AN ENGINEERING DESIGN APPROACH TO LITHIUM-ION CELLS - MODULAR KIT CONFIGURATION FOR AN INNOVATIVE TECHNOLOGY APPLICATION

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Abstract

Introducing a significant fleet share of electric or plug-in hybrid electric vehicles seems indispensable for vehicle manufacturers to fulfil CO2-emission regulations. The cost situation for lithium-ion batteries is one of the key limitations for the market potential of electric vehicles. This work introduces a value based engineering approach for the application in this specific technology.
General quantitative relations between cost and function are determined by using a detailed lithium-ion cell model, which links material properties, design parameters and costs to the key functions storable energy and available power.
The optimal cost situation is identified when the power to energy ratio of the cell directly matches the power and energy requirement of the vehicle. For a multiple project portfolio this implies a specific cell for each vehicle project. The potentially large number of cell types seems unfavorable for OEMs especially due to onetime expenses in development and validation. Therefore a genetic algorithm optimization is applied to determine the cost optimal electrode designs and number of cell versions to address an exemplary vehicle portfolio case.

Keywords: Design costing, Platform strategies, Optimisation, Lithium-Ion Batteries, Electric Vehicles

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1 INTRODUCTION

The actual CO2-effect of electric vehicles will heavily depend of the energy source mix used for power generation (Millo et al., 2014). Nevertheless vehicle manufacturers will need to equip a notable share of their fleet with electrified powertrains to comply with CO2-emission regulations (e.g. European Parliament, 2014). Currently one of the key limitations for the market potential of electrified vehicles is the cost situation of lithium-ion batteries (Sakti et al., 2014). Other energy storage or conversion technologies such as fuel cells are mostly in the development phase and do not seem to have substantial cost benefits over lithium-ion technology in the medium term (Chu et al., 2012 and McKinsey, 2010). The development of lithium-ion technology has been covered by several authors from industry and science, e.g. Nelson et al. (2012) and Berger (2012). Most of these studies conclude a cost per energy prognosis based on a description of the cell design and function or a material and supply chain evaluation. Ultimately these forecasts are likely to benefit all vehicle manufacturers.

In this paper it will be argued that vehicle manufacturers and lithium-ion cell suppliers are able to gain a competitive edge, by considering requirements more accurately for the cell design to avoid over-engineering and excessive costs. Beyond the optimization of the lithium-ion cell for one specific product this approach addresses the cost optimal layout of a modular cell kit for multiple applications.

2 ENGINEERING DESIGN APPROACH TO LITHIUM-ION TECHNOLOGY

A systematic engineering design approach seems indispensable for vehicle components to account for the large number of trade-off requirements (Vietor, 2011). In order to enable cost-focussed optimization of lithium-ion cells an engineering design approach tailored for this dynamic field of application is derived. As both phenomena - cost reductions and functional enhancements - have the potential to contribute to the advancement of the technology a value based approach was chosen. The inventor of value management Lawrence D. Miles (1961) defined the term *value* as a relation of function and cost. It is not intended to investigate specific engineering solutions based upon their *value*, but to derive general quantitative relations between cost and function. To enable a future roadmap for cell performance and cost the model needs to integrate new material data and apply technological improvements as modifications of the quantitative relation between cost and function.

The methodology chosen in this paper is depicted in Figure 1. It is based upon the definitions of "Functional Requirements" and "Design Parameters" as described in the Axiomatic Design Theory (Suh, 2001) and the Concept of Characteristics-Properties Modelling (Weber, 2008). The starting point of the design process in the application for lithium-ion cells is the solution set and the requirement set. The solution set is driven by the predicted availability of certain technologies (e.g. cathode materials) at the planned start of production of the lithium-ion cell. The requirement set is customer driven and might contain vehicle range or acceleration requirements. In the next step a cell model is derived in which the relations between the characteristics of the product design (e.g. electrode thickness) and the functions (e.g. maximum power) are determined or approximated. As the cell model provides a detailed description of the bill of materials for a certain cell design, the respective cost per function of this design can be calculated. The benefit of the model goes beyond calculation for specific cells since it makes use of the general relations between characteristics and functions. This enables the user of the model to determine the additional cost for incremental changes of one function or how this change affects other functions.

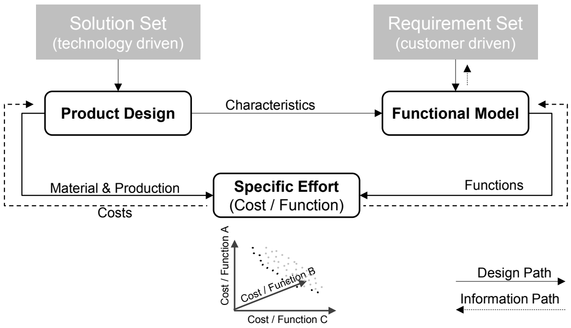

Figure 1. Cost Focussed Engineering Design Approach for Lithium-Ion Batteries

The lithium-ion application deviates from many mechanical design problems insofar as some of the characteristic-property relations are not fundamentally understood on physics level. The quantification of the relation between cell life and electrode properties would be an example (Vetter et al., 2005).
Another challenge of this application originates from uncertainty. On the one hand uncertainty is created from the fast changing technical solution set: As many new materials and innovative cell designs are currently under research, characteristics and properties are hard to predict for future years. However, this would be relevant to relate the vehicle engineering process to the energy storage technology available as automotive development cycles are usually greater than five years.
Ambiguities also occur on the requirement side. At this point, only few conventional car customers have experience with electrical vehicles. Therefore, customer studies need to be perceived with care: the degree to which e.g. range and power of an electric vehicle determine the buyer behaviour or justify higher pricing can hardly be predicted based on experiences of conventional products (Gourville, 2006).

2.1 Cell Modell

The developed lithium-ion cell model described in this section considers the design characteristics most critical for the cell function (*2.1.1*). These are the mass of the anode and cathode active material, the electrode thickness, the electrode area and the design of the housing.
Range is one of the most critical properties of electric vehicles. Therefore, it seemed reasonable to use *storable energy* (*2.1.2*) as one of the key functions in the cell model. *Available Power* (*2.1.3*) is currently one of the most differentiating functions of conventional vehicles - this also seems to apply to electrical vehicles. Therefore, *available power* and *storable energy* were considered two of the most important battery functions from the customer perspective (Lieven et al., 2011) (Lamp, 2013).

2.1.1 *Cell Design Characteristics*

Lithium-ion donor materials as cathodes and intercalation materials as anodes are considered *active materials* in the following. In most of the state of the art lithium-ion cell designs, lithium-transition oxides serve as cathode materials and graphites as anode materials. All other components that are necessary for the function of a lithium-ion cell (e.g. separator, electrolyte, current collectors, housing) do not contribute directly to the energy storage. These are considered *passive materials* respectively. The share of active and passive material in the lithium-ion cell is relevant for the cost of storable energy and the cost of power (Tschech et al., 2014).
The coating thickness of the cathode D_k was used as the variation parameter to modify between power-oriented and energy-oriented cells. The relationship to the other material parameters is described in equation 1. The porosity of the anode ε_a and the cathode $\varepsilon_k$was assumed 30 %. The mass of the anode active material $m_{AM,a}$ and cathode active material $m_{AM,k}$ is a fraction of the total anode and cathode masses m_a and m_k. The other portion of the electrode mass is binder and conductive carbon m_{BC}. Material properties such as specific active material capacities $c_{spez,AM}$ their densities ρ can be adapted for the materials to be investigated. In a constant cell volume, an anode-cathode area ratio of 1,085 and a capacity ratio of 1,05, the anode coating thickness D_a can be described as a function of the cathode coating thickness D_k by the following relationship:

$$D_a = \frac{\frac{1{,}05 * C_k}{c_{spez,AM,a} * \frac{m_{AM,a}}{m_a}} / (\rho_{AM,a} * \frac{m_{AM,a}}{m_a} + \rho_{BL,a} * \frac{m_{BC,a}}{m_a}) / (1 - \varepsilon_a)}{\frac{C_k}{c_{spez,AM,k} * \frac{m_{AM,k}}{m_k}} / (\rho_{AM,k} * \frac{m_{AM,k}}{m_k} + \rho_{BL,k} * \frac{m_{BC,k}}{m_k}) / (1 - \varepsilon_k)} * 1{,}085 * D_k \qquad (1)$$

The considered geometric cell formats for this investigation were VDA standardized prismatic cells (Deutsches Institut für Normung, 2011) and the cylindrical 18650-consumer cell format.

2.1.2 *Cell Function - Storable Energy*

Applying the same operating conditions temperature, state of charge (SOC), charge and discharge rates, the storable energy of the cell linearly correlates with the mass of the anode and cathode active material. Data of the active materials currently available for anode and cathode including their densities, specific capacities and electrical potentials were taken from Ozawa (2009), Graf (2013) and Reddy (2013). The energy of the cell is calculated for material at low discharge rates (1/3-1/10C), assuming an irreversible capacity of the active material of 10 % (Han et al., 2004).

2.1.3 ***Cell Function - Available Power***

To determine the maximum cell power a state of equilibrium between the thermal power generated by the internal resistance of the cell and maximum dissipated heat is presumed. The considered state of charge (SOC) is 90 %. For a Lithium-Nickel-Cobalt-Manganese-Oxide cathode with a one third composition of Ni, Co and Mn (NMC-111) the specific voltage at 90 % SOC is U_{SOC90} = 4,05 V. This was considered as the starting voltage of the pulse. For the maximum power the following term applies:

$$P_{max} = U_{SOC90} * I_{max} - P_{loss} \tag{2}$$

The maximum cell power is available when the transmittable thermal power P_{out} corresponds to the power loss P_{loss} generated by the internal resistance of the cell R_i :

$$P_{out} = P_{loss} = R_i * {I_{max}}^2 \tag{3}$$

The relationship between generated and transmitted thermal power is a simplified description of the actual thermodynamic relation in the cell. The assumption is conservative but seems reasonable as cell life is strongly affected by high temperatures. Using a detailed thermodynamic cell is promising for the identification of ways to increase the maximum power. An example for maximum power values being higher than described by equation 2 would be a sufficient heat capacity of the cell to absorb the heat loss of the internal resistance. In this case the cell performance would not be limited by the transmittable thermal power P_{out} but by local hot spots on the electrode surface.

For further considerations it is necessary to describe the relation between the electrode surface and the cell maximum power. A constant resistance per electrode area unit $R_{spez,A}$ is assumed. The internal resistance of the cell can be scaled to the electrode surface A_0 using the following term:

$$R_{spez,A} = R_0 * A_0 = R_1 * A_1 \tag{4}$$

The underlying internal resistance R_0 is determined as ~ 0.8 mΩ from a measurement of layered oxide cathode with an area A_0 of 4 m² at 90 % SOC and 25 °C. In a fully used cell volume the maximum cell power can be described as a function of the electrode surface:

$$P_{max} = U_{SOC90} * \sqrt{\frac{P_{out}}{R_0 * A_0} A_1} - P_{loss} \tag{5}$$

At constant $R_{spez,A}$ the maximum current I_{max} and thus the maximum cell power P_{max} can be expressed as a square root function of the electrode surface.

This is a simplification since the internal resistance of the cell is assumed to be independent of the coating thickness of the electrode. Nevertheless this approximation seems reasonable because

- considering the same volume utilization in a cell housing larger electrode surfaces at the same time directly lead to smaller electrode thicknesses and
- the area-specific impedance behaves constant in a wide range at moderate discharge rates, as studies of the Argonne National Laboratory show (Gallagher et al., 2009).

The surface of the cell housing is considered as an additional scaling factor for maximum power. The reference dissipated heat was assumed to be 100 W ($P_{out,0}$) for the can surface $A_{can,0}$ of the VDA standardized *EV2* format (Deutsches Institut für Normung, 2011). The maximum heat dissipation of a cell with the can surface $A_{can,1}$ can be described as following:

$$P_{out,1} = P_{out,0} * \frac{A_{can,1}}{A_{can,0}} \tag{6}$$

Summarized, the maximum power at SOC 90% can be described as a function of the electrode area A_1 and the can surface $A_{can,1}$:

$$P_{max} = U_{SOC90} * \sqrt{P_{out,0} * \frac{A_{can,1}}{A_{can,0}} / (R_0 * A_0) / A_1} - P_{out,0} * \frac{A_{can,1}}{A_{can,0}} \tag{7}$$

2.2 Cost Optimal Design of Li-Ion Cells for Specific Vehicle Projects

To determine the relation shown in Figure 2 certain material properties needed to be assumed. NMC-111 was considered cathode material and artificial graphite anode material. Binder and conductive carbon had a weight share of the electrode material between 3 % and 10 %. Furthermore, the model considers a coated single-layer polyethylene separator with a thickness of 25 µm. The electrolyte mass in the cell was obtained by assuming an electrolyte density of 1.3 g/cm³. The electrolyte volume corresponds to the pore volume of the separator, the cathode and the anode coating. In order to describe the relations of storable energy, power and cost the coating thickness of the cathode were varied between 10 µm and 100 µm. The anode layer thickness was derived from the cathode thickness based on equation 1. Maximum volume utilization of the electrode roll in the respective cells was considered in each case, taking into account typical dimensions for connectors within the cell (Tschech et al., 2014).

Results of the cell model describing the influence of different housings on cell costs and performance are depicted in Figure 2. The costs are described per energy unit on the y-axis. They are expressed as a function of the power-to-energy-ratio (P/E-ratio) of the cell on the x-axis. Larger P/E-ratios lead to higher cost per energy, as the energy per cell decreases by reduced active material content. At the same time the cost per cell slightly increases since separator and copper foil cost exceed those of the electrode coating per volume unit based on the considered cost data for cell materials (Appendix, Table 2). From Figure 2 it can be concluded that the relation between P/E-ratio and cost per energy is close to linear based on the assumptions of the cell model. The relation between P/E-ratio of the cell and cost per kWh can be approximated by the following linear correlation, where $c_{celltype}$ is the cost per energy for one specific cell type. Changes of any design feature or material property lead to a change of the line equation. In Figure 2 cell types are differentiated by geometric format.

$$c_{celltype} = m_{celltype} * \left(\frac{P}{E}\right) + b_{celltype} \qquad (8)$$

Due to the simplification of the power calculation assumptions equation 8 should be considered an approximation of the relation between cost and function. Nevertheless it correlates well with cell models results in the literature (Sakti et al., 2014).

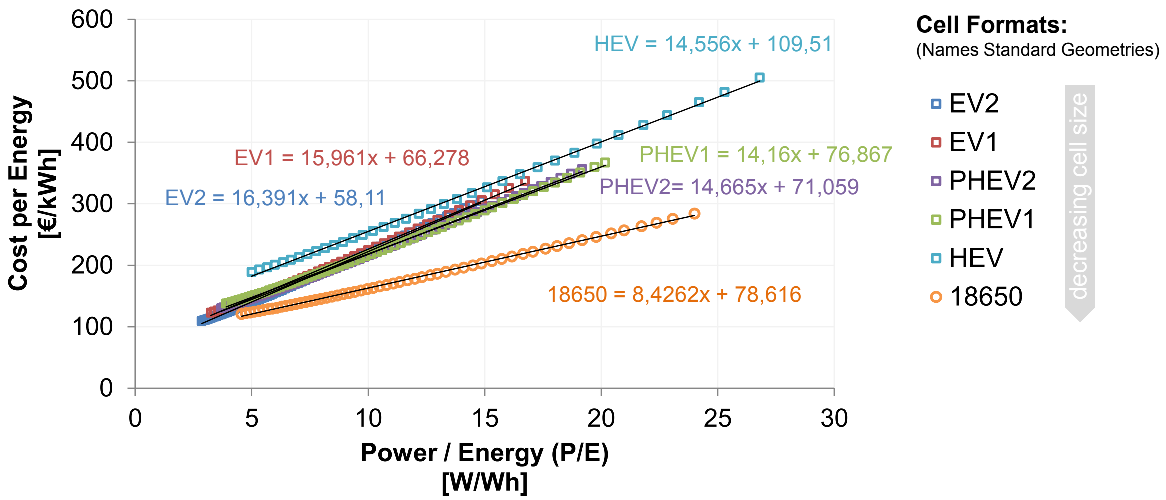

Figure 2. Power-Energy-Cost Relation (Cost Data: Table 2, Exchange Rate: 1,30 $/€)

The cost difference between small and large cell formats can be explained by the power assumptions of the cell model. Smaller prismatic formats have a larger y-axis intercept $b_{celltype}$ and smaller slope $m_{celltype}$ than most of the larger formats. The y-axis intercept is mainly determined by the cost share of active to passive material. Therefore large format prismatic cells and the inexpensive 18650 cylindrical cell concept have an advantage. The slope depends mainly on the power capability of a cell, e.g. it is driven by the relative surface to volume ratio. Small formats have an advantage of a flat slope due to their high surface to volume ratio. This enables good heat dissipation (Equation 8). Large cells have an advantage in energy driven applications whereas small formats are favourable for

applications with high power requirements. The intersection of the graphs points out the P/E-ratio at which it would be beneficial from a cost standpoint to switch to another cell format.
Based on this analysis the lithium-ion cell should precisely match the requirements of the powertrain for a cost optimal utilization. An oversizing of the P/E-ratio, i.e. the available power, would lead to unnecessary high costs per storable energy unit (€/kWh). If a P/E-ratio below the requirements of the vehicle is chosen, an oversizing of the energy content would be necessary in order to fulfil power requirements. It would overcompensate the lower cost per kWh of a smaller P/E-ratio.

2.3 Cost Optimal Design of Li-Ion Cells in Multiple Vehicle Projects

As described above an ideal fit of P/E-ratio of the cell and the vehicle requirements should be targeted to reach minimum costs. This implies the cell design should be specifically adapted to each vehicle project it is planned to be used in. However, this would lead to a dedicated cell to be developed and validated for each vehicle project. Such a strategy contradicts the usual automotive development process tailoring modular kits to reduce the number of component variants. Therefore, the methodology described in this section aims to identify the optimal configuration of a cell modular kit for a multi-project vehicle portfolio. It solves the trade-off between:

- many cell variants, a good match of requirements and solutions, high onetime expenses
- few cell variants, oversizing energy or power and low onetime expenses.

The approach is described by using an exemplary vehicle portfolio as shown in Table 1. It is derived by projecting the current offer of electrified vehicles for a usual vehicle development cycle of five to seven years. Battery electric vehicles are assumed to be launched in the compact (C) and midsize (D, E) segment, each with three versions - budget, comfort and sport. Today the compact segment is served for example by the Volkswagen eGolf, BMW i3, Nissan Leaf while the Tesla Model III is announced in the midsize segment. In the luxury segment (F) an electric vehicle and a power oriented plug-in electric vehicle (PHEV) such as the current Fisker Karma or Tesla Model S is anticipated. Energy and power requirements are broken down to battery level. Due to the efficiency loss of the inverter and electric motor this means available power output on the wheel will be around 85-90% (Ahman, 2000) of the battery power. Furthermore, the energy relevant for providing the required range of the electrified vehicle will be lower than the described installed energy. In a battery electric vehicle (BEV) around 15% of the installed battery capacity is not useable due to deep discharge prevention and voltage measurement inaccuracy. Due to high power requirements in a PHEV the shrinking voltage at lower SOC reduces the unusable energy around 30% for PHEV applications. Methods to identify the cost optimal configuration of a modular cell kit need to consider planned vehicle quantities as they may serve as a weight function for the decision of optimal P/E cell designs.

Table 1. Example Vehicle Portfolio (fictional)

Battery Power [kW]	Battery Energy [kWh]	Power / Energy Ratio [1/h]	Vehicle Segment
100	25	4,0	BEV (C-Segment)
120	30	4,0	
150	35	4,3	
150	50	3,0	BEV (D&E Segment)
200	40	5,0	
250	60	4,2	
320	25	12,8	PHEV (F-Segment)
400	85	4,7	BEV (F-Segment)

In Figure 3 the vehicle portfolio is illustrated in a power to energy (P/E) diagram. The x-axis represents the installed energy while the y-axis indicates the battery power. The blue circles represent the vehicle projects. The center of each circle represents the power and energy requirement for the respective vehicle's battery. The cell costs in are determined by the P/E-ratio of the (initially randomly) chosen cell design which is represented by the P/E line. The P/E-ratio is characteristic for one specific cell design. Along the P/E line the storable energy and available power of a battery can be scaled by adding cells of the same design. By doing so the ratio of power and energy remains constant. Power and energy requirements that are not on the P/E line cannot be fulfilled without either:

- establishing a new cell design with a P/E-ratio that exactly matches the vehicle requirement
- keeping only the one considered cell and oversizing either power or energy content by adding more cells to the battery pack

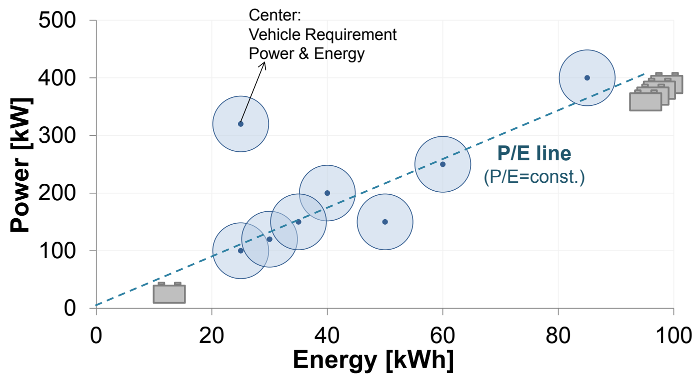

Figure 3. P/E Cell Design in Vehicle Portfolio

To calculate the cell cost per vehicle two cases need to be considered as shown in Figure 4. Case 1 describes a situation where the P/E-ratio of the chosen cell design is smaller than the required P/E-ratio of the vehicle's battery. In this case the power requirements would not be fulfilled if only the required energy of the vehicle $E_{vehicle}$ times the planned vehicle quantity $Q_{vehicle}$ would be implemented. Instead an oversizing of the vehicle's energy content would be necessary to fulfil the power requirements. The oversized energy content is represented by the distance between the energy requirement of the vehicle and the cell energy at the point of the same power (Figure 4). The oversizing of the energy can be expressed as the quotient of the P/E-ratio of the vehicle requirements and the P/E-ratio of the considered cell:

$$C_{cell,vehicle} = \left(m_{celltype} * \left(\frac{P}{E}\right)_{cell} + b_{celltype}\right) * E_{vehicle} * Q_{vehicle} * \frac{\left(\frac{P}{E}\right)_{vehicle}}{\left(\frac{P}{E}\right)_{cell}} \quad (9)$$

In Case 2 the P/E-ratio of the considered cell is larger than the P/E-ratio of the vehicle. The cost per energy of the respective P/E-ratio of the cell only needs to be multiplied by the required energy of the vehicle. As the P/E-ratio for the cell exceeds vehicle requirements in this case the power of the battery is oversized. The oversized power is represented in by the distance between the power requirement of the vehicle and the cell power at the point of the same energy content (Figure 4).

$$C_{cell,vehicle} = \left(m_{celltype} * \left(\frac{P}{E}\right)_{cell} + b_{celltype}\right) * E_{vehicle} * Q_{vehicle} \quad (10)$$

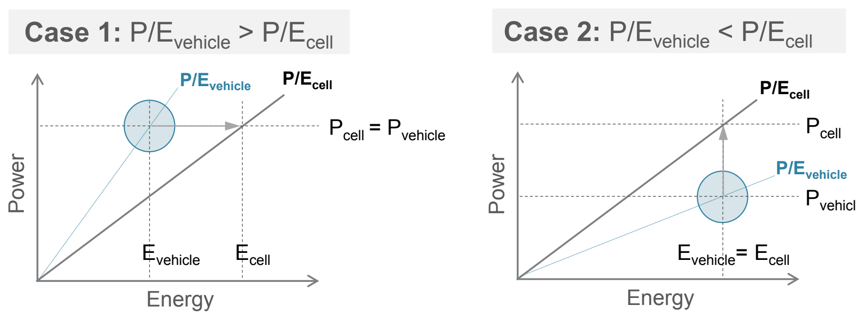

Figure 4. Cases for Calculation of Cell Cost per Vehicle

To identify the cost optimal cell design, the sum of the cost differences d between the P/E line and all (t) vehicle requirements needs to be minimized. As the vehicles planned quantities vary the cost impact of the vehicle projects differ significantly. Therefore the cost difference d_n of the vehicle project (n) includes the weighting by the respective vehicle quantity Q_n. The ideal P/E-ratio of one cell serving the whole vehicle portfolio can be identified by solving the optimization problem:

$$\min \sum_{n=1}^{t} \min d_n \quad (11)$$

For the optimization of more than one cell design (j) the cost differences for each vehicle need to be compared to each P/E line of the m considered cells. For each of the vehicle projects the P/E line with the minimum cost is identified out of the considered cells. As illustrated in Figure 5 this approach is a comparison of the cost effect of power oversizing (exemplified by $d_{2,1}$) and energy oversizing (exemplified by $d_{2,2}$). The optimization problem of multiple (m) P/E lines for a vehicle portfolio with t different power-to-energy requirements could be expressed as:

$$\min \sum_{n=1}^{t} \min_{1 \leq j \leq m} d_{n,j} \qquad (12)$$

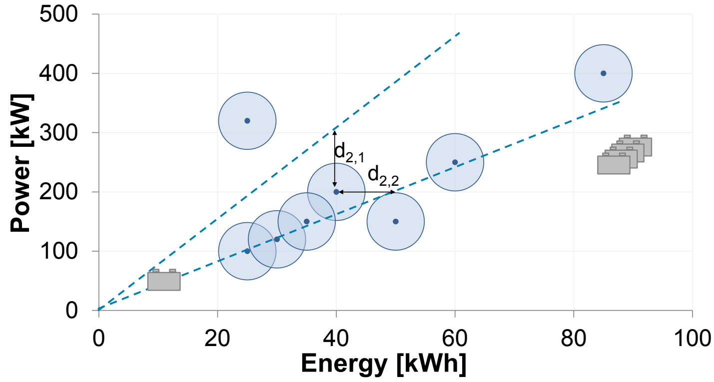

Figure 5. Optimization of Multiple P/E Cell Designs

As an example the optimization for more than one cell design is applied to the vehicle portfolio of Table 1. The P/E-ratios vary from 3,0 (BEV D/E-Segment) to 12,8 (PHEV F-Segment). For this portfolio five optimal P/E-ratios should be determined and no solutions are assumed outside the boundary of $P/E_{min} = 3{,}0$ and $P/E_{max} = 12{,}8$. The area between maximum and minimum P/E-ratio is scanned in 0,1 steps. This leads to approximately 67,91million solutions for P/E-ratio combinations. If the optimization algorithm ran systematically through all combinations based on equation 11, this would lead to 40 calculations (5 P/E cell designs, 8 vehicle projects) per set of P/E-ratio combination. Hence, about 2,72 billion operations would be needed to identify the optimal 5 P/E configurations.

For numerical optimization methods this already shows that a systematic full scanning of the solution space does not seem reasonable. Restrictions of the solution space as the limitation of cell numbers due to discrete operation voltage levels of currently available inverters would even further increase the complexity of the problem. Therefore a heuristic approach was chosen and a genetic algorithm (GA) was implemented. Similar to other directed heuristic optimization techniques, GAs reduce the calculation time significantly by selection of new chromosome generations based on their *fitness* relative to the optimization criteria. This optimization criterion was the accumulated cell cost for all vehicles of the portfolio. The P/E-ratios were the considered chromosomes in this application. The used optimization algorithm was GAnetXL by Savić et al. (2011).

The result of the optimization process for the exemplary vehicle portfolio is shown in Figure 6. The four identified P/E-ratios cover the full range of P/E requirements and each match one of the vehicle requirements directly.

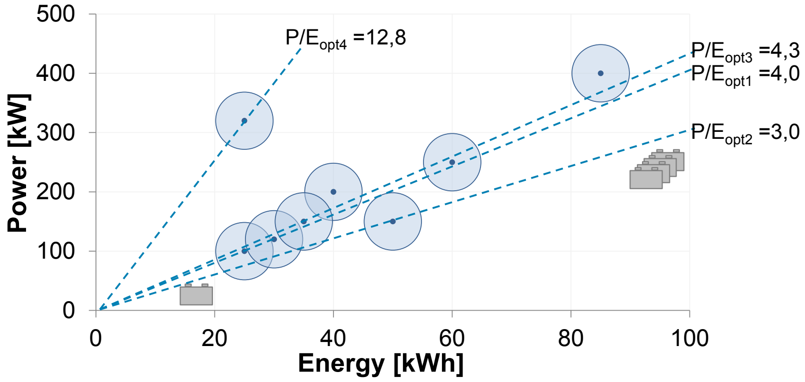

Figure 6. Cost Optimal Set of P/E-ratios for Example Vehicle Portfolio

In addition to the cost optimal P/E values the model intends to identify the optimal number of P/E cell variants. As long as the number of different vehicle requirements is larger than the number of P/E cell designs adding additional P/E designs is favourable from a variable cost perspective. In this case every additional P/E cell design reduces the average oversizing of the battery. As soon as the number of cells

reaches the number of different P/E vehicle requirements additional P/E cell designs would not cause costs benefits anymore, since all requirements could be already matched by one P/E cell design.
However, from a onetime-expense perspective, a limited number of component versions is beneficial since costs for development and validation, production changes and the provision of spare parts can be reduced. For validation a total of 200 prototype battery packs with 50 kWh are assumed. With this premises a cost optimum of 4 P/E designs is identified for the vehicle portfolio of Table 1 (Figure 7).

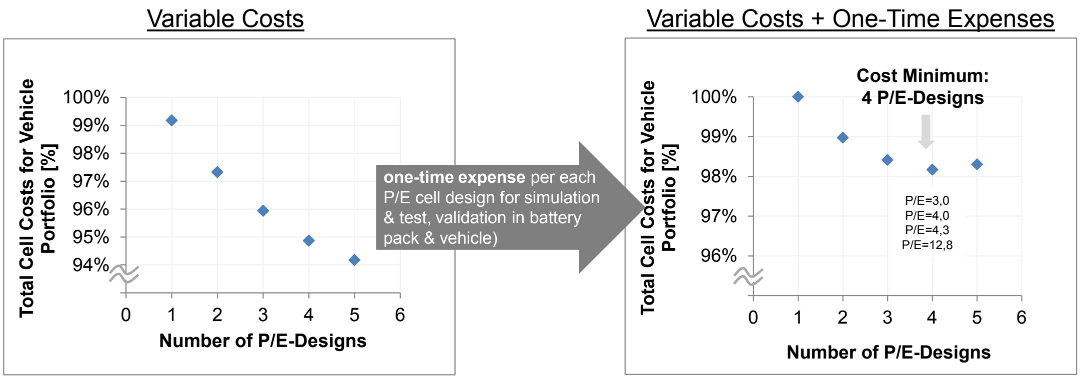

Figure 7. Cost Optimal Number of Cell Designs

3 CONCLUSION AND DISCUSSION

In this paper an engineering design approach supporting the development process of cost optimal lithium-ion cells based on vehicles requirements was introduced. The concept can be considered an expansion of value engineering idea as it focuses on utilizing quantitative relations between function and costs for applications in dynamic technology environments like lithium-ion cells. Using a detailed cell model a quantitative relation between the available power, storable energy and the correlated cost is derived and approximated as a linear equation. This model enables a flexible integration of new material properties, e.g. specific capacities and densities for future cathodes or anodes. The derived relations were used to determine the cost implication of different cell designs based on the requirements of vehicle projects. It was shown that the approach could not only be used for optimization according to one specific set of requirements, but successfully applied to a whole product portfolio. Based on the requirements of vehicle drivetrains and the available lithium-ion technology the cost optimal modular kit of lithium-ion cells was identified. This optimal modular cell kit is described by the number of cell versions and their P/E-ratios.
Further research needs to be conducted to account for the effect of voltage restriction of the inverter, as it is assumed to counterbalance the cost benefit of larger cells by the more flexible integration of small cell formats. For more detailed power calculations enhanced thermal modelling of the cell and pack should be considered.

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APPENDIX

Table 2. Cost Data most optimistic last two years (Berger, 2012), (Nelson et al., 2012), (Rempel et al., 2013) and (Brodd et al., 2013)

	Component		Cost		Source
Material Cost	Cathode	NMC-111	24,50	$/kg	Berger, 2012
	Anode	Graphite	18,00	$/kg	Berger, 2012
	Binder	PVDF	10,00	$/kg	Nelson et al., 2012
	Binder	CMC/SBR	10,00	$/kg	Nelson et al., 2012
	Conductive Carbon	Carbon Powder	6,80	$/kg	Nelson et al., 2012
	Electrolyte	LiPF6, Solvent	17,00	$/kg	Rempel et al., 2013
	Separator	Monolayer PE Coated	1,50	$/m²	Rempel et al., 2013 (+$0,50 ceramic)
	Anode Foil	Copper	16,85	$/kg	Nelson et al., 2012
	Cathode Foil	Aluminium	9,83	$/kg	Nelson et al., 2012
	Can & Cap	EV	5,35	$/Pcs.	Rempel et al., 2013 (scale surface)
	Can & Cap	PHEV	3,30	$/Pcs.	Rempel et al., 2013 (plus surcharge hardcase)
	Can & Cap	HEV	2,28	$/Pcs.	Rempel et al., 2013 (scale surface)
	Can & Cap	18650	0,17	$/Pcs.	Brodd et al., 2013 (q350Mio cells/Y)
Producti	EV		7,34	$/Pcs.	Nelson et al., 2012 (scale to capacity)
	PHEV		4,55	$/Pcs.	Nelson et al., 2012 (scale to capacity)
	HEV		3,44	$/Pcs.	Nelson et al., 2012(scale to capacity)
	18650		0,33	$/Pcs.	Brodd et al., 2013 (350Mio cells/Y)
O	Overhead & Profit		16%		Berger, 2012