Efficiency Analysis – Coastal Marine Engine

Briefing

Coastal Marine Engine, a marine diesel service and sales business based in Seattle, Washington underwent a change of ownership in 2018. Since acquiring the company, owner, Martin Anderson has implemented new policies and procedures resulting in substantial growth and increased profitability. With the company's recent expansion an examination of current processes was requested to provide insights to further refine these systems.

Data Processing Log (Page Six for Analysis)

Data manipulation and cleaning was conducted in RStudio to leverage the efficiency and accuracy of the R language. All data was collected and supplied by Coastal Marine Engine. Due to a system change, data availability is limited to data between January 2021 and December 2022. As the data was collected in house, it is believed to be accurate, complete and free of bias. Note: by nature of the design of the system, some labor efficiency data is self-reported and *may* demonstrate bias. Steps were taken to control for this during analysis.

Set up environment for data manipulation/cleaning

```r
install.packages("readxl")
install.packages("tidyverse")
install.packages("lubridate")
install.packages("stringer")

library(readxl)
library(tidyverse)
library(dplyr)
library(lubridate)
library(plyr)
```

Import raw datasets

```
coastal_df <- read_xlsx("Labor Efficiency Data 2022.xlsx")

employee_hours_df <- read.csv("employee_hours.csv")

opcode_translation <- read_xlsx("Op Code Listing Data 2022.xlsx")

commercial_designations <- read_xlsx("Commercial_Data.xlsx")
```

Examine the structure of raw data for dissimilarities. All data types appear synonymous between sets.

```
str(coastal_df_clean)
str(employee_hours_df)
str(opcode_translation)
str(comercial_designations)
```

Correct column names as dataset was exported incorrectly/Remove first row

```
coastal_df <- rename(coastal_df, c("Labor...1" = "Date"))

coastal_df <- rename(coastal_df, c("Labor...2" = "EmployeeNum"))

coastal_df <- rename(coastal_df, c("Technician" = "TechnicianName"))

coastal_df <- rename(coastal_df, c("Start" = "StartTime"))

coastal_df <- rename(coastal_df, c("Stop" = "StopTime"))

coastal_df <- rename(coastal_df, c("Labor...6" = "HoursWorked"))

coastal_df <- rename(coastal_df, c("Hours" = "HoursBilled"))

coastal_df <- rename(coastal_df, c("Work" = "WorkOrderNum"))

coastal_df <- rename(coastal_df, c("WO...9" = "WorkOrderType"))

coastal_df <- rename(coastal_df, c("Creation" = "CreationDate"))

coastal_df <- rename(coastal_df, c("Complete" = "CompetionDate"))

coastal_df <- rename(coastal_df, c("WO...12" = "Status"))

coastal_df <- rename(coastal_df, c("...13" = "OpCode"))

coastal_df <- rename(coastal_df, c("...14" = "Comments"))
```

```
coastal_df <- coastal_df[-c(1),]

employee_hours_df <- employee_hours_df[-c(1),]

comercial_designations <- comercial_designations[-c(1),]
```

Remove null rows and convert null HoursBilled to 0

```
coastal_df_clean <- coastal_df %>%
  filter(!is.na(Date))

employee_hours_df <- employee_hours_df %>%
  filter(!is.na(Total.Hours))

comercial_designations <- comercial_designations %>%
  filter(!is.na(Billing))

comercial_designations <- comercial_designations %>%
  filter(!is.na(Tax))
```

Replace NA values with 0 to allow for calculative operations

```
coastal_df_clean$HoursBilled[is.na(coastal_df_clean$HoursBilled)] <- 0
```

Add designation for Commercial/Leisure vessels

```
comercial_designations$Type <- ifelse(comercial_designations$`Work Order` == "USLNH"|
                                      comercial_designations$`Work Order` == "uslnh"|comercial_designations$Tax == "3"|
                                      comercial_designations$Tax == "5", "Commercial", "Liesure")

comercial_designations$Type <- comercial_designations$Type %>%
  replace_na("Liesure")
```

Remove non-technician personnel

```
coastal_df_clean <- coastal_df_clean %>%
  filter(TechnicianName != "Willow Yanarell") %>%
  filter(TechnicianName != "Richard Coe") %>%
  filter(TechnicianName != "Larry Lougheed") %>%
  filter(TechnicianName != "Scottwell Callo") %>%
  filter(TechnicianName != "Mike Bock") %>%
  filter(TechnicianName != "Justin Coulter") %>%
  filter(TechnicianName != "Adjustment Tech") %>%
  filter(TechnicianName != "Martin Anderson")
```

```r
employee_hours_df <- employee_hours_df %>%
  filter(Employee != "WILLOW YANARELLA") %>%
  filter(Employee != "RICHARD COE") %>%
  filter(Employee != "LARRY LOUGHEED") %>%
  filter(Employee != "SCOTTWELL CALLOWAY") %>%
  filter(Employee != "MIKE BOCK") %>%
  filter(Employee != "JUSTIN COULTER") %>%
  filter(Employee != "ADJUSTMENT TECH") %>%
  filter(Employee != "AMANDA QUINN") %>%
  filter(Employee != "BRITTNEY NEWTON") %>%
  filter(Employee != "JORDAN HARMANING") %>%
  filter(Employee != "JULIO SOTELOAGUILAR") %>%
  filter(Employee != "NICK GUNTHER") %>%
  filter(Employee != "ROBERT ELLIS") %>%
  filter(Employee != "Total Hours")
```

Remove Jobs that are still open as they will impact accuracy of worked/billed analysis

```r
coastal_df_clean <- coastal_df_clean %>%
  filter(Status == "C")
```

Modify datatypes for easier analysis

```r
coastal_df_clean$Date <- as.POSIXct(coastal_df_clean$Date, format="%m%d%y")
coastal_df_clean$StartTime <- as.POSIXct(coastal_df_clean$StartTime, format="%H:%M:%S")
coastal_df_clean$HoursWorked <- as.numeric(coastal_df_clean$HoursWorked)
coastal_df_clean$HoursBilled <- as.numeric(coastal_df_clean$HoursBilled)
```

Remove hours worked/billed less than 0

```r
coastal_df_clean <- coastal_df_clean %>%
  filter(!HoursWorked < 0)
```

Add Column for difference between hours worked and billed

```r
coastal_df_clean$HoursLost <- coastal_df_clean$HoursWorked - coastal_df_clean$HoursBilled
```


Add Column for difference between hours worked and billed

```r
coastal_df_clean$HoursLost <- coastal_df_clean$HoursWorked - coastal_df_clean$HoursBilled
```

Add column for paid time off (Holiday, sick, vacation)

```
employee_hours_df$OffTime <- employee_hours_df$Holiday + employee_hours_df$Sick..Hourly +
  employee_hours_df$Vac..Hourly.1.3 + employee_hours_df$Vac..Hourly.4.5 + employee_hours_df$Vac..Hourly.5.
```

Create individual datasets for employees

```
hours_Worked_df <- aggregate(coastal_df_clean$HoursWorked, list(coastal_df_clean$TechnicianName), FUN=sum)
hours_Worked_df <- rename(hours_Worked_df, c("Group.1"="Employee"))
hours_Worked_df <- rename(hours_Worked_df, c("x"="HoursWorked"))
hours_Worked_df$Employee <- toupper(hours_Worked_df$Employee)


hours_Worked_df$Employee <- gsub("BOBBY MURPHY", "ROBERT MURPHY", hours_Worked_df$Employee)
hours_Worked_df$Employee <- gsub("AARON KALOUSTIA", "AARON KALOUSTIAN", hours_Worked_df$Employee)
hours_Worked_df$Employee <- gsub("FERNANDO SORIA", "FERNANDO SORIA MOLINA", hours_Worked_df$Employee)
```

Create individual dataset for hour calculations

```
hours_clocked <- aggregate(employee_hours_df$Total.Hours, list(employee_hours_df$Employee), FUN=sum)
hours_clocked <- rename(hours_clocked, c("Group.1"="Employee"))
hours_clocked <- rename(hours_clocked, c("x"="HoursClocked"))

hours_off <- aggregate(employee_hours_df$OffTime, list(employee_hours_df$Employee), FUN=sum)
hours_off <- rename(hours_off, c("Group.1"="Employee"))
hours_off <- rename(hours_off, c("x"="HoursOff"))
```

Combine employee and hourly datasets

```
hour_comparison_df <- join(hours_Worked_df, hours_clocked, type = "inner")
hour_comparison_df <- join(hour_comparison_df, hours_off, type = "inner")
```

Create column for calculation of unaccounted hours. Deduct HoursOff to ensure accuracy.

```
hour_comparison_df$Discrepancy <- hour_comparison_df$HoursClocked - hour_comparison_df$HoursWorked
hour_comparison_df$Discrepancy <- hour_comparison_df$Discrepancy - hour_comparison_df$HoursOff
```

create new dataset of translated opcodes as opcodes changed and translations for earlier codes are not available.

```r
opcode_slim <- coastal_df_clean

opcode_slim <- opcode_slim %>%
  filter(!is.na(OpName))
```

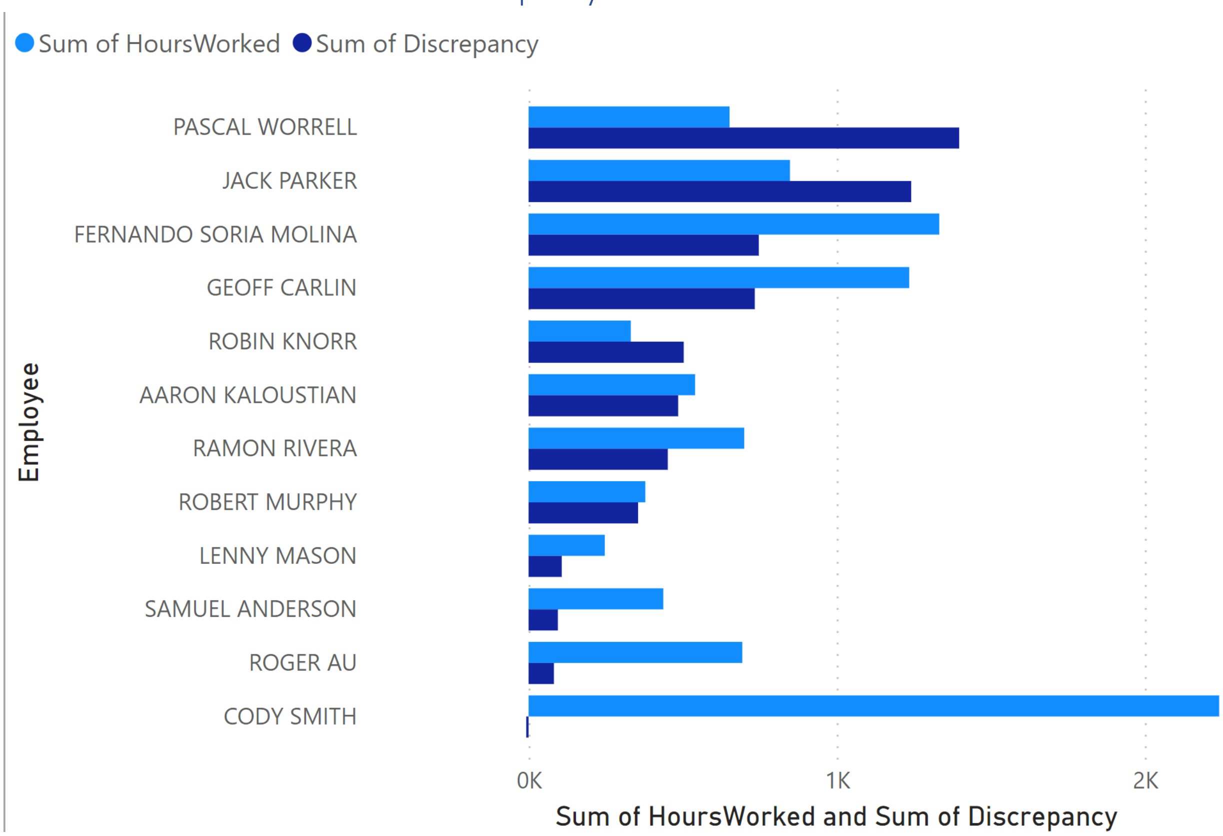
Export data for analysis/visualization in Power BI

```r
write.csv(coastal_df_clean, 'coastal_clean.csv')
write.csv(hour_comparison_df, 'hours_comparison_clean.csv')
write.csv(opcode_slim, 'opcode_slim_clean.csv')
write.csv(commercial_designations, 'commercial_clean.csv')
```

Analysis

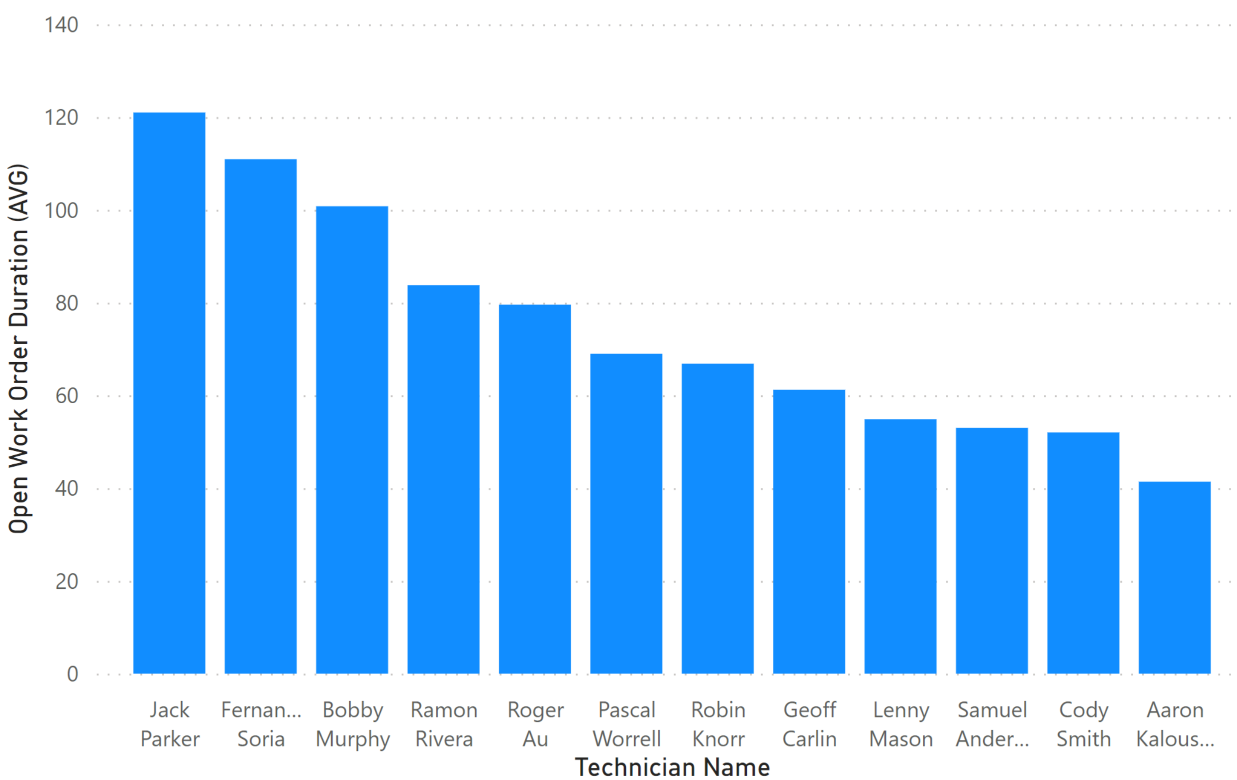
This initial analysis focuses on three primary components; labor efficiency, commercial vs. leisure, and impact of inventory on processes. In addition to the findings in this report, there are several identifiable data practices that could be advantageous to the business and would greatly improve the specificity of future analyses. Those practices are outlined below.

Technician Accountable Hours Discrepancy



An examination of technician hourly accountability illustrates a discrepancy between **hours worked** (the sum of hours technicians have logged to workorders or opcodes through the Dock Master system) in light blue, and **discrepancy hours** (the sum of hours in which a technician is clocked in via Quickbooks Time and unaccounted for via a workorder or opcode) dark blue. Sick, vacation, and holiday hours have been normalized to ensure accuracy. Pascal Worrell and Jack Parker represent stark discrepancies with approximately 100% and 50% more hours unaccounted for than those that are, respectively. My initial assumption was that there was a systemic factor that would account for these discrepancies, however Cody Smith demonstrates otherwise. With both the highest number of hours worked of any technician and with every on-the-clock hour accounted for in the system, he disproves my suspicions of a systemic root to these differences. Additional data/a conversation with the business owner may provide further insights.

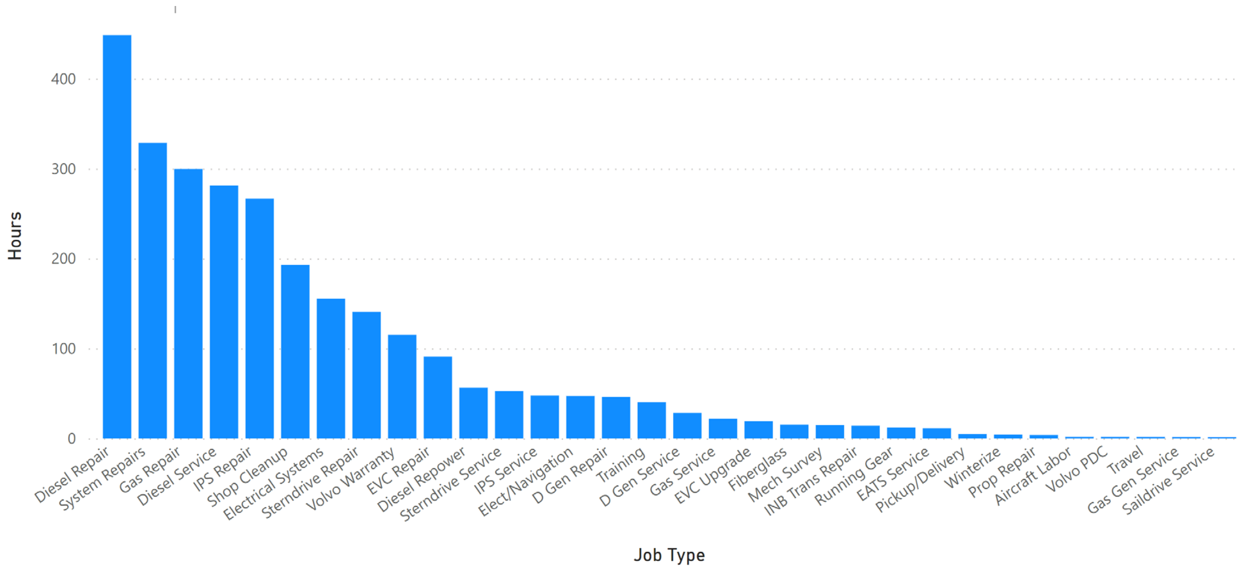
Work Order Duration by Technician



Open workorder duration isn't in and of itself a strong metric for technician assessment. Given the variable complexity of different job types (opcodes) and the variable distribution of job types among technicians, it is expected that certain technicians will consistently be assigned to more or less complex tasks. It is notable however that the extremes of this chart mirror the *Accountable Hours Discrepancy* chart (page 1) despite **Open Work Order Duration** hours having a negative correlation to **Discrepancy Hours** (Accountable Hours Discrepancy chart, above). Jack Parker and Fernando Soria continue to define the upper 25%, and Cody Smith and Samuel Anderson the lower 25%.

Note: The data provided does not account for the duration impact of office personnel. It is assumed for this analysis that the impact of workorder closure processes for office personnel will average across all technician personnel.

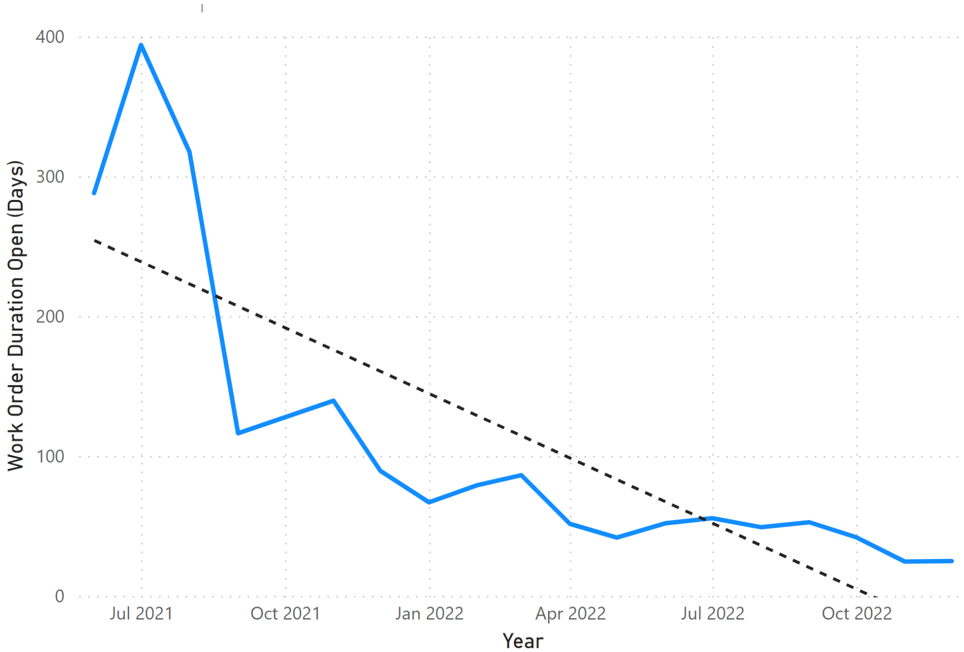
Hourly Allocation by Job Type Company Wide



The **company wide** labor allocation chart illustrates five job types(opcodes), diesel repair, system repair, gas repair, diesel service, and IPS repair account for nearly 60% of all logged hours within the company. Importantly, opcodes were recently changed/updated, and the subsequent visualization is a reflection of an ~6 month subset of the data. An analysis of this data in the future would reflect a more appropriately sized sample.

Graphs are provided for individual technicians at the end of this report. These visualizations serve to outline the labor usage by job type for each employee.

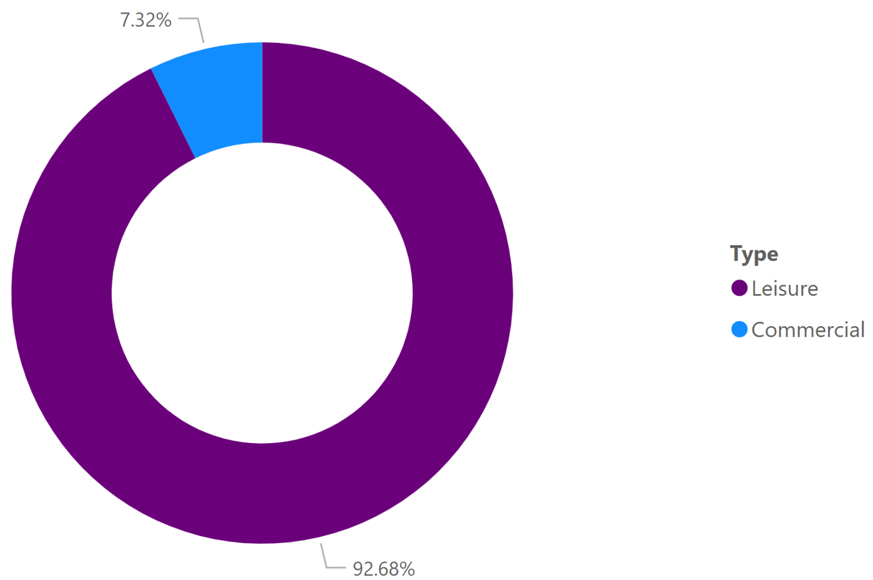
Work Order Duration Across Time



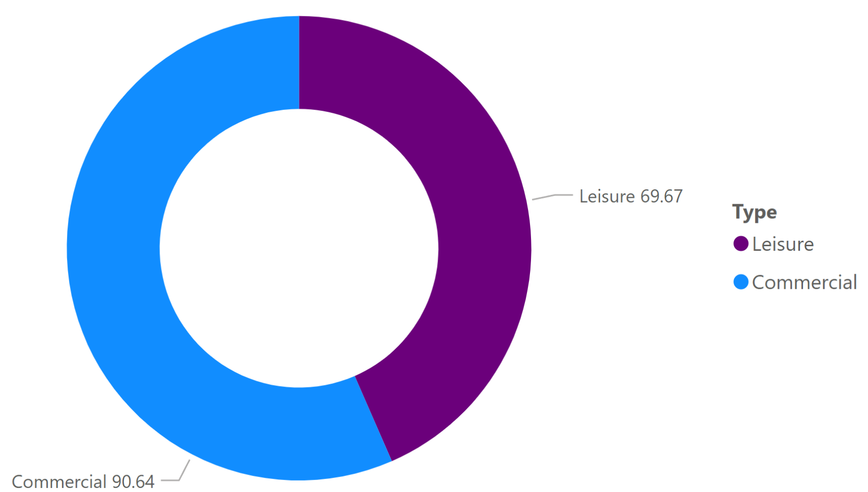
Dramatic improvements have been made in work order closure rates. Peaking in July 2021, workorder duration has decreased an average of 15% per quarter, with the largest improvement taking place between august 2021 and September 2021, a duration reduction of 64%.

It is important to note that workorder closure rates are a reflection of both technician rate of completion as well as office personnel's rate of closure, indicating a companywide improvement in processes.

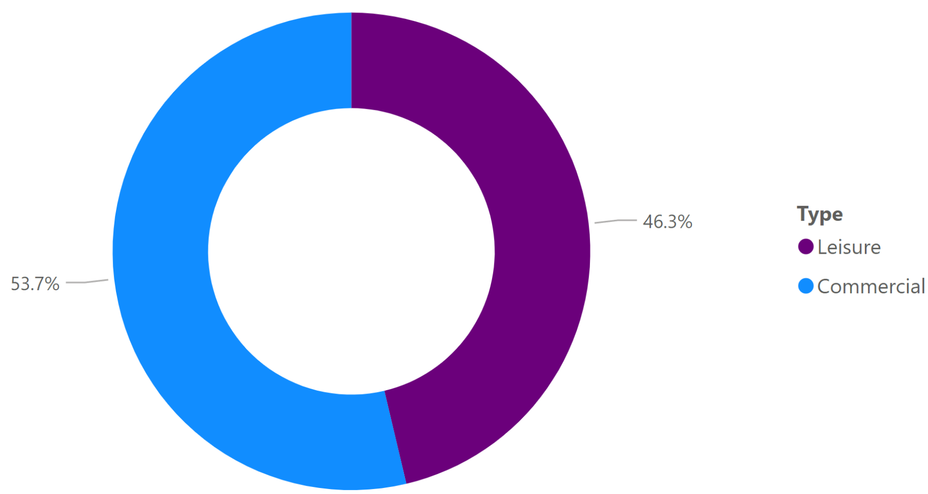
Number of Workorders (Commercial vs. Leisure)



AVG. Workorder Duration (Commercial vs. Leisure)

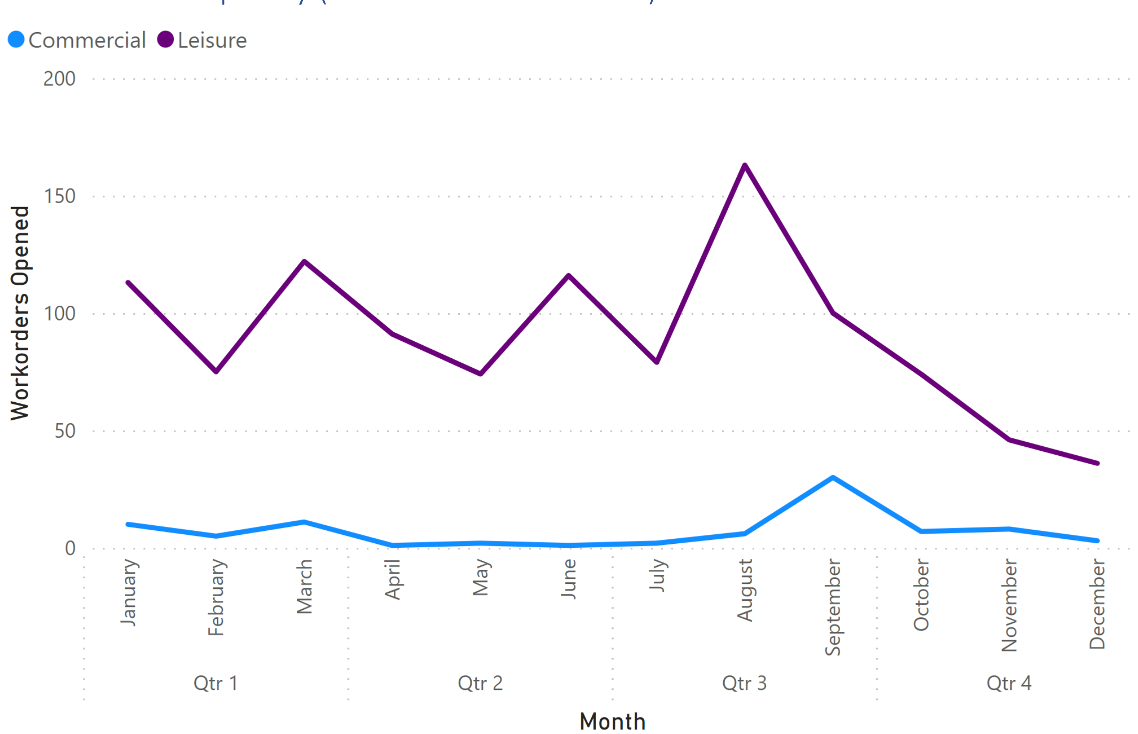


AVG. Hours Billed (Commercial vs. Leisure)



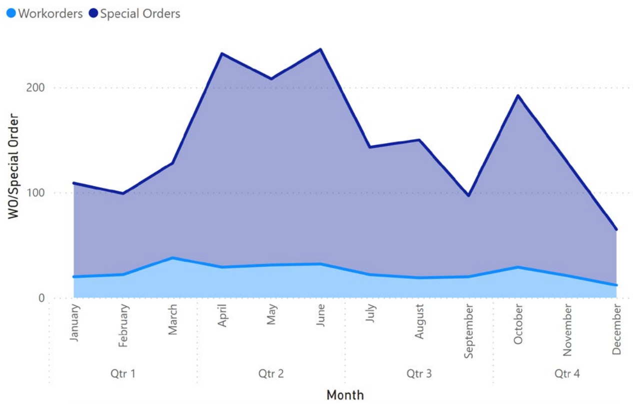
While workorders for leisure vessels far outnumber those for commercial vessels (~92%), the average workorder duration for commercial vessels was 23% higher than those for leisure vessels. Subsequently, billable hours averaged 14% higher for commercial workorders than leisure. Additional revenue opportunities may exist in commercial-centric marketing.

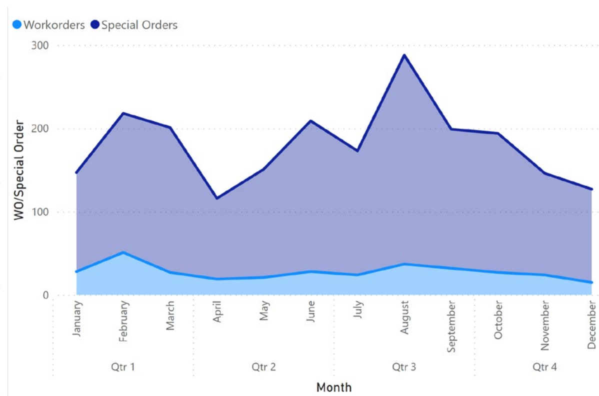
Workorder Frequency (Commercial vs. Leisure)



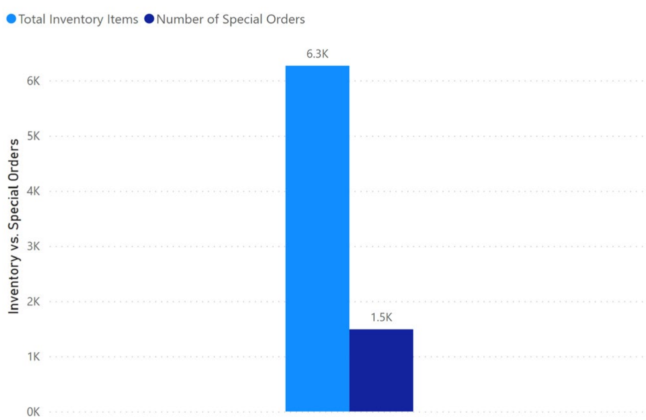
The month of September represented a notable spike in commercial workorders, with four times the annual average. This increase is likely an indication of a reduction of seasonal commercial activity but should not be discounted in commercial marketing considerations. This commercial spike coincides with a declination in leisure workorder creation, likely too an artifact of the transition into the holiday season with November and December representing an ~50% reduction of the annual average.

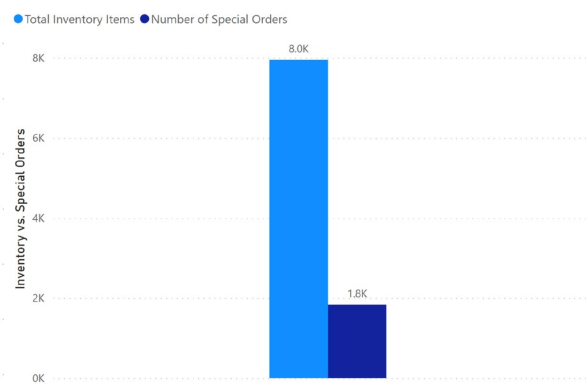
Workorder vs Special Order 2021 2022





Inventory vs Special Order 2021 2022





An analysis of inventory efficiency was conducted in two ways; an examination of the relationship between the rate of special orders and number of workorders created as well as an examination of the relationship between the rate of special orders and total inventory on hand. Both of these examinations suggest an improvement in special order rates, albeit a negligable one (~1%).

It is important to note that the data pertaining to improvements in inventory capacity (the largest contributing datapoint for special order reduction) was very limited, as inventory expansion only occoured three months prior to this analysis. Future analyses would provide a more accurate representation of the impact of inventory expansion.

Conclusions

Technician Data

For any business owner, information is a powerful tool. Understanding where and how your labor dollars are being spent provides insights for refinement and improvement. Currently 39% of all technician hours are unaccounted for or otherwise untracked within the Dock Master system. There is a tremendous opportunity to better examine and improve upon labor efficiency through stricter adherence to the already-instantiated opcode logging system. An expectation of **no more than a 15% discrepancy** would account for more than **two thousand labor hours annually**, or at an estimated hourly rate of $33/hr. **$66,000 per year** in labor dollars, or **$338,000** in prospective revenue based on a shop rate of $169/hr. As exemplified by technician Cody Smith, this is not an unrealistic expectation.

Commercial Opportunities

Several metrics indicate the company is well poised to capitalize on growth in the commercial market. With an average of %14 more billable hours on commercial workorders, there is no question as to the profitability of these accounts. An impressive reduction in workorder turnaround is a key metric in meeting the expectations of these customers as they often have a narrow service window. The addition of rapid response via aircraft is a particularly attractive option for commercial customers willing to pay a premium for further expedited service. Marketing strategies should take into account the notable increase in commercial workorders in the month of September.

Inventory/Process Efficiency

While this report demonstrated little improvement in rates of Special Orders, the workorder closure improvements should not be overlooked as an indication of potential inventory/process improvement. Of all of the components within this report, none would benefit more from a larger sample size than the examination of inventory's impact on efficiency. Given that inventory improvements were made only months before this analysis, an identical examination of 2023's data would be more adequately supported by an appropriate sample size.

Considerations for Future Analyses

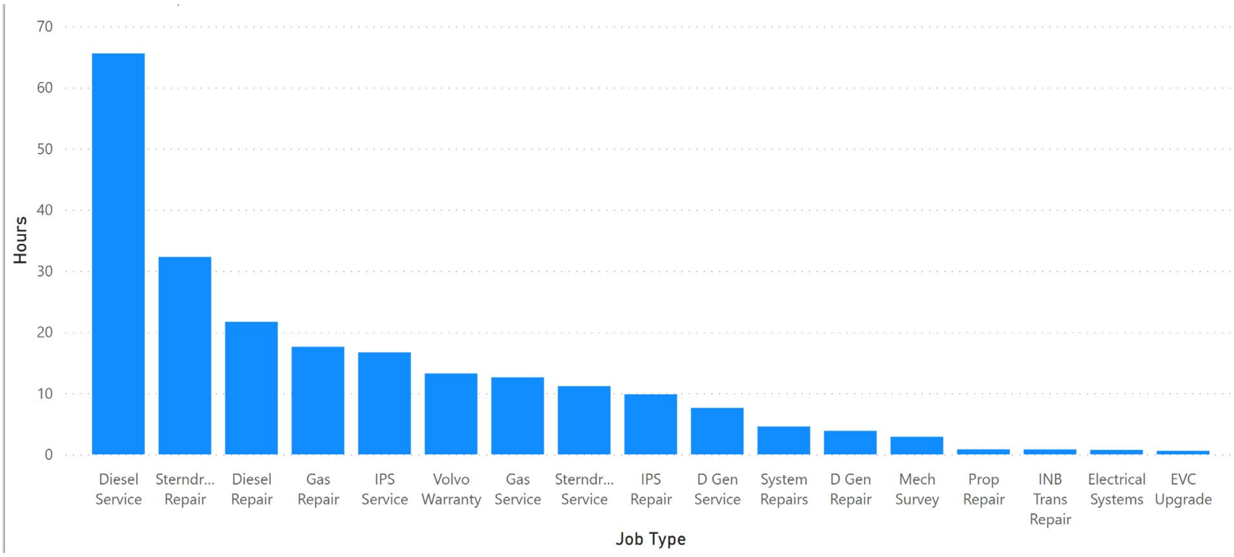
There were several limitations within the available data that posed challenges. As previously mentioned, inventory improvement data was well below the threshold of reasonable sample size.

Improvements to technician logging adherence will result in a much larger body of actionable data.

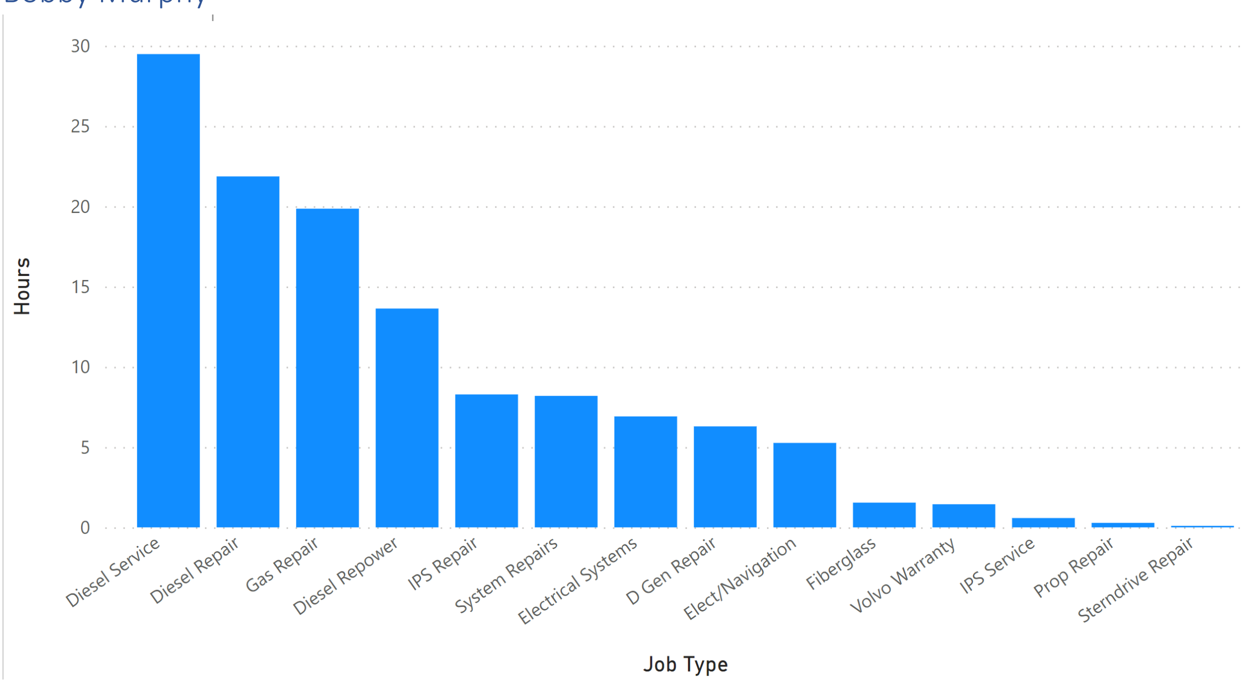
System logging of the original technician on any workorders where rework is being conducted will allow for analysis of technician efficacy and improved insights into training opportunities.

Marketing data (date of published ads, ad target, publication name, etc.) will allow for an examination of advert effectiveness.

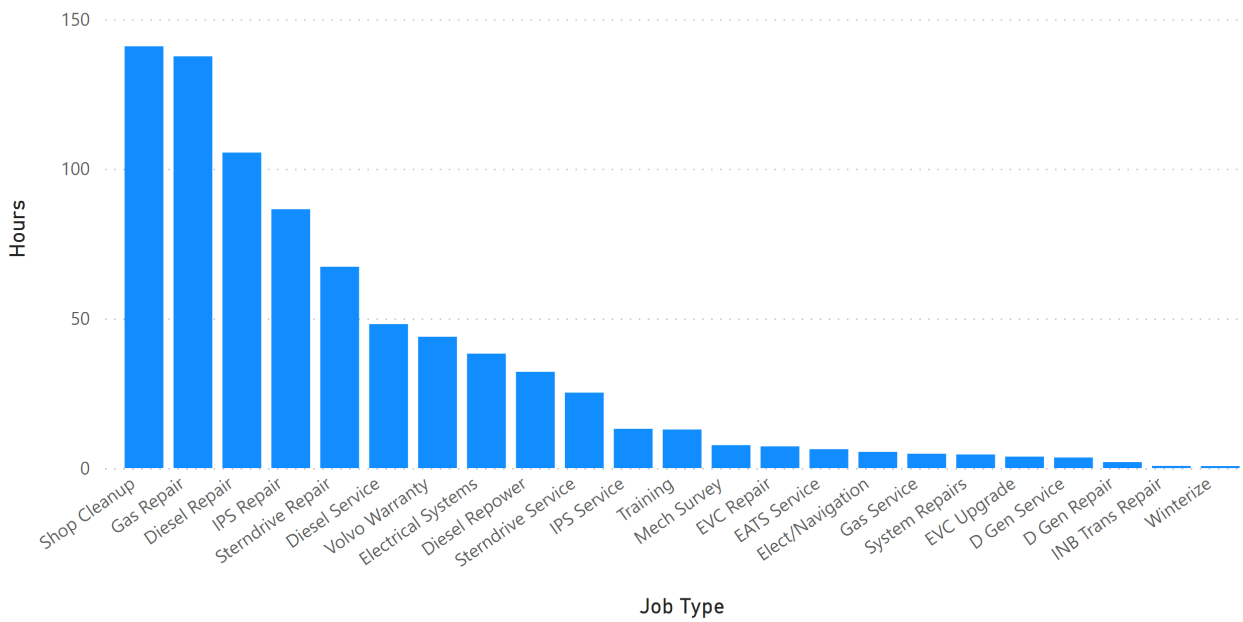
Aaron Kaloustia



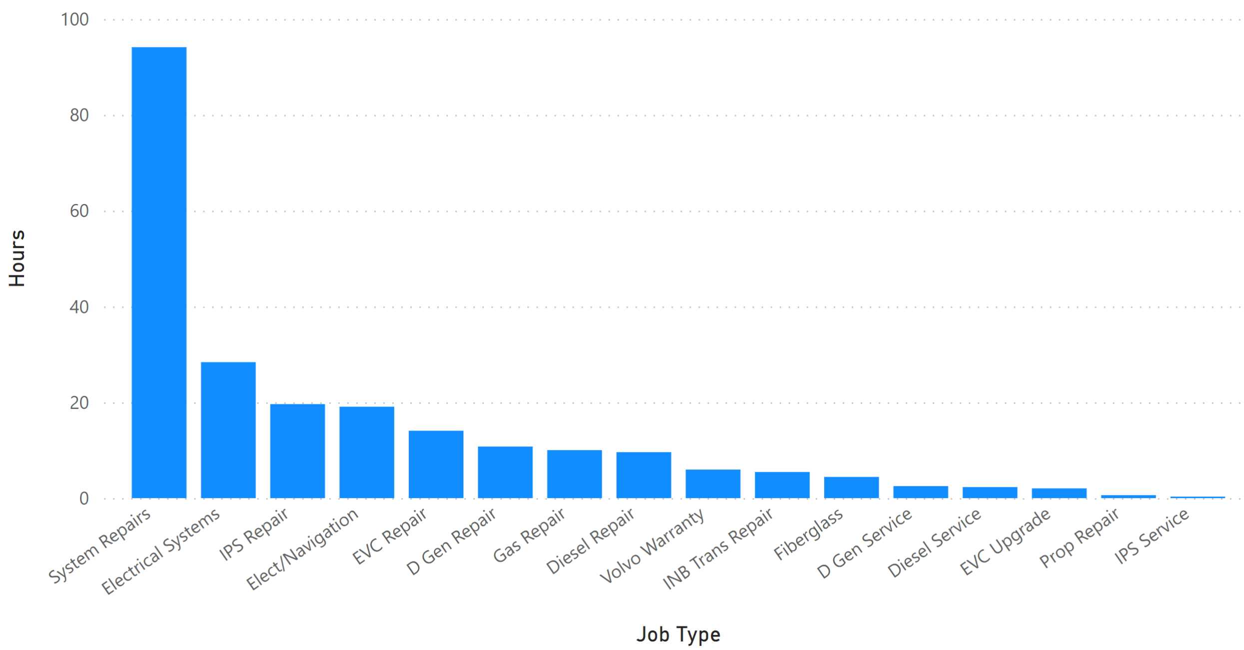
Bobby Murphy



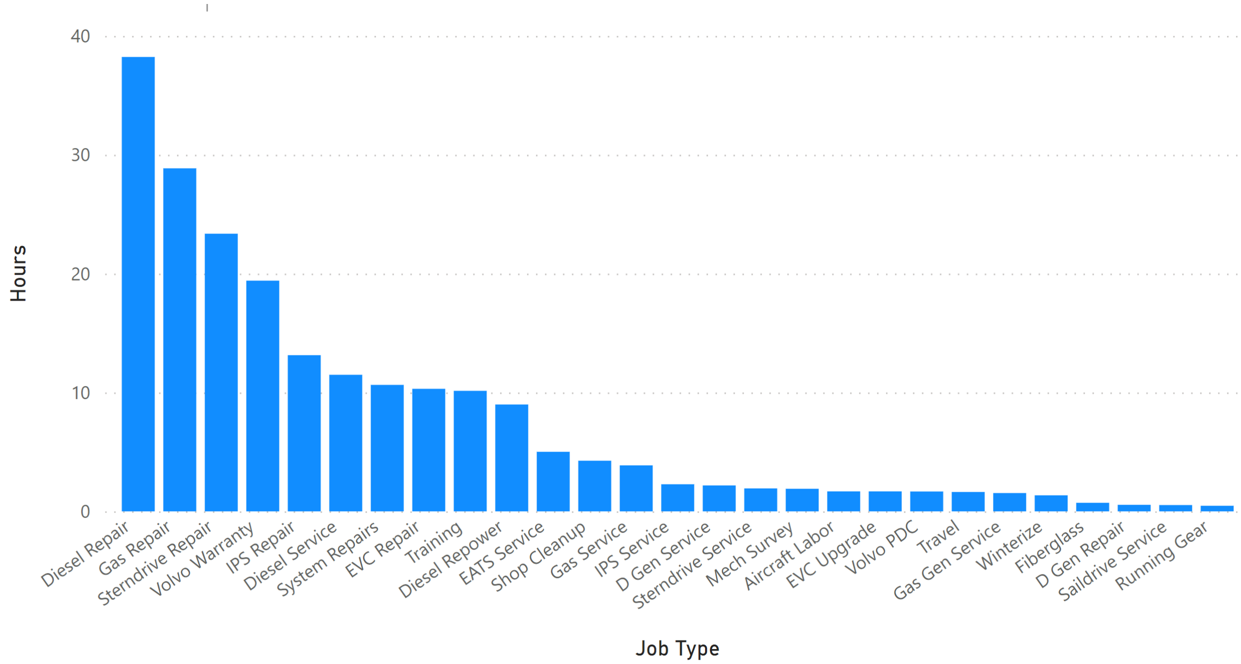
Cody Smith



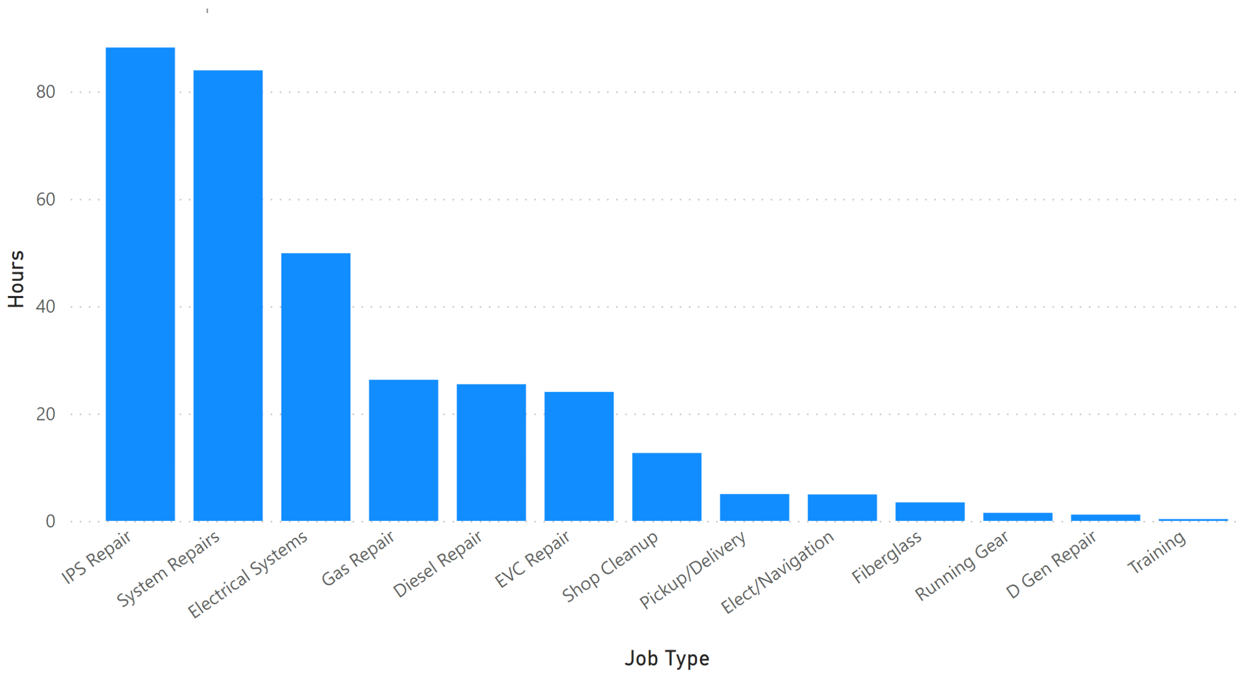
Fernando Soria



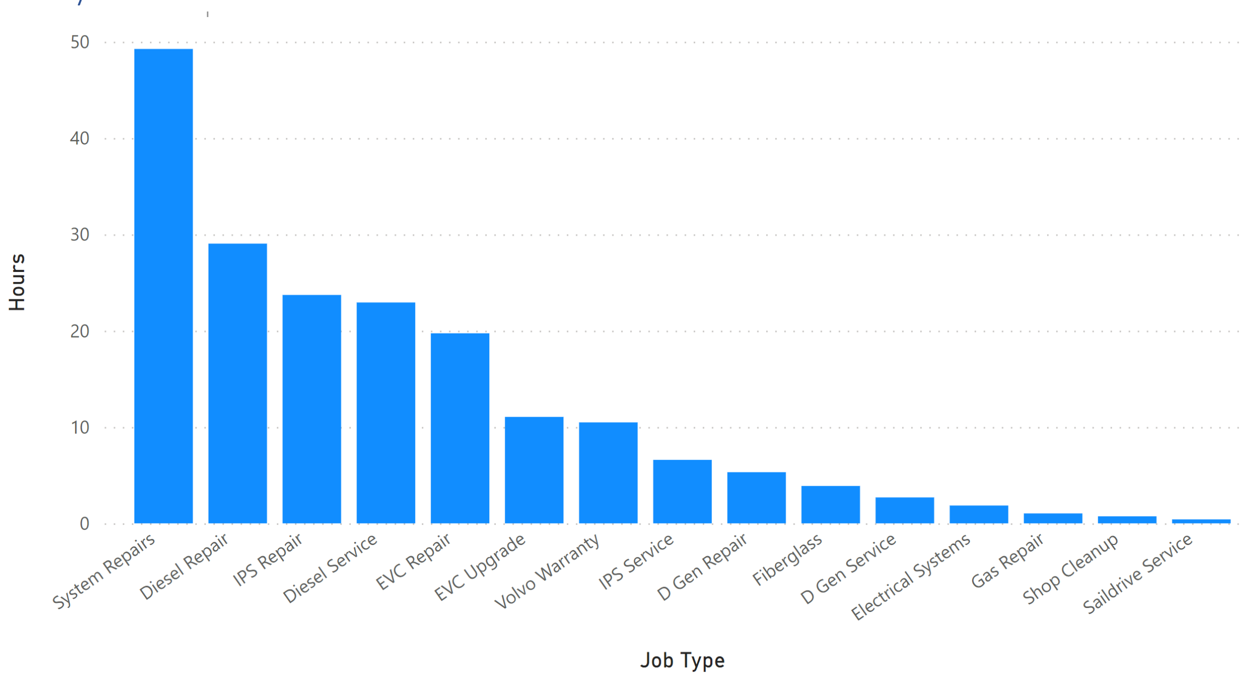
Geoff Carlin



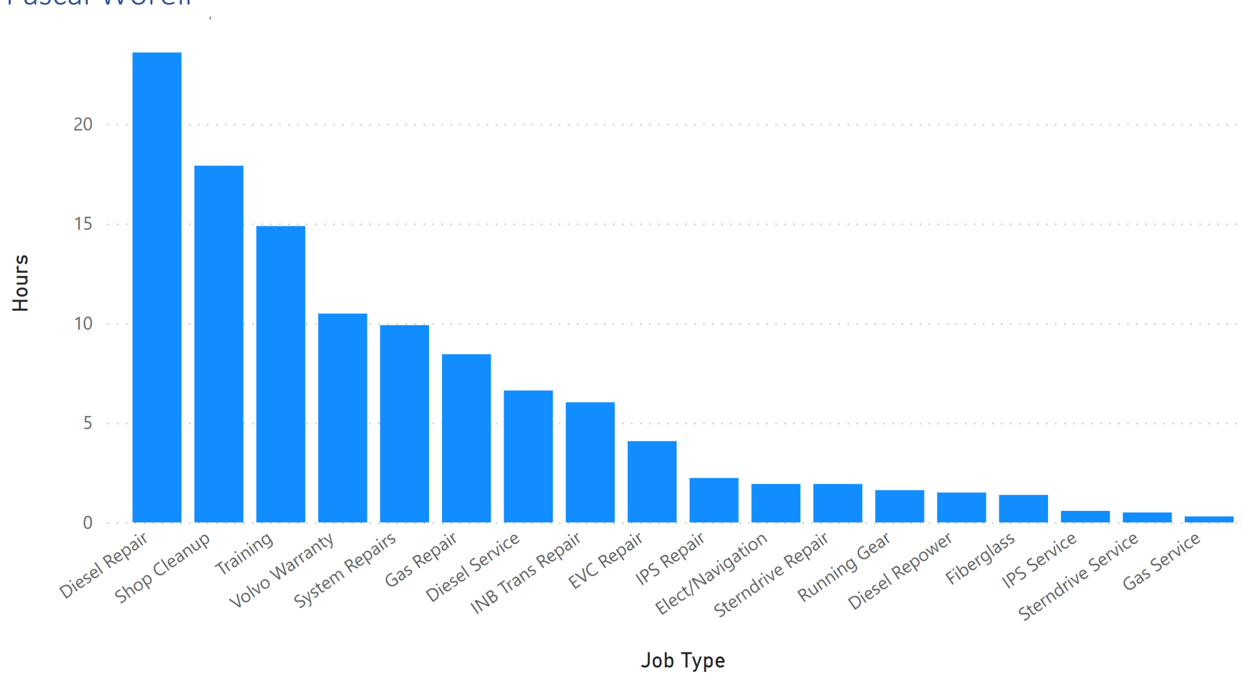
Jack Parker



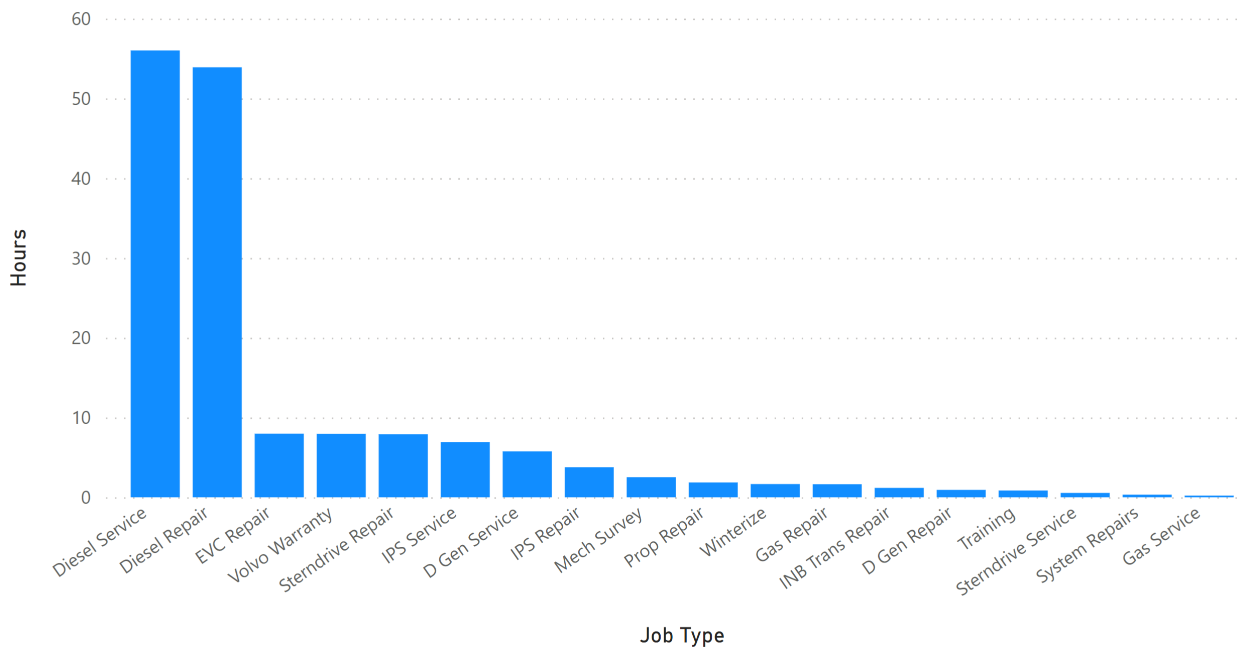
Lenny Mason



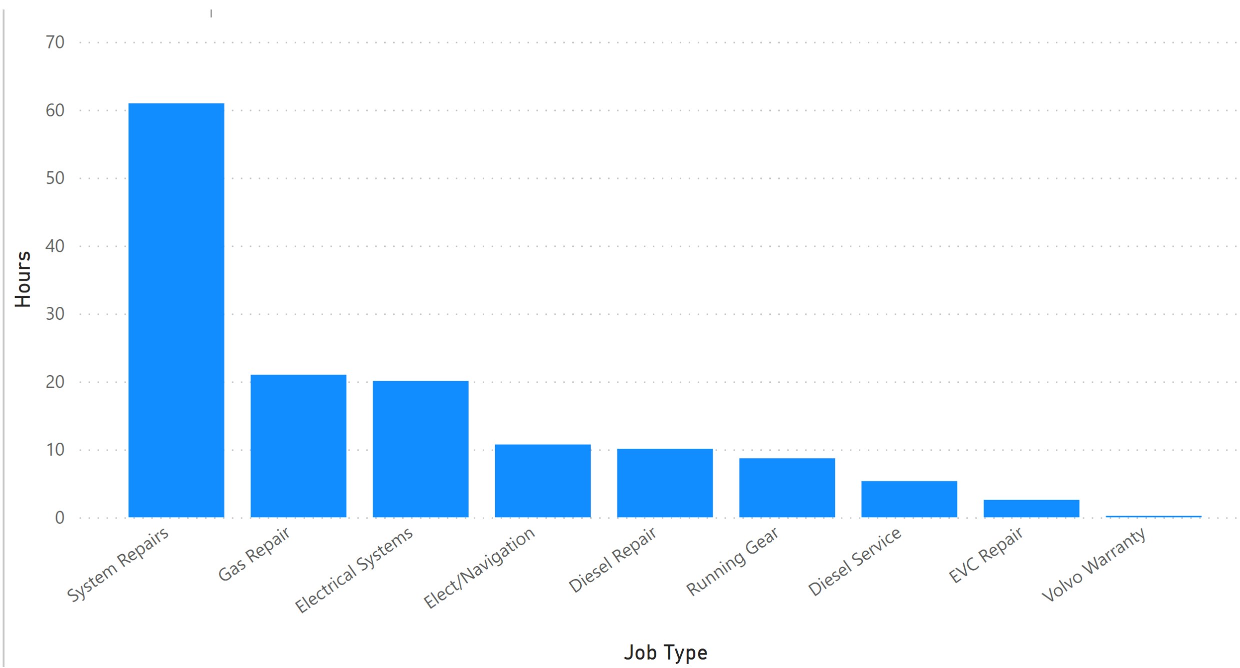
Pascal Worell



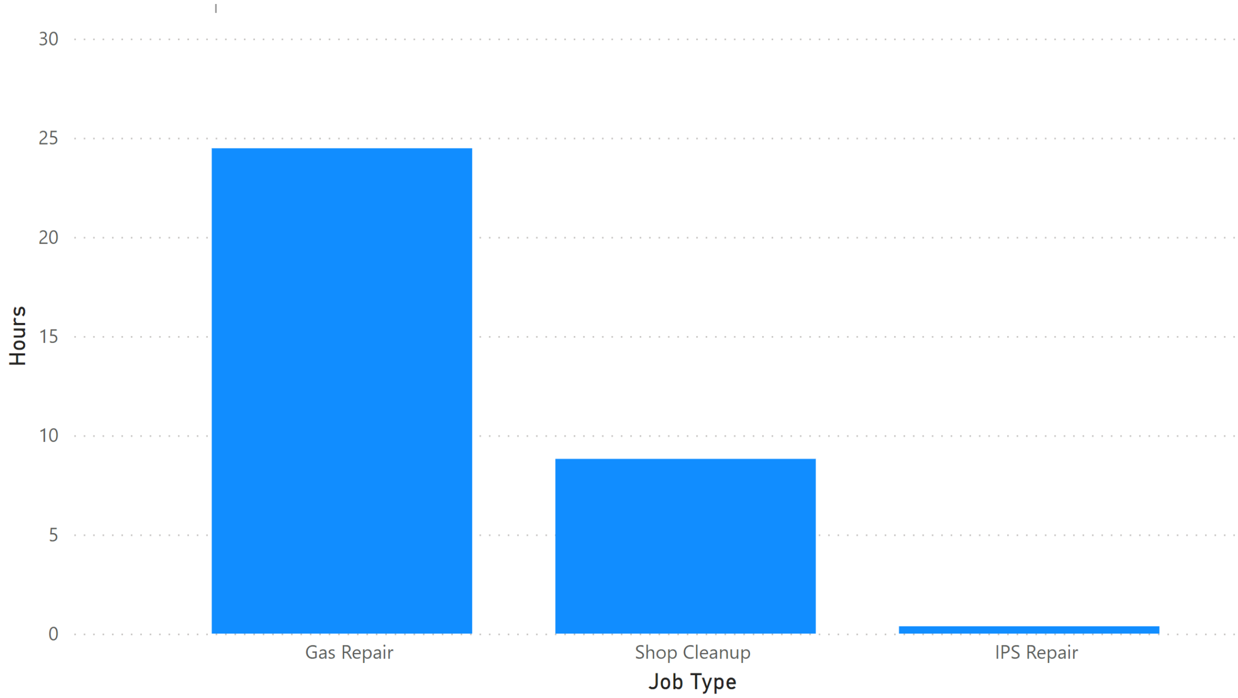
Ramon Rivera



Robin Knorr



Roger Au



Samuel Anderson