Structural Analysis for Fault Diagnosis and Sensor Placement in Battery Packs

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Abstract—Energy storage systems for transportation and grid applications, and in the future for aeronautical applications, require the ability of providing accurate diagnosis to insure system availability and reliability. In such applications, battery packs may consist of hundreds or thousands of interconnected cells, and of the associated electrical/electronic hardware. This paper presents a systematic methodology for approaching some aspects of the design of battery packs, and in particular the development of diagnostic strategies, using cell models and structural diagnosis methods. First, the analytical redundancy that is intrinsic in the battery system is determined. Then, graph-theoretic tools are used to construct general structural models of two common battery pack topologies, and illustrate how the redundancy present in different measurements (current, voltage, and temperature) can be used to improve monitoring and diagnosis of a battery system. Possible sensor placement strategies that would enable the diagnosis of individual sensor faults and individual cell faults for different battery topologies are analyzed as well. While the work presented in this paper is only one step in the design of a large battery pack design, it is an important and needed advancement.

Index Terms—battery pack, fault diagnosis, structural analysis, analytical redundancy, sensor placement.

I. INTRODUCTION

Among the energy storage technologies, lithium-ion batteries (LIB) have demonstrated great capability in improving system efficiency, emissions, management of uncontrollable sources (e.g., renewable resources, regenerative braking), controllability and power quality, system level reliability, delay system expansion/investments, weight, flexibility and modularity in several energy applications. Major automotive companies around the world are researching and launching electric vehicles [1]. The aircraft industry and federal agencies, such as NASA, have also invested in the research on more electric aircraft that can transport both people and cargo [2, 3]. Similarly, electric utilities are seeking to use energy storage as a cost-effective way of supporting renewable power production and distribution [4, 5]. While LIB are characterized by high energy/power density, negligible memory effect and low self-discharge rate when compared to other energy storage technologies, their widespread use is usually limited by [7, 9]: i) reliability and durability of the performance at extreme conditions or over time; ii) design of cells and battery systems that satisfy safety requirements; iii) complexity of large-scale battery pack; iv) weight overhead of Battery Management System (BMS), sensing, packaging, and cooling; v) charging rate limitation, especially when high energy density cells are considered; and vi) cost.

Nevertheless, the integration of LIB in a system usually requires that battery cells are connected in series and/or in parallel to form modules, which then are assembled into battery packs to meet the energy and power requirements of vehicles and grid applications, resulting in systems that are large-dimensional and that have complex interconnections [8]. One of the open problems is the ability to properly monitor the operation of such complex systems, and to diagnose their health. When assembling a large battery pack, two fundamental topologies are commonly used: parallel-series, and series-parallel [8, 10], as shown in Fig. 1 where $i$ is the series index and $j$ is the parallel index. A battery pack is composed by $n \times m$ cells, where $n$ indicates the number of elements in series and $m$ the number of elements in parallel. The behavior of a battery pack cannot be modeled by understanding the behavior of a single cell, as the complex interconnections of cells and modules causes interactions that may limit the system performance. Because of differences in cell electrical and thermal characteristics and in cell aging, the energy/power density and the durability and safety of the battery packs will be reduced to a certain extent compared with individual cell [11]. It is therefore very important to understand the behavior of large battery pack systems, which are defined by their electrical topology, by their cooling system architecture, and by the design of their battery management system. Among them, efficient sensing and fault tolerant design are important elements in the design of a battery pack. In this paper we focus on one particular aspect of the battery pack system design: the ability to diagnose faults and failures.

Methods for fault diagnosis for lithium-ion battery systems can be classified into model-based, knowledge-based, and data-driven ones [12]. The most widely used knowledge-based methods include graph theory-based (fault tree analysis) [13], expert system [14], and fuzzy logic-based [15]. These diagnostic methods employ the basic knowledge and real-time observation of the battery system. Although the principle is easy to understand, before the fault diagnosis decision is made, further research is needed on the fault mechanism, knowledge acquisition and knowledge representation. Data-driven methods include signal processing [16–19], machine learning [20–22], and information fusion [23]. The advantage of these methods is that they can directly analyze and process operating data to detect failures without relying on models. The limita-

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The subject of battery pack modeling is complex, as it may require consideration of electrochemistry, electrical system, thermal behavior, and control (BMS that is responsible for charge equalization, thermal management, safety etc.) [10], [54]. In this paper we are focused on describing the systems aspects of the battery pack, and in particular the interaction between the electrical and thermal behavior of the elements with sensing and monitoring systems. Thus, equivalent electrical circuit models (ECMs) and lumped-parameter heat exchange models [55], [56] are usually adopted for system level fault diagnosis, thanks to the possibility of locating voltage, current and temperature sensors. For simplicity, a zeroth order ECM is employed as the basis of the analysis of this paper. Note that the methodology proposed in this paper can be extended to higher order ECMs. The equations below describe a basic electrothermal model that captures the essential behavior of the generic $ij$ battery cell. The model is composed of 4 constraints
(c₁, c₂, c₃, c₄).

\[ c_1 : V_{ij} = V_{oc,ij} - R_{ij}I_{ij} \]  
\[ c_2 : \frac{dSoC_{ij}}{dt} = -\frac{I_{ij}}{Q_{ij}} \]  
\[ c_3 : V_{oc,ij} = f(SoC_{ij}) \]  
\[ c_4 : m_{cp} \frac{dT_{ij}}{dt} = R_{ij}(I_{ij})^2 - Q_{TM,ij} \]

where, \( V \) represents the cell terminal voltage, \( I \) represents the input current. Eq. (1) is the calculation of state of charge (SoC) using the Coulomb counting method where, \( Q \) is the cell capacity. The open circuit voltage \( (V_{oc}) \) is a function of the SoC, as shown in Eq. (2). Based conservation of energy, Eq. (3) shows the energy conservation equation of a cell including the heat generation \( (RI^2) \) and the heat extracted by the thermal management \( (Q_{TM}) \). \( T \) is the temperature of the cell. \( m \) represents cell mass and \( c_p \) the specific heat capacity at constant pressure. For the purpose of structural analysis, we assume that the \( R \) and \( Q \) are constant and not dependent on SoC and \( T \).

For the battery pack architectures shown in Fig. 1 an electrical model can be derived applying Kirchhoff’s Laws and including a load current \( I_{BP} \). For example, in the \( nSmP \) topology:

\[ \sum_{j=1}^{m} I_{ij} = I_{BP} \quad (i = 1 \ldots n) \]  
\[ V_{i1} = \cdots = V_{ij} = \cdots = V_{im} \quad (\forall i = 1 \ldots n) \]  

For \( mPnS \) topology:

\[ \sum_{j=1}^{m} I_{j} = I_{BP} \quad (I_{ij} = I_j \quad \forall i = 1 \ldots n) \]  
\[ \sum_{i=1}^{n} V_{i1} = \cdots = \sum_{i=1}^{n} V_{ij} = \cdots = \sum_{i=1}^{n} V_{im} \quad (\forall j = 1 \ldots m) \]  

B. Structural model of battery

Structural analysis investigates the model constraint structure \[35\], i.e., the connections between known variables, unknown variables, and faults. No matter what type of model is used, one can generate a corresponding structural model in the form of a bipartite graph. These mathematical equations can be a set of algebraic equations, derivative equations or just a function to describe the relationship between variables. A structural representation is a bipartite graph with a set of system constraints, variables and edges \( (C, Z, \text{and } \varepsilon, \text{respectively}) \). The set of variables \( (Z) \) include unknown variables \( (X) \) and known variables \( (K) \). The constraints for a single cell are listed in Eqs. (1)-(4), where \( i = 1, j = 1 \). The model has 4 constraints \( C = \{c_1, c_2, c_3, c_4\} \) and 5 unknown variables \( X = \{V_{11}, I_{11}, V_{oc,11}, SoC_{11}, T_{11}\} \). The bipartite graph of the single cell system is shown in Fig. 2 where variables are represented by circles while the constraints are represented by bars. An edge connects a variable and a constraint and it is not oriented. A structural model may also be represented by a corresponding incidence matrix in which the rows represent system constraints and the columns represent variables. The elements of the incidence matrix are defined as follows: if a variable appears in a constraint, the element is 1, otherwise 0. The incidence matrix of the single cell system is shown in Table I.

C. Matching on a structural model

The basic principle of structural analysis is to find matchings, that is, causal assignments between unknown variables and the constraints in a structural model. If an unknown variable is matched with a constraint, it can be calculated from this constraint. If an unknown variable is not matched, it cannot be calculated. If there are multiple ways for unknown variables to be matched, the resulting analytical redundancy can potentially be used for fault detection and isolation. An accurate definition of matching can be found in [35]. Basically, if we employ bipartite graph as the structural model, a matching is a subset of \( \varepsilon \). Any two edges in a matching do not share common node \( (C \text{ or } Z) \), which means it associates one constraint with one specific variable. Matching is not unique, as different matchings may be found for a system. Fig. 3 lists three possible matchings for the single cell system. The black thinner lines represent unmatched edges, while the red bold lines represent matched edges. A matching can be further defined as a complete matching based on the number of edges \( (|\varepsilon|) \), constraints \( (|C|) \), and variables \( (|Z|) \) contained in the matching. A matching is said to be: i) complete with respect to \( C \) if \( |\varepsilon| = |C| \); ii) complete with respect to \( Z \) if \( |\varepsilon| = |Z| \); iii) if only unknown variables \( (X) \) are considered, a matching is said to be complete if \( |\varepsilon| = |X| \). In Fig. 3, (a) and (b) are two complete matchings with respect to constraints; (c) is an incomplete matching.

When no measurement is considered, a single cell system has \( X = 5 \) and \( C = 4 \), thus a complete matching can be find only with respect to constraints. In fact, the system of Eqs.
The degree of the analytical redundancy (AR) circles represent faults. matched edges, blue circles represent known variables and red on bipartite graph, see Fig. 4(b). The red lines represent the a complete matching with respect to unknown variables can be achieved by adding the following constraints to the following equation:

\[ y_u = u + f_{y_u} \]  

where \( y \) denotes the real time sensor reading and is a known variable, \( f_y \) denotes the sensor fault (\( f \neq 0 \) indicates that the sensor failed). \( u \) is the actual value of the sensed current, voltage or temperature.

As example, a complete matching of the system of Eq.s 1-4 can be achieved by adding the following constraints to measure current and voltage of the single cell:

\[ c_5 : y_{t_{11}} = I_{11} + f_{y_{t_{11}}} \]  
\[ c_6 : y_{V_{11}} = V_{11} + f_{y_{V_{11}}} \]  

The model includes 6 constraints and 5 unknown variables. The degree of the analytical redundancy (AR) becomes 1 and a complete matching with respect to unknown variables can be found, as shown in Fig. 3(a). Matching can be reflected on bipartite graph, see Fig. 4(b). The red lines represent the matched edges, blue circles represent known variables and red circles represent faults.

\[ AR_{single\ cell} = 1 \quad \text{when} \quad \exists y_{t_{11}} \text{ and } y_{V_{11}} \]  

\[ IAR_{single\ cell} = -1 \]  

The addition of a sensor to measure an unknown variable \( X \) increases the number of known variables and constraints, however it introduces the possibility of a fault, as shown in Fig. 4(a) and Fig. 4(b). The circle represents the real time sensor reading and is a known variable, \( f \) denotes the sensor fault (\( f \neq 0 \) indicates that the sensor failed). \( u \) is the actual value of the sensed current, voltage or temperature.

As example, a complete matching of the system of Eq.s 1-4 cannot be solved to calculate the 5 unknown variables. Thus, the intrinsic analytical redundancy (IAR) of a single cell is -1.

\[ IAR_{single\ cell} = -1 \]  

Fig. 3: Two complete matchings (a), (b) and an incomplete matching (c)

Fig. 4: (a) an example of complete matching, (b) matching in the bipartite graph

Fig. 5: Oriented graph for single cell system with a current and a voltage measurement

D. Oriented graph

An oriented graph is a matching that assigns orientation of some edges. For matched constraint, the edge that connects the matched variable and the constraint is called a matched edges whose orientation is from the constraint to the variable. Other edges that connects the non-matched variables and the constraint are called non-matched edges with an orientation from non-matched variables to the constraint. For constraint that is not matched, all edges’ orientation are from variables to the constraint. The non-matched constraints generate a zero output, which represents analytic redundant relations (ARRs) of the model. ARRs are used to generate residuals as fault indicators for the purpose of fault diagnosis. Fig. 5 shows the oriented structural graph for a single cell system.

The oriented graph defines a set of computational sequences \( S = \{ S_1, S_2, S_3 \} \) to calculate the unknown variables:

\[ S_1 = \{(c_5, I_{11}), (c_2, SoC_{11}), (c_3, V_{oc,11})\} \]
\[ S_2 = \{(c_5, I_{11}), (c_4, T_{11})\} \]
\[ S_3 = \{(c_6, V_{11})\} \]

where, the pair \((c, x)\) means variable \( x \) is computed from constraint \( c \). The order of the pairs defines a computational sequence. Note that \( c_2 \) and \( c_4 \) are differential equations, and when we use their integral causalities, the knowledge of initial values are required. The oriented graph results in an alternated chain that starts from the known variables and alternates successively between two nodes [35]. For the oriented graph shown in Fig. 5, the alternated chain based on the computational sequence \( S_1 \) can be expressed as:

\[ y_{t_{11}} \rightarrow c_5 \rightarrow I_{11} \rightarrow c_2 \rightarrow SoC_{11} \rightarrow c_3 \rightarrow V_{oc,11} \]  

Based on the alternated chain, the structural reachability is defined as [35]: a variable \( z_2 \) is reachable from a variable \( z_1 \) if there exists an alternated chain from \( z_1 \) to \( z_2 \). The circle in gray represent the ARR of the model. In Fig. 5, \( c_1 \) is the ARR for a single cell system with the matching we choose in Fig. 4. A residual based on the sensor set \( \{y_{t_{11}}, y_{V_{11}}\} \) that is capable of detecting the two faults \( \{f_{y_{t_{11}}}, f_{y_{V_{11}}}\} \) is

\[ r = y_{V_{11}} - f[SoC_{11,0}, \frac{1}{Q} \int_0^t y_{t_{11}}(t) dt] + R_{y_{t_{11}}} \]
\[ = f_{y_{V_{11}}} + R_{f_{y_{t_{11}}}} \]
where, SoC_{11,0} represents the initial value of SoC_{11}. The residual r in Eq. (15) is obtained by substituting all matched constraints to c_1 to eliminate unknown variables and make it only contain known variables. A violation of any constraint that is used to generate the residual will result in a non-zero residual indicating a fault. In fact, the residual in Eq. (15) is the only residual generator for a single cell with current and voltage measurements. When there isn’t a fault, r should be 0. Notice that this residual is sensitive to both f_{y_{11}} and f_{y_{v1}}.

### III. Extending the Structural Model to Battery Modules and Packs

As discussed previously, the intrinsic analytical redundancy of a single cell is -1 (Eq. (9)). In the same way, the intrinsic analytical redundancy (IAR) of the battery system is also -1 for both nSmP and mPnS topologies, when no sensors and faults are considered.

\[
IAR_{\text{battery pack}} = -1
\]  

To increase the analytical redundancy and provide the ability to design diagnostic algorithms, sensors are needed in the battery system. In this section, we use graph-theoretic tools to understand how different measurements (current, voltage, and temperature) can add analytical redundancy to the system, and how this analytical redundancy is linked to system diagnosability. Based on the general structural models of the two common battery pack topologies, their intrinsic properties are analyzed, also in the presence of faulty cells.

#### A. Single cell

The structural model of a single cell represented by a bipartite graph is shown in Fig. 2. Without sensing, we cannot solve for the unknown variables. If we have a current measurement or temperature measurement for a single cell, the resulting structural graph is shown in Fig. 6(a) and (b), respectively. Every unknown variable is easily reachable from the measurement (known) because an alternated chain can be found to exist for both cases. If we introduce a voltage measurement for a single cell, then the structural graph is as shown in Fig. 6(c). Notice that in this case, the three constraints \{c_1, c_2, c_3\} form a loop which requires the three constraints to be solved simultaneously. While it is true that in the case of a voltage measurement we can still calculate all unknown variables, it is not as easy to compute these variables as was the case with a current or a temperature measurement. This indicates that, in principle, current and temperature sensors can provide cell information with less computational work compared to voltage sensor. If both current and voltage measurements are available, all the unknown variables are easily reachable, see Fig. 6(d). The redundancy of the single cell system becomes 1, which means there will be an ARR that can be used for fault diagnosis.

#### B. nSmP versus mPnS

The nSmP and mPnS topologies are shown in Fig. 1(a) and Fig. 1(b), respectively. The system equations are listed in Eq. (1)-(8). The number of equations is always 1 less than the number of unknown variables which indicates that the intrinsic redundancy of the battery system is -1 for both topologies.

Based on the battery pack model, the calculation of SoC, V_{oc} and T for one cell is isolated from another cell. There are only current and voltage connections between cell to cell, and it is reasonable to condense the structural graph of each single cell to one node, as shown in Fig. 7. With the simplified graph structure, it is possible to obtain a generalized structural model of the mPnS and nSmP topologies as shown in Fig. 8 and Fig. 9 respectively. These generalized structural models can help analyze the effect of a faulty cell (for example a short circuit), or the effect of cell-to-cell variation (for example due to uneven aging of cells). Given a fixed load current and considering that cell_{11} in Module 1 has anomalous behavior compared to the other cells (again, due to a fault or to a change in some physical parameter). For the nSmP topology, all module currents equal the pack current (see Fig. 1(a)) and remain unchanged. As shown in Fig. 8 any defect in cell_{11} will result in an imbalance between I_{11}, \cdots, I_{1j}, \cdots, I_{1m}, in Module 1. The impact of the defective cell is limited to the module it belongs to and the other modules will not be affected by the defective cell. In the mPnS topology, the current in each module is equal to the individual cell current, and the pack current is the summation of all the module currents (see Fig. 1(b)). The variation of cell_{11} will affect I_{11} and I_{1}^{M}. Then the change of I_{1}^{M} will cause unbalance between
Fig. 8: Structural model for \( nS^M \) (\( V^M_i \) represent the voltage of the \( i \)th module)

Fig. 9: Structural model for \( mP^nS \) (\( I^M_j \) represent the current of the \( j \)th module)

\( I^M_1, \ldots, I^M_i, \ldots, I^M_m \). The influence of a defective cell will therefore spread to the whole battery pack, as shown in Fig. 8. This is a very important intrinsic property of the two battery pack topologies, and it motivates the analysis and models presented in the following section. Note that, we only apply the simplification shown in Fig. 7 to the bipartite graphs of \( nS^mP \) and \( mS^nP \) topologies. The sensor placement analysis in the following section is based on using the system incidence matrix without any simplification.

IV. SENSOR PLACEMENT FOR FAULT DETECTABILITY AND ISOLABILITY ANALYSIS

In this section, we develop a systematic methodology to find the minimal sensor sets that can potentially provide the two common battery topologies with enough ARRs to develop diagnostic algorithms that can achieve complete isolation for all the faults we have considered so far. In other words, with the sensor installation guide developed in this section, it is possible to design algorithms to generate residuals, each sensitive to a unique fault.

Fault detectability of a system model can be determined by performing a Dulmage-Mendelsohn (DM) decomposition of the system incidence matrix, which divides the structural model into three subsystems: under-determined (\( M^- \)), just-determined (\( M^0 \)), and over-determined (\( M^+ \)) \[36\], as shown in Fig. 10. If the incidence matrix has no over-determined subsystem, then it is not possible to detect or isolate any faults.

As discussed in Section II and III, if sensors are not included in a battery system (whether consisting of a single cell or of \( mP^nS \) and \( nS^mP \) topologies), the system is under-determined (Eqs. (9) and (16)), and there is no analytical redundancy in it to permit diagnosis. It is clear, then, that sensors are necessary to achieve analytical redundancy in a battery pack. As example, by adding two sensors the system will have an over-determined subsystem. The addition of different sensor types in different locations will result in the generation of different over-determined subsystems. Different combinations of sensors and the presence of different faults will give rise to different fault detectability properties, and it may take more than two sensors to insure detectability of all faults. If faults are detectable by adding the appropriate sensors, it will then possible to generate a residual, that is, a signal used as a fault indicator that is sensitive to these faults. Based on the DM decomposition of the system incidence matrix, a fault is structurally detectable if the equation containing the fault variable is in the over-determined part of the system \[38\]. A second property of interest is fault isolability, defined as follows \[57\]: fault \( f_i \) is isolable from fault \( f_j \), if there exists a residual that is sensitive to \( f_i \) but not \( f_j \). If we look back to Eq. (15), it can be found that in a single cell instrumented with a current sensor and a voltage sensor, the two sensor faults are detectable but are not isolable from each other. Based on the DM decomposition, if fault \( f_i \) is to be structurally isolable from fault \( f_j \), the equations containing these two faults must be in different equivalence classes of the over-determined subsystem. A more detailed explanations of equivalence classes may be found in \[44\].

Detectability and isolability analysis can be easily performed using the Structural Analysis Toolbox developed by Frisk et al. \[45\]. In the next subsection, the faults considered in this study are introduced and a fault detectability and isolability analysis is performed for a single cell, the generalized \( nS^mP \) and \( mP^nS \) topologies.
A. Battery modeling with faults

A battery pack can exhibit anomalous behavior due to many reasons, including short circuit (internal or external to the cell), resistance increase and/or capacity fade due to accelerated aging, sensor fault, or BMS fault \[ [38]. In this work, two types of faults are considered: sensor fault and short circuit faults; these may occur at the cell or module level in the battery pack. Short circuit faults are especially important because, unlike other anomalies that would still permit the system to operate (e.g. battery degradation), a short circuit may lead to thermal runaway and result in a catastrophic failure.

![Diagram of internal and external short circuit in a cell](image)

Fig. 11: Diagram of internal and external short circuit in a cell

Short circuit faults (internal and external) are depicted in the circuit diagram of Fig. 11. The internal short circuit is represented by a parallel resistance \((R_{scI})\) connected to the cell \([29]. The external short circuit is similarly represented by a parallel resistance \((R_{scE})\) externally connected to a cell or a module. The fault model for internal short circuit is given by:

\[
I_{scI,ij} = \left( \frac{V_{ij}}{R_{scI}} \right) f_{scI,ij} 
\]

where, \(f_{scI,ij}\) represents the internal short circuit current fault and is a binary variable with value 1 when the fault is present, and \(I_{scE,ij}\) the internal short circuit current. In the case of an internal short circuit, Eq. (3) remains the same while Eqs. (1), (2), and (4) result in the following equations (18)-(20).

\[
V_{ij} = V_{scI} - R_{ij}(I_{ij} + I_{scI,ij}) 
\]

\[
d\text{SoC}_{ij} = -\frac{(I_{ij} + I_{scI,ij})}{Q_{ij}} 
\]

\[
mC_{p} \frac{dT_{ij}}{dt} = R_{ij}(I_{ij} + I_{scI,ij})^2 - Q_{TMS_{ij}} 
\]

The fault model for the external short circuit in:

\[
I_{scE} = \left( \frac{V_{E}}{R_{scE}} \right) f_{scE} 
\]

where, \(f_{scE}\) (a binary variable) represent the external short circuit fault, and \(I_{scE}\) the external short circuit current. When we consider a module, that is the composition of multiple cells, then the voltage \(V_{E}\) across the short circuit resistance \(R_{scE}\) depends on how many cells are shorted by the external short circuit. For example, as shown in Fig. 13 and 14 later, if we consider the external short circuit at the module level, for the external short circuit in Module \(i\) in \(n\) cell topology, \(V_{E,i} = V_{i1} = \cdots = V_{ij} = \cdots = V_{in};\) for the external short circuit in Module \(j\) in \(m\) cell topology, \(V_{E,j} = V_{ij} = \cdots = V_{nj}. I_{scE}\) will appear in the KCL equations, (Eq. (5) or (7)). For example, for a single cell system as shown in Fig. 11, the external short circuit fault can be modeled as:

\[
I_{scE,11} = \left( \frac{V_{11}}{R_{scE}} \right) f_{scE,11} 
\]

\[
I_{11} = I_{BP} + I_{scE,11} 
\]

The redundancy of the battery system model with short circuit faults remains \(-1\), because the addition of an unknown variable to the system is balanced by the introduction of a new equation.

Sensor faults modeling was introduced in Section II.C, see Eq. (10).

B. Fault detectability and isolability analysis and sensor placement for single cell

The mathematical model of a single cell system with faults is shown in Eqs. (3), (18)-(20), (22) and (23) with \(i = j = 1\). The set of short circuit faults that are included in the model is \(\{f_{scI,11}, f_{scE,11}\}\). The set of sensor faults depends on what sensors are added to the battery system. For the single cell system, the possible sensor positions are \(\{I_{BP}, I_{11}, V_{11}, T_{11}\}\).

### TABLE II: Fault detectability and isolability matrix without sensor and with one sensor (ND=Non Detectable; NA=Non Applicable)

| Sensor Faults | \(f_{scI,11}\) | \(f_{scE,11}\) | \(f_{y_{BP}}\) | \(f_{y_{11}}\) | \(f_{y_{V_{11}}}\) | \(f_{y_{T_{11}}\) |
|--------------|---------------|---------------|-------------|-------------|----------------|-------------|
| no sensor    | ND            | ND            | NA          | NA          | NA             | NA          |
| \(y_{I_{BP}}\) | ND            | ND            | NA          | NA          | NA             | NA          |
| \(y_{I_{11}}\) | ND            | ND            | NA          | NA          | NA             | NA          |
| \(y_{V_{11}}\) | ND            | ND            | NA          | NA          | NA             | NA          |
| \(y_{T_{11}}\) | ND            | ND            | NA          | NA          | NA             | NA          |

### TABLE III: Fault detectability and isolability matrix with two sensors (ND=Not Detectable; D=Detectable; NI=Not Isolable; NA=Not Applicable)

| Sensor Faults | \(f_{scI,11}\) | \(f_{scE,11}\) | \(f_{y_{BP}}\) | \(f_{y_{11}}\) | \(f_{y_{V_{11}}}\) | \(f_{y_{T_{11}}}\) |
|--------------|---------------|---------------|-------------|-------------|----------------|-------------|
| \(y_{I_{BP}}, y_{V_{11}}\) | D,NI | ND | NA | D,NI | D,NI | NA |
| \(y_{I_{11}}, y_{T_{11}}\) | D,NI | ND | NA | D,NI | D,NI | NA |
| \(y_{V_{11}}, y_{T_{11}}\) | D,NI | ND | NA | D,NI | D,NI | NA |
| \(y_{I_{BP}}, y_{V_{11}}\) | D,NI | D,NI | D,NI | D,NI | D,NI | NA |
| \(y_{I_{BP}}, y_{T_{11}}\) | D,NI | D,NI | D,NI | D,NI | D,NI | NA |
| \(y_{I_{BP}}, y_{V_{11}}\) | D,NI | D,NI | D,NI | D,NI | D,NI | NA |

Table III shows the fault detectability and isolability matrix for the single cell system without sensors, and with only one
Fig. 12: DM decompositions of 1S1P battery system with (a) no sensor or with sensor set: (b) \( \{ y_{1P} \} \), (c) \( \{ y_{I1}, y_{V1} \} \), (d) \( \{ y_{I1}, y_{V1}, y_{1P} \} \), (e) \( \{ y_{I1}, y_{V1}, y_{BP1}, y_{BP2} \} \), (f) \( \{ y_{I1}, y_{V1}, y_{BP1}, y_{BP2} \} \). sensor. It can be seen that all faults cannot be detectable with a single sensor. The DM decomposition shown in Fig. 12(a) and (b) show that with no sensor, the system is under-determined (7 equations and 8 unknowns) and with one sensor (choose sensor \( \{ y_{1P} \} \) as an example), the system becomes just-determined.

Table III shows the fault detectability and isolability matrix for the single cell system with 2 sensors. There are 6 possible sensor sets. With sensor sets \( \{ y_{I1}, y_{V1} \}, \{ y_{I1}, y_{T1} \}, \{ y_{V1}, y_{T1} \} \), all the internal short circuit faults and sensor faults are detectable, while the external short circuit fault is not. As shown in the DM-decomposition result (choose sensor set \( \{ y_{11}, y_{V11} \} \) as an example, shown in Fig. 12(c)): the equation containing the external short circuit fault signal \( f_{scE,11} \) is in the just-determined part, which means \( f_{scE,11} \) is not detectable. Equations containing fault signals \( f_{scE,11}, f_{y_{11}}, f_{y_{V11}} \) are in the over-determined part and in the same equivalence class (gray box). Thus, these three faults are detectable but not isolable from each other. Table III shows that with the other three sensor sets \( \{ y_{1P}, y_{V11} \}, \{ y_{1P}, y_{V11} \}, \{ y_{1P}, y_{T11} \} \) all faults can be detectable, but are also not isolable. The DM-decomposition results of one of these sensor set illustrates this as well (choose sensor set \( \{ y_{1P}, y_{V11} \} \) as an example, shown in Fig. 12(d)): all the equations containing fault signals are in the over-determined part, which indicates all faults can be detectable. However, all equations containing fault signals are in the same equivalence class, which indicates that these faults are not isolable from each other.

Table IV shows the fault detectability and isolability matrix for the 1S1P system with 3 sensors. With sensor set \( \{ y_{I1}, y_{V1}, y_{T1} \} \), all faults can be detectable except for the external short circuit fault. With sensor sets \( \{ y_{I1}, y_{V1}, y_{1P} \}, \{ y_{I1}, y_{T1}, y_{1P} \}, \{ y_{1P}, y_{T1}, y_{1P} \} \), all faults are detectable. The internal short circuit fault and all sensor faults can be uniquely isolable, while the external short circuit fault and the load current sensor fault can be isolable from other faults but these two faults cannot be isolated from one another. From the DM-decomposition result (choose sensor set \( \{ y_{I1}, y_{V1}, y_{1P} \} \) as an example, shown in Fig. 12(e)), it can be seen that: all faults are located in the over-determined part. The equations containing fault signals \( f_{scE,11} \) and \( f_{y_{BP}} \) are in the same equivalence class, which means they are not isolable from each other but they are isolable from other faults. The equations containing fault signals \( f_{scE,11}, f_{y_{I1}}, f_{y_{V11}} \) are in the different equivalence
isolated from each other. From the table it can be seen isolable from other faults but these two faults cannot be circuit fault and the load current sensor fault can be faults can be uniquely isolable, while the external short detectable. The internal short circuit fault and all sensor

matrix for the single cell system with 4 sensors. With classes which means these faults can be uniquely isolable.

The set of internal short circuit faults we seek to diagnose short circuit fault signal in it, as shown in Figs. 13 and 14. To represent internal short circuit faults at the cell level, every cell has the possibility of suffering from an internal short circuit. We begin with the generalized nSmP topology of Fig. 1(a). In general, the set of sensor faults that needs to be diagnosed depends on the selected sensor set. Further, every cell has the possibility of suffering from an internal short circuit. To represent internal short circuit faults at the cell level, every cell in both battery pack topologies is modeled with an internal short circuit fault signal in it, as shown in Figs. 13 and 14. The set of internal short circuit faults we seek to diagnose is \( \{f_{sc,11}, f_{sc,12}, \ldots, f_{sc,1m}\} \), for either topology. As for modeling external short circuit faults, the fault models will vary with each topology.

A generalized diagram including internal and external short circuit faults for the nSmP topology is shown in Fig. 13. Note that, we only discuss cases when \( m > 1 \), which means in each module there are at least two cells in parallel.

Every module has the possibility to suffer from external short circuit, as shown in Fig. 13. The set of external short circuit faults that needs to be diagnosed is \( \{f_{scE,1}, f_{scE,2}, \ldots, f_{scE,n}\} \). The possible sensor positions are \( \{I_{BP}, u_{11}, \ldots, u_{ij}, \ldots, u_{nm}\} \), where \( u \) represents current, voltage or temperature of each cell. Table VI lists the minimal sensor set to achieve fault isolability for nSmP battery pack. In order to uniquely isolate each fault, the sensor set installation needs to meet both of the following two requirements:

1) each cell should be equipped with a sensor \( Z \) which can measure current or temperature;
2) two sensors to measure the load current \( I_{BP} \) when \( n = 

TABLE IV: Fault detectability and isolability matrix with three sensors (ND=Not Detectable; D=Detectable; NI=Not Isolable; I=Isolable; UI=Uniquely Isolable; NA=Not Applicable; )

| \( f_{sc,11} \) | \( f_{scE,11} \) | \( f_{y_{BP,1}} \) | \( f_{y_{11}} \) | \( f_{y_{V,11}} \) | \( f_{y_{T,11}} \) |
|----------------|----------------|----------------|----------------|----------------|----------------|
| \( \{y_{111}, y_{V,11}, y_{T,11}\} \) | D,UI | ND | NA | D,UI | D,UI | D,UI |
| \( \{y_{111}, y_{V,11}, y_{BP,1}\} \) | D,UI | D,I | D,I | D,UI | D,UI | NA |
| \( \{y_{111}, y_{T,11}, y_{BP,1}\} \) | D,UI | D,I | D,I | D,UI | NA | D,UI |
| \( \{y_{111}, y_{T,11}, y_{BP,2}\} \) | D,UI | D,I | D,I | D,UI | NA | D,UI |
| \( \{y_{111}, y_{T,11}, y_{BP,1}, y_{BP,2}\} \) | D,UI | D,I | D,I | D,UI | NA | D,UI |

TABLE V: Fault detectability and isolability matrix with four sensors (ND=Not Detectable; D=Detectable; NI=Not Isolable; UI=Uniquely Isolable; NA=Not Applicable; )

| \( f_{sc,11} \) | \( f_{scE,11} \) | \( f_{y_{BP,1}} \) | \( f_{y_{111}} \) | \( f_{y_{V,11}} \) | \( f_{y_{T,11}} \) |
|----------------|----------------|----------------|----------------|----------------|----------------|
| \( \{y_{111}, y_{V,11}, y_{T,11}, y_{BP,1}\} \) | D,UI | D,I | D,I | D,UI | D,UI | NA |
| \( \{y_{111}, y_{V,11}, y_{BP,1}, y_{BP,2}\} \) | D,UI | D,I | D,I | D,UI | D,UI | NA |
| \( \{y_{111}, y_{T,11}, y_{BP,1}, y_{BP,2}\} \) | D,UI | D,I | D,I | D,UI | NA | D,UI |
| \( \{y_{V,11}, y_{T,11}, y_{BP,1}, y_{BP,2}\} \) | D,UI | D,I | D,I | NA | D,UI | D,UI |

Fig. 13: Diagram of internal and external short circuit for nSmP battery pack topology
TABLE VI: Summary of the minimal sensor set to achieve fault isolability for nSmP topology \((n > 0, m > 1)\) (Z represents current or temperature)

| \# of module | Topology | Sensor set | \# of sensors | \# of choices |
|--------------|----------|------------|---------------|---------------|
| n=1          | 1SP      | \{y_{BP1,1}, y_{BP1,2}, y_{x11}, y_{x12}\} | \(2 + 1 \times 2\) | \(2^2\)       |
|              | 1SP      | \{y_{BP1,1}, y_{BP1,2}, y_{x11}, y_{x12}, y_{x13}\} | \(2 + 1 \times 3\) | \(2^3\)       |
|              |          |            | \ldots        | \ldots        |
|              | 1SmP     | \{y_{BP1,1}, y_{BP1,2}, y_{x11}, \ldots, y_{x1j}, \ldots, y_{x1m}\} | \(2 + 1 \times m\) | \(2^m\)       |
| n=2          | 2SP      | \{y_{BP1,1}, y_{BP1,2}, y_{x11}, y_{x12}, y_{x22}\} | \(1 + 2 \times 2\) | \(2^{2m}\)    |
|              |          |            | \ldots        | \ldots        |
|              | 2SmP     | \{y_{BP1,1}, y_{x11}, \ldots, y_{x1j}, \ldots, y_{x2m}\} | \(1 + 2 \times m\) | \(2^{2m}\)    |
| n>2          | 3SP      | \{y_{x11}, y_{x12}, y_{x21}, y_{x22}, y_{x23}, y_{x32}\} | \(3 \times 2\) | \(3^{3m}\)    |
|              |          |            | \ldots        | \ldots        |
|              | 3SmP     | \{y_{x11}, \ldots, y_{x1j}, \ldots, y_{x3m}\} | \(3m\) | \(3^{3m}\)    |
|              |          |            | \ldots        | \ldots        |
|              | nSmP     | \{y_{x11}, \ldots, y_{x1j}, \ldots, y_{xnm}\} | \(nm\) | \(2^{nm}\)    |

TABLE VII: Summary of the minimal sensor set to achieve fault isolability for mPnP topology \((n > 1, m > 0)\) (Y represents voltage or temperature)

| \# of module | Topology | Sensor set | \# of sensors | \# of choices |
|--------------|----------|------------|---------------|---------------|
| m=1          | 1PS      | \{y_{BP1,1}, y_{BP1,2}, y_{Y11}, y_{Y21}\} | \(2 + 1 \times 2\) | \(2^2\)       |
|              | 1PS      | \{y_{BP1,1}, y_{BP1,2}, y_{Y11}, y_{Y12}, y_{Y13}\} | \(2 + 1 \times 3\) | \(2^3\)       |
|              |          |            | \ldots        | \ldots        |
|              | 1PS      | \{y_{BP1,1}, y_{BP1,2}, y_{Y11}, \ldots, y_{Y1j}, \ldots, y_{Y21}\} | \(2 + 1 \times n\) | \(2^n\)       |
| m>1          | mPnP     | \(B_j = \{Y_i\}, i = 1, \ldots, n\) \(A_j \subseteq B_j\) and there are \((n - 1)\) elements in \(A_j\) | \(2 + m \times (n - 1)\) | \(2^{n-1} \times \left(\frac{n - 1}{n}\right)^m\) |

1; one sensor to measure the load current when \(n = 2\); no sensor is needed to measure the battery pack current when \(n > 2\).

The number of load current sensor varies with \(n\). This is true because as the battery pack scales up, the variable \(I_{BP}\) will be contained in a greater number of equations (instances of KCL), see Appendix A.A. As a result, the redundancy of \(I_{BP}\) increases automatically without the need of sensor.

D. Generalized mPnP topology

A generalized diagram including internal and external short circuit faults for the mPnP topology is shown in Fig. 14. Note that we only consider cases when \(n > 1\), which means in each module there are at least two cells in series. For mPnP topology, if more than one module suffers from an external short circuit, it is not possible to isolate these external short circuits from one another. So, when we perform the sensor placement for fault isolability, only one external short circuit is considered in the pack, and therefore only one external short circuit fault \(\{f_{sc,j}\}\) is to be diagnosed. If Module \(j\) is suffering from an external short circuit, all cells in this faulty module are shorted by this fault as shown in Fig. 14. Since every module has the possibility of experiencing an external short circuit, we find the minimal sensor set that can achieve faults isolability regardless the location of external short circuit. For the mPnP topology, the possible sensor positions are \(\{I_{BP}, u_{111}, \ldots, u_{ij}, \ldots, u_{nm}\}\). \(u\) represents current, voltage or temperature.

Table VII lists the minimal sensor set to achieve fault isolability for mPnP topology regardless the location of external short circuit fault signal. To uniquely isolate each fault, the sensor set installation needs to meet the following two requirements at the same time:

1) when \(m = 1\), each cell should be equipped with one sensor \(Y\) which can measure voltage or temperature; when \(m > 1\), in each module, \(n - 1\) cells should be equipped with a sensor \(Y\) which can measure voltage or temperature. These \(n - 1\) cells can be chosen arbitrarily
from the $n$ cells in each module;

2) duplicate sensors to measure the load current $I_{BP}$.

As explained for the case of $nSmp$ topology, the need of multiple load current measurements depends on how many times the variable $I_{BP}$ appears in equations. Since in the equations of the $mPnP$ topology, $I_{BP}$ appears only once (see Appendix A.B), two load current sensors are needed to achieve complete fault isolation. If two $mPnP$ packs are connected in series, only one load current sensor is needed. If more than two $mPnP$ packs are connected in series, a load current sensor is no longer necessary because of the redundancy of $I_{BP}$ intrinsically contained in the equations (instances of KCL).

V. Final Comments and Remarks

The methodology for battery pack fault diagnosis illustrated in this paper is based on understanding and exploiting the analytical redundancy in the system. The analytical redundancy required for fault diagnosis is in part inherently present in the analytical equations of the system, and in part added by installing sensors, which, in the context of structural analysis, convert unknown variables into known variables and help us determine which variables play a key role in diagnosing the faults.

The minimal sensor set to achieve internal short circuit fault isolation is an intrinsic characteristic of each topology. For the $nSmP$ topology, the cells in each module are in parallel so they share the same voltage. Thus only by adding current or temperature sensor can we achieve fault isolation at the cell level. For $mPnP$ topology, the cells in each module are in series so there is only one current. Thus, only voltage or temperature sensors can add redundancy to permit fault isolation at the cell level. This duality is a natural consequence of series vs. parallel circuits. On the other hand, temperature sensors can be effective in both topologies, as they are in principle sensitive to the heat generation caused by an internal short circuit. On the contrary, in our models, the external short circuit does not play a role in the heat balance equation. While temperature sensors could in principle be very useful, it is not practical to install temperature sensors in each cell due to: i) their slow dynamic response; ii) their cost; and iii) the difficulty in physically mounting the sensors at the manufacturing stage.

Today, the most common sensor set for battery packs used in automotive applications includes\[59\]: i) a load current sensor to measure $I_{BP}$; ii) voltage sensors for each cell to permit voltage balancing and overcharge protection functions in the BMS (in the $nSmP$ topology cells that are in parallel share a single voltage sensor, in the $mPnP$ topology each cell has its own voltage sensor); iii) a temperature sensor per module. In this paper, we refer to these sensor sets as the traditional ones. To evaluate the diagnosability for traditional sensor set, thermal model at module level is needed to provide a module temperature variable ($T^M$) to permit place a temperature sensor per module.

Thermal model for Module $i$ in $nSmP$ topology:

\[
T_i^M = \frac{1}{n} \sum_{j=1}^{m} k_{ij} T_{ij} \tag{24}
\]

Thermal model for Module $j$ in $mPnP$ topology:

\[
T_j^M = \frac{1}{n} \sum_{i=1}^{n} k_{ij} T_{ij} \tag{25}
\]

Where $k_{ij}$ represents the weighted average temperature of the module and it depends on the distance between the $ij$th cell and the temperature sensor. This model assumes that thermal connections among cells follow the same architecture of the electrical connections within the module, and that there is no thermal interaction between modules.

An $nSmP$ battery pack with a traditional sensor set has the ability to detect all faults. As for isolability, a traditional sensor set can isolate faults in a module from faults in another module while it fails to isolate every fault within the module (at the cell level). For example, Fig. [15] shows the fault isolability matrix of a 3S3P battery pack with a traditional sensor set. It can be seen that the battery pack current sensor fault can be uniquely isolated from the other faults, while faults in Modules 1 and 2 are also isolated from each other. However, the minimal sensor set does not include voltage sensors, which suggests that in a $nSmP$ battery pack equipped with only the minimal sensor set, the BMS would not be able to perform voltage balancing.

For a $mPnP$ topology battery pack with the traditional sensor set, the faults in each cell can be uniquely isolated. The battery pack current sensor fault and the external short circuit fault cannot be isolated from each other, but can be
isolable from the three internal short circuit faults. If the 3P3S circuit fault in each cell are isolated from each other while class and cannot be isolated from each other. Internal short and external short circuit fault fall in the same equivalent sensor set. It can be seen that the load current sensor fault fault isolability matrix of 3P3S topology with the traditional external short circuit is in

isolated from the other faults. In each module, the temperature sensor fault is not isolable from the internal short circuit faults. Similarly, we choose 3P3S as an example and assume that the external short circuit is in Module 1. Fig. [16] shows the fault isolability matrix of 3P3S topology with the traditional sensor set. It can be seen that the load current sensor fault and external short circuit fault fall in the same equivalent class and cannot be isolated from each other. Internal short circuit fault in each cell are isolated from each other while in each module, the module temperature sensor fault is not isolable from the three internal short circuit faults. If the 3P3S topology battery pack were installed with the minimal sensor set \( \{ y_{1BP}, y_{1MP}, y_{1V1}, y_{1V2}, y_{1V3}, y_{1V21}, y_{1V22}, y_{1V23}, y_{1V24}, y_{1V25} \} \) derived in this paper, all faults could be uniquely isolated from each other. Note that in the minimal sensor set case two instead of three voltage sensors are sufficient for each module (series string) to achieve fault isolation, no matter in which module the external short circuit fault occurs. Further note that this reduces the total sensor count to 8, instead of 13. This reduction in sensor count would be more prominent as the number of cells in the pack increases. On the other hand, this sensor configuration may not be optimal from a voltage balancing perspective.

Finally, it should be pointed out that as long as the sensor set selected in a pack design includes as a subset the minimal diagnostic sensor set for isolability derived in this paper, multiple design objectives can be met.

VI. CONCLUSION

The work presented in this paper uses the tools of structural analysis for diagnosis to derive some fundamental characteristics of two principal battery pack topologies from a diagnostic perspective. The equivalent circuit models and lumped-parameter heat exchange models used to represent each cell permit the determination of the analytical redundancy that is intrinsic in the battery system (always -1 regardless of pack topology and number of cells). The methods developed in this work are first applied to the simplest representation (a single cell) to illustrate how one can select a minimal sensor set to achieve detectability and isolability of faults, and are then generalized to the \( nSnP \) and \( mPmS \) topologies to yield results that are generally applicable to either topology regardless of cell number. Further, the model and methods applied to a single cell can be applied in exactly the same way at the module level, regardless of the module internal configuration, thus making this approach completely scalable - a property that is very important when one considers applications with hundreds or thousands of individual cells, such as in automotive, aerospace and grid support applications.

While the work presented in this paper is only one step in the design of a large battery pack design, it is an important and needed advancement. For future work, we are interested in exploring the system observability index criteria associated with different measurements to better select optimal sensor sets that would permit meeting diagnostic requirements while also considering constraints in sensor cost and ease of installation, as well as the requirements of the battery management system.

APPENDIX A

A. Model for \( nSnP \) topology battery pack with faults:

\[
\begin{align*}
\begin{array}{c}
V_{ij} = V_{oc,ij} - R_{ij}(I_{ij} + I_{scE,ij}) \\
\frac{dC_{ij}}{dt} = -\left( I_{ij} + I_{scE,ij} \right) \\
V_{oc,ij} = f(SoC_{ij}) \\
\frac{d}{dt}(\frac{dV_{ij}}{dt}) = \frac{R_{ij}}{Q_{TMS}} \\
I_{scE,ij} = \left( \frac{V_{ij}}{Q_{TMS}} \right) \frac{dI_{ij}}{dt} \\
I_{scE,ij} = \left( \frac{V_{ij}}{Q_{TMS}} \right) \frac{dI_{ij}}{dt} \\
I_{ij} + I_{ij} + \cdots + I_{ij} = I_{BP} + I_{scE,ij} \\
V_{ij} = V_{ij} + \cdots + V_{ij}
\end{array}
\end{align*}
\]

B. model for \( mPmS \) topology battery pack with faults:

\[
\begin{align*}
\begin{array}{c}
V_{ij} = V_{oc,ij} - R_{ij}(I_{ij} + I_{scE,ij}) \\
\frac{dC_{ij}}{dt} = -\left( I_{ij} + I_{scE,ij} \right) \\
V_{oc,ij} = f(SoC_{ij}) \\
\frac{d}{dt}(\frac{dV_{ij}}{dt}) = \frac{R_{ij}}{Q_{TMS}} \\
I_{scE,ij} = \left( \frac{V_{ij}}{Q_{TMS}} \right) \frac{dI_{ij}}{dt} \\
I_{ij} + I_{ij} + \cdots + I_{ij} = I_{BP} + I_{scE,ij} \\
V_{ij} = V_{ij} + \cdots + V_{ij}
\end{array}
\end{align*}
\]
in Fig.14, c number NNX17AJ92A).

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