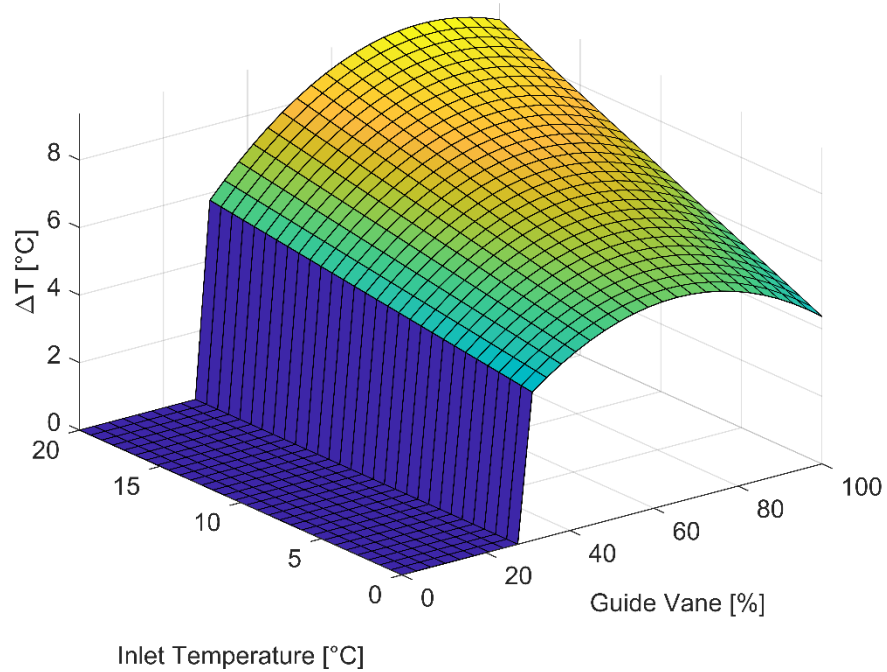


Figure 80: Refrigeration plant 6: 3-D surface curve of characteristic model (constant flow)

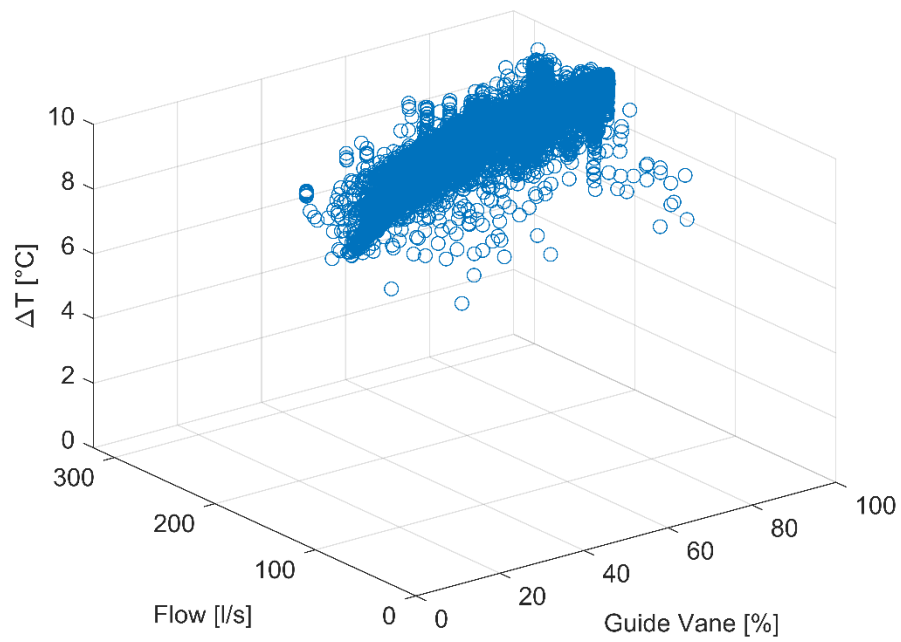


Figure 81: Refrigeration plant 6: 3-D scatter plot of operating data

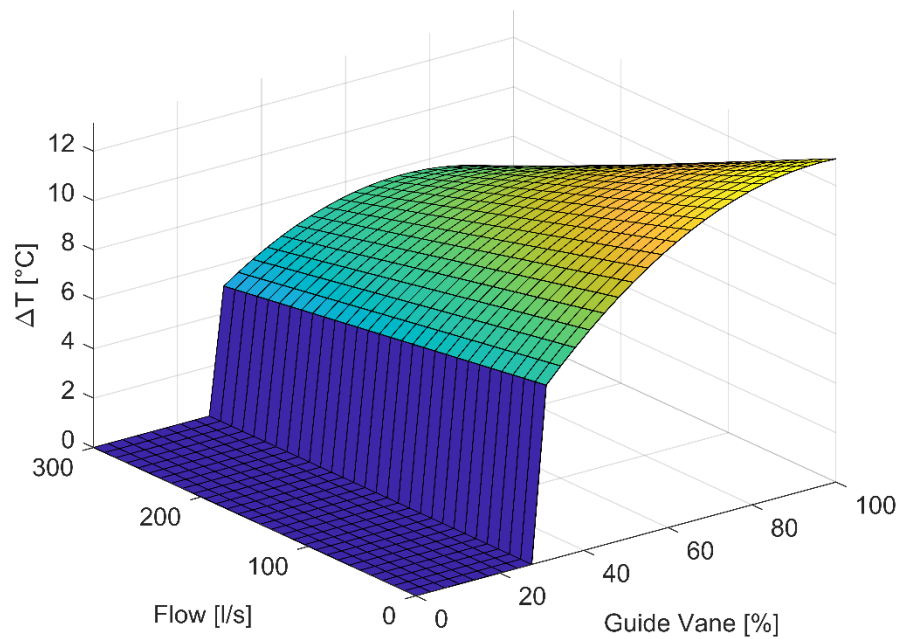


Figure 82: Refrigeration plant 6: 3-D surface curve of characteristic model (constant inlet temperature)

A.8 Refrigeration plant 7

Figure 83 compares the power consumption operating data and the characteristic equation for refrigeration plant 7. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

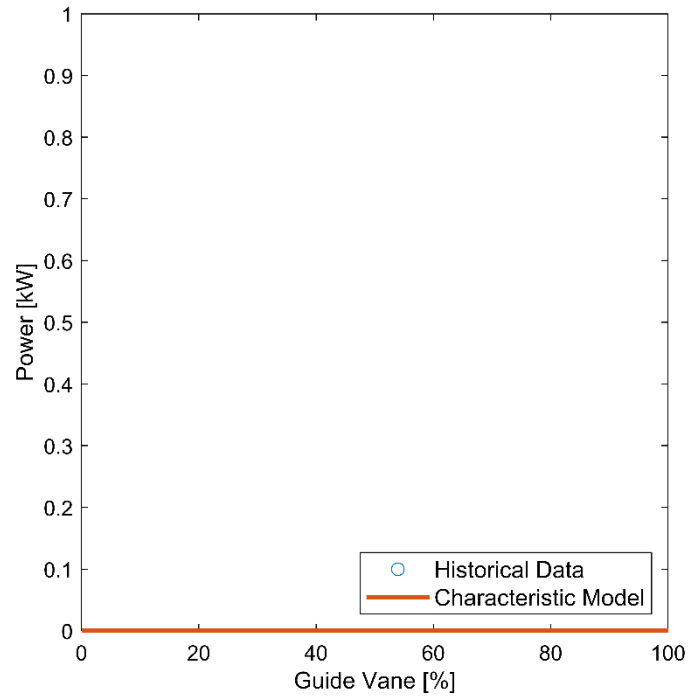


Figure 83: Refrigeration plant 7: power characteristic model

The operating data for refrigeration plant 7 is shown in Figure 84 and Figure 86. The operating data was used to obtain the constants for the characteristic equation. Figure 85 and Figure 87 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

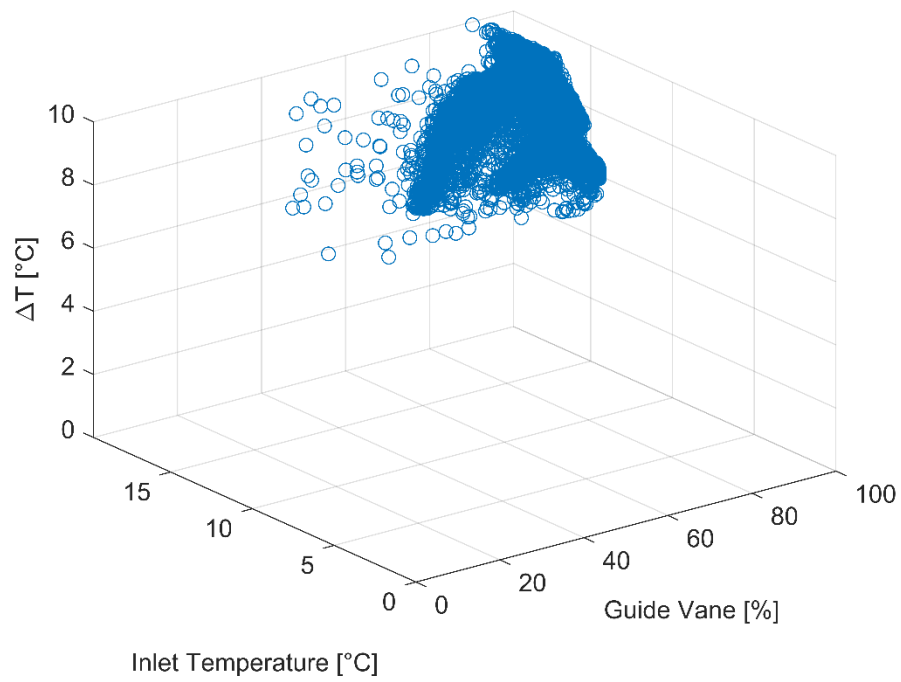


Figure 84: Refrigeration plant 7: 3-D scatter plot of operating data

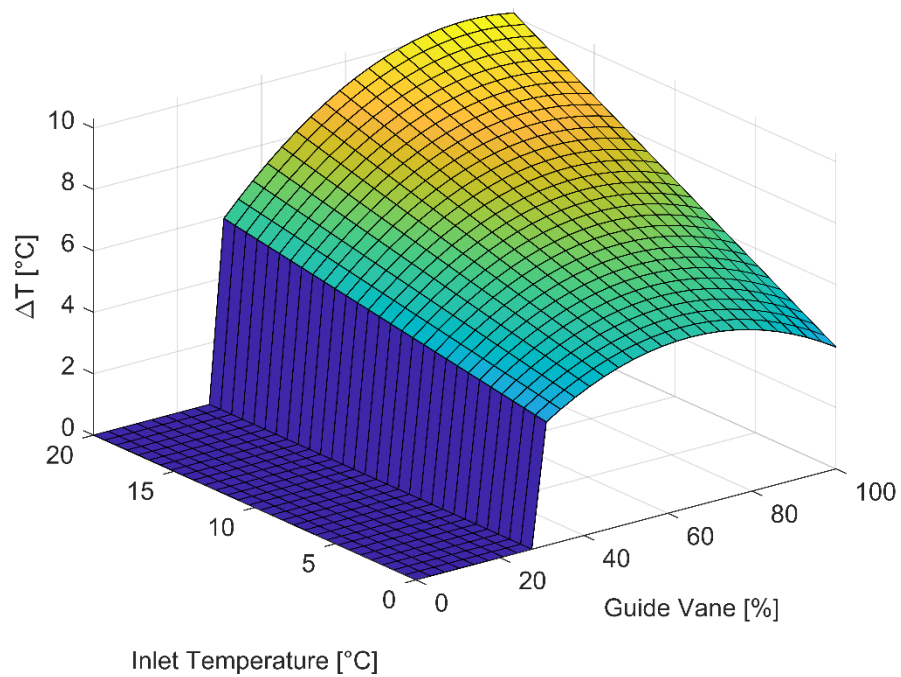


Figure 85: Refrigeration plant 7: 3-D surface curve of characteristic model (constant flow)

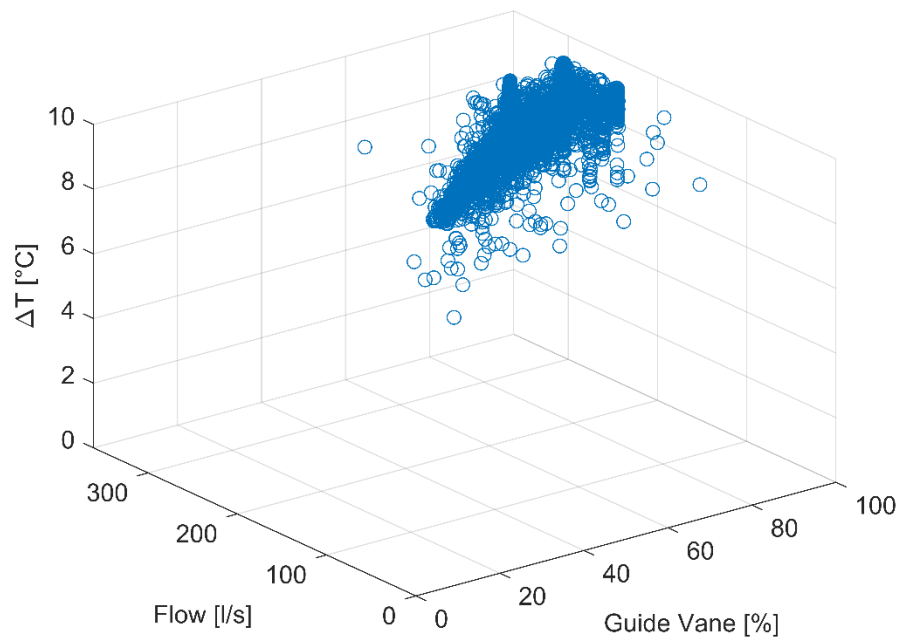


Figure 86: Refrigeration plant 7: 3-D scatter plot of operating data

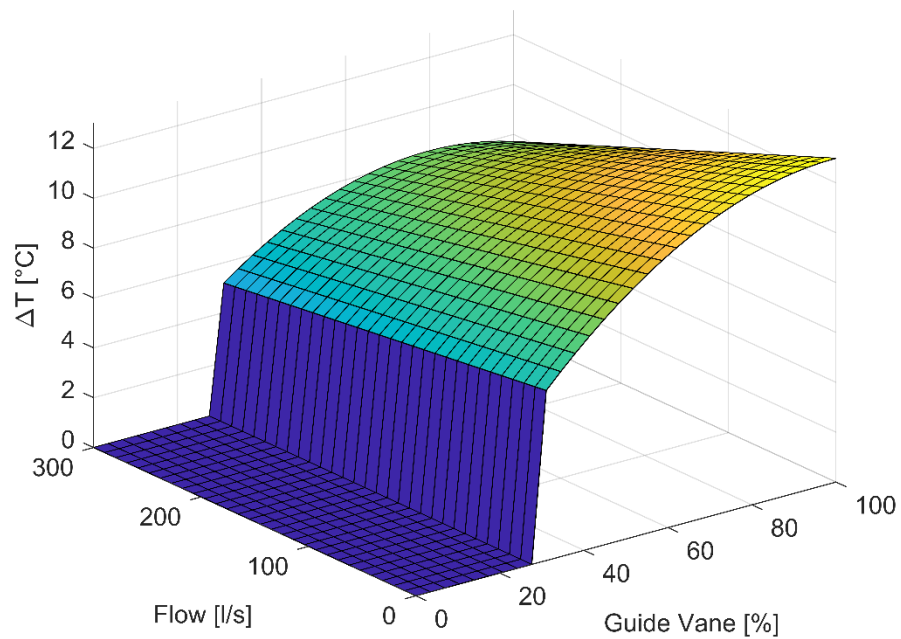


Figure 87: Refrigeration plant 7: 3-D surface curve of characteristic model (constant inlet temperature)

A.9 Refrigeration plant 8

Figure 88 compares the power consumption operating data and the characteristic equation for refrigeration plant 8. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

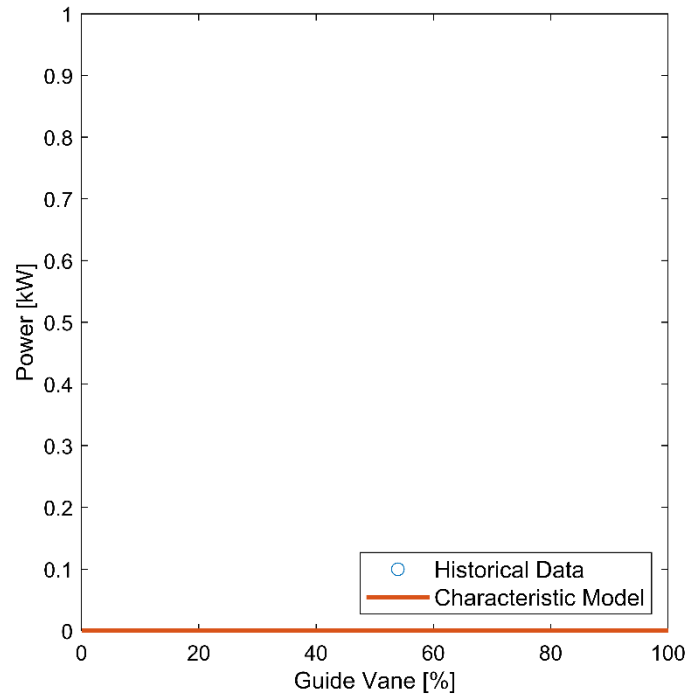


Figure 88: Refrigeration plant 8: power characteristic model

The operating data for refrigeration plant 8 is shown in Figure 89 and Figure 91. The operating data was used to obtain the constants for the characteristic equation. Figure 90 and Figure 92 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

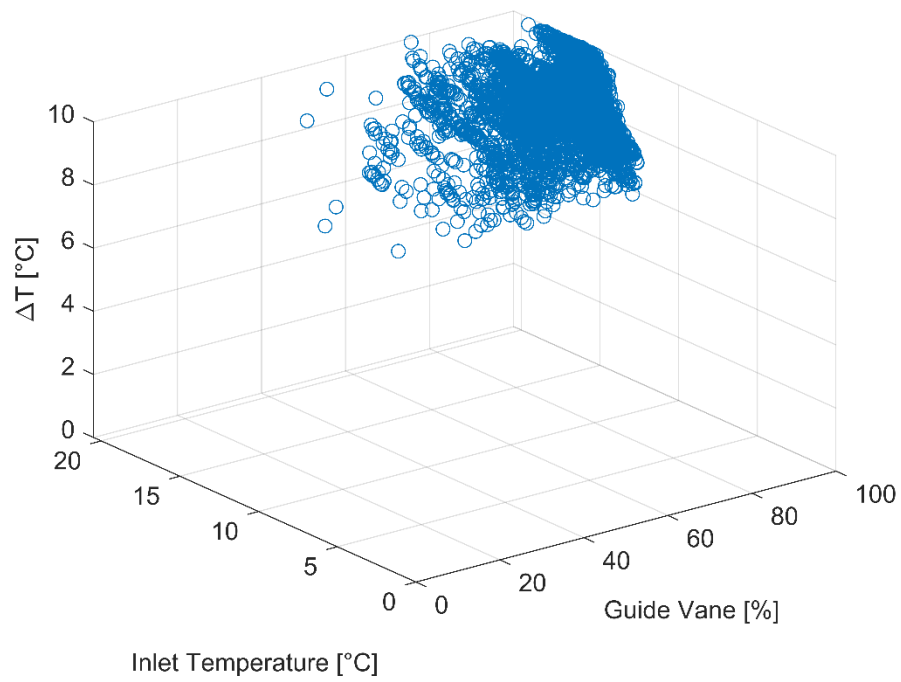


Figure 89: Refrigeration plant 8: 3-D scatter plot of operating data

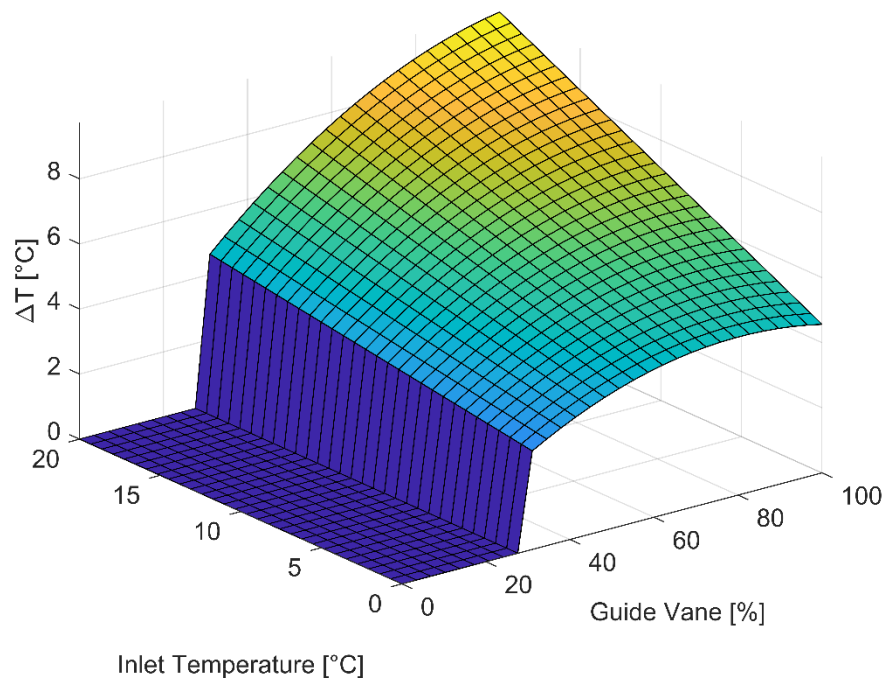


Figure 90: Refrigeration plant 8: 3-D surface curve of characteristic model (constant flow)

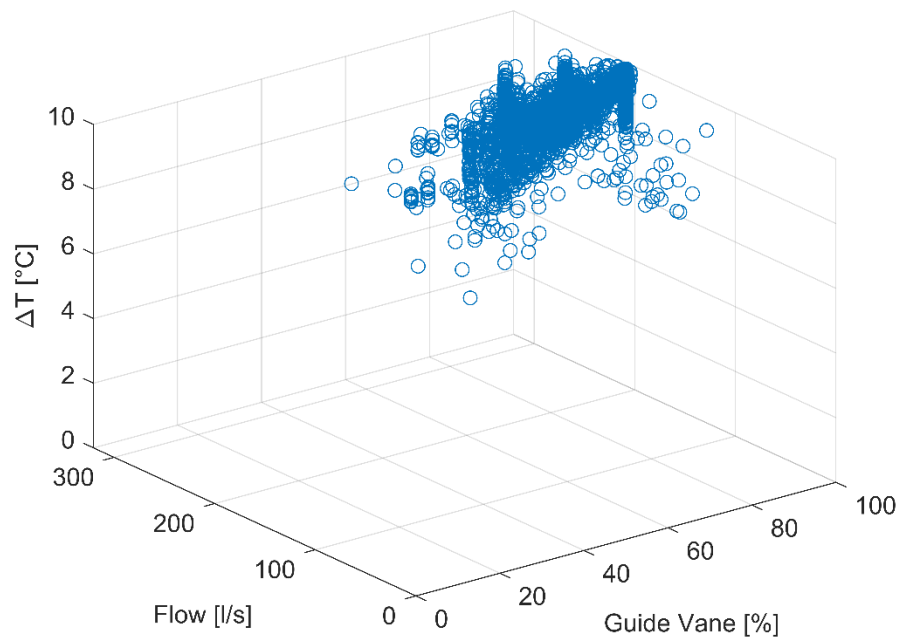


Figure 91: Refrigeration plant 8: 3-D scatter plot of operating data

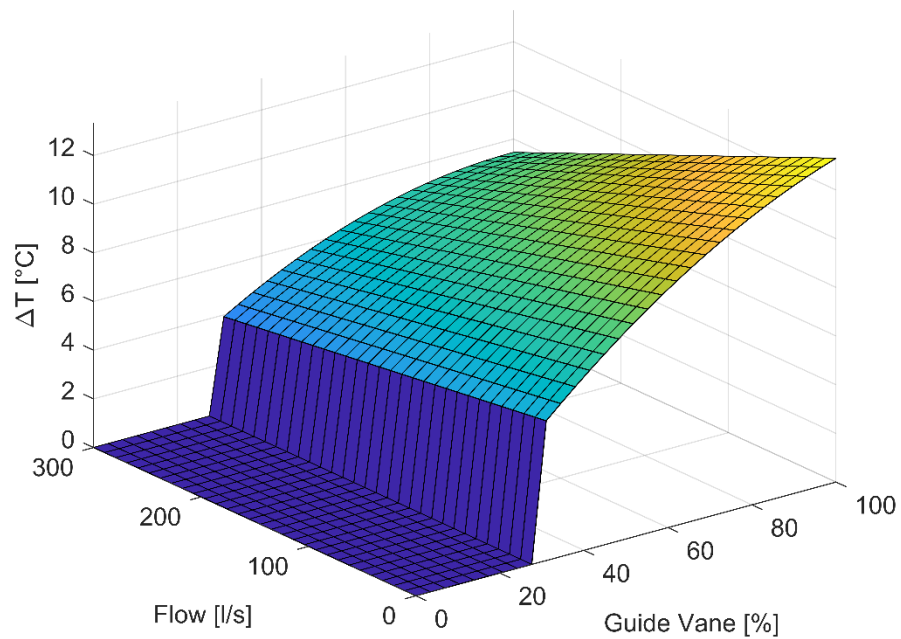


Figure 92: Refrigeration plant 8: 3-D surface curve of characteristic model (constant inlet temperature)

A.10 Refrigeration plant 9

Figure 93 compares the power consumption operating data and the characteristic equation for refrigeration plant 9. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

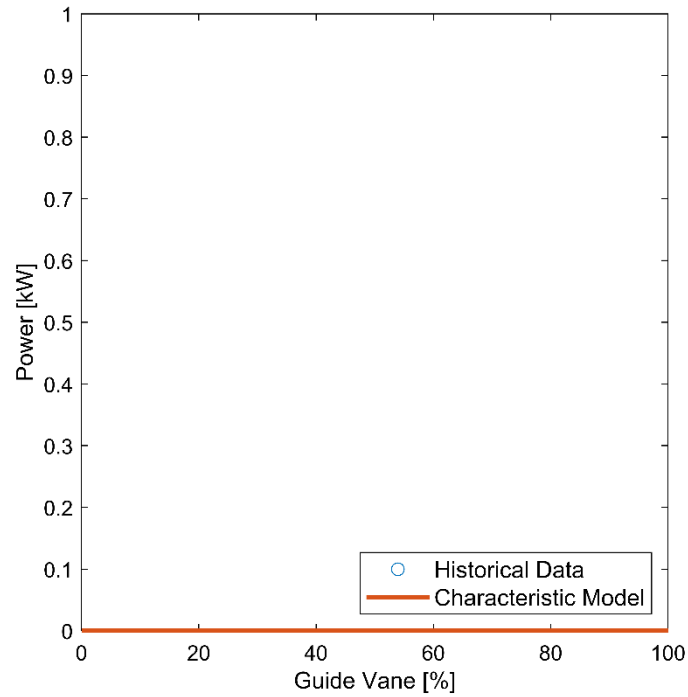


Figure 93: Refrigeration plant 9: power characteristic model

The operating data for refrigeration plant 9 is shown in Figure 94 and Figure 96. The operating data was used to obtain the constants for the characteristic equation. Figure 95 and Figure 97 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

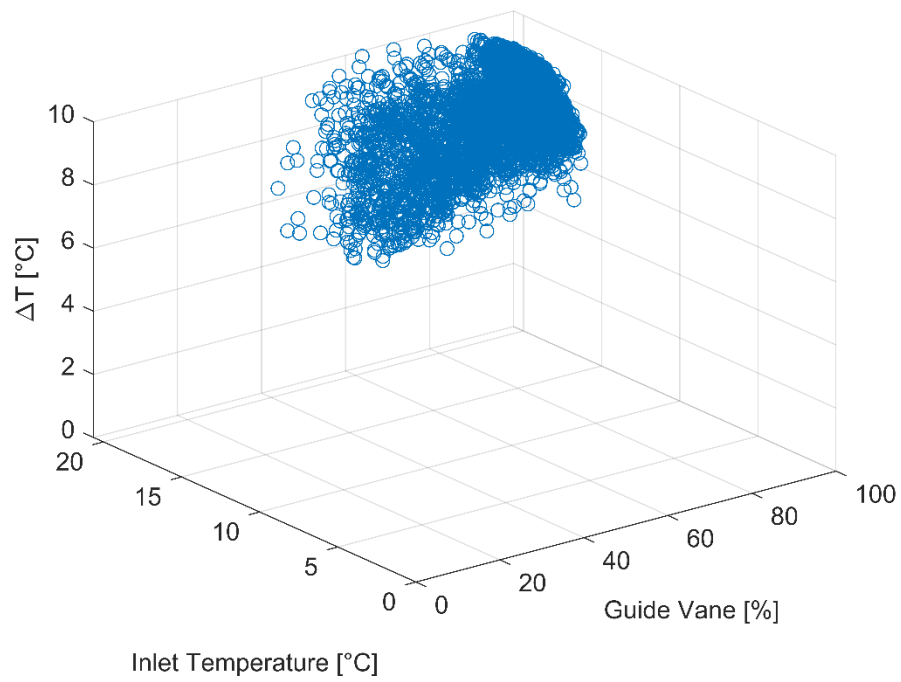


Figure 94: Refrigeration plant 9: 3-D scatter plot of operating data

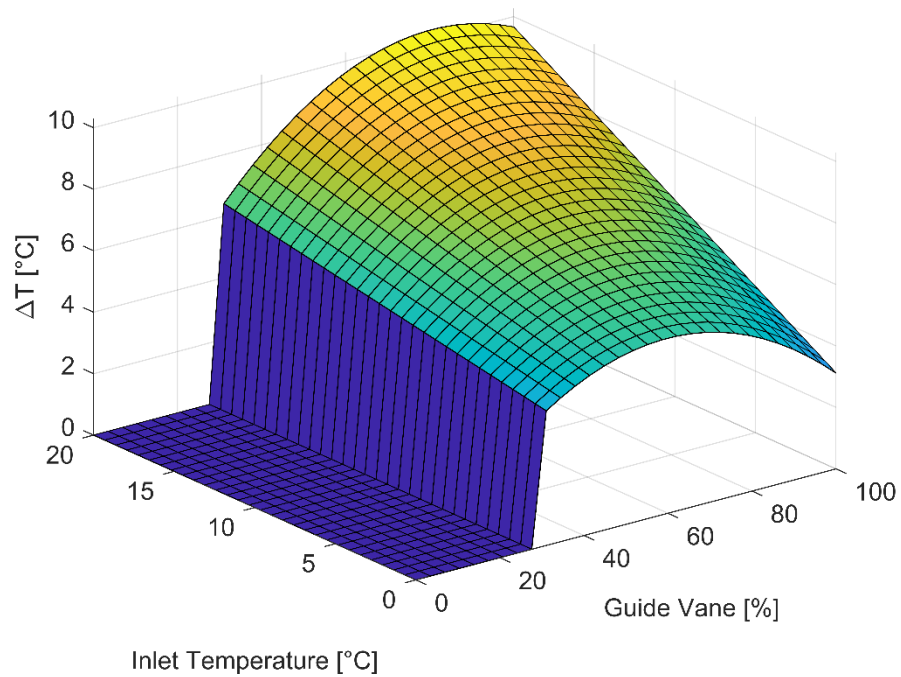


Figure 95: Refrigeration plant 9: 3-D surface curve of characteristic model (constant flow)

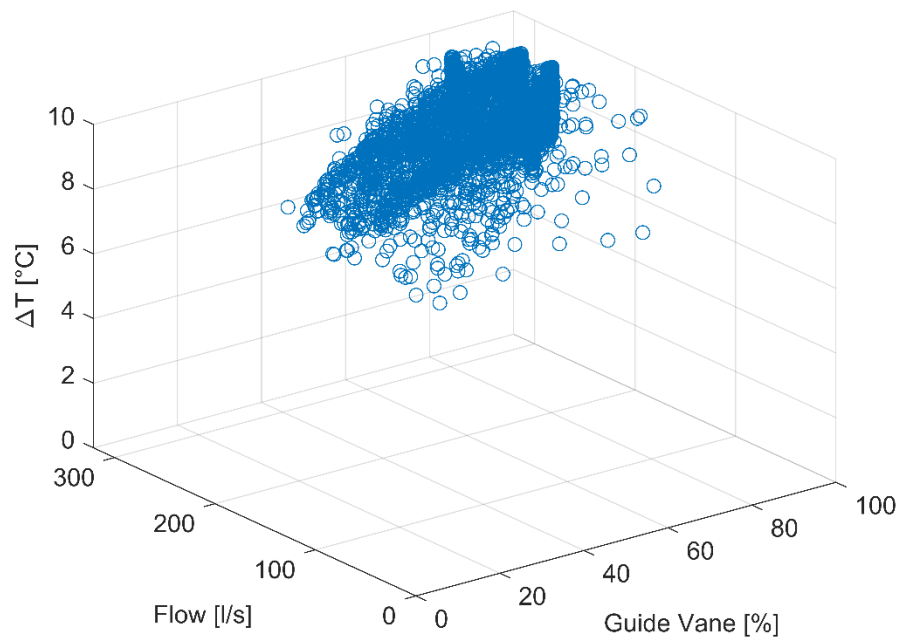


Figure 96: Refrigeration plant 9: 3-D scatter plot of operating data

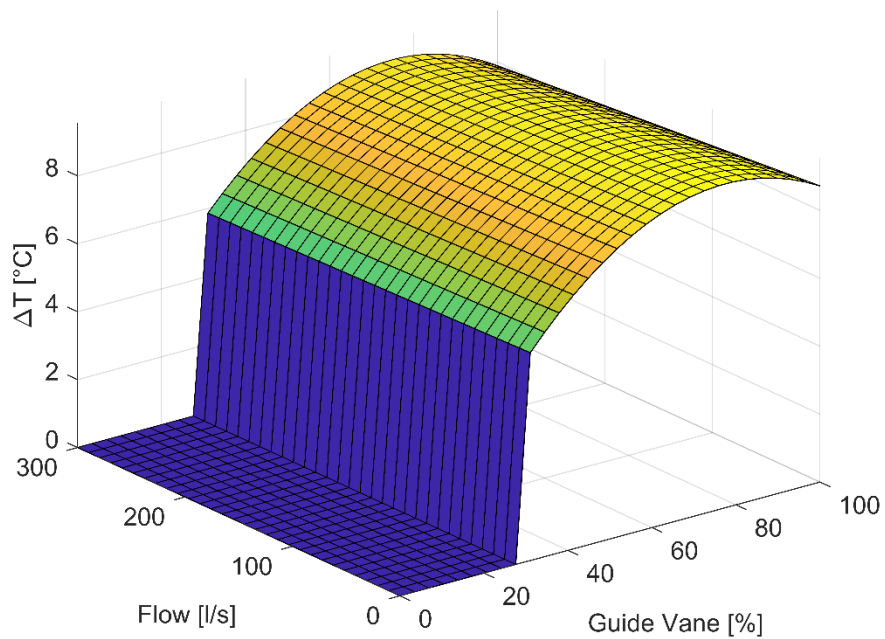


Figure 97: Refrigeration plant 9: 3-D surface curve of characteristic model (constant inlet temperature)

A.11 Refrigeration plant 10

Figure 98 compares the power consumption operating data and the characteristic equation for refrigeration plant 10. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

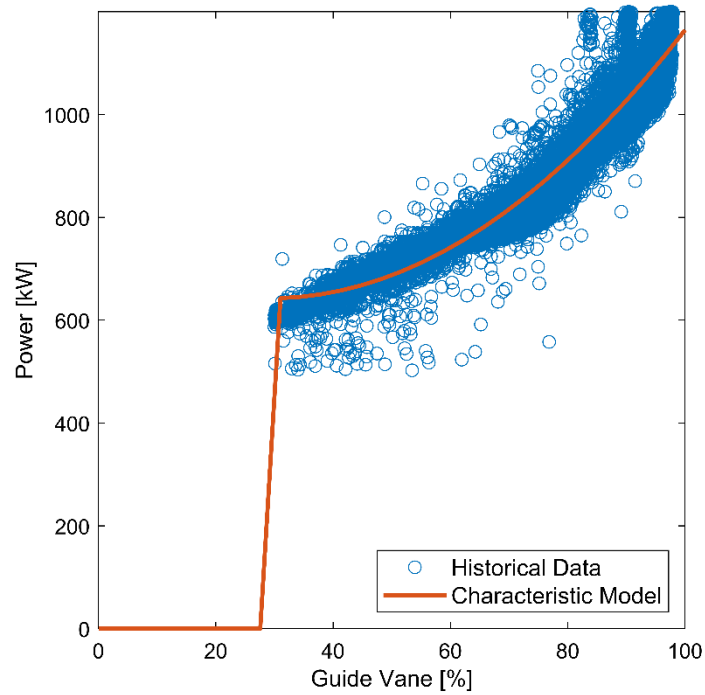


Figure 98: Refrigeration plant 10: power characteristic model

The operating data for refrigeration plant 10 is shown in Figure 99 and Figure 101. The operating data was used to obtain the constants for the characteristic equation. Figure 100 and Figure 102 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

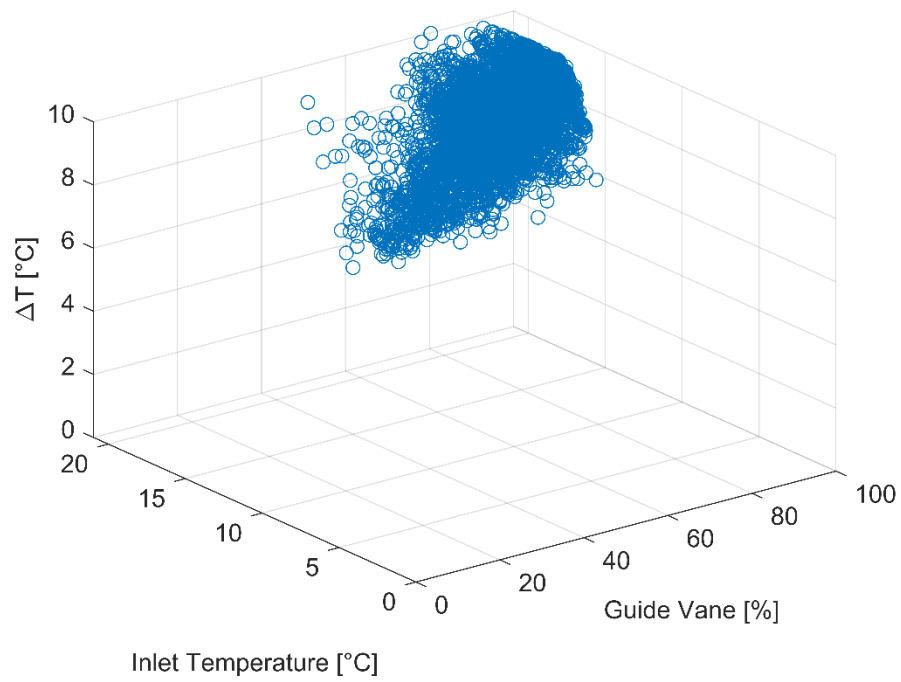


Figure 99: Refrigeration plant 10: 3-D scatter plot of operating data

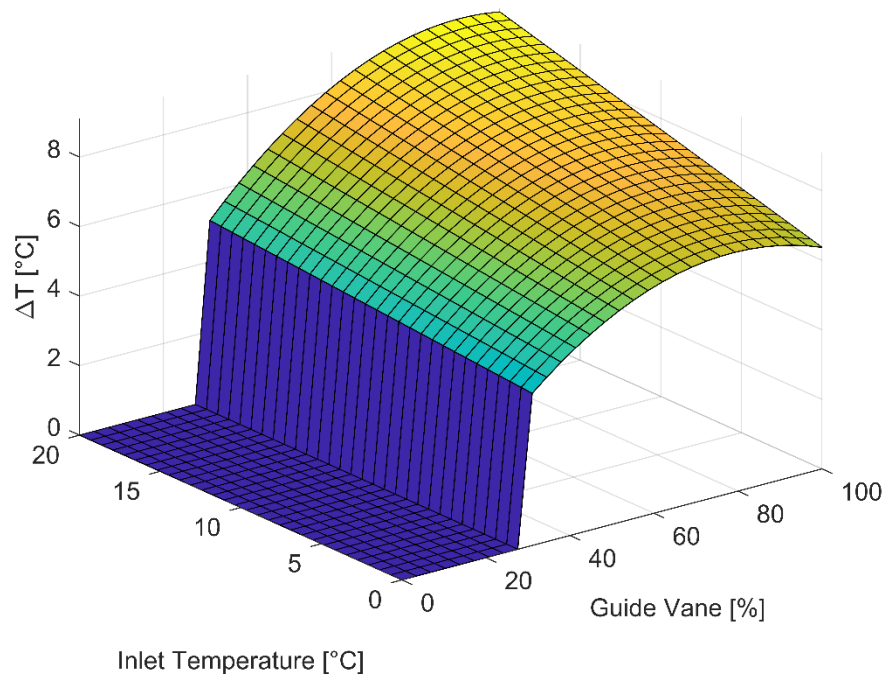


Figure 100: Refrigeration plant 10: 3-D surface curve of characteristic model (constant flow)

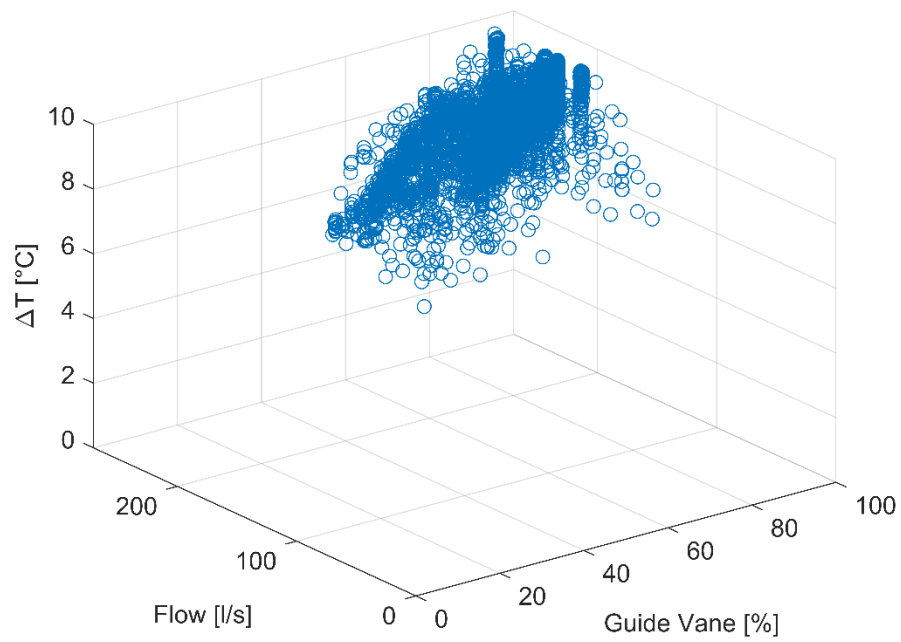


Figure 101: Refrigeration plant 10: 3-D scatter plot of operating data

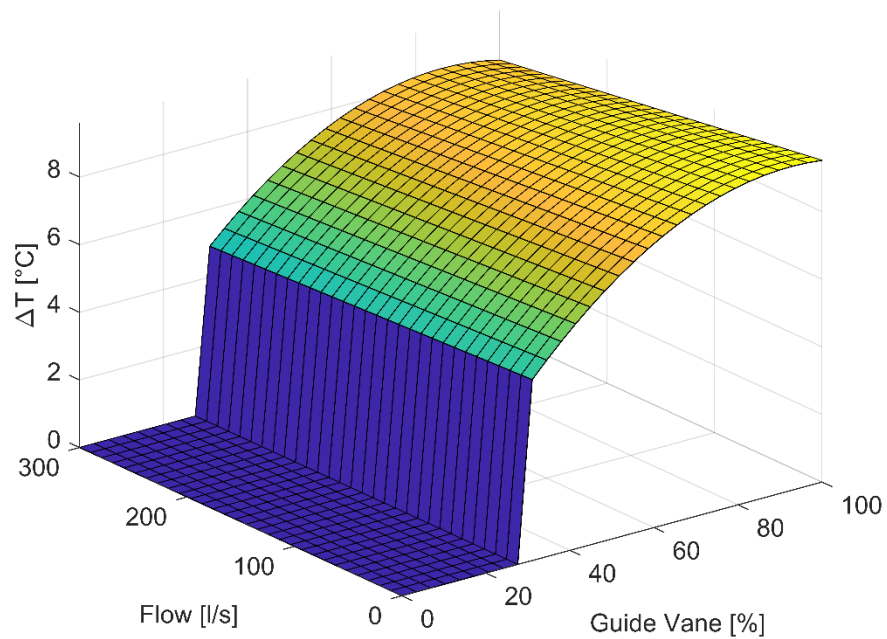


Figure 102: Refrigeration plant 10: 3-D surface curve of characteristic model (constant inlet temperature)

A.12 Refrigeration plant 11

Figure 103 compares the power consumption operating data and the characteristic equation for refrigeration plant 11. The power consumption data is visualised as a scatter plot while the characteristic equation is depicted as a line.

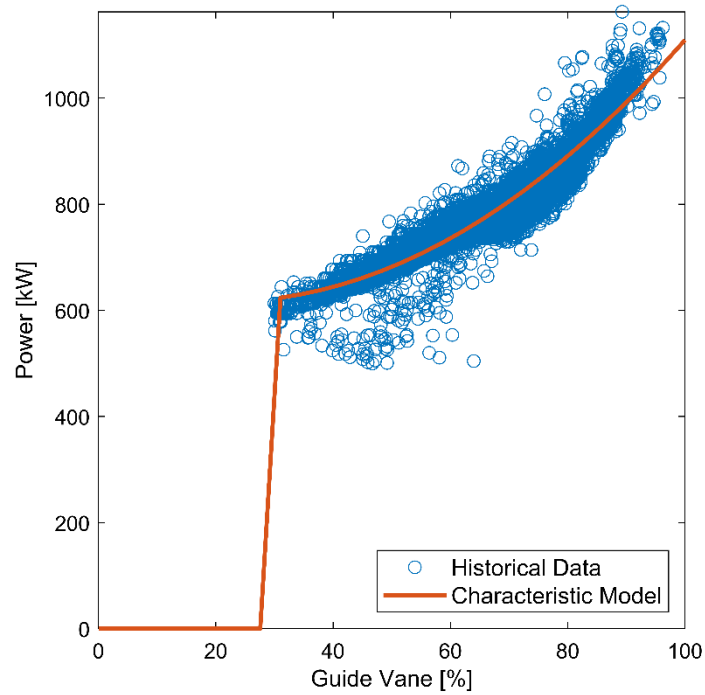


Figure 103: Refrigeration plant 11: power characteristic model

The operating data for refrigeration plant 11 is shown in Figure 104 and Figure 106. The operating data was used to obtain the constants for the characteristic equation. Figure 105 and Figure 107 show the characteristic equation for constant inlet flow and constant inlet temperature, respectively.

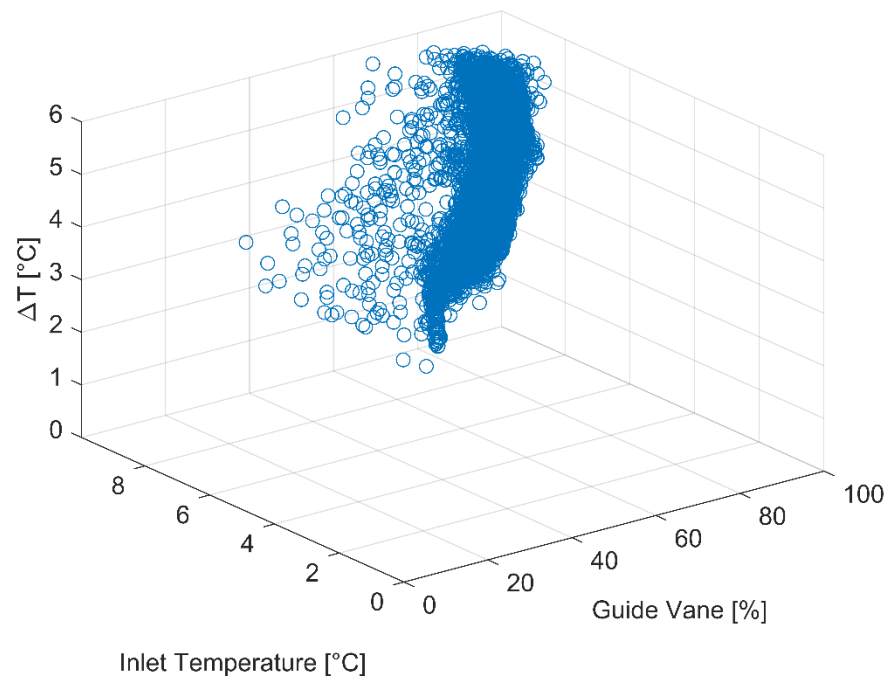


Figure 104: Refrigeration plant 11: 3-D scatter plot of operating data

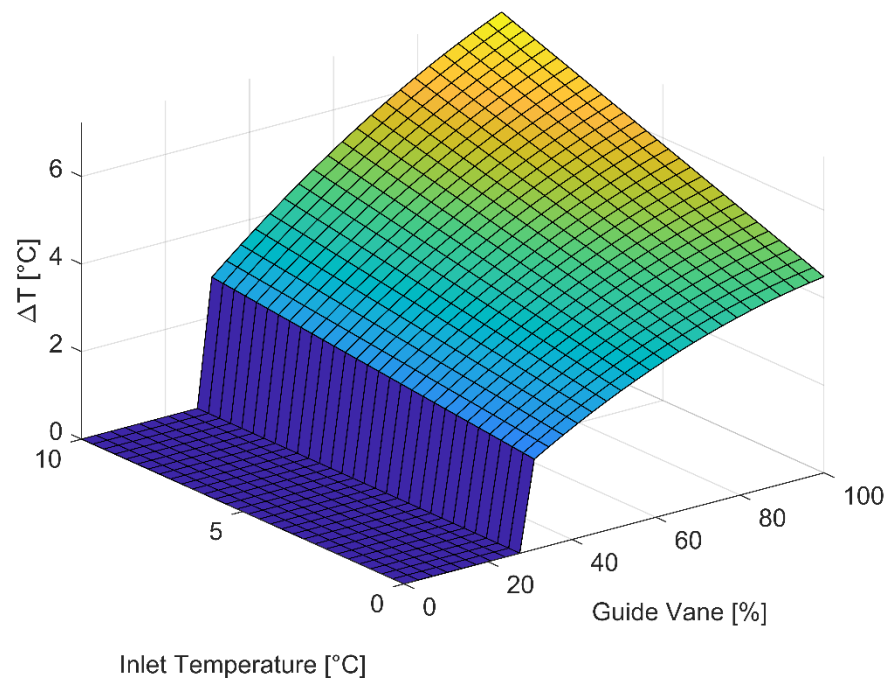


Figure 105: Refrigeration plant 11: 3-D surface curve of characteristic model (constant flow)

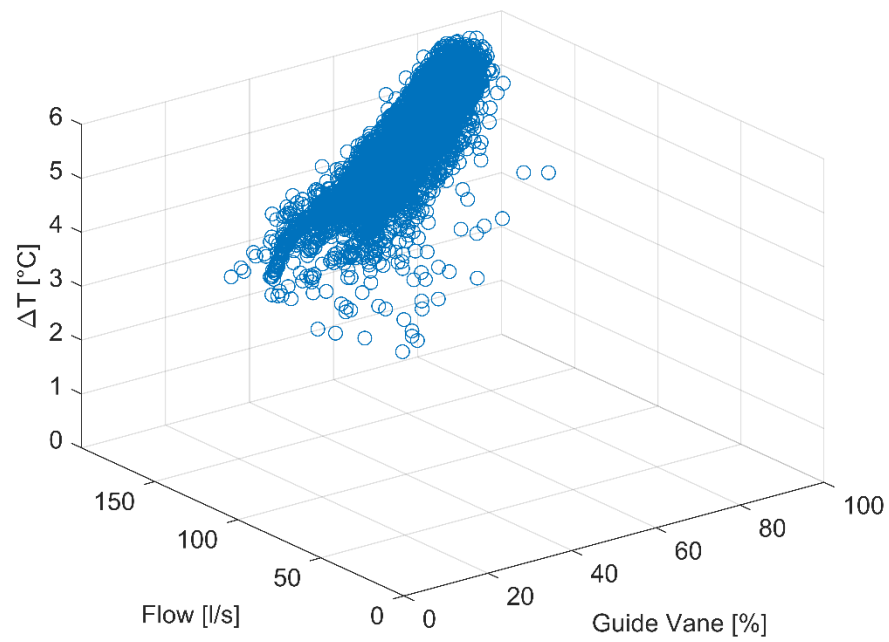


Figure 106: Refrigeration plant 11: 3-D scatter plot of operating data

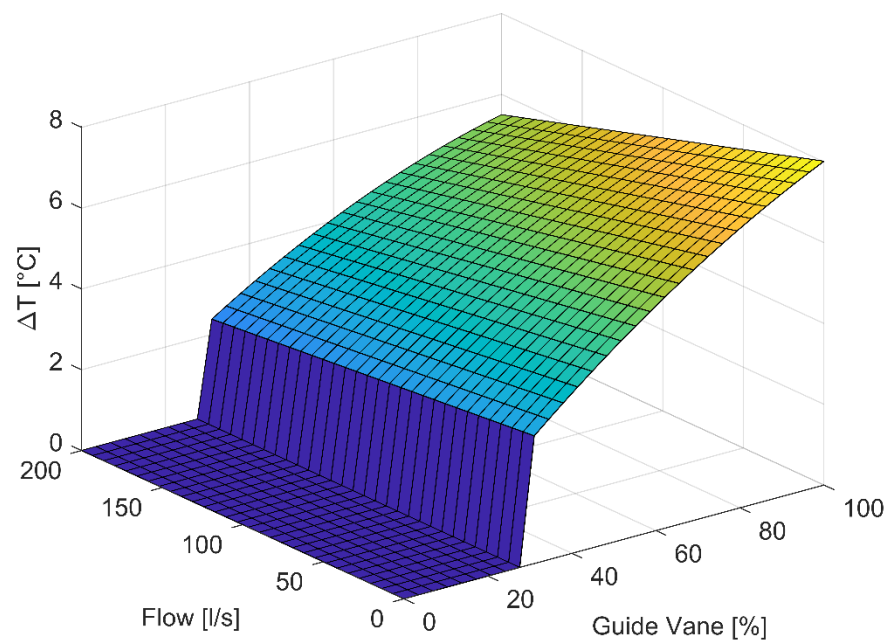


Figure 107: Refrigeration plant 11: 3-D surface curve of characteristic model (constant inlet temperature)

APPENDIX B DATA TABLES

The operating data for the refrigeration plants was filtered, as discussed in Section 2.2.3 on page 37. Table 22 provides an example of the filtered operating data for a single refrigeration plant.

Table 22: Example: filtered refrigeration plant operating data for a single refrigeration plant

ΔT [°C]	Inlet temperature [°C]	Flow [l/s]	Guide vane angle [%]
7.04	10.07	160.03	91.15
6.90	8.82	166.13	85.77
6.83	8.92	160.05	88.86
6.81	8.58	159.99	89.21
6.81	8.76	159.94	87.14
6.79	10.39	160.03	82.98
6.78	10.33	160.01	87.90
6.78	8.91	159.99	88.40
6.76	8.14	179.89	90.03
6.69	8.74	159.99	86.20
6.69	8.18	159.96	87.53
6.67	7.57	180.39	91.29
6.66	8.57	160.07	85.27
6.64	7.84	179.67	90.03
6.63	7.76	161.55	85.17
6.62	8.25	159.96	88.92
6.62	8.29	165.77	82.24
6.62	9.35	158.89	87.37
6.61	9.91	160.01	85.55
6.61	8.50	159.91	85.99
6.59	10.60	149.37	83.61
6.59	9.30	159.99	87.10
6.58	10.19	159.99	79.67
6.57	8.59	160.07	84.39
6.55	7.69	179.57	88.56
6.55	8.39	167.43	81.47
6.55	11.08	160.01	76.85
6.54	9.93	160.01	80.51
6.54	9.53	160.06	84.65

The cost savings achievable are summarised in Table 23, Table 24 and Table 25. Table 23 summarises the tariff, present power consumption and optimised power consumption profiles for the low-demand season. Table 24 summarises the tariff, present power consumption and optimised power consumption profiles for the high-demand season. Table 25 summarises the cost savings for the low- and high-demand season as well as the total cost savings achievable.

Table 23: Low-demand season power consumption comparison

Time of day [hh:mm]	Weekday tariff [R/kWh]	Present power consumption [kW]	Optimised power consumption [kW]
00:00	0.41	9 595.32	10 939.05
00:30	0.41	9 629.33	10 748.76
01:00	0.41	9 668.20	10 658.94
01:30	0.41	9 647.95	10 596.55
02:00	0.41	9 637.85	10 349.01
02:30	0.41	9 641.48	10 367.92
03:00	0.41	9 615.64	10 385.37
03:30	0.41	9 634.76	10 331.74
04:00	0.41	9 598.47	10 292.73
04:30	0.41	9 556.33	10 107.98
05:00	0.41	9 550.60	10 194.77
05:30	0.41	9 502.67	11 728.55
06:00	0.41	9 527.97	11 897.56
06:30	0.65	9 453.17	11 648.80
07:00	0.65	9 365.65	11 800.90
07:30	0.94	7 763.76	733.89
08:00	0.94	7 076.24	2 602.44
08:30	0.94	7 221.42	6 477.32
09:00	0.94	7 777.46	7 138.99
09:30	0.94	8 712.34	7 231.56
10:00	0.94	9 220.66	5 548.32
10:30	0.65	9 330.50	12 249.26
11:00	0.65	9 389.81	9 844.69
11:30	0.65	9 409.57	9 472.54
12:00	0.65	9 427.79	9 612.88
12:30	0.65	9 557.33	9 748.58
13:00	0.65	9 555.25	10 057.47
13:30	0.65	9 574.19	10 220.11
14:00	0.65	9 613.37	10 390.53
14:30	0.65	9 652.81	10 572.27
15:00	0.65	9 653.11	10 763.86
15:30	0.65	9 631.38	10 825.71
16:00	0.65	9 586.27	10 902.26
16:30	0.65	9 564.34	11 144.81
17:00	0.65	9 549.95	12 567.62
17:30	0.65	9 564.35	12 930.92
18:00	0.65	9 483.23	13 014.74
18:30	0.94	7 284.89	0.00
19:00	0.94	6 234.59	0.00
19:30	0.94	6 234.17	0.00
20:00	0.94	7 497.61	2 741.09
20:30	0.65	8 912.70	11 052.36
21:00	0.65	9 415.21	10 622.35
21:30	0.65	9 543.90	10 241.49
22:00	0.65	9 566.43	9 111.38
22:30	0.41	9 563.20	11 520.62
23:00	0.41	9 582.70	10 967.05
23:30	0.41	9 613.01	10 757.48

Table 24: High-demand season power consumption comparison

Time of day [hh:mm]	Weekday tariff [R/kWh]	Present power consumption [kW]	Optimised power consumption [kW]
00:00	0.47	6 897.02	9 796.22
00:30	0.47	6 906.51	8 384.90
01:00	0.47	6 889.35	8 368.81
01:30	0.47	6 823.54	8 420.64
02:00	0.47	6 844.58	8 252.05
02:30	0.47	6 711.13	8 363.84
03:00	0.47	6 708.11	8 030.97
03:30	0.47	6 828.89	8 271.07
04:00	0.47	6 807.24	8 934.08
04:30	0.47	6 793.27	9 658.71
05:00	0.47	6 816.29	9 887.44
05:30	0.47	6 918.66	10 015.86
06:00	0.47	6 875.99	10 072.56
06:30	2.88	5 660.32	0.00
07:00	2.88	5 028.50	0.00
07:30	2.88	4 592.68	0.00
08:00	2.88	4 404.30	0.00
08:30	2.88	4 786.71	1980.26
09:00	2.88	5 217.26	1980.27
09:30	0.87	5 684.21	8 637.74
10:00	0.87	6 213.43	7 682.44
10:30	0.87	6 292.07	7 463.34
11:00	0.87	6 160.40	7 598.27
11:30	0.87	6 065.45	7 474.05
12:00	0.87	6 104.74	7 580.84
12:30	0.87	6 142.24	7 649.09
13:00	0.87	6 199.80	7 765.62
13:30	0.87	6 155.86	7 923.33
14:00	0.87	6 177.02	8 117.96
14:30	0.87	6 227.24	8 421.94
15:00	0.87	6 485.66	8 284.57
15:30	0.87	6 700.93	8 544.68
16:00	0.87	6 862.30	8 572.60
16:30	0.87	6 943.31	9 095.74
17:00	0.87	6 989.28	10 576.94
17:30	2.88	5 951.74	0.00
18:00	2.88	5 068.99	0.00
18:30	2.88	4 857.34	0.00
19:00	2.88	5 225.17	0.00
19:30	0.87	5 980.29	8 686.72
20:00	0.87	6 482.55	8 637.39
20:30	0.87	6 529.38	8 641.90
21:00	0.87	6 697.56	8 509.11
21:30	0.87	6 797.21	8 451.10
22:00	0.87	6 918.99	8 186.76
22:30	0.47	6 958.24	8 186.76
23:00	0.47	7 041.81	9 243.34
23:30	0.47	7 051.42	7 974.36

Table 25 summarises the cost savings for the low- and high-demand season as well as the total cost savings achievable.

Table 25: Cost savings summary

Cost Savings	
High-demand season	R2 700 000
Low-demand season	R6 800 000
Total	R9 500 000