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WILDFIRE MODELING: DESIGNING A MARKET TO RESTORE ASSETS

A thesis proposal submitted in partial satisfaction

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by

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Abstract of the Thesis

Wildfire Modeling: Designing a Market to Restore Assets

by

Ramandeep Bagri, ECE, UCSC, 2022

In the past decade, summer wildfires have become the norm in California (CA), United States of America (USA). These wildfires are caused due to variety of reasons. The state collects wildfire funds to help the impacted customers. However, the funds are eligible only under certain conditions and are collected uniformly throughout California. Therefore, the overall idea of this project is to look for quantitative results on how electrical corporations cause wildfires and how they can help to collect the wildfire funds or charge fairly to the customers to maximize the social impact.

The research project aims to propose the implication of wildfire risk associated with vegetation, and due to power lines and incorporate that in dollars. Therefore, the project helps to solves the problem of collecting wildfire funds associated to each location and incorporate with energy prices to charge their customers according to their wildfire risk related to the location to maximize the social surplus for the society.

The first section of the thesis shows the wildfire analysis and determines the risk based on each location (project focus is at California and it's counties). The proposal will use the previous year's data to forecast the wildfire risk as the next step to solve

the wildfire modeling. Electrical corporations are also taking actions to prevent the wildfires from their system using Public Safety and Power Shutoffs (PSPS) events. The primary purpose of the PSPS event is to de-energize the selected circuits depending on weather data. We are focusing on the PSPS events data to see if the frequency of PSPS events targets the low-income areas in order to avoid customer exploitation due to unrevealed characterization of the location. Therefore, we are using a data-driven approach to maximize the social surplus for the customers and reveal the impact of PSPS strategy on the customers.

The second part of the thesis determines the variable wildfire risk associated with each location using an energy pricing strategy that is the location marginal price method. These findings suggest that designing wildfire risk premium using a Risk-based Economic Dispatch and Location based marginal pricing method gives electrical corporations information to operate the developed methodology. The goal is to collect the wildfire funds based on the customers living at high-risk areas or living at low-risk areas instead of charging all customers almost around $6 uniformly from all customers throughout CA every month.

The thesis findings will help to calculate the risk premium involving wildfire risk associated with the location and incorporate the risk into pricing. The research of this submitted proposal provides the potential contribution towards detecting the utilities associated wildfire risk in the power lines, which can prevent wildfires by controlling the line flows of the system. Ultimately, this proposal's goal is a social benefit to save money for the electrical corporations and their customers in California, who pay "Wildfire Fund/charges" each month $5.85/KWH. Therefore, this proposal will propose methods to collect wildfire funds with maximum customer surplus for future generations.

Chapter 1

Introduction

1.1 *Wildfire and Climate Change*

Wildfires have become the priority of electrical corporations (Follow: Appendix: Part A) in recent years because of their destruction and damage to their own system, society, and life losses. Therefore, working to improve the wildfire modeling and charges for customers is the goal for the study.

As some part of the literature shows, wildfires are much more likely because of climate change, due to warming temperatures [3], [4], [5] [6] [7], [8] [9].

Moreover, addressing the above change in climate is not easy to resolve. The only reason is that climate change is a process of layers in each sector: production, electricity, polymers, chemicals, and many other industries collectively responsible for climate change. In the electricity market, addressing climate change means addressing the cause for electrical corporations impacting due to climate change. One significant impact is extreme events such as high winds or scorching weather. Such extreme events can ignite the wildfire due to the cause of electrical corporations. Therefore, this research addresses wildfire and its issues related to electrical corporations to address climate change problems.

1.2 *Wildfire and Electrical Corporations*

Numerous factors ignite the wildfires, and this project only involves the cause of wildfire due to electrical corporations. As discussed earlier, one of the significant factors that lead to wildfire is extreme weather conditions from climate change, for instance, high winds [10]. High winds speeds, [11] with “gusts of up to 140km/h measured at the Potrero weather station” [12] have the potential to cause conductor slap or breakdown or failing power line equipments [13], [14], [15]. Due to dry vegetation, and low moisture content on the ground can cause fire immediately and leads to wildfires. Besides climate change, many other factors ignite a wildfire. In the past, the wildfires are due to “lighting, human activity, debris burning, campfires, vehicle sparks, dry vegetation, electrical corporations” [10], [14] exotic grasses [16]. 5% of the wildfires are ignited by utilities, that is power lines [10] and were devastating due to which wildfire became a priority for the electrical corporations. Therefore this research will evaluate the destruction caused by CA wildfires using Cal Fire (Cal Fire means ”California Wildfires.) data [2], regardless of a cause, because the data does not provide the information of cause, which makes the work challenging. Here, the assumption is that wildfire destruction is the same no matter its cause. Therefore, here the project’s focus is to look at wildfire data and address how to prevent such destruction at a high level.

One of the significant examples of impacting electrical corporations is the destruction caused by 2017 to 2018 North California wildfires that covered $150,000$ acres of land and further destroyed $13,972$ residences, 528 commercial structures, and 4293 other buildings, and 86 lives lost [17]. Such destruction and damage due to the cause of wildfires and all costs together totaled $\$30$ billion to PG&E, and they declared bankruptcy

[17]. The main factors behind PG&E bankruptcy were wildfires, which are ignited by their system [17]. There is no doubt that the destruction caused by PG&E was massive. Along with that, negatively impacting society, this destruction also burned their own assets (distribution poles/lines or equipment's damage) and increase the damage cost.

Furthermore, to resolve the impacting electrical corporations situation during wildfires situation, California legislation passed three bills as a part of California Wildfire Funds at the legislation level: AB1513, AB1054 (amends from AB1513), and AB111 [18], [17]. Under Bill AB1054, California state issues, allows the Public Utility Commission in California (CPUC) to authorize the rate-making and rule-making for electrical corporation and allows them (electrical corporation) to request financing for the impacting customers for their assets at commission (CPUC) [18]. Also, it allows the authorities to differentiate the electrical corporations requests for finance needs at their customer level or their own cost. As well, this bill allows the authorities to do their rule-making to collect the bonds of the issue to finance the electrical corporations [18] under CPUC.

In addition, the AB1054 Bill creates the California Wildfire Safety Advisory Board to help the electrical corporations and provide recommendations on their mitigation plans for issue wildfire under the authorization of Public Utilities Commission [18]. Meanwhile, AB1054 [18] allows the Department of Water Resources (DWR) to authorize the financial state-issued bonds and also will enable them to recover the bonds as well [18]. Further, Bill establishes the Department of Water Resources Charge Fund and makes DWR responsible for issuing the wildfire bonds for electrical corporations and recovering those costs.

Hence, DWR initially capitalized the California Wildfire Fund from short term $2Billion loan from the state of California's Surplus Money Investment Fund called "SMIF", which is the fund within the state's pooled money investment account. Along with IOU's (only PG&E, SDG&E, SCE) contributions [19], [20] along with SMIF loan [20], the total was $\$10.1$Billion and further according to the order's of CPUC, the fund was collectible from the Jan 2021 [21].

Wildfire Fund at state-level supports only eligible claims reimbursement [22], [23]. Additionally, the California Wildfire Fund is available for electrical corporations for Wildfire eligible claims [24]. Those eligible claims are 1) When IOU's (Independent owned utilities) equipment or infrastructure ignites the fire [22] 2) Capitalized fund during wildfires to the electrical corporations, the responsibility of the recovery is on electrical corporations, and ratepayers [24]. In this process, DWR is responsible for [22]:

1. Recover the wildfire given fund from ratepayers
2. Handle the responsibility of Issuing and recovering the paid $\$10,500,000,000$ in bond so far.
3. Keep updating the financial records with CPUC and any excess or deficiency in the collection and maintain revenue requirement approximately $\$902,000,000$ per year.
4. Also, if there is any deficiency in the amount, then DWR has to offer should write to CPUC and CPUC likely return in 30 days about increasing the charges [22].

Therefore, DWR issued the allowances needed to the utilities to provide financial support. So far, regardless of how much is allocated to each electrical corporation. DWR is collecting $21 Billion as in-claim paying capacity, which is split between IOU's contribution and their ratepayers [25]. As DWR is responsible for charging ratepayers, they begin charging ratepayers in their territory IOU service areas the Wildfire "non-bypassable Charge of $\$5.80$/MWh ($\$0.00580$/kWh) in 2020, beginning October 1, 2020.

In addition, $5.79/MWh ($0.00579/kWh) in 2021, these rates are calculated under the reasoning to collect revenue for the 2021 Revenue Requirement Period, $902.4 million as required by the Act and Decision $19-10-056$" [25].

1.3 *Significance of the Proposal*

As policies and regulations show a need for wildfire funds and collecting non-bypassable charges from all customers, the DWR strategy is to collect partial funds from ratepayers. However, this thesis proposes an alternative to their strategy to collect revenue for wildfires by charging all customers equally non-bypassable charges. The charging rates here are ineffective and insufficient for practice. This thesis proposal agrees as legislature comments on bill [18]

> "With an increased risk of catastrophic wildfires, the electrical corporations' exposure to financial liability resulting from wildfires that were caused by equipment has created increased costs to ratepayers".

Therefore this project will fill the gap to get the insights from Cal Fire data about the structure of wildfires and how likely wildfire is related to each location. This thesis will provide a solution by charging customers according to their location and incorporating those wildfire charges in energy prices as energy prices are based on location marginal price.

This problem is solved by CA ISO, in general. Below, figure 1.1 explains the project's overall idea from basics to modeling and its impact. The project focus is only on those wildfires which electrical corporations ignite. In generalizing the damage from wildfires, the project uses Cal Fire data to measure the damage to the public, as the damage to the public is massive. The DWR issues the bonds to electrical corporations to support them financially to help their impacting customers. Further, DWR is also responsible for recovering the funds and charging all electrical corporation ratepayers uniformly, regardless of their wildfire risk location. This project contributes to defining the risk based on the site and assessing the method that allows DWR to charge the ratepayers according to the wildfire risk accordingly, under the California Public Utilities Commission (CPUC) supervision.

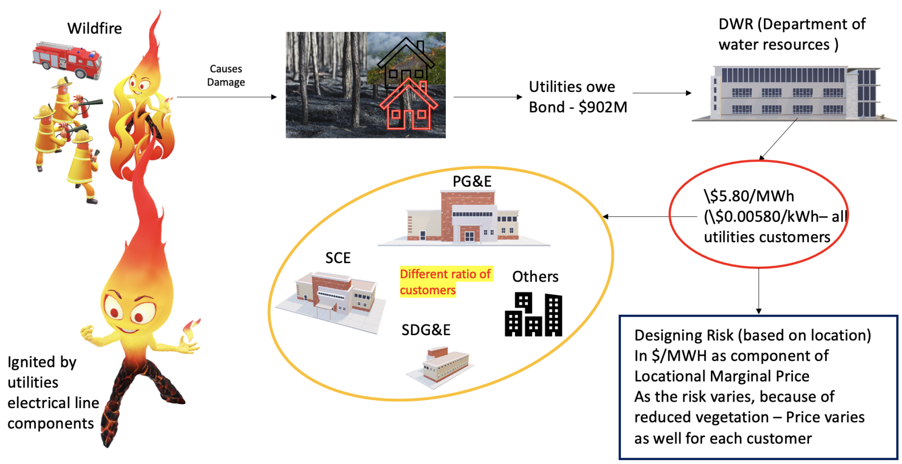

Figure 1.1: Overall, idea of the project, Wildfire and Restoring Assets

1.4 *Expected Outcomes from the Proposal*

Overall, this thesis will meet the social goals by saving money for the 's customers in California, who pay "Wildfire Fund" each month $5.85/KWH, regardless of their location. This work will also potentially contribute to determining wildfire risk associated with the power lines to avoid future wildfires from utilities.

1.5 *Organization of the thesis*

The remainder organization of the proposal is as follows. Chapter 2 presents the literature review of the wildfires due to utilities and their impact. Next, Chapter 3 focuses on the Cal fire data and insights into wildfires structure based on locations. The Chapter 4 describes the PSPS events relation to the location based on their income. Then, Chapter 5 describes the proposed method for calculation location-based charges using location marginal pricing. Future work for the wildfire modeling related to IOU's interest is discusses briefly in Chapter 6.

Chapter 2

Literature Review

2.1 *Electrical Corporations Causing Wildfires*

Electric utilities can cause a wildfire [10], [16], [26] and one of the significant factors that lead to wildfire is extreme weather conditions, for instance, high winds [10]. High winds are most likely to cause power lines faults or conductor clashing/slap [26] or vegetation Interference leading to distribution system faults [26]. There are three cases when the line fault occurs: most safe is no arc, just a sustained or momentary fault [27] in the power lines, second is the arc, and third is conductor clashing/slap or breakdown. Energized power line breakdown can cause direct arc ignition [26]. During line faults, there is the release of high current and leads to molten metal particles, burning embers, burning fluids [26] which can most likely ignite the fire [26], [15]. Due to dry grassland, low moisture content on the ground, ignition is immediate, leading to wildfires. The studies in literature explain the following wildfire risks: vegetation issues [16], vegetation uncertainty (related to a tree falling on power lines) [12], conductor clashing during extreme weather conditions [12], the impact of the weak infrastructure of Distribution and Transmission Network [12], congestion of transmission power lines [26] and excessive heating in the system's equipment due to the harmonics and this problem is more frequently seen in the distribution network [28], [15]. In next few sections, we will overview the cause of wildfires from electrical corporations point of view.

2.1.1 Wildfires Causing due to Vegetation

In past studies have shown [12] how the electric power systems equipment, parts impact during these high winds or weather uncertainty [29], [30], [31]. Further, the impact of these events glimpse during catastrophic losses that lead to arcing or ejection of high-pressure heat loss that triggers the fire or ignites the fuel, which is often exotic grasses [16], [32], [30] and sparks the fire [12], [32], [33], [34], [13], [26], [15]. Such catastrophic fires occur when the power line conductor and other objects are in contact, here objects could be any†hing fallen on power lines, for instance, vegetation. Moreover, the vegetation, also known as "Tree-related" causes have been igniting the fires in two ways. First is when vegetation contacts the conductor directly and causes high impedance fault to ground [12]. Secondly, vegetation falling on power lines or supporting infrastructure causes the conductors to come in contact with each other causing phase-to-phase fault or causing the breakdown of the phase and resulting in ground faults. Sparks or flames produced from the conductor or failed equipment leads to the fire [15]. There are some instances of wildfires due to vegetation and those instances are Rice fire, California, in 2007 caused by 12kV conductor operated by San Diego Gas and Electric Company (SDG&E), which destroyed 3840ha and destroyed 206 homes. Another instance is Beechworth-Mudgegonga fire, Victoria Australia from 2009 that caused $34,000$ha area burned and two fatalities followed by loss of 38 homes [12]. Thus, vegetation accidents during extreme weather conditions impact electric power systems which further amplify the situation from sparks to wildfires [34], [35], [15].

2.1.2 Wildfires Causing due Weak Infrastructure or Failed Appratus

The literature also describes other reasons which causes wildfires involving electrical corporations lines and those reasons are: weak infrastructure, and conductor clashing to leading several wildfires [15], [15]. Those wildfires are either due to failure of electrical infrastructure, conductor, or other failed equipment [13], [26] whose life is ending, coming in contact with the live conductor that causing sparks or flames during extreme weather conditions. Among all, the most common cause seen in the literature is drowned conductors [13], [15]. Such causes are from weak infrastructure that occurred in the past are Kilometre East Fire, Victoria Australia 2009, Guejito fire, California 2007, Malibu California 2007, and Coleraine Victoria Australia 2009, which collectively burned 207, 265 ha, lost 1242 homes and lost, 119 lives [12], [15], [14]. Therefore, the weak infrastructure of electrical corporations has caused an enormous loss to society.

2.1.3 Wildfires Causing due to Conductor Clashing/Slap

Conductor clash/slap is the defined in literature as [26]

> "two conductors make contact or flashover causing a phase-to-phase fault"

Furthermore, the extreme uncertainties such as bad weather conditions can cause conductor clashing which has been seen in past literature [15], [14] causing the fire. The Witch fire, California in 2007 occurred due to two conductor clash on 69kV transmission line and then fires combined due to conductor clashing. The conductor melting or high flames led to Guejito fire and "cause massive loss of burn 80, 000 ha and 1141 homes, and two fatalities" [12]. Another such conductor clashes example is the Pomborneit-Weerite fire Victoria Australia 2009, where the arcing was between 66kV and 22kV [12]. Therefore extreme weather uncertainties and power line flow at their capacity have proven more dangerous and pose the risk of wildfire much more significance with conductor clashing/ their sparks and melting fuels. This literature assumes that power line flows can likely exploit the situation under mild or extreme weather conditions and lead to spark/conductor melting into a wildfire.

2.1.4 Wildfires Causing due to Overloading line

As past studies [26] have shown that overload and line congestion have direct relationship. Recent studies proved that the overloading line have high propabability of causing arc and line flow under line limit has less propobabilty of occuring an arc [26]. Author also concludes that congestion causes thermal stress on power lines which increases the probability of occurance fault in the distribution lines [26]. Our work is based on their suggested research goals to mitigate the arc from the line congestion [26].

2.1.5 Wildfires Causing due to Harmonics in the system

Electric power lines usually have high currents flowing through them. It is well known from previous studies that arcing may be caused due to damaged power lines carrying high currents, as well as transformers and power machinery [36] [37]. Arcs may have different lengths (long and short arcs), and they may also have nonlinear behaviour in terms of their intensity, with respect of the underlying line flow. Due to undesireable harmonics created in the power systems from arcing, it is of paramount importance to model its negative effects, as disscussed in [36]. Such arcs can reach an arc up to 2240^oC [38]. As disscussed earlier arc leads to wildfires in high gust winds at low moisture content [26].

2.2 *Determining Potential Cause for Wildfires*

As literature shows all different factors that can cause sparking via molten metals, arcs in the power lines or equipment failure or catastrophic weather conditions. Those different factors are dry vegetation, sparking electrical components, sparking components, electrical line components failures/overheating due to harmonics in the system [28], weak infrastructure, overloading lines causing sparks, fuel moisture content [26], air temperature [26], high winds [26] can cause fire and leads to more dangerous wildfire. Given the vast multitude of reasons why wildfires may be caused [14], we need to focus on a the purpose of modeling. Since power lines are highly energized when operational, any fault or catasatrophic damage to the lines can cause significant sparking, leading to ignition of dried vegetation and shrubbery. As discussed earlier, the high current realse from energized line causeing phase to ground fault and causing the arcs or sparks leads to wildfire with favoured weather conditions and this same reasoning is also noticed in [38], [15], [15].

From the above, we can conclude that a highly energized line, upon breaking or suffering a catastrophic failure can ignite nearby vegetation with low moisture content and under high winds leads to wildfires. However, there is a lack of sufficient literature which *specifically* provides a quantitative relation between line flows and wildfire intensity. Though recent study [26] proved that the congestion and probabilty of arc occurance corelation exists. Therefore, our proposed work uses the another approach model that use thermal limits to relaese the congestion and shows guidance to our proposed work. Our work is the mitigated solution controlling line flows which assume are directly related to the wildfire arc ignition and protect the system at high level.

Hence, as stated above, we assume throughout the rest of the project that higher line flows can lead to more intense wildfires (i.e. wildfire intensity and damage caused due to it are increasing functions of line flows). This assumption is borne well by observing available data.

2.3 *Prioritizing line flows for Wildfire Modeling*

The past studies provide the directions fro our work for wildfire modeling. In this thesis prioritizing the two significant causes, and those are 1) vegetation power 2) lines working over their thermal limits under congestion.

As the literature shows that during extreme weather conditions such arcs can ignite the wildfire [13] and high gust winds can ignite the dry vegetation and fuel the fire to wildfires [38]. As a result, we find support for the hypothesis that equation 2.1 can help us in wildfire modeling. We cannot control the environment, but by controling the line flows according to forced conditions, we can help to reduce the uncertainity involved in the situation to catch wildfires and this is also supported in literature [26].

We are considering Forced Outage Constraint (FOC) in relation to line flows, to control the line flow . FOC is a parameter which can be controlled by operator to set the maximum line flow to be $FOC\%$ of the default maximum line flow. The operator will make such a choice depending on the risk from setting a certain value of FOC. Thus, we assume that risk of a line is a function of FOC of that line.

Our work is focused on defining the wildfire risk used in this chapter and it's correlation to FOC of power lines. The defined wildfire risk $WR_{t,x}$, for a time period t and location x is dependent on the vegetation of the location. We define wildfire risk as follows.

Wildfire risk: Wildfire risk is a numerical quantity, denoted by $WR_{t,x}$, which varies temporally (time denoted by t) as well as spatially (geographical location denoted by x), such that probability of wildfire at a given location and time is an increasing function of risk. Most likely, as a wildfire is uncertain, the pattern from previous wildfire events in each year might not be helpful. As our work is more focused on the real-time incoming data, time series forecasting might not accurately predict. In contrast, literature shows that deep learning is the faster approach in real-time for predicting the vegetation color.

Last but not least, as our work is more focused on power lines and wildfire risk $(WR_{t,x})$ is associated to location (x). The past studies [26] shows that our assumption is most likely true that the wildfire risk is directly proportional to the line flows and can be written as:

$$WR_{t,x} = FOC_{x,t} \tag{2.1}$$

Hence, the line flows are controllabe using risk at each node or associated to the house risk or location based risk. The calculation of FOC for each location is the scope of the work.

Chapter 3

Use Data-Driven Technique to Determine that Wildfire Risk is based on the Location

3.1 *Motivation of Using Data*

Wildfire data is available in each country where wildfire events occurened recently and interested, follow the references for wildfire data at international level [39] [40], national level [41], [42], [43] and state level, USA [2] for future references. As literature shows, wildfires cost in dollars was approximately $10.1Billion, which the Department of Water Resources invested/paid to IOU [20]. Other wildfires funds are collected to help the future wildfires. As the climate changes, wildfires are inevitable, especially in scorching weather, and the risk associated with those fires increases. It also adds layers of definite risk with human errors (Using loosen/fatigued conductors or exhausting the power lines, i.e., working over their thermal limits). Therefore, understanding the wildfire data from the decade will help minimize human errors and reduce their risk.

In past studies, the data has given scientific ways to carry out numerical weather analysis, and fire prediction for wildfire modeling [44]. Their data collection is captured from “Internet sources, input from aerial photographs and sensors” [44] and the “system is controlled by non-Gaussian ensemble filter capable of assimilating out-of-order data” [44]. As past studies using data were successful example is the motivation for using the Cal fire data [2].

3.2 *About Data*

The Cal Fire means ”California Wildfires. The Cal Fire data is available at the Cal fire website [2]. This work uses data available from the period 2013 to 2022. As past studies have shown, there are 5% of the wildfires are ignited by utilities, that is, power lines [10] in California, USA. This data provides an overall idea of the destruction of wildfires in California from the past decade. Data does not have causes defined, due to which it is challenging to find what is the exact cause of each wildfire event. Overall, this data will help to generalize the idea of the structure of the wildfire’s destruction, loss, and damage in California. Also, understanding the complete Cal Fire structure will evaluate the situation better for wildfire modeling for risk associated to each location. Therefore, the purpose of the data exploration is to understand the structure of California “Cal Fire” data and to find the risk associated to each location [2]. For data processing follow (Appendix, Part B) details.

3.3 *Determining the Risk Dependent on the Location*

Determining the data-driven risk is done by using the preliminary data exploration techniques. As shown in past studies, [11], that house location and vegetation around determines the probability of risk of getting that house on fire [11]. In addition, we want to generalize the risk based on the location, power lines, and real-time vegetation data. The risk during wildfires events increases due to weather uncertainty and leads to fire or sparks or arcs. These elements (fire or sparks or arcs), as literature supports, lead to fire and further escalate to wildfire. Wildfire spreads more quickly than any burning fire at equipment failure or sparks at power lines or drowned conductors conditions. This fire spreading across the land is measured by each wildfire event (in acres). The data shown in table 3.1 shows the average number of acres burned during wildfire events each year in the past decade. This data reflects that 2019 was the safest year compared to others in the past decade, with average acres burned being little more than 1k, and the following year 2020 had the highest acres of land burned, around 10k acres per event, and 2020 became a most devastating year in wildfires history.

Table 3.1: Average Data of Acres Burn/Year, California Results [2]

Year	Acres Burned (average data of events/year)
2013	3524.38
2014	3910.34
2015	4176.38
2016	2918.75
2017	3392.26
2018	5184.84
2019	1093.64
2020	10418.52
2021	2107.41

The rough approximation from the table 3.1 data shows that a minimum of 1k of acres burning during wildfire events can be commonly expected and prepared accordingly if fire/ wildfire ignites. The vegetation dryness or moisture content is different in the soil as literature describes that wildfire is fueled by dry vegetation. Moisture in the vegetation depends on the location. If the location is Riverside, as table 3.2 shows the data, the vegetation will likely be almost dry due to hot weather and low moisture and have a maximum number of wildfire events in the county. Imperial is next to Riverside; however, the number of wildfire events in the Imperial is minimum among other 57 counties and sub areas of the counties shown in data in table 3.2.

Interestingly, in general, “California has a land area of 155,812.8 square miles or 99720192 acres. It is the third-largest state by area.” [45], and over almost a decade, total acres burned 233098563 acres which is 42.87% of entire California. The wildfire incidents in California, which are the base for each county’s modeling, are visualized in figure 3.1. It represents all 57 counties (figure 3.1, data), except San Francisco county, which means that missing data doesn’t exactly mean it’s a safe county. Still, it’s a safe county because there is no vegetation to ignite the fire and most of its electrical work is underground. Review of Wildfire Management Techniques—Part I: Causes, Prevention, Detection, Suppression, and Data Analytics

The wildfire incidents which are the base for the modeling in each county is visualized in figure 3.1 and map visualization in figure 3.2.

During a wildfire, the destruction and damage to land are shown in figure 3.3, representing the color code as the range for the burned area (in acres). Some counties are easy to visualize, such as light green, where the damage from average wildfire is 10k acres, followed by Fresno and San Diego. Approximate the estimate using past data shown in table 3.2. Average of the acre burned, each wildfire incident burn at-least 1k acres of the land at minimum in all 57 counties. Therefore, the exploration technique used for Cal Fire data demonstrates that Wildfire risk is associated with the specific location. Due to this, our work argues that DWR wildfire charges are insufficient and ineffective for practical use. This shows the need to calculate the wildfire risk associated with the location in dollars.

Table 3.2: A Statistical Data, Counties, California, Results

County Name	Frequency	Percentage	Cum. Percentage	Total acres burned	mean (Total acres burnedat each incident)
Riverside	9576	9.1	9.1	4929456	520.86
Fresno	6464	6.1	15.2	25126578	3887.16
San diego	5544	5.3	20.5	4164720	766.70
Butte	5112	4.9	25.4	13724424	2684.75
San luis obispo	4836	4.6	30.0	6525314	1366.84
Shasta	4745	4.5	34.5.	11591060	2442.79
Monterey	4590	4.4	38.8.	18786690	4092.96
Siskiyou	4464	4.2	43.1.	23497560	5439.25
Tehama	3876	3.7	46.8	3605156	930.12
San bernardino	3654	3.5	50.2	5378050	1471.82
Los angeles	3162	3.0	53.3	6903207	2218.97
Lake	3015	2.9	56.1	6304633	2091.09
Santa clara	2982	2.8	59.0	939259	314.98
Madera	2924	2.8	61.7	2188512	748.46
Kern	2590	2.5	64.2	4854215	1901.38
Mendocino	2409	2.3	66.5	3161265	1312.27
El dorado	2132	2.0	68.5	5434052	2612.53
Tulare	2112	2.0	70.5	4364400	2164.88
Trinity	2068	2.0	72.5	4264498	2268.35
Humboldt	1914	1.8	74.3	1365606	713.48
Tuolumne	1890	1.8	76.1	21148540	11620.08
Contra costa	1700	1.6	77.7	381100	224.18
Santa barbara	1550	1.5	79.2	2514300	1676.20
Mariposa	1350	1.3	80.5	9712890	7194.73
Lassen	1250	1.2	81.7	4814075	4097.09
Yuba	1200	1.1	82.8	786500	683.91
San benito	1188	1.1	83.9	359910	302.95
Alameda	1044	1.0	84.9	214488	205.49
Sonoma	1020	1.0	85.9	6161880	6041.06
Calaveras	1015	1.0	86.9	243425	239.83
Napa	980	0.9	87.8	216874	221.30
Placer	966	0.9	88.7.	1487870	1617.25
Plumas	924	0.9	89.6	13143372	14224.43
Stanislaus	903	0.9	90.4	509163	563.86
Sacramento	900	0.9	91.3.	486660	540.73
Solano	860	0.8	92.1	309858	360.30
Ventura	782	0.7	92.9	836604	1069.83
Merced	774	0.7	93.6	598044	772.67
Inyo	756	0.7	94.3	1636173	2164.25
Yolo	744	0.7	95.0	1142474	1675.18
Nevada	570	0.5	95.6	148950	261.32
Mono	540	0.5	96.1	1356696	3140.50
Marin	496	0.5	96.5	329344	664
Orange	481	0.5	97.0	2585560	5375.38
Amador	462	0.4	97.4	61149	132.36
San joaquin	432	0.4	97.9	646464	1496.44
Santa cruz	378	0.4	98.2	28350	75.00
Glenn	315	0.3	98.5	137480	436.44
Modoc	252	0.2	98.7	686525	2802.14
Colusa	246	0.2	99.0	36408	148
San mateo	204	0.2	99.2	8568	42
Del norte	180	0.2	99.3	24165	134.25
Kings	175	0.2	99.5	1422100	8126.29
Sutter	172	0.2	99.7	125990	732.50
Sierra	170	0.2	99.8	1633564	12011.50
Alpine	144	0.1	100.0	47520	440
Imperial	25	0.0	100.0	6875	275
Total	105207	100.0	100.0	233098563	2245.33

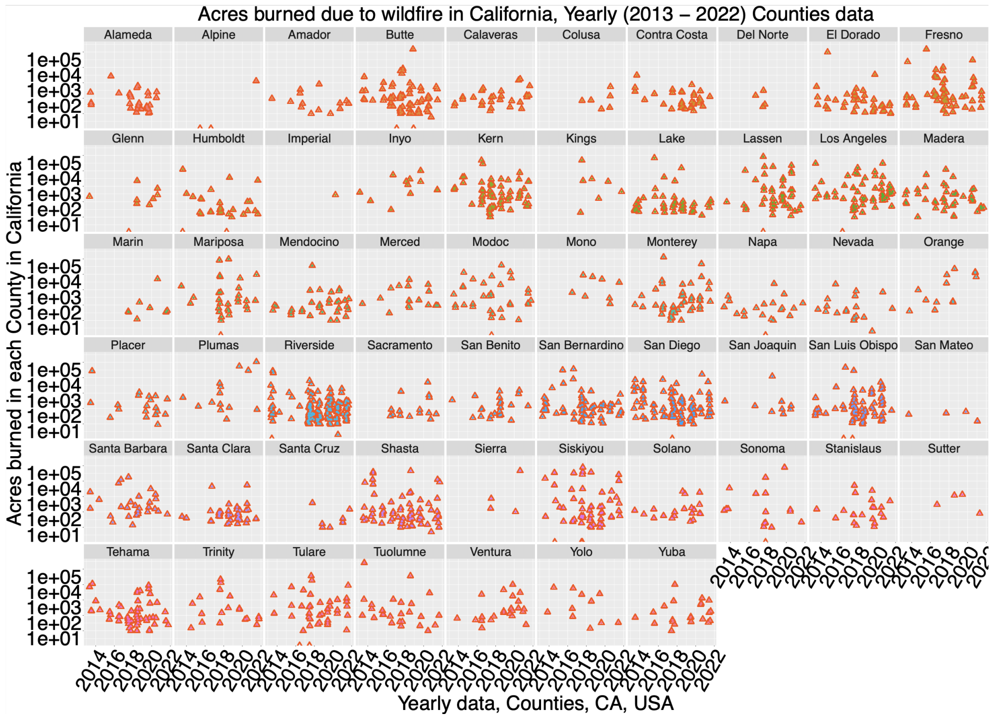

Figure 3.1: Each data-point is the wildfire incident data,
Counties, CA, USA

3.4 *Proposed Risk Model Disscussion*

The data shows the need to calculate the wildfire risk associated with the location in dollars. The project's first step is to define the wildfire risk and basic terminologies. We define wildfire risk as follows.

Wildfire risk: Wildfire risk is a numerical quantity, denoted by $WR_{t,x}$, which varies temporally (time denoted by t) as well as spatially (geographical location denoted by x), such that probability of wildfire at a given location and time is an increasing function of risk.

Note that the above definition of risk leaves open a large number of ways to actually define the numerical quantity that we will call risk. For example, economists have defined risks as shown in [46–48]. In the case we do risk analysis for a specific geo-

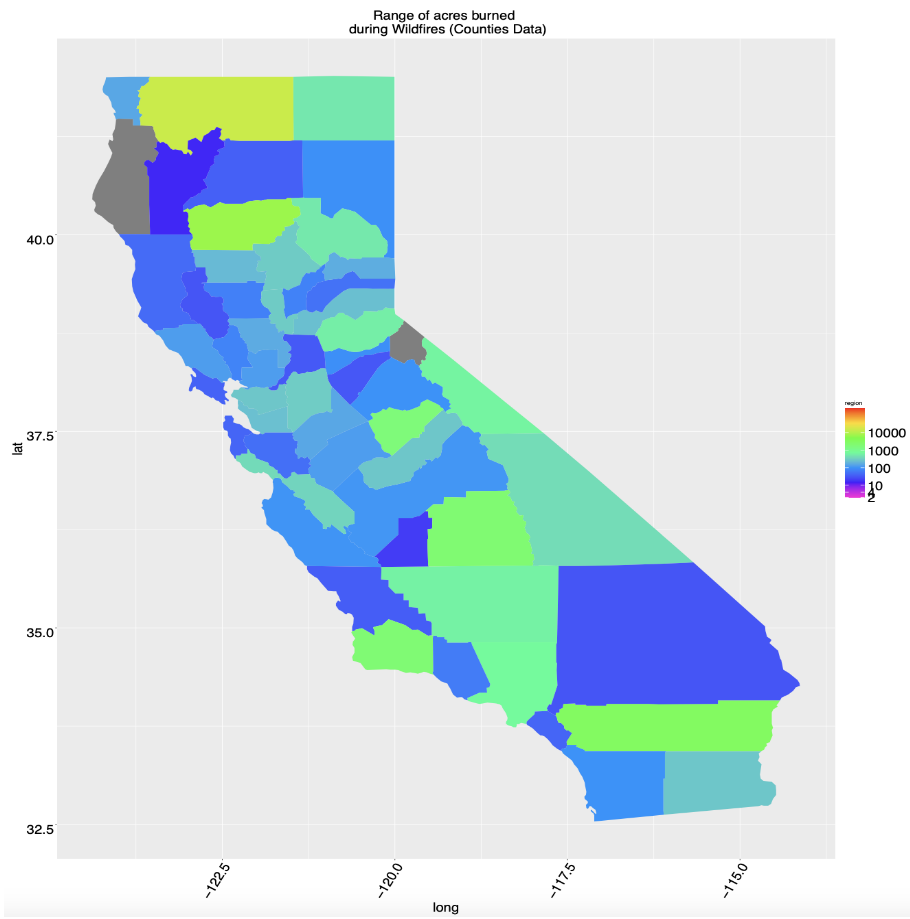

Figure 3.2: Wildfire data for the CA, counties

graphical location, we drop the x subscript.

Studying the risk numbers for the case of wildfires is important. In order to simplify wildfire risk analysis, we propose splitting different wildfires into six categories depending on said fire's associated risk number.

1. Very Low Wildfire Risk (VLWR)

2. Low Wildfire Risk (LWR)

3. Medium Wildfire Risk (MWR)

4. High Wildfire Risk (HWR)

5. Very High Wildfire Risk (VHWR)

6. Drastic Wildfire Risk (DWR)

We came up with an approach to categorise any given fire into one of the above categories. The proposed approach assumes that we have access to the vegetation color (or any other visual information) around the potential wildfire area.

3.4.1 Wildfire Risk Modeling: Proposed Approach to Determine Risk

Here the assumption is that the vegetation color is associated with the vegetation risk. Past studies [49] show that the dry vegetation will most likely become fuel much quicker than the wet vegetation. Therefore, the risk associated with the dry vegetation is much higher and marked as Drastic Wildfire Risk, VHWR. The risk associated with the damp and growing vegetation depends on the vegetation's color. The wildfire risk depends on the associated color risk related to the vegetation's color as shown in Table 3.3 below.

Table 3.3: Define: Vegetation Risk and Color Associated to it, California Results

Risk	Recognizing Vegetation Color, Names
Very Low Wildfire Risk (VLWR)	Dark Green
Low Wildfire Risk (LWR)	Light Green
Medium Wildfire Risk (MWR)	Faded Green
High Wildfire Risk (HWR)	Yellow
Very High Wildfire Risk (VHWR)	Orange
Drastic Wildfire Risk (DWR)	Red

The risk associated with the vegetation color needs real-time data of vegetation for each location, and such data could be satellite pictures of CA or a data set with colors in them [49], [50], [51], [52]. Artificial intelligence techniques such as deep learning

[53], [54], [55], [56], [57] may be used to directly classify imagery of a given fire into its risk category. The scope of this work remains in the future.

3.5 *Conclusion*

The highlights of the Cal Fire data, there are chances of fire occurance in all 56 counties except in San Fransisco, but their chance of occurance depends on the location risk. Next, the minimum average acres burn in all these years regardless of counties is 1k and maximum was 10k. Some counties such as Riverside, San Deigo are at high risk and some such as Alpine, Imperial are at low risk. The data provides the decision-making strategy for our work to solve the problem for Wildfire Risk associated with the location.

Chapter 4

Uncovering Hidden Patterns of PSPS Data and Income of the Counties based on the Location

4.1 *Motivation of Using PSPS Data*

Motivation behind the uncovering the patterns of PSPS events is that in California there is a wide range of population. According to living cost, some areas are high income areas and some are low income areas. Our project is based on designing the location based price approach according to the Wildfire risk associated to the location. Moreover, the PSPS events is an approximated solution to reduce the risk of the wildfires. There are two approaches that wildfire risk can be reduced by reducing the line flows are given below.

- Reduce the demand at two ends of the line (or just one node) (PSPS way + included in proposed work)

- Reroute the power flows (Proposed Work)

Therefore, the PSPS way is another approximate solution to reduce the wildfire risk and is giving us the motivation to review the impact of de-energizing the circuit to reduce the wildfire risk. This will provide us the chance to reduce any negative impact related to the wildfire risk on society.

4.2 *Overview of the PSPS Data - in process*

Under the recommendations of the DWR, the utilities introduced the PSPS (Public Safety Power Shutoffs) program to control the distribution network by de-energizing only impacted circuits from extreme weather conditions to avoid the wildfires from their system equipment. However, there are some health concerns around when the power is de-energized from the impacted circuits [58] in the network. The past study represented the mental health concerns with PSPS event and it is associated with trauma with prevoius wildfire experience. PSPS is most likely the closest possible engineering solution to address the emergency for the utilities in extreme weather conditions which is approved by California Public Utilities Commission [59]. The de-energizing the circuit decision is taken using seven-day weather forecasting data and Fire Potential Index (FPI) [59]. Using the FPI index, significant power cut-offs were made, due to which this program is still not much appreciated socially and faces criticism [59]. Below is the data [60] collected from the CPUC website for the PSPS events for showing the total number of customers impacted is shown below:

Since the PSPS program started in 2013, table 3.6 also shows the Probability of PSPS events in table 3.7. This data does show that PG&E has the highest number of customers impacted. If we rely on past data, to predict number of events in the future, there is higher probability that PSPS events will happen in PG&E territory. The SCE (Southern

Table 4.1: Total number of customers impacted of all utilities in CA, USA Results

Utility Name	No. of PSPS Events	Total No. of Customers Impacted	percentage	Prob
Pacific Corp	25	4512	0.5	0.0045
PG&E	2919	2789400	56	0.535
SCE	1748	528843	33.5	0.320
SDG&E	519	195584	10.0	0.095
Total	5456	3518339	.	

California Edison) has the second-highest number of customers impacted, followed by SDGE (San Diego Gas & Electric). Interesting insights are that frequency of the PSPS event occurring in the northern part of California in PG&E territory is highest among all utilities even little more than 50% of total PSPS events in California. This means that frequency of de-energizing a few lines due to high-speed winds/uncertainty is high. It is likely this does bring attention and anxiety because customers are impacted. According to the frequency, Pacific Corp's impacted 4k customers, which is the lowest, but their probability is yet to review with their total customers.

Therefore, the PSPS data provides some numbers. Still, it is unclear that utilities have a higher risk or more safety measures due to the high frequency of the wildfire events and similar doubt for the other utilities further analysis is still ongoing. The PSPS data [61] shows the impacted customers from all different categories and interesting thing is the data have locations and further work on graph remains in future.

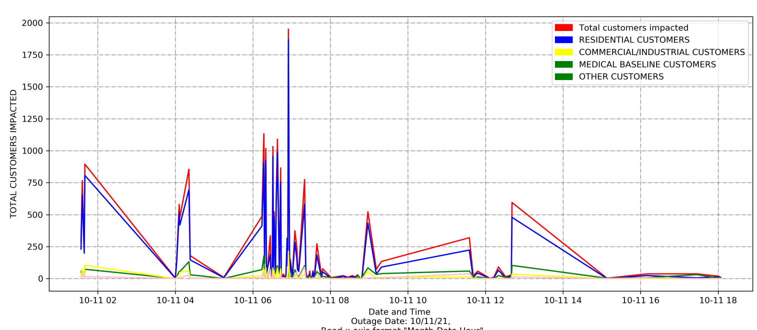

Figure 4.1: Outage PSPS Data (Date: 10/11/21)

The PSPS data in figure 4.1 shows how customers' PSPS experience varies in a day, and surprisingly, it changes each hour, and the most impacting customers are residential customers. Indeed, location data will be more interesting, and further work remains in future work. There are more questions related to the PSPS events. We collected the economic (GDP, personal income based on the location) data for the counties. This data processing is at its initial stage to reveal the location-based economic impact of PSPS events on society.

4.3 *Results and, Conclusion*

The PSPS outages events impact negatively to the customers, this data shows that how each customers categor is impacted and most of them are residential customers who are impacting most. Based on location data analysis remains in the future work.

Chapter 5

Wildfire Risk Based Locational Marginal Pricing

5.1 *Motivation behind using Risk-based SCED Model*

The motivation behind using Risk-based Security Constrained Economic Dispatch (Risk-based SCED) [62] instead of traditional EDC is the relation between the probability of occurring arc and congestion [26]. As the past studies show, as the congestion increases the chances of the occurance of arc increases [26]. In other words, during congestion, the overloading line can increase the chances of occurring arc more than at regular line operation. Therefore we are using the RB-SCED model as the base case to eliminate the congestion.

5.2 *Traditional Economic Dispatch Problem*

Traditional economic dispatch problem has only one primary constraint, which is to meet the demand according to the given generation over a given time horizon, while considering peak and off-peak hour loads [63]. The traditional EDC problem is solved in literature using many different approaches [64], [65], [66], [67]. The objective function of the traditional problem is to choose the level of operation of each generator to minimize total system cost subject to demand level [63]. It was being solved, for example, by the PJM. Here, PJM stands for Pennsylvania–New-Jersey–Maryland Interconnection, ISO [68]. For the current project, uses data represented in recent studies [1], though initially it was published in PJM ISO training documents.

On a fundamental level, the traditional economic dispatch problem can be formulated as follows. The objective function of the constrained optimization problem can be written as follows:

$$\text{Minimize}_{\{P_i\}} \quad \sum_{i=1}^{N_G} c_i P_i \tag{5.1}$$

The optimization is subject to the following constraints and given constrain (8) is primary constraint to meet the demand and given as follows 5.2:

$$\sum_{i=1}^{N} P_i - \sum_{i=1}^{N} D_i - \text{Loss} = 0, \ \forall i = 1, 2, \cdots, m; \tag{5.2}$$

The following equation (9) limits each generating unit capacity or in other words upper and lower bound on each generating unit and is written as follows 5.3:

$$\sum_{i=1}^{N} P_i^{min} \leq \sum_{i=1}^{N} P_i \leq \sum_{i=1}^{N} P_i^{max} \tag{5.3}$$

Then, follows with positive inequality constraints (5.2,5.3) as shown below:

$$\sum_{i=1}^{N} P_i^{min} \geq 0 \tag{5.4}$$

$$\sum_{i=1}^{N} P_i^{max} \geq 0 \tag{5.5}$$

5.3 *Wildfire Risk-Based EDC Decomposition*

Risk-based economic dispatch problem (RB-EDP) has been developed from Security constrained economic dispatch problem (SCED) in recent work in controls and used as the base case for wildfire modeling in reference [62]. This project contributes to the base modeling of RB-SCED by considering the re-dispatch problem for wildfire risk. Few assumptions of the linear DC model optimal power flow it assumes that the reactance (X_{ab}) of the power lines is much greater than the resistance (R_{ab}) [69]. Voltage amplitude is the same at all buses at 1p.u and changes in voltage angle $\theta_A - \theta_B$ from one end of a line to another are small [69]. These assumptions result in power flow, f_{AB}, where f represents power flow from bus A to bus B is proportional to current I_{AB}, which I_{AB} represents current flow from bus A to bus B. Also, power flow, f_{AB} is proportional to the difference in the voltage angle $\theta_A - \theta_B$. Kirchhoff's current law states that sum of current incoming and leaving the node is zero is obeyed in the DC model, but the DC model (current model used in the project) does not consider losses.

The organization of the work is as follows firstly, the Table 4.1 displays the sets and indices involved, Table 4.2 represents Parameters, Table 4.3 represents Variables, then represents linear programming transmission loss in DCOPF. Then traditional Economic-dispatch modeling and finally we have re-dispatched the Risk-based economic dispatch problem including wildfire risk for prospective transmission system operator (TSO) decision-making process, different location marginal price (LMP) is described for charging each node for prospective distribution system operator (DSO) decision-making process. The optimal generation unit dispatch and location energy prices use the Location marginal pricing (LMP) method. Location marginal pricing is derived from a security-constrained economic dispatch model and comprises three LMP components. Those three LMP components are Energy, Marginal Loss, and congestion. Risk-based Security Constrained Economic Dispatch (Risk-based SCED) introduced in [62] to design the Risk-based location marginal pricing by reducing or eliminating the congestion on transmission lines to secure the system at post contingency level. The risk derived in the reference paper drives the risk component in a price signal to reflect the system's overall security level [62], used to reflect the investments needed in the transmission lines using the risk component. This proposal re-designs the location marginal price using a security-constrained economic dispatch problem to charge customers according to the wildfire event or post-hazardous conditions associated with the location. As literature has shown that high severity index of flames/sparks increases the wildfire risk, therefore this proposal uses the test model approach of RB-EDC, RB-LMP [62]. This test model is considered for testing several circumstances of the wildfire event or at post -contingency state so that we can prove that by controlling the line flows at post contingency state using wildfire severity index, FOC (work influence from [62]). This will likely reduce the risk of sparks from extreme events/conductor clashing/conductors melting at the breakdown phase during the energized network. Before doing the modeling, let's define the decision variables and non-decison variables.

Table 5.1: Non-Decision Variables

N	Number of buses
L	Number of branch, $\mathcal{L}, \mathcal{L}'$, where, $\mathcal{L}$-Lines not at risk, $\mathcal{L}'$-Lines at risk
$c_i, \quad \forall\, i \in [N]$	Cost of generation of marginal unit power at bus i
$VOLL_i \quad \forall \{i \,\vert\, i \in [N]\}$	Value of lost load at bus i and bus i is adjacent to a line $l' \in \mathcal{L}'$
$D \quad \forall\, i \in [N]$	Demand at bus i, where $d_i \quad \forall\, i \in [N]$
$PTDF \quad \in \mathbb{R}^{\mathbb{L}\times\mathbb{N}}$	PTDF Matrix
T_l^{min}, T_l^{max}	Default line flow limits, $\quad \forall\ l \in \mathcal{L} \cup \mathcal{L}'$
$a_j^l, b_j^l\, \forall\, j \in \{1, ..., H_l\}, \quad \forall\, l \in \mathcal{L} \cup \mathcal{L}'$	Coefficients of piecewise linear risk function for line l
$\tilde{FOC}_l \quad \forall\, I \in \mathbb{R}$	Forced outage constraint for not at risk line l
$FOC_{l'}^{min}, FOC_{l'}^{max}, \quad \forall\, l \in \mathcal{L}'$	Upper and lower bounds for FOC of at-risk lines
$X_{i'}^{min}, X_{i'}^{max} \quad \forall\, i \in [N]$	Upper and lower bounds on generation at bus i
$r_{i'}^{min}, r_{i'}^{max} \quad \forall\, i \,\vert\, i \in [N]$	Bus i is adjacent to a line $l' \in \mathcal{L}'$ Upper and lower bounds on ratio of demand power actually provided buses i adjacent to at-risk lines l'

As the formulation is influenced from literature [62], the modeling is based on min-

Table 5.2: Decision Variables

$X_i, \quad i \in [N]$	Total generation at bus i
$Y_i, \quad i \in [N]$	Total injections at bus i
$FOC_{l'} \quad \forall\, l \in \mathcal{L}'$	Forced outage constraint of lines at risk
$r_i \quad \forall\, \{i \,\vert\, i \in [N]\}$	Bus i is adjacent to a line $l' \in \mathcal{L}'$ ratio of demand power actually provided to buses i adjacent to at-risk l'

imizing the production cost of generating units X_i to meet the demand. This objective function have some constraints. Therefore, this problem is called constraint optimization problem.

In the objective function, we want to minimize the total cost for the running generation units X_i efficiently with given marginal cost for each generating unit c_i and value of loss load r_i along with given cost for lossing each load. The objective is given for Wildfire Risk-Based - Economic Dispatch Constraint (WRB-EDC) problem as follows:

$$.\text{Minimize}_{X_i, Y_i, FOC_{l'}, r_i} \quad \left(\sum_{i=1} c_i\, X_i \right) + \left(\sum_{i \in I_{\mathcal{L}'}} r_i\, VOLL_i \right) \tag{5.6}$$

Y_i is the net injection equals generation represented as X_i minus demand D_i for buses which are not at risk given in equation 5.7. We have several contraints associated to the decision variables, and are represented as follows:

$$X_i \,-\, D_i \,=\, Y_i \qquad \forall i \in [N]/I_{\mathcal{L}'} \tag{5.7}$$

For buses, adjacent to the risk lines, injection Y_i equals generation X_i minus reduced load $r_i\, D_i$ in equation 5.8.

$$X_i \,-\, r_i\, D_i \,=\, Y_i \qquad \forall i \in [N]/I_{\mathcal{L}'} \tag{5.8}$$

Load satisfaction for buses adjacent to the risk lines should follow upper and lower bounds represented as follows in equation 5.9:

$$r_i^{min} \leq r_i \leq r_i^{max} \qquad \forall\, i \in [I_{L'}] \tag{5.9}$$

and further upper and lower bounds are limited as follows 5.10:

$$0 \leq r_i \leq r_i^{max} \leq \; 1 \qquad \forall\, i \in [I_{L'}] \tag{5.10}$$

Generation in these equations 5.7 and 5.8, follows the upper and lower limits in equation 5.11:

$$X_i^{min} \leq X_i \leq X_i^{max} \qquad \forall\, i \in [N] \tag{5.11}$$

Sum of the injections Y_i is zero i.e power is conserved in the network is written as follows in equation 5.12:

$$\sum_{i=1}^{N} Y_i \;=\; 0 \tag{5.12}$$

Under normal operating conditions all branches lines flows are normal and their upper an dlower bound limits are represented as follows 5.13:

$$T_l^{min} \leq [(PTDF)\,(Y)]_l \leq T_l^{max} \qquad \forall\, l \;\in \mathcal{L} \tag{5.13}$$

Under wildfire scenario, when there is wildfire risk under some branches then power flow of those lines are scaled down by FOC value in order to limit the maximum and minimum flows is represented as follows 5.14:

$$T_{l'}^{min}\, FOC_{l'} \leq [(PTDF)\,(Y)]_{l'} \;\leq\; T_{l'}^{max}\;\; FOC_{l'} \qquad \forall\, l' \;\in \mathcal{L}' \tag{5.14}$$

Generation in these equations 5.7 and 5.8, follows the upper and lower limits in equation 5.15:

$$FOC_{l'}^{min} \leq FOC_{l'} \leq FOC_{l'}^{max} \qquad \forall\, l' \in [\mathcal{L}'] \tag{5.15}$$

and further FOC values, which are constant parameters and are limited as follows 5.16:

$$0 \leq FOC_{l'}^{min} \leq FOC_{l'}^{max} \leq\; 1 \qquad \forall\, l' \in [\mathcal{L}'] \tag{5.16}$$

Further, assume that line at risk l' is assumed $\mathcal{L}$ in our model to be picewise linear function of $FOC_{l'}$. Correspondinly the below constraint 5.17 says that peicewise linear risk should be less than an upper bound $\overline{Risk_l'}$

$$Risk_l\;(FOC_{l'}) \leq \overline{Risk_{l'}} \qquad \forall\, l' \;\in\; \mathcal{L}' \tag{5.17}$$

There is equivalent way to represent peice wise linear function given as follows in equations 5.18, where j index is each piece of the piecewise linear function :

$$\text{Maximize}_{j\,\in\,[H_{l'}]} \quad a_j\; FOC_{l'} + b_j \leq\; \overline{Risk_l'} \qquad \forall\, l' \in \mathcal{L}', \forall j \in [H_{l'}] \tag{5.18}$$

5.3.1 Wildfire Risk-Based LMP Component

The simple way to approach the constrained optimization to solve for optimal solution. One of the famous approach is by following the first-order necessary condition or Karush-Kuhn-Tucker (KKT) Conditions [70]. According to the necessary conditions for the constrained problem the theorem as follows.

First-Order Necessary Conditions/ KKT Conditions Suppose x_* is a local solution of

$$Minimize \quad f(x) \tag{5.19}$$

Subject to:

$$h_j(x) = 0, \quad j = 1 \cdots n_e \tag{5.20}$$

$$g_j(x) \geq 0, \quad j = 1 \cdots m \tag{5.21}$$

Where f,h and g are continuously differential, and LICQ holds at x^*. Then there are Lagrange multipliers $\lambda^* \in R^{n_e}$ and $\mu^* \in R^{n_i}$, such that

$$\begin{aligned} \frac{\partial L}{\partial x}(x^*, \lambda^*, \mu^*) = 0 & \\ h_j(x^*) = 0, j = 1 \cdots n_e \\ g_j(x^*) \geq 0, j = 1 \cdots n_i \\ \mu_j\, g_j(x^*) = 0, j = 1 \cdots n_i \\ \mu_j\ \geq 0, j = 1 \cdots n_i \end{aligned} \tag{5.22}$$

where,

$$\begin{aligned} L(x, \lambda, \mu) = f(x) - \lambda_1\, h_1(x) \cdots - \lambda_{n_e}\, h_{n_e}(x) \\ - \mu_1\, g_1(x) \cdots - \mu_{n_i}\, g_{n_i} \end{aligned} \tag{5.23}$$

By following the first order conditions or KKT Conditions, first step is to write Partial derivative of the above equations following the KKT conditions of RB-EDC problem:

$$\psi(X_i, r_i, FOC_{l'}, Risk_{l'}, \lambda, \mu) = \sum_{i=1}^{\mathrm{N}_g} \mathrm{c}_i * \mathrm{P}_i + \sum_{i=1}^{N_g} \mathrm{VOLL}_i * r_i \tag{5.24}$$

$$- \lambda_1[(\mathrm{X}_i - \mathrm{D}_i - \mathrm{Y}^i) \tag{5.25}$$

$$- \lambda_2 \mathrm{Y}_i \tag{5.26}$$

$$- \lambda_1^{l'}[X_I - r_i Di - Y_i] \tag{5.27}$$

$$- \mu_1^{l'}[r_i - r_i^{min}] \tag{5.28}$$

$$- \mu_2^{l'}[r_i^{max} - r_i] \tag{5.29}$$

$$- \mu_3^{l'}[1 - r_i^{max}] \tag{5.30}$$

$$- \mu_1[X_i - X_i^{min}] \tag{5.31}$$

$$- \mu_2[X_i^{max} - X_i] \tag{5.32}$$

$$- \mu_3[PTDF(X_i - D_i) - T_l^{min}] \tag{5.33}$$

$$- \mu_4[T_l^{max} - PTDF(X_i - D_i) \tag{5.34}$$

$$- \mu_4^{l'}[PTDF(X_i - D_i) - T_{l'}^{min}(FOC_{l'})] \tag{5.35}$$

$$- \mu_5^{l'}[T_{l'}^{max}(FOC_{l'}) - PTDF(X_i - D_i)] \tag{5.36}$$

$$- \mu_6^{l'}[FOC_{l'} - FOC_l^{min}] \tag{5.37}$$

$$- \mu_7^{l'}[FOC_{l'}^{max} - FOC_{l'}] \tag{5.38}$$

$$- \mu_8^{l'}[1 - FOC_{l'}^{max}] \tag{5.39}$$

$$- \mu_9^{l'}[Risk_{l'}(FOC_{l'}) - Risk_{l'}] \tag{5.40}$$

$$- \mu_{10}^{l'}[Risk_{l'} - Risk_{l'}^{min}] \tag{5.41}$$

$$- \mu_{11}^{l'}[Risk_{l'}^{max} - Risk_{l'}] \tag{5.42}$$

$$\tag{5.43}$$

Partial derivative with respect to unit change in generating unit will provide us with $-\frac{\partial \mathcal{L}}{\partial X_i}$ which is also equivalent to $\frac{\partial \mathcal{L}}{\partial D_i}$ and known as location marginal price, finally terminology of our interest.

Given equations at optimal solution,

$$\begin{aligned}\frac{\partial \psi}{\partial X_i} &= \mathrm{c}_i - \lambda_1 - \mu_3[\mathrm{PTDF}_l] + \mu_4[\mathrm{PTDF}_l] \\ &+ \lambda_1^{l'} - \mu_4^{l'}[\mathrm{PTDF}_{l'}] + \mu_5^{l'}[\mathrm{PTDF}_{l'}] \\ &- \cancel{\mu_1} + \cancel{\mu_1} \\ &- \cancel{\mu_2} + \cancel{\mu_2}\end{aligned} \tag{5.44}$$

Taking the partial derivative with respect to unit change in value of loss load as considered decison varaible and is written as follow $-\frac{\partial \psi}{\partial r_i}$:

$$\begin{aligned}\frac{\partial \psi}{\partial r_i} &= -\lambda_1^{l'} - D_i \\ &- \cancel{\mu_2^{l'}} + \cancel{\mu_2^{l'}} + \mu_3^{l'}\end{aligned} \tag{5.45}$$

Taking the partial derivative with respect to unit change in $FOC_{l'}$ as considered decison varaible and is written as follow $-\frac{\partial \psi}{\partial r_i}$:

$$\begin{aligned}\frac{\partial \psi}{\partial FOC_{l'}} &= -\mu_5^{l'}\, T_{l'}^{max} + \mu_4^{l'}\, T_{l'}^{min} \\ &- \cancel{\mu_6^{l'}} + \cancel{\mu_6^{l'}} \\ &- \cancel{\mu_7^{l'}} + \cancel{\mu_7^{l'}} + \mu_8^{l'} \\ &- \mu_9^{l'} Risk_{l'}\end{aligned} \tag{5.46}$$

Above equation can also be written in LMP explicit form using above interpretation, of LMP -$\frac{\partial \mathcal{L}}{\partial X_i}$ is equivalent to $\frac{\partial L}{\partial D_i}$. Therefore, below is interpretation with unit change in demand and written as follows:

$$
\begin{aligned}
\frac{\partial \psi}{\partial X_i} &= \mathrm{c}_i + \lambda_1 + \mu_3[\mathrm{PTDF}_l] - \mu_4[\mathrm{PTDF}_l] \\
&- \lambda_1^{l'} + \mu_4^{l'}[\mathrm{PTDF}_{l'}] - \mu_5^{l'}[\mathrm{PTDF}_{l'}] \\
&+ \cancel{\mu_1} - \cancel{\mu_1} \\
&+ \cancel{\mu_2} - \cancel{\mu_2}
\end{aligned}
\tag{5.47}
$$

Therefore, for LMP components are interpreted as follows:

$$
\begin{aligned}
\mathrm{LMP}_i^{\mathrm{Energy}^l} &= \lambda_1 \\
\mathrm{LMP}_i^{\mathrm{Congestion}_l} &= \mu_1[\mathrm{PTDF}_l] + \mu_2[\mathrm{PTDF}_l] \\
\mathrm{LMP}_i^{\mathrm{Energy}^{l'}} &= -\lambda_1^{l'} \\
\mathrm{LMP}_i^{\mathrm{Congestion}_{l'}} &= \mu_1^{l'}[\mathrm{PTDF}_{l'}] + \mu_2^{l'}[\mathrm{PTDF}_{l'}] \\
\mathrm{LMP}_i^{\mathrm{Wildfire}_{l'}} &= -\mu_5^{l'}\, T_{l'}^{max} + \mu_4^{l'}\, T_{l'}^{min} + \mu_8^{l'} \\
&- \mu_9^{l'} Risk_{l'} \\
\mathrm{LMP}_i^{\mathrm{VOLL}_{l'}} &= -\lambda_1^{l'} - D_i + \mu_3^{l'}
\end{aligned}
\tag{5.48}
$$

Designed components yet need to be tested for results, yet only change in $FOC_{l'}$ is tested for results so far.

5.4 *Results*

Wildfire risk based LMP model uses IEEE PJM 5 Bus data as shown in figure 4.1.

Following are the results using above model. Software used for calculating PTDF is Mat Power [71] and RB-SCED modeling in AMPL. Results are organized as follows:

1. Given varying values of safety parameter $FOC_{l'}$ for all power transmission lines (Using same line flow limit: ab = 400MW, de = 240MW for all cases)

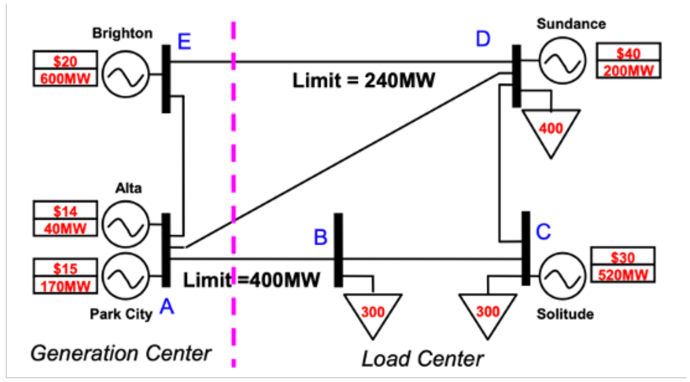

Figure 5.1: The PJM 5-bus system [1]

- $FOC_{l'} = 1$, when there is no restrictions for all line flows
- $FOC_{l'} = 0.75$, when a little restriction for all line flows
- $FOC_{l'} = 0.50$, moderate restrictions for all line flows
- $FOC_{l'} = 0.25$, huge restrictions for all line flows

2. Given varying values of line limits of line with $de\ FOC_{l'} = 0.5$ for all cases.

   - Limit = 240MW, Everything is normal
   - Limit = 120MW, Fire is getting severe, to change the line flows due to increasing wildfire risk injected
   - Limit = 60MW, Fire is severe enough to reduce limit for 3 to 50% rated capacity
   - $FOC_{l'} = 0.25$, huge restrictions for all line flows

3. Deleting each line to simulate loss (disabling) of that line due to concerns of a wildfire in it's vicinity ($FOC_{l'} = 0.5$ and line limits same as above, unless the line is getting disabled).

   - Line "ab" = 0

- Line “ad” = 0
- Line “ae” = 0
- Line “bc” = 0
- Line “cd” = 0
- Line “de” = 0

4. Then summarize the results for $FOC_{l'} = 0.5$, analyze the change in unit price line flows and collected data at each line loss scenario due to wildfire event.

Below are all summarized results:

Part 1 Below the data shown in table $FOC_{l'} = 1$ as shown in 4.5, when there is no restrictions and all lines are flowing at normal rate of 95% (depending on operator, a limit of 95% may be set for the safety reasons of their capacity.

Table 5.3: At normal conditions, generation price and line flows for each unit for $FOC_{l'} = 1$

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	249.684	0	Bus a	23.4891
Unit A, Alta.	40	Bus b	-300.	ad	186.7985	0	Bus b	28.19
Unit C, Solitude	323	Bus c	-23.52	ae	-226.4789	0	Bus c	30
Unit D, Sundance	0	Bus d	-400	bc	-50.316	0	Bus d	34.9688
Unit E, Brighton	466	Bus e	466.479	cd	-26.7958	0	Bus e	20
				de	-240			

$FOC_{l'} = 0.75$ as shown in table 5.6, when weather uncertainty (due to bad weather alarms, instead of PSPS events), lead the engineers to reduce the line flows to their 75% of line capacities shows in literature [62] that can highly likely reduce the wildfire risk by avoiding sparks/conductor clashing/conductor breakdown, melting/ equipment failure sparks. By reducing limits, it is also highly likely we are reducing the impact of high winds and their causes on lines flowing. This makes the line flows safe to deliver power economically even under alarming weather situation. The down side is that by reducing limit to 75% of the capacity, the generating units will become expensive as compared to all line flows at normal rate. As a result, we pay the more generating unit price for meeting the load. Reducing line limits can potentially contribute to load shedding and we might not be able to meet all the loads.

Table 5.4: At $FOC_{l'} = 0.75$

, generation price and line flows for each unit, becomes expensive

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	154.6374	0	Bus a	23.4891
Unit A, Alta.	40	Bus b	-300.	ad	154.9266	0	Bus b	28.19
Unit C, Solitude	510	Bus c	210	ae	-99.5639	0	Bus c	30
Unit D, Sundance	0	Bus d	-400	bc	-145.3628	0	Bus d	34.9688
Unit E, Brighton	279	Bus e	279.5639	cd	65.0734	0	Bus e	20
				de	-180	31.1526		

$FOC_{l'} = 0.50$as shown in table 5.7, when line flows are 50% percent, unit prices are expensive and total generation cost increases. This helps to prevent the extreme sparks under extreme weather and reduce the capability to ignite the any fire from lines during line clashing. Such scenarios will be preventive measures for reducing the occurence of a wildfire event. As a result, we pay higher generating unit price for meeting the load. This might cause some load shedding due to reduced limit, and we might not be able to meet all the loads.

Table 5.5: Line flows at at half of the capacity, generation price and line flows for each unit

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	130.8763	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-300.	ad	110.6429	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	220	ae	-31.5193	0	Bus c	33.3611
Unit D, Sundance	118.4807	Bus d	-281.5193	bc	-169.1237	0	Bus d	40
Unit E, Brighton	151.5193	Bus e	151.5193	cd	50.8763	0	Bus e	20
				de	-120	41.6233		

$FOC_{l'} = 0.25$, as shown in Table 5.8, when line flows are only 25%, there is no optimal solution because technically, there is no way to run the power lines at 25% of their capacity, so units prices become inefficient. Therefore, no optimal solution and operator is forced to shut down.

Table 5.6: Shut down situation, when line flows are 25%, no optimal solution

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	0	Bus a	0	ab	0	0	Bus a	0
Unit A, Alta.	0	Bus b	-300.	ad	0	0	Bus b	0
Unit C, Solitude	0	Bus c	0	ae	0	0	Bus c	0
Unit D, Sundance	0	Bus d	0	bc	0	0	Bus d	0
Unit E, Brighton	0	Bus e	0	cd	0	0	Bus e	0
				de	0	0		

Part 2

Given varying values of line limits of line de $FOC_{l'} = 0.5$, as shown in table 5.9, for all cases. Limit = 240MW, Everything is normal Follow Table 5.1 for results, when line "de" is flowing at normal rate and full capacity (it depends on operator, full capacity can be 100% of any from 95 to 99%, which helps to eliminate the line congestion at prior stage proven by [[62]]).

Another scenario is when the Limit = 120MW, which means the line limit is reduced to 50% of it's thermal limit, because the fire risk around the line is severe, so changing the line flows will help to reduce the risk of wildfire due to power lines. As a result, we pay higher generating unit price for meeting the load. This might cause some load shedding due to reducing limit as, we might not able to meet all the loads, and that's a trade off we will be paying.

Table 5.7: Line "de" 50 percent of it's thermal limit

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	40	Bus a	210	ab	110.9596	0	Bus a	24.6618
Unit A, Alta.	170	Bus b	-300.	ad	65.6898	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	220	ae	33.3507	0	Bus c	33.3611
Unit D, Sundance	243.3507	Bus d	-156.6493	bc	-189.0404	0	Bus d	40
Unit E, Brighton	26.6493	Bus e	26.6493	cd	30.9596	0	Bus e	20
				de	-60	41.6233		

This shows when thermal Limit = 60MW, which means wildfire risk injected is getting severe enough to reduce limit for 25% rated thermal capacity, as shown in Table 5.10, which forces operator to shut down the system.

Table 5.8: Line "de" 25 percent of it's thermal limit

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	0	Bus a	0	ab	0	0	Bus a	0
Unit A, Alta.	0	Bus b	0.	ad	0	0	Bus b	0
Unit C, Solitude	0	Bus c	0	ae	0	0	Bus c	0
Unit D, Sundance	0	Bus d	0	bc	0	0	Bus d	0
Unit E, Brighton	0	Bus e	0	cd	0	0	Bus e	0
				de	0	0		

Part 3 Losing any one line (n-1 scenario) to simulate loss disabling due to wildfire, when given $FOC_{l'}$ = 0.5, as shown in Table 5.11, which means all lines are flowing at 50% of it's capacity. The first case is loss of line between node a and b:

Table 5.9: Loss of line ab

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	0	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-300	ad	110.6429	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	220	ae	-31.5193	0	Bus c	33.3611
Unit D, Sundance	118.4807	Bus d	-281.5193	bc	-169.1237	0	Bus d	40
Unit E, Brighton	151.5193	Bus e	151.5193	cd	50.8763	0	Bus e	20
				de	-120	41.6233		

Losing any one line (n-1 scenario) to simulate loss disabling due to wildfire, when given $FOC_{l'}$ = 0.5, as shown in Table 5.12, which means all lines are flowing at $50\%$of it's capacity. The second case is loss of line between node "a" and "d". As it is clear from the table below, that operating cost for loss of any one line is (N-1) scenario and it remains same for any "(N-1) scenario" and line flows shifts accordingly to meet the load. Due to loss of line, it might not be possible to meet complete demand.

Similar observations for loss of line between node "a" and "e" to observe the line flows, "(N-1 scenario)" to simulate loss disabling due to wildfire.

Table 5.10: Loss of line ae

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	130.8763	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-300	ad	110.6429	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	220	ae	0	0	Bus c	33.3611
Unit D, Sundance	118.4807	Bus d	-281.5193	bc	-169.1237	0	Bus d	40
Unit E, Brighton	151.5193	Bus e	151.5193	cd	50.8763	0	Bus e	20
				de	-120	41.6233		

Similar observations for loss of line between node "b" and "c", "N-1 scenario" to simulate loss disabling due to wildfire, as shown in Table 5.13:

Table 5.11: Loss of line bc

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	130.8763	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-300	ad	110.6429	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	220	ae	-31.5193	0	Bus c	33.3611
Unit D, Sundance	118.4807	Bus d	-281.5193	bc	0	0	Bus d	40
Unit E, Brighton	151.5193	Bus e	151.5193	cd	50.8763	0	Bus e	20
				de	-120	41.6233		

Similar observations for loss of line between node "c" and "d", (n-1 scenario) to simulate loss disabling due to wildfire, as shown in Table 4.15:

Similar observations for loss of line between node "d" and "e", "N-1 scenario" to simulate loss disabling due to wildfire, as shown in Table 5.15:

Table 5.12: Loss of line cd

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	130.8763	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-300	ad	110.6429	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	220	ae	-31.5193	0	Bus c	33.3611
Unit D, Sundance	118.4807	Bus d	-169.1237	bc	0	0	Bus d	40
Unit E, Brighton	151.5193	Bus e	0	cd	50.8763	0	Bus e	20
				de	-120	41.6233		

Table 5.13: Loss of line de

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	200	0	Bus a	19.3235
Unit A, Alta.	40	Bus b	-300	ad	170.1368	0	Bus b	32.4956
Unit C, Solitude	520	Bus c	121.2271	ae	-160.1368	0	Bus c	30
Unit D, Sundance	118.4807	Bus d	-400	bc	-100	0	Bus d	23.1367
Unit E, Brighton	151.5193	Bus e	368.7729	cd	21.2271	0	Bus e	20
				de	0	41.6233		

Therefore, it is concluded that "(N-1) scenario" during wildfire event is more expensive than from N scenario under normal operating lines, which is already observed in literature. Below is the summary of the results for analyzing the change in unit price line flows and collected data at each line loss scenario due to wildfire event. Analyze the generation cost at each generating unit, when $FOC_{l'} = 0.5$, as shown in 4.16.

Table 5.14: Summarizing the results for observing the unit prices, under the condition of line flows at 50% of their capacity

Generating Units	Cost of line "de" 240MW line limit	Cost of line "de",120KW line limit	Cost of line "de",60MW line limit	Cost, lines normal limit flow	Cost,loss of line, "ab"	Cost,loss of line, "ad"	Cost,loss of line, "ae"	Cost,loss of line, "bc"	Cost,loss of line, "cd"	Cost,loss of line, "de"
Unit A, Park City	170	170	0	170	170	170	170	170	170	170
Unit A, Alta.	40	40	0	40	40	40	40	40	40	40
Unit C, Solitude	520	520	0	520	520	520	520	520	520	520
Unit D, Sundance	118.4807	243.3507	0	118.4807	118.4807	118.4807	118.4807	118.4807	118.4807	118.4807
Unit E, Brighton	151.5193	26.6493	0	151.5193	151.5193	151.5193	151.5193	151.5193	151.5193	151.5193
Total	1000	1000	0	1000.	1000.	1000.	1000.	1000	1000	1000

Analysis of the line flows at each line, when $FOC_{l'} = 0.5$, as shown in table 4.17:

Table 5.15: Summarizing the results for observing the line flows, under the condition of line flows at 50% of their capacity

Lines	Normal operation, "n" lines	"de", 240MW	120MW line limit	60MW line limit	Loss of line, "ab"	Loss of Line, "ad"	Loss of line, "ae"	Loss of line, "bc"	Loss of line, "cd"	Loss of line, "de"
ab	130.8763	130.8763	110.9596	0	0	130.8763	130.8763	130.8763	130.8763	200
ad	110.6429	110.6429	65.6898	0	110.6429	0	110.6429	110.6429	110.6429	170.1368
ae	-31.5193	-31.5193	33.3507	0	-31.5193	-31.5193	0.	-31.5193	-31.5193	-160.1368
bc	-169.1237	-169.1237	-189.0404	0	-169.1237	-169.1237	-169.1237	0	-169.1237	-100
cd	50.8763	50.8763	30.9596	0	50.8763	50.8763	50.8763	21.2271	0	21.2271
de	-120	-120	60	0	-120.	-120	-120	-120	-120	0, Dual V 41.6233

Results are summarized below in Table 5.18 , when there is increasing of the 1MW load at load bus B $(301MW)$, under the same condition as $FOC_{l'} = 1$ during the extreme weather cases along the limited line flows. The below table summarizes the results for the generating unit price and line flows and net injections. Table 5.18 shows that with the increase in load at 1MW,

Table 5.16: Summarizing the results for observing the line flows, under the condition of line flows at 50% of their capacity

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	131.2783	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-301	ad	110.5729	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	219	ae	-31.8512	0	Bus c	33.3611
Unit D, Sundance	119.0279	Bus d	-280.8512	bc	-168.7217	0	Bus d	40
Unit E, Brighton	151.9721	Bus e	151.8512	cd	50.2783	0	Bus e	20
Total	1001			de	-120	41.6233		

Increasing the 1MW load at load bus C (301MW), under same condition as $FOC_{l'} = 1$ it is observed that there will be only change in $\$1$ difference to the operator, which is economical, as shown in table 4.19:

Table 5.17: 1MW load increase at load bus C $(301MW)$

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	131.2783	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-301	ad	110.5729	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	219	ae	-31.8512	0	Bus c	33.3611
Unit D, Sundance	119.0279	Bus d	-280.8512	bc	-168.7217	0	Bus d	40
Unit E, Brighton	151.9721	Bus e	151.8512	cd	50.2783	0	Bus e	20
Total	1001			de	-120	41.6233		

Increasing the $1MW$ load at load bus d $(401MW)$, Under same condition as $FOC_{l'} = 1$, it is observed that there will be only change in $1\$$ difference to the operator, which is economical, as shown in Table 5.19:

Table 5.18: 1MW load increase at load bus d (401MW)

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	130.3282	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-300	ad	110.7382	0	Bus b	30.9428
Unit C, Solitude	520	Bus c	220	ae	-31.0664	0	Bus c	33.3611
Unit D, Sundance	119.4807	Bus d	-282.0664	bc	-168.6718	0	Bus d	40
Unit E, Brighton	151.5193	Bus e	151.0664	cd	51.3282	0	Bus e	20
Total	1001			de	-120	42.6233		

Below results are summarized , when there is increasing the $1MW$ load at bus B (301MW), under the condition as $FOC_{l'} = 0.75$, as shown in Table 5.21, during the extreme weather cases along the limited line flows. Below table summarizes the results for the generating unit price and line flows and net injections. This shows that model is efficient to work when there is extreme weather and injecting risk at each location, can also provide the efficient economical results and meeting load enough for demand.

Increasing of the 1MW load bus (D 401), Given $FOC_{l'} = 0.75$, as shown in table 5.22. This meets mostly all requirements. Increasing the 1MW load at load bus B

Table 5.19: 1MW load increase at load bus B $(301MW)$, when line flows at 75% of it's capacity

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	154.8562	0	Bus a	23.4891
Unit A, Alta.	40	Bus b	-301	ad	154.8887	0	Bus b	28.19
Unit C, Solitude	511.2551	Bus c	211.2551	ae	-99.7449	0	Bus c	30
Unit D, Sundance	0	Bus d	-400	bc	-146.1438	0	Bus d	34.9688
Unit E, Brighton	279.7449	Bus e	279.7449	cd	65.1113	0	Bus e	20
	1001			de	-180	31.1526		

(301MW), under the condition as $FOC_{l'} = 0.75$ limiting line flow, the below table summarizes the results for the generating unit price and line flows and net injections. This shows the model is efficient to work when there is extreme weather and line flow risk at each location, and can also provide the efficient economical results and meeting enough load for demand.

Table 5.20: 1MW load increase at load bus B (301MW), when line flows at 75% of it's capacity

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	154.0356	0	Bus a	23.4891
Unit A, Alta.	40	Bus b	-300	ad	155.0314	0	Bus b	28.19
Unit C, Solitude	511.933	Bus c	211.933	ae	-99.067	0	Bus c	30
Unit D, Sundance	0	Bus d	-401	bc	-145.9644	0	Bus d	34.9688
Unit E, Brighton	279.067	Bus e	279.067	cd	65.9686	0	Bus e	20
Total	1001			de	-180	31.1526		

Increasing the $1MW$ load bus (D 401), Given $FOC_{l'} = 0.75$, as shown in Table 5.23. This meets mostly all requirements. When there is increasing of the 1MW load at load bus D, under the condition as $FOC_{l'} = 0.75$ during the extreme weather cases along the limited line flows. The below table summarize the results for the generating unit price and line flows and net injections. This shows that model is efficient to work when there is extreme weather and injecting risk at each location, can also provide the efficient economical results and meeting load enough for demand.

Table 5.21: Increasing the 1MW load bus (D 401) when lines are flowing at 75% of it's capacity

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	154.6372	0	Bus a	23.4891
Unit A, Alta.	40	Bus b	-300	ad	154.9266	0	Bus b	28.19
Unit C, Solitude	511.4361	Bus c	210.4361	ae	-99.5639	0	Bus c	30
Unit D, Sundance	0	Bus d	-400	bc	-145.3628	0	Bus d	34.9688
Unit E, Brighton	279.5639	Bus e	279.5639	cd	65.0734	0	Bus e	20
Total	1001			de	-180	31.1526		

Last but not least observation is that line flows are $FOC_{l'} = 0.50$, as shown in Table

5.24. During a wildfire event, we lost line ae and observed how much system is costly. The system costs $\$1000$, which means, lowering the power line flows at 50% of their capacity, we can meet the demand and during PSPS warning scenario's and reduce the risk of wildfire from power lines whilealso eliminating the anxiety of the people from PSPS event and it is cost efficient as shown in below table.

Table 5.22: Loss of line "ae" and lines are flowing at 50% of it's capacity

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	130.8763	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-300	ad	110.6429	0	Bus b	30.9428
Unit C, Solitude	520.00	Bus c	210.4361	ae	0	0	Bus c	33.3611
Unit D, Sundance	118.4807	Bus d	-281.5193	bc	-169.1237	0	Bus d	40.000
Unit E, Brighton	151.5193	Bus e	151.5193	cd	50.8763	0	Bus e	20
Total	1000			de	-120	41.6233		

Another observation is that when there is increase in $1MW$ demand at bus B while all line flows at their 50%, $FOC_{l'} = 0.50$, as shown in Table 5.25. The system costs $\$1000$, which means that by lowering the power line flows to 50% of their capacity, we can meet the demand and during PSPS warning scenario's and reduce the risk of wildfire from power lines. Also eliminate the long hours of de-energizing the power and associated anxiety people may have from this PSPS event. Plus it is cost efficient as shown in the below table, where there is only a $\$1$ with change in $1MW$ demand.

Table 5.23: Increase in 1MW demand at bus B while all line flows at their 50%, $FOC_{l'} = 0.50$

Generating Units	Total Generation Cost	Bus name	Node Injection, MW	Line name	Line flows, MW	Dual Variable, flows	Bus Name	Net injection Dual
Unit A, Park City	170	Bus a	210	ab	131.4245	0	Bus a	24.6618
Unit A, Alta.	40	Bus b	-301	ad	110.5477	0	Bus b	30.9428
Unit C, Solitude	520.00	Bus c	220.4361	ae	0	0	Bus c	33.3611
Unit D, Sundance	119.0279	Bus d	-280.9721	bc	-169.5755	0	Bus d	40.000
Unit E, Brighton	151.9721	Bus e	151.9721	cd	50.4245	0	Bus e	20
Total	1001			de	-120	41.6233		

5.5 *Discussion*

By defining risk at each location, we control the line flows as predicted, and we calculate the Wildfire risk based each unit price to charge customers according to risk injected in line flows. Optimal solutions vary from controlling line flows to emergency state to shutting down the line to prevent further damage during or before wildfire event, using $FOC_{l'}$ parameter and reducing the amount of power delivered to customer.

5.6 *Conclusion*

This results in the re-dispatched risk based problem for wildfire risk at the given risk model providing an efficient strategy to charge customers accordingly to the risk injected. This project will overall save the money of the customers by charging in the way which makes recovering wildfire costs fair and cost effective for the utility. Also it will reduce the PSPS events. This project also meets the society goals of saving money for the customers in California, who pay Wildfire Fund each month at the rate of $\$5.85/KWH$, regardless of their location. This work shows potential contribution towards reducing utilities associated risk to the power lines causing wildfires by controlling the line flows of the system.

Chapter 6

Future work of the Project

This project provides the test model that produces efficient results while there is wildfire risk associated to power line flows and given risk associated to the location under extreme conditions. However,so far this study does not include the DC line losses in modelling, assume the no DC loss model. Therefore, the first part of the future study is to incorporate the DC line losses in the wildfire modeling. Next, as the IOU's continue the PSPS events, this project most likely will explore the PSPS data events and income level of the PSPS events linked to location to determine, if there is enough social surplus and consumer surplus associated. Then, part of the future study is to design the piece wise linear risk function, most likely relating to the color of vegetation data and to wind speed plus, designing the injected risk at each location. Literature prouded significant guidance that wind speed is highly co-related to risk of vegetation catching fire due to te potential for the sparks or conductor clashing melting/ fire due to equipment failure. Last but not least, the study has the scope for determining the risk using artificial intellligence, at each location to incorporate the variable risk in dollars.

Appendices

Part A

1. Electrical Corporations in California

    - Pacific Gas and Electric Company (PG&E),
    - San Diego Gas & Electric Company (SDG&E),
    - Southern California Edison (SCE),
    - PacifiCorp d.b.a. Pacific Power (PacifiCorp),
    - Liberty Utilities (CalPeco Electric)
    - LLC (Liberty CalPeco), and
    - Bear Valley Electric Service, a Division of Golden State Water Company (Bear Valley)

Part B

The data processing is done using RStudio, using macOS Monterey, version 12.2, Mac Book Pro (13-inch, 2020), Processor 1.4 GHz Quad-Core Intel Core i5, Memory 8 GB 2133 MHz LPDDR3, Graphics Intel Iris Plus Graphics 645 1536 MB.

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