Analysing the impact of motor design on inverter thermal behaviour using network-based sensitivity analysis

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ABSTRACT

Vehicles are complex systems composed of multiple interdependent subsystems. A design change in one subsystem can lead to either beneficial or detrimental effects on others, making it essential to understand how design choices propagate through the system. This paper focuses on the traction chain in rail vehicles, specifically the interaction between two critical subsystems: the traction motor and the inverter. Since the inverter supplies the current and voltage required by the motor, changes in motor design can affect the inverter's thermal behaviour. We analyse this interaction to understand how motor design influences the temperature evolution of inverter power electronic components. To achieve this, we apply a framework that integrates network theory, structural equation modelling (SEM), and sensitivity analysis. First, analytical models of a three-phase induction motor and an inverter thermal model are developed. A reverse breadth-first search is used to identify all input parameters that influence the inverter temperature. Global sensitivity analysis (GSA) isolates the most influential inputs, enabling the construction of a reduced network graph. Then, SEM and local sensitivity analysis (LSA) are applied to quantify the relationship between motor design parameters and inverter temperature, yielding a coefficient that captures the strength of the dependency. This approach provides an alternative representation of the multidisciplinary interactions between subsystems. It also helps identify key change propagation paths, making it easier for designers to anticipate and manage the consequences of design changes. By reducing analytical

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complexity and clarifying subsystem interdependencies, the framework supports more efficient early-stage design, potentially reducing the number of iterations needed to reach a satisfactory solution.

1. INTRODUCTION

The transition from silicon (Si) to silicon carbide (SiC) semiconductors has enabled several benefits such as reduced volume and weight, improved efficiency, and improved thermal performance (Lindahl et al., 2021).This meant that instead of using active cooling using liquid or forced-air cooling using fans, a passive cooling system known as car motion cooling using the airflow surrounding the vehicle in motion can be used. However, the benefits were not limited to the inverter performance but also improved the operation and acoustic noise levels of the motor. This highlights the intricate interdependency between these two subsystems and necessitates a deeper understanding of the interaction.

Moreover, from an operational perspective, this interdependency becomes more relevant under dynamic conditions. The energy dissipation in inverters is high during acceleration, where the demand from the motor is high, while vehicle speed is low, resulting in limited convection cooling. Conversely, at higher speeds, cooling improves due to increased airflow, but the demand from the motor reduces. This imbalance between heating and cooling introduces transient, non-steady state thermal behaviour in the inverter. Consequently, an inadequately designed motor may operate in the inefficient region leading to unfavourable thermal behaviour in the inverter irrespective of the inverter's design. This motivates the need for a more detailed analysis on which aspects of motor design influences the inverter's thermal behaviour and in what way.

However, with such complex systems, it becomes challenging to identify the cause of an observed change and the corresponding change propagation path, especially with the traditional model representations. This may be attributed to the traditional approach's limitations in capturing complex interactions (O'Reilly et al., 2016).

To address this challenge, several tools and methods were developed including machine learning techniques (Charisi et al., 2025), optimisation algorithms for early-stage design exploration (Pillai et al., 2020), multi-layered network-based approaches (Brownlow et al., 2021), and sensitivity analysis-based techniques (Opgenoord et al., 2016). Although these approaches address various limitations of the traditional approach, they focus on isolated aspects. To overcome this challenge, in the author's previous work (Abburu, 2023; Abburu et al., 2024), a framework was proposed that integrates network theory and Global Sensitivity Analysis (GSA). The framework provides an alternative representation to complex models and identifies the change propagation path between the input and output. This enables reduction in model complexity while preserving the ability to analyse the cause and effect of design changes on both output and the intermediate variables. Thus, offering the designers a clear insight into the consequences of their design choices.

Utilizing this framework, the present paper investigates the interaction between two subsystems within the traction chain of a rail vehicle. Specifically, the influence of the 3-phase induction motor design on the thermal behaviour of the inverter's power electronic components is analysed. Subsequently, a function that defines the relationship between the motor design inputs and the temperature behaviour of the inverter components is determined and a coefficient that represents the strength and direction of the influence is calculated.

2. FRAMEWORK

In this section, a brief account on the framework that is utilised to analyse the influence between the two subsystems is provided. There are five major aspects of the framework as shown in Figure 1.

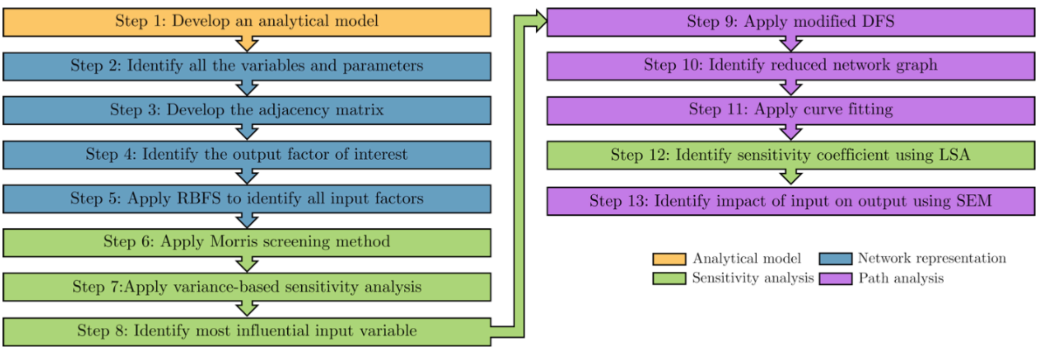

Figure 1: Framework for quantifying impact of an input on an output

In Step 1, an analytical model of the complex multidisciplinary subsystem consisting of multiple subsystems is developed. Subsequently using all the variables, input, and output parameters of the analytical model identified in step 2, an adjacency matrix is developed in step 3. With the adjacency matrix, network representation of the analytical model is then developed. Subsequently, an output of interest is chosen as the starting point of the analysis in step 4, and a Reverse Breadth First Search (RBFS) algorithm is applied in step 5 to identify all the intermediate variables and inputs that influence the chosen output are determined. This results in a reduced network graph. However, since not all intermediate variables and inputs may not have a significant effect on the output, initially the most influential inputs are identified using Global Sensitivity Analysis methods. Specifically, in step 6, Morris Screening method is applied to filter the insignificant inputs (Morris, 1991), and in step 7, for the filtered inputs, the Sobol indices are identified using the Polynomial Chaos Expansion (PCE) approach (Sudret, 2008). This provides the strength and ranking of influence of the inputs on the output. For the most influential inputs, a modified Depth First Search algorithm is applied in step 9 to identify all the paths that a specific input can take to reach the output. This provides all the intermediate variables that are influenced for a given input and output and hence, an even more reduced network graph in step 10. In step 11, curve fitting techniques are applied to derive a function that defines the relationship between the identified input and the chosen output. Finally, in step 12 and 13, using structural equation modelling and local sensitivity analysis a coefficient that indicates the strength and direction of influence of the input on the output is calculated.

3. SUBSYTEM INTERACTION ANALYSIS

In this section, the interaction between the traction motor design and thermal behaviour of the inverter is analysed. One of the primary functions of the inverter is to supply the necessary current and voltage for motor operation. Additionally, as indicated in Eq. (1), a major component in calculating the power loss of the inverter includes the voltage (V_{in}) and current (I_{max})values of the motor along with the inverter dependent variables such as switching frequency (f_s), the latency in time for switching on (t_{on}) and off(t_{off}), and the load resistance of the inverter (R_d). This displays a clear intrinsic connection between the subsystems and the two variables, voltage and current of the motor, will act as the interface edges between the network models of the two subsystems.

$$P_{loss} = 0.5 V_{in} I_{max} f_s (t_{on} + t_{off}) + 0.5 R_d I_{max}^2 \quad (1)$$

The analysis of the influence of motor design on the thermal behaviour of the inverter is performed by utilizing the framework described. Initially, an analytical model of a 3-phase induction motor and a cooling model of an inverter that captures the temperature evolution of the power electronic components in the inverter are developed. The outline of the combined motor and inverter model is depicted in Figure 2.

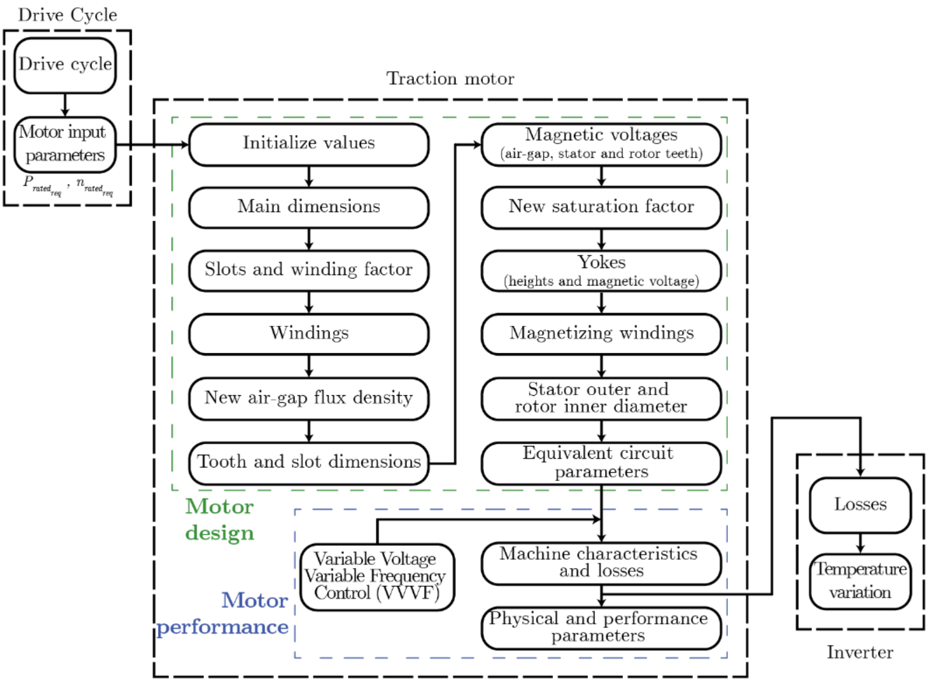

Figure 2: Overall procedure for the combined traction motor and inverter model.

Then, an adjacency matrix is developed using all the variables and parameters in the model. Subsequently, the adjacency matrix is used to develop a network representation of the combined analytical model. There are 238 factors in the developed network model. According to the framework, a variable of interest needs to be chosen as a starting point of the analysis. Since power loss is a main component that influences the thermal behaviour of the inverter and temperature is a more practical metric for evaluating the thermal performance, in this paper, temperature of the power electronic components at the base plate is chosen as the output of interest. Using Reverse Breadth First Search

(RBFS) algorithm, all the intermediate variables, parameters, and inputs that influence the temperature evolution in inverter are determined and a reduced network graph is obtained. The number of factors to consider at this stage has reduced from 238 to 178 i.e. nearly 25% reduction in the complexity of the analysis.

However, there are still several inputs and intermediate variables influencing the output of interest. However, not all the inputs have a significant effect on the output. Therefore, Global Sensitivity Analysis methods are used to identify the most influential inputs, and the strength and direction of these inputs on the output. Specifically, initially Morris screening method is utilized to filter the insignificant inputs and identify the direction of the influential inputs. The results from the Morris screening method are shown in Figure 3. The figure on the left shows the result from the old estimator which calculates the mean and standard deviation of the output while modifying one input at a time. However, in the presence of nonmonotonic functions, this estimator might give incorrect results as the positive and negative values in the function can negate each other. Thus, an absolute estimator is proposed and the results from the new estimator is shown in the right-side figure of Figure 3. It can be observed from Figure 3 (left) that the rated power is on the left axis, indicating an inversely proportional relationship with the base temperature. Thus, using Morris screening method the influential input and its direction of influence is identified.

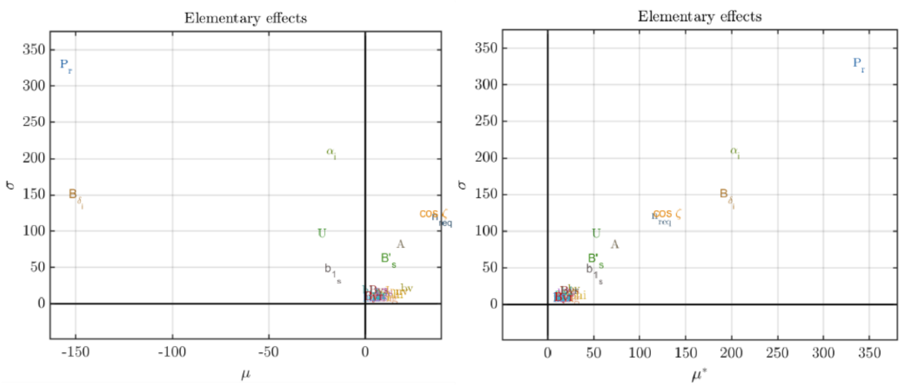

Figure 3: Results of Morris screening method with old estimator (left) and new estimator (right) applied with base temperature as output of interest.

Subsequently, the Sobol indices of the influential inputs are calculated using the PCE approach. The Sobol indices provide a quantitative comparison of the influential inputs providing a metric to measure the strength and ranking of the influence of the inputs. The Sobol indices of the influential inputs are shown in Figure 4.

It can be observed that the rated power is predominantly the most influential input and therefore, in this analysis, the influence of rated power on the temperature of the base plate in inverter is analysed. It must be noted that typically GSA is performed on scalar quantities and temperature is inherently time dependent. Therefore, the maximum temperature observed over the operative drive cycle is used as a representative scalar metric for the sake of simplicity. However, it is worth mentioning that there are cluster-based GSA techniques that can capture temporal or spatial dependencies which shall be considered in future work.

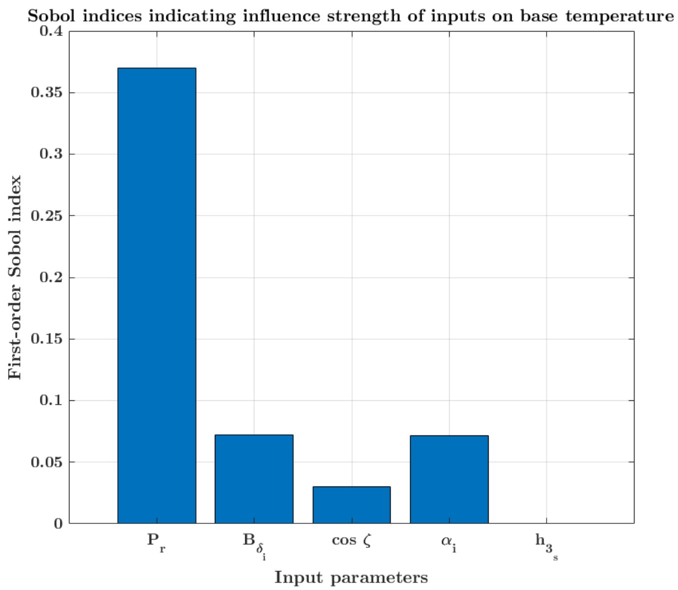

Figure 4: Sobol indices indicating strength of influence of inputs over base temperature

Following this step, a modified Depth-First Search (DFS) algorithm is used to identify the various paths that the input could take to reach the output of interest. This results in a further reduced network graph with just the intermediate variables that get influenced by changing the rated power and in turn influence the change in the base plate temperature. The reduced network graph from the modified DFS is shown in Figure 5.

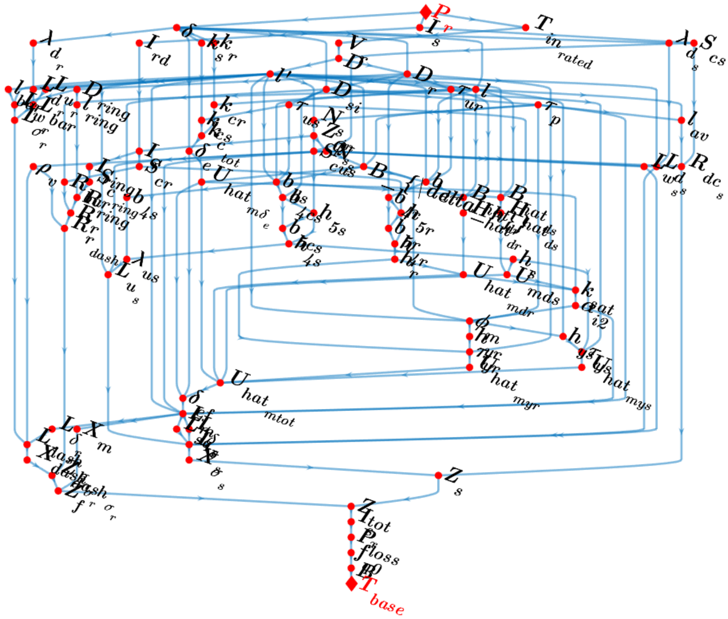

Figure 5: Reduced network graph obtained using modified DFS depicting all paths between rated power (P_r) and base plate temperature T_{base}

At this stage, the number of factors to consider has reduced to 100 from the original 238 factors i.e. reducing the size of the network to consider by nearly 57%. However, the network graph still contains a large number of paths that the input can take to reach the output, specifically, 3568 paths. Therefore, to further reduce complexity and enhance interpretability, the principles of Structural Equation Modelling is applied here. More specifically, the Wright's multiplication rule which states that the effect of an independent variable on a dependent variable through one or more mediating variables is approximately equal to the sum of the product of path coefficients along all possible causal pathways that connect the independent and dependent variable (Wright, 1934) . Mathematically WMR can be described using Eq. (2).

$$S_{Total} = \sum_{p=1}^{n} \prod_{i=1}^{k} w_{i_p} \tag{2}$$

Therefore, in this analysis since the intent is to identify the influence of rated power on the base plate temperature, the intermediate variables are not analysed. However, if the intent is to analyse the impact of the input on the intermediate variables and how the intermediate variables in turn influence the output of interest, a function representing each edge in the network must be derived. In this paper, for the sake of simplicity, only the input, key interface parameters, and the output are considered.

With the key factors in the network identified, a relationship between the input and output is derived using curve fitting. To perform the curve fitting, first a parametric study is performed by varying the identified influential input, required rated power, and plotted against the maximum base plate temperature as displayed in Figure 6. This essentially means that for a specific operational drive cycle with specific power and speed requirements, the capability of the motor power is increased. With each increment of required rated power of motor, a separate motor configuration is obtained which then produces a different maximum base plate temperature. It can be observed from Figure 6 that there are distinct clusters formed, and this can be attributed to the presence of design margins. The reasoning behind these clusters is discussed further in Section 4. Moreover, it can be observed that there is an overall trend of decrease in the maximum base plate temperature with the increase in required rated power. Using the MATLAB curve fit toolbox, a function that represents this overall trend of rated power and maximum temperature is identified. The resulting curve fit is displayed in Figure 6 and the relationship from the curve fit is identified as Eq. (3).

$$T_{base_{max}} = -0.0013 P_r + 1060.3 \tag{3}$$

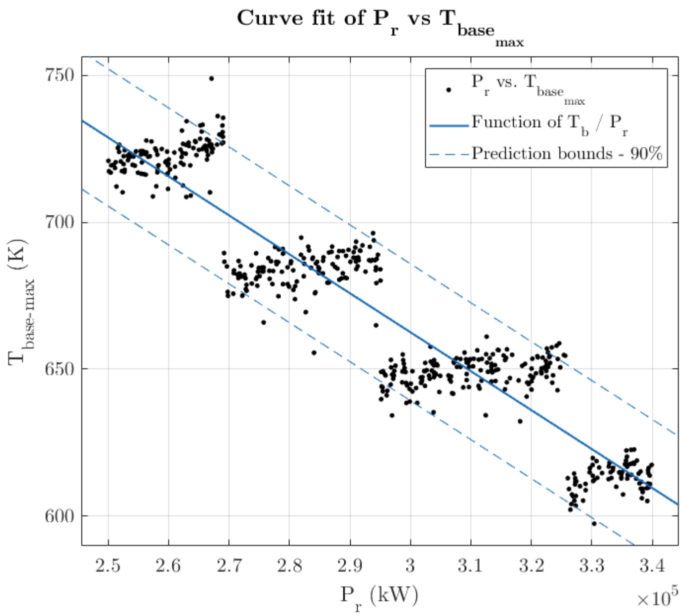

Figure 6: Curve fit depicting the relationship between rated power and base temperature

Subsequently, using the identified function, a sensitivity coefficient that indicates the strength and direction of influence of the input on the output is calculated using Local Sensitivity Analysis techniques as -0.0013. In fundamental terms, this indicates for every 1 kW increase in rated power, the base temperature value decreases by 0.0013 K. The fitted model includes a 90% prediction interval, indicating that there is a 90% probability that future observations will fall within the prediction bounds.

4. DISCUSSION

The analysis of the influence of motor parameters on the thermal behaviour of the inverter components revealed that the motor input, required rated power had the highest influence on the chosen output of interest, temperature of the base plate in inverter components. For performing curve fitting, the maximum base plate temperature was plotted against different required rated power values and displayed in Figure 6. It can be observed from Figure 6 that there are distinct clusters for a specific range of motor power. This behaviour can be attributed to the presence of design margins of certain components within the traction motor model. These margins allow for variations in the input up to a certain limit without significantly impacting the component's output. In this design margin, the components act as change absorbers. However, when the inputs are modified beyond these margins, the components begin to either propagate or multiply the incoming changes. This result in the output shifting noticeably, leading to a transition from one cluster to another. Furthermore, by performing curve fitting and calculating a coefficient to indicate the strength and direction of influence showed that the rated power and base plate temperature have an inversely proportional relationship. This means that for a given operational drive cycle with specific power and speed requirements, using a more powerful motor will reduce the maximum temperature. This trend is reasonable, because for the same performance demands, a more powerful motor experiences less operational stress and will operate close to the efficient region. Thereby, leading to reduced operational temperatures. However, there is a trade-off that needs to be considered. A more powerful motor might reduce the operational temperature, but it also results in a larger and heavier motor, which may lead to space and weight constraints. This could further negate the volume and weight reduction achieved by switching from Si to SiC semiconductor. Therefore, this trade-off shall be further explored in future work.

5. CONCLUSION

In this paper, utilizing the integrated framework, the relationship between motor input parameters and thermal behaviour of the inverter components is derived and a coefficient indicating the strength and direction of the influence is calculated. Additionally, by performing this analysis, the various intermediate variables that are influenced and in turn influence the inverter temperature is identified. This information can help the designers understand not only the influence of modifying the input on the output, but also which intermediate variables are being impacted. Furthermore, the approach demonstrated the ability to couple a static model (motor) with a dynamic model (inverter cooling), thereby validating the framework's applicability to multi-scale subsystem interactions. However, a representative scalar value from the dynamic temperature value was used to analyse the influence of the input. To address this limitation, cluster-based GSA shall be explored in future work. Notably, this approach reduced the number of factors to consider by 57%. However, even with the reduced network model, there were large number of factors and paths to consider. A more efficient method to deal with such situation will be explored more in future work.

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