Survival of Behind the Meter Generation Projects

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ABSTRACT

California's Self Generation Incentive Program (SGIP) was created in 2001 to help address the state's energy crisis, providing incentives for the installation of distributed generation technologies that help meet a utility customer's electricity needs. The 2001 electricity crisis is behind us, but the SGIP continues to provide grid resiliency benefits through the ongoing operation of onsite generation technologies. In 2018 and 2019 technologies that had received SGIP funding provided a combined estimated 4,081 GWh of onsite electricity generation and 520 MW during the top CAISO hour, fostering grid resiliency. The number of new SGIP applications for onsite generation projects, however, has decreased significantly in recent years while existing projects continue to age and be decommissioned. As a result, it is not clear how long the SGIP generation fleet will provide its current level of grid benefits.

This paper uses SGIP data to estimate technology specific survival curves to assess the share of projects that will remain operational in future years, identify characteristics that increase the likelihood of decommissioning, and develop estimates of future available capacity. California's long history using behind the meter generation to promote resiliency enables us to assess how these generation technologies decay in a real-world setting, providing other jurisdictions with better information on factors and the timing of decommissioning that can influence their program plans.

Introduction

Since 2001 the SGIP has been helping to address California's energy needs, contributing to grid resiliency by offering financial incentives for the operation of onsite generation. The SGIP has provided incentives for a variety of generation technologies, including combined heat and power (CHP) fuel cells (FC-CHP), electric only fuel cells (FC-Elec), internal combustion engines (ICE), gas turbines (GT), microturbines (MT), pressure reduction turbines (PRT) and wind turbines (WD). During 2018 and 2019 these SGIP resources provided an estimated combined 4,081 GWh of onsite electricity generation and 520 MW of load reduction during the top CAISO hour as presented in Figure 1 below.

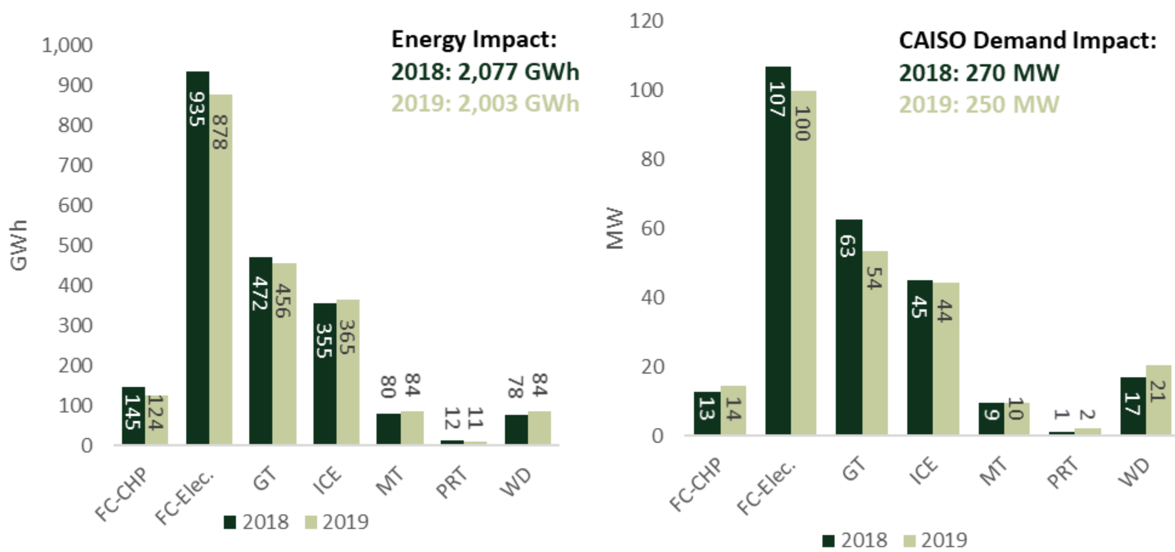

Figure 1: Annual electricity generation (a) and CAISO peak hour demand impact (b) by technology type and calendar year (GWh)

As of the end of 2019, the SGIP had incentivized 718 MW of onsite generation capacity, 147 MW of which were installed in 2018 and 2019. However, new applications for SGIP generation technologies and their associated capacity have diminished significantly since 2017, resulting in a sharp decline in SGIP capacity additions in 2020 and 2021.[1] Figure 2 below shows the capacity of SGIP applications submitted by year and technology.

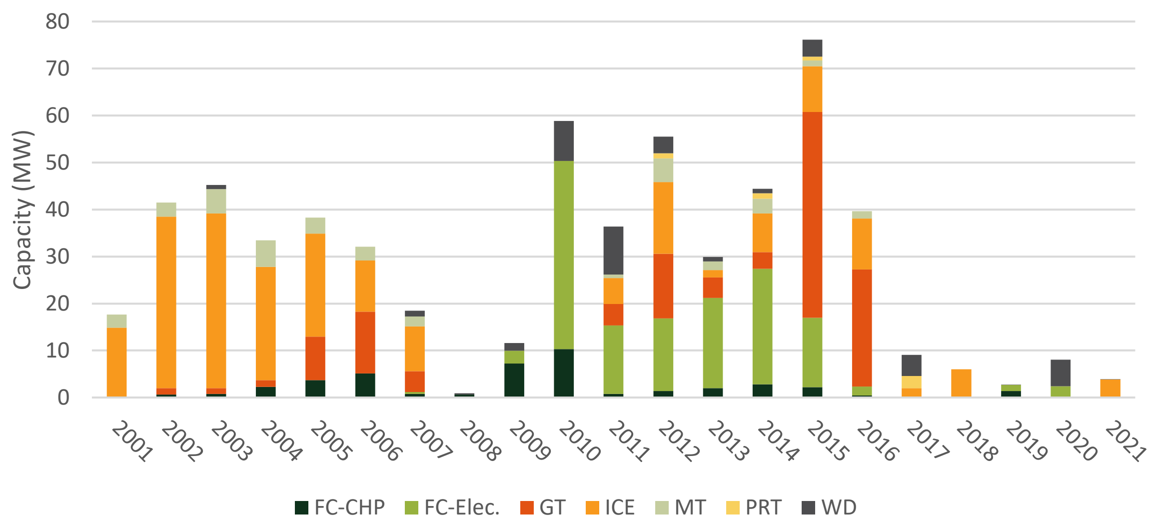

Figure 2: SGIP onsite generation capacity of applications by technology, program years 2001 - 2021

[1] The decrease in new SGIP generation project activity is largely the result of a transition in the SGIP to energy storage technologies.

Compounding the impact of the decreasing number of applications for SGIP generation technologies is the roughly 77 MW (of the 718 MW (11%)) of SGIP generation capacity that has been decommissioned and is permanently inactive. Figure 3 illustrates that ICE projects have the largest share of decommissioned capacity while FC-CHP and microturbine projects account for additional decommissioned capacity.

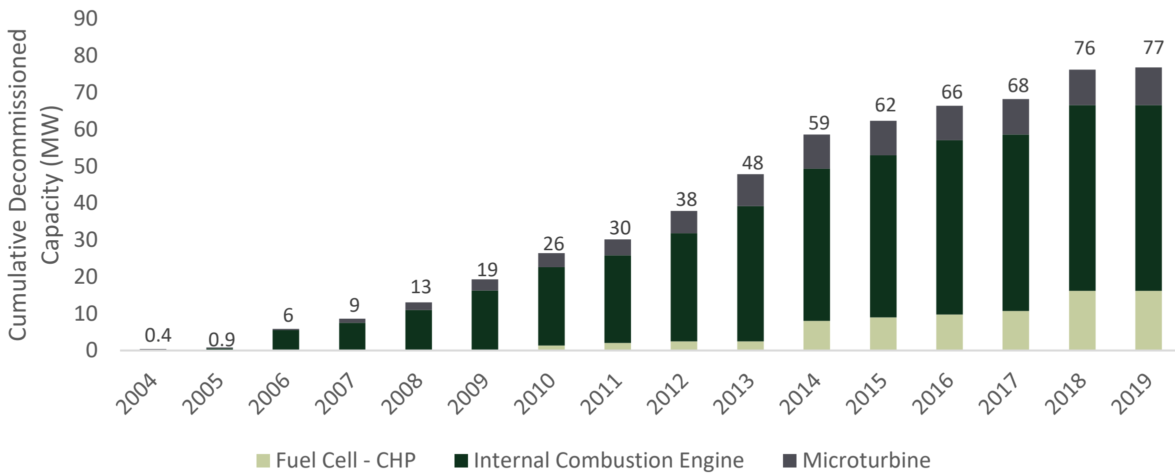

Figure 3: Cumulative rebated capacity of decommissioned systems by year and system type

The declining number of new SGIP onsite generation projects, combined with existing project aging and rising decommissioning, leads to questions about how long, and at what level, SGIP behind the meter generation projects will promote resiliency. This paper uses SGIP data to estimate survival curves to assess the share of projects that will remain operational in future years, identify characteristics that increase the likelihood of decommissioning, and develop estimates of future available capacity. California's long history using behind the meter generation to promote resiliency enables us to assess how these generation technologies decay in a real-world setting, providing other jurisdictions with better information on factors and the timing of decommissioning that can influence their program plans.

Only ICE, MT and FC-CHP projects are examined in this paper as these are the technologies types that had been decommissioned as of the start of 2020. In all, the evaluated projects make up 514 of the 895 SGIP generation projects that have been installed as of the start of 2020.[2]

Survival Analysis

There are a variety of survival analysis methods that can used to estimate time-to-event (survival at time *t*) probabilities. For this paper, three survival analysis methods are used for examining SGIP ICE, MT, and FC-CHP project survival probabilities and expected operational longevity. These methods include non-parametric modeling with Kaplan Meier (KM) estimators, Cox Proportional Hazard (Cox) modeling and parametric modeling. Descriptions of these methods are provided below:

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[2] SGIP project counts and totals exclude all FC-CHP projects less than 40 kW. This technology suffered significant failure rates which ultimately led to the return of program funds.

Non-Parametric Kaplan-Meier estimator: The KM estimator is a non-parametric technique of estimating and plotting the survival probability as a function of time. Where the estimator at time t is equal to:

$$\hat{S} = \prod_{i:t_i \leq t} (1 - \frac{d_i}{n_i})$$

where:

t_i is the time where at least one event occurred
d_i the number of events that happened at time t_i
n_i the number of observations at risk at time t_i

The resulting survival curve is then represented by a step function of decreasing survival probabilities over time. The primary benefit of the KM estimator is that it only requires time to event information and does not require assumptions about the underlying distribution of the data (Lewinson, 2020). Additionally, it allows for log rank statistical testing to determine whether survival curves within groups are statistically different from one another. However, the KM estimator does not allow for an estimation of the magnitude of various predictors for an event, nor does it allow for a hazard ratio[3] to be established between predictors (Klien, 2014; Lewinson, 2020). KM is excellent for visualizing survival curves, but it is less useful for making survival predictions compared to other methods.

Cox Proportional Hazard Model: The Cox model is a logistic regression-based model that estimates the impact of project specific characteristics on survival probabilities. Unlike the KM estimator, the Cox model does not produce a survival curve or function. Rather, the main benefit of the Cox proportional hazard model is that it produces estimations of the hazard ratios which are used to compare project characteristics as risk factors for project decommissioning. The hazard ratio is defined as the ratio of hazards (or event probabilities) between two levels of an explanatory variable and allows for consideration of relative risks (Charn, 2020).

With the Cox model, however, the hazard ratios, or the relative risk of decommissioning between characteristics, are assumed to be constant for all time *t.* It is likely that the model's constant hazard ratio assumption is not consistent with reality, but the Cox model is a powerful tool for exploring and identifying risk factors

Parametric Modeling: Similar to the Cox model, parametric modeling is a regression based approach that allows for multiple covariates to be considered simultaneously. Additionally, parametric modeling assumes a defined parametric distribution of survival curves. This allows for both time constant hazards, such as an exponential distribution, and time varying hazards, such as Weibull distributions, to be considered (Klien, 2014; Charn, 2020).

In this paper, we first use KM and Cox modeling to examine the relationship between various project characteristics and the probability of survival and visually explore the general shapes and distributions of

[3] The hazard ratio is the ratio between hazard rates, or probabilities of an event. It compares the relative risk of an events between to two levels of a factor.

survival functions. We then use the insights gained from KM and Cox modeling to develop a parametric model to predict when operational projects will become decommissioned.

Survival Curves and Proportional Hazards

SGIP ICE, MT and FC-CHP KM survival analysis curves are presented in Figure 4 through Figure 8 below. Each survival curve represents a different grouping of the projects included in the analysis. These groupings include technology type, fuel type, capacity, normalized operation and maintenance (O&M) costs and project vintage. Additionally, Table 1 describes the pairwise log rank tests and identifies whether within grouping survival curves are statically significant from each other or not.

When looking at the survival curves presented below, the life of the project in years is presented on the x-axis, while the y-axis presents the probability of survival (or probability of remaining as an active, non-decommissioned project) at time *t*. Tick marks along the survival curve represents a censored project, i.e. a project that has survived up to time *t,* but leaves the sample at time *t,* which represents the end of the analysis period ("present day") for that project. These survival curves are discussed after Table 1 below.

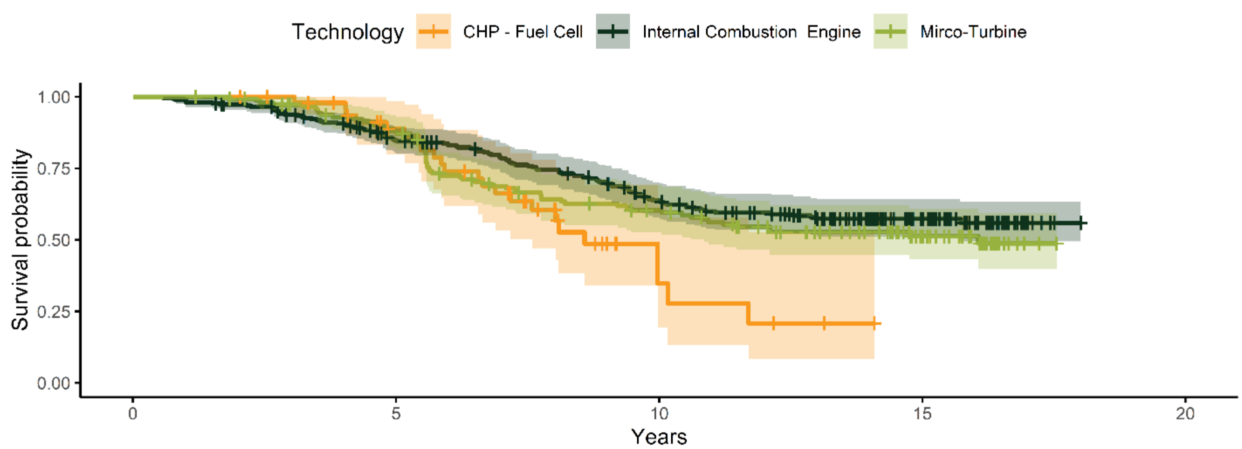

Figure 4: KM survival curves by technology

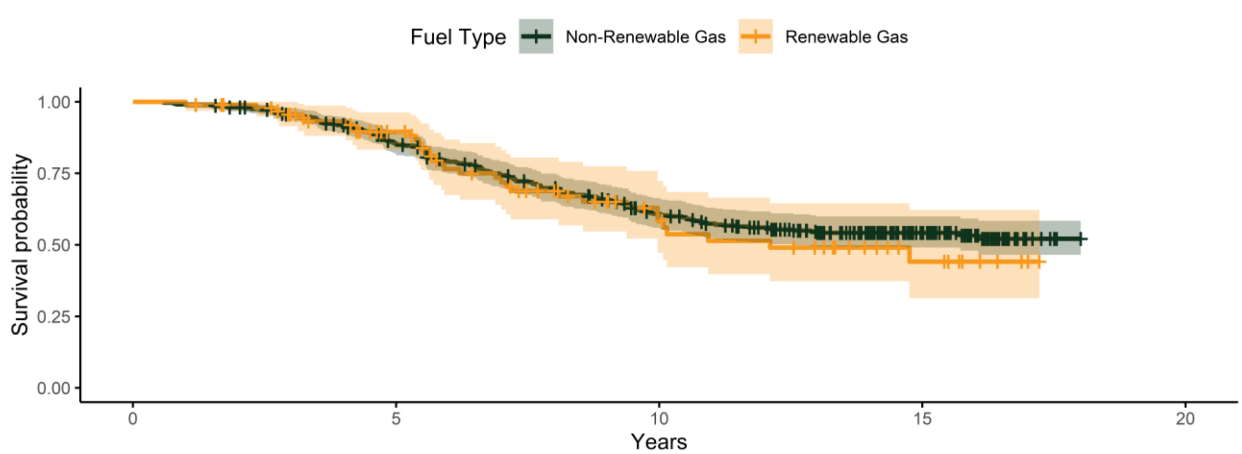

Figure 5: KM survival curves by fuel type

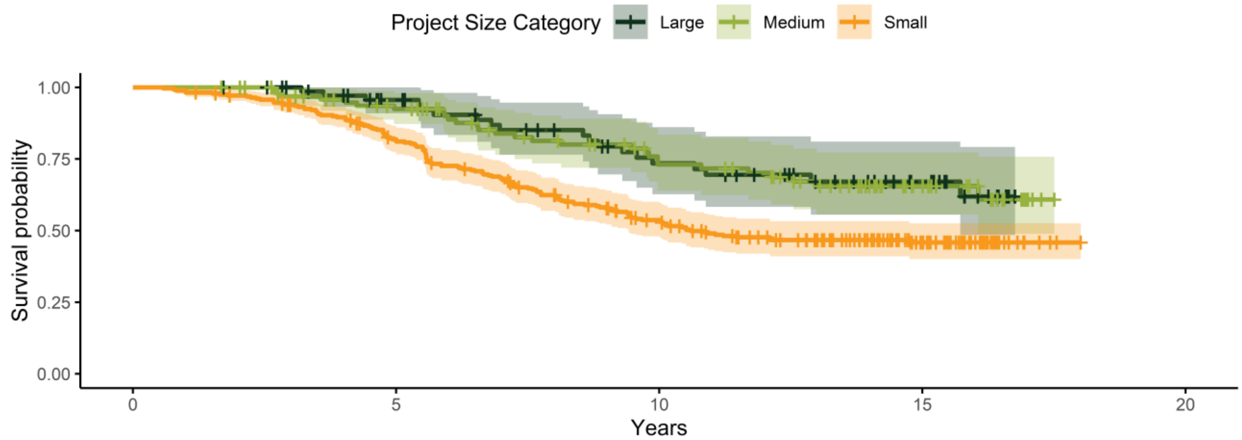

Figure 6: KM survival curves by project size

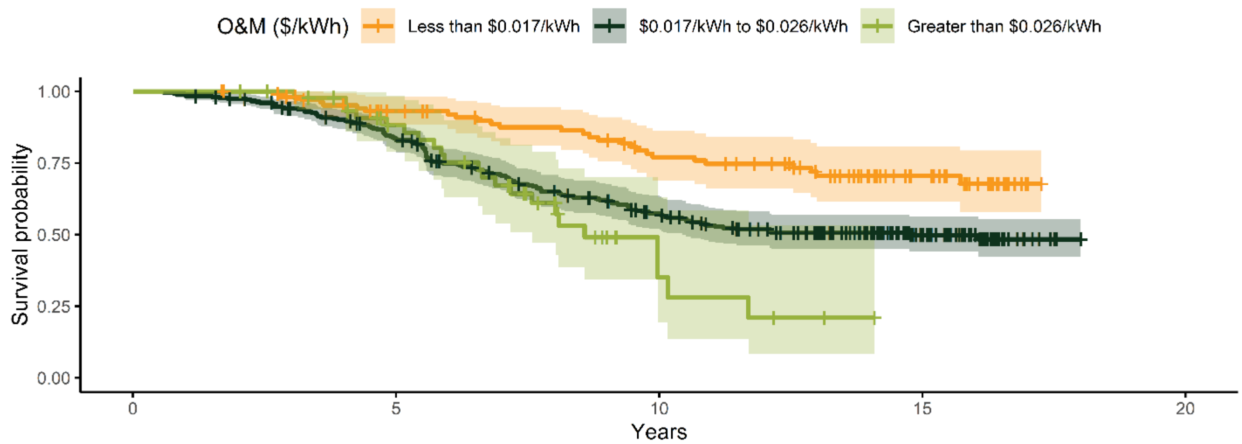

Figure 7: KM Survival Curves by O&M $/kWh

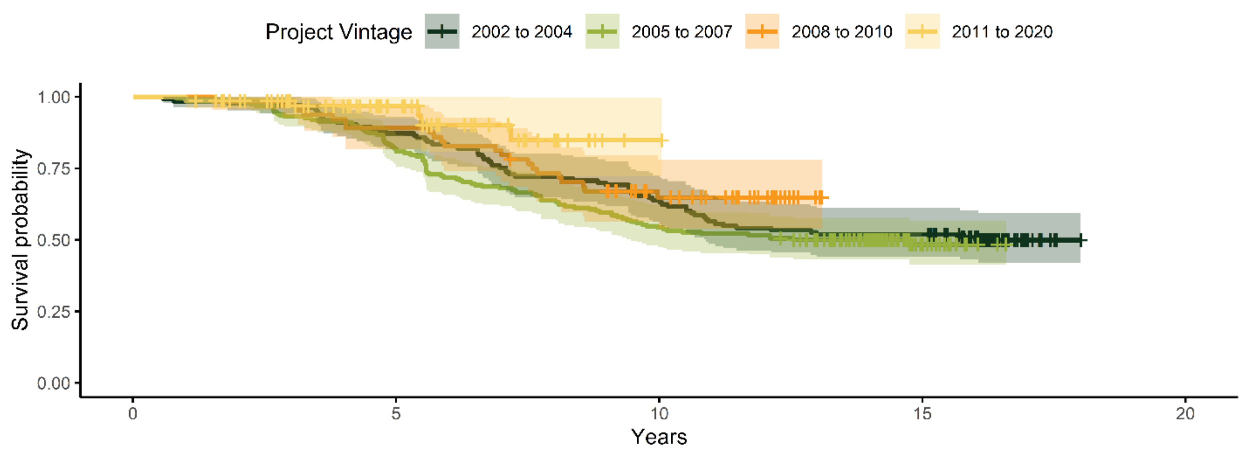

Figure 8: KM Survival Curves by Project Vintage

Table 1: Pairwise log-rank test comparisons

Category	Comparison group A	Comparison group B	p-value	Statistically significant different survival curves
Technology	Fuel Cell	Micro Turbine	0.236	No
		Internal Combustion Engine	0.024	Yes
	Micro Turbine	Internal Combustion Engine	0.140	No
Fuel Type	Renewable	Non-Renewable	0.630	No
Size Category	Large	Medium	0.945	No
		Small	0.009	Yes
	Medium	Small	0.003	Yes
O&M ($/kWh)	Greater than $0.026/kWh	$0.017/kWh to $0.026/kWh	0.135	No
		Less than $0.017/kWh	0.001	Yes
	Less than $0.017/kWh	$0.017/kWh to $0.026/kWh	0.000	Yes
Project Vintage	2002 - 2004	2005 - 2007	0.359	No
		2008 - 2010	0.362	No
		2011 - 2020	0.082	No
	2005 - 2007	2008 - 2010	0.091	No
		2011 - 2020	0.008	Yes
	2008 - 2010	2011 - 2020	0.092	No

The ICE, MT, and FC-CHP survival curves presented in Figure 4 do not appear to take a linear path. The survival curves tend to show increasing hazard rates (probability of decommissioning) after 5 years of operation and then a decrease for ICE and MT after 10 years of operation. For FC-CHP projects, there is another increase in hazard rates around 10 years. The shapes of the technology survival curves are consistent with SGIP incentive requirements and FC-CHP maintenance requirements. SGIP generation projects receive a partial upfront incentive and then undergo a 5-year Performance Based Incentive (PBI) period where projects are required to remain operational to receive incentives. After the five year PBI period ends no more incentives are paid out and the decision to decommission a project does not impact future incentives payments. Therefore, decommissioning is a firm level decision likely based on the facilities' needs and the costs and benefits of operating the technology. Additionally, fuel cells generally require their stack (the electricity producing component of the system) to be replaced every five years, which results in a significant increase in fuel cell O&M costs at five year increments (years 5, 10, and 15). As seen, the observed survival probabilities for Fuel Cell-CHP projects decrease substantially at 5 and 10 years coinciding with necessary stack replacements.

When examining the survival curves of project characteristics in Figure 4 through Figure 8, two categories of characteristics with significant differences in curves stand out; project size and O&M costs. Projects are placed into small, medium, and large capacity bins based on their system capacity (kW). In general, there is no statistical difference between the large and medium capacity project survival curves; in fact, they are nearly identical. Smaller SGIP projects, however, have lower probabilities of survival, or are decommissioned at a higher rate, than larger and medium capacity projects.

O&M costs also appear to play a significant role in technology survival. The O&M costs used in this analysis are typical O&M costs and are a function of system capacity and technology type, and do not reflect the actual O&M costs experienced by individual SGIP projects. O&M costs are also normalized for this analysis. The total O&M cost is divided by anticipated annual energy production assuming an 80% capacity factor. Previous SGIP O&M literature reviews have found that O&M costs for ICE and MT average $0.022/kWh while FC-CHP project's necessary stack replacements lead to higher O&M, averaging $0.05/kWh (Verdant, 2020). The KM survival analysis uses estimates of O&M that vary by technology and size. As seen above, O&M costs appear to play a significant role in survival probabilities, especially when comparing projects with smaller O&M costs with those with larger costs. In general, projects with estimated O&M cost less than $0.017 per kwh have a statistically significant higher survival probability for all time *t* after five years.

While it is certainly important to identify characteristics that yield different survival curves, it is equally important to identify characteristics that do not appear to influence survival (or the likelihood of decommissioning). One such characteristic is the fuel types used to power generation projects. While current SGIP program rules require renewably sourced fuel, legacy SGIP projects could be fueled by natural gas or renewable sources. Importantly, these fuel types can have very different costs in terms of both $/BTU and in necessary infrastructure to source the fuel. For example, bio-methane from a landfill or diary may require additional cleaning before it can be used by an onsite fuel cell or ICE. Despite this, non-renewable and renewable gas projects do not have statically different survival likelihoods and their survival curves largely lie on top of each other. Suggesting that the fuel source and relative fuel price differences do not play a significant role in decommissioning decisions, while maintenance costs or the need to undertake maintenance to continue operation appear to influence the likelihood of decommissioning.

Project vintage also does not appear to impact the survival probabilities. The similarity, or lack of significant difference, between program vintages suggests that these projects have similar life cycles and it should be expected that the probability of survival is not dependent on the year the project began operating or the program rules applicable during project installation. Given this, it can be expected that recent ICE, MT and FC-CHP installations will follow similar survival paths to past projects. While there is a statistical difference in the survival curves of projects that began operation between 2005 to 2007 and 2011 to 2020, the large degree of censoring[4] of these projects will likely result in a shift in the survival curve in future years. The relationship between the year of installation (vintage) and decommissioning needs future study as more recent projects have had a chance to mature.

While using KM survival curves is an excellent way to explore the relationship between an independent variable and the likelihood of survival, it does not allow for a direct comparison of hazards (the likelihood of decommissioning) within segments of a group or multiple variables at the same time. We use a Cox model to analyze the relative risk of the normalized O&M costs, capacity size bin, project vintage bins and fuel types on the likelihood of decommissioning. It should be noted that technology type is not included in the model because it is highly correlated with O&M. Size is also correlated with O&M costs, therefore capacity bins were used in place of actual capacity size (kW). Given that O&M costs are relatively small in magnitude, the values input into the model were transformed from $/kWh to $/100/kWh (or cents/kWh).

[4] Censoring is the result of a study participant leaving the before experiencing an event. In this case, censored SGIP projects are those projects who have survived through "present day" and leave the analysis because they provide no additional information beyond time *t.*

Additionally, medium and large capacity bins were collapsed into a single category given their similar KM survival curves. While project vintage and fuel type were largely insignificant in the KM analysis, they are included to identify independent impacts and mitigate the potential for bias in other covariate estimates. Table 2 below presents the results of the Cox model.

Table 2: Cox proportional hazards of the likelihood of decommissioning

Category	Parameter	Coeff.	Hazard Ratio - exp(coeff)	p-value	HR lower 95% CI	HR upper 95% CI	Statistically significant
O&M Cost	O&M Cost (Cent/kWh)	0.331	1.393	0.000	1.175	1.651	Yes
Capacity	Capacity Size -Small	0.444	1.560	0.0126	1.100	2.211	Yes
Project Vintage	Vintage -2005 to 2007	0.071	1.073	0.665	0.789	1.477	No
	Vintage - 2008 to 2010	-0.436	0.646	0.0883	0.391	1.067	No
	Vintage - 2011 to 2020	-1.239	0.290	0.0124	0.110	0.765	Yes
Fuel Type	Non-Renewable	0.198	1.219	0.3149	0.828	1.795	No

For categorical variables, one factor level is dropped from the output and represents the baseline case. For example, there is no fuel type hazard ratio for renewable fuel, only non-renewable. In this case renewable fuel is the baseline for the non-renewable fuel hazard rate. It compares the relative risk of decommissioning of a non-renewably fueled project to renewably fueled projects. In other words, the Hazard ratio of 1.219 estimates that the risk of decommissioning is 1.219 times higher (or 21.9% greater) for non-renewable fueled projects than for those fueled by renewables (although this is not statically significant). For numerical or continuous variables, the hazard ratio represents the marginal increase in the hazard rate for a unit increase. In other words, for every $0.01 in O&M $/kWh the relative risk of decommissioning increased 39%. For ease of the reader, Table 3 presents the key takeaways and interpretations of significant hazard ratios in Table 2.

Table 3: Interpretation of significant hazard ratios

Parameter	The probability of decommissioning…
Normalized O&M Cost (Cent/kWh)	*Increases by 39%* for every $0.01 increase in O&M $/kWh
Capacity Size - Small	is *56% higher* for small sized capacity projects compared to medium and large sized capacity projects
Project Vintage - 2011 to 2020	is *71% lower* for projects installed between 2011 to 2020 compared to projects installed from 2002 to 2004

The Cox proportional hazard model does not consider time varying effects, as a result all hazard ratios are assumed to be constant and averaged from year 0 through the end of the analysis period. As noted earlier, the KM models suggest ICE, MT and FC-CHP projects have nonlinear survival curves and time varying hazard rates. For this reason, the Cox model is not appropriate for making forecasts for when a project may be decommissioned. However, the findings from the Cox model provide insight into generalized risk, especially for when a project's age is not known off hand.

Estimated Available Capacity for Future Years

One objective of this study is to understand how many ICE, MT and FC-CHP projects will remain active and what level of capacity they will provide into future years. To this end we employ a parametric model to predict at what age each active ICE, MT and FC-CHP project will become decommissioned, which is then related back to provide estimated available capacity in 2023, 2025 and 2030.

After review of the KM survival curves and hazard rates, we assume a Weibull distribution for our parametric survival model. The Weibull distribution allows for time varying hazards, allowing hazards to increase, remain constant and increase with time *t*. Additionally, we use the same model specification used in the Cox modeling, which includes normalized O&M costs, capacity size bin, project vintage bins and fuel types. Model diagnostics are presented in Table 4 below.

Table 4: Weibull parametric survival model coefficients

Parameter	Coefficient	SE	p-value
Intercept	3.759	0.168	0.000
O&M Cost (Cent/kWh)	-0.253	0.061	0.000
Capacity Size -Small	-0.328	0.128	0.011
Project Vintage -2005 to 2007	-0.103	0.115	0.372
Project Vintage - 2008 to 2010	0.146	0.184	0.427
Project Vintage - 2011 to 2020	0.808	0.369	0.029
Renewable	-0.141	0.140	0.315
Log Scale	-0.339	0.065	0.000

From the resulting model, we then predict the "age" that each active SGIP project will become decommissioned and then back into the year a specific project will no longer be an active generation resource. Figure 9 below describes the forecasted share of decommissioned projects and capacity of ICE, MT, and FC-CHP projects and the overall number or currently active SGIP projects that will remain active each year into the future.

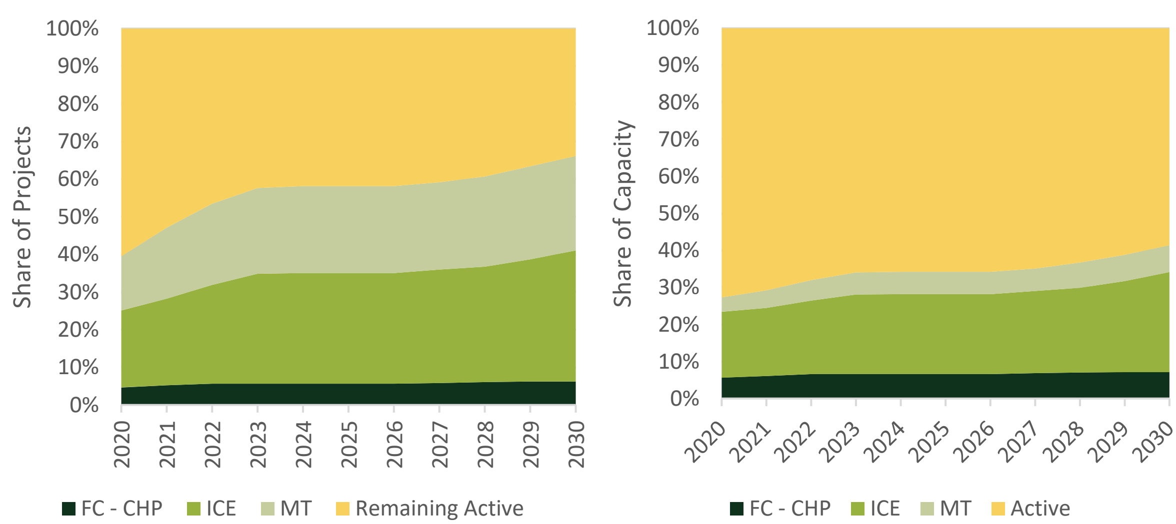

Figure 9: Estimated decommissioned share of projects (A) and capacity (B) by technology and year

Turning to project count first, the model estimates a steady increase in the number of decommissioned SGIP ICE, MT, and FC-CHP projects though 2023 before the rate of project decommissioning slows between 2024 and 2028. By 2023 it is estimated that 58% of incentivized SGIP ICE, MT, and FC-CHP projects will be decommissioned and increase to 66% of projects by 2030. While we anticipate that the majority of these technologies will no longer be operational within a few years, a large share of the additional decommissioned project count comprises smaller MT projects. As indicated in the analysis above, larger capacity projects tend to have higher survival probabilities at time *t* compared to those with smaller capacities.

As mentioned earlier, roughly 77 MW of incentivized capacity was decommissioned prior to 2022. By 2023 we estimate that decommissioned capacity will increase to 96.5 MW (34% of capacity) and to 171.1 MW (41% of capacity) by 2030. Overall, we expect the majority (59%) of ICE, MT, and FC-CHP capacity to remain active through 2030.

Table 5 and Table 6 below provide estimates of available remaining ICE, MT, and FC-CHP project counts and capacity from existing SGIP projects in 2023, 2025, and 2030. As seen, we estimate there will be 184.8 MW of remaining capacity in 2023, 184.1 MW in 2025 and 163.8 in 2030.

Table 5: Estimation of remaining active project counts in 2023, 2025, and 2030

Technology	Total count of incentivized projects of 1/1/2020	Actual count of active projects prior to 2020	Forecasted count of remaining projects		
			2023	2025	2030
FC- CHP	55	32	25	25	22
ICE	301	200	150	149	121
MT	158	90	34	32	22
Total	514	322	209	206	165

Table 6: Estimation of remaining available capacity in 2023, 2025, and 2030

Technology	Total incentivized capacity (MW) as of 1/1/2020	Actual available capacity prior to 2020	Forecasted remaining available capacity (MW)		
			2023	2025	2030
FC- CHP	42.4	26.7	23.2	23.2	21.6
ICE	205.4	155.0	143.9	143.7	128.4
MT	36.1	25.9	17.7	17.3	13.8
Total	283.9	207.5	184.8	184.1	163.8

Key Findings and Future Research

Overall, SGIP generation projects will continue to provide grid resiliency benefits into future years through continued operations of legacy projects and new capacity additions. However, the available capacity of incentivized SGIP projects is expected to decrease over the next few years as a result of project decommissioning and decreases in the overall capacity additions from new SGIP generation projects. Between 2018 and 2021, less than 15 MW of capacity in new SGIP project applications were submitted compared to the forecasted 22 MW of decommissioned capacity between 2020 and 2023. While the SGIP has shifted its focus away from generation technologies in favor of storage technologies, it is still important to understand the underlying condition of the SGIP generation fleet. There are several takeaways from the decommissioning analysis that can benefit the SGIP and other BTM generation programs and the resiliency benefits they provide.

Key findings for the analysis include:

- The longevity of generation projects appears to be heavily influenced by their upkeep and maintenance costs. In each of the three survival analysis methodology, it was found that lower O&M costs resulted in statically significant increases in survival probabilities at time *t.*

- The analysis also found that fuel types had no statistically significant influence on survival, suggesting that the fuel source and relative fuel price differences do not play a significant role in decommissioning decisions.
    - The combined O&M and fuel type results may point to the importance of the need to undertake maintenance to continue technology operation instead of strictly cost considerations as a primary determinant of decommissioning. Easy access to maintenance knowledge and skills may be important in decommissioning decisions.

- Smaller ICE, MT, and FC-CHP projects have a higher probability of decommissioning at a given time *t*. While the upfront cost of the system and the share of load the generation system provides was not included in this analysis, larger system may represent a larger investment for host customers, who then have a bigger interest in keeping their system online and operational.

- The findings from the Cox proportional hazard model help to describe the independent impact of technology characteristics on the likelihood of failure. Designing programs or providing resources to limit the negative influence of these characteristics on future decommissioning decision may add to the reliability of these technologies.

- We estimate that two-thirds of existing incentivized ICE, MT, and FC-CHP projects will be decommissioned by 2030, however, the majority of capacity will still be available. It is estimated there will be 184.8 MW of remaining capacity in 2023, 184.1 MW in 2025 and 163.8.4 in 2030.

Some areas for future research include:

- The KM analysis found that project vintage largely does not influence the estimated survival of ICE, MT, and FC-CHP technologies. However, the Cox model and parametric analysis found that projects that received their upfront incentive between 2011 and 2020 had statically higher probabilities of survival at time *t* compared with those projects installed in prior years. However, the authors do not put significant weight in this finding due to conflicting results between models and a high degree of censoring in younger projects. This finding should be revisited once these projects have had a chance to mature.

- This study does not explore the impact of upfront project costs or customer utility bill savings from the generation technologies when estimating the factors influencing decommissioning. These may have important effects on project survival and should be explored in future work.

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