batteries

MDPI

Article

Further Cost Reduction of Battery Manufacturing

Amir A. Asif [1] and Rajendra Singh [2,*]

1 Holcombe Department of Electrical & Computer Engineering, Clemson University, Clemson, SC 29634, USA; aasif@g.clemson.edu

2 Holcombe Department of Electrical & Computer Engineering and Automotive Engineering, Clemson University, Clemson, SC 29634, USA

* Correspondence: srajend@clemson.edu; Tel.: +1-864-656-0919

Academic Editor: Maciej Swierczynski
Received: 14 February 2017; Accepted: 12 May 2017; Published: 1 June 2017

Abstract: The demand for batteries for energy storage is growing with the rapid increase in photovoltaics (PV) and wind energy installation as well as electric vehicle (EV), hybrid electric vehicle (HEV) and plug-in hybrid electric vehicle (PHEV). Electrochemical batteries have emerged as the preferred choice for most of the consumer product applications. Cost reduction of batteries will accelerate the growth in all of these sectors. Lithium-ion (Li-ion) and solid-state batteries are showing promise through their downward price and upward performance trends. We may achieve further performance improvement and cost reduction for Li-ion and solid-state batteries through reduction of the variation in physical and electrical properties. These properties can be improved and made uniform by considering the electrical model of batteries and adopting novel manufacturing approaches. Using quantum-photo effect, the incorporation of ultra-violet (UV) assisted photo-thermal processing can reduce metal surface roughness. Using in-situ measurements, advanced process control (APC) can help ensure uniformity among the constituent electrochemical cells. Industrial internet of things (IIoT) can streamline the production flow. In this article, we have examined the issue of electrochemical battery manufacturing of Li-ion and solid-state type from cell-level to battery-level process variability, and proposed potential areas where improvements in the manufacturing process can be made. By incorporating these practices in the manufacturing process we expect reduced cost of energy management system, improved reliability and yield gain with the net saving of manufacturing cost being at least 20%.

Keywords: lithium-ion (Li-ion) battery; battery manufacturing; advanced process control (APC); rapid thermal processing; industrial internet of things (IIOT)

1. Introduction

Energy storage has evolved at a rapid rate in the last couple of decades. For a long time, battery storage was mostly used for starting engines, few emergency backup and portable devices, toys, etc. Ubiquitous zinc-carbon (dry cell) battery and lead-acid battery were the key players for portable applications and the automotive industry, respectively. However, due to the rise of consumer electronics and the convenience of recharging, nickel metal hydride (NiMH) and nickel cadmium (NiCd) batteries also gained mainstream popularity. The arrival of lithium-based batteries changed the scenario by offering higher energy efficiency and density, in addition to its longer shelf life, fast charge and discharge, etc. [1]. Though it was reported that lithium-ion (Li-ion) batteries have slight memory effect [2], it is less prominent than NiCd and NiMH batteries. Li-ion batteries have high gravimetric (Wh/kg), high volumetric (Wh/L), high cycle life, and high energy efficiency, etc. [3]. Li-ion has gravimetric energy density in the range of 110–160 Wh/kg, while such ranges for lead acid, NiMH and NiCd are 30–50, 45–80 and 60–120, respectively in Wh/kg [4]. Armand et al. [5]

published a detailed comparison of battery chemistries in terms of future applications and their environmental impacts where Li-based batteries performed better than the others did. With ramped up production, Li-battery price is showing a downward trend, and manufacturers, such as Tesla, are utilizing volume manufacturing to push the cost down [6]. In order to curb dependence on fossil fuel and reduce carbon emissions, the world is leaning more towards renewable energy (wind and solar) for electricity generation, and also towards EVs for surface transportation. Both of these sectors have high degrees of correlation with battery cost and performance. Apart from portable electronics, at this moment, the emerging market for the Li-ion battery can be categorized in two key segments: (a) renewable and grid energy storage, and (b) electric transportation. As sustainable energy sources, there is plenty of renewable energy (sunlight and wind) [7] for human beings on earth, and in recent years, energy harvesting installations (PV and wind turbine) are growing at an astronomical rate. Due to the intermittent nature of solar and wind energy generation, it is also creating a large demand for energy storage. However, due to the advancements in technology and volume manufacturing, the cost of batteries is following the price reduction trend of photovoltaic (PV) modules [8]. Cost reduction of battery manufacturing will further reinforce the position of renewable energy as a viable alternative to fossil fuel. Using locally generated direct current (DC) power from PV [9] and utilizing batteries for local storage can potentially transform the global electrical energy infrastructure [10]. This scheme also offers better efficiency and resiliency [11]. As the energy infrastructure is undergoing a gradual transformation, smart grid is also gaining attention. The use of front-of-the-meter (central grid energy storage) and behind-the-meter (energy storage at consumer premises) are increasing and thus, driving up the demand for batteries [12]. One of the largest batteries in the world, the 400-MW peak hour battery, is based on Li-ion technology [13]. The PV industry has used practices that were tested, implemented and perfected in semiconductor manufacturing, and thus made significant improvements in reducing the process variability [14]. This adoption of technology allowed the PV industry to deliver superior performance and to reduce cost. The battery industry can use similar fundamental concepts to transform the battery manufacturing processes. Driven by the continuous increase in energy density and reduction in cost [15], a recent report predicted 11.6% compound annual growth for Li-ion battery that will reach $77.42 billion in 2024 [16]. Solid-state battery is also garnering attention [17,18], and it is projected to grow in the near future [19]. Li-ion with silicon anode [20], Li-air [21], etc., are also showing promise for future applications.

On the other frontier, the surface transportation sector is also creating a huge market for batteries that actively participate in drive train rather than just supplying starting power to the engine. Energy economics, carbon foot-print reduction and eco-minded consumer behavior are driving the growth of electric vehicle (EV), hybrid electric vehicle (HEV) and plug-in hybrid electric vehicle (PHEV) markets, and thus, demand for batteries for such applications are also increasing. Further cost reduction of batteries would also bring the price of EV and HEV down, and place them at a more competitive price point with respect to the conventional internal combustion vehicles. Li-ion battery is also used for such applications. In some car batteries, Li account for approximately 5% of materials and less than 10% of the cost [22]. There is even an example where an EV manufacturer ventured into its own battery manufacturing (Tesla Gigafactory) and has achieved 35% battery cost reduction to lower the cost to below $125/KWh [23]. The same EV company introduced battery storage for PV generated electricity (Tesla Powerwall) [24].

EVs, power grid management, energy storage requirements, along with growth in renewable energy, will fuel the growth in the battery industry [25]. For low-cost manufacturing, the abundance of raw materials is a necessary criterion [26]. At the current usage rate, recent surveys and estimation data indicate that there is enough lithium for the next 365 years [27]. New processes for lithium extraction from minerals are also being explored [28]. There is some volatility in spot price of lithium and its commonly used compound, i.e., lithium carbonate. Moreover, lithium is sourced from a few countries and a handful of companies control the major part of the supply [29]. In March 2016, the peak price was US $20,000/ton approximately [29]. Recent (January 2017) pricing is in the vicinity of

~$15,000/ton [30]. In most cases, the manufacturers alone cannot control the price of the raw materials. Large-scale manufacturers can buy in larger quantities and claim discounted bulk pricing in some cases. However, the manufacturers have more control at every step of in-house manufacturing. It is very important for battery manufacturers to find processing and manufacturing changes that will further reduce the manufacturing cost for lithium and solid-state batteries. The purpose of this paper is to present process variability in battery manufacturing and provide other manufacturing directions that can provide further cost reduction of manufacturing of Li-ion and solid-state batteries.

2. Problem Definition

All manufacturing processes have inherent statistical variability. This is also true for the electrochemical and solid-state cells that form a complete battery. For control purposes, the measurement has to be precise enough before any corrections can be made [31]. In manufacturing, unidentified problems cannot be fixed, and control cannot be meaningful without measurements [31]. However, the best and most suitable measurement system will be different for each specific process. Therefore, the measurement scheme, data collection, analysis and feedback need to be tailored to each process. A useful measure of this can be expressed in terms of process (P) to tolerance (T) ratio. The ratio P/T is defined as [32]:

$$\frac{P}{T} = \frac{6\ \sigma_{\text{precision}}}{lim_{\text{upper}} - lim_{\text{lower}}} \tag{1}$$

where $\sigma_{\text{precision}}$ is square root of sum of repeatability and reproducibility of measurement, lim_{upper} and lim_{lower} are upper and lower limits of tolerance, respectively. Semiconductor industry uses a value smaller than 10% for P/T [32]. As the transistor size shrunk, the process control also became more stringent to maintain the final yield [31]. In spite of having a very small tolerance, the semiconductor industry has achieved high yield for integrated circuits (IC) with ultra-small dimensions. Even, 10 nm transistor technology is now at mass production [33]. Meticulous attention has been paid to defects of semiconductors and interfaces [34]. The whole IC industry is a noteworthy example of process control. Their cost reduction is mostly generated by the in-house cost control, i.e., yield improvement, increased process efficiency, increased throughput, etc. Through process improvement, the silicon wafer manufacturers are able to offer superior quality wafers at a lower price. Most importantly, the successful IC manufacturers achieved high yield with tight process control, and are able to ship a larger number of finished products. The manufacturers that used tighter process control and larger Si wafer in their manufacturing process, remained competitive. The reliability of semiconductor products has helped this industry to enjoy stable growth. The reliabilities of transistors and their gates are treated with high importance in semiconductor fabrication [35]. Now, the reliability of battery and lifetime modeling is also drawing attention [36]. Apart from all these, researchers in industry or academia may discover that a new electrode, a new electrolyte, particular material substitution, or a new chemical processing step in battery can reduce cost and improve yield. However, this ongoing type of research is beyond the scope of this manuscript. Instead, manufacturing practice and cost reduction will be the key focus, assuming that the desired chemistry, recipe, material, etc. are already selected.

As stated before, the PV industry has made immense improvements in processing by adapting many well-known practices from the semiconductor industry [37]. The battery industry can also adapt some proven practices and processes from PV and semiconductor industries.

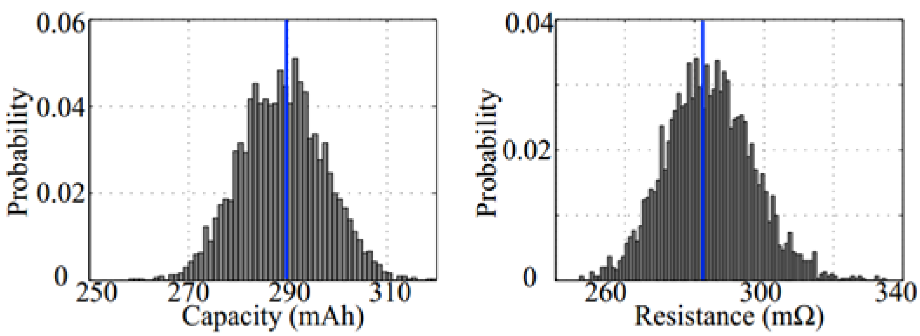
In this article, we will refer to an individual electrochemical or solid-state cell as "cell". When several such cells are combined together, it will be referred as "battery pack", which may include the battery management system (BMS) with sensors, controllers, processing unit, etc. On many instances of real life application, cells may be arranged according to the need to achieve a desired voltage level and capacity.

Due to tolerances during the manufacturing process, the final product may exhibit variability. This is applicable for battery manufacturing as well. These variability issues present a big challenge for batteries since the manufacturing process consists of the assembly of sub-components (e.g., electrolyte, electrode, separator, etc.) which may come from different locations and vendors [38]. However, cell-to-cell variability had been analyzed from the viewpoint of chemical and physical phenomena, and the system-level design requires analytical models that account for the variability in the manufacturing process [38]. The electrochemical models, such as pseudo 2-dimentional (P2D), single particle (SP), porous electrode polynomial (PP), etc. are powerful tools and their contribution should not be underestimated. Detailed comparisons of these models can be found in review articles, such as [39]. It is possible to use an electrochemical model to accurately estimate the effects of process variation on a cell. However, the system-level design and variation of electric systems might be handled effectively by analytical electrical models [38]. Stroe et al. [40] also used an electrical model to characterize battery pack performance. When multiple electrochemical cells are present, it is important to understand the role of variability on the behavior of the final battery pack. Zhang et al. [41] demonstrated one such example by experiment, modeling and parameter extraction for a multi-cell battery.

Shin et al. [38] demonstrated a combined cell-to-cell variation model by: (i) identifying the target lithium battery structure, (ii) modeling capacity and internal resistance, and (iii) model parameter analysis. By random variable assignment (based on mean and variance), 10,000 random cells were generated, arranged in arrays and simulated in MatLab Simulink [38].

Figure 1 [38] shows a statistical distribution of cell performance for Li-ion cells in terms of capacity and resistance. The desired statistical distribution of the cell capacity in Figure 1 should have (a) a mean centered at higher value, i.e., the mean should move right, and (b) have a smaller (narrower) variation. Similarly, the statistical distribution of resistance should have (a) smaller mean value, i.e., move towards left, and (b) have a smaller (narrower) variation. As shown in Figure 2 [38], it was demonstrated that if an array consists of cells with less variance, it could perform better than the one that has more variance among its constituent cells. Therefore, with narrower statistical distribution, it is possible to extract more power from the array of cells.

We may consider the single electrochemical cell as the building block, and can connect such cells to form a battery pack of desired voltage (e.g., 12 V). Using smaller battery packs in series and parallel combination, higher voltage (e.g., 48 V) and higher capacity (e.g., 100 KWh) can be achieved. Therefore, the variation of output from one cell to another is unwanted as its adverse effect will ripple to the battery pack and eventually, to the whole (large) battery installation. Therefore, variation reduction should start from the smallest constituents -the cells, and then, applied on subsequent steps or blocks gradually. Variation reduction among cells can contribute significantly in boosting the overall performance of a large energy storage installation. While investigating the thermal imbalance between cells, Christen et al. [42] mentioned that variation in resistance can significantly reduce the lifetime of a battery.



(**a**) (**b**)

Figure 1. Probability distribution of the (**a**) cell capacity and (**b**) resistance profile of the sample cells. From [38].

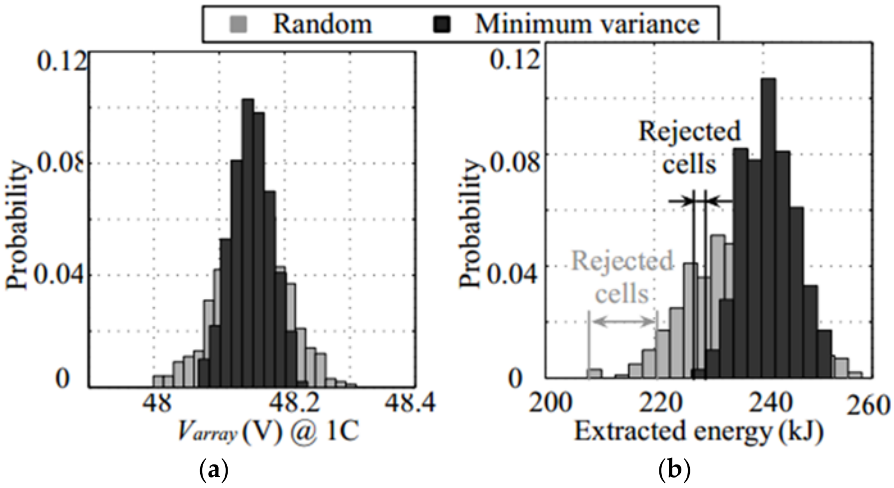


Figure 2. Comparison of (**a**) estimated array voltage (V_{array}) with 1C discharging current and (**b**) extracted energy from sample battery arrays formed by random selection and variance minimization. From [38].

Any kind of high variation in electrochemical cell performance may require discarding many of the manufactured cells. Moreover, due to the presence of different types of materials, e.g., anode, cathode, solvents, and other chemicals, the statistical distribution can become wider, and eventually produce inferior end results. Santhanagopalan and White [43] have shown that the variation in cathode thickness and cathode particle size can cause measurable differences in their Nyquist responses.

The importance of process control and variation can be illustrated through a very relevant example from the PV manufacturing process. A PV module is the series and parallel arrangement of solar cells. Due to the series and parallel types of connection, the worst performing solar cell dominates the overall performance of the whole PV module. The statistical distribution and non-uniformity among solar cells causes lower efficiency in energy conversion in a PV module when compared to the efficiency of the best performing solar cell. The improvement in individual solar cell efficiency does not translate directly into improved PV module efficiency. Cell-to-cell performance variation can reduce the achievable power output, because the worst performing cell will pull down the overall performance of the module [14]. The percentage change in module efficiency from single cell efficiency can be considered as an indicator of how closely the process could be controlled and what are the degrees of variation among cells. A smaller change in a silicon solar cell to module efficiency is a clear indicator that these cells can be manufactured with the least amount of variation. Due to process uniformity, the efficiency of the silicon PV module is only slightly lower than the efficiency of the individual cell, and it is best among commercial solar panels [44]. On the other hand, for many R&D cells, high variability and inability to control the process are key hurdles for entering mass production [45]. This is a stellar example of what can be achieved through process control.

Li-ion batteries employ BMSs to ensure safe and reliable operation of the battery pack. The BMS needs to monitor many parameters (e.g., total and individual voltage and current, temperature, impedance, etc.). It also performs critical tasks of estimation of battery states which includes state of charge (SOC), state of health (SOH), state of function (SOF), etc. Moreover, depending on the specific application, BMS may perform on-board diagnosis, safety control and alarm, charge control, equalization, thermal management, networking, information storage, etc. SOC estimation can be done through several methods, such as open circuit voltage, ampere-hour integral, battery model-based estimation, neural network model, Fuzzy logic, Kalman filter, sliding mode observer, etc. Each of these has its own advantages and drawbacks, and they are significantly different in their computational loads and error margins [46]. Lu et al. [46] also presented a table comparing different BMS chips available on the market. Stuart and Zhu [47] demonstrated BMS for large Li-ion cells used in EVs. If more uniformity is present among cells and they perform in a harmonious way, a less computationally powerful (and cheaper) BMS may be used. Equalization can be done at battery (with several cells) level, or at an individual cell level. The non-uniformity in remaining capacity and the need for equalization can be caused by, among other reasons, non-uniformity of self-discharge or non-uniformity in Coulombic efficiency [46]. Uniform electrical performances may lead to a greater application of passive BMS, which is cheaper than active BMS.

In essence, for achieving higher performance and lower manufacturing cost of batteries, the electrochemical cells need to have smaller process variation, i.e., uniform physical and chemical properties.

3. Proposed Changes in Lithium-Ion Battery Manufacturing to Address Process Variability

Li-ion manufacturing has several steps that vary from manufacturer to manufacturer. Processing steps are also dependent on the selected chemistry. After prototyping, a desired cathode, anode and other chemicals are selected for forming the cell. Depending on the selections and arrangements, the cell potential and performance will be different. Common steps that are carried out in manufacturing include the anode and cathode preparation and coating with chemicals. For solvent removal, usually some drying steps are used. Electrodes, electrolytes, binders, separator materials, etc. are assembled to form a complete cell. Finally, the cells are tested, graded and packaged as a full battery pack, which may just contain one cell or multiple cells. The goals from a manufacturer's point of view are: reducing the variability of each step at minimum level, and to get the final product without having large deviation from the targeted numbers. Implementing several changes in the manufacturing process, which are described in the following paragraphs, would help accomplish this goal.

3.1. Advanced Process Control

To reduce process variability, battery manufacturing processes need to shift from statistical process control (SPC) to advanced process control (APC). Besides the semiconductor industry, the benefits of APC have been well documented in other industries, such as petroleum [48] and pharmaceutical [49]. Battery manufacturing facilities should deploy more in-situ measurements so that the process can be kept within tighter control. Harks et al. [50] published a detailed review on in-situ measurements for a Li-ion battery. Adaptation of "within the batch control", "batch-to-batch control" and "batch production control" can establish control and optimization on "one batch", "multiple batches" and "all produced batches", respectively.

Based on concepts discussed in [51], we can consider a simplified case of the qualitative relationship between yield and performance, as depicted in Figure 3. The current production point "P" is on a line that defines a simplified linear relation (with negative slope) between yield and performance. In the real world, such simple correlations may not exist, but this simple, linear relation is sufficient to illustrate the point being discussed. Along this line, an increase in either production or performance will sacrifice the other. In other words, if the allowed window for quality is narrow, more products will have to be discarded. Consequently, the yield will decrease. Similarly, if more products are passed as acceptable, then the overall quality will be compromised. Inclusion of APC can slide the line to the right, and move the point P to the new position with higher performance (point A) or higher yield (point B) while keeping the other parameters unchanged. Even improvement in both performance and yield may be achievable (point C). For R&D and small-scale manufacturing, there are commercially available battery manufacturing tools and equipment that closely resemble the technology used in IC manufacturing [52].

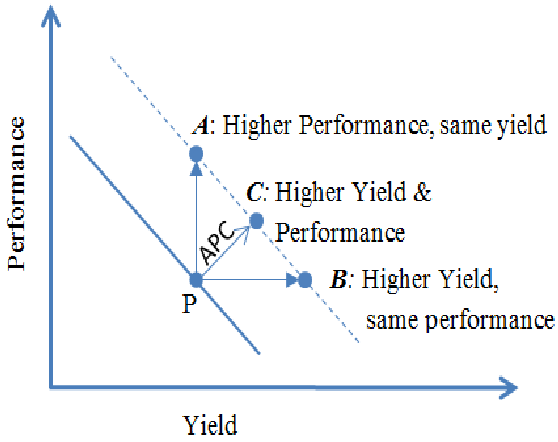


Figure 3. Shifting a simplified yield-quality line with the use of advanced process control (APC). Modified from [51].

3.2. Modifying Process Mechanism

In a study carried out on solid-state electrolyte for Li-ion cells, the researchers concluded that variation in the cooling rate results in variation of ionic conductivity [53]. Therefore, the thermal process needs to be controlled precisely to keep cooling rate consistent in all batches. The improvement in battery technology can come from utilizing the insight gained from the equivalent circuit model of the battery proposed in [54]. Young et al. [55] included battery capacitance (C_b), self-discharge resistance (R_p), internal resistance for charge (R_{2c}), internal resistance for discharge (R_{2d}), over-voltage resistance for charge (R_{1c}), over-voltage resistance for discharge (R_{1d}) and over-voltage capacitance (C_1). The equivalent circuit of Figure 4 [55] provides a simple guideline for uniformity which dictates that when connecting more than one cell to form a battery pack, the contributing cells need to have the same values of C_b, R_p, R_{2c}, R_{2d}, R_{1c}, R_{1d} and C_1.

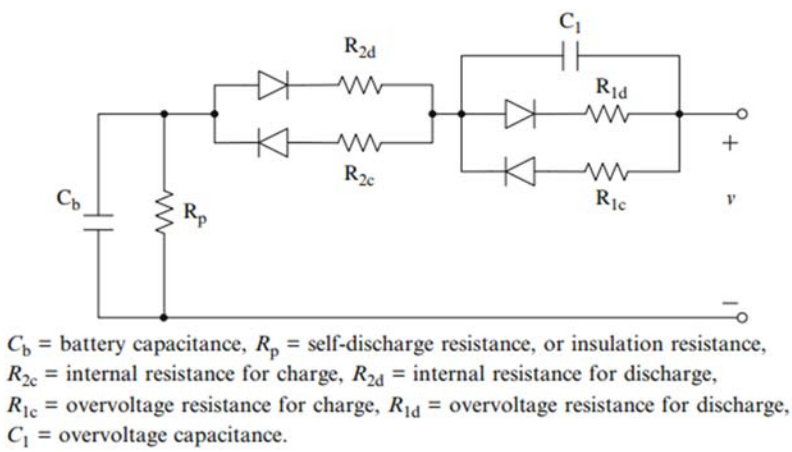


Figure 4. Equivalent circuit model of a battery. Taken from [55].

With the desired goal of reducing cell-to-cell variation, the focus has to be on the contributing factors that are responsible for the process variation. Analytical expression presented by Sikha et al. [56], and the resistance and capacitance models of Shin et al. [35] provide insight into the battery performance. This model can be used to further breakdown and identify the key contributors to cell properties, as shown in Figure 5 [38]. Controlling these variables will eventually lead to the control over the cell performance.

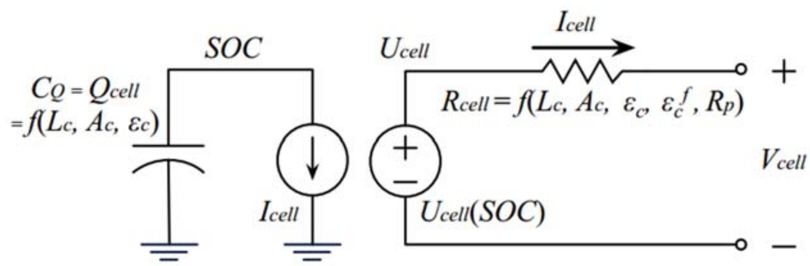


Figure 5. Equivalent circuit model showing the contributors to capacity and resistance properties. It is used for investigating the cell-to-cell variation. Taken from [38].

The most important parameters that control the resistance of the cell (R_{cell}) are thickness of cathode (L_c), area of cathode (A_c), porosity of cathode (ϵ_C), filler porosity of cathode (ϵ_C^f) and radius of solid spherical particles (R_p). The cathode thickness variation leads to undesired results [38]. Since the reactions take place on the surface of the electrode, surface roughness plays a very important role in determining the resistance in an electrochemical cell.

As compared to conventional furnace processing (CFP), the semiconductor industry uses rapid thermal processing (RTP) for most of the thermal processing steps. In the case of CFP, resistive heaters are used to create photons with wavelength in infrared region and the thermal mass of the system is large. On the other hand, incoherent light sources are used to create photons with wavelength from ultra-violet (UV) to infrared region and the thermal mass is small. Due to different operating mechanisms, the processing temperature and thermal cycle times are lower in RTP and the performance, yield and reliability of semiconductor products processed by RTP are superior to CFP [57]. A detailed mechanism of operating principles of RTP can be found in [57]. The photon-matter interaction can be summarized by the simple expression: "photon + matter = thermal effects + quantum effects". The wavelength of photon dictates the degree of thermal and quantum effects in RTP. The effects of different wavelengths in RTP are illustrated in Figure 6. The typical radiation spectrum of furnaces operating in temperatures less than about 1500 °C lies in the infrared region.

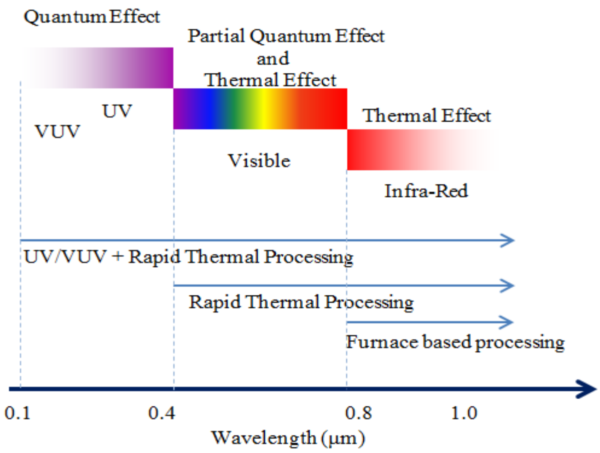


Figure 6. Radiation spectrum distribution for thermal processing techniques.

When the materials are exposed to photons of the infrared region, (>0.8 μm) only the thermal effects are operative. When infrared and shorter wavelength photons (<0.8 μm) interact with the materials, both quantum effects and thermal effects take place. As compared to CFP, RTP provides: (i) higher throughput, (ii) lower microscopic defects, and (iii) lower operating temperatures [57]. RTP can also lead to lower surface roughness. For identical processing temperatures, Ratakonda et al. [58] reported the surface roughness of RTP samples processed for 122 s and CFP samples processed for 162 s.

The surface roughness of screen printed silver contacts were 189 nm and 548 nm, respectively [58]. In line with our previous work on rapid thermal processing [57], Xue et al. [59] have shown very recently that the use of ultraviolet light in the curing process of composite electrode fabrication can reduce the processing time. These results prove that UV assisted curing is a promising route to substantially reducing the capital and operational costs of Li-ion battery electrode manufacturing [59].

In Li-ion cell formation process, the films of the chemical composites are put on electrodes and then dried by heating to drive out the solvents. In this step, higher temperature assists faster drying, but higher temperature has an adverse effect on the metal electrode surface. Adverse effects of high temperature curing are also observed in wafer-level packaging chips. The increase in curing temperature leads to cracking and warping [60]. The RTP assisted drying in Li-ion cell manufacturing will allow the process to take place at a lower temperature, and thereby no adverse effects will be observed. Similar to semiconductor manufacturing, RTP is expected to make a positive impact in Li battery manufacturing.

3.3. Synthesis of the Raw Materials with Uniformity, Supply Chain and Industrial Internet of Things

Synthesis of the raw materials with more uniformity can lead to variation reduction in the final product. Properties like porosity of cathode (ϵ_{c}), filler porosity of cathode ($\epsilon_{\mathrm{c}}^{\mathrm{f}}$), and radius of solid spherical particles (R_{p}) can be tuned through chemistry as well as careful sourcing. As reported by Sikha et al. [56], when solid particles are present in the cell, their radii are important in determining the electrical properties. As shown in the following equations, for both anode or cathode of Li-ion cell, the local impedance (Z_{loc}), single particle impedance (Z_{p}), and solid phase diffusion resistance (R_{diff}) are correlated [52]:

$$Z_{\mathrm{loc}} = f\left(Z_{\mathrm{p}}\right) + f(\mathit{other\ variables}) \tag{2}$$

$$Z_{\mathrm{p}} = \frac{1}{f(R_{\mathrm{dif}}) + f(\mathit{other\ variables})} \tag{3}$$

$$R_{\mathrm{dif}} = -\frac{R_{\mathrm{p}}}{D_{\theta}F}\,\frac{\mathrm{d}U}{\mathrm{d}c} \tag{4}$$

In the above equations, D_{θ} is the diffusion coefficient of Li^{+} ion in solid phase, U is open circuit potential, and c is solution phase concentration. Thus, the particle's geometric dimension can contribute to electrical properties. Whenever permissible, APC should be used in the synthesis so that that the distributions of radius of these particles stay in a tight range of distribution. In [61], the Li-ion battery reaction and parasitic reaction were modeled, and it was shown that the performance of the battery depends on particle radius and film thickness. For certain composition, the Li_4GeS_4-$LiPS_4$ ionic conductivity of as high as 2.2×10^{-3} S/cm is observed [62]. However, the undesired variation in the composition reduces the ionic conductivity by almost three orders of magnitudes, to 10^{-6} S/cm [62]. This decreased conductivity will cause higher interfacial resistance at the interfaces, and this effect becomes more dominant in bulk type solid state Li-ion battery compared to its thin film counterpart [63].

In any manufacturing process, the operation technology (OT) is comprised of devices, sensors, and software used to control the equipment and the plant. Information technology (IT) utilizes all necessary technology for information processing. In recent years, the convergence of IT and OT has given rise to the internet of things (IoT) which improves the overall system performance. Virtually every facet of human life is supposed to benefit from IoT and by year 2025, the potential economic impact of 11.1 trillion USD is estimated [64]. In the context of manufacturing, IoT is referred to as the industrial internet of things (IIoT) [65]. IIoT is a potential pathway to increasing efficiency in manufacturing [66]. As shown in Figure 7, the incorporation of IIoT can provide business critical information that can prove to be crucial in manufacturing of products. In battery manufacturing, the materials are to be sourced from different vendors and the finished products are distributed through distributors or sold to customer companies. IIoT can significantly influence the supply chain [67].

For example, the manufacturer can instantly be aware of the entry of the raw materials into its premises from the suppliers, and track it throughout the manufacturing facility. Inclusion of IIoT across the global supply chain can offer an end-to-end visibility and mitigate the instances of downtime [68]. Traditional methods of manual entry to and exit from inventory can be inaccurate or out of date whereas IIoT can streamline the inventory. As discussed earlier, minute changes in material properties (e.g., variation in particle radius) can affect battery performance. Thus, sourcing of material can be improved by IIoT. The manufacturing line can prepare for any changes in previous stages (including material properties data from suppliers) using information communicated via IIoT. A smart supply chain can provide efficiency and superior performance in the final product.

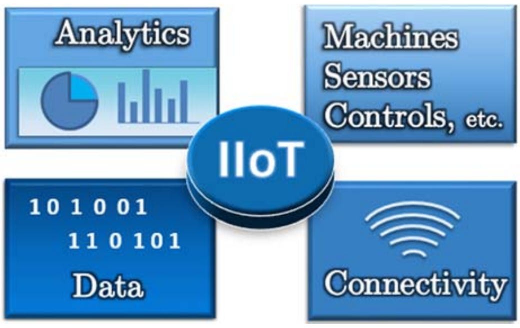


Figure 7. Industrial internet of things (IIoT) framework that utilizes connectivity, data, and analytic tools to communicate effectively with machines.

Due to adequate data gathering through IIoT, many potential problems can be detected at an early stage of manufacturing. The early detection of manufacturing problems can lead to corrective measures saving wastage in discarded products, compensation, product recalls, etc. [69]. The data gathered through the IIoT platform can point out inefficiencies and problems at a faster pace, save time and money and support an integrated business intelligence approach. In conventional manufacturing, a quality check of the finished product may reveal defects and then corrective actions may be initiated by a human operator. In IIoT, the quality issues can be relayed to the beginning of the assembly line, even to another location, in seconds, and corrective actions may be administered within a short period of time. IIoT with radio frequency identification (RFID) tags can be a very powerful tool for tracking material/product movement inside the factory premise. If some of the components or materials are identified to be the cause of a quality problem, RFID tags can point to all of the materials, components, finished/unfinished goods that contain the possibly defective materials or parts. Our proposed approach of in-situ measurements and sensor deployment to incorporate tighter process controls are in line with the current practices in some industries (e.g., IC manufacturing, solar cell manufacturing, etc.). On top of that, IIoT will add an additional reach and provide visibility to the overall manufacturing process control that may span from the raw materials supply chain to the end user.

In this era, customers may look for manufacturers who are capable of making necessary changes in the product to meet a set of provided requirements. This has given rise to agile manufacturing (AM), which allows manufacturer to respond quickly if there is a change from customer or market while maintaining the quality and cost [70]. Digital manufacturing [71] has the potential of changing every link in the manufacturing value chain, R&D, supply chain, factory operations, even marketing and sales. Complex manufacturing systems, such as aerospace and defense, are making efficient use of such technology [71].

4. Discussion

The strategies for a manufacturer should be selected based on its size, business models and goals. Large-scale global battery manufacturers (Panasonic, Samsung, LG Chem, Tesla, Hitachi, etc.) enjoy economy of scale, and each has their own strength in chemistry, process, expertise, innovation and intellectual property. Tesla even tried to go further in vertical integration and acquire ownership of a lithium mine [72]. Smaller companies lack the large-scale advantages, but may have a certain market segment and customers with specific requirements or advantages for niche applications. Regardless of size, all manufacturers need to innovate and implement manufacturing practices that would allow them to survive and remain profitable. The points put forward in preceding sections are not alternatives to innovations in chemistry or battery research. Rather, these outlined points are to be practiced when the battery work has moved into the production phase form the R&D phase. As outlined earlier, the adoption of some new steps can lead to potential improvements in battery manufacturing with the net result of lower cost. First of all, variability from one electrochemical cell to another should be reduced. Then, this practice can be expanded for the case of battery-to-battery variability. To accomplish this, APC should be adopted to establish precise measurement and control. Metal electrodes can benefit from having less surface roughness, which can be achieved by using RTP in place of CFP. RTP also allows faster and lower temperature processing while keeping the thermal stress at the minimum level. In semiconductor manufacturing, RTP has a proven track record for improving reliability, increasing yield and reducing variability. Similarly, adoption of RTP in battery manufacturing will be beneficial. The uniformity of materials that constitute an electrochemical cell is also important since some of their physical properties (e.g., particle radius) dictate their behavior and movements during cell operation. IIoT can establish an efficient and streamlined manufacturing process that can transform the dynamics of production.

Precise measurement is the pre-requisite for controlling the process [31], and this might add some capital cost for the equipment. However, better process control can outweigh the capital cost factor by providing higher throughput, better use of raw materials, re-processing cost reduction, etc. [73].

Overall, these proposed improvements will require some capital investments in equipment, software and manpower, but the resulting improvement in yield due to defect reduction will help reduce the cost of ownership (*COO*) given by the following equation [74]:

$$COO = \frac{Fixed\ Cost + Variable\ Cost + Cost\ Due\ to\ Yeild\ Loss}{Throughput \times\ Coposite\ Yeild\ \times Utilization} \quad (5)$$

The steps proposed in this paper would increase the throughput, yield and material utilization and decrease the battery manufacturing cost, due to higher yield. Thus, the net result will be reduction of *COO*. With incorporation of all the proposed changes, we expect to manufacture higher quality batteries at a cheaper cost. All the proposed changes are presented in concise graphical form in Figure 8.

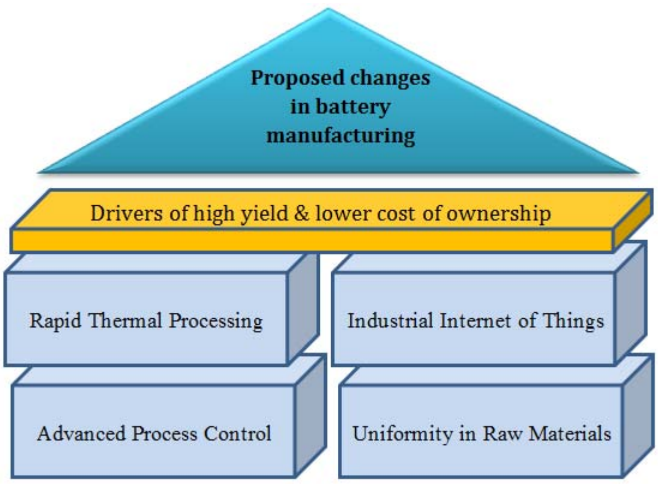


Figure 8. Proposed changes and their impact to bring down cost of ownership (COO).

5. Conclusions

Process variation in manufacturing is one of the key factors that reduces optimal battery performance and leads to higher manufacturing cost. There is room for improvement in controlling the process variations observed in battery manufacturing. In this paper, we have emphasized that the variation from cell-to-cell is crucial for energy storage application. The SPC used currently by battery manufacturers should be replaced by APC to gain better control over the manufacturing process. The use of RTP in place of CFP is suggested in all thermal process steps to reduce process variability and improve the performance and reduce cost of batteries. IIoT has the potential to manage manufacturing in a more efficient and agile manner. Besides research in materials and chemistry, these steps can help a manufacturer to produce in an efficient way while delivering the best quality product. The battery industry needs to act quickly to be prepared for the future when battery storage plays a very important role in stationary applications for power storage, as well as in EVs used in the surface transport sector.

Acknowledgments: The authors would like to thank the anonymous reviewers for their valuable suggestions.

Author Contributions: Rajendra Singh conceived the concepts; and Amir A. Asif performed the data collection. Both authors wrote the paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ehrlich, G.M. Lithium-Ion Batteries. In *Handbook of Batteries*, 3rd ed.; Linden, D., Reddy, T.B., Eds.; McGraw-Hill: New York, NY, USA, 2001.
2. Sasaki, T.; Ukyo, Y.; Novak, P. Memory effect in a lithium-ion battery. *Nat. Mater.* **2013**, *12*, 569–575. [CrossRef] [PubMed]
3. Nita, N.; Wu, F.; Lee, J.T.; Yushin, G. Li-Ion Battery Materials: Present and Future. *Mater. Today* **2015**, *18*, 252–264. [CrossRef]
4. What's the Best Battery? Available online: http://batteryuniversity.com/learn/archive/whats_the_best_battery (accessed on 20 January 2017).
5. Armand, M.; Tarascon, J.M. Building better batteries. *Nature* **2008**, *451*, 652–657. [CrossRef] [PubMed]
6. Shahan, Z. Tesla's Battery Prices Falling Faster than Everyone Else's. Available online: https://cleantechnica.com/2016/06/08/teslas-batteries-cheaper-everyone-elses-knew-cool-ev-battery-charts (accessed on 20 January 2016).
7. Perez, R.; Zweibel, K.; Hoff, T.E. Solar Power Generation in the US: Too Expensive, or A Bargain? Available online: http://www.asrc.cestm.albany.edu/perez/2011/solval.pdf (accessed on 20 January 2017).
8. Why Moore's Law Does Not Apply to Clean Technologies. Greentech Media. Available online: http://www.greentechmedia.com/articles/read/why-moores-law-doesnt-apply-to-clean-technologies (accessed on 20 January 2017).
9. Singh, R.; Shenai, K. DC Microgrids and the Virtues of Local Electricity. *IEEE Spectrum*. 6 February 2014. Available online: http://spectrum.ieee.org/green-tech/buildings/dc-microgrids-and-the-virtues-of-local-electricity (accessed on 20 January 2017).
10. Singh, R.; Asif, A.A.; Venayagamoorthy, G.K. Transformative role of photovoltaics in phasing out alternating current based grid by local dc power networks for sustainable global economic growth. In Proceedings of the 43rd IEEE PV Specialist Conference, Portland, OR, USA, 5–10 June 2016.
11. Asif, A.A.; Singh, R.; Venayagamoorthy, G.K. Ultra-low cost and solar storm secured local DC electricity to address climate change challenges for all economies. In Proceedings of the IEEE-CU Power System Conference, Clemson, SC, USA, 8–11 March 2016. [CrossRef]
12. Lacey, S. How Distributed Battery Storage Will Surpass Grid-Scale Storage in the US by 2020. Available online: https://www.greentechmedia.com/articles/read/how-distributed-battery-storage-will-surpass-grid-scale-storage-in-the-us-b (accessed on 20 January 2017).

13. Fialka, J. World's Largest Storage Battery Will Power Los Angeles. Available online: https://www.scientificamerican.com/article/world-s-largest-storage-battery-will-power-los-angeles/ (accessed on 20 January 2017).
14. Singh, R.; Alapatt, G.F.; Lakhtakia, A. Making solar cells a reality in every home: Opportunities and challenges for photovoltaic device design. *IEEE J. Electron Devices Soc.* **2013**, *1*, 129–144. [CrossRef]
15. Advanced and Post Lithium-Ion Batteries 2016–2026: Technologies, Markets, Forecasts. Available online: http://www.prnewswire.com/news-releases/advanced-and-post-lithium-ion-batteries-2016-2026-technologies-markets-forecasts-300182252.html (accessed on 20 January 2017).
16. Transparency Market Research. Lithium-Ion Battery Market Is Projected to Reach US $77.42 bn in 2024; Global Industry Analysis, Size, Share, Growth, Trends and Forecast 2016–2024. Available online: http://www.marketwatch.com/story/lithium-ion-battery-market-is-projected-to-reach-us-7742-bn-in-2024-global-industry-analysis-size-share-growth-trends-and-forecast-2016---2024-tmr-2016-09-19 (accessed on 20 January 2017).
17. Kato, Y.; Hori, S.; Saito, T.; Suzuki, K.; Hirayama, M.; Mitsui, A.; Yonemura, M.; Iba, H.; Kanno, R. High-power all-solid-state batteries using sulfide superionic conductors. *Nat. Energy* **2016**, *1*, 16030. [CrossRef]
18. Hu, Y.S. Batteries: Getting solid. *Nat. Energy* **2016**, *1*, 16042. [CrossRef]
19. Gradne, L. Solid-State and Polymer Batteries 2017–2027: Technology, Markets, Forecasts. Available online: http://www.idtechex.com/research/reports/solid-state-and-polymer-batteries-2017-2027-technology-markets-forecasts-000498.asp (accessed on 20 January 2017).
20. Xu, C.; Lindgren, F.; Philippe, B.; Gorgoi, M.; Bjorefors, F.; Endstrom, K.; Gustafsson, T. Improved Performance of the silicon anode for li-ion batteries: Understanding the surface modification mechanism of fluoroethylene carbonate as an effective electrolyte additive. *Chem. Mater.* **2015**, *27*, 2591–2599. [CrossRef]
21. Grande, L.; Paillard, E.; Hassoun, J.; Park, J.B.; Lee, Y.J.; Sun, Y.K.; Passerini, S.; Scrosati, B. The lithium/air battery: Still an emerging system or a practical reality? *Adv. Mater.* **2015**, *27*, 784–800. [CrossRef] [PubMed]
22. Atacama, S.P. An Increasingly Precious Metal. *The Economist*. 14 January 2016. Available online: http://www.economist.com/news/business/21688386-amid-surge-demand-rechargeable-batteries-companies-are-scrambling-supplies (accessed on 21 January 2017).
23. Lambert, F. Tesla Is Now Claiming 35% Battery Cost Reduction at 'Gigafactory 1'—Hinting at Breakthrough Cost below $125/kWh. Available online: https://electrek.co/2017/02/18/tesla-battery-cost-gigafactory-model-3/ (accessed on 24 April 2017).
24. Tesla Powerwall. Available online: https://www.tesla.com/powerwall (accessed on 21 January 2017).
25. Mims, C. In Battery Revolution, a Clean Leap Forward. *Wall Street J*. 15 March 2015. Available online: http://www.wsj.com/articles/in-battery-revolution-a-clean-leap-forward-1426461806 (accessed on 21 January 2017).
26. Singh, R. Why silicon is and will remain the dominant photovoltaic material. *J. Nanophotonics* **2009**, *3*, 032503. [CrossRef]
27. There Enough Lithium to Maintain the Growth of the Lithium-Ion Battery Market? Greentech Media. Available online: http://www.greentechmedia.com/articles/read/Is-There-Enough-Lithium-to-Maintain-the-Growth-of-the-Lithium-Ion-Battery-M (accessed on 21 January 2017).
28. Deign, J. An Australian Company Says Its New Extraction Process Could Bring Unlimited Lithium Supplies. *Greentech Media*. 1 June 2015. Available online: https://www.greentechmedia.com/articles/read/new-process-promises-unlimited-lithium-supplies (accessed on 21 January 2017).
29. What Price Lithium, the Metal of the Future? Available online: http://fortune.com/2016/06/06/lithium-price-tesla-metal-future/ (accessed on 21 January 2017).
30. Bohlsen, Lithium Miner News for the Month of January 2017. Available online: http://seekingalpha.com/article/4040100-lithium-miner-news-month-january-2017 (accessed on 21 January 2017).
31. Cappel, R.; Sullivan, C.P. Yield and Cost Challenges at 16 nm and Beyond. Available online: http://electroiq.com/blog/2016/02/yield-and-cost-challenges-at-16nm-and-beyond/ (accessed on 21 January 2017).
32. Kundu, S.; Sreedhar, A. *Nanoscale CMOS VLSI Circuits: Design for Manufacturability*; McGraw-Hill, Inc.: New York, NY, USA, 2010.
33. Samsung Starts Industry's First Mass Production of System-on-Chip with 10-Nanometer FinFET Technology. Available online: https://news.samsung.com/global/samsung-starts-industrys-first-mass-production-of-system-on-chip-with-10-nanometer-finfet-technology (accessed on 21 January 2017).

34. Bhhuiyan, M.; Poddar, S.; Misra, D.; Tapily, K.; Clark, R.D.; Consiglio, S.; Wajda, C.S.; Nakamura, G.; Leusink, G.J. Impact of cyclic plasma treatment on oxygen vacancy defects in TiN/HfZrO/SiON/Si gate stacks. *Appl. Phy. Lett.* **2015**, *106*, 193508. [CrossRef]
35. Bhhuiyan, M.; Misra, D. Multilayered ALD $HfAlO_x$ and HfO_2 for high-quality gate stacks. *IEEE Trans. Device Mater. Reliab.* **2015**, *2*, 229–235. [CrossRef]
36. Smith, K.; Neubauer, J.; Wood, E.; Jun, A.; Pesaran, M. *Models for Battery Reliability and Lifetime Applications in Design and Health Management*; Battery Congress: Ann Arbor, MI, USA, 2013.
37. Singh, R.; Colombo, L.; Schuegraf, K.; Doering, R.; Diebold, A. *Guide to State-of-the-Art Electronic Devices in Semiconductor Manufacturing*, 1st ed.; Burghartz, J.N., Ed.; Wiley-IEEE Press: New Jersey, NJ, USA, 2013; pp. 121–132.
38. Shin, D.; Poncino, M.; Maci, E.; Chang, N. Statistical model of cell-to-cell variation in Li-ion batteries for system-level design. In Proceedings of the 2013 IEEE International Symposium on Low Power Electronics and Design (ISLPED), Beijing, China, 4–6 September 2013.
39. Santhanagopalan, S.; Guo, Q.; Ramdass, P.; White, R.E. Review of models for predicting the cycling performance of lithium ion batteries. *J. Power Sources* **2006**, *156*, 620–628. [CrossRef]
40. Stroe, D.; Swierczynski, M.; Stroe, A.; Kær, S.K. Generalized characterization methodology for performance modelling of lithium-ion batteries. *Batteries* **2016**, *2*, 37. [CrossRef]
41. Zhang, J.; Ci, S.; Sharif, H.; Alahmadm, M. Modeling discharge behavior of multicell battery. *IEEE Trans. Energy Convers.* **2010**, *25*, 1133–1141. [CrossRef]
42. Christen, R.; Rizzo, G.; Gadola, A.; Stock, M. Test method for thermal characterization of Li-ion cells and verification of cooling concepts. *Batteries* **2017**, *3*, 3. [CrossRef]
43. Santhanagopalan, S.; White, R.E. Quantifying cell-to-cell variations in lithium ion batteries. *Int. J. Electrochem.* **2012**, *2012*, 3295838. [CrossRef]
44. Wessof, E. SunPower Holds World Record for Most Efficient Rooftop Solar Panel again. Available online: https://www.greentechmedia.com/articles/read/SunPower-Again-Holds-Record-For-Worlds-Most-Efficient-Rooftop-Solar-Panel (accessed on 12 March 2017).
45. Asif, A.A.; Singh, R.; Alapatt, G.F. Technical and economic assessment of perovskite solar cells for large scale manufacturing. *J. Renew. Sustain. Energy* **2015**, *7*, 043120. [CrossRef]
46. Lu, L.; Han, X.; Li, J.; Hua, J.; Ouyanga, M. A review on the key issues for lithium-ion battery management in electric vehicles. *J. Power Sources* **2013**, *226*, 272–288. [CrossRef]
47. Stuart, T.A.; Zhu, W. Modularized battery management for large lithium ion cells. *J. Power Sources* **2011**, *196*, 458–464. [CrossRef]
48. Canney, W.M. Advanced Process Control Powers Developments in Operations Management. *Oil Gas J.* **2004**, *102*, 50–53.
49. Undey, C.; Ertunç, S.; Mistretta, T.; Looze, T. Applied advanced process analytics in biopharmaceutical manufacturing: Challenges and prospects in real-time monitoring and control. *J. Process Control* **2010**, *20*, 1009–1018. [CrossRef]
50. Harks, P.P.R.M.L.; Mulder, F.M.; Notten, P.H.L. In situ methods for li-ion battery research: A review of recent developments. *J. Power Sources* **2015**, *288*, 92–105. [CrossRef]
51. Bauer, M.; Craig, I.K. Economic Assessment of Advanced Process Control—A Survey and Framework. *J. Process Control* **2008**, *18*, 2–18. [CrossRef]
52. Thin Film Battery. Available online: http://www.ulvac.com/applications-products/app.cfm?cid=58&scid=156 (accessed on 23 January 2017).
53. Romanenko, K.; Jin, L.Y.; Madsen, L.; Pringle, J. Anisotropic MRI Contrast Reveals Enhanced Ionic Transport in Plastic Crystals. *J. Am. Chem. Soc.* **2014**, *136*, 15638–15645. [CrossRef] [PubMed]
54. Salameh, Z.; Casacca, M.; Lynch, W.A. A mathematical model for lead-acid batteries. *IEEE Trans. Energy Convers.* **1992**, *7*, 93–98. [CrossRef]
55. Young, K.; Wang, C.; Wang, L.Y.; Strunz, K. Electric Vehicle Battery Technologies. In *Electric Vehicle Integration*, 1st ed.; Garcia-Valle, R., Lopes, J.P., Eds.; Springer: New York, NY, USA, 2013; pp. 15–56.
56. Sikha, G.; White, R.E. Analytical expression for the impedance response for a lithium-ion cell. *J. Electrochem. Soc.* **2008**, *155*, A893–A902. [CrossRef]
57. Singh, R. Rapid isothermal processing. *J. Appl. Phys.* **1988**, *63*, R59–R114. [CrossRef]

58. Ratakonda, D.; Singh, R.; Vedula, L.; Rohatgi, A.; Mejia, J.; Narayan, S. Rapid thermal processing of screen printed ohmic contacts. *J. Electrochem. Soc.* **1997**, *144*, 3237–3242. [CrossRef]
59. Xue, Z.; Hu, L.; Amine, K.; Zhang, Z. High-speed fabrication of lithium-ion battery electrodes by UV-curing. *Energy Technol.* **2015**, *3*, 469–475. [CrossRef]
60. Knotts, J.; Morano, J. Next-generation wafer-level processing through customized materials. *Chip Scale Rev.* **2015**, *19*, 55–56.
61. Kang, J.; Conlisk, A.T.; Rizzoni, G. Integration of capacity fading in an electrochemical model of Li-ion batteries. *J. Solid State Electrochem.* **2014**, *18*, 2425–2434. [CrossRef]
62. Kanno, R.; Murayama, M. Lithium ionic conductor Thio-LISICON: The Li_2S, GeS_2, P_2S_5 System. *J. Electrochem. Soc.* **2001**, *148*, A742–A746. [CrossRef]
63. Ohta, N.; Takada, K.; Zhang, L.; Renzhi, M.; Osada, M.; Sasaki, T. Enhancement of the high-rate capability of solid-state lithium batteries by nanoscale interfacial modification. *Adv. Mater.* **2006**, *18*, 2226–2229. [CrossRef]
64. The Internet of Things: Mapping the Value beyond the Hype. Available online: http://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/The%20Internet%20of%20Things%20The%20value%20of%20digitizing%20the%20physical%20world/Unlocking_the_potential_of_the_Internet_of_Things_Executive_summary.ashx (accessed on 25 January 2017).
65. Turbide, T. Manufacturing Embraces the Industrial Internet of Things. Available online: http://searchmanufacturingerp.techtarget.com/opinion/Manufacturing-embraces-the-Industrial-Internet-of-Things (accessed on 2 February 2017).
66. Xu, L.D.; He, W.; Li, S. Internet of things in industries: A survey. *IEEE Trans. Ind. Inform.* **2014**, *10*, 2233–2243. [CrossRef]
67. Gartner. Five Ways the Internet of Things Will Benefit the Supply Chain. Available online: http://www.gartner.com/smarterwithgartner/five-ways-the-internet-of-things-will-benefit-the-supply-chain-2/ (accessed on 3 February 2017).
68. Morley, M. The Brilliant Disruptive Potential of IoT. Available online: http://www.itproportal.com/2015/03/28/the-brilliant-disruptive-potential-iot (accessed on 3 February 2017).
69. Bi, Z.; Xu, L.D.; Wang, C. Internet of things for enterprise systems of modern manufacturing. *IEEE Trans. Ind. Inform.* **2014**, *10*, 1537–1546.
70. Zhang, L.; Luo, Y.; Tao, F.; Li, B.H.; Ren, L.; Zhang, X.; Guo, H.; Cheng, Y.; Hu, A.; Liu, Y. Cloud Manufacturing: A New Manufacturing Paradigm. *Enterp. Inform. Syst.* **2014**, *8*, 167–187. [CrossRef]
71. Hartmann, B.; King, W.P.; Narayanan, S. Digital Manufacturing: The Revolution Will Be Virtualized. Available online: http://www.mckinsey.com/business-functions/operations/our-insights/digital-manufacturing-the-revolution-will-be-virtualized (accessed on 3 November 2016).
72. Fehrenbacher, K. Tesla Tried to Buy a Lithium Startup for $325 Million. Available online: http://fortune.com/2016/06/08/tesla-lithium-startup-simbol (accessed on 3 February 2017).
73. Nikačević, N.M.; Huesman, A.E.M.; Hof, P.M.V.; Stankiewicz, A.I. Opportunities and challenges for process control in process intensification. *Chem. Eng. Process. Process Intensif.* **2012**, *52*, 1–15. [CrossRef]
74. Sohn, S.Y.; Moon, H.U. Cost of ownership model for inspection of multiple quality attributes. *IEEE Trans. Semicond. Manuf.* **2003**, *16*, 565–571. [CrossRef]