Developing Long-Term Energy and Carbon Emission Modelling for the Operational Activities of Ports: A Case Study of Fremantle Ports

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Declaration

I declare that this dissertation is the product of my own research and work. All external information and sources have been acknowledged and referenced where appropriate.

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Abstract

The port and maritime industry contributes significantly to global greenhouse gas emissions. As such, there is increasing pressure for ports to decarbonise their operations. Despite the availability of multiple port carbon inventory and emission reduction guidance documents, no published methodologies currently exist for the development of port energy consumption and carbon emission forecasting. To fill this information gap, a methodology was developed through the review and experimentation with established forecasting techniques. The 'ISCA' *Base Case Approach* was adopted as a scaffolding for model development, largely to test the usability of the approach, currently in pilot. The approach consists of a baseline scenario and an 'actual case' scenario. A combination of qualitative, quantitative - time series and quantitative - causal modelling techniques were incorporated into the methodology. Linear and non-linear regression analysis curve-fitting techniques were selected as the most appropriate time-series modelling method for long-term energy and emissions projections, with simple linear regression analysis used for causal models. The methodology was tested through its application in a case study for Fremantle Ports.

As a result of obligations from the state government to reach net-zero emissions by 2050, Fremantle Ports required the development of long-term energy consumption and carbon emission projections for its internal operations and container terminals to 2050. Using a bottom-up strategy, categorising energy consumption and greenhouse gas emissions by trade type, energy type and facility, the methodology successfully developed long-term energy and emissions projections. As per this modelling, energy consumption at Fremantle Ports is expected to increase 53% under the baseline scenario and 46.5% under the actual case scenario (Figure 1). Despite increases of energy consumption at the port, greenhouse gas emissions are expected to decrease 71% and 74% under the baseline and actual case scenarios, respectively (Figure 2). These drastic emissions reductions are predominantly the result of projected scope 2 emission factor decreases as grid renewable electricity generation capacity increases. The usability of the ISCA *Base Case Approach* for energy and emissions modelling was found to be adequate, although issues were experienced distinguishing constant and variable energy use. Additionally, it is recommended that a third scenario is incorporated into the approach.

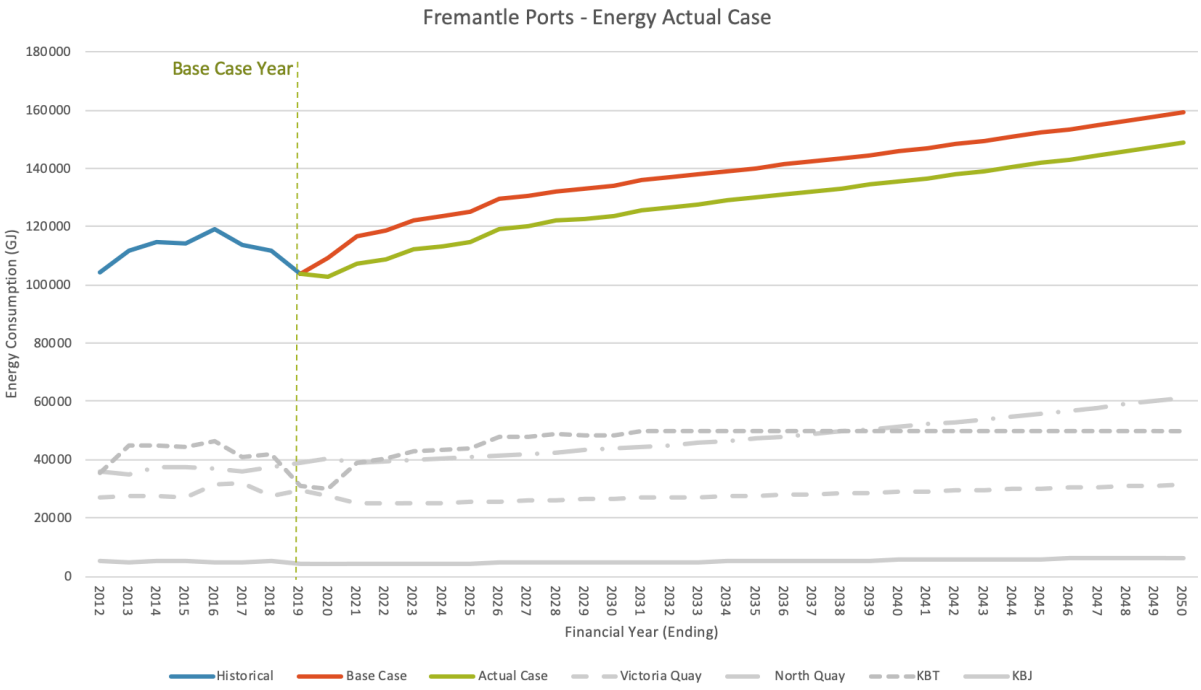

Figure 1: *Fremantle Ports' internal and container terminal energy consumption Base Case and Actual Case. Grey lines represent the contribution of different facilities within the port.*

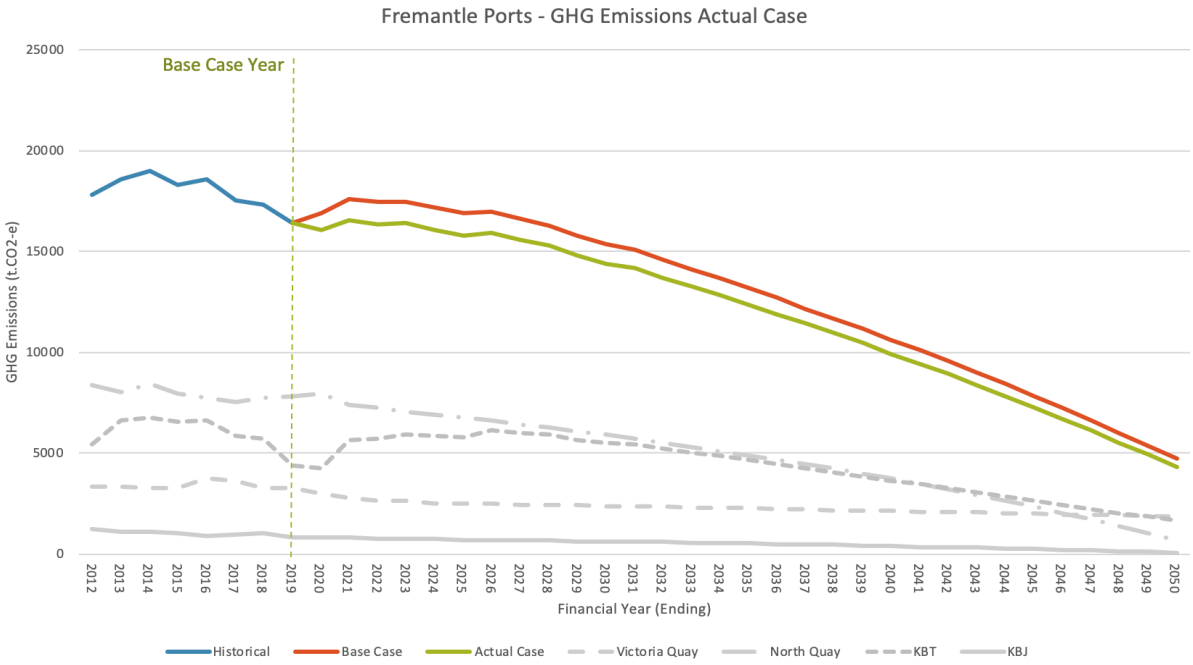

Figure 2: *Fremantle Ports' internal and container terminal GHG emissions Base Case and Actual Case. Grey lines represent the contribution of different facilities within the port.*

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Abbreviations

General

GHG	–	Greenhouse gases
FY	–	Financial year
SWIS	–	South West Interconnected System

Units

ppm	–	Parts per million
t.CO_2-e	–	Tonnes of carbon dioxide equivalent units
GJ	–	Gigajoule
kWh	–	Kilowatt hour

Organisations

IPCC	–	International Panel on Climate Change
ISCA	–	Infrastructure Sustainability Council Australia
IS	–	Infrastructure Sustainability
IAPH	–	International Association of Ports and Harbors
WPCI	–	World Ports Climate Initiative
IMO	–	International Maritime Organisation

Fremantle Ports specific

VQ	–	Victoria Quay
NQ	–	North Quay
KBT	–	Kwinana Bulk Terminal
KBJ	–	Kwinana Bulk Jetty
FP	–	Fremantle Ports

1 Introduction

The international maritime industry is currently responsible for 2.5% of global greenhouse gas emissions (IMO, 2014); roughly 1.7 times greater than the total annual emissions of Australia (Department of the Environment and Energy, 2019). Whilst initially slow to enact emission reduction targets, the tide is changing for the industry and it is increasingly acknowledging its climate change responsibilities. In 2018, the International Maritime Organisation (IMO) adopted a strategy to reduce greenhouse gas (GHG) emissions of the international shipping sector by 50% of 2008 levels by 2050 (European Union, 2019). Later that year Maersk, the world's largest shipping company, made a commitment to be carbon neutral by 2050 (Maersk, 2019). This has been followed by numerous other ports and shipping companies around the world making similar commitments (IAPH, nd).

This growing movement within the industry is putting greater pressure on ports and other maritime businesses to make emission reduction commitments. This pressure is not just from a desire to retain a positive brand image but pressure is often coming from parent organisations, including governments, that have made carbon neutrality commitments themselves, as well as from trading partners which provide attractive economic incentives for businesses to reduce their emissions (NSW Ports, 2019).

Within the port industry, there is a growing number of organisations that have either made commitments for carbon neutrality or are actively reducing their GHG emissions. Ports of Auckland have set a target for decarbonisation by 2040 (Ports of Auckland, 2018); NSW Ports have not made public a decarbonisation plan, however, have begun reducing their GHG emissions, with a 20% reduction between 2015 and 2019 (NSW Ports, 2019), and; Port of Brisbane has set a 24% emissions reduction target by 2024/25 (Port of Brisbane, 2019). Outside of the ANZ region, Europe's largest port, the Port of Rotterdam, has committed to carbon neutrality by 2050 (Port of Rotterdam, 2020). The Port of Los Angeles and Port of Long Beach, the first and second largest ports in the USA, have set a target of an 80% emission reduction of 1990 levels by 2050 (Vock, 2019; Pacific Ports Clean Air Collaborative, 2012).

Despite a growing list of ports having begun a transition towards decarbonisation, the industry is still largely lacking the required quantity of data to perform comprehensive asset-to-asset and network-to-network comparisons (ISCA, 2017). As such, facilities are required to develop their own energy and carbon emission modelling, often in-house. Multiple documents and methodologies are available for the development of carbon inventories for infrastructure entities and ports. Notable examples include the *Carbon Footprinting for Ports: Guidance Document* (WPCI, 2010), the IAPH *Toolbox for Greenhouse Gases* (IAPH, nd) and the *Port Emissions Toolbox* (IMO & IAPH, 2018). In regard to the development of energy consumption and GHG emission forecasting, however, documentation is severely lacking. This is the case not just for the operations of ports but also for the operations of infrastructure assets more broadly. As such, there is a need in industry for the development of a long-term energy consumption and GHG emission modelling methodology and use-case. For this dissertation project, such a methodology has been developed and then tested using Fremantle Ports' internal operations as a use-case.

1.1 The Port of Fremantle

In 2019 the Western Australian government set a target of net carbon neutrality for all state-owned operations by 2050 (Government of Western Australia, 2019).
As a wholly owned enterprise of the Western Australian Government, Fremantle Ports[1] is obliged to mirror the state government's target, noting in its *Environmental Management Plan 2020-21* an objective to reduce their overall carbon emissions. As part of this objective, Fremantle Ports requires the development of Base-Case energy and carbon emissions modelling for their operational assets to 2050 to assist with the identification of potential carbon emission reductions, determine the risks and opportunities associated with such reductions, and ultimately develop a path towards decarbonisation in line with the State's commitment.

[1] The term Fremantle Ports and the Port of Fremantle is used to describe the Port Authority's operations in Fremantle and in Kwinana, approximately 20 km south of Fremantle, Western Australia,

1.2 Objectives and research questions

The key objective of this project is to develop a simple yet robust long-term energy consumption and greenhouse gas emission projection methodology and use-case. The use-case will focus on the on-going operational activities of ports, but will also be largely be applicable to the operational activities of non-port related infrastructure and medium sized entities. The methodology will be tested through its utilisation in a case study for Fremantle Ports' internal operations.

To keep consistency with sustainable infrastructure ratings in the Australia/New Zealand region, the energy and GHG emissions modelling will follow the guideline of the ISCA (Infrastructure Sustainability Council of Australia) *IS Operations Technical Manual* and associated *Base Case Approach* (ISCA, 2017). This will enable infrastructure projects in Australia and New Zealand to utilise the methodology developed by this dissertation and be eligible for the associated IS Rating's Ene (Energy and Carbon) credits. As the IS operations rating has only been awarded to a small number of assets, and is considered to be still in pilot, this dissertation project also offers the opportunity to provide an example and analysis of the usability of ISCA's *Base Case Approach*.

As such the ISCA *Base Case Approach* (ISCA, 2017) will also be tested for its usability in developing long-term energy and emissions projections for port applications. This will be conducted by incorporating the approach in the modelling methodology.

Primary research question:

- *What is the best approach for developing long term energy consumption and greenhouse gas emission projections for Australian ports?*

Secondary research questions:

- *Why is energy consumption and greenhouse gas emission projections crucial for ports and infrastructure?*
- *What are the long-term South West Interconnected System (SWIS) electricity network scope 2 and 3 emission factors likely to be as renewable energy penetration increases?*
- *Does the ISCA Base Case Approach provide adequate usability and function for the development of operational energy and GHG emission base case and actual case projections?*
- *Is it possible for a port's internal operational GHG emissions to reach net-carbon neutrality?*

1.3 Rationale of the study

Physical infrastructure assets for transport, energy, water, waste and communications directly contribute to 15% of Australia's total greenhouse gas emissions, influencing an additional 55% of the country's emissions via the activities they facilitate (ISCA, Climate Works, ASBEC, 2020). As part of Australia's Paris Agreement commitment to reduce GHG emissions by 26-28% below 2005 levels by 2030 (UNFCC, 2015), the nation's infrastructure industries hold a direct responsibility for the reduction of the nation's greenhouse gas emissions.

To enable such reductions, infrastructure assets require an understanding of their 'business-as-usual' and 'actual' energy consumption and GHG emissions into the future. At present, however, detailed operating data is largely not available to directly compare infrastructural assets' energy and GHG emissions data (ISCA, 2017). As such, to allow future greenhouse gas emission reduction targets to be made, infrastructure assets and associated entities are required to develop their own energy consumption and GHG emission projections.

Australia's industry standard sustainable infrastructure council 'ISCA' (Infrastructure Sustainability Council of Australia) provides documentation outlining a process with which to develop energy and GHG emission projections; however, the documentation falls short of providing any technical methodologies to assist in its development. Additionally, publicly available literature is not readily available to guide the development of long-term energy and GHG emission projections for the operational activities of infrastructural assets, including ports.

The maritime industry is responsible for transporting over 90% of the world's trade (UN-Business Action Hub, 2020) and contributes to 2.5-3.5% of global GHG emissions. Whilst the majority of these emissions are released by ships directly, the world's ports provide crucial infrastructure for the industry and hold large influence towards improved sustainability and maritime GHG emission reductions.

This report aims to establish the methodology required to develop sound energy consumption and GHG emission projections for port infrastructure, in association with the ISCA Base Case Approach, and provide a use-case in the form of a case-study with Fremantle Ports' internal operations.

1.4 The necessity for long-term energy and GHG emission projections

In 2013, the European Union developed a strategy to reduce the amount of greenhouse gas emissions released by the union's shipping sector (European Union, 2019). The strategy consists of 3 key steps:

- **Monitoring, reporting and verification** of CO_2 emissions from large ships using EU ports
- **Greenhouse gas reduction targets** for the maritime transport sector
- **Further measures** including market-based measures in the medium-to-long term

The first step of the EU's carbon emission reduction strategy highlights the importance of carbon emission knowledge gathering in the process of effective carbon management. To best position organisations to develop carbon management strategies and, ultimately, set targets for carbon emission reductions it is essential that energy and emission inventories are developed and projections generated.

Whilst energy and carbon inventories are essential for the development of carbon neutrality strategies, they only provide organisations with an outlook of the past and present, leaving future energy consumption and GHG emissions unknown. To be able to begin carbon management and set realistic energy and emission reduction targets, an organisation must have at least a basic understanding of their future energy consumption and carbon emissions. Such projections help determine expected emissions growth rates, the quantity of emissions that will need to be abated in the future and, ultimately, what degree of abatement is practically and economically feasible over a given timeframe. As such, long-term energy and GHG emission projections provide a vital tool for making realistic and feasible, yet still ambitious, emission reduction targets. Additionally, robust projections can reduce the risk of embarrassing set-backs and readjustments of targets later down the line.

The partial or entire reduction of an organisation's greenhouse gas emissions is often a difficult task and can take years to decades to materialise, depending on the size and complexity of an organisation and its dependency on emission-intensive processes and energy sources. In the context of the port industry, an energy and carbon emission reduction strategy might involve overhauling diesel equipment, replacement of fossil fuel consuming vehicles, vessels and equipment with their electric or biofuel consuming counterparts and installing renewable energy infrastructure. Elements of such projects may take several years to implement,

where-as elements such as the large-scale use of bio-diesel and electric vessels may not be economically feasible or commercially available for much longer (APAC Biofuel Consultants, 2017; Gear, 2019). When considering the long-term nature of many of these projects, the necessity for long-term energy and emissions projections becomes clear. Projections can provide an effective management and reporting tool for organisations, allowing them to develop carbon management strategies and compare observed and expected energy and emissions reductions against modelled business-as-usual scenarios. This can empower an organisation's management to focus on key areas of concern and develop strategies to lower their GHG emissions.

1.5 Limitations

As with all research projects, there will be some limitations associated to the research and development of this study. These limitations are identified below.

Statistical limitations

There exists a large range of techniques for determining correlations between data sets and developing forecasts and projections. The statistical methods to undertake these tasks vary greatly; from the simpler trend and regression analyses methods to the much more complex machine learning methods utilising neural networks and artificial intelligence. Whilst all effort will be made to equally understand and review all possible statistical modelling methods, the more complex modelling techniques utilising computer simulations, artificial intelligence and Support Vector Machines often require access to niche software and in some cases require computer programming abilities, tools and expertise which may not be readily available for this research. However; it is the opinion of the author that any statistical methods which require such niche statistical tools and expertise would likely be less favourable a method for infrastructure entities and medium size businesses, especially when adequate and more simple techniques are available.

Focus on port infrastructure

The methodology to be developed by this report will be focused primarily on a port infrastructure's internal operations. As such, there may become a bias towards modelling methods which favour this kind of infrastructure. Whilst this may pose some barriers to the methodology's wider integration with other infrastructure assets,

entities and medium sized businesses, it is expected that any barriers will only be slight and that the general methodology will still remain applicable.

Limitations of time and data availability

The thoroughness and completeness of the case study that will be developed with Fremantle Ports will ultimately be determined by the availability of Fremantle Ports' operational data. Limitations of the availability of trade and business operational data, as well as the time span and frequency of historical energy data, may dampen the robustness and thoroughness of modelling. Additionally, the study will be constrained by time availability and the short study period of this dissertation. Whilst all effort will be made to ensure this study is as comprehensive as possible, time constraints must be acknowledged.

1.6 Structure of the dissertation

This dissertation contains five chapters.

The first chapter contains the background of the project and relevant dissertation information, including general objectives and research questions. The requirement for long-term energy and GHG emission projections is introduced as a stepping stone towards setting carbon emission reduction targets.

Chapter two contains a comprehensive literature review of port energy and carbon emission management documentation and existing energy projection methodologies. Statistical modelling techniques is researched and analysed, providing the basis of the development of this report's energy consumption and GHG emission projection methodology.

In Chapter three, the development of long-term energy consumption and GHG emission projections is developed for Fremantle Ports' internal operations. This provides a case study for the report, and aids in testing and demonstrating the methodology. This chapter is broken down into sections based on the ISCA Base Case Approach; Base Case Proposal development; Base Case model development; and Actual Case model development, concluding with the findings of the case study.

Chapter four provides a comprehensive discussion of the methodology developed by this project and utilised for the case study. An analysis of the usability and function of

the ISCA Base Case Approach is included, as well as a brief analysis of the opportunities for ports to reach net carbon neutrality.

The dissertation is concluded in a fifth and final chapter, offering final recommendations and opportunities for future research.

2 Literature Review and Methodology

A key objective of the literature review is to identify published methodologies to guide energy consumption and carbon emission modelling and inform the development of long-term projections at the multi-decadal level for an individual organisation or infrastructural facility. However, after a thorough investigation, it became apparent that there is very little literature and documentation publicly available.

The majority of available literature on energy and GHG emission modelling, forecasting and projecting focuses predominantly on large scale scopes at the level of entire nations, or industries at the regional and national level (Abdullah & Pauzi, 2015; Pao & Tsai, 2012). Additionally, there is a significant bias in the literature towards short- and medium-term forecasting, and where longer-term projections are developed, they are usually restricted to forecasts of just several years.

Although not directly applicable to the scope of this dissertation, the literature was still able to offer notable insight into possible approaches and techniques for the development of long-term energy consumption and GHG emission projections

2.1 Port-specific energy and carbon emission management

The port industry provides the vital infrastructure to facilitate the transfer of maritime trade with terrestrial trade infrastructure such as road and rail transportation. With 90% of the worlds trade passing through ports, port infrastructure is a crucial element of the global economy (UN-Business Action Hub, 2020). Whilst data specifically referring to the total GHG emissions of global port infrastructure is not readily available, the maritime industry as a whole contributes approximately 2.5% of global greenhouse gas emissions, equivalent to 1.7 times the total carbon emissions of Australia (IMO, 2014; Department of the Environment and Energy, 2019). Despite contributing significantly to global greenhouse gas emissions, maritime trade is currently the most emissions-efficient mode of trade transport, with a slightly lower emissions intensity than rail and significantly lower than truck and air freighting (Figure 3) (IPCC, 2014). The lower emissions-intensity and price competitiveness of shipping means its use as a primary mode of global trade transport will only continue to expand well into the future (UNCTAD, 2019) and with it the role of sustainability

initiatives and carbon emission management within the port industry.

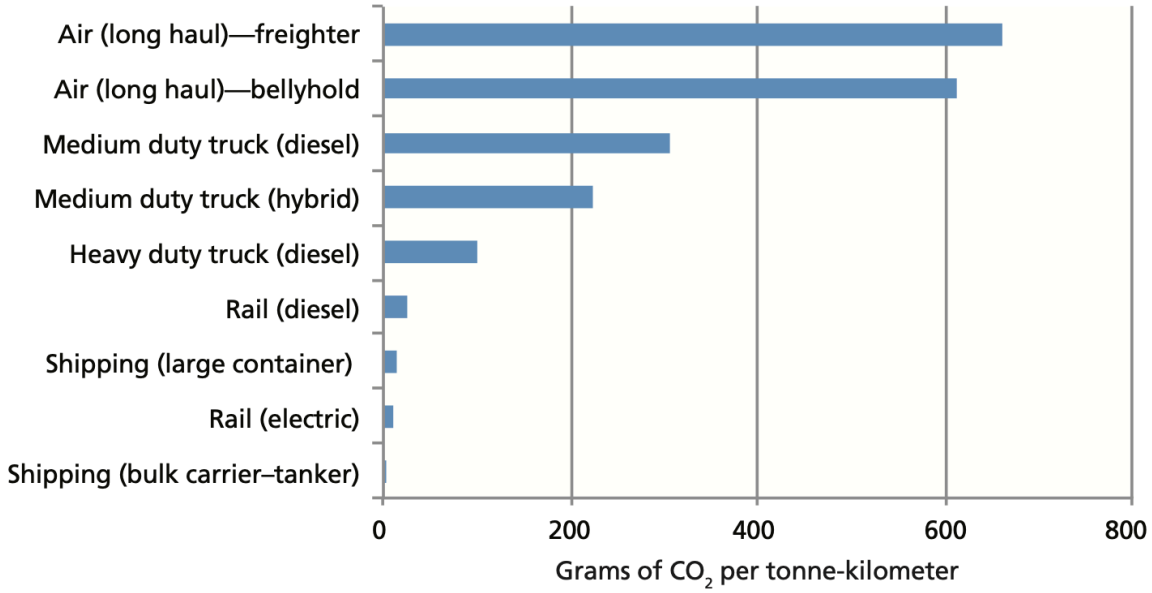

Figure 3: *Average carbon intensity of freight transport modes* ***(IPCC, 2014).***

There has been a growing movement towards climate change awareness and energy and carbon management within the global port industry and, as such, an increasing number of ports are developing energy and emission inventories and committing to emission reduction targets. The growing interest and pressure for climate change mitigation and sustainability initiatives within the industry has led to the development of several organisations to offer guidance and provide a place for collaboration and information sharing.

The leading organisations within this space are the International Association of Ports and Harbours (IAPH) and associated World Ports Climate Initiative (WPCI) group. WPCI began in 2008 under an initiative of IAPH to provide a mechanism for ports to better manage climate change mitigation requirements. After organising 55 ports from around the world to sign the C40 World Ports Climate Declaration, WPCI, in conjunction with IAPH, has developed the *Air quality and Greenhouse Gas Toolbox* to provide ports with the information they need to best address air quality and climate change issues (IAPH, nd). The toolbox includes recommendations for business policy changes and provides a business case for early climate change mitigation action for ports. Additionally, the toolbox includes a recommended six step process for port carbon management:

1. Develop Current Inventory
2. Establish Emissions Baseline and Forecast
3. Set Goals
4. Develop Strategies
5. Monitor Progress
6. Adaptation Planning

Whilst this provides a useful strategy for port carbon management, the toolbox does not go into significant detail regarding each step and leaves much for interpretation.

In regard to the development of carbon emission inventories for ports, two comprehensive guidance documents are available; *Carbon Footprinting for Ports – Guidance Document* by WPCI and IAPH (WPCI, 2010), and the more recent, updated version; *Port Emissions Toolkit* by the International Maritime Organization (IMO) and IAPH (IMO & IAPH, 2018). These documents detail the developmental process for greenhouse gas emission inventories and provide a list of available resources and information sources. The documents present three common approaches for developing a port carbon emissions inventory:

- Activity-based: Utilising equipment specific activity data such as actual energy consumption, engine ratings and equipment or vessel operation hours. Energy consumption figures are converted into greenhouse gas emissions values through the use of emissions factors.
- Surrogate-based: This approach uses use-cases to approximate an entity's emissions source data, activity data, energy consumption data, or emissions per activity data.
- Hybrid: This method utilises different aspects of both of the above methods. Hybrid methodologies commonly use the activity-based approach for the energy use of port infrastructure and equipment, and the surrogate-based approach for visiting ships; of which energy consumption data can be harder to quantify more precisely.
- visiting ships; of which energy consumption data can be harder to quantify more precisely.

Depending on the complexity required for the inventory, a hybrid approach appears to be the most common. A literature review of available port carbon emission inventories found five out of the six inventories analysed utilised a hybrid approach. A case study of the Port of Chennai's carbon inventory found the port employed an activity-based approach for terrestrial port infrastructure and port-operated vessels and equipment, however, used a surrogate-based approach for visiting commercial vessels and non-port operated on-road vehicles (Misra, Panchabikesan, Gowrishankar, Ayyasamy, & Ramalingam, 2017). This division of inventory methodologies was also used by container terminal ports in Mumbai (Chowhan,

Hiremath, & Asolekar, 2012) as well as the Port of Vancouver (Port of Vancouver, 2015), Port of Brisbane (PAE Holmes, 2010) and the Port of Los Angeles (Starcrest Consulting Group, 2019). The outlier of this review was the Port Authority of New York and New Jersey's carbon inventory. It used a surrogate-based approach with an external surrogate to estimate emissions data for infrastructural electricity data, employing factors such as passenger counts and trade volumes to guide emissions estimates (Southern Research Institute, 2010). This method was chosen due to the high complexity of the port, with five electricity providers spanning two states.

The scope of carbon management strategies changes on a port-by-port basis, although scope 1 and 2 emissions sources are always included (IMO & IAPH, 2018). The largest point of variance is for scope 3 emissions, with main differences regarding the inclusion of:

- Port tenants' and port contractors' emissions
- Visiting ship's emissions
- Trucks and rail transport emissions to and from the port

The extent to which these scope 3 emissions are included is diverse, with some ports such as the Port of Rotterdam limiting its scope 3 emissions to activities it has direct operational control over (WPCI, 2010). On the contrary, some ports, such as the Port of Vancouver (Port of Vancouver, 2015) and the Port of Los Angeles, include scope 3 emissions for all cargo related emissions sources, such as; visiting ship movements and trade truck/rail movements at a geographical boundary beyond their administrative control (WPCI, 2010). It is to be noted, however, that according to the *Carbon Footprinting for Ports – Guidance Document* by WPCI and IAPH (WPCI, 2010) non-operational carbon emissions associated to a source's life cycle analysis are usually not included in a port's carbon management scope.

In regards to establishing emissions baselines and projections, very little documentation is readily available. The aforementioned toolbox by IAPH highlights the importance of mid- and long-term GHG emission baselining and forecasting, however does not provide any methodology to develop such forecasting, beyond stating to "use the latest published cargo forecasts" (IAPH, nd). The IMO and IAPH's *Port Emissions Toolkit* provides a slightly more detailed section on Port emissions forecasting, including a very short case study on the ports of Los Angeles Long Beach (IMO & IAPH, 2018). The importance of setting a base-line year to provide a

basis for forecasting is mentioned, as well as the necessity for the development of several scenarios, including high- and low-emission scenarios, and scenarios with differing levels of trade growth. Whilst the information provides a decent overview of emissions forecasting considerations and industry best-practise, it does not provide any detailed methodology to guide the technical development of emission projection modelling. In the requirement for long-term emissions projections, the port industry currently does not have any published and publicly available methodologies.

2.2 Energy forecasting and projection methodologies

Because of the lack of guidance documentation available for the development of energy and carbon emission projections within the port industry, a review of methodologies was conducted more broadly, beyond the maritime sector. This section summarises the literature review conducted for the research of energy consumption and GHG emissions model development methodologies.

Energy consumption data can be reliably used to estimate greenhouse gas emissions using energy content and emission factor calculation methods, such as those developed by the Australian Government's National Greenhouse and Energy Reporting scheme (Australian Government, 2008). As such, for operations where the majority of emissions are the result of energy consumption, emission values can be easily calculated from energy consumption models. Similar strategies of GHG emission forecasting have been used successfully in the past, including a study of shipping emissions in the Chongqing municipality of China (Wei & Zhao, 2010) as well as for a study calculating and forecasting the GHG emissions of diesel generators (Jakhrani, Othman, Rigit, Samo, & Kamboh, 2012).

The technical methodologies used to develop energy and emissions projections and forecasts have evolved significantly over the years. Methods are usually categorised as either qualitative or quantitative (Singh, Ibraheem, Khatoon, & Muazzam, 2013), with quantitative methods further classified as either time series forecasts or explanatory forecasts (Makridakis, Wheelwright, & Hyndman, 1998).

2.2.1 Qualitative forecasting

Qualitative forecasting uses methods based on opinion, capitalising on information provided by human expertise. Qualitative forecasting is usually used when quantitative data is incomplete or inexistent yet expert knowledge is readily available (Makridakis, Wheelwright, & Hyndman, 1998). Qualitative forecasting techniques can involve conducting surveys (Suganthia & Samuel, 2012), face-to-face meetings, as well as utilising the Delphi, or Estimate-Talk-Estimate, methodology amongst a panel/group of experts (Kauko & Palmroos, 2014). Additionally, these techniques are often used as a means of 'triangulating' or validating quantitative models and have been shown to improve the accuracy of quantitative energy projections when used in conjunction (Chen & Kung, 1984).

2.2.2 Quantitative – Time series forecasting

According to *Forecasting Methods and Applications: Third Edition* (Makridakis, Wheelwright, & Hyndman, 1998), quantitative forecasting can be applied when three conditions exist:

- Historical information is available
- This information can be quantified as numerical data
- Aspects of the past pattern will continue into the future

Quantitative methods utilise numerical data to discover past trends, using these trends to develop forecasts and projections. Time series forecasting is predominantly used when an explanatory (predictor) variable cannot be found, with statistical techniques utilised to extrapolate past trends into the future. (Makridakis, Wheelwright, & Hyndman, 1998).

There exists several common conventional (traditional) time-series forecasting techniques. The most common techniques include autoregression models such as ARMA and ARIMA, and parametric trend analysis or curve fitting models.

Autoregression models use a statistical technique to regress variables on their past values (Singh, Ibraheem, Khatoon, & Muazzam, 2013). Autoregressive-moving-average (ARMA) models and Autoregressive Integrated Moving Average (ARIMA) models follow the same principal, however differ in that ARMA models require a stationary data set, whereas ARIMA models can be used on data with a moving mean (Daut, et al., 2017). ARMA and ARIMA models can be very effective at

producing short- and medium-term forecasts and can handle seasonality and cyclical patterns very well. For this reason they are widely applied to electric load profile and weekly or annual electricity demand forecasting (Singh, Ibraheem, Khatoon, & Muazzam, 2013; Ghalehkhondabi, Ardjmand, Weckman, & Young, 2016).

Parametric trend analysis, also known as curve fitting, uses linear and non-linear regression to match mathematical equations to observed data, using these equations to extrapolate forward (Abdullah & Pauzi, 2015). Statistical analysis between historical data and modelled data can provide p and R^2 values to best determine the most statistically significant equation. This method can also utilise qualitative expertise to best determine the most appropriate equation, based on knowledge of future developments (Ghods & Kalantar, 2008). Within the literature, trend analysis methods were used by Kone and Buke (2010) to develop 20-year projections of 25 countries' carbon dioxide emissions. Their study compared this method to more complex CO_2 emissions projections developed by the US Department of Energy and found their projections fit within an acceptable range. Whilst not as commonly used as autoregression models, this forecasting technique can provide an effective qualitative/quantitative hybrid model for developing long-term projections and forecasts. It also has the advantage of being relatively simple to conduct and does not require large quantities of historical data or complex parameters (Kone & Buke, 2010).

2.2.3 Quantitative – Explanatory forecasting

Explanatory forecasting methods are used when the values of a dependent variable can be explained by one or more independent variables. If such relationships are discovered, changes in the independent (or predictor) variable(s) will proportionately affect the output of the dependent (or response) variable to a predictable degree (Makridakis, Wheelwright, & Hyndman, 1998). Explanatory forecasting can provide very robust results when a strong explanatory relationship exists and reliable forecasts of explanatory data are available. There are two main conventional methodologies for developing explanatory models; simple linear regression and multiple linear regression. Other, more complex methods using artificial intelligence and machine learning will be explained in section 2.2.4 below.

Simple linear regression analysis is a statistical method of predicting a single y value based off a single x value. It determines a relationship between two variables in the form of a linear equation:

$$y = a + bx + e$$

where *a* is the y-intercept, *b* denotes the slope of the line, and *e* is amount of error between the observed and expected values.

Multiple linear regression models follow a similar process as simple linear regression models, however, differs in that it incorporates multiple independent/predictor variables. Multiple linear regression models can be more complex than those using simple linear regression, however, can provide more robust and powerful forecasting when more than one factor influences the response variable (Makridakis, Wheelwright, & Hyndman, 1998). Multiple linear regression follows the form:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_k x_k + e$$

where *a* is the y-intercept, *b* denotes the slope of the line, and *e* is amount of error between the observed and expected values.

For both techniques, the ordinary least squares method is used to calculate coefficients to best fit the equation to observed data (Makridakis, Wheelwright, & Hyndman, 1998). By assessing the quantity of error between the observed and expected data, R^2 and p values can be analysed and the statistical fitness of the model determined.

Simple and multiple linear regression analyses have been widely used for forecasting energy consumption and GHG emissions (Suganthia & Samuel, 2012; Daut, et al., 2017; Ghalehkhondabi, Ardjmand, Weckman, & Young, 2016; Abdullah & Pauzi, 2015). Examples include using weather, price, and consumer income to predict electricity consumption in the US (Harris & Lon-Mu, 1993); using per-capita consumption rates and population to predict electricity consumption in Turkey (Tunc, Camdali, & Parmaksizoglu, 2006) and determining a relationship between the number of customers, the price of electricity and the number of tourists and electricity consumption in Northern Cypress (Egelioglu, Mohamad, & Guven, 2001).

2.2.4 Artificial intelligence modelling techniques

A recent review of electrical energy consumption forecasting techniques (Daut, et al., 2017) found artificial intelligence models have, in recent years, become the most

widely used energy forecasting methods. This conclusion was similarly reached by a 2015 analysis of GHG emission forecasting methodologies (Abdullah & Pauzi, 2015). Complex and advanced computer learning methods are used to quantify past trends and develop explanatory modelling. The most common artificial intelligence techniques use artificial neural networks (ANN), and support vector machines (SVM).

These methods have grown in popularity largely due to their powerful ability to solve and model nonlinear problems and data sets (Daut, et al., 2017). One of the downsides is their requirement for large quantities of input 'training' data, however the development of SVMs has provided improvements in this space. Developing AI-based modelling can be time consuming and typically requires a higher level of expertise and greater computer resources than those required by traditional quantitative methods (Damborg, 1990). AI techniques have been found to be very accurate for developing energy demand forecasts with examples of its use including; using weather variables like temperature, humidity, wind speed, brightness of the sun, global radiation, precipitation and vapor pressure to predict monthly energy consumption (Islam, Al-Alawi, & Ellithy, 1995) and using temperature, hour, day, input load and output load to develop load predictions (González & Zamarreño, 2005). Computer learning methods have also been used to develop accurate GHG emission forecasts by (Radojević, Pocajt, Popović, Perić-Grujić, & Ristić, 2013). A study by Ionescu & Candau (2007), however, found that by developing linear regression and AI models side-by-side that satisfactory predictions could be developed by more simple linear regression models when relationships were linear.

2.2.5 Error Analysis

Error analysis is an important tool to accompany energy and emissions model development. By calculating and comparing each model's errors (the difference between observed and forecast values), an idea of the model's accuracy can be materialised. This can help in ensuring the best model is chosen for the data. An effective method for determining a model's error is by calculating its mean absolute error (MAE) and its mean absolute percentage error (MAPE). The difference between MAE and MAPE values is that MAE presents the mean error in terms of the actual units of the model, where-as MAPE presents the mean error as a percentage (Makridakis, Wheelwright, & Hyndman, 1998).

MAE is calculated in the form:

$$MAE = |Y_t - F_t|$$

MAPE is calculated in the form:

$$MAPE = \left|\frac{Y_t - F_t}{Y_t}\right|$$

Where Y is the observed value, F is the forecast value and t represents the time period.

2.3 GHG emission calculation methodologies

In order for the calculation of greenhouse gas emissions, the first step involves the development of long-term energy consumption projections as described above. The second step involves the utilisation of appropriate greenhouse gas emission factors to convert projected energy consumption values to carbon emission values. This follows the process of GHG emission estimating that is widely used in the development of carbon emission inventories (IMO & IAPH, 2018). The third step projects any GHG emissions included in the scope that are not associated with the entity's energy consumption, and can be projected independently using one of the forecasting techniques explained in the previous section. A version of this process was successfully demonstrated by Say and Yucel (2006) to project GHG emissions in Turkey, using energy consumption figures and emission factors provided by the IPCC, and also by a 2010 study using energy consumption forecasts to estimate the future GHG emissions of shipping in Wanzhou, China (Wei & Zhao, 2010).
Energy based carbon emissions calculations typically follow the following form:

$$Emissions = \sum_{i=1}^{n} (Energy\ consumption)_i \times EF$$

where n is the number of energy consumption sources and EF is the emission factor for that energy type.

Because the precise value of the emission factor has such a strong influence on carbon emission calculations, it is crucial that these values originate from reliable sources. The UN's IPCC has developed a comprehensive set of guidelines including a database of emission factors, as well as emission factors for non-energy related GHG emissions (Olivier & Peters, 2005). Within Australia, the Australian Government provides the annually updated *National Greenhouse Accounts Factors* document (Australian Government, 2008). Other reliable emission factor sources

include those published by the European Union and US EPA (IMO & IAPH, 2018). It is recommended by the IMO & IAPH (2018), however, that if available, emission factors should be sourced from documentation provided by the local country to provide the most locally accurate values.

Emission factors can change over time, and depending on the energy type, these changes can have a significant impact on an entity's emissions. For example, from 1990 to 2019, the South West Interconnected System (SWIS) electricity grid of Western Australia scope 2 emission factor fell 39%; from 1.13 to 0.69 kg.CO_2-e/kWh (Department of the Environment and Energy, 2019). As such, for the development of GHG emissions projections and forecasts, future emission factor assumptions and modelling needs to be developed for the span of the emissions projection. Some assumptions can include the future mix of renewable energy used for electricity generation, the timeline of such implementations and if the emission factor for fossil fuels such as diesel and petrol will change over time. There is very little literature available to guide the development of emission factor forecasts. However; national and state government climate change mitigation policy and emissions reduction targets, in collaboration with historical emission factor trends, can provide useful tools for the development of qualitative and quantitative emission factor projections.

2.4 Long-term forecasting and scenario development

For forecasting and projecting into the long-term, several considerations must be made. Firstly, long-term historical data becomes increasingly important the further into the future model is projecting, as past data can provide hints as to whether or not a current, shorter-term trend is likely to continue (Makridakis, Wheelwright, & Hyndman, 1998). Additionally, qualitative, expert knowledge can help prevent the development of unrealistic projections, especially if such projections use time-series modelling techniques. For example, if an exponential curve provides the best fit for fuel consumption data from the past five years, the forecasted values may become unrealistically large over the span of a decade or two.

A projection's assumptions may only influence small variations in the short-term, however, can lead to large variations of values in the long-term. In order to account for such variability, scenarios can be built for the development of long-term

projections. Scenarios can allow alternative projections to be developed side-by-side, providing insight into how different circumstances and assumptions influence the modelled data. They can also increase the robustness of models in the event that future observations align with one scenario more closely than another. Scenarios can be developed objectively by extrapolating historical megatrends, applying established correlations, or subjectively by making specific assumptions about certain aspects of the future (Makridakis, Wheelwright, & Hyndman, 1998).

Different scenarios can consider social, political and economic changes, as well as the impact of technological developments. A case study on Portugal's future energy supply (Fortes, Alvarenga, Seixas, & Rodrigues, 2015) considered two complex economic and political scenarios including one in which Portugal becomes increasingly unstable and is unable to invest significantly in future infrastructure; and an alternative scenario in which Portugal's economy continues to grow, stimulating innovation and technological advancement, placing the country in a position to expand its renewable energy infrastructure significantly. Another approach is to focus on the price, and hence consumption, of a fuel source, as was done in a study by Gori, Ludovisi & Cerritelli (2007). This study developed three scenarios for the price of oil including parabolic, linear and chaotic behaviour. A study by Intarapravich et. al. (1996) used a simpler approach to scenario development, using three different energy demand scenarios including high, low and business-as-usual. Wei and Zhao (2010) similarly included a business-as-usual scenario for their study on CO_2 emission forecasting from shipping in Wanzhou, China.

The inclusion of business-as-usual scenarios, also known as a base-case or baseline, can provide a projection of the energy consumption or carbon emissions of a business if they continue their current operational practices unchanged into the future. This approach can be very useful for comparing current and future sustainability initiatives against a scenario in which such initiatives are not implemented. The Infrastructure Sustainability Council of Australia (ISCA), the peak infrastructure sustainability organisation in Australia and New Zealand, includes such scenarios in its *Base-Case Approach* energy and carbon emission forecasting guidelines (ISCA, 2017).

The *Base-Case Approach* is a strategy developed as part of ISCA's Infrastructure Sustainability rating scheme to provide assets with a mechanism to compare their actual sustainability performance against a business-as-usual, or Base Case, scenario. The approach consists of two scenarios:

- A 'Base-Case Footprint' where-by consumption and emissions continue without any sustainability initiatives, using business-as-usual operational practices projected onwards from a baseline or 'Base-Case' period/year.
- An 'Actual Case Footprint' which contains actual observed data from the Base-Case period/year onwards and includes consumption and emissions modelling assuming sustainability initiatives and more efficient operational activities are implemented.

As per the *IS Operations Technical Manual* (ISCA, 2017), the scenarios above must include changes in asset utilisation and asset services demand like changes in trade or increases in local population. The scenarios must also consider any planned upgrades and expansions, and also include operational trends such as seasonal or periodic fluctuations (ISCA, 2017). An example of the Base Case and Actual Case scenarios can be seen in Figure 4. In this example, observed and expected energy efficiencies have resulted in the Actual Case scenario predicting lower energy consumption than the Base Case scenario.

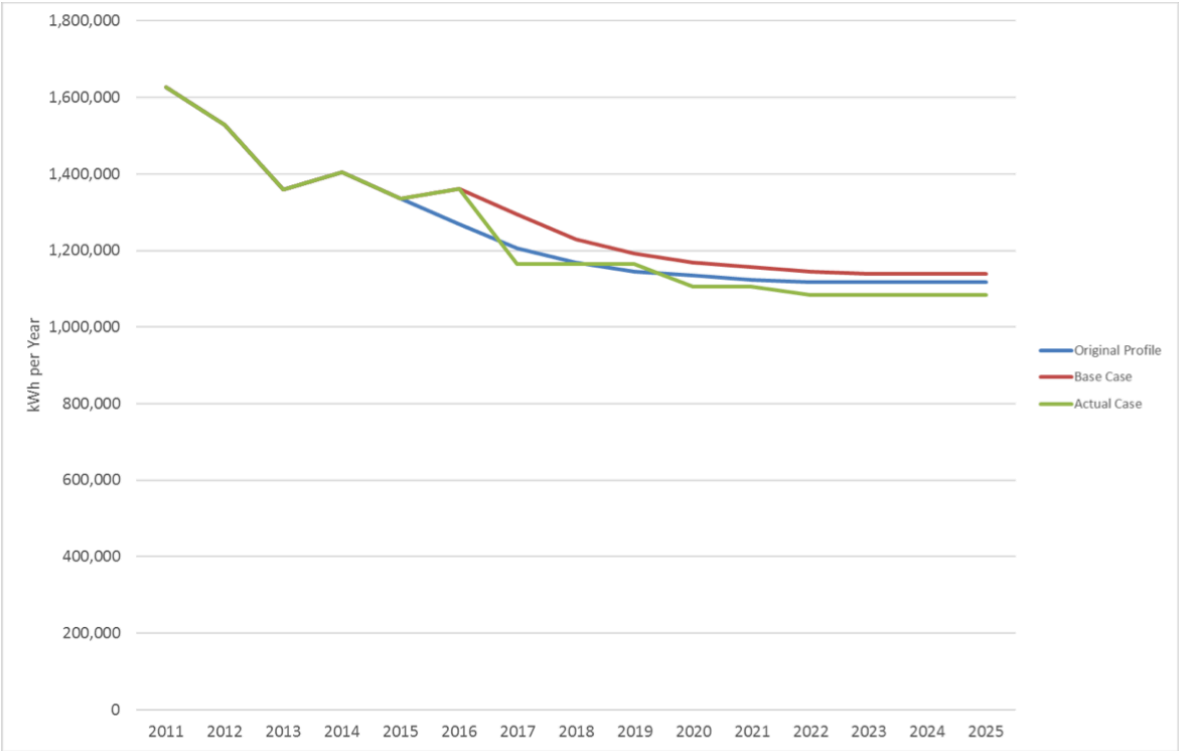

Figure 4: *An example Base Case and Actual Case projection from the IS Operations Technical Manual* ***(ISCA, 2017)****.*

2.5 Projection methodology summary

As mentioned in section 2.1, the IAPH has developed an effective carbon management guideline for the port industry. The case study in chapter 4 of this report will focus on step 2 of the IAPH guideline - *Establish Emissions Baseline and Forecast* - and assume that a current energy and carbon emission inventory has already been developed for the port. As has been detailed above, a variety of different techniques exists for the development of long-term energy and carbon emission projections. This section of the report will summarise the methodologies which will be followed for the development of the case study on Fremantle Ports in chapter 4.

For the development of energy and emissions projections, this report will follow the general scaffolding, assumptions and scenarios as set out by the *ISCA Base Case Approach* in the *IS Operations Technical Manual v1.2* (ISCA, 2017) and mentioned above in section 2.4. ISCA is an organisation which provides rating schemes and guidance for infrastructural sustainability within the Australia/New Zealand region. ISCA has developed a forecasting/projection strategy, known as the *Base Case Approach*, to help assets demonstrate reductions and measure performance changes for its Ene-1 (Energy and Carbon), Wat-1 (Water) and Mat-1 (Materials) Rating credits (ISCA, 2017). As per the objectives of this dissertation project, the *ISCA Base Case Approach* will be followed to test its usability for the development of energy consumption and GHG emission projections for ports.

The ISCA *Base Case Approach* consists of three components, the first of which is the *Base Case Proposal.* This component establishes the basis for the modelling and includes a historical data analysis as well as definition of the scope and development of any predictive/modelled assumptions required for modelling.

The second component of the approach comprises of the development of the “Base Case” – a projection following a business-as-usual scenario where-by consumption and emissions continue without any sustainability initiatives, using business-as-usual operational practices, projected onwards from a baseline or ‘Base-Case’ period/year.

The third component consists of the development of the “Actual Case” projection; combining actual observed data with energy and emissions projections, assuming sustainability initiatives and more efficient operational activities are implemented.

The model development methodology is explained in more detail below.

2.5.1 Base Case scenario model development

As the ISCA *Base Case Approach* (ISCA, 2017) does not contain information regarding specific forecasting/projection techniques, the approach was expanded and adapted as necessary to best align with port operations and the requirements of the project’s scope.

The Base Case model was developed by analysing and projecting each facility’s energy and emission data by source type, using an activity-based, bottom-up approach. This helped discover historical macro and micro trends within the system and will ideally create more complex and accurate projections.

For the development of the models, historical data was statistically compared against Key Performance Indicators (KPIs), historical trade data and other port operational data to uncover the existence of key influencing drivers. Traditional linear regression was conducted to determine the presence of any relationships. A relationship was considered statistically significant if its p-value is less than or equal to 0.05, as is common in scientific practice. Statistical calculations were conducted using the SPSS statistics software (IBM Corp, 2019). Different forecasting techniques were experimented with to best determine the most appropriate model type. Once a model was developed, it was tested using historical data, with predicted and actual values compared using error analysis techniques as described in section 2.2.5. If the values aligned adequately and the model met qualitative requirements, then it was considered as fit for purpose.

For quantitative, explanatory models, future explanatory variable values were obtained from already developed forecasts. If not available, projections needed to be developed using qualitative and quantitative time-series modelling techniques.

GHG emissions will be calculated using historical and projected energy consumption data as per methods outlined in section 2.3. The Australian Government’s National Greenhouse Account Factors will provide the emission factors used for GHG

emission calculations (Australian Government, 2008). These emission factors will provide the most locally accurate emission factors for fuel sources used by the port, as is recommended by IAPH (2018).

As per the ISCA Operations Technical Manual *Chapter A Guide to the Using Resources Theme* (ISCA, 2017), the Base Case Footprint model was predominantly focused on constant energy consumption. Variable energy consumption was included in Base Case modelling if it is indiscernible from constant energy consumption or if it is of a relatively consistent amount year on year and hence for all intents and purposes can be considered constant.

2.5.2 Actual Case scenario model development

As mentioned above, the ISCA *Base Case Approach* needs to be expanded and adapted where appropriate for its use in developing modelling for the port.

For the development of the Actual Case model, modelling developed for the Base Case scenario was adapted, incorporating the facility's actual recorded energy consumption and GHG emission calculations onwards from the Base-Case year/period to the present. This allows for direct comparison between the observed and projected values, highlighting the facility's recent performance against the Base Case. This also repositions the model to fit with recently observed changes in the facility's energy use and emissions.

For future years, the corresponding Base Case model was applied, but adapted to incorporate anticipated impacts of current or expected sustainability initiatives and efficiency improvements. Energy or emission reduction strategies that have been developed by the port will be incorporated into the modelling here.

For current and future sustainability initiatives or operational efficiency improvements, the facility's planned sustainability initiatives will need to be identified, including the expected start and end dates of the initiative's implementation. Any expected reductions will need to be calculated and justified. This will create a material and quantitative means of projecting energy and GHG emission reductions for the facility over the coming years and provide the template for the development of any future energy or GHG emission reduction-strategy impact modelling.

3 Case study: Fremantle Ports

3.1 Introduction to the port and context of the project

Fremantle Ports is a Western Australian Government owned enterprise responsible for facilitating trade through the Port of Fremantle. The port is Western Australia's largest general cargo port, Australia's fourth largest container port and is the primary port for the Perth metropolitan region. Fremantle Ports provides and maintains shipping channels, cargo berths, navigation aids, the Fremantle Passenger terminal, trade handling equipment, storage sheds, road and rail transport infrastructure and other public amenities such as water and power within the port's limits (Fremantle Ports, 2018). Fremantle Ports operates four facilities across two harbours. The Inner Harbour, adjacent to the City of Fremantle, contains the facilities of Victoria Quay (VQ) and North Quay (NQ). The Outer Harbour lies 20km south of Fremantle contains the Kwinana Bulk Terminal (KBT) and Kwinana Bulk Jetty (KBJ) facilities (Figure 5) (Fremantle Ports, 2018). For more background information of these facilities, see *Appendix 3: Fremantle Ports facilities information.*

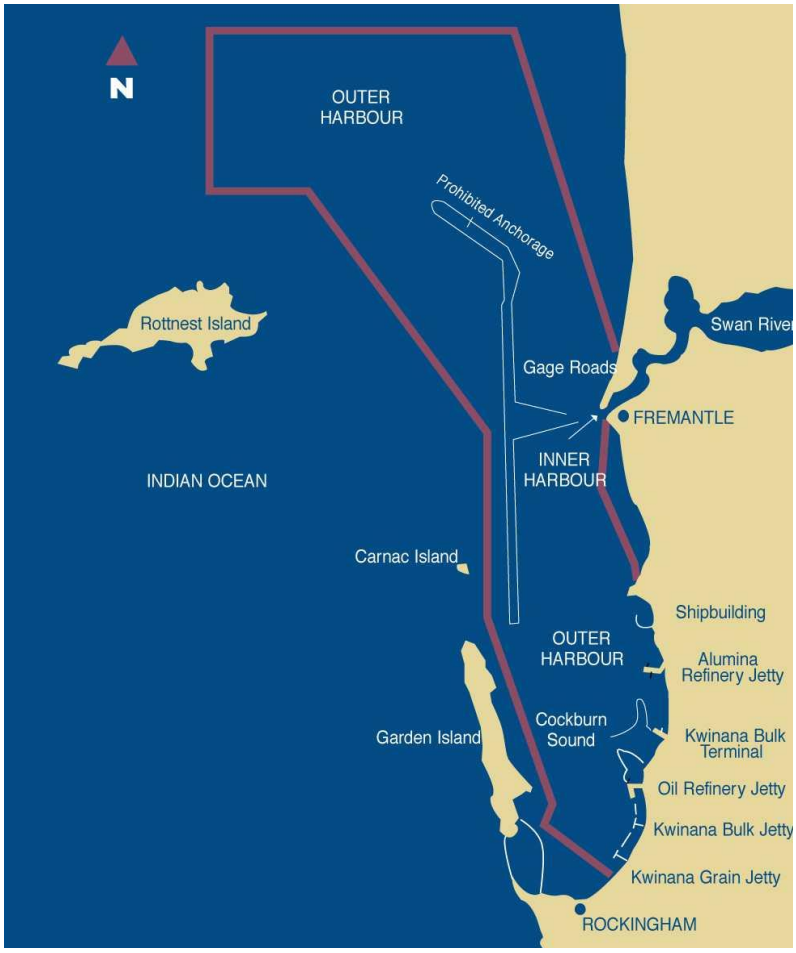

Figure 5: *Location of the Port of Fremantle and its declared waters* ***(Fremantle Ports, 2018)****.*

3.1.1 Why use Fremantle Ports as a case study?

Fremantle Ports was selected as the case study for this project for a number of reasons. One of the reasons comes down to a matter of timing. The port has developed energy and carbon emission inventories for its internal operations since FY 2011/12, however; with the release of the Western Australian Government's net carbon neutrality target in 2019, Fremantle Ports was in need of long-term energy and carbon emission projections to 2050. This coincided with the early stages of this dissertation project in February 2020, providing a mutually beneficial opportunity for both parties.

Fremantle Ports is a large and essential, well known infrastructural asset in the Perth metropolitan region. Due to the its size and relative complexity, including its facilitation of multiple trade types and consumption of multiple energy types, the port provides a great testing ground for energy and emissions modelling. Additionally, the necessity for qualitative, quantitative – time series, and quantitative – explanatory model types allowed for multiple modelling techniques to be developed and tested comprehensively with real-world data.

3.2 Base Case Proposal development

As per the *ISCA Base Case Approach*, the Base Case Proposal is the first stage in the development of Base Case and Actual Case energy and GHG emission modelling (ISCA, 2017). The Base Case Proposal provides an overview of the modelling process and sets the groundwork for model development. It consists of an analysis of historical data and identifies the model scope and assumptions. How these steps are contained within the *Base Case Approach* can be seen under the "Define assumptions" heading in the Base Case process diagram in Figure 6 below.

3.2.1 Historical data analysis

The analysis of historical data can identify changes and trends of past energy use and GHG emissions and uncover any relationships that might exist with operational and external factors. As with any historical analysis, the greater the quantity of data available, the greater the resolution of the findings. The *IS Operations Technical Manual* suggests 5 to 10 years of data is sufficient, although this figure depends on the requirements of the model and length of the projection (ISCA, 2017).

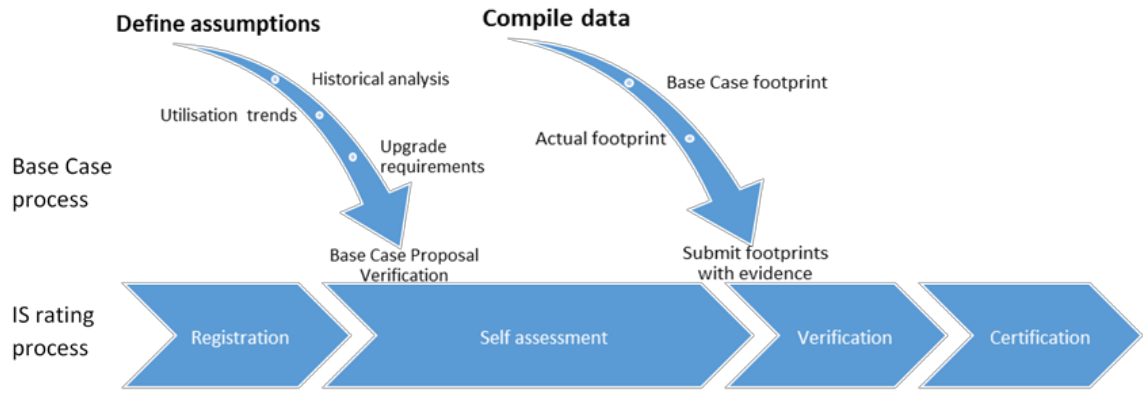

Figure 6: *A brief overview of the Base Case Approach and how the Base Case process fits into the IS rating process* ***(ISCA, 2017)****.*

Fremantle Ports has been compiling energy and carbon emission inventories annually since FY 2011/12 for all internal operations, with exceptions for Victoria Quay's small craft pens, which have fuel use data going back to FY2002/03, and NQ's container terminals, which only have electricity data available since 2017. Smart meters were installed at VQ, NQ and KBJ in December 2016, providing greater resolution of electricity consumption within the facilities. Energy consumption data was collected by recording diesel refill amounts at the KBT and VQ small craft pens diesel storage tanks, through fuel receipts and fuel cards for vehicle fuel consumption, and for electricity consumption; manual meter readings were conducted for all sites prior to December 2016, with smart meters providing electronic metering at VQ, NQ and KBJ thereafter.

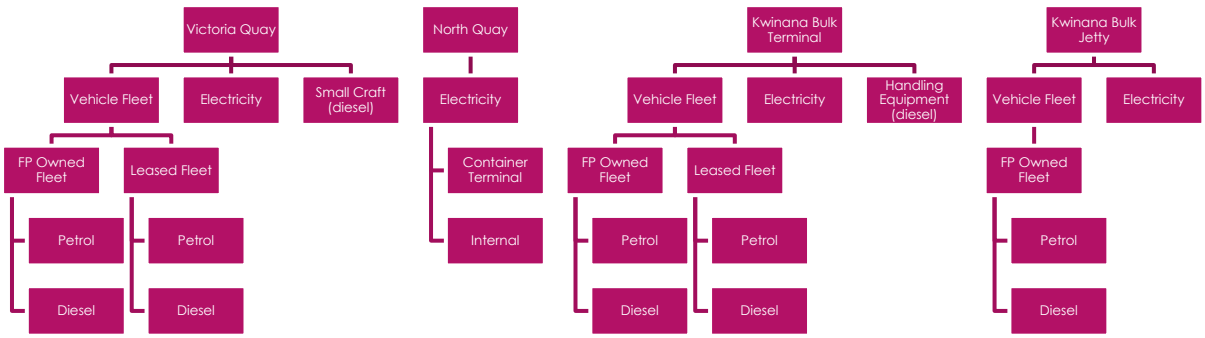

Figure 7: *Energy consumption source categories, as per the Fremantle Ports energy and emissions inventory.*

Data was compiled into MS Excel (Microsoft Corporation, 2018) per facility, and categorised by energy type and operational source. These categories are shown

diagrammatically in Figure 7, above. Historical data was analysed visually using graphing tools in MS Excel and statistically using IBM's SPSS statistics software (IBM Corp, 2019).

For the facilities' vehicle fleet fuel consumption data, records were only available at an annual resolution. Data was analysed visually, with fuel consumption changes and trends explained qualitatively with expert knowledge of the fleets' historical operations. No quantitative explanatory factors were identified for vehicle fleet fuel consumption trends, with internal vehicle policy changes and a general shift from petrol- to diesel-fuelled vehicles denoted as the likely driving motives for observed changes. Such trends be seen for Victoria Quay's vehicle fleet fuel consumption in Figure 8.

Where monthly energy use data was available, tests were conducted to determine if seasonal trends existed year-on-year. Whilst medium-term cycles will likely only have a small influence on long-term data projections, they can offer hints of the existence of possible causal relationships. A mild seasonal trend can be seen in Victoria Quay's internal electricity consumption in Figure 9, with on average slightly lower electricity consumption during the summer months. No quantitative explanatory factor was able to be identified to explain this trend.

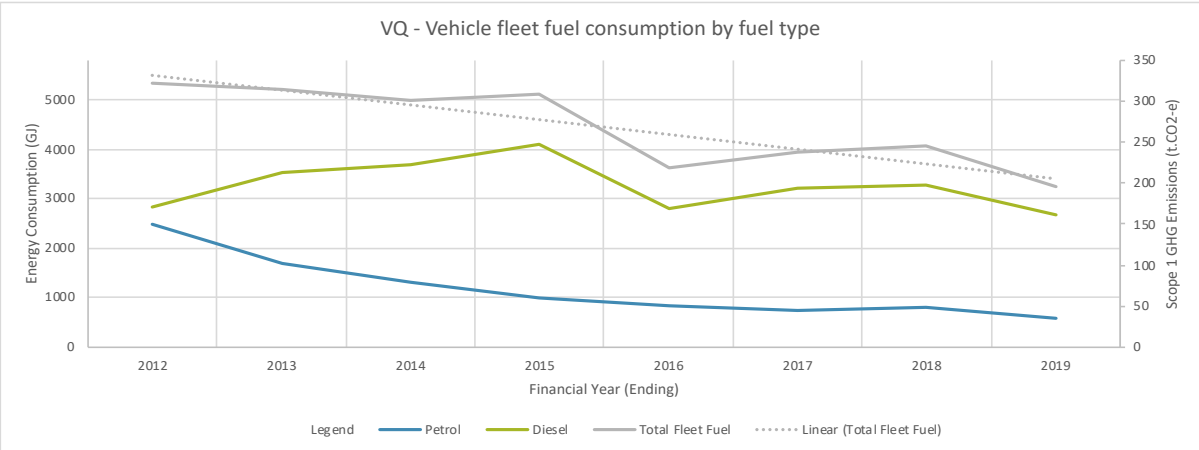

Figure 8: *The Victoria Quay vehicle fleet saw a trend of decreasing petrol consumption over the historical years, compared to steady diesel consumption.*

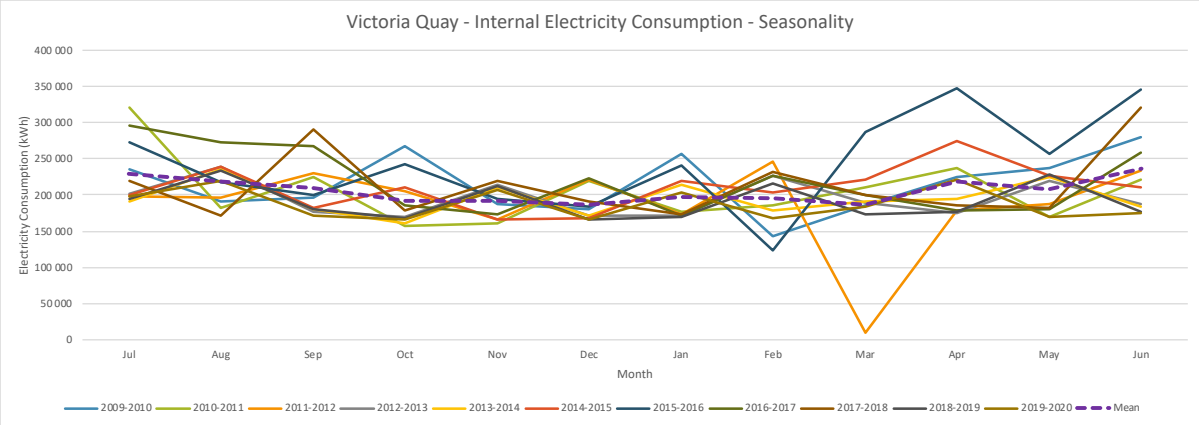

Figure 9: *Seasonal trends as observed in Victoria Quay's internal electricity consumption.*

When month-to-month energy consumption data was highly variable, data smoothing techniques were employed to help identify larger-scale trends. A 12-month moving average was used to smooth historical electricity consumption data at KBJ, as is seen in Figure 10, assisting the identification of consumption trends and changes that would otherwise have been difficult to determine from the noise.

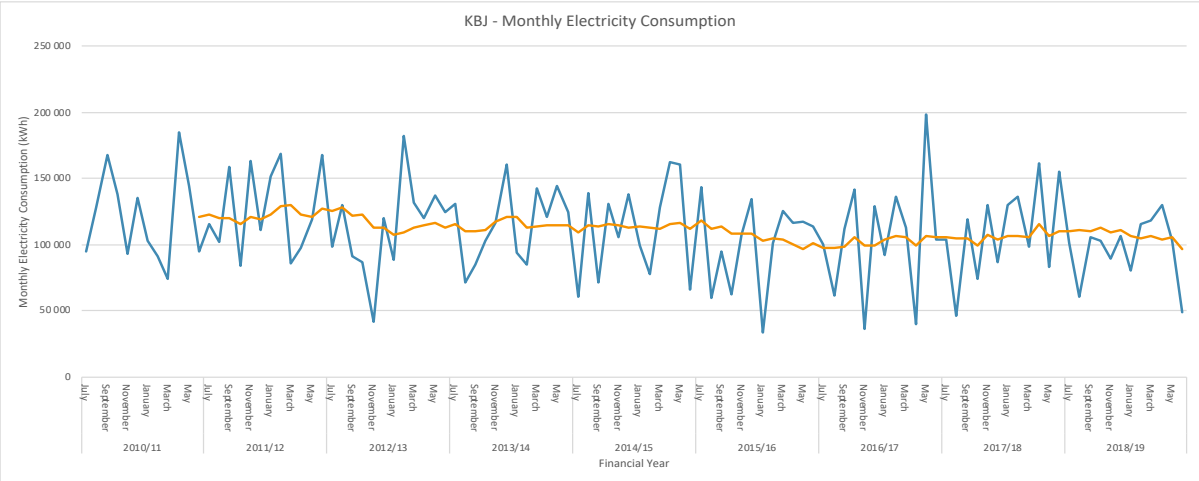

Figure 10: *Data smoothing: a 12-period moving average was used uncover underlying trends for KBJ's electricity consumption data.*

Where causal relationships were visually suspected, ANOVA (analysis of variance) statistical tests were run to determine the statistical significance of relationships. Causal relationships were mostly identified for energy consumption sources that are highly dependent on trade volumes. This includes KBT's electricity, KBT's trade-handling-equipment diesel consumption, KBJ's electricity consumption and the electricity use of North Quay's container terminals. The general process started with visual relationship identification, followed by statistical analysis to determine the statistical significance of the relationship, as can be seen in Figure 11.

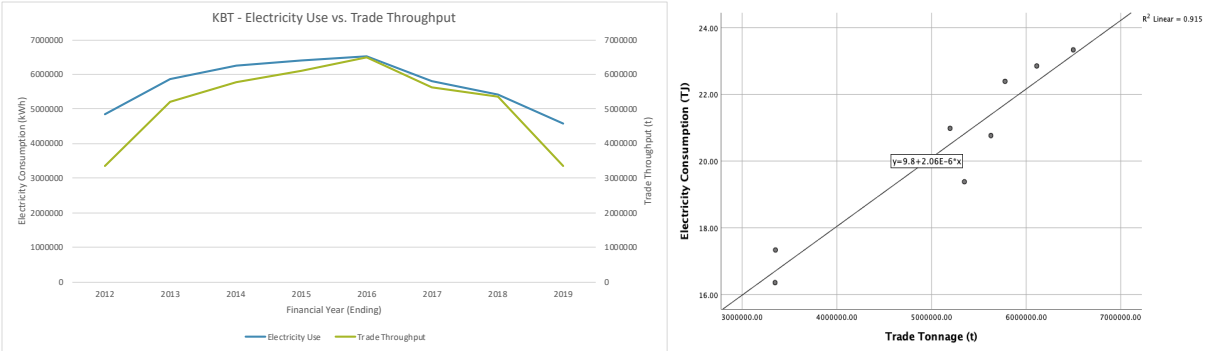

Figure 11: Left: *A relationship was visually identified between KBT's electricity use and trade throughput.* ***Right:*** *This relationship was confirmed to be statistically significant using ANOVA tests in SPSS with a p-value of less than 0.002* ***(IBM Corp, 2019)****.*

A statistically significant relationship was also found between Victoria Quay's small craft diesel consumption (primarily pilot vessel operations) and the quantity and size of commercial ships visiting the port. The link between pilot vessel fuel consumption and ship visits is clear; commercial ships require pilot guidance into port. Qualitative research of vessel operations determined the connection between fuel use and ship size, pilot vessels must meet large ships further offshore (Figure 12).

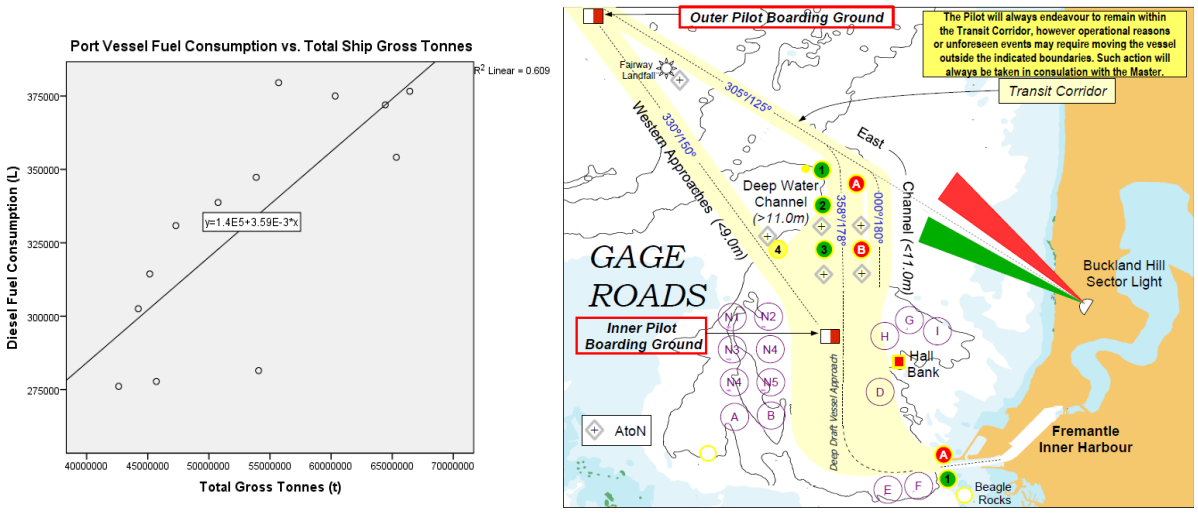

Figure 12: Left: *A statistically significant relationship was found between VQ's small craft diesel consumption and the quantity and size of commercial ships visiting the port. The statistical analysis determined a p-value of less than 0.002.* ***Right:*** *The relationship between fuel consumption and ship size was explained qualitatively as larger ships require pilot vessel guidance from further offshore (Outer Pilot Boarding Ground) than smaller ships which only required guidance from the Inner Pilot Boarding Ground.*

3.2.2 Base Case year selection

As per the ISCA *Base Case Approach,* a Base Case year is a period which adequately represents a business's 'typical' operational year and is representative of energy combustion and carbon emissions prior to any significant sustainability or

energy efficiency implementations. With this in mind, a Base Case year was selected for each facility;

- **VQ – FY 2015/16**. In December 2016, Fremantle Ports installed an energy management system across VQ, NQ and KBJ, thereafter implementing energy efficiency measures such as switch timers and widespread LED lighting replacements. FY 2015/16 represented a year of typical energy consumption for VQ, prior to the implementation of these energy efficiencies.
- **NQ – FY 2017/18.** Whilst the implementation energy efficiency measures began at NQ at the beginning of 2017, electricity meter recordings for NQ's container terminal only began with the installation of smart meters and the energy management system. For this reason, the earliest year available, FY 2017/18, was chosen.
- **KBT – FY 2018/19**. KBT's energy consumption has been largely inflated over the last several years as a result of above average iron-ore exports. With the termination of iron-ore exports at the beginning of FY 2018/19, this year best represented 'normal' use.
- **KBJ – FY 2016/17.** Considering energy efficiency implementations beginning in 2017 and above average energy consumption in FY 2015/16, FY 2016/17 constituted the most typical year prior to the establishment of energy efficiency measures.

3.2.3 Project scope and assumptions

The second part of the Base Case Proposal is focused on defining the project's scope and any underlying assumptions required for modelling.

<u>Organisational scope</u>

Modelling will account for energy consumption and GHG emissions under Fremantle Ports' direct operational control in the Port of Fremantle's Inner and Outer Harbour. Energy consumption and GHG Emissions attributed to Fremantle Ports' tenant operations and visiting ships are not within the organisation's direct control and are excluded from the Base Case and actual case projections. This is with the exception of the North Quay container terminals, which have been included due to their high operational importance to the port. Locomotive and truck movements not directly operated by Fremantle Ports are also excluded from energy and carbon projections.

Whilst this organisational scope is significantly narrower than many of those described in IAPH's *Tool Box for Greenhouse Gases* (IAPH, nd), this scope was developed by Fremantle Ports because it only covers emissions sources that they have direct operational control over. Fremantle Ports consider that this scope will provide a more accurate projection of their organisation's direct emissions.

Operational scope

As per the *IS Operations Technical Manual* (ISCA, 2017), in accordance with Australian and International Standards AS ISO 14064.1 (ISO, 2006), scope 1 and 2 emissions must be included in Base Case projections and estimations. Hence, this project's modelling will include all quantifiable energy consumption and scope 1 and scope 2 GHG emissions from sources as mentioned in Figure 7. The Technical Manual notes that "energy use or GHG emissions that is likely to account for more than 5% of the total consumption from Scope 1 and 2… in constant energy consumption is considered significant and must be included". As such, energy consumption and GHG emissions associated with the consumption of natural gas will not be included in the operational scope as it represents less than 0.0001% of the port's total energy consumption and less than 0.001% of the port's GHG emissions, far below ISCA's 5% threshold as described above.

Scope 3 emissions that will be included in the operational scope are those associated with:

- Electricity; Emissions attributed to extraction, production and transport of fuel burned at generation and to electricity lost in delivery and transmission in the distribution network.
- Transport Fuel; Emissions attributed to extraction, production and transport of fuel burned at the facilities.

Other scope 3 GHG emissions are considered inconsequential; with combined values on average less than 1.1% of the port's total greenhouse gas consumption. Additionally, much of the excluded scope 3 emissions have limited historical data available and, in some cases, have arbitrary emissions factors, creating difficulties for developing assumptions and GHG emission projections.

Business and operational assumptions

Table 1: *Key business operational assumptions made for the development of Fremantle Ports' energy consumption and GHG emissions Base Case and actual case projections.*

Assumption	Notes and potential sources to support the assumption
The general purpose of the facilities will remain the same and Fremantle Ports will not develop or acquire any other facilities and place it under the operational control of the VQ, NQ, KBT or KBJ facilities throughout the forecast period.	As of the time of writing, the Western Australian Government's Westport taskforce is investigating strategies for the Port of Fremantle to handle future increases in trade. A recent announcement proposed a move of Fremantle Ports' Inner Harbour facilities to a new purpose-built port in Kwinana, as early as 2032 (Shepherd, 2020). Whilst this would result in drastic changes to Fremantle Ports' future energy consumption and GHG emissions, the proposal is currently only at the business-case level. With no current plan for construction or development, there are presently too many unknowns for any specific Westport strategy to be incorporated within Fremantle Ports' Base Case projections. As such, it has been decided that Fremantle Port's Base Case projections will assume facilities remain in their present form and function for the extent of the forecast period.
There will be no supply constraints or port capacity limitations for the duration of the Base Case forecast period, besides those otherwise identified.	Trade and Base Case forecasts are presented on an unconstrained basis, meaning they represent the projected volume of energy consumption, GHG emissions and import and export flows without taking into account port capacity limitations or supply constraints, besides those otherwise identified. This is in line with trade forecasts created for the port by Deloitte Access Economics (Westport, 2018).
The Base Case forecasting will assume that there are no major GHG emission or energy policy changes, new economic/environmental incentive developments or significant technological advances.	This assumption addresses the uncertainty and difficulty inherent in forecasting the impact of 'known unknowns' (E.g. forecasting for the introduction of a national carbon tax or for widespread adoption of electric vehicles). As the Base Case provides, by definition, a 'business-as-usual' projection, any policies, economic/environmental incentives, technologies or the like that are not implemented or do not exist at the time of the Base Case year will not be included in the projections.
The rate of voluntary emissions reductions and energy efficiencies in the Base Case year will remain constant in future years.	Base Case projections reflect 'business-as-usual' trends and hence rely on the assumption that future voluntary emissions reductions and energy efficiencies are not included in the projection. Voluntary emissions reduction and energy efficiency programmes that are in place as of the Base Case year will, however, be included in Base Case projections (U.S. Environmental Protection Agency, 2013).
There will not be any major change in electricity and fuel costs per unit, and any changes that do occur will not have a significant impact on energy consumption.	The variability and uncertainty of future electricity and fuel prices makes this factor difficult to include in the modelling. Additionally, the variability of behavioural and business responses to fluctuations in energy prices adds further complexity. To reduce the risks inherently involved in forecasting these changes, and to maintain relative simplicity in modelling, changes in energy costs will be assumed to have no significant effect on energy use and carbon emissions.

Constant and variable energy consumption

The *IS Operations Technical Manual* describes constant energy use as consumption which is relatively constant year-on-year, including; stationary uses, mobile usage, normal asset utilisation and standard preventative and reactionary maintenance. Variable consumption is considered as energy use related to significant unplanned works, capital enhancements/upgrade works and abnormal asset utilisation. All energy data provided by the port was considered by internal port energy managers as constant energy use. A lack of qualitative and quantitative information from the port prevented any further identification of historical variable energy consumption.

Design life

For the purpose of the energy and emissions projections, Fremantle Ports and its material components are expected to operate beyond the 2050 timeframe of the modelling. It must be noted, however, that in preparation for future population growth and an increase of maritime trade, an external taskforce was set up in 2018 by the Western Australian Government to investigate potential expansion strategies for the Port of Fremantle. As the investigation is still ongoing, for the purpose of the Base Case and actual case projections, it will be assumed that there will be no major changes to the function of this port's facilities within the timeframe of the modelling.

3.2.4 Emission factor forecasting and assumptions

A sensitivity analysis was conducted to determine the influence that changes in emissions factors will have on the port's calculated GHG emissions. It found that for Victoria Quay, a scope 2 emission factor drop from its current level of 0.69 kg.CO_2-e/kWh to zero would result in a 42% reduction of the facility's emissions. As such, it was deemed essential that scope 2 emission factor projections be developed.

To better understand what renewable electricity capacity may look like in 2050 on Western Australia's South West Interconnected System (SWIS), current renewable energy policies were analysed. In August 2019, the Western Australian Government announced a target to achieve net carbon neutrality across all sectors of the Western Australian economy by 2050 (Government of Western Australia, 2019). This brought Western Australia in line with carbon neutrality targets of other Australian states, however, behind; South Australia, the ACT and Tasmania, whom have announced targets for 100% renewable energy generation between the 2020 and 2040, and;

Victoria and Queensland, which have committed to 50% renewable energy generation by 2030 (Weisbrot, Baxter, Bourne, Stock, & Ivit, 2019). In March 2020, a private member's bill entered into the Parliament of Western Australia proposing a renewable energy target of 100% by June 2030, although as of September 2020, the bill has not yet progressed beyond its second reading and its future is unknown (Clifford, 2020). Renewable electricity generation is considered to release null or negligible scope 2 greenhouse gas emissions. As such, it is assumed that under a scenario where-by the SWIS generates electricity from 100% renewable sources, the scope 2 emissions of SWIS connected infrastructure would be zero. Using the above information and extrapolating historical scope 2 emission factors for the SWIS (Australian Government, 2008), four scenarios were developed (Figure 13).

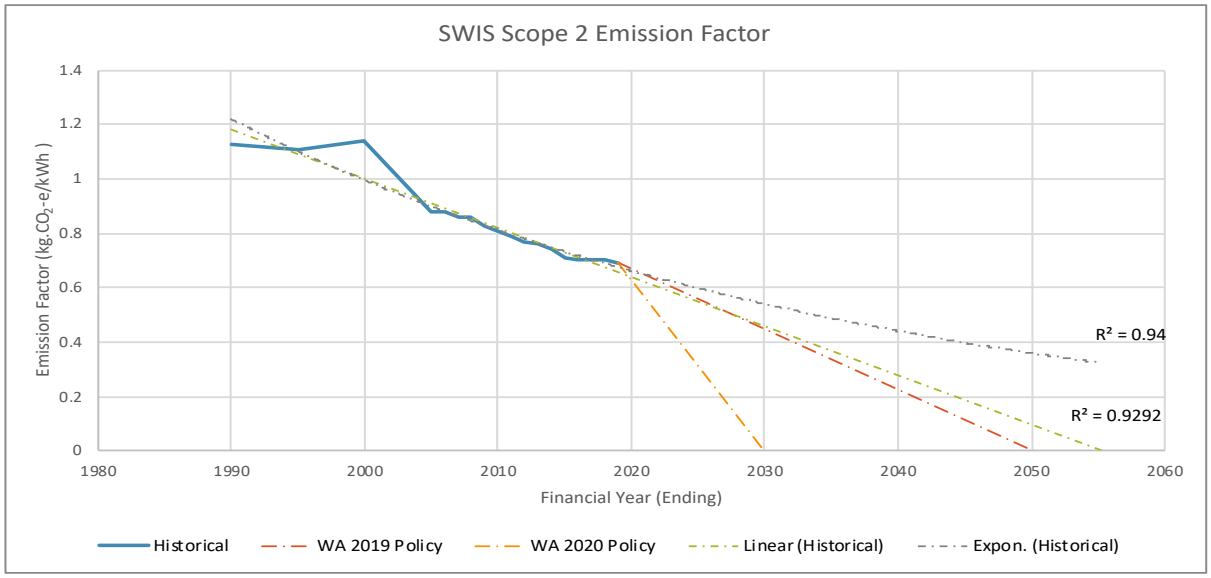

Figure 13: *Scope 2 SWIS emission factors; historical and projected. Four scenarios were developed. The WA 2019 policy scenario was selected as the most robust scenario.*

Recent research by the Australian National University (Lu, Blakers, & Stocks, 2016) found electricity generation from 100% renewable energy sources is currently possible for the SWIS using existing technology. Considering this research, interstate targets, Western Australia's existing targets and the uncertainty of the future progress of the private member's bill, the year at which Western Australia's electricity generation is sourced from 100% renewable sources will be assumed to be 2050. This may be a conservative assumption, although provides, in the author's opinion, the most robust scenario. It will be assumed that the SWIS scope 2 emission factor will decline linearly until it reaches zero.

A sensitivity study was also conducted to determine the influence of emission factor changes on scope 3 electricity GHG emissions. The analysis found that whilst the port's total emissions were only marginally sensitive, a drop from the current emission factor to zero had a large impact on scope 3 emissions, resulting in Victoria Quay's scope 3 emissions dropping 58%. Therefore, it was considered important to develop scope 3 electricity emission factor projections for the SWIS to 2050.

The Australian National University study (Lu, Blakers, & Stocks, 2016) developed a renewable energy generation mix that would be feasible for the state by 2030. Their proposed generation mix was used to develop a potential scope 3 emission factor for electricity generation in the SWIS in 2050. Unlike with scope 2 emissions, scope 3 emissions for renewable energy projects consist of those released indirectly by electricity generation and can include emissions released during the manufacturing, construction, maintenance, transportation and end-of-life periods of renewable energy infrastructure. As each renewable energy technology has different indirect environmental impacts, a literature review was conducted to determine the likely scope 3 emission factor for each technology. Afterwards, the generation mix proposed by Lu, Blakers & Stocks (2016) was used to predict a 2050 S3 electricity emission factor for the SWIS. Results of these calculations can be seen in Table 2.

Table 2: *Projected electricity generation mix and scope 3 emission factors for the SWIS in 2050.*

Generation Type	Annual Electricity Penetration (TWh)	Percent Mix	Estimated EF (g.CO2-e/kWh)			
Wind	8.2	45%	34.1		0.01527978	kg.CO2-e/kWh
Biogas-fuelled OCGTs	1.7	9%	58.24		0.00541027	kg.CO2-e/kWh
Pumped Hydro	1.9	10%	20		0.0020765	kg.CO2-e/kWh
Large-scale Solar PV	2.3	13%	49.9		0.00627158	kg.CO2-e/kWh
Rooftop Solar PV	4.2	23%	53		0.01216393	kg.CO2-e/kWh
Total	**18.3**	**100%**	**215.24**	2050 SWIS S3 EF	0.04120208	kg.CO2-e/kWh

Renewable energy technology emission factors were estimated using the following resources: for wind and large-scale solar PV (Nugent & Sovacool, 2014); and for pumped hydro and rooftop solar PV (Amponsah, Kington, Aalders, & Hough, 2014). For biogas-fuelled OCGTs (Open Cycle Gas Turbines), emission factors vary drastically depending on the type of biogas combusted. South-western Western Australia currently has seven biogas electricity generation facilities, all of which use gas generated from landfills (AEMO, 2017). The life-cycle emission factor of landfill

gas was estimated to be 65 g.CO_2-e/MJ of un-combusted gas by Jury, Benetto, Koster, Schmitt, & Welfring (2010). Using this value and assuming a thermal efficiency of OCGTs of 31% (Lu, Blakers, & Stocks, 2016), a scope 3 emission factor for biogas-fuelled OCGTs in the SWIS was calculated as 58.24 g.CO_2-e/kWh (Table 2). For the sake of this emission factor forecast, it is assumed that Western Australia will continue to only use biogas sourced from landfills to 2050. However, it is entirely possible, perhaps even necessary, that other types of biogas are used in the future. Results of the scope 3 SWIS emission factor projection is provided in Figure 14.

It was assumed that the SWIS scope 3 emission factor will transition linearly from its current value to its value in 2050. Additionally, it is assumed that the S3 emission factor of each renewable technology will not decrease between now and 2050.

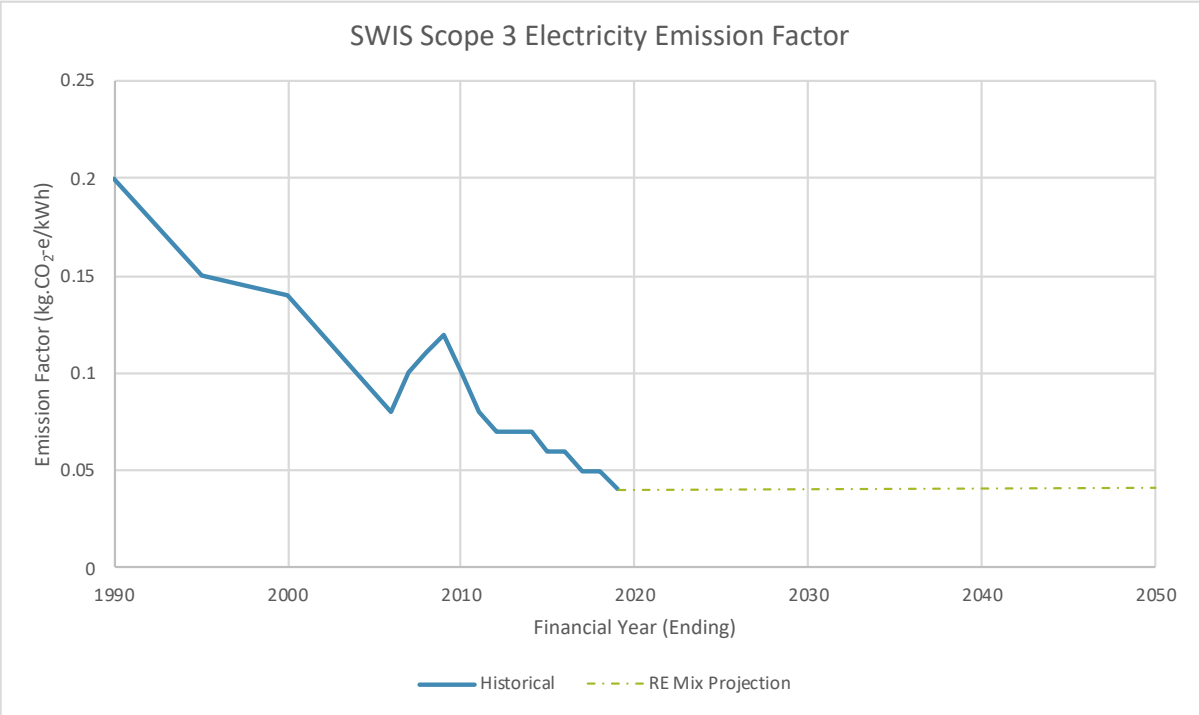

Figure 14: *Historical and projected SWIS Scope 3 Emission Factor. A linear trend has connected the current value of 0.040 to the projected value of 0.041 kg.CO_2-e/kWh.*

In regard to the scope 2 and 3 emission factors for diesel and petrol liquid fuels, historically these values have remained relatively stable (Australian Government, 2008). As such, the assumption has been made that these values will not change from their value in 2019 through to the year 2050.

3.3 Base Case model development

This part of the Base Case Approach focuses on the development of energy and emissions projections using a business-as-usual scenario. This projection, hereafter denoted as the 'Base Case', is intended as a mechanism to compare actual and expected energy and emissions reductions against, providing an effective tool to measure the impact of energy efficiency improvements and emission reduction targets. As was described in section 2.5.1 of this report, Base Case modelling was developed with a bottom-up approach and utilised a combination of time-series/qualitative models and causal/explanatory models.

3.3.1 Time-series/qualitative models

As described in section 2.2.2 and 2.5.1, for instances where explanatory variables were not able to be identified for historical energy data, time-series models were used. This was the case for Fremantle Ports' vehicle fleet energy consumption, as well as Victoria Quay and North Quay's internal electricity consumption.

Autoregressive techniques such as ARMA and ARIMA models are commonly used time-series based models, widely used for forecasting short- and medium-term electricity demand. This is largely due to the tool's strengths in predicting seasonal and cyclical patterns (Makridakis, Wheelwright, & Hyndman, 1998). For the development of vehicle fleet projections, autoregressive techniques were experimented with to determine their usability. ARIMA modelling with exponential smoothing was used because of its compatibility with the data sets' non-stationary mean. As can be seen in Figure 15, the model's five-year forecast appears adequate, however, when forecast out to 2050, several issues with the ARIMA modelling can be identified. Firstly, due to the highly variable nature of the data sets, with no distinguishable cycles or patterns, the ARIMA model struggled to fit the data-set. This negated one of the strengths of autoregressive modelling, replicating cycles into the future. As such, the ARIMA model developed simple linear projections, often with low R^2 values. This created a significant issue for data-sets with a negatively sloping mean, as is the case for ARIMA modelling of Victoria Quay's leased petrol vehicle fleet, as seen in Figure 16. In this instance, the model projected negative petrol consumption from approximately FY 2021/22 onwards. One of the other key

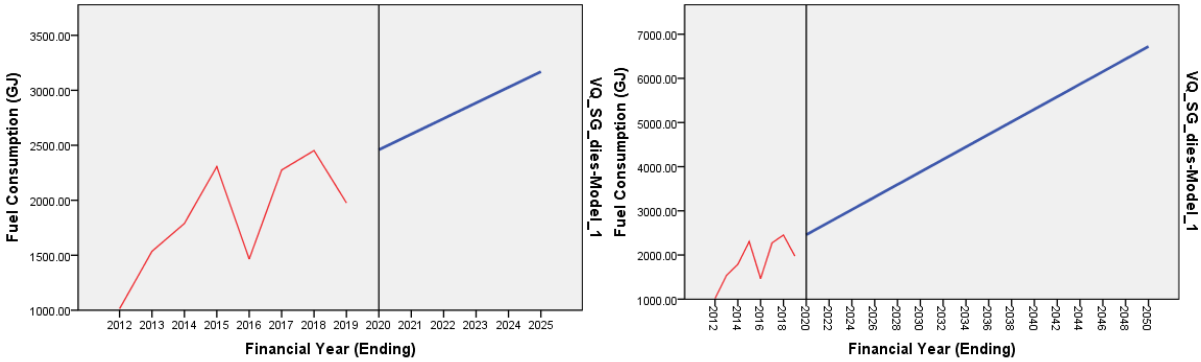

Figure 15: *ARIMA modelling for Victoria Quay's leased diesel vehicle fleet with a low R^2 value of 0.376. The chart on the left displays forecasting to 2025, the chart on the right displays forecasting to 2050.*

issues found with ARIMA modelling was its inability to consider qualitative factors. For example, expert qualitative knowledge expects VQ's leased vehicle fleet petrol consumption to level out shortly after 2020 which is information that can't be incorporated in ARIMA modelling. Ultimately the lack of flexibility, inability to incorporate qualitative forecasts and non-cyclical nature of the historical data proved autoregressive models inadequate for the development of energy projections for Fremantle Ports.

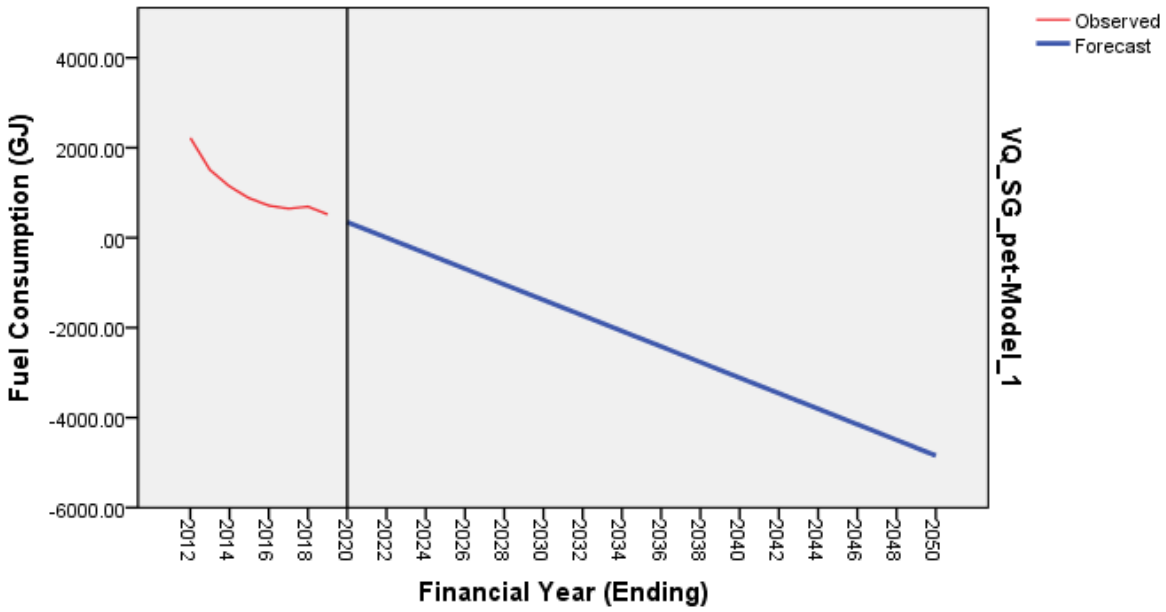

Figure 16: *ARIMA modelling for Victoria Quay's leased petrol vehicle fleet with a high R^2 value of 0.908. The modelling projected negative fuel consumption shortly after 2020.*

Linear and non-linear regression analysis was also experimented with. This technique uses the least squares method to fit equations to observed values. Regression analysis was run using SPSS statistics software (IBM Corp, 2019) for values prior to and including the base case year, with values regressed against the

year. Models were chosen according to R^2 and p values. Qualitative forecasts from internal port expertise helped guide the selection of models when multiple fit to a statistically adequate degree. The results of a regression analysis of VQ's leased petrol vehicle fleet can be seen in Table 3. For this data-set, four models returned satisfactory R^2 and p values. These models were graphed using MS Excel (Microsoft Corporation, 2018) to FY 2049/50 and are shown in Figure 17. The equation for this particular model is:

$$Fuel\ Consumption\ (GJ) = 2324.7668 \times (Financial\ Year\ (Ending) - 2011)^{-0.6988}$$

Table 3: *Results of a regression analysis of VQ's leased fleet petrol consumption.*

Dependent Variable: Pet_SG_GJ_BCyrs									
Equation	Model Summary					Parameter Estimates		Chosen Model	Justification
	R Square	F	df1	df2	Sig.	Constant	b1		All models have a very high R2 value. The
Linear	0.924	36.246	1	3	0.009	2384.42	-364.117		power model offers the best middle
Logarithmic	0.998	1221.154	1	3	0	2193.561	-941.507		ground between alignment with historical
Power	0.986	214.585	1	3	0.001	2324.767	-0.699	X	data and alignment with qualitative fuel
Exponential	0.987	221.188	1	3	0.001	2765.692	-0.281		consumption forecasts from the port.

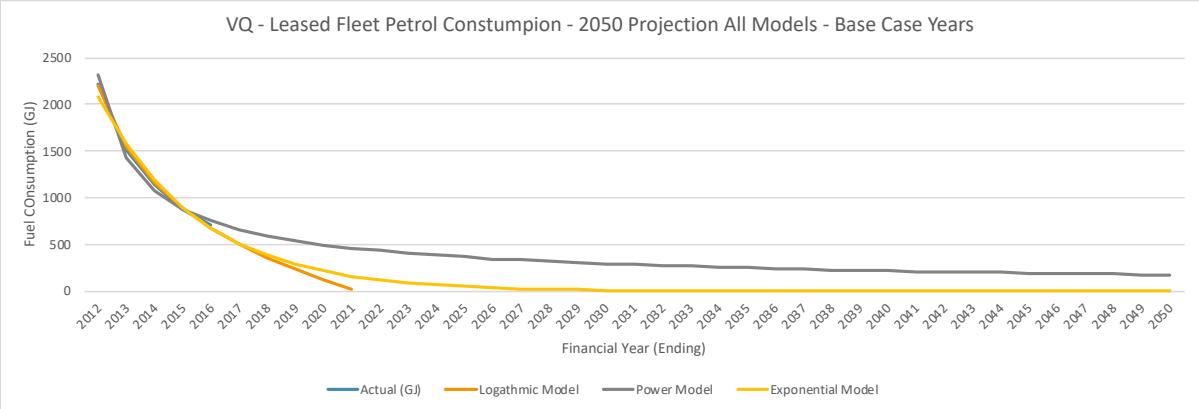

Figure 17: *Statistically adequate models were graphed using MS Excel* ***(Microsoft Corporation, 2018)*** *to help align models with qualitative forecasts.*

This modelling method, whilst less objective than auto-regressive models, offered a powerful means of combining quantitative and qualitative forecasting techniques. Additionally, the added flexibility allowed models to be tailored as required. As such, linear and non-linear regression analysis techniques were adopted for all non-causal models. The statistical summaries and model choice justifications for all time-series based models can be seen in *Appendix 5: Base Case time-series model statistical summaries.*

3.3.2 Causal/explanatory models

Where causal relationships were identified, explanatory (independent) variables were used to predict energy consumption (dependent variable) values. As mentioned in section 2.2, explanatory models can include conventional models, such as basic and multiple linear regression models, and more complex computer-learning models such as artificial neural networks (ANN), and support vector machines (SVM).

Support vector machine (SVM) models were investigated for the development of explanatory energy modelling because of their ability to run using a relatively small amount of observed data points, compared to ANN models. Weka 3 SVM software (University of Waikato, 2019) was experimented with, however, as a result of limitations in the quantity of 'learning' data available and the complexity and intricacy of the software, was ultimately abandoned. Whilst support vector machines may be able to offer significant statistical power for forecasting, linear regression techniques have been shown to provide comparably robust modelling using a simpler development process, when relationships are linear (Ionescu & Candau, 2007). As such, with causal relationships identified as linear, simple linear regression modelling techniques were pursued.

Simple linear regression analysis was conducted using SPSS statistics software (IBM Corp, 2019) to determine the statistical significance of any relationships identified. For Kwinana Bulk Jetty and Kwinana Bulk Terminal, relationships were identified between trade volumes and trade-handling-equipment electricity and diesel consumption. Because of variations in handling methods, the quantity and type of energy consumed for the movement of trade differed significantly depending on the commodity. To get a snapshot of the quantity of energy consumed per commodity, historical energy consumption ratios were calculated, with each commodity given an 'energy per tonne' value. Energy consumption ratios used for the modelling can be seen for KBT in Table 4 and KBJ in Table 5, below. The ratios were then used to develop adjusted annual trade throughputs for the two facilities per energy type. Linear regression analysis was run between adjusted trade values and observed energy consumption values. This provided a more accurate representation of each commodity's energy consumption and allowed for more robust energy modelling when using commodity trade forecasts. Figure 18 demonstrates the accuracy

improvement after adjusting trade volumes respective of each commodity's electricity consumption, with the model's R^2 value improving from 0.915 to 0.980.

Table 4: *KBT energy consumption ratios per commodity.*

Commodity	Electricity (kWh/t)	Diesel (L/t)
Clinker	2.236935804	0.032286196
Granulated Slag	2.535219913	0.529337687
Gypsum	1.750105483	0.149278403
Nutcoke	2.535219913	0.529337687
Bauxite	0.9	0.096698901
Silica Sand	1.477773328	0.223303838
Iron Ore	0.590508077	0.35474843
Spodumene & Non-Metallic Mineral Product	0.652012318	0.223303838
Black Coal	0.590508077	0.35474843
LPG	0	0

Table 5: *KBJ energy consumption ratios per commodity.*

Commodity	Grouping	Electricity Use Rating
Silica Sands	Export - Mobile Conveyor	0
Phophates, potash, urea, ammonium sulphate	Import - Bulk Material Hoppers	1
Sulphur	Import - Siwertell	1
Coal, cement clinker, gypsum, slag residue, soy bean meal, phophates, potash, urea	Import - Small Mobile Hoppers	0
Liquid Petroleum Gas (LPG)	Pipeline	0

The handling method used for commodities traded through KBJ was not as consistent as for KBT, and so commodities were grouped per handling method prior to the adjustment of trade values (Table 5). For the development of energy projections, commodity trade forecasts (provided by Fremantle Ports) were adjusted as per the energy consumption ratios above and then run through the energy model to calculate dependent variable (energy consumption) values. The result can be seen in the KBT electricity consumption Base Case projection, Figure 19, below. The linear equation developed for this model is:

$$y = 2004013 + 0.824954 \times (Electricity\ adjusted\ trade\ throughput)$$

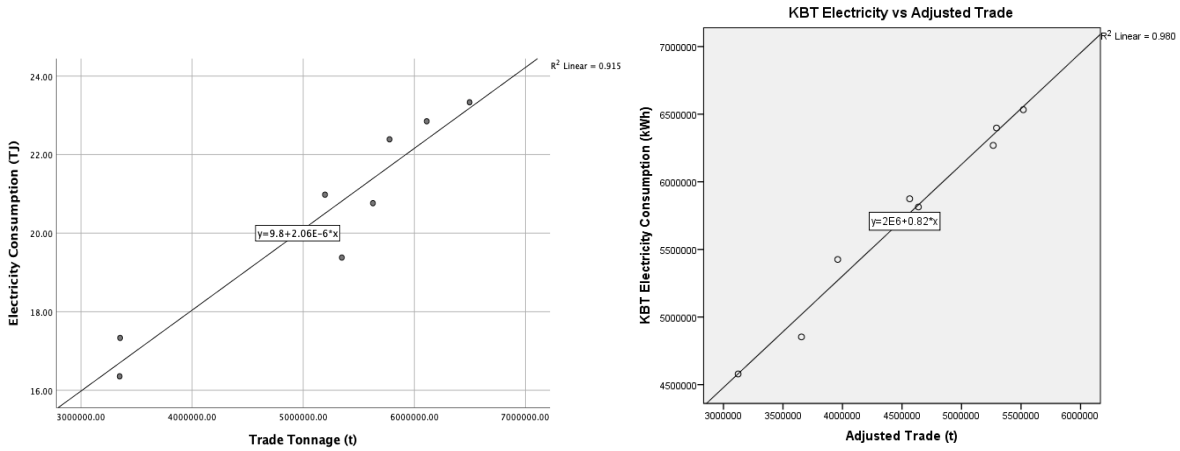

Figure 18: *Actual (left) and adjusted (right) trade volumes for KBT, regressed against electricity consumption. After adjusting trade volumes respective of each commodity's electricity consumption, the R^2 value of the model improved from 0.915 to 0.980. The model had a p value of less than 0.000.*

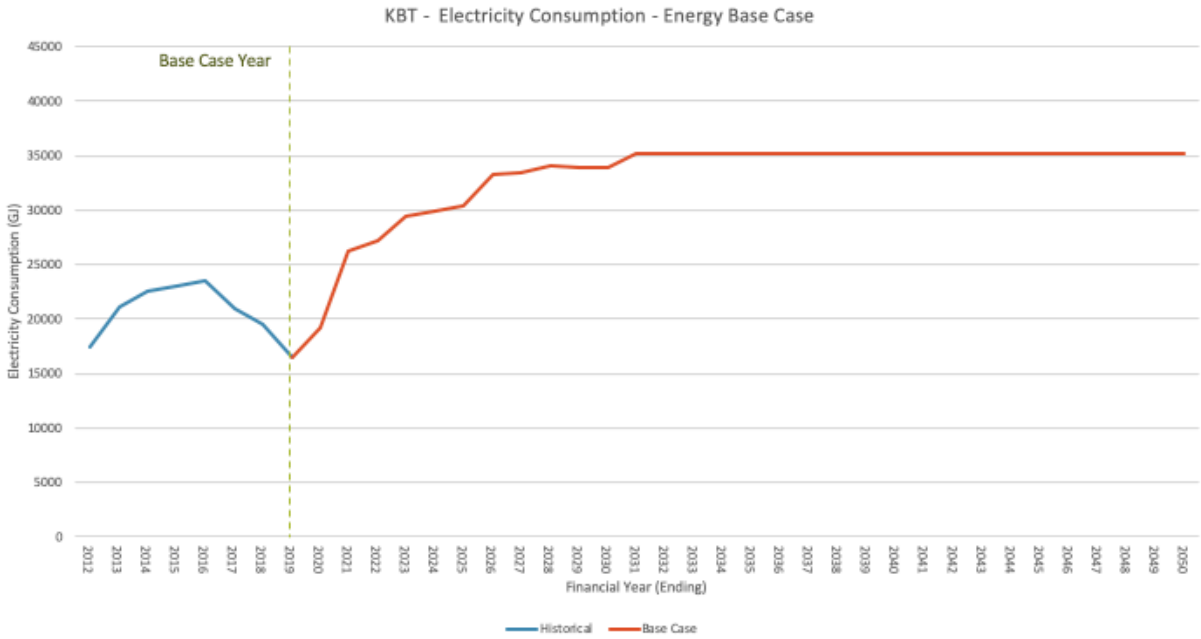

Figure 19: *KBT electricity consumption Base Case projection to FY 2049/50. This explanatory model utilised trade forecasts developed by Fremantle Ports to project future energy consumption.*

Table 6: *Linear regression models developed for KBT and KBJ.*

KBT Electricity Consumption (kWh):						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*trade (adjusted) (t)*	Equation
Simple linear	0.98	299.31	0.000	2004013.34	0.824954	y = 2004013 + 0.824954 * (Electricity adjusted trade throughput)
KBT Diesel ST Consumption (L):						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*trade (adjusted) (t)*	Equation
Simple linear	0.783	21.674	0.003	289842.663	0.139	y = 289842.7 + 0.139 * (Diesel adjusted trade throughput)
KBJ Electricity Consumption (kWh):						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*trade (adjusted) (t)*	Equation
Simple linear	0.896	25.89	0.015	613814.264	0.706	y = 613814.264 + 0.706 * (Electricity adjusted trade throughput)

An explanatory relationship was also identified for North Quay's container terminal. In this instance, however, container trade throughput shared a similar form and handling method and did not need to be adjusted, with raw trade data able to be regressed directly against container terminal electricity consumption. Fremantle Ports' internal container trade forecast AAGR (average annual growth rate) of 3% was used to develop future explanatory variable values. The statistical details of this model can be seen in Table 7, below.

Table 7: *Linear regression model developed for NQ's container terminal electricity consumption.*

NQ Container Terminal Electricity Consumption (kWh):						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*trade (TEUs)*	Equation
Simple linear	0.187	8.964	0.005	344773.073	6.516139	y = 344773.0734 * 12 + 6.516139 * (Projected Container Trade in TEUs)

For the explanatory relationship identified between VQ's small craft diesel consumption, visiting commercial vessel size and the number of commercial vessels arriving per year, a statistically significant model was developed (
Table 8). As no commercial ship data projections were available from the port, these were developed using the time-series and qualitative modelling technique described in section 3.3.1. Projected values were then used as the explanatory variable in the small craft diesel consumption model. The commercial ship forecasts and Base Case energy model developed for VQ's small craft diesel consumption can be seen in Figure 20 and Figure 21, respectively.

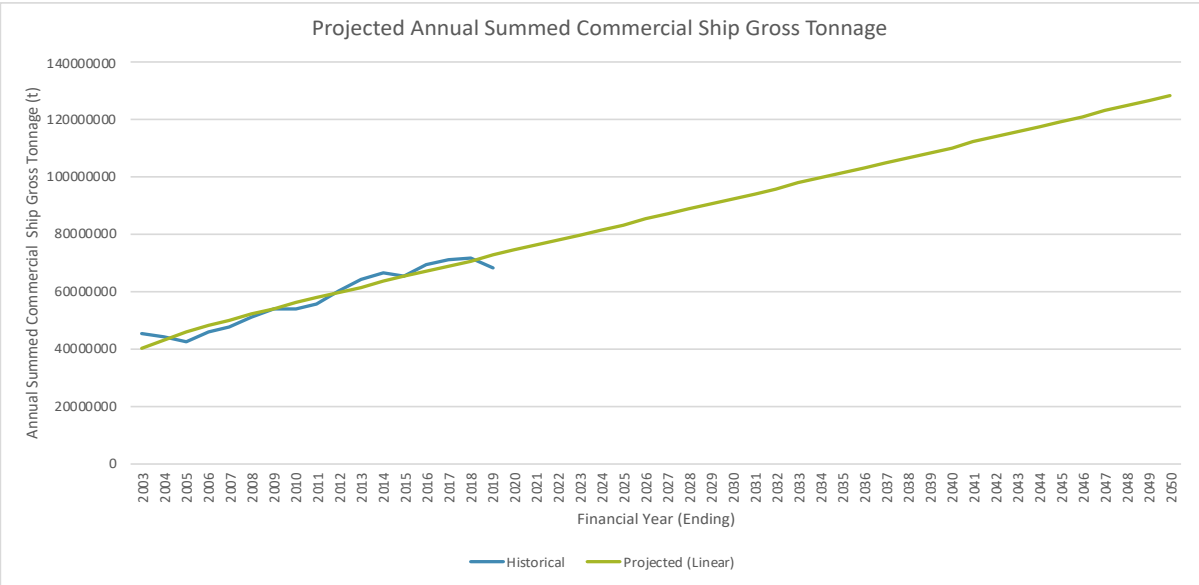

Figure 20: *Projected commercial ship summed gross tonnage (ship visits * average size (GT))*

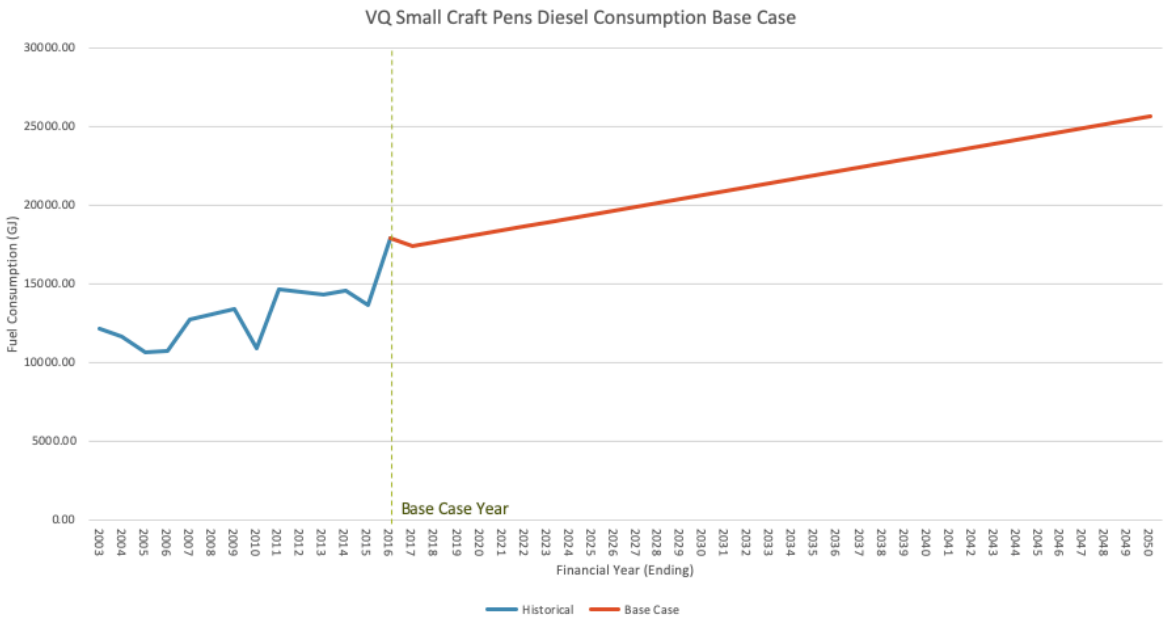

Figure 21: *Base Case projection for Victoria Quay's small craft diesel consumption to FY 2049/50.*

Table 8: *Linear regression model developed for VQ's small craft diesel consumption.*

VQ Small Craft Diesel Consumption (GJ):						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*Summed annual com ship GT (TEUs)*	
Simple linear	0.608691	8.964	0.00165	140369.802		0.003595
Equation						
y = 140369.801707 + 0.003595 * (Projected Ship Visits * Projected Average Gross Tonnage) + 2398.371686						

3.3.3 Error analysis

An error analysis was conducted for each model to ensure their adequate fitness to observed data (see section 0 for more information). For each model, the Absolute Percentage Error of each observed data point is calculated against the corresponding forecast value, as is explained in *Forecasting Methods and Applications* (Makridakis, Wheelwright, & Hyndman, 1998). The Mean Absolute Percentage Error (MAPE) was then calculated to present an error value for the model. An example can be observed for KBJ's electricity consumption model in Table 9 and Figure 22, below. MAPE values for all models developed are listed in Table 10. MAPE values for explanatory models range between 3.3 and 7.1%, with time-series models ranging between 4 and 21%. The exception is the high MAPE values for KBT's and KBJ's Fremantle Ports owned vehicles, a result of high fuel use variability and low initial fuel use values during early years of the historical period.

Table 9: *Error Analysis and Mean Average Percentage Error (MAPE) of KBJ's electricity consumption model.*

Error Analysis (all historical years)			
Associated FY (Ending)	Observed (kWh)	Expected (kWh)	Absolute Percent Error
2011	1 447 943	1 207 754	16.59%
2012	1 523 134	1 252 182	17.79%
2013	1 348 581	1 239 265	8.11%
2014	1 375 993	1 384 913	0.65%
2015	1 337 480	1 339 442	0.15%
2016	1 208 616	1 238 581	2.48%
2017	1 262 601	1 244 289	1.45%
2018	1 322 805	1 300 574	1.68%
2019	1 161 041	1 330 099	14.56%
		MAPE	7.05%

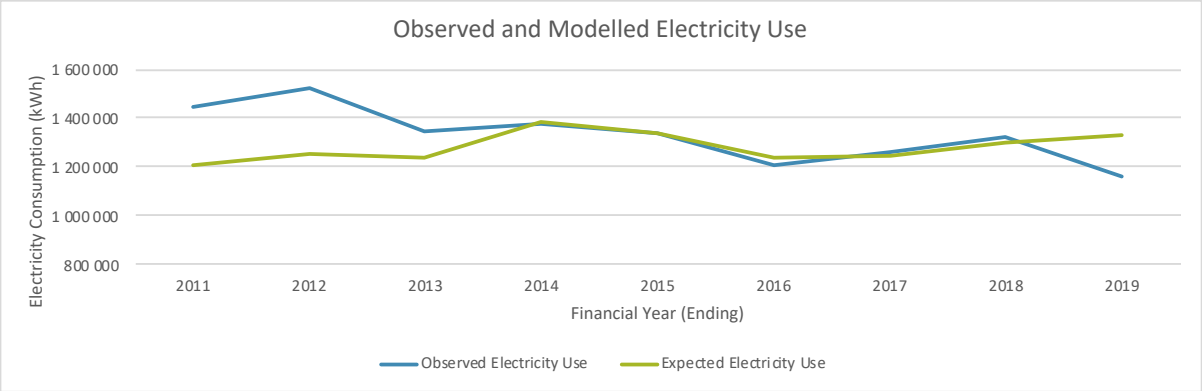

Figure 22: *KBJ's electricity consumption model - observed and expected values.*

Table 10: *Mean Absolute Percentage Errors (MAPE) for all models developed, by model type.*

Dependent Variable	Model Type	MAPE	Dependent Variable	Model Type	MAPE
VQ Vehicle Fleet Leased Petrol	Time Series	4.29%	KBT Vehicle Fleet Owned Diesel	Time Series	50.46%
VQ Vehicle Fleet Owned Petrol	Time Series	20.77%	KBJ Vehicle Fleet Owned Petrol	Time Series	124.67%
VQ Vehicle Fleet Leased Diesel	Time Series	11.64%	KBJ Vehicle Fleet Owned Diesel	Time Series	77.97%
VQ Vehicle Fleet Owned Diesel	Time Series	11.34%			
VQ Internal Electricity	Time Series	6.34%	VQ Small Craft Diesel	Explanatory	7.10%
NQ Internal Electricity	Time Series	11.05%	NQ Container Terminal Electricity	Explanatory	3.33%
KBT Vehicle Fleet Leased Petrol	Time Series	9.98%	KBT Handling Equipment Diesel	Explanatory	6.47%
KBT Vehicle Fleet Leased Diesel	Time Series	17.92%	KBT Electricity	Explanatory	4.39%
KBT Vehicle Fleet Owned Petrol	Time Series	80.45%	KBJ Electricity	Explanatory	7.05%

3.3.4 Conversion from Energy Base Case to Emissions Base Case

Historical energy consumption values were converted into scope 1, 2 and 3 greenhouse gas emission values using emission factors sourced from the Australian National Greenhouse Accounts Factors documents (Commonwealth of Australia, 2019). Future GHG emissions were calculated using forecast emission factors as described in section 3.2.4 of this report.

3.4 Actual Case model development

The Actual Case scenario largely builds off the models developed for the Base Case, however, differs in that actual values observed from the Base Case year to the present are incorporated into the model. Additionally, for future years, the Actual Case model includes sustainability initiatives and operational efficiency improvements. The Actual Case model provides an effective tool to compare actual and expected energy/emissions reductions to a 'business-as-usual' scenario.

Once observed data is incorporated into the Actual Case model, qualitative information is gathered regarding current and planned sustainability initiatives and energy efficiency improvements. Information such as the expected start and end date of initiatives can help estimate how the impacts of sustainability measures will be spread over time. If enough data is available, sustainability and energy efficiency impacts can be quantitatively calculated. As an example, VQ's internal electricity consumption Actual Case is shown in Figure 23, below. For this example, observed energy data is included in the Actual Case to FY 2019/20. Fremantle Ports is currently planning to replace metal halide floodlighting with LED floodlighting along four of Victoria Quay's berths. The expected energy use reduction per bulb was calculated and then multiplied by the number of bulbs that will be replaced. As this project is expected to take two years to complete, the energy reduction was divided by two to equal 119 136 kWh energy reduction per year from FY 2020/21 to 2021/22.

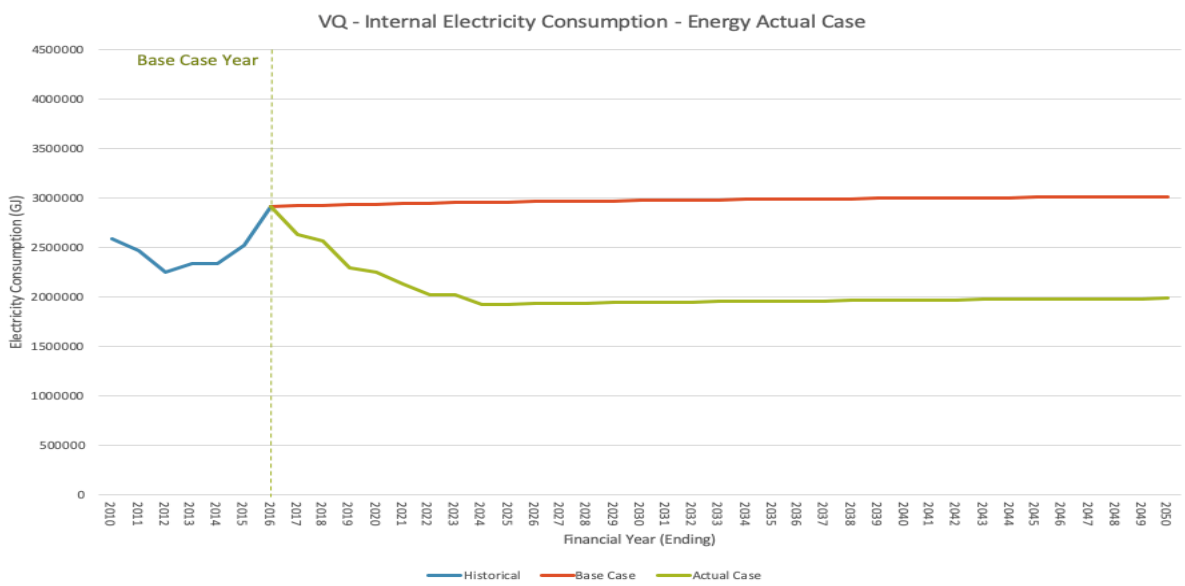

Figure 23: *Actual Case projection for VQ's internal electricity consumption.*

When precise quantitative energy reduction data was not available a qualitative approach was required. This was the case for Victoria Quay's small craft diesel consumption and GHG emissions Actual Case. At the end of FY 2019/20, Fremantle Ports replaced their primary pilot vessel *Berkeley* with the more fuel-efficient *Genesis* vessel. Precise fuel consumption data was not available for the *Genesis* at the time of writing, however; internal expertise expects a fuel efficiency improvement of approximately 10%. A quantitative estimation for the fuel consumption of the *Genesis* was calculated by finding 10% of the average annual fuel consumption of the *Berkeley* vessel over its operational years (FY2015/16 to FY2019/20) and reducing current and projected fuel consumption values by this amount from FY2020/21 onwards. The result can be seen in Figure 24, below.

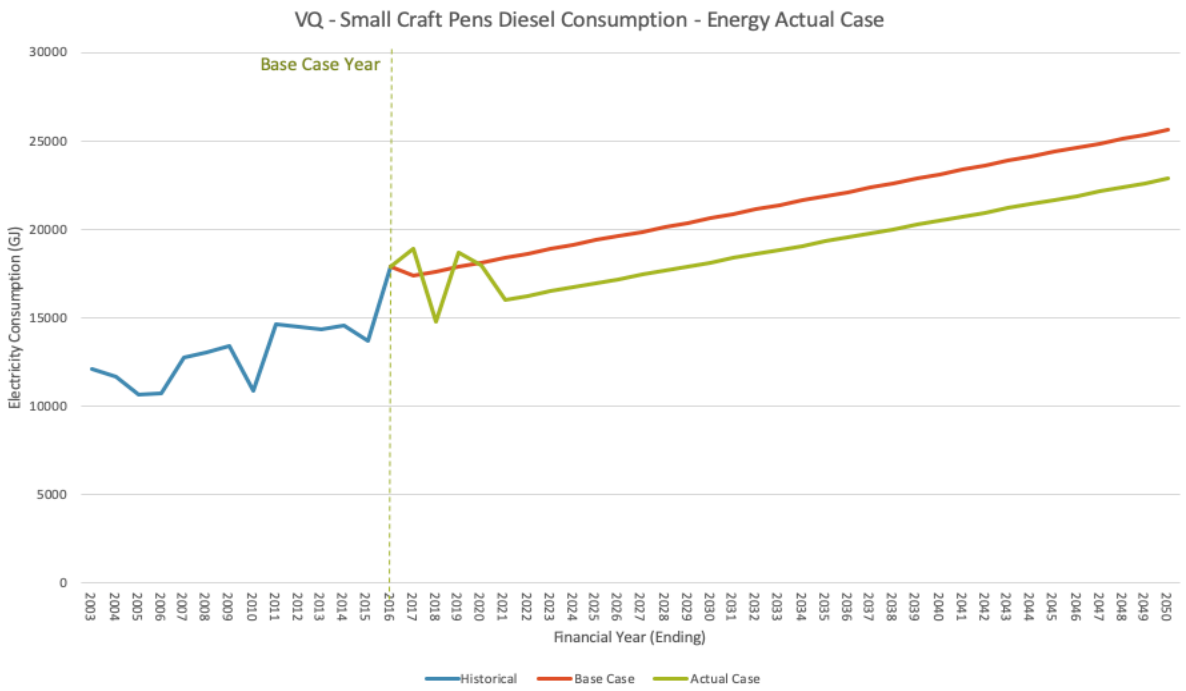

Figure 24: *Actual Case projection for VQ's small craft diesel consumption. Observed data is included to FY 2019/20, with expected energy efficiencies calculated for future years.*

3.5 Case study results

Case study results are presented graphically below, with the Base Case projection in red, the Actual Case projection in green and historical data up until the Base Case year in blue. The Actual Case projections of the subsets of each facility are displayed in grey on the chart. This is to provide information on the 'break-up' of each facility's energy consumption and GHG emissions, in regard to energy consumption source.

3.5.1 Victoria Quay

Base Case modelling expects Victoria Quay's energy consumption to increase to 2050, most notably a result of increasing small craft diesel consumption. Actual case modelling identified that medium-term small craft and internal-electricity energy-efficiency measures will largely counteract energy use increases, keeping VQ's energy consumption below Base Case year values well into the future (Figure 25).

Energy efficiencies and a dropping scope 2 emissions factor are expected to decrease VQ's scope 2 emissions to zero by 2050. GHG emissions from the facility's small craft are expected to increase and become the single largest contributor from FY 2023/24 onwards. The facility's vehicle fleet contributes miniscule amounts of GHG emissions compared to other sources (Figure 26).

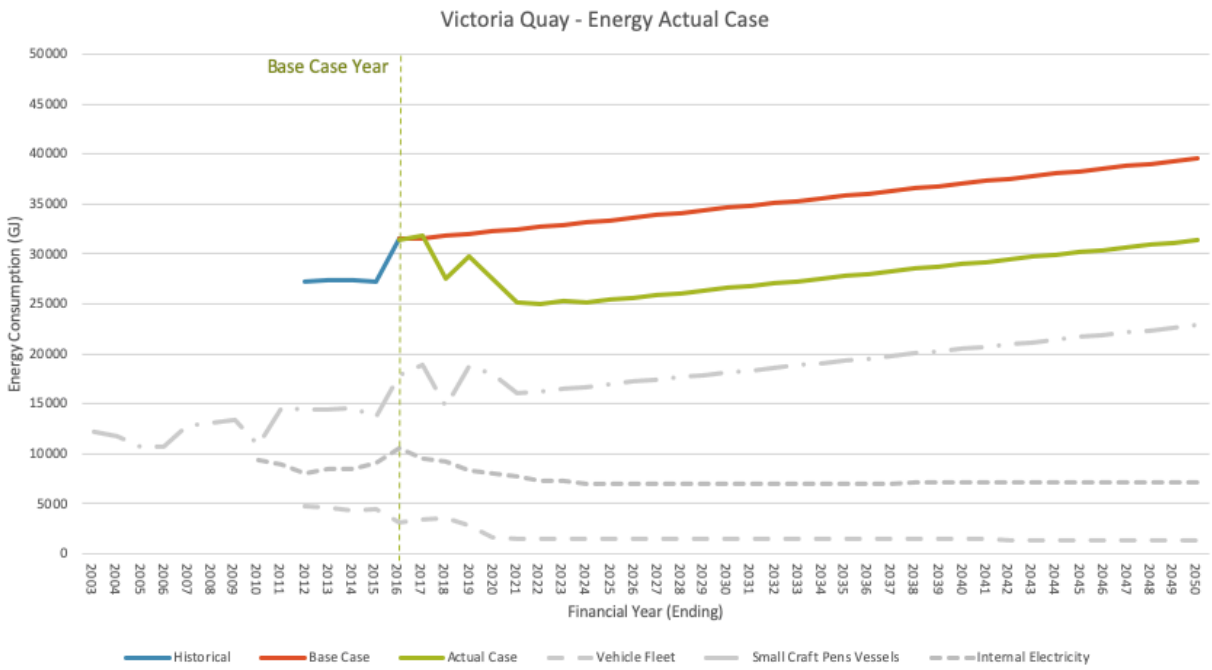

Figure 25: *VQ's energy Actual Case. Grey lines represent a break-down of the facility's energy use sources.*

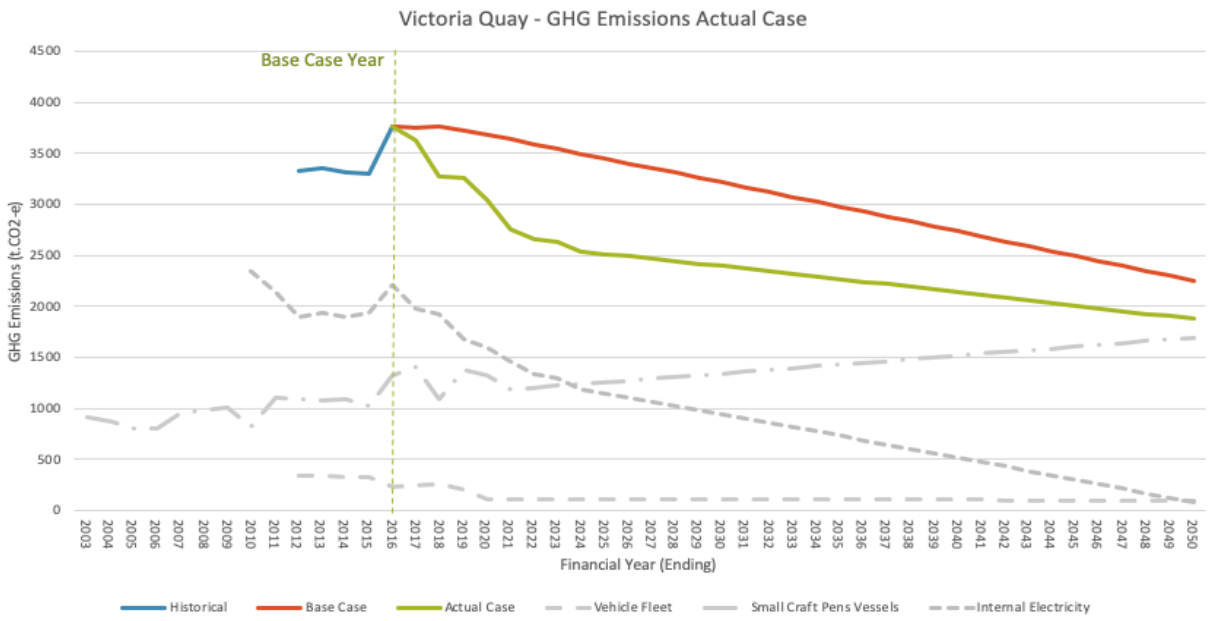

Figure 26: *VQ's emissions Actual Case. Grey lines represent a break-down of the facility's emission sources.*

3.5.2 North Quay

Base Case and Actual Case modelling for North Quay project stable energy consumption for internal use and exponential growth for the facility's container terminals electricity use. Container terminal electricity consumption is expected to increase 59% from FY 2019/20 to FY 2049/50. The container terminals are the dominant consumer of electricity at the facility, with 6.5 times greater consumption than internal use in 2019 and will likely reach 10 times the size by 2050 (Figure 27).

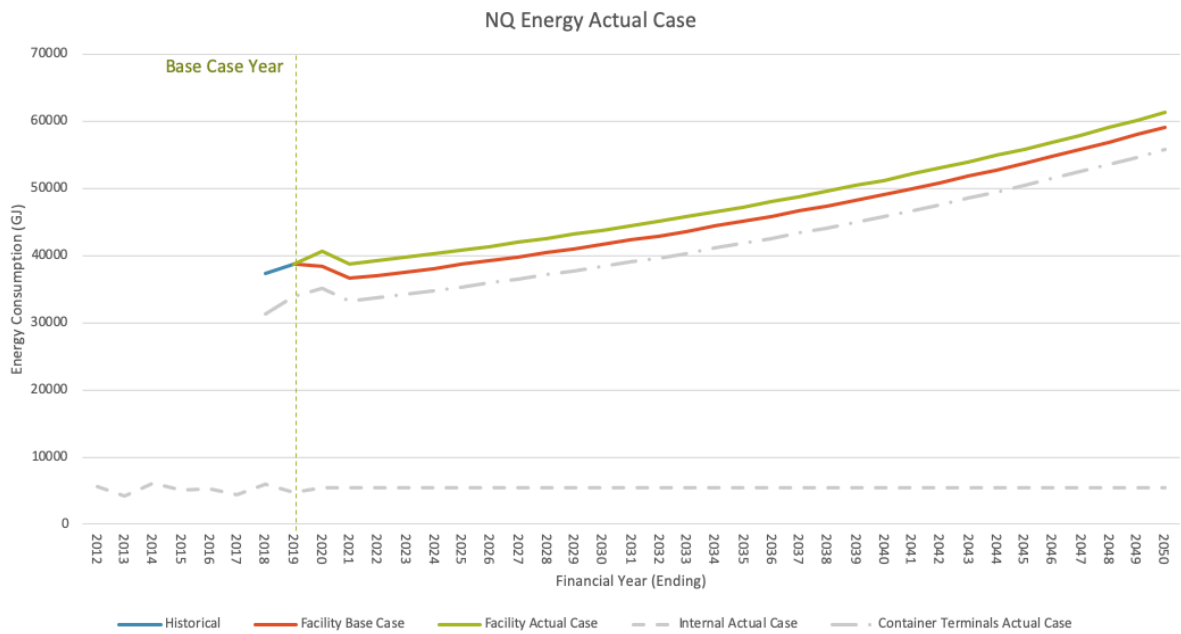

Figure 27: *NQ's energy Actual Case. Grey lines represent a break-down of the facility's energy use sources.*

As NQ's energy use is predominantly electricity based, emissions for the facility will be heavily influenced by decreases in the SWIS scope 2 emission factor (Figure 28). This will counteract notable increases of the facility's electricity consumption (Figure 27). Residual GHG emissions towards mid-century are expected to be entirely comprised of scope 3 electricity generation emissions.

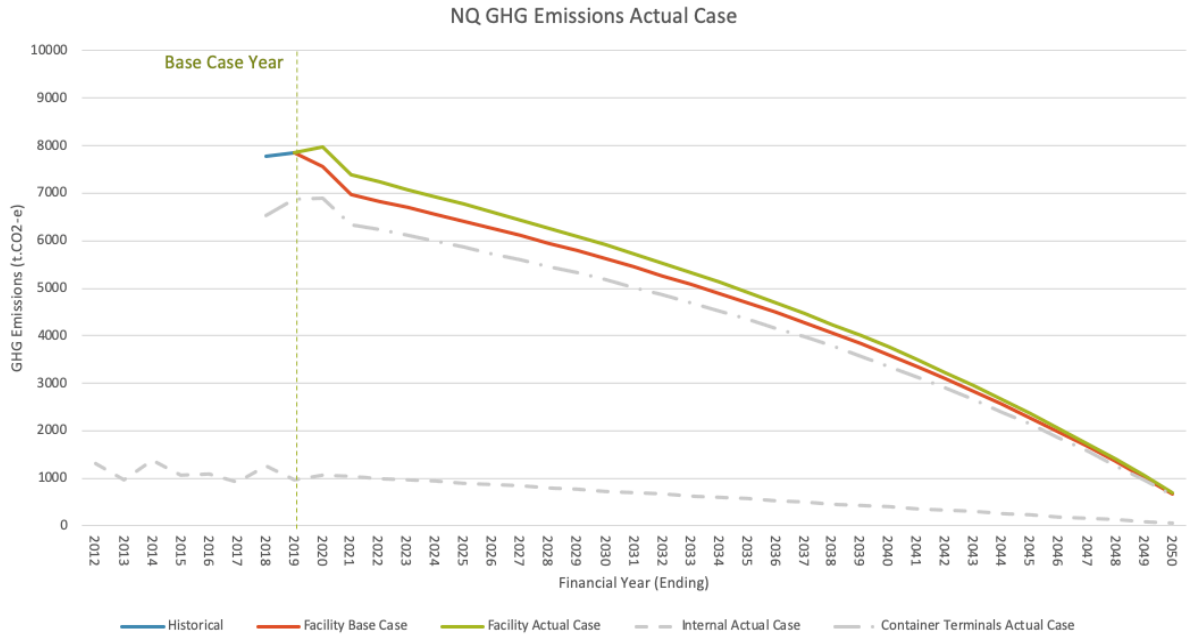

Figure 28: *NQ's emissions Actual Case. Grey lines represent a break-down of the facility's emission sources.*

3.5.3 Kwinana Bulk Terminal

Modelling projected a significant increase in electricity consumption and a mild increase of trade-handling-equipment diesel consumption for KBT to FY 2031/32. In this year, the facility's trade is expected to reach a maximum capacity of 6.5 million tonnes throughput. From then onwards, assuming no major infrastructural upgrades, KBT's energy use is expected to remain stable till 2050. Despite relatively equal energy consumption between electricity and diesel in historical years, commodities requiring electric powered trade-handling-equipment are expected to increase in volume compared to commodities requiring diesel powered equipment (Figure 29).

Electricity use is the largest source of GHG emissions for KBT. SWIS emission factor decreases will counteract electricity consumption growth to the end of the projection period. Diesel-powered trade-handling-equipment is expected to become the largest GHG emission source for the facility in the mid-2040s (Figure 30).

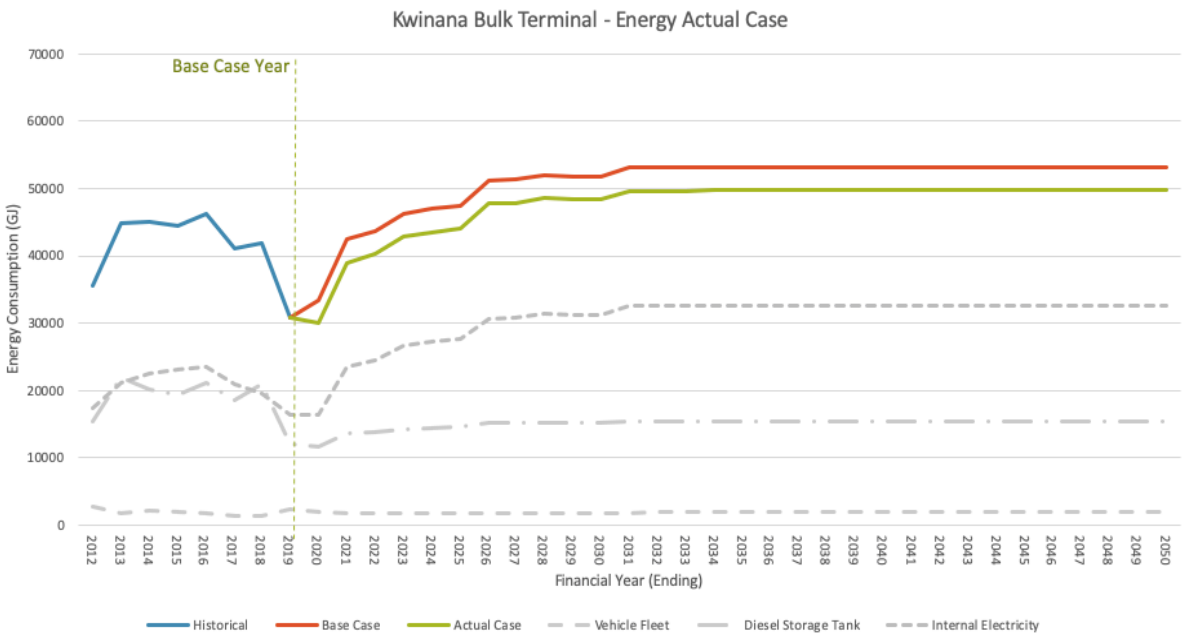

Figure 29: *KBT's energy Actual Case. Grey lines represent a break-down of the facility's energy use sources.*

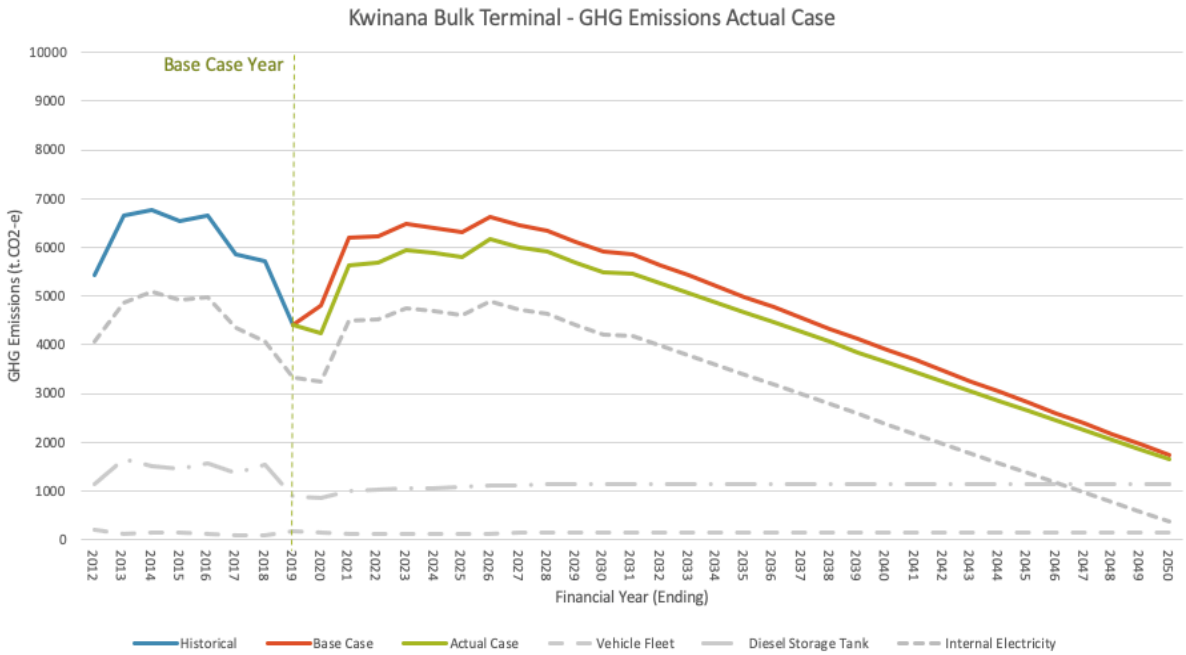

Figure 30: *KBT's emissions Actual Case. Grey lines represent a break-down of the facility's emission sources.*

3.5.4 Kwinana Bulk Jetty

As a result of forecast trade increases to 2050, KBJ's electricity Base Case projects a notable increase in consumption. Because of changes in the facility's operational practises in early 2018, however, KBJ's Actual Case suggests a less energy intensive future for the facility (Figure 31). KBJ's vehicle fleet fuel consumption is miniscule compared to electricity consumption and is expected to remain stable.

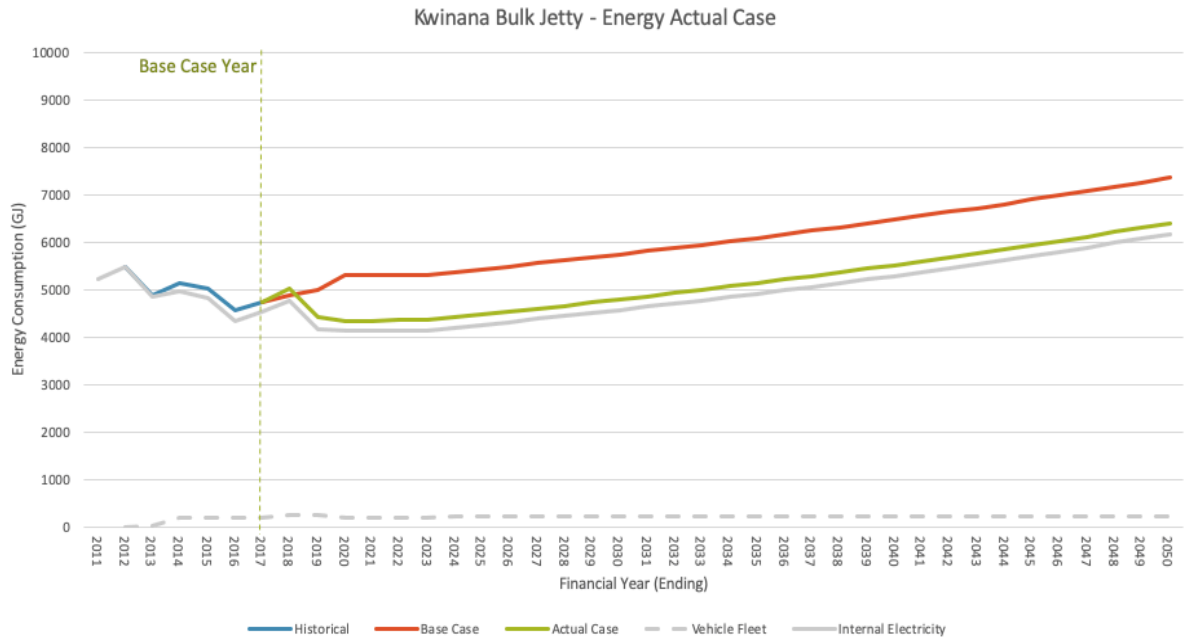

Figure 31: *KBJ's energy Actual Case. Grey lines represent a break-down of the facility's energy use sources.*

KBJ's GHG emissions are expected to decrease almost entirely by 2050, despite increases in electricity consumption. This is mostly the result of projected reductions of the SWIS scope 2 emission factor. Remaining emissions in 2050 are expected to be from the facility's vehicle fleet and scope 3 emissions from electricity use.

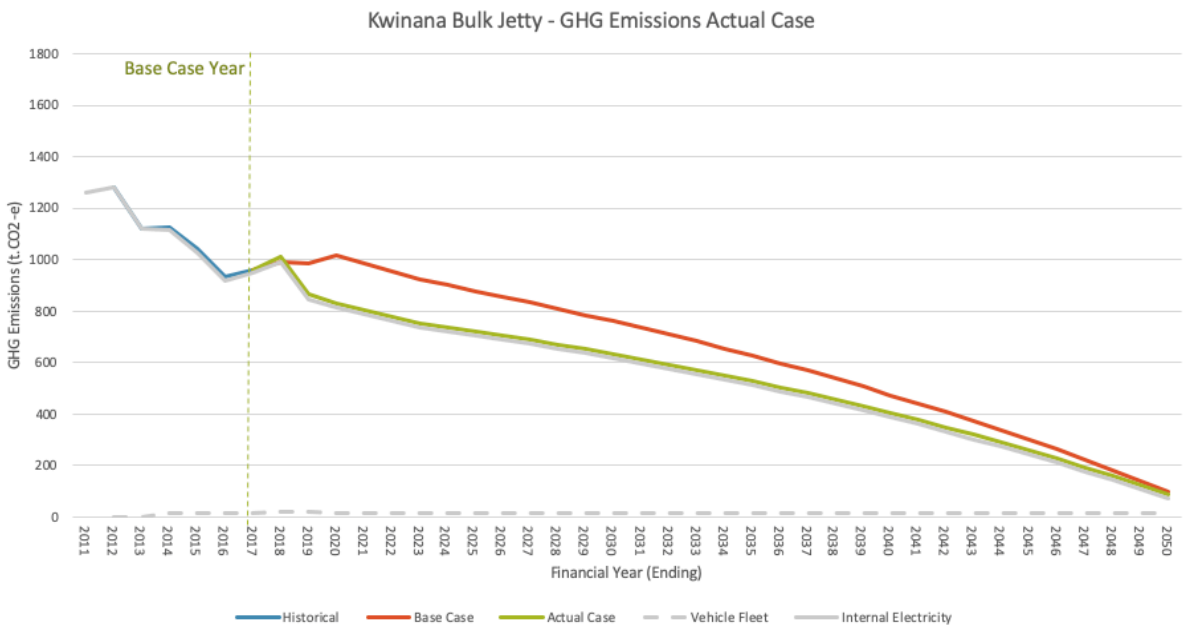

Figure 32: *KBJ's emissions Actual Case. Grey lines represent a break-down of the facility's emission sources.*

3.5.5 Total port energy consumption

In Financial Year 2018/19, the energy consumption of Fremantle Ports' internal operations and container terminals was 103 768 GJ. Whilst the port's energy consumption decreased by 1 200 GJ in FY 2019/20, it is expected to increase 53% to 159 258 GJ by FY 2049/50 under the Base Case scenario. Modelling suggests the majority of this growth will be the result of increases in electricity use at KBT and North Quay's container terminals, although increases of Victoria Quay's small craft diesel use and KBT's trade handling equipment diesel use will also likely contribute.

KBT, VQ and NQ's container terminals are the port's largest consumers of energy and have the greatest influence over the port's total energy consumption. Modelling expects KBT's energy use to grow substantially compared to VQ in coming years. The energy consumption of KBJ is considerably less than the aforementioned facilities, 11-14% of the energy consumption of other facilities in FY 2018/19. The port's vehicle fleet is miniscule relative to total facility energy use, representing 4-10% of total energy consumption and is expected to remain steady to 2050.

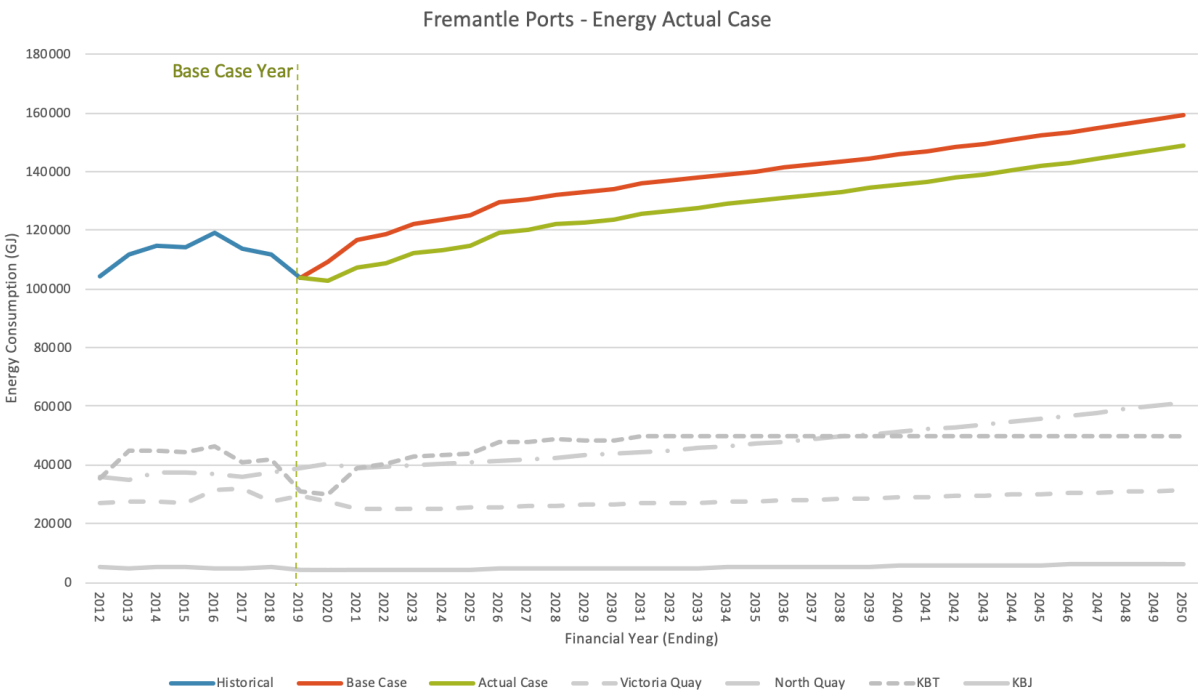

Figure 33: *Fremantle Ports' internal and container terminal energy consumption Base Case and Actual Case. Grey lines represent the contribution of different facilities within the port.*

The result of current and planned sustainability and energy efficiency measures across the port is expected to result in a 6.5% (10 358 GJ/year) decrease of energy

consumption by 2050, relative to the Base Case. A graphical representation of Fremantle Ports' Base Case and Actual Case energy projections can be viewed in Figure 33, below.

3.5.6 Total port GHG emissions

In Financial Year 2018/19, Fremantle Ports calculated that they released 16 389 t.CO_2-e (tonnes of carbon dioxide equivalent) as a result of internal operational activities and electricity use at NQ's container terminals. This is down from a high of 19 018 t.CO_2-e in FY 2013/14. Looking forward, GHG emissions are expected to rise slightly over the next couple years as a result of increased trade-related electricity use at KBT. This is not expected to continue, however, as SWIS scope 2 emission factor reductions will largely counteract any further energy consumption increases. By 2050, the port's emissions are expected to decrease by 71% to 4 756 t.CO_2-e under the Base Case scenario and by 74% to 4 322 t.CO_2-e under the Actual Case scenario (Figure 34).

In FY 2018/19, Fremantle Ports' scope 2 emissions represented 82% of the port's total GHG emissions. Assuming electricity generation of the SWIS becomes 100% renewable by 2050 (see section 3.2.4), Fremantle Port's scope 2 greenhouse gas emissions will drop to zero by mid-century. As a result, modelling suggests Fremantle Ports' total emissions will decrease drastically without any major operational or infrastructural changes. In 2050, the largest sources of GHG emissions are expected to be from the operation of diesel-powered small craft and trade handling equipment. These are expected to contribute 1612 t.CO_2-e (44%) and 1081 t.CO_2-e or 29% of total port emissions, respectively. Additionally, the modelling projects that the vehicle fleet will contribute 324 t.CO_2-e (8.8%) of the port's GHG emissions by 2050. These operations will need to be the focus of decarbonisation efforts if the port is to meet their 2050 goal for net carbon neutrality.

Scope 3 emissions are projected to contribute the remainder of the port's 2050 emissions, with scope 3 liquid fuel emissions contributing 461 t.CO_2-e or 13% of total port emissions and scope 3 electricity emissions contributing 587 t.CO_2-e or 16%.

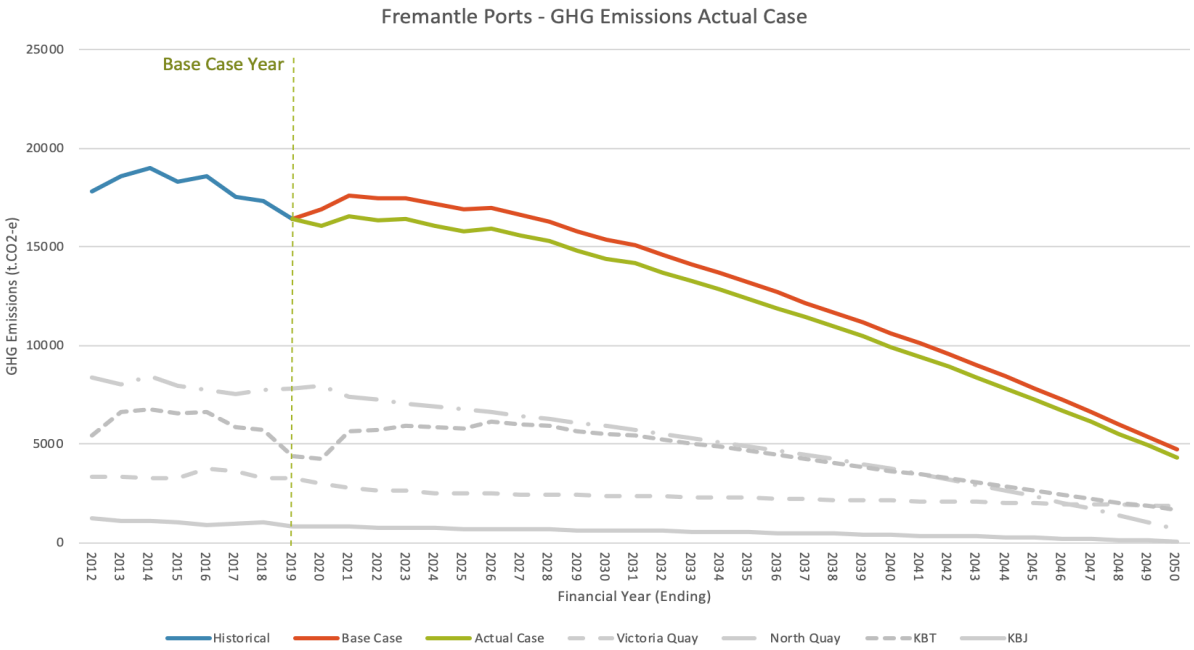

Figure 34: *Fremantle Ports' internal and container terminal GHG emissions Base Case and Actual Case. Grey lines represent the contribution of different facilities within the port.*

4 Discussion

The United Nation's International Panel on Climate Change (IPCC) has warned that a global temperature increase above 1.5°C will worsen the severity of climate change impacts and the frequency at which impacts occur (IPCC, 2018). Many recent devastating environmental and social events, including Australia's catastrophic 'black summer' bushfires in 2019/20, mass bleaching events on the Great Barrier Reef in 2016, 2017 and 2020 and unprecedented locust swarms in east Africa, have been determined to be either caused or exacerbated by climate change (Flannery, 2020; Great Barrier Reef Marine Park Authority, 2020; Munang, 2020). Considering such severe impacts are already being experienced at only 1.15°C of warming (NOAA, 2019), there is widespread concern of what further temperature increases will entail. Greenhouse gas emissions have increased on average 1.5% per year over the last decade. To meet the 1.5°C target of the Paris Climate Agreement, global emissions will need to decrease by 7.6% per year to 25Gt (gigatonne) annual global emissions by 2030. This is the equivalent of the estimated CO_2 emissions reduction resulting from the Covid-19 pandemic in 2020, repeating annually (Le Quéré, et al., 2020). For every year that global climate action lags, the more intense emissions reductions will need to be. If countries began acting sufficiently in 2010, annual emission reductions would only need to be 3.3%. Conversely, if action is delayed to 2025, the annual emissions reductions necessary to keep global warming below 1.5°C will rise to 15.4% per year (United Nations Environment Programme, 2019). The result of emissions reduction gaps on global temperature increases can be seen in Figure 35. If current emission rates continue, we will reach a point where-by a smooth transition towards global decarbonisation is not feasible and either the global economy or emissions reduction targets will need to be sacrificed. For the mean-time, limiting global warming to 1.5°C is still possible, however, requires urgent and large-scale action.

The case study presented in Chapter 3 of this report has displayed the feasibility for infrastructural assets to attain net carbon neutrality by mid-century. Base line modelling developed as part of this report expects Fremantle Ports' internal operations and container terminal GHG emissions to decline 71% of current levels by 2050, predominantly as a result of increased renewable electricity generation on

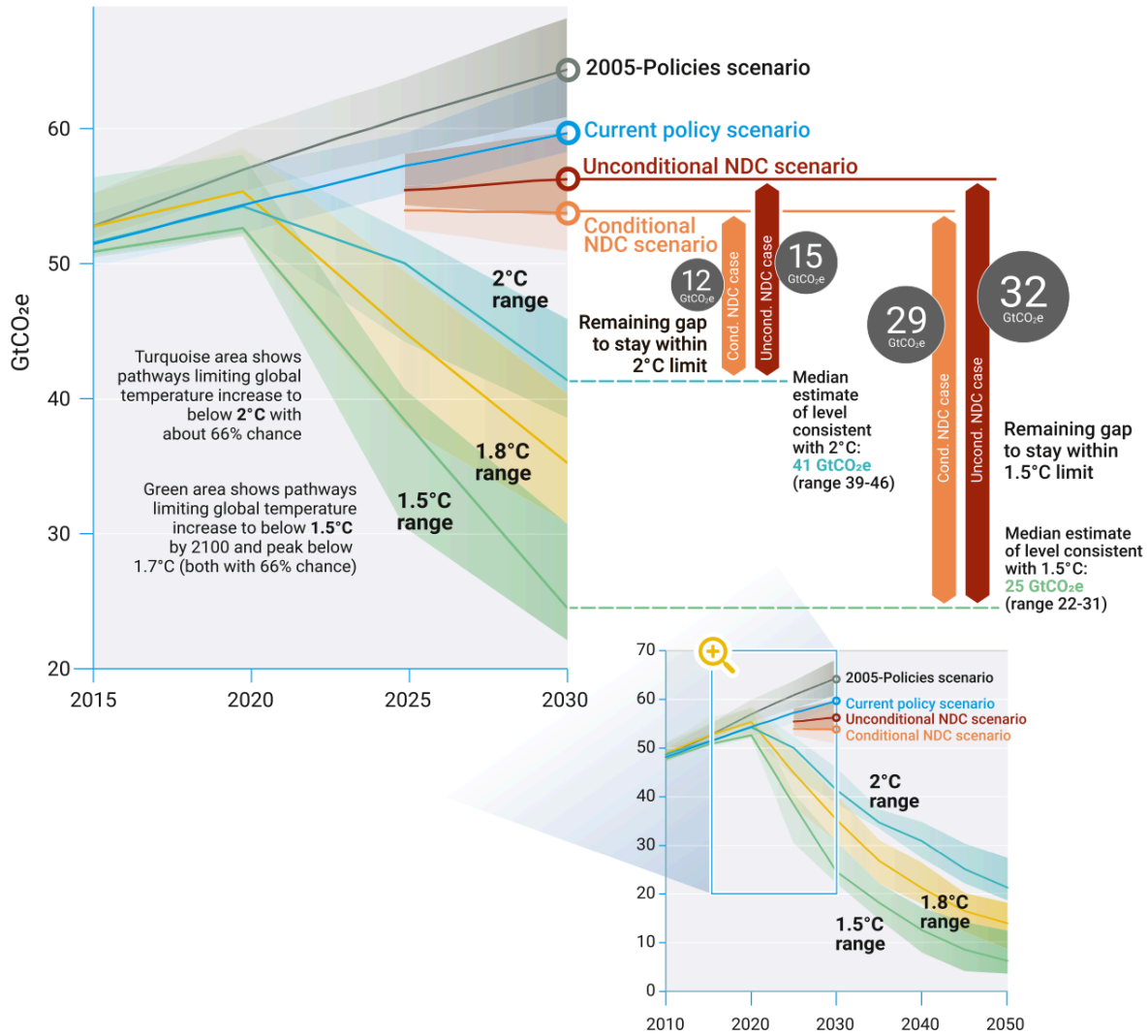

Figure 35: *Global GHG emissions under different scenarios and the emissions gap by 2030* ***(United Nations Environment Programme, 2019)****.*

the grid. Recent and upcoming energy and operational efficiency improvements are modelled to provide an additional 3% emissions reduction. Whilst under the Actual Case modelling Fremantle Ports will still contribute 4 322 t.CO_2-e, the port's projected decrease of emissions, despite only small climate change mitigation actions, highlights the attainability of carbon neutrality for ports and infrastructure assets over a long time-span. This is, of course, under the assumption that other facets of the economy similarly work towards decarbonisation. The global uptake of, and investment in, renewable energy and carbon-neutral technologies will in turn increase the feasibility of organisational carbon neutrality. Whilst not included in this report's Actual Case scenario, it is likely that as renewable electric, hydrogen and biofuel technologies become more affordable and available in the mainstream market, they will begin to phase out carbon-intensive alternatives. Under such a

scenario, organisations and infrastructure assets will be able to decarbonise smoothly, cost effectively and with only small direct internal action. With carbon neutral technology advancing rapidly, and affordability increasing year-on-year (United Nations Environment Programme, 2019), the question is no longer if decarbonisation of an organisation's operations is possible, but rather how quickly it can happen and for what cost. The answer to these two questions will likely be the deciding factor as to whether the world's challenge to limit global warming to 1.5°C is successful.

4.1 The robustness and usability of this methodology

The modelling methodology used for this report successfully developed long-term energy consumption and GHG emission projections for Fremantle Ports. Whilst the true robustness of the modelling will not be known until several years down the line, error analyses indicated an acceptable level of fitness between modelled values and observed/validation values for most models.

The use of linear and non-linear regression analysis methods for the development of time-series modelling provided a flexible and statistically sound technique. Whilst autoregression techniques such as ARMA and ARIMA would likely provide more robust forecasting in the short- and medium-term, especially where seasonal or other patterns exist, the ability to incorporate qualitative forecasts in the modelling proved to be vital for projecting into the long-term. Qualitative information, for example surrounding government regulations and business policy changes, can have large, long-term influences on a facility's energy consumption and emissions. Such qualitative information is not easily incorporated into autoregressive models, besides being used to validate qualitative fitness after development. Whilst it is possible that complex artificial intelligence modelling may provide more powerful and robust projections, the linear and non-linear regression analysis methods conducted in this report provide a simple yet statistically and qualitatively sufficient means of developing long-term energy consumption and GHG emission projections.

Error analyses of the time series models developed for this report consistently found Mean Absolute Percentage Error (MAPE) values of less than or equal to 20%. Whilst this value is higher than what would be considered ideal, it still resembles an adequate level of fitness considering the highly variable nature of the historical data

(Lewis, 1982). Four of the twelve time-series models displayed MAPE values significantly higher than 20%, however, this is predominantly a result of the scale sensitivity of the MAPE technique and the tendency for its values to become extreme when dealing with low-volume data. This highlights one of the weaknesses of the Mean Absolute Percentage Error analysis technique, and perhaps the 'Mean Absolute Deviation / Mean' error analysis method would be better suited for this application (Stellwagen, 2019). It is to be noted that time-series modelling techniques are typically considered less robust that causal models, and that causal models should be used where statistically significant explanatory relationships are present (Makridakis, Wheelwright, & Hyndman, 1998).

Where causal relationships were discovered, the use of simple linear regression was found to be an effective and powerful method to model energy consumption to explanatory variables and develop long-term energy consumption and GHG emissions projections. The MAPE values of causal models developed in Chapter 4 were all less than or equal to 7%, indicating strong fitness of modelled data to observed values. Limitations of data availability posed the largest barrier to model robustness, especially for the development of North Quay's container terminal energy model, of which historical energy data was only available for two years prior.

The energy-consumption-by-commodity-type techniques used for KBT and KBJ proved to be an effective method to incorporate complex variations of energy consumption into simple linear equations. Multiple regression analysis was experimented with, however, it was found that the adapted simple regression method used above provided for greater fine-tuning of commodity energy use data (both quantitatively and qualitatively). The weaknesses of these models are based around the accuracy of historical and predicted commodity-energy-consumption ratios. Whilst the energy consumption ratios quantitatively developed for commodities that have been historically traded through the facilities are likely considerably reliable, those qualitatively predicted for commodities yet to be traded may be inaccurate. If new commodities become key imports/exports in the future, small inaccuracies in predictions can lead to large errors in energy and emissions projections down the line. Additionally, unlike with time-series projections, causal projections rely heavily on explanatory-variable forecasts. This opens up a key vulnerability for the method; if explanatory variable forecasts materialise into poor representations of reality, energy

and emissions projections will similarly become inaccurate. These shortcomings are mostly the result of limitations of historical data availability and explanatory variable forecast robustness and not a reflection of the modelling technique itself. Whilst complex computer learning based modelling techniques may provide more robust projections where non-linear relationships are present (Ionescu & Candau, 2007), for the modelling of linear-causal relationships, simple linear regression using the least squares method was found to provide a simple yet powerful method for developing long-term energy consumption and GHG emissions projections.

Some of the notable benefits of this methodology include the low expertise and software requirements necessary for the development of projections. Whilst SPSS statistics software (IBM Corp, 2019) was used for the development of this report's case study projections, Microsoft Excel (Microsoft Corporation, 2018) can similarly be used for linear regression analysis using the free Analysis Toolpak add-on. This prevents the necessity for organisations to purchase and learn expensive and often complex statistics software, increasing the accessibility of this methodology drastically.

One thing to be considered regarding the application of this methodology to the case study is the limited size of the project's scope. Fremantle Ports' energy and emissions projections were limited to the boundary of the organisation's internal operations and the port's container terminals. This is in contrast to the often much broader operational scope of ports' carbon inventories (IAPH, nd). Additionally, only scope 3 emissions related to energy use are included in the projections. Despite this, it is believed that the methodology developed by this report will be able to be adequately adapted for larger scopes within the port and greater infrastructure industries.

4.2 Analysis of the ISCA Base Case Approach

The modelling methodology developed as part of this dissertation project followed the general baselining process laid out by the Infrastructure Sustainability Council of Australia's (ISCA) *Base Case Approach* (ISCA, 2017). By following the *ISCA Base Case Approach*, infrastructure assets are using what could become an industry standard energy and carbon forecasting methodology, providing easy model

comparisons throughout the infrastructure industry. Additionally, modelling developed by infrastructural assets that follow the *Base Case Approach* have the potential to become eligible for IS Rating Scheme Ene-1 and Ene-2 (Energy and Carbon) credits (ISCA, 2017). For these reasons, the use of ISCA's *Base Case Approach* has become increasingly attractive. However, despite providing an adequate scaffolding for the development of energy and carbon emissions baselines and projections, the *Base Case Approach* contains major information gaps, especially regarding the provision of specific modelling techniques, for which none are mentioned. For this reason, as well as to acknowledge the increasing desirability of its use, the *Base Case Approach* was incorporated into the modelling methodology, ultimately testing its usability for the development of long-term energy consumption and GHG emissions projections. A critical analysis of the approach is written below.

4.2.1 Variable/constant energy consumption

For the purpose of the IS rating scheme, ISCA has specified two types of energy consumption (ISCA, 2017);

- Constant consumption: "Resource use which is relatively consistent year on year."
- Variable consumption: "Resource use caused by activities that are relatively unplanned and/or change year to year depending on upgrades, budget/funding, responses to incidents or reactive maintenance."

The definition of these two terms in the *IS Operations Technical Manual* is arbitrary. Firstly, both terms include energy and emissions related to 'reactive maintenance'. Secondly, intermittent and abnormal demand and utilisation is considered as variable consumption; not to be included in the Base Case modelling. The point at which consumption is considered as intermittent or abnormal is subjective and may lead to the development of projections which distort the actual consumption of the facility.

Further, the ability for organisations to retrospectively identify the specific energy usage of variable consumption sources to an accurate degree can be very difficult. In the Fremantle Ports case study, for example, construction work was undertaken at North Quay during the historical period. As a capital enhancement, this energy consumption would be considered as 'variable' under ISCA's definition. However, whilst electricity consumption did increase in the year that works were undertaken, sufficient data was not available for the facility to determine what proportion of the

electricity use was a result of construction work and what was from standard operational practises. As such, all internal electricity consumption at North Quay was decided to be considered as ‘constant consumption’.

As a result of difficulty distinguishing variable from constant energy consumption, both quantitatively and qualitatively, as well as to include what was considered a more accurate representation of the port’s total energy consumption and emissions, all historical energy consumption from Fremantle Ports was considered as ‘constant’ energy consumption and included in model development.

4.2.2 Baselining: Setting a Base Case year

The setting of a baseline or ‘Base Case’ year is an essential part of developing baseline forecasts and projections. For the designation of a Base Case year, the *Base Case Approach* states to choose a period which is “representative of the asset’s performance prior to the implementation of efficiency initiatives”. Whilst this brief sentence on the topic should be elaborated in the documentation, the general approach presented is credible. By selecting a period prior to the implementation of energy efficiencies and emissions reductions, the facility can include previous sustainability improvements in their Actual Case and compare these to their Base Case projection. One difficulty experienced when developing the Fremantle Ports case study was the selection of a Base Case year when there were different ‘standard’ operating years amongst energy consumers within a single facility. Ultimately, compromises had to be made, with the facility’s largest energy consumers typically dictating the Base Case year selection.

4.2.3 Use of the term ‘footprint’

A small drawback of the *Base Case Approach* is the frequent misuse of the term ‘footprint’. As defined by the International Organisation for Standardisation (ISO) documentation on carbon foot-printing (ISO/TS 14067:2018); a carbon footprint refers to an asset’s life cycle greenhouse gas emissions, including emissions released during the manufacture, construction and disposal of the materials, equipment and infrastructure of an asset (ISO, 2018). As operational emissions inventories are typically not concerned with such broad a scope and depth of analysis, the term that would more appropriately describe what is developed using

the *Base Case Approach* is a 'carbon inventory' forecast/projection (IMO & IAPH, 2018).

4.2.4 Scenario inclusion

The *Base Case Approach*'s incorporation of a base line scenario and an actual case scenario provides powerful projections, allowing the comparison of observed and expected energy consumption and emissions to a situation under business-as-usual. As is noted in the *IS Operations Technical Manual* (ISCA, 2017), this provides a quantifiable means to demonstrate past and planned reductions of energy consumption and GHG emissions.

However, despite these strengths, the approach may benefit greatly with the inclusion of an additional scenario. A third scenario diverging from Base Case and Actual Case assumptions would provide greater flexibility and robustness to the projections. One such scenario, for example, may assume a low-carbon future where-by electric vehicles and hydrogen-powered vessels are the norm by 2040. Alternatively, a scenario may be developed under the assumption that the scope 2 emission factor of the electricity grid does not decrease to zero in the coming decades as projected, and as such the facility is responsible for high levels of emissions. The use of three different scenarios for energy forecasting has been demonstrated by Intarapravich et. al. (1996), incorporating; high, low and business-as-usual energy demand scenarios. It is believed that a similar scenario approach, adapted for carbon intensity, would benefit the *Base Case Approach* significantly.

4.2.5 Recommendations

The general process of the *Base Case Approach,* comprises of three sections; the Base Case Proposal, Base Case footprint and Actual Case footprint. Whilst this approach was considered adequate for the development of long-term energy consumption and GHG emissions projections, as tested in Chapter 3, there are several recommendations to its use which would improve its general usability.

The book *Forecasting Methods and Applications* by Makridakis et. al. (1998) includes a five-step process for the development of forecasts and projections:

1. **Problem definition** – developing a deep understanding of the problem at hand, how the forecasts will be used and definition of any assumptions required for modelling.
2. **Gathering information** – gathering qualitative and quantitative information, historical analysis.

3. **Preliminary (exploratory) analysis** – data smoothing, trend and relationship discovery.
4. **Choosing and fitting the models** – experimenting with different models and choosing the best technique.
5. **Using and evaluating a forecasting model** – forecasts/projections are developed using the methods chosen in step 4 and an evaluation of the models is conducted.

This process provides a clear and streamlined approach to forecasting, consisting of a more grounded and easily followed strategy, with a greater focus on model development, than what is presented in ISCA's *Base Case Approach*. To gain the benefits of both model development approaches, it is recommended that Makridakis et. al.'s five-step strategy (1998) is aligned with and incorporated into the *Base Case Approach*, as demonstrated in Figure 36, below.

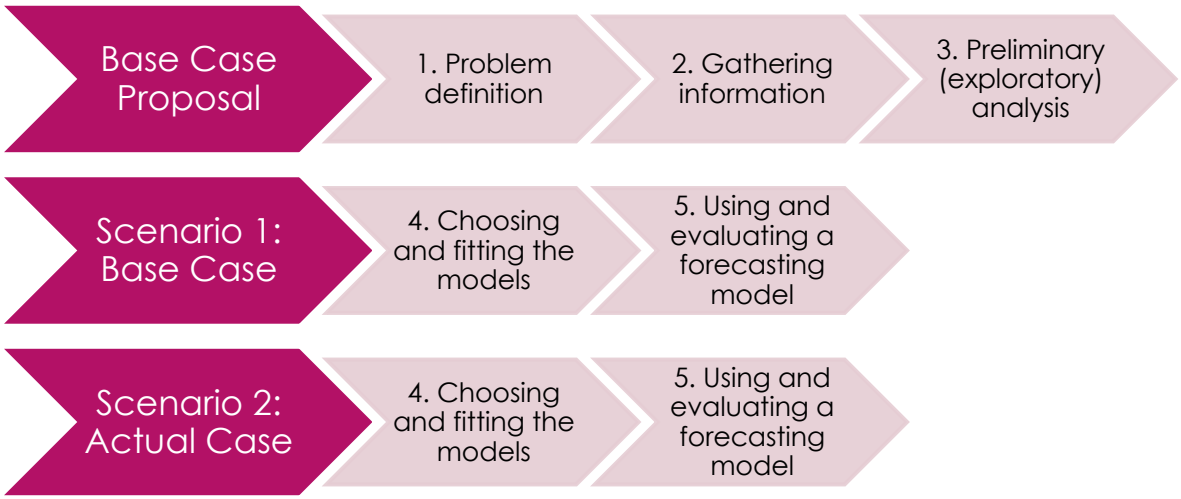

Figure 36: *Alignment of Makridakis et. al.'s five-step strategy* ***(1998)*** *with ISCA's Base Case Approach* ***(2017)****.*

Additionally, it is recommended that a third scenario is developed alongside the Base Case and Actual Case scenarios, as described in section 4.2.4 above, to allow for greater flexibility and usability of projections.

4.3 Opportunities for ports to reach net carbon neutrality

Ports, businesses and infrastructure assets around the world are facing increasing pressure to implement climate change mitigation policies, reduce greenhouse gas emissions and actively work towards attaining net carbon neutrality. To achieve carbon emission reductions, a number of mechanisms can be used by ports. These include: programmes and policies to reduce emissions from internal operations; lease requirements and tariff charges to encourage emissions reductions from port

tenants; outreach and climate change education programs; incentive schemes to incentivise tenants, customers and partner organisations to improve their sustainability; and the purchase of carbon offsets (IAPH, nd).

One of the largest causes of emissions from ports' internal operations are scope 2 emissions. However, as was demonstrated in the Fremantle Ports case study, increasing grid renewable electricity capacity will continue to result in declining scope 2 emission factors for much of the developed world's electricity networks. As a result, port and infrastructure assets will very likely see drastic scope 2 emission reductions in the coming decades. However, if a port's requirement to mitigate scope 2 emissions outpaces increases of grid renewable energy penetration, scope 2 emission mitigation measures may need to be employed directly by the organisation. Many ports have significant potential for the installation of on-site renewable electricity generation using technologies such as solar-PV, wind turbine, tidal-stream and battery storage. This can provide a financially attractive and low carbon alternative to grid supplied electricity (Amponsah, Kington, Aalders, & Hough, 2014; IRENA, 2019). Large capacities of onsite renewable energy infrastructure have been installed in many European ports, including 200MW of wind energy at the Port of Rotterdam, 45MW of wind energy at the Port of Antwerp and 11GWh per year of solar PV generated electricity at the Port of Amsterdam (Sdoukopoulos, Boile, Tromaras, & Anastasiadis, 2019). Fremantle Ports has the ability to generate its own renewable energy within the area of its facilities, and has investigated options to install wind turbines on the breakwaters and solar PV on its buildings and truck waiting/parking areas.

Besides the carbon emission reduction benefits mentioned above, the installation of onsite renewable energy can provide several other opportunities for ports which may be beneficial regardless of emission reduction targets. These opportunities include:

- Increased resilience and power security (whether climate change is induced as a risk or not).
- Cost benefits associated to self-generation of electricity.
- Potential to sell excess electricity to tenants or the grid, creating an additional revenue stream.
- Customer/stakeholder pressure or reputational/ business benefits due to the use of renewable energy. This may be an important consideration where there are cruise ship and ferry terminals.

If the installation of renewable energy infrastructure is not feasible for a specific port, Corporate Renewable Power Purchase Agreements with renewable electricity generation projects can provide an effective means for obtaining carbon neutral electricity (Business Renewables Centre-Australia, 2019).

In regard to demand-side scope 2 emissions mitigation, this can largely be achieved by improving a port's energy efficiencies. Electricity energy efficiency opportunities for ports include; implementing energy management systems and smart meters to provide more accurate, real time electricity monitoring; switching traditional lighting to LED lighting; installing berth lighting sensors and dimming switches; utilising electric motor speed switching and controlling, such as switching electric motors in trade handling equipment to idle to when not in use (PEMA, 2011); implementing the 'passive house concept' on buildings and warehouses to reduce HVAC (heating, ventilation and air conditioning) energy requirements (Sdoukopoulos, Boile, Tromaras, & Anastasiadis, 2019), and; improving container trade handling efficiencies (Dulebenets, Moses, Ozguven, & Vanli, 2017).

The most difficult challenge for ports striving for carbon neutrality is the mitigation of their scope 1 emissions released from the combustion of fossil fuels. As the use of renewably sourced electricity increases, scope 1 emissions will likely become the dominant source of a port's internal operational emissions. In order to achieve carbon neutrality, ports will need to undertake significant changes to vessels, vehicles and diesel-powered trade-handling equipment. Emission reduction opportunities for port vessels such as tugboats and pilot vessels include hybridisation and the use of alternative fuels (Table 11). Hybrid tugboats using diesel-electric-hybrid technology are increasingly being developed, with several in use in the Port of Rotterdam, Port of Luleå and ports of Los Angeles and Long Beach (Sdoukopoulos, Boile, Tromaras, & Anastasiadis, 2019; Bojarski, 2019). In 2019, the world's first fully electric powered tugboat was purchased by Ports of Auckland, with delivery expected in 2021 (Foster, 2019). Hydrogen cells offer a promising carbon neutral fuel source, depending on the energy used for its production. Whilst currently in its early stages, there is growing interest in the future of hydrogen powered vessels, with the Port of Antwerp recently purchasing the world's first hydrogen powered tugboat in 2019 and Japan's largest tugboat

manufacturer *Tokyo Kisen* aiming to release its first hydrogen-electric-hybrid tugboats in 2022 (Port of Antwerp, 2019; Tokyo Kisen, 2019).

Table 11: *Main alternative fuel and energy sources for vessels, and associated fuel savings potential* ***(Halim, Kirstein, Merk, & Martinez, 2018)****.*

Measures	Potential Fuel Savings
Advanced biofuels	25–100%
Synthetic fuels (hydrogen and ammonia)	0–100%
Liquid natural gas (LNG)	0–20%
Fuel cells	2–20%
Electricity and hybrid propulsion	10–100%
Wind assistance	1–32%

As seen in Chapter 3, diesel-powered trade-handling equipment represents one of the largest sources of emissions from a port's landside operations. To mitigate these emissions, the most common methods currently implemented involve the full electrification of the equipment and diesel-electric hybrid solutions. The use of alternative fuels, such as LNG and hydrogen fuel cells, will likely become available in the future, however, are currently in the piloting and testing phase (Sdoukopoulos, Boile, Tromaras, & Anastasiadis, 2019). The transition of a port's vehicle fleet to low carbon alternatives is currently possible for small vehicles, with petrol-electric hybrid and full electric options available on the market. Options for utility and industrial vehicles, however, are very limited, although several electric and hydrogen variants are expected to be released over the next couple years (Guthrie, 2020).

Whilst there are many significant merits to reducing the greenhouse gas emissions of a port, it is to be noted that the emissions released by ships between ports is of a much greater magnitude (Halim, Kirstein, Merk, & Martinez, 2018). As such, the impact that a port can have on reducing global GHG emissions can be greatly increased by encouraging and facilitating the sustainability of visiting ships. Mechanisms such as providing discounted berthing rates for more sustainable ships can incentivise vessels to reduce their overall emissions. Such a mechanism is currently being employed by NSW Ports (NSW Ports, 2019). Additionally; providing an onshore power supply (cold-ironing) can reduce a vessel's in-port emissions (depending on the emission factor of the local grid electricity); as can increasing trade loading/unloading efficiencies; and reducing the time a ship is required to idle in port. Fremantle Ports is also proposing to facilitate a hydrogen-powered heavy-

vehicle trial, providing hydrogen refuelling in the Inner Harbour to encourage the uptake of hydrogen-powered on-road trade transport technologies (Western Roads Federation, 2018).

As the impacts of climate change become more evident, the pressure and necessity for ports to decarbonise their operations will only increase. Through the utilisation of the methods detailed above, ports can very readily begin their transition to a carbon neutral future. Whilst it may be difficult for ports to decarbonise their mobile operations completely using currently available and affordable technology, continuing technological developments and price decreases will increase accessibility in the coming years. With the IMO announcing plans in 2018 for a 50% reduction of global shipping emissions by 2050 (European Union, 2019) and many ports around the world having begun the process towards decarbonising their stationary and mobile operations (Sdoukopoulos, Boile, Tromaras, & Anastasiadis, 2019), the maritime industry faces a powerful opportunity to protect their assets and decarbonise the sector.

5 Conclusions

With the impacts of climate change intensifying every year, there is growing pressure and necessity for the maritime industry to decarbonise their emissions. Being the gateway between terrestrial and maritime trade operations, ports hold a powerful position to not only reduce their own greenhouse gas emissions, but also those of the ships, trucks and locomotives on which global trade depends. Highlighted by the progressive contributions of IAPH and WPCI, as well as by notable sustainable ports including the Ports of Auckland, ports of Long Beach and Los Angeles, and the European ports of Rotterdam and Antwerp, ports are increasingly identifying themselves as the drivers for climate action within the maritime industry.

To assist ports with identifying and reporting their energy consumption and greenhouse gas emissions, several guidelines have been developed, including WPCI's *Carbon Footprinting for Ports: Guidance Document* (2010) and IAPH/IMO's *Port Emissions Toolkit* (2018). Despite the comprehensiveness of these documents, there is currently no publicly available methodologies guiding the development of long-term energy consumption and greenhouse gas emissions projections for ports or infrastructure assets. As per this requirement, this dissertation report has successfully developed and tested a methodology utilising qualitative and quantitative forecasting techniques, using curve fitting, linear and non-linear regression models for time-series models and linear regression analysis using the method of least squares for causal/explanatory models. The baselining scaffolding and scenario development technique provided by ISCA's *Base Case Approach* was successfully integrated into the methodology and was demonstrated to be adequately usable for developing long-term energy and emissions baselines and projections.

The case study on Fremantle Ports found that baseline energy use is expected to increase 53% by 2050. Baseline GHG emissions, however, are expected to decrease by 71% over the same time frame as a result of projected increases of grid renewable electricity generation and the associated drop of scope 2 emission factors. The Actual Case model identified a 6.5% decrease of energy consumption and 3% decrease of GHG emissions by 2050, relative to the Base Case scenario.

As with Fremantle Ports, increases of renewable electricity generation in coming decades will likely result in scope 1 emissions sources becoming the dominant form of emissions from facilities' internal operations. These will likely become the focus of emissions mitigation strategies moving forward, as ports join the global economy in decarbonisation efforts. Whilst the immediate and complete decarbonisation of a port's internal operations would currently be challenging and expensive, ongoing technological advancements regarding stationary and mobile energy use electrification and the uptake of carbon neutral alternative fuels such as hydrogen fuel cells and biofuels are making the transition to net carbon neutrality an increasingly achievable, affordable and attractive goal.

5.1 Final recommendations

This report has developed a practical methodology for the development of long-term energy consumption and GHG emission projections for port operations. As part of this report's case study, several recommendations were deduced that will assist with any port energy and emissions projections developed in the future. Firstly, to represent a more comprehensive view of the total emissions released as part of port infrastructure and trade operations, a port's scope 3 emissions should include emissions from tenants, visiting ships and land-side trade transport to a certain degree within the port's administrative boundary, as is identified in the *Port Emissions Toolkit* (IMO & IAPH, 2018). Secondly, if using the ISCA *Base Case Approach*, its integration with the five-step forecast development process created by Makridakis, Wheelwright, & Hyndman (1998) is recommended, as discussed in section 4.2.5 and Figure 36 above. Finally, it is recommended for model development that at least a third scenario is included, to provide greater usability, flexibility and robustness to the projections and cover a wider range of possible futures.

5.2 Future research

This report focused primarily on developing long-term energy consumption and emissions projections for the internal operations of ports, using conventional forecasting techniques. Possible future research includes experimentation with artificial intelligence and machine learning forecasting methods in the context of

infrastructure and port operations. Whilst these techniques can provide increased model robustness, it is not known whether such benefits are great enough to justify the trade-offs of time, model complexity and statistical/programming expertise when applied to the development of port energy consumption and GHG emissions projections. Additional future research opportunities include widening the scope of the current project and adapting it for use with broader infrastructure related assets as well as non-infrastructure related private businesses. Additionally, further research is required to develop specific carbon management strategies for ports. This includes determining the economic feasibility and abatement impacts of emission mitigation strategies and investigating the transitional risks of decarbonising a port's operations, including any business fiscal impacts.

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Appendices

Appendix 1: Emissions forecasts versus emissions projections

It is important to note the difference between emissions forecasts and emissions projections.

Emissions projections are concerned with estimations of future data on the scale of years to decades. As long-term data estimations can be very hard to predict, differing scenarios are often formulated. Projections provide estimations under the expectation that sets of assumptions (such as future trade growth rates, emission factor change rates etc.) continue for the period of the projection. They do not typically attempt to account for unknown future impacts such as those that are the result of future policy or economic changes, or technological developments (Department of Industry, Science, Energy and Resources, 2019).

Emissions forecasts, on the contrary, are typically estimations of future data at a shorter time-scale, although long-term forecasts can also exist. Forecasts attempt to speculate more-so on how emissions are impacted by incidents such as changes of technology, human behaviour and government policies. This can mean that forecasts offer higher detail estimations, however at the expense of increased risk if such speculations turn out to be incorrect. For this reason, forecasts are usually suited better for short-term periods where highly detailed speculations are more reliable (Department of Industry, Science, Energy and Resources, 2019).

As the scope of this project involves developing energy and emissions modelling at the scale of decades, as well as to best utilise time, data and resource restraints, the energy and emission modelling methodology that was developed as part of this project was be more closely aligned to an ‘emissions projection’.

Appendix 2: Emission scopes

In GHG emission accounting and reporting, emissions are usually broken up into three different scopes. Scope 1 emissions are those released as a direct result of an activity at the facility level. Scope 2 emissions reflect those released as an indirect consequence of the use of electricity (or other energy type) generated off-site. Scope 3 emissions consists of indirect emissions, other than scope 2, that are released in the broader economy as a result of the activities of a facility. How these scopes are adapted for ports and port operations is demonstrated in Figure 37, below.

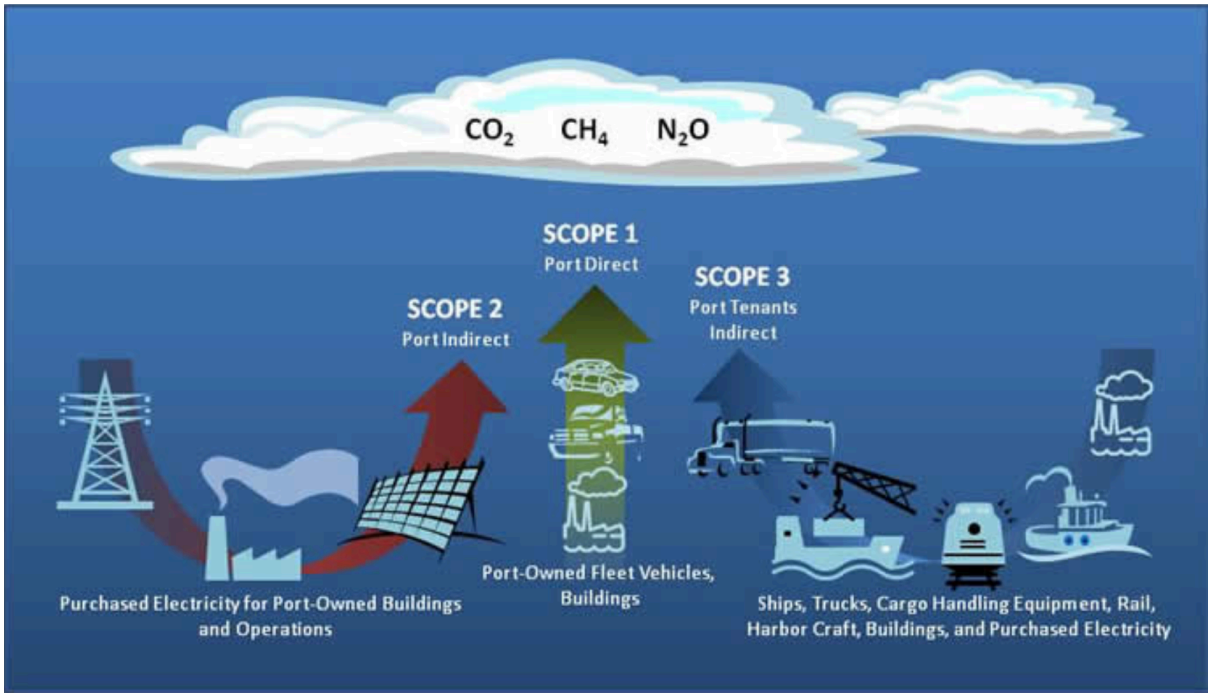

Figure 37: *The three different categories of GHG emissions scopes, as the pertain to port operations* ***(IAPH, nd)****.*

Appendix 3: Fremantle Ports facilities information

Victoria Quay

Located on the southern bank of the Inner Harbour, Victoria Quay is a mixed-use facility with varying infrastructural requirements. The facility contains six common user berths, four for cargo handling and two for vessel lay-up. Adjacent to the common user berths is secure storage for break-bulk trade and up to 800 motor vehicles (Fremantle Ports, n.d.). At the north-eastern end of Victoria Quay, the Small Craft Pens contain berths for the port's pilot and emergency vessels, as well as a 10kL-diesel-tank refuelling station. Other infrastructure includes multiple carparks, the Fremantle Passenger Terminal, ferry terminal, Fremantle Ports Administration Building and several other port sheds and buildings. The facility currently has a tenant occupancy rate of around 50%, with 59% of the facility's electricity consumption attributable to tenants in financial year 2018/19.

North Quay

On the northern bank of the Inner Harbour, lies the mixed-use facility; North Quay. NQ contains four common user berths with secure storage for break-bulk trade and motor vehicles. The container terminals at North Quay contain four berths and specialised container handling equipment. A train line links the North Quay container terminals to key sections of the greater Perth rail network. There is also a light to medium industrial area, utilised predominantly by trade and maritime based businesses (Fremantle Ports, n.d.). Fremantle Ports operates very little of North Quay directly, with around 93% of the facility's electricity use attributed to external businesses, including the two container terminals.

Kwinana Bulk Terminal

Kwinana Bulk Terminal, located in the Outer Harbour, is primarily a bulk material import/export facility. The KBT facility contains storage sheds and silos, rail tippler infrastructure, two grab loaders for the movement of material to/from ships, hopper systems, conveyor systems, an LPG pipeline, stockpile storage areas as well as a small, single storey workshop/office building (Figure 39). The main materials historically traded through KBT are cement clinker, gypsum, spodumene, bauxite

and iron ore. Fremantle Ports currently operates 100% of the facility, although it has been wholly leased in the past (Department of Environment Regulation, 2012).

Figure 38: *The Fremantle Inner Harbour, home to Victoria Quay and North Quay. Yellow shades represent Fremantle Ports land* ***(Fremantle Ports, 2019)****.*

Kwinana Bulk Jetty

Similar to KBT, Kwinana Bulk Jetty facilitates the loading and unloading of bulk material products. The facility contains two berths along a single jetty and has trade handling infrastructure including a conveyor system, self-contained fully enclosed auger-type continuous unloader, a hopper system (Figure 40). Material storage and processing facilities are not internally operated at KBJ. Fremantle Ports operates around 60% of the facility (in regards to electricity consumption), with the remainder attributed to tenant operations. The main materials historically traded through KBJ are fertilisers, potash, slag residue, sulphur, urea, cement clinker, and more recently; silica sands (Department of Environment Regulation, 2012).

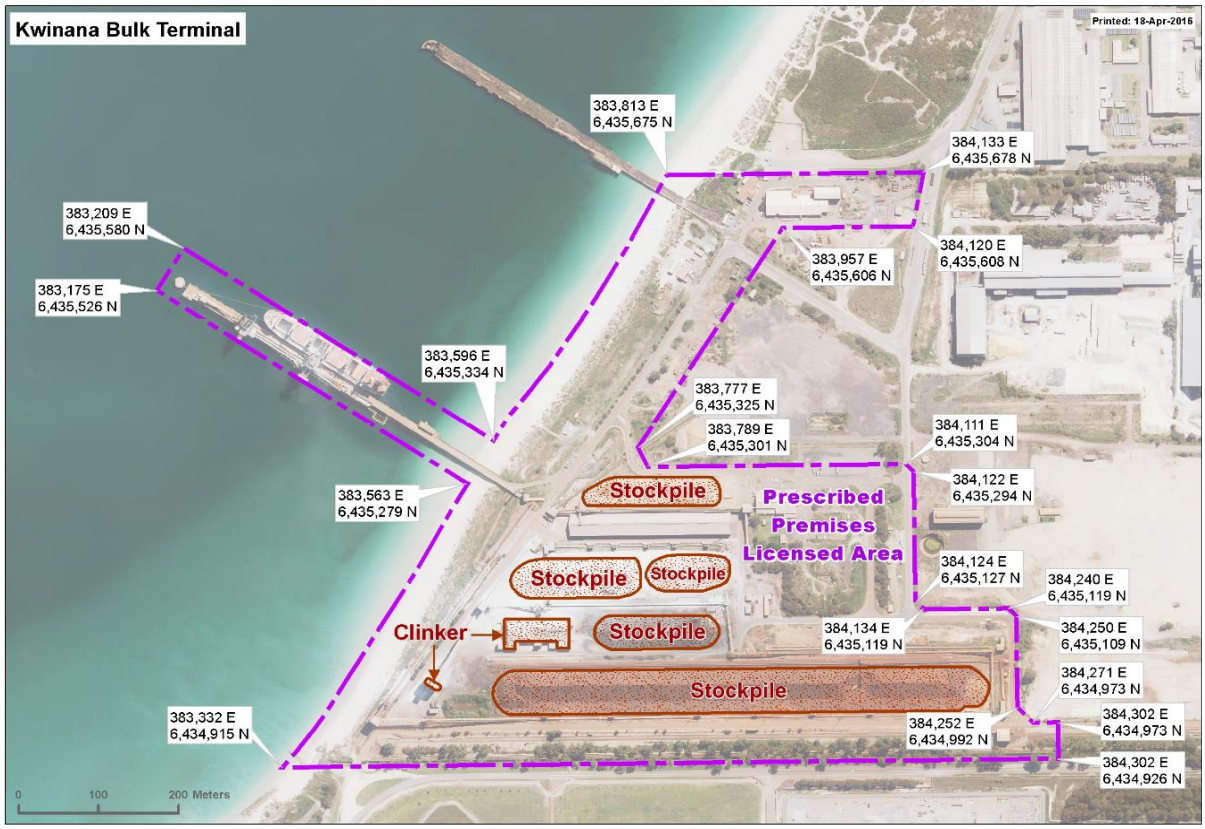

Figure 39: *A labelled satellite image of Kwinana Bulk Terminal. The dashed purple line denotes the boundary of the facility* ***(Department of Environment Regulation, 2012)****.*

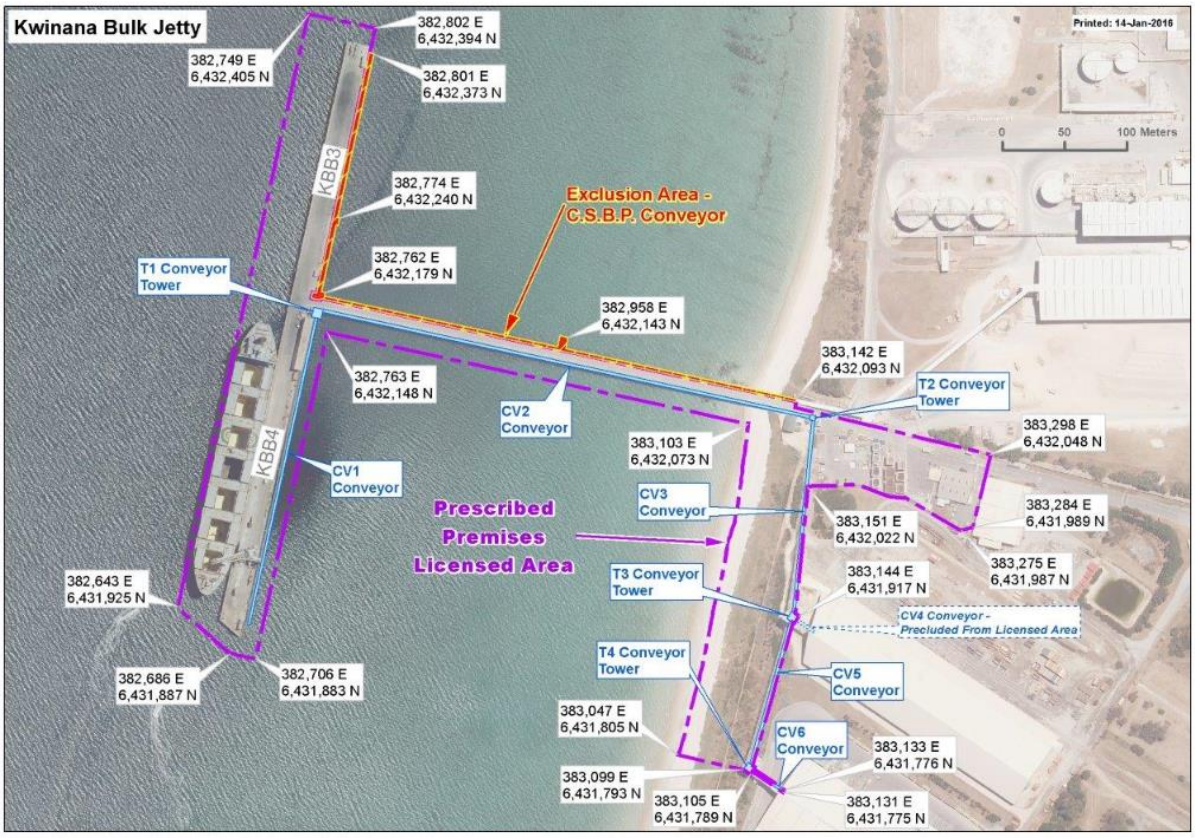

Figure 40: *A labelled satellite image of Kwinana Bulk Jetty. The dashed purple line denotes the boundary of the facility* ***(Department of Environment Regulation, 2012).***

Appendix 4: Projected SWIS Emission Factor values

See Figure 13 and Figure 14 for a graphical representation of these projections.

Historical SWIS Scope 2 Emission Factor		
Linear Equation:	y=-0.022258064516129x + 45.629032258065	
	Historical	Projected
FY ending	EF (kg.CO2-e/kWh)	EF (kg.CO2-e/kWh)
1990	1.13	
1995	1.11	
2000	1.14	
2005	0.88	
2006	0.88	
2007	0.86	
2008	0.86	
2009	0.83	
2010	0.81	
2011	0.79	
2012	0.77	
2013	0.76	
2014	0.74	
2015	0.71	
2016	0.7	
2017	0.7	
2018	0.7	
2019	0.69	0.69
2020		0.67
2021		0.65
2022		0.62
2023		0.60
2024		0.58
2025		0.56
2026		0.53
2027		0.51
2028		0.49
2029		0.47
2030		0.45
2031		0.42
2032		0.40
2033		0.38
2034		0.36
2035		0.33
2036		0.31
2037		0.29
2038		0.27
2039		0.24
2040		0.22
2041		0.20
2042		0.18
2043		0.16
2044		0.13
2045		0.11
2046		0.09
2047		0.07
2048		0.04
2049		0.02
2050		0.00

Historical SWIS Scope 3 Emission Factor		
Linear Equation:	y=0.000038776677419354704x−0.03829011	
	Historical	Projected
FY ending	EF (kg.CO2-e/kWh)	EF (kg.CO2-e/kWh)
1990	0.2	
1995	0.15	
2000	0.14	
2005	0.09	
2006	0.08	
2007	0.1	
2008	0.11	
2009	0.12	
2010	0.1	
2011	0.08	
2012	0.07	
2013	0.07	
2014	0.07	
2015	0.06	
2016	0.06	
2017	0.05	
2018	0.05	
2019	0.04	0.04
2020		0.0400
2021		0.0401
2022		0.0401
2023		0.0402
2024		0.0402
2025		0.0402
2026		0.0403
2027		0.0403
2028		0.0403
2029		0.0404
2030		0.0404
2031		0.0405
2032		0.0405
2033		0.0405
2034		0.0406
2035		0.0406
2036		0.0407
2037		0.0407
2038		0.0407
2039		0.0408
2040		0.0408
2041		0.0409
2042		0.0409
2043		0.0409
2044		0.0410
2045		0.0410
2046		0.0410
2047		0.0411
2048		0.0411
2049		0.0412
2050		0.0412

Appendix 5: Base Case time-series model statistical summaries

Time-series based models developed as part of this case study's Base Case projections are listed in Table 12, below. Equations take the form as described online in *IBM Statistics V24.0 documentation* (IBM, 2016).

Table 12: *Time-series regression-analysis model statistical summaries, parameter estimations and model choice justifications developed for Fremantle Ports Base Case energy consumption projections.*

VQ Electricity Consumption (kWh): Base Case Years (2010 - 2016)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant (b0)*	*b1*	Equation
Logarithmic	0.033	0.169	0.698	2415181.221	58228.7	Y = b0 + (b1 * ln([Financial Year Ending] - 2009))
Justification	The Logarithmic model provided the best balance between qualitative forecasts and statistical analysis values. Qualitative forecasting expects VQ internal electricity consumption to remain steady into the future. For this reason, Linear, Compound and Exponential models are not compatible, despite having the best p-value.					
NQ Internal Electricity Consumption (kWh): Base Case Years (2012 - 2019)						
Model Type	Model Summary			Parameter Estimates		
	R Square	F	Sig.	Constant (b0)	b1	Equation
S	0.012	0.075	0.794	14.153	0.05	Y = e^(b0 + (b1 / ([Financial Year Ending] - 2011)))
Justification	All models had a very low R2 value and a very poor p value. This indicates highly variable data over time. Despite this, a slight downward trend is identifiable in all models. This is likely due to energey efficiencies undertaken since 2016. NQ internal electricity consumption is not expected to be affected by port trade. For a business as usual projection, assuming no new energy efficiencies, electricity consumption is expected to flatten off and not change over time.					
VQ Leased fleet petrol consumption (GJ): Base Case Years (2012 - 2016)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Power	0.986	214.585	0.001	2324.767	-0.699	Y = b0*(([Financial Year Ending] - 2011)^(b1))
Justification	All models have a very high R2 value. The power model offers the best middle ground between alignment with historical data and qualitative fuel consumption forecasts.					
VQ Fremantle Port owned fleet petrol consumption (GJ): Base Case Years (2012 - 2016)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Power	0.062	0.198	0.687	30.966046	-0.1318	Y = b0*(([Financial Year Ending] - 2011)^(b1))
Justification	All models have a low R2 value. This model offers the best mix between alignment with historical data and alignment with qualitative fuel consumption forecasts from the port.					
VQ Leased fleet diesel consumption (GJ): Base Case Years (2012 - 2016)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
S	0.659	5.794	0.095	7.699557	-0.7519	Y = e ^ (b0 + (b1 / ([Financial Year Ending] - 2011)))
Justification	The S Curve Model has the lowest P value, highest R2 value, and fits qualitative fuel consumption forecasts from the port the adequately. This was consistent when modelling with all historical years and also for pre-base case years.					
VQ Fremantle Port owned fleet diesel consumption (G	Parameter Estimates					
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Power	0.533	3.424	0.161	1587.79141	-0.2206	Y = b0*(([Financial Year Ending]-2011))^(b1))
Justification	Of the models tested, only four had appropriate values when extrapolated to 2050: Inverse, logarithmic, power, S Curve. Other models either went into negative values or very high positive values before 2050. Th Power model offers the best middle ground between alignment with historical data and alignment with qualitative fuel consumption forecasts from the port. The Power Model has the lowest P value and highest R2 value of the four models deemed appropriate.					
KBT Leased fleet petrol consumption (GJ): Base Case Years (2012 - 2019)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Power	0.949	112.799	0	1815.273621	-0.7432	Y = b0*(([Financial Year Ending]-2011))^(b1))
Justification	All non-linear models had very high R2 values and very low P values (except for S Curve Model). The Power curve had a very high statistical significance and correlated well with qualitative fuel consumption forecasts made by the port.					
KBT Fremantle Ports owned fleet petrol consumption (GJ): Base Case Years (2012 - 2019)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Inverse	0.171	0.824	0.415	23.145146	-18.234	Y = b0 + (b1 / ([Financial Year Ending] - 2011))
Justification	All models had very low R2 values and very low P values. The Inverse curve had slightly better statistical significance. All three models correlated reasonably well with qualitative fuel consumption forecasts made by the port.					
KBT Leased fleet diesel consumption (GJ): Base Case Years (2012 - 2019)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Logarithmic	0.139	0.968	0.363	829.679839	150.64	Y = b0 + (b1 * ln(([Financial Year Ending] - 2011)))
Justification	All models had very low R2 values and very low P values. When considering qualitative fuel consumption forecasts from the port (increasing slightly then levelling off), the logarithmic and power curves offered the best fit. Of these, the logarithmic model has the better R2 and P values. This dataset includes the FY 2018/19 anomaly.					
KBT Fremantle Ports owned fleet diesel consumption (GJ): Base Case Years (2012 - 2019)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Logarithmic	0.465	5.212	0.063	-8.300113	89.6724	Y = b0 + (b1 * ln(([Financial Year Ending] - 2011)))
Justification	All models had very low R2 values and very low P values. From qualitative knowledge of the facility's diesel fuel consumption, consumption growth predicted by the linear model is considered too large. Out of the remaining models, the logarithmic model provided the best R2 value and P value and best fit fuel consumption growth expectations and					
KBJ Fremantle Ports owned fleet petrol consumption (GJ): Base Case Years (2012 - 2017)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Logarithmic	0.727	10.629	0.031	-1.72046	4.91435	Y = b0 + (b1 * ln(([Financial Year Ending] - 2011)))
Justification	Logarithmic and Linear models had adequately strong R2 and P values. The linear model fitted the data the best, however when considering qualitative fuel consumption forecasts made by the port (fuel use will flatten off, see proposal), the logarithmic model was considered the best fit for the Base Case.					
KBJ Fremantle Ports owned fleet diesel consumption (GJ): Base Case Years (2012 - 2019)						
Model Type	Model Summary			Parameter Estimates		
	R Square	*F*	*Sig.*	*Constant*	*b1*	Equation
Inverse	0.782	14.314	0.019	239.796224	-263.86	Y = b0 + (b1 / ([Financial Year Ending] - 2011))
Justification	All models had adequately strong R2 and P values. The logarithmic model had the best R2 and P values of all models tested, however the inverse model best fit with qualitative fuel consumption forecasts made by the port (fuel use will flatten offl) and had the lowest normalised error outside of the variable period from FY 2011/12 to FY 2012/13.					