1 Experience Curve Development and Cost Reduction Disaggregation for Fuel Cell Markets in Japan and
2 the US
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8 **Abstract:**

9 Technology learning rates can be dynamic quantities as a technology moves from early development to
10 piloting and from low volume manufacturing to high volume manufacturing. This work describes a
11 generalizable technology analysis approach for disaggregating observed technology cost reductions and
12 presents results of this approach for one specific case study (micro-combined heat and power fuel cell
13 systems in Japan). We build upon earlier reports that combine discussion of fuel cell experience curves
14 and qualitative discussion of cost components by providing greater detail on the contributing mechanisms
15 to observed cost reductions, which were not quantified in earlier reports. Greater standardization is added
16 to the analysis approach, which can be applied to other technologies. This paper thus provides a key
17 linkage that has been missing from earlier literature on energy-related technologies by integrating the
18 output of earlier manufacturing cost studies with observed learning rates to quantitatively estimate the
19 different components of cost reduction including economies of scale and cost reductions due to product
20 performance and product design improvements. This work also provides updated fuel cell technology
21 price versus volume trends from the California Self-Generation Incentive Program, including extensive
22 data for solid-oxide fuel cells (SOFC) reported here for the first time. The Japanese micro-CHP market is
23 found to have a learning rate of 18% from 2005-2015, while larger SOFC fuel cell systems (200kW and
24 above) in the California market are found to have a flat (near-zero) learning rate, and these are attributed
25 to a combination of exogenous, market, and policy factors.
26

27 **Keywords:** PEM fuel cells, solid oxide fuel cells, combined heat and power systems, technology learning
28 rates, experience curves, technology deployment programs

1. Introduction - Fuel Cells in Stationary Applications

Fuel cells are both a longstanding and emerging technology for stationary and transportation applications, and their future use may be critical for the deep decarbonization of global energy systems. For example fuel cell (FC) systems are being considered for a range of stationary and specialty transport applications due to their ability to provide reliable power with cleaner direct emissions profiles than fossil fuel combustion-based systems. Existing and emerging applications include primary and backup power, combined heat and power (CHP), materials handling equipment such as forklifts and airport handling equipment, and auxiliary power applications such as auxiliary power units in diesel truck cabins. As a chemical energy conversion process, fuel cells have intrinsically higher efficiency and much lower criteria pollutant emissions than coal or gas combustion-based plants [1]. Stationary applications are also less constrained to the weight and size limitations of vehicles. In addition, fuel cells can serve as a reliable source of base load power in comparison to intermittent wind or solar photovoltaic supply sources. If fuel cells become widely available they could help to displace coal plants and improve public health outcomes due to the elimination of coal-fired air pollutants such as fine particulate matter, and they might also displace nuclear plants and avert the disposal issues associated with nuclear waste. Fuel cell systems also can qualify as distributed generation systems and as power supply sources close to load, they may not trigger transmission line construction or line losses.

Stationary fuel cell systems are not deployed in high volumes today due to a number of reasons that limit the market adoption of new technologies. In particular, market adoption of FC systems is constrained by their high initial capital costs and durability issues [2]. If FC lifetime is not proven in demonstration programs, for example, potential owners such as commercial building operators are not likely to invest in them. Similarly, if FC equipment is demonstrated to have equivalent to better lifetime than incumbent technology, but with much higher capital cost, market adoption will be low in the absence of other incentive programs.

The ultimate vision of a hydrogen economy -- where H_2 is produced renewably and fed into a fuel cell which produces no emissions -- is constrained by the above fuel cell system cost and reliability

constraints, the cost and efficiency issues of generating renewable hydrogen, and the cost and infrastructure of storing and transporting hydrogen with the equivalent availability and convenience of existing fuel or energy carrier types. Currently, H₂ is predominantly produced from converting natural gas to H₂ using steam methane reforming, a process which results in greenhouse gas emissions.

The U.S. Department of Energy (DOE) has historically invested in fuel cell technology development and deployment of FC systems (e.g. roughly \$95 million in fiscal year 2015), with recent reported success in the material handling and backup power segments, and there continues to be support from the federal government in terms of federal tax credits for stationary FC power systems.¹ At the state level, there are various state incentive programs such as the Self-Generation Incentive Program in California (SGIP) which provides performance-based incentives for facilities that install qualifying distributed power and heating technologies such as fuel cells.² Internationally, fuel cell development is progressing in many countries including Japan, Europe, and Australia. International deployment programs include renewable portfolio standards in South Korea that include fuel cells with renewable biogas and CHP targets in Germany that include fuel cell CHP systems.³ The nuclear accident at Fukushima in Japan has increased concerns about nuclear power plant safety and long term viability and is another driving force for the greater deployment of non-nuclear low carbon energy sources and low-carbon distributed generation.

Proton exchange membrane (PEM) fuel cells and solid oxide fuel cells (SOFC) have been an active area of research for material development and characterization, fuel cell stack manufacturing processes, stack and system operation and characterization, and management of reactants and heat [3-6]. Both PEM fuel cells and other types of fuel cells have been an active area of development for a wide set of diverse applications from heat and power in residential applications [7] to bus transportation [8] and waste water treatment [9].

¹ <http://energy.gov/savings/business-energy-investment-tax-credit-itc>, accessed 10 March 2015.

² <http://www.cpuc.ca.gov/sgip/>, accessed 22 December 2016.

³ See for example, <http://www.fuelcellenergy.com/applications/financial-incentives/international-incentives/>, accessed 1 June 2015.

Globally, fuel cell shipments have grown at 15% by MW and 37% by unit per year from 2009-2014, led by the stationary sector which shipped over 80% of the units in 2014 [10]. About two-thirds of MW shipped in 2014 was in Asia, led by Japan, with about 30% of total MW shipped to North America. Solid oxide fuel cell (SOFC) MW shipments have increased from 1.1 MW in 2009 to 32.3 MW in 2014 with molten-carbonate fuel cells (MCFC) growing from 18 MW to 70 MW. Currently, the transportation market is a very small fraction of the overall fuel cell market, but that may shift if fuel cell vehicles continue to be introduced and are more widely adopted. Toyota introduced a fuel cell passenger vehicle in November 2014 and Honda in March 2016.

As we look into future applications, a key challenge for policy-makers and technology market forecasters who seek to track and/or accelerate their market adoption is the ability to forecast market costs of the fuel cells as technology innovations are incorporated into market products. Specifically, there is a need to estimate technology learning rates, which are rates of cost reduction versus production volume. Learning rates can dynamic quantities and should be updated on a periodic basis to understand price reduction trends and the potential impacts of deployment programs, technology development, exogenous factors, and other factors. For example, to our knowledge, a price versus cumulative volume trend for the SOFC fuel cell market in California under the state's Self-Generation Incentive Program (SGIP) has not been published.

In this paper, we look retrospectively to estimate learning rates for two fuel cell deployment programs: (1) the micro-combined heat and power (CHP) program in Japan, and (2) for SOFC fuel cell systems in California, the latter for the first time. These two examples have a relatively broad set of historical market data and thus provide an informative and international comparison of distinct fuel cell technologies and government deployment programs. This report thus provides a critical update on fuel cell costs from an experience curve perspective and disaggregates observed cost reduction components using a direct manufacturing cost model.

A generalized procedure for disaggregating experience-curve cost-reduction components is described and applied to the Japanese fuel cell micro-CHP market. This approach utilizes a vendor-level

manufacturing cost model and known features of the Japanese fuel cell market are synthesized to estimate system cost reductions due to economies of scale, product performance improvement, and product design improvements. This approach provides an explicit decomposition of observed fuel cell system cost reduction elements for the first time.

We describe the empirically-observed learning rates as a function of production maturity and compare the policy and external environments for both cases. We discuss general observations and pertinent policy lessons from the two case studies along with how the cost reduction disaggregation analysis can be generalized to other technologies. We explore the differences in the technology development ecosystem and market conditions that may have contributed to the observed differences in cost reduction and draw policy observations for the market adoption of future fuel cell technologies.

This work highlights the critical importance of updating experience curves over time since with changes in technology, regulations, and international market conditions, changes in the slope of the experience curve can be observed. The Japanese micro-CHP market is found to have a learning rate of 18% from 2005-2015, while larger SOFC fuel cell systems (200kW and above) in the California market are found to have a flat (near-zero) learning rate, and these are attributed to a combination of exogenous, market, and policy factors described below. The technical and policy contributions of this paper are the first comparative experience curve analysis of past fuel cell technologies in two distinct markets, and the first quantitative comparison of a detailed cost model of fuel cell systems with actual market data. The resulting approach is applicable to analyzing other fuel cell markets and other energy-related technologies, and highlights the data needed for cost modeling and quantitative assessment of key cost reduction components.

1.1 Technology Learning

Technology learning is widely recognized as a mechanism through which technology costs reductions can occur, a concept originating from observations that manufacturing processes improve as production increases [11]. This has important implications for understanding past technology developments and program benefits, as well as forecasting technology growth for policy planning and scenario modeling.

Thus as federal and state governments make investment and policy decision in energy technology research, development, and deployment, the learning rate of FC systems and technologies are important as a factor for projecting future technology costs and technology adoption. (Deployment programs here refer to a broad range of programs, from education and awareness programs, to financial incentive programs, to design competitions, to federal testing and performance standards). For example, assuming a certain learning rate for the future defines the market adoption that is needed to meet a certain cost target and an appropriate incentive structure. Making an erroneous learning rate assumption that is too conservative (or too aggressive) could lead to an inefficient policy that is too generous (or insufficient) to meet the policy target.

Experience curves are the most common framework for assessing technology learning and cost reduction with increasing production volume [12]. These curves are found, empirically, to follow a power law as shown in Equation 1, with the rate of cost reduction a power law function of cumulative production volume.

$$\text{Equation 1. } C(t_2)/C(t_1) = (V(t_2)/V(t_1))^{-b}$$

Where: $C(t_2)$ = cost at time t_2

$C(t_1)$ = cost at time t_1

$V(t_2)$ = cumulative production volume at time t_2

$V(t_1)$ = cumulative production volume at time t_1

b = empirically observed parameter

The percent by which cost decreases for every doubling of production is referred to as the learning rate ($LR = 1 - 2^{-b}$), while the fraction of initial cost remaining after every doubling of production is defined as the progress ratio ($PR = 1 - LR$). Learning rates are important parameters and in many cases are taken as exogenous assumptions in future energy system planning and scenario analysis [13-14]. Learning rates in this case are critical input parameters in regards to future technology costs and market adoption potential.

Learning curves, which directly relate cumulative production to labor costs, are a subset of experience curves, which relate cumulative production to overall cost or price (although the terms “learning curve” and “experience curve” are often used interchangeably). Therefore, learning curves reflect short-run learning-by-doing, while experience curves incorporate a much broader set of cost components [15]. Shifts in production cost may be reflected in the experience curve by a change in the learning rate, or slope of the curve. Similarly, we refer to a “learning rate” here as defined above, although the term “experience rate” may be more accurate.

Market prices are often utilized as a proxy for a product’s manufactured costs since market prices are more directly observable than manufacturing costs. However, prices can mask the cost structure of a product and introduce uncertainties in the product’s technology learning due to pricing and market effects. Despite these caveats, market prices are often used for experience curve analyses.

1.2 Literature Review – Non-Fuel Cell Energy-related Technologies

Forty-one non-fuel cell studies were reviewed from the recent literature since 2012 to assess the state-of-the art analysis and uniqueness of this work. These studies can be classified in three general categories: (1) critiques, compilations, and calculations of past learning rates [16-31]; (2) “top-down” studies that typically use previously estimated learning rates as an input into forecasting models for future learning rates and costs [32-48]; and (3) “bottom-up” studies that attempt to explain the components of observed learning rates through a consideration of factors including learning-by-doing, technology R&D, manufacturing, labor, and material costs, and other exogenous factors [49-56]. We focus on the third category here since it is most relevant. For example, earlier top-down studies have estimated and derived learning rates in power plant component costs from empirical observations to estimate future cost reductions, but this category of studies does not derive component costs from bottom up manufacturing considerations [34,48]. We find a gap in the literature in that none of the previous papers utilize a “bottom-up” direct manufacturing cost model to estimate cost reduction components from product performance, product design improvements, and economies of scale. This work is thus unique in that it

utilizes a well-documented direct manufacturing cost model to estimate cost reduction components of a well-defined experience curve (the Japanese micro-CHP fuel cell market) for the first time. Other studies contain elements of this approach but we believe the linkages made here are more direct and more transparent than earlier reports. Note that other higher-level modeling approaches consider somewhat abstracted concepts of “learning-by-doing” and “learning-by-searching” and we provide more explicit linkages of observed cost reductions to actual product-related performance data and product attributes.

Qiu and Anadon [49] disaggregates the learning rate in the Chinese wind turbine market from 2003-2007 and into two key parts: learning-by-doing and learning-by-searching (e.g., technology R&D) utilizing a “Cobb-Douglas production model coupled with a bottom up engineering model.” Unlike this paper, the paper does not quantify other cost reduction components such as economies of scale with a manufacturing cost model and does not discuss balance of plant costs.

The most widely cited recent papers are papers are two on solar PV. Bazilian et al. [50] provides some disaggregation of observed cost reductions (for example in the price of inputs polycrystalline silicon) but the approach is qualitative and illustrative rather than an explicit linkage of a manufacturing cost model to falling costs and economies of scale. Some manufacturing costs are provided but are not tied to production volume and do not include balance of system costs. Goodrich et al. [51] provides an assessment of overall solar PV costs in 2010 in the residential, commercial, and utility market segments by compiling module, bill-of-material costs, installation and mark-ups, and also projects the cost reduction potential in 2020 for each market. The 2020 values take module prices as an input and the study does not compare cost component breakdowns to observed learning rates.

Another solar PV paper (Candalise et al. [52]) “describes, and considers the causes of, recent changes in PV costs and prices at module and system level” but is largely qualitatively descriptive and does not utilize a manufacturing cost model. The authors note that “overall, it is not straightforward to fully disentangle module price reductions due to reduced production costs related to device and production processes improvements and economies of scale along the PV module value chain.” Gan et al.

[53] estimated PV module cost “using the learning curve concept” and integrated silicon prices as an additional factor to examine its role in production cost changes.

Some studies consider detailed production costs and future cost reduction opportunities in established areas such as wood production and petroleum production but without presenting a well-defined historical experience curve for comparison (deWit et al. [54], Aguilera [55]); and others provide detailed techno-economic performance and cost reduction potential for emerging technologies such as synthetic natural gas production and power cogeneration with carbon capture and storage (Li et al.[56]) but again with insufficient industry activity to generate an experience curve.

1.3 Literature Review – Fuel Cell Experience Curves

While several papers have reported fuel cell experience curves, experience curves with actual market data is more limited and published experience curves with recent data are even more limited. Historic examples of fuel cell experience curves have limited production volume and time series data. Rivera-Tinoco et al. [57] find early commercial learning rate for solid oxide fuel cells (SOFC) slowing down to a learning rate of 5% in the early commercial phase from an apparent 44% learning rate in the pilot phase. However, no published reports for recent SOFC experience curves in the California fuel cell market were found. Schoots et al. [58] find that proton exchange membrane fuel cells (PEM) in transportation have a learning rate of 21% for a global cumulative capacity of 100 MW, but this only represents on the order of a few thousand vehicles (e.g., $100 \text{ kW} * 1000 \text{ units} = 100 \text{ MW}$ for Toyota Mirai fuel cell vehicle at 114 kW peak power). This paper cites eight references for PEM learning curves, but of the eight, one is very old (from 1995), and six of the eight are manufacturing cost modeling papers and not actual data. Thus the actual data for this technology is extremely limited. Mayer et al. [59] uses a two-factor experience curve approach to project 2020 costs for PEM fuel cells and lithium-ion batteries. This work relies on extensive patent analysis and is not a bottom up manufacturing cost modeling approach.

Three recent reports (Staffell and Green [60], Dodds et al. [61], and Harikishan et al. [62]) present data for the learning rate of the Japanese and Korean micro-CHP market from initial introduction

to early commercialization with a learning rate of about 19% in the pilot phase of development slowing to 13% in the commercial phase in Japan. Staffell and Green provide a general discussion of manufacturing cost considerations based on James et al. [63] and attribute a slowing in the learning rate to the observation that balance of plant costs dominate overall system costs as manufacturing volumes increase, that those component costs have a slower cost reduction than the fuel cell stack which makes up a larger fraction of costs at low volume. Dodds et al. provide an overall market review of hydrogen fuel cell systems for heating and discussion of micro-CHP systems market trends in Japan and Korea. Hiroshi [64] provides a more updated technical analysis of the Japanese micro-CHP technology including detailed thermodynamic analysis and power and heat output shapes of representative systems, as well as an assessment of the long term competitive price target and CO₂ savings for these systems in Japan. Neij [65] notes that many earlier fuel cell studies utilize experience curves for cost analysis, but most assume a learning rate rather than presenting a historical time series of price data (e.g., [66] and [67]). Thus an updated look at fuel cell experience curves is essential to provide the latest assessment of fuel cell cost trends and to provide more detailed analysis of observed cost reductions.

2. Japan's Micro-CHP program and the California SGIP Program

In this section we highlight some of the key similarities and differences in the two regions' fuel cell programs. We discuss the implications of these findings together with the empirically derived cost reduction results in the Discussion section below.

Both case studies produce systems with fuel cells as an energy provider and in both cases there were initially generous subsidies from the government, which are now declining. Comparison of the two programs shows marked differences in many areas: markets, energy prices, development models, and environmental and exogenous factors. The role and stated goals of the government are more directed and specified in Japan with a target annual volume in 2020 and 2030; whereas the U.S. policy is to provide incentives to offset higher capital costs without a policy mandate to install a specified target number of units nationwide by a certain date.

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Table 1. Japan's Micro-CHP program and the California SGIP

Case	Japan Ene-farm	California SGIP
Companies	Toshiba, Panasonic, AISIN	Bloom Energy, Fuel Cell Energy, Doosan (formerly ClearEdge Power/UTC Power)
Company Type	Large diverse	Dedicated FC (BE and FCE), Large diverse (Doosan)
System Application	Residential micro-CHP	Commercial power
System Size	0.7-1 kW	200-500 kW
Incumbent Energy Source Costs	\$0.26/kWh, Japan residential \$1.08/therm LNG import price	\$0.11/ kWh, U.S. commercial \$0.447/therm NG city gate price
Incentive Structure	Decreasing over time (\$12000 per system to \$3300 from 2009-2014)	Decreasing by 10% annually (currently \$1830/kW), plus 30% Federal tax credit
Long Term Target	\$5000/unit ^a and 5.3M units in 2030; 1.4M units in 2020 (Japan Government) [68]	\$1300/kW in 2020 (U.S. DOE)

NG = natural gas; LNG = liquefied natural gas; DOE = Department of Energy

^a Total price to consumer, including delivery and installation

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Micro CHP has received much attention recently for household applications [69] and in novel micro grid deployments [70], and past studies have highlighted system efficiency and system flexibility [71]. Joint development of fuel cell micro CHP in Japan is organized by several organizations such as the New Energy and Industrial Technology Development Organization (NEDO), the Fuel Cell Commercialization Conference in Japan (FCCJ), and governmental organizations. Additionally, the Advanced Co-generation and Energy Utilization Center Japan (ACEJ) works to advance Ene-farm sales and maintenance activities through publications and training programs. Under this arrangement, joint development is conducted by city gas companies, LPG companies, and industrial partners including Toshiba Fuel Cell Power Systems, Aisin Seiki, and Panasonic [72]. In contrast, U.S. development is more confined within single companies such as Bloom Energy and Fuel Cell Energy. For a given market, there are more players and a more competitive environment in Japan whereas there are fewer players in stationary power market segments in the U.S. For example, Bloom Energy is virtually the only supplier for medium sized commercial markets from 100 to 350 kW, with the Doosan/UTC Power phosphoric-acid fuel cell (PAFC) system starting at 400 kW.

Both U.S. and Japan develop multiple fuel cell technologies. The Ene-farm program has both PEM (Toshiba, Panasonic) and SOFC (Aisin Seiki) market entrants with PEM capturing most of the market share at present. In the U.S., the mid-sized commercial market is represented by SOFC (Bloom Energy), phosphoric acid fuel cells (Doosan/UTC Power), and molten-carbonate fuel cell systems at the MW-sizes.

The Japan Ene-farm product features a much smaller fuel cell power level than the fuel cell systems in the California SGIP – almost two orders of magnitude smaller at the nominal 0.7-1 kW power level. The Japan Ene-farm project is based on PEM fuel cell technology for the largest players (Toshiba and Panasonic) and SOFC technology for other vendors including Aisin Seiki. The California SGIP is also open to different fuel cell technologies, but current technology entrants are dominated by SOFC technology, followed by molten-carbonate (MCFC) and PAFC technology.⁴

Distributed generation systems are more economically favorable in regions with high prices for electricity purchased from the grid and relatively low natural gas prices. The cost difference between the price of electricity and the cost of natural gas, or spark spread,⁵ is about twice as high in Japan for both sectors as it is in the U.S. as Japan has a much higher cost of electricity compared to the U.S. for both residential and commercial sectors.

There is also a significant difference in the types of companies producing fuel cells in the two regions. In Japan, large, diverse and presumably more stable companies such as Toshiba and Panasonic only receive a tiny fraction of annual total revenue from annual sales from micro-CHP, whereas U.S. companies such as Bloom Energy and Fuel Cell Energy are dedicated fuel cell companies. UTC Power in the U.S. was a part of a large conglomerate United Technologies, but was sold to ClearEdge in 2013 (which subsequently filed for bankruptcy in 2014 and was purchased by Korean conglomerate Doosan).

⁴ The following website has a map of California fuel-cell installations:
http://www.nfcr.uci.edu/3/FUEL_CELL_INFORMATION/CALIFORNIA_INSTALLATIONS/index.aspx,
accessed on 22 December 2016.

⁵ More exactly, the spark spread is defined by the following equation: Spark spread (\$/MWh) = power price (\$/MWh) – [natural gas price (\$/mmBtu) * heat rate (mmBtu/MWh)], where the heat rate for a natural gas combined cycle gas plants is typically at 7000Btu/kWh, or a conversion efficiency of about 50%.

3. Data Collection and Cost Reduction Disaggregation Approach

Data from California's SGIP program is drawn from a publically available database of information managed by the California Center for Sustainable Energy [73]. Cost data from this database represents total eligible system costs and thus includes non-fuel cell "balance of plant" or "balance of system" costs such as power electronics and air handling subsystems as well as installation costs. SGIP installed costs included systems that have been approved and/or constructed and are split into technology type (SOFC, PEM, PAFC, or MCFC). Data for fuel cell micro-CHP in Japan is drawn from market sources and publicly reported cost data from fuel cell-related websites and from technical conferences and trade shows.

In disaggregating experience curves and cost reduction, contributions from economies of scale, product design improvements, learning by doing, and competition are expected. The approach for disaggregating cost reductions is as follows and is depicted in Figure 1:

1. Determine learning rate from experience curve constructed with annual sales and price data.
2. Develop a manufacturing cost model or adopt an adjacent technology cost model, describing
 - a. Manufacturing cost versus annual production volume
 - b. Manufacturing cost dependence on critical materials
 - c. Product performance specifications and/or parametric relationships with cost
3. Obtain knowledge of number of manufacturers and manufacturing volumes over time. From this, estimate the increase in production volume as an input to manufacturing cost model.
4. Obtain information on product design. From this estimate changes in product materials, configuration, and/or layout as inputs to the manufacturing cost model.

Key steps are thus determining the increase in manufacturing volume from year 1 to year N and translating product design, performance, and integration information into cost reductions through material savings, assembly savings, or process impacts on cost model.

Figure 1. Disaggregating a technology's experience curve price reduction

Figure 1 shows the observed cost reduction disaggregated into economies of scale, learning by doing, and product design improvement. In this case, the remaining cost reduction residual is lumped into “other factors” such as product mark-up and marketplace competition. In practice, “learning-by-doing” -- interpreted here as manufacturing process learning or improvements in factory productivity or factory yield (i.e. the ratio of saleable output to material inputs) over time -- will not be directly observable. One way for accounting for this is as an adjustable parameter in the manufacturing cost model that has the general functional behavior of monotonically improving yield with increased volume of production whose functional dependence may be drawn from other manufacturing technologies.

This approach is predicated on the availability of a manufacturing cost model. The U.S. Department of Energy has sponsored several cost models in the past for a number of technologies (e.g., batteries, LEDs, fuel cells). Disaggregating cost reduction in this way is a bottom-up manufacturing cost modeling approach; an alternative “top-down” approach might focus more on market structure, pricing strategy and pricing power on the supply side. The bottom-up approach is analytically tractable in the sense that it can utilize publically available data such as the cost or cost trends of components installation costs, while other cost factors can be obtained from publically available market reports.

In addition to a suitable manufacturing cost model, this approach assumes the availability of the data sets in Figure 1 that are inside of the dashed boxes. These may include:

- Economies of scale: Production knowledge and number of suppliers are either drawn from publically available data or inferred from market reports.
- Product design improvement: Performance specifications such as product design improvement or performance changes over time are assumed to be publically available. Information about component integration or component cost reductions (e.g., the cost of a power inverter from a third-party supplier) is assumed to be known.

3.1 Annual Production Volume

We model the Japanese market as being served by two primary vendors in the 2009-2015 time frame, Panasonic and Toshiba, who both produce PEM FC systems. These two primary vendors produced about 1,300 units in 2009, increasing to about 20,000 units in 2014. These assumptions are consistent with sources obtained through the U.S. Department of Energy and market reports in the general media [74].

3.2 Fuel Cell System Cost Modeling Example

The U.S. DOE has supported fuel cell system cost modeling for many years for both stationary [75] and automotive systems [76]. We choose the cost model of Wei et al. [75] for 1 kW systems as a representative cost model for this analysis. This is a bottom-up cost model for CHP fuel cell systems assuming a vertically integrated fuel cell stack manufacturer and largely purchased balance of plant components. Each stack component is modeled starting from equipment costs, and factoring in material, operating costs, and labor costs. Figure 2 shows the output of the modeled direct manufacturing costs of a 1 kW CHP PEM fuel cell system for a fuel cell stack vendor as a function of annual production volume and broken down by stack costs, fuel processor costs, and non-fuel processor balance of plant costs (e.g., power inverter, supporting pumps, and auxiliary boiler). The fuel processor is the subsystem that provides hydrogen fuel to the fuel cell stack assuming a natural gas input line. In this case the fuel processor

consists of two primary parts: (1) a natural gas purification system and (2) a steam reforming unit to decompose the natural gas into hydrogen fuel.

Figure 2. LBNL Direct Cost Model, 1kW CHP system [75]. Overall system cost is dominated by balance of plant costs above an annual production volume of several hundred units per year. Note that this cost does not include corporate markups (e.g., sales and marketing and profit margin) and installation costs.

This depiction allows the delineation of fuel cell stack manufacturing costs (“Stack Cost” in Figure 2) and non-fuel cell components such as fuel processor and other balance of plant components. At higher production volumes, overall costs shift from the fuel cell stack to the non-fuel cell stack components. As volume increases, the stack becomes a much smaller component of costs with the assumption that normalized fuel cell stack costs (cost per kW) drop rapidly at higher volumes due to greater tool utilization and learning-by-doing manufacturing improvements such as defect inspection and real-time process control. One reason BOP costs are higher is because they are largely purchased off-the-shelf components and a system vendor would pay equipment markups. Over time, BOP integration of components, in-house production, or supplier contract negotiations is expected to reduce these costs. Material costs are seen to be a very small portion of overall costs.

The largest cost reduction component with increasing annual production volume is the reduction in capital costs. This “economies of scale” is observed due to tool sets achieving a higher rate of

utilization, and therefore capital (equipment) costs are amortized over a larger number of annual units. Material costs dominate at higher volume. The largest cost reduction is achieved from increasing annual production from 100 to 1,000 units, but thereafter about 20% cost reduction is achieved for every ten-times increase in annual production volume.

Actual market price in 2009 was about \$30,368 in 2013 U.S dollars (2013\$) corresponding to vendor production of about 1,300 units per year, and dropped to \$15,239 in 2014 at about 20,000 units per year and includes installation [77]. We choose 2014 as an end state year rather than 2015 for three reasons: (1) reports for performance improvements and system design improvements are from the 2012-2014 time frame; (2) the volume data in 2014 represents full calendar year sales, whereas 2015 may not; and (3) the reported cost reduction from 2009-2014 and from 2009-2015 are very similar at 50% and 52%, respectively. The cost model estimates a direct cost of \$13,576 per unit at 1,300 units per year for a base 0.7kW system. Increasing volume to 20,000 in 2014 reduces the modeled cost by 24% to \$10,301 per system. Note that this modeled cost does not include corporate markups and installation costs. A corporate markup of 100% is assumed to cover general and administrative costs (G&A), sales and marketing costs (S&M) and other costs. Earlier financial analysis of publically-traded fuel cell companies in North America financial statements indicate a corporate markup of 40-50% just for G&A and S&M. A larger markup may be appropriate in the early commercialization phase to account for additional costs such as non-recurring R&D expenses and any product startup costs not accounted for in Figure 2. A corporate markup of 100% would give a price of \$27,151 at 1,300 units per year and \$20,601 at 20,000 units per year. We take an installation factor of 10-20% additional cost, which yields an installed price range of \$29,866-\$32,581 at 1,300 units per year to \$22,661-\$24,721 at 20,000 units per year versus the observed \$30,368, and \$15,239 market prices. The cost model result implies to an approximate 24% cost reduction due to economies of scale from 2009 through 2014. Note that Hiroshi [64] and METI [77] report fuel cell prices in yen which are interpreted as nominal yen here. Accounting for inflation in Japan gives a negligible correction to the learning rates computed for nominal yen. A fixed exchange rate of

97.43 yen to the dollar was used to convert Japanese inflation-corrected yen values to 2013 US dollars in the data below.

At the lower volume the LBNL modeled cost range is in close agreement with the observed market price, but at the higher volume, the cost model is 50-60% higher than the observed price since product design, product performance, and corporate margins and installation price factor are held static. In other words, the cost model result in Figure 2 gives an estimate of economies of scale from capital cost, labor cost, material costs and other cost reductions that accrue from higher annual production volume but not from other product design, performance, and integration improvements. Although the LBNL cost model is in good agreement with the observed market price at the 1300 unit per year annual volumes, there are multiple uncertainties that factor into the estimated range of total costs including process yield, “make versus buy” decisions for system components, labor costs, and corporate markup, all of which may change over time. The LBNL cost model assumes a high degree of automation above 1,000 units per year and process yield for each stack module of approximately 80%.⁶ At this or lower production volumes, costs may quite high if production facilities still rely on manual processing and assembly which may drive up cycle times and labor costs and lower process yield. The LBNL cost model was developed assuming a manufacturer in the US and some manufacturing costs are higher in Japan, such as energy costs, although recent costs of labor are reasonably well matched⁷ and costs of components may not differ significantly. The fuel cell stack process yield may be lower than that assumed in the LBNL model due to the lack of fully developed and characterized process modules and immature or insensitive defect metrology.

⁶ An exception to this statement is that the fuel cell stack assembly module yield is assumed to be much higher than 80% since any loss at this step would necessitate scrapping all the value-added steps from other process modules. Overall Process yield is held fixed at the two annual production volumes of 1000 and 10,000 units per year. Actual “learning-by-doing” yield improvements from process learning, improved defect metrology, and real-time process control are expected but not known. However, since the fuel cell stack is in general a much smaller fraction of overall system costs than the balance of plant, this yield improvement factor is a not a major contribution to overall costs under these assumptions.

⁷ Labor costs are well matched (see <http://www.bls.gov/news.release/pdf/ichcc.pdf>, accessed 20 March 2015).

Despite these uncertainties, the shape of the curve is still believed to be representative of economies of scale for a more automated production facility. Another cost model for PEM CHP systems funded by the DOE reports 20% cost reduction from 1,300 to 20,000 units [63], similar to the dependence depicted here. The cost modeling approach offers a model of the economies of scale associated with scaling up of production and improved capital utilization, i.e., it isolates the economy of scale factor. Note that the economy of scale cost reduction factor in this case is independent of the corporate markup and installation factors since we are assuming these two factors are constant scaling factors across the range of annual manufacturing volumes.

3.3 Cost reduction from reported product design improvements

Information on product design is used to estimate changes in product materials, configuration, and/or layout as an input to the cost model. Through published reports and conferences, material costs and design integration have been reported from both Toshiba and Panasonic.

For material costs both Toshiba and Panasonic report a 10-15% reduction in number of cells and 20% reduction in platinum (Pt) used [68,74,78]. A reduction in the number of cells corresponds to lower Pt content by a proportional amount, so most of the Pt reduction is assumed be achieved from cell count reduction rather than reduction in Pt areal-loading. From the LBNL cost model sensitivity analysis, this translates into about 10% lower stack costs from lower material and assembly costs.

Toshiba reports 40% fewer components through improved design integration, for example the transition from discrete inverter and control board to an integrated inverter and multilayer printed circuit board [74]. We estimate this design integration translates to between 15-25% lower balance of plant costs from process consolidation and lower material costs.

The total cost reduction from cell count reduction and greater balance of plant integration can then be inferred based on the relative mix of costs from the fuel cell stack and balance plant shown in Figure 2. At 20,000 units per year, the fuel cell stack is estimated to make up about 10% of the total system cost. Total unsubsidized price reduction from 2009-2014 thus is estimated to be 19% from product performance and product design improvement.

4. Summary of Results

Table 2 has a summary of experience curve learning rates. A learning rate of 18% is observed in Japan for fuel cell micro-CHP from 2005 to 2015 (Figure 3) versus a fairly flat learning rate for fuel cells systems in California (Figure 4). A learning rate in the range of 0-5% is quoted in Table 2 for three different fuel cell technologies. The average learning rate for the three technologies in Figure 4 is 3.9%, but all three of the three technologies (SOFC, PAFC, and MCFC) have a very poor fit and thus a flat learning rate. The relatively flat learning rate in California is consistent with the very low learning rate for early commercial SOFC systems in Europe reported in [57].

The Japan micro-CHP fuel cell system was in pre-commercialization phase from 2005-2008 and commercialized in 2009. According to Staffell and Green [60], prices dropped in 2008 in anticipation of commercial competition and then stayed flat in 2009 and 2010 as manufacturing costs caught up with sales prices. Because of this visible discontinuity in prices, we do not split the experience curve into a pre-commercialization and commercialization phase, since the large price drop in 2008 would lead to a higher learning rate from 2005-2008 (25%) and the flat prices in 2009 and 2010 would lead to a lower learning rate from 2009-2014 (17%), and both of these rates could be artifacts of the commercial pricing strategy in 2008. Since 2009, over 100,000 units have been delivered. The experience curve presented in Figure 3 shows the cost reduction from 2009 to 2014 is estimated to be 50% using the data points on the curve. The main data set is from Japan's Ministry of Economy, Trade and Industry (METI) [77]

Table 2. Summary of experience curve learning rates for stationary fuel cells considered in this work

Product	Years	Learning Rate from this Work
Stationary Fuel Cells	2001-2015	LR (avg.) ~ 0-5% (California) LR ~18% Japan Micro-CHP 2005-2015

Figure 3. Observed cost reduction for Japan micro-CHP system cost from 2005-2015 with a learning rate of 18%.

A table of cost reduction disaggregation elements is shown in Table 3. Overall cost reduction from 2009 to 2014 is 50%, using reported system costs as shown by the data points in Figure 3. If however, the price was reduced sharply in 2008 in preparation for the launch of the commercial phase in 2009, the cost reduction could be higher. Using the fit line in Figure 3, the cost reduction from 2009 to 2014 could be as high as 58%. System vendor production volume increased by about one and a half orders of magnitude from approximately 1,300 units per year to about 20,000 units per year and is estimated to give 20-24% cost reduction from economies of scale from the cost modeling discussion above. Design improvements in fuel cell stack and balance of system components are estimated to contribute about 19% cost reduction as described above. This leaves a residual of 19-35% for cost reduction of other factors. In other words, the observed cost reduction can be explained by three components or roughly comparable magnitude: economies of scale, product design improvements, potential cost reductions in installation cost and other soft costs, and other factors. Other factors can include reduction in margin (smaller difference in market price to manufacturing cost) and purchased component cost savings from increased competition among suppliers. This latter factor is distinct from economies of scale since economies of scale implies a capital cost savings from increased tool utilization

and material cost savings from volume discounts from a given vendor, but component price reductions from increased buying power due to additional supplier competition is an additional factor. Note the savings in Table 3 are not additive but rather represent the relative savings percentage for each element, i.e., a total 50% savings is given by the expression $[1 - (1-24\%)*(1-19\%)*(1-19\%)]$ or $[1 - (1-20\%)*(1-19\%)*(1-23\%)]$.

Table 3. Summary of cost reduction disaggregation in fuel cell micro-CHP in Japan from 2009-2014.

Years	LR	Cost Reduction (observed)	Manufacturing Cost Model	Est. CR from Economies of Scale	Est. CR from Technology/ Design	Est. CR from Other factors (Margin, competition, etc.)
2005-2014	18%	50-58%	Low Temperature PEM CHP Direct Manufacturing Cost Model (Wei et al., 2014)	20-24%	19%	19-35%

LR = learning rate; CR = cost reduction

Figure 4. Reported costs of fuel cell total system cost per kW for the California SGIP program for (a) SOFC electric power systems, and (b) PAFC, and MCFC CHP systems.

The reported costs of fuel cell systems installed in California as reported in the SGIP database [73] is shown in Figure 4. Although the total installed power is comparable to the Japan CHP case (e.g. 100 MW for SOFC), the number of installed units is much lower than the Japanese case because the size per system is much higher (typically 400-700 kW). There is a very low or near zero cost reduction observed in California. (The face-value power-law learning rates for SOFC, PAFC, and MCFC in California, are -1%, 8.5%, and 4.2%, respectively, but in all cases the R^2 -fit is very low.) Note also that over time, greater performance monitoring and reporting requirements for the SGIP program may have contributed to higher system prices.

The California SGIP costs represent total system costs that are eligible for the state SGIP incentive and thus includes installation costs in addition to capital costs. These system costs include balance of plant costs such as fuel processor costs, air handling equipment, installation costs permitting costs, and other soft costs. Since there are a range of possible installation sites and installation scenarios, especially for the case of combined heat and power installations, there is an additional source of variation in costs that has not been explored in this work. For example, some sites may have enclosures or pre-poured concrete landing areas, some may have electrical connections in place already, some may be linked to biogas systems, and so on. Normalizing across the range of heterogeneous installation and site-specific factors would require detailed study of each site and was beyond the scope of this work. We include systems from the SGIP database with the following status: (incentive) “payment completed,” or “payment in process,” since these systems have been installed and have been verified in the field. Including all non-suspended, non-cancelled projects in the database with in-process application status (e.g., in “technical review” or “program administrator review”) does not change the learning rate conclusions.

The SOFC fuel cell system does not show any cost reduction. The SOFC vendor, Bloom Energy has stated that the fuel cell module is 40 kW [79] and base system size is 200 kW. The cumulative volume of approximately 100 MW thus represents about 500 systems units cumulative production or on the order of hundreds of systems (~20 MW) per year. For reference, the volumes shown in Figure 4a

represent about eight doublings in volume. Assuming a constant learning rate of 5%, 10%, or 15%, this number of doublings would correspond to an underlying cost reduction of 34%, 57%, and 73%, respectively, as opposed to the flat price trend that is observed.

Similarly the PAFC and MCFC reported system costs do not show a discernible cost reduction (corresponding to reported data from Doosan/UTC Power and Fuel Cell Energy, respectively), with average system costs between \$8,000-9,000 per kW. This data set represents a small number of units and both of these technologies are more mature technologies compared to the SOFC case, so it is possible that this data set represents a flat portion of the experience curve. For reference, the near term 2015 DOE target for installed cost with natural gas is \$3,000-4,000 per kW.

Both of these plots are segregated by geography, but limiting the micro-CHP data to Japan is warranted because there is miniscule production of fuel cell micro-CHP systems outside of Japan. California represents over 50% of the fuel cell market in the U.S., so the California SGIP database is a reasonable representation of fuel cell system costs across the U.S.

Table 4 shows a summary of subsidy or incentive levels for fuel cell micro-CHP in Japan and SOFC fuel cell systems in California. In general, the annual percentage decrease in incentive levels are much higher in Japan than California. The four-year average annual decrease from 2012-2015 is 12% in California compared to an average annual decrease of 26% in Japan.

Table 4. Summary of incentives for fuel cell micro-CHP in Japan and SOFC fuel cell systems in California under the SGIP program.

	California SGIP Incentive for SOFC Systems (2010\$/kW)	Annual Percentage Decrease	Japan Ene-Farm Subsidy (1000 Yen/Unit) [68]	Annual Percentage Decrease
2009			1400	
2010	5000		1300	7%
2011	3000	40%	1030	21%
2012	2600	13%	700	32%
2013	2270	13%	450	36%
2014	2017	11%	330	27%
2015	1816	10%	300	9%
2015	1640	10%		

5. Discussion

Some key considerations and differences in the Japan and California case are described in this section including development, market, technology, and policy factors.

The target annual volume in 2020 and 2030 for Japan's micro CHP provides more "market certainty" in the Japan case, where both fuel cell providers and supply chain vendors can count on a certain overall market volume trend and associated total revenue projection. From Table 4 above, the declination in subsidies has been steeper in Japan than in California which may result in a greater downward pressure on cost reduction in Japan than in the California market. Additionally, the market for distributed power and CHP systems is more favorable in Japan due to the higher spark spread, which is much larger in Japan as quantified above for residential and commercial markets.

Japan's joint development model may also provide more resources and R&D efficiency, as coordination among participants and perhaps the existence of a national mandate for the number of units would make it more appealing for companies to participate. A deeper understanding of the workings of the joint development model and its benefits and tradeoffs may be needed in future analyses of similar technologies.

The Japan Ene-farm product features a much smaller fuel cell power level than the California case and therefore the relative mix of non-fuel cell balance of plant and fuel-cell stack or fuel cell “hot box” costs differ. Fuel cell stack costs are expected to be a higher component of overall system costs at higher fuel cell power levels, as balance of plant costs are more “amortized” with larger system sizes [75]. If fuel cell stack cost reduction is very difficult, this may allow more nominal cost reduction for smaller fuel cells systems through balance of plant costs reductions such as more integrated design of balance of system components. Other possible differences in cost versus system size are safety measures such as leak detection equipment, but this was not extensively studied in this report.

Japanese FC system suppliers are dominated by large, diverse companies such as Panasonic and Toshiba in concert with large utility companies such as Tokyo Gas and Electric Company. An argument could be made that this provides greater resources for more sustained development in Japan, compared to dedicated fuel cell system companies more common in the U.S. The exception to this in the U.S. is UTC Power, a subsidiary of a large, multinational corporation, United Technologies. However, the eventual sale of UTC Power was potentially driven in part is because cost reduction is harder to achieve for larger FC systems as noted above and perhaps UTC Power did not foresee a growing market with no national mandate for sales volume in place as there is in Japan.

Exogenous factors should not be underestimated. The Fukushima nuclear accident in 2011 led to a huge shift in primary energy consumption in Japan away from nuclear power, and fuel cell systems figure prominently in Japan’s most recent national energy plan. Before the Great East Japan Earthquake and Tsunami March 2011, nuclear power constituted 28.6% of primary energy in Japan [68]. After the nuclear shutdowns stemming from the nuclear accidents at the Fukushima Nuclear Power Plant complex, nuclear power plunged to only 1.7% of primary energy in Japan in 2012. During this time, the fraction of primary energy from fossil fuels (oil, natural gas, and coal) increased from 62% prior to the tsunami to 88% in 2012. Thus there has been a greater impetus in Japan to develop greater energy efficiency and install more distributed energy systems since this cataclysmic event.

Both the micro-CHP and California FC costs, as system costs, do not necessarily reflect the underlying cost of the fuel cell stack. Therefore, it is possible in the California case that the fuel cell stack has achieved a level of cost reduction that is hidden within the overall system cost. More likely is that U.S. fuel cell manufacturers are seeking to recoup their investment costs and may not have the resources to invest heavily in R&D. Also, there is less competition in the U.S. medium sized commercial power and CHP markets: systems at 100-700 kW can be served by Bloom Energy SOFC (power only) systems; the Doosan/UTC Power PAFC system is in multiples of 400 kW; and Fuel Cell Energy's MCFC systems are in the MW range, with virtually no other competitors. This marketplace of limited competition provides less of a downward force on pricing and also limits the development of a diverse supply chain. Understanding of the extent to which existing incentives may support prices in a less than competitive environment could benefit from further investigation in the context of designing responsive deployment and incentive programs.

Another important factor for the greater adoption of fuel cell systems is maintenance cost and in particular equipment replacement costs as highlighted by Dodds et al.[61] for MCFC systems and Ainscough, et al. for compressor reliability [80]. As capital costs or "first costs" are reduced, the life-cycle cost and affordability of fuel cell systems could be limited in the future by equipment replacement costs, e.g., the need for stack replacement costs after only a few years of operation or the need to replace key component costs such as compressors or power inverters prior to the fuel cell system's full rated lifetime. A detailed assessment of these costs is beyond the scope of this work but is an important area for improvement and overall cost of ownership.

The cost modeling approach is applicable to other technologies, but subject to the availability of a suitable cost model showing cost dependency with production volume, data availability in production volumes over time, and product design and performance information. A rough performance model, either as part of the cost model or as an accompanying model element, is also needed in order to translate reported performance and design improvements to material and manufacturing cost reductions. In the case of the Japan micro-CHP market, all three elements of analysis are available: a readily available cost

model, vendor production data, and publically reported system performance and design improvements. In the case of SOFC technology in California, very little information has been available about system design and performance changes over time.

Finally, “learning-by-doing” in terms of process yield and process control is difficult to assess without detailed industry process knowledge and information such as critical defect densities, but follow up research can perhaps gain insights from historical data or modeling from other adjacent industries.

6. Conclusions

Learning rates are not static and evolve with technology learning, policy environments, and market changes. Here, we have described a promising further approach for integrating cost analysis studies with observed learning rates that can be a framework to be applied to other technologies and countries. Using this approach provide quantitative estimates for contributing mechanisms for cost reductions in Japanese stationary fuel cell market that could not be revealed in earlier qualitative approaches . The advantages of this approach are that it can provide bottom-up assessment of cost reductions due to economies of scale, and either reported product performance and design improvements or anticipated improvements can be directly modeled for potential future cost reductions. We would like to see similar objective and quantitative approaches applied to other emerging and established technologies to better understand the contributing factors and opportunities for technology cost reduction. For example, this approach could be utilized to analyze the potential for future cost reductions in fuel cell electric vehicles and battery electric vehicles. Similarly, experience curve datasets should be updated regularly (e.g., annually or biannually) and this analysis approach is amenable to re-computation and revision on a regular basis as well.

The Japan micro-CHP program benefits from several factors such as more favorable market conditions (e.g. higher spark spread) and greater competition, while the recent exogenous shock of the 2011 tsunami has also accelerated the policy and market acceptance of distributed generation and fuel cell systems. The U.S. market is harder to enter due to much less expensive grid electricity and lower gas prices, which make it harder for fuel cell distributed electricity systems to compete with grid electricity.

Japan has a different technology development model than the U.S., with more joint development as well as a long-term national mandate for the market adoption of FC CHP systems. The U.S. has not supported joint development as widely. The Japan micro-CHP has had much greater cost reductions than the California stationary fuel cell system market under the SGIP program with the micro-CHP case having much higher unit volumes (number of systems per year) than FC systems in California.

To the extent that price data can be used as a rough proxy to infer technology learning and cost, deployment programs in and of themselves may not lead to significant cost reduction, as seen in the California fuel cell market. These programs may further require a strong development environment, government mandates for market adoption, and in the case of fuel cell distributed generation, more favorable market conditions and the presence of exogenous factors.

We demonstrate a bottom-up cost modeling approach that can be applied to disaggregate observed experience curve cost reduction and use the approach to estimate the cost reduction components in the Japanese micro-CHP program into three components: economies of scale, product design improvements, and other residual effects. This approach provides insight into the technology dependencies and economies of scale of product and system manufacturing and can be applied to other technologies. The approach requires a cost model framework and information about industry participants, vendor production volumes, and evolving product performance and design information.

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Figure 1. Disaggregating a technology’s experience curve price reduction

Figure 2. LBNL Direct Cost Model, 1kW CHP system [75]. Overall system cost is dominated by balance of plant costs above an annual production volume of several hundred units per year. Note that this cost does not include corporate markups (e.g., sales and marketing and profit margin) and installation costs.

Figure 3. Observed cost reduction for Japan micro-CHP system cost from 2005-2015 with a learning rate of 18%.

Figure 4. Reported costs of fuel cell total system cost per kW for the California SGIP program for (a) SOFC electric power systems, and (b) PAFC, and MCFC CHP systems.

Table 1. Japan’s Micro-CHP program and the California SGIP

Table 2. Summary of experience curve learning rates for stationary fuel cells considered in this work

Table 3. Summary of cost reduction disaggregation in fuel cell micro-CHP in Japan from 2009-2014.

Table 4. Summary of incentives for fuel cell micro-CHP in Japan and SOFC fuel cell systems in California under the SGIP program.