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Electric Vehicle Thermal System Concept Development for Multiple Variants Using Digital Prototype and AI

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Abstract: The automotive industry is experiencing a surge in system complexity driven by the ever-growing number of interacting components, subsystems, and control systems. This complexity is further amplified by the expanding range of component options available to original equipment manufacturers (OEMs). OEMs work in parallel on more than one vehicle model, with multiple vehicle variants for each vehicle model. With the increasing number of vehicle variants needed to cater to diverse regional needs, development complexity escalates. To address this challenge, modern techniques like Model-Based Systems Engineering (MBSE), digitalization, and Artificial Intelligence (AI) are becoming essential tools. These advancements can streamline concept development, optimize thermal and HVAC system design across variants, and accelerate the time-to-market for next-generation EVs. The development of battery electric vehicles (BEVs) needs a strong focus on thermal management systems (TMSs) and heating, ventilation, and air conditioning (HVAC) systems. These systems play a critical role in maintaining optimal battery temperature, maximizing range and efficiency, and ensuring passenger comfort. This article proposes a digital prototype (DP) and AI-based methodology to specify BEV thermal system and HVAC system components in the concept phase. This methodology uses system and variant thinking in combination with digital prototype (DP) and AI to verify BEV thermal system architecture component specifications for future variants without extensive simulation. A BEV cabin cooling requirement of 22 °C to be achieved within 1800s at a high ambient temperature (45 °C) is required, and its verification is used to prove this methodology.

Keywords: electric vehicles; thermal management systems; HVAC systems; automotive system complexity; model-based systems engineering; digitalization; artificial intelligence

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1. Introduction

OEMs spend years in battery electric vehicle (BEV) development, which involves extensive research, design, and testing. Every system within the electric vehicle, from the battery to the thermal management system and its components, needs meticulous engineering, often exceeding three years. Relying only on a heterogeneous simulation approach and physical prototypes carries many risks. Systematic development approaches like Systems Engineering with up-to-date methodologies are required to develop complex systems like vehicles. System Engineering processes contain requirements derivation, systems specifications, integration, and verification and validation (V&V) [1].

A compact and efficient thermal system is required for electric vehicles to manage fluctuating heavy thermal loads from time to time. Vehicle efficiency can be reduced by up to 50% [2] if climate control is not optimized because cabin cooling takes a significant portion of battery energy. Heat waste shortage makes EV cabin heating a challenge. Different heating and cooling methods and strategies are required to control complex EV cooling systems. A thermal management system protects [3,4] vehicle components from overheating, makes them operate in the optimal range, and helps achieve passenger comfort and durability targets [4]. Thermal management responds to the heating and cooling demands of components and the passenger cabin. This helps increase range and comfort. It also helps achieve homologation requirements like windshield defogging and deicing [4].

A thermal system with liquid battery cooling contains a refrigerant and coolant loop. The refrigerant loop controls the temperature of the vehicle cabin while the coolant loop maintains battery temperature within limits. The chiller interconnects two loops and provides super cooling to the battery. This increases efficiency because cooling via a refrigerant circuit will consume more energy than operating the battery coolant circuit due to the need for the air compressor in the first case [5].

Use cases represent a cornerstone of system validation, enabling development engineers to verify that the system functions as intended under various scenarios and operational environments. By incorporating normal and extreme use cases into the testing process, engineering teams can proactively identify and address potential issues, ultimately leading to a more robust and reliable system [6].

BEV thermal management and HVAC systems directly impact driving range, comfort, and overall efficiency, making them essential for customer satisfaction and brand differentiation. Stakeholder requirements are the roadmap for building a successful BEV thermal management system. Meeting requirements on specific use cases is important to make sure the final thermal system is exactly what was intended. Requirements and use cases serve as a foundation for automotive system development. Any modification to these elements has cascading effects on the system architecture and behavior, requiring careful analysis and adjustment to maintain system integrity and performance [7].

The BEV thermal management system (TMS) architecture is based on the vehicle's specific needs and thermal requirements. The TMS architecture has separate cooling circuits for the electric drive unit and the high-voltage battery. TMS requirements and architecture aim to maintain optimal temperatures for the battery and other components to maximize their performance and efficiency [8].

The International Council of System Engineering (INCOSE) vision for 2035 [9] paints a picture of systems engineering heavily reliant on digitalization and AI (Artificial Intelligence) to tackle complex systems efficiently. These techniques are crucial for the future of the automotive product development field. In the next sections, the digital prototype (DP) and AI-based methodology to specify BEV thermal system and HVAC system components in the concept phase are explained. This methodology uses system and variant thinking in combination with digital prototype (DP) and AI to verify BEV thermal system architecture component specifications for the future variant without extensive simulation. A BEV cabin cooling requirement of 22 °C in the 1800s at a high ambient temperature (45 °C) use case is verified to demonstrate this methodology.

The rest of this article is structured as follows. In Section 2, the BEV TMS digital prototype development methodology is explained. In Section 3, digital prototype layers are described. In Section 4, the current variant component specification prediction using DP is explained. In Section 5, DP-based methodology capability enhancement using ANN to predict future variant HVAC component specifications is explained.

2. BEV TMS Digital Prototype

System Engineering [4] relies on creating and maintaining multiple documents to capture system information, while Model-Based System Engineering (MBSE) formalizes the use of models throughout the system development cycle. MBSE supports system requirements design analysis, verification, and validation from conceptual design to later life cycle phases (Table 1).

Table 1. Summarizes the differences between SE and MBSE.

	System Engineering (SE)	Model-Based System Engineering (MBSE)
Approach	System information is captured in documents	Use of models throughout the system development life cycle
Representation	Document based	Graphical models (e.g., SysML, UML) [10] to represent system aspects
Benefits	-Accuracy depends on the quality of documentation -Challenge of managing consistency and version control	-Data-centric specifications enable automation and optimization -Provides deeper systems understanding without increasing costs -Facilitate communication among development teams

Systems Engineering (SE) is based on four interlocking pillars: processes, methods, tools, and people [9]. The MBSE methodology [6] works through requirements derivation, systems specifications, integration, verification, and validation. Use cases define the purpose of the system [11] and how it interacts with system users and other systems; therefore, clarity about use cases helps to focus on features that deliver value. Use cases represent how the system will be used by its intended users in different operational environments and life cycle stages. These scenarios encompass functionalities performed by users under various operational conditions. Use cases serve as a foundation for effectively validating the system behavior, which involves executing these scenarios with actual users in their operational environment. This practical approach ensures the system functions are designed within a real-world context. It is imperative to test the system beyond nominal operating conditions on use cases like charging and driving. It is important to consider maintenance use cases [4].

Driving: Electric vehicle (EV) thermal management maintains optimal battery temperature. Heating the battery during cold weather improves driving range because temperature reduces battery efficiency. The HVAC system regulates cabin temperature and defrost windows.

Charging: Maintaining the battery within a specific temperature range during charging enhances charging efficiency. Maintaining battery cell temperature within a required temperature during fast charging ensures rapid charging with minimal losses, and efficient thermal management enables fast charging times [12].

Maintenance: Maintaining component temperature extends their lifespan; overheating can degrade battery cells while excessively affecting motor efficiency. Effective thermal management ensures durability and reliability. The capable thermal system enables the use of integrated components along with a thermal management system, which enhances performance and simplifies design.

Stakeholder requirements [13] explain the purpose of the system. Requirements define what the system must have to meet the expectations. This makes all the stakeholders working on system development focused. Requirements [7] also make sure the system will perform in all operational environments, and they specify how systems must interact with other systems by identifying interfaces that avoid issues with the battery and other components' performance of the system. The definition of requirements creates accessibility between the purpose of the system use cases and stakeholder requirements. Requirements also act as the definition of the scope of the system development and ensure the final system meets all the requirements.

The BEV thermal requirements [4] revolve around components that require conditioning during high and low temperatures and passenger comfort. Examples of representative thermal system requirements are listed in Table 2.

The BEV TMS [4] architecture is based on vehicle-specific needs and thermal requirements. The thermal management system architecture has separate cooling circuits for the electric drive unit and the high-voltage battery. The cooling circuit containing the drive unit uses an electric pump and a radiator to manage heat. The high-voltage battery cooling circuit, along with the refrigeration circuit, uses three-way valves to cool the battery.

- By a chiller using a refrigerant circuit;
- By a radiator using waste heat from the electric drive;
- By combining both methods.

The BEV thermal management system control functions determine the best cooling method based on inputs like ambient temperature and coolant temperatures. The system also includes heating for the HV battery and passenger cabin using electric heaters. The TMS requirements and architecture aim to maintain optimal temperatures for the battery and other components to maximize performance and efficiency.

The INCOSE Vision 2035 [13] heavily emphasizes the role of digitalization and AI in system development. The vision predicts the future where MBSE becomes the standard practice. This involves using a digital model throughout the development process, which allows for simulation analysis and optimization. AI can be integrated into model systems and engineering tools to automate tasks and improve decision-making.

Table 2. Thermal system requirements [4].

Subsystem	Feature	Description
Electric Drive Unit (EDU)	Radiator Cooling	Cooling with 50%/50% water/glycol mixture Coolant temp @EDS inlet: 65 °C Condition: Driving
High-Voltage Battery	HV Battery Cooling HV Battery Cooling HV Battery Heating	cooling with 50%/50% water/glycol mixture Condition: Charging Condition: Fast charging at a high temperature of 45 °C To meet charging target at very low-temperature Active heating @, e.g., −20 °C
Passenger Cabin	Cooling	Cooling requirements 25 °C in 15 min @45 °C
	Heating	Heating requirements Active heating

The vision acknowledges that the system will become increasingly complex in the future. Both digitalization and AI can help manage this complexity by automating routine tasks, providing data analysis, and identifying potential issues early in the development process. It also emphasizes the need for more efficient and effective systems and engineering practices. AI analyses the amount of data to optimize system decisions and performance, while digital tools can streamline communication and collaboration. It recognizes that digitalization and AI will require a skilled workforce, including engineers who understand how to use these tools effectively and how to integrate them into existing systems and engineering processes.

Figure 1 shows the TMS digital prototype development in the context of system engineering. It is developed using principles of MBSE and product life cycle management. The digital prototype allows utilization in the early phases of development [14] ("frontloading") combined with other systems simulation capabilities to predict thermal system components specifications of the future thermal system variant.

A TMS digital prototype is a physical system representation. It is a combination of simulation models built using MATLAB/Simulink and Simscape [15]. A prototype is an essential part of the digital master and digital twin. It is difficult to include all the systems in the model for simulation purposes. Therefore, the virtual prototype can be adapted for specific activities.

Digital prototypes incorporate existing knowledge from current TMS use cases, requirements, architecture, and components specification and thermal system control software knowledge (MATLAB 2024a) [16]. It also considers knowledge from the MBSE processes methods and existing tools. Virtual prototypes incorporate existing knowledge from current TMS use cases, requirements, architecture, and components specification and control software. It also considers knowledge from the MBSE processes methods and existing tools.

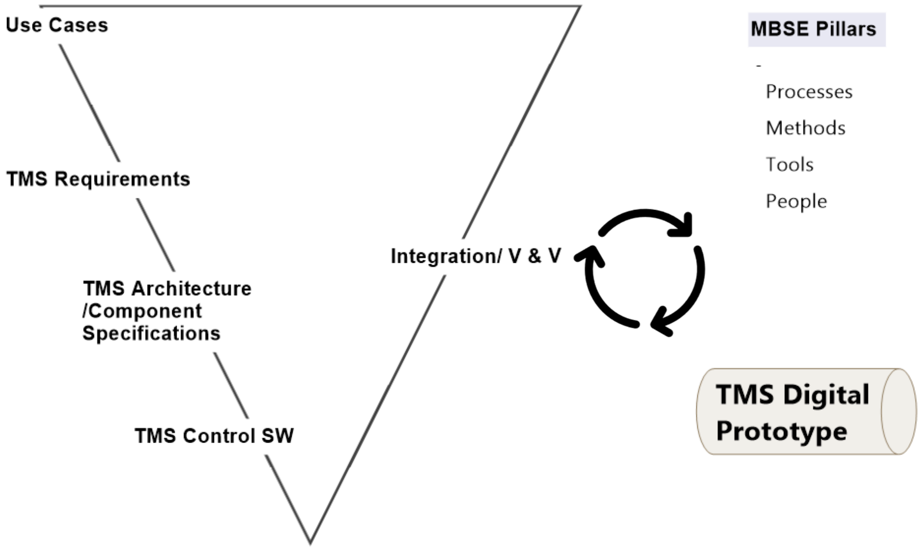

Figure 1. Thermal management system virtual prototype development methodology.

3. Digital Prototype Layers

The development platform strategy with virtual prototypes includes layers such as the model backbone, execution backbone, automation backbone, data backbone, and process backbone [16]. The number of layers in a BEV TMS digital prototype depends on the specific need and complexity of the prototype. Mainly, a digital prototype should have requirements, such as a thermal system and other systems models, architecture layers, an execution layer, and a data processing layer.

3.1. Requirements Layer

The BEV TMS digital prototype requirements layer drives the system behavior and performance. Its functionality ensures the prototype lines match the vehicle's overall objectives. The digital prototype's requirements layer integrates performance metrics such as the following:

- Temperature ranges for HV battery, motor, power electronics, and cabin;
- Heating and cooling are required for optimal performance;
- Energy efficiency targets for the thermal system;
- Comfort levels for passengers;
- Specifies weight volume and cost restrictions for the thermal system;
- Defines material compatibility requirements;
- Outlines packaging constraints and integration challenges;
- Specifies failsafe mechanism and redundancy requirements;
- Specifies operating temperature and humidity ranges;
- Serviceability requirements;
- System lifetime and maintenance intervals;
- Ensures adherence to relevant safety and performance regulations;
- Tracking of requirements throughout the development process;
- It is the basis for testing and validation.

3.2. TMS Model/Architecture Layer

The model layer incorporates architecture and implementation methodology and explains what components to connect from simulation and hardware to run a virtual prototype. This layer outlines the scope of the thermal management system and its interaction with other vehicle components. It specifies the system's input and output parameters and defines communication protocols with other control units.

3.3. TMS Model Execution Layer

The execution layer is mainly concerned with coupling and has clarity about co-simulation and real-time simulation and addresses issues related to technical challenges [16] like multi-domain, multitool, multivendor, and mathematical challenges related to models like multi-method, multi-solver, and multi-rate simulation. During all development phases, it is possible to run extensive simulations at a low cost, which increases in later stages due to hardware involvement. Automation layers decide which test to run early in the development process.

3.4. Data Processing Layer

The data layer deals with massive data generated after virtual prototype simulation. It includes a lot of data related to simulation model parameters and test results. This layer is important to keep on track related to traceability and avoiding any duplications. Every requirement for the TMS has a related parameter, which has a set value [16], as shown in Figure 2.

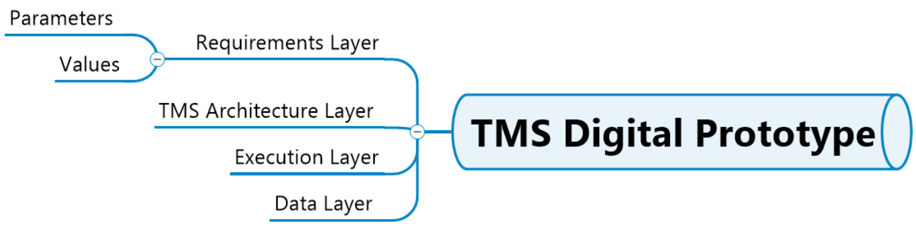

Figure 2. TMS digital prototype layers and the relation between requirements and parameters.

4. Digital Prototype Application

A digital prototype, as discussed in previous sections, is understood to be used as a digitalization strategy within organizational product development methodology. The digital prototype application depends on the purpose of use and capacity of digitalization implementation within an organization. The scope of this research is to show how a digital prototype of a BEV TMS in combination with the AI technique (ANN) can be used to enhance components specification methodology instead of using costly development methods using physical components, use of test rigs, and physical vehicle prototypes. In this section, component specification for the current variant using a DP is explained.

4.1. Problem Statement

The selection of HVAC components is important for the overall efficiency and performance of the BEV [17]. The right components can significantly impact vehicle range and efficiency. Inefficient HVAC components can consume more battery power, reducing the overall vehicle driving range [18]. By optimizing components for the heat pump [19], the system can maximize energy recovery, improving the range. The right components ensure optimal cabin temperature, leading to driver and passenger comfort; proper filtration and ventilation systems contribute to a healthy cabin environment. Optimized temperature control of the battery is important for its longevity and performance, and efficient cooling prevents overheating, which can degrade battery capacity and safety [12]. Compact and lightweight components optimize vehicle weight distribution and packaging space. All the components should fit in the vehicle architecture without any issues. Properly designed components minimize noise and vibration, enhancing passenger comfort.

A trade-off between performance and cost is important for overall vehicle profitability. Components' durability must withstand the rigorous use of vehicles, ensuring long-term vehicle reliability.

Using digital prototypes instead of physical prototypes will reduce cost and development time [20]. Vehicle manufacturers often work on the development of multiple vehicle variants. Developing a digital prototype based on one vehicle variant and simulating it by changing requirements will confirm component specifications and architecture integrity to continue with series development.

4.2. Vapor Compression Refrigeration Cycle

The vapor compression refrigeration cycle, as shown in Figure 3, is the foundation for cooling systems in air conditioners and refrigerators. A refrigerant [3] can be in liquid or gaseous form. When the refrigerant evaporates (transition from liquid to gaseous), a refrigerating capacity is generated, facilitating cooling even below the ambient temperature. The heat released during condensation (gas to liquid) is used to heat the compartment. Compressors in refrigerant circuits enable flow at the desired pressure so that evaporation and condensation happen at the desired temperature.

The refrigerant cycle starts from the compressor to the point when the refrigerant exits the evaporator, and this cycle continues until the compressor turns off [21]. Materials absorb heat when changing from liquid to gas. Heat is transferred from the change of state of the refrigerant and is removed from the passenger compartment. The refrigerant cycle has the following phases:

1. Compressor compresses low-pressure gas into a hot, high-pressure gas;
2. Condenser condenses hot high-pressure gas into warm, high-pressure liquid. The cool air absorbs the heat of the refrigerant and changes it back to liquid;
3. Over-expansion refrigerant is changed from a warm, high-pressure liquid into a cold, low-pressure liquid;
4. Refrigerant evaporates into gas when it passes through an evaporator; when refrigerant leaves the evaporator, it is a cool, low-pressure gas.

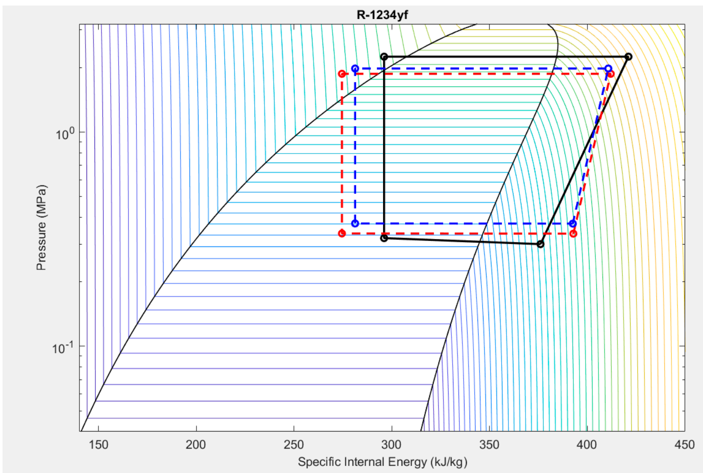

Figure 3. Pressure and enthalpy operating points of initial and base variant refrigeration cycle for 2 use cases (**black**: initial ref cycle, **red**: 50 kph, and **blue**: 100 kph).

The refrigerant cabin cooling system follows the ideal vapor compression cycle described above. It is essential to tune components in the refrigerant system to avoid system pressure and temperature runaway [3,21]. The refrigerant undergoes energy transfer that causes substantial and rapid density changes.

HVAC Component Specification (Base Variant)

The following steps [15] are used to size the base variant HVAC system model, as described in the flow chart in Figure 4. This HVAC model is a building block of the digital prototype.

1. Define the operating region of the refrigeration cycle using a P-H diagram (Figure 3);
2. Build a testing architecture for the evaporator using a system-level condenser evaporator block within the ideal flow source and reservoir blocks for boundary conditions;
3. Implement a thermostatic expansion valve into the evaporator architecture;
4. Build a testing architecture for the condenser using the system-level condenser of the evaporator block with the positive displacement compressor block and using two-phase and moisture reservoir blocks for the boundary condition;
5. Connect the previous two architectures using the receiver accumulator block;
6. Remove the two-phase reservoir and close the loop.

This will provide nominal sizing of the component, and the model can be tested beyond nominal settings.

In the next step, defining the parameters for an evaporator, condenser, thermostatic expansion valve, and receiver accumulator is required [17]. Firstly, pressure must be created in the architecture for the simulation. Define nominal operating conditions are defined as follows in Table 3.

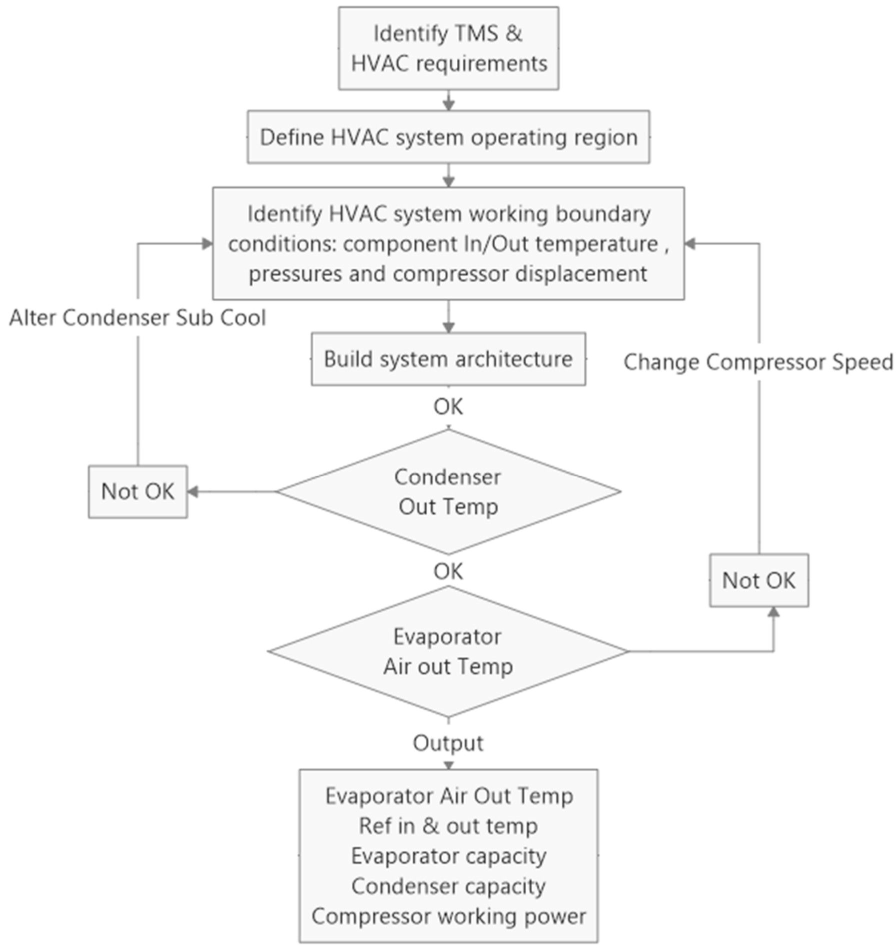

Figure 4. Base variant HVAC sizing process [17,21].

- The condenser temperature (saturation) is set higher than the outside temperature to enable heat transfer. There should be a delta between the condenser and ambient temperature;
- The evaporator temperature (saturation) is set lower than the component temperature to enable heat transfer to refrigerant. There should be a delta between the evaporator and component temperature;
- Subcooling at the condenser outlet is set to specify enthalpy endpoints of the high and low-pressure lines in the cycle (Table 4).

Table 3. Nominal HVAC system operating condition definition.

Ambient Temperature	**45 °C**
Desired cabin temperature	22 °C
Cooling capacity	10 kW
Refrigerant	R1234yf

Table 4. Operating cycle pressure and enthalpy settings.

Location	Point #	Specific Pressure (MPa)	Specific Enthalpy (kJ/kg)	Description
Evaporator out	1	0.3	376	Corresponds to a superheat of 10 °C
Condenser in	2	2.25	421	Corresponds to a Temperature of 90 °C approximately.
Condenser out	3	2.25	296	Corresponds to sub-cooling of 10 °C
Evaporator in	4	0.3	296	Corresponds to vapor quality of 0.26

Refer to Figure 4 for a visual representation of the corresponding P-H diagram.

Evaporator capacity and condenser capacity are calculated using Equations (1) and (2) as given below from [17]:

$$\text{Evaporator Capacity} = \dot{m}_{\text{air}} \left(h_{\text{air}} + h_{\text{Evaporator out}}\right) \tag{1}$$

where the following is defined:

$\dot{m}_{\text{air}}$ = Inlet air mass flow rate;
h_{air} = Enthalpy of evaporator inlet air;
$h_{\text{Evaporator out}}$ = Enthalpy of evaporator outlet air.

$$\text{Condenser Capacity} = \dot{m}_{\text{air}} \left(MR_{\text{air}} + MR_{\text{Evaporator out}}\right) \tag{2}$$

where the following is defined:

$\dot{m}_{\text{air}}$ = Inlet air mass flow rate;
MR_{air} = Moisture of inlet air;
$MR_{\text{Evaporator out}}$ = Moisture of evaporator outlet air.

The results of the current variant component specification can be reviewed in Appendix B.

5. Future Variant HVAC Sizing

Changing use cases and requirements significantly impact the thermal system model, affecting both its architecture and behavior. The system contains specific models, which are computer-aided design (CAD) models comprising mechanical functionality and system models that are developed with MATLAB/Simulink [17]. Specific models and system models can overlap, containing the same information being used differently. It is important to reduce overlapping between models [16].

Impact of Requirement Change on Architecture: Changes in requirements might necessitate additional components or subsystems to fulfill new functionalities. For example, adding new capabilities to the thermal system would require sensors, actuators, and advanced control system functions. Current components may need upgrading or modification to meet new performance expectations, for example, to meet flow requirements to cool down the battery, and an upgraded coolant pump is required. Changes in requirements can alter how components interact with other components or sub-systems. This may require more complex communication with other systems. Sometimes, fundamental changes in requirements might necessitate a complete review of system architecture.

Impact of Requirements Change on System Behavior: Upgraded requirements directly impact the system behavior. Additionally, use cases might introduce new system modes or operating conditions. Changes in requirements often translate to different performance targets, and altered requirements can change how the system responds to inputs, for example, if the time to cool down the cabin for customer comfort is required to upgrade compressor performance.

In the previous sections, digital prototype-based HVAC sizing for the current variant is explained. A digital prototype is developed using available data in the feasibility and concept phase, and the digital prototype has been incorporated with requirements and use cases. Component specifications are calculated for the current variant. In this section, the digital prototype-based HVAC component sizing prediction method is established for future variants when the digital prototype is already available and is required to predict component specifications for future variants.

For future variant component specifications, digital prototype capability is enhanced with an artificial neural network (ANN) to save development time and cost. A neural network [15] is an adaptive system inspired by the human brain. It learns from data using interconnected nodes or neurons arranged in layers. These networks can recognize patterns, classify data, and predict future events by breaking down inputs into layers of abstraction. During training, the weights between neurons are adjusted to improve performance. The structure includes an input layer, one or more hidden layers, and an output layer, with each neuron in the layer using the output from the previous layer as input [22].

For this methodology, Vehicle average speed (kph), Compressor displacement (cc), compressor speed (rpm), Condenser saturation temperature, evaporator saturation temperature, and sub-cool requirements are used as inputs to predict evaporator capacity, condenser capacity, evaporator out-air temperature, evaporator in and out refrigerant temperature and compressor working power. For each prediction output, a separate neural network has been developed. Inputs and outputs can be seen in Figure 5.

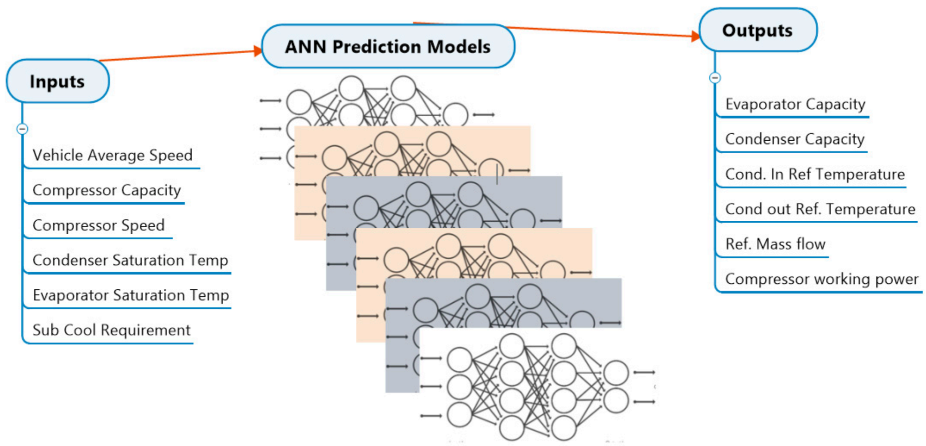

Figure 5. Artificial neural networks structure, inputs, and prediction parameters.

5.1. DP and Neural Networks (ANN) Structure

The methodology using the digital prototype for HVAC components specification prediction is shown in Figure 6. Considering the changing requirements in the future system, specific changes in the model have been implemented. A testing design of the experiment is implemented, and a simulation is run using the developed design of the experiment (DOE). A modified model for future variant HVAC components specifications contains an artificial neural network block that processes available data after the design of the experiment is run.

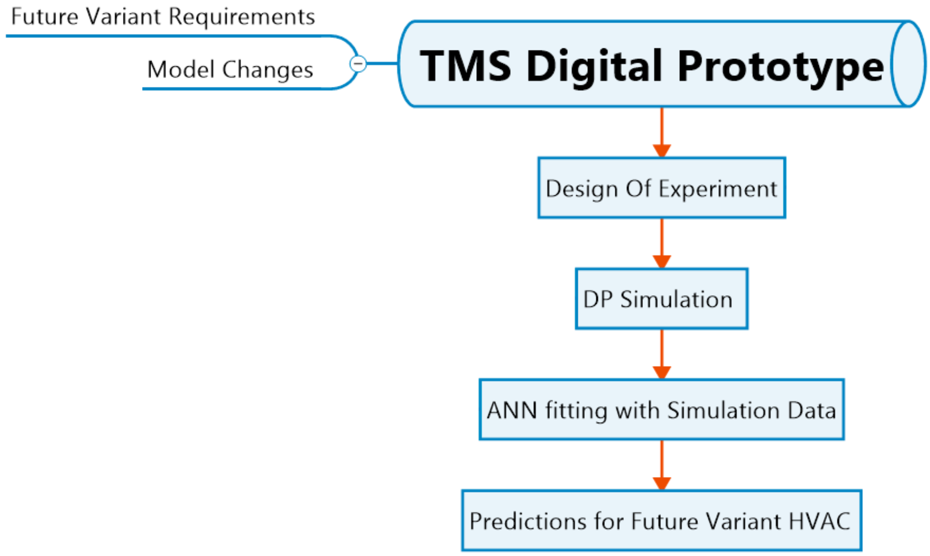

Figure 6. Relationship between TMS DP and ANN.

5.2. Prediction Features

Sub-cooling is refrigerant cooling below its condensation temperature to ensure that the refrigerant enters the expansion valve in a liquid state to increase cycle efficiency. This ensures the refrigerant is fully liquid, maximizing the cooling capacity of the system and reducing the risk of flash gas formation, which can lead to inefficient cooling and increased energy consumption. On the other hand, the temperature increases of the refrigerant vapor above its boiling point, which is measured at the evaporator outlet and ensures that the refrigerant is fully vaporized before entering the compressor. This helps to ensure vapor enters the compressor, preventing liquid refrigerant from causing any damage to the compressor and correcting superheat levels so that the evaporator is fully utilized, enhancing the overall cooling performance.

5.3. Predictors and Response Variables Correlation

To characterize the correlation between the input (Figure 7) and output variables, the Pearson correlation coefficient is used [23]. The correlation coefficient provides two values: the correlation coefficient (rho) with the range [−1,1] and the correlation coefficient p value with [0,1]. The correlation coefficient signifies the linear correlation between two variables; the +1 value indicates a perfect positive correlation, −1 indicates the perfect negative correlation, and zero indicates no linear relationship between the two variables. The p values represent the probability of the current observation occurring in the sample data; the smaller the value, the more stable the correlation between the tube variables. The correlation coefficient is given by Equation (3).

$$[rho(a,b),\ p\ val] = \sum_{i=1}^{n}(Xa,i - \overline{X}a)(Yb,i - \overline{Y}b)/\left\{\sum_{i=1}^{n}(Xa,i - \overline{X}a)^2 \sum_{i=1}^{n}(Yb,j - \overline{Y}b)^2\right\}^{1/2} \quad (3)$$

where n is the length of each column, X, and Y are the variable values, and $\overline{X}$, $\overline{Y}$ are the mean values of corresponding inputs.

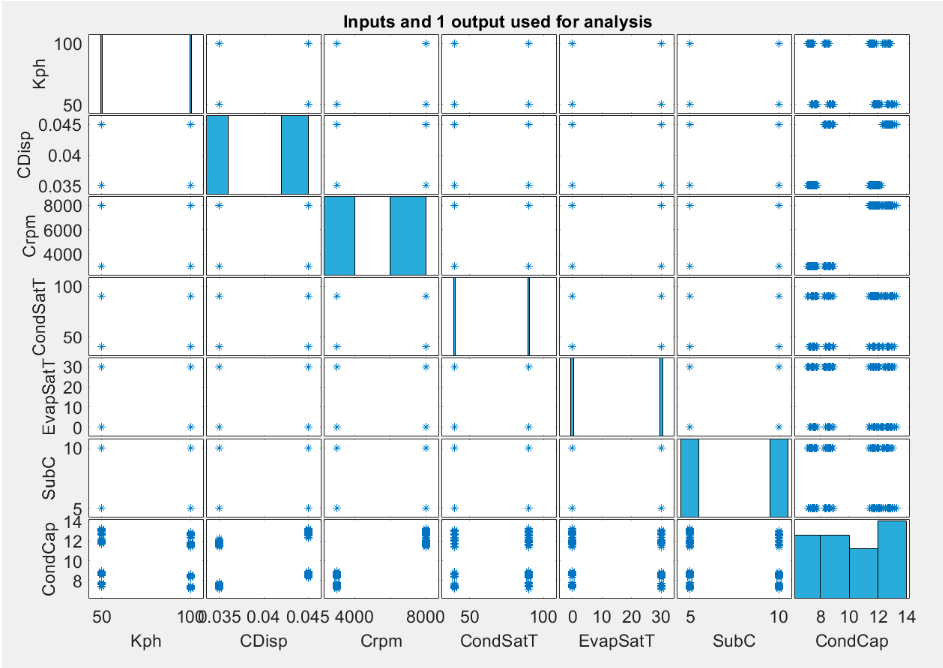

Figure 7. Input variables are used for refrigerant system component specification prediction and predicted output condenser capacity in the last columns.

Figure 8 illustrates the correlation between compressor speed and predicted variables is the strongest.

	Kph	CompDisp	CompRpm	CondSatT	EvapSatT	Sub cool	Cond Cap	Copm Work Pwr	Ref mass Flow
Kph	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0716	0.0437	0.0090
CompDisp	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.2392	0.2291	0.2432
CompRpm	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.9656	0.9706	0.9683
CondSatT	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0164	0.0066	0.0120
EvapSatT	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	-0.0011	0.0110	-0.0124
Sub cool	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	-0.0210	-0.0096	-0.0081
Cond Cap	-0.0716	0.2392	0.9656	0.0164	-0.0011	-0.0210	1.0000	0.9900	0.9941
Copm Work Pwr	0.0437	0.2291	0.9706	0.0066	0.0110	-0.0096	0.9900	1.0000	0.9970
Ref mass Flow	0.0090	0.2432	0.9683	0.0120	-0.0124	-0.0081	0.9941	0.9970	1.0000

Figure 8. Correlation between input and 2 of the output variables.

5.4. ANN Training Algorithm

For this problem the Levenberg-Marquardt [24] backpropagation algorithm is used, which is an algorithm to train neural networks; it is particularly effective for nonlinear least square problems. This algorithm combines the strength of the cause Newton algorithm and gradient descent, making it robust and efficient [15,25]. This is a faster algorithm compared with the standard gradient decent method, especially when the initial guess is close to the optimal solution. This algorithm starts with an initial guess for the network weights and biases. It computes the Jacobian metric, which contains the first derivative of the network error concerning the parameters. It is possible to adjust the parameters using a combination of the Gauss–Newton method and gradient descent, which involve solving a linear system that balances between these two methods controlled by damping factor and converges, i.e., when the changes in parameters become sufficiently small, or the maximum number of iterations is reached.

The Levenberg–Marquardt algorithm uses an approximation to the Hessian matrix by following a Newton-like update rule for the parameters from [15,24,25] in Equation (4):

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (4)$$

where the following is defined:

J^T is the Jacobian metrics of partial derivatives;
e is the vector of residuals (errors);
I is the identity metric;
μ is the damping factor.

The damping factor is adjusted based on the performance of the algorithm. If the step reduces the cost function, μ is decreased; otherwise, if the cost function increases, then μ is increased.

5.5. ANN Performance Index

The neural net fitting process starts with importing data and splitting it into training validation and test sets. For this exercise, 15% of data has been allocated to validation and test sets, and 70% has been used as fitting data. The Levenberg–Marquardt Optimization algorithm is used to update weight and bias values; this is the fastest training algorithm, although it requires more memory than other algorithms [15].

Two-layer feedforward neural networks (Appendix D) are used to fit the input-output relationship; given that enough neurons are in the hidden layer, layers that are not output layers are called hidden layers. Performance is measured in terms of mean square error (MSE), which can be analyzed in the Figure in Appendix D; MSE rapidly decreased as the network was trained. The performance of each of the training validation and test sets can be analyzed in the figure. The final network is the network that performed best on the validation set.

Another measure of how the neural network fits the data can be analyzed in a regression plot, which is applied to all the samples in the data. The regression plot in Figure in Appendix D shows the actual network output fitted in terms of the associated target values. If the network has learned to fit the data well, the linear fit to this output target relationship should closely intersect the bottom left and top right corners of the plot. If this does not happen, then further training with more hidden neurons is required.

It can be observed in Figure 8 that the coefficient of correlation R is nearly equal to one, which indicates that data fitting quality is very good. From the coefficient of correlation, the coefficient of determination can also be calculated (R^2), which indicates the proportionate amount of variation in the response. It is the proportion of the total sum of squares explained by the model. R squared, a property of the fitted model, is a structure with two fields.

Ordinary (unadjusted) R-squared:

$$\mathrm{R}^2 = \mathrm{SSR/SST} = 1 - \mathrm{SSE/SST} \quad (5)$$

R squared adjusted for the number of coefficients:

$$\mathrm{R}^2\ \mathrm{adj} = 1 - (\mathrm{n} - 1/\mathrm{n} - \mathrm{p})\mathrm{SSE/SST} \quad (6)$$

SSE is the sum of the squared error;
SSR is the sum of squared regression;
SST is the sum of the squared total;
n is the number of observations;
p is the number of regression coefficients.

Another indication of how well the neural network has fitted the data is the error histogram, as shown in Appendix D Figure. This figure shows how the other sizes are distributed. Most errors (Target—Modelled), as defined in Equation (7), are near zero, with very few errors far from that.

$$e = T - Y \tag{7}$$

A comparison of actual and predicted condenser capacity, using one of the artificial neural networks fitted above, can be seen In Figure 9.

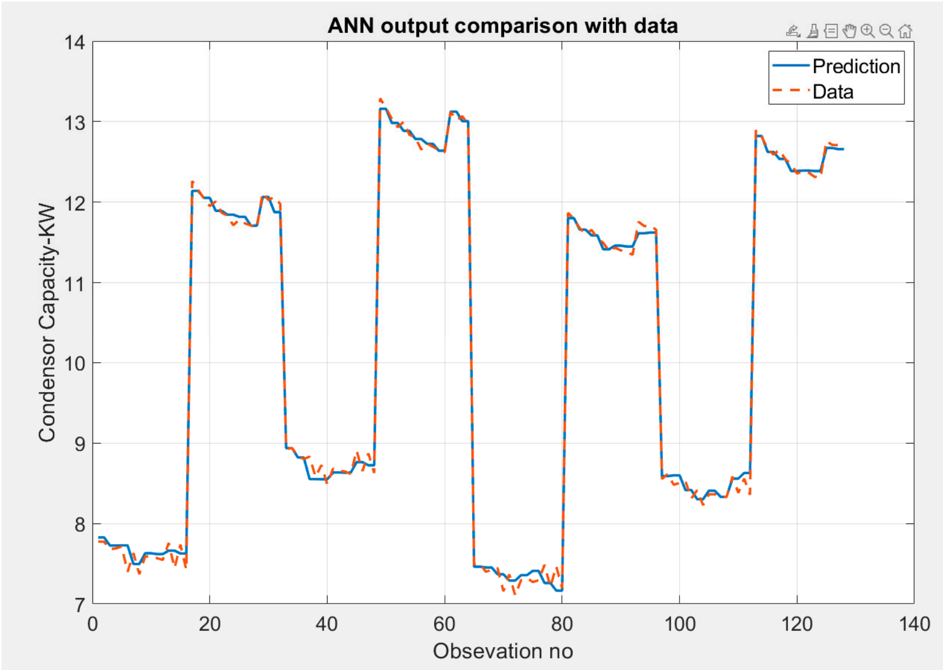

Figure 9. Comparison of actual and predicted condenser capacity using ANN.

6. Future Variant HVAC Component Specification Prediction

Using a fixed compressor, evaporator, and condenser inputs, as in Appendix C, the two constant vehicle speed use cases (50 and 100 kph) were considered for base variant component specification predictions. However, artificial neural networks enable future variant component prediction for many different use cases. In the next figures, results are plotted against compressor working power at different vehicle speeds ranging from 50 kph to 100 kph. All these simulations were performed with compressor displacement of 45 cc, 40 cc, and 35 cc, compressor speeds of 7500, 7200 rpm, and 6800 rpm, condenser condensation temperature of 80 °C, evaporated condensation temperature of 5 °C, and subcooling settings of 5. Digital prototypes and artificial neural networks enable the prediction of different operating points by changing one of the above inputs.

Figure 10 shows different performance metrics against vehicle speed ranging from 50 to 100 kph. Evaporator capacity above 90 kph cases were above 7.4 kW. For compressor displacement of 35 cc and 6800 rpm, it was noticed that the evaporator capacity was nearly the same, matching with the compressor displacement of 40 cc and compressor speed of 7200 rpm PM. Condenser capacity and refrigerant mass flow followed the same trend for all vehicle speed use cases. Condenser capacity was found to reduce between 50 and 100 kph for all three simulated cases, while refrigerant mass flow was found to increase; in all three cases, mass flow remained between 0.08 and 0.1 kg/s.

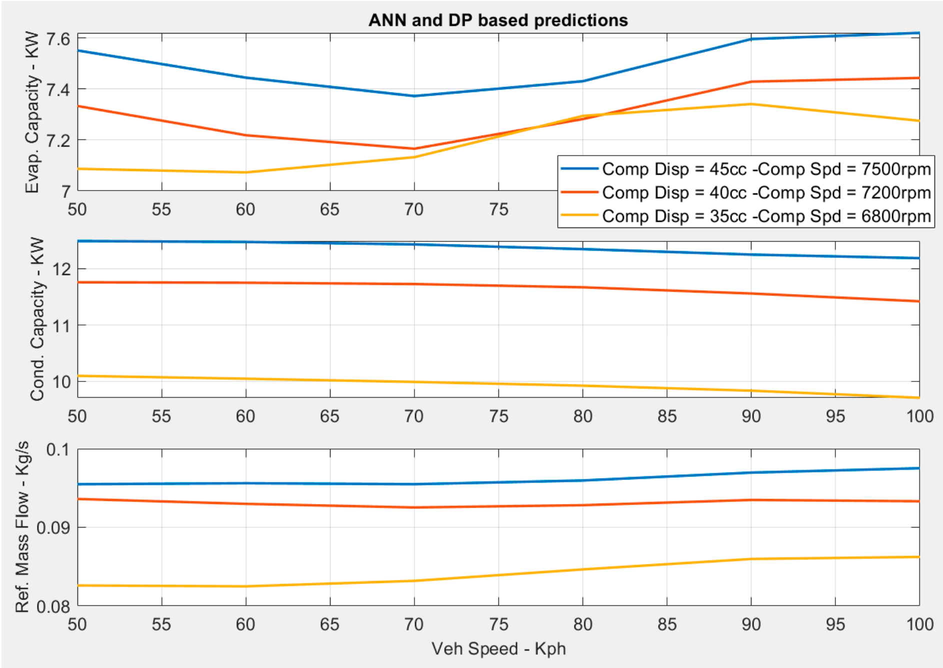

Figure 10. ANN and DP-based prediction results for evaporation capacity, condenser capacity, and refrigerant mass flow. The simulation was performed for six different use cases ranging from 50 to 100 kph.

The refrigerant temperature entering and exiting the condenser is shown in Figure 11. For the first case of compressor displacement 45 cc and compressor speed 7500, the condenser entering temperature was above 100 °C, which reduced below 26 °C after the condenser.

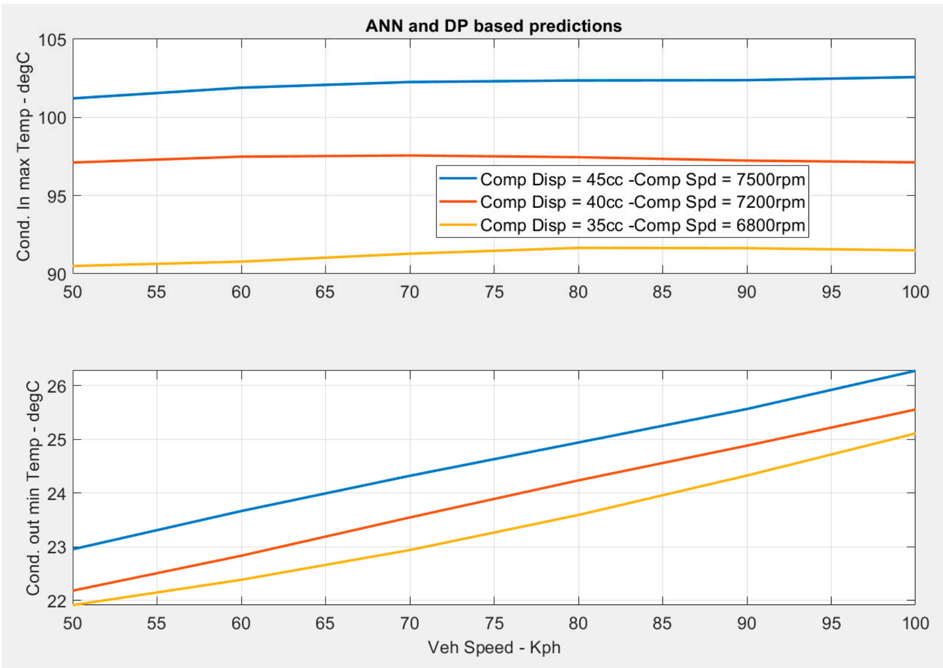

Figure 11. ANN and DP-based prediction results for condenser in and out refrigerant temperatures. The simulation was performed for six different use cases ranging from 50 to 100 kph.

Predictions based on digital prototypes and artificial neuron networks for temperature requirement and HV battery state of charge (SOC) consumption are shown in Figure 12.

It is noted that for a lower capacity compressor, it took longer (more than 1200 s) to meet cabin temperature set point requirement; a similar time has been seen with a vehicle high-speed case. The state of charge was found to increase linearly with vehicle speed, with the maximum state of charge reduced to about 8% in the 100 kph case. It is noticed that with the current coolant pump and compressor setting, the battery cooling requirement was not met at 1800 s.

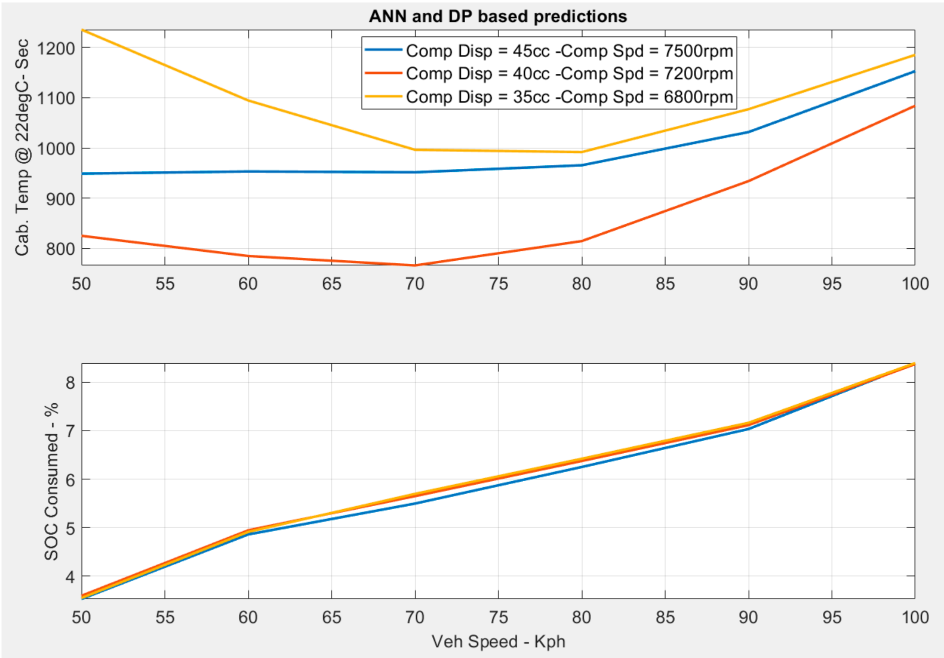

Figure 12. ANN and DP-based prediction results for the time at which cabin temperature requirements were met and the state of charge consumption. The simulation was performed for six different use cases ranging from 50 to 100 kph.

7. Conclusions

Using the MBSE approach, the BEV thermal system design is discussed, and the concept of DP is defined. A typical architecture is derived from use cases, requirements, and TMS functions. Further, an application example is defined, relating to the HVAC sizing which is critical to overall BEV performance.

The fundamentals of a typical refrigerant cycle are explained. The DP-based HVAC component sizing prediction method is established for current variants when DP is already available. The capability of DP is enhanced in combination with ANN, which is explained. It is used to predict component specifications for future variants. Condenser and evaporator performance contribute to an efficient BEV HVAC system and were predicted using ANN for multiple vehicle drive cycle use cases for cabin temperature comfort targets requirement. Refrigerant mass flow, condenser in and out refrigerant temperature, time to reach cabin requirement temperature, and SOC consumption were also predicted using DP and ANN-based methodology.

Automotive systems are becoming complex, and manufacturers work on more than one vehicle variant in parallel. By changing requirements from variant to variant, the thermal system is required to verify and validate for modified components. Model-Based Systems Engineering helps develop complex systems to streamline development processes, but with increasing development complexity, it is required to use MBSE with artificial intelligence techniques to reduce development time and cost. By using this methodology, thermal management, and HVAC system components specifications have been verified for future variants in very little time compared with the current variant for which all the simulation processes have been followed.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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

Appendix A

Table A1. Vehicle Specifications.

Vehicle Specification	**Base Variant**	**Future Variant**	
Vehicle Class	Passenger car	Passenger car	Units
Mass	1800	2200	kg
Powertrain	Pure Electric	Pure Electric	
Drive	RWD	AWD	
Front eMotor Power	X	75	kW
Rear motor Power	160	160	kW
Acceleration Performance (0–100 kph)	10	8	Sec
Maximum Speed	130	160	kph
AC charging Power (max)	22	22	kW
DC charging Power (max)	50	150	kW
Battery Rated Energy	60	110	kWh

Vehicle specifications for two different vehicle variants, the current variant for which HVAC component sizing specifications have been predicted using DP and the future variant for which HVAC component specifications have been predicted with enhanced methodology using DP and ANN.

Appendix B

Table A2. Requirements.

Vehicle Requirements	**Base Variant**	**Future Variant**	
Use case	Value	Value2	Attribute
Max Vehicle Speed @40 °C for 20 min, @22 °C Cabin Temp.	120	160	Performance Comfort
Vehicle Driving Range @WLTP @22 °C	350	430	Efficiency
Vehicle Driving Range @WLTP @−15 °C	250	320	Efficiency Comfort
Cabin Temperature @40 °C and 50 kph, 1000 W/m^{2}K, 20% Humidity	22 °C	22 °C	Comfort
Cabin Temperature @−15 °C and 50 kph	22 °C	22 °C	Comfort
Thermal System Requirements			
160 kph, 22 °C Ambient Temp.	Reject 10 kW	Reject 12 kW	(from EDU)
22 °C	Reject 5 kW	Reject 7 kW	(from HV Battery)
Cooling System Requirements			
EDU Coolant Flow @22 °C	7	12	
EDU Coolant Flow @60 °C	10	15	
HV Battery Coolant Flow @40 °C	10	15	
Air Temperature @Evaporator Outlet	5 °C	5 °C	

Thermal system requirements [4] used for current and future variants of HVAC component sizing prediction.

Appendix C

Table A3. Base Variant HVAC Sizing Results.

Use Case		50 kph	100 kph
CompDisp	CC	0.035	0.035
CompRpm	rpm	6500	6500
CondSatT	°C	80	80
EvapSatT	°C	5	5
Subcool		5	5
Evaporator Capacity	kW	7.72	7.28
Condenser Capacity	kW	10.93	11.37
Compressor Power	kW	2.61	3.56
Cond Out min Temp	°C	20.11	23.79
Cond In Max Temp	°C	80.96	100.45
Ref Mass Flow	kg/s	0.085	0.092
Cab Temp @22 °C	sec	1016	822
SOC Consumed	%	2.48	6.29

Digital prototype (DP) based simulation results for the current variant. Use cases (50 kph, 100 kph) were simulated. Inputs are highlighted in grey.

Appendix D

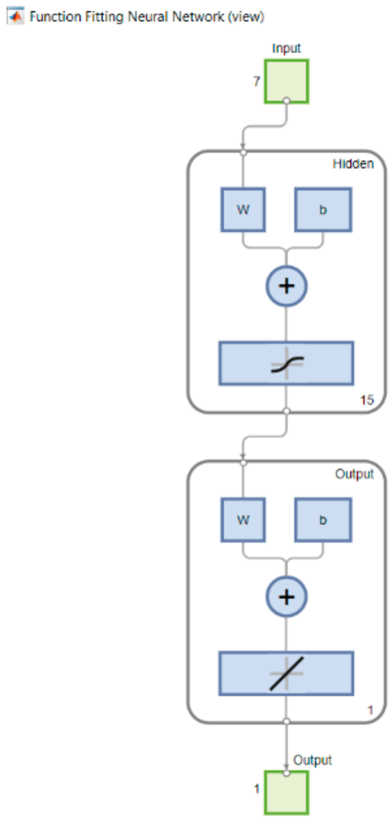

Figure A1. Two-layer feedforward neural networks for condenser capacity prediction.

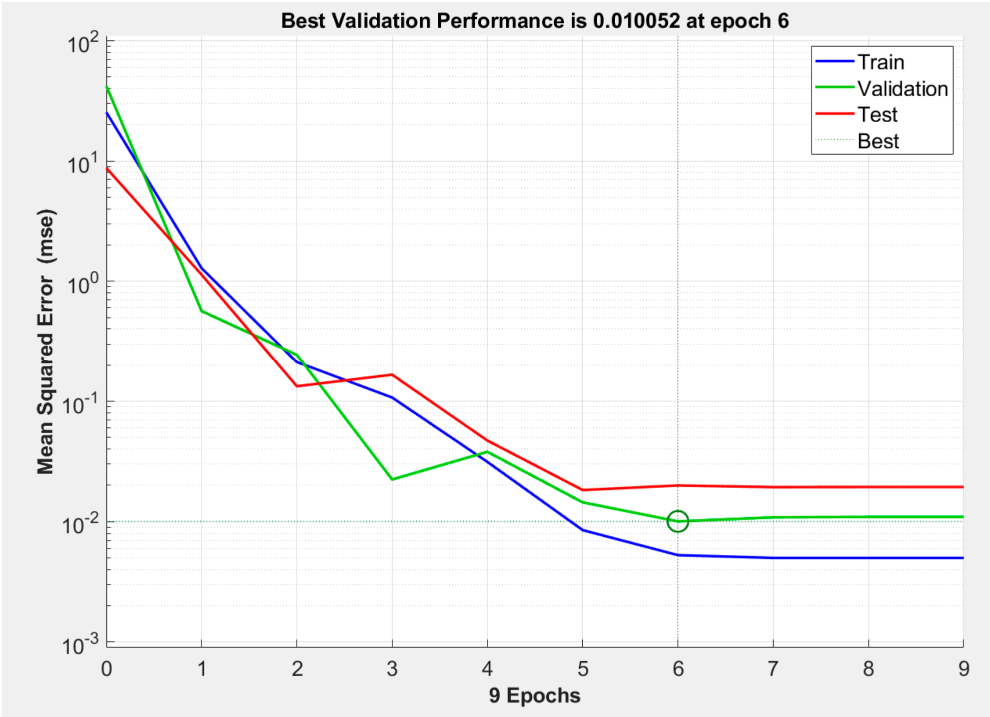

Figure A2. Performance for each of the training validation and test sets for condenser capacity prediction.

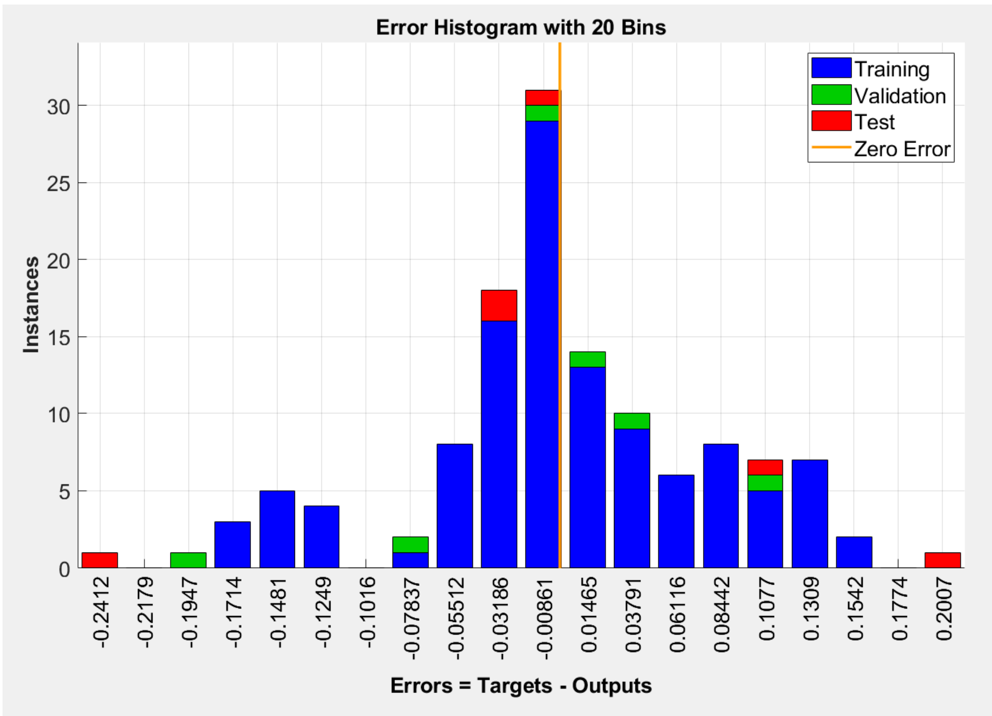

Figure A3. Error histogram for condenser capacity prediction.

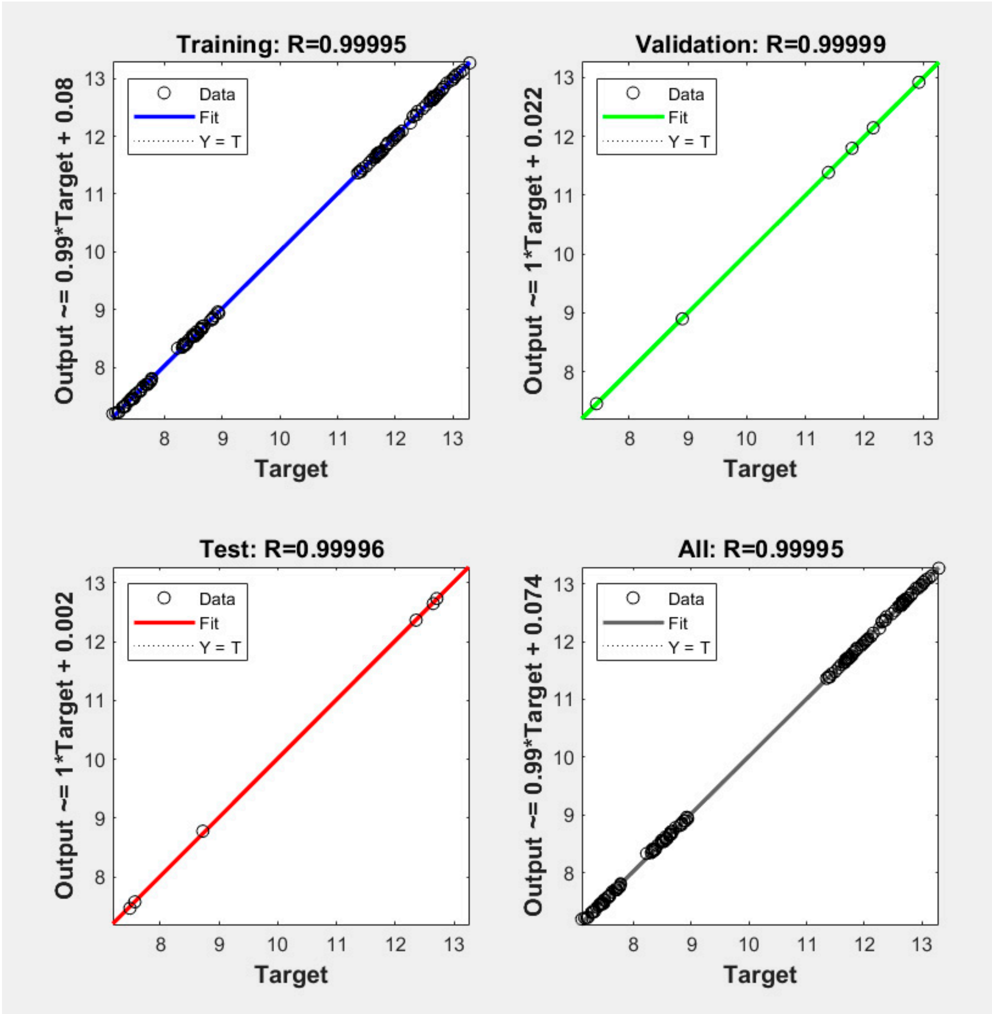

Figure A4. Regression plot for Condenser capacity prediction.

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