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SURFACE SHIP SAFETY PREDICTIVE ANALYSIS

by

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SURFACE SHIP SAFETY PREDICTIVE ANALYSIS

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This research seeks to find root causes of Class A or B mishaps in Navy surface ships in order to identify ships at risk for future mishaps. Additionally, by looking at data from ships that experienced mishaps between 2012 and 2017, and by searching beyond the root cause of specific causal factors for these incidents, we may be able to determine if indicator variables could have predicted the ships were at risk. We explored the LHD, LPD (*San Antonio* Class), and CG ship classes, as these classes experienced the most mishaps between 2012 and 2017. We used linear regression, descriptive statistics, time-series analysis, and data optimization as the primary methods to examine our collected data. We implemented a reverse-forecasting, or "backcasting," approach to correlate variables to LHD, LPD, and CG class ships that experienced a Class A or B mishap in the studied years. We were unable to identify a correlation in the numerous data sets. Small amounts of correlation were found in the data models, but nothing statistically significant that would help predict future mishaps.

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LIST OF ACRONYMS AND ABBREVIATIONS

3-M	Maintenance and Material Management
ATG	Afloat Training Group
CASREP	Casualty Report
CAC	Common Access Card
CG	Ticonderoga-Class Cruiser
COMLANTFLTINST	Commander, Naval Surface Force, Atlantic Instruction
COMPACFLTINST	Commander, Naval Surface Force, Pacific Instruction
COMNAVSEASYSCOM	Commander, Naval Sea Systems Command
COMNAVSEAINST	Commander, Naval Sea Systems Command Instruction
COMNAVSURFLANT	Commander Naval Surface Force, Atlantic
COMNAVSURFPAC	Commander Naval Surface Force, Pacific
CO	Commanding Officer
COMFLTFORCOMINST	Commander, United States Fleet Forces Command Instruction
DoD	Department of Defense
DFS	Departure from Specification
HFACS	Human Factors Accident Classification System
IFOM	Board of Inspection and Survey (INSURV) Figure of Merit
INSURV	Board of Inspection and Survey
INSURVINST	Board of Inspection and Survey Instruction
JFMM	Joint Fleet Maintenance Manual
LHD	Wasp-Class Amphibious Assault Ship
LPD	San Antonio-Class Amphibious Transport Dock Ship
MFOM	Maintenance Figure of Merit
NEURS	Navy Energy Reporting System
NSWC	Naval Surface Warfare Center
OPNAVINST	Chief of Naval Operations Instruction
OPTEMPO	Operating Tempo
PERS-41	Surface Warfare Officer Personnel Department

TYCOM	Type Commander
UAV	Unmanned Aerial Vehicle

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I. INTRODUCTION

This research sought to provide a predictive tool to identify ships at risk of Class A and B mishaps based on current inspections, certifications, assessments, visits or other current events and incidents onboard a ship that might help identify ships at risk for future mishaps. We examined a number of variables to include casualty report counts, casualty report durations, departure from specifications report counts, timing of critical billet changes, safety assessment scores, Board of Inspection and Survey (INSURV) inspection results, steaming hours as a measure of operating tempo (OPTEMPO), and duration of maintenance availability periods as a measure of OPTEMTO, each of which may prove to contribute toward the manifestation of a mishap. This research focused on the Wasp-Class Amphibious Assault Ship (LHD), San Antonio-Class Amphibious Transport Dock Ship (LPD), and Ticonderoga-Class Cruiser (CG) with the hopes of potentially extending to additional ship classes. By analyzing the data from ships that have experienced mishaps and by going beyond root cause of specific causal factors for that incident, we may be able to determine the relationship of numerous indicator variables that may have predicted the ship was at risk.

A. BACKGROUND

The military takes precautions to minimize risk in all activities. Guidance for investigation of Navy and Marine Corps mishaps is defined in the Chief of Naval Operations Instruction (OPNAVINST) 5102.1D CH-2 signed 2010. Our research focused on mishaps that have occurred for a select set of ship classes from 2012–2017. Mishaps are classified by severity (A, B, C) and may change as additional information is gathered throughout the investigation process. OPNAVINST 5102.1D CH-2 provides the official definitions of all three classes of DoD Mishaps.

> The definition of a Class A mishap is when total cost of damages to Department of Defense (DoD) or non-DoD property is an amount of $2 million or more; a DoD aircraft is destroyed; or an injury and/or occupational illness result in a fatality or permanent total disability. A

> Class ‘B’ mishap results in a total cost of damages to DoD or non-DoD property of $500,000 or more, but less than $2 million; an injury and/or occupational illness resulting in permanent partial disability or when three or more personnel are hospitalized for inpatient care (beyond observation) as a result of a single mishap. A Class ‘C’ mishap results in a total cost of damages to DoD or non-DoD property of $50,000 or more, but less than $500,000; or an event involving one or more DoD personnel that results in one or more days away from work. (Department of the Navy, 2010, p. 2-1)

The mishaps investigated for this research include government property damage (shipboard equipment) and personnel injury. As our research progressed, one element of data that was identified as a potential factor in mishap correlation was Casualty Reports (CASREP) for a given command. The Navy’s current CASREP guidance is directed in the Commander, Naval Surface Forces Pacific/Commander, Naval Surface Forces Atlantic (COMNAVSURFPAC/ COMNAVSURFLANT) Instruction 3040.2 from 2013. The purpose of a CASREP is to report an equipment degradation to the operational commander that will impact readiness. CASREPs are classified in three categories (C-2, C-3, and C-4) to differentiate the severity. C-4 is the most severe while C-2 is the least severe. The guidance on classification can be found in OPNAVINST 5513.3C. C-4 CASREPS must be updated every 72 hours, C-3 updates occur every 10 days, C-2 updates not to exceed 30 days (Department of the Navy, 2013). Reporting CASREPs and equipment casualties are very important for making sure the ship gets the attention needed and repairs conducted in a timely manner. For the purpose of our research, we looked very closely at the number of CASREPs a specific unit had in all categories of severity leading up to the mishap. We also attempted to determine if there was an increasing trend or spike in number submitted. In addition to CASREP counts we also examined CASREP duration. CASREP duration was the cumulative number of hours each CASREP was open for a particular month. For example, if a ship had ten CASREPs in a month for ten hours each, then the total CASREP duration for that month would be 100 hours. Once a CASREP is closed it is no longer updated and does not contribute to the

CASREP duration for that particular month. CASREP duration numbers were also separated by CASREP category.

Another critical piece of data that was recommended for review was Departure from Specifications (DFS). The Joint Fleet Maintenance Manual provides us with the US Navy's definition of DFS.

> Specifications are engineered requirements such as type of materials, dimensional clearances, vibration levels, flow rates, and physical location in which ship components are installed, tested, and maintained. All ships are designed and constructed to specific technical and physical requirements and it is imperative that every effort be made to maintain all ship systems and components to their designed specifications. (Department of the Navy, 2017, p. V-1-8-1)

On occasion these specifications cannot be met and this is reported with a DFS. The approving official of a DFS is usually a technical organization, which is designated by Commander, Naval Sea Systems Command (COMNAVSEASYSCOM). The two classes of DFSs are major and minor, with sub classifications of permanent and temporary. Permanent requires no additional repair and is approved to be permanent throughout the life cycle of the ship and is approved only by COMNAVSEASYSCOM. The Joint Fleet Maintenance Manual also provides clarification between a major and minor DFS.

> A major DFS is one that affects performance, durability, reliability or maintainability, interchangeability, effective use of operation, weight or appearance, health or safety, system design parameters, such as schematics, flow, pressures, or temperatures; or compartment arrangements or assigned function. A minor DFS is considered any condition that is not a major DFS. (Department of the Navy, 2017, pp. V-1-8-3–V-1-8-6)

Trends in DFSs highlight areas of concern to technical organizations like COMNAVSEASYSCOM. Identifying these trends early assists COMNAVSEASYSCOM in preventing mechanical issues before they occur.

Naval ships experience rigorous inspections in all areas across the life cycle of that platform. Mandated by Congress every five years is an inspection called the Board of Inspection and Survey (INSURV). All naval vessels are expected to be in compliance with INSURVINST 4730.5R, May 2014. As recommended by our research sponsor, COMNAVSURFPAC, we collected INSURV scores due to their relevance to the materiel condition, warfare preparedness, and readiness of the ships we were researching as part of this study. As stated in INSURVINST 4730.1R, this instruction provides the guidance for conducting INSURV trials and inspections. Furthermore, the instruction provides guidance on where to obtain checklists needed by ship's crew to prepare the ship for the INSURV inspection and presentation (Department of the Navy, 2014). INSURV Scores are based on the INSURV Figure of Merit (IFOM) percentage. As stated in the INSURV inspection handbook July 2017, IFOM is an overall ship grade computed from the average of the weighted equipment operational capabilities and demonstration scores and is included in the formal post inspection message. A locally generated document created by INSURV clarifies the IFOM scoring in greater detail. Before adopting the IFOM scoring, the Board previously graded material readiness as Satisfactory, Degraded, of Unsatisfactory. As stated from INSURV document 3.2.1, in order to establish a more objective and consistent material readiness metric, the Board eliminated the mission area construct and began scoring ships based on a weighted average of the material condition of equipment in functional areas and the results from system demonstrations. During the inspection, up to 100,000 shipboard material items are inspected depending on the ship class. Functional areas, previously known as warfare areas, demonstration scores are weighted based on their importance to the platform's primary mission and are averaged to form an overall IFOM score. The final scoring will be between 0.0 and 1.0 and is compared to other ships of the same class to assess the strength or weakness of the score.

The U.S. Navy is very detailed in tracking energy usage on afloat units. OPNAVINST 4100.11C describes the U.S. Navy's policy and reporting requirement for Navy Energy Reporting System (NEURS). NEURS provides the inventory information, re-supply, sale, and consumption of F76 and JP-5 types of fuel aboard all ships. In accordance with the OPNAVINST 4100.11C, all commissioned ships, except nuclear submarines must submit NEURS reports monthly to document fuel consumption. These reports can be prepared utilizing the applicable Fleet instructions: Commander, Atlantic Fleet Instruction (COMLANTFLTINST) 4100.3 and Commander, Pacific Fleet Instruction (COMPACFLTINST) 9261.1A. The objective of the NEURS reporting and database is to consolidate asset employment, scheduling, monitor consumption, and enhance awareness. Knowledge of how much fuel any given unit is consuming is an important part of this study.

Ships will enter and exit many dry dockings and maintenance activities throughout their life. To gain awareness on OPTEMPO and if a ship was recently in a maintenance repair status, we utilized the Fleet Engineers for COMNAVSURFPAC and their scheduling team for the past and upcoming statuses of when a ship entered and exited a specific maintenance availability period. Whether this maintenance availability period was a short pier-side availability or a dry-docking availability, it is important to compare the data from recent availabilities to when a mishap may have occurred. Upon exiting a major overhaul, ships encounter numerous turnover of crew and generally have a less experienced crew than prior to entering. Following major repairs, the specific unit will undergo many inspections to begin the re-certifying of every warfare area and training the crew for upcoming events. This is a very vulnerable time in a ship's life, as it begins to regain operational tempo from a period of not being underway for a significant amount of time and usually less trained crew than a ship that has successfully completed the basic training cycle at the peak of their sustainment with a qualified crew.

The Commanding Officer (CO) of Navy ships typically turns over and has a change of command every 18 months, as discussed in the Surface Warfare Officer Personnel Department (PERS-41) Surface Warfare Officer projected timeline. This timeline can be adjusted for various reasons but for the purpose of this research our modeling used 18 months as the as the average amount of time a CO is in command for any given unit. Identifying the length of time for which a CO was in command of a ship and the seniority of that specific CO are or could be important pieces of data relating to the occurrence of a mishap.

This research used ship safety data to identify possible leading indicators of a mishap. Each afloat unit undergoes a Safety Inspection from the Naval Safety Center every two years or where it fits best in their operational schedule. The Naval Afloat Safety Pre-Survey Message is a message sent to the ship being inspected prior to the safety team's arrival. It explains the requirements and guidance of the upcoming safety inspection and how ships are to prepare. As our research is safety driven, we thought the data collected in the safety inspections might help identify where a specific unit was not in compliance with the safety guidance and isolate contributing factors for a mishap occurring.

B. RESEARCH OBJECTIVE

In an era of limited resources, the Navy is consistently asked to search for ways to reduce its costs and to perform with increased efficiency. In the area of safety, we seek to learn how and why Class A and B mishaps occur. In addition, we seek to identify trends common to ships that have and have not experienced Class A and B mishaps. We note that there likely exist numerous, highly correlated and predictive variables that may show causation into the likelihood of mishap occurrence. Also, we may discover new insight into the identification of other avenues to explore and minimize these incidents. We performed this analysis across the LHD Wasp class, LPD San Antonio class, and CG Ticonderoga class ships due to these ship classes having disproportionately large number of mishaps compared to other ship classes during the last 5 years. The goal was to develop a predictive tool for identifying ships at risk before mishaps occur and to help identify potential and appropriate timeframes for command interventions.

C. PROBLEM STATEMENT

Class A and B mishaps cost the DoD millions of dollars and in the worst-case scenarios result in loss of life or permanent disability. Class A and B mishaps can also result in the loss of aircraft or serious degradation to the ability of ships to perform their mission. Currently the U.S. Navy does not have a capability to identify ships at risk of experiencing a Class A or B mishap. The ability to identify U.S. Navy ships that are statistically likely to experience these mishaps before they happen could potentially save millions of taxpayer dollars. More importantly, this research could save the lives of U.S. Navy Sailors.

D. SCOPE AND LIMITATIONS

The scope of this research was limited to the LHD Wasp class, LPD San Antonio class, CG Ticonderoga class, and the mishaps which occurred on those ship classes from the year 2012 to 2017. The limitations inherent to this type of research and analysis are related to the quality, availability, and consistency of the data gathered. No statistical model, especially one of this nature, can infer a cause-and-effect relationship between mishaps and variables.

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II. LITERATURE REVIEW

Our literature review indicated that this is the first time Class A and Class B mishaps are being predicted in this manner perhaps due to the specificity of this research. However, multiple studies have been conducted to attempt to correlate variables with ship safety mishaps or accidents in the commercial sector as well as within the DoD. One study conducted at the Naval Postgraduate School (NPS) that researched the relation of Command Safety Assessment Survey data and U.S. Naval Aviation mishaps found only limited value in the correlation of Command Safety Climate and mishaps (Le, 2017). This research concluded that blame and punishment are not constructive in efforts to promote safety within the workplace. Another study conducted at NPS attempted to compare the validity of stochastic models developed to predict maintenance-related mishaps in Naval Aviation against models using the variable Poisson process (Fry, 2000). This research attempted to perform similar studies of models with a much larger dataset that will include data that are not solely related to safety, but also maintenance, manning, and inspections results to provide a more comprehensive snapshot of the organization.

The review of literature for this research included textbooks, previous NPS research, and case studies in the fields of regression analysis, time series analysis, trend estimation, descriptive statistics, and data optimization. The textbooks cited focus on the study of statistics, with a major emphasis on linear regression. The previously conducted research reviewed focus on mishaps in the Navy and various methods used to correlate mishaps to variables.

A. PREVIOUS WORK

Previously conducted research includes Le's (2017) analysis of the correlation of U.S. Navy helicopter mishaps to flight hours and Lacy's (1998) analysis of U.S. Navy afloat mishaps and the human factors involved. Although we were unable to find bodies of work with specific regard to the use of regression and U.S. Navy afloat mishaps, there is a significant body of work regarding regression and Naval Aviation mishaps. The study conducted by Le that attempts to correlate number of flight hours to naval rotary wing mishaps provides a comparable methodology for the work performed in this study. Le developed models to explore the correlation between the Naval Aviation mishaps and the effects of DoD spending cuts, reduction of flight hours, pilot fatigue, and pilot proficiency. The scope of Le's research was limited to the H-60 platform and parallels our research which is limited to the LHD Wasp class, LPD San Antonio class, and CG Ticonderoga class. Our use of simple linear regression to determine whether the variables we captured are correlated to the occurrence of a mishap aboard a surface ship is similar to that of Le's use of logistic regression. Through the use of logistic regression, Le was able to find statistically significant effects between the established control and dependent variables used in the study.

Lacy conducted research which focused on applying the Human Factors Accident Classification System (HFACS), traditionally used by the Navy and Marine Corps to investigate and attribute cause to aviation mishaps, to the afloat and subsurface platforms. This illustrates the potential to apply research in the aviation mishap field to afloat platform mishaps.

B. REGRESSION ANALYSIS

Linear regression provided much of the foundation for the conclusions drawn by this research. Montgomery, Peck, Vining, and Vining (2012) define linear regression as the statistical method used for examining two or more variables the association between them. Montgomery et al. also note that regression models do not imply a cause-and-effect relationship between variables and that they may only be aids in confirming a cause-and-effect relationship, not the sole basis. Hocking (2013) explains that the squared correlation, denoted by R2, will be called the square multiple correlation or coefficient of determination. According to Weisberg (2013), R2 is a scale-free one-number summary of the strength of the association between the independent variable and the dependent variable in a given data set.

In our research and using to the tools available to us we calculated R2 in decimal notation and converted the number to a percentage for concision. Percentages for R2 values in linear regression will be between 0 and 100%. A 0% R2 value indicates no correlations between the variables used, whereas a 100% correlation indicates a direct and strong relationship between the variables used. In our case, the likelihood that we are attempting to predict is the occurrence of Class A or Class B mishap aboard specific U.S. Navy surface ship types. The regression analysis we attempted was between the occurrence of a mishap and each of the variables listed in the overview that we were able to obtain in our data collection phase.

C. TIME SERIES ANALYSIS AND TREND ESTIMATION

The ultimate goal of this research was to prevent mishaps before they occur and thus a focus on time and prediction was needed to identify when an intervention is needed. Time series analysis provides a very basic means of identifying trends. According to Kirchgässner (2013), the study of consistencies in collections of variables over time is time series analysis. Time series analysis can also makes use of observed regularities to predict future developments. The regularities that our research sought to identify were trends among our independent variables leading up to a mishap.

Trend estimation is a form of statistical analysis that focuses on the identification of trends in time series data. This form of statistical analysis will be used in conjunction with time series analysis to visually identify trends as we plot our independent variables as a time series.

D. DESCRIPTIVE STATISTICS

The goal of statistical analysis is to simplify a substantial amount of data by sorting, grouping, illustration and summary statistics. Our research sought to analyze shipboard data (specifically LPD San Antonio Class, LHD, and CG) in order to identify correlations that may be defined as statistically significant in predicting Class A and B mishaps. As the military seeks to understand why mishaps occur, there have been a significant number of studies in many areas that attempt to find the underlying factors. Giese, Carr, and Chahal (2013), conducted a study examining mishap statistics for Unmanned Systems (UAV) and human factors that may have contributed to the mishaps. Giese et al. (p. 1191) stated, “The history of UAV mishaps in general are a good measure of the role of human factor failures, due to the severity of resulting failures and the expected rigor of processes associated with documenting and investigating aviation mishaps.” As with any research and statistical analysis, the quality and amount of data available are extremely important to the number of models that can be built to construct a detailed analysis of your collected data.

Statistics is a technique whereby data are gathered, arranged, analyzed, and examined for simple visual representation and to aid in decision-making. In this study, descriptive statistics provides the basic features of our data by allowing us to simplify and generalize our data. Descriptive statistics are also used to legitimize inferences of statistical results taken from a group or large dataset (Peatman, 1947). The data obtained in this research range from 2009 to 2017 and the associated mishaps range from 2012 to 2017. The data were either collected only for, or narrowed down to, the ship classes identified above. This will be explained in detail in Chapter III (Methodology) Section A. The DoD has utilized statistics in numerous safety related research areas to identify causes of specific phenomenon, whether that phenomenon is a safety related mishap or other failure in equipment. A study conducted by the Naval Health and Research Center in 1984 performed an analysis of the underlying variables in diving accidents and mishaps. The study’s objective was to determine the most commonly occurring underwater mishaps and to determine the underlying factors that contributed to these mishaps (Blood & Hoiberg, 1984).

Our research relied heavily on the variables and data associated with studied surface ships to identify a correlation in our modelling. The descriptive analysis presents quantitative descriptions in a manageable way and provides summaries either in a quantitative form that are considered summary statistics or in a visual form to include graphical representation. Data must be condensed before being utilized as a foundation for extrapolation. When given a set of raw data one of the most useful ways of summarizing that information is to find an average of that set of data. Finding a simple average when looking at a specific set of data might seem elementary but depending on the research being conducted, this can be very helpful in identifying outliers.

Visual representation of data is an essential part of descriptive statistics; the most commonly used method of sorting large data sets is a graphical representation. Other visual methods include pie charts, bar charts, histograms, and data plots. Having the capability to present research in one of these forms provides a clear representation of the data gathered and the significance of the outcome. The primary goal of a chart diagram is to provide a quick display that is easy to read and interpret. The importance of descriptive statistics to this study, in tandem with time series analysis, is to allow for the presentation of raw data in a manner which can comprehend and interpreted quickly.

E. DATA OPTIMIZATION

Data Optimization aims at the preparation and sound representation of the statistical outcome. It is also used on raw data from the sources to produce a viable report. Optimization provides a powerful toolbox to solve data analysis and learning problems (Wright, 2013) and aids in maximizing the speed and efficiency with which data are retrieved. Optimization tools are mixed and matched to address data analysis tasks and goals of the project. Data mapping is a process that entails conversion or reconciliation of data from its source in order to utilize the data in a model.

Data optimization includes the use of software equipped with specific features for the execution purposes. A basic optimization has objective functions that one seeks to maximize on, while the variables place limits on the boundaries of the domain of the variables. Optimization is thus important to this research as it allows us to more efficiently present the data and subsequent finding of the study.

In *Regression Modeling Strategies*, Nuñez et al state the value of data optimization as it relates to regression analysis.

> When building a model, one should use a statistical method that matches the structure of the data being modeled and is suited to the sample size by limiting the number of variables according to the number of events. (Nuñez, Steyerberg, & Nuñez, 2011, pp. 502–503)

This is aided by optimization in conjunction with descriptive statistics. As stated by Nuñez et al, Optimization supports regression modelling by measuring the practicality of the final model with respects to normalization measures. If resources allow, test the prediction model on other data. Optimization has several benefits as it can clearly indicate a significant relationship between dependent variables and an independent variable. Also, optimization can be used to illustrate the impact of multiple independent variables on a dependent variable. Safety and mishaps can be examined using many optimization techniques. Research conducted by Longborough University utilized optimization safety analysis of obstacle evasion for UAVs. Srikanthakumar, Liu, and Chen (2012, p. 12) stated, "Local and Global optimization methods are applied to the problem of evaluating a worse-case condition and parameters for the UAV collision avoidance systems." This starts with evaluating criteria and utilizing optimization methods to identify worse case scenarios in UAV flight patterns. Previous studies and this current research optimize data in order to represent trends and clearly display outcomes to the audience.

F. SUMMARY

Our research is comprised of different statistical methods in order to reach a conclusion from the data sample. Regression, descriptive statistics, modeling, and analysis are forms of predictive modeling that allow us to investigate the relationship between dependent and independent variables; in addition to exploring the causal effect relationship between variables (Menard, 2002). The sources and information reviewed that were similar to our research all have different approach methods for analyzing their data. A broad range of safety related studies have shown the relevance and significance of statistical methods in data collection. The related previous works and research along with the use of regression analysis, time series analysis, trend estimation, descriptive statistics, and data optimization have been reviewed for use in this study.

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III. METHODOLOGY

A. RESEARCH APPROACH

The research approaches taken in this study center on correlating independent variables to dependent variables. The dependent variable is the occurrence of a Class A and B mishap aboard the LHD Wasp class, LPD San Antonio class, and CG Ticonderoga class ships from May 2012 to January 2017. The independent variables used include Commanding Officer turnover dates in relation to mishaps dates, CASREP counts, CASREP duration, number of DFSs, INSURV inspection scores, Safety Assessment scores, and Operating Tempo (OPTEMPO) as extrapolated from shipyard availability periods. Linear regression was used as the main method for finding correlation. Where linear regression was not feasible, an analysis of the trends in relation to the mishap dates was performed. The attempt to correlate the independent and dependent variables was in hope of building a predictive model which could identify ships at risk for Class A and B mishaps. However, no consistently significant correlation was discovered with the variables used in our analysis.

B. DATA COLLECTION

When beginning to collect data for this research, we narrowed down the ship classes to be studied based on the mishap reports provided by the COMNAVSURFPAC Force Safety Team (N-05). The majority of mishaps were found in the LHD Wasp class, LPD San Antonio class, and CG Ticonderoga class ships. Our data collection was narrowed to only these three classes for the remainder of this research. N-05 is involved in the Pacific Fleet to gain knowledge and report on operational safety, occupational safety, and recreational / off-duty safety for all units within their chain of command. Overall, data kept in the surface warfare community were found to be decentralized and difficult to gain. Access to numerous website portals, some requiring Common Access Card (CAC) login, was needed. In addition, the support from many Department of Defense (DoD) affiliated research commands was vital to obtain the data in the areas identified as significant for possible mishap identifiers.

Casualty reports were identified as an important piece of data for this research, as they can aid in understanding a ship's readiness and materiel issues. Gaining access to Maintenance Figure of Merit (MFOM) data was the first objective in pulling various CASREP data. The MFOM system is the formatting and maintenance website where all naval units can create, update, monitor, and cancel CASREPs. Upon gaining access to MFOM, it was found that all data are current and do not reflect historical reports that would be needed to perform this section of the research.

Having to look for a different course of action, we found that the Corona, CA Naval Surface Warfare Center (NSWC), comprised of active duty, retired, and civilian engineers who perform data analysis in a variety of areas for Naval ships was able to assist in extracting numerous historical CASREP data for our researched ship classes. NSWCs are a subcomponent of COMNAVSEASYSCOM. NSWC Corona's website provides us with the official mission statement of the command.

> NSWC Corona's mission statement is to serve warfighters and program managers as the Navy's independent assessment agent throughout systems' lifecycles by gauging the Navy's warfighting capability of weapons and integrated combat systems, from unit to force level, through assessment of those systems' performance, readiness, quality, supportability, and the adequacy of training. (Naval Surface Warfare Center, n.d.)

The CASREP data received included the ship classes pertaining to this research with the number of CASREPs each unit had in numerical count, broken down according to the severity (Category 2–4) for each month within the date range 2009–2017. We obtained data as far back as 2009 in order to ensure sufficient predictive data would be available for all our mishaps. Our earliest mishap occurred in 2012 and it was our goal to obtain data at least five years prior to the earliest mishap for each of our variables. In addition to the count and severity, the CASREPs duration in hours were used in this research. For each month, the duration of how many CASREPs were open in that particular month for any given ship was another portion of the data derived in the CASREP portion of the data analysis.

DFS data were important for this research. DFS data were stored in the Electronic DFS CAC protected website. E-forms is a web-based workflow application that supports multiple electronic engineering forms. Not only does it provide a workflow process, but it also stores the data for historical analysis and review. There are options to perform a search by Submarines, Carriers, and Surface Navy assets. In addition, there is a capability to initialize a DFS or view active, pending, overdue, and archived departures. The archived DFS reports gathered in support of this research ranged from 2009–2017. As the reports were extracted, we were able to sort the data in a cleaner fashion by viewing how many DFSs any unit had in the years or months prior to a mishap.

Board of Inspection and Survey (INSURV) report data were identified as significant. These inspections are mandated by congress and performed every five years to examine the proficiency of underway demonstrations in addition to the materiel status of the ship. The INSURV command, based out of Norfolk, VA has numerous departments that collect and analyze the data from the numerous inspections conducted each year on all platforms. For the purpose of this research, we utilized the plans, analysis, and report departments within the command for providing the data on the platforms of interest. The data derived here were historical inspection results from 2009–2017 reported in decimal form (.00–.99). We were able to view the previous INSURV inspection results prior to a mishap and compare that with units that did not have a mishap.

Additional data were collected to understand the Operational Tempo of that particular unit. We were able to obtain data for the amount of fuel consumed (in gallons) in any given month, and the number of hours a unit spent underway and not underway. No later than the 3rd day of every month NEURS data are gathered by every ship and submitted via Navy message and consolidated on the Type

Commanders readiness management system. The NEURS report has data consisting of days underway, hours underway, hours not underway, fuel consumed in gallons underway, and fuel consumed in gallons not underway, among other pieces of energy related reported data. Type commander's energy data analysis departments use these reports and numbers from each ship to develop quarterly fuel reports and develop class baselines. For our research, COMFLTFORCOMINST 4790.8C Section 3, the Maintenance and Material Management (3-M) System database explains how NEURS fuel and underway data are obtained and loaded in the database (Department of the Navy, 2017). Upon gaining access to this database, we were able to filter and extract the NEURS data from 2009–2017 for our researched classes.

Shipyard data are very relevant to our research. Knowing if a ship was previously in a maintenance availability can be used to determine the operational tempo of that unit. Maintenance availabilities vary in length and are extremely important for the upkeep of all ships. You can argue that ships lose proficiency when in a longer maintenance availability period than ships with short availabilities. The Type Commander (TYCOM) Fleet Maintenance schedulers track and plan all repair activities for the ships within their respective Fleet concentration area. The Fleet Maintenance schedulers provided historical data for all the ships we requested. The information provided consisted of past maintenance availabilities, location of repairs, and length of time a ship was in the availability.

Commanding Officer (CO) information and the amount of time a given CO was in command is important to this study. For this research, PERS-41 was the source of data on the average amount of time a CO normally holds a position before a change of command is conducted. The Surface Warfare Community Career path is not strictly adhered to by every Surface Warfare Officer, but it does provide a general view on milestones and the average time spent in specific positions throughout a career. The average time for a CO to be in command is 18 months as shown in Figure 1. During our data collection phase, we attempted to obtain historical CO turnover data from, type commands manning departments, PERS-41, and Surface Warfare Officer School. However, none of those organizations claimed to maintain the historical data we requested for this research. We were able to obtain most of the information we needed from the ship's public website. However, the public websites for the ships we researched did not all have an up-to-date Past Leadership section and we had to directly contact some of the ships to obtain the dates we needed. Each Executive Officer currently serving on that unit provided the historical data for previous Commanding Officers on that unit dating back to 2009.

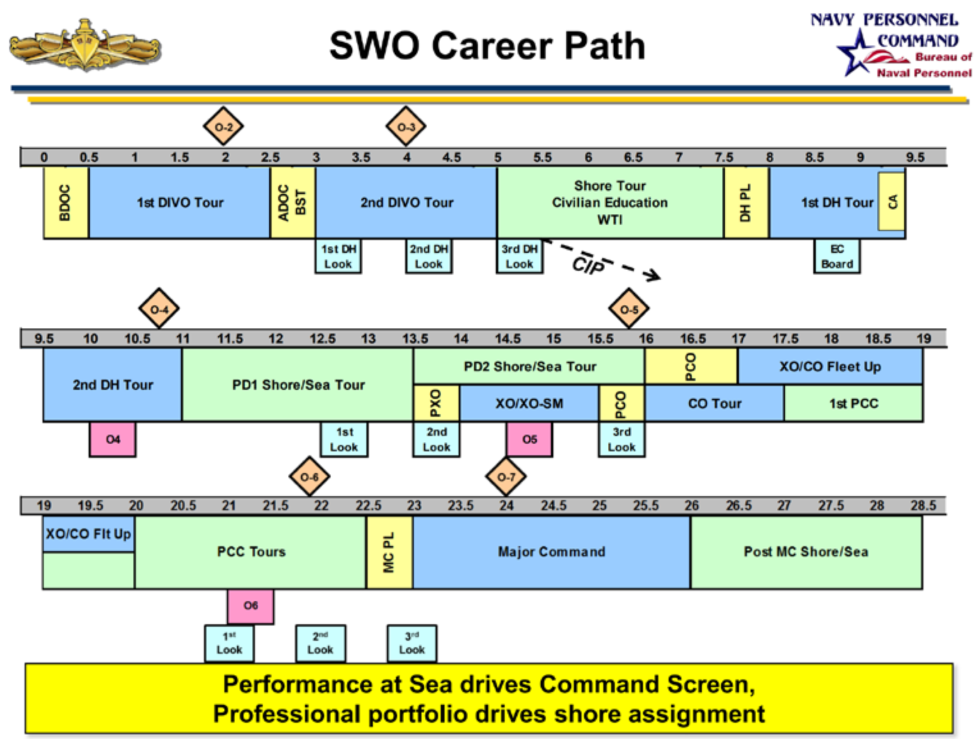

Figure 1. Career Path Indicating 18 Month Command at Sea Tour.
Source: Naval Personnel Command (2018).

Every two or three years, at times that best fit within a ship's schedule, a ship will undergo a safety inspection conducted by the Naval Safety Center Command. The Naval Safety Center provided the historical safety reports for our researched units. The data contained within these reports lists the discrepancies, the surveyor's detailed notes and survey checklists that were used in the descriptive statistics portion of the data examination. Discrepancies categorized as significant would include failure to comply with designated safety instruction, fire hazards, improper ventilation, improper maintenance of safety of life items, and improper storage of hazardous material. All other discrepancies would be included in total discrepancies.

C. LINEAR REGRESSION ANALYSIS

Linear regression analysis was conducted to attempt to find correlation between mishaps and CASREP counts, CASREP duration, DFSs, steaming hours underway, and steaming hours not underway.

The first data set used to conduct regression analysis contained all ships of the LHD Wasp class, LPD San Antonio class, and CG Ticonderoga class in addition to totals of each independent variable used for the 2009–2017 timeframe (see Table 1). For the dependent variable, mishaps, there was one column which contained the number of mishaps that each ship had during the 2009–2017 timeframe. R-squared values were obtained for each variable across all three ship classes for the entire time frame. In addition to the R-squared values across all ship classes, R-squared values were also obtained using deviation from the class average for each independent variable. For example, the most statistically significant R-squared value we calculated for this model was based on the deviation from the class average number of CAT 2 CASREPs. The R-squared value was 8.59%, which in terms of linear regression means that only 8.6% of the total variation is explained by the relationship between the two variables. This would indicate very little correlation between the two variables. Every other R-squared value calculated using this data set was less than 8.59%.

Table 1. First Linear Regression Dataset

Ship	Mishaps	Total DFS	DFS Class AVG DEV	Total CAT 2 Count	CAT 2 Count Class AVG DEV	Total CAT 3 Count	CAT 3 Count Class AVG DEV	Total CAT 4 Count	CAT 4 Count Class AVG DEV	Steaming Hrs U/W	Steaming Hrs U/W Class AVG DEV	Steaming Hrs Not U/W	Steaming Hrs not U/W Class AVG DEV	Total Steaming Hrs	Total Steaming Hrs Class AVG DEV
CG-52	0	173	-119	1013	-163	118	-74	7	-3	22386	2765	5837	-171	28223	2594
CG-53	0	222	-70	870	-306	116	-76	17	7	19111	-510	5241	-767	24352	-1277
CG-54	2	326	34	1095	-81	89	-103	6	-4	17643	-1978	4223	-1785	21866	-3763
CG-55	0	482	190	1277	102	147	-45	7	-3	18809	-812	6246	238	25055	-574
CG-56	0	474	182	1338	163	425	233	18	8	22312	2691	5734	-274	28046	2417
CG-57	0	134	-158	1117	-59	94	-98	1	-9	19708	87	6311	303	26019	390
CG-58	0	288	-4	1345	170	416	224	13	3	20540	919	4598	-1410	25138	-491
CG-59	0	205	-87	952	-224	132	-60	6	-4	18354	-1267	6117	109	24471	-1158
CG-60	0	372	80	1261	86	172	-20	9	-1	20582	961	5144	-864	25726	97
CG-61	2	385	93	1285	110	168	-24	11	1	20869	1248	7432	1424	28301	2672
CG-62	1	217	-75	1311	136	122	-70	4	-6	20189	568	6615	607	26804	1175
CG-63	0	201	-91	785	-391	127	-65	8	-2	16774	-2847	5416	-592	22190	-3439
CG-64	0	178	-114	775	-401	128	-64	4	-6	21419	1798	4501	-1507	25920	291
CG-65	0	167	-125	995	-181	103	-89	3	-7	16899	-2722	5148	-860	22047	-3582
CG-66	1	279	-13	1337	162	447	255	18	8	21628	2007	6257	249	27885	2256
CG-67	0	344	52	1335	160	131	-61	1	-9	21064	1443	5434	-574	26498	869
CG-68	0	294	2	1611	436	206	14	13	3	24754	5133	8931	2923	33685	8056
CG-69	1	259	-33	1309	134	258	66	14	4	20056	435	7435	1427	27491	1862
CG-70	0	225	-67	1155	-21	165	-27	5	-5	14142	-5479	3985	-2023	18127	-7502
CG-71	0	190	-102	895	-281	144	-48	10	0	20247	626	4778	-1230	25025	-604
CG-72	0	608	316	1588	413	343	151	17	7	17691	-1930	8675	2667	26366	737
CG-73	1	240	-52	1212	37	164	-28	21	11	16484	-3137	8122	2114	24606	-1023
LHD-1	3	416	159	1798	641	195	37	5	1	18245	-4247	8200	-153	26445	-4400
LHD-2	1	253	-4	734	-423	168	10	1	-3	19667	-2825	7490	-863	27157	-3688
LHD-3	1	343	86	1483	326	240	82	2	-2	21482	-1010	6842	-1511	28324	-2521
LHD-4	0	214	-43	1031	-126	109	-49	3	-1	26272	3780	5883	-2470	32155	1311
LHD-5	1	269	12	1305	148	199	41	7	3	27271	4779	13347	4994	40618	9774
LHD-6	0	218	-39	1174	17	70	-88	5	1	24912	2420	11124	2771	36036	5192
LHD-7	2	201	-56	937	-220	147	-11	3	-1	21850	-642	9973	1620	31823	979
LHD-8	1	144	-113	796	-361	137	-21	6	2	20236	-2256	3962	-4391	24198	-6647
LPD-17	0	297	90	1020	322	214	122	18	11	18588	2546	5908	1017	24496	3563
LPD-18	0	273	66	867	169	128	36	11	4	23983	7941	7439	2548	31422	10489
LPD-19	0	422	215	1134	436	187	95	19	12	25427	9385	8329	3438	33756	12823
LPD-20	1	257	50	659	-39	79	-13	4	-3	19924	3882	5805	914	25729	4796
LPD-21	3	193	-14	1408	710	79	-13	4	-3	17896	1854	5069	178	22965	2032
LPD-22	0	98	-109	440	-258	58	-34	1	-6	10173	-5869	3404	-1487	13577	-7356
LPD-23	2	108	-99	303	-395	39	-53	1	-6	10779	-5263	2784	-2107	13563	-7370
LPD-24	0	128	-79	275	-423	21	-71	2	-5	9659	-6383	3122	-1769	12781	-8152
LPD-25	0	88	-119	172	-526	27	-65	0	-7	7951	-8091	2160	-2731	10111	-10822
		R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2
		0.10%	0.80%	4.46%	8.59%	0.35%	0.00%	2.74%	0.16%	0.32%	2.04%	2.18%	0.09%	0.02%	0.87%

The second data set used was similar to the first, but the time frame for the independent variables was shortened to 2011–2017 to include only data from one year prior to our earliest mishap. Tables 2, 3 and 4 collectively are the second dataset. In addition to CASREP counts, this model added CASREP durations. This model yielded more significant findings, but still nothing genuinely conclusive. For the second data set, linear regression analysis was also conducted within each class. The R-squared values calculated within class of ship were more significant than those calculated across all ships. The most statistically significant R-squared value from this model was the CAT 4 CASREP Duration variable for the LPD class and the value was 43.99%. The second most significant R-squared value was the steaming hours underway variable for the LHD class and the value was 42.87%.

Table 2. Second Linear Regression Dataset (CG Only)

Ship	Mishaps	Total DFS	Total CAT 2 Count	CAT 2 Duration	Total CAT 3 Count	CAT 3 Duration	Total CAT 4 Count	CAT 4 Duration	Steaming Hrs U/W	Steaming Hrs Not U/W
CG-52	0	151.0	736.0	41933.4	125.0	3848.5	6.0	122.4	17048.0	4975.0
CG-53	0	180.0	761.0	53577.7	119.0	4001.6	11.0	853.0	17720.0	4667.0
CG-54	2	302.0	1035.0	76971.8	99.0	5030.9	5.0	383.4	13497.0	3604.0
CG-55	0	397.0	976.0	51135.6	161.0	4663.6	4.0	142.6	14662.0	4640.0
CG-56	0	389.0	1053.0	73404.1	450.0	20394.9	11.0	272.1	16431.0	4385.0
CG-57	0	130.0	897.0	64907.6	104.0	3703.9	1.0	126.6	12766.0	4822.0
CG-58	0	251.0	1052.0	53747.0	434.0	12159.7	11.0	103.6	17255.0	3673.0
CG-59	0	199.0	771.0	49230.4	140.0	4750.2	4.0	71.1	12236.0	2367.0
CG-60	0	233.0	873.0	49137.7	207.0	7329.9	8.0	45.4	13838.0	4168.0
CG-61	2	296.0	1000.0	49805.8	180.0	7072.4	8.0	617.2	17893.0	6430.0
CG-62	1	197.0	984.0	85854.1	151.0	5699.2	4.0	918.1	14610.0	5747.0
CG-63	0	156.0	606.0	47015.9	150.0	12514.6	8.0	1191.9	10650.0	4400.0
CG-64	0	136.0	512.0	15162.2	134.0	1982.3	1.0	3.0	15704.0	3179.0
CG-65	0	135.0	768.0	53866.0	137.0	7720.1	0.0	0.0	9171.0	4133.0
CG-66	1	259.0	1274.0	69149.8	474.0	20441.7	18.0	568.1	15113.0	5006.0
CG-67	0	304.0	1114.0	70876.7	142.0	5497.0	0.0	0.0	14272.0	3793.0
CG-68	0	238.0	1188.0	65778.5	222.0	10019.2	13.0	623.4	18702.0	4813.0
CG-69	1	237.0	1101.0	59731.0	284.0	8610.6	12.0	149.9	13840.0	3868.0
CG-70	0	213.0	951.0	66352.9	181.0	10394.4	3.0	53.7	9536.0	2954.0
CG-71	0	181.0	742.0	45127.9	165.0	5019.7	10.0	302.7	15185.0	3509.0
CG-72	0	559.0	1372.0	75107.2	352.0	13991.8	14.0	734.8	11840.0	5899.0
CG-73	1	195.0	917.0	72398.1	202.0	12971.1	6.0	427.5	15470.0	7431.0
		R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2
		1.01%	8.05%	11.16%	0.00%	0.26%	1.58%	6.97%	3.08%	15.20%

Table 3. Second Linear Regression Dataset (LHD & LPD)

Ship	Mishaps	Total DFS	Total CAT 2 Count	CAT 2 Duration	Total CAT 3 Count	CAT 3 Duration	Total CAT 4 Count	CAT 4 Duration	Steaming Hrs U/W	Steaming Hrs Not U/W
LHD-1	3	361.0	1161.0	143796.4	218.0	12324.0	2.0	147.9	13348.0	5481.0
LHD-2	1	221.0	473.0	30351.6	188.0	7659.7	0.0	0.0	13939.0	4034.0
LHD-3	1	294.0	1307.0	107964.2	294.0	12584.9	2.0	422.3	18202.0	5676.0
LHD-4	0	162.0	808.0	50009.0	128.0	2657.2	1.0	8.1	20846.0	4881.0
LHD-5	1	237.0	1168.0	92426.5	223.0	6854.2	6.0	154.4	19700.0	9130.0
LHD-6	0	195.0	1032.0	110443.9	86.0	4004.1	1.0	9.0	17136.0	9924.0
LHD-7	2	172.0	712.0	46947.3	167.0	5631.1	3.0	30.6	16530.0	6388.0
LHD-8	1	124.0	674.0	57353.2	137.0	13058.3	4.0	1046.0	19029.0	3582.0
		R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2
		35.35%	1.87%	11.83%	21.22%	30.00%	3.87%	0.11%	42.87%	5.14%
LPD-17	0	229.0	867.0	78434.1	286.0	14725.9	5.0	62.9	16795.0	5167.0
LPD-18	0	206.0	692.0	61183.4	165.0	6163.9	0.0	0.0	18959.0	4688.0
LPD-19	0	386.0	981.0	65639.4	187.0	9820.8	13.0	817.2	19214.0	5452.0
LPD-20	1	196.0	547.0	37488.6	79.0	3288.5	1.0	1.3	18118.0	5472.0
LPD-21	3	174.0	773.0	62551.3	79.0	6315.7	3.0	1782.0	16319.0	4413.0
LPD-22	0	98.0	440.0	25274.0	58.0	3729.5	1.0	48.1	10173.0	3404.0
LPD-23	2	108.0	303.0	21058.7	39.0	1750.0	1.0	70.0	10779.0	2784.0
LPD-24	0	128.0	275.0	16908.3	21.0	433.8	2.0	11.2	9659.0	3122.0
LPD-25	0	88.0	172.0	8812.9	27.0	695.6	0.0	0.0	7951.0	2160.0
		R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2
		2.90%	0.17%	0.48%	8.49%	1.76%	2.11%	43.99%	0.68%	0.02%

Table 4. Second Linear Regression Dataset (Across All Classes)

Ship	Mishaps	Total DFS	Total CAT 2 Count	CAT 2 Duration	Total CAT 3 Count	CAT 3 Duration	Total CAT 4 Count	CAT 4 Duration	Steaming Hrs U/W	Steaming Hrs Not U/W
[redacted]										
		R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2
		0.31%	0.77%	8.49%	0.42%	0.33%	1.23%	10.19%	0.81%	3.04%
[redacted]										

D. TIME SERIES ANALYSIS AND TREND ESTIMATION

In addition to linear regression analysis, we also attempted to identify trends in various timeframes leading up to a mishap using time series analysis and trend estimation. For this portion of our research, we graphed each applicable variable on a time series graph for time periods of three, six, and twelve months. The data selected for each time series graph encompasses the values of a particular variable for a timeframe leading up to a recorded shipboard mishap. For example, we graphed the steaming hours underway variable data for the 12-month period leading up to each recorded mishap. Figure 2 depicts the graph. We then attempted to identify general trends such as increases, decreases, or spikes that were common to all or most ships on the graph. In addition to performing this type of analysis for each variable for all the recorded mishaps, we did a ship class analysis of the same type in order to attempt to identify trends within specific classes of ships. The objective was to identify increases or decreases leading up to a mishap, such as a steady increase in steaming hours underway prior to the occurrence of a mishap. If trends are identified with one or more variables, then some predictive value may be extrapolated from the trends.

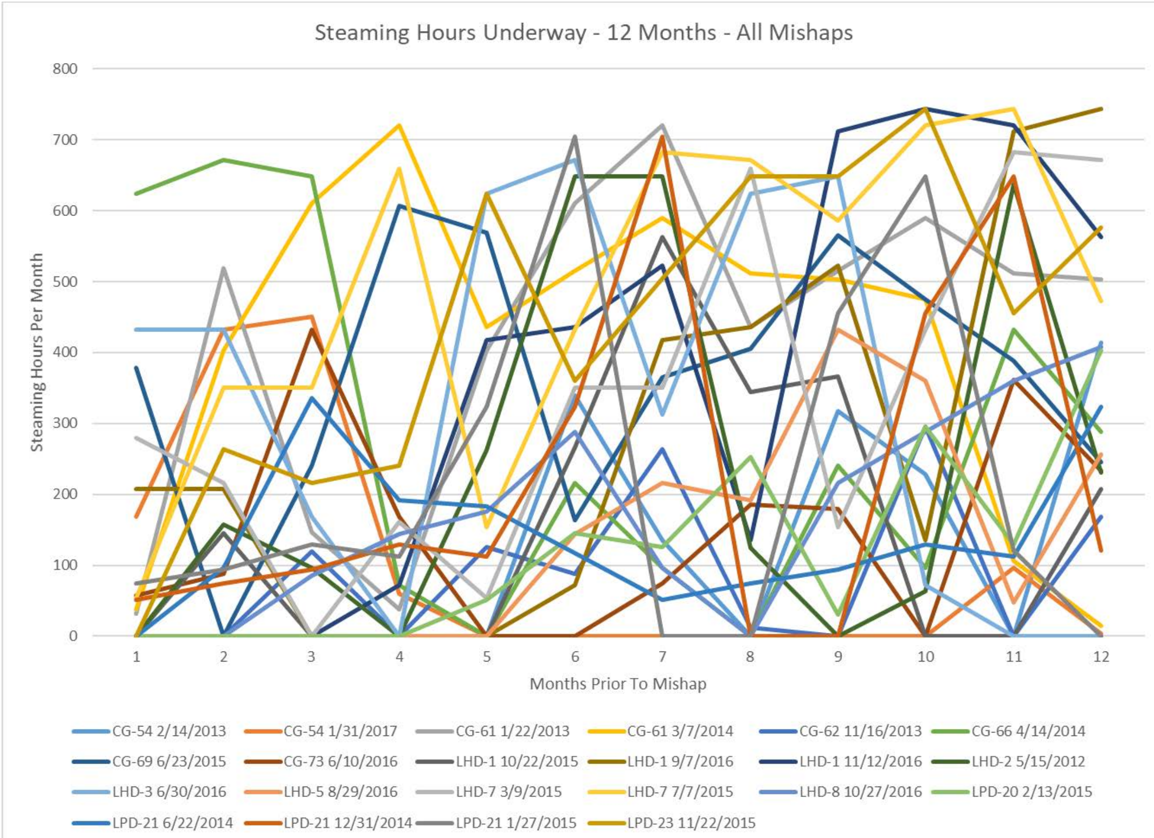

Figure 2. Steaming Hours Underway 12 Months Prior to All Mishaps

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IV. RESULTS

In this chapter we present the results of our attempts to find correlations between the data we were able to collect and the likelihood of a mishap occurring on the three classes of ships we studied. In addition, we'll discuss some of the characteristics of the mishaps studied that may have impacted the results of our work.

A. LINEAR REGRESSION

The first attempt at linear regression yielded no statistically significant correlations to number of mishaps with any of the independent variables. The first dataset's independent variables included the total number of DFSs, total number of CAT 2 CASREPs, total number of CAT 3 CASREPs, total number of CAT4 CASREPs, total steaming hours while underway, total steaming hours while not underway, and total steaming hours. In addition to the independent variables listed above, a class average was calculated for each class and the deviation from the class average for each variable was also used as independent variables for the first model. The dependent variable was the number of Class A & B mishaps that each ship had within the time frame of the first data set. The first dataset covers the 2009–2017 timeframe. The reason we started with 2009 was that for all of our data sources used in linear regression, the common starting date for all independent variable data was 2009. The linear regression model provided an R2 value for each of the 14 variables across all ships. None of the R2 values were of statistical significance and would not adequately infer any correlation. The highest R2 value provided an 8.59% correlation between mishaps and the deviation from the class average for total CAT 2 CASREP count. This value is potentially inflated because LHD-1 had three mishaps, the highest of any LHD in the dataset and coincidentally had the highest total CAT 2 CASREP count in its class and therefore the highest deviation from the class average. However, as LHD-1 is the first ship in its class and the oldest ship in its class; the high number of CAT 2 CASREPs is potentially explained by its age and the trend of increasing CAT 2 CASREP with age is generally seen in all ships of the class. This could potentially indicate a higher correlation of mishaps with the ship's age than with CAT 2 CASREP counts.

Due to the very low significance of the R^2 values provided by the first model, some changes were made to the linear regression methods used in the second dataset to obtain more significant values. The second attempt at linear regression was performed on a modified dataset similar to that of the first model. The changes included shortening the time frame from 2009–2017 to 2011–2017. This change was made to decrease the data in the dataset because the first mishap we studied occurred in 2012 and we theorized there may be a stronger correlation with the data only one year prior to the first mishap versus data including the five years prior to our first mishap. The earliest mishap in our dataset occurs in 2012 and independent variable data that included data from five years prior to the first mishap may have been contributing to the low correlation of the first model. In addition to the time frame change, linear regression analysis was also conducted within class as well as across all ships to attempt to see if correlations were more significant within ship classes. Also, since linear regression was being conducted within ship classes; the variable regarding deviations from class averages was removed in the second dataset.

The results of the linear regression analysis performed on the second dataset did yield more statistically significant results. However, we do not believe the results were significant enough to yield potential predictive value. Four independent variables stood out as being the most statistically significant and those were, in order of significance CAT 4 Duration for LPDs, Steaming Hours Underway for LHDs, Total DFSs for LHDs, and CAT 3 Duration for LHDs. The strongest correlation in the second dataset was that between number of mishaps and the CAT 4 Duration variable for LPDs. This variable was calculated by cumulatively adding the number of hours a ship had a CAT 4 CASREP open during the 2011–2017 timeframe. The resultant R2 value for the correlation between LPD mishaps and CAT 4 Duration was .4399 or 44%. However, this figure is skewed by USS *New York* (LPD-21), which has the most mishaps in the LPD class with three mishaps during the timeframe. USS *New York* has the highest CAT 4 Duration with 1782 hours and coming in second is USS *Mesa Verde* (LPD-19) with less than half of that at 817 hours. The other three semi-significant variables, are all within the LHD class. Steaming Hours Underway, Total DFSs, and CAT 3 Duration are skewed by USS *Wasp* (LHD-1), which also has the highest number of mishaps in the ship class. The degree to which the variables are skewed by USS *Wasp* is to a lesser degree than USS *New York*. However, the statistical significance of the correlations is fairly low to begin with. Steaming Hours Underway for LHDs is 42%, Total DFSs is 35%, and CAT 3 Duration is 30%. The next closest significant value was CAT 3 Count for LHDs at 21%.

We can say with a fair amount of certainty that the variables used in this linear regression analysis do not have potential to provide predictive value for the future of shipboard mishaps.

B. TIME SERIES ANALYSIS AND TREND ESTIMATION

The results of the time series analysis and trend estimation provided us with no clear trends for any of the variables which we plotted. All of the graphs show a fairly random distribution for each variable and for reach time frame. All of the time series graphs generated as part of this research are included the in Appendix for future reference and research.

C. DESCRIPTIVE STATISTICS AND DATA OPTIMIZATION

The CO turnover data, shipyard maintenance availabilities, safety inspection reports, and INSURV scores datasets were analyzed using descriptive statistics, data optimization, and trend analysis.

For the CO turnover data, we only gathered data for the ships that experienced a mishap between 2012–2017, so our examination only included the mishap ships. The way in which attempted to identify a trend or pattern was to average the length of time a CO was in command prior the mishap date for all ship classes combined. Based on the PERS-41 Surface Warfare Officer career path, the average length of time for a CO tour is 18 months. Including all researched ship classes together, the average amount of time a CO was in command prior to a mishap was 232 days, roughly 7.5 months. With this result, an argument could be made that ships are more likely to experience a mishap in the first half of the CO's tour, as depicted in Figure 3.

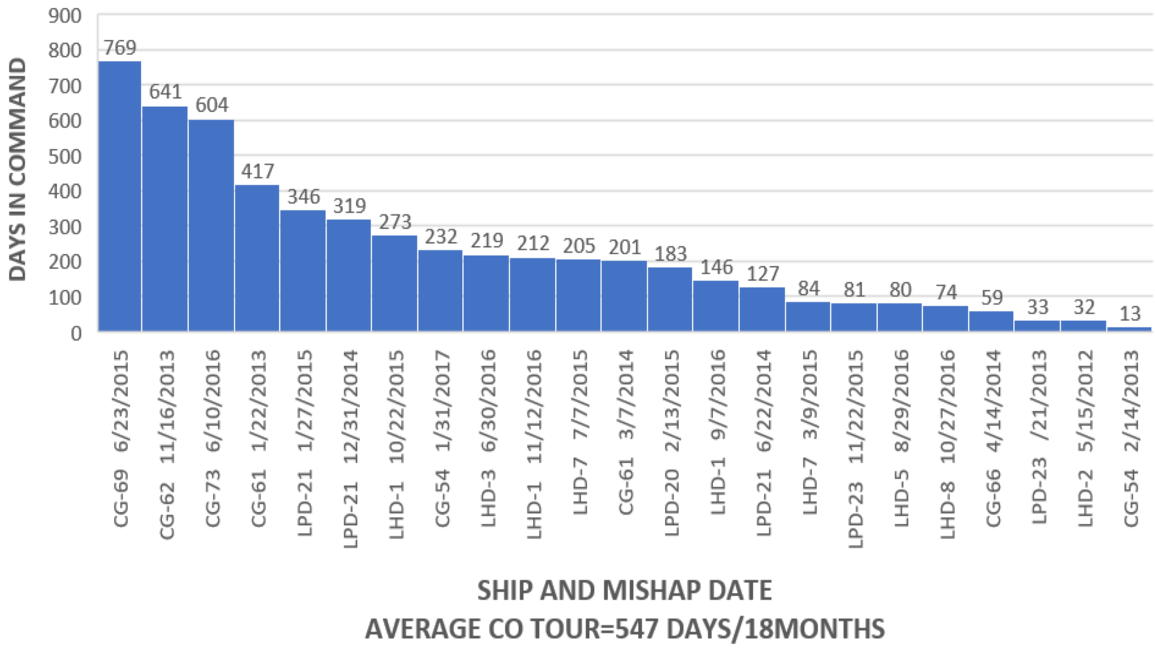

Figure 3. CO Days in Command Prior to Each Mishap

Maintenance availability data prior to the mishap were important to this research; mainly, the most recent repair availability and the length of time spent in that specific availability. For all ships that experienced a mishap in all classes, the average number of days in the most recent availability prior to the mishap was 269 days, roughly nine months. This is a significant amount of time dedicated to repairing a ship and minimizing underway experience. In addition, the projected amount of crew turnover that occurs in a lengthy availability increases, which can increase mishap probability. As indicated in Table 5, four ships were in the availability when the mishap occurred and were not included in the average. The number of days between the end of the most recent availability period and the occurrence of a mishap was an average of 500 days.

Table 5. Number of Days Since Ending Availability Prior to Mishap

Ship	**Mishap date**	**Start Date of Most Recent Avail Prior to Mishap**	**End Date of Most Recent Avail Prior to Mishap**	**Days of Avail**	**Days since ending AVAIL to MISHAP**
LHD-1 WASP	11/12/2016	09/03/13	11/26/14	449.00	717
LHD-1 WASP	10/22/2015	09/03/13	11/26/14	449.00	330
LHD-1 WASP	9/7/2016	09/03/2013	11/26/2014	449.00	651
LHD-2 ESSEX	5/15/2012	08/26/2009	11/04/2009	70.00	923
LHD-3 KEARSARGE	6/30/2016	06/13/2016	02/24/2017	256.00	in avail
LHD-5 BATAAN	8/29/2016	01/07/15	01/25/2016	383.00	217
LHD-7 IWO JIMA	7/7/2015	01/23/13	12/11/2013	322.00	573
LHD-7 IWO JIMA	3/9/2015	01/23/13	12/11/2013	322.00	453
LHD-8 MAKIN ISLAND	10/27/2016	04/27/2015	12/11/2015	228.00	321
LPD-20 GREEN BAY	2/13/2015	07/10/2013	06/13/2014	338.00	245
LPD-21 NEW YORK	6/22/2014	01/14/13	08/16/2013	214.00	310
LPD-21 NEW YORK	1/27/2015	01/14/2014	08/16/2014	214.00	164
LPD-21 NEW YORK	12/31/2014	01/14/2015	08/16/2015	214.00	in avail
LPD-23 ANCHORAGE	11/22/2015	08/06/2013	12/16/2013	132.00	706
LPD-23 ANCHORAGE	5/21/2013	08/06/2014	12/16/2014	132.00	in avail
CG-54 ANTIETAM	2/14/2013	02/14/2012	07/06/2012	143.00	223
CG-54 ANTIETAM	1/31/2017	04/26/2016	11/22/2016	210.00	70
CG-61 MONTEREY	3/7/2014	02/19/2014	08/14/2015	541.00	in avail
CG-61 MONTEREY	1/22/2013	12/01/2011	05/03/2012	154.00	264
CG-62 CHANCELLORSVILLE	11/16/2013	04/17/2012	03/29/2013	346.00	232
CG-66 HUE CITY	4/14/2014	09/29/2010	05/13/2011	226.00	1067
CG-69 VICKSBURG	6/23/2015	06/16/2010	11/11/2010	148.00	1685
CG-73 PORT ROYAL	6/10/2016	09/22/2014	06/12/2015	263.00	364
		Avg Avail Days when Mishap Occurs:	269.70	Avg Days from Ending Avail to Mishap:	500.78

The safety inspection data are grouped together for all ship classes in Table 6. The data are comprised of the number of discrepancies each particular unit had during the previous inspection prior to a mishap. The discrepancies are grouped by Total, Significant, and Repeat. The three ship classes researched are then broken up by the average number of discrepancies in that particular ship class and compared to the individual unit to see how they fared. We did not come to a conclusion based on the safety inspections that identified any particular trend in the number of discrepancies when compared to the average between each class.

Table 6. Safety Inspections Results Prior to Each Mishap

Ship	Mishap date	Date Safety Report	Total	Significant	Repeat
LHD-1 WASP	11/12/2016	11/4/2014	182	53	58
LHD-1 WASP	10/22/2015	11/4/2014	182	53	58
LHD-1 WASP	9/7/2016	11/4/2014	182	53	58
LHD-2 ESSEX	5/15/2012	8/24/2012	154	19	43
LHD-3 KEARSARGE	6/30/2016	10/31/2014	135	32	49
LHD-5 BATAAN	8/29/2016	1/13/2015	141	67	49
LHD-7 IWO JIMA	7/7/2015	3/7/2014	148	16	33
LHD-7 IWO JIMA	3/9/2015	3/7/2014	148	16	33
LHD-8 MAKIN ISLAND	10/27/2016	3/14/2014	118	11	40
LPD-20 GREEN BAY	2/13/2015	10/22/2014	157	63	55
LPD-21 NEW YORK	6/22/2014	10/22/2013	129	25	35
LPD-21 NEW YORK	1/27/2015	10/23/2013	129	25	35
LPD-21 NEW YORK	12/31/2014	10/24/2013	129	25	35
LPD-23 ANCHORAGE	11/22/2015	10/27/2014	106	19	0
LPD-23 ANCHORAGE	5/21/2013	10/27/2014	106	19	0
CG-54 ANTIETAM	2/14/2013	12/10/2013	164	18	43
CG-54 ANTIETAM	1/31/2017	12/11/2013	164	18	43
CG-61 MONTEREY	3/7/2014	12/9/2013	175	20	50
CG-61 MONTEREY	1/22/2013	12/10/2013	175	20	50
CG-62 CHANCELLORSVILLE	11/16/2013	10/1/2013	174	7	0
CG-66 HUE CITY	4/14/2014	8/1/2011	122	27	7
CG-69 VICKSBURG	6/23/2015	4/2/2014	113	9	18
CG-73 PORT ROYAL	6/10/2016	2/5/2013	194	14	42
		Class Averages (safety report years combined)			
			Total	Significant	Repeat
		LHD Average	154	36	47
		LPD Average	126	29	40
		CG Average	160	17	32

INSURV inspection scores are depicted in Table 7. This tabular presentation did not show a strong correlation between mishap date and the previous INSURV score when compared to the class average of the year when that specific mishap occurred. Two instances within the class average column did not have data to compare the previous INSURV score with. Also, USS *New York* and USS *Anchorage* did not have INSURV data because they are new ships. There is not an evident correlation between the previous score being relatively lower than class average that would indicate a factor possibly contributing to a mishap. Also, with INSURV inspections occurring about every five years, the previous score could be at the extreme five years from the mishap occurring, making the timeframe too long and therefore the data become irrelevant to this research. It appears that ships score near the class average and in a few instances above or below, leading to a conclusion that INSURV data does not contribute to mishap prediction.

Table 7. INSURV Inspection Score Prior to Each Mishap

Ship	Mishap Date	INSURV Score Prior to Mishap	Class Average (Mishap Year)
LHD-1 WASP	11/12/2016	0.79	0.81 (2016)
LHD-1 WASP	10/22/2015	0.79	0.74 (2015)
LHD-1 WASP	9/7/2016	0.79	0.81 (2016)
LHD-2 ESSEX	5/15/2012	0.77	no data
LHD-3 KEARSARGE	6/30/2016	0.74	0.81 (2016)
LHD-5 BATAAN	8/29/2016	0.67	0.81 (2016)
LHD-7 IWO JIMA	7/7/2015	0.82	0.74 (2015)
LHD-7 IWO JIMA	3/9/2015	0.82	0.74 (2015)
LHD-8 MAKIN ISLAND	10/27/2016	0.79	0.81 (2016)
LPD-20 GREEN BAY	2/13/2015	0.7	0.72 (2015)
LPD-21 NEW YORK	6/22/2014	no data	0.73 (2014)
LPD-21 NEW YORK	1/27/2015	no data	0.72 (2015)
LPD-21 NEW YORK	12/31/2014	no data	0.73 (2014)
LPD-23 ANCHORAGE	11/22/2015	no data	0.72 (2015)
LPD-23 ANCHORAGE	5/21/2013	no data	no data
CG-54 ANTIETAM	2/14/2013	0.89	0.8 (2013)
CG-54 ANTIETAM	1/31/2017	0.87	0.82 (2017)
CG-61 MONTEREY	3/7/2014	0.85	0.83 (2014)
CG-61 MONTEREY	1/22/2013	0.85	0.8 (2013)
CG-62 CHANCELLORSVILLE	11/16/2013	0.82	0.8 (2013)
CG-66 HUE CITY	4/14/2014	0.89	0.83 (2013)
CG-69 VICKSBURG	6/23/2015	0.84	0.83 (2015)
CG-73 PORT ROYAL	6/10/2016	0.83	0.82 (2016)

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V. SUMMARY, CONCLUSIONS, FUTURE RESEARCH, AND RECOMMENDATIONS

A. SUMMARY

The ultimate goal of our research was to provide a predictive tool to identify ships at risk of Class A and B mishaps, but we were unable to provide that tool using the data we were able to collect and analyze. Although we did find some correlations in the data we analyzed, none of the correlations we discovered were statistically significant enough to create the foundation for a tool with predictive capacity. We believe most of the value of this research will be in identifying which variables can be safely disregarded in further research to provide a predictive capability of mishaps.

B. CONCLUSIONS

The linear regression analysis portion of our research yielded no statistically significant correlations between the dependent variable of the occurrence of a shipboard mishap and the independent variables listed here:

- Number of DFSs
- CAT 2 CASREP Count
- CAT 2 CASREP Duration
- CAT 3 CASREP Count
- CAT 3 CASREP Duration
- CAT 4 CASREP Count
- CAT 4 CASREP Duration
- Steaming Hours Underway
- Steaming Hours Not Underway
- Total Steaming Hours

This conclusion is based on the results of the linear regression technique used, which did not yield a coefficient of determination higher than 44% for any one variable. The coefficient of determination is a mathematical value which measures the correlation between the dependent and independent variables. Most of the coefficients of determination for the independent variables were significantly lower than 44%, but the ones of note were discussed in Chapter IV.

For the time series analysis portion of our research, we attempted to represent a significant finding by graphing prior to each mishap, each independent variable for a three, six, and twelve-month time frame prior to each individual mishap. This time series and trend analysis did not yield any obvious trends with all of the variables showing a random distribution for each of the time frames we graphed. Without any clear trend, we were unable to build a foundation for a predictive tool using this methodology.

Our research used other methods besides linear regression and time series analysis. Using the mean in data analysis was another approach for facets of our data. From the mean analysis comparing CO length of time in command individually and with all units that experienced mishap, it was evident that most COs were in the first half of their command tour when a mishap occurred. The other pieces of data that used mean analysis such as the safety inspection reports and INSURV reports did not show areas that were evidently above or below the mean leading us to a conclusion that the data was non-causative.

C. FUTURE RESEARCH

This research was to identify factors that could assist in predicting Class A or B mishaps on Navy ships, and then build a model to be used in mishap prediction. As we progressed and gathered our data, many pieces of shipboard data and inspection results were identified as elements that could be used in our models and mishap prediction analysis. Future research with the goal of developing a predictive model to draw a conclusion on specific events can be conducted many different ways. People have opinions about what types of data will help in drawing a conclusion as a predictive tool is developed. As researchers continue to analyze future mishaps, their work can be utilized to further guide in the selection of variables that may provide predictive value. If mishaps occur in a specific department, we recommend conducting an internal analysis first prior to attempting to extrapolate meaning from data external to that department.

Each mishap from 2012–2017 that was reviewed for this study was very different, and arguments can be made that these need to be analyzed differently and separately, but this research grouped them all together to obtain a conclusion. Mishap types range from service member Injury to equipment damages, amongst others. Trying to predict mishaps is a challenging task. All events need to be looked at separately before pulling various pieces of historical data to look for possible contributing factors.

For instance, if a ship were to have a mishap as a result of or in relation to an engineering equipment casualty, we recommend investigating that mishap in isolation of other mishaps. Some elements of our data collection and research may be relevant to future mishaps that are related to engineering equipment casualty. For example, since this is a projected engineering mishap, we recommend using engineering logs, training program assessments, and personnel manning numbers to look for potential causes for that mishap. This approach can be taken for a mishap experienced in any department, where you can gather data specific to that mishap. Also, behavior analysis and assessing the culture or climate of a command may assist investigators in drawing different conclusions from a typical mishap investigation.

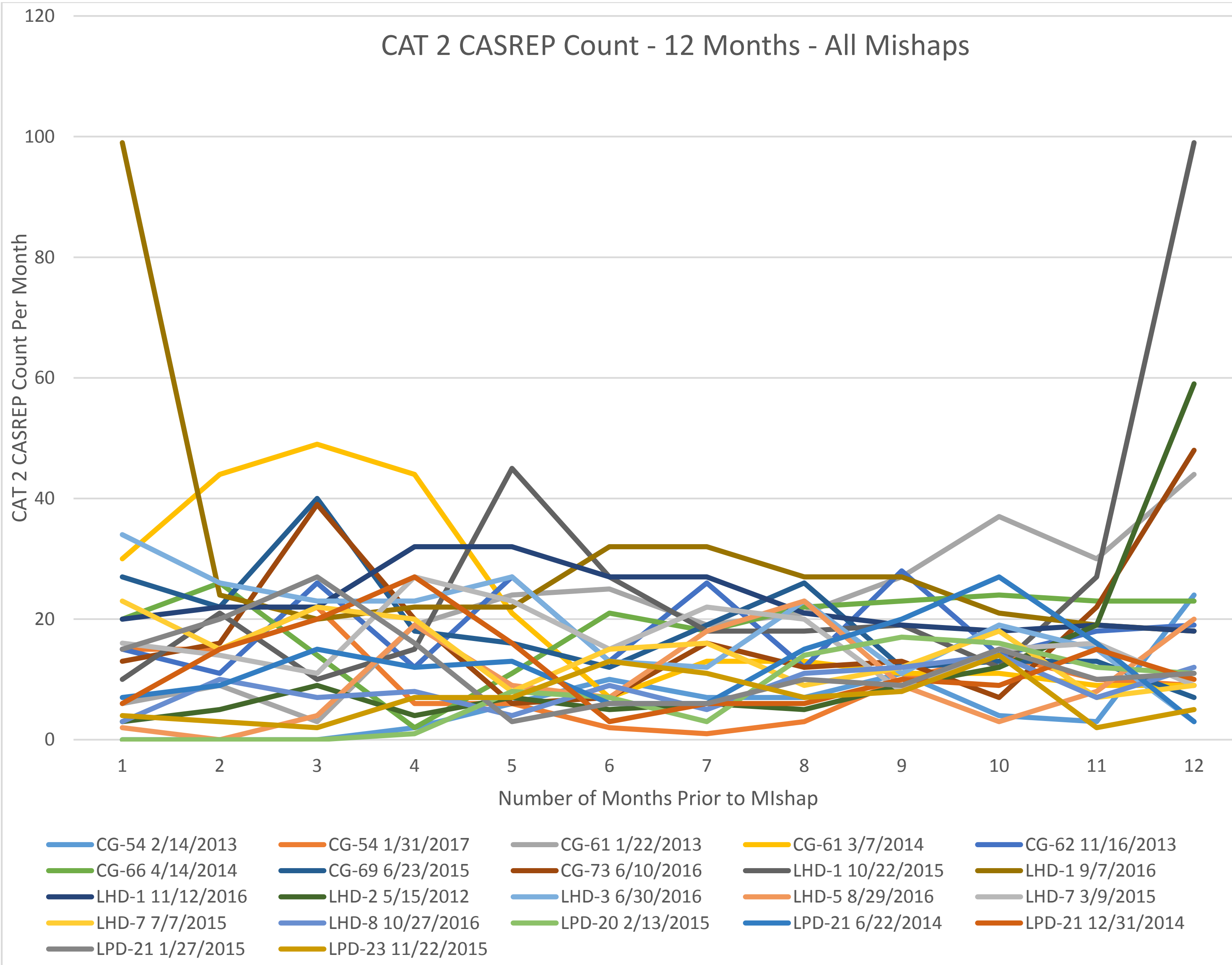
The gathering of such large amounts of historical data posed a significant challenge due to the numerous organizations that we had to contact to obtain it. Determining which organizations would have the data necessary was another challenge. There were data recommended for this study that might have an impact on our models and the conclusions drawn. As we contacted Afloat Training Group (ATG) in the data collection phase, it was found that data kept in these commands didn’t go back far enough to support this research. We learned previous training cycle inspection reports were not kept in a database or hard copy for numerous commands. As future research is conducted, we recommend ATG keep an up to date database for ship training cycle reports and individual warfare certifications and inspection results. Early on in this research, we identified ATG data as a top factor in ship readiness evaluations, but were unable to utilize this area of focus in our data collection and analysis, as the data were unavailable to review.

Other areas were identified as potential data collection items for this research, but mainly due to poor data records kept at numerous individual commands, we were unable to attain records for crew certification, 3-M, ship manning fit and fill data, Navy Enlisted Classification (NEC) shortfalls, navigation check ride reports, and additional crew intangibles such as a crew swap or homeport shift. As other research is conducted, from our experience, these records would aid in an analysis but historical data are not kept for these areas of focus.

Future research would greatly benefit if shipboard data are consolidated to a small number of data archives, aiding in the data collection and filtering to specific events. As previously discussed, mishap events differ drastically, and building a model tailored to identify factors when combining all the mishaps together is a huge challenge. Future models and research would benefit from our research data but with other internal behavior analyses of individual ships, factors leading or contributing to mishaps might be discovered.

APPENDIX. TIME SERIES AND TREND ANALYSIS CHARTS

Included for future research are graphs for each variable that was applicable. The graphs range in time frames from three to twelve months prior to each mishap. Each variable was graphed for each ship that had a mishap between 2012 and 2017. Each variable was also graphed by ship class to attempt to identify trends within ship classes.



CAT 2 CASREP Count - 12 Months - All Mishaps
CAT 2 CASREP Count Per Month
Number of Months Prior to MIshap
0
20
40
60
80
100
120
1
2
3
4
5
6
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
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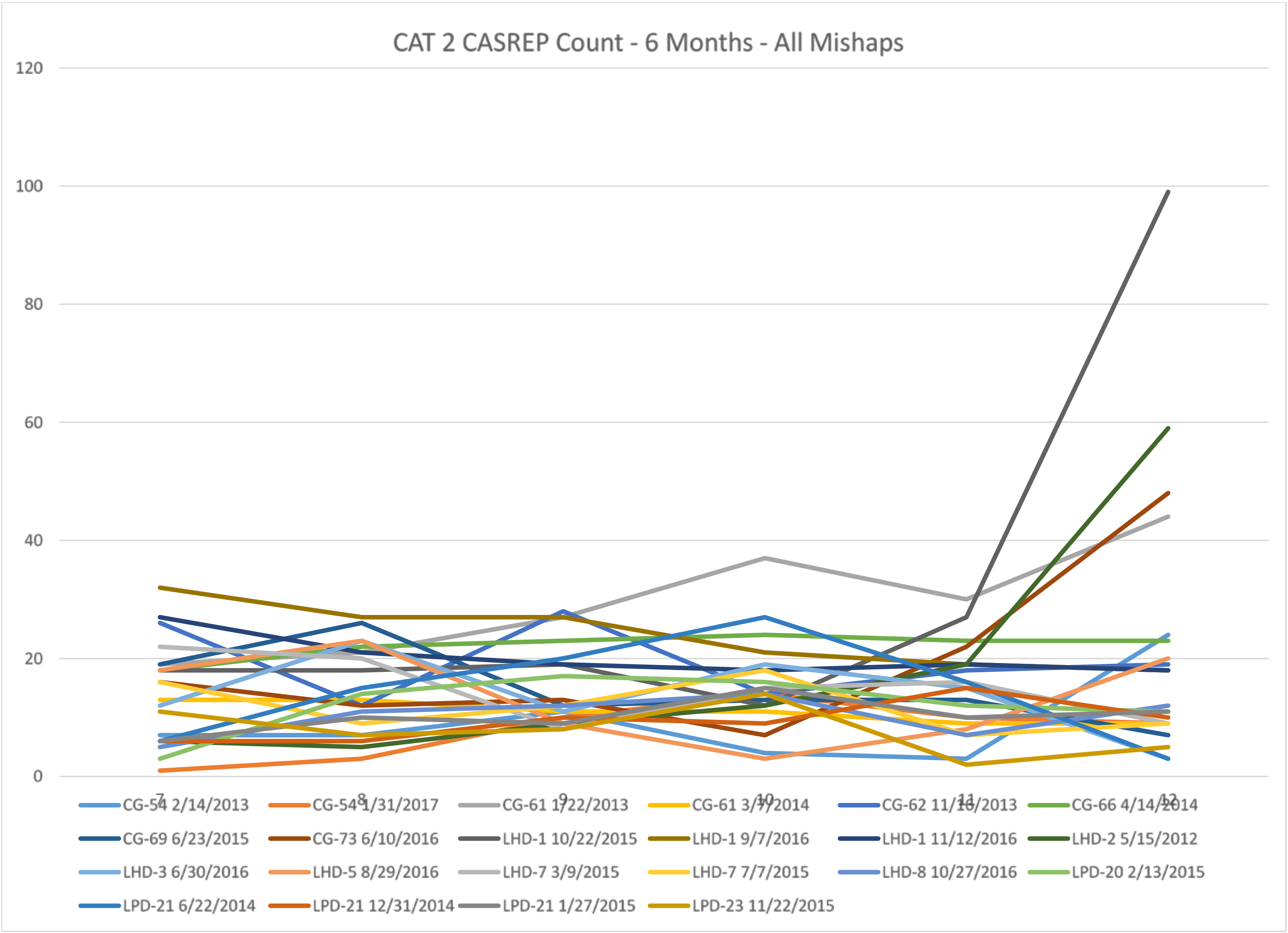
LPD-23 11/22/2015



CAT 2 CASREP Count - 6 Months - All Mishaps
120
100
80
60
40
20
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
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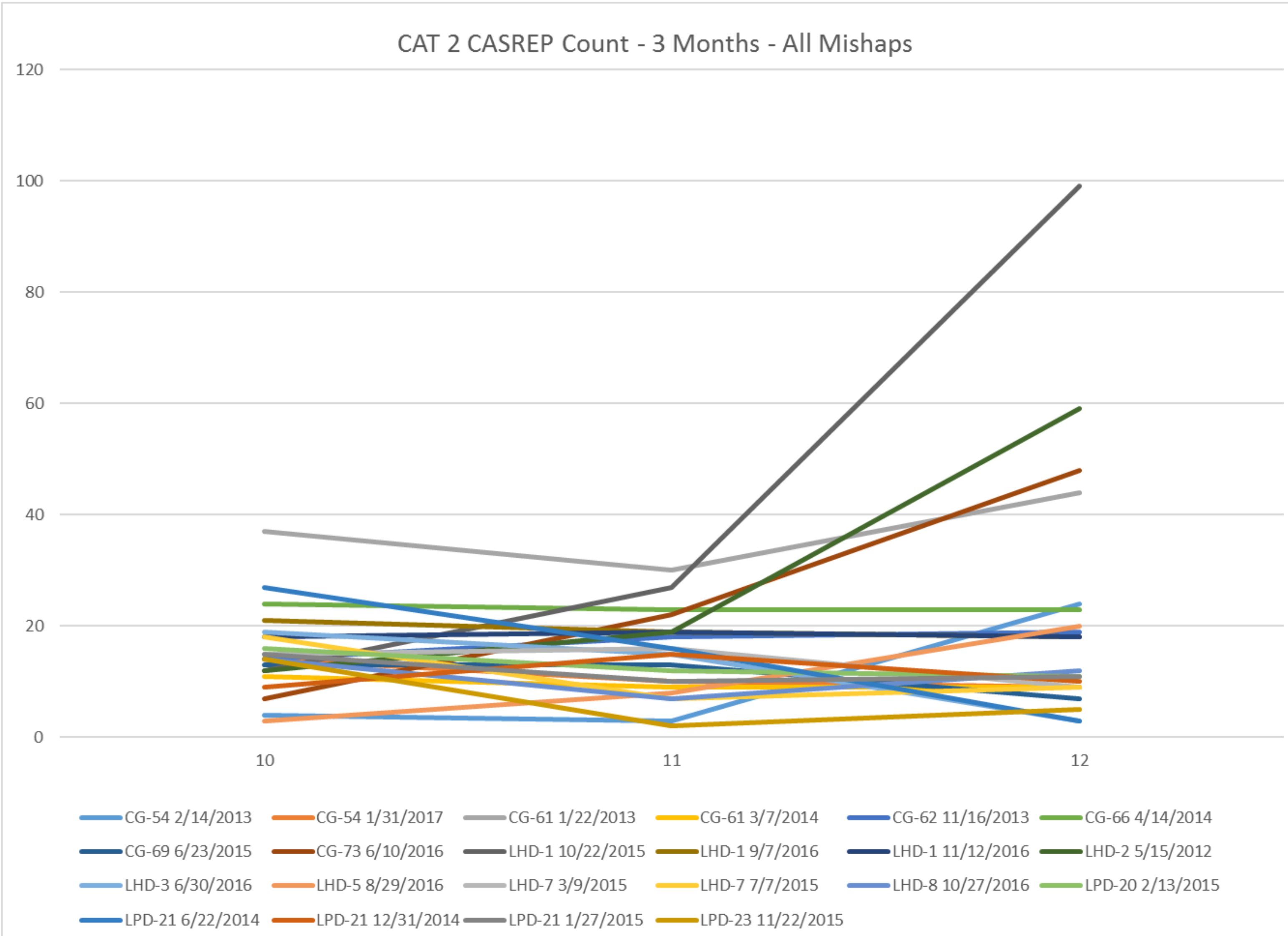
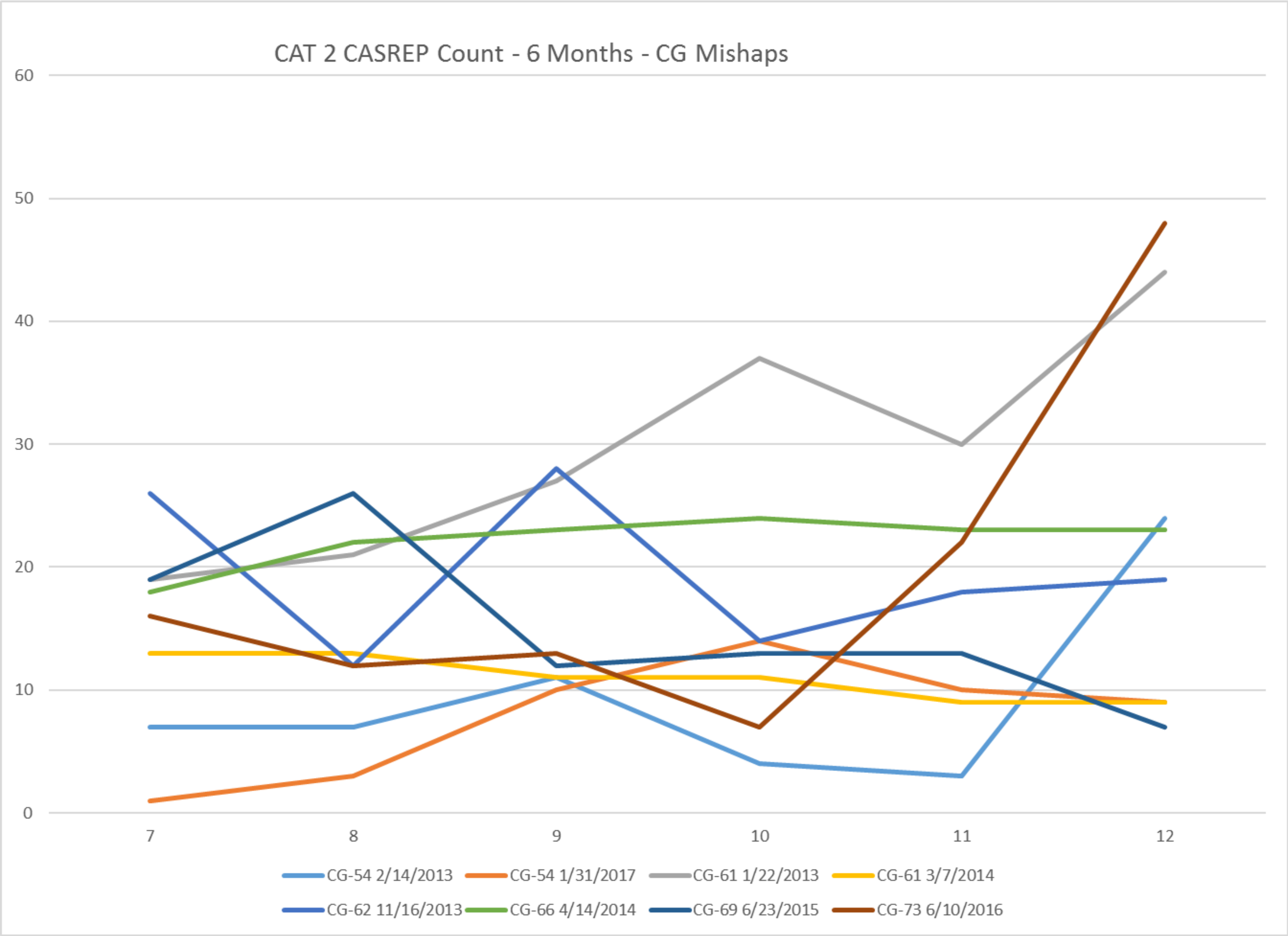
LPD-23 11/22/2015


CAT 2 CASREP Count - 3 Months - All Mishaps
120
100
80
60
40
20
0
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


CAT 2 CASREP Count - 6 Months - CG Mishaps
60
50
40
30
20
10
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
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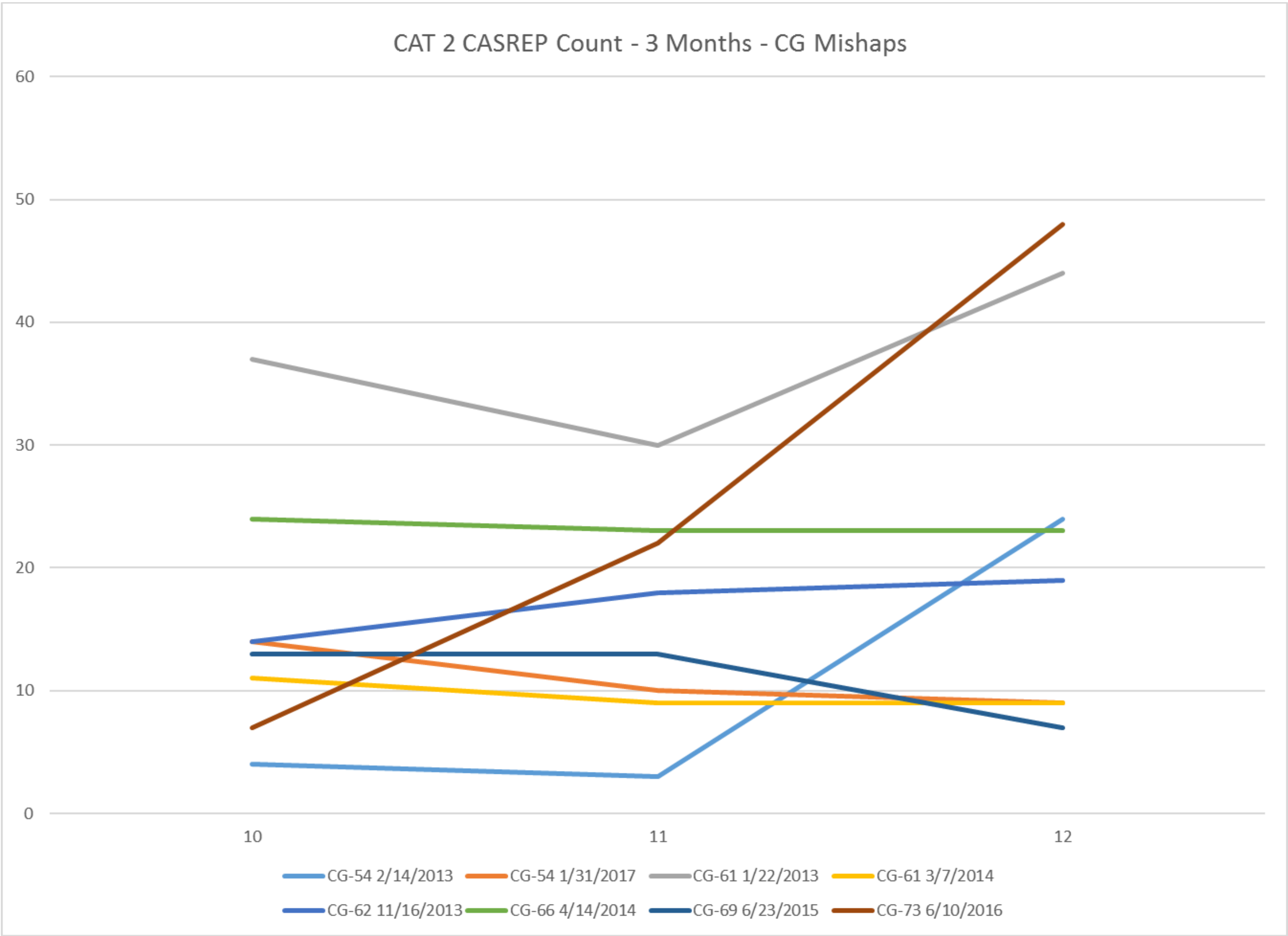
CG-73 6/10/2016


CAT 2 CASREP Count - 3 Months - CG Mishaps
60
50
40
30
20
10
0
10
11
12
CG-54 2/14/2013
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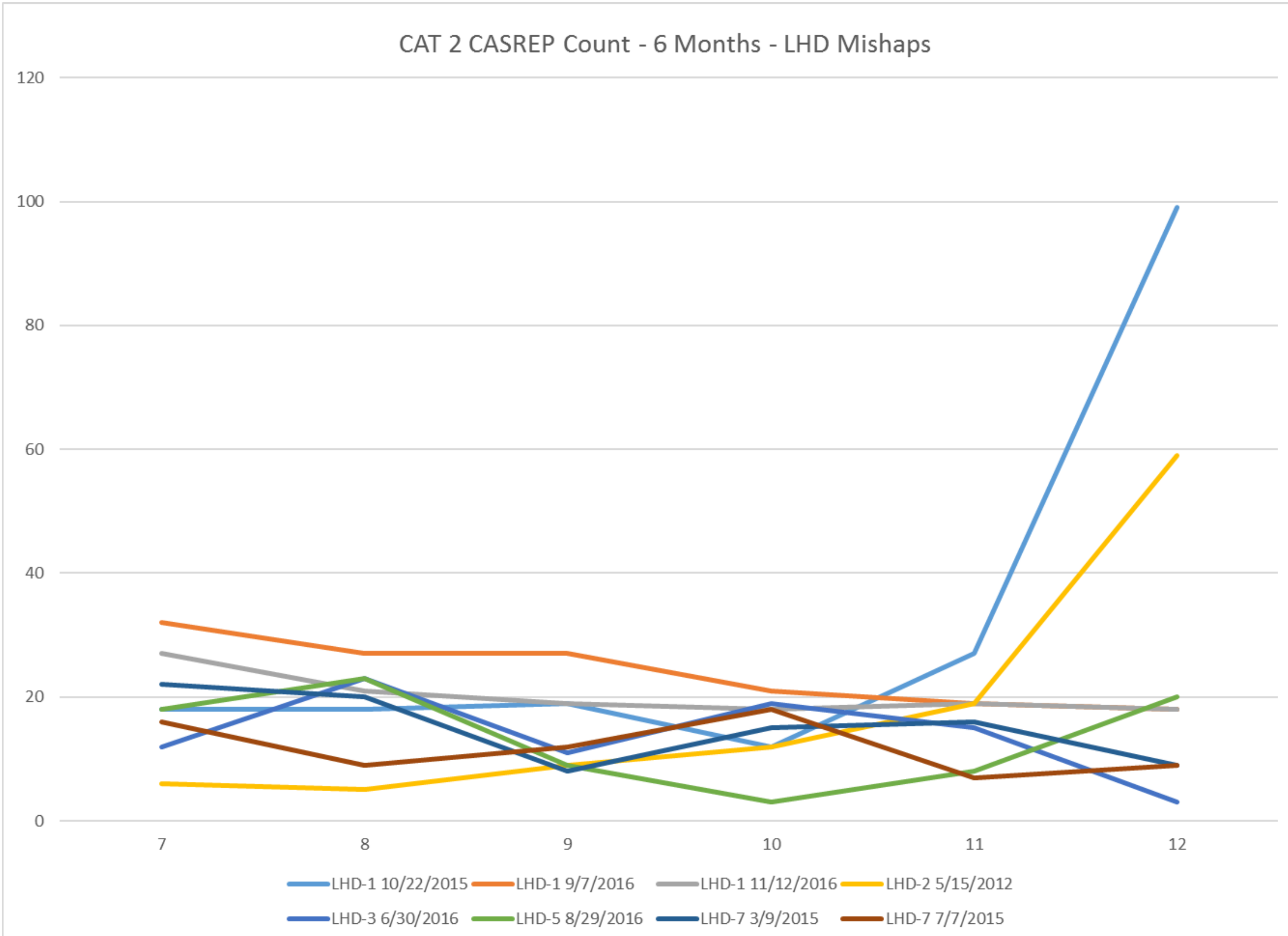
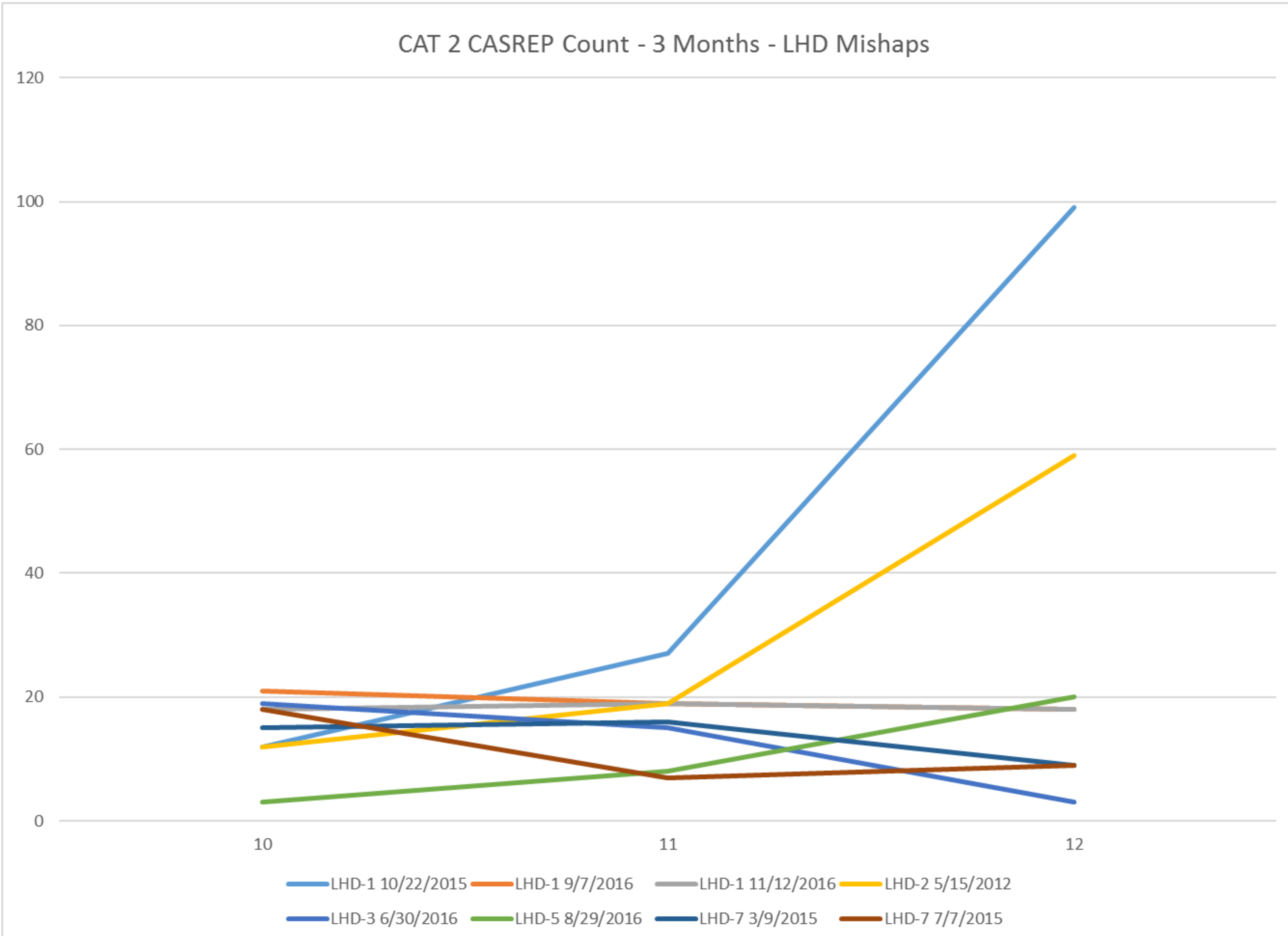
CG-73 6/10/2016



CAT 2 CASREP Count - 6 Months - LHD Mishaps
120
100
80
60
40
20
0
7
8
9
10
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015


CAT 2 CASREP Count - 3 Months - LHD Mishaps
120
100
80
60
40
20
0
10
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
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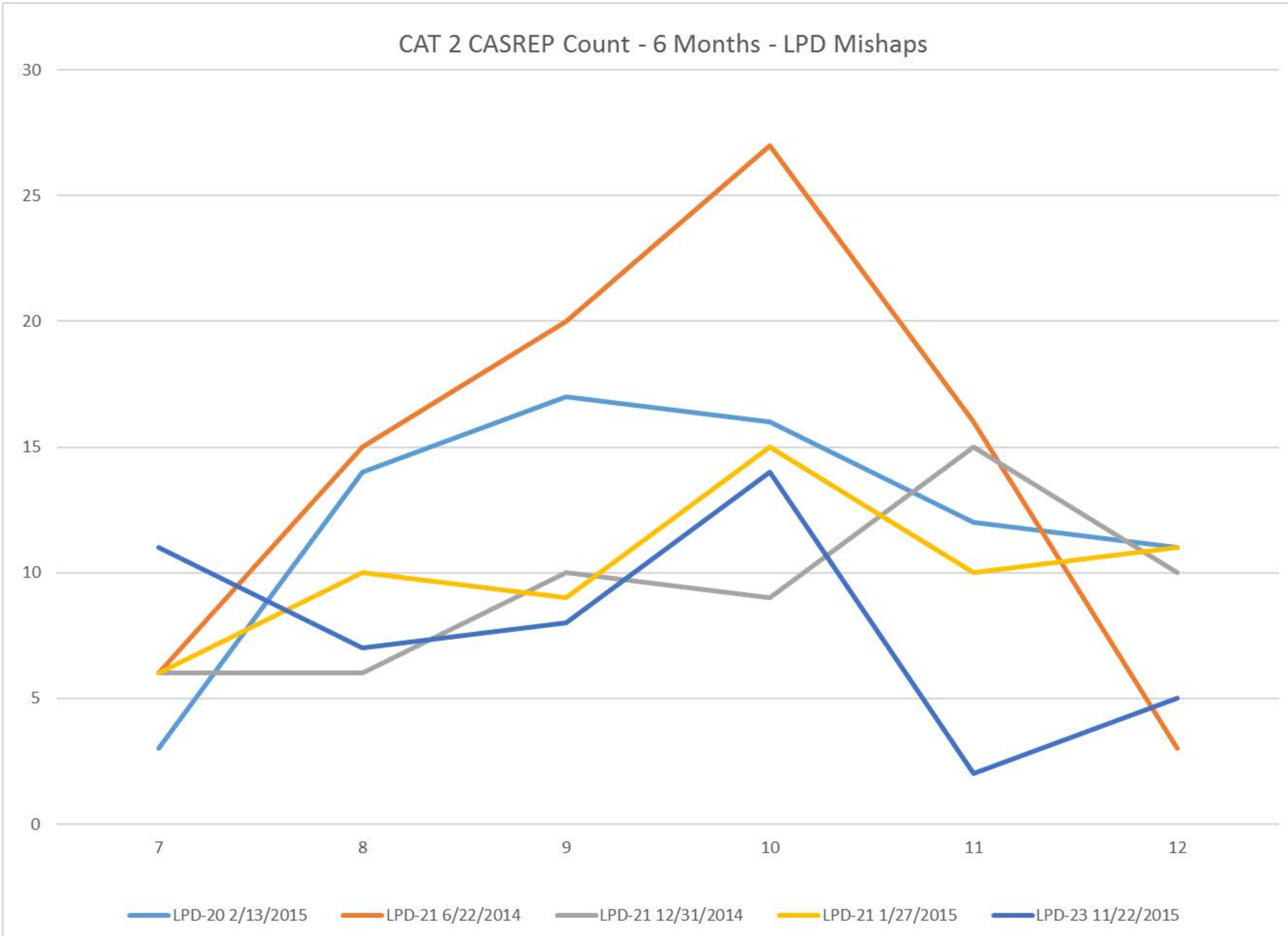
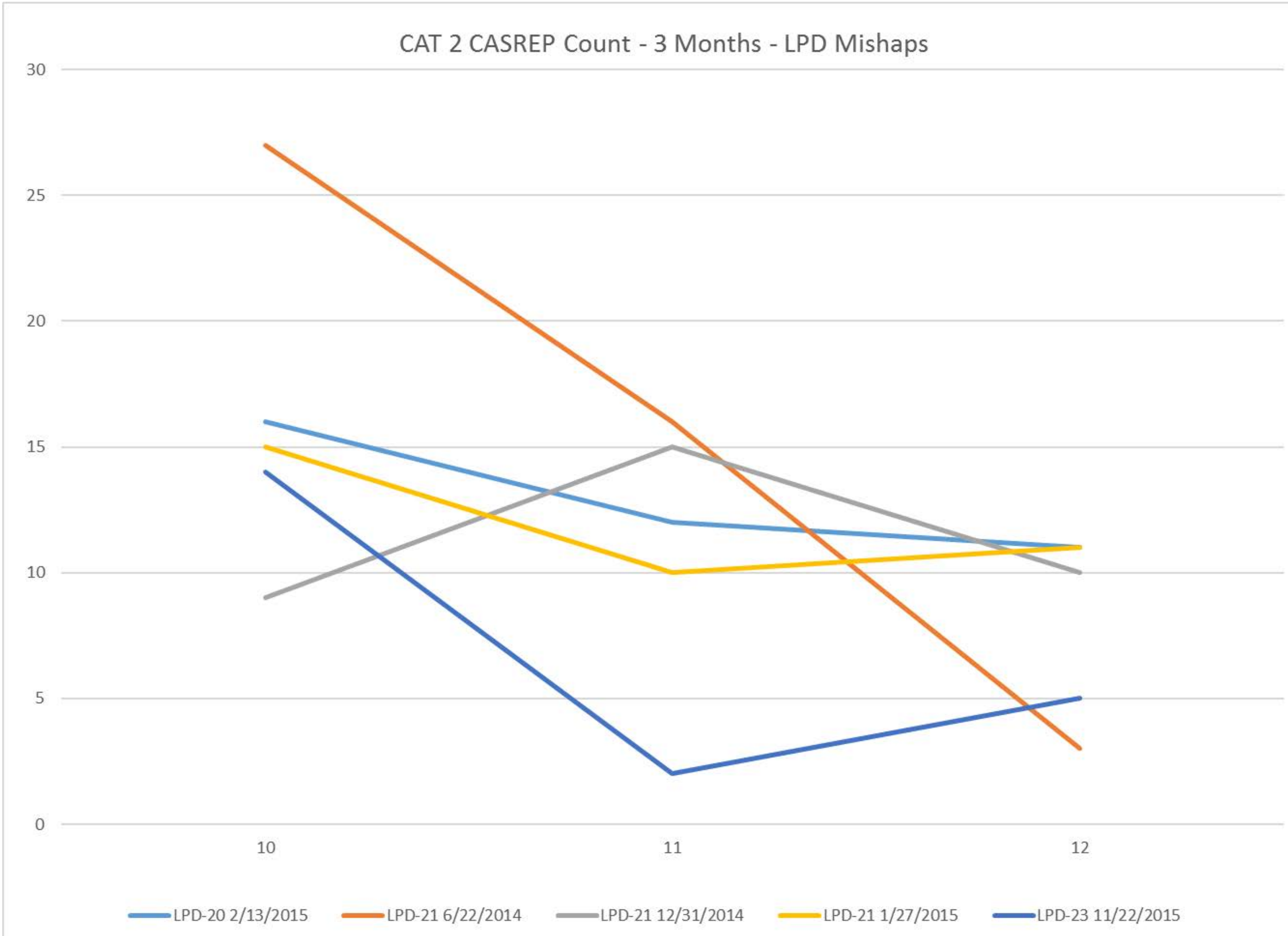
LHD-7 7/7/2015



CAT 2 CASREP Count - 6 Months - LPD Mishaps
30
25
20
15
10
5
0
7
8
9
10
11
12
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015



CAT 2 CASREP Count - 3 Months - LPD Mishaps
30
25
20
15
10
5
0
10
11
12
LPD-20 2/13/2015
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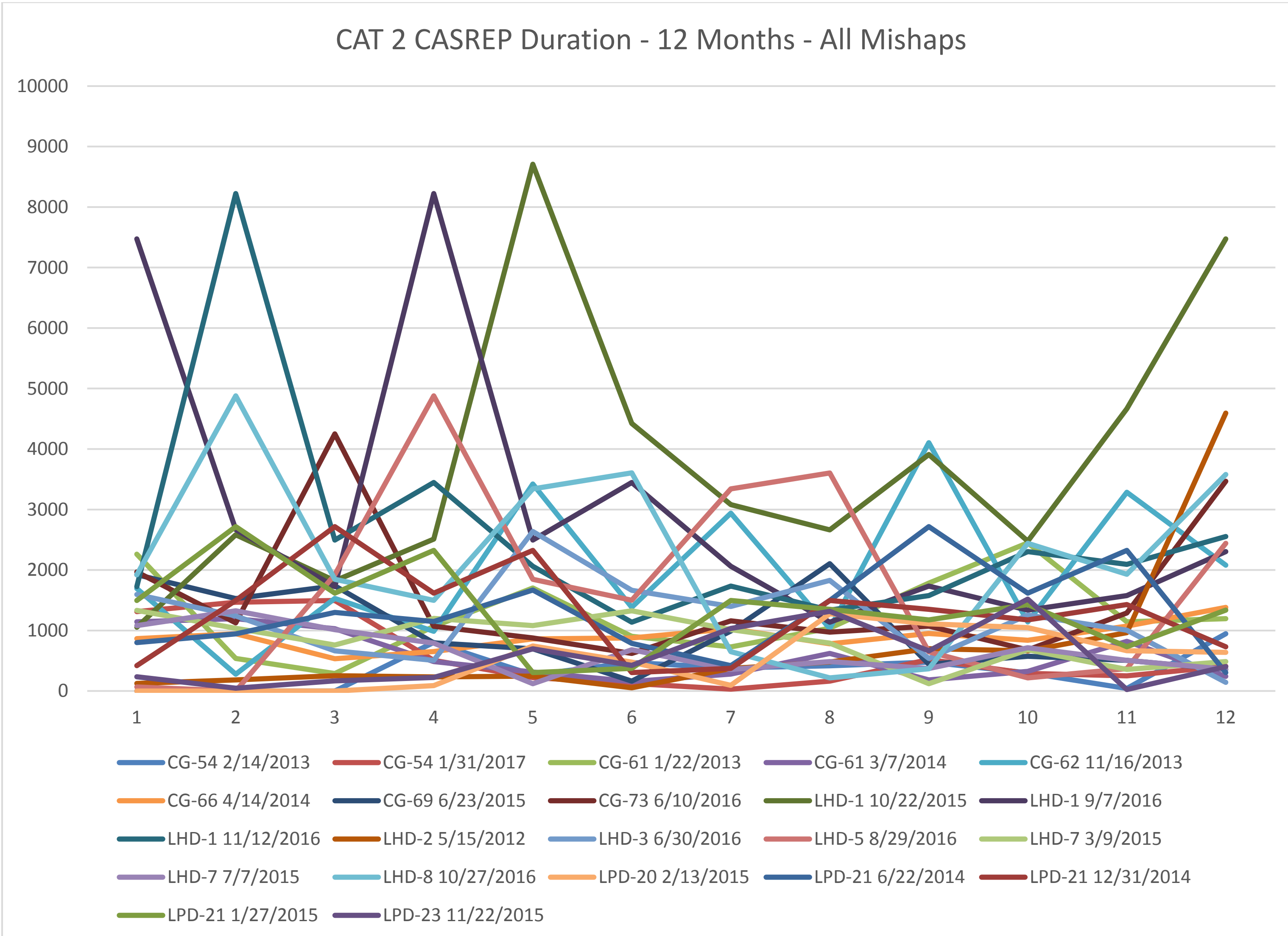
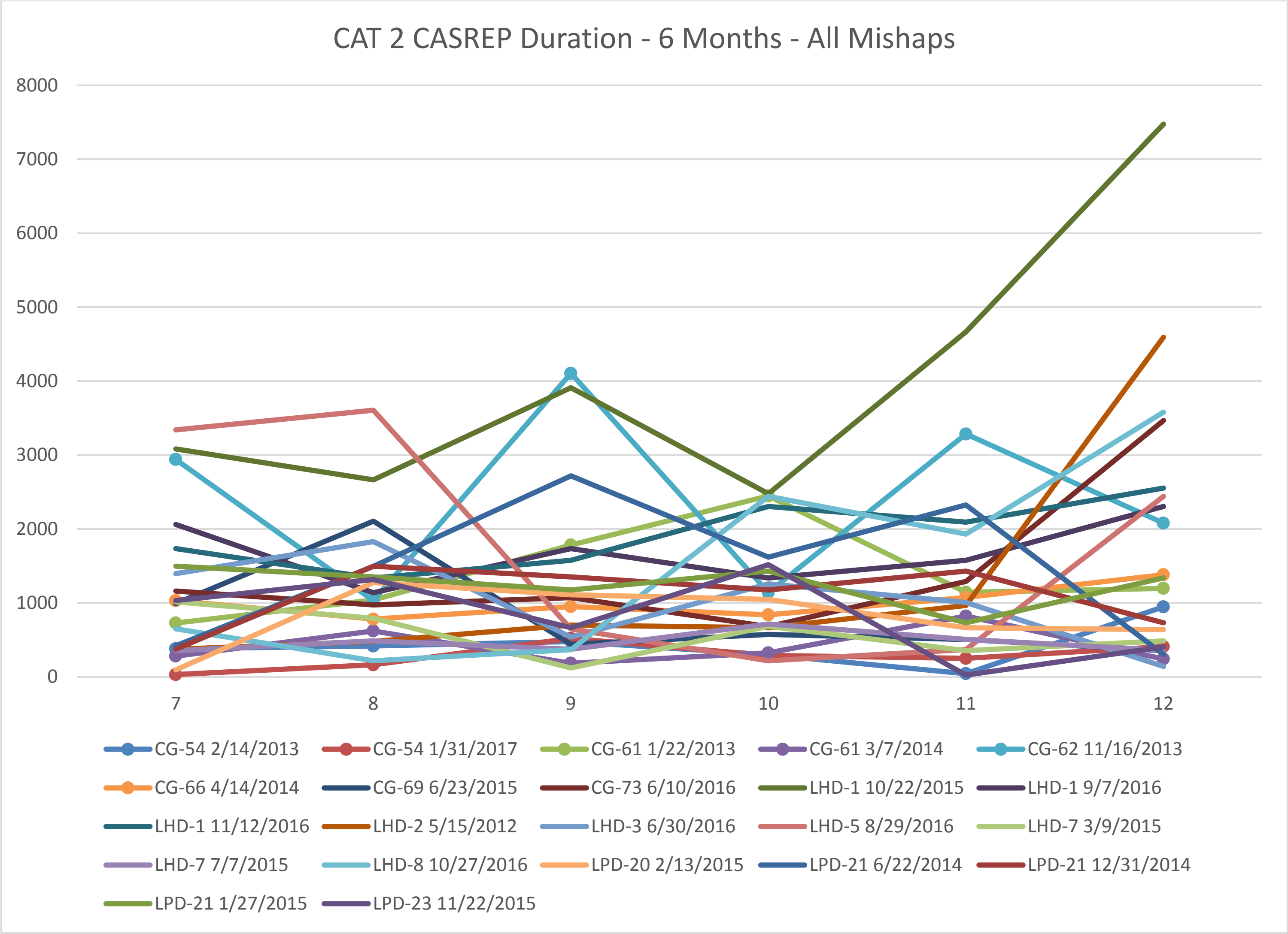
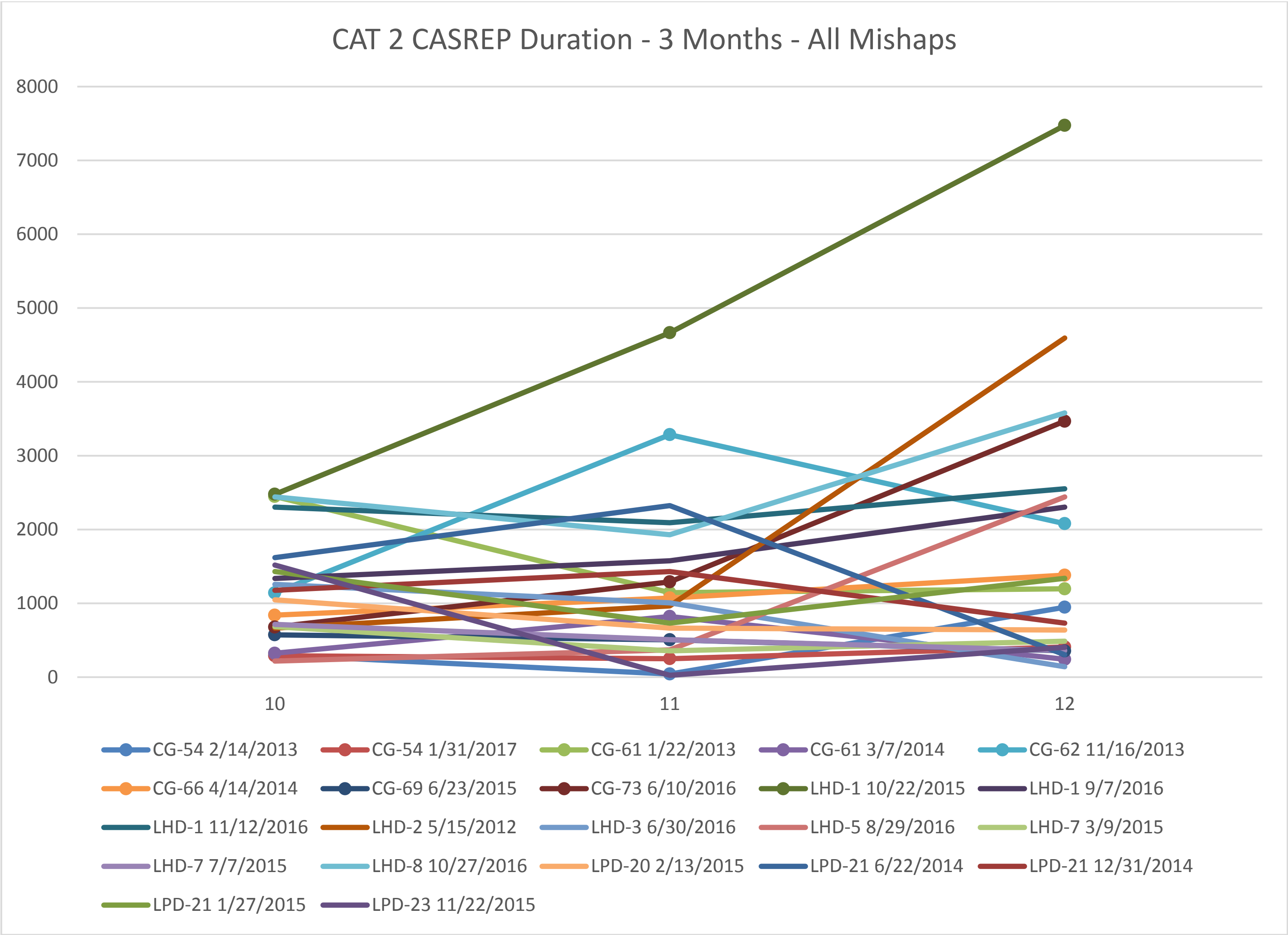
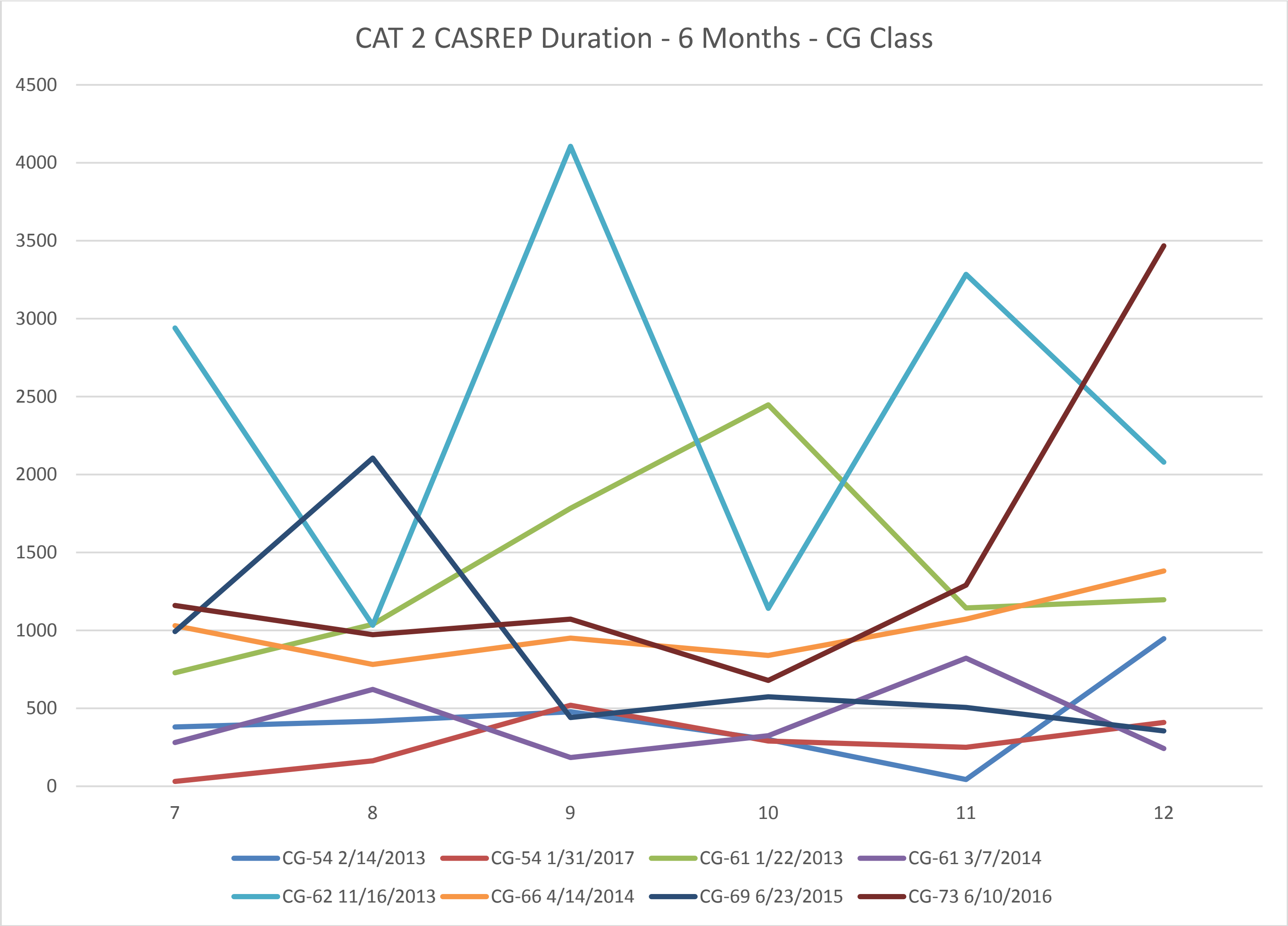
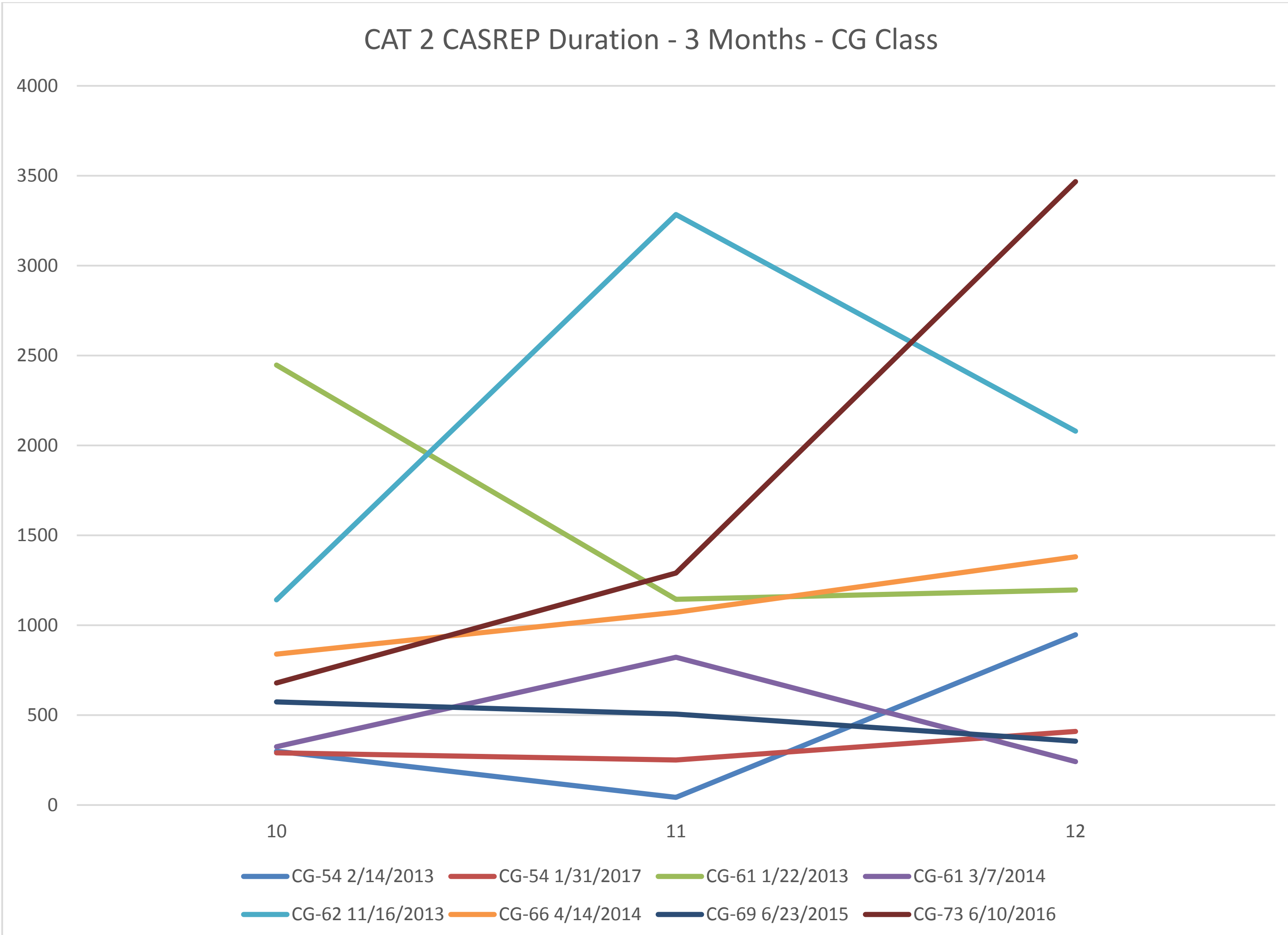
LPD-23 11/22/2015

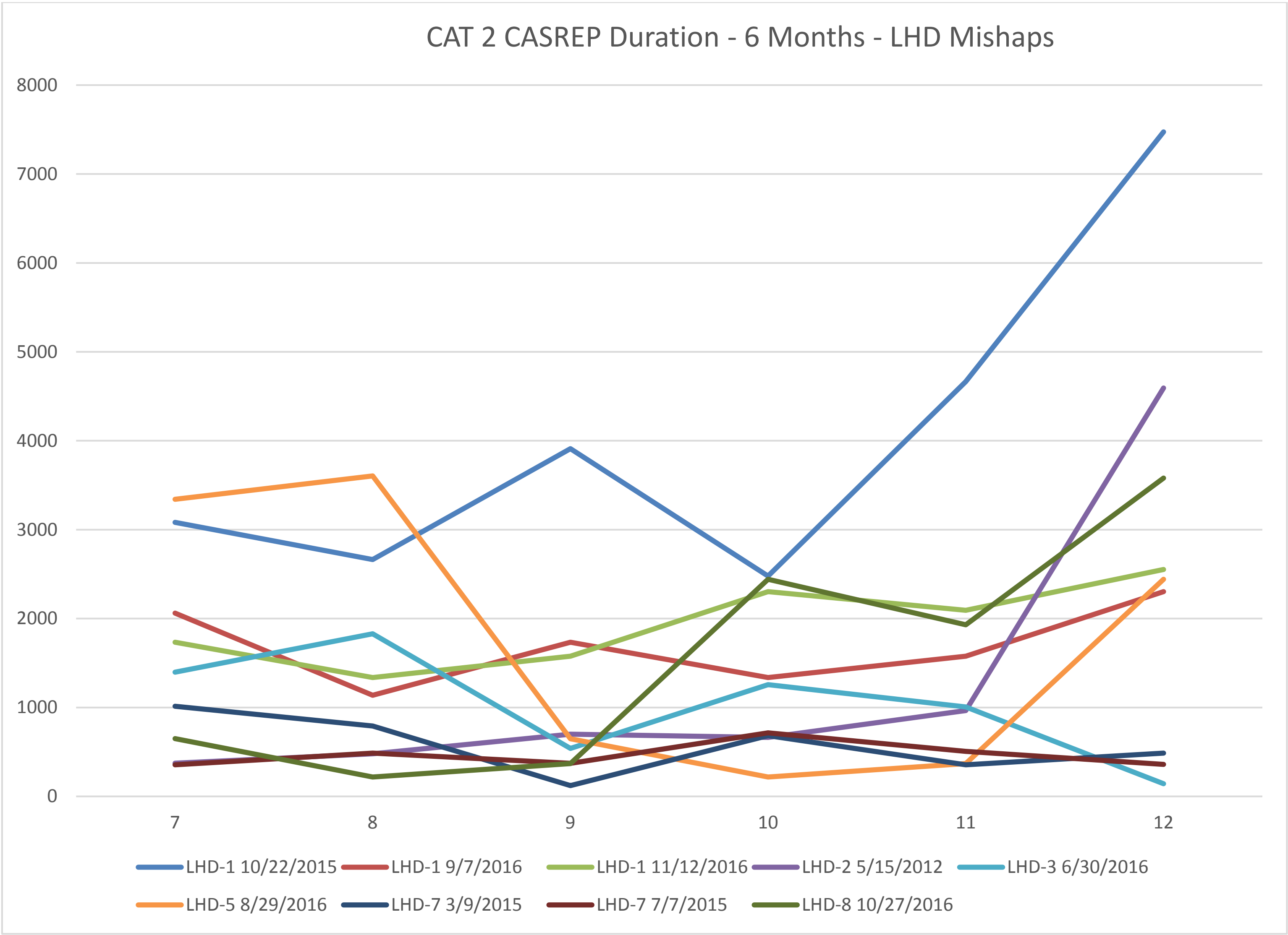

CAT 2 CASREP Duration - 12 Months - All Mishaps
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1
2
3
4
5
6
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

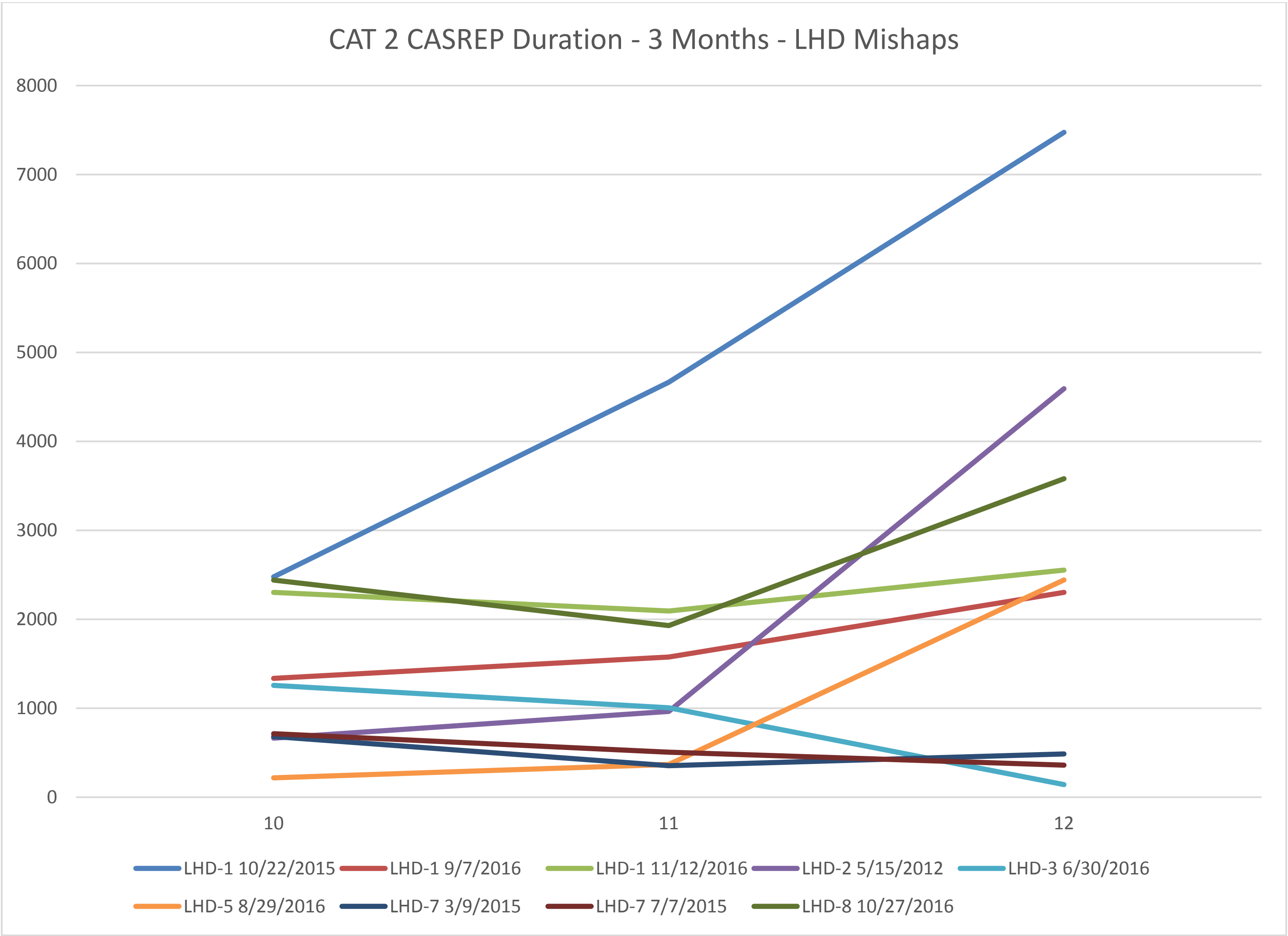

CAT 2 CASREP Duration - 6 Months - All Mishaps
8000
7000
6000
5000
4000
3000
2000
1000
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

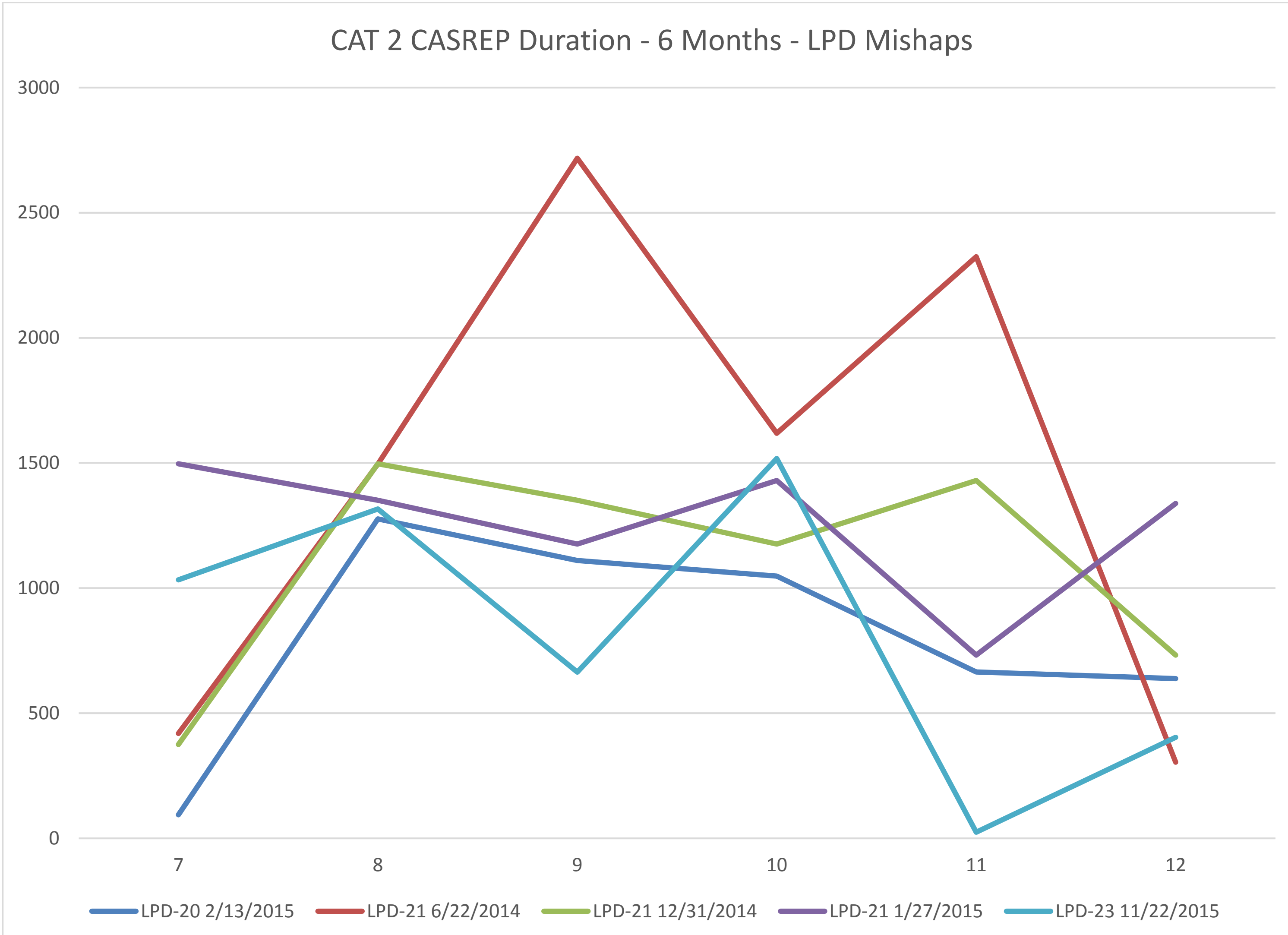

CAT 2 CASREP Duration - 3 Months - All Mishaps
8000
7000
6000
5000
4000
3000
2000
1000
0
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

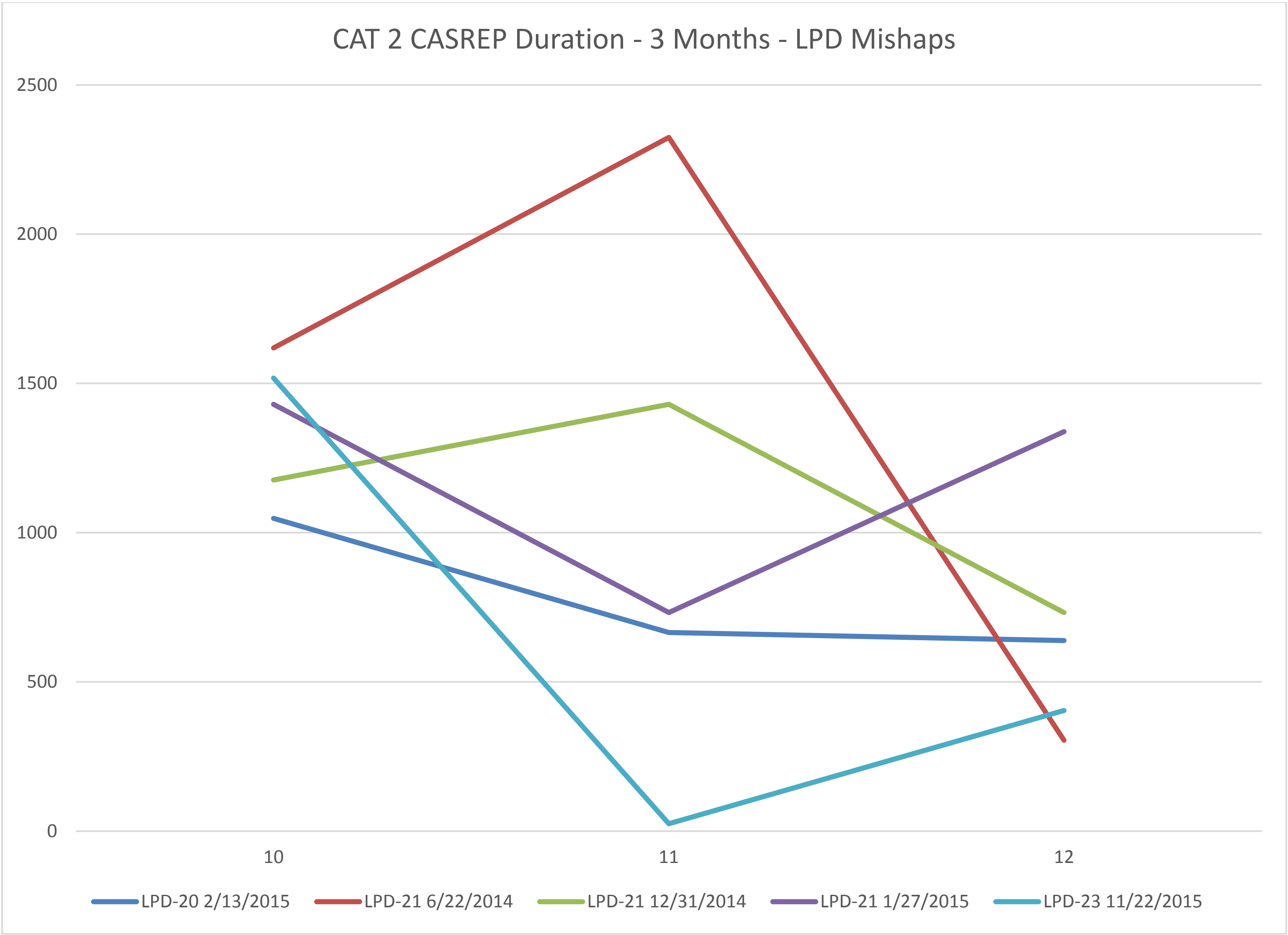

CAT 2 CASREP Duration - 6 Months - CG Class
4500
4000
3500
3000
2500
2000
1500
1000
500
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016

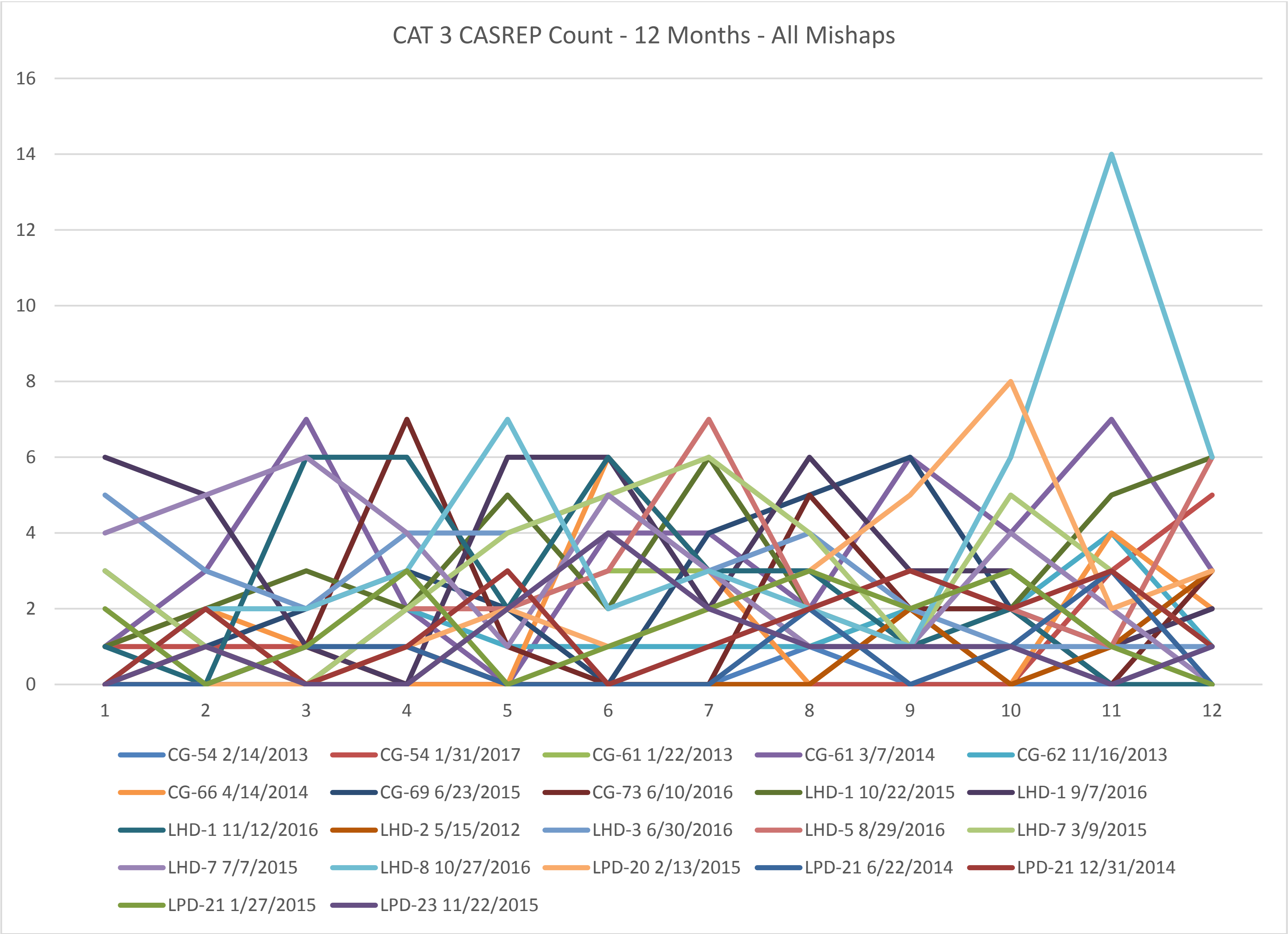

CAT 2 CASREP Duration - 3 Months - CG Class
4000
3500
3000
2500
2000
1500
1000
500
0
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016

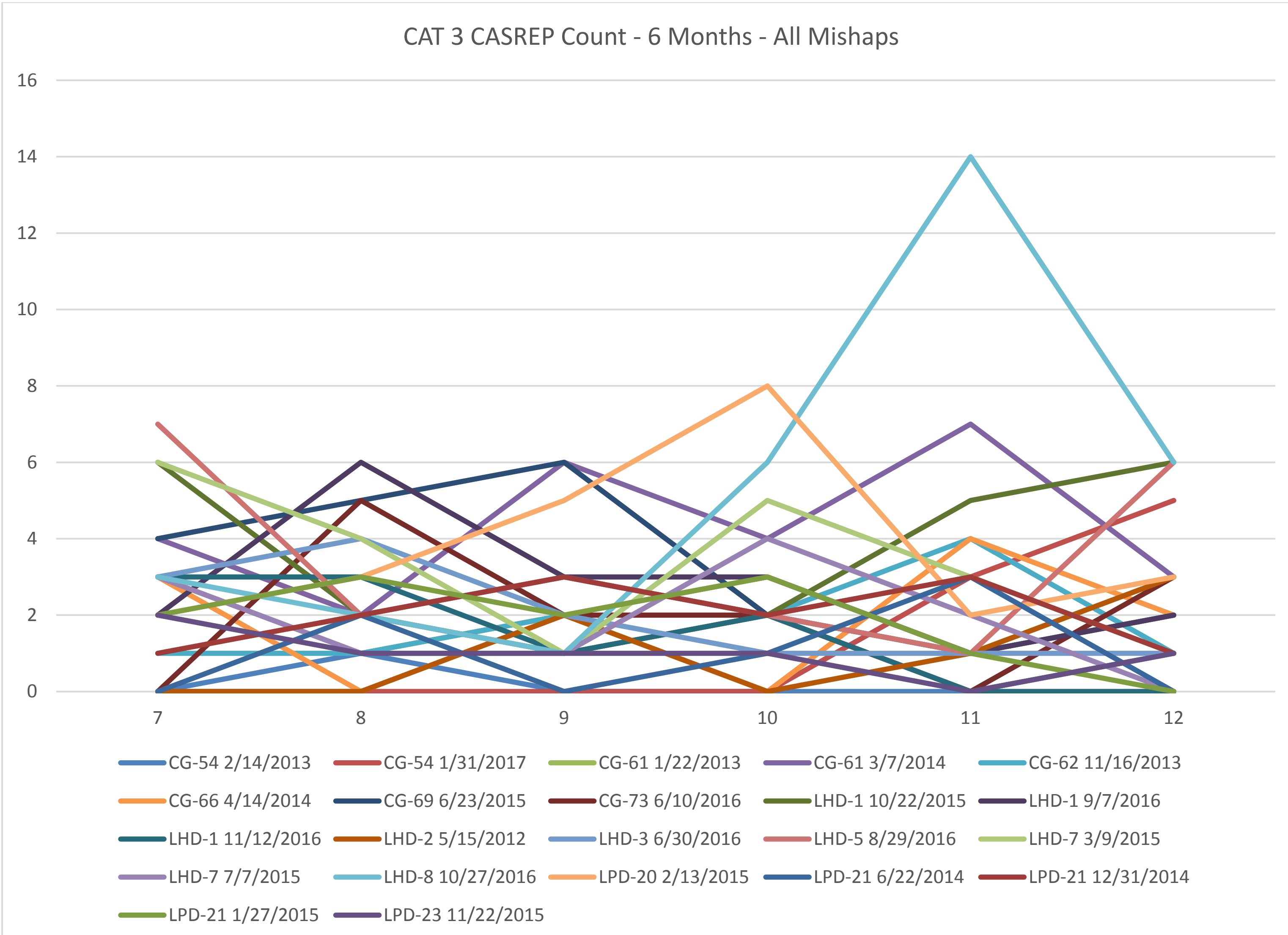

CAT 2 CASREP Duration - 6 Months - LHD Mishaps
8000
7000
6000
5000
4000
3000
2000
1000
0
7
8
9
10
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016


CAT 2 CASREP Duration - 3 Months - LHD Mishaps
8000
7000
6000
5000
4000
3000
2000
1000
0
10
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016

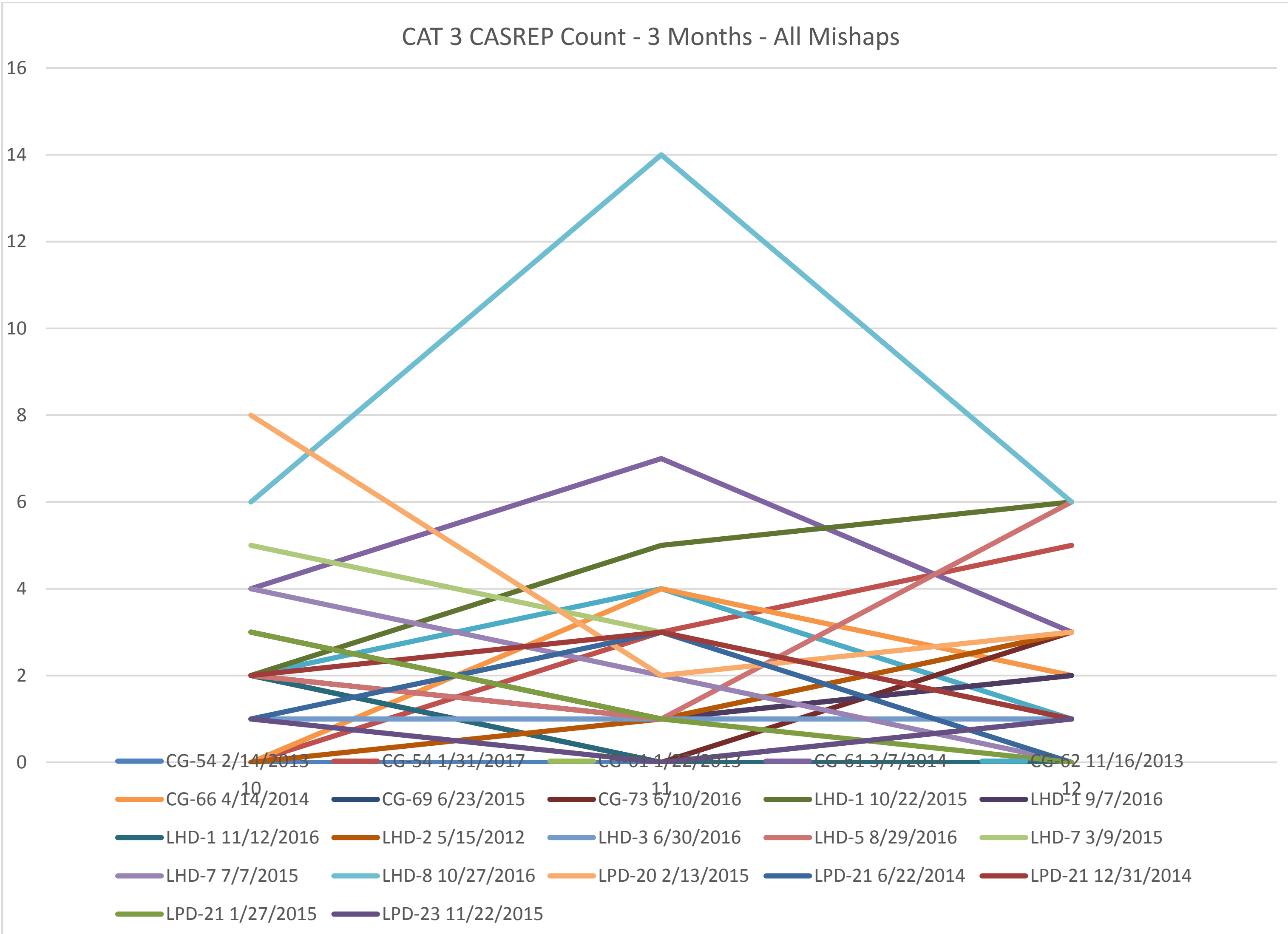

CAT 2 CASREP Duration - 6 Months - LPD Mishaps
3000
2500
2000
1500
1000
500
0
7
8
9
10
11
12
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


CAT 2 CASREP Duration - 3 Months - LPD Mishaps
2500
2000
1500
1000
500
0
10
11
12
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

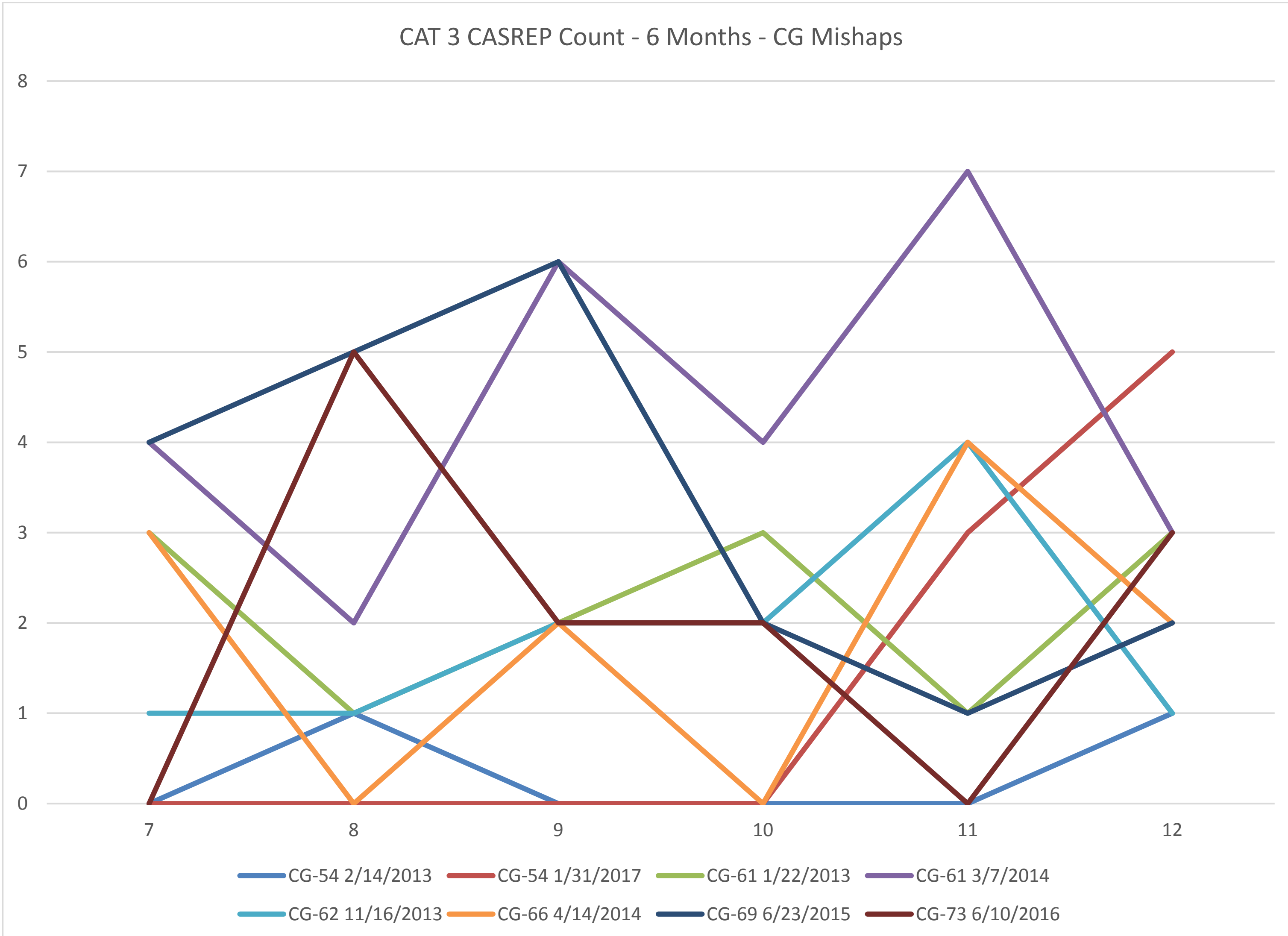

CAT 3 CASREP Count - 12 Months - All Mishaps
0
2
4
6
8
10
12
14
16
1
2
3
4
5
6
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015



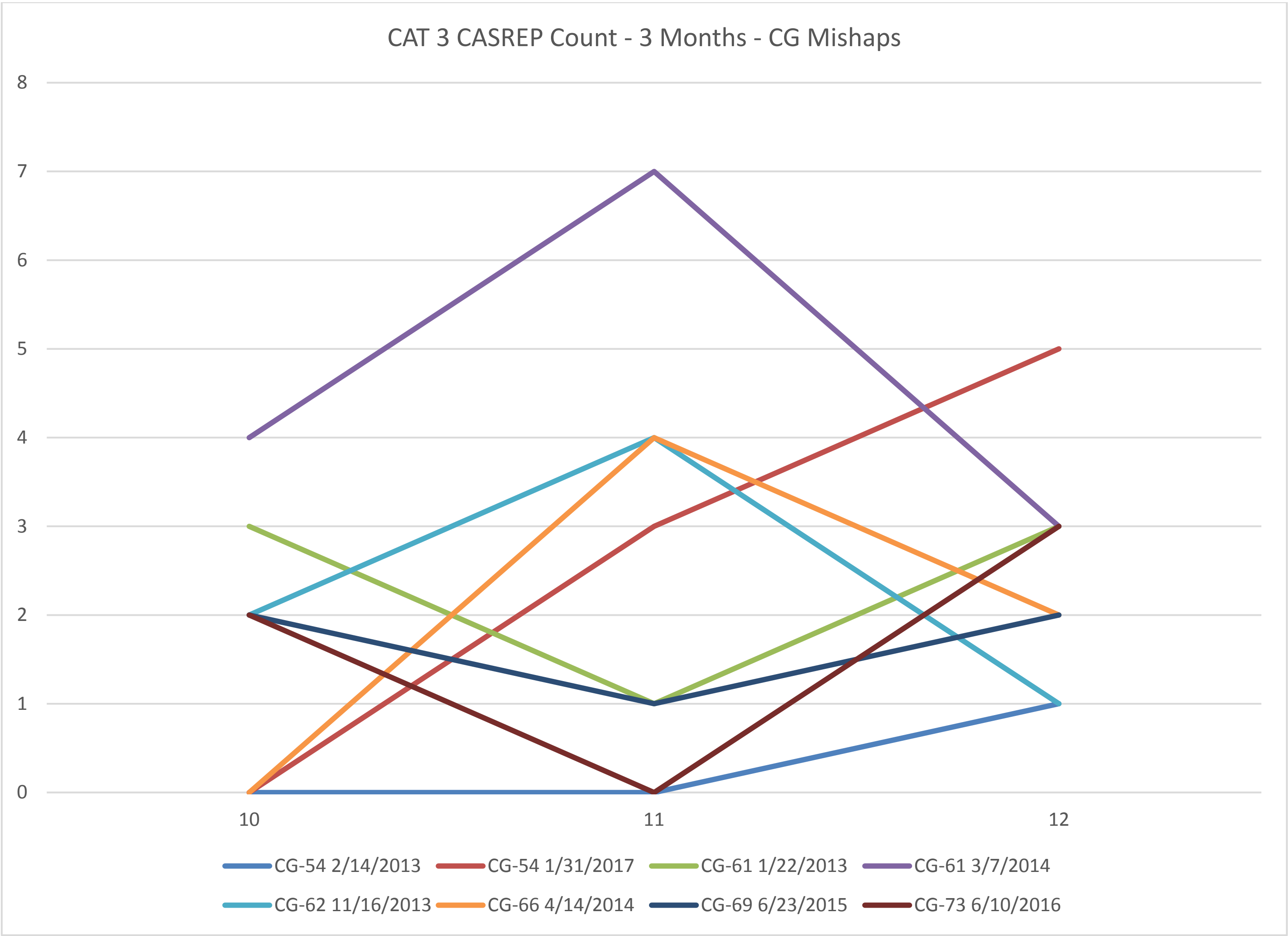
CAT 3 CASREP Count - 6 Months - All Mishaps
16
14
12
10
8
6
4
2
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

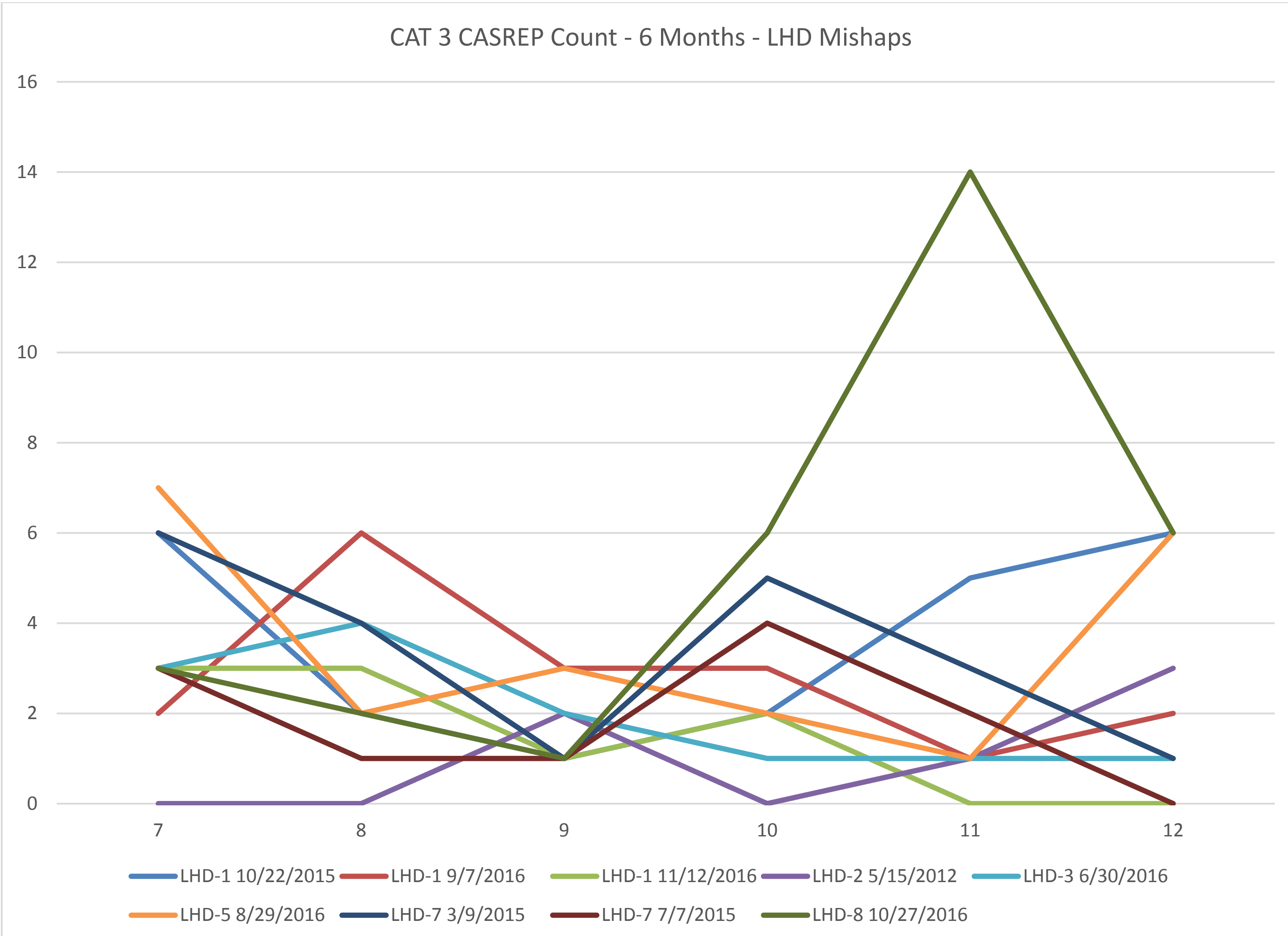


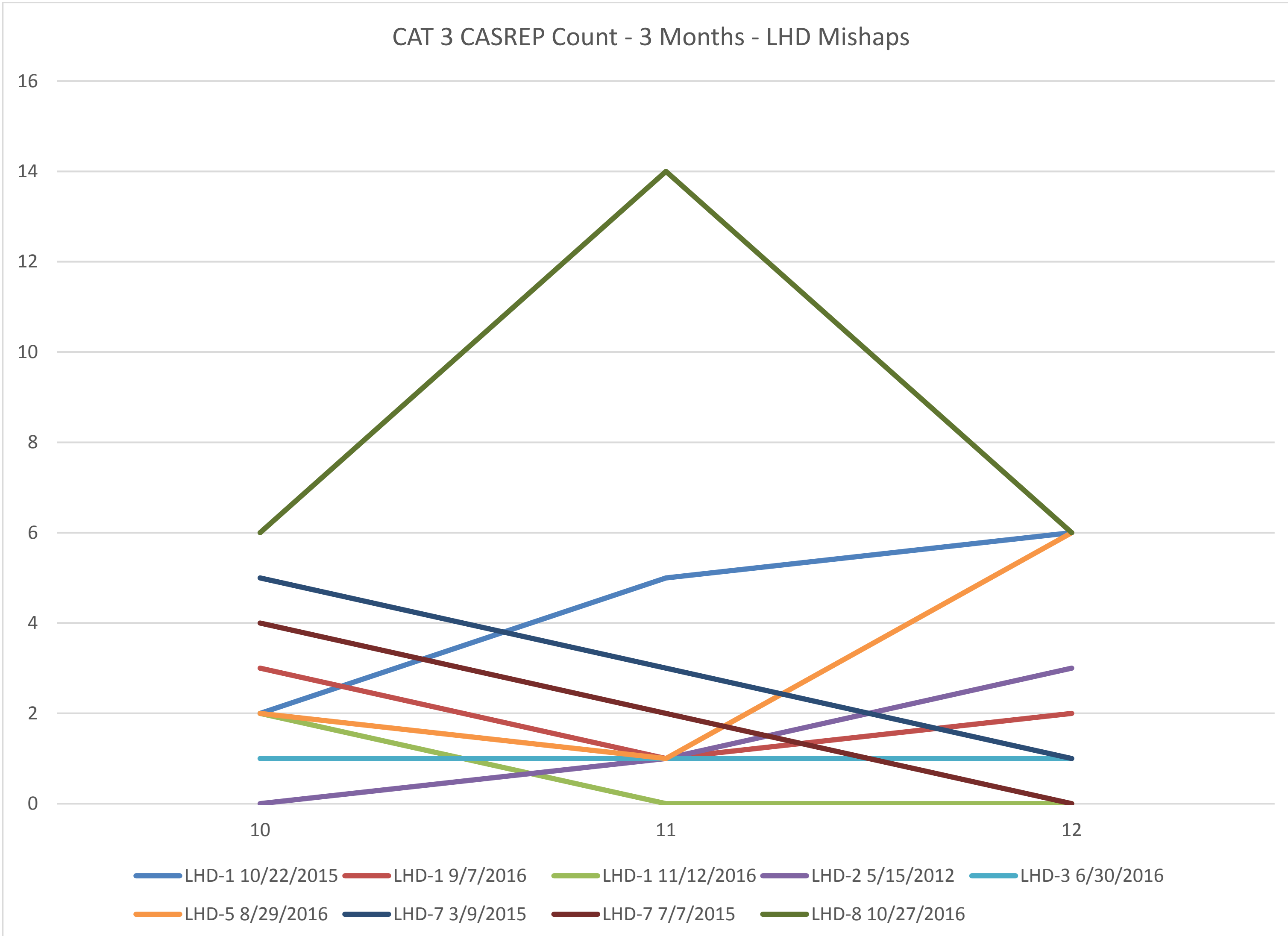
CAT 3 CASREP Count - 3 Months - All Mishaps
16
14
12
10
8
6
4
2
0
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

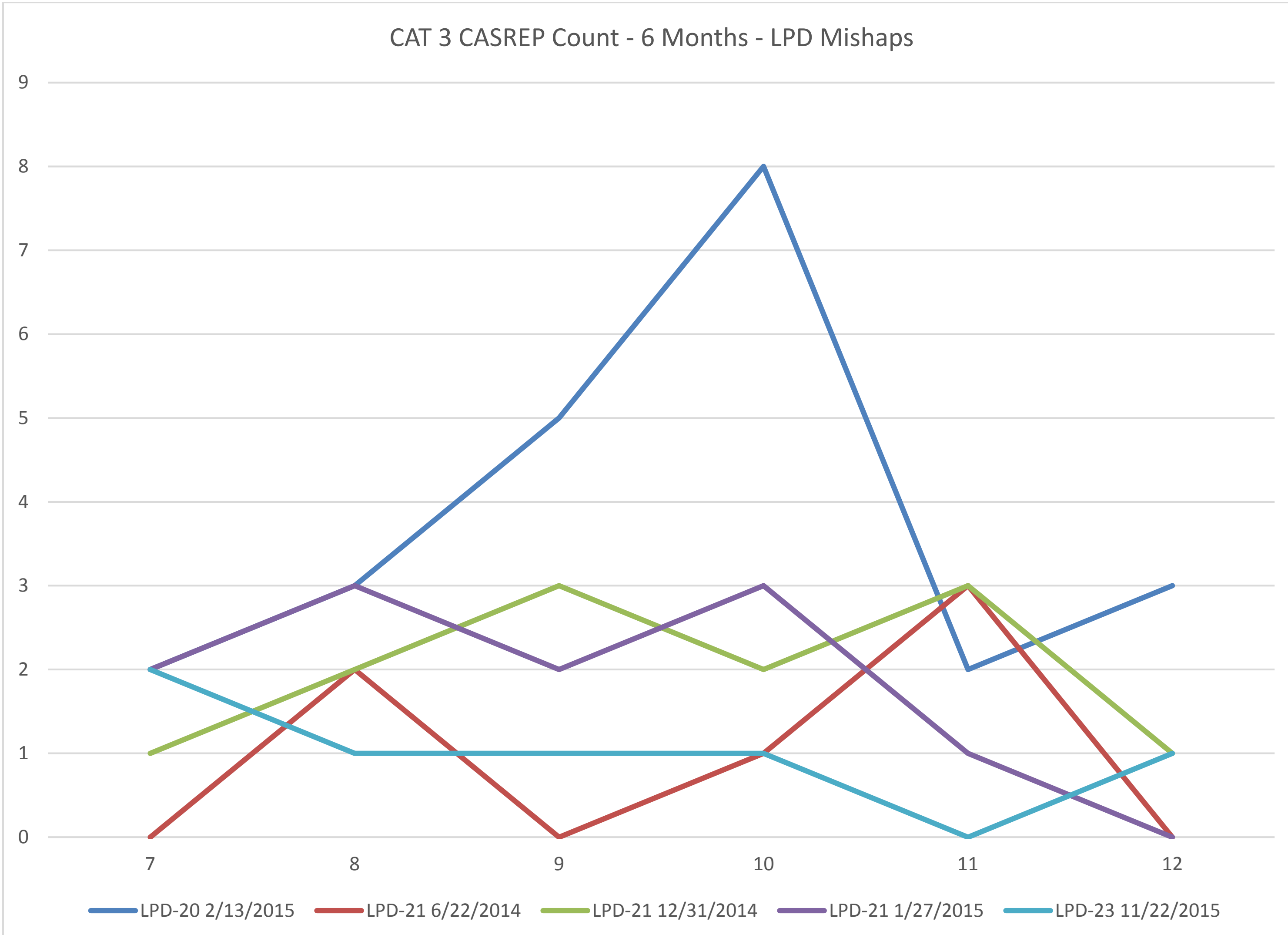


CAT 3 CASREP Count - 6 Months - CG Mishaps
8
7
6
5
4
3
2
1
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016

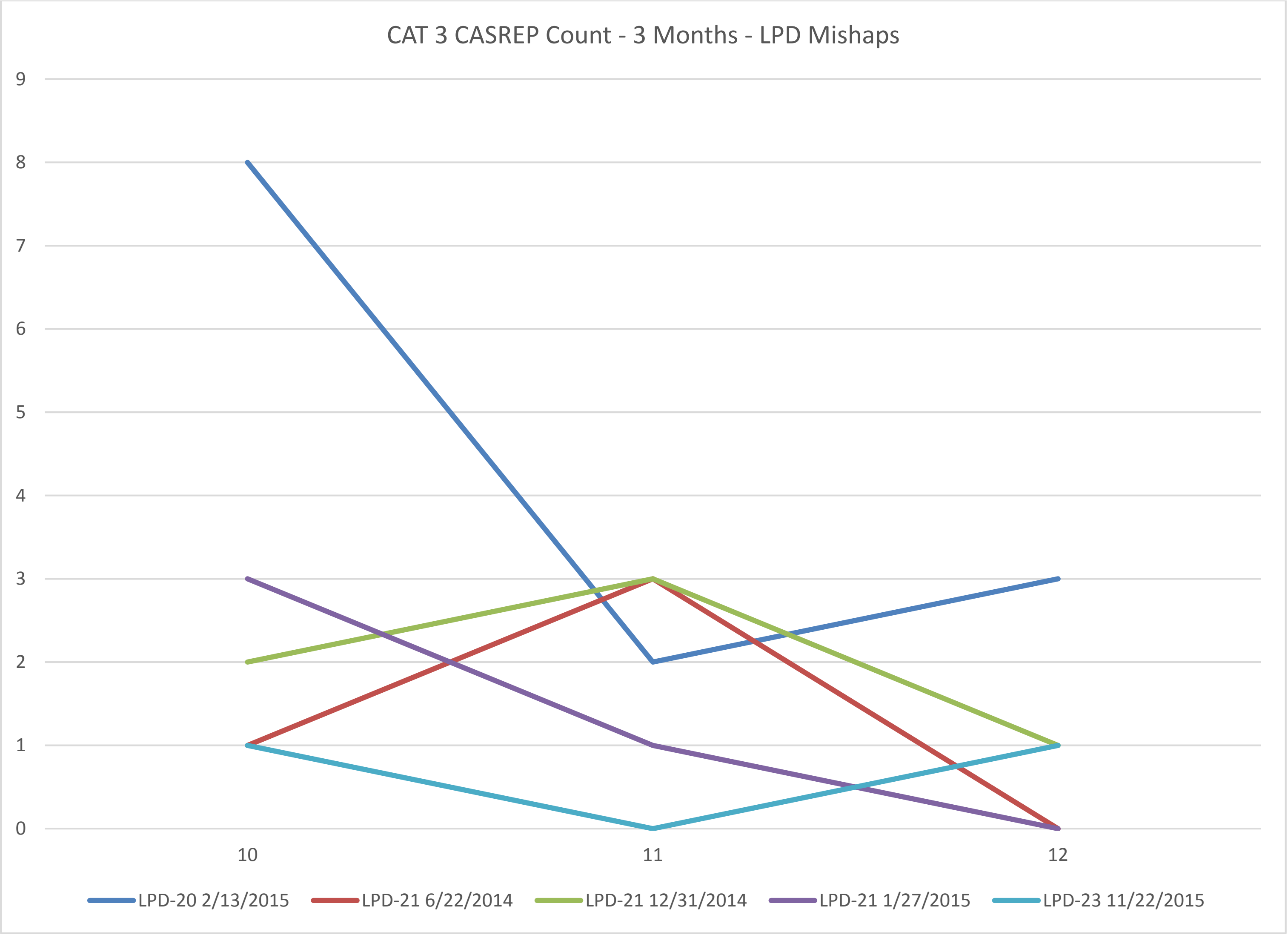

CAT 3 CASREP Count - 3 Months - CG Mishaps
8
7
6
5
4
3
2
1
0
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016

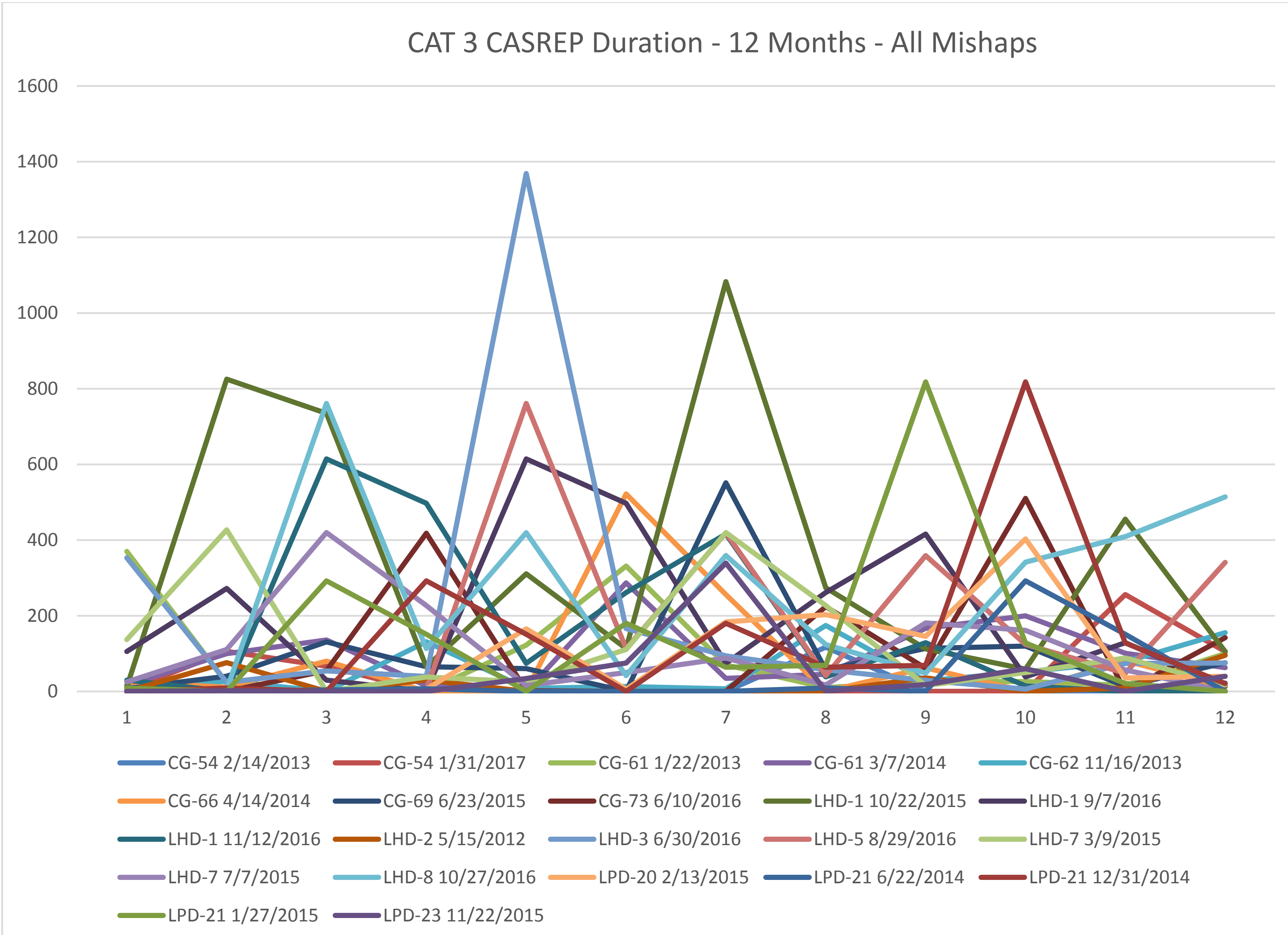

CAT 3 CASREP Count - 6 Months - LHD Mishaps
16
14
12
10
8
6
4
2
0
7
8
9
10
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016

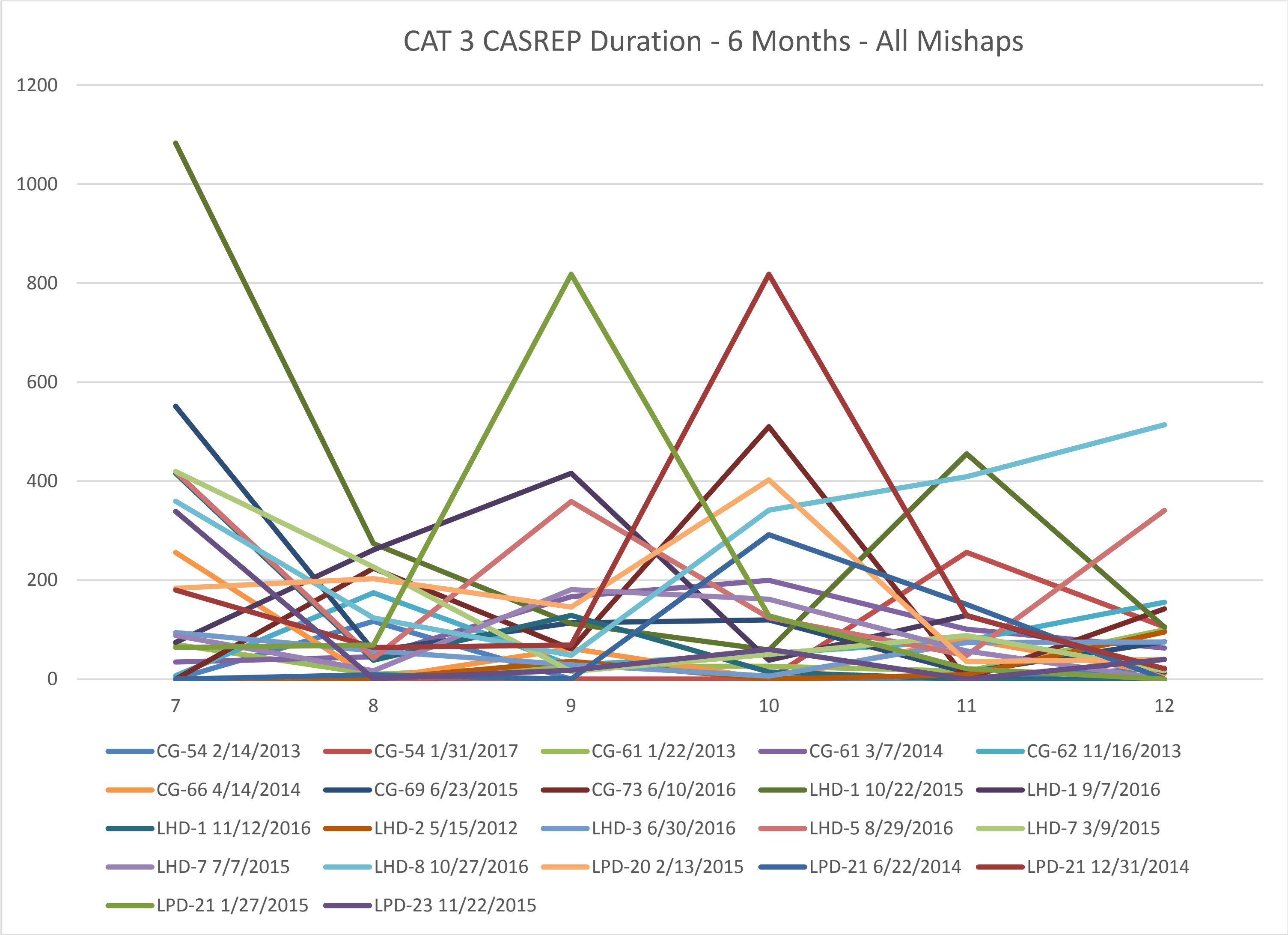

CAT 3 CASREP Count - 3 Months - LHD Mishaps
16
14
12
10
8
6
4
2
0
10
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016



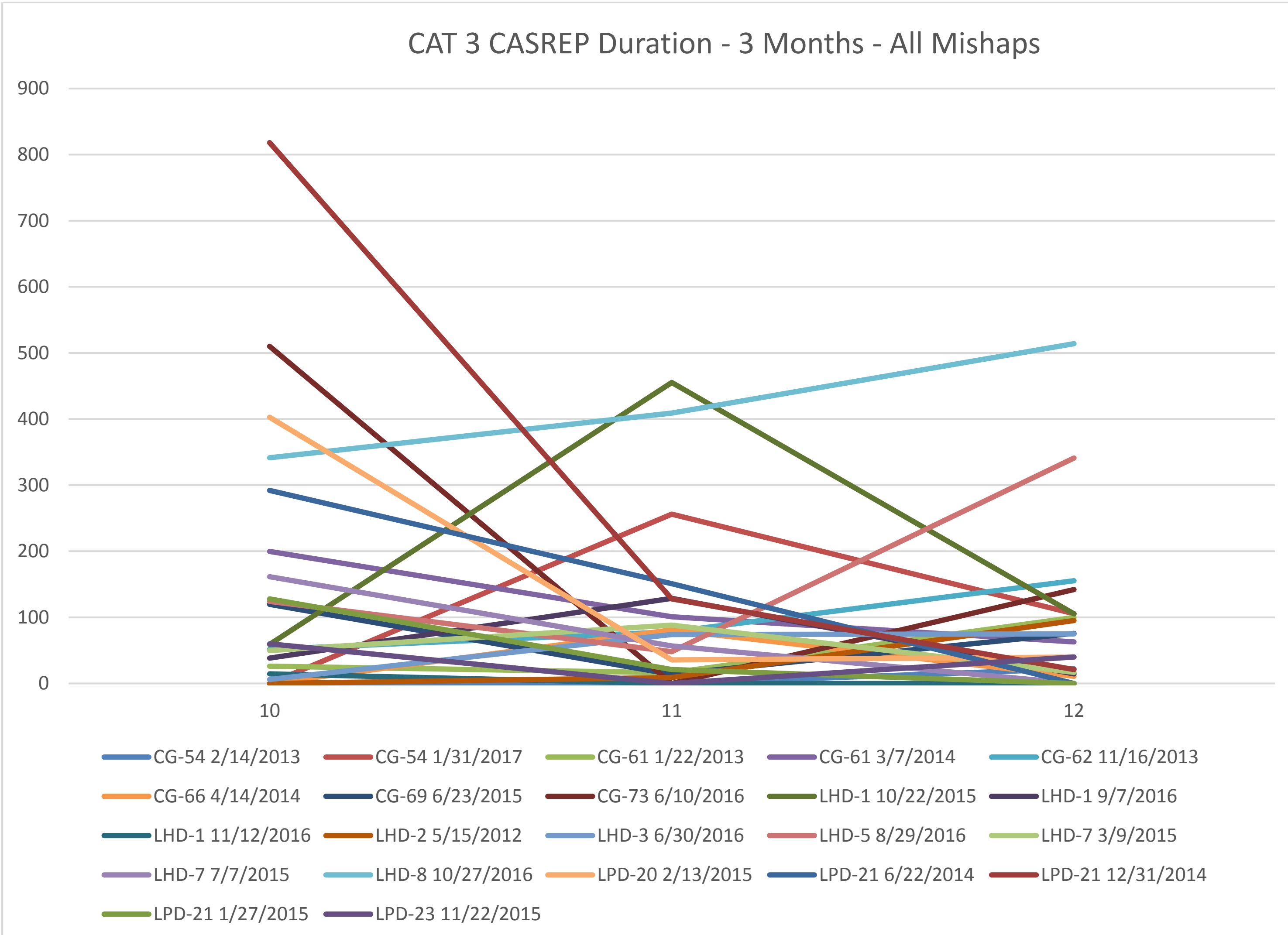
CAT 3 CASREP Count - 6 Months - LPD Mishaps
0
1
2
3
4
5
6
7
8
9
7
8
9
10
11
12
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


CAT 3 CASREP Count - 3 Months - LPD Mishaps
9
8
7
6
5
4
3
2
1
0
10
11
12
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

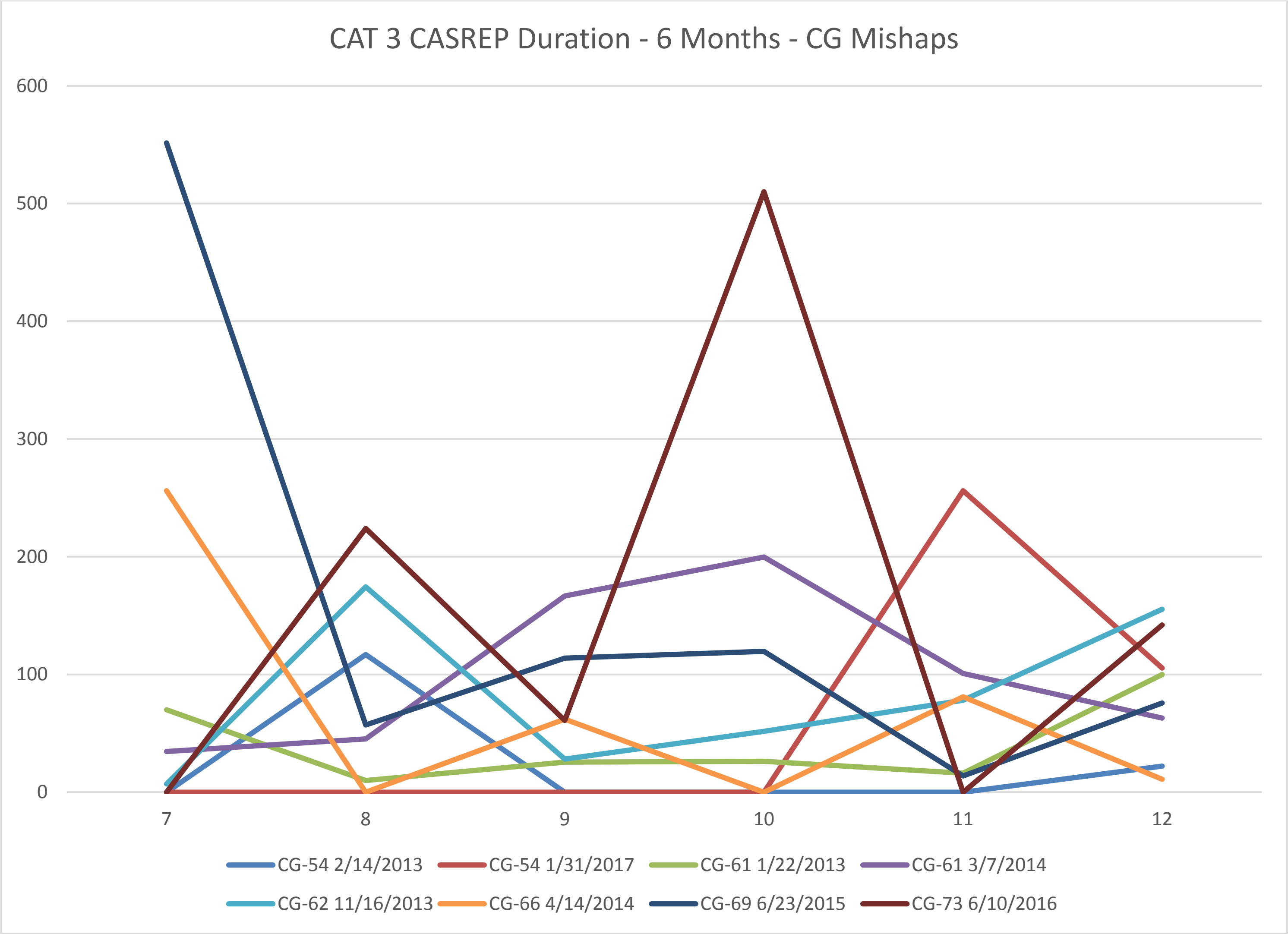

CAT 3 CASREP Duration - 12 Months - All Mishaps
1600
1400
1200
1000
800
600
400
200
0
1
2
3
4
5
6
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

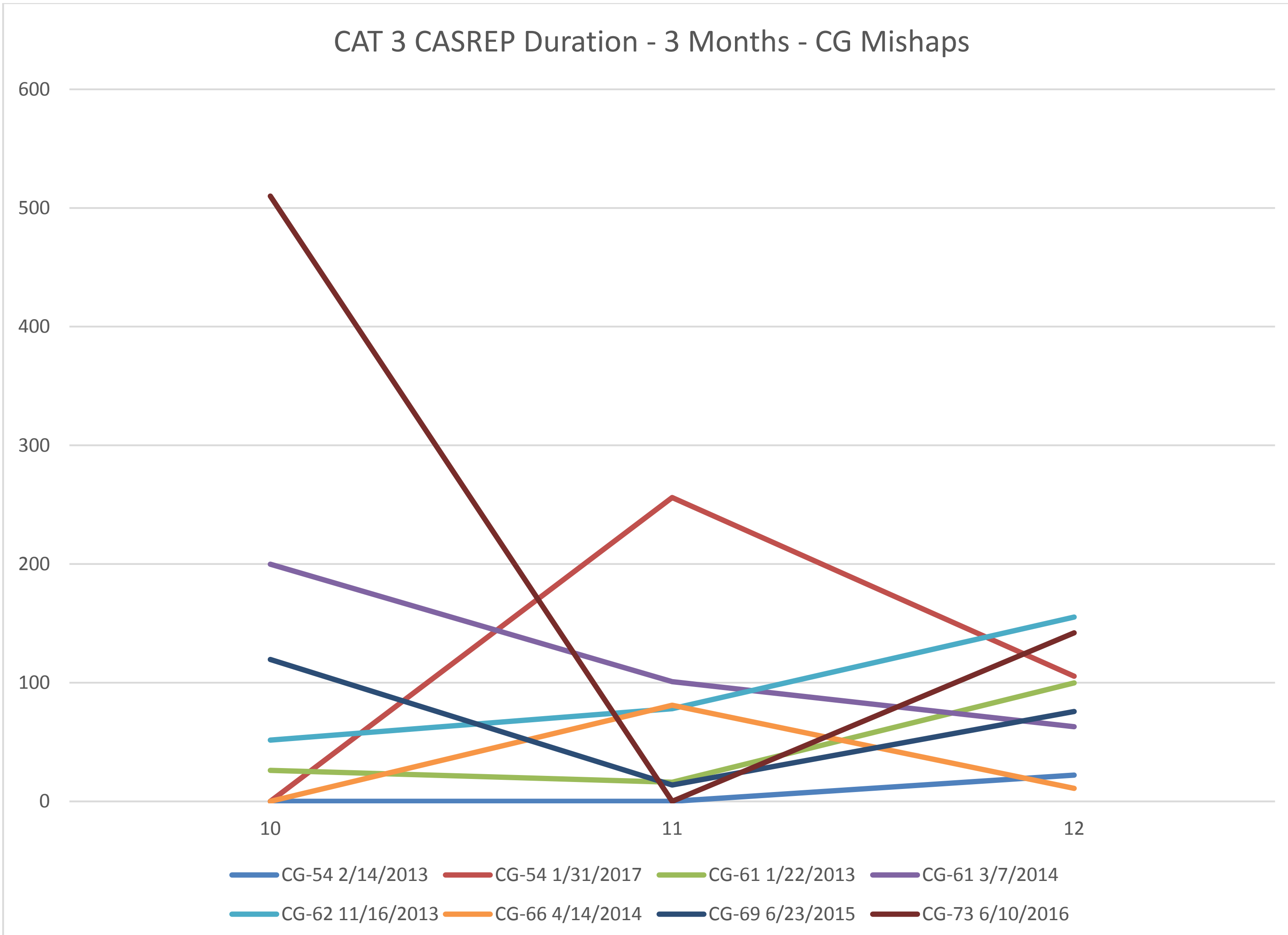


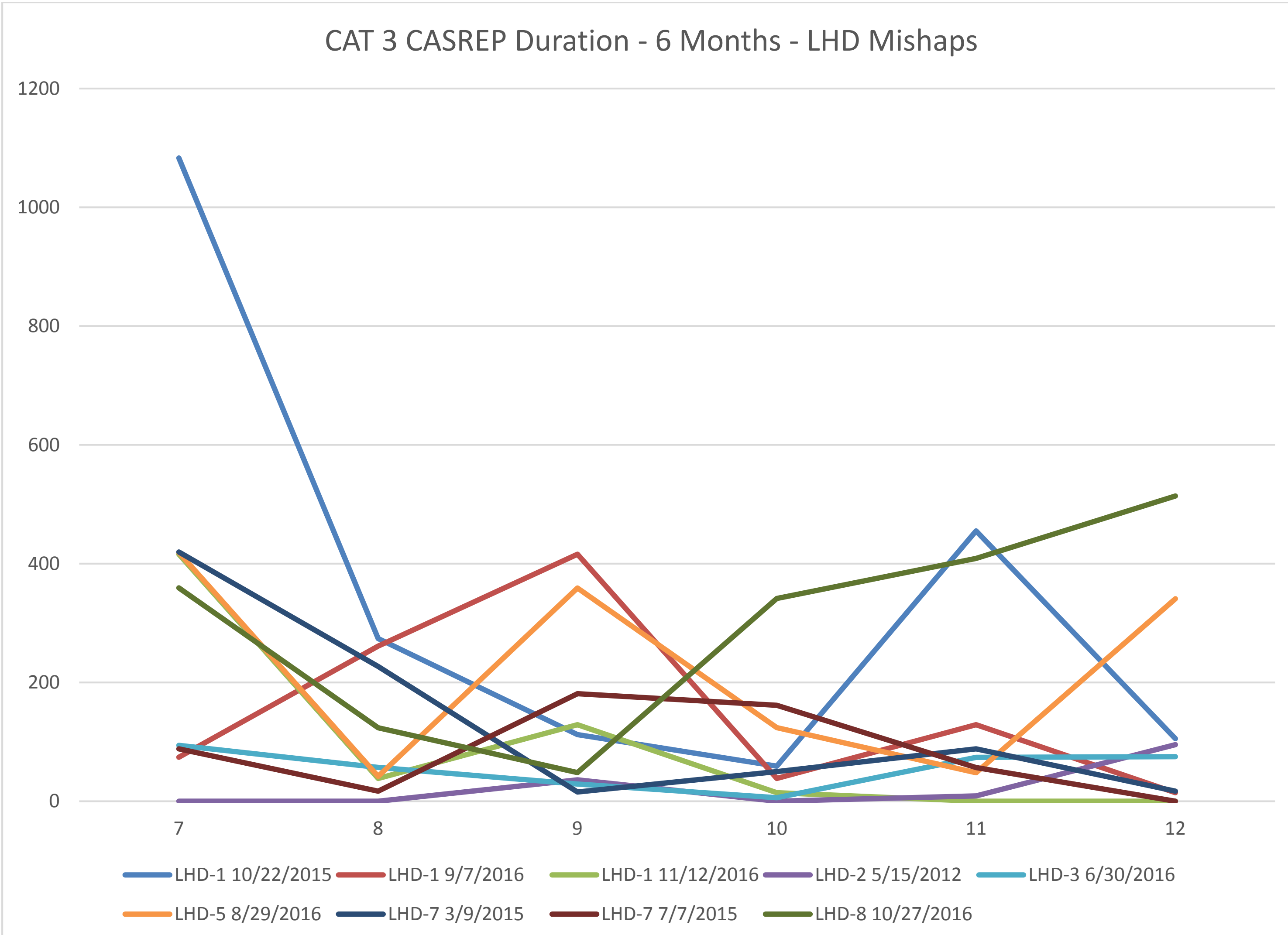
CAT 3 CASREP Duration - 6 Months - All Mishaps
1200
1000
800
600
400
200
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

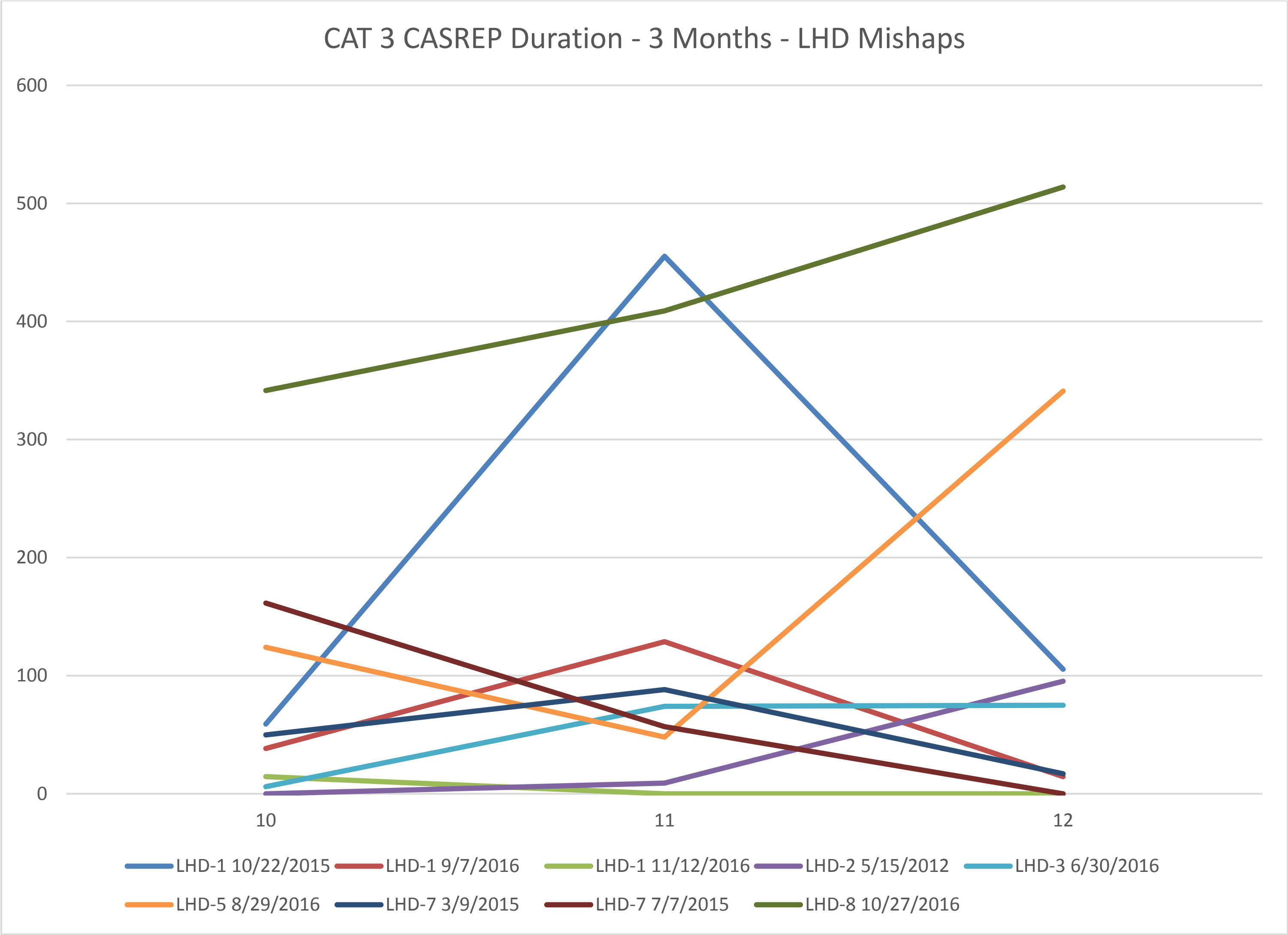


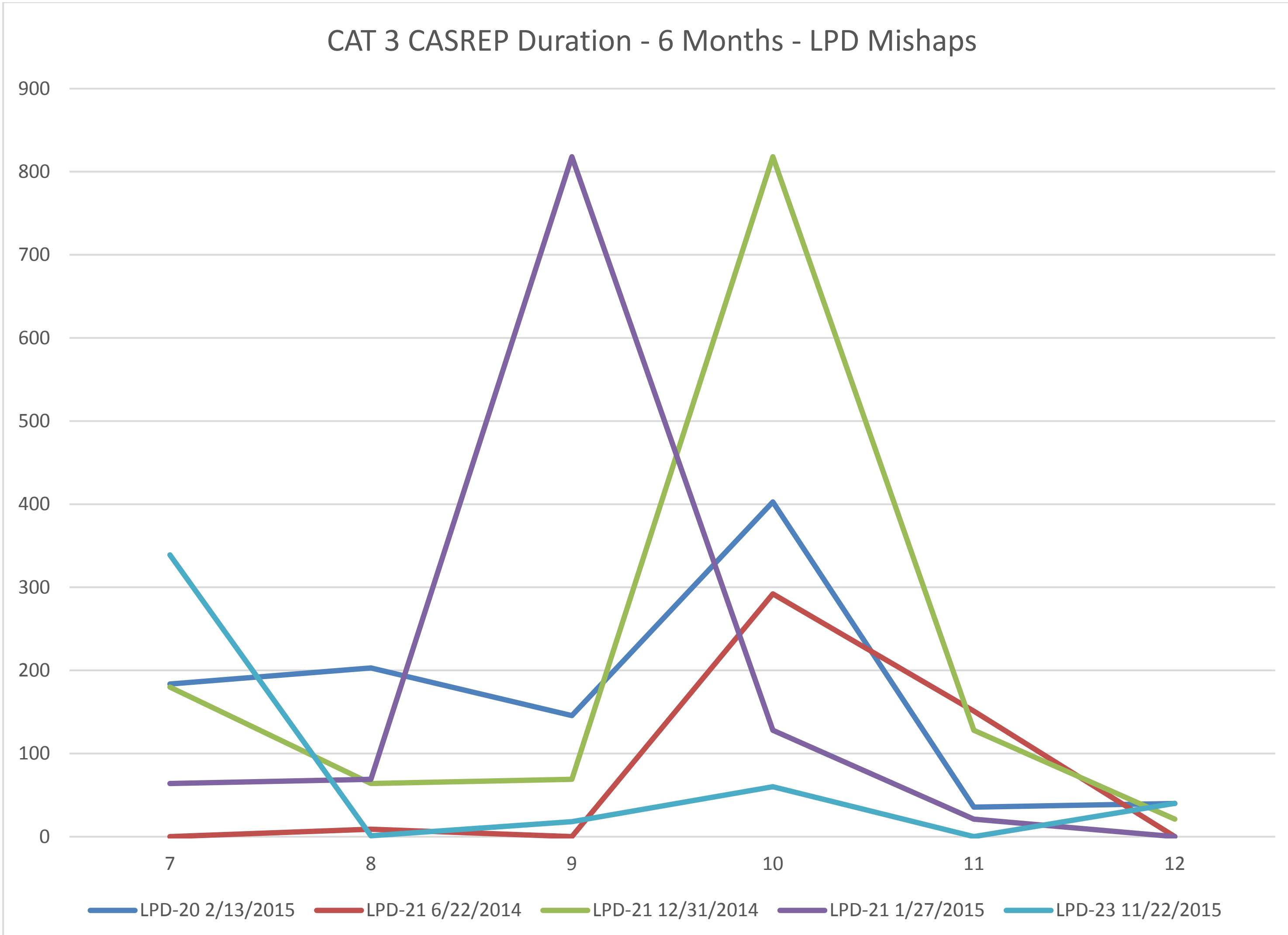
CAT 3 CASREP Duration - 3 Months - All Mishaps
900
800
700
600
500
400
300
200
100
0
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

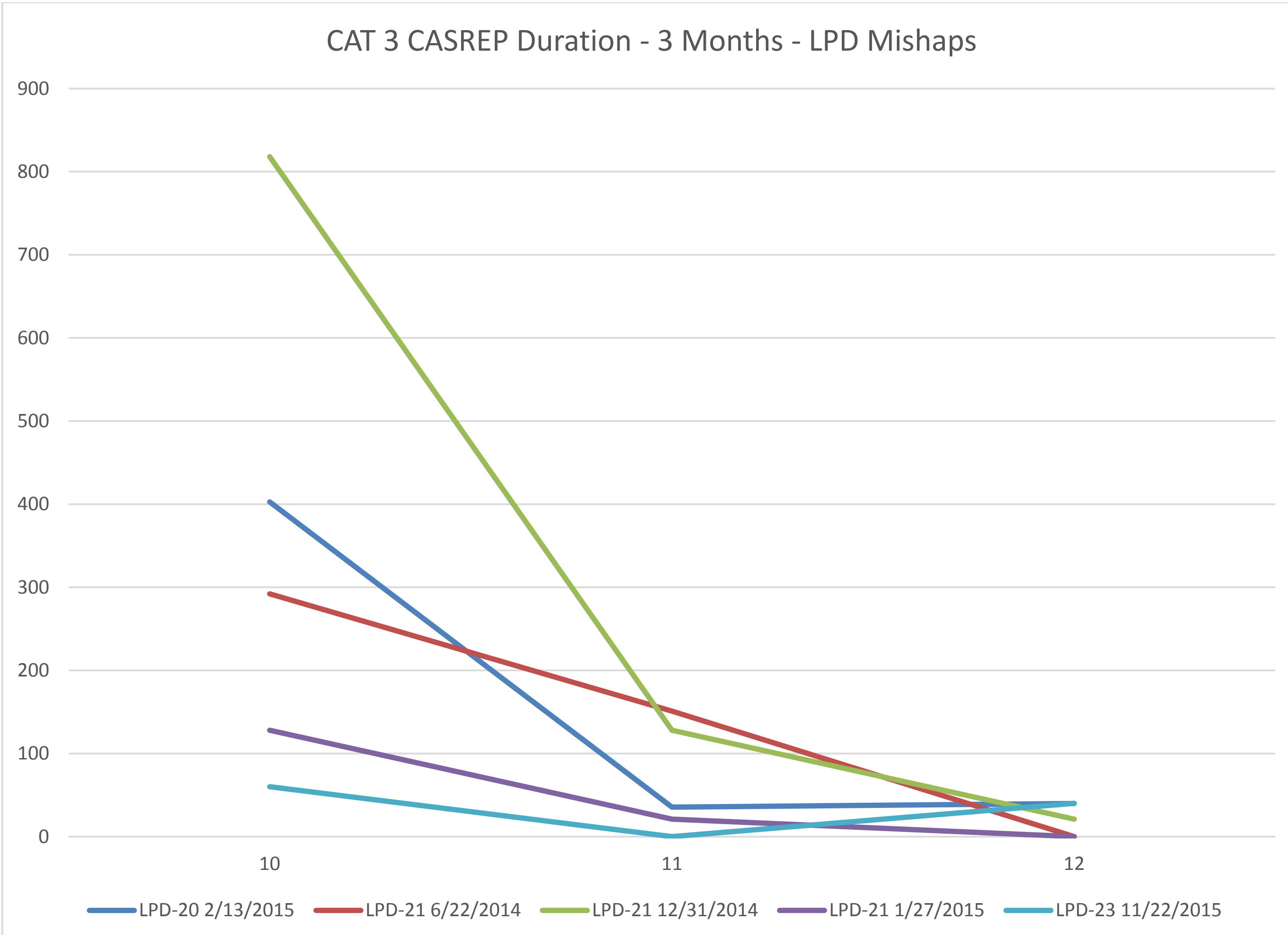

CAT 3 CASREP Duration - 6 Months - CG Mishaps
600
500
400
300
200
100
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016

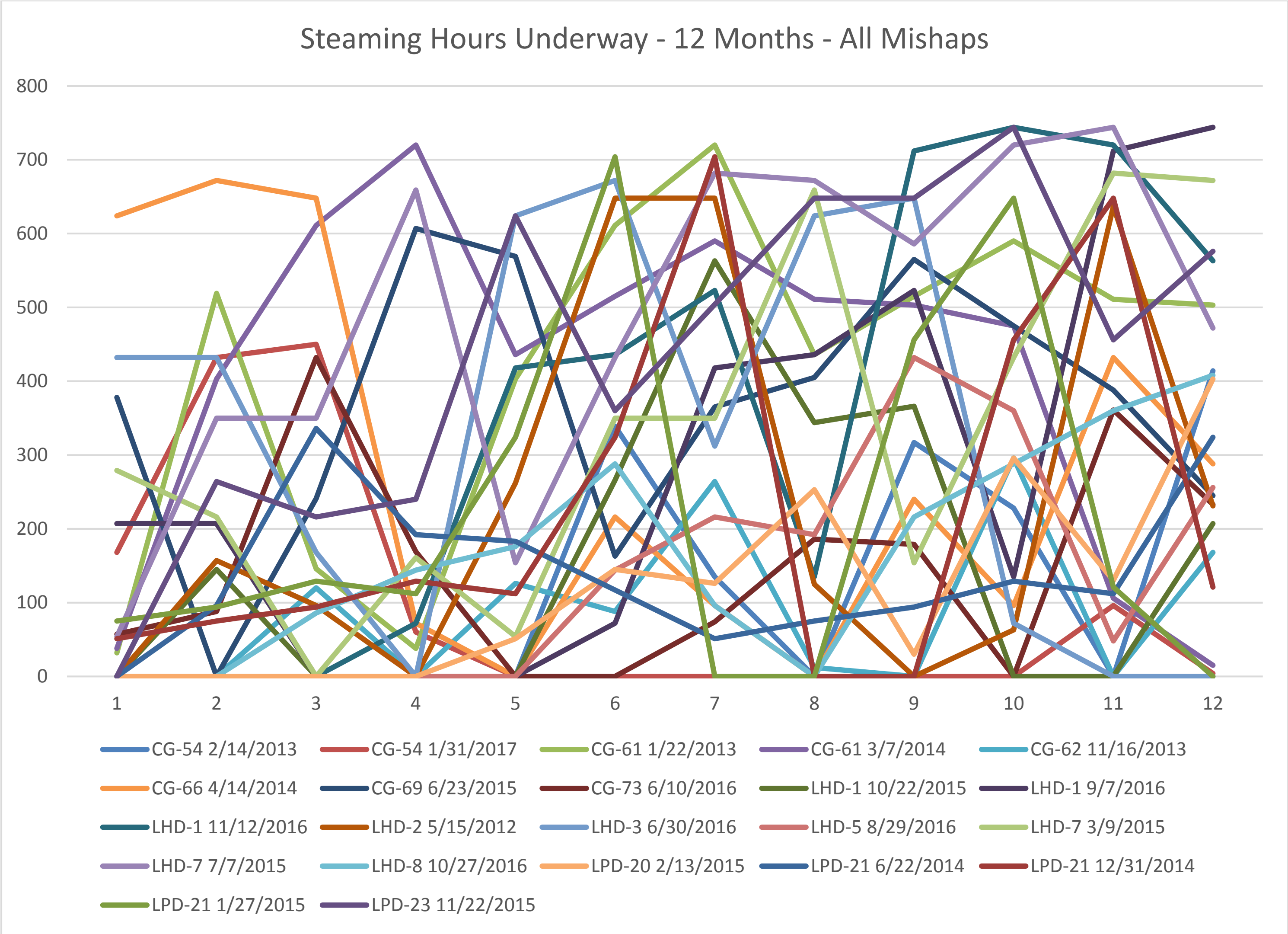

CAT 3 CASREP Duration - 3 Months - CG Mishaps
600
500
400
300
200
100
0
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016

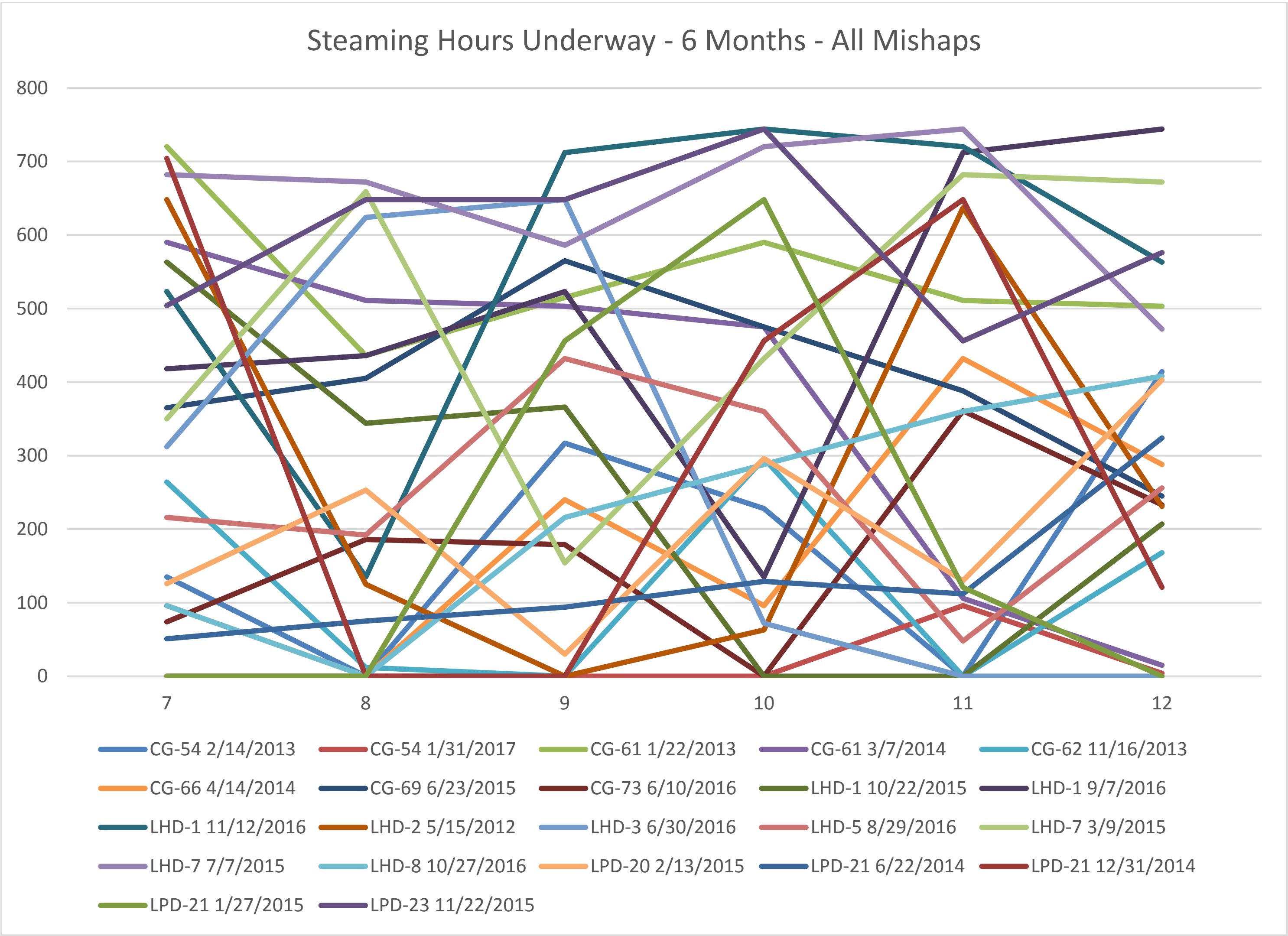

CAT 3 CASREP Duration - 6 Months - LHD Mishaps
1200
1000
800
600
400
200
0
7
8
9
10
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016


CAT 3 CASREP Duration - 3 Months - LHD Mishaps
600
500
400
300
200
100
0
10
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016


CAT 3 CASREP Duration - 6 Months - LPD Mishaps
900
800
700
600
500
400
300
200
100
0
7
8
9
10
11
12
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


CAT 3 CASREP Duration - 3 Months - LPD Mishaps
900
800
700
600
500
400
300
200
100
0
10
11
12
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


Steaming Hours Underway - 12 Months - All Mishaps
800
700
600
500
400
300
200
100
0
1
2
3
4
5
6
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


Steaming Hours Underway - 6 Months - All Mishaps
800
700
600
500
400
300
200
100
0
7
8
9
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
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LPD-21 1/27/2015
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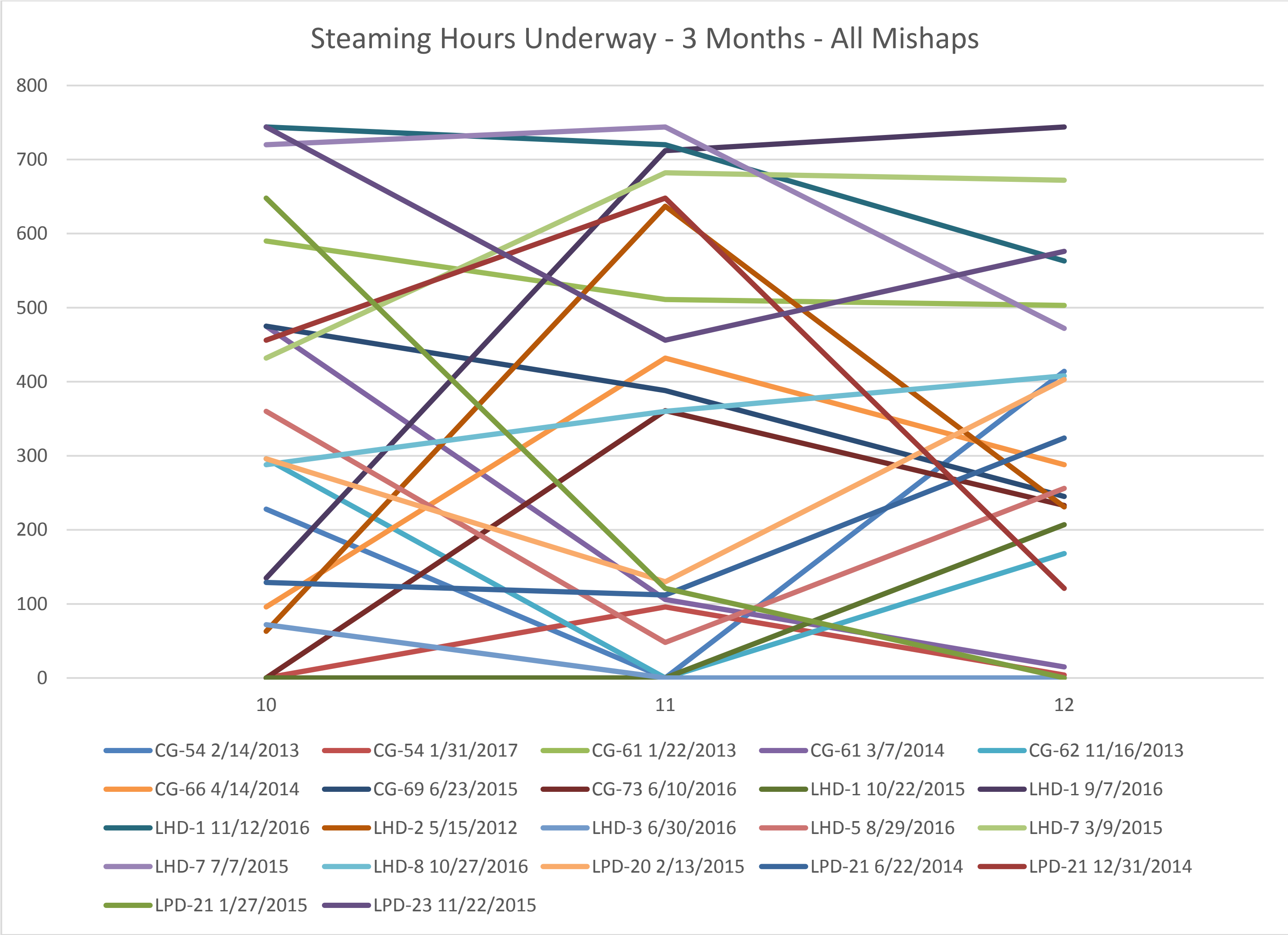
Steaming Hours Underway - 3 Months - All Mishaps
800
700
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CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
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LPD-21 6/22/2014
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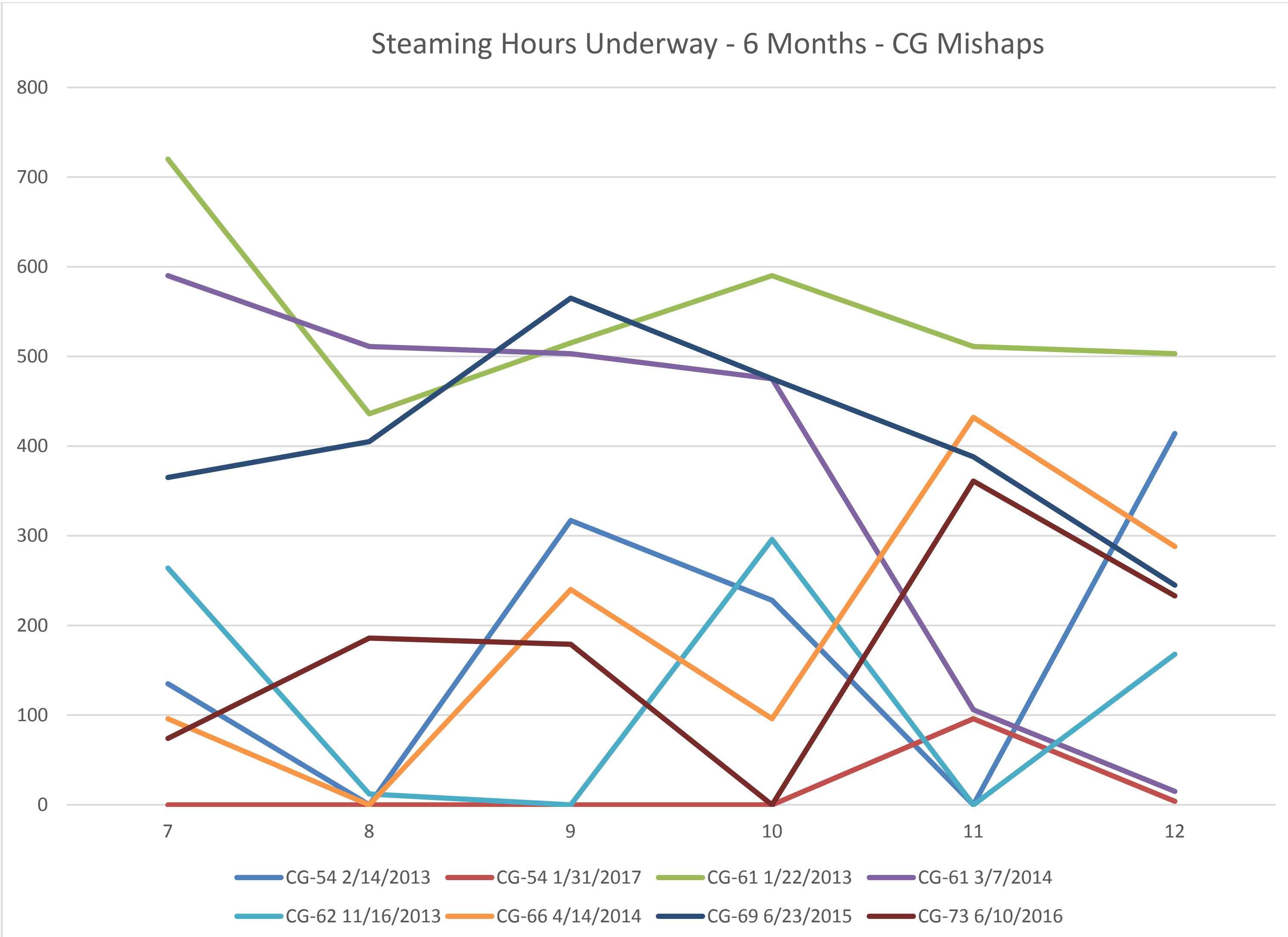
Steaming Hours Underway - 6 Months - CG Mishaps
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CG-54 2/14/2013
CG-54 1/31/2017
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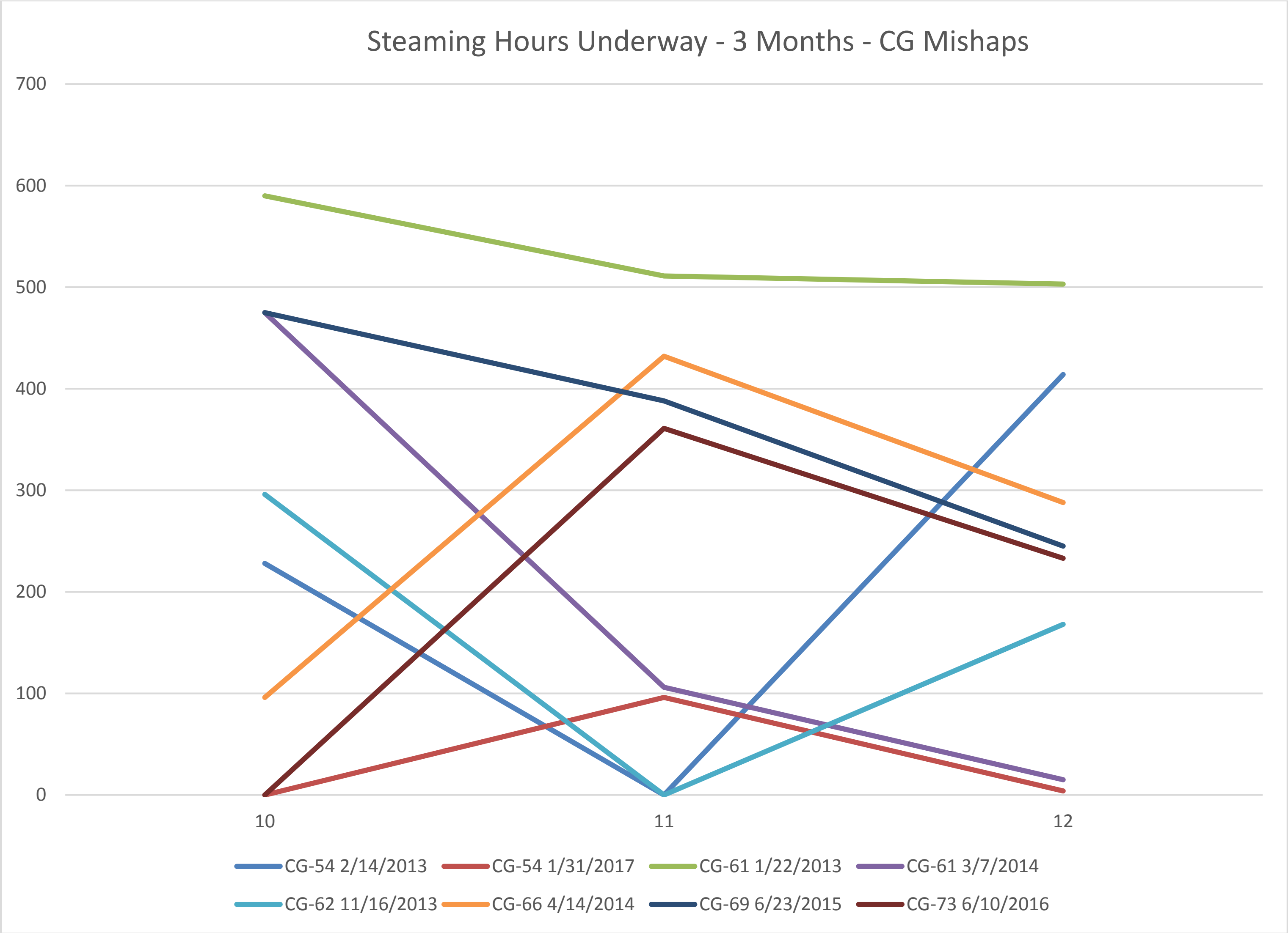
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016


Steaming Hours Underway - 3 Months - CG Mishaps
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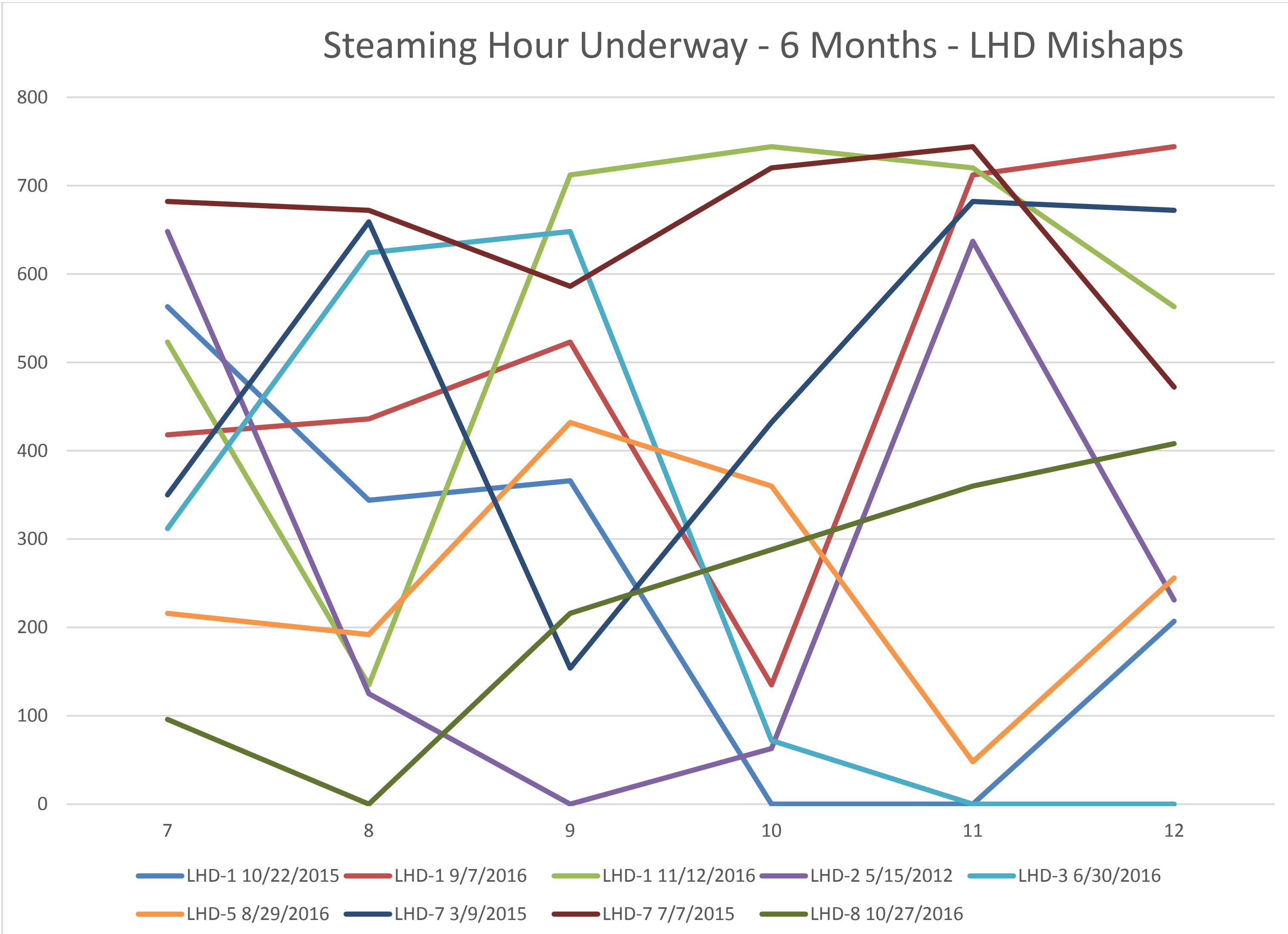
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016



Steaming Hour Underway - 6 Months - LHD Mishaps
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LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
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LHD-5 8/29/2016
LHD-7 3/9/2015
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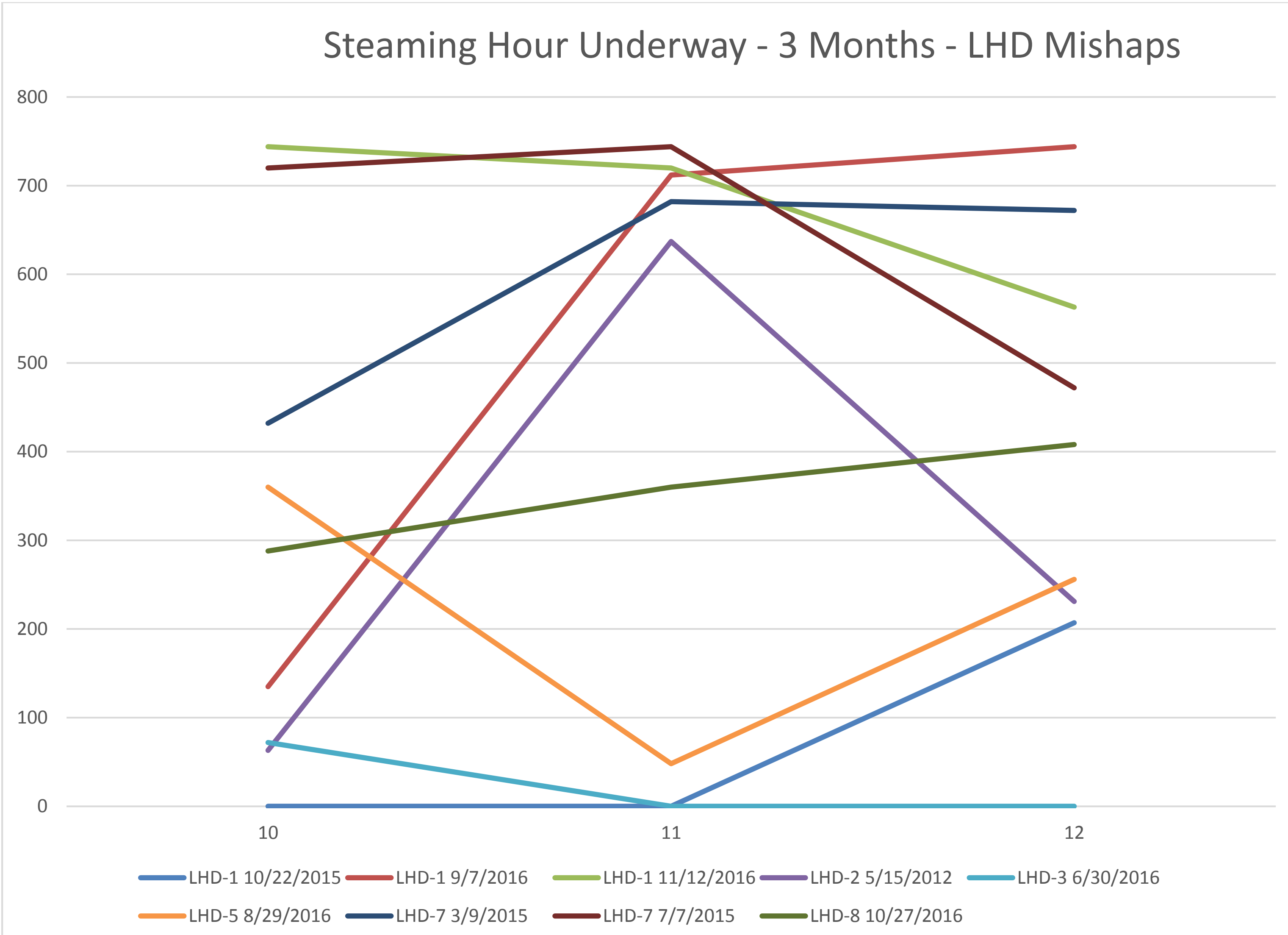
Steaming Hour Underway - 3 Months - LHD Mishaps
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LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
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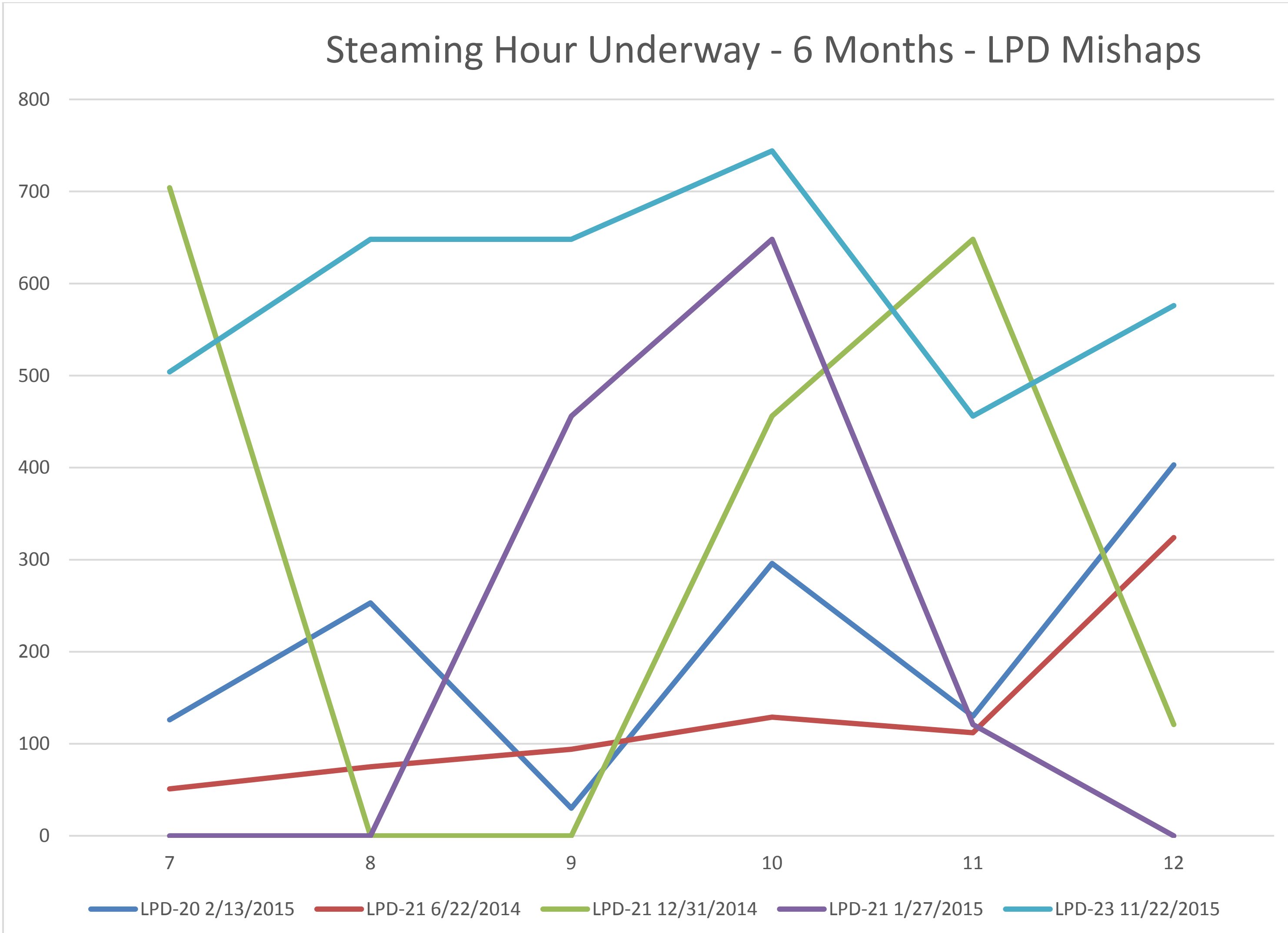
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016


Steaming Hour Underway - 6 Months - LPD Mishaps
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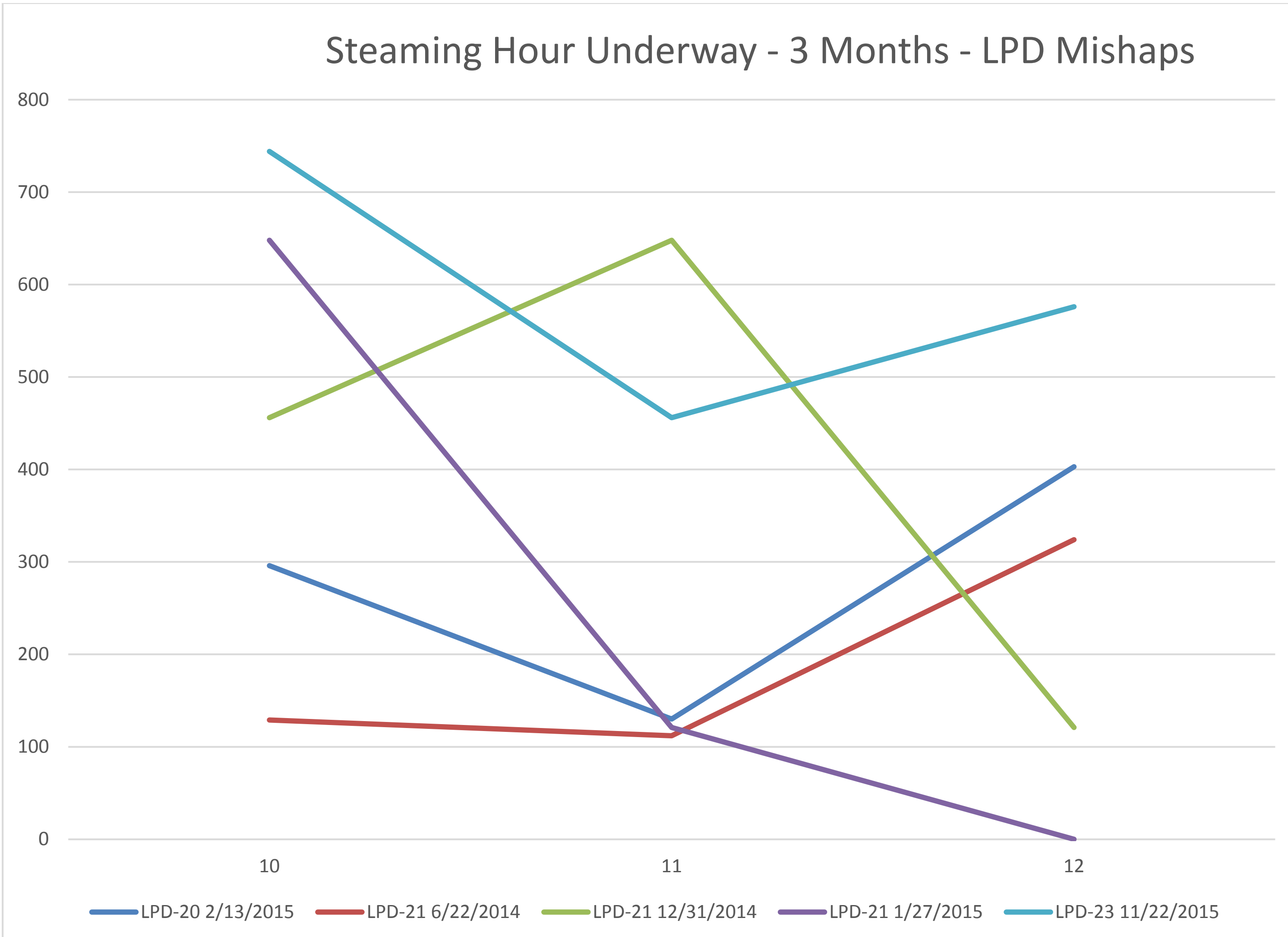
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015



Steaming Hour Underway - 3 Months - LPD Mishaps
800
700
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LPD-21 6/22/2014
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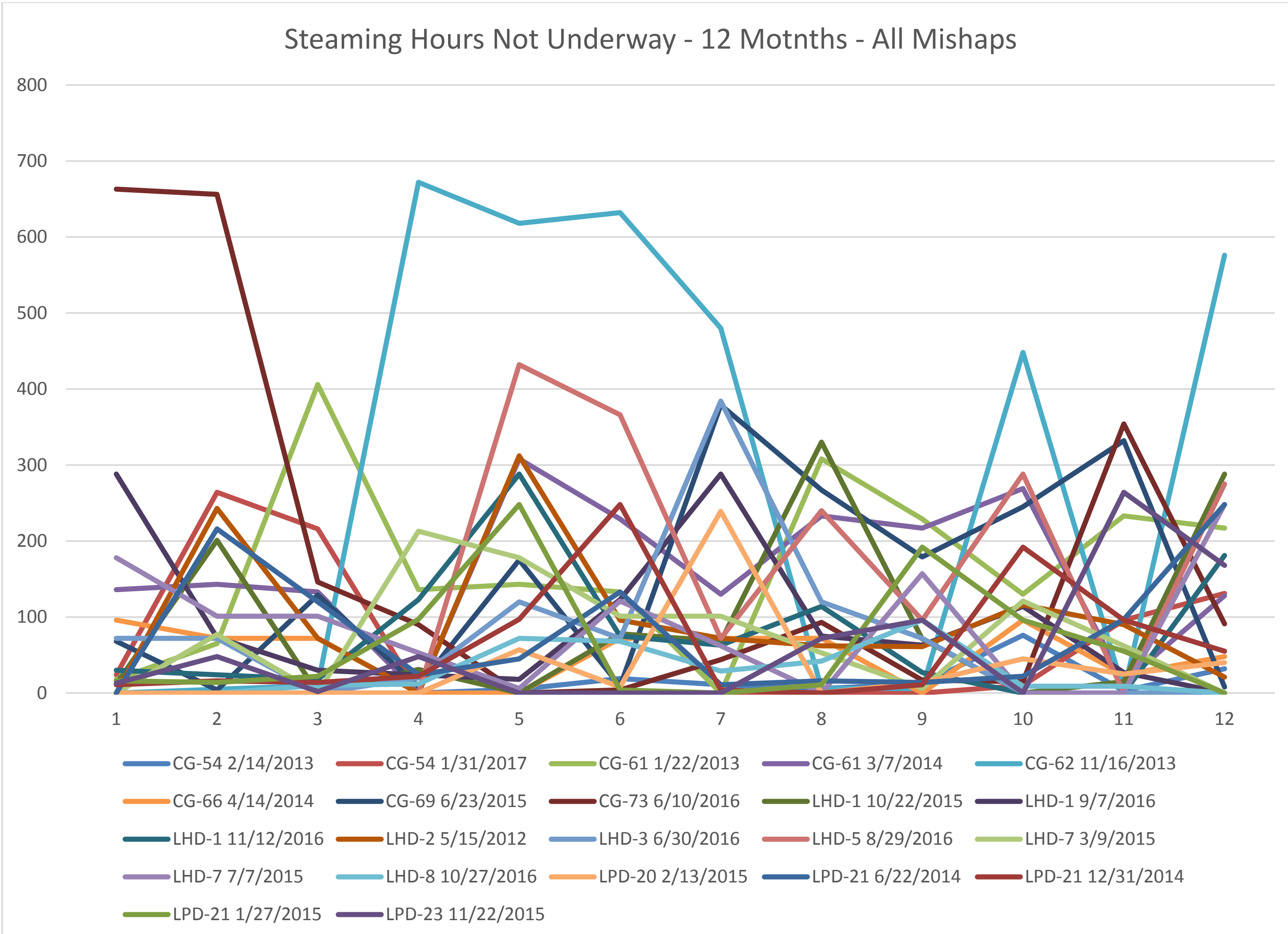
LPD-21 1/27/2015
LPD-23 11/22/2015


Steaming Hours Not Underway - 12 Motnths - All Mishaps
800
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500
400
300
200
100
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CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
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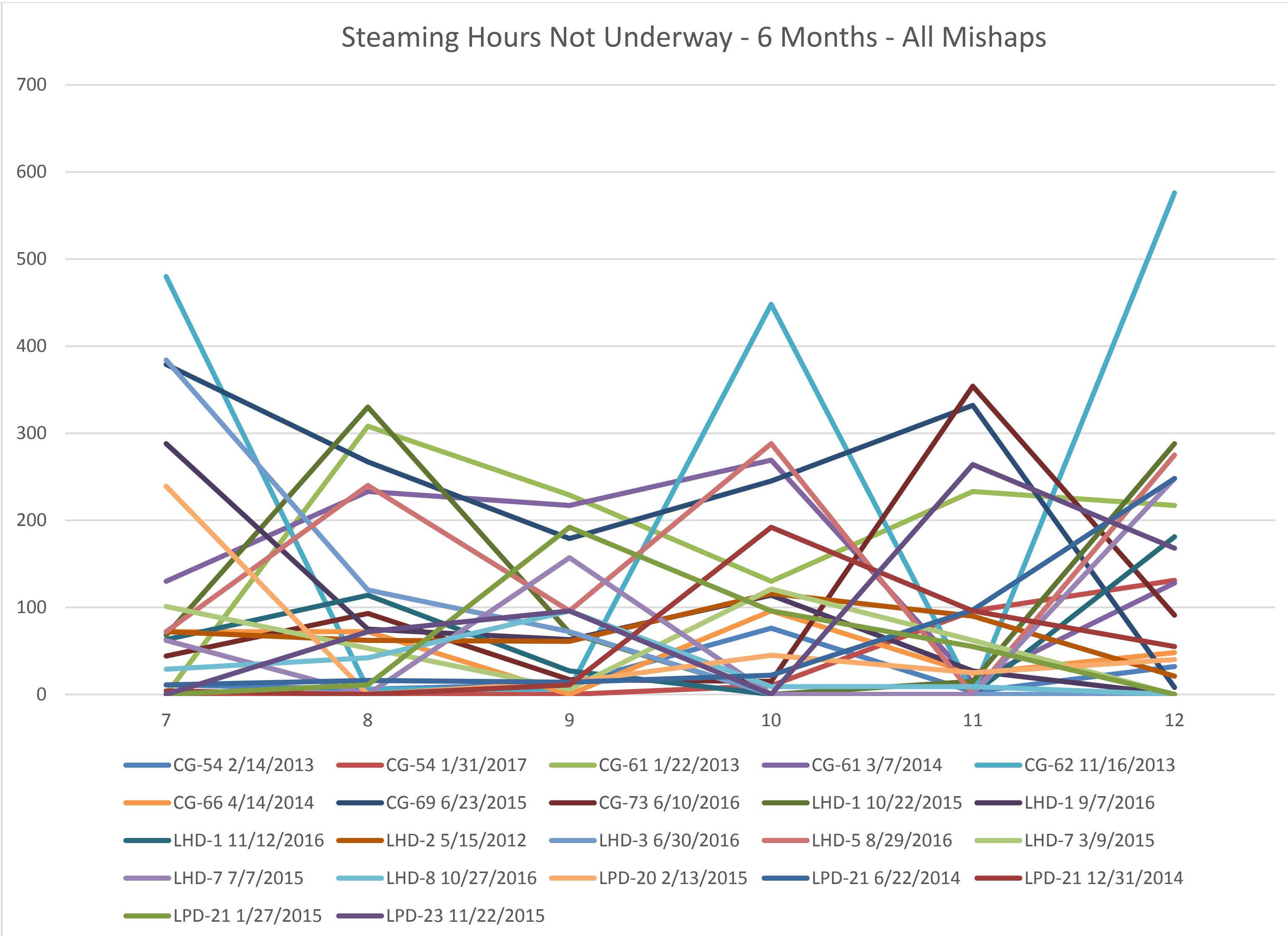
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


Steaming Hours Not Underway - 6 Months - All Mishaps
700
600
500
400
300
200
100
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CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
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LHD-8 10/27/2016
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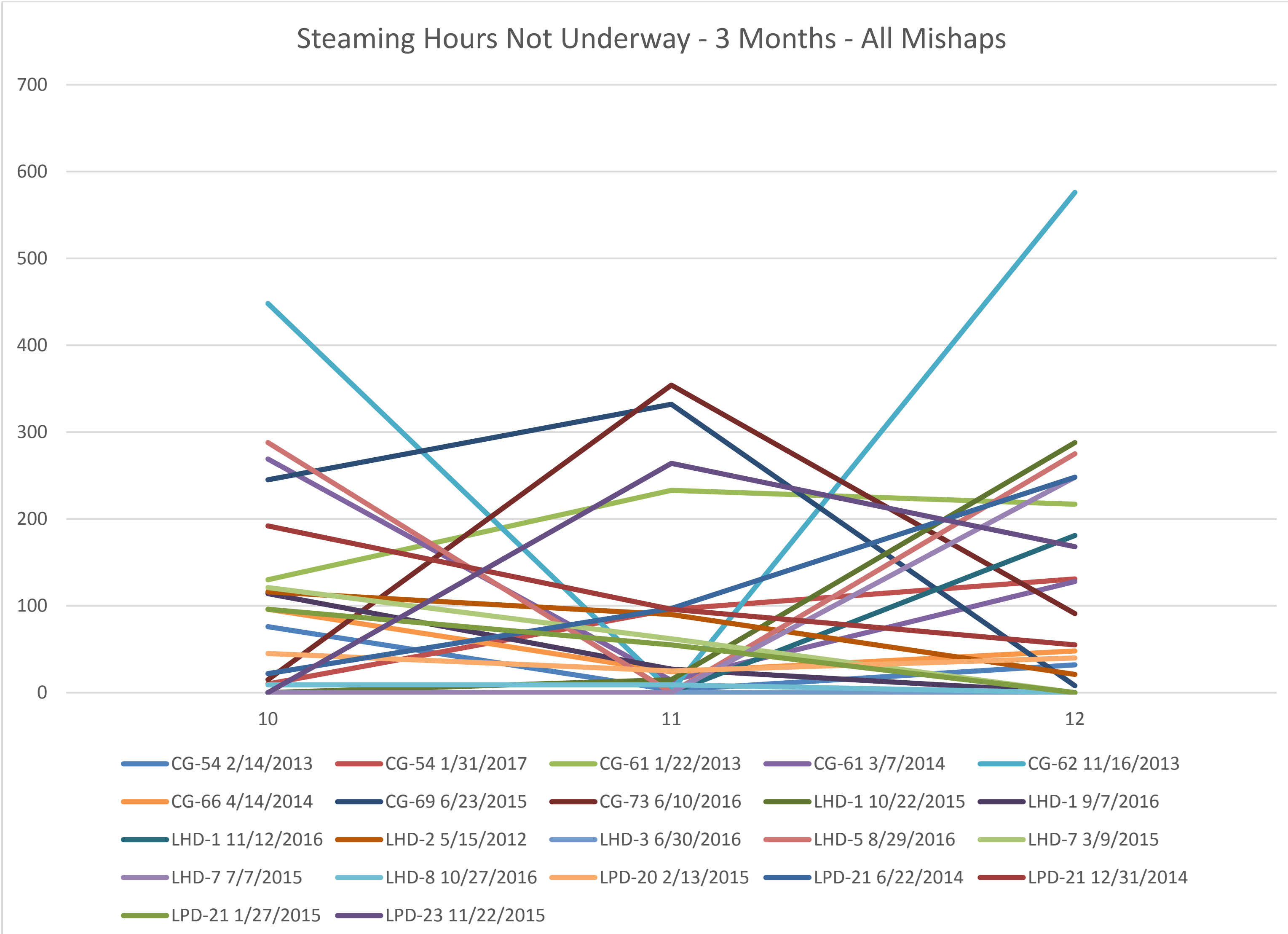
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


Steaming Hours Not Underway - 3 Months - All Mishaps
700
600
500
400
300
200
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CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
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LHD-1 11/12/2016
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LHD-7 3/9/2015
LHD-7 7/7/2015
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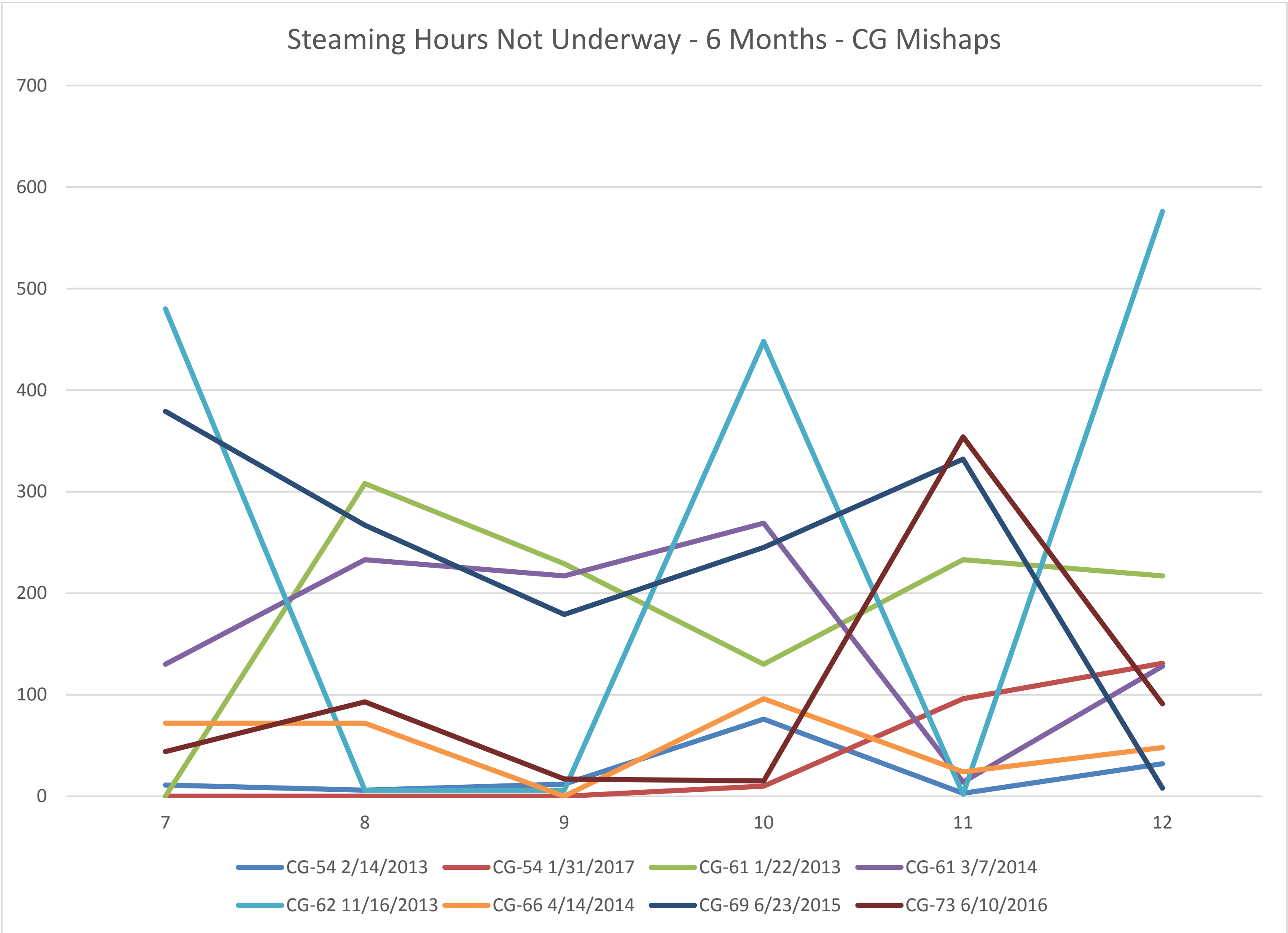
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015



Steaming Hours Not Underway - 6 Months - CG Mishaps
700
600
500
400
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CG-54 2/14/2013
CG-54 1/31/2017
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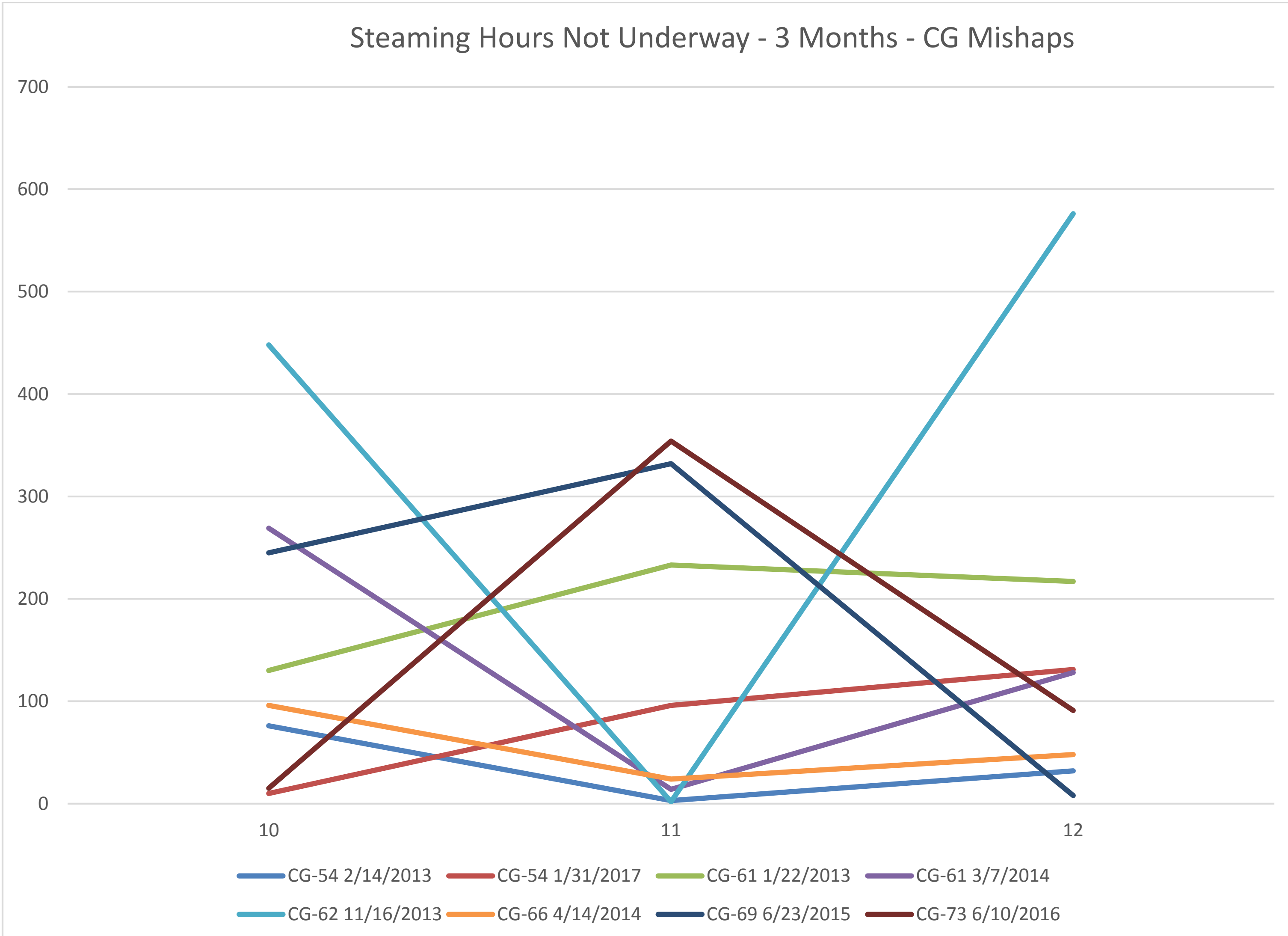

Steaming Hours Not Underway - 3 Months - CG Mishaps
700
600
500
400
300
200
100
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11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
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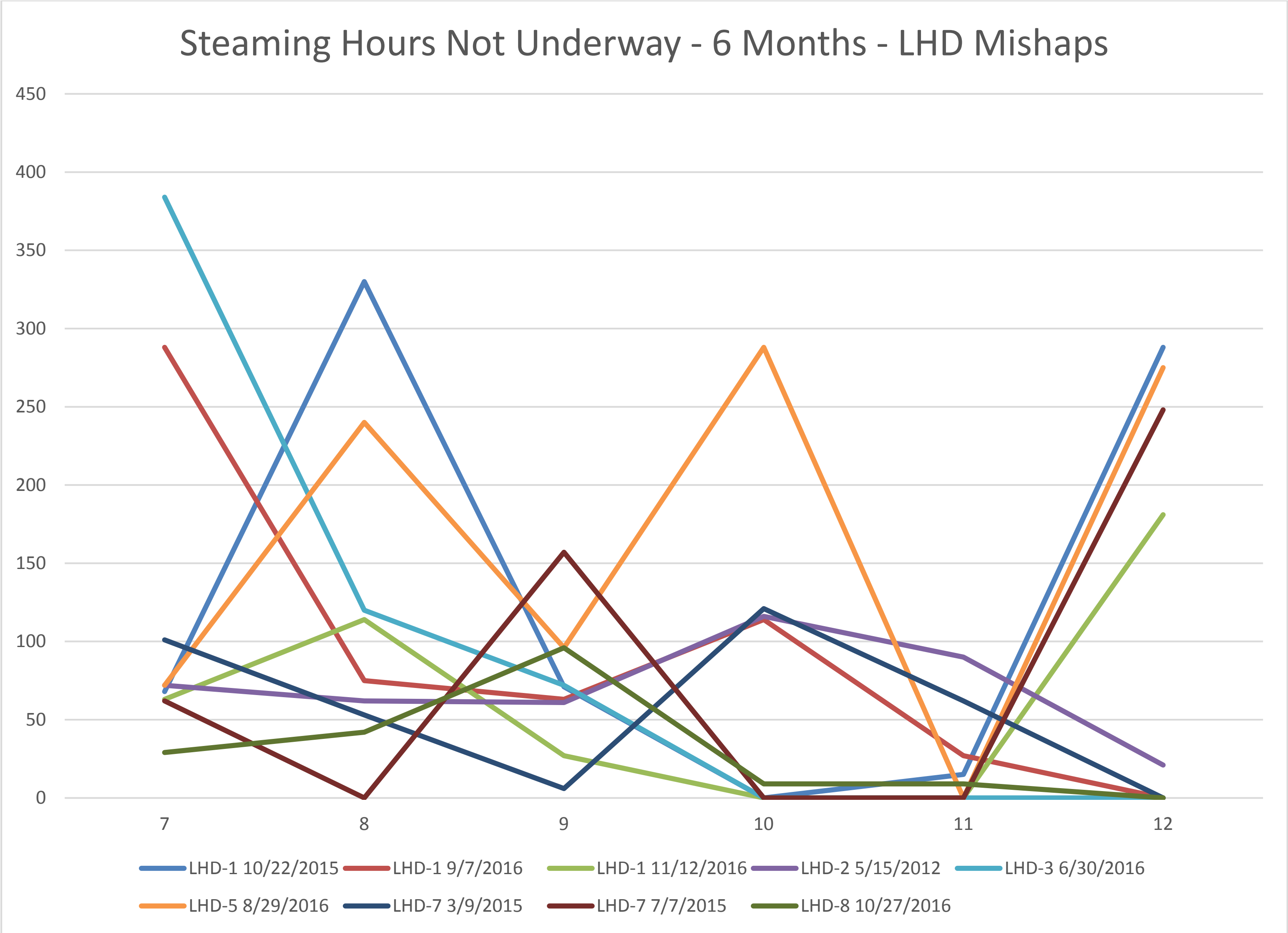
Steaming Hours Not Underway - 6 Months - LHD Mishaps
450
400
350
300
250
200
150
100
50
0
7
8
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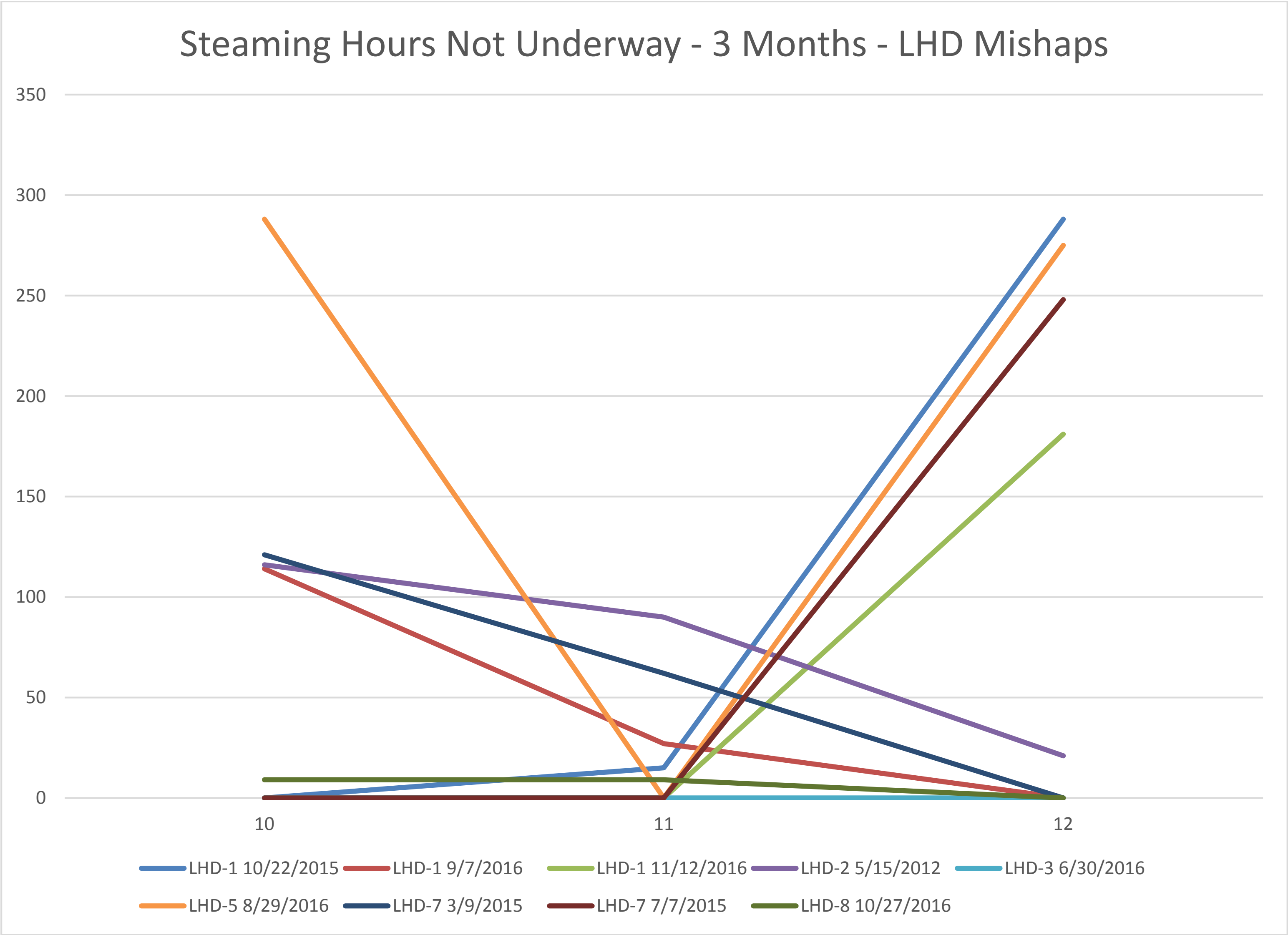
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016


Steaming Hours Not Underway - 3 Months - LHD Mishaps
350
300
250
200
150
100
50
0
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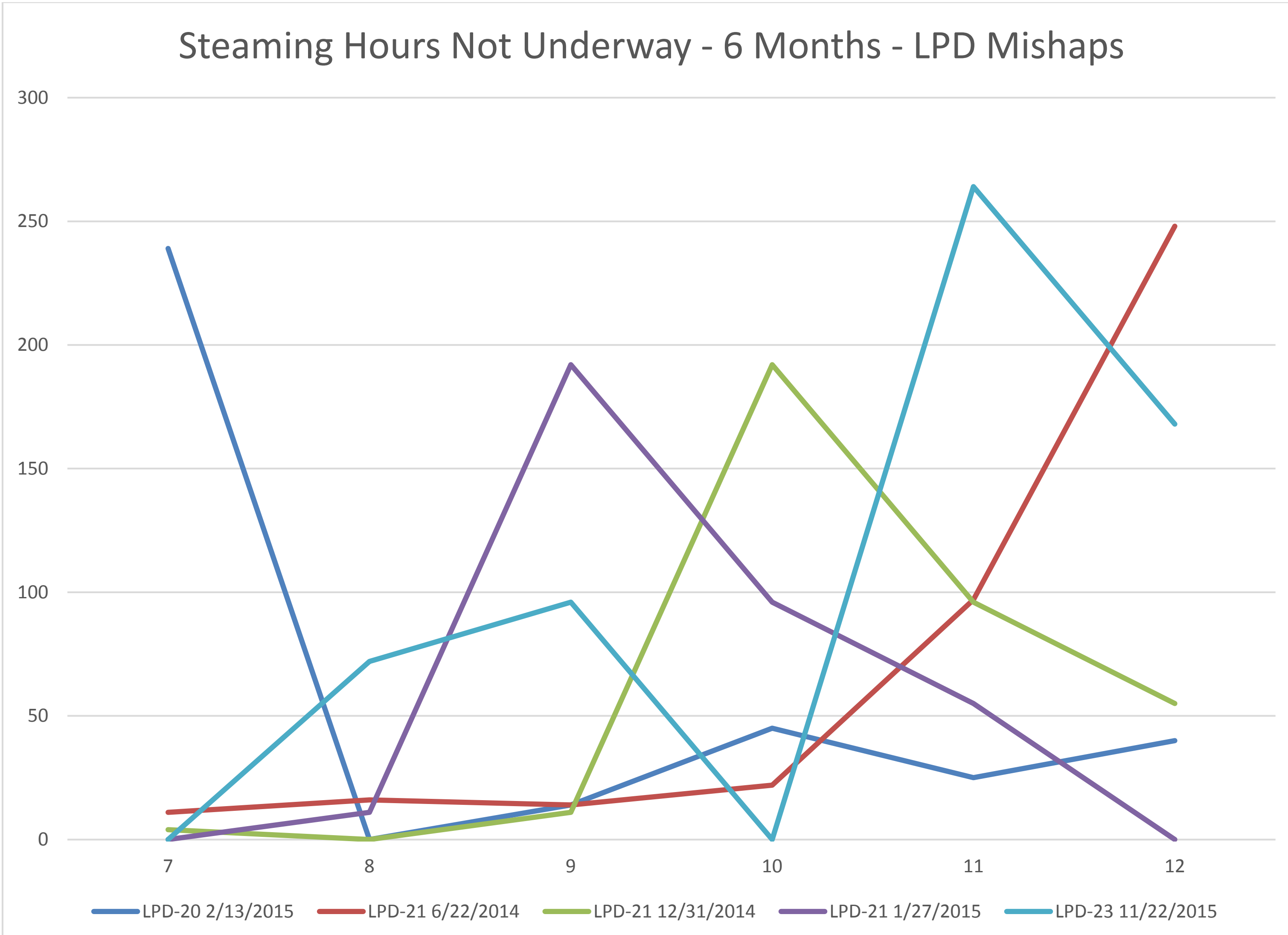
11
12
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016


Steaming Hours Not Underway - 6 Months - LPD Mishaps
300
250
200
150
100
50
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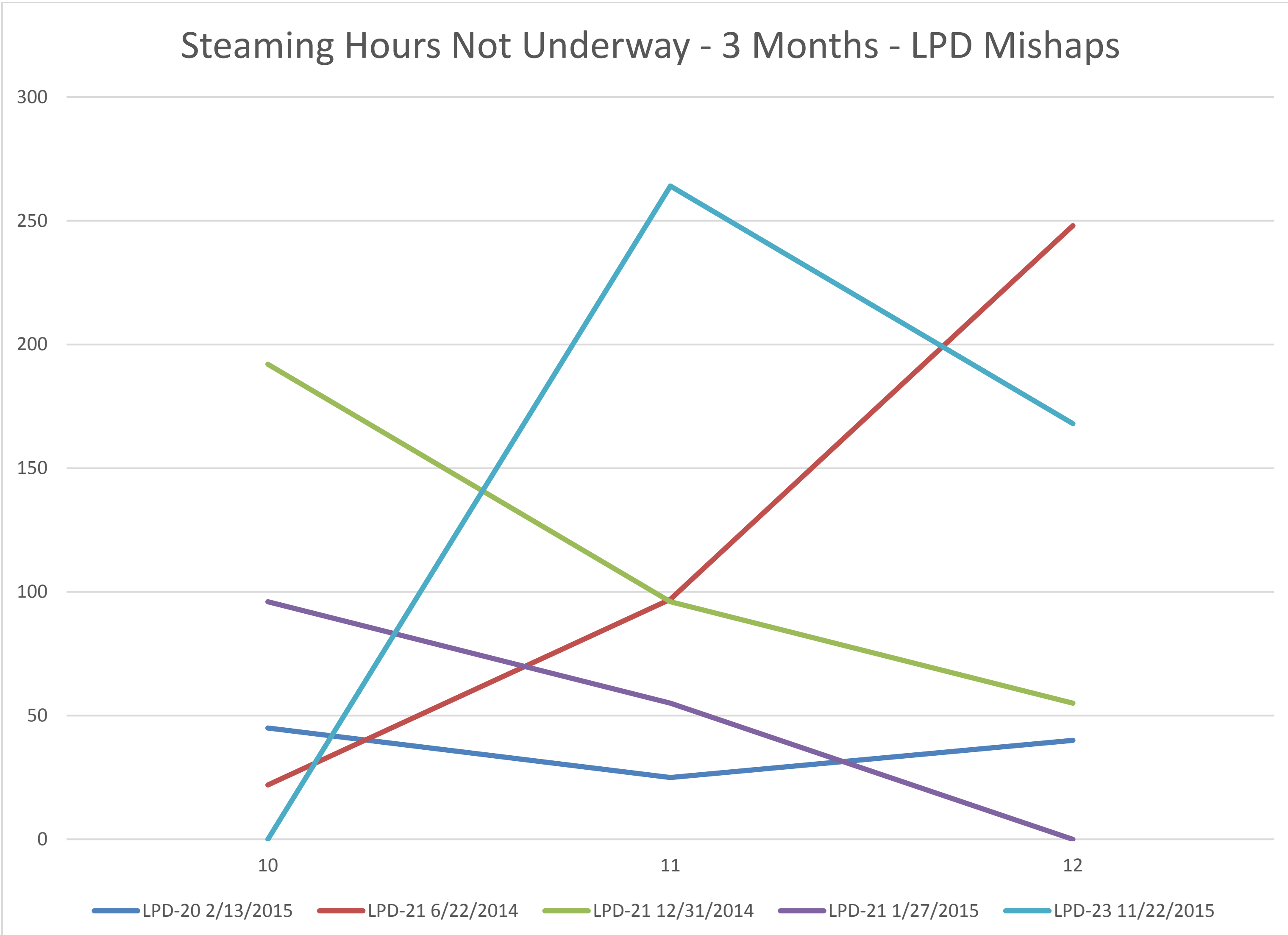
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015


Steaming Hours Not Underway - 3 Months - LPD Mishaps
300
250
200
150
100
50
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11
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LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
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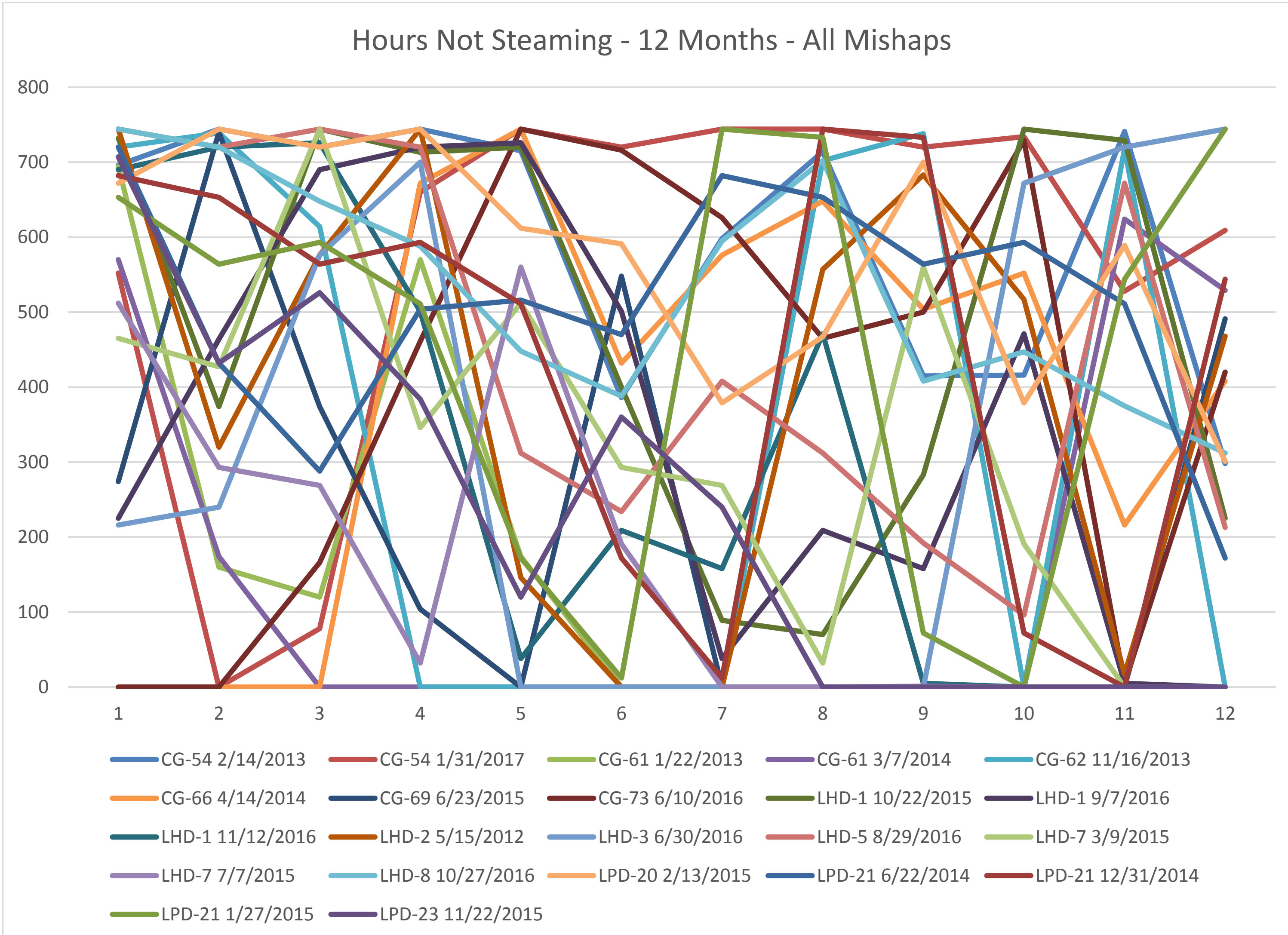
Hours Not Steaming - 12 Months - All Mishaps
800
700
600
500
400
300
200
100
0
1
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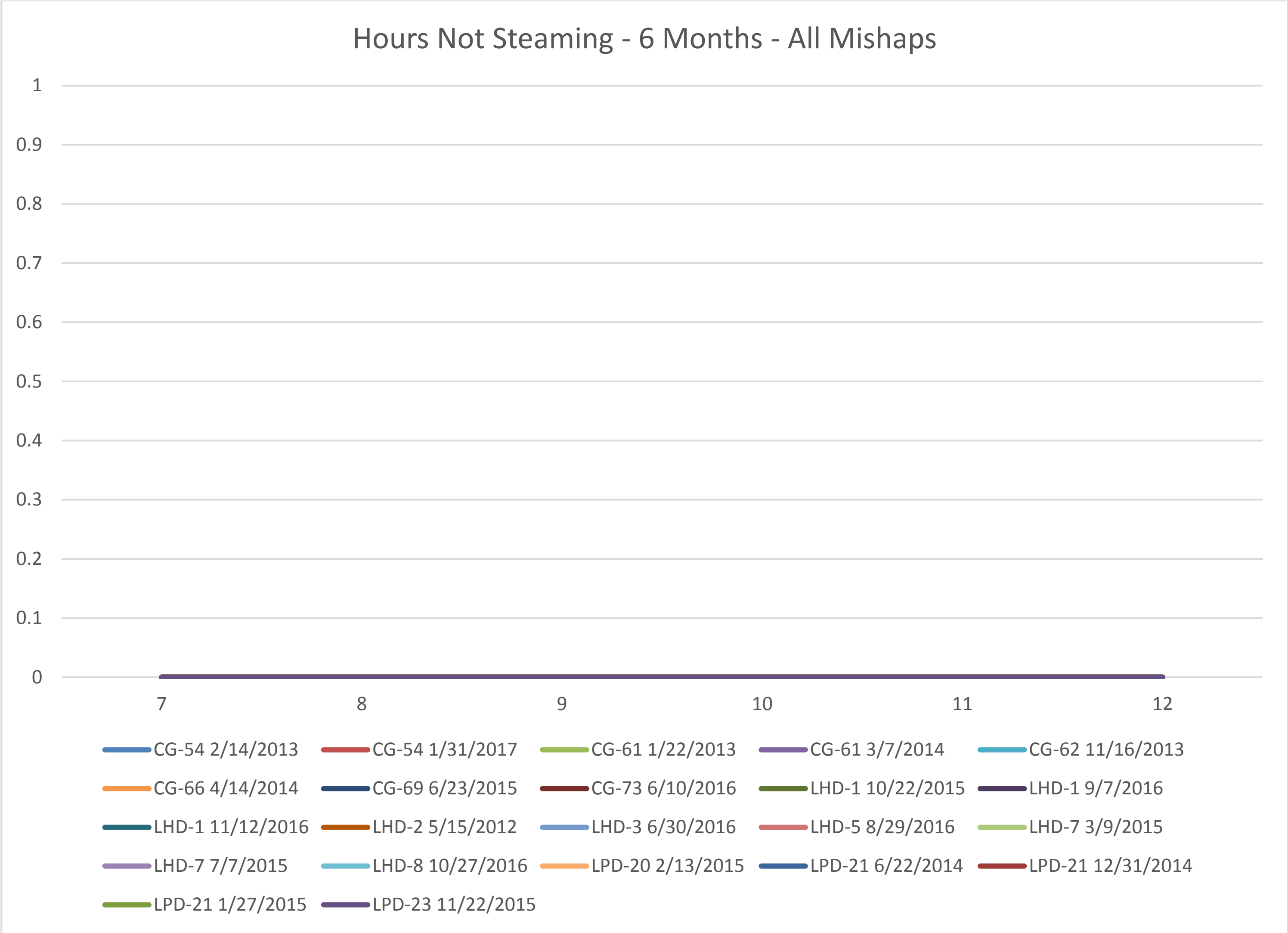
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
CG-69 6/23/2015
CG-73 6/10/2016
LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
LHD-3 6/30/2016
LHD-5 8/29/2016
LHD-7 3/9/2015
LHD-7 7/7/2015
LHD-8 10/27/2016
LPD-20 2/13/2015
LPD-21 6/22/2014
LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015



Hours Not Steaming - 6 Months - All Mishaps
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
7
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CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
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LHD-1 11/12/2016
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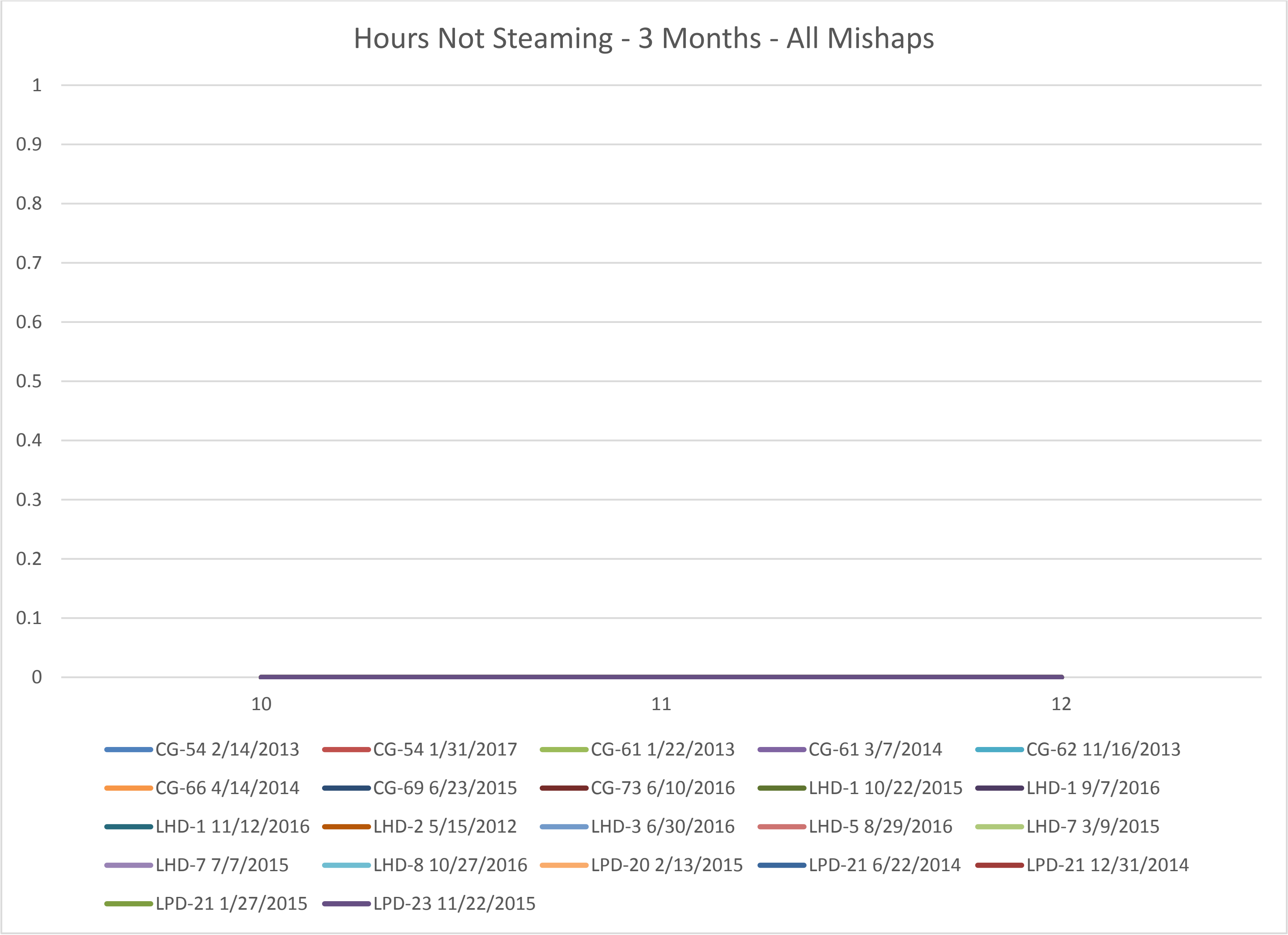
Hours Not Steaming - 3 Months - All Mishaps
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10
11
12
CG-54 2/14/2013
CG-54 1/31/2017
CG-61 1/22/2013
CG-61 3/7/2014
CG-62 11/16/2013
CG-66 4/14/2014
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LHD-1 9/7/2016
LHD-1 11/12/2016
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LHD-7 3/9/2015
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LHD-8 10/27/2016
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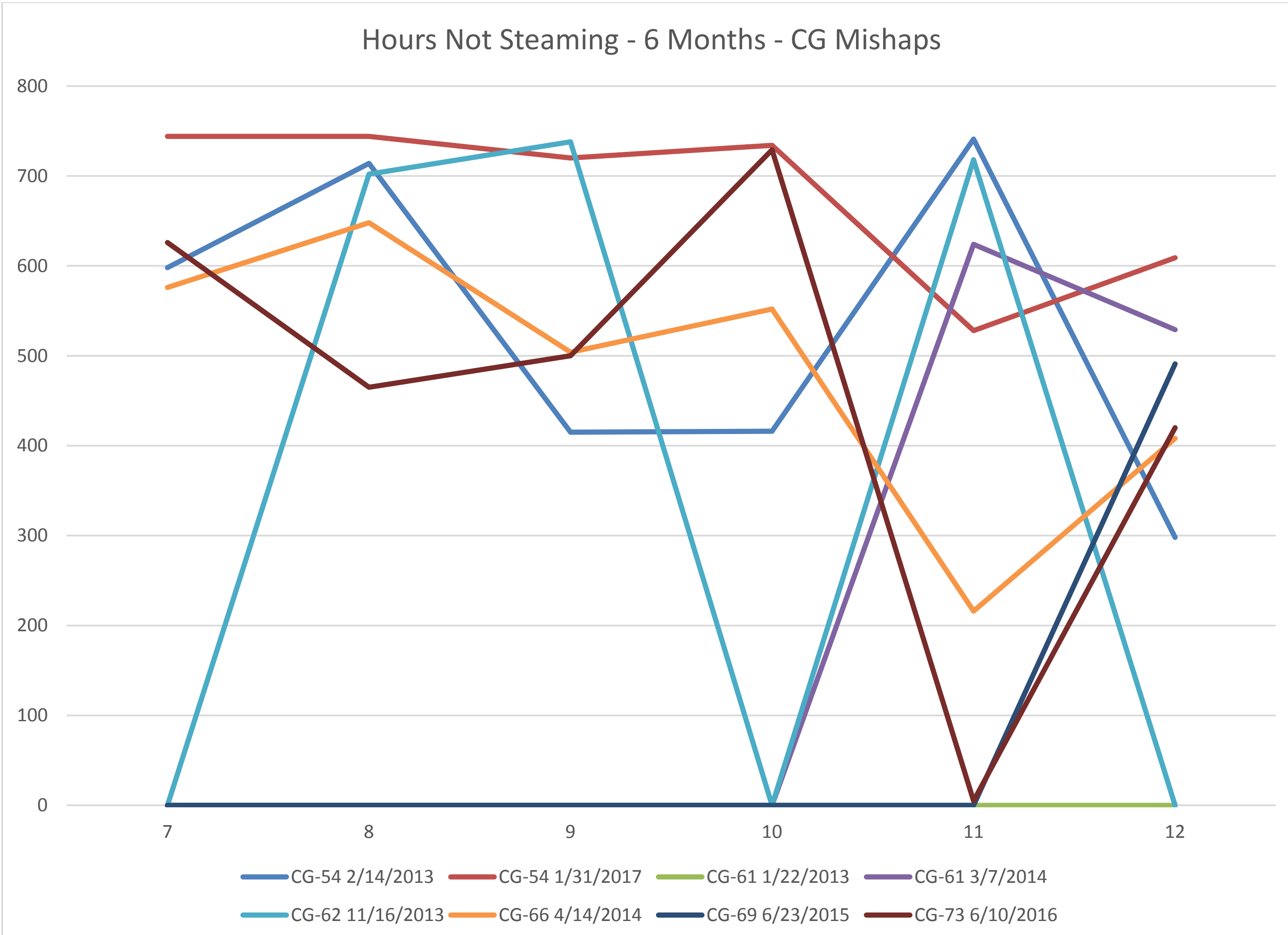
Hours Not Steaming - 6 Months - CG Mishaps
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CG-54 2/14/2013
CG-54 1/31/2017
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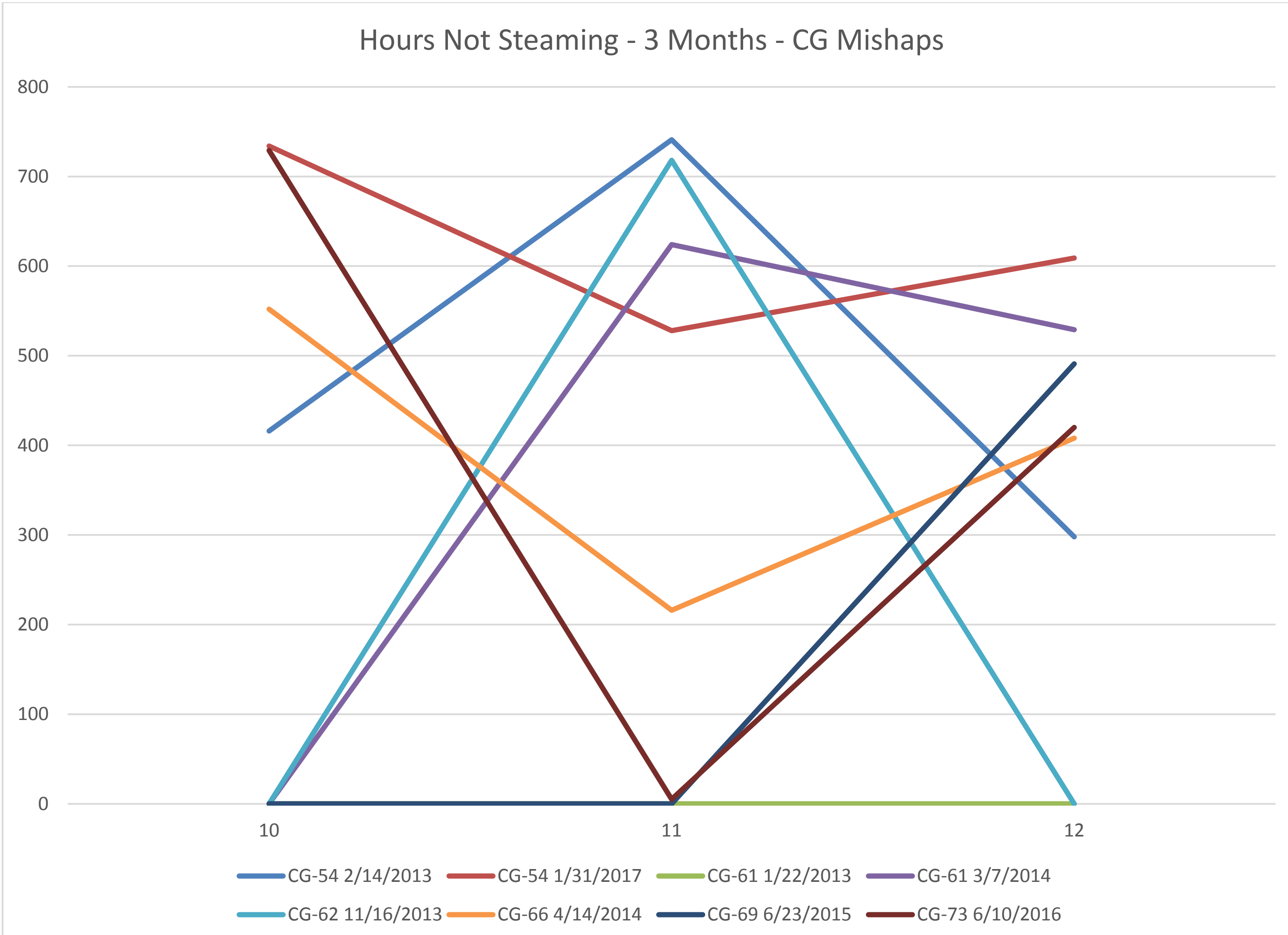
Hours Not Steaming - 3 Months - CG Mishaps
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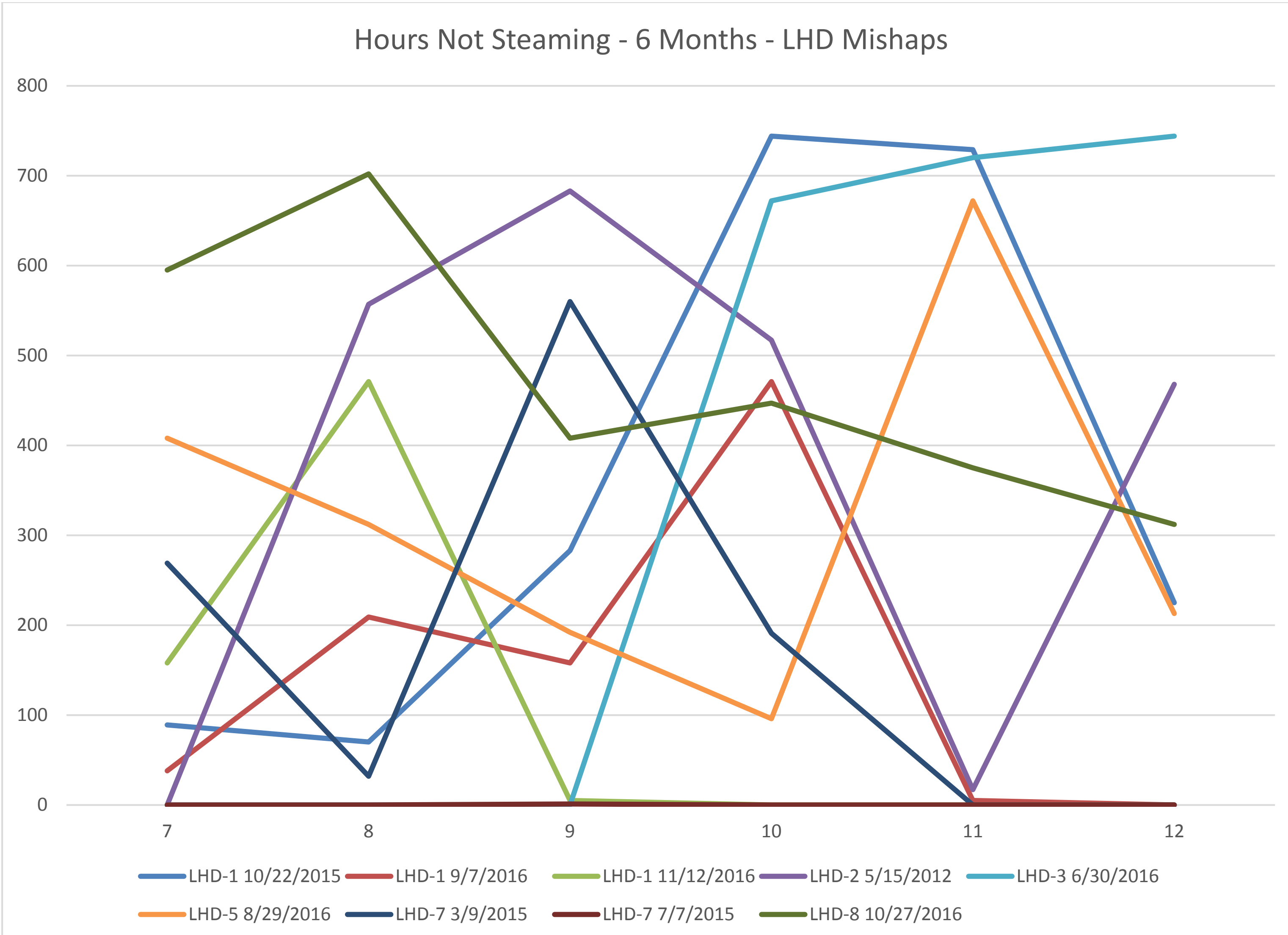

Hours Not Steaming - 6 Months - LHD Mishaps
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LHD-1 10/22/2015
LHD-1 9/7/2016
LHD-1 11/12/2016
LHD-2 5/15/2012
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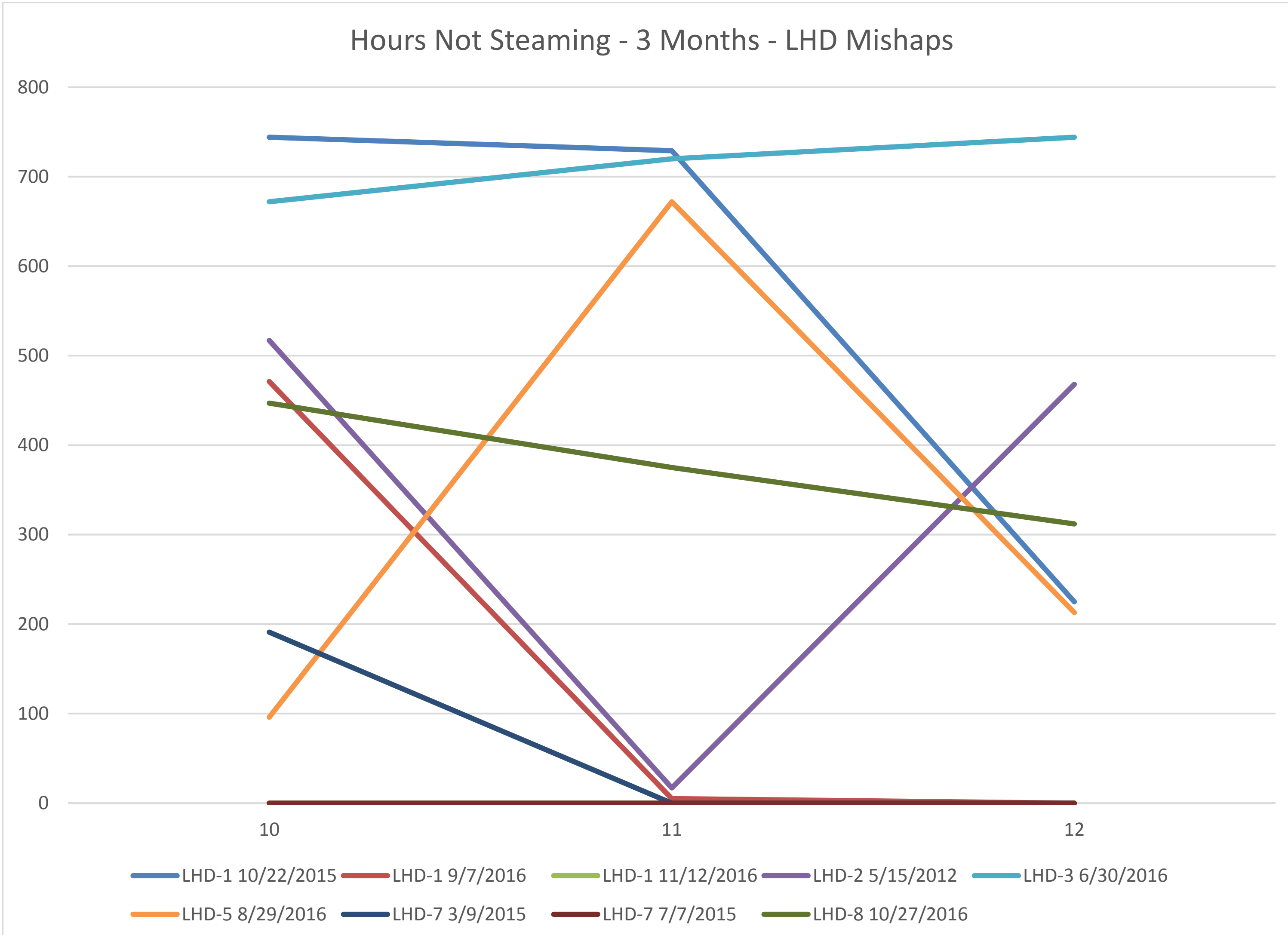
Hours Not Steaming - 3 Months - LHD Mishaps
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LHD-1 9/7/2016
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LHD-2 5/15/2012
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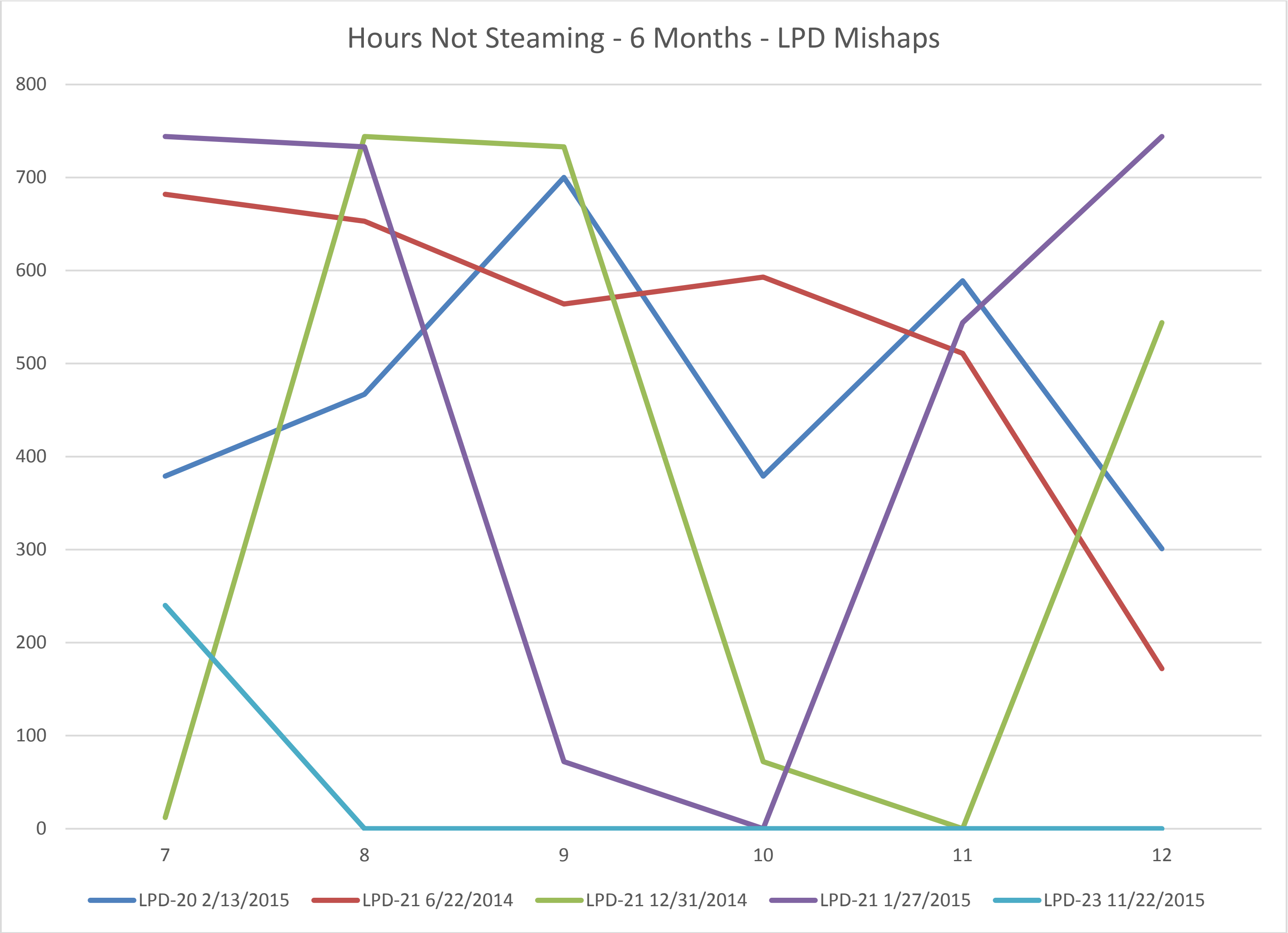
Hours Not Steaming - 6 Months - LPD Mishaps
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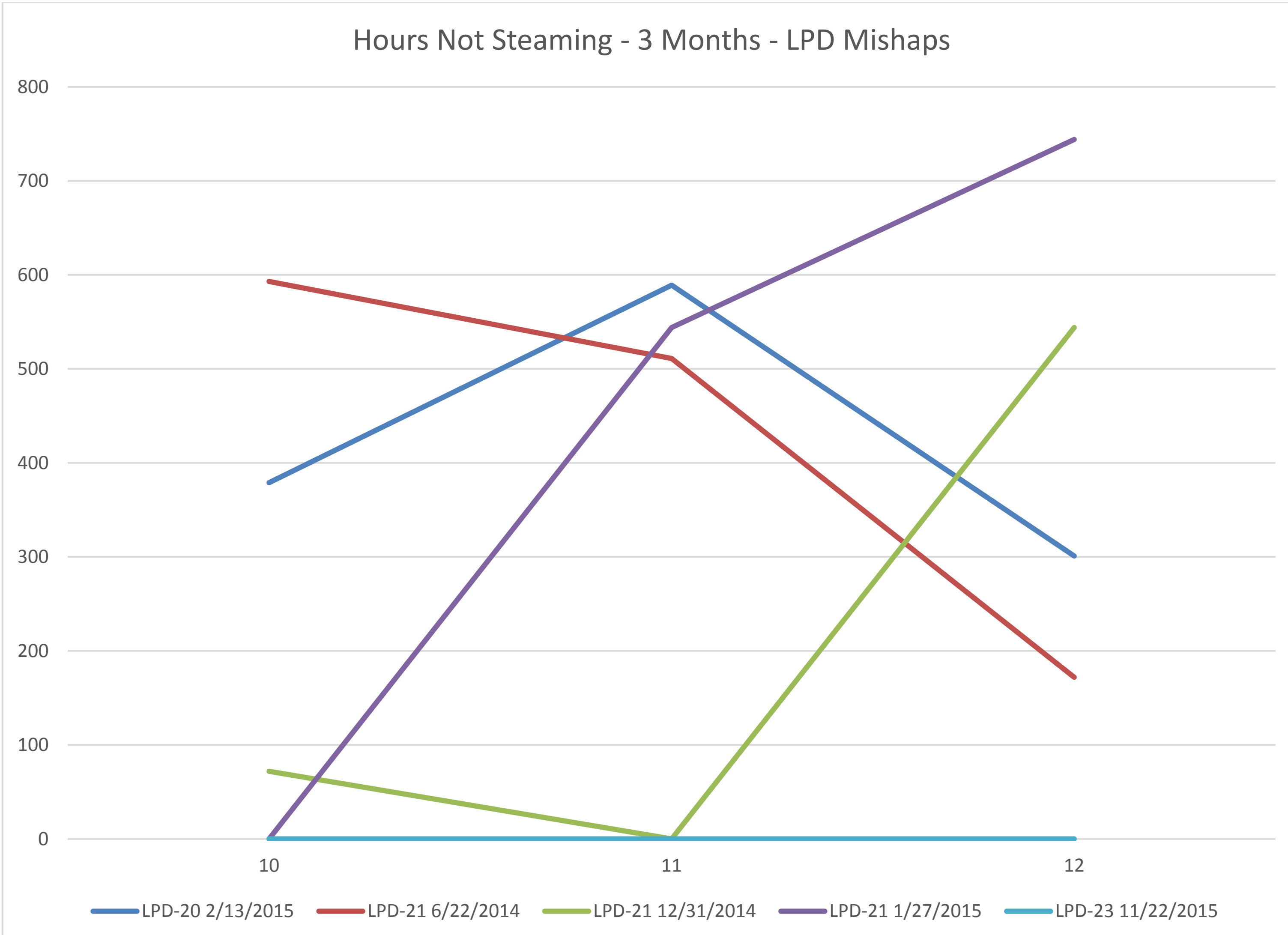

Hours Not Steaming - 3 Months - LPD Mishaps
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LPD-21 12/31/2014
LPD-21 1/27/2015
LPD-23 11/22/2015

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