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A Top-Down Approach to Simplifying Carbon Emission Forecasting for Improved Project Development and Environmental Accounting in Offshore Oil and Gas Production

by

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Abstract

A combination of factors including environmental, resource availability, investor weariness and public perception of the oil and gas industry challenge the competitiveness of the sector in Norway and around the world. One frequent topic of discussion addressed in these areas of concern, as well as an opportunity for improvement, is the generation of CO_2 from upstream oil and gas production. Forecasting these emissions serves many purposes and may alleviate some of these challenges while benefiting the environment. Currently, emission forecasting in the industry may not meet current needs, are complex, and can be done more simplistically. This study has aimed to produce a novel and simplified means to estimate upstream oil and gas emissions. Through a data-driven statistical method, emission and production volume histories as well as drainage strategy at the asset level were analyzed to build two emission models. The methodology derived in this thesis is not currently used in upstream emissions calculations and is novel for the oil and gas industry. The results of the modeling demonstrate the models' ability to approximate emissions using less data, resources and knowledge than were previously needed while also providing a level of accuracy desired for industry workflows including already established requirements for project and business development in Equinor. The benefits these models provide allow emission forecasting to be less hindered by data requirements, more able to meet today's growing demands and accelerate decision-making abilities to meet future needs. Further, the methodology is flexible and applicable to numerous industrial process which signifies a green light for expanding the use of data and furthering digitalization efforts within the oil and gas industry and elsewhere.

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List of Abbreviations

Abbreviation	Long Form
BAT	Best Available Techniques
bbl	Barrel (of oil)
boe	Barrel of oil equivalent
Ca_2^+	Calcium
$CaCO_3$	Calcium Carbonate
CH_4	Methane
CO_2	Carbon Dioxide
CO_3^{2-}	Carbonate
CVP	Capital Value Process
DG	Decision Gate
DPN	Development Production Norway
ESG	Environmental, Social and Governance
GWP	Global Warming Potential
H_2O	Water
HCO_3^-	Hydrogen Carbonate
IEA	International Energy Agency
IR	Infrared
KV	Kvitebjørn and Valemon
M	Meter
MIS	Management Information System
MW	Megawatt
N_2O	Nitrous Oxide
NCS	Norwegian Continental Shelf
NPD	Norwegian Petroleum Directorate
OPGEE	The Oil Production Greenhouse gas Emission Estimator
RNB	Revised National Budget
RCP	Representative Concentration Pathways
W	Watt

1 Introduction

A culmination of climate change, abandonment of long-held investment theories, divestment trends, climate policies, and socio-economic factors have placed pressures on the oil and gas industry to be more environmentally conscious. While, at the same time, growth in populations and economic prosperity have created increased demands for energy. For the time being, this necessitates increased oil and gas production. This fact has been used by oil and gas, and energy companies as a reason for continuing and increasing oil and gas operations. However, a dwindling of resources in new field developments has forced operators on the Norwegian Continental Shelf (NCS) to exploit many smaller business opportunities. These potential developments require screening and assessment for environmental impacts. Currently, CO_2 emission estimations — one aspect of environmental impacts — are deduced from resource-intensive data, which may inhibit the rate of development from matching that of demand on the NCS. The theory section provides an understanding of the significance of climate change and its science as well as the theory that underlies the interplay of socio-economic, financial and environmental factors that must be managed in the oil and gas industry.

1.1 Problem Statement

The oil and gas industry has been faced with challenges including climate policies, investor relations and, more specifically to Norwegian oil and gas production, smaller new discoveries than previously before. As a result, the ability to quickly and easily assess and communicate climate risks is needed to increase attractiveness for some investors and allow for easier alignment with climate policies. The issue of shrinking field size has meant that more discoveries need to be assessed in order to meet the growing global demand for energy. This needs to be accomplished while heeding the challenges and risks (both financial and environmental) brought about by climate change. Improved emission forecasting is one opportunity that can help in accomplishing this. With faster and less demanding emission estimating abilities, new opportunities can be assessed in terms of their climate impact and feasibly at a rate that is commensurate to their demand and minimizes climate risk, thereby attracting investors. A forecasting model that is simple, accurate and, easy to use is not yet available but could prove very useful in managing and addressing these issues.

1.2 Objective

The objective of this thesis is to elucidate the usefulness of statistical and predictive analytics for building models for upstream emissions, and potentially elsewhere, in the oil and gas industry. Further, the study aims to uncover the accuracies, strengths, and limitations of such models to inform any continuance of this form of model construction. Ultimately, this thesis aspires to provide a simple, accurate, and easy way of modeling emissions that can effectively respond to some of the problems faced today by the oil and gas industry.

1.3 Collaboration with Industry

The work contained within this thesis has primarily been performed in Equinor's offices in Stavanger, Norway. Equinor is a large oil and gas (energy) company that is interested in new ways of understanding, estimating, and quantifying emissions for business development and environmental purposes as well as meeting financial and stakeholder interests. Equinor has put considerable effort into their climate road map which serves to inform investors in interested members of the public. The company acknowledges climate science and the scientific consensus surrounding the issue. As such, Equinor was receptive to supporting this unique thesis when the idea was proposed to the company. Equinor has provided historical emission data, Revised National Budget (RNB) reports, a desk, laptop, as well as support and guidance.

Part 1 - Theory

2 Global Climate Change

The effects of climate change are far-reaching and affect the world's natural environments, livelihoods, political policies and investment decisions. These aspects of climate change are given in support of the better forecasting abilities within the oil and gas industry as climate change is the underlying impetus for change in the industry.

2.1 The Science and Socio-Economic Significance of CO_2 Emissions from the Perspective of the Environment – A Synopsis

This section serves to give a thorough overview of climatic drivers and their effects so that the primary aspect of this paper — forecasting of CO_2 emissions (discussed later) — can be understood fully within the topic of its importance: climate change.

Additionally, this chapter provides the science of climate change as it relates to greenhouse gasses and their fate. Also, it provides an overview of how climate factors have progressed to today's state and the anticipated effects of changing climate going into the future**.** Climate change is a fact that necessitates the investigation into its human contributions such as emissions of CO_2 and is the basis of political, regulatory and investment pressures as well as industry initiatives. Ecological and socio-economic case studies are presented in relation to climate change and its effects. An effort has been made to illustrate examples closely relevant to Norwegian industries and ways-of-life.

2.2 Climate Change

Climate is a measure of the mean and variation in meteorological measurements such as temperature, precipitation and other weather phenomena over a sustained period of time; classically, 30 years (WMO, 2018b).

Although, term "Global Warming" is often used interchangeably with "Climate Change", it should be noted that both refer to changes in climate overall (Kennedy & Lindsey, 2015).

2.3 Greenhouse Gasses

Greenhouse gasses are named for their ability to produce a greenhouse-like effect with regards to the energy and heat within the atmosphere. Their presence derives both from anthropogenic sources such as industrial activities and agriculture as well as natural processes like biodegradation, seepages, and geological processes (U.S. EPA, 2018). The atmospheric effects of these alter many climate-related functions.

2.4 The Science

2.4.1 Radiative Forcing

Radiative forcing is an energy balance concept that describes the overall energy flux (typically of Infrared (IR) energy) that enters and exits Earth's atmosphere (ACS, 2012). This balance can be influenced by various disturbances (IPCC, 2014, p. 664). For Earth's atmosphere to be kept at a consistent temperature, the thermal energy sequestered from the absorption of IR radiation within Earth's atmosphere must be equivalent to the total amount of energy lost to space (ACS, 2012). Changes in the Earth's energy budget due to changes in the atmosphere, land, ocean, biosphere and cryosphere can create radiative forcing effects that, in turn, change the climate (IPCC, 2014, p. 127).

2.4.2 Dipole moments and absorptive properties

The ability of a molecule to absorb radiation within the IR spectrum is directly linked to its dipole moments, which are specific to each molecule, e.g., CO_2 or H_2O. These dipole characteristics dictate which wavelengths of IR light are absorbed as well as the strength of the absorption. The absorption of IR radiation by greenhouse gasses converts non-vibrational energy into thermal, vibrational energy (ACS, 2012). As the dipole moments for each greenhouse gas are different, so is the extent to which each greenhouse gas can absorb and convert IR radiation (Briggman, 2018).

2.4.2.1 Global Warming Potential and CO_2 Equivalents

Global Warming Potentials (GWP) have been developed for greenhouse gasses to standardize their warming effect. This concept recognizes a greenhouse gas' ability to affect radiative forcing and the duration of this effect by assigning each greenhouse gas (aside from CO_2) a global warming potential. The GWP communicates a gas' propensity, weight per weight, to enhance global warming relative to CO_2. To manage different gas properties, the potential weighs the effect of a gas over a 100-year period. As an example, a kilogram of methane emissions, which has a global warming potential of 34, when climate change feedbacks are factored in, has the equivalent warming effect of 34 kilograms of CO_2 across a 100-year horizon. Discounting feedback mechanisms, methane has a GPW factor of 28 (IPCC, 2014, p. 714). This ability of the GWP allows for a standardized quantification of warming effects across all greenhouse gas emissions.

When global warming potentials are applied to a quantity of greenhouse gas emissions, the CO_2 equivalence of those emissions are determined as CO_2e. This can be applied to quantities of multiple emissions as well with the given equation:

$$CO_2e\ (tonnes) = \sum_{i=1}^{\#Greenhouse\ Gas\ Species} (tonnes_i\ x\ GWP_i)$$

(Shires, Loughran, Jones, & Hopkins, 2009).

2.4.2.2 Atmospheric Warming

Warming of the atmosphere occurs when vibrational energy produced from the absorbance of IR radiation by greenhouse gasses is transferred to other atmospheric gasses. This process applies to the warming that is required to compensate for energy losses from the atmosphere to space and climatic changes associated with global warming (ACS, 2012). The increased atmospheric presence of greenhouse gasses increases the chance that IR radiation will be absorbed and converted to thermal energy rather than lost to space.

2.4.3 Climate Sensitivity

Climate Sensitivity is a concept that relates changes in radiative forcing to changes in the average surface temperature on Earth. A model that approximates the effect of changes in the net-flux of radiation on surface temperature is as follows:

$$\Delta F = \varepsilon\sigma\left(T_p + \Delta T\right)^4 - (1 - \alpha)S_{(avg)}$$

Where:

ΔF is the change in radiative forcing

ε is the effective emissivity of the planetary system

σ is the Stefan-Boltzman constant

T_p is the average surface air temperature

ΔT is the change in surface air temperature

α is the Earth's albedo

and $S(avg)$ is the average solar energy flux

Manipulation of this sensitivity equation results in the following model which provides an approximation for the change in surface air temperature as a function of changes in radiative forcing.

$$\Delta T = \frac{T_p \Delta F}{[4(1-\alpha)S_{avg}]}$$

The contribution of greenhouse gasses to the surface air temperature of the planet is significant. The climate sensitivity model above estimates that greenhouse gasses in our atmosphere account for 33°C of surface air warming. Without the warming properties of greenhouse gasses, the average near-surface temperature on Earth would be -18°C.

Analysis of historical data has shown that changes in radiative forcing from atmospheric CO_2 and CH_4 levels account for 20-25% of previously observed temperature increases. This seemingly low percentage is due to the model's inability to capture the secondary effects of a warming atmosphere, which, if included, would show these two gasses have a larger role in the historical warming of the atmosphere. These secondary effects come from climate influencers which act as positive feedback mechanisms (ACS, 2012)**.**

2.4.4 Water as a Climate Influencer

Like other greenhouse gasses, water exhibits a dipole moment allowing it to absorb IR radiation. Atmospheric water presents a challenge when assessing its climate impact. Water exists in three phases in the atmosphere: solid, liquid and gas. Both the location and phase states of atmospheric water affect radiative forcing differently (ACS, 2012)**.**

2.4.4.1 Water as Vapor

Water vapor is the most important of the greenhouse gasses (ACS, 2012); it has a large absorption spectrum and high heat capacity (Henshaw, Charlson, & Burges, 2006). Relatively, water vapor provides warming that is two to three times greater than CO_2 (IPCC, 2014, p. 574-666). Despite its importance, the influence that atmospheric water vapor has on radiative forcing is difficult to quantify in radiative forcing models (ACS, 2012). This is largely due to the short-lived nature of water vapor in the atmosphere; atmospheric water vapor has a residence time on the scale of days whereas other climate-influencing gasses have multi-year residence times. Furthermore, the water vapor content of the atmosphere is highly variable and is largely influenced by surface air temperatures. Due to this, changes in atmospheric water vapor composition is not directly influenced by human activity. It does, however, act in a positive feedback mechanism for anthropogenic climate change gasses (ACS, 2012).

2.4.4.2 Water as Cloud

Changes in the presence and location of atmospheric water vapor affect cloud formation (ACS, 2012). For cloud formation to take place, air must either cool or become oversaturated to initiate nucleation which forms nascent water or ice droplets (IPCC, 2014, p. 578-579).

Clouds, like water vapor, influence radiative forcing. However, the location of a cloud in the atmosphere affects whether the cloud has positive (warming properties) or negative (cooling properties) radiative forcing (ACS, 2012). This is because clouds contribute to the planetary albedo, reflecting energy back to space (Henshaw, Charlson, & Burges, 2006) while also absorbing IR radiation (ACS, 2012) — thus acting as a heating blanket.

Clouds that exist at high altitudes have an overall warming effect (ACS, 2012), adding 30W/m^2 to the global energy budget. These icy clouds higher in the atmosphere reflect little incoming solar energy back to space. However, they absorb heat reflected from the Earth's surface which results in a warming effect.

Lower clouds tend to be composed of liquid water (as opposed to ice). This means the cloud will have a high albedo, reflecting sunlight away from the Earth's surface. This changes the global energy flux by removing 50W/m^2 from the budget. These clouds, however, only provide an overall cooling effect during the day (Lemonick, 2010).

2.4.4.3 Water in Oceans

Oceans influence the climate indirectly by acting as climate sinks, absorbing both atmospheric heat and CO_2. From 2007 to 2017, the oceans have absorbed one-quarter of anthropogenic CO_2 emissions (Heinze et al., 2014) and 90% of warming effects (Gray, 2017). This removal of atmospheric CO_2, while outpaced by additions of anthropogenic emissions to the atmosphere, lessens the extent that dissolvable greenhouse gasses contribute to a warming effect (Heinze et al., 2014). Furthermore, the absorption of heat from the atmosphere has lessened the full warming potential of anthropogenic greenhouse gasses (Gray, 2017).

2.4.5 Climatic Feedback Mechanisms

The warming trend of the climate and near-surface air temperature is highly attributed to the effects of anthropogenic activity. However, warming itself exacerbates other mechanisms that contribute to a warming climate, thus creating a feedback loop. This section considers positive feedback effects in a warming climate as this is the dominant global climatic trend.

2.4.5.1 Water Vapor

As a result of warming temperatures, water vapor content in the atmosphere will be able to increase because the atmosphere will have a higher carrying capacity for water vapor (IPCC, 2014, p. 586) as vapor pressure increases by 7% for every degree Celsius increase in temperature (ACS, 2012). The feedback effect measured for this mechanism is $(1.1\ W)/(m^2 \cdot °C)$ meaning that 1.1 watts of energy is added to the net budget per degree Celsius square meter (IPCC, 2014, p. 574-666).

A further warming effect of water vapor is observed from the conversion and transfer of energy. Water vapor carries with it the latent heat of vaporization. When condensation occurs, the latent heat of evaporation (now called the latent heat of condensation) once contained in the vapor phase is transferred to the atmosphere as thermal energy (Henshaw, Charlson, & Burges, 2006). This phenomenon will occur at greater rates with climatically driven increases in atmospheric water vapor since both evaporation and condensation will increase.

2.4.5.2 Clouds

Cloud simulation models predict that changes in cloud composition will result in less low and mid-level cloud coverage. The extent of this reduction is uncertain due to variability amongst predictive models. Clouds in these levels are highly associated with cooling effects due to their high albedos (IPCC, 2014, p. 589) and weak abilities to absorb IR radiation (ACS, 2012). Thus, a warming climate will lead to a smaller amount of cloud cooling effects which will further the warming effect.

In addition, mid-level storms tracks are expected to migrate poleward. This emerging migratory pattern and its effects have already been observed. The movement of these clouds and storm systems to polar regions will lessen the effect their albedos have on the global energy balance as there is far less radiative exposure in the extreme latitudes (IPCC, 2014, p. 1070).

2.4.5.3 Oceans

The solubility of a gas in an aqueous solution, such as the ocean, is directly proportional to the partial pressure of the gas at the surface of the solution, assuming equilibrium conditions. It is well known that dissolved gasses such as CO_2 become less soluble with increasing solvent temperature. Warming ocean temperatures, which are observed as the near-surface air warms with climate change, will diminish the capacity of the oceans to store and absorb carbon (Gray, 2017). Thus, the oceans will be less able to absorb CO_2 and theoretically could become a source of CO_2 emissions in the future.

2.4.5.4 Carbon in Permafrost

In the Northern Hemisphere, 24% of snow and ice-free landmass is permafrost, soil that is frozen for at least two or more consecutive years. Approximately 1.5 trillion tonnes of carbon is frozen in the permafrost; double what is contained in our atmosphere. This frozen carbon is in the form of plant and animal matter that, due to its frozen state, has yet to decompose. As the permafrost thaws, previously frozen biomass will be degraded by bacteria and archaea. The degradation processes performed by these microbes yield emissions of CO_2 and CH_4, respectively. This is of great concern because, rather than being a store for carbon, former permafrost will be a new source of both CO_2 and CH_4. (Cho, 2018). Climate projections show that the greatest warming will occur near the poles where permafrost is found (IPCC, 2014, p. 1061). This is confirmed by the observation that polar regions have already warmed at a rate that is twice the global average (Schuur et al., 2015). Emissions from thawing permafrost will cause continuous cycle of warming and further thawing. The International Panel on Climate Change does not account for emissions from the biodegradation of permafrost in their climate models (Cho, 2018), meaning that these emissions and their effects have yet to be accounted for in current climate projections.

2.5 Current Trends and Effects Related to Climate Change

2.5.1 Emissions and Atmospheric Concentrations of CO_2

Emissions of CO_2 are currently higher than any previous levels on record. Since the 1960s, the emissions of CO_2 from industry and fossil fuel use has grown precipitously, while the CO_2 contribution from land use change has remained relatively constant. As a result, the uptake of CO_2 via the oceans, the terrestrial environment, and the atmosphere have increased proportionally (WMO, 2018b).

2.5.2 Air Temperature

Near-surface temperature observations show a warming trend from the onset of the industrial revolution with the most recent five-year segment showing the greatest observed average temperatures (WMO, 2018b). The warming trend has shown that the global climate has warmed 1.1° C since 1860 with the most rapid warming occurring since the 1970s where the average annual warming has been 0.1°C per decade (Blunden, Arndt, & Hartfield, 2018). The observed temperature changes during this time frame reflect natural temperature variations and human-induced radiative forcing effects which account for the upward trend (Hansen et al., 2013).

2.5.3 Ocean Temperature

In 2017, the ocean heat content reached a record high of $1.581 x 10^{23}$ Joules. The heat in the oceans' upper layers is reflective of the oceans' temperature (WMO, 2018b). The heat content of the oceans will increase concurrently with the warming of the atmosphere and has been observed since measurements began in the 1950s (Dahlman & Lindsey, 2018).

2.6 The Future Climate

2.6.1 Climate Change Commitment

The future of the climate is highly dependent on several factors — mainly human activity. However, the global climate is a part of a complex system that will take years, and perhaps centuries, to equilibrate. Thus, some of the anthropogenic contributions to the environment have yet to affect climate. The amount of climate change yet to be realized by past anthropogenic activities is called "climate change commitment". A large driver for this effect is the CO_2 and heat storage capacity of the oceans as well as the oceans' long retention time. Eventually, this stored carbon and heat will reach an equilibrium state and affect climate. These latent effects of heat and CO_2 sequestered by the ocean will be seen in the future (IPCC, 2014, p. 1102).

2.6.2 Representative Concentration Pathways

To approximate future climate trends, future human activities need to be known or assumed. Some estimations of future activities are used to understand future emissions and form a picture of a future climate. Databases called representative concentration pathways (RCPs) have been developed by four modeling teams that contain their own assumptions regarding future trends in emissions, concentrations, and land use changes. The RCPs contain assumptions for greenhouse gas emissions based on analysis of future activities and relevant climate and regulatory policies. Four common RCPs have been developed (Bjørnæs, 2015). The information contained within these databases is used as inputs to derive the impact of future emissions and their radiative forcing effects. This common data allows researchers across the globe to have a standardized set of future assumptions with which the implications of climate change can be explored (Vuuren et al., 2011). From the climate projections that are constructed utilizing RCPs, researchers and analysists can make inferences regarding socio-economic and ecological outlooks (Wayne, 2013).

2.6.2.1 RCP 8.5

RCP 8.5 was developed by the International Institute for Applied System Analysis and reflects assumed levels of atmospheric pollutants given high emission conditions. By 2100, the RCP data reflects a threefold increase in CO_2 emissions in comparison to those observed today. Other assumptions reflected in the data are that 1) the world's population will reach 12 billion by 2100, 2) that methane emissions will grow drastically, and 3) that there is a high reliance on fossil fuels which is unimpeded climate policies. The scenario presented by RCP 8.5 represents the "Worst Case Scenario" for the future of the environment and "business as usual" for policy, energy and fossil fuel use.

2.6.2.2 RCP 6

RCP 6 reflects intermediate emissions assumptions. In this concentration pathway, the National Institute for Environmental Science in Japan predicts that radiative forcing will reach a stable point soon after 2100. The basis for this assumption accounts for the current rate of technological and strategic development targeted at reducing greenhouse gas emissions. The future projections provided by RCP 6 align with a heavy reliance on fossil fuels, an intermediate level of energy intensity, and stable CH_4 emissions. Additionally, the pathway assumes that CO_2 emissions will peak in 2060 at a level that is 75% higher than that of today's annual CO_2 emissions.

2.6.2.3 RCP 4.5

RCP 4.5 was developed by researchers from the Pacific Northwest National Laboratory. The pathway reflects a slightly more ambitious outlook for actions taken to reduce emissions than RCP 6. It consists of assumptions including lower energy intensity, strong reforestation programs, decreased croplands, strict climate policies and CO_2 emissions peaking at 2040 at levels only slightly above those observed today.

2.6.2.4 RCP 2.6

RCP 2.6, developed by PBL, the Netherland's Environmental Assessment Agency, sets a limit on radiative forcing of $3.1W/m^2$ before a reduction to $2.6W/m^2$. According to RCP 2.6, this will happen by 2100. This projected trend for radiative forcing would require declining oil use, low energy intensity, a world population of 9 billion by 2100 and increased cropland use. In terms of CO_2, this pathway assumes that CO_2 emissions will not increase — instead, it will begin declining after 2020 with eventual net negative emissions 2100. Additionally, it assumes that CO_2 concentrations will peak in 2050 as the climate change commitment from past activities is realized. After this point, the data anticipates a drop in CO_2 concentrations in 2100 to approximately 400ppm (Bjørnæs, 2015).

2.6.3 Atmospheric GHG Concentrations, Radiative Forcing and Temperature

The assumptions given from each of the four main RCP models show an overall increase in CO_2, CH_4 and N_2O from 2000 to 2100. These projections trend well with each scenario's energy and oil consumption projections and fuel mix assumptions (Vuuren, 2011).

2.6.4 Anticipated Changes due to Future Climate States

2.6.4.1 Hydrological Cycles

Modeling of the hydrological cycles accounts for several changing environmental factors caused by climate change. With reference to RCP 8.5, models predict that precipitation will increase through the tropics and temperate regions; areas typically considered "wet". Despite increases in precipitation, it is predicted that relative humidity and soil moisture will decrease globally, especially across Southern Europe and Western Asia.

Droughts are projected to become increasingly severe and more frequent as climate change continues. First are anticipated precipitation decreases in the Mediterranean, the Caribbean and Central America, southwestern United States, and South Africa. These areas are also expected to have a significantly reduced soil moisture (IPCC, 2014, p. 1118). During a total of three months in 2017, 25% of the globe was in a state of drought (WMO, 2018b). A general conclusion is that wet regions will become wetter while dryer regions will get dryer (WMO, 2018a).

2.6.4.2 Increased Ocean Acidification

Absorption of CO_2 in the oceans has resulted in ocean acidification. This process takes place through the following chemical equilibrium:

$$CO_2 + H_2O \leftrightarrow H_2CO_3 \leftrightarrow H^+ + HCO_3^- \leftrightarrow 2H^+ + CO_3^{2-}$$

The amount of CO_2 dissolved in the oceans is proportional to the partial pressure of CO_2 (which increases with its atmospheric concentration). As such, emissions of CO_2 are proportional to the acidification of the ocean, assuming a completely mixed atmosphere (Snoeyink & Jenkins, 1980).

Atmospheric concentrations of CO_2 have been inversely proportional to the pH of ocean waters as expected, given the carbonate system described above (WMO, 2018b).

The absorption of CO_2 into the ocean has resulted in a decrease in pH of 0.1 since the beginning of the industrial revolution (IPCC, 2014, p. 52). This decrease in pH represents a 26% increase in hydronium concentrations in the ocean (IPCC, 2014, p. 52). By the year 2100, under models assuming a continuation of heavy fossil fuel use, the pH of the ocean will decrease by 0.3 - 0.4 pH units which results in a 2 - 2.5 times greater concentration in hydronium ions, relative to pre-industrial conditions (Houghton et al., 2001).

2.6.5 Economic and Ecological Impacts of Climate Change and its Drivers

The anticipated impacts of climate change and continued emissions of CO_2 and other greenhouse gasses are copious; freshwater and inland water systems will be affected in addition to marine and terrestrial ecosystems. However, the consequences of continued climate change extend further than environmental impacts. Human security, livelihood, poverty, and food security will be impacted as well. These effects are well laid out by the Intergovernmental Panel on Climate Change.

2.6.5.1 Northern Atlantic Cod Stock Case Study – An Ecological Impact of Warming Air Temperatures

In the Arctic, a region particularly sensitive to climatic changes, warming air temperatures have caused Arctic sea ice to retreat, i.e., melt. The effect of warming temperatures and accelerated Arctic ice melt results in large amounts of non-saline water to exit the Arctic (Greene, Pershing, Cronin, & Ceci, 2008). This discharge of non-saline water changed sea circulatory patterns and altered oceanic stratigraphy. As a result, ecosystems of the North Atlantic were markedly changed. In the early 1990s, the North Atlantic cod industry faced a fish stock collapse and fishing cessations were put in place to aid in stock recovery. However, these efforts were primarily hampered by cold fresh waters occupying the northern reaches of the North Atlantic Cod's habitable range (Greene & Pershing, 2007). This also impacted other fish markets and stocks have failed to rebound in the Northern Atlantic since the initial collapse. However, southern cod stocks (those below 44°N) rebounded by a factor of 4.4, with respect to biomass, ten years after fishing restrictions were put in place. The likely reason for this is that southern cod stocks reside in a separate hydrological regime in terms of temperature and stratification from their northern counterparts (Frank, 2005). The continual influx of cold, low-saline water, from climate change driven ice melt, continues to affect cod stocks in the Northern Atlantic. The annual cod catch for 2018 represents a 20.7% decrease from the annual average catch from 2013-2018. By 2006, North Atlantic Cod catch had decreased 45% from 1997 in Norway.

North Atlantic Cod are not the only fisheries affected in this time frame; deep water prawn catches had declined by 81% from 2002 to 2017 (Statistics Norway, 2019a). These recent low catch records are accompanied by low salmon, sea trout and char catches in 2018 which were the lowest in the past 30 years (Statistics Norway, 2019b).

2.6.5.2 Changing Global Hydrocycles

Warming global temperatures are predicted to shift cloud coverage to the more northern latitudes. Accompanying this shift are increases in precipitation for the northern regions and accelerated warming (IPCC, 2014, p. 1070).

The Sámi people, who are the only recognized indigenous European population, inhabit what is known as Sápmi, which overlies northern parts of Norway, Sweden, Finland, and Russia (Wing, 2019). They have long been reindeer herders which carries cultural significance and pride. Climate change has brought unusually warm winter temperatures to the areas where reindeer graze, leading to freeze-thaw conditions which result in thick ice formation making it difficult, if not impossible, for reindeer to access the vegetation that lies beneath the ice cover. As a result, many reindeer have starved. Additionally, warmer temperatures have led to an abundance of insects to the herding lands which pose a threat to calves. Ultimately, these climate consequences induce vulnerability to the Sámi people (Rees, Stammler, Danks, & Vitebsky, 2007).

These freeze-thaw cycles might also impact fruit production in Norway. Some crops such as cherries and apples are sensitive to frost after fruit blossoms have developed (Eccel, Rea, Caffarra, & Crisci, 2009). Cherry farmers have relied on slow warming springtime weather to keep blossoms from forming before the threat of frost has passed. Climate change has altered when fruit trees will form their blossoms, making them more susceptible to frost damage. Further damage to fruit crops can come from increased sun exposure and immigration of crop harming insects to northern climes (Severson, 2019).

2.6.5.3 Impact of Ocean Acidification

2.6.5.3.1 Ecological

Ocean acidification affects calcareous marine organisms such as clams, oysters, sea urchins (Cooley & Doney, 2009) and corals (Gazeau et al., 2007). As oceans become more acidic, the ability of these, and similar organisms, to form their shells and skeletal structures diminishes. Decreasing pH lowers carbonate ion concentrations, which are vital for the construction of shells and affect the vitality of many marine organisms (Cooley & Doney, 2009). Calcium carbonate, $CaCO_3$ (seashell), formation requires the presence of free CO_3^{2-} and Ca_2^+. However, CO_3^{2-} exists within a pH driven pathway with CO_2; thus, free CO_3^{2-} is chemically dependent upon CO_2 concentrations. In acidic conditions, CO_3^{2-} exists in lower concentrations as it is converted to its conjugate acid (HCO_3^-). Under these conditions, therefore, carbonate ion (CO_3^{2-}) is less environmentally available.

Further, it is observed that free CO_2 concentrations increase with acidification as HCO_3^- becomes free CO_2 thus furthering the impacts upon calcareous organisms.

$$CaCO_3 + CO_2 + H_2O \rightarrow Ca^{2+} + 2HCO_3^-$$

Chemical Equation for Seashell Dissolution

Acidification also negatively affects survivability, growth, development, and abundance of mollusks, corals and echinoderms. Additionally, studies have shown a reduction of photosynthetic calcifying algae abundance of 80%. Algae populations whose abundance is not affected display a 27% reduction in photosynthetic activity (Kroeker et al., 2013).

While calcareous organisms such as mollusks and corals represent only a fraction of marine species, these organisms are needed for filtering, shelter, and sustenance; their importance is high. Acidification has the potential to disrupt food webs which other marine species rely upon (Cooley & Doney, 2009).

2.6.5.3.2 Socio-economic

Ocean acidification has the potential to cause several socio-economic disturbances including income, vulnerability and food scarcity. According to Armstrong et al. (2012), a decrease in pH of 0.5 from preindustrial times would have impacts costing 10 million US dollars per year for Norway's fisheries. The financial impacts of acidification for Norway are dwarfed by those to be suffered from the decline of coral reefs, which is placed at almost 1.1 trillion USD per year under the SRES A1B scenario (Brander et al., 2012) — a scenario which is similar to RCP 8.5. Subsistence fishing communities would also be affected; having little recourse from declining food stocks upon which they rely (Rojas-Rocha, 2014).

3 Climate-Related Political and Economic Frameworks

3.1 The Paris Agreement - A Global Political Consensus

The Paris Agreement, set in place in 2015, launched what is arguably the most ambitious plan to lessen the effects of climate change. The goal of the agreement is to keep global temperature warming to less than two degrees Celsius, in comparison to preindustrial times, through a strengthening of responses aimed at targeting climate change. The agreement builds a foundation for financial mobilization and infrastructure for technological developments structured to assist nations in meeting their climate objectives.

The agreement is structured into goals including maintaining temperatures below two-degrees above pre-industrial temperatures. Further, the agreement makes a goal of initiating global peaking of greenhouse gas emissions as soon as possible, that is, to continually reduce greenhouse gas emissions. Maintaining sinks and reservoirs of greenhouse gasses, such as rainforests and other carbon sequestering entities is encouraged through the agreement. Of the 197 parties that have been a part of the Paris Convention, from which the eponymous agreement originates, only 13 parties have yet to ratify their commitment to climate change mitigation through its framework.

Ultimately, these ambitions require that carbon emissions be drastically reduced or offset such that there are no net carbon emissions and that the net-zero carbon ambition must be reached by 2080 – 2100 to limit climate change to two degrees and must be reached by 2060 – 2080 to return to the 1.5-degree benchmark. However, industry and energy generation must reach net-zero emissions even sooner for these ambitions to be met (Rogelj, Schaeffer, & Hare, 2015).

The emission goals presented within the agreement serve as a benchmark for emissions which companies and industries aim to align themselves (Åsnes, Personal communication, March 22, 2019).

3.1.1 Carbon Pricing

For industries and companies often associated with CO_2 emissions, e.g., the oil and gas industry, alignment with the Paris agreement and its goals are not solely a matter of environmental concern or social concern. Shareholder pressure brought Statoil (now Equinor) to recognize its role in the changing climate and what actions are needed to reduce the company's climate impact (Statoil, 2016). Further, companies are realizing climate related risks related to their operations, some of which have major financial implications.

Placing a price on CO_2 emissions has been introduced to aid in the transition to a low carbon future. Effectively a fee on carbon emissions, pricing aids economies in transitioning to a low carbon profile. The additional cost of carbon emissions for the energy and oil and gas industries lessens their competitiveness in relation to renewables which are then advantaged by the carbon pricing. Pricing schemes have the additional benefits of increasing resource efficiency and building "resilience to risks inherent in deep structural change" for the oil and gas industry.

The carbon-pricing gap, which describes the difference between current rates for carbon emissions, and a benchmark carbon rate need implementation in order for climate-related ambitions to be met. Measurement of this gap over time has shown that the gap is narrowing; this suggests that there is growing support for carbon rate policies globally (OECD, 2018).

Although Norway already has carbon-pricing schemes in place since 1991, international operations will be affected by the carbon-pricing gap trend. Equinor supports a price on carbon emissions and assumes a $50/tonne carbon rate for all new business developments unless there is a rate in place for that locale that is higher (Equinor, 2018).

3.2 Investing in the Era of Climate Change

Climate change carries economic risks which shape investment decisions. In fact, investors are advised that economic growth should no longer be assumed to be highly resultant from fossil fuel energy sectors (Mercer, 2019). Concerns over climate change have influenced and changed where investors are placing their money and what considerations make up good investment decision making. Political and regulatory pressures that have been or will be implemented in order to meet climate goals will undoubtedly affect industries with large carbon footprints, such as the oil and gas industry. This chapter serves to outline the financial implications and consequences of climate change policies for the oil and gas industries.

3.2.1 Oil and Gas Investment Theory until 2014

Investment theory is the knowledge that serves as the basis for investment decisions (Goetzmann, 2000). For the oil and gas industry, investment theory had long held that a company's long-term financial prospects were based on four key factors: 1) sales volumes, 2) cost to produce, 3) product value, and 4) proven reserve size. The driving investment assumption was that reserves were equated to rewards.

3.2.2 Current Investment Theory

This ideology changed with the shale boom in the United States. New technology allowed for a new source of oil, unconventional oils, to be brought into the market. As a result, companies were able to increase their reserves drastically. This boom brought about a massive increase in proven reserves and a surfeit of oil – production was no longer under constraint – and proven reserves where no longer a valuable investment metric. This new abundance of oil brought about by the shale revolution, and related geopolitical factors, dramatically lowered the price of oil.

Oil companies could no longer demand high prices for their products. Assets and reserves that required high oil prices to recuperate investment capital lost their economic value. As a result, reserves as a key investment metric was replaced by cash flow.

Previously investors knew prices would rise after downturns, and even expensive projects would generate favorable returns. “The shale boom, and the accompanying price collapse, has undercut that idea, but no new investment narrative has emerged to take the place of the old one” (Sanzillo, Hipple, & Williams-Derry, 2018) (p. 19). This change meant that oil and gas companies would be evaluated by investors based on how revenue and profits are affected by oil prices which, in turn, has meant that oil and gas have become speculative investments (Sanzillo, Hipple, & Williams-Derry, 2018).

3.2.3 Climate Risks for Corporations

According to Karsten Löffler, “Institutional investors require actionable information to adequately reflect climate risks and opportunities into asset allocation. While global warming is a fact, we face great uncertainty around policy measures and the financial impacts in the nearer term are little understood” (Mercer, 2019). This means that climate change presents several challenges for companies. One challenge, in particular, is alignment with policies such as the Paris Agreement, which some in the oil and gas sector state they aim to do already. Climate policy alignment requires that companies consider the performance of their own assets to build a corporate level overview. This is an area that would benefit from improved emission modeling which would allow for continual alignment assessments and refinement of strategy.

3.2.3.1 Stranded Assets

Assets (fossil fuel energy and generation resources) can become stranded if they are no longer able to provide economic return before reaching the end of their economic lifetime (PRI, 2015). The marginal profitability of assets is negatively impacted by climate policies, including carbon pricing; thus, the risk and exposure for assets are increased. This is of concern in the oil and gas industry as the Paris agreement and other political and regulatory forces move closer to implementing taxes and fees for carbon emissions. However, reporting from Wood Mackenzie shows that an imposed carbon tax of 50 USD per tonne carbon emitted would not strand any oil and gas assets (Flowers, 2018).

3.2.4 Climate Risk for Investors

Organizations must also think about investors – what their demands are and what influences them to invest. Climate change presents an unavoidable impact on investment returns, which necessitates its incorporation into investment decisions as a new return variable (Mercer, 2019).

The Financial Stability Board has created a Task Force on Climate-related Financial Disclosures which aims to provide investors and other stakeholders with climate-related financial risk disclosures. The project focuses on three climate related risk types, physical, liability and transition risks. This work will serve to guide companies, based on what the financial markets want in terms of climate risk management, so that climate risks can be appropriately measured and responded to (Task Force on Climate-related Financial Disclosures, 2019).

3.2.5 Investing with ESG

The practice of environmental, social and governance (ESG) investing, which focuses on these non-financial dimensions of performance (Duuren, Plantinga, & Scholtens, 2015), is commonly used by governing boards that want to incorporate sustainability into their portfolios. Investment analysis using ESG aims to understand whether, and to what extent, corporate financial performance is influenced by the company's conduct on social and environmental issues. This way of financial investment screening is a notable change from the former practice of negative screening which excluded certain industries and investment types from being a part of investment portfolios (Caplan, Griswold, & Jarvis, 2013). This technique allows for corporations to be benchmarked against their peers (RBC, 2012) and for best-in-class investment selection whereby investment decisions are made based on certain environmental criteria having been met and performance against peers. As such, this shift in investment ideology presents an opportunity for oil and gas companies who are venturing into renewables as their performance in that sector might bring investor interest or provide a hedge for the company.

3.2.6 The Divestment Trend

Resilience in the face of climate change is not the only factor affecting investments in the oil and gas sectors. A moral plea for action on climate change has led to a global divestment campaign from the fossil fuels industry. Since the campaign's inception, approximately 1000 investment firms, representing $6.24 trillion in assets, have made commitments to divest from the fossil fuels industries (Arabella, 2018).

Financially, renewables demonstrate the highest positive sensitivity to changes and implementation of climate change policies due to an increased ability to compete against fossil fuels. Oil, as an industry sector, is second most sensitive to climate policy with a guaranteed 1% reduction of returns on investments. Additional variability brings this figure to 4%, which reflects the effects of climate policy that is expected to exist in more severe climate scenarios. To contrast, renewables stand to increase their returns on investment by 3.5% over the same period (Mercer, 2019).

4 Global Energy Outlook

The oil and gas industry is faced with numerous challenges from climate and social issues, the effect of carbon pricing on profit margins, investment uncertainty and shrinking resources. However, the world still needs oil and gas – the industry cannot simply be abandoned.

Rapid levels of population and economic growth, particularly in emerging market economies, has resulted in equally paced energy demands. In 2017, global energy demand grew by 2.1% which represents more than a two-fold growth in demand over the previous year. This trend reflects growing global prosperity but poses new challenges, especially in terms of how these demands will be met and the resulting environmental impacts of meeting these demands (OECD, 2011).

Energy sourced from renewables has grown dramatically, meeting around 30% of the global energy demand. Despite the growth in renewables, energy generation from fossil fuels continues to be the predominant supplier in the global energy mix. This continued reliance on fossil fuels and increases in global energy led to an increase in global emissions of 1.4% for 2017, representing an all-time high (IEA, 2018).

This increasing global energy demand trend is expected to continue, and the demand for oil is expected to grow for until 2025, at a minimum (Figure 4-1).

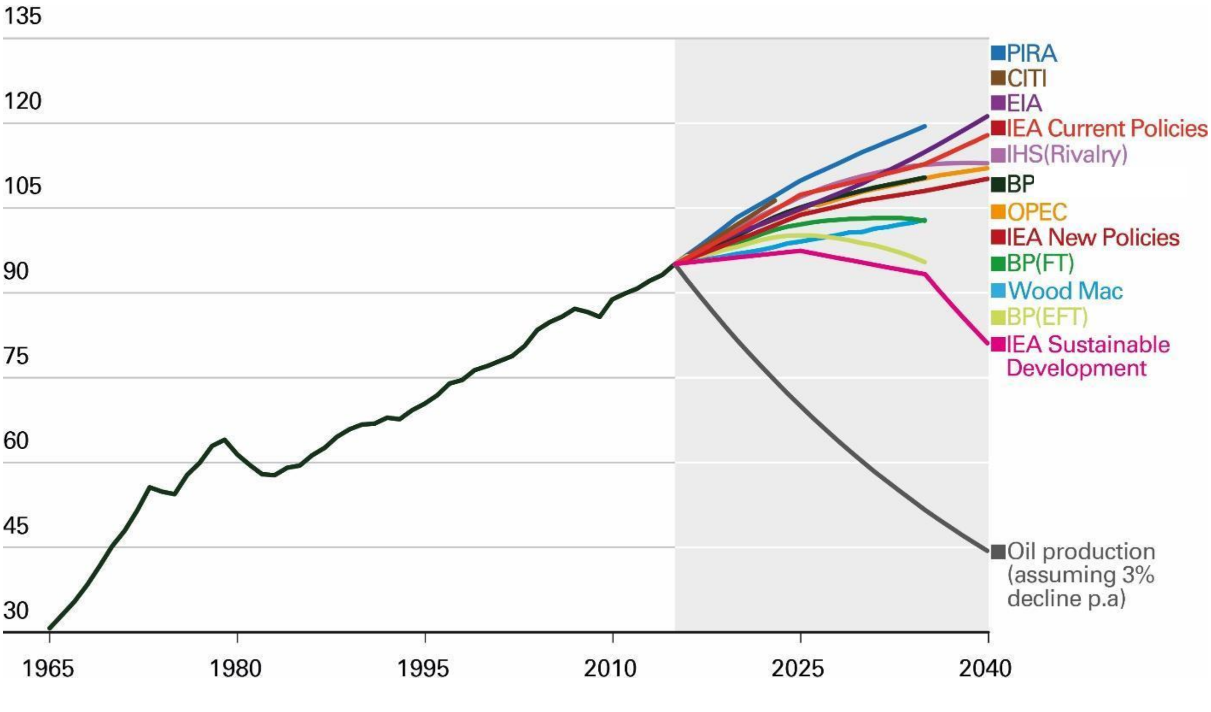

Figure 4-1. Oil demand trends and projections for various energy outlooks in millions of barrels of oil per day from 1965 to 2040 (Dale).

4.1 Energy Scenarios

Energy scenarios, which are presented in Figure 4-1, use research and analysis to develop an idea what the future might look like in terms of how much energy will be required and from where that energy will come. This is similar to the representative concentration pathways which are used to make discernments and predictions about the future. The world energy scenarios assess what the future of energy might look like leading up to 2040 with regards to what energy needs will demand (Accenture Strategy, & Paul Scherrer Institute, 2016). In addition, oil and gas companies have made their own oil demand outlooks for the future. However, these are generally not the basis of international standards but may reflect policy and the company's own ambitions. Equinor provides three such scenarios; reform, renewal and rivalry, of which, renewal provides an outlook lower than all the outlooks provided in Figure 4-1 aside from the 3% decline projection (Equinor, 2019a).

4.1.1 IEA Outlooks

Three scenarios have been developed by the International Energy Agency (IEA) based on sets of assumptions which reflect policy changes with regard to emissions and climate issues. These scenarios are, the Sustainable Development Scenario, the New Policies Scenario, and the Current Policies Scenario (IEA, 2018).

The Sustainable Development Scenario reflects changes that should or will need to occur for nations to align themselves with the Sustainable Development Goals outlined by the United Nations. The IEA Sustainable Development scenario is based on the implementation of climate policies needed to meet the goals of the Paris Agreement (Dale). Under this scenario, new oil and gas opportunities must be developed to meet global needs (Figure 4-1).

The two other scenarios from IEA are Current Policies and New policies. They show, respectively, the anticipated demand for oil should, policies as they are today, are left unchanged and should policies slated to be implemented take effect. Both scenarios display futures with a reliance on oil that is higher than what is needed in order to be aligned with the Paris Agreement.

The cessation of oil production and fossil fuel consumption would result in a significant reduction in greenhouse gas emissions with enough of an impact to curtail further warming and changing of the climate. However, there is not enough energy production capacity to meet the energy needs of the globe now or in the future without fossil fuels as part of the energy mix

(Accenture Strategy, & Paul Scherrer Institute, 2016). As such, all scenarios, including those aligned with the Paris Agreement, project increased oil demand in the near future.

4.2 Energy Resources and Development Practices on the NCS

Resource development, in terms of volume on the Norwegian Continental Shelf, has grown at a much smaller rate than in the early years of NCS oil exploration (Figure 4-2).

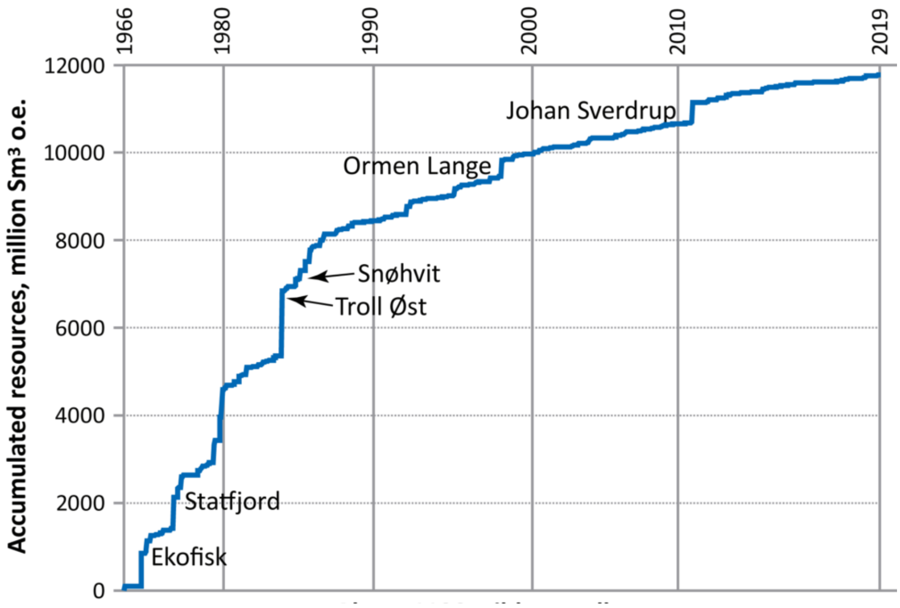

Figure 4-2. Accumulation of oil resource discoveries on the Norwegian Continental Shelf from 1966 to 2019 (Norsk Petroleum, 2019).

This means that an increasing number of smaller discoveries need to be considered so that new developments can meet consumption levels and future demands. This is evidenced in the fact that, since production began on the NCS, 100 fields have produced oil and gas. In 2018, 85 discoveries were in the process of consideration for development, most of which are small tie-backs (Norwegian Petroleum Directorate, 2018).

4.2.1 Business case screening through CVP

The capital value process (CVP) (Figure 4-3) is a structured and standardized approach to maturing business opportunities into operations that are both competitive and profitable. Each stage of the multistage process is demarcated by a decision gate (DG). Progression through these stages represents higher levels of project maturity. This process is embedded in workflows within Equinor to align business developments with its corporate and climate strategy to promote safety, high value and low carbon projects (Equinor, 2018). The delineation of the CVP process via the DGs ensures that certain criteria are met when entering and exiting a DG (Walden, 2015, p. 362) as maturation through the CVP is dependent upon whether certain stakeholder criteria are met. The standardization and structure of the CVP allow an organization to optimize its portfolio through the prioritization of the project through the organization's value chain (Equinor, 2018) as well as implement climate (and other) strategy into work flows.

New developments are screened through the CVP which includes estimations of the project's anticipated carbon emissions and evaluation of best available techniques (BAT). This is of particular importance considering Equinor's emphasis on low carbon operations. The understanding of the emissions generated from the extraction of resources from a new discovery is important; profit margins will be affected by emissions through carbon pricing and stakeholders and investors will be influenced by the amount risk the proposed development is exposed to in terms of its emissions.

Lifetime emissions of CO_2 and CO_2 intensity are included in business case and project development studies and decisions as well as in sustainability risk identification and assessments. CO_2 emissions and CO_2 intensities are significant considerations for a new project because they may become significant cost drivers, uncertainties and/or project stoppers. Currently, for project development, the assessments of CO_2 and CO_2 intensities can be qualitative, based on experience and are informed by the power and main driver concept selections (Fosen, 2018).

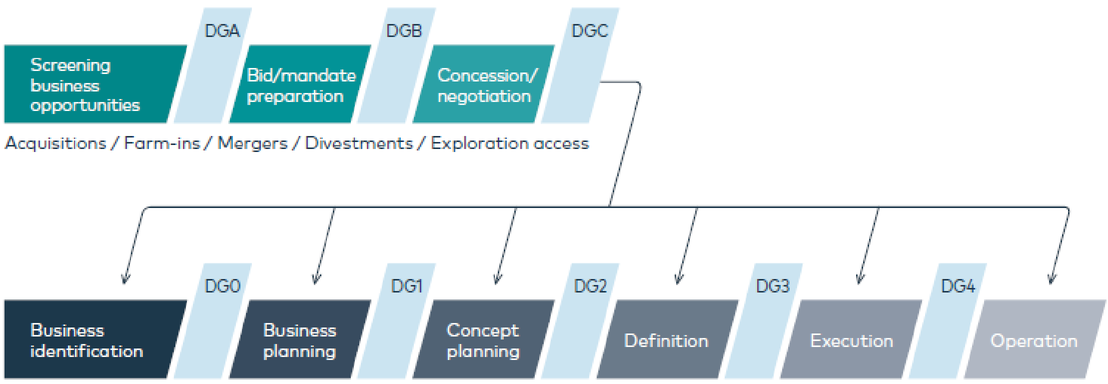

Figure 4-3 Structure and Process flow of the Capital Value Process (Equinor, 2018).

Equinor does not have any formal requirements as to the accuracy of CO_2 emission forecasting through each DG. However, the CVP process has requirements for accuracy for cost estimations which internalize emissions of CO_2 into subsequent cost estimations (Folgerø, 2015). Internal requirements dictate that energy demands be assessed through various concepts in the early phases, DG0 to DG3. Equinor's environmental technical requirements state that the emissions intensity for conventional oil production is to be limited to 8kg CO_2 per barrel of oil equivalent produced. Should this target not be attainable, an application for deviation must be submitted before a concept is selected at DG2 for environmental approval (Nilsen, 2019). This assessment focuses on the energy demand (which is relatable to emissions) based on rotational machinery needed to carry out production and injection. From DG2 to DG3, a more detailed assessment is to be made (Folgerø, 2015).

4.2.2 Further Emission Considerations in Project Development

Emission assessments for project development are included in an environmental budget scheme for each project. Along with the budget, emission assessments are used to derive potential environmental and social impacts as well as to determine and develop potential mitigative strategies.

4.2.3 Forecasted Emission Reporting to the Norwegian Government through the RNB

The Revised National Budget (RNB) is a budgetary summary that accounts for natural resource use and reserves. It primarily serves to provide an overview of Norwegian natural resources in terms of their annual extraction and quantities in place. The overview of the status and forecasted consumption of natural resources allows the Norwegian Government to make budgetary decisions and to determine oil policy (among others). Oil companies are required to submit annual forecasting reports regarding production, cost, income and, environmental discharges and emissions to the RNB (Norwegian Petroleum Directorate, 2018).

While this reporting has traditionally served to inform policymakers with regards to budgetary concerns and oil policy, the RNB also provides environmental forecast data, including emissions estimates, which are used to guide climate and environmental policy in Norway.

Foreseeable production volumes and anticipated emissions are reported to RNB on an annual basis for each installation. The prognoses are revised annually, meaning that new forecasts are produced each year.

5 Technical Background

The aim of this section is to provide an understanding of where and how CO_2 emissions originate through combustive processes and the carbon emission driving processes in upstream operations that occur offshore.

5.1 Combustion and Emissions

Combustion is an exothermic oxidation process that consumes a fuel source and oxygen. The exothermic nature of the reaction allows the chemical process to be self-sustaining being limited only by the availability of fuel and oxygen (Speight, James G. 2013). Often, fossil fuels such as coal, natural gas and other petroleum distillates serve as the fuel in combustion processes (API, 2009).

Combustion is not solely a chemical process; heat dispersion and conduction, bulk gas flow, and the diffusion of chemical constituents are all physical properties associated with combustion. As such, combustion is both a chemical and physical process (Speight, James G. 2013).

The purpose of combustion is generally energy production through the conversion of kinetic energy to useable work. With regards to gas turbines, the primary energy generator in the offshore oil and gas industry, the kinetic energy of the exhaust gas stream is converted into mechanical energy through the central shaft to produce electricity (Travers, 1996).

5.1.1 By-products of Combustion

While energy is the desired derivative of combustion, by-products, generally considered undesirable, are produced during the combustion process. CO_2 is one of two primary combustion by-products, the other being water. The production of CO_2 and water via the combustion process is understood through the following generalized balanced chemical combustion equation (API, 2009):

$$C_xH_yO_z + \left(x + \frac{y}{4} - \frac{z}{2}\right) O_2 \rightarrow (x)CO_2 + \left(\frac{y}{2}\right) H_2O$$

where

x = stoichiometric coefficient for carbon;

y = stoichiometric coefficient for hydrogen; and

z = stoichiometric coefficient for oxygen.

The equation is theoretical and represents an ideal situation which assumes complete and efficient combustion. This is not the characteristic of real systems.

Non-ideal conditions result in the incomplete combustion of hydrocarbons, which generates emissions of methane, carbon monoxide, volatile organic compounds and nitrous oxides. A modified version of this chemical equation serves as a basis for the estimation of emissions from volumes of hydrocarbons combusted (API, 2009).

5.2 Carbon Emissions from the Oil and Gas Industry

Corporate emissions, across all industries, are be characterized into three scopes: 1, 2 and 3. Together these scopes serve as the international standard for which corporations measure and categorize their emissions.

Scope 1 emissions consists of direct emissions. These emissions are a result of fuel combustion, vehicle use, and other emissions from assets owned by the company.

Emissions in scope 2 are a result of energy generated elsewhere and imported to perform functions at an asset controlled by the company. Emissions that are included in scope 3 have occurred through the activities of the company but originate from sources that are not owned by the company. This scope captures emissions from the transport, transformation and end use of oil and gas products when considering the oil and gas industry (Greenhouse Gas Protocol). Comparatively, Equinor's scope 1, 2 and 3 CO_2 emissions were 14.4, 2.8 and 314 million tonnes in 2018 (Equinor, 2019).

5.2.1 Emission System Boundaries

The CO_2 emissions assessed and predicted in this thesis will focus on the upstream emissions (emissions within scope 1) that are a result of, or are necessary for, the production of oil and gas, i.e., emissions from the operation of the installation and the production and processing of the well stream using activities that are performed by the installation.

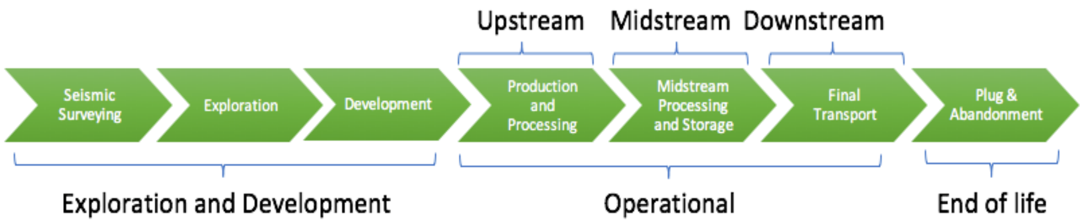

Figure 5-1. System boundaries and value chain location of thesis scope. Emissions boundaries (top text) within the lifecycle and value chain (bottom text) for offshore oil and gas production (adapted from Fløysvik, 2018).

The upstream activities, and hence upstream emissions, are the first segment in the operational lifecycle of an installation. Traditionally, upstream emissions include all activities performed and required to support and produce oil and gas and transport to the refinery gate (Fløysvik, 2018) if transported by pipeline.

5.3 Emissions Estimations of Upstream Activities

5.3.1 Energy Factors and Energy Demand

The production of oil and gas on an offshore oil and gas platform requires a slew of processes to transform the raw material extracted from the reservoir into useable and exportable products with each process possessing its own energy demand.

The energy demand at an installation reflects various processes that are needed to acquire raw material and process the useable and non-useable components of the well stream. Additional energy demand is required to provide a habitable living condition for offshore workers.

The Energy demand for an offshore oil and gas installation is the sum of the products of the energy factors and the quantity of attributable activity performed.

$$Energy\ Demand\ = \sum(Energy\ Factor_i\ \cdot Quantity_i)$$

The characteristics of the reservoir and the oil itself influence energy demand in addition to the production processes that are utilized (Gordon, Brandt, Bergerson, & Koomey, 2015).

Assessments and predictions of energy demand for reporting have traditionally relied upon energy factor inventories. Installation specific factors are contained in assumption documents, which describe the operational energy demands that exist on a platform. These estimations are built upon the assumption that the installations operate in a steady state regarding annual baseline energy demand. Further, it is assumed that a linear relationship exists between the amount of activity performed and the energy demanded. However, Nonlinear relationships between overall emissions and the quantity of gas injected into reservoirs have been observed (Åsnes, Personal communication, March 22, 2019).

Production volumes of oil and gas, water and gas injection, and volumes for gas lift need to be established so that an annual energy demand estimation can be established. Additionally, the baseline energy demand for the platform needs to be determined and built into emission estimation calculations.

5.3.2 Emissions Sources

Numerous sources of emissions exist in offshore oil and gas production. Gas turbines, engines, boilers, and flaring represent four common combustion sources for offshore oil and gas production and are, therefore, primary emission drivers in this sector of the oil and gas industry.

Gas turbines produce energy through the combustion of fuel gas in a compressive ignition system. For offshore installations in Norway, gas turbines are the primary energy production method for offshore installations. As such, they constitute the most significant portion of emissions of CO_2 for Norwegian Continental Shelf installations (The Norwegian Oil and Gas Association, 2017). In 2017, CO_2 emissions from turbines represented 84% of all CO_2 emissions on the NCS.

Energy generation in offshore oil and gas production may also utilize engines, which are primarily used on drilling rigs. However, their usage constitutes approximately 6% of carbon emissions for upstream activities in Norway (Figure 5-2).

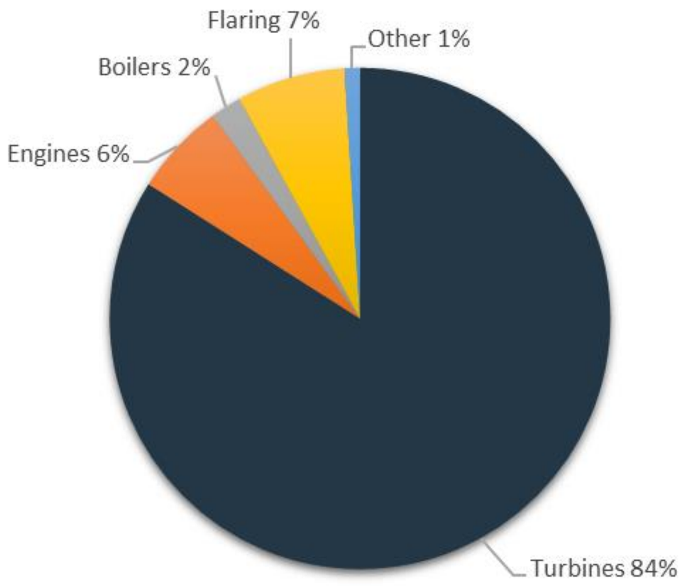

Figure 5-2. Distribution of CO_2 emissions by upstream source on the NCS in 2017 (Adapted from Norsk Olje og Gass, 2018).

While production related processes drive most emissions, the flaring of gas, which on the Norwegian Continental Shelf is typically reserved as a safety measure, adds to overall carbon emissions. Flaring represented 7% of CO_2 emissions on the NCS in 2017 (Norsk Olje og Gass, 2018) Flaring intensity shows much more variability globally and exerts significant influence on emission metrics such as CO_2/boe. In instances where flaring is high, pronounced effects on emissions metrics are observed (Skone & Gerdes, 2008). This difference can be attributed to the strict regulations and carbon pricing schemes that exist in Norway, and a lack of incentives for reduced flaring internationally.

The distribution of emissions by source for Equinor's operations (from which the data in this thesis is based) is similar to the distribution observed on the NCS as Equinor is the primary operator on the NCS and accounts for 80% of NCS production (Åsnes, Personal communication, May 24, 2019).

5.3.3 Emission Drivers

Carbon emissions generated by a platform or installation that is not supplied or supported by external energy supply, i.e. power from shore or offshore wind, are predicated on the installation's energy demand. This is because energy demand is most often met by gas turbines which generate emissions (Lommasson, 2015). As such, energy-demanding activities are also most often emission driving activities. Typical processes that have high energy demands are gas and water injection and gas compression as well as the operational needs of the platform, which is a static energy demand.

5.3.4 Emission Factors

Quantification of emissions produced by a platform is achieved using emission factors. These factors relate energy demand to the emissions produced when meeting the energy demand. These factors are based on three things: 1) the stoichiometric relationship between hydrocarbons and CO_2 generated in the combustive process, 2) the energy derived from combustion, and 3) the efficiency of the combustive process.

This method of CO_2 estimation requires that all, or most, energy-demanding processes be known. For business development in Equinor, all energy demanding processes above 1MW are to be accounted for in determining the energy demands at an installation (Fosen, 2018). Energy demands will be further refined to include smaller components at a later stage (Åsnes, Personal communication, May 24, 2019).

5.4 Forecasting

Forecasting is a method that uses identifiable factors and their effect on a given value of interest to provide estimates of what that value of interest may be in the future. Thus, forecasts provide a tangible idea of what the future is likely to hold.

In the context of CO_2 emissions in the oil and gas industry, forecasting serves several important functions. Forecasting of emissions allows for oil and gas operators to assess their emissions against internal and external climate goals which call for reductions in CO_2. It also allows for corporations to assess the level of exposure that their assets have when carbon taxation schemes are applied to their operations. Further, it allows to corporations to assess their climate strategies.

Forecasting of emissions from the oil and gas sector allows for oil and gas corporations to be more transparent with climate impacts of their activities and, in addressing and mitigating anticipated emission, assure investors of the corporation's sustainability and attract increased investments.

5.4.1 Qualitative and Quantitative Forecasting

There are two different types of forecasting approaches. The first is a qualitative approach to modeling. In this approach, the model predictors use inputs to generate a qualitative response. The second approach is quantitative and uses predictors to generate an estimate of a quantity. With regards to CO_2 forecasting, if a qualitative approach to modeling is used, the model outputs could be, for example, acceptable levels of CO_2 or unacceptable levels of CO_2. A quantitative approach to modeling will yield values for outputs, for example, tonnes CO_2 emitted per year. The model developed for this thesis is quantitative, as such, further discussion on modeling will be focused on aspects of quantitative modeling.

5.4.2 Methods of Quantitative Forecasting

Qualitative forecasting consists of two general categories: time series and causal methods.

The time series methodology assumes that observed trends and patterns of the forecasted variable are relatable to the passage of time, e.g., age and height in adolescence. This methodology requires that observations are taken at regular intervals to extrapolate the time dependency of the forecasted variable (Stranden, 2014).

5.4.2.1 Causal methods

Causal methodologies attempt to use relationships between the model predictors and the model output to derive coefficients for the model parameters. This is done by using historical observation and the influence the model parameters have on that observation. Many methods exist for deriving causal relationships. The two most common are simple regression and multiple regression. The difference between the two is that simple regressions assume that a single independent variable is responsible for the model output while multiple regression methods assume and make use of various factors that contribute to the model output – there are multiple independent variables.

5.4.2.1.1 Simple Regression

The simplest form of simple regression is a line with the formula

$$y = mx + b$$

Where:

y = model output (the dependent variable)

m = is the slope of the line generated by the regression

x = model input (independent variable)

b = the point y that corresponds to the line's horizontal position when x is 0

Many iterations of this linear form exist to accommodate logarithmic, exponential and other relationships.

5.4.2.2 Multiple Regression

The multiple regression follows the form:

$$y = m_1\, x_1 + m_2\, x_2 + m_i\, x_i + b$$

Where:

y = model output (the dependent variable)

m_i = is the slope of the line generated by the regression for the i^{th} variable

x_i = model input for the i^{th} variable (independent variable)

b = the point y that corresponds to the lines position when x is 0

5.4.2.3 The Forecasting Process

Forecasting is not a perfect science; the estimations that forecast models produce sometimes fail to match the actual data that the forecast represents. This is likely due to an underlying assumption that there exists inherent stability within the system that is modeled. This is to say, what is expected to occur based on past observations of parameters and the resulting effects, represents an unchanging dictum that is unaffected by external influences and in a broader sense, reality.

The building of a forecasting model should follow a stepwise process. The process involved with forecast construction will likely vary somewhat due to the nature and intention of its purpose. The following is a nine-step example of how forecast construction could be carried out based on Stranden (2014) and Mester (2018).

First, an understanding of the purpose and need of the forecast should be determined. This gives a sense of the level of detail that is required to produce estimations that meet the desired accuracy. This step will also help to define what resources will be needed to undertake the forecast construction process.

Second, the item that should be forecasted should be selected. In the case of this thesis, the selected item is CO_2 emitted from turbines to meet the energy demanded from upstream processes offshore.

Third, the forecast must have an intended time horizon, short term, mid-range or long term. The time horizon is selected based on the purpose of the forecast. It should be kept in mind that forecasts tend to lose accuracy with increased time horizons. As such, the basis of the modeling process in this thesis utilizes, initially, the first 20 years of historical data.

Fourth, the type of forecast model to be employed should be selected and based upon the time horizon selected for the forecast.

Fifth, data should be gathered and examined. When collecting the data, consideration should be given to what the source of the data is (Stranden, 2014).

Sixth, the data that is collected may need to be partitioned into two sets, a training set and a test set. This depends on how readily available new data can be acquired after the model is made and the relative diversity of the data sources. If new data is continually available, then the usefulness of segregating data may not need to be considered. In the partitioning process, one dataset will be the training set. This is used as the basis for the model and defines the parameters and their coefficients. The other set is used as the test set, which is used to test and validate the model (Mester, 2018).

Seventh, the model selection process in step four should be validated. The available data should be able to fulfill the requirements for the model.

Eighth, the model should be applied to ensure that the model derives reasonable results for the model outputs given the data inputs.

Ninth, the model should now be used to fulfil its intended purpose (Stranden, 2014).

5.5 Forecasting of Upstream CO_2 Emissions in the Oil and Gas Industry

Forecasting of upstream CO_2 emissions in the oil and gas industry is typically conducted causally. Models are built upon facility specific equipment, their associated energy demand and the efficiency with which energy is generated offshore predictions of future production volumes (API, 2009).

5.5.1 Example of Existing Models for Emission Forecasting for Upstream activities

5.5.1.1 OPGEE

The 'Oil Production Greenhouse gas Emission Estimator' (OPGEE) is a life cycle assessment emission model for emissions for all sectors and scopes of the oil and gas industry. OPGEE accounts for up to 50 parameters, many of which will have assumed values unless otherwise inputted by the user (Gordon, 2015). The model is highly detailed, accounting for parameters like frictional forces between the well stream and pipelines. It is an account of all, if not many, of the engineering and physical energy consuming factors in the industry (El-Houjeiri, Masnadi, Vafi, Duffy, & Brandt, 2017). The model relies on a minimum of four primary parameters. The accuracy of the model has been shown to receive no further benefit after having values for more than ten primary parameters (Gordon, 2015). The model is complex and takes a high level of familiarity to use.

5.5.1.2 NEMS Forecaster

NEMS is an environmental accounting firm that provides annual RNB emission estimations (which the models in this thesis are comparable to) through their environmental forecasting software. Understandably, documentation of the model and its development is not publicly available. However, the estimation provided by NEMS requires knowledge of each installation from reservoir and facility engineering specialists to develop modeling parameters which were mentioned in 5.3.1.

5.5.2 Existing Parameter Development

Parameters that are the basis for RNB estimations are derived from assumptions constructed by reservoir engineers who characterize the production reservoirs and the volumes to be extracted, injected, cleaned, discharged, and exported to create a theoretical inventory of mechanical needs for production. From these assumptions, a theoretical platform is designed based on capacities that should be required at a predetermined peak production level. The theoretical platform serves as a basis for the number of production components such as pumps and compressors that will be in use at the platform. The energy demand of each component is summated and converted to units of CO_2 based on energy load and turbine efficiencies (Åsnes, Personal communication, March 22, 2019). The assessment of an installation's component inventory provides a way to isolate and analyze environmental impacts throughout industrial processes based on the function a process serves. This is the basis of bottom-up model development, which is the method of emission modeling across all current emission models in the industry (Fløysvik, 2018). Development of energy demand and emission models using the bottom-up methodology is time consuming, resource intensive (Åsnes, Personal communication, March 22, 2019).

5.6 Inverse Modeling and Predictive Analytics

Inverse modeling is a modeling process where inputs and outputs are known. Model parameters are statistically derived through regression or are determined through physical understanding by relating observations to the variables that produce them (Brasseur & Jacob, 2017). This is the basis of top-down modeling which is easier and less resource intensive given that data exists and is available.

5.6.1 Novelty & Benefits

Some models exist for CO_2 emissions in upstream oil and gas production. However, none that are publicly available attempt to produce estimations using a statistically based top-down methodology, where observations of historical input values are the basis of parameter development. This is a significant change in the way emissions are quantified for upstream oil and gas production. Additionally, none of the existing models work with the level of simplicity that is attempted within the scope of this thesis.

A benefit of the top-down modeling process is that it removes some of the inherent uncertainties within bottom-up modeling. As such, top-down based models can be used to validate emission inventories, which means that increased transparency and accountability are benefits of the top-down modeling (Frost, 2015). This form of modeling emissions was used to verify emission statements from Volkswagen, who were resultantly found to be cheating emissions, which led to a major scandal and the company losing 20% of their value (Ross, 2015).

Part 2 – Modeling

6 Methods

6.1 Data Sources

Data for historical CO_2 emissions from turbines was obtained through the Management Information System (MIS), a relational database of emissions and other environmental accounting parameters available in Equinor. The data obtained from MIS in this thesis is also accessible externally for each specific field through annual environmental reports from the Norwegian Oil and Gas Association.

Historical values for injection volumes and production values were obtained through the Norwegian Petroleum Directorate's (NPD) Diskos database and by data request made to the NPD.

Quality control of the collected data was performed and verified against internal documentation contained within Energy Components; an Equinor database.

Forecasted data reported to the Norwegian Government though RNB was obtained through an internal data request.

Turbine efficiencies and inventories were sourced from RNB assumption document libraries.

6.2 Data and Installation Selection

Eleven installations were selected based on a) being located on the Norwegian Continental Shelf, b) being operated by Equinor, and c) their relative simplicity with regards to where volumes originate and end in terms of processes that are typical to installation-based production.

The eleven selected installations were:

Grane
Gullfaks
Heidrun
Kristin
Kvitebjørn & Valemon
Norne
Sleipner
Snorre
Visund
Åsgard

NPD factpages were consulted to understand the network of facilities on the NCS to ensure that production and injection volumes were properly allocated in the historical library. Information from NPD factpages was also used to combine installations that share significant portions of work to determine if separate facilities should be treated as a single installation.

Kvitebjørn and Valemon were combined, and their combined data acts as a single installation in all assessments in this thesis. A significant amount of production processes are shared between these two installations, which supports the assumption that these two installations can be assessed as one.

6.3 Modeling Procedure

A historical library was constructed with regards to the parameters of interest and CO_2 emissions. These parameters were injection of gas and water, oil production and gas export volumes, and emission values for each installation. Historical data consisted of values resulting from activities during calendar years. The library was constructed relationally with reference to operational age. For this modeling process and throughout this thesis ‘age’ is with reference to the calendar year of startup.

Data from the library was then segregated based on installation age. The segregated sub-datasets were run through regression software, which yielded statistical analyses consisting of R, R^2 and the f-significance based on the set of derived parameters. This form of modeling was performed continually to provide further refined datasets and parameters.

During the model development process, visual analyses of R, R^2 and significance-f values were done to build and refine sub-datasets based on when, in an installation’s lifetime, models produced statistically appropriate approximations.

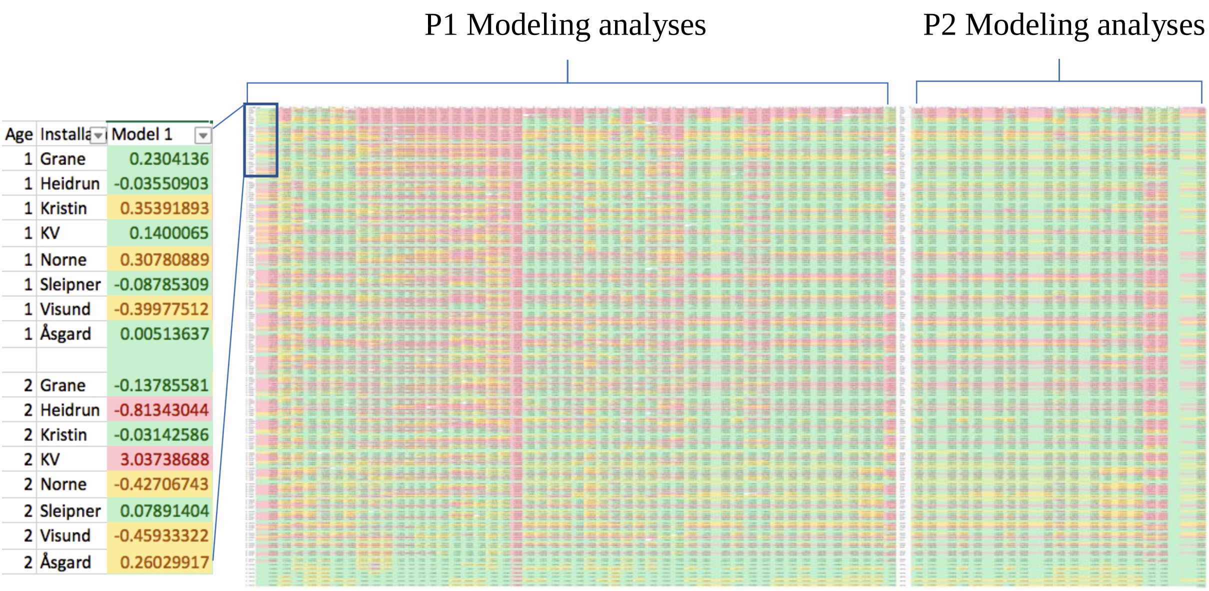

Figure 6-1 Size, structure, and layout of the color-assisted visual analysis process for P1 and P2 model development process with zoomed inset (left).

The parameters from the sub-dataset modeling were used to generate emission estimates based on historical parameters. Percent errors were calculated for each estimation. The calculated errors were color-coded into three error groups; errors ranging from -25% to 25% were green, errors between -50% and -25% and 25% and 50% were yellow, errors outside of the +/- 50% range were red. These error ranges were arbitrarily chosen. Visual analysis of the errors was qualitatively conducted to further refine the sub-datasets by identifying which, if any of the installations, may not be suited for modeling (Figure 6-1).

One model was selected for P1 modeling, which does not consider oil production volumes as a parameter. A second model was selected for the P2 model, which, in addition, to the parameters considered by P1, considers oil production volume. These two models were selected based on their respective statistical quality and their qualitative fit.

The ability of each model to produce emission estimations was performed on an installation to installation basis. Correlations between the resulting predictions and the historical emissions, which they aimed to predict, were calculated.

The earliest RNB document (which are produced annually) for each installation was selected to provide the "first" forecast of the installation's environmental performance (Table 8).

P1 and P2 parameters, as well as emission projections, were obtained from these documents and built into a library. The oldest projections were selected, and data from them was segregated similarly to the historical data from which the models were built. For the assessment of predictions to RNB, it was assumed that projections for volumes of CO_2 injected and gas lift could be combined with, and considered as, gas injection volumes. Old forecast data was then put through the models and projections based on modeling for RNB was compared to projections from P1 and P2 models based on RNB forecasts of key parameters.

6.4 Comparison of Model Estimations

P1 and P2 models were used to produce emission estimates for each installation on a yearly basis by assessing parameters in RNB and historical parameters.

6.4.1 Integrations

P1 and P2 emissions estimates based on historical parameters were integrated for each respective installation in the training and test group. These estimates were compared with reference to the integration of their respective historical emissions. These estimations were done with a lifetime and trimmed historical time frame. The trimmed time excluded years of operation with poor data quality. Generally, these were years prior to 1999 where reporting of injection volumes did not require quality control; a fact that is evident through an examination of historical injection volumes. Additionally, years of operation which were more than 30 years in the installation's lifetime were removed. External factors that affect an installation's environmental performance and are not incorporated into the P1 and P2 modeling assumptions hence the exclusion of years above 30.

P1 and P2 emissions estimates based on RNB parameters for each field were integrated. P1 and P2 emission estimates were compared, separately, to RNB emissions estimated with reference to the integration of their respective historical emissions.

P1 and P2 emissions estimates based on RNB parameters for each field were integrated and compared with reference to the integration of their respective RNB emissions predictions.

P1 and P2 emissions estimates based on historical for each field were integrated. P1 and P2 emission estimates were compared, separately, to RNB emissions estimated with reference to the integration of their respective historical emissions.

P1 and P2 emissions estimates based on historical parameters for each field were integrated and compared with reference to the integration of their respective historical emissions. Data for this comparison was separated to compare results of P1 with RNB and P2 with RNB.

Visual representations of the comparisons were produced with a dashed blue line representing a "perfect fit" and two solid blue lines representing errors/deviations of +/- 20%. The level of accuracy highlighted by these error lines aligns the results with DG3 in the CVP so that results are understood in a useful manner.

From these comparisons, annual average emission deviations were calculated. The deviations were divided by the years assessed for each installation to produce an annual average model deviation.

The validity of the emission integrations for P1 and P2 modeling was examined through an assessment of historical and modeled emission correlations for Njord, Statfjord and Oseberg Sør. These were selected randomly from the test set. Further assessment of the modeling results supports the validity of the models.

6.4.2 Modeled vs Historical

Test data for the modeling assessment were selected based on appropriateness, i.e., low data quality and non-modellable years (year 1 and years after 30 years of operation) were removed from the modeling procedure when measuring modeling quality.

Historical parameters for each year were used as inputs for P1 and P2 modeling for Njord, Statfjord and Oseberg Sør. The historical emissions were used to calculate percent errors for emissions estimations for each year. Historical emissions and percent errors were plotted against P1 and P2 estimates separately.

The correlation between historical emissions and estimated emissions was calculated from this data for each installation assessed.

6.4.3 Historical, RNB and Estimations of each Field

Historical and RNB parameters were used as inputs for P1 and P2 modeling for Brage, Oseberg Sør, Statfjord, Veslefrikk, Njord and Volve. These six were the remaining Equinor NCS installations (which met the same criteria as the training set) after the training set was selected. Brage, however, is no longer operated by Equinor. Historical emissions and RNB predictions and emissions estimations from P1 and P2 were assessed, and the various emission values were plotted for each model.

6.4.4 Source of Emission Deviations

Predicted parameters for Volve from RNB 2009 were compared to historical parameters across the same time frame: 2008 to 2016. The deviation from expected was calculated in terms of a percentage. Volve was randomly chosen to serve as an illustrative example of the concept. The extent to which this concept effects NCS installations is outside the scope of the thesis. This single example may, however, be used to assume the same of deviations for other NCS installations.

Predicted Emissions from RNB 2009 for Volve and historical emissions were compiled for the years 2008-2016 and were compared to P2 modeling estimations using the respective parameters of each.

7 Results

7.1 Model Development

50 models were developed and tested through the data-driven refinement process before a model was selected as representative for P1 modeling. 30 models were developed and refined through the same process before one was selected as a representative model for P2 modeling.

7.2 Model Parameters

Analysis of the sub-datasets yielded the emissions factors for each model's respective production parameters. The quality of the models' fit and quality of parameters were assessed to ensure that the models would properly assess data when applied to test data (Table 1).

Table 1. Parameters and quality assessment measurements from P1 and P2 model development

Parameter/Quality Measurement	Units	Parameter Value		Parameter (p-value) and Model Quality	
		P1	P2	P1	P2
Intercept	Tonnes CO_2	50830.70545	37438.05173	0.143424063	0.024903113
Gas Export	Tonnes CO_2/Sm^3	3.85936E-05	2.87289E-05	0.000502689	3.34037E-09
Gas Injection	Tonnes CO_2/Sm^3	3.88435E-05	4.73785E-05	0.00107825	1.82729E-11
Water Injection	Tonnes CO_2/Sm^3	0.015701426	0.01292028	0.000178577	1.5867E-05
Oil Production	Tonnes CO_2/bbl	--	0.000510105	--	0.405136403
Significance F	--	--	--	1.49379E-06	0.000510105
Multiple R	--	--	--	0.962978898	0.952754851
R squared	--	--	--	0.927328358	0.907741806

The low (closer to zero) significance F values show that both P1 and P2 model parameter values were derived through the statistical process and not by chance. The P values for P2 model parameters are significantly lower than those of P1 meaning that the P2 parameter values are better fit to the training data.

7.3 Model Application Quality

7.3.1 Training Data

7.3.1.1 P1 Modeling

A total of 945 input points representing the training data were run through each model in the development process using P1 parameters. This modeling resulted in 315 outputs (emission estimates) for each model. 207 (66.1%) of the emissions estimates for the selected P1 model were within +/- 25% of their true historical value. 252 (80.5%) of the emissions estimates for the P1 model were within +/- 50% of their true historical value. After removing input outliers (data known to be not suited for these models as mentioned before), 76.5% and 90.6% of the emissions estimates were within +/- 25% and +/- 50%, respectively, of their true historical value.

7.3.1.2 P2 Modeling

A total of 1260 input points representing the training data were run through each model in the development process using P2 parameters. The testing of this data in the 30 P2 models resulted in 9450 outputs (emission estimates). The model developed through the modeling process for P2 modeling found 206 (65.8%) of the emissions estimates were within +/- 25% of their true historical value. 261 (83.4%) of the emissions estimates for the P2 model were within +/- 50% of their true historical value. After removing input outliers 75.7% and 93.3% of the emissions estimates were within +/- 25% and +/- 50%, respectively, of their true historical value.

7.3.2 Test Data

The test data, after being narrowed for data quality and appropriateness, consisted of 156 input sets for P1 modeling and 111 sets for P2 which represents 33:67 and 26:74 test:training splits, respectively. Modeling of the test data using P1 modeling found that 96 estimations were labeled green while 33 were yellow and 11 were red. This resulted in 68% of the P1 estimations being within +/- 25% and 92% of the P1 estimations within +/- 50% of their historical emission. Analysis of P2 modeling on the test data found that the model 82 (73.9%) and 106 (95.5%) were within +/- 25% and +/-50% of their historical emissions, respectively.

7.4 Emission Integrations

7.4.1 Explanation of Visualization Layout

Emission integrations represent lifetime CO_2 emissions estimations (y-axis) for an installation within an appropriate time horizon relative their respective the historical or RNB lifetime CO_2 emissions (x-axis). The dashed blue line represents perfect modeling while the solid blue lines represent +/- 20% deviation boundaries.

7.4.2 Model Construction with Training Data

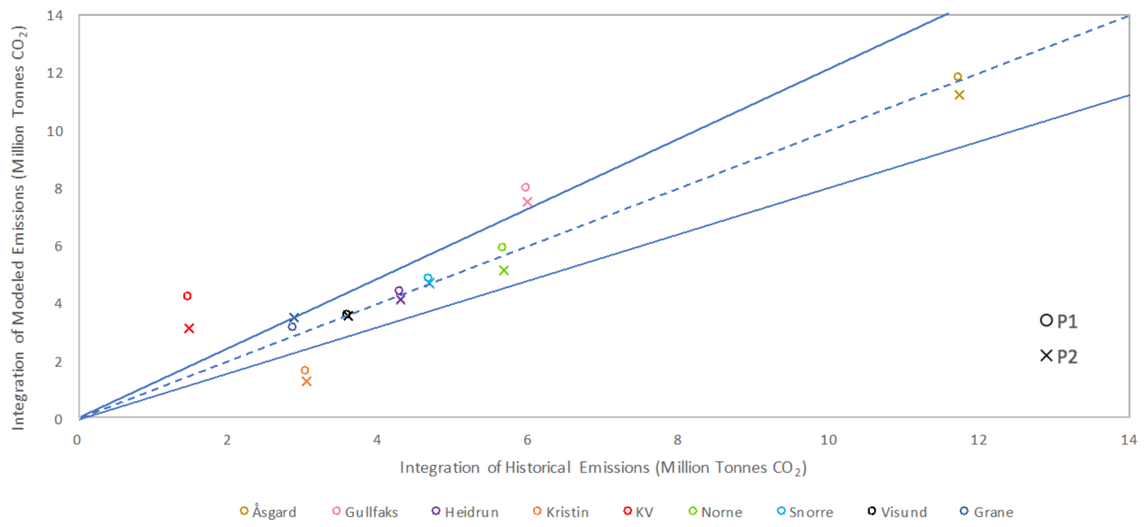

Figure 7-1 Integration of emission predictions from P1 and P2 modeling using trimmed historical parameters referenced to historical emission baseline for trimmed training set data.

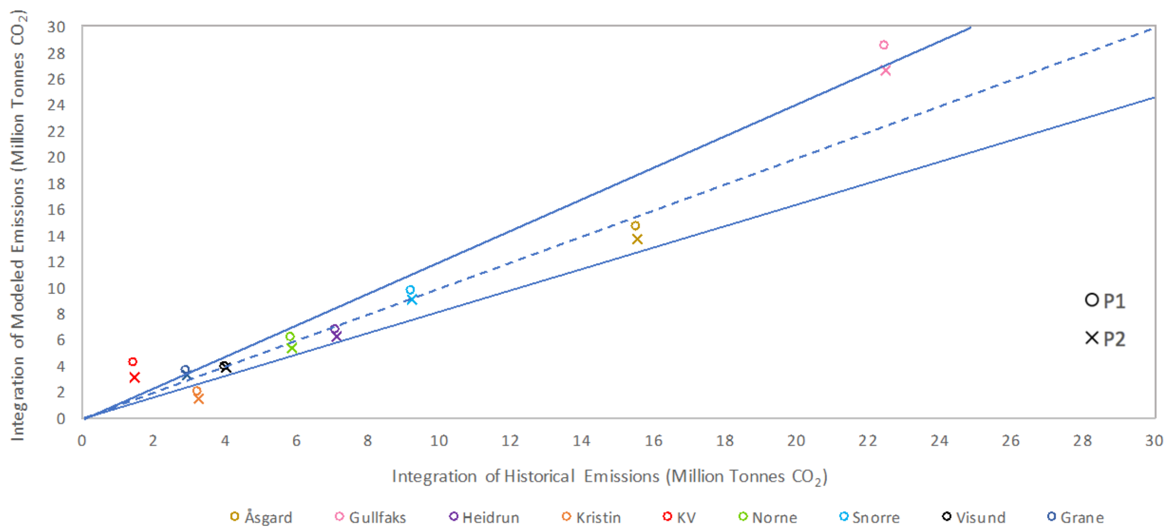

Figure 7-2 Integration of emission predictions from P1 and P2 modeling using historical parameters referenced to historical emission baseline for the lifetime of the training set data.

P1 and P2 emission estimations for training set installations assessed with reference to their historical emissions are shown in (Figure 7-1 and Figure 7-2). Estimations in Figure 7-1 represent a retrospective adjustment of the training data to meet quality requirements, while Figure 7-2 makes no such adjustment. Kristin, KV were consistently outside the error range in both trimmed and lifetime assessments. Gullfaks and Grane had estimations both inside and outside of the +/- 20% error region. The results show large variance in years assessed between trimmed and lifetime assessments as well as deviations from historical emissions (Table 3).

7.4.3 Validation with Test Data

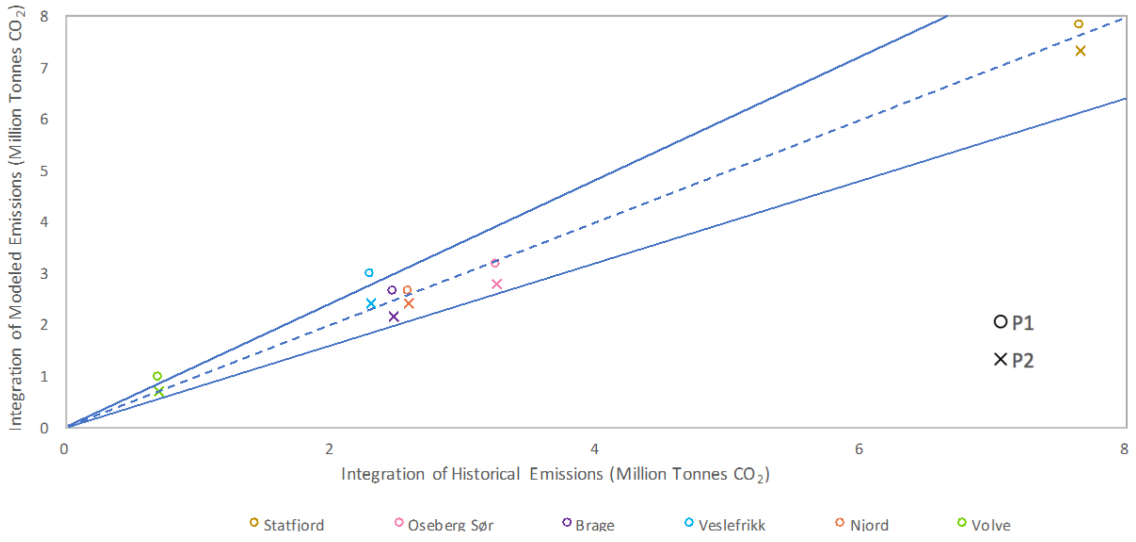

Figure 7-3 Integration of emission predictions from P1 and P2 modeling using trimmed historical parameters referenced to historical emission baseline for test set data.

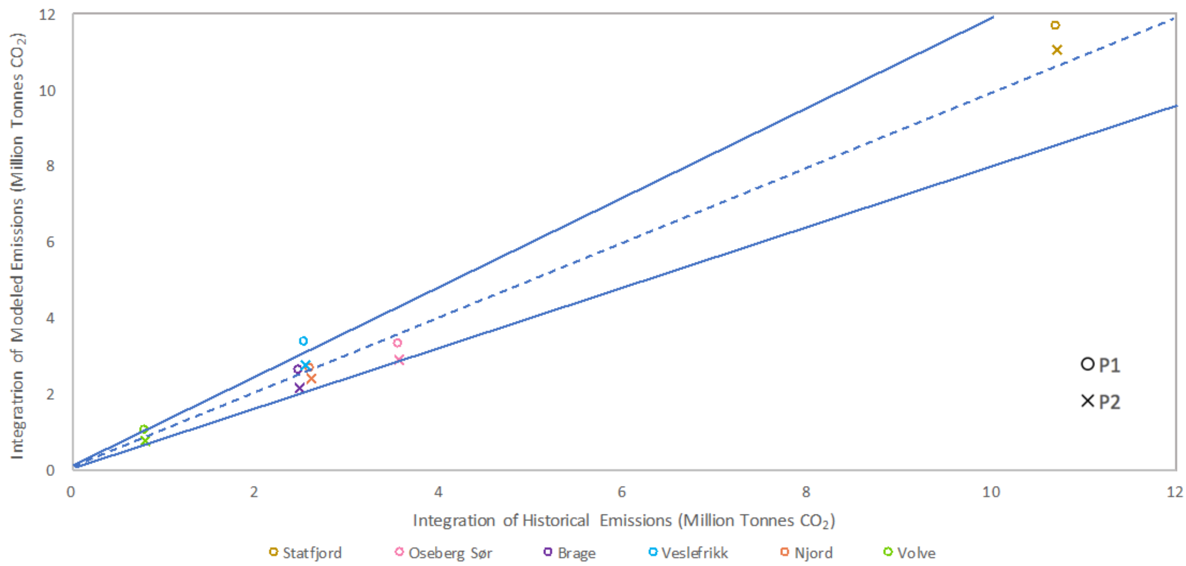

Figure 7-4 Integration of emission predictions from P1 and P2 modeling using historical parameters referenced to historical emission baseline for test set data.

The accuracy of P1 and P2 emission estimates for the test-set data on an installation by installation basis based on historical parameters are referenced to historical emissions (the dashed blue line) (Figure 7-3 and Figure 7-4). P1 estimations for Volve and Veslefrikk were outside of the error region in both trimmed and lifetime assessments (Figure 7-3). Each of the test installations had modeled emissions within 10% of their historical emission integration (Table 4).

7.4.4 Integrations for Model Application

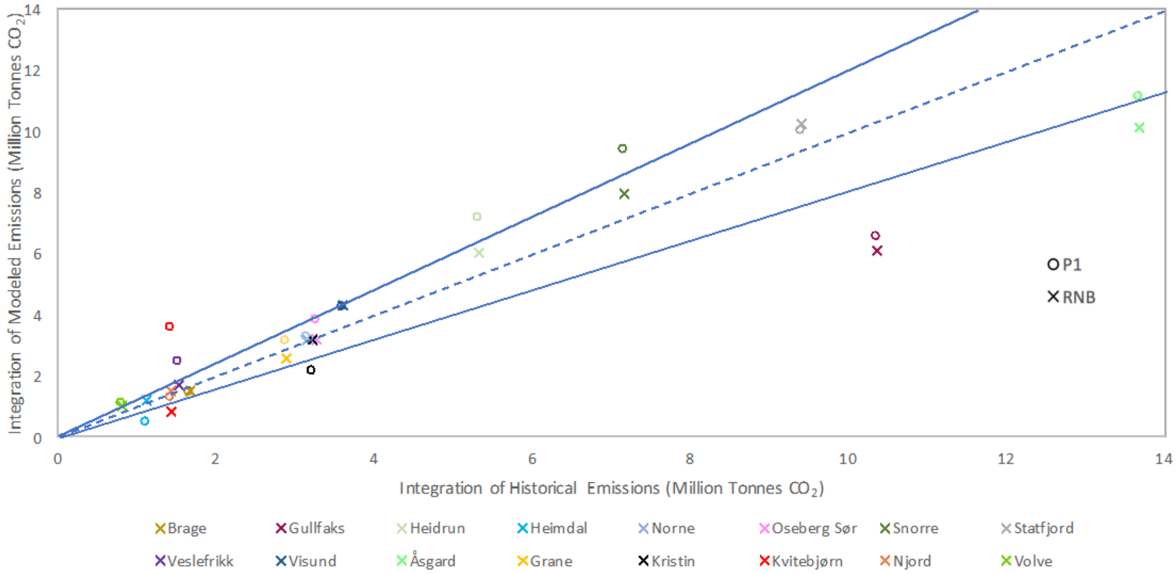

Figure 7-5 Integration of emission predictions from RNB and P1 modeling of RNB parameters referenced to a historical emission baseline.

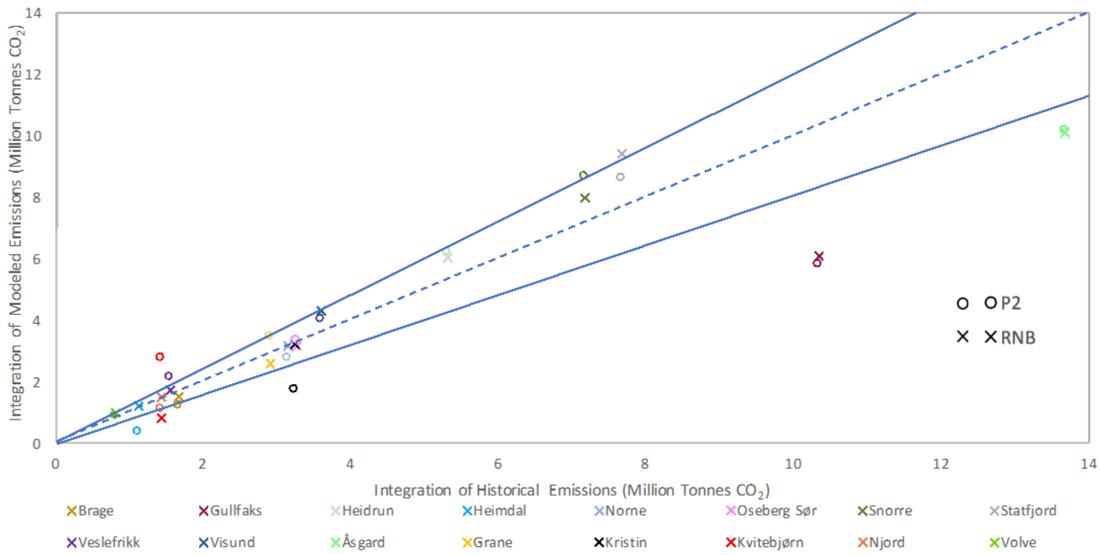

Figure 7-6 Integration of emission predictions from RNB and P2 modeling of RNB parameters referenced to a historical emission baseline.

Figure 7-5 and Figure 7-6 show what would have been predicted if P1 or P2 models were used to make emissions estimates, rather than RNB forecasting. Lifetime RNB estimations are shown relative to each model. The dashed blue line provides a reference of how close, P1, P2, and RNB estimates were to approximating historical emissions. Five RNB estimations and nine estimates from P1 and P2 modeling were greater than +/-20% from their respective historical emissions. Nine of the 16 installations had P1 or P2 estimates where deviations from historical were less than that from RNB estimates. 13 of the 16 P1 and 10 of the 16 P2 emissions were within +/- 20% of RNB estimations (Table 6).

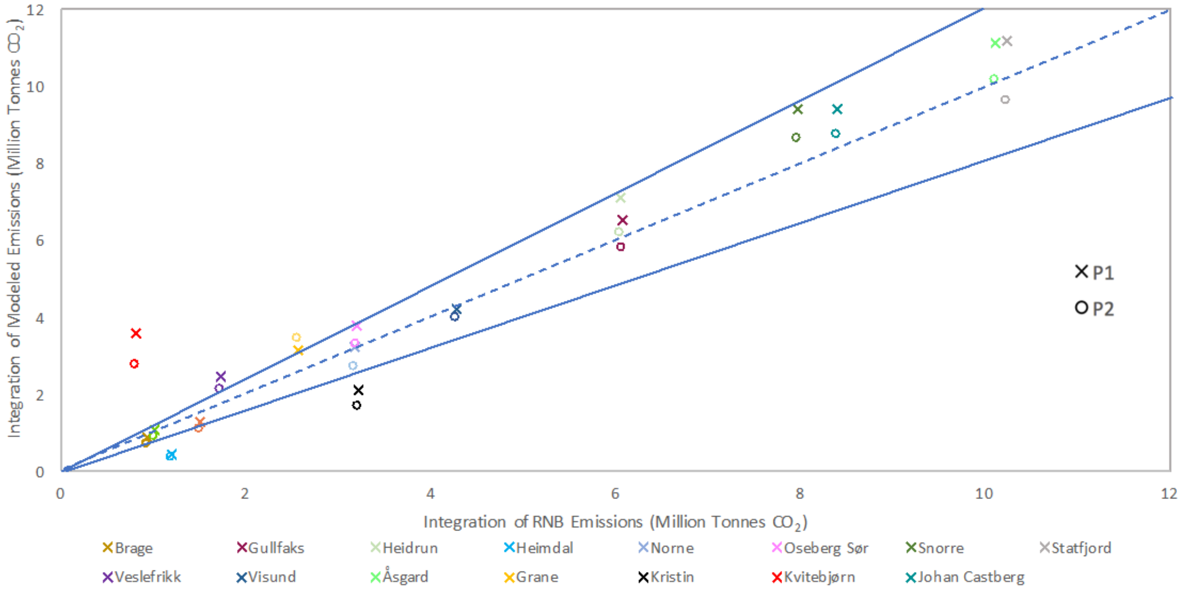

Figure 7-7 Integration of emission predictions from P1 and P2 modeling using RNB parameters referenced to RNB emission baseline.

The closeness of P1 and P2 emission estimates to those of RNB (the dashed blue line), given the same inputs is shown in Figure 7-7. Twelve P1 and nine P2 estimations were within the +/- 20% error range from their respective RNB emissions. Combining the results of P1 and P2 found that six of the seventeen installations did not have emissions estimates within 10% of RNB emissions (Table 6).

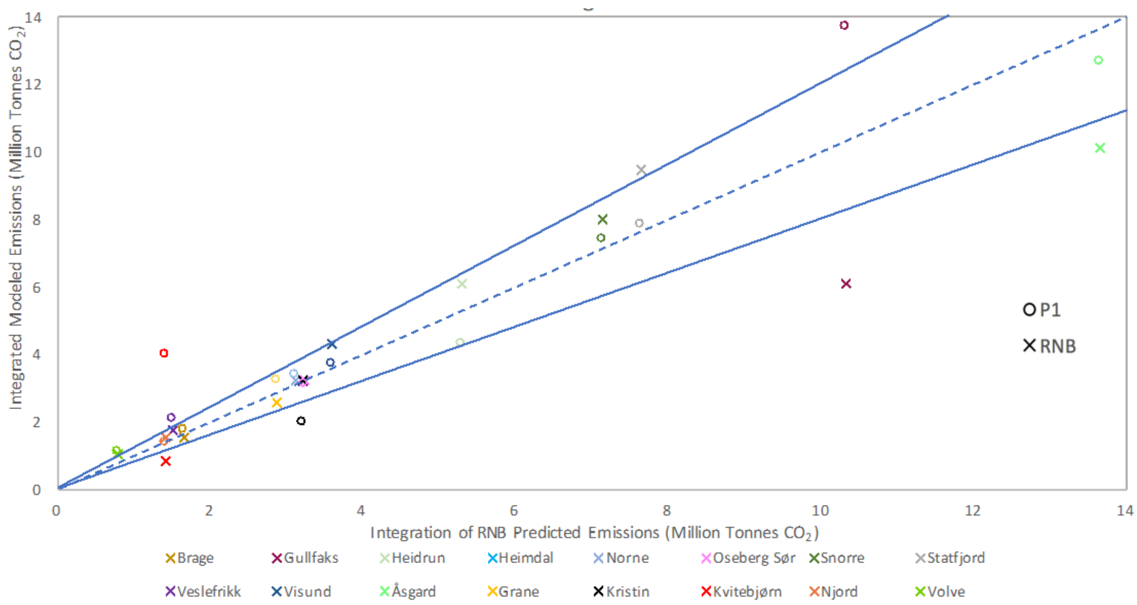

Figure 7-8 Integration of emission predictions from RNB and P1 modeling using historical parameters referenced to the historical emission baseline.

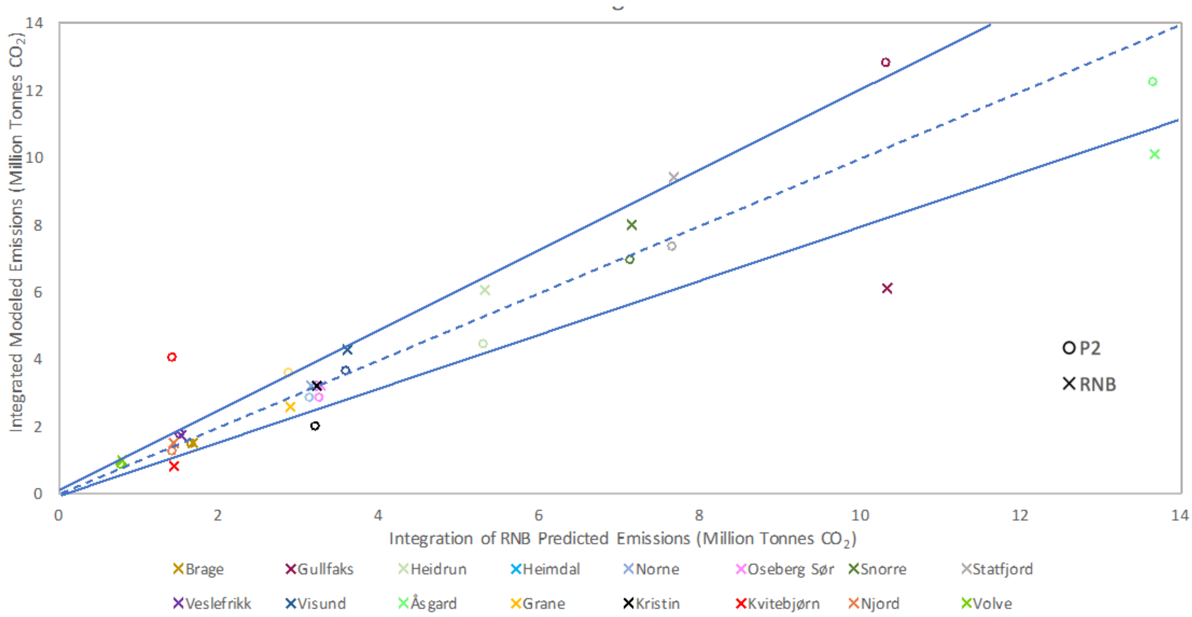

Figure 7-9 Integration of emission predictions from RNB and P2 modeling using historical parameters referenced to the historical emission baseline.

The accuracy of P1 and P2 emission estimates using historical parameters and RNB estimates on an installation by installation basis is referenced to historical estimations (the dashed blue line) (Figure 7-8 and Figure 7-9). These figures show how well P1 and P2 modeling approximates historical emissions when the estimations are based on the parameters that their models are built upon. 12 RNB, 10 P1 and 11 P2 estimations were within the +/-20% error range from their respective historical emissions. 10 of 16 installations had emission estimations from P1 or P2 modeling that approximated historical emissions better than RNB (Table 7).

7.5 Installation Level Emission Estimations

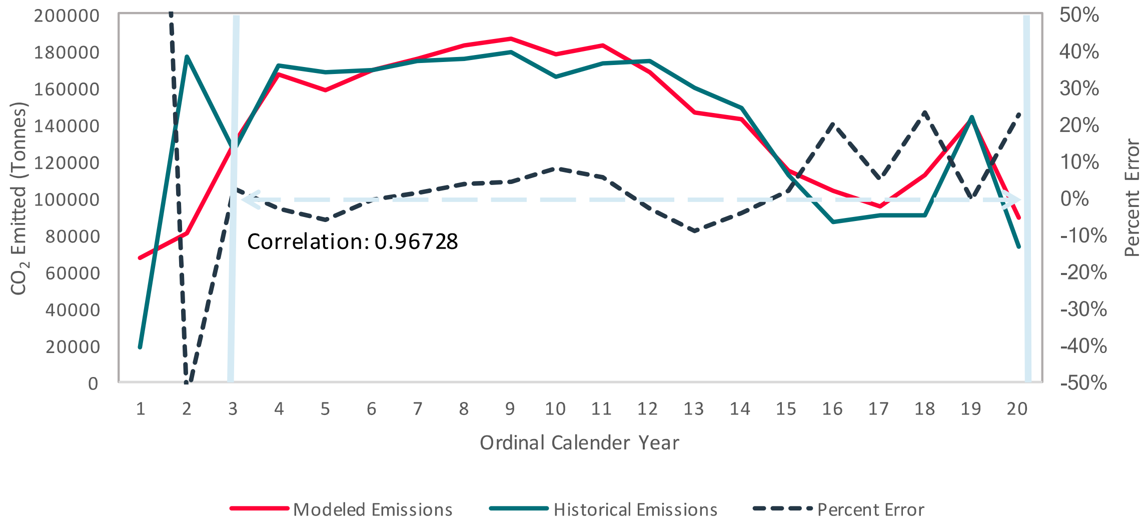

Figure 7-10 Historical emissions and P1 emission estimates based on historical parameters for Njord for the first 20 years of operation. Percent error (black) and time frame for which emissions were correlated (blue) are shown by dashed lines.

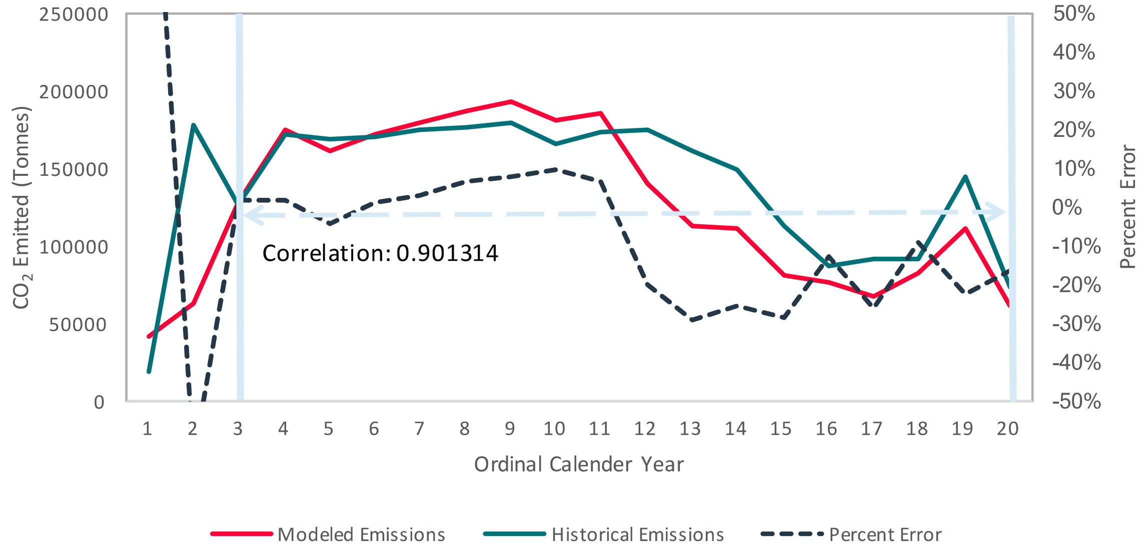

Figure 7-11 Historical emissions and P2 emission estimates based on historical parameters for Njord for the first 20 years of operation. Percent error (black) and time frame for which emissions were correlated (blue) are shown by dashed lines.

Emission estimates from Njord were within +/- 10% relative to historical emissions for years 3-16. The same error window for P2 estimates exists from year 3 to 11. The P1 and P2 estimations had a correlation of 0.96728 and 0.901314, respectively, with regards to the historical emissions from turbines (Figure 7-10 and Figure 7-11).

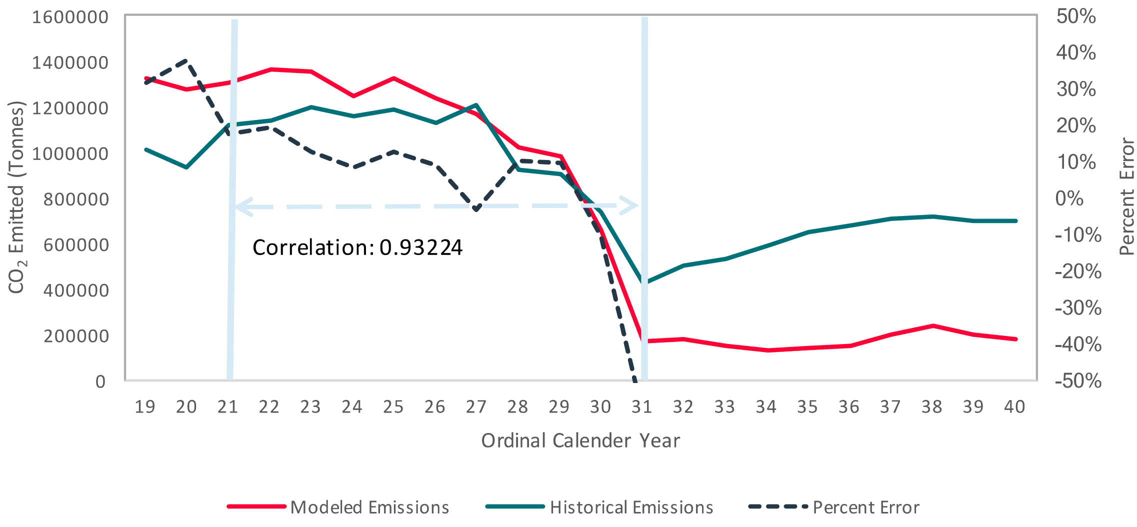

Figure 7-12. Historical emissions and P1 emission estimates based on historical parameters for Statfjord for years 19-40. Percent error (black) and time frame for which emissions were correlated (blue) are shown by dashed lines.

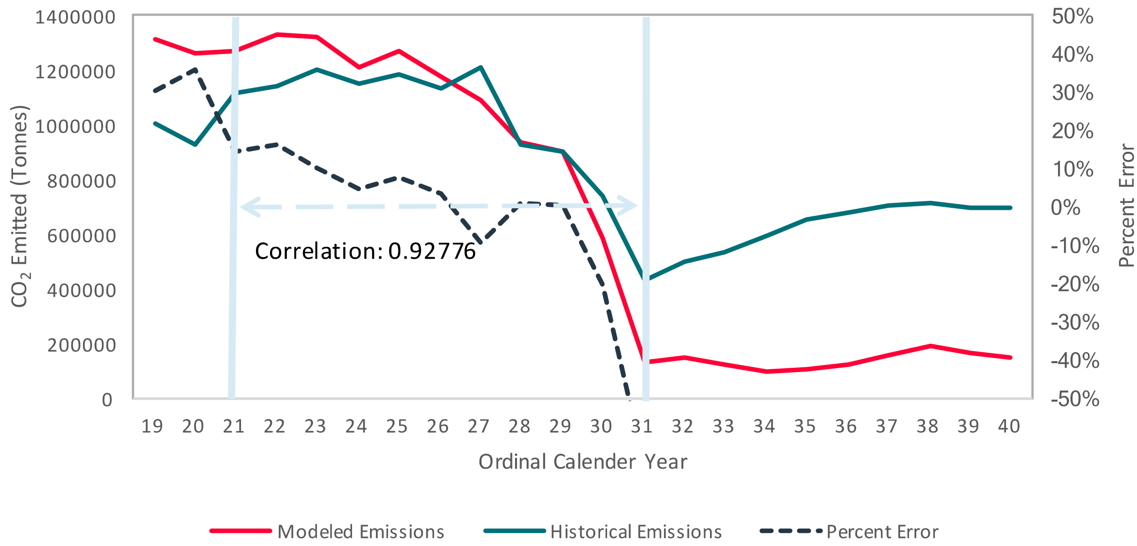

Figure 7-13 Historical emissions and P2 emission estimates based on historical parameters for Statfjord for years 19-40. Percent error (black) and time frame for which emissions were correlated (blue) are shown by dashed lines.

P1 and P2 emission estimations for Statfjord had a correlation of 0.93224 and 0.92776, respectively, with regards to the historical emissions within timeframes of 21-30 years. Deviation from historical emissions exceeds +/- 20% in years after 30 for both P1 and P2 estimations (Figure 7-12 and Figure 7-13).

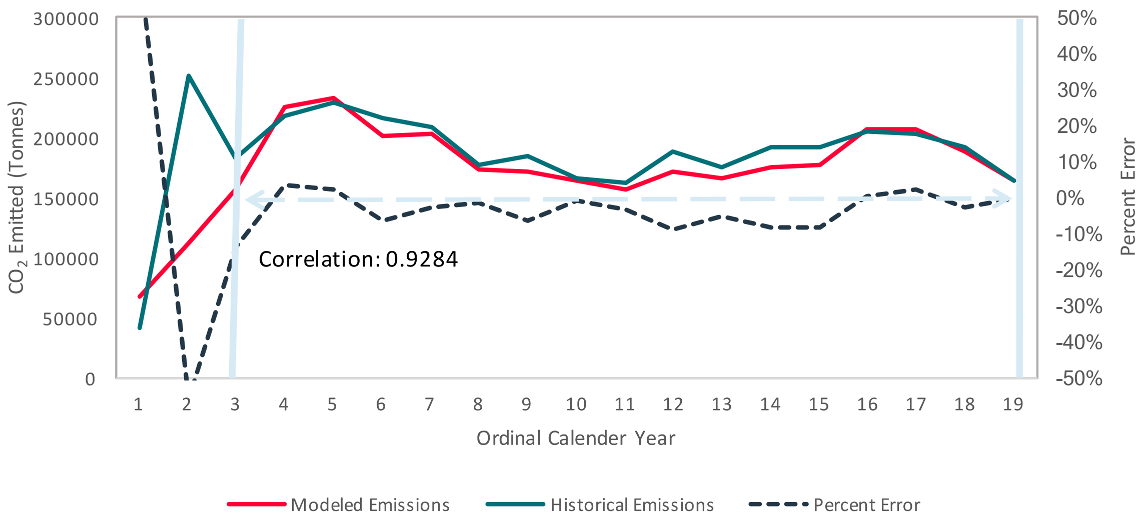

Figure 7-14 Historical emissions and P1 emission estimates based on historical parameters for Oseberg Sør for the first 19 years of operations. Percent error (black) and time frame for which emissions were correlated (blue) are shown by dashed lines.

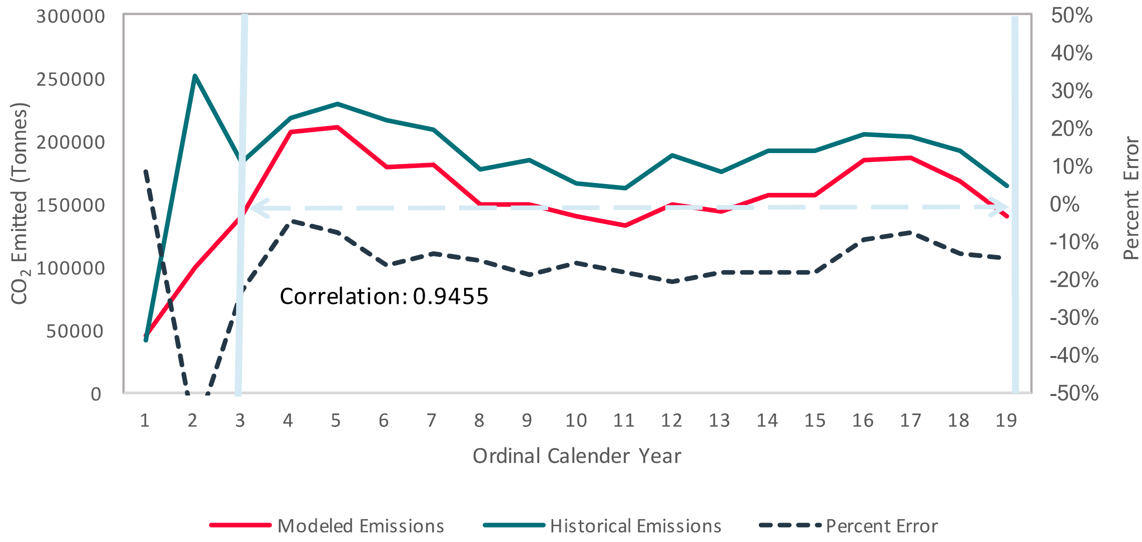

Figure 7-15 Historical emissions and P2 emission estimates based on historical parameters for Oseberg Sør for the first 19 years of operations. Percent error (black) and time frame for which emissions were correlated (blue) are shown by dashed lines.

P1 and P2 estimations had a correlation of 0.93224 and 0.92776, respectively, with regards to the historical emissions within timeframes of 3-19 years of operation for Oseberg Sør. Deviation from historical emissions exceeds +/- 20% in years after 30 for both P1 and P2 estimations (Figure 7-14 and Figure 7-15).

Table 2. Correlations between historical and P1 and P2 emission estimates for Njord, Statfjord and Oseberg Sør.

	Correlation of Modeled Emissions to Historical Emissions	
Installation	P1	P2
Njord	0.96728	0.901314
Statfjord	0.93224	0.92776
Oseberg Sør	0.9284	0.9455

Correlations between the historical and modeled emissions show relatively strong correlations for both P1 and P2 modeling (Table 2).

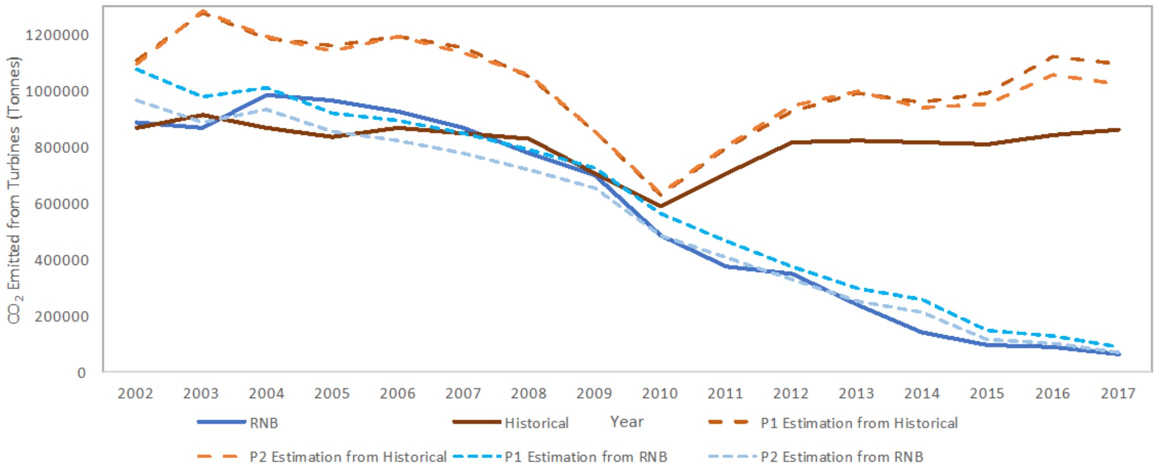

Figure 7-16 RNB predicted and historical emissions and P1 and P2 emission estimates based on RNB and historical parameters for Gullfaks from 2002 to 2017.

Deviations for P1 modeling ranges from 1.3% to 27.1% representing emission deviations of 10518 and 63735 tonnes of CO_2, respectively. P2 modeling of RNB parameters yielded deviations of 0.8% to 11.7% representing emission deviations of 33154 and -113719 tonnes of CO_2, respectively. P1 and P2 estimations based on historical data show overestimation relative to historical emissions (Figure 7-16).

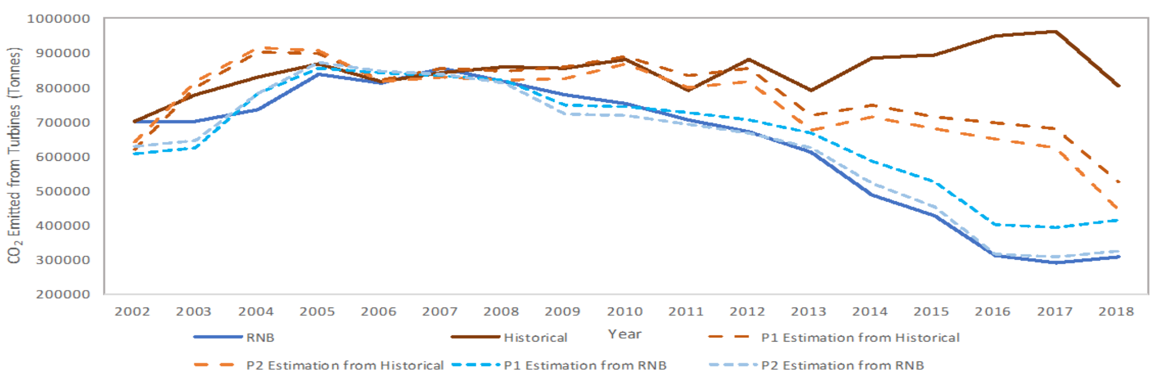

Figure 7-17 RNB predicted and historical emissions and P1 and P2 emission estimates based on RNB and historical parameters for Åsgard.

P1 and P2 modeling of RNB parameters for Åsgard closely follow RNB emission estimates. The first 20 years of predictions provided by RNB P2 gives and deviations ranging from 0.2% to 16.5% while P1 modeling resulted in deviations ranging from 0.01% to 42.7% during the same time frame. These deviations correspond to emissions errors of -1662, -26835, 112 and 123893 tonnes of CO_2, respectively (Figure 7-17).

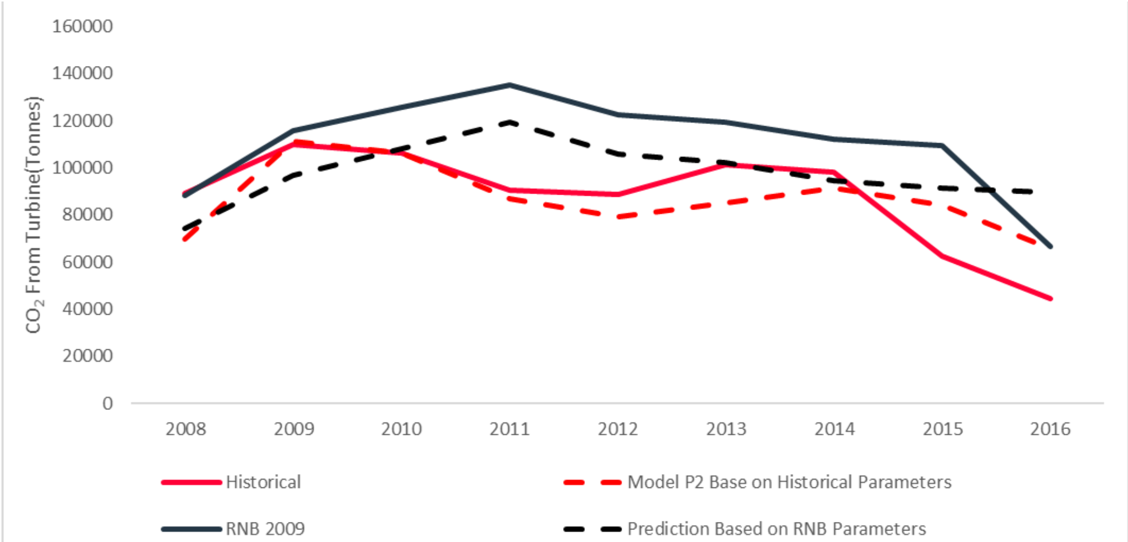

Figure 7-18 RNB predicted and historical emissions and P2 emission estimates based on RNB and historical parameters for Volve from 2008 to 2016.

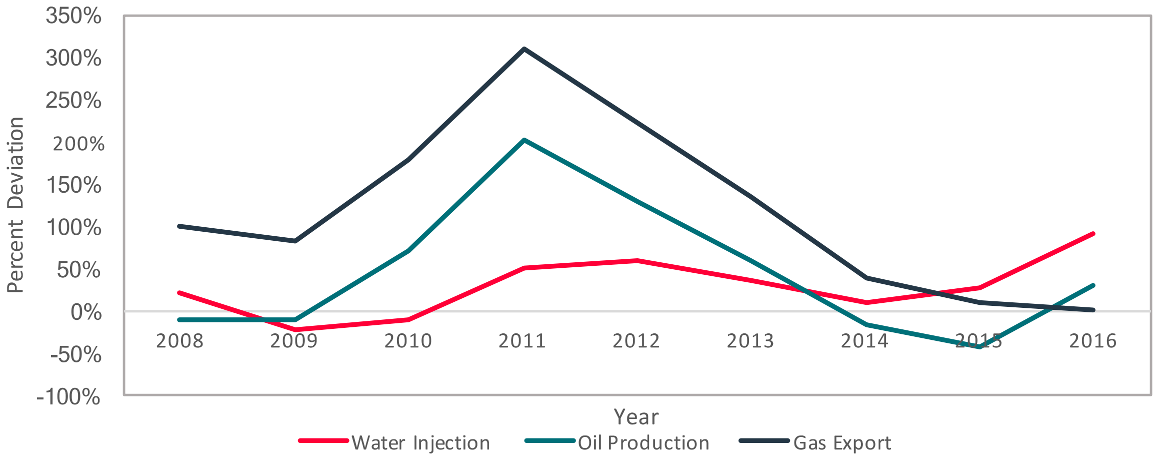

Figure 7-19 Deviation of RNB production parameters from historical parameter values for Volve.

Emission estimates for Volve based on RNB parameters resulted in estimations above those observed historically for 2011, 2012, 2015 and 2016 (Figure 7-18). Parameter estimation deviations (Figure 7-19) show the significant positive deviation in parameter estimations for corresponding to the same years where RNB overestimated emissions.

7.6 New Field Estimations

Johan Castberg is a field currently under development and is anticipated to begin production in the latter portion of 2022. The field is located in the Barents Sea within the NCS. Drainage strategy supporting reservoir production includes both gas and water injection. Platform-based energy demand will be supplied by gas turbines (Equinor, 2017). Despite not exporting gas volumes, the drainage and energy generation strategies for Johan Castberg make the installation fit for P1 and P2 modeling.

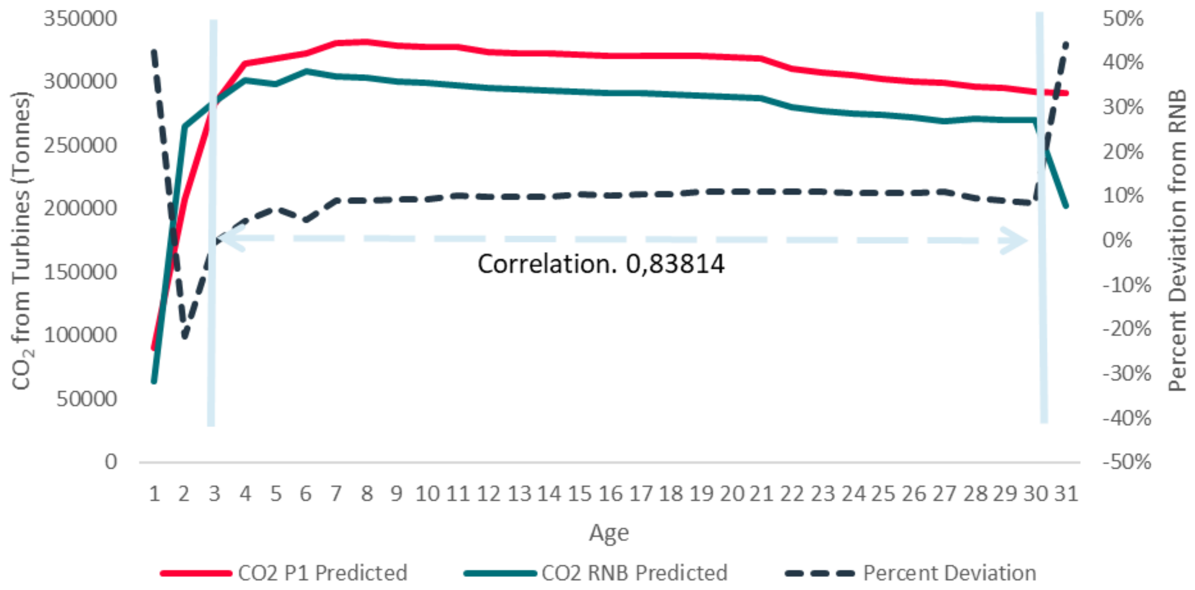

Figure 7-20 RNB emission predictions and P1 emission estimates based on RNB parameters for Johan Castberg. Percent error (black) and time frame for which emissions were correlated (blue) are shown by dashed lines.

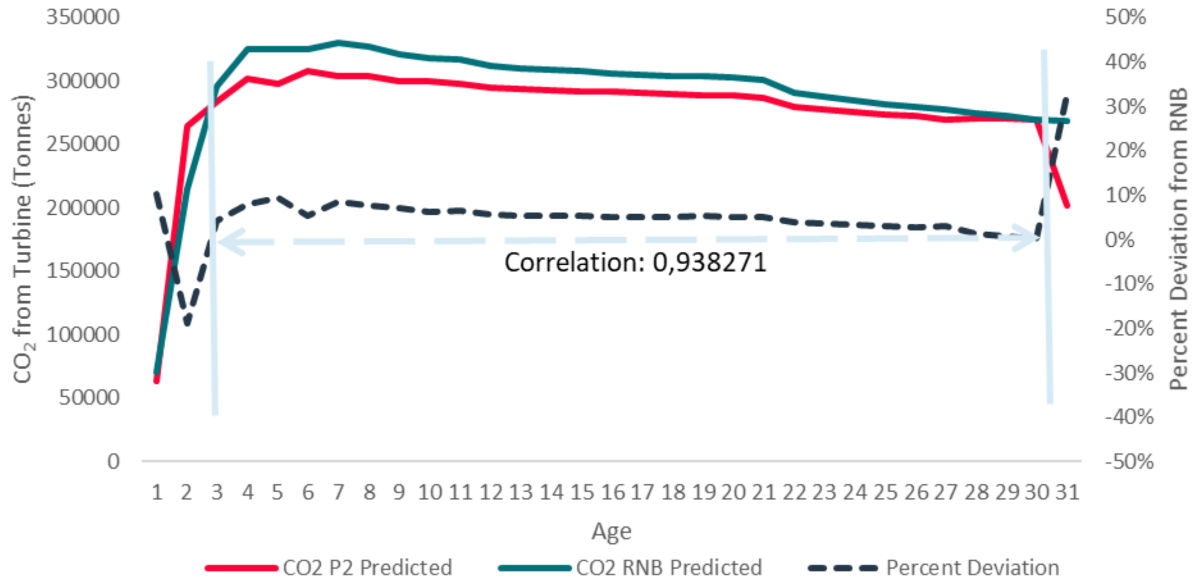

Figure 7-21 RNB emission predictions and P2 emission estimates based on RNB parameters for Johan Castberg. Percent error (black) and time frame for which emissions were correlated (blue) are shown by dashed lines.

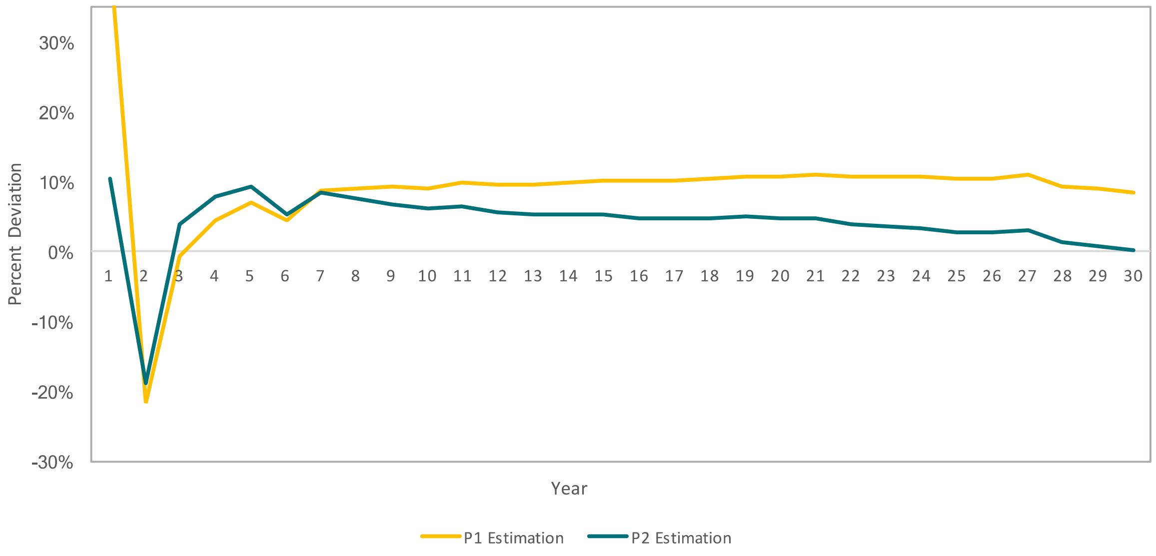

Figure 7-22 Percent deviation of P1 and P2 emission estimates based on RNB parameters from RNB emission predictions for Johan Castberg.

P1 and P2 emission estimates using RNB parameters deviate from RNB estimates by a maximum of 11% and 10% respectively in years 3-30 of the lifetime for Johan Castberg (Figure 7-22). P1 and P2 emission estimates had correlations of 0.83814 and 0.938271 with RNB emission estimations (Figure 7-20 and Figure 7-21). P2 estimates of Johan Castberg from year 3-30 deviated 4.79% from RNB (Figure 7-22).

8 Discussion

8.1 Data challenges

The sourcing of data from various sources has created slight and unavoidable incongruencies. The assessment of the results is minimally affected. However, as a result, it behooves the reader to be provided with a more explanatory version of the results to avoid any conflation.

Data quality and availability have had a structural impact on how data and results can be shown and interpreted. Injection data reported to the NPD for water and gas before 1999 did not have any quality control. This fact is apparent in the historical data records. The effect of this data issue is attributed to the poor match for emissions estimates for Statfjord in years 19 and 20 (Figure 7-13). As a result, sizable amounts of data were precluded from being used in the model building process as well as from the model analysis process.

For some of the older installations assessed in this thesis, the first 20 years of operation and the earliest years of predictions from RNB show minimal overlap. As such, it becomes difficult to compare integrated modeling and prediction results as P1 and P2 models are no longer assessing parameters within their intended forecasting horizon. Theoretical comparison, in these instances, through extrapolation of the results could support multiple conclusions.

As an illustrative example, Gullfaks started production in 1986, as such the first 13 years of production data was not able to be utilized. Since the intention of the model is to predict within a 20-year horizon, that leaves a six-year window where the scope of the models developed within this thesis overlap with available data for the installation.

A further complication in the comparison of RNB emission predictions to P1 and P2 predictions is that RNB records do not go back to the start of many installations. Thus, the window for which fair comparisons between the P1 and P2 predictions to those of RNB are often slim. As a result, despite the ability of P1 and P2 modeling to closely approximate historical emissions, RNB modeling does appear to perform better in the integrations, but this is likely because the integrations are based on years that would disadvantage P1 and P2 modeling and that RNB is continually adjust for each installation on an annual basis. While helpful in providing estimations, continual refinement is quite resource intensive.

8.2 Modeling

8.2.1 Fitness

The validity of the methodology derived in this thesis, that is, how well the modeling parameters are a reflection of real parameters, was found to be quite good with the ability of the models to replicate actual emissions from the training data from which they were derived (Figure 7-1 and Figure 7-2). This is also supported by the statistical fitness of the model parameters (Table 1). The fitness of the P1 and P2 test modeling to historical emissions, along with the statistical quality of the parameters, suggests that the assumptions made in building the models are not overly generous.

Application of the models to test data (Figure 7-3 and Figure 7-4) show that the models are able to provide reasonable emission estimations for installations that were not influential in the statistical parameter development for P1 and P2 models, i.e., the training set data. This finding supports the modeling assumption that relative homogeneity exists between activity levels and resulting emissions for Equinor's assets on the NCS.

Emissions estimates from the modeling of RNB parameters yielded close approximations to emissions (Figure 7-5 and Figure 7-6). These estimations demonstrate the models' ability to predict emissions as they would in practical application within the industry. The practical use and implementation of these models, using RNB parameters to generate emissions estimates, is, while possible, not a part of the models' construction. The models were designed based on historical parameters and historical emissions, not RNB inputs. This could explain the deviations that are observed when emission estimates from RNB parameters are compared to historical emissions. RNB predictions for Kvitebjorn and Kristin display much better accuracy than P1 and P2 modeling (Figure 7-7). This suggests the need for high-pressure, high-temperature fields to be assessed as a separate category, i.e., a P3 model should be developed specifically for production from this type of reservoir. Application of the models shows a good ability to approximate RNB for most other installations (Figure 7-7).

Comparison of modeled emission integrations based on historical data and RNB emissions integrations relative to historical data shows that, in general, P1 and P2, using their intended inputs, perform better than RNB when approximating actual emissions (Figure 7-8 and Figure 7-9).

Correlations found between emission estimates for P1 and P2 modeling to historical emissions (Table 2) when assessing historical production parameters, gives strong evidence that the integrated results for P1 and P2 modeling reflect the models' ability to approximate emissions. This shows that the integrated results for P1 and P2 emissions estimates is not a result of a combination of overestimates and underestimations that, ultimately, average out**.** The same conclusion was made for modeling of RNB parameters through visual analysis of RNB predictions and emissions estimates based on RNB parameters (Figure 7-16 and Figure 7-17).

Analysis of emission estimates for Volve (Figure 7-18) show an overestimation of historical emissions and predicted emissions beginning in 2010 and going through to 2013. Modeling of historical parameters does not show similar deviation meaning that P2 modeling provided a closer estimation of emissions than did RNB using RNB data. A possible explanation for this deviation is that the assumed parameters in RNB might not always provide the most accurate predictions. Comparison of RNB and historical production parameters applicable to P1 and P2 modeling (Figure 7-19) shows, most notably, increasing trends in overestimations of gas export and oil production volumes. This trend continues until 2011, with two and three-fold overestimations, respectively, and aligns well with both modeling of RNB parameters and RNB emissions estimates. Inaccurate predictions, however, may be inherent to forecasting which accepts a certain level of uncertainty.

8.2.2 Data Trimming

Trimming of historical data to exclude low-quality data and years outside the models' forecasting horizon improved deviations from historical. This benefit was generally observed in a single model, though two installations benefitted from trimming in both P1 and P2 models from improved data quality. Åsgard (P1, P2), Grane (P2), Heidrun (P1), Norne (P2) Snorre (P1), Visund (P1), Oseberg Sør (P1, P2), Velsefrikk (P2) and Volve (P2) had improvements in integrated emission estimates with trimmed data (Figure 7-1, Figure 7-2, Figure 7-3 and Figure 7-4).

8.2.3 Discrepancies

8.2.3.1 Startup years

Within the first two calendar years of operation, installations are working up to efficient production capacities. Additionally, data from MIS show that there is considerable energy demand from non-production, start-up related processes which are met by turbines. These factors skew the relationship between turbine emissions and production values that are assessed by the P1 and P2 models. As such, the P1 and P2 models do show discrepancies during these first two years (Figure 7-10, Figure 7-11, Figure 7-14 and Figure 7-15) as the models are trained for more efficient production profiles than are exhibited during this period.

8.2.3.2 Drainage Strategy

Two drainage strategies, water and gas injection, were primary factors in both models in this thesis. Both models assume drainage strategy in making emissions estimates. Years where drainage strategy changes to pressure depletion, as in the case of Statfjord beginning in year 31 of operation (when late life operations began), there is a marked change in the ability of the models to match historical emissions given historical production parameters (Figure 7-12 and Figure 7-13).

8.2.3.2.1 Installations producing from High-Pressure High-Temperature Reservoirs

The ability of the P1 and P2 models to estimate the historical emissions for KV and Kristin show less of a fit than the estimations for the other installations that were assessed. The apparent lack of accuracy for these three installations can be explained. Each of these installations produces through pressure depletion as they produce from high-temperature, high-pressure reservoirs. This means that there is no gas or water injection at these fields. The P1 and P2 models distribute the share of emissions across each of their respective model parameters through a statistical process. As such, fields that do not have one or more of the model parameters in their production are likely to have less accurate emission estimations and predictions from models generated through this and similar statistical methodologies.

8.2.3.3 Aging

The results of P1 and P2 modeling show that estimation of historical emissions is possible through these models. The model works particularly well with installations aged 3-20 years. Some installations show good modeling with these approaches in even later years of operation though this may be due to tie-backs to existing facilities; tie-backs deliver a non-aged source of oil and gas to the installation which has lower water content which is typical of younger fields. The delivery and processing of water from the well steam is assumed in the P1 and P2 models. P1 and P2 models assume a steady state ratio for water-oil volumes that is consistent with water cuts typical of installations aged in the range of 1-7 years. However, as the amount of water in the well stream increases with age (Masnadi & Brandt, 2017), volumes of oil put into the models contains more water than is assumed by the modeling process. This phenomenon would result in an underestimation of emissions, which is observed for Åsgard with P1 and P2 modeling performed on the historical parameters (Figure 7-17). This is also seen in the modeling of RNB parameters for Gullfaks and Åsgard (Figure 7-5 and Figure 7-6). RNB predictions and estimates based on RNB parameters for Gullfaks and Åsgard (Figure 7-7) show relative closeness, suggesting that RNB predictions also struggle to account for aging. Emission predictions from RNB also show this underestimation with both P1 and P2 models closely approximating RNB predictions.

8.2.3.4 Scale

Gullfaks is a large production facility relative to the others in the training set. Estimations for Gullfaks also show a lack of accuracy in relation to historical emissions integrations. An analysis of energy drivers has suggested that there is an economies-of-scale at play regarding the emissions generated to provide energy for injection volumes. As a result, the statistical modeling process used in this thesis would produce emission factors for injection volumes that are higher than what may be observed at Gullfaks. Similarly, the emission predictions would be overestimated for other large installations. Annual emission estimations show a continual and sizable overestimation for emissions for Gullfaks (Figure 7-16) as do the estimations for Statfjord (Figure 7-12 and Figure 7-13), another large field on the NCS. The overestimations for Statfjord appear less significant than Gullfaks. This may be because historical emissions at Statfjord are elevated due to age related effects, thus making the historical emissions closer to the supposedly overestimated modeled emissions which might mask this phenomenon slightly.

8.2.3.5 Comparability of Results

8.2.3.5.1 Comparisons of RNB and P1 and P2 modeling

Naturally, a comparison of RNB results to P1 and P2 modeling results would be a valuable part of this discussion. However, it is not possible, at least within the scope of this thesis, to understand why RNB predictions deviate or match historical. RNB emission estimations have not been made using the historical parameters; they are based on historical predictions. Deviations between historical RNB estimation parameters and predicted parameters could have a positive effect or negative effect on the accuracy of the emissions. Ultimately, it is not within the scope of this thesis to make that discernment.

Comparison of RNB to historical emissions should be made with care in knowing that it is unlikely that the predicted parameters in RNB, which are the basis of RNB emissions, are the same as what was observed and recorded in the historical data. For this reason, it is expected that RNB emissions deviate from historical emissions, as shown in Figure 7-19. Similarly, the comparison of P1 and P2 modeling, using RNB parameters, and RNB emissions predictions provides what the emissions prediction would have been had P1 or P2 modeling been used. However, a comparison of how well P1 and P2 modeling, with RNB parameters, performs in approximating historical emissions or RNB emissions is not the fairest of comparisons. This is because P1 and P2 models are based solely on historical data and are not meant to approximate RNB predictions, although they can.

The accuracy of RNB emission estimates is predicated on the assessment's ability to know the production volumes for a given year. It seems that this can be done with relative accuracy for short term forecasting; 5-7 years. That is to say, that even if an RNB emission estimation is, for example, 50% higher than what would occur for that year, the error might not have arisen from the inner mathematical workings of RNB modeling. Instead, the deviation could have arisen from anticipated production volumes that did not come to represent accurately the production that was to take place. Due to this, this thesis does not aim to understand the accuracy of RNB emission forecasts and the quantitative measure of this is outside the scope of this project. However, the application of the models to RNB parameters often results in emission approximations that are better than RNB predictions.

8.2.3.5.2 Comparison of P1 and P2 Modeling

The quality of the P2 model parameters (Table 1) fit its training data better than P1 model parameters did. An assumption in P1 modeling that emissions arising oil production can be simplified into other production processes may be the reason for this observation. The variability of gas to oil ratio across the training installations was not investigated but is generally quite variable on the NCS. Thus, assuming a highly variable into non-related parameters would likely lead to reduced fit.

The fact that each model was derived from their own training sets (not the same one) could be another factor in the discrepancy between the quality of each model and their respective parameters.

The limited ability to make conclusive comparisons between the models' parameters affects an important question in furthering this study; "How many parameters are needed to provide a reasonable emission estimate?". For the intents and purposes of this thesis, the models and the parameters that they involve are adequate. The increased modeling quality that is observed between P1 and P2 modeling speciously suggests that more data makes for better modeling. In this case, this statement makes sense, the additional parameter (oil production volume) is one that is, understandably, essential to this study. However, it is possible that additional parameters may not be as essential or have consistent and strong relationships to emissions and therefore, may make models with additional considerations worse or at least unimproved. Further modeling and assessments could clarify this question should more accurate results be desired.

8.3 Usability for CVP

The integration of historical emission estimates for P1 and P2 models on the training dataset shows a good fit to historical emissions (Figure 7-1 and Figure 7-2). Additionally, per annum assessments of the same show high accuracy and correlation with understandable exceptions. Further assessment of the model upon test data shows that the model, rather consistently, predicts emissions within +/-20% or less, excluding explainable outliers. This degree of accuracy would suffice for all decision gates for the advancement of new projects in Equinor's corporate value process. This assumes that lifetime emissions estimation requirements are developed to be equally as stringent as cost estimations in the corporate value process.

Modeling of emissions for Johan Castberg, an installation not yet in operation shows that predictive modeling provides emission estimates that very closely resemble that which are included in RNB (Figure 7-20, Figure 7-21 and Figure *7-22*). The strong correlation between RNB emission estimates and predictively modeled estimates suggests that the parameters assessed in P2 modeling capture the essential energy driving process well. The modeling results assessed over a forecast horizon of 30 years resulted in a deviation of 422037 tonnes of CO_2 (14068 tonnes/year), representing a deviation of 4.9% from RNB projections. This suggests that the P2 emission estimating process gives results with high similarity to RNB estimations.

8.4 Consideration of Model Limitations

The assumptions of this model and its limitations should be understood when performing assessments. The specific models in this thesis are generalizations and are limited by installation age and drainage strategy. However, other models could be developed using the same methodology to make estimations for the types of installations where estimations in P1 and P2 modeling chronically deviate from historical emissions.

The installations assessed in this thesis all use a deviant of the General Electric LM 2500 turbine, a single cycle turbine. The average efficiency of those in use on Equinor operated installations is 37.1% with efficiencies ranging from 35% - 39%. The efficiency of a turbine directly affects the amount of CO_2 emissions generated from production processes. As such, this efficiency range is assumed in the models. Installations using gas turbines with efficiencies outside of this range or combined cycle turbines will experience deviations in emission estimations that are inversely proportional to the deviation in turbine efficiency of the turbines at the installation.

Likewise, installations where turbine generated energy is supplemented by an external energy source, particularly through electrification, will also have deviations in emission assessments from P1 and P2 modeling. The CO_2 equivalent of the energy demand met by external sources could, however, be factored in after P1 and P2 modeling.

Further, due to the relationship between energy demand and emissions, the P1 and P2 models could be used to estimate the quantity of energy required to offset emissions to meet a desired intensity or to eliminate emissions resulting from meeting energy demands.

These abilities will be highly useful as an assessment of electrification is now required for all new development projects on the Norwegian Continental Shelf.

9 Conclusion

Forecasting of emissions in the oil and gas industry is used for licensing, mitigation, budgeting, communication and policy alignment. However, the methods currently employed in the industry are resource intensive and encumber the progression that needs to be made in meeting climate change challenges and global energy demand. This study has developed models using statistics and big data, which provide potential solutions for these problems. The models give close emission estimates using fewer inputs than have been required in with other forecast models while also meeting accuracy requirements of established standards, meaning that the models could be integrated into existing workflows. As a result, new modeling techniques may allow for improved process efficiencies in meeting future energy needs. The strengths and weakness of the models produced were understood and provide reason and aim for further development and investigation. Moreover, the success of this modeling endeavor should be seen as a way that data can be used to benefit both the industry and environment through greater ease with which emission estimates can be made. These results give a green light for further investigation into CO_2 emission modeling which should be carried out to refine the models in this thesis or to devise new models using big data and digitalization to provide other new solutions for environmental accounting and industries.

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Appendix

Table 3. Detail of results represented in Figures 7-1 and 7-2.

	Years Assessed		Average Annual Deviation (Tonnes CO_2)				% Error Years Assessed			
			Trimmed		Lifetime		Trimmed		Lifetime	
Installation	Trimmed	Lifetime	P1	P2	P1	P2	P1	P2	P1	P2
Åsgard	15	20	2555	2540	-43162	-87541	0.33	-4.44	-5.58	-11.31
Grane	15	17	41684	16149	15935	37903	21.89	8.48	9.38	22.32
Gullfaks	7	19	279937	217219	312050	216327	32.87	25.51	26.43	18.32
Heidrun	14	25	4512	-186613	-14860	-35178	1.48	-4.36	-5.24	-12.40
Kristin	12	15	-117617	-1750168	-93012	-118547	-46.70	-57.91	-43.39	-55.30
KV	15	15	179037	1622530	167847	101408	183.36	110.78	183.36	110.78
Norne	20	23	11967	-520549	8652	-24287	4.24	-9.21	3.41	-9.57
Snorre	13	24	12815	13856	14303	-7285	3.57	0.30	3.72	-1.89
Visund	17	21	-3340	-26186	-10518	-9089	-1.58	-0.73	-5.51	-4.76

Table 4. Detail of results represented in Figures 7-3 and 7-4.

	Years Assessed		Average Annual Deviation (Tonnes CO_2)				% Error Years Assessed			
			Trimmed		Lifetime		Trimmed		Lifetime	
Installation	Trimmed	Lifetime	P1	P2	P1	P2	P1	P2	P1	P2
Statfjord	10	20	97272	39264	7579	-17959	1.98	-4.69	9.10	3.67
Oseberg Sør	17	19	-6731	-28111	-12050	-33035	-3.52	-14.70	-6.46	-17.71
Brage	14	21	11449	-22458	7633	-14972	6.49	-12.73	6.49	-12.73
Veslefrikk	20	30	33575	5156	27233	6758	29.24	4.49	32.28	8.01
Njord	18	18	3481	-9897	3481	-9897	2.43	-6.90	2.43	-6.90
Volve	8	9	30570	950	27832	-1313	34.83	1.08	31.65	-1.49

Table 5. Detail of results represented in Figures 7-5 and 7-6.

		Average Annual Deviation (Tonnes CO_2)			% Error Years Assessed from Historical			% Deviation from RNB Estimate	
Installation	Years Assessed	RNB	P1	P2	RNB	P1	P2	P1	P2
Brage	6	-27475	-32689	-76984	-9.95	-11.84	-27.88	-1.89	-16.04
Gullfaks	13	-328757	-295449	-349029	-41.33	-37.14	-43.88	4.19	-6.74
Heidrun	17	43016	107474	51307	13.79	34.45	16.45	20.66	-18.00
Heimdal	8	8304	-82463	-97338	5.95	-59.07	-69.73	-65.02	-10.66
Norne	12	2170	10921	-34002	0.83	4.18	-13.02	3.35	-17.20
Oseberg Sør	17	-4158	31260	3270	-2.17	16.35	1.71	18.52	-14.64
Snorre	17	47546	131663	86863	11.31	31.31	20.65	20.00	-10.65
Statfjord	12	145018	195107	79377	22.71	30.56	12.43	7.84	-18.13
Veslefrikk	23	7864	40078	26177	11.84	60.33	39.41	48.50	-20.93
Visund	17	39966	35527	23033	18.90	16.80	10.89	-2.10	-5.91
Åsgard	16	-224222	-160456	-221737	-26.24	-18.78	-25.95	7.46	-7.17
Grane	16	-20677	15431	35291	-11.46	8.55	19.56	20.01	11.01
Kristin	14	-793	-78907	-108662	-0.35	-34.36	-47.31	-34.01	-12.95
Kvitebjørn	14	-43945	153300	94552	-43.45	151.56	93.48	195.00	-58.08
Njord	11	6092	-12698	-28216	4.72	-9.85	-21.88	-14.57	-12.04
Volve	9	22622	31191	10048	25.73	35.47	11.43	9.74	-24.04

Table 6. Detail of results represented in Figures 7-7

Installation	Years Assessed	Average Annual Deviation (Tonnes CO_2)		% Error Years Assessed	
		P1	P2	P1	P2
Brage	6	-6616	-34888	-4.29	-22.64
Gullfaks	13	33308	-20272	7.14	-4.34
Heidrun	17	64458	8291	18.16	2.34
Heimdal	8	-90767	-105643	-61.37	-71.43
Norne	12	8751	-36172	3.32	-13.74
Oseberg Sør	17	35419	7429	18.93	3.97
Snorre	17	84116	39317	17.97	8.40
Statfjord	12	79612	-53769	9.34	-6.31
Veslefrikk	23	32213	18312	43.36	24.65
Visund	17	-4440	-16933	-1.77	-6.74
Åsgard	16	63766	2485	10.12	0.39
Grane	16	36108	55968	22.60	35.03
Kristin	14	-78114	-107869	-34.13	-47.13
Kvitebjørn	14	197245	138497	344.81	242.11
Njord	11	-18790	-34308	-13.92	-25.41
Volve	9	8569	-12574	7.75	-11.37
Johan Castberg	31	32163	11480	11.88	4.24

Table 7. Detail of results represented in Figures 7-8 and 7-9.

Installation	Years Assessed	Average Annual Deviation (Tonnes CO_2)			% Error Years Assessed		
		RNB	P1	P2	RNB	P1	P2
Brage	6	-27475	11468	-76984	-9.95	4.15	-13.90
Gullfaks	13	-328757	253746	-349029	-41.33	31.90	23.09
Heidrun	17	43016	-61897	51307	13.79	-19.84	-17.46
Heimdal	8	8304	0	-97338	5.95	n/a	n/a
Norne	12	2170	16835	-34002	0.83	6.45	-11.32
Oseberg Sør	17	-4158	-11561	3270	-2.17	-6.04	-14.70
Snorre	17	47546	13303	86863	11.31	3.16	-3.37
Statfjord	12	68728	12632	79377	8.77	1.98	-4.69
Veslefrikk	23	7864	22755	26177	11.84	34.26	10.16
Visund	17	39966	5125	23033	18.90	2.42	-0.73
Åsgard	16	-224222	-65611	-221737	-26.24	-7.68	-10.87
Grane	16	-20677	16931	35291	-11.46	9.38	22.32
Kristin	14	-793	1915521	-108662	-0.35	-40.43	-40.43
Kvitebjørn	14	-43945	3954456	94552	-43.45	179.25	179.25
Njord	11	6092	-4908	-28216	4.72	-3.81	-14.62
Volve	9	22622	27832	10048	25.73	31.65	-1.49

Table 8. RNB annual report used for each installation

Installation	RNB Annual Report
Brage	2004
Gullfaks	2004
Heidrun	2004
Heimdal	2004
Norne	2004
Oseberg Sør	2004
Snorre	2004
Statfjord	2004
Veslefrikk	2004
Visund	2004
Åsgard	2004
Grane	2005
Kristin	2005
KV	2005
Njord	2008
Volve	2008
Johan Castberg	2019