THE OPERATIONAL EFFICIENCY OF INDIAN PETROLEUM REFINERIES

A thesis submitted to the
University of Petroleum and Energy Studies

For the award of
Doctor of Philosophy
in
Management (Oil & Gas)

BY
Jignesh M. Joshi

March 2021

SUPERVISOR(s)

Dr. Narendra N. Dalei
Dr. Pratik Mehta

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UNIVERSITY WITH A PURPOSE

School of Business
University of Petroleum and Energy Studies
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Dedication

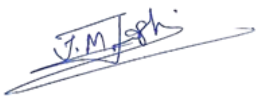
To…

My father's departed soul and beloved mother, wife and daughters.

September - 2021

DECLARATION

I declare that the thesis entitled "**The Operational Efficiency of Indian Petroleum Refineries**" has been prepared by me under the guidance of **Dr. Narendra N. Dalei**, Assistant Professor (Economics) and Head Centre for Energy, Environment and Sustainability Studies, School of Business, UPES, Dehradun. No part of this thesis has formed the basis for the award of any degree or fellowship previously.



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CERTIFICATE

I certify that Mr. Jignesh Joshi has prepared his thesis entitled "***The Operational Efficiency of Indian Petroleum Refineries***", for the award of PhD degree of the University of Petroleum & Energy Studies, under my guidance. He has carried out the work at the Department of Oil & Gas Management, University of Petroleum & Energy Studies.

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ABSTRACT

The prudent combination of technological, economic, and other factors can enhance the performance of any manufacturing units. Indian petroleum refineries are no exception to this. Presently, Indian refineries are under tremendous pressure to minimize the operating costs to enhance profit. Moreover, because of complex configuration and less moneymaking industry, most investors are not interested to invest in this business that impact on the oil refinery expansion projects and infrastructure development. Therefore, refiners have to be more cautious and vigilant in regulating the production costs and enhancing an operational efficiency to generate more revenue, which necessitates to find the new strategies and ideas to optimise and ensure efficient use of all resources in the oil refinery. Thus, this is predominant for identifying the key drives that help the refiners for succeeding in every day production activity. Given this, the present study estimates the gross refining margin and evaluating operational efficiency of the Indian oil refineries. Moreover, the study identified the improvement targets for the refineries those were inefficient in India.

The gross refining margin is estimated by using panel data of thirteen refineries of India financial year 2010-11 to 2018-19. The study used Pooled OLS, Fixed effect, and Random effect Models as well as Feasible Generalized Least Squares and Panel Corrected Standard Error to check the robustness of the results. The present study found that refinery complexity, capacity utilisation and distillate yield significantly and positively influenced gross refining margin, whereas refinery fuel and loss significantly and negatively influenced it.

Furthermore, the assessment of operational efficiency (OE) of the oil refineries could also be instrumental in the improvement of overall performance and the GRM (gross refining margin). Hence, the study evaluated OE of 7 oil refineries of India by using DEA (Data envelopment analysis) in primary stage and random effect GLS and Tobit regression model in the second stage. The empirical results found that that the Reliance Industries Limited and Chennai Petroleum Corporation Limited

refineries are found more efficient refineries than the rest of the sampled refineries, attaining their efficiency scores of 0.9593 and 0.9782 respectively during the study period, whereas the refineries like the Indian Oil Corporation Ltd., and Hindustan Petroleum Corporation Ltd., were identified the less efficient refineries. Additionally, results also found that the Bharat Petroleum Corporation limited, Mangalore refinery and petrochemical limited and Nayara energy limited are found to be moderate performers during the study period. The second-stage regression analysis suggested three explanatory variables; utilisation rate and distillate yield are significant and positive in explaining variations in refinery efficiency, whereas operating cost significantly and negatively influenced it.

The study recommends that Indian refiners should invest more in secondary process unit as well as advanced technology to enhance the complexity and distillate yield in order to increase the gross refining margin and also adopt the waste heat recovery, flare gas recovery and best operating practices in order to reduce fuel and loss of refinery. It is suggested to form policy to replace the existing fossil fuel-based energy source with the most competitive and cheaper renewable energy sources. That will reduce the production cost of refinery and trigger the operational performance.

The findings and their suggested recommendation of this study help policymakers to improve policies towards the enhancement of operational efficiency by an efficient combination of technological, economic and market tactics.

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First and foremost, praises and thanks to the God, the Almighty, for His showers of blessings throughout my research work to complete the research successfully.

I would like to express my deep and sincere gratitude to my research supervisor, Dr. Narendra N. Dalei, Assistant Professor (Economics) and Head Centre for Energy, Environment and Sustainability Studies, School of Business, UPES, Dehradun for giving me the opportunity to do research and providing invaluable guidance throughout this research. His dynamism, vision, sincerity and motivation have deeply inspired me. He has taught me the methodology to carry out the research and to present the research works as clearly as possible. It was a great privilege and honor to work and study under his guidance. I am extremely grateful for what he has offered me. I could not have imagined having a better advisor and mentor for my Ph.D. study. I would also like to thank him for his friendship, empathy, and great sense of humor. I am extending my heartfelt thanks to his wife, family for their acceptance and patience during the discussion I had with him on research work and thesis preparation.

My sincere thanks also go to my external guide **Dr. Pratik N. Mehta** for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis.

I extend my sincere thanks to all the SRC members and fellow faculties of UPES for providing valuable comments and suggestions. Their perspectives have indeed helped me in shaping the thesis in its current form. They have been very kind and generous in sharing their knowledge whenever I required. Their research inquisitiveness inspires all the UPES research scholars for setting high standard research work.

Finally, to my caring, loving, and supportive wife, **Mittal Joshi**: my deepest gratitude. Your encouragement when the times got rough are much appreciated and duly noted. It was a great comfort and relief to know that you were willing to provide management of our household activities while I completed my work. My heartfelt thanks.

Jignesh M. Joshi

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Chapter 1: INTRODUCTION AND OVERVIEW

1.1 INTRODUCTION

Oil refineries play a major role in the refining of crude oil and its transformation into consumable products. The crude oil passes through various refining processes and converts into several kinds of valuable finished products. The fuel needed for different energy purpose in all the type of business has been developed from petroleum refining process with great complex procedures in the oil and gas sector (Worrell et al., 2005). Petroleum refining is one of the key industries of the economy. A refiner always seeks a higher margin in profit for survival as well as for expansion of the refinery. The difference in price between the finished products that a refinery produces and crude oil that a refinery process is the gross refining margin of a refinery. The eventual desire of functioning a refinery is to produce high value-added products, but the primary aspiration includes raising the gross refining margin.

In oil refining, the input (crude oil) cost and the output (refined) cost are more volatile, those are impacted by changes in supply and demand at the regional, local and global levels. As the changes in environmental regulation, altering demanding patterns followed by the rise in the global competition among the refineries, the refineries should think for new innovative strategies to be more profitable.

When we talk about the refinery margin, the oil refinery business is a less profit-making business than the other sector of oil and gas according to the historical data (Mohamed A., 2010). Because of the complex configuration and less money-making industry, most investors are not interested to invest in this business that impacts the oil refinery expansion projects and infrastructure development. Moreover, Crude oil is the valuable feedstock for the oil refinery, and any change in the price of it will impact significantly the raw material costs in the refinery. For this reason, oil refineries have to give attention to different approaches to minimize the overall production cost and to be competitive in the market. Other than the price of crude oil, current stringent environmental regulations levied by the government authorities have also raised the production costs of final cleaned products coming out from the refinery (Fahim et al., 2010). In addition, profit margin fluctuations of refinery and petrochemical plants have encouraged these sectors to find new ways to make a profit and be competitive (Elham et al., 2019). Therefore, refiners have to be more cautious and vigilant in regulating the production costs and enhancing efficiency to generate a higher gross refining margin.

Moreover, the Covid-19 pandemic and the oil crisis have taken a heavy toll on demand for transport fuels such as gasoline and jet fuel leading to severe margin compression for refineries. Faced with this existential crisis, global refiners are being forced to reinvent themselves in a bid to survive (Alex K., 2020). Meanwhile, refinery margins remain squeezed tight, some are turning their facilities into biofuels plants, and others are planning permanent closures. Refining margins are at a historic low as demand for refined oil products returns more slowly than many may have hoped after the easing of the lockdowns. And now, with the second wave of infections sweeping through Europe, that return could be even reversed (Irina S., 2020).

The petroleum refinery stands for eight principal industries in India. The energy demand is still rising mainly in the developing countries (Shahsavari and Akbari, 2018) that require to invest for expanding crude oil processing. The investment can be done if the refinery generates a good margin from the current operation. Presently, refineries are under tremendous pressure to minimize operating costs. As such oil refinery has to enhance their efficiency to increase gross refining margin and to keep refinery in operation, which necessitates finding the new strategies and ideas to optimise and ensure efficient use of all resources in the oil refinery. There are two competing methods for estimating the relative efficiency across refineries, the first, the non-parametric Data Envelopment Analysis (DEA) approach (Charnes et al., 1978); and the second parametric stochastic frontier analysis (SFA) approach (Kumbhakar and Lovell, 2003). Schoyen and Odeck (2013) concluded that the DEA approach is more popular than SFA as DEA can handle multiple inputs and outputs.

In this challenging environment, operational efficiency is more prior for a successful company. Hence the corresponding organization must enhance the net efficiency for competitive marketing success. The excellence in the organizational performance is not attained till it moves towards the optimal efficiency that leading to the achievement of operational strategy (Nigel and Michael, 2011).

In this aspect, it is necessary to analyse the internal efficiency of the refinery that detects the overall development of GRM in the future. The current study is considered as a small attempt for knowledge updating in this scenario.

1.2 CONCEPT OF PROFIT, GROSS REFINING MARGIN AND OPERATIONAL EFFICIENCY

1.1.1 Profit

Profit is referred to as an engine that drives the business enterprise. Further, the efficiency of a business enterprise is calculated by the profit earned. The profit is essential for each company for long time survival. Additionally, profit is the key variation between the total expenses and total income. From the study (Duck and Jorvis, 1999), it is observed that profit is the factor of the motivation behind conducting business.

Profit is vital for all types of business, and the business is completely lifeless without profit. Most of the business enterprise’s objective is earning more profit. From the study (Pandey I.M., 2001), it is observed that the key difference between the total expenses as well as the total revenue is profit. Also, profits are the ultimate outputs of companies, where they have no future if they fail.

When looking from an accounting viewpoint, the profit represents more income than the expenses. From the study (Langley, 1978), it is observed that there will be a definite loss if the expenses are higher than revenue. Here, revenue is defined as the earnings of the business.

1.1.2 Gross refining margin

The gross refining margin is termed as the difference between the value of petroleum products, such as gasoline and diesel, when they leave the refinery and the value of the crude oil entering the refinery. The values are identified by the market based on the inventory, geopolitical, demand, and other factors. Margins are estimated based on a single barrel. A crude oil barrel, when chemically cracked, develops entire fractionates such as diesel, petrol, LPG, and furnace oil, possessing various applications. The price of every sample has been seemed to be different and the GRM for refining is more if it produces more high valued products like Petrol, naphthalene, and petrol. Similarly, another factor affecting the GRM is fuel loss value (the used-up oil in processing the refinery or system loss). In general, GRM is characteristically represented dollars/barrel.

The final selling price of the products, which consumers need to pay has been fixed mainly based on market demand. The price where the transportation fuels such as diesel and petrol are sold cannot be lowered or raised without the permission of the government. Several markets, regulatory and political factors affect the refined product prices and crude oil price results in price instability. The price instability intensely affects the revenue of the product that affects the refinery's margin. The changes in the crude oil price possess a considerable influence on the general profitability since crude oil price change does not reflect immediately the sale price of the refined product.

The refinery margin is characteristically unstable. The main components in the calculations are done by several market factors, demand, and supply, comprising wider economic and geopolitical conditions associated with highly localized factors concerned with outages, accidents, or weather conditions. It is crucial to denote that the refinery margin is not compulsorily related to the cyclic effects of the exploring and production function.

1.1.3 Efficiency

The efficiency concept was initiated in 1957 by Farrell. Further, efficiency is referred to the capability of a firm for obtaining the maximum amount of outputs from the given input. Thus, the term efficiency is meant for enhancing operational aspects for realizing the maximum amount of profit till it reaches the limit (Joly, 2012).

Further, efficiency is calculated for the management, supervision, machinery, material as well as manpower. Efficiency is utilized for measuring performance based on the expectations in terms of standardized objectives. This concept is old as philosophy, management, or economic science due to the conventional measurement of performance. Moreover, efficiency generally refers to obtain more output from the same input. From the study (Siklosi A., 2009), it is observed that an increase in efficiency can be accomplished by utilizing more resources and reducing expenditures.

1.1.4 Operational Efficiency

The term OE (Operational Efficiency) is referred to as cautious and profitable usage of resources that are available in a particular organization or a combination of these resources that can increase the production or reduce the production costs (Dhillon and Vachharajani, 2012). The resources may be humans, machines, tools, equipment, materials, capital, etc. The operational efficiency identifies the inefficient resources as well as processes that adversely affect the profit of the organization. Also, it assists in forming policies that improve productivity and enhance operational efficiency.

OE is the percentage measurement of the management's capability for generating sales revenue and controlling costs. Moreover, OE deals with the minimum wastage and maximum resource capability. Operational efficiency is concerned with identifying wasteful resources and process that drains the profit of the organization. Further, the improvement of OE has a direct impact on the profit margin of the company. In the context of business, OE is referred to as the ratio between the input to run business and output that is gained from business. Moreover, when improving OE, the ratio of output to input improves. Where the inputs are: cost, headcount, time and the outputs are: money, opportunities, complexity, speed, quality, innovation, new customers, market differentiation, the productivity of headcount, and customer loyalty (S Ramesh, 2014).

OE deals with the minimum wastage and maximum resources to provide quality services and goods to the consumers. OE designs a new work process, which improves productivity as well as quality. Moreover, OE is improved as the company's profit improved (E.F. Weston and J.F. Brigham, 1968).

OE indicates the management of income and utilizes them for generating profits. The maximum OE is varied for every individual organization, where all the enterprises utilize various types of methods for maximizing OE and minimizing inefficiencies that smother growth. OE is capable for a business for distributing services or goods with high qualities. This can be accomplished by reorganizing the process of the company for responding effectively in a cost-effective manner. OE is referred to as removing the inefficiencies as well as gaining the finest business activities. It is the variation between the failure and survival of the business (E. F. Weston and J. F. Brigham, 1990).

The operational efficiency of the organization is the ability for utilizing the prevailing resources to the maximum extent (E. F. Weston and J. F. Brigham, 1990). OE generally refers to the effective usage of material as well as human resources, material funds, equipment, and tools as well as machines. Using these, will increase the outputs of services and goods and also reduce costs. OE is the tactical planning of an organization for keeping a balance between productivity and cost. Moreover, it finds the wasteful processes which contribute to the drainage of resources as well as the organizational profits. It deals with minimum waste and maximum resource benefits for providing good services to customers. The inputs that do not process to useful output are considered as waste. That means creating more services and goods by maintaining the same production level or by utilizing fewer resources (Amey, 1970).

OE can be beneficial in improving profitability by reducing the cost of the raw materials per unit and exercise the required control in the selling expenses as well as the administrative expenses (Batra, 2016).

1.3 INDIAN OIL REFINERY OVERVIEW

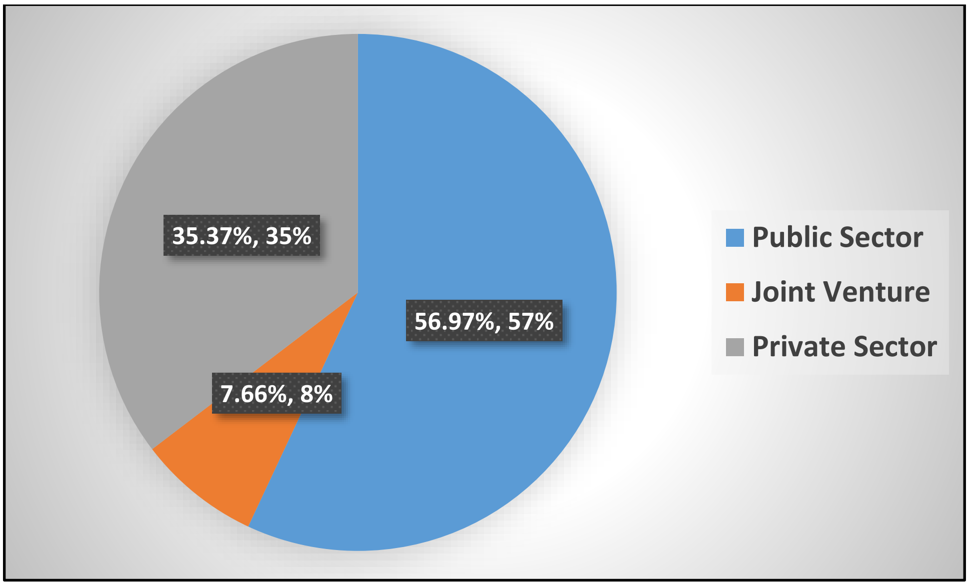
The Indian refining sector exceeds in the establishment of global players. India is developing as a refining hub and the corresponding capacity exceeds the present demand. The refining capacity has been found to increase from 62-million metric ton/ annum (MMTPA) in the year 1998 to

239 MMPTA on the first of April 2017, including 22 refineries with 3 under private sectors, 2 under joint sectors and, 17 under the public sectors. By the end of the 12th five-year plan, refinery capacity is expected to reach 307.37 MMTPA (PPAC, 2018). The petroleum refinery stands for the eight principal industries in India. India is one of the largest oil importers that need refineries to meet its growing demand. India's current refining capacity is 230 MMTPA, including currently commissioned 15 MMTPA of IOCL refinery at Paradip (Table 1-1).

Table 1-1 Installed Refinery Capacity in India

Source: Petroleum planning and analysis cell

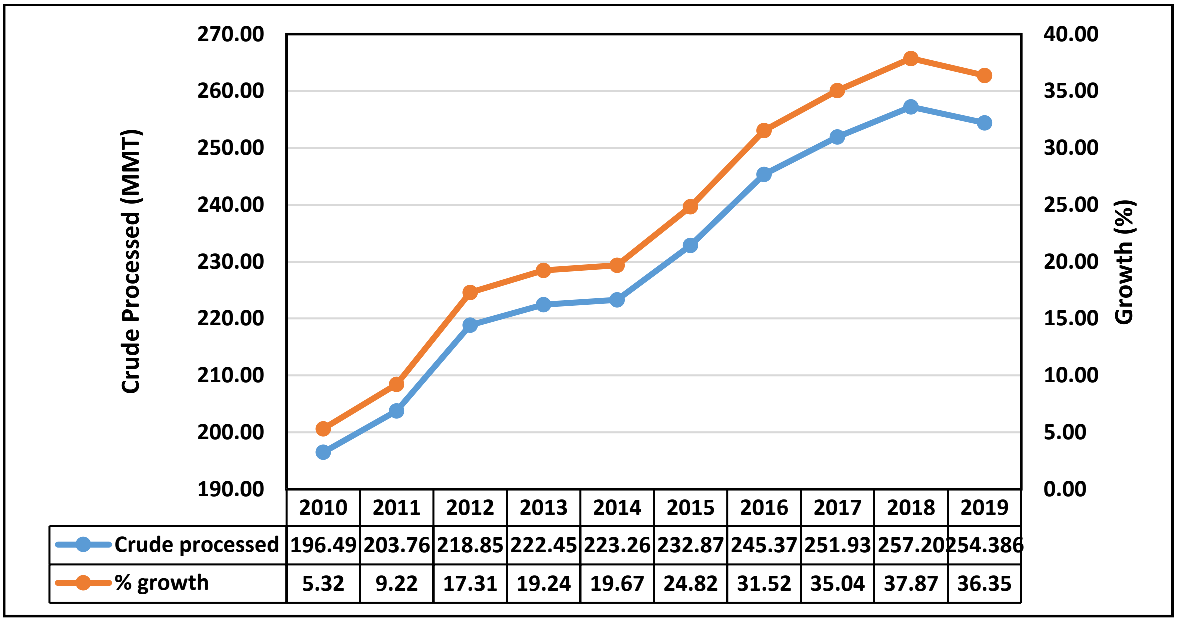
S.No.	Refinery Location	Name of the Company	Name Plate Capacity (MMTPA)*
		PSU Refineries	
1	Digboi, Assam	Indian Oil Corporation Limited	0.65
2	Barauni, Bihar		6
3	Guwahati, Assam		1
4	Bongaigaon, Assam		2.35
5	Kovali, Gujarat		13.7
6	Mathura, U.P		8
7	Haldia, West Bengal		7.5
8	Paradip, Odisha		15
9	Panipat, Haryana		15
10	Mumbai, Maharashtra	Hindustan Petroleum Corporation Limited	7.5
11	Visakhapatnam, Andhra Pradesh		8.3
12	Mumbai, Maharashtra	Bharat Petroleum Corporation Limited	12
13	Kochi, Kerala		15.5
14	Manali, Tamil Nadu	Chennai Petroleum Corporation Limited	10.5
15	Nagapattinam		1
16	Numaligarh, Assam	Numaligarh Refinery Ltd.	3
17	Mangalore, Karnataka	MRPL	15
18	Tatipaka, AP	ONGC	0.066
	Total		142.066
		JV Refineries	
19	Bathinda, Punjab	HPCL Mittal Energy Ltd.	11.3
20	Bina, MP	Bharat Oman Refinery Ltd.	7.8
	Total		19.1
		Private Sector Refineries	
21	SEZ, Jamnagar, Gujarat		35.2
22	Vadinar, Gujarat	Essar Oil Limited	22
23	DTA-Jamnagar	Reliance Industries Limited	33
	Total		88.2
	Grand Total		251.366



Source: Petroleum planning and analysis cell

Figure 1-1 Share of Indian Refiners

Figure 1-1 shows that the public sector is dominating the refinery industry with a 56.97% (142.066 million metric tonnes) share in the total refining capacity. Whereas the share of the joint venture is not much significant as it only consists of 7.66% (19.1 million metric tonnes) of total refining. The private sector is playing a vital role and contributing significantly 35.37% or 88.2 million metric tonnes in total refining capacity.



Source: Petroleum planning and analysis cell

Figure 1-2 Refinery crude processed Capacity vs Growth

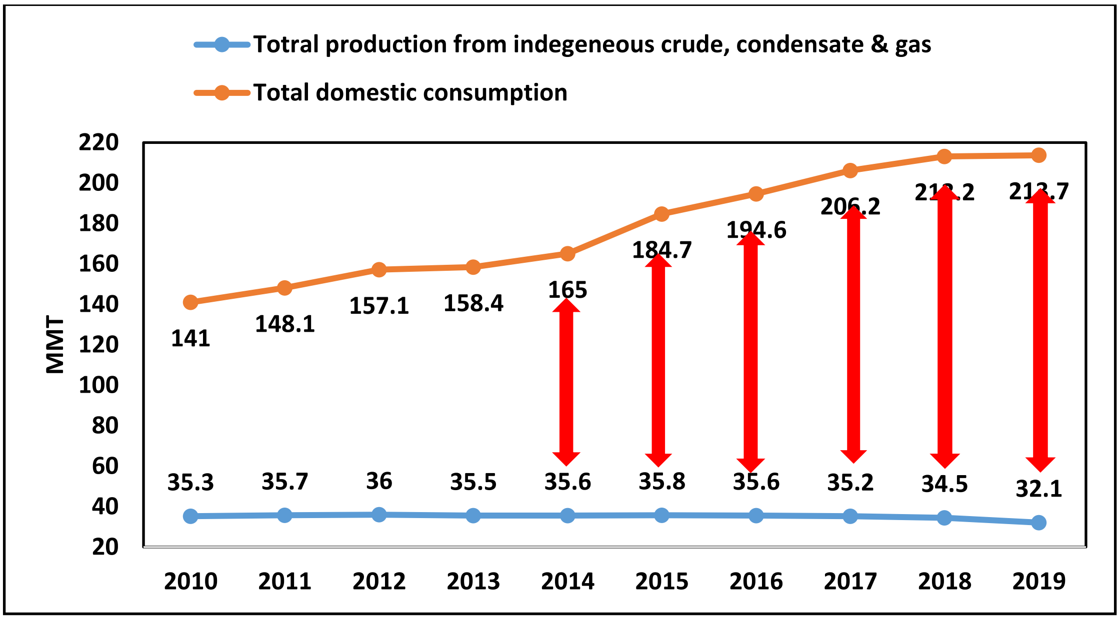
Figure 1-2 shows that there has been a considerable increase in crude processing capacity of the refinery in India over the years, although during 2013 and 2014 there was no substantial capacity expansion. The refining crude processing capacity stood at 223.26 MMTPA, after that it turned the table and noticed the growth in refining crude processing capacity. However, the growth was found to drop in the year 2019 indicating a drop in refinery capacity utilization.

Hydrocarbon Vision 2025 developed signified 95% of self-sufficiency in the diesel group and private players, thereby developing a global-wide competitive industry. Following the report, the country needs more than 277 MMTPA petrol products and 358 MMT refining for achieving 90% self-attainment.

1.4 STATEMENT OF THE PROBLEM

Indian refineries influence the decision-making and strategic planning for different crucial sectors of the Indian economy. Hence, India's GDP is largely affected by the Indian refineries as it is one of the major suppliers to central and state assets (Mahesh et al., 2016).

India is mostly dominated by the rural population, which largely uses noncommercial sources to meet the energy requirement. As this segment of India moves towards urbanization, the call for energy use is anticipated to increase. The growth in energy demand (percentage of world energy demand) is anticipated to increase from 5.58% in the year 2017 to 11% in the year 2040 (Mark, 2019), therefore the oil refinery will play a crucial role in satisfying the growing demand and become an advantageous industry for investment. Hence, an Indian refiner always seeks a higher margin in profit for survival as well as for expansion of the refinery.

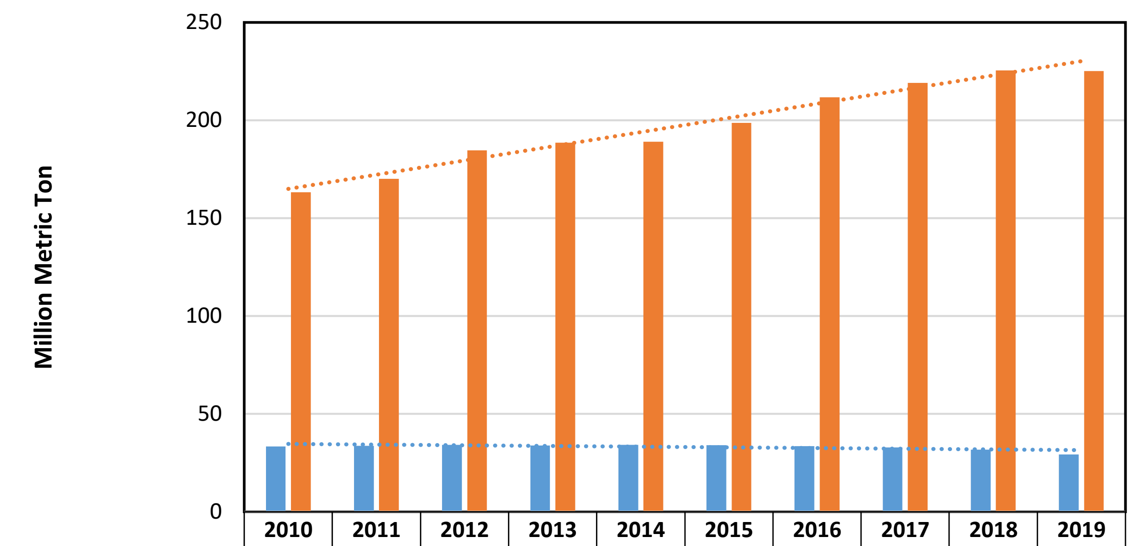


Source: Petroleum planning and analysis cell

Figure 1-3 Total product consumption vs production from Indigenous crude, condensate and gas

However, the growing demand increases the petroleum product consumption in India, and this increase in demand for petroleum products is not satisfied by the indigenous crude oil itself. Figure 1-3 shows the wide gap between the total domestic product consumption and the production from indigenous energy sources. It indicates that the Indigenous crude oil production is not enough to fulfill the rising demand for petroleum products. This raised demand for crude oil consumption that was fulfilled by importing the crude oil from external sources.

Figure 1-4 presents the indigenous and imported crude oil processed in Indian refineries for the last ten years. It represented that India has not the self-sufficiency in the production of crude oil and hence it is important to import crude oil for filling this gap.



	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Indigenous crude	33.3	33.7	34.2	33.9	34.2	34.1	33.5	32.8	31.7	29.3
Imported crude	163.2	170.1	184.7	188.6	189	198.7	211.8	219.1	225.5	225.1

Source: PPAC

Figure 1-4 Imported Crude and Indigenous Crude oil

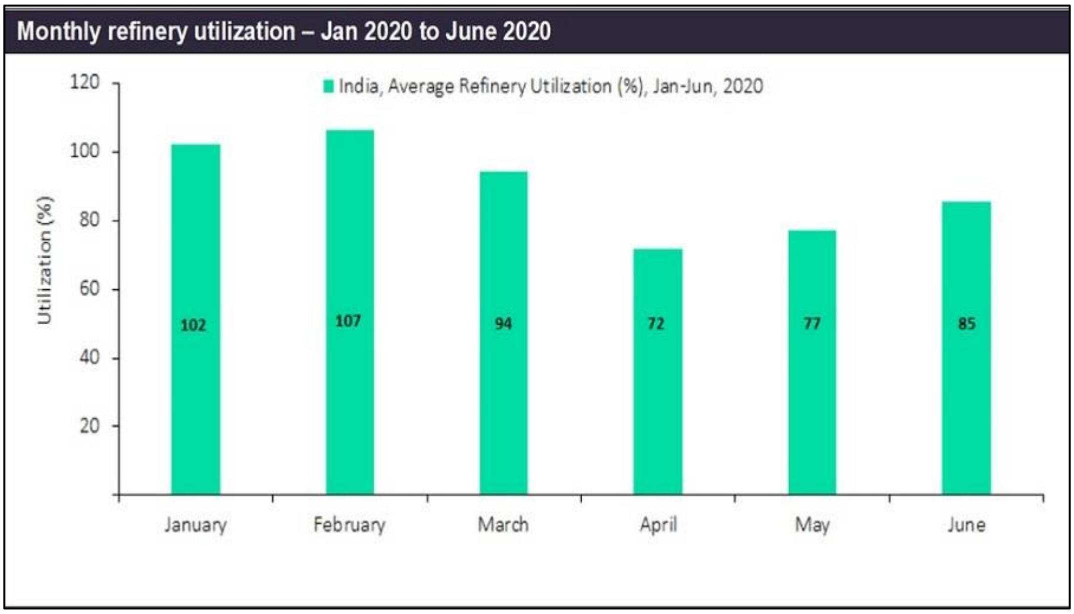
In India, the supply of imported crude oil increased suddenly from 70.72 billion US$ in 2016-17 to 87.37 billion US$ in 2017-18 and the dependence on crude oil import to fulfill the country's need increased to 83.7 percent in 2018-19 financial year from 82.9 percent in 2017-18 (Moody's article, 2019). With the growing demand for energy in India, the consumption of crude oil is anticipated to grow. The consumption of crude oil is projected to increase in India from 221.76 MMT (million metric tonnes) in 2017 to 500 MMT (million metric tonnes) by 2040 (Mark, 2019). But the production of indigenous crude oil is not adequate for fulfilling the increasing crude oil demand. Hence, it is essential to import crude oil and fill the gap generated by demand and supply.

The import becomes costly in India with the increase in international crude oil prices, which increases the Indian crude basket price because of transportation cost and cost of various taxes and duties. The production cost of oil refineries increases with higher Indian crude basket prices, which reduces the profit margin of oil refineries in India. The crude price is not under the control of refiners and drains the profitability of the refinery.

Moreover, with stricter environmental regulations in India, the specification for the final finished products produced from the refineries are very stringent. Additionally, to enhance the quality of fuel with energy-centric and intensive processing units to meet Euro III and Euro IV norms to transport fuels, to upgrade the bottom of the barrel into value-added products; the energy consumption of Indian oil refineries is mostly increased. Such environmental control influences more on the economic efficiency of the oil refinery that causes high production costs and reduction in the profit margin of the refinery.

The expansion of the Indian refineries also goes along with the increase in energy utilisation in oil refineries. Therefore, the petroleum refining industry in India, as one of the major energy users, utilises around 33.1% of the total energy used by the industrial sector, while the industrial users consume 56% of the total energy consumed in India (International Energy Agency, 2020). The energy consumption by oil refineries is reported 239.1 Mtoe (Million ton of oil equivalent) in the year 2018 (PPAC, 2019), while it was reported 180.7 Mtoe in the year 2014 (PPAC, 2015); indicating 1.32 times higher energy consumption than the year 2014. Energy costs account for 40% of operating costs in the refinery industry. This large amount of energy consumed in the oil industry increases the production cost and increases the pressure on the refineries to look forward to optimise the energy use that improves the profit margin.

In addition, COVID-19 heavily impacted key end-use segments such as transportation and manufacturing sectors among others, hitting the demand for fuel products in India. Several Indian refineries have reduced their operating capacities, while a few others have suspended operations to outlast the current crisis (Figure 1-5). India’s refinery utilization in March 2020 fell by around 12% compared to February 2020 as the demand for fuel products fell, with nationwide lockdown being imposed from March 23, 2020, onwards. Although the situation is gradually getting back to normalcy, demand for diesel is not expected to gain a sudden surge as the heavy industries are coping with their recovery challenges. However, the operating cost of the refinery was not reduced with the fraction of utilisation rate. Hence, lower capacity utilisation with stable operating costs drains the profit margin of Indian refineries (Carla S., 2020).



Source: Ministry of petroleum and natural gas, Government of India.

Figure 1-5 Average refinery utilisation

Moreover, the public sector refineries are operated to generate the product mix. Those products are essential to meet the energy demand and to serve the people of India. Hence, even the economics favored the production of highly valuable products (i.e., propylene, etc.) from the refinery, the public sector refineries are forced to produce low-value fuel (i.e., fuel oil, kerosene, diesel, etc.) which requires to fulfill the basic requirement of industries and for the citizen of India. The objective of the public sector refineries is to serve the people of India whereas the main objective of the private sector refineries is profit maximisation. Therefore, the product mix of the government-owned refineries is a constraint and thus affects its profit and efficiency.

In conclusion, the net effect of these challenges decreases the refining margin of Indian oil refineries. "To meet these challenges, there is an urgent need to explore and adopt innovative solutions to create and add value from the existing assets, improve process and energy efficiency, yield optimization and process integration," said Mr. Sanjiv Singh, Director-refineries at the nation's largest fuel retailer Indian Oil Corporation (IOC) (ETEnergy word, 2016). Additionally, increase in production costs have reduced investment in this sector by the public as well as private organisation that impact on the oil refinery expansion projects and infrastructure development. As such oil refinery has to increase gross refining margin and to keep refinery in operation, which necessitates finding the new strategies and ideas to optimise and to ensure efficient use of all resources in the oil refinery.

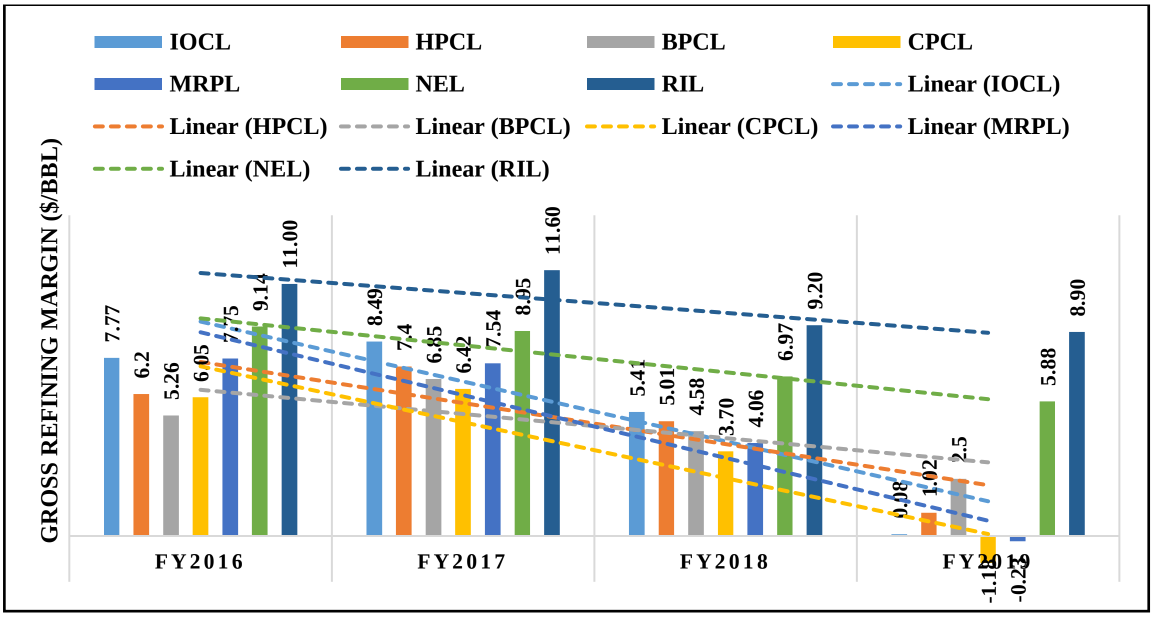
1.5 MOTIVATION/ NEED FOR THE RESEARCH

- The petroleum refinery has the largest earning capacity and has significant importance in the Indian economy. The Indian Petroleum refineries play a crucial part in inducing the speedy expansion of the economy of the country by attaining 15% of the total GDP.
- The oil industry is not only an institution for the maximization of shareholder wealth but also an administrative and social organization possessing the capacity for initiating its growth and thereby contributing to the economic growth of the country.
- Indian oil Industry is affected by a variety of problems such as inadequate utilisation of capacity, lack of finance for expansion and modernization, shortage of crude oil and high production cost, stringent product specifications; those resulted in GRM dropping.
- Hence, investors are not interested to invest in this business that impacts the oil refinery expansion projects and infrastructure development.
- Despite low GRM, the excellence in operational strategy can improve the GRM of the Indian oil refinery. The profitable and cautious use of resources available in an organization or combination of these resources can reduce the production costs and increase the GRM.
- Need for a systematic and scientific way to define, prioritise and drive to enhance the operational efficiency that can increase the GRM.

1.6 BUSINESS PROBLEM

Requiring huge investment to upgrade the product quality, to meet the stringent specification, product mix for public sector refineries, absence of valuable feedstocks, higher operating costs, and energy costs affect refinery business negatively and result in low GRM. This low GRM results in its inability to raise sufficient funds to meet its immediate obligations as well as to fulfill the purpose of the expansion and modernization of the refinery.”

Proving business problem



Source – Petroleum planning and analysis cell

Figure 1-6 Gross refining margin (USD per barrel) of Indian oil refineries from FY2017 to FY2020

Figure 1-6 reveals that the gross refining margins of Indian oil refineries are gradually decreasing from FY2017 to FY2020. The trend lines for each refinery are showing downward trends over the last four years. However, the refining margins of the private refineries are dominating higher compare to public sector refineries. Additionally, Fitch expects the Indian oil refineries' GRM to average USD (US dollar) 1.0-1.5 per barrel in FY2021 given the weak macroeconomic environment and high product inventories (Fitch rating, 2020).

Hence, this low GRM is the current problem for the Indian oil refineries and needs to find various operational strategies to maximise the profit from the same installation and technologies.

Chapter 2: LITERATURE REVIEW

2.1 SEARCH PROCESS

This Chapter discusses the economic literature reviewed related to profit, the concept of efficiency and production frontier models. Owing to this aspect, the keywords used for the literature review are oil refinery, manufacturing industry, profit, refinery profit margin, gross refining margin, efficiency, operational efficiency and data envelopment analysis. The numerous articles, manuscripts and reports are reviewed in this chapter. This section divides the production function literature review into mainly three theme-based groups. The first group deals with production function according to the concept of profit/ profit margin for various firms and industries. The second group deals with production functions according to the concept of profit in oil refineries. The third group deals with production function according to the concept of efficiency measurement. Given the large volume of theoretical and empirical literature in the field of efficiency measurement, the review of empirical studies in the third group is further subdivided into three namely: a review of empirical comparative studies on efficiency measurement, a review of empirical comparative studies on efficiency measurement especially in oil refineries and finally a review of empirical comparative studies on operational efficiency measurement.

2.1.1 Profit/ Profit margin in manufacturing industries

The working capital of the firms is one of the actors for a firm’s profitability. Regarding it, Jain, P.K. (1993) analyzed the WCM (Working Capital Management) of 7 paper companies that belongs to the Indian private as well as the public sector. Further, the study revealed that, during the period of the study, a declining trend was registered by the private-sector paper companies, whereas the ratio has more fluctuated in government sector paper companies. The study Soenen, L.A. (1993) has examined that the relation between the net-trade cycle as working capital and return on investment, the outcomes represented a negative relation between the net-trade cycle as well as return on the assets. Moreover, Reddy and Rao (1996) have examined that the practices of working capital management in HCL (Hindustan Cables Ltd,.) on the assumption that the policies of working capital had a great impact on the firm's profitability as well as liquidity. Also, the study was based on the information and data that was obtained from annual reports of the HCL for the year 1989 -1990 to 1993 – 1994. The study has established that with effective use and control of current assets, the improvement in working capital should be noticed. Moreover, Garcia and Martinez (2007) have analysed the effect of working capital management on the profitability of SMEs. Also, they identified an inverse relationship between a firm's profit and working capital.

Additionally, the actors of the profitability are analysed by the work of Vishnani, S. and Shah, B.K. (2006); Rao, M.P. (1985) and Deepak Chawla (1986). Vishnani, S. and Shah, B.K. (2006) empirically examined the relationship between liquidity and profitability in Indian Consumer Electronics Industry for a period from 1994 – 1995 to 2004 – 2005. Here, twenty-three companies were selected where the study collected the relevant data from the CMIE database. Of twenty-three companies, 9 companies represented negative relation between the profitability, where the rest of the companies showed a positive relationship between these two variables. Rao, M.P. (1985) analyzed the impacts of profitability on the ratio of debt inquiry in engineering firms. The study showed a negative relation i.e., high debt-equity ratios meant low profitability. The operational efficiency of the company as well as the reasonable rate on the capital of the owner depends on profits earned by the company. Deepak Chawla (1986) explained the profitability trends of the man-made Fiber industries of India. Further, the study obtained the relevant data from seventeen companies for the period 1963-1964 to 1977-1978. The increments in the excise duties can be related to the industry's profitable decline.

Sanjay B. (2010) stated that the firm profitability is said to be strongly influenced by the external and the internal variables such as inflation rate, component costs, organization growth, management of liquidity and the organization size. The study tried to find the variables that judge the Indian

Cement Industry's profitability. Further, the study covered all the Indian cement firms from 2001 – 2008. For determining profitability, stepwise regression has been utilized on the study variables. Finally, the outcome of the study showed that the rate of inflation, rate of interest, operating profit ratio, firm's age as well as liquidity has performed a major role in the determination of the Indian cement industry's profitability.

Nagarajan and Burthwal (1990) have assessed the association among the profitability and its structure of the same by utilizing the sample of 38 pharmaceutical organisations prevailing in India starting from the period of 1970 and ending in the year 1982. This evaluation has illustrated the most important identification of the profitability of the organisations in the same industry, found to be vertical integration which was under the situation of price control measures. The advertising and the size factor do not appear to be the main identification marks. The coefficient percentage of growth was found to be important and turned to be the positive ones, which analysed the factors relying on the required side of the organization had a strong influence in the same profitability than compared to that of the supply boundary.

Chandrasekaran, N. (1993) has made a study on the determinants focusing on the profitability prevailing in the stream of cement firms. This paper has a goal of figuring out the inferences in the influence of the policies which have paved the way to the modification in the distribution norms and the price factors which were related to that in the cement firm. The identification factors in profitability have been by the usage of the methodology of general least squares. On the basis of general existing prevailing theories and the associated empirical tasks in the economy range, these variables have been picked up. This paper then concluded the efficient flow in the management of inventory level and also in the management of the recent assets seem to have significant to enhance the profitability.

James Ted (1997) has yielded the new authorization on the identification factors in the profitability of the manufacturing organizations in Australia, assessing the distinct organization range dataset of organization performance commenced from the period of 1983 and terminated in 1993.

On the inferences of the estimations which has the basis on the undertaking of the standardized oligopoly design, the resultant economic data have revealed that the trailed profitability was found to be the determinant of recent margin of its profit, and the organization concentration has found to be positive one associated to the profit margin rate. Additionally, the real wage inflation and union density seem to the negatively related to the organization's profit.

Kasturi et al. (2016) identified that the BA (Bat Algorithm) produces optimized outcomes when compared to other algorithms and improves the profit of the industry of airline. They found that effective flight plans could also diminish the cost of fuel, time-based cost, total distance, speeds, shifting passengers and freights. Subiakto et al. (2012) studied the asset allocation strategy of SMEs to improve profit. They found that the strategy of asset allocation along with periodical rebalancing provides better returns. Moreover, SMEs could significantly improve their sustainability as well as profit when they utilize this strategy. Yangyang and Prem (2016) found that the profit could be enhanced by increment in the capacity of production and with more operation modes shifts. Endang C. (2012) conducted the profitability analysis of the smaller as well as medium enterprises that supports the Indonesian telecommunication business. The study identified that these companies must consistently strive for improving capability of research and development, technology as well as technical skills to enhance the profit margin.

Sidhu and Gurpreet (1993) assessed the factors which have an impact on the profitability of textile industrial firms in India. In this paper, an effort has been made to detect the main variables in the textile firms in India with the utilization of empirical information fetched from the Bombay stock exchange directory in 1983. To detect the factors influencing profitability, the methodology of regression analysis has been evolved. On the analysis part, there seems to be no more apparent association between capital intensity and present profitability. The firm age had been usually the negative response in it but found to be a not important association with present profitability which pinpointed in the fact that the textile industry in India, requires modernization and is found to be absolute.

Vijayakumar, A. (1998) assessed the profitability and the identification of the size of the corporate. To focus the scope of the paper, the public sector firms in India have been selected. The data associated with the growth, profitability, size have been gathered from the yearly reports which have been published by the public enterprises' bureau prevailing in India. The procedure of moderate average, multiple regression analyses, correlation and linear regression have been utilized in the method. Interfirm analysis has implied that the growth was found to be positively and significantly related to size prevailing in all the segments except in textile firms. He further revealed that the size factor has been related positively to the profitability in overall all firms.

Shin and Soenen (1998) have marked the association between the firm's profitability and the cash conversion cycle in the prevalence of high-listed American firm samples. The working capital has been maintained and also had a strong influence on liquidity and profitability. The association between risk-adjusted stock, Net trading cycle length and corporate profitability has been observed by utilizing the regression and correlation analysis. It seems to exhibit a heavy negative association between the lengths of the industrial net trading cycle and the profitability. On the basis of the inferences, one of the suitable paths to make the shareholder value was to diminish the industrial net trading cycle.

Agarwal, R.N. (1999) learned the growth and profitability in the manufacturing firm of automobile industry prevailing in India. The goal of the paper was to assess the influence of policy modifications prevailing from the period of 1981 to the year 1982 on the growth and profitability of the industries. The factor profitability seems to be explored majorly by the diversification, age of the firms, industry policy dummy variable and the vertical integration. The significant identification factors influencing the growth of the industries have been found such as firm policy dummy variables, expansion of capacities, gross sustained profits and diversification.

Simon and Mark (2011) reviewed the performance of the industry by examining the role of share of the market, diversification and concentration. The analysis of the profitability of 722 big Australian industries ranging from the period from 1993 and up to 1996 has been undertaken. This analysis inference presented that the firm concentration has a good positive impact on the profitability by the implementation of regression procedure. The industrial market share was found to be appearing to possess an important linear relation with profitability. However, the non-monotonic association is important.

Tze-Wei et al. (2002) assessed the association between the financial capital and profitability for the total of 1276 small organizations from the time starting from 1992 and ending to the year 1997. The findings revealed a statistically positive association between capital growth and profitability. When there is the divergence of the financial capital into equity and the debt factor, the resultant data revealed the importantly establish the positive association between the equity financing and profitability. But also, there will be an important negative relationship between debt financing and profitability. The profitability of the small organization has been positively associated with the organization's previous profitability and the external economic conditions.

Tulay and Gulizar (2002) analysed the association of each conversion cycle of the cash with the indulgence of liquidity, debt structure and profitability. The analysis of the paper revealed that the cash conversion cycle was associated with the liquidity ratio rates positively and the association to return on the equity and the asset negatively. The large leverage ratio will influence profitability and liquidity factors adversely.

Padmaja M. (2002) analysed that the profitability of the industries will have a dependency on the size, region and age. She also presented that the quality rate of the earning which has a dependency on leverage management, asset management and cost management. Also, she has evidenced that the liquidity of the earning will have an influencing impact on the quality of the earning and profit.

Ghosh S. K. and Maji S.G. (2003) analysed the usage of the operating profitability and the present assets. Information of the eleven organizations of the tea and the cement industries have been gathered for the time period starting from the year 1992 to 1993 and completed in the year 2001 to 2002. The paper finalized the degree of the present assets that have been related positively to that of the operational profitability of the industry.

Eljelly, A. (2004) observed the association entity between the liquidity and the profitability factor of the organization taken specifically on the sample bunch of joint-stock firms prevailing in Saudi Arabia by the utilization of the regression and correlation analysis. The findings were found to be stable and significant effects for the liquidity management in several Saudi oriented firms. The paper presented that there would be a negative association between liquidity and profitability indicating components such as the cash gap and the current ratio in the sample provided.

John G. et al. (2005) demonstrated the determinant indicators of the profitability for the service area organizations and the manufacturing firms prevailing in Italy, UK, Belgium and France for the year of 1993 to the end of 2001. The study amalgamated the empirical design which has been utilized by the researchers in accounting, finance, strategic management and industrial economics. There has been proof of the negative relationship between size and profitability, but the relationship among the profitability and the market share found to be the positive ones which also has the strong durability in the manufacturing sector than the others. The affinity between the profitability and the gearing ratio tended to be negative but in the case of the industries with large liquidity, triggers to be more profitable.

Agiomirgianakis G. et al. (2006) analysed the financial determinant of the employment growth and the industrial profitability by utilizing the panel of 3094 manufacturing organizations of Greek from the period of 1995 and ending to 1999 in front of the accession of the country to the monetary union in Europe. The study has indulged the regression models step by step. The independent variables used were the location, exports, size and the age, and the count of financial ratio which describes the capital structure, employee productivity, asset structure, reliance on debt and the managerial efficiency factor. The finding has revealed that the exports, debt structures, sales, age and size would have been involved in the organizational growth. The results in the economy have identified that the exports, size, age, growth, investment growth, reliance on debt on the constant asset along with the effective management of influence profitability and the assets.

Ghosh and Maji (2006) have established the try to analyses the influence of the operation on the leverage on the profitability in the four Manufacturing sectors in India such as chemical, tea, pharmaceutical and paper. The size of the sample comprised of seventy-two Indian firms which belong to the specified four industries for the period of twelve years from the period of 1990 to 1991 and from the range from 2000- 2001. Analyses of the study identified that despite the identifications of the operating leverage measures or the profitability of the variables. Both variables were related in a positive way for all the firms.

Andreas S. (2010) determined the identification components of organization profitability and also identified valuable relative significance by the utilization of high Australian organization panel from the time starting from 1995 to the range of 2005. The findings revealed that the profitability has been identified by the range of organizational characteristics and their sector consequences have been found relevant but at a small level.

Alessandro and Paolo (2009) analysed the identification components of the profitability and productivity of Italian firms which were operating in the firm sector. The inference has underlined the significance of the complexity of the operation and the financial management in accordance to illustrate the design of the productivity and the profitability rank rate in the period of 1998 to the year 2002. They have also determined that the enterprises in Italy were not been found static enough to be competitive in the innovative areas and technological sectors.

The kind of literature reviewed in this section mostly presented the financial indicators relations with the profitability of the manufacturing industries. Some of them also included the firm’s size, complexity association with the profitability.

2.1.2 Refinery Profit/ gross refining margin

The gross refining margin concept of the refineries has been analyzed by the many numbers of scholars which have been carried out by the developed and advanced countries. The prices of the crude oil and products, utilization factor, operational efficiency and the structure of the refinery are included in some of the determinants which would have an impact on the gross reefing margin of the refinery (Amani, 2020).

The optimization model has been developed by the usage of mathematical techniques in most times for example the nonlinear programming model and the linear model (Nikolaos, 2004). Kunal (2015) has designed the model to evaluate the gross refining margin by acting out the blending problems of crude oil. This model could estimate that the density of the products and sulfur have been included within the market specifications and the demand to generate a sufficient refining margin.

Cerda et al. (2018) have designed a pair of mixed-integer nonlinear programming (MINLP) strategies to allocate the crude blending mechanism prevailing in the oil refineries. This model would imply the approach to uplift the lower cost viscous and heavy crude oil by blending with the sweet crude oil and light crude oil to increment the gross refining margin. Also, in addition, Amit and Tukaram (2013) have designed the mathematical design to raise the gross refining margin with the integration of the secondary process units and the real-time product blending mechanism. Tareq et al. (2019) outlined the serious integer mixed integer non-linear programming models for the thirty-two operating refineries in the region of Kuwait. This model would assume the restrictions of the material balance and the energy balance of the mentioned crude oil and also increase the summation of the refinery profit. Kyungseok et al. (2017) designed the prediction model for the change in the conversion rate and yield while processing the lube hydro mechanism for each crude blend. Also, the prediction models have been assimilated in the optimization approach in the refinery for the enhancement of the summarized gross refining margin.

Laith et al. (2016) associated the gross margin with the emissions by outlining the mixed-integer nonlinear programming model comprising of the operating refineries prevailing in the region of Saudi Arabia. The findings of the mathematical model have revealed that plants would improve the refinery margin, which could attain the higher pollutant decrement. Fayez and Mohammed (2017) have outlined the mathematical design to improvise the profitability of the oil refineries as it is capable of the implementation of several technologies to decrement nitrogen dioxide emissions. The outcome of the paper has concluded that the profit can be improvised by the decrement in nitrogen dioxide emissions. Long J. et al. (2015) have reformed the operating parameters and optimisation models for the fluidized catalytic cracking unit – FCCU. The outcome of the optimization design defined that the high profit from the fluidized catalytic cracking unit results in the increment in the refinery margin of the total refinery.

Diana et al. (2012) designed the mathematical non-linear programming – NLP design for the optimization of the operating parameters of the crude distillation process and also it augments the production to enhance the gross refining margin. Chau et al. (2015) identified that by moving out of maximum gasoline operation mode, the Fluidized Catalytic Cracking Unit (FCCU) could enhance the overall refining margin. Moreover, Saeid (2009) revealed that the refiner could optimize the performance of the various process by implementing the Microprocessor-based real-time optimization (RTO). RTO would implement several crucial actions which include performing the process modeling and real-time refinery management. It is found to be the very prevalent effective path for the improvement of the economic performance and in the reduction of the overhead cost.

Chaudhuri et al. (2018) and Johnson et al. (2002) suggested increasing the yield of petrochemical products, seems these products are high value-added products and creates more profit. The paper assumes to undertake the integrated strategy, majorly for the focus of the petrochemical items and also the new approaches which are needed to enhance the profitability of the refineries. Further, Zhao et al. (2017) formulated a mixed-integer nonlinear programming model to improve the production planning and showed that the integrated tactic gives more overall profit margin of various operational units in oil refinery and ethylene plant simultaneously, which is not able to achieve with traditional methods. Mouret, S. et al. (2009) developed a new continuous-time scheduling design to admit the crude oil scheduling conflicts with the motive of increasing the gross margins. They have identified the count of the priority slots which will progress to improvise the gross margin.

Further, the refinery can improve profitability by modifying the hydrogen network in the oil refinery (Mohammad et al., 2014 and Zhang et al., 2001). An integrated hydrogen network reduces investment costs and operating costs of the refinery, thus raises the profitability of oil refineries. Hallale (2001) detected the methodologies to merge the static sources of H_2 in oil refineries to increment the recovery of H_2 and also to improvise the profitability. Koldachenko et al. (2012) observed that the hydrocrackers are often a key factor in the achievement for the higher refinery agility and also in sustaining the sync with the fluctuations of the market to improvise the gross refining margins.

Not only optimisation model can enhance the gross refining margin, but the gross refining margin of the oil refinery can be enhanced by a decrement in the headcount, reducing the several costs and also by uplifting the high value-added products percentage (Showing and Lihlian, 1999). Brad V. (2012) suggested that refiners could increase the refinery margin by optimizing the refinery operations, decreasing the use of energy and reducing the operational costs. This study also revealed that the increase in effectiveness and refinery efficiency can boost the refinery's profit margin. Russell et al. (1996) undertook the study on profitability and efficiency of 14 oil refineries prevailing in the region of North America for twelve years. The inferences have projected that they would increase the profit by conserving the resources, improvising the substitution of the resource and removing the waste.

In addition, an AspenTech was used to supply and implement a multivariate controller, DMCplusTM, as part of an upgrade of the FCC. The up-gradation of automation in the FCC unit allowed the unit to operate very close to its economic limits and expanded the profit margin (Petroleum Review, 2000). BOC Process Gas Solutions has developed unique industrial-gas-based solutions to help oil refiners to upgrade crude bottoms to clean, high performed and value-added fuels while reducing smog-forming emissions of NOx and Sox. It will help in increase of the refinery profit margin (Hydrocarbon processing, 2001).

Antonio et al. (2019) showed that the switching from gasoline production to aromatics products mitigates the problem of overall refining margin volatility and decreasing the demand for petroleum products. However, its success depends on the pricing of the gasoline and the configuration of the aromatics plant. Jafari (2009) stressed the importance of maintaining existing plants and machinery with minimum investment while trying to achieve maximum returns from the existing equipment and production installations; decision-making strategies; calculations and forecasts; refining margin trends; and methods to improve refinery margins.

In addition, Zurlo (2016) identified that the decline in gross refining margin is the result of an increase in crude oil variability and stringent environmental as well as product quality regulations. Crude variability can make refinery operations quite tough to withstand as efficient operations. It makes operation difficult since it interrupts optimizing the current refinery configuration. Further, it has been implied that the reliability of the equipment has been prevailed as the crucial on present preference for the oil refineries to enhance the profit factor. CFA (2013) identified that the refineries have to maximize asset utilization by reducing down-time for maintenance, repair and investment, and minimize operating costs which include energy, labor and maintenance to improve profitability. Masri et al. (2005) revealed that energy consumption is a significant determinant, which intercedes the petroleum refining cost. The study shows that the refinery's profit margin and performance can be increased by reducing energy consumption. The efficient use of energy reduces the refining cost and archives more profit. Romulo et al. (2011) evaluated the energy consumption of Brazilian oil refineries in comparison with the refinery of the United States for a period from 1930 to 2008. The findings showed that the complex refinery compared to the less complex refinery consumes less energy for producing the high value-added products and thus increases the refinery's margin. Appert and Favennec (2008) said that the level of complexity of oil refineries is directly related to the gross refining margin, which accepts that the higher the complexity the higher the gross refining margin. C. Drumm et al. (2013) defined that due to the higher price of crude oil, energy cost reduction is a "key lever" to reduce the overall expenses and respectively to improve profitability.

R Mahesh and N Thangaraj (2016) have observed the liquidity position and the profitability of the petroleum industry in India. They have also implied that the profitability of the specified companies in the petroleum industry which found to be satisfactory, but the position of liquidity in the study period has been inadequate. The rate of growth, for the case study, has been deteriorated during the study period. Vijayakumar and Kadirvel (2003) have observed that the age was factor found to be the strong determinant of the profitability involved by the leverage, size, inventory, current ration factor, vertical integration and the expenses covered to that of the growth rate and the sales ratio. Duraipandi and Nallaswamy (2015) have observed the profitability of the oil refineries in India. They noticed that the status regarding the earnings per share and dividend payout ratio in the specified oil refineries, which is under review presents a good performance. The decreasing tendency of the rate of profit is the evidence of the hostile consequences of the several process controls, investment, distribution, output and expansion, which has been implemented by the government on the period of time.

2.1.3 Production function and efficiency measurement

Production theory delivers a suitable background to evaluate the production function and allocative efficiency levels of a firm. In microeconomic theory, a production function is defined in terms of the maximum output that can be produced from a specified set of inputs, given the existing technology available to the firms involved. A production function is used to define a benchmark to measure how efficiently production processes use inputs to generate outputs. Hence, one important purpose of the production function is to address allocative efficiency in the use of the production process. The papers by Debreu (1951) and Koopmans (1951) mark the origin of discussion on the measurement of productivity and efficiency in the economic literature. The work of Debreu and Koopmans was first extended by Farrell (1957) to measure productivity and efficiency. To estimate the efficiency function, a probability frontier production function was introduced by Timer (1971). Later a Stochastic Frontier Analysis (SFA) was presented by Aigner et al. (1977). The second approach is nonparametric, which was first introduced by Farrell (1957). Farrell’s approach has been extended by Charnes et al. (1978) giving rise to what is known as data envelopment analysis (DEA). Charnes et al. (1978) reformulated Farrell’s approach into calculating the individual input saving efficiency measures by solving a linear programming problem for each unit under the constant returns to scale (CRS) assumption while Banker et al. (1984) extended it to the case of variable returns to scale (VRS), since the imperfect competition, financial constraints may cause a firm not to be operating on an optimal scale, the assumption upon which CRS is appropriate. Approaches to efficiency measurement are broadly specified into parametric and non-parametric approaches.

Many empirical studies have applied the frontier models since the pioneering work of Farrell (1957). However, given the large volume of theoretical and empirical literature in the field of efficiency measurement, a general review of comparative studies in oil refineries and other sectors is provided.

2.1.3.1 Empirical studies on efficiency measurement

Jung et al. (2005) have manipulated the technical efficiency of the steel and iron industry. They have implied that privatization of the government firms has been found likely to enhance the efficiency to a high extend technically. The organization's technical efficiency was found to be positively related to the level of production, which is analyzed by the summarized world production share of steel. The paper also concluded that attempts to uplift the equipment and the technologies seem to the crucial to the quest for efficiency in the steel and iron industry.

The paper has been established by Jajri and Ismail (2006) to research the inclinations associated with technical modification, TFP growth and the efficiency in the manufacturing area prevailing in Malaysia. Data analysis has been implemented out on the basis of data, which has been gained from the survey of manufacturing industries between the period starting from 1985 and ends in 2000, which was collected by the department of statistics in Malaysia with the help of Data Envelopment Analysis. The analysis of the paper has implied that within the period of study, the increase in the TFP growth factor, where the growth would be highly qualified to the technical efficiency. Nonetheless, technological developments indicated an increasing trend over time.

Hokkanen (2014) evaluated the technical efficiency of Finnish firms in the various sectors, using both panel data and cross-section techniques. The study found significant variations in the technical efficiency in the meantime, prevailing in the models where industrial-specific heterogeneity has been oriented.

Asheghian (1982) has attempted to evaluate the technical efficiency of the foreign and the local firms in Iran with the perspective to yield the intra organizational efficiency equalization, which has been established on the 3 key contents that also include the total factor productivity. The findings have turned out to the conclusion, which implies that the joint venture organizations globally led to be very technically efficient in comparison with the local organizations.

Ozlem and Ertugraul (2003) summarized factor productivity modifications and the technical efficiency by the estimation of a translog stochastic frontier functionality for manufacturing firms in turkey in the specified provinces. This methodology has gathered the technical modifications and had time-changing technical efficiency consequences. The stochastic frontier function has been analysed by the usage of panel data comprised on the focus of the 18 provinces in turkey from the period of 1990 and up to 1998. The performance analysis of the private and the public sector have been analysed individually. The apparent reasons for the various performances of the regions in accordance with the efficiency have been taken into the discussion. In this study, the consequences of the average organization size, time period and regional production share have been taken into the discussion.

Okoye et al. (2007) applied a random frontier trans-log production and cost functions for measuring the allocative efficiency level associated with the determinants in the production of smallhold cocoyam at Anambra, Nigeria. These parameters of the above-described function have been determined with the use of the maximum likelihood process. The analytical report depicted that the discrete farm allocative performance to about 65%. The study determined that age and education are significantly and negatively related to allocation efficiency. The study also found that the farm size coefficient possesses a negative and significant correlation with one another. The use of fertilizer, credit access followed by farm access was observed to be directly and significantly related to the allocation efficiency.

Kamel Helali and Maha Kalai (2015) investigated the development of technical efficiency in the Turkish manufacturing sector. The predominant objective of the study is to determine the explanatory constraints such as economic, allocative and technical efficiency in the Tunisian manufacturing sector. From the analysis, they observed two kinds of random production models with the corresponding variable inefficient term like Translog models and Cobb-Douglass. The study collected panel data from industries for measuring technical efficiency. These determinations found that a normal range of allocative, specialized and financial efficiencies was found to be correlated to 76%, 77% and 58% respectively. The constant deviations from the province could be the representation of either low aggressive weight from the distant rival areas for the duration of 1961 to 2010. The overall mean efficiency score has been observed to be 77% and the study has no evidential report in the constant increase in the efficiency range.

Randolph Tan (2006) has predicted the technical efficiency modification in the manufacturing firms prevailing in Singapore from the period 1975 and up to the year 1998 by the utilization of the Malmquist index. The resulted data have implied that in the level of average, it has been noticed several enhancements in the technical efficiency in the period for the total manufacturing. This has been widely documented resulted of data from the previous analysis of stochastic frontier. Chiranjib and Buddhadeb (1994) have drawn inferences that the inter-temporal efficiency modifications in the manufacturing prevailing in India. The findings have been importantly decisive. The technical efficiency has been diminishing over time. Along with this TFP modification has aided in understanding the tendency of the development in industry in the current occurrence. It has been determined that the inquiry indulging into the source components of the inter-industry efficiency modifications implies that the profit, positive role, skill and labour would have an impact as the positive role. Whilst the intensity task of capital has been against the usual beliefs. Agarwal R.N. (2001) accessed the technological modification, overall productivity growth, the technical efficiency in the industry firm-wise and also in the group-wise sector. The findings found that the major level of the organizations had been the lower ranges of the technical efficiency and this competency has not enhanced in the time period. But the growth level of the technical competency has been noted in some of the organizations prevailing in the engineering area sector and many organizations in the petroleum selling and producing area sector.

Ruhul S. and Kalirajan (1997) attempted to calculate the capacity realization index followed by the decomposition of the overall factor productivity growth into the difference in capacity realization and technical progression of food processing Bangladesh Industries. The research data were obtained from the Census of manufacturing industries that have been conducted yearly by BBS (Bangladesh Bureau of Statistics). For this process, the firm data on the food processing factories of the selected area from the period of 1981 to 1991 has been utilized. Both the non-production and production works have been chosen in this analysis. The study utilized a stochastic coefficient frontier. The production function method has been processed based on Farrell's work. Cobb –Douglas function form might be utilized extensively in the functional analysis of the stochastic frontier production. These results represented the existence of a major difference in the capacity realization among the firms, even though few experienced and significant development over the corresponding sample period. The study discovered that the output growth over various firms has been occurred due to the input growth by decomposition of output growth to the input growth as well as the change in the technical progress and capacity realization change.

Alias et al. (2010) analyzed the efficiency of the wood furniture firm by the detection of the technical efficiency utilizing the stochastic frontier production model. This proof has suggested that more organizations would operate underneath the efficiency range, which confirms the conventional perspective view that labor-intensive organizations have been inefficient. Arup Mitra (1999) has observed the total factor productivity progress and the technical efficiency in Indian firms. The resulted data have concluded that the efficient utilization of resources has been provided to the increment in the total factor productivity. Figueira, C. et al. (2006) have evaluated the influence of ownership on the efficiency of the African banks. They found that governments in the emerging markets and the developing world have taken various measures over the last two decades to enhance bank efficiency and competing practices among the banks. Some of these measures include the denationalization of state-owned banks, development of a new regulatory framework and removal of entry obstructs to foreign investment.

John M. (1984) has influenced the association between the technical efficiency and the organization size in the 4 manufacturing firms. Which are machine tools, printing, shoes and soap. The study revealed that variations in technical efficiency were due to the average experience of the entrepreneur, labour force experience, age of establishment, equipment’s age and level of capacity utilization. There was only a little evidence of a systematic relationship between firm size and technical efficiency. Goldar, B.N. and Agarwal, R.N. (1992) estimated firm-specific efficiency indices for top 100 engineering firms and found that the efficiency is lower for large public sector firms compared to small firms in the private sector. Anup M. (1999) studied the total factor productivity growth and technical efficiency for Indian industries. He found that the acquisition of technological capabilities, efficient utilization of resources and infrastructure development are some of the factors which possibly have contributed to the increase in the total factor productivity growth.

The Data envelopment analysis (DEA) has been utilized for several companies for the evaluation of relative efficiency since its origin. The study Han et al. (2015) has utilized this DEA model for measuring energy efficiency. Further, the study Iliyasu and Zainal (2016) has applied this model for determining the technical efficiency of freshwater pond-culture and has shown that the farmers’ age, experience, extension training and water management have positive impacts on technical efficiency. Almawsheki and Shah (2015) measured the technical efficiency for the 19 container terminals in the Middle Eastern region to explore the valuable information required to develop the resource utilization for the container terminals and to improve the operational efficiency. Similarly, Ueasin et al. (2015) measured the technical efficiency for the Rice Husk power generation in Thailand. Two concepts, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) were adopted to analyse a group of 57 biomass power plants. Input surpluses of capacity and rice husks were highlighted to improve unit efficiency. The study encouraged more utility plants to use rice husk for electricity generation and to minimise the production cost. Blomberg et al. (2012) applied the DEA model to assess the energy efficiency for the pulp and paper mills. The results suggested that future energy efficiency programs could be better targeted at explicitly promoting technological progress as well as at addressing the most important information and behavior-related failures. Mousavi et al. (2011) applied DEA to assess the efficiency of apple producers in Tehran province in Iran. A DEA was applied to analyze the efficiency of farmers, discriminate efficient farmers from inefficient ones and identify wasteful uses of energy to optimize the energy inputs for apple production in Tehran province, Iran. The results of the DEA application revealed that there was a great potential for improving energy and economical efficiencies of apple producers with effective use of inputs chemical fertilizers and chemicals.

In addition, Azadeh et al. (2007) analysed energy efficiency for energy-intensive manufacturing processes with the use of the DEA model. Four energy-intensive manufacturing sectors are discussed in this paper: iron and steel, pulp and paper, petroleum refining and cement manufacturing sectors. The proposed model utilizes an integrated DEA, PCA, NT approach with DEA for assessment, optimization and sensitivity analysis and PCA and NT approaches for verification and validation. The results of the proposed approach end in a ranking of manufacturing sectors, verification, optimization and determination of critical indicators.

Park and Lesourd (2000) determined the efficiencies of 64 conventional fuel power plants operating in South Korea. Their results showed that the null hypothesis of equality of means between all fuel types could be accepted. In addition, they found that the efficiency for the oldest plants is significantly smaller than the newer ones. A comparison of the plants' efficiencies by geographical area revealed no significant difference. Lam and Shiu (2001) measured the technical efficiency of China's thermal power generation based on the cross-sectional data for 1995 and 1996.

According to their results, municipalities and provinces along the eastern coast of China and those with rich supplies of coal achieved the highest levels of technical efficiency. They also found that fuel efficiency and the capacity factor significantly affect technical efficiency. Nemoto and Goto (2003) evaluated productive efficiencies of Japanese electric utilities over 1981–1995. Results indicated that utilities are efficient in their use of variable inputs and that the inefficiency is attributable to a failure in adjusting quasi-fixed inputs to their optimal levels. Thakur (2006) assessed comparative efficiencies of Indian state-owned electric utilities (SOEUS), and the impact of scale on the efficiency scores was also evaluated. Their results indicated that the performance of several SOEUS is sub-optimal, suggesting the potential for significant cost reduction. It was also found that bigger utilities display greater inefficiencies and have distinct scale inefficiencies. Vaninsky (2006) estimated the efficiency of electric power generation in the United States from of 1991 to 2004 using DEA. His results point to relative stability in efficiency from 1994 through 2000 at levels of 99–100% with a sharp decline to 94–95% levels in the following years.

Barros and Peypoch (2007) analysed the technical efficiency of hydroelectric generating plants in Portugal between 1994 and 2004. They concluded that the hydroelectric generating plants are very distinct and therefore any energy policy should take into account this heterogeneity. It is also concluded that competition, rather than regulation, plays a key role in increasing hydroelectric plant efficiency.

An input-oriented DEA model is applied to compare 34 coal-fired power units in China by Song et al. (2014). Two efficiency indices, generalized energy efficiency and special energy efficiency are defined and analysed. Relations between these two energy efficiency indices and non-comparable factors including quality of coal, load factor, capacity factor, parameters of mainstream and cooling method are studied. Comparison between energy efficiency evaluation results of the two indices is conducted. Results show that these two kinds of energy efficiency are more sensitive to the load factor than the capacity factor. The influence of the cooling method on energy efficiency is larger than that of mainstream parameters. The influence of non-comparable factors on the special energy efficiency is stronger than that on the generalized energy efficiency. Barros (2008) used a two-stage method to determine the technical efficiency of Argentina's airports for the period 2003 to 2007. The DEA tool was utilised to evaluate the airports' technical efficiency that established which airports performed most efficiently. The truncated regression model with bootstrapping indicated that the process of internationalization and public scrutiny significantly contributed to improving the airport's efficiency.

Moreover, the overall technical efficiency of 14 coal industries in China was investigated by Chenglinv et al. (2020). They operated a Tobit regression model to investigate the effect of various determinants on the efficiency of coal industries. This paper identified the positive and negative effects of various influencing factors on the safety management efficiency of coal enterprises and analysed the main reasons that hinder the improvement of safety efficiency. Safety investment, enterprise-scale and labor productivity are significantly positively related to safety management technical efficiency, while safety training person time and employee's quality are negatively correlated. Shuai and Zhang (2020) assessed the efficiency of the green economy for the year 2007 to the year 2018 in context to China, considering the time series data of different areas of the country. The consequence of environmental norms on the efficiency of China's green economy was verified by the Tobit model.

Umit (2018) evaluated the productive efficiency of 95 large wind farms in Texas. The Tobit estimator was applied to study the influence of key determinants on productive efficiency. The study found that elevation, rotor diameter, hub height and blade of the turbine have a significant impact on productive efficiency, while the age of the turbine harms the productive efficiency of the wind farms. Aydin (2013) analysed the efficiency performances of the 21 Turkish electricity distributions companies. The Tobit regression estimator has been presented to analyse the differences in the efficiency with their determinants. In response to the results gathered, the density of the customer of the area and private ownership would positively influence the efficiencies. Nor Diana et al. (2014) have carried out DEA to determine the technical efficiency of the cash crop producers in the region in eastern Malaysia. On the Basis of the inferences, the resulted data would reveal that depending on the family labor, participation as the association and the years of experience were all the important determinants in the efficiency level for the IADP farmers in the sector of agriculture. Parker (1999) utilized DEA to assess the technical efficiency of the British airport authority after and before the privatization and also been implied that the privatization had no significant influence on the part technical efficiency.

2.1.3.2 Empirical studies on refinery efficiency measurement

Kah-Hin and C. Yeo (2012) have the conclusion that the significance of energy efficiency is due to the low refining margins and large environmental costs. In crude oil processing, fouling in the preheat train heat exchangers has been the main problem in the oil refinery for years. The increased energy requirements, operating problems and the greenhouse gases emissions which have been raised from the inefficiencies due to the process of fouling have been illustrated. The mathematical design which is suitable in the prediction of the dynamic tendency of a shell and tube heat exchanger experiencing fouling has been utilized to evaluate the environmental influence of crude distillation unit and to evaluate the costs. By the usage of this model, the options of retrofit have been proposed for the industrial unit in existence which led to the enhanced efficiency of energy (Francesco Coletti, 2009).

Romulo S. and Roberto (2011) analysed the energy efficiency in the crude oil refinery in Brazil in association with crude oil refining in the US between 1930 and up to 2008. The objective of the paper presents that the increased complexity of the refinery has decreased the consumption of energy for the great value-added products. Also, the study presents that the enhancements in the efficiency of energy would result in the high-quality items and the incremental processing of the oil. Brad V. (2012) confessed that the refiners would elevate the profitability by the optimization of the refinery operation, and also in diminishing the usage of the operational costs and the energy. This paper also confessed that the increment in the refinery efficiency and the effectiveness can lifts the profitability.

Eller et al. (2011) evaluated the technical efficiency of seventy-eight oil refineries from the classification of nations without the point of considering the environmental dimension of the oil sector thus concluding the fact where the enterprise of government has a negative influence on the scoring efficiency. Vijayakumar and Gomathi (2013) have counted the capability of the 7 Indian refineries in the period of 1996 to the year 2011 by the methodology of the Malmquist productivity index and DEA. The influence of the fiscal reforms on the total factor productivity has been assessed by them which later been incremented by the rate of 8.60 percentage while in the whole period.

Zhao and Zhang (2010) have undergone the studies to assess the performance of the oil refinery in China by the utilization of the data envelopment analysis, and also similarly the efficiency and the profitability of fourteen oil refineries in North America have been implemented by Thompson et al. (1996). The results have implied that the oil refineries would increase the income by the removal of waste, enhancing resource substitution and conserving resources. It has been inferred that the production cost has been eliminated by the implementation of the environmental management system. Bevilacqua and Braglia (2002) calculated the environmental efficiency of oil refineries in Italy over the years 1993-1996 considering emissions from the refineries. They found that production cost was reduced by implementing an environmental management system.

Francisco et al. (2012) assessed the environmental efficiency. The opinion was that technological development within oil refineries was largely encouraged by environmental restrictions on the quality of increment in petroleum products. At an initial look, the goals might appear to contradict and foster a technological alteration in terms of reducing raw materials with the objective of increasing production, both in terms of volume produced and environmental quality. As well as a drop in emissions thereby, ensuring a superior level of environmental efficiency. Additionally, Mekaroonreung and Johnson (2010) assessed the technical efficiency of the oil refineries in the US. A total of 113 oil refineries have been indulged in the paper and their efficiency has been evaluated for the period from 2006 to 2007. The undesirable outcome of the production process has been considered in the paper and illustrated that the desirable outcomes theoretically were eliminated due to the environmental protocols when compared with that of the outcomes by the other refineries.

Keyvan and Agnieszka (2019) have evaluated the oil refinery efficiency with the period starting from 2011 and 2015. The resulted data would present that the unprofitable products were important and it has been adversely influenced the total efficiency. Al-Najjar and Al-Jaybajy (2012) have implemented the DEA upon the 80 firm samples in Iran from the period of 2009 and to end in 2010. Their analysed results have confessed that the best level of application of DEA tool to solve the restrictions inefficiency and also in observation of the efficiency. Based on the resultant data, the efficiency of the oil refineries analyzed was around 82 percentage and 87 percentage. In the later phase, the inefficient refineries have been analysed to detect the regions, where the usage of resource manifestation decrement to be pointed returning to the scale.

Azadeh et al. (2017) assessed the inverse influences of the organizational and the managerial factors and relative efficiency for the 41 gas refineries in the utilization of the statistical methodologies and DEA. The DEA resulted from data that have inferred that the flexibility and the learning relative efficiency factors had a strong impact on the organizational and the managerial factors and revealed that the managerial factors have a weak impact on relative efficiency in comparison to the organizational factor. The outcomes of the statistical methodologies have presented that the information found to be reliable and also confessed the strong association between the managerial and organizational factors. Azadeh et al. (2015) have applied the merge of multivariate strategy and Artificial Neural Networks to assess the efficiency of the 5 Iran gas refineries from the period of 2005 and up to 2009 in the consideration of the non-financial indicators and the financial indicators. The refineries have been rated in the rank level by the usage of the methodologies of Principal Component Analysis (PCA), Artificial Neural Networks (ANN) and Data Envelopment Analysis (DEA). The analysis in the sensitivity has been detected that the DEA has been the most noise resistant methodology in its best level and the resultant data for both the financial factors and for combined operational indicators have been differing slightly.

Additionally, energy efficiency in the petroleum refining industry has been analyzed using the non-parametric data envelopment analysis approach with physical data. The moderate-heavy boiling point of the refined products has been utilized as the structural indicator in the model proposed. Also, the data envelopment analysis has been utilized as the sensitivity tool for the analysis for the detection of the capabilities, the relevant way of power consumption enhancement and the process of optimization. The outcomes presented that the capability of the savings in the fossil fuels which found to be higher than the power consumption in the oil refineries (Azadeh et al., 2008).

Song and Zhang (2009) have presented the SVM model to analyse and for the prediction in the efficiency of the oil refinery. In response to the similar characteristics of the VEM model in comparison to the DEA model, it has been an inference that the SVM model would apply to the anticipation of oil refinery is effective or not.

Tavana et al. (2020) introduced the fuzzy network DEA techniques to assess the technical efficiency of nine refineries in Iran between 2015 and 2016. They confirmed that the results are very useful to explain the variation in the efficiency. This outcome presented that the resource utilization management, specifically energy and capital found to be irrelevant and deficient in the investment.

C. Bergh and B. Cohen (2012) have established the present chances for enhancing the efficiency of energy in established refineries and grasping the impacts which lead or follow the execution of the energy efficiency changes in the South African refining firm. The goal of the thesis has been inspired by the incremental problems, which have been faced including the sulfur regulation of clean fuels, IMO marine standards of the fuel, and an incremental shift in the distillates of the middle entity, which have altogether evolved in the incremental energy intensity in refineries. Further, the problems of the incremental energy factor for the cost, authenticate the requirement for the mitigation of the influences on the refineries in South Africa, which are presently the fourth quartile concerning energy efficiency performance.

Al Obaidan and Scully (1992) studied that the variations in technical efficiency between privately owned and state-owned global oil refineries that have integrated operations within the fields of refining as well as extraction. The outcomes from the study indicated that the level of technical efficiency of state-owned refineries was said to be half of those refineries that were privately owned. Wolf C. (2009) scrutinized the scale, technical and allocative efficiency between 44 integrated oil refinery firms. The inferences of the paper indicated the technical efficiency of public sector refineries ranged between 61 to 65 percent as compared to refineries that were said to be owned privately and operated for profit.

DEA Malmquist has been utilized for the detection of the source of the total factor productivity growth, which would facilitate the policy producers to get the industrial performance and to follow the procedures for the increased efficiency and productivity in the specified Indian oil refineries. The influence of fiscal reforms on the total factor productivity has been assessed, which has been evaluated to have an incremental percentage of 8.60 while in the whole period (Vijayakumar and Gomathi, 2013). Bansal R. (2018) has taken the DEA - BCC model design to gauge the technical efficiency of the 22 oil and gas sectors. To assess the efficiency, three input variables, namely, combined materials consumed and manufacturing expenses, employee benefit expenses and capital investment; and two output variables – operating profit after tax and operating revenues have been taken forward. The inference also cleared that the (59%) 13 in the total of 22 companies have been found efficient technically. The inefficient segments are required to enhance in terms of output and input variables and turn the mentioned targets have been allocated to the same.

2.1.3.3 Empirical studies on operational efficiency measurement

Liu et al. (2010) evaluated the operational efficiency of power generation in thermal power plants in Taiwan in the period of 2004 and up to 2006 by the application of the model of DEA. In inference to the results, the power plants illustrated the operational efficiency in the period of 2004 and up to 2006. The merge rotation cycle of the power plants was the most efficient in all the plants. The most significant variable in the model of DEA is the heating value of the total fuels. Amani (2020) observed and analysed the operational efficiency of the oil refinery, considering the period of study from 2008 to 2017. The sampled refineries were included from the four major countries. The findings direct that the refineries from the United

States and Canada have revealed the higher performance since these regions could be comprised of large and complex refineries, which has utilized the greater pioneering technology. Hasan et al. (2016) have examined the operational efficiency of the airport prevailing in Turkey from the period of 2009 and lead to the period in 2014. The simor-wilson bootstrapping regression estimator was adopted to estimate the determinants as explaining the variation of efficiency. They suggested valuable inputs to enhance the airport's efficiency by improving the operating hours of airports and reducing the percentage of international traffic. Wai Hong et al. (2014) analysed the operational efficiency of the Asia-Pacific airport commencing from the year 2002 and up to 2011. Truncated regression with bootstrapping was used by them to analyse the influence of empirical elements on the factor of efficiency. The findings would imply that the percentage rate of the international passengers, an increment in the GDP per capita and the size of the airport hinterland have been of the strong influences on the operational efficiencies in the airport.

Kaviani and Abbasi (2016) have implemented the DEA design model to evaluate the operational efficiency of the Iran cement industry. The manager of highly graded organizations can enhance the operations effectiveness factor in the competitive sector to obtain the maximum efficiency and also sustain the status positions in the better practices in the market. In addition to this, the low-ranked companies would standardize the highly graded firms and would also enhance operational performance. Moreover, modifying the present operations approaches and deteriorating the tradeoffs among the 5 competitive benefits would pave the way to attain a high grade among the competitors of the market. Okwanga, B. et al. (2015) have determined the consequence of the management factors which includes the organizing, planning, leading and also in the participation of the communication, the impact of the financial resources to operational efficiency and the restrictions which have been taken apart by the entrepreneurs in the attempt to attain the operational efficiency.

Carlos and Peter (2007) have pinpointed the operational and financial performance utilizing the DEA method in the Italian airports. The findings would have implied that the airports with the high level of workload unit have been turned to more efficient than the low workload airports.

Moreover, large airports, with a higher book value of assets, tend to have higher efficiency scores than those with lower values. Lam et al. (2009) evaluated the several dimensions of the operational efficiency prevailing in the regions of mainly Asian pacific airports by the model of DEA, which would similarly address price factors and the external macroeconomics. Joseph S. (2000) has analysed the operational efficiency of the 44 main United States airports by the usage of the DEA and few developments. Efficiency measures are based on four resource input measures including airport operational costs, the number of airport employees, gates and runways, and five output measures including operational revenue, passenger flow, commercial and general aviation movement, and total cargo transportation. The results indicated that operations managers should evaluate and benchmark their performances with airports having similar characteristics. Haritha and Phani (2009) have shown that the domestic organizations which of them mostly been prevented by the governance structures of the family enjoy greater efficiencies than the associated multinational pharmaceutical major. After the phase of preventions for the organization size and levels of the initial efficiency, it has been found that the high grades of the innovation by the high research and development investments and the ancient establishments have been related with high-level efficiencies in comparison with the lesser research and development and fresh counterparts.

Haritha S. (2009) evidenced that a majority of the inefficient firms are operating in the fading returns scale area and it defines probable savings through the benchmark input targets. The analysis of the second stage targeted at the exploration of the root cause analysis of the inefficiencies findings that the labour substitution for the capital should be the cause to the various classifications of the inefficiencies in the firm of Indian component industry. The empirical findings also imply that irrespective of the global auto chain, higher average inventories are required for higher operational efficiencies in the Indian context. Sung H. P. et al. (2018) have implemented the DEA model –window analysis and slacks-based measure – DEA to evaluate the time series data starting from the period of 2007 and ends to 2016. The findings stated that the operational efficiency of the coastal ferries in Pohang, Mokpo, Jeju and Incheon have reduced and the inefficient one is the Busan in 2016. The finding results can empower the government companies and ferry companies to assess the influence of the ferry tragedies on the operational efficiency of coastal ferries and also helps in the development of the appropriate approaches to enhance the performance of the ferry industry in the South Korean area.

Hugo K.S. et al. (2016) considered organisations social media edges as the deliberate resources for the enhancement of the operational performance and also presented that the organisation's social media deliberates would enhance the innovativeness and operational efficiency. Haritha and Rajiv (2016) have been implemented the two-stage empirical analysis. The inferences suggested that when some of the regulatory and structural factors have a non-desirable influence on the performance of the airport, the lower cost carrier has adjusted to attain significant operational efficiency. Additionally, it has been found that cost efficiency has been driven by the classified factors, it is the technical efficiency that has provided the good market performance by the power pricing in the airline industry in India. Dhillon and Vachhrajani (2012) inference that the organization's performance can be improvised either by producing the additional sales capacity per rupee of the investment or by the escalation of the profit margin per rupee of the sales factor. The enhancement of the activity and the profitability is the mark of the overall efficiency in the fund utilization and the process of the operations. The findings present that there is a non-significant positive association between the summation of profitability and operational efficiency. Baik B. (2010) assessed the association between the organization's performance and the operational efficiency of the operation. They also analysed whether the efficiency of the operation would be defined from the analysis of frontier would enhance forecasting of the profitability? The inferences results have implied that the analysis-based efficiency modification of frontier has positively related with the present and future modifications in the profitability. The study findings of the research have stated that the modifications in the efficiency have been positively related to the future returns and the organizations which would enhance the efficiency, which would present the higher profitability modifications in the future and present regions.

2.2 KEY OUTPUTS FROM THE LITERATURE REVIEW

- Various technologies, modes of operation and optimization strategies are identified for the petroleum industry to enhance the profit margin.
- Impact evaluation of the various factors on the refinery profit has been done for the case of Brazil, US and china refineries (Mostly covered refineries from the developed countries).
- Variables such as types of crude oil, product yields, energy consumption, complexity, and capacity utilisation are identified to estimate the refinery profit.
- Fixed effect and random effect models are mostly used for panel data analysis.
- Studies presented for Indian refineries are considered only various financial ratios for the profitability analysis. (i.e., Gross Profit Margin Ratio, Net Profit Ratio, Operating Profit Ratio, Expense Ratio, etc.)
- Distinctive studies have been done on operational efficiency evaluation for the airport industry, pond culture, container terminals, power generation thermal units, etc. and other industries.
- One literature is available in the public domain that analyses the operational efficiency of the refineries in the context of four major regions (U.S. and Canada; Europe; Asia-Pacific; Africa and the Middle East).
- Determinants of efficiency are investigated to explain the variation in efficiency for the airport, container terminals, freshwater ponds, etc.
- OLS and Tobit models are widely used to explain the variation in efficiency in most of the studies.
- The Cobb-Douglas and Translog production function have been used to estimate the total factor productivity.
- Various theoretical models, such as the stochastic frontier model and nonparametric data envelopment model have been proposed for efficiency measurement. The data envelopment analysis model is found widely used model for efficiency measurement.
- Production frontier, as well as cost frontier function’s theoretical models, have been shown in theoretical studies, which gives the maximum possible output from a given set of inputs.

2.3 RESEARCH GAPS

- The impact of identified factors on refinery profit is not evaluated for the Indian condition. Hence, the impact of identified factors on the refinery's profit is required to be analysed for the Indian scenario.
- The fuel and loss of the refinery are not included in estimating the refinery profit in the existing works of literature.
- It is common to have cross-sectional dependence as well as temporal dependence in the data set of the time-series cross-sectional model, which results in the wrong estimation. This problem is overlooked in the existing works of literature. It needs to propose a model that can mitigate the problem of cross-sectional and temporal dependence.
- About refineries, the literature on efficiency has been limited to the application of DEA methodology.
- The important output variable "Gross reefing margin" is overlooked in the existing literature.
- Determinants of the oil refinery's efficiency are not investigated in the existing literature.
- No literature has identified the peer group refineries for each inefficient refinery and specified the improvement targets for input or output variables to be efficient.
- The operational efficiency of Indian oil refineries is not analysed till now in the existing literature. No database on the operational efficiency of Indian refineries is readily available in the public domain.
- No literature identified and explained the plan/ structure for Indian refineries so that inefficient refineries can attain the optimum operational efficiency. The structure is required to identify the determinants that can explain variation in operational efficiency of the Indian refineries.
- Does not provide the roadmap for the operation efficiency enhancement for Indian refineries.
- Most of the studies used production factors in the production frontier and cost frontier model. The concept of the profit frontier model is rarely used in some empirical studies. The profit frontier function gives the maximum profit that can be achieved given output price and input prices. To measure the allocative efficiency, the profit frontier function

is more suitable.

- The data envelopment theoretical model has not been used to measure the allocative efficiency and to identify the production frontier in Indian oil refineries.

This chapter has keenly presented and discussed the past reviews which are related to the operational efficiency measurement and profit margin of industries, with various types of variables and different periods of study. Among the different Industries of reviews, no one reviews do not handle the gross refining margin of the oil refineries in India. Also, the available studies on efficiency measurement of oil refineries have not explained the relation of the explanatory variables on refinery efficiency. The literature review provides DEA applications in different business sectors and different countries. However, the authors did not encounter any study that measures and documents the performance of oil refineries in India. Hence, it is not possible to know precisely which refineries are using their resources more efficiently than the others. So, the present study attempts to fill the existing gap.

2.4 RESEARCH PROBLEM

Refineries do not commonly operate with perfect efficiency. Inefficiencies occur at many levels in an organization, including production lines. Operational efficiency can help in enhancing profit by way of reduction in the per-unit cost of raw material. It is a need of time to take a complete review of the refinery's GRM and operational efficiency in the context of India to determine which factors are more important for lower efficiency and GRM; to see that how it can be controlled. Essentially, the theoretical problem is to explain why refineries may produce below the frontier production function for the industry; the empirical problem is how the different factors are impacting the refinery's GRM? Further, what is the operational efficiency levels of the Indian refineries and what are the key determinants of efficiency that can explain the variation in refinery efficiency?

2.5 RESEARCH QUESTIONS

RQ-1: What is the impact of key determinants on the gross refining margin of the Indian oil refineries?

RQ-2: What is the operational efficiency of the Indian oil refineries?

2.6 RESEARCH OBJECTIVES

RO-1: To identify the impact of key determinants on the gross refining margin of the Indian oil refineries.

RO-2: To measure the operational efficiency of the Indian oil refineries and to identify the variables that can explain the variations in the operational efficiency of the oil refineries.

2.7 THEORETICAL UNDERPINNING

The theory of production has provided a beneficial architecture for estimating the production function as well as the efficiency levels of a company. The production theory has been concerned with the nature of the conversion process by means of the conversion of input into output. Further, inputs are referred to services or goods that move into the production process. Also, as the economists referred to it, inputs are referred to anything which a company purchases for the production process. On the other hand, the outputs are services or goods that come out of the production process. Further, this theory has involved certain fundamental principles of economics. Also, these include the correlation between the commodity prices as well as the prices of productive factors that are utilized for producing commodities. The production function is the main concept of the theory of production.

Moreover, the production function has signified a technical relation between physical inputs and outputs of the company, for the given state of technology, the relation can be written as,

$$Q = f\,(L, K, N) \quad \text{..} \quad (2.1)$$

Here, L, K and N are the factor inputs like labor, capital, and land. And Q is said to be the output level for the company.

In order to satisfy this mathematical equation of the function, the production function is assumed normally for specifying the maximum amount of outputs that are obtained from the given inputs. Therefore, the production function has described a boundary for representing the output limits that are obtained from every possible input combination. A cost frontier provides the minimum cost levels, where it is feasible for producing certain output levels, at the given input prices. Whereas the profit-frontier function provides maximum profit levels that can be accomplished at given input and output prices (Forsund et al., 1980).

The production function's predominant purpose is to address the allocative efficiency in the usage of inputs in production. In the assumptions, where the maximum output is obtained from the inputs, that allowed the economists for abstracting away from the managerial as well as technological problems and to concentrate on the problems of allocative efficiency that are related to the economic choices. Further, the allocative efficiencies are concerned with the managerial decision makings about factor allocations of production that are within the firm's control. It also refers to the ability to combine the inputs as well as outputs in optimal proportions.

2.7.1 Firm level production function and efficiency measurement

The relation between output levels that are produced as the input levels vary is the production function. Figure 2-1 depicted an S-shaped production function with single input as well as a single output. Also, firm A seems to be technically inefficient, and firm B is efficient, because, holding a fixed input level Firm B produces the highest feasible output.

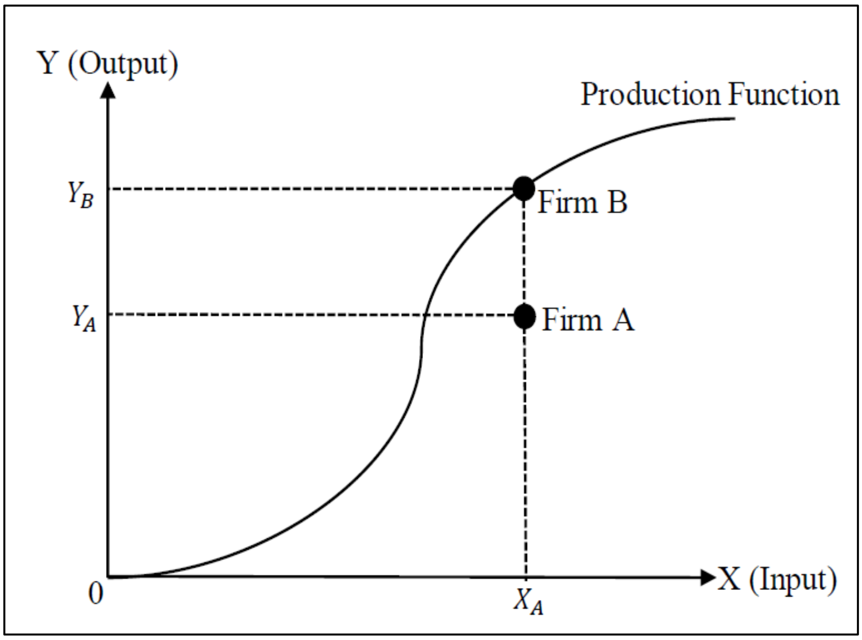


Figure 2-1 Production function and efficiency estimation

The study constructed the production function for defining a benchmark that measures the efficient use of inputs for generating outputs in the production process. Further, when giving similar levels of input resources, the inefficiencies are indicated by lower output levels. Moreover, in competitive markets, if the firms are far from production function as well as if it has been inefficiently operated, it needs to increase the productivity for avoiding the business disruptions.

Theoretically, the usage of the production function method seems to be better for estimating the efficiency of the firm. From the study Bauer et al. (1998), for the regulatory purpose, the frontier efficiency is far superior to standard financial ratio from account statements like ROA (return on assets). This is due to, the frontier-efficiency measures try to eliminate the effects of differences in several exogenous factors that affect the standard financial ratio.

In this study, the petroleum refineries of India are profit-maximizing companies. Further, the production theory that is utilized in the research, concentrates on the production function of the refineries. The production function derived for the oil refineries may be written as:

Petroleum product = *f* (total assets, operational expenses, refinery size, employees, crude oil)................. (2.2)

As the production function differentiates the allocative efficiencies of the oil refineries, this is the key area of the refineries. This production function is somehow different from the traditional production function given above. Here, the operational cost has been introduced in the traditional production function. This function specifies that the refinery can attain maximum output in production at the lowest possible operating cost or total cost. This production function presupposes the efficiency as well as states the maximum outputs that are obtained from each feasible input combination. Greater the efficiency, the better the production function.

The concept of efficiency has been initiated by (Farrell, 1957). From the study (Farrell, 1957), efficiency is said to be the capability of a company for obtaining the maximum outputs from the given input sets.

$$Efficiency = \frac{output}{input} \ldots\ldots\ldots\ldots\ldots\ldots \quad (2.3)$$

Therefore, the efficiencies in the refineries are to enhance operational aspects for realizing the maximum profits until it reaches the limit. However, Farrell's approach has been limited by the number of inputs/outputs. In order to overcome these limitations, Charnes et. al. (1978) introduced the CCR-DEA model for handling multiple inputs and outputs for measuring relative efficiency. Further, the presence of multiple inputs and outputs, the relative efficiency is defined as,

$$Relative\ efficiency = \frac{weighted\ sum\ of\ output}{weighted\ sum\ of\ input} \ldots\ldots\ldots\ldots \quad (2.4)$$

It is understood that the higher the ratio, the more efficiency. The units that get the value 1 are known as the efficient units, whereas others are known as inefficient units. Also, this kind of efficiency configuration will become a focus of the benchmarking activity.

The production theory has delivered a suitable background for evaluating the relative efficiency levels of the company. There are two competing techniques for the evaluation of relative efficiency on the basis of cross-sectional data for the oil refineries in India. Primarily, the non-parametric DEA (Data envelopment analysis) method (Charnes et al., 1978); and secondly, the parametric SFA (stochastic frontier analysis) method

(Kumbhakar and Lovell, 2003). Schoyen and Odeck (2013) have concluded that the DEA method seems to be much popular than SFA. Therefore, the DEA-based model has been developed as well as established to measure efficiency. The production function that highlighted the multiple inputs and multiple outputs can substantially reduce the errors because of the unnecessary estimation of parameters, as well as efficiently neglect the subjective factors and also simplifies the algorithms (Chen and Jia, 2017).

In operation management, the concept of 'production frontier' (Clark, 1996) and 'asset frontier' (Lapre and Scudder, 2004) are introduced, but the profit frontier is rarely shown in the field of operation management. This study introduced the profit frontier DEA model to measure the operational efficiency of Indian oil refineries. The cost input variable i.e., the liability of the firm is not being introduced in the field of operational management, where the DEA model is used. Additionally, in the profit frontier model, the gross income from the output 'product' has been used in the DEA model whereas the profit per unit of raw material is not introduced to date. This study is mainly focused on the profit frontier DEA model to measure the operational efficiency of oil refineries in the context of India. This model introduced firm liability as an input variable and gross refining margin as the output variable to measure the OE. The gross refining margin indicates profit per metric ton of crude oil processed in the refinery. Hence, the output variable 'profit per unit of feed' has been introduced in this study.

2.7.2 DEA (Data Envelopment Analysis)

DEA tool is said to be a comprehensive method that is utilized for the assessment of relative efficiency of the identical decisive units, knows as DMUs (decision making units), where it utilized multiple inputs as well as multiple outputs. DEA is also a mathematical program approach that detects the best practice across similar organizations that converts multiple inputs to multiple outputs. The DEA evaluates the comparative performances of the identical decisive units as a ratio of weighted addition of output to weighted addition of input, where the maximum efficiency score is restricted to 1. The study by Charnes et al. (1978), suggested the first DEA model that was named DEA-CCR that assumes CRS (constant return to scale).

Assuming that there are *n* DMUs, each one has '*m*' inputs and '*s*' outputs, then the efficiency of the *p*'s DMU is given by the following model suggested by Charnes et. al. (1978):

$$\left.\begin{aligned} &\max \quad \frac{\sum_{k=1}^{s} v_k \, y_{kp}}{\sum_{j=1}^{m} u_j \, x_{ji}} \\ &s.t \quad \frac{\sum_{k=1}^{s} v_k \, y_{kp}}{\sum_{j=1}^{m} u_j \, y_{ji}} \leq 1 \qquad \forall\, i \\ &\qquad v_k , u_j \geq 0 \quad \forall\, k, j \end{aligned}\right\} \quad \text{.......... (2.5)}$$

Here, k =1 to s and j =1 to m and i =1 to n. y_{ki} is the amount of the output that was produced by DMU i, and x_{ji} is the amount of input j that was utilized by the DMU i, and v_k is the weight assigned to the output k, and u_j is the weight assigned to the input j. The model and the dual forms are called DEA models with a constant return to scale (CRS). Here the CRS indicated that doubling of the DMU inputs would result in the doubling of outputs, (SCRC, 1997). Also, there are diseconomies or no economies of scale, and the organization size has not been considered to measure the efficiency. In order to overcome the limitations of this model, Banker, Charnes, and Cooper (BCC) extended the CCR models for handling issues with VRS. The new model (BCC-VRS) which is referred to by initials of the authors, was capable to deal with the issues that exhibit increasing, constant as well as decreasing returns to scale (Banker et. al., 1984). Researchers from a variety of domains have identified that DEA is an excellent method for measuring efficiency (Liu et al., 2013).

DEA linked the outputs with the corresponding inputs for determining the efficiency scores as well as improvement targets. Moreover, the primary step of the methodology was to build a convex envelope of the entire assessed units. This is known as the 'efficient frontier' and all units are lying on this specific frontier are categorized as efficient, whereas others are classified as inefficient. Further, the efficiency level is given by calculated scores for every unit that quantifies the ratio of the weighted outputs to the weighted inputs. In the secondary step, the DEA determined the targets for the inefficient units to become efficient through the projection to the efficient frontier.

The following is the illustrative example of DEA

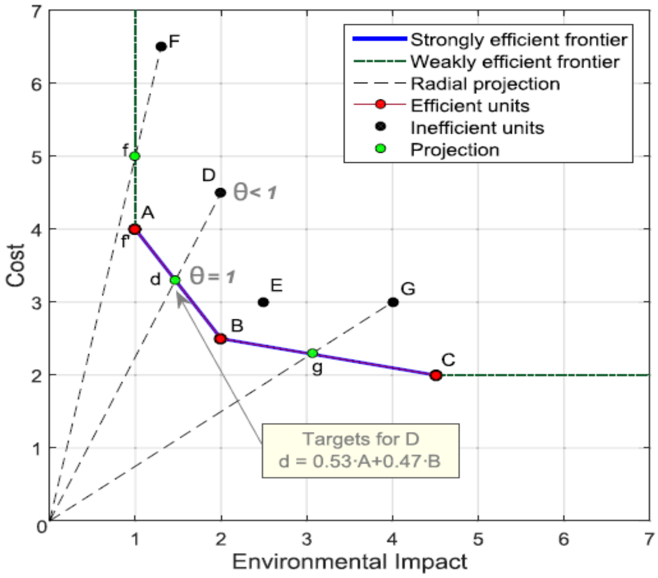


Figure 2-2 Graphical representation of the DEA results

As in the simplified process, the analysis has been constrained to the economic input (cost), environmental input (environmental impact) and one output. Figure 2-2 implies the graphical notation of Data envelopment analysis results. The efficient technologies determined by the red circle denotes the effective frontier which represents the convex envelope described in blue color. The inefficient systems have been illustrated by the black circle, wherein the radial protrusions on the frontier have been represented by the green circle. As been in observation of Figure 2-2, technology ‘A’, technology ‘B’ and technology ‘C’ have low values of input for the similar output and thus been determined as the efficient, where their efficiency equals one.

The line interlinking them would define the piece-wise linear one of the efficient frontiers. On the next side, the representation of D, E, F and G have been considered as efficient due to the efficiency score θj which is lesser than 1. Data envelopment analysis also quantifies the inefficiency magnitude by the reference to the efficient frontier. For example, the technology D efficiency has been fetched from the ratio level of the 2 segments, one representing which goes from 0 to the intersection point among the radial projection of D and the efficient frontier; and the one which interlinks 0 and D (i.e., the ratio between 0d and 0D). The score of efficiency denotes the scope to which the inputs would be decreased proportionally to attain the frontier. Hence the D notation would lower the input to the range 73.3 percentage of the present level in accordance to be efficient. Point ‘d’ has been defined by the linear combination of both A and B, is shown as the set of reference by the usage of linear weights which is equal to 0.5 and 0.4 presented by the model of DEA.

The Data envelopment analysis strategy can be classified in accordance with to kind of data (panel or cross-sectional) and the variable available. (Quantities and prices or quantities). Technical efficiency can be predicted with the quantities, wherein the prices or allocative efficiency can be estimated with the quantities and prices. It has been decomposed into its allocative components and the technical components in the economic strategy. Consecutively, the main part of the model of DEA utilizes the quantity information and evaluates the technical efficiency, in spite that the procedure can be adapted in an easy way to the economic efficiency calculation in the condition, where prices are reliable and available. In this study of research, the production function has been considered as the frontier function of profit and it has been utilized to assess and evaluate the efficiency of the operation in the oil refineries. This function of profit frontier would yield the maximum value of profit which can be accomplished with the given input prices and the provided output prices (Forsund et al., 1980).

In the current study, the quantitative variable of cross-sectional data would be beneficial to analyse the efficiency of the refineries, where the output is the profit value of the oil refineries and the input value is evaluated by the measured cost. By the implementation of the Data envelopment analysis method, it creates the economic association between the output and the inputs, which is predicted and defines the levels of efficiency and the slacks to detect the variable that does not prevail as the limitations to the production.

This phenomenal method detects the better practices and the sources of inefficiency between the peer groups on the basis of the efficiency score evaluated for each refinery. The implementation of DEA as the complementary strategy to maintain the rankings of the refinery provides various benefits. First, the Data envelopment analysis prevents the usage of weightings as they are improvised in the application process of the methodology. Second, yields lower insight on how to improvise the performance and provide the directions to lower-performing refineries. The third level, inherently accounts for the refinery size, permits reasonable assessments between refineries and gives quantitative improvement targets. These all features would promote DEA as an attractive tool for the comparison of the refineries.

Chapter 3: RESEARCH DESIGN AND METHODOLOGY

The two objectives of this research are; (1) to identify the impact of various factors on the gross refining margin of Indian oil refineries; (2) to measure the operational efficiency of the Indian oil refineries and to identify the variables that can explain the variations in the operational efficiency of the oil refinery. Considering the use of physical and financial quantitative data in this research for both objectives, the research design is considered for this study is quantitative research. Moreover, the methodology for each objective is described separately in sections 3.1 and 3.2.

3.1 GROSS REFINING MARGIN AND ITS DETERMINANTS ANALYSIS

3.1.1 Data set

In oil refineries, there is no change in the production function of the public sector as well as private sector refineries. However, the configuration, complexity and product mix of each refinery is different. Even in the case of only public sector refineries, these factors are also varying. Hence, the operational performance and strategies to operate for each refinery are different. Any change in the operational strategies impacts the efficiency of the refinery. It indicates the heterogeneity in the sample. Moreover, this study focused on suggesting improvement targets to inefficient refineries after analysing the best practices of the efficient refinery. Hence, without considering the structure of the refinery, the outcome of the analysis will give valuable feedback to the inefficient refineries to become efficient. So, both public and private refineries are considered in the sample frame. However, to avoid the issue of error in results and produce realistic results, refineries are selected at various stages to make it simple for data collection.

The techniques used to identify the sample refineries are probability multistage sampling techniques. In the first stage, the all-Indian oil refineries have been selected according to the data availability and data adequacy for the financial year 2010–11 to 2018–19 as a larger number of observations gives conclusive and valid results. Refineries with an installed capacity of fewer than 5.0 MMTPA were excluded from the study in the second stage of sampling because the inclusion of refineries those are having less installed capacity may not give the real results. Hence, The Numrligarh refinery is excluded from the study. Further, the Bharat Oman Refineries Limited (BORL) and the HPCL Mittal Energy Limited (HMEL) refineries were excluded from the research as they were commissioned in the year 2011 and 2012 respectively and inputs from these two refineries are inadequate (The most modern and recently commissioned refineries namely BORL and HMEL share only 3.10% and 4.50% of the total installed capacity of the Indian refineries whereas the earlier commissioned refineries share the 92.40% of the total installed capacity).

Considering the above facts, the panel data set of 13 Indian oil refineries is used for the first objective and these data set are a good representative of the condition of oil refineries in India. The refineries included in this study are shown in Table 3-1.

Table 3-1 Capacity wise Indian Refineries

S. No.	Company	Refinery Location	Capacity (MMTPA)
1	Indian oil corporation limited	Barauni	6.00
2	Indian oil corporation limited	Koyali	13.70
3	Indian oil corporation limited	Haldia	7.50
4	Indian oil corporation limited	Mathura	8.00
5	Indian oil corporation limited	Panipat	15.00
6	Hindustan petroleum corporation limited	Mumbai	6.50
7	Hindustan petroleum corporation limited	Vishakh	8.30
8	Bharat petroleum corporation limited	Mumbai	12.00
9	Bharat petroleum corporation limited	Kochi	9.50
10	Chennai Petroleum corporation Limited	Manali	10.50
11	Mangalore Refinery and Petrochemicals Limited	Mangalore	15.00
12	Nayara Energy Limited	Vadinar	22.00
13	Reliance Industries Limited	Jamnagar	66.00

Source: PPAC

The annual panel data were collected for thirteen Indian refineries from the financial year 2010-11 to 2018–19. Data were collected from the annual as well as sustainability reports of the selected refineries, websites such as Petroleum Planning and Analysis Cell, Ministry of Petroleum and Natural Gas, Government of India.

3.1.2 Theoretical background and variable Selection

The aim of the refinery is always to gain profit. Hence, the refinery has to understand the impact of various determinants on profit to attain this aim and that is the first objective of this study. The gross refining margin is used as a proxy for the profit margin of the refinery in this study. This variable has been never used by the oil refinery in estimating the refinery's profit. There are various variables, which are impacting the profit of the refinery. As refinery's profit changes because of the change in refinery configuration, change in capacity utilisation and also change in other variables, J. B. Clark's dynamic theory of profit is considered as the foundation theory for the given research problem. Prof. J. B Clark propounded the theory of profit in the year 1900. In this research, the impact of identified variables on the refinery profit will be going to be evaluated. These identified variables are always dynamic, so the refinery profit always keeps on changing based on the change in identified variables. Hence, the given research objective is supported by the "The Dynamic Theory of Profit".

According to J. B. Clark, profit arises only in a dynamic economy, that is, in an economy where changes are taking place and not in a static economy. The static economy is one in which things do not change significantly or remains unchanged. On the contrary, the dynamic economy is characterized by generic changes such as improvement in production techniques, change and increase in the product yield, changes in capacity utilisation, change and decrease in loss. The major function of an entrepreneur is to work in a dynamic economy to take the advantage of these changes and promote his business, reduce costs, and expand sales. Clark believed that those entrepreneurs who successfully takes the advantage of these changes in the dynamic economy make the pure profit, which is in addition to the normal profit.

Based on the dynamic theory of profit, various kinds of literature have been reviewed in chapter – 2 to identify the association of determinants to refinery's profit. Amani, (2020); Masri et al. (2005); Romulo et al. (2011); Brad V., (2012); Zurlo, (2016); Johnson et al., (2002) studied the association of variables like refinery complexity, specific energy consumption, distillate yield and capacity utilisation to refinery profit. In this study, the explanatory variables to explain variation in gross refining margin were identified by considering two approaches: (1) The explanatory variables were identified from the theory built reviewed literature; and (2) explored the new variables that can explain the variation in refinery GRM. Prior researches have suggested possible hypotheses regarding the impact of refinery complexity, specific energy consumption, distillate yield and capacity utilisation variables on refinery profit in their work. They analysed these variables for their statistically significant impact on the refinery's profit. Here, we have also introduced one more variable i.e., fuel and loss in this study to analyze its impact on the refinery's profit.

Considering these two aspects of data selection, the main independent variables were included to examine their influence on the gross refining margin of the refineries are shown in Table 3-2. The sample size for the study, comprising of all the included thirteen refineries for 10 years is 117.

Table 3-2 Determinants of gross refining margin

Name of variables	UoM	Citation in existing literature/ new variable	Sources of Data
Dependent variable			
Gross refining margin	Rs. /MT	Not used in existing literature for estimation	Companies' annual report.
Independent variables			
Refinery Complexity	NRGF	Amani, (2020)	Centre of hydrocarbon technology; Companies' annual report.
Specific energy consumption	MBN (Mbtu/ bbl/ NRGF)	Masri et al. (2005); Romulo et al. (2011); Brad V., (2012)	Petroleum planning and analysis cell; Companies' sustainability report.
Distillate yield	Percentage (%)	Zurlo, (2016); Johnson et al., (2002)	Petroleum planning and analysis cell; Companies' annual report.
Capacity utilization	Percentage (%)	CFA, (2013); Amani, (2020)	Petroleum planning and analysis cell; Companies' annual report.
Fuel and Loss	Percentage (%)	New variable	Petroleum planning and analysis cell; Companies' annual report.

3.1.3 Hypothesis and conceptual framework

Based on the hypotheses that have emerged from the previous theory-built literatures and the addition of new variables (See Table 3-2), the hypotheses developed for this study are as follows:

Hypothesis (a): Refinery complexity (RC)

H0: $\beta 1 = 0$ vs. H1: $\beta 1 \neq 0$

The null hypotheses assumed that there is no statistically significant relationship between Refinery GRM and Refinery complexity (RC).

Hypothesis (b): Capacity utilisation (CU)

H0 : $\beta 2 = 0$ vs. H1 : $\beta 2 \neq 0$

The null hypotheses assumed that there is no statistically significant relationship between Refinery GRM and capacity utilisation (CU).

Hypothesis (c): Specific energy consumption (MBN)

H0 : $\beta 3 = 0$ vs. H1 : $\beta 3 \neq 0$

The null hypotheses assumed that there is no statistically significant relationship between Refinery GRM and specific energy consumption (MBN).

Hypothesis (d): Distillate yield (DY)

H0 : $\beta 4 = 0$ vs. H1 : $\beta 4 \neq 0$

The null hypotheses assumed that there is no statistically significant relationship between Refinery GRM and distillate yield (DY).

Hypothesis (e): Fuel and Loss (FL)

H0 : $\beta k = 0$ vs. H1 : $\beta k \neq 0$

The null hypotheses assumed that there is no statistically significant relationship between Refinery GRM and Fuel and Loss (FL).

With these selected all variables, the conceptual framework for the oil refinery business was developed for estimating the refinery's GRM is shown in Figure 3-1.

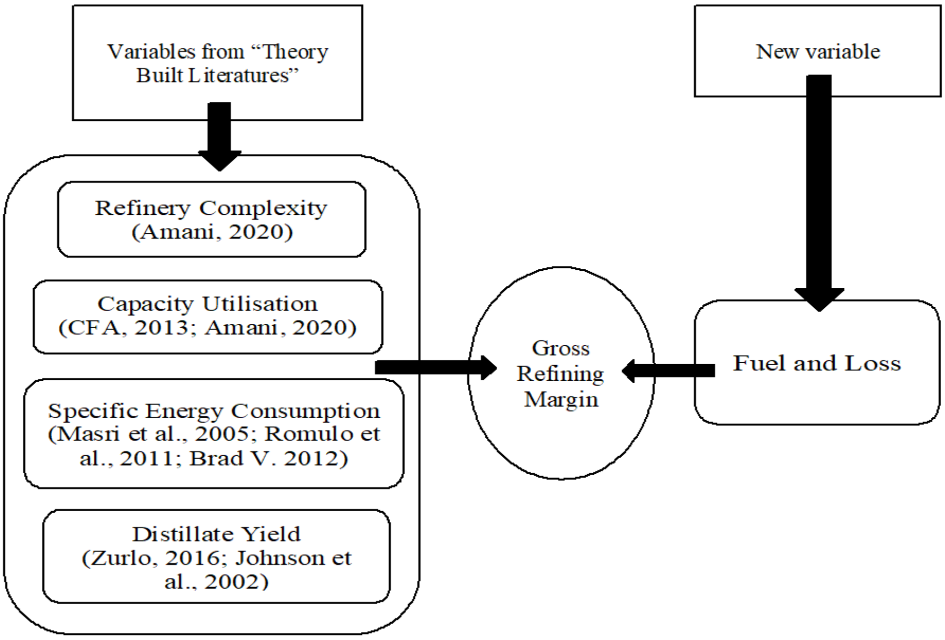


Figure 3-1 Refinery Margin: Conceptual Framework

3.1.4 Definitions of selected variables

3.1.4.1 Refinery Complexity

The refinery complexity quantifies refineries process unit's type and their capacity which are related to the atmosphere distillation. The process units are fixed assets in a refinery, and that is characterized by applied technology, size, number and process unit's type. The factors of complexity were introduced for refineries comparison that is relative to their intensity of capital and sophistication and to simplify and quantify the classification. Furthermore, the complexity factors are assigned by each process unit (Kaiser, 2017), due to the mix of product changes, energy use varies over time in the refinery.

The Indian refinery complexity is measured in NRGF. Hence, the NRGF is selected as an independent variable to evaluate the relationship with the GRM of the Indian refinery. An amalgamated NRGF of the Indian refinery is derived, first by multiplying the throughputs of specific process units with their specific energy factors, which is called the equivalent throughputs of specific units. Secondly, the sum of equivalent throughputs of all units is divided by the throughput of the crude distillation unit. For example,

Energy factor of CDU X Throughput of CDU = Equivalent throughput of CDU

Therefore,

$$\text{Amalgamated NRGF} = \frac{\text{Sum of Equivalent throughput of all units}}{\text{Throughput of crude distillation unit}} \ldots (3.1)$$

3.1.4.2 Capacity Utilisation

Capacity utilisation is defined as the fraction of capacity utilized practically for specified processing capacity (Ingo and Jorn, 2015). It is the ratio of the actual feed rate to the installed capacity. Capacity utilisation is calculated using this formula:

$$Capacity\ Utilisiation = \frac{Actual\ level\ of\ feed\ input}{Installed\ capacity} X100 \ldots\ldots (3.2)$$

3.1.4.3 Distillate Yield

The net input of unfinished oils and input of crude oil produces the finished product. Hence, the percentage of the finished product is represented as refinery yield. To transform the crude oil into a finished product there are many refinery processes but still, the first phase of the process is known as distillation. Distillate yield is the general classification for one of the petroleum fractions produced in conventional distillation operations. It includes diesel fuels and fuel oils.

3.1.4.4 Specific Energy consumption

The specific energy consumption is the energy consumed per unit mass of the crude oil processed. The refinery configuration is also considered while evaluating the refinery energy consumption. The unit is developed to compare the energy performance of different configurations. The unit to measure energy performance is the MBN in India. It is a British thermal unit (Btu) per barrel (bbl) per energy factor (NRGF) and it is referred to as MBN.

3.1.4.5 Fuel and Loss

The losses in the refinery operation are identified by computing accurate mass balance across the refinery. There are different types of losses in the refinery. Some of them are identifiable losses and some are unidentifiable losses (Triple EEE., n.d.). The losses because of evaporation, flaring and seepage are classified as identifiable losses whereas losses because of sampling and chemical losses are classified as unidentifiable losses. Apart from losses, the fuel consumed inside the refinery is also the internal use of saleable products; which may be used for selling and generating revenue for the refinery.

3.1.5 Estimation strategy

The current study is based entirely on the relationship between the refinery profitability and its influencing variables. The multiple regression model, which is a statistical model, is used to estimate the association between gross refining margin and various factors. For preliminary analysis, the pooled ordinary least square (OLS) model was used to estimate the gross refining margin with the help of refinery complexity (RC), specific energy consumption (SEC), distillate yield (DY), capacity utilization (CU); and Fuel and loss (FL).

Gujarati (1995) has introduced the logarithmic transformation of the panel data to avoid the problem of Heteroskedasticity. This logarithmic transformation compresses down the numbers in statistical analysis and gives the effective empirical results and finest estimation of the dependent variable. Frequently, Khraief et al. (2016) and Zaman et al. (2015) performed logarithmic transformation in literature. Hence, the econometric specification of pooled OLS is given in Equation (3.3).

$$ln\ GRM_{it} = \alpha_{it} + \beta_1\ ln\ RC_{it} + \beta_2\ ln\ SEC_{it} + \beta_3\ ln\ DY_{it} + \beta_4\ ln\ CU_{it} + \beta_5\ ln\ FL_{it} + u_{it} \ldots (3.3)$$

Where, *lnGRM, lnRC, lnSEC, lnDY, lnCU* and *ln FL* are the logarithmic of gross refining margin, refinery complexity, specific energy consumption, distillate yield, capacity utilization and Fuel and loss of refinery respectively.

3.1.5.1 Fixed effect and random effect:

The assumption in the case of pooled OLS model is that the independent variables and the error term are associated with the dependent variable linearly and the effect of time-specific and cross-sectional does not exist, which is not true for the panel data. Hence, the analysis is done using the panel data econometrics technique. This technique permits refinery-specific and time-specific effects. The refinery GRM is then estimated using the following fixed effect and random effect models respectively.

$$ln\ GRM_{it} = \alpha_i + \beta_1\ ln\ RC_{it} + \beta_2\ ln\ SEC_{it} + \beta_3\ ln\ DY_{it} + \beta_4\ ln\ CU_{it} + \beta_5\ ln\ FL_{it} + u_{it} \quad ... (3.4)$$

$$ln\ GRM_{it} = \alpha + \beta_1\ ln\ RC_{it} + \beta_2\ ln\ SEC_{it} + \beta_3\ ln\ DY_{it} + \beta_4\ ln\ CU_{it} + \beta_5\ ln\ FL_{it} + u_{it} + \varepsilon_{it} \quad (3.5)$$

Where, ε_{it} is the error term (within-entity error), while u_{it} in the above model is an individual effect i.e., refinery specific and time specific effects

Further, the selection between pooled OLS model and fixed effect model is done by conducting F-test. This F-test is conducted to see the goodness-of-fit of the fixed-effect model in comparison with pooled OLS model. In addition, the Breusch-Pagan LM Test is conducted to compare the suitable model between pooled OLS and the random effect model. Lastly, the final model is determined between the fixed and random effect models using the Hausman test.

3.1.5.2 Validity/ Diagnosis test

The panel data has repetitive observations over time; thus, has the problem of cross-sectional dependence. Because of coexistent association across the units and unit-level heteroskedasticity, panel data frequently display non-spherical errors. Therefore, the panel data has been tested for serial correlation, heteroskedasticity and cross-sectional dependence.

- Whether the data are having any cross-sectional dependence or not is being checked by conducting the Breusch-pagan LM test and Pesaran's test.
- Further, the Wooldridge test for autocorrelation is conducted to check whether the data are having any serial correlation or not.
- In addition, the modified Wald test for heteroskedasticity is conducted to check whether data are having heteroskedasticity problems or not.

3.1.5.3 Feasible generalized least square and panel-corrected standard errors estimators

When fitting linear models to time-series cross-sectional data, it is common to have heteroskedasticity and serial correlation issues. Hence, it is essential to address these issues to get consistent and conclusive results. Nevertheless, it is better to use a non-spherical error structure to improve inference and estimation by feasible generalized least squares (FGLS) estimator (Parks R., 1967), which was promoted in the public eye by Kmenta (1986). But the confidence interval generated by this estimator is too small and non-spherical errors are ignored because of fewer gains in efficiency.

Therefore, the panel-corrected standard errors (PCSE) estimator was suggested by Beck N. et al. (1995), which is robust to the possibility of non-spherical errors. The panel-corrected standard errors (PCSE) estimator is robust not only to unit heteroskedasticity but is also robust against possible contemporaneous correlation across the unit, which is common in panel data. Therefore, panel data are further estimated with the following panel-corrected standard errors estimator (PCSE) defined by Beck N. et al. (1995). However, to check the robustness of the PCSE model, the FGLS model is also performed.

3.2 OPERATIONAL EFFICIENCY ANALYSIS OF INDIAN OIL REFINERIES

3.2.1 Data set

The probability sampling method is used for the given study. The refineries with an installed capacity of fewer than 5.0 MMTPA are excluded from the study because the inclusion of refineries having less installed capacity may not give a valid result. Hence, The Numrligarh refinery is excluded from the study. Further, the Bharat Oman Refineries Limited (BORL) and the HPCL Mittal Energy Limited (HMEL) refineries are excluded from the research as they were commissioned in the year 2011 and 2012 respectively and inputs from these two refineries are inadequate

The refineries are selected for the second objective are: Indian oil corporation limited (IOCL); Hindustan petroleum corporation limited (HPCL); Bharat petroleum corporation limited (BPCL); Chennai petroleum corporation limited (CPCL); Mangalore refinery and petrochemicals limited (MRPL); Nayara energy limited (NEL) and Reliance industries limited (RIL).

This study used annual panel data from these 7 Indian refineries, representing the nine years of data from 2010 to 2018 from annual reports of the selected refineries, Indian government websites (i.e., Petroleum Planning and Analysis Cell and ministry of petroleum and natural gas).

3.2.2 Input and output variables

The precision of the study depends on the selection of variables for the identified refineries. DEA commonly does not use cost and price data to study the efficiency of DMUs, only physical variables are used for measuring the efficiency (Bichou, 2013). But Iliyasu and Zainal (2016) considered the combination of both physical and price data to evaluate the operational efficiency of DMUs. As this study, analyzing the operational performance of the refinery, the financial variables have been considered in this study for estimating efficiency.

Referred to the literature reviewed and data availability, we selected three input and two outputs variables for the study to estimate the operational efficiency of the refineries (Table 3-3).

Table 3-3 Input and output variables

Name of variables	UoM	Citation in existing literature/ new variable	Sources of Data
		Input variables	
Total expenses	Rs in crore	(Amani, 2020); (Joseph S, 2000); (Haritha S and B. V. Phani, 2009); Azadeh et al. (2015); Sueyoshi (2000)	Companies' annual report.
Total assets	Rs in crore	(Haritha S, 2009) and (Amani, 2020)	Companies' annual report.
Total liabilities	Rs in crore	New variable	Companies' annual report.
		Output variables	
Net profit	Rs. In crore	Azadeh et al. (2015) and (Amani, 2020)	Companies' annual report.
Gross refining margin	Rs./ MT	New variable	Companies' annual report.

The rule of thumb is recommended to attain an acceptable level of discrimination power is that the number of refinery observations (DMUs) must be equal to or higher than the product of the number of input and output variables used for DEA analysis (Boussofiane et al., 1991; Tsui et al., 2014). In this study, we considered seven petroleum refineries as DMUs for that selected year. Therefore, the total numbers of DMUs under observations are more than the product of the number of input and output variables used, concluding high validity of data set for DEA model.

3.2.3 Theoretical framework

The work of (Amani, 2020); (Joseph S, 2000); (Haritha S and B. V. Phani, 2009); Azadeh et al. (2015); Sueyoshi (2000) have suggested total expenses and total assets as input variables for the production function to measure efficiency. Azadeh et al. (2015) and (Amani, 2020) have suggested net profit as an output variable to measure efficiency in their work. Moreover, total liabilities as an input variable and gross refining margin as output variable have been added in this study to measure the operational efficiency for oil refineries.

With all variables of Table 3-3 identified from the theme-based literature in section 2.1 and based on the theory of production function as well as the concept of efficiency measurement by data envelopment analysis, the conceptual framework is developed for this study is shown in Figure 3-2.

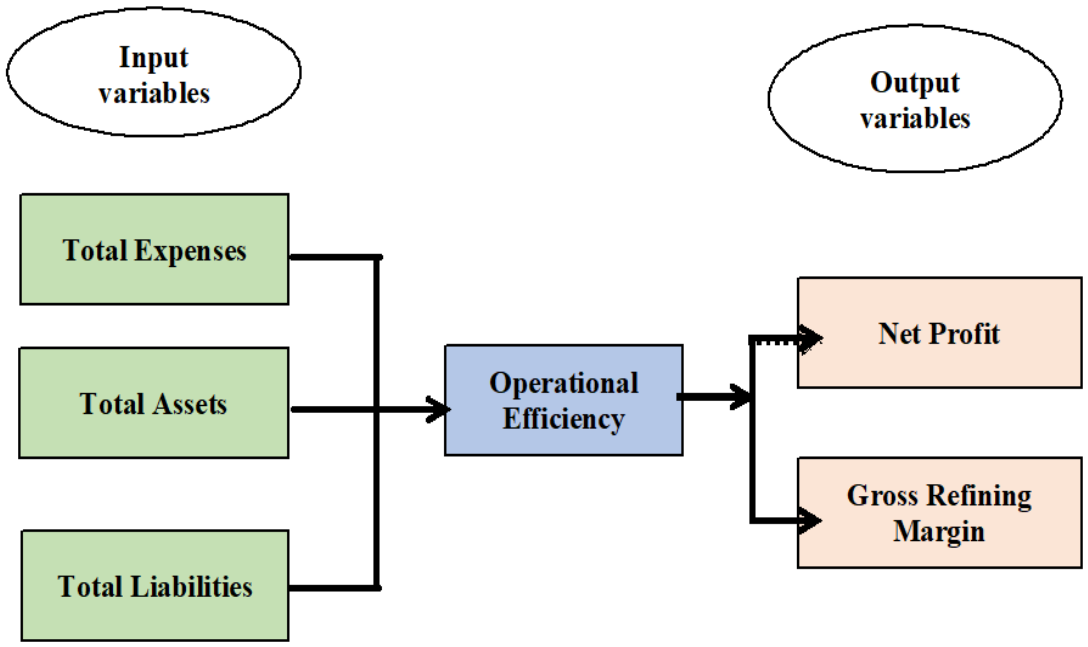


Figure 3-2 Operational Efficiency: Conceptual Framework

3.2.4 Data Envelopment Analysis (DEA) model

The methodology that has been proposed for this research is the DEA method. The DEA is largely a non-parametric approach that is founded on linear programming. DEA calculates the relative performance of DMUs as the ratio of the weighted sum of outputs to the weighted sum of inputs. DEA involves two models to evaluate operational efficiency. Charnes et al. (1978) proposed the first DEA model which was named DEA-CCR as a mark of respect to the authors, which assumes a constant return to scale (CRS). The DEA model which was proposed later offered a hypothesis of variable returns to scale (VRS) and was termed as DEA-BCC (Banker et al., 1984), after the authors who proposed it. Researchers from diverse domains have found DEA to be an excellent methodology to model efficiency measurement (Liu et al., 2013). The DEA methodology attempts to establish which organizations from within a selected sample defined a production frontier that was efficient (Charnes et al., 1978). In this case, refineries are termed as decision-making units. The concept of decision-making units is presented in a similar manner to that of entities, where each of the entities is measured as a part of a group that uses inputs to generate outputs (Roman and Gotiu, 2017). The outcome of the measurement created in score efficiency ranged from 0 to 1 and represented a degree of efficiency that is acquired by the refineries. In general, DMU is efficient if it attains the extreme score of 1, or otherwise, the DMU is inefficient (Malik et al., 2018).

Any decision-making units that are inefficient can be made more efficient with a projection onto the frontier. The orientation of the model is what determines the direction of projections for decision-making units that are inefficient (Jahanshahloo and Afzalinejad, 2006). The DEA model could either be output or input-oriented. Models that are output-oriented would tend to expand the output as much as possible and at the same time maintaining control over the inputs. In the model that is input-oriented, any units that are made inefficient are rendered efficient by proportionately lowering the inputs and at the same time, proportions related to outputs are maintained at a constant (Barra and Zotti, 2014).

In this study, the selection of orientation (input or output) is done based on the variables over which refineries have the utmost control (Banker et al., 1984). The refinery operates in such a way that it has more control over input variables than on the outputs. The input orientation aims to minimize the inputs (i.e., Total expenses, total assets and total liabilities) as much as possible to produce a given output (i.e., net profit and gross refining margin) while keeping the refinery in operation with its current technology mix. This is realistic anticipation for the refineries operating in developing countries like India, where shorten the production cost is most significant due to financial constraints. Hence, an input-oriented model is reflected more appropriate than an output-oriented model;

Next is the assumption of returns-to-scale for the refinery operation. According to Coelli et al. (2005), the constant returns-to-scale DEA model is only appropriate when the refinery is operating at an optimal scale. A refinery does not operate at an optimal scale because of some factors, such as imperfect competition, financial constraints, and socio-economic restrictions. For example, some of them are commissioned many years back and operating with old technology, whereas some refineries are recently commissioned and operating with new technology. Although some refineries are not commissioned long ago, still they are struggling to grow. Even the location of the refineries is not identical; like some refineries are on sea cost, getting advantage of sea transport facility i.e., Single buoy mooring (SBM). Hence, it is not appropriate to use a constant return to scale since the small-scale refineries are unfairly compared with the most productive scale-size refineries. Therefore, the variable returns-to-scale (VRS) DEA model for manufacturing units is often assumed in refinery studies, especially in developing countries. To sum up, the input-oriented VRS model has been applied to estimate the operational efficiency (OE) of Indian refineries for the period from 2010 to 2019 using the software STATA 13.0 version.

In VRS input-oriented model, consider there are n numbers of DMUs such as DMU_1, DMU_2, DMU_3, …, DMUn. Each DMU_j, (j = 1, ..., n) custom 'm' inputs x_{ij} (i = 1,...,m) and produces 's' outputs y_{rj} (r = 1,...,s). Let the DMU_j to be estimated on any sample be labeled as DMU_o (o = 1, 2,..., n). The competence of each DMU_o, is established by resolving the below linear programming, which is recognized as a multiplier system in DEA. The input orientated VRS model can be described according to Banker et al., (1984) as below:

$$Minimise\theta_0 + \varepsilon\left(\sum_r S_r^+ + \sum_i S_i^-\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.6)$$

$$s.t. \sum_j \lambda_j x_{ij} + S_i^- = \theta_0 x_{io}; i = 1, \ldots, m \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.7)$$

$$\sum_j \lambda_j y_{rj} - S_r^+ = y_{ro}; r = 1, \ldots, s \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.8)$$

$$\sum_j \lambda_j = 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.9)$$

$$\lambda_j, S_i^-, S_r^+ \geq O;\ \forall i, j, r; \theta_o\ Unconstrained \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.10)$$

This model is executed n times in categorizing the relative competence marks of whole DMUs. For DMU_o under evaluation, x_{io} and y_{ro} are the i^{th} input and r^{th} output respectively. θ_0 represents the input-oriented efficiency score of DMU_o. In general, DMU is efficient if it attains the extreme score of 1, or otherwise, the DMU is incompetent.

3.2.5 Inefficiency assessment

Further, the inefficiency assessment for inefficient refineries has been done to define the improvement targets and members of peer groups. A one-year data set (i.e., 2019) is considered for examining the inefficiency assessment of the refinery. The analyses will identify the proportion of variables (input and output) which in turn will enable to improve the efficiency of inefficient refineries (Gonzalez et al., 2019). For the year 2019, the efficiency scores are computed by using Eqs. (3.6-3.10). Apart from the efficiency score, the improvement targets for the inefficient units are also provided by this model. The improvement targets are calculated from the values of λ_j, S_r^+, and S_i^-. Once inefficient units are decided, each one is correlated against the subgroup of efficient units, which is called the 'peer groups' for inefficient units. The slack variables S_r^+ and S_i^- denote the excess input and shortage of output, which can be reduced or increased respectively, to make an efficient unit. For inefficient $DMU_{j'}$, the improvement targets that its inputs i ($x_{ij'}$) should attain to make an efficient unit are given in Eq. (3.11). Here, x_{ij} is the input values of the inefficient unit in the reference set, while $\theta_{j'}$, λ_j, and S_i^- are obtained from the VRS input-oriented model Eqs. (3.6-3.10).

$$target\_input_{j'i} = \sum_j \lambda_j x_{ij} = \theta_j x_{ij'} - S_i^- \qquad \forall i \in I, d' \in D, j' \in J \quad \ldots (3.11)$$

Where λ_j are the coefficients that multiply the members of the peer group of $DMU_{j'}$, $\theta_{j'}$ is the efficiency score of the inefficient unit 'j', whereas S_i^- is a slack variable representing the surplus amount by which the input i should be reduced to become strongly efficient.

Along with DEA input-oriented, the results of inefficiency assessment will direct that how much proportion of input variables are to be reduced for making inefficient refineries to efficient refineries.

3.2.6 Determinants of operational efficiency

The explanatory variables to explain variation in oil refinery efficiency were identified by considering two approaches: (1) To avoid the problem of repetitive use of the same variable and probability of getting confusing or unfair results, the refinery input and output variables of the DEA model will not be used again as the determinants in the regression analysis (Lin, 2008); and (2) An effort was made to develop other determinants that can explain the variation in the refinery efficiency while using regression analysis.

Considering these approaches, five key determinants were identified to explain variations in refinery efficiency. These data represent Indian oil refineries' operational aspects. The key determinants used to investigate the determinants of inefficiency in Indian oil refineries are summarized in Table 3-4.

Table 3-4 Determinants of operational efficiency.

Determinants	Unit	Description
Refinery complexity	NRGF	Indicates the configuration of refinery i.e., Adoption of more secondary processes.
Utilization rate	Percentage (%)	The ratio of the actual crude processed to the installed (Design) capacity of the refinery.
Distillate yield	Percentage (%)	The ratio of the total distillate (light, medium and heavy) production to the amount of crude processed.
Specific energy Consumption	MBN	Energy consumed in a refinery, measured as MMBtu/barrel of crude oil processed/ refinery energy factor (NRGF).
Operating costs	Rs in crore	Expenses are associated with the maintenance and administration of a business on a daily basis. It includes operating and overhead expenses.

3.2.7 Generalised least square (GLS) and Tobit regression model

The efficiency scores derived from the DEA results were used as the dependent variables in the second stage regression analysis. Regression analysis was conducted for various determinants related to the oil refineries to investigate the impact of the most significant determinants that can explain variations in refinery efficiency. Banker and Natarajan

(2008) stated that the OLS regression model is a fair and reliable estimator and it gives a more satisfactory result in second stage analysis, which is supported by McDonald (2009), He claimed that efficiency scores are the fractional data and these efficiency scores are not determined by the process of censoring data. He further recommended that the OLS regression model is the most pertinent method. However, the dependent variable is assumed as a linear function of independent variables and the error term in the OLS model. It also assumes that the simultaneous correlation across the units, unit-level heteroskedasticity and cross-sectional dependence is not present, which is not true for the case of time series data, so it will not give conclusive results in regression. A generalised least squares (GLS) estimator is an alternative model for second-stage regression analysis, where the errors have equal variances and are uncorrelated. A random-effects model is used as a means to accommodate firm-level effects, therefore following model is used for regression:

$$\theta^* = \alpha + \beta X_{it} + u_{it} + \varepsilon_{it} \quad (3.12)$$

Where θ^* is the efficiency score of the specific refinery 'i','t' is the year of evaluation, Parameter 'α' specifies the value of θ^* where all values of the explanatory variables are zero, while 'β' specifies the average change in θ^* and it is associated with a unit change in X_{it} after accounting for the explanatory variables in the model, 'u_{it}' in the above models is an individual effect. i.e., refinery-specific and time-specific effect (between entity error) and 'ε_{it}' is the error term (within-entity error).

On other hand, our dependent variable efficiency score is a censored variable having restrictions in its values that range from 0 to 1 theoretically in the present study. Therefore, given that the range of efficiency score is theoretically between 0 and 1 (Asongu et, al., 2017), GLS may be inappropriate. So, to control the issue of a restricted range of dependent variables, the determinants of inefficiency are examined by the Tobit regression model mostly in earlier studies (Alam F, 2011; Cinemre et al., 2006; Kaliba et al., 2006).

Tobin was the one who introduced Tobit's model by including a censored regression model of the economy and analysed it in the econometric literature for the first time (Tobin, 1958; Hayashi, 2016). Further, the efficiency score bounds between 0 and 1 value and is derived from DEA, thus it is more appropriate to use it as a simulation analysis to examine the operational efficiency determinants. Several scholars used the Tobit Model in their study (Mar et al., 2013; Hussien, 2011; Nyagaka et al., 2010; Fried et al., 1999). Therefore, the Tobit model is a suitable model for time-specific panel data and fraction data. Using the Tobit model, the equation is revised as,

$$OE_{it} = \begin{cases} OE_{it}^{*} \; if \; OE_{it}^{*} > 0 \\ 0 \; if \; OE_{it}^{*} \leq 0 \end{cases} \quad (3.13)$$

However, this equation is further revised to control for the cross refinery and time errors in censored panel data set and random effect Tobit model is written as below:

$$OE_{it} = \partial_1 + \partial_2 RC_{it} + \partial_3 SEC_{it} + \partial_4 UR_{it} + \partial_5 SDY_{it} + \partial_6 OC_{it} + u_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots \; (3.14)$$

To check the robustness of the Tobit model, the random effect GLS model is also performed and compare with the Tobit model. As the Tobit model is the decisive model for the study, the outputs of the Tobit regression model are only discussed.

Chapter 4: IMPACT EVALUATION OF THE VARIOUS FACTORS ON REFINERY'S GROSS REFINING MARGIN

4.1 PRELIMINARY ASSESSMENT

4.1.1 Descriptive statistics

Table 4-1 shows the descriptive statistics expressed as mean and standard deviation of variables along with gross refining margin (Objective-1).

Table 4-1 Refinery wise summary Statistics

Refinery	Variables	Ln (GRM)	Ln (RC)	Ln (SEC)	Ln (DY)	Ln (CU)	Ln (FL)
IOCL-Koyali	Mean	2650.33	6.13	67.96	79.18	99.23	9.29
	Std. Dev.	944.80	0.10	8.52	3.70	3.05	0.45
	Min	1782.31	5.98	57.40	70.70	94.60	8.60
	Max	4460.47	6.24	76.10	83.10	104.04	9.80
IOCL-Mathura	Mean	1512.64	5.34	65.83	73.62	108.15	8.01
	Std. Dev.	1530.57	0.15	7.45	2.16	11.03	0.85
	Min	-981.81	5.20	58.00	68.90	83.01	6.60
	Max	3447.95	5.55	78.20	76.10	121.71	8.90
IOCL-Panipat	Mean	1938.22	6.89	60.14	83.07	100.32	9.41
	Std. Dev.	1398.36	0.96	8.42	1.06	4.53	1.09
	Min	-883.18	5.82	49.90	81.90	91.07	7.90
	Max	3910.30	8.41	71.70	84.89	104.36	10.60
IOCL-Haldia	Mean	1593.14	5.30	68.89	67.46	102.41	8.94
	Std. Dev.	1354.56	0.19	13.20	1.75	4.71	0.46
	Min	-676.95	5.01	52.50	64.38	91.71	8.30
	Max	3344.66	5.51	83.00	69.88	107.62	9.50
IOCL-Barauni	Mean	1615.12	5.49	70.89	86.93	104.18	9.14
	Std. Dev.	1329.16	0.06	11.39	1.56	5.73	0.21
	Min	-537.98	5.38	58.30	84.96	95.50	8.70
	Max	3206.94	5.60	84.40	89.00	111.02	9.40
HPCL-Mumbai	Mean	2412.64	5.30	85.33	75.14	115.13	7.30
	Std. Dev.	1116.16	0.29	5.60	2.24	6.20	0.40
	Min	830.32	4.83	76.10	72.30	100.84	6.60
	Max	3882.49	5.83	94.60	77.70	123.31	7.80
HPCL-Visakh	Mean	1734.45	4.53	81.74	74.47	106.22	7.41
	Std. Dev.	988.73	0.33	3.45	2.14	8.68	0.19
	Min	502.11	4.11	77.30	72.10	93.69	7.10
	Max	3094.92	4.92	86.30	78.80	117.75	7.70
BPCL-Mumbai	Mean	2172.35	4.74	68.98	82.25	110.79	4.87
	Std. Dev.	779.47	0.18	4.37	2.18	6.04	0.72
	Min	1096.80	4.52	64.70	79.57	105.70	4.00

Refinery	Variables	Ln (GRM)	Ln (RC)	Ln (SEC)	Ln (DY)	Ln (CU)	Ln (FL)
	Max	3430.40	4.95	77.30	86.10	123.11	6.51
BPCL-Kochi	Mean	2166.07	4.62	80.31	82.60	101.94	6.80
	Std. Dev.	718.72	0.82	5.51	2.43	7.96	0.96
	Min	1124.93	3.79	71.60	78.87	90.93	5.30
	Max	3297.00	6.31	89.90	85.70	112.75	8.00
CPCL	Mean	1851.36	5.86	79.97	70.44	94.32	9.56
	Std. Dev.	891.92	0.86	13.23	2.37	4.70	0.49
	Min	395.20	4.71	62.50	66.30	86.65	8.90
	Max	3033.50	6.86	95.80	73.70	98.61	10.30
MRPL	Mean	1976.23	6.23	70.61	75.22	101.01	8.76
	Std. Dev.	1270.48	0.89	11.06	2.02	7.62	1.58
	Min	-286.92	4.90	57.92	72.31	85.32	6.80
	Max	3811.93	7.36	86.30	77.39	108.21	10.20
NEL	Mean	3439.34	6.78	65.14	80.95	95.26	5.75
	Std. Dev.	1250.50	1.51	7.54	6.42	10.25	0.41
	Min	1487.01	4.34	58.69	69.36	74.98	5.10
	Max	5187.85	8.32	78.70	85.06	104.59	6.30
RIL	Mean	4193.29	9.59	50.90	85.22	111.38	7.87
	Std. Dev.	1026.37	0.07	0.82	0.59	5.41	0.65
	Min	2806.98	9.48	49.62	84.29	101.39	7.20
	Max	5481.09	9.69	52.20	85.89	116.96	8.80

SD- Standard Deviation, Max- Maximum, Min- Minimum

Table 4-1 reveals that the minimum value of GRM is the lowest for the IOCL- Mathura refinery, while the RIL refinery shows the highest maximum valve of GRM. It is also shown that the standard deviation value of GRM is the highest for IOCL- Mathura refinery, indicating that the refinery faces more fluctuation of GRM during this period. Nevertheless, the mean value of GRM is the highest for the RIL refinery, signifying that the RIL refinery scored better on the average GRM value. The BPCL-Kochi refinery shows the minimum standard deviation value for GRM. It shows that BPCL-Kochi refinery has very little spread out of GRM data from the Mean value, indicating less interruption in operation to achieve GRM for this period. In addition, the standard deviation value of refinery complexity is the highest for the NEL refinery, representing the large change in the complexity of the refinery from the year 2010 to 2018. The NEL refinery has commissioned secondary processing units in the turnaround of the year 2012. Hence, the complexity has been augmented for the NEL refinery, while the rest of the refineries are not showing more change in complexity in this period. The standard deviation value for SEC is the highest for CPCL refinery because of the implementation of the residue up-gradation project to increase the percentage of high Sulphur crude processing. While the standard deviation value for SEC is lower for the RIL refinery, representing that the performance of this refinery is consistent for this variable during the period of study. The standard deviation value for DY is also the highest for the NEL refinery because of the increase in installed capacity in the year 2011 from 10 MMTPA to 22 MMTPA and commissioning of the secondary processing unit to increase the distillate yield. It also shows that the standard deviation value for SEC and DY are lower for the RIL refinery, representing that the performance of this refinery is consistent for both variables during the period of study. While the standard deviation value of CU and FL are lower for the IOCL-Koyali and the HPCL-Visakh refineries respectively, indicating that performance is consistent for both variables from the year 2010 to 2018.

4.1.2 Pearson correlation test

Table 4-2 Pearson correlation test of input and output variables

	Gross refining margin	**Refinery complexity**	**Specific energy consumption**	**Distillate yield**	**Capacity utilisation**	**Fuel and Loss**
Gross refining margin	1.0000					
Refinery complexity	0.4287***	1.0000				
Specific energy consumption	0.1705*	-0.6194***	1.0000			
Distillate yield	0.4029***	0.3528***	-0.2649***	1.0000		
Capacity utilisation	0.2980***	0.0806	-0.0355	0.2391***	1.0000	
Fuel and Loss	-0.2751***	0.2510**	-0.0483	-0.2583***	-0.2950***	1.0000

Note: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively.

Additionally, the correlation between variables is estimated by the Pearson correlation test. The result is summarized in Table 4-2. It reveals the significant positive and negative relationship between input and output variables.

4.1.3 Unit root test

According to the definition of the cointegration relationship, it is essential to conduct a stationarity test of each variable before constructing the cointegration model. An important feature of stationary time series is that shock to economic variables in a period will decay with time, while any shock will have permanent effects on nonstationary time series with the stochastic trends. The stationarity test is a test for the existence of a stochastic trend. In other words, it is used to verify whether the time variable has a unit root.

Table 4-3 Unit root tests

Variables	**Levin Lin Chu**	**Fisher type- Augmented Dickey fuller test**
	At level	
	Statistic	Statistic
Gross refining margin	-3.9094***	66.36***
Capacity utilisation	-3.0131***	77.18***
Distillate yield	-30.1082***	76.60***
Fuel and loss	-2.3471***	36.44*
Refinery complexity	-6.5612***	17.66
Specific energy consumption	-5.1226***	18.71
	First difference	
	Statistic	Statistics
ΔGross refining margin	-	102.84***
ΔCapacity utilisation	-	237.93***
ΔDistillate yield	-	125.85***
ΔFuel and loss	-	97.30***
ΔRefinery complexity	-	117.69***
ΔSpecific energy consumption	-	93.86***

Note: * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level.

Results in Table 4-3 show that series are stationary at levels for Levin Lin Chu test whereas Fisher type – Augmented Dickey fuller test shows that series are not stationary at levels. However, become stationary at first differences; they are said to be integrated of the first order, I(1). In this case, it has been concluded that there is no need to test for the existence of a cointegration relationship between these series.

4.2 POOLED OLS, FIXED EFFECT AND RANDOM EFFECT MODELS

Table 4-4 Pooled OLS, fixed effect and random effect estimators' result

Variables	Explanatory variables – Gross Refining Margin		
	Pooled Ordinary least square model	**Fixed effect model**	**Random effect model**
	Model – (1)	**Model – (2)**	**Model – (3)**
Refinery complexity	531.29***	-6.17	531.29***
Specific energy consumption	23.08*	10.66	23.08**
Distillate yield	29.68	140.86***	29.68
Capacity Utilization	19.12	37.96*	19.12
Fuel and Loss	-272.22***	-237.76	-272.22***
Constant	-4664.70*	-11537.66***	-4664.70**
Observation	117	117	117
R2	0.3960	-	-
Adjusted R2	0.3688	-	-
R2- Within	-	0.3162	0.2027
R2- Between	-	0.1940	0.8050
R2- Overall	-	0.2067	0.3960
Wald chi2(5)	-	-	72.78***
F-test	2.55**		
Breusch-Pagan LM test for random effects	0.00		
Hausman Test	26.23***		

Note: The probability values in the square brackets are derived from the F-test, Breusch-Pagan LM test and Hausman test. The standard error values are shown in the parentheses. * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level.

Table 4-4 indicates that the refinery complexity, specific energy consumption and capacity utilisation are found to be statistically significant and have a positive impact on gross refining margin, whereas fuel and loss are found to be statistically significant but have a negative impact on gross refining margin in OLS and random effect model. In addition, the fixed-effect model indicates that distillate yield and capacity utilisation have shown statistically significant and positive, whereas fuel and loss has shown a statistically significant and negative impact on gross refining margin.

Here, the selection of the model is done based on the F-test, Breusch-Pagan LM test and Hausman test. The F-test has been conducted between pooled OLS and Fixed Effect models to select the more conclusive and better model. It is found that the null hypothesis of the F-test is rejected, indicating that the Fixed Effect Model is much better and conclusive than the pooled OLS model for our panel data set. In addition, Breusch and Pagan Lagrangian multiplier test is conducted between pooled OLS and Random Effect Model to select the more conclusive and better model. It is found that the null hypothesis of the LM test is accepted, signifying that the pooled OLS model is much better and conclusive than the Random Effect Model for a given panel data set. Moreover, the Hausman test is used to check the more efficient model to explain the outcome between the fixed effect and random effect model. It is found that the null hypothesis of the Hausman test is strongly rejected, concluding that the fixed effect estimator is a more preferred estimator than the Random Effect Model. Here, both the F-test and the Hausman test have shown that the fixed effect model is a more accurate and conclusive estimator.

4.3 VALIDITY/ DIAGNOSIS TEST FOR PANEL DATA

However, the coefficients of the refinery complexity, specific energy consumption, and fuel and loss are found to be insignificant in a fixed-effect model, which cannot justify the results and raise the question of the results' validity. One probable reason is that the fixed effects model may assume the presence of heteroskedasticity and serial correlation. Hence, diagnostic checks are essential for checking the model's validity. Panel data are having repetitive observations over time; hence the panel data postulates the problem of cross-sectional dependence, serial correlation, and heteroskedasticity. The results of the diagnosis test are summarized in Table 4-5.

Table 4-5 Diagnosis of the estimated models

Tests	Gross refining margin
Breusch-Pagan LM test of independence chi2 (78)	269.055*** [0.0000]
Pesaran's test of cross-sectional independence	15.318*** [0.0000]
Wooldridge test for autocorrelation: F (1,12)	45.637*** [0.0000]
Modified Wald test for group wise heteroskedasticity: chi2 (13)	179.56*** [0.0081]

Note: The probabilities values are shown in the square brackets. * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level

In the case of Cross-sectional dependence tests (Breusch-Pagan LM test and Pesaran's test for cross-sectional independence), the null hypothesis is rejected. The Cross-sectional dependence statistics in both the tests is significant at a 1% level, indicating the presence of cross-sectional dependence in the data set. In the case of serial correlation tests, the null hypothesis of the Wooldridge test for autocorrelation is rejected. The F-statistics in this test is significant at a 1% level, indicating the presence of serial correlation in the data set. Similarly, in the case of the modified Wald test for group-wise heteroskedasticity, the chi2 statistics in the model is significant at a 1% level and accepted the null hypothesis, indicating the presence of Heteroskedasticity in the data set.

It is evident that both the F-test and the Hausman test suggested the fixed effect model as the preferred model, however, due to the presence of cross-sectional dependence and heteroskedasticity in the data set, the inferences drawn from the fixed effect model are not conclusive. To address the issue of heteroskedasticity, serial correlation and cross-sectional dependence for panel data, the feasible generalized least squares (FGLS) and panel corrected standard error (PCSE) estimators are used to estimate the gross refining margin of refineries.

4.4 FGLS AND PCSE ESTIMATIONS

The results of the FGLS and PCSE are summarised in Table 4-6.

Table 4-6 FGLS and PCSE estimations

Variables	Explanatory variables – Gross Refining Margin	
	Feasible Generalized Least Squares	Panel Corrected Standard Error
	Model (4)	Model (5)
Constant	-3824.13***	-4664.70
	(886.34)	(24.785)
Refinery complexity	522.37***	531.29***
	(45.32)	(121.45)
Specific energy consumption	15.98***	23.08
	(5.38)	(20.34)
Distillate yield	22.65***	29.68**
	(8.25)	(15.05)
Capacity utilisation	20.38***	19.12*
	(4.08)	(10.93)
Fuel and loss	-244.36***	-272.22***
	(34.36)	(77.95)
No. of Obs.	117	117
R2	-	0.3960
Wald chi2(5)	76.71***	147.64***

Note: The standard error values are shown in the parentheses. * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level.

Results in Table 4-6 show that the coefficients of refinery complexity, specific energy consumption, distillate yield and capacity utilisation are positive while the coefficients of fuel and loss is negative, which is consistent with our expectation. In addition, a comparison of models (4) and (5) indicates that the results of the FGLS estimator are close to the results of the PCSE estimator, which also increases the reliability of the regression results. The results reveal that the gross refining margin increases with an increase in refinery complexity, specific energy consumption, distillate yield and capacity utilisation, while decrease with an increase in more internal fuel consumption and loss of refinery, keeping other factors constant. However, the FGLS estimator ignored the non-spherical errors and produces unsuitably small standard error estimates. Therefore, the panel corrected standard errors (PCSE) model is selected as the decisive model for estimating the refinery's gross refining margin.

In model-(5), the coefficients suggest that controlling all other factors, an increase in complexity by 1% increase the gross refining margin by 531.29% statistically at a 1% level of significance, while if the distillate yield increases by 1% then the gross refining margin increases by 29.68% statistically at 5% level of significance. Ceteris paribus, if the refinery fuel consumption and loss increase by 1% then the gross refining margin decreases by 272.22% statistically at a 1% level of significance. Similarly, other things remaining constant, if the capacity utilisation increases by 1% then the gross refining margin raises by 19.12% statistically at 10% level of significance.

The result shows that refinery complexity has a positive and significant impact on gross refining margin, representing that the refinery with higher complexity has a better chance to increase gross refining margin controlling all other factors. Higher complexity means the refinery has the secondary processing units to upgrade the low valued fractions. It will increase the yield of high value-added fractions (i.e., light and middle distillate yield), indicating an increase in GRM. Hence, the result revealed that the refinery with higher complexity has a better chance to increase the gross refining margin.

The findings also show that the distillate yield (lighter + middle yield) has a positive and significant impact on gross refining margin, indicating that refinery with higher distillate yield tends to have higher gross refining margin individually keeping other factors constant. The distillate fractions are the most valuable finished products of the refinery against heavier yield or low-grade fractions such as fuel oil. Therefore, higher distillate fractions mean the refinery is able to generate more value-added fractions and increase the GRM. On other hand, the heavier fractions are low-valued products generated from the Indian refineries. The higher production of the heavier fractions decreases the overall pricing of the finished products and resulted in a decline in the gross refining margin of the Indian refineries.

The result also shows that capacity utilisation has a positive and significant impact on gross refining margin, representing that the refinery with higher capacity utilisation has a better chance to increase gross refining margin controlling all other factors. Capacity utilization indicates maximise the use of installed capacity and processing more amount of crude than the designed capacity. A factor that lowers the capacity utilization is the unwanted downtime that occurred in the refinery operation. More the shutdown occurs, the capacity utilization of the refinery gets down and becomes less efficient. Hence, the increase in capacity utilisation impacts the refinery's GRM positively.

However, that the variable "fuel and loss" have a negative and significant impact on gross refining margin, representing that the refinery with higher fuel consumption and loss has shown a decrease in gross refining margin controlling all other factors. Fuel and loss are nothing but the use of refined finished products of the refinery for internal consumption and losses of them in sampling, vaporization and handling. Larger unwanted consumption and loss of these finished products in refinery indicate the loss of refinery's GRM. Hence, the refinery with large fuel and loss results in lower GRM.

Moreover, the results show that the coefficient of specific energy consumption has a positive impact on the refinery's GRM, but it is not statistically significant, which is also true according to our expectations.

4.5 RELIABILITY/ STABILITY CHECKING OF MODEL

As the model finalized in the study is the econometrics model and has been selected after various diagnostic tests. Hence, there is no need to check for the reliability test of the model. However, the findings of the PCSE model are compared with existing research works and found that the direction of the coefficients of the selected determinants in this study is supported by the various works available in the public domain. The findings of the study revealed that capacity utilisation has been found to be a positive and significant actor for GRM. This finding gain support from the conclusion drawn by CFA (2013) and Romulo et al. (2011). They also concluded the same thoughts that the improvement in capacity utilisation of oil refineries can enhance the refinery profit. Nevertheless, the results of the PCSE test also said that the distillate yield has a positive and significant impact on the GRM and this finding is also suggested by Chaudhuri et al. (2018) and

Johnson et al. (2002). They concluded that the higher distillate fractions and petrochemical products increase the profit margin. The results also said that the GRM of the Indian oil refinery can be enhanced with an increase in complexity. Amani (2020) and Romulo et al. (2011) also identified that the refinery can improve the profit with raise in complexity. Hence, according to the similarity of the results with previous works, it can be concluded that the decisive PCSE model is reliable, and results drawn from the application of this model are also conclusive.

Moreover, the final models FGLS and PCSE are tested for reliability. The average value of all the determinants is used in both models and results are compared with the actual GRM value of these periods. If the findings match with the actual GRM value (i.e., 2250.40 Rs. /MT), the model can be considered reliable (See Figure 4-1).

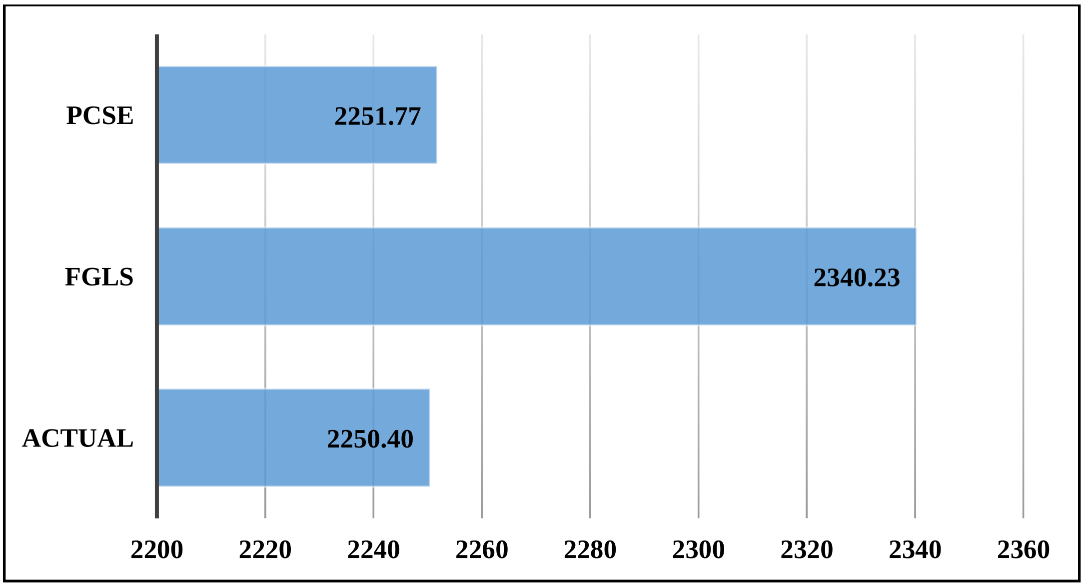


Figure 4-1 Actual vs FGLS vs PCSE GRM comparison for reliability of models

Figure 4-1 shows that while running both models, it was found that the output obtained in terms of GRM by FGLS estimator is 2340.23 Rs. /MT, which is more than the actual GRM value. While the output obtained by the PCSE model is 2251.70 Rs. /MT, which is very close to the actual GRM value of this study period. Hence, the PCSE model is more reliable according to the output obtained as well as variation of variables with GRM is also matching with the existing research works.

Chapter 5: OPERATIONAL EFFICIENCY EVALUATION OF INDIAN OIL REFINERIES

5.1 PRELIMINARY ASSESSMENT

5.1.1 Descriptive statistics

The descriptive statistics of input and output variables for 7 Indian oil refineries are summarised in Table 5-1 for the period 2010 to 2018.

Table 5-1 Descriptive Statistics.

		Inputs			**Outputs**	
		Total expenses (Rs. in crore)	**Total assets (Rs. in crore)**	**Total liabilities (Rs. in crore)**	**Net profit (Rs. in crore)**	**Gross refining margin (Rs. /MT)**
2010	Mean	49941.63	27369.44	9074.708	1065.141	2005.46
	Std. Dev.	25369.09	12305.29	3107.733	957.0121	439.60
	Min	29505.01	11082.73	3313.02	-170.57	1493.71
	Max	92341.11	42738.04	13320.31	2896.15	2806.98
2011	Mean	64124.05	31250.04	16512.69	626.11	1620.60
	Std. Dev.	29303.47	11321.52	6892.72	1163.98	692.28
	Min	38857.86	14177.92	9160.06	-952.48	1015.95
	Max	109923.80	43877.36	26348.60	2914.28	3023.24
2012	Mean	71649.06	31750.77	16473.12	499.86	1757.02
	Std. Dev.	34821.29	13647.30	6739.02	1491.72	1245.30
	Min	43267.67	14480.68	9485.55	-1814.40	395.20
	Max	131016.90	48381.04	27452.28	3047.82	3672.58
2013	Mean	77109.24	35581.03	17312.52	1099.99	2205.70
	Std. Dev.	38132.56	15167.48	5475.63	1212.91	963.11
	Min	46781.25	13119.66	8916.27	-285.91	1184.27
	Max	142830.00	54035.12	25471.39	3306.50	3592.74
2014	Mean	67439.86	34768.58	14323.58	1458.03	1603.04
	Std. Dev.	35343.20	15371.91	3480.85	1130.43	1637.52
	Min	38295.10	10163.35	7653.26	-36.17	-286.92
	Max	125872.70	58462.07	18064.65	3463.47	3855.50
2015	Mean	49660.15	36767.97	15424.90	1976.66	3456.05
	Std. Dev.	29663.86	17357.71	5051.14	1210.89	1222.59
	Min	25204.79	10685.72	6172.74	738.44	2428.36
	Max	101514.20	65801.22	22745.32	3618.55	5187.85
2016	Mean	58903.04	38055.88	15722.64	2400.13	3736.05
	Std.	33428.42	21692.58	6875.87	1656.71	980.05

		Inputs			Outputs	
		Total expenses (Rs. in crore)	**Total assets (Rs. in crore)**	**Total liabilities (Rs. in crore)**	**Net profit (Rs. in crore)**	**Gross refining margin (Rs. /MT)**
	Dev.					
	Min	33076.81	11169.25	5499.04	-535.90	2587.20
	Max	115804.90	77913.05	22575.78	4260.99	5410.48
2017	Mean	64245.85	39152.81	17015.44	2523.84	3864.44
	Std. Dev.	36172.50	24734.63	7714.33	1735.87	824.52
	Min	37143.51	13129.56	7670.74	271.98	3033.50
	Max	129530.80	87629.43	27053.62	5119.20	5481.09
2018	Mean	77373.26	45409.90	18083.36	2042.94	2849.62
	Std. Dev.	41727.96	32917.86	9321.99	2142.87	986.33
	Min	44282.31	14260.99	7277.04	-199.16	1895.84
	Max	156812.30	112191.00	30857.93	5725.36	4713.99

Std. Dev.- Standard Deviation, Max- Maximum, Min- Minimum

The statistics show huge differences between the oil refineries with reference to input and output points. For the case of input variables, the total liability shows a huge degree of dissimilarity. Moreover, the average total expenses and total assets have been increased from the year 2010 to 2018. The average total expenses and total assets increased by 1.55 times and 1.66 times respectively from the year 2010 to 2018.

With regard to output variables, the average gross refining margin of the oil refineries has shown an increase of 1.42 times from the year 2010 to 2018, whereas net profit has increased by 1.9 times for the study period. The mean value of net profit and gross refining margin has increased by 52.1% and 70.3% respectively, during the study period.

5.1.2 Pearson correlations test

Before applying DEA, the correlation between input and output variables is conducted by the Pearson correlation test. This test identifies the significant relations among them and gives an idea to understand how a change in one variable may impact the performance of the refinery in other correlated conditions. The result is summarised in Table 5-2. It reveals the positive and negative significant relationship among all input and output variables.

Table 5-2 The results of Pearson correlations.

	Total Expenses	**Total Assets**	**Total Liabilities**	**Net Profit**	**Gross Refining Margin**
Total Expenses	1.0000				
Total Assets	0.2454*	1.0000			
Total Liabilities	0.5487***	0.7332***	1.0000		
Net Profit	0.2210*	0.7289***	0.3626***	1.0000	
Gross Refining Margin	-0.2939*	0.5122***	0.1950	0.5626***	1.0000

Note: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively.

5.2 THE OPERATIONAL EFFICIENCY INDICES AND ANALYSIS

The VRS input-oriented model was used in this study for the DEA analysis of 7 refineries in India during the period of 2010 to 2018. The DEA analysis was conducted to compute the operational efficiency scores using Eqs (3.6) - (3.10). The refineries with an efficiency score of '1' are considered efficient refineries. Figure 5-1 represents the DEA efficiency scores of 7 Indian oil refineries during the period of 2010-2018. It shows a heat map, which represents the efficiency scores of each sampled refinery for the defined time period. Each cell is coloured in accordance with the efficiency score value allocated to each refinery - higher efficiency scores represent darker shade whereas lower efficiency scores represent a lighter shade.

Name of refineries	2010	2011	2012	2013	2014	2015	2016	2017	2018
IOCL	0.535	0.339	0.323	0.323	0.337	0.520	0.717	0.827	0.429
HPCL	0.338	0.243	0.220	0.241	0.390	0.437	0.708	0.732	0.508
BPCL	0.443	0.357	0.368	0.456	0.537	1.000	0.824	0.892	0.610
CPCL	1.000	0.746	0.720	0.797	1.000	1.000	1.000	0.906	0.735
MRPL	0.894	0.632	0.586	0.527	0.662	1.000	1.000	0.933	0.650
NEL	0.857	0.617	0.675	0.680	0.746	1.000	0.916	0.823	0.601
RIL	1.000	0.870	0.893	0.871	1.000	1.000	1.000	1.000	1.000

Figure 5-1 DEA efficiency scores of Indian oil refineries (2010-2018)

Figure 5-1 shows that the Reliance industries limited and CPCL refineries were found to be the best performers for the entire study period. The RIL refinery mostly attained the full efficiency score for the study period, except decline in the year 2011, 2012 and 2013. The efficiency score of CPCL refinery was dropped in the year 2011, 2012 and 2013 and achieved a full efficient score from the year 2014 to 2016, again decline in the years 2017 and 2018. The average efficiency scores of RIL and CPCL refineries were found 0.9593 and 09782, which are closest to '1' among all refineries. As the RIL and CPCL refineries produced a high amount of distillate products (valuable finished products) and noticed higher conversion per ton of crude oil compared to all other refineries during the period of study, the RIL refinery was found to be the best performer. Moreover, various processes configuration optimisation and higher complexity of RIL refinery enhanced the efficiency and gained a competitive advantage over other refineries.

On other hand, The IOCL and HPCL refineries are the least efficient refineries for the period 2010 to 2018 because these refineries have never attained the efficiency score '1' during the entire study period. The average efficiency scores of IOCL and HPCL are 48.34% and 42.42% respectively during the study period. The IOCL could not achieve the full efficiency score during the study period because of less capacity utilisation. The percentage of capacity utilisation of IOCL remained below 100% during the study period. As the distillate production of the HPCL refinery remained lower compared to other refineries, the HPCL refinery was found to be the least performed refinery in the study period. Also, the advantageous high sulfur crude oil processing in HPCL refinery was lower, which also cause drags it to lower efficiency.

Moreover, BPCL was found to be the efficient refinery only for the year 2015 and found inefficient for the rest of the study period. However, the average efficiency score of the BPCL refinery was 60.96% for the entire study period; which can be considered as a moderate performer. The BPCL refineries were found as moderate efficient refineries because of underutilisation and over-investment in refinery resources. The MRPL and the NEL refineries are also found to be moderate performers during the study period since all refineries were found efficient at least once among ten years period and having an average efficiency score of 76.48% and 76.82% respectively. In addition, the BPCL, NEL and MRPL refineries have attained the full efficiency score in the year 2015 and displayed a drop in efficiency for the rest of the years. The gradual increase in the energy costs of the MRPL refinery, which drained the refinery's profit and was found as a moderate efficient refinery. On other hand, the higher fuel consumption and less crude oil processed in the NEL refinery impacted operating costs, which affected the operational efficiency. Hence, the NEL refinery is also found as a moderate efficiency refinery.

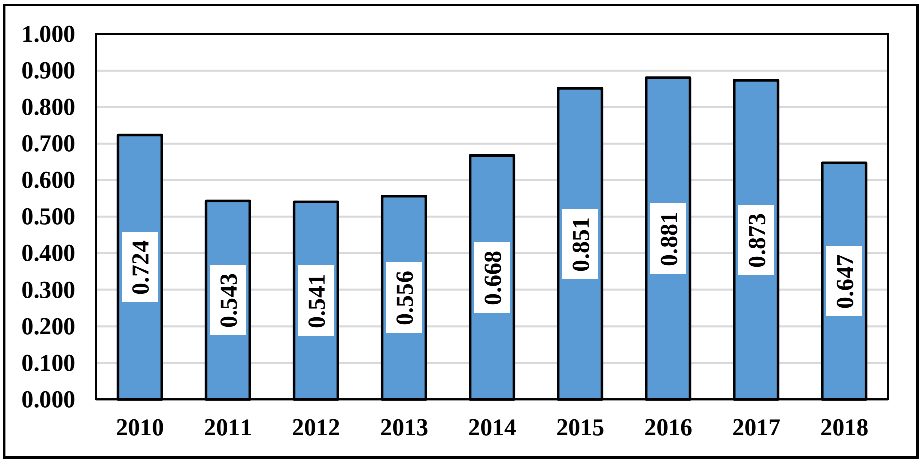


Figure 5-2 Average DEA efficiency scores

The analysis of average DEA efficiencies scores has been considered an important tool in measuring the competitiveness of various sectors (Sengupta, 1995). The average DEA efficiency scores are shown in Figure 5-2. It reveals that the average efficiency scores from the DEA model show a rising trend from the year 2011 to 2016. Further, the average efficiency score is declining in the years 2017 and 2018. It indicated that the inputs were not used efficiently in Indian oil refineries during the period 2010-2018. The highest average efficiency score of 88.1% was reported for the year 2016 and the smallest efficiency score of 54.1% was reported for the year 2012, which interpreted that the refineries could reduce their input use by about 45.9% with the current level of technology network to be efficient.

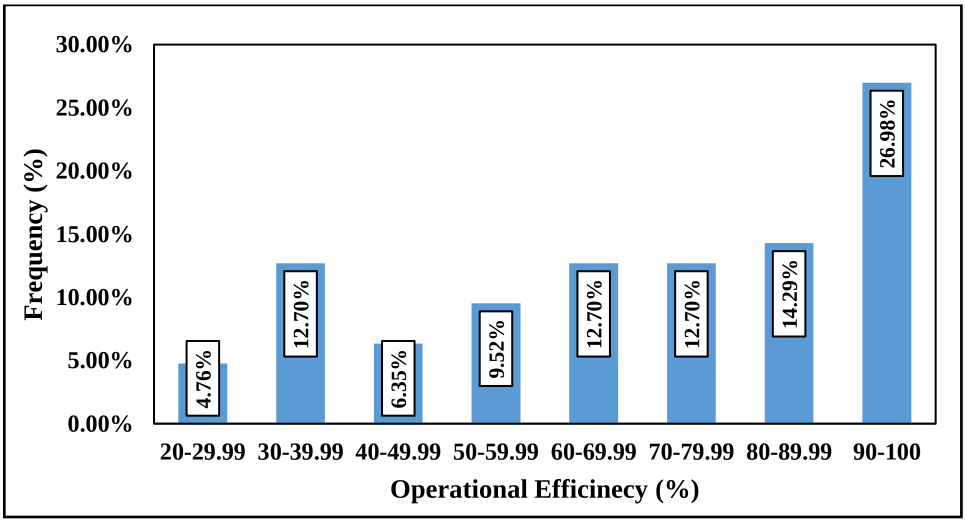


Figure 5-3 Frequency distribution of operational efficiency (2010-2018)

Additionally, the frequency distributions of operational efficiency in Indian oil refineries are shown in Figure 5-3. It shows that major Indian oil refineries fall within the operational efficiency scores in the ranges of 80-89.99 (14.29%) and 90-100 (26.98%). Even 12.70% of refineries are also fallen in the range of efficiency scores 70-79.99. It shows that the most of oil refineries are operated best to the production frontier. However, 46.06% of Indian oil refineries have efficiency scores less than 70%.

Table 5-3 The results of Pearson correlations

	Operational efficiency indexes	Net Profit	Gross refining margin
Operational efficiency indexes	1.0000		
Net Profit	0.2925**	1.0000	
Gross refining margin	0.6114***	0.5626***	1.0000

Note: ** and *** indicate that the explanatory variable is significant at the 0.05 and 0.01 significance level respectively.

Moreover, the correlation between operational efficiency indexes, net profit and GRM was conducted by Pearson correlation test. The result is summarised in Table 5-3. It reveals the positive significant relationship among operational efficiency indexes and GRM s well as with net profit. The increase in operational efficiency will increase the gross refining margin and net profit of Indian oi refineries, which is also as per expectations. Hence, the information on slack variables and improvement targets are essential for inefficient refineries to meet with their peer group, which are showing best practices.

5.3 INEFFICIENCY ASSESSMENT

DEA also shows additional facts applicable for inefficient refineries, which is called slack of variables. The slack variable analysis gives definite recommendations to assist each inefficient refinery to become efficient, by minimising the amount of input to crop the same amount of output efficiently. A characteristic benefit of the DEA model is to determine the improvement targets for units that are identified as inefficient. These improvement targets take appropriate corrective action by identifying the foremost causes of inefficiency. An inefficiency assessment has been done for the data set of the year 2019, as discussed in the methodology section.

Table 5-4 The efficiency scores of the selected refineries during the period of 2019

DMUs	Refineries	DEA efficiency indexes	Members of peer groups		
DMU_1	IOCL	0.5729	DMU_5 (MRPL)	DMU_7 (RIL)	-
DMU_2	HPCL	0.8488	DMU_4 (CPCL)	DMU_7 (RIL)	-
DMU_3	BPCL	0.9270	DMU_4 (CPCL)	DMU_6 (NEL)	DMU_7 (RIL)
DMU_4	CPCL	1.0000	-	-	-
DMU_5	MRPL	1.0000	-	-	-
DMU_6	NEL	1.0000	-	-	-
DMU_7	RIL	1.0000	-	-	-

Note: DMU - Decision making units

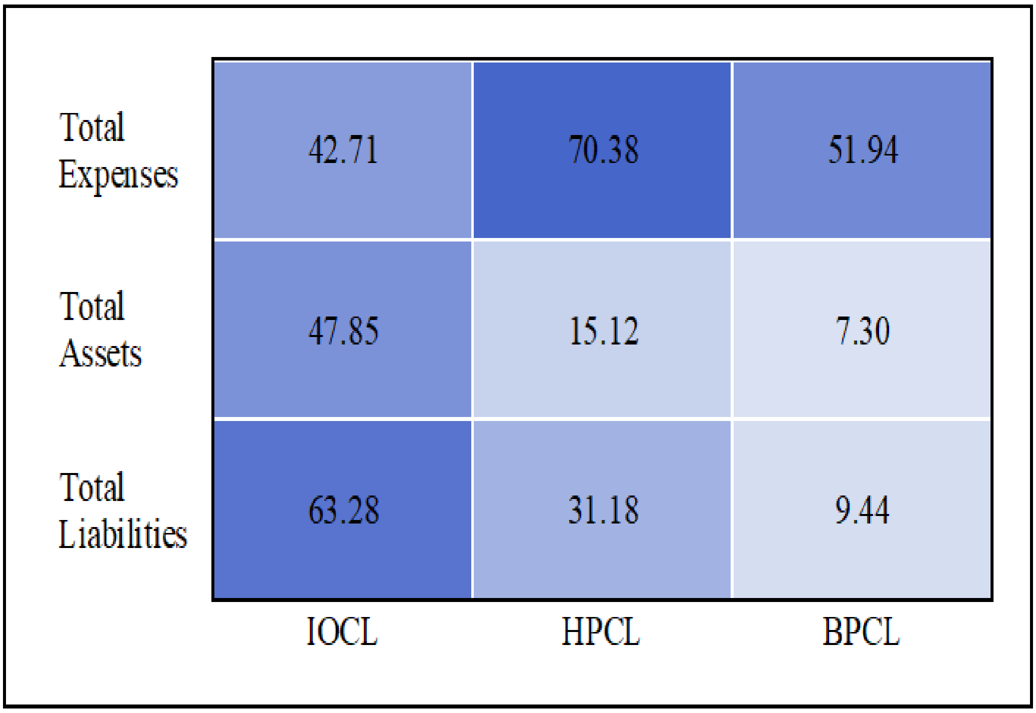


Figure 5-4 Improvement targets (%) for the inefficient refineries

The efficient and inefficient refineries are identified by using Eqs. (3.6-3.10) and are summarised in Table 5-4. The improvement targets that its inputs should attain to make the refinery efficient were determined using Eq. (3.11). The improvement targets for each refinery are summarised in Figure 5-4. It shows a heat map, which represents the percentage reductions for input variables in a given dimension to make the refinery efficient. Each cell is coloured in accordance with the reduction value allocated to each input - higher reduction targets represent a darker shade. Furthermore, the IOCL is the smallest inefficient refinery for the year 2019. It should reduce its total expenses, total assets and total liabilities by 42.71%, 47.85% and 63.28% respectively to make a strongly efficient refinery. The 'peer groups' are the efficient refineries, which defined the projection of inefficient refineries to the efficient frontier. The peer groups for each inefficient refinery with peer's weight are shown in Figure 5-5. In particular, the inefficient refinery should observe the best practices of its peers, which shows the equivalent level of output. The inefficient refinery has to formulate the policies and implement them, so the inefficient refinery attains the input targets.

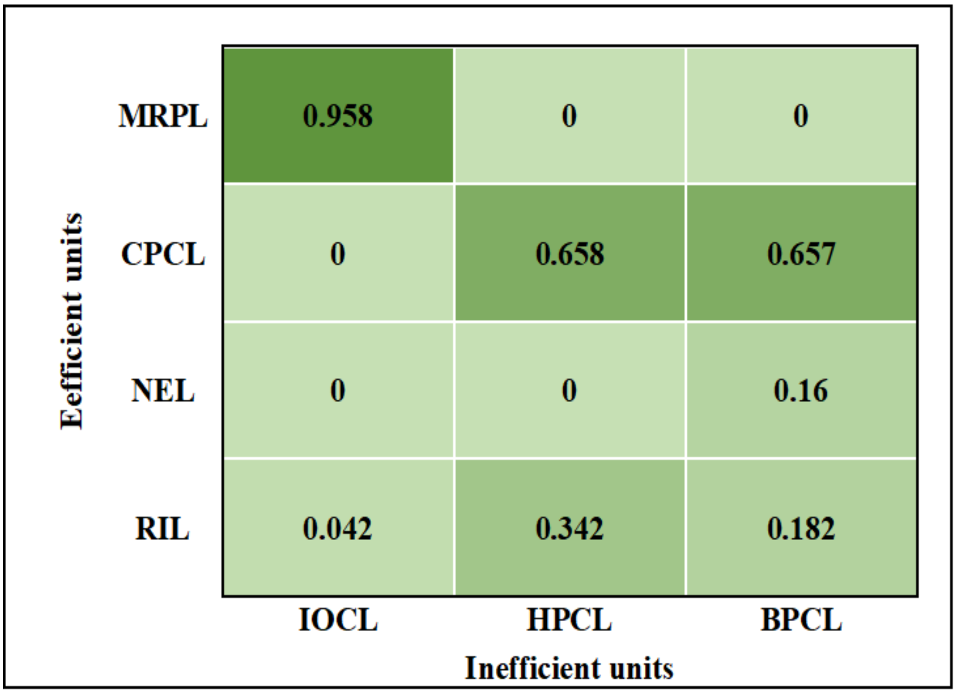


Figure 5-5 Peers used by the inefficient refineries to attain their improved targets.

In petroleum refineries, the practices used by the peer group's refineries are never identical and cannot be implemented directly without any feasibility study by inefficient refineries because of differences in complexity and configuration. However, the concept of optimisation and operating practices of peer group's refinery can be implemented by inefficient units after doing required changes according to their system.

Considering the concept of optimisation used in peer groups' refineries (MRPL, CPCL, NEL and RIL), the inefficient refineries should pay attention to process integration technology (pinch technology) for each unit in the refinery that will identify the scope of improvement in heat integration. The pump around and feed preheat trains heat duty are to be monitored for energy efficiency, and exchangers should be periodically cleaned when they drop in heat duty is observed because of fouling in exchangers. Further, waste heat recovery, flare gas recovery and power recovery can improve heat integration and reduce the energy demand for inefficient units. The inefficient refinery has to improve the maintenance and monitoring practices, which will increase the reliability of equipment and reduce the unplanned breakdown of the equipment, which reduces the loss and improve the profit margin. Additionally, selecting proper sizing of motors, high-efficiency motors, use of variable speed drives, trimming of pump's impeller, use of multiple pumps, correct sizing of pumps, air preheating, reduce leaks, sealing of rotating equipment, better pipe insulation and improved steam use also contribute in reduction of production cost and turnaround times. These all practices of the efficient frontier refinery can add to the operational efficiency enhancement for the inefficient refineries.

5.4 ESTIMATING THE DETERMINANTS OF OPERATIONAL EFFICIENCY

5.4.1 Unit root test

According to the definition of the cointegration relationship, it is essential to conduct a stationarity test of each variable before constructing the cointegration model. An important feature of stationary time series is that shock to economic variables in a period will decay with time, while any shock will have permanent effects on nonstationary time series with the stochastic trends. The stationarity test is a test for the existence of a stochastic trend. In other words, it is used to verify whether the time variable has a unit root.

Table 5-5 Unit root tests

Variables	Levin Lin Chu	Fisher type- Augmented Dickey fuller test
At levels		
	Statistic	**Statistic**
VRS-input oriented efficiency indexes	-4.209***	11.83
Refinery complexity	-6.141***	15.94
Specific energy consumption	-4.264***	6.49
Utilisation rate	-1.398*	118.48***
Distillate yield	-24.799***	23.60**
Operating costs	-4.556***	22.53*
First difference		
	Statistic	Statistics
Δ VRS-input oriented efficiency indexes	-	53.58***
Δ Refinery complexity	-	46.66***
Δ Specific energy consumption	-	33.73***
Δ Utilisation rate	-	195.35***
Δ Distillate yield	-	54.19***
Δ Operating costs	-	30.61***

Note: * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level.

Results in Table 5-5 show that series are stationary at levels for Levin Lin Chu test whereas Fisher type – Augmented Dickey fuller test shows that series are not stationary at levels. However, become stationary at first differences; they are said to be integrated of the first order, I(1). In this case, it has been concluded that there is no need to test for the existence of a cointegration relationship between these series.

5.4.2 Random effect GLS and Tobit model

Further analysis was conducted to estimate the determinants of operational efficiency. Table 5-6 delivers the indication of explanatory variables used in the pooled OLS, two-way random effects generalised least square model and Tobit regressions model of the study. All the coefficients of this model are not equal to zero, and significant which implies our model is good.

*Table 5-6 **Determinant's relationship with operational efficiency***

Dependent variable = DEA operational efficiency indexes				
Explanatory variables	**Random effect GLS model**		**Random effect Tobit model**	
	Coefficient	**t-value**	**Coefficient**	**t-value**
Refinery complexity	-0.0230	-0.82	-0.0118	-0.46
Specific energy consumption	0.0027	1.02	0.0036	1.35
Utilization rate	0.0066*	1.80	0.0071**	2.12
Distillate yield	0.0129**	1.93	0.0099*	1.66
Operating Costs	-6.37E-06***	-5.17	-6.36E-06***	-6.61
Constant	-0.6251	-1.25	-0.5608	-1.26
Observation	63	-	63	-
R-sq within	0.3315			
R-sq between	0.7951			
R-sq overall	0.5935			

Note: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively.

From the result, three explanatory variables were noticed as the significant performers that explain variations in refinery operational efficiency among the selected Indian oil refineries in all models, which includes utilisation rate, distillate yield and operating costs. However, the random effect GLS model gives inconsistent and biased results in the case of a censored dependent variable while in this case; operational efficiency is a censored variable (i.e., the score is laid between 0-1). Therefore, the random effect Tobit model is considered as a determining model for the study.

Additionally, to check the impact of refinery ownership, one dummy variable is added along with identified explanatory variables of operational efficiency. The number '0' is assigned for the public sector refinery whereas the number '1' is assigned for the private sector refinery. Both random effect GLS and Tobit models are performed to check the impact of refinery ownership on operational efficiency. The results of both models are summarised in Table 5-7.

*Table 5-7 **Refinery ownership relationship with operational efficiency***

Dependent variable = DEA operational efficiency indexes				
Explanatory variables	**Random effect GLS model**		**Random effect Tobit model**	
	Coefficient	**t-value**	**Coefficient**	**t-value**
Refinery complexity	-0.0043	-0.17	-0.0146	-0.55
Specific energy consumption	0.0050*	1.77	0.0037	1.38
Utilization rate	0.0084**	2.51	0.0074**	2.17
Distillate yield	0.0056	0.97	0.0087	1.33
Operating Costs	-6.71E-06***	-7.38	-6.54E-06***	-6.38
Refinery ownership	0.0432	0.62	0.0363	0.42
Constant	-0.5035	-1.02	-0.5057	-1.08
Observation	63	-	63	-
R-sq within	0.3014			
R-sq between	0.8673			
R-sq overall	0.6188			

Note: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively.

The results in Table 5-7 reveal that the privately-owned refinery shows a positive relationship with operational efficiency. However, the impact is not statistically significant.

Table 5-6 shows that the ‘Utilisation rate’ variable was found to be a positive and significant actor (at 5% level) in random effect GLS and Tobit estimations, and suggests that if a refinery is able to increase its utilisation rate, this might positively influence its operational efficiency; every percentage increase in the utilisation rate of oil refinery could result in an increase of the Indian oil refinery’s operational efficiency by 0.007 units. The higher refinery’s utilisation rate allows a refinery to generate more revenues by processing an additional amount of crude oil than the designed capacity and minimising the downtime in the refinery; this will positively affect a refinery's operational efficiency.

The Variable ‘distillate yield’ was found to be a positive and significant actor at 10% level for the random effect GLS model and the random effect Tobit model. The positive coefficient suggested that a higher amount of distillate yield could trigger higher operational efficiency for Indian oil refineries; for every percentage increase in distillate yield produced by an oil refinery, its operational efficiency increase by 0.009

units. Distillate yield from an oil refinery essentially quantifies the level of capital intensity and sophistication within a refinery. In refinery operation, the less complex refinery brings down the distillate production and revenues; this will negatively affect an oil refinery's operational efficiency.

Additionally, the variable 'operating costs' was found to be a negative and significant actor at 1% level for random effect GLS model and random effect Tobit model, indicating that increase in operating costs will decrease the refinery operational efficiency by $6.54X10^{-6}$ points statistically. It indicates that the costs that occurred due to maintenance, inventory, wedges, marketing, insurance, research and development, etc. are higher for Indian oil refineries, which impact negatively to the refinery's efficiency.

Moreover, the results of the Tobit model revealed that the variable 'refinery complexity' has a negative, but insignificant impact on the operational efficiency of oil refineries in India, indicating that, the more complex refineries were found to be less efficient during the study period, which is not as per our expectations. It indicates that even though Indian refineries enhanced their complexity in the study period, but the impact of other variables is more and nullifying the role of complexity in efficiency enhancement.

The variable "specific energy consumption" was found to be positive, but the insignificant actor for the Tobit model, indicating that an increase in the refinery specific energy consumption will increase the refinery operational efficiency, which is also not as per our expectations. We can also say that this higher energy consumption will be reversing the impact of higher complexity in the case of Indian oil refineries and bring down operational efficiency. The positive impact specifies that energy consumed in Indian oil refineries is not optimal because of unwanted breakdown/ shutdown. The unwanted downtime increases the energy demand for the refinery to re-establish all the operational activities of the refinery. Mostly the utilisation rate of the public sector refineries is quite less compared to private refineries, which drives more energy demand. Further, the refineries commissioned many years back are still running with obsolete technology that requires a large amount of energy to produce the same amount of output as the efficient technology.

Moreover, a comparison of the random effect GLS regression model and Tobit regression model revealed that the estimation drawn from the random effect GLS regression model is more or less close to the estimation drawn from the Tobit regression model, which also increases the reliability of the conclusions drawn from the regression results.

5.5 STABILITY TEST OF THE BCC MODEL

In order to verify the stability of our DEA model, the stability test was conducted by omitting one input variable at a time (Liu et al., 2010). Four models are developed for this test. Model 1 is the full-complete model without canceling any variable (primal model), Model 2 drops out one input ‘‘total expenses’’, Model 3 omits another input ‘‘total assets, and Model 4 deletes the other input ‘‘total liabilities’’ from the original set. Each of the removed variables is returned before the next deletion, thus maintaining the same degrees of freedom. Results of the stability test are shown in Table 5-8. The individual efficiency scores across models reveal that our results are stable across all specifications. As expected, Models 2, 3, and 4 have less efficient DMUs than Model 1, partly due to a decrease in the dimensionality of the DEA approach and larger data set.

Table 5-8 BCC efficiency results of four models from stability test.

DMUs	**Year**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
IOCL	2010	0.535	0.535	0.535	0.477
	2011	0.339	0.282	0.339	0.339
	2012	0.323	0.268	0.322	0.323
	2013	0.323	0.263	0.309	0.323
	2014	0.337	0.283	0.337	0.328
	2015	0.520	0.372	0.497	0.520
	2016	0.717	0.717	0.627	0.717
	2017	0.827	0.827	0.600	0.827
	2018	0.429	0.398	0.390	0.429
HPCL	2010	0.338	0.334	0.335	0.297
	2011	0.243	0.241	0.238	0.243
	2012	0.220	0.220	0.205	0.219
	2013	0.241	0.238	0.214	0.236
	2014	0.390	0.390	0.390	0.337

DMUs	Year	Model 1	Model 2	Model 3	Model 4
	2015	0.437	0.437	0.437	0.400
	2016	0.708	0.708	0.642	0.708
	2017	0.732	0.732	0.499	0.732
	2018	0.508	0.508	0.354	0.508
BPCL	2010	0.443	0.438	0.418	0.410
	2011	0.357	0.357	0.282	0.357
	2012	0.368	0.368	0.274	0.368
	2013	0.456	0.456	0.349	0.456
	2014	0.537	0.537	0.476	0.537
	2015	1.000	1.000	0.968	1.000
	2016	0.824	0.824	0.683	0.824
	2017	0.892	0.892	0.785	0.892
	2018	0.610	0.610	0.516	0.598
CPCL	2010	1.000	1.000	1.000	0.956
	2011	0.746	0.735	0.674	0.746
	2012	0.720	0.706	0.576	0.720
	2013	0.797	0.797	0.585	0.797
	2014	1.000	1.000	0.690	1.000
	2015	1.000	1.000	1.000	1.000
	2016	1.000	1.000	0.997	1.000
	2017	0.906	0.879	0.758	0.906
	2018	0.735	0.735	0.556	0.735
MRPL	2010	0.894	0.753	0.891	0.894
	2011	0.632	0.523	0.632	0.631
	2012	0.586	0.579	0.586	0.576
	2013	0.527	0.390	0.527	0.526
	2014	0.662	0.506	0.641	0.662
	2015	1.000	0.444	1.000	1.000
	2016	1.000	1.000	1.000	1.000
	2017	0.933	0.919	0.893	0.933
	2018	0.650	0.650	0.637	0.633
NEL	2010	0.857	0.476	0.857	0.846
	2011	0.617	0.360	0.617	0.611
	2012	0.675	0.518	0.626	0.675
	2013	0.680	0.574	0.595	0.680
	2014	0.746	0.420	0.720	0.746
	2015	1.000	1.000	0.927	1.000
	2016	0.916	0.758	0.858	0.916
	2017	0.823	0.793	0.783	0.813
	2018	0.601	0.493	0.601	0.571
RIL	2010	1.000	1.000	1.000	0.936
	2011	0.870	0.867	0.854	0.768
	2012	0.893	0.893	0.886	0.753
	2013	0.871	0.870	0.855	0.746
	2014	1.000	1.000	1.000	0.796
	2015	1.000	1.000	1.000	1.000
	2016	1.000	1.000	1.000	1.000
	2017	1.000	1.000	1.000	1.000

DMUs	Year	Model 1	Model 2	Model 3	Model 4
	2018	1.000	1.000	1.000	1.000
Average		0.698	0.649	0.648	0.682
No. of efficient DMUs		14	13	10	11

In addition, The Spearman rank correlation test is also conducted and the correlation coefficients between Model 1 and the other three models are found in the range 0.856–0.986 (Table 5-9). These correlation coefficients are statistically different from zero at the 1% level of significance, which means that the results are positively related and stable across model specifications.

Table 5-9 Spearman rank correlation test

	Model 1	Model 2	Model 3	Model 4
Model 1	1.000			
Model 2	0.923***	1.000		
Model 3	0.958***	0.856***	1.000	
Model 4	0.986***	0.900***	0.934***	1.000

Note: *** indicate that the explanatory variable is significant at the 0.01 significance level.

Chapter 6: CONCLUSIONS AND POLICY RECOMMENDATIONS

6.1 CONCLUSION

In this study, we estimated gross refining margin using panel data econometric tools. The study found that the fixed effect model is the most appropriate model as suggested by the Hausman test among fixed effect and random effect models. For consistency of the results, four diagnosis tests have been done to identify the presence of cross-sectional dependence, autocorrelation and heteroskedasticity among the panel data set. However, due to the presence of cross-sectional dependence and heteroskedasticity in the data set, the inferences drawn from the fixed effect model are not conclusive. Therefore, the gross refining margin was estimated by using the FGLS and PCSE estimators. However, The FGLS estimator ignores the non-spherical errors. Therefore, the PCSE model was selected as the decisive model for estimating GRM.

While analysing the determinants of the refinery's GRM, four important explanatory variables were found to reason for the known variations in the refinery's GRM in the Indian region. The variable "refinery complexity" was found to be a positive and significant driver for refinery's GRM, meaning that the more complex refinery triggered higher refinery's GRM compared to the less complex refinery. The "capacity utilisation" of oil refineries was found to be a positive and significant driver for refinery's GRM, representing that a higher utilisation rate of refinery increased the gross refining margin. Similarly, the "distillate yield" was found to be a positive and significant actor to explain variation in refinery's GRM, indicating that increase in distillate yield also triggered higher gross refining margin. Moreover, the variable "fuel and loss" was found to be a negative and significant driver for the refinery's GRM, meaning that higher fuel consumption and loss in the refinery declined the refinery's GRM.

Moreover, one more objective of this study is to measure the operational efficiency of oil refineries in India. Total seven numbers of oil refineries have been selected in the sample frame for the period of 2010-2018, and identify the key determinants that can explain the fluctuation in refinery efficiency. The DEA model was used for evaluating the operational efficiency in the first stage of analysis and it was followed by GLS and Tobit regression analysis in the second stage of analysis. The empirical results found that that the RIL and CPCL refineries are found more efficient refineries, whereas the IOCL and HPCL refineries were found the least efficient refineries. The BPCL, MRPL and NEL were found to be moderate performers during the study period.

While analysing the determinants of refinery efficiency, three important explanatory variables were identified as the reason for changes in efficiency in regions of India. The utilisation rate of oil refineries was found to be a positive and significant driver for refinery efficiency, representing that a higher utilisation rate of refineries increased operational efficiency. Moreover, distillate yield was found to be a positive and significant actor to explain variation in refinery efficiency, indicating that an increase in distillate yield also triggered higher operational efficiency. The variable operating costs were identified to be negative as well as the substantial driver for the refinery efficiency, which increases operating costs has reduced the OE of Indian oil refineries.

6.2 POLICY RECOMMENDATIONS

Operational efficiency is concerned with identifying wasteful resources and process that drains the profit of the organization. Firms with higher operational efficiency can minimize the cost, maximize the output, and thus operate under the profit maximization level of output. (E. F. Weston and J. F. Brigham, 1990). A perfectly competitive market is a market where competition is at its utmost level. The operational efficiency helps in gaining a higher market share and attain more profit with the intention to sustain competitiveness in the market (Amani, 2020).

To increase the oil refinery's GRM in the perfect market, operational efficiency is a tool to optimise the resources and enhance the GRM. The findings of this study can be successfully used to attain profit and improve efficiency in a competitive market. The study revealed that operational efficiency is a crucial factor for a refinery's GRM. For enhancing profitability and competitiveness, variety of recommendations were suggested for enhancing the refineries' operational efficiency and GRM:

- The refiner has to process the low-cost and low-grade crude oil to gain more profit, but processing this kind of crude is quite difficult with obsolete technology. The refiner has to focus on installing more secondary processes to process the low-grade crude oil, thus producing more value-added fractions from the refinery. Mostly, the public sector refineries are sharing a major percentage of the crude oil processing in India, but the complexity level of public sector refineries is lower than the private sector refineries. Moreover, the metallurgy of the existing pipelines should be changed to process high TAN (Total acid number) crude oil, this crude oil is an advantageous crude oil and having a low price. The processing of low-cost crude oil helps the increase refinery's GRM. Therefore, the Indian refineries have to augment the process technology during revamp project, so they can process sour crude effectively and generate more revenue.
- The Indian refiners should take measures to enhance complexity by adopting more secondary units as well as petrochemical complexes in the refinery to generate profit. The naphtha production in the Indian refinery is more surplus than the demand. Hence, surplus naphtha should be converted to petrochemicals for value addition by integrating refinery with petrochemical complex.
- The latest energy-efficient equipment is to be installed by the refineries to bring down the specific energy consumption and pulling more GRM. Further, the Indian refiners must study the overall site heat integration program and they should identify the area, where the energy can be optimized.
- The Indian refiner has to explore the new advanced technology and catalyst system capable of processing difficult feeds with higher Sulphur, Nitrogen, metals to produce more distillate cuts. Further, Indian refiner has to implement residue up-gradation projects, with resulting improvements in their distillate yield. Higher distillate fractions tend to have higher overall products' pricing and hence more gross refining margin. Therefore, policies to enhance distillate yield

will certainly increase the gross refining margin.

- The Indian refinery has to minimize the loss in the refinery. The perfect mass balance of the input and output of the refinery should be carried out and loss minimization strategies to be formed. The major loss in the refinery has occurred during unit start-up activity when flaring and draining activities are carried out until the unit is stabilized. Hence, the unplanned shutdown of the unit generates more loss, while starting it again. The availability and reliability of the unit is the key factor to minimize the refinery loss. Therefore, best operating and maintenance practices are to be implemented in the processing unit to improve the reliability and availability of the unit, which reduces the excessive use of resources and gives a competitive advantage.
- The refinery with higher fuel and loss augments the costs and reduces gross refining margin. Thus, there should be policy and technological intervention to minimize consumption of refined finished products of the refinery for internal consumption and losses in order to increase the GRM of refineries.
- It is required for paying attention to using energy as well as to reformulate the policy regarding the use of energy in the refinery. It is suggested to form policies to replace the existing fossil fuel-based energy source with the most competitive and cheaper renewable energy sources. That will reduce the production cost of the refinery and trigger operational performance.
- The Indian oil refineries need to import more crude oil to maximise capacity utilisation because it is not economical to run a refinery at low throughput.
- Apart from all these factors, the Indian refiners must take actions to enhance the economic performance by cultural and behavioral change.
- This study recommends introducing policies in India and the rest of the world to increase the technical efficiency of inefficient refineries by technological intervention and now it is the responsibility of concerned authorities to allow refineries for major technological intervention by providing grants to increase their efficiency.
- The findings and their suggested recommendation of this study help policymakers to improve policies towards the enhancement of operational efficiency by an efficient combination of technological,

economic and market tactics.

6.3 CONTRIBUTIONS TO THEORIES

Several studies (Tanja and Heikki, 1998; Almawsheki and Shah, 2015; Eller et al., 2011; Hokkanen, 2014; Diana et al., 2014) have utilized the production factors in the cost frontier model as well as in the production frontier model. The profit frontier model is been rarely utilized in certain empirical studies (Azadeh et al., 2015). Here, this study has utilized the profit frontier model in the context of oil refineries that were utilized for the first time for measuring the efficiencies of oil refineries. The profit frontier model provides maximum profit which can be accomplished at given input prices and output prices. The DEA measures the efficiency of the series of DMUs utilizing the linear programming models. The data envelopment theoretical model has not been used to measure the allocative efficiency and to identify the production frontier in Indian oil refineries. The contribution of the thesis comprises an efficient assessment using the DEA model over the existing methods followed by explaining the variation of the key determinants of profit frontier refinery. The liability of the firm was considered as one of the input variables in the DEA model. This variable has not been introduced and missing in the existing theoretical literature. Moreover, the gross refining margin variable is the unit that specifies the profit per unit of feed used in the organisation. This output variable is dynamic in nature and utilisation of it in the profit frontier model is the contribution of this thesis, where the profit frontier model is developed to measure the operational efficiency. Furthermore, the predominant features of the employed modeling applications were also analyzed. These theoretical implications of the DEA model in the context of the oil refineries of India are contributing to the field of theoretical knowledge by efficiency measurement.

6.4 CONTRIBUTIONS TO LITERATURE

Although the inferences of this study have been drawn from the collected data of oil refineries of India, this study offers contributions by delivering some primary analysis on refinery operation as well as finds the characteristics that might explain the variations on refinery OE. This study also provides valuable information to the refiner to reform policy toward efficiency improvement.

This study estimated gross refining margin as a dependent variable, which was overlooked in the existing literature. In addition, the fuel and loss of the refineries are never included in the existing literature to estimate the refinery profit. The findings of the results have contributed to the prevailing literature by the identification of key determinants of the GRM and explain their variation on the GRM.

Additionally, this study first time conducted the inefficiency assessment on the refinery sector. These kinds of assessments were never applied to the refinery sector in past literature. This assessment identified the inefficient refineries and suggested the improvement targets for each inefficient refinery. This valuable information is lacking in the existing literature on refinery efficiency. Furthermore, the inefficient assessments of inefficient refineries have been made by the projection of effective frontier with peer groups as well as suggesting some improved targets. Also, the study feels this existing gap and contributed by providing inputs for forming the policies as well as identifying some efficient strategies for making them more effective.

The study has made some contributions to literature reviews by illuminating the OE of the oil refineries in India as well as estimated the determinants of OE. Also, the findings might be implemented in refineries in various other countries.

6.5 LIMITATIONS OF THE RESEARCH

Although the findings of this study are found realistic and applicable in a practical manner, this study has certain limitations as described below:

- The data for greenhouse gas emissions from oil refineries are not available. Hence, this variable is not included in this study to understand its impact on gross refining margin.
- Secondly, this study was also limited by not opting variables, such as refinery running hours. The unwanted shutdown in the refinery and breakdown of the equipment reduces the total running hours of the refinery and impact the gross refining margin. The variable total

running hours is also useful in determining operational efficiency. Unfortunately, such important dimensions of refinery efficiency measurements could not be incorporated in this study.

- Moreover, the input and output data selected for this study are not available and not provided by the individual refinery of the public sector group companies, like IOCL, BPCL and HPCL. Hence, recommendations suggested can be implemented after properly completing the feasibility study for each refinery that comes under the public sector.
- In petroleum refineries, the practices used by the peer group's refineries are never identical and cannot be implemented directly without any feasibility study by inefficient refineries because of differences in complexity and configuration.

6.6 FUTURE SCOPE OF THE RESEARCH

Although a sincere effort has been made for this comprehensive study, still there will be scope for further research in this area:

- As an extension of this study, it might be useful to comprise the variable "greenhouse gas emission" of oil refineries to estimate the gross refining margin.
- In addition, refinery integrated with the petrochemical complex can also be included in the future study to see the variation in gross refining margin.
- It is better to identify the determinants of the operating costs in oil refineries and identify the variation of each variable with the operating costs. The results give great input to enhance the operational efficiency by minimising the input costs, keeping the same production with existing infrastructure.
- Moreover, instead of putting all refinery in one data set, the selection of the refinery can be done in different clusters considering the installed capacity or refinery complexity. The result obtained from the refineries of the same characteristics will give more precise recommendations to policymakers.
- The public sector and private sector refineries efficiency assessment should be done independently to get more appropriate, relevant and

feasible results.

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ANNEXURES

Annexure – A Results with data standardization

Table A-1 Pooled OLS, fixed effect and random effect estimators' result

Variables	Explanatory variables – Gross Refining Margin		
	Pooled Ordinary least square model	**Fixed effect model**	**Random effect model**
	Model – (1)	**Model – (2)**	**Model – (3)**
Refinery complexity	0.5774***	-0.0067	0.5774***
Specific energy consumption	0.2132**	0.0985	0.2132**
Distillate yield	0.1406	0.6674***	0.1406
Capacity Utilization	0.1292	0.2564**	0.1292
Fuel and Loss	-0.3260***	-0.2847	-0.3260***
Constant	2.98e-09	3.74e-09	2.98e-09
Observation	117	117	117
R2	0.3960	-	-
Adjusted R2	0.3688	-	-
R2- Within	-	0.3162	0.2027
R2- Between	-	0.1940	0.8050
R2- Overall	-	0.2067	0.3960
Wald chi2(5)	-	-	72.78***
F-test	2.55**		
Breusch-Pagan LM test for random effects	0		
Hausman Test	26.23***		

Note: The probability values in the square brackets are derived from the F-test, Breusch-Pagan LM test and Hausman test. The standard error values are shown in the parentheses. * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level.

Table A-2 FGLS and PCSE estimations

Variables	Explanatory variables – Gross Refining Margin	
	Feasible Generalized Least Squares	**Panel Corrected Standard Error**
	Model (4)	**Model (5)**
Refinery complexity	0.5774***	0.5774***
	(0.1018)	(0.1319)
Specific energy consumption	0.2132**	0.2132
	(0.0924)	(0.1879)
Distillate yield	0.1406*	0.1406**
	(0.834)	(0.0713)
Capacity utilisation	0.1292**	0.1292*
	(0.0769)	(0.0738)
Fuel and loss	-0.3260***	-0.3260***
	(0.0833)	(0.0933)
Constant	2.98e-09	2.98e-09
	(0.0715)	(0.1955)
No. of Obs.	117	117
R2	-	0.3960
Wald chi2(5)	76.71***	147.64***

Note: The standard error values are shown in the parentheses. * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level.

Data standardization is the procedure of fetching data into an even format that permits experts and others to examine and utilize the data. In statistics, standardization denotes to the procedure of putting dissimilar variables on the same scale so as to compare scores between different types of variables. Data standardization permits experts to examine the data and attain the decisive results from the dissimilar variables. Additionally, no change was observed in level of significance and direction of coefficients in this result when compared with results shown in Table 4-6.

Annexure – B Results with reducing the magnitude of GRM's unit

Table B-1 Pooled OLS, fixed effect and random effect estimators' result

Variables	Explanatory variables – Gross Refining Margin		
	Pooled Ordinary least square model	**Fixed effect model**	**Random effect model**
	Model – (1)	**Model – (2)**	**Model – (3)**
Refinery complexity	0.5311***	-00058	0.5311***
Specific energy consumption	0.0230**	0.0106	0.0230**
Distillate yield	0.0297	0.1408***	0.0297
Capacity Utilization	0.0191	0.0379**	0.0191
Fuel and Loss	-0.2721***	-0.2383	-0.2721***
Constant	-4.6635	-11.531	-4.6635
Observation	117	117	117
R2	0.3960	-	-
Adjusted R2	0.3688	-	-
R2- Within	-	0.3162	0.2028
R2- Between	-	0.1945	0.8050
R2- Overall	-	0.2070	0.3960
Wald chi2(5)	-	-	72.77***
F-test	2.55**		
Breusch-Pagan LM test for random effects	0		
Hausman Test	26.23***		

Note: The probability values in the square brackets are derived from the F-test, Breusch-Pagan LM test and Hausman test. The standard error values are shown in the parentheses. * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level.

Table B-2 FGLS and PCSE estimations

Variables	Explanatory variables – Gross Refining Margin	
	Feasible Generalized Least Squares	**Panel Corrected Standard Error**
	Model (4)	**Model (5)**
Refinery complexity	0.5215***	0.5311***
	(0.0455)	(0.1214)
Specific energy consumption	0.0160***	0.0230
	(0.0053)	(0.0203)
Distillate yield	0.0227***	0.0297**
	(0.0082)	(0.0150)
Capacity utilisation	0.0203***	0.0191*
	(0.0041)	(0.0109)
Fuel and loss	-0.2440***	-0.2721***
	(0.0344)	(0.0779)
Constant	-3.8327	-4.6635
	(0.8916)	(3.0959)
No. of Obs.	117	117
R2	-	0.3960
Wald chi2(5)	394.12***	147.68***

Note: The standard error values are shown in the parentheses. * indicates significance at 10% level, **indicates significance at 5% level, *** indicates significance at 1% level.

The magnitude of the GRM's unit was reduced by dividing each value of GRM by 1000. It has been done because the magnitude of GRM's unit is quite higher than the other independent variables and results into larger coefficient with independent variables. To reduce the coefficient's value in results, we need to reduce the magnitude of the GRM's unit by dividing with 1000. The new unit becomes 1000 units of the existing units i.e., '000Rs/MT. Additionally, no change was observed in level of significance, direction and magnitude of coefficients in this result when compared with results shown in Table 4-6.

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