Supervised-Learning-Based Optimal Thermal Management in an Electric Vehicle

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ABSTRACT Due to the increasing market share of electric vehicles (EVs), the optimal thermal management (TM) of batteries has recently received significant attention. Optimal battery temperature control is challenging, requiring a detailed model and numerous parameters of the TM system, which includes fans, pumps, compressors, and heat exchangers. This paper proposes a supervised learning strategy for the optimal operation of the TM system in an EV. Specifically, for TM subsystems, individual artificial neural networks (ANNs) are implemented and trained with data obtained under normal EV driving conditions. The ANNs are then interconnected based on the physical configuration of the TM system. The trained ANNs are replicated using piecewise linear equations, which can be explicitly integrated into an optimization problem for optimal TM scheduling. This approach enables the application of a mixed-integer linear programming solver to the problem, ensuring the optimality of the solution. Simulation case studies are performed for the two operating modes of the TM system: i.e., integrated and separate modes. The case study results demonstrate that the ANN-based model successfully reflects the operating characteristics of the TM system, enabling accurate battery temperature estimation. The proposed optimal TM strategy using the ANN-based model is verified as effective in reducing the total energy consumption, while maintaining the battery temperature within an acceptable range.

INDEX TERMS Artificial neural network, battery temperature, electric vehicles, mixed integer linear programming, piecewise linear equations, supervised learning, thermal management.

NOMENCLATURE

- **AC** air conditioning
- **ANN** artificial neural network
- **EV** electric vehicle
- **EWP** electric water pump
- **GA** genetic algorithm
- **LTR** low-temperature radiator
- **MILP** mixed integer linear programming
- **NARX** nonlinear auto-regressive network with exogenous inputs
- **NMSE** normalized mean squared error
- **PSO** particle swarm optimization
- **PE** power-electronics
- **ReLU** rectified linear unit
- **SL** supervised learning
- **TM** thermal management

Sets and Indices:

- $t, \tau$ superscripts for time
- $\min, \max$ subscripts for minimum and maximum values
- $i, j, o, h$ subscripts for $i_{th}$ and $j_{th}$ neurons, output neuron, and $h_{th}$ hidden layer
- $s, s'$ subscripts for $s_{th}$ and $s'_{th}$ subsystems
- $se$ subscripts for segments of linearized activation function
- $u$ subscripts for controllable devices in TM system
- $b, cp, fn, p, pe$ subscripts for battery, compressor, radiator fan, electric water pumps, and power electronics
- $bi, ro$ subscripts for battery inlet and radiator outlet
- $c, e, y$ subscripts for controllable inputs, environmental inputs, and outputs

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The market share of electrified vehicles has been increasing continuously due to environmentally friendly policies and the falling prices of battery packs [1], [2]. The supply of electric vehicles (EVs) has significantly increased, along with those of other types of vehicles, such as plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), and fuel cell hybrid vehicles (FCHVs) [3], [4]. Since a large battery capacity is required for vehicle operation, significant attention has been paid to the thermal management (TM) of batteries [5]–[8] for lifetime and performance improvement. As shown in Table 1, several studies [9]–[16] were conducted on optimal battery TM, involving physics-based modeling of TM systems for various types of vehicles. In [9] and [10], the optimal operation of a TM system was achieved using simple optimization algorithms with the pre-determined operating rule and the iterative investigation of the controllable, discretized input combinations, respectively. In [11]–[14], the optimization problem was formulated with the objective function consisting of the costs for the total power consumption and corresponding battery temperature variation. The objective function also included the heat loss [9], [15] and the fuel consumption and gas emission [16]. For optimal TM, the power inputs of fans and pumps were commonly considered as controllable inputs, mainly due to the simplicity of device modeling. Compressors are rather complicated but have high power ratings, significantly affecting the power consumption and battery temperature. In [15] and [16], the output currents of the battery were actively controlled, for example, to reduce the power and heat losses for the case in which the EVs were parked in cold weather.
In [9]–[16], the “perfect” optimal operations of the TM systems were achieved using fully informed physics-based models; however, physics-based modeling often requires numerous parameters to reflect nonlinear operating characteristics of TM system components such as batteries, pumps, compressors, and heat exchangers. Most of the parameters remain unidentified and significantly vary by component size, type, and manufacturer. Therefore, in practice, the physics-model-based TM strategies discussed in [9]–[16] should be accompanied with parameter estimation techniques. This makes them time-consuming and difficult to apply to real EVs that are currently in daily service.

Due to recent advances in sensing and data technologies, increasingly large amounts of data on EV driving and TM system operation can be collected and processed in real time [17]. This motivates developments and applications of various machine learning algorithms [18], [19] to resolve the challenges associated with the physics-model-based TM strategies discussed in [9]–[16] should be accompanied with parameter estimation techniques. This makes them time-consuming and difficult to apply to real EVs that are currently in daily service.

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The trained ANNs can be used to predict variations in battery temperature for changes in TM system operation with respect to conditions including fan power, coolant flow rate, vehicle speed, and ambient temperature. The ANNs can be further exploited for the optimal operation of the TM system, as discussed in [20] and [21], although these studies were focused on buildings, rather than EVs. Note that the optimal operation of the TM system using the ANN-based modeling approach likely differs from the “perfect” optimal operation using the physics-based modeling method. In [22] and [23], the ANNs were treated as black-box models, requiring iterative, heuristic algorithms (e.g., GA and PSO) for optimization problem solving. The solutions of these algorithms often fall into one of the numerous local optima owing to the use of random mutation or random values. Therefore, the optimization problem needs to be solved iteratively to select the best local optimal solution among those obtained so far, leading ultimately to a significant increase in the computational time.

Based on these observations, this paper proposes a new SL-based strategy for the optimal operation of the TM system in an EV. Specifically, in the proposed strategy, an ANN-based model is implemented for each subsystem of the TM system that affects the battery temperature. The individual ANNs are trained with data obtained under normal EV driving conditions and then interconnected based on the physical relationships between the subsystems. The trained, interconnected ANNs are then represented using a set of explicit, piecewise linear equations, which can be directly integrated into the constraints of an optimization problem for TM scheduling. The piecewise linearization enables extension of the feasible solution area with boundaries set by the mixed-integer linear constraints. The problem can then be solved within reasonable computational time using non-iterative, deterministic mixed-integer linear programming (MILP) in off-the-shelf package (i.e., IBM ILOG CPLEX Optimizer [24]). Case studies were performed for the driving cycles consisting of urban dynamometer driving schedule (UDDS) and highway fuel economy test (HWFET) schedule. The results confirm that the ANN-based model successfully reflects the operating characteristics of the TM system, enabling accurate battery temperature estimation. Consequently, the proposed strategy using the ANN-based model effectively reduces the power consumption of the TM system while maintaining the battery temperature within an acceptable range.

The main contributions of this paper are summarized as:

- To our best knowledge, this is the first study in which an ANN-based model of a TM system has been implemented and replicated using piecewise linear equations for integration into the optimization problem. This mitigates the necessity of obtaining physics-based modeling parameters and hence improves the applicability to various types of EVs.
For each TM subsystem, individual ANNs are trained and interconnected based on the physical relationships between the subsystems. This enhances the modeling performances of the ANNs, improving the accuracy of the battery temperature estimation.

A simple procedure has been developed to select ANN architectures for minimal over-fitting. This enhances the generalizability of the ANNs in reflecting the operating characteristics of the TM subsystems, improving the performance of the SL-based TM system operation.

Case studies have been performed for two TM modes: integrated and separate. The case study results confirm the effectiveness of the proposed strategy, for the two TM modes and two common driving cycles, in reducing the total power consumption while maintaining the battery temperature within an acceptable range.

The remainder of this paper is structured as follows: Section II presents the ANN-based model of the TM system. Section III explains the ANNs linearization and the optimization problem. Section IV presents the case study results. Section V concludes the paper.

### II. ANN-BASED THERMAL MANAGEMENT

#### A. THERMAL MANAGEMENT SYSTEM

Fig. 1(a) and (b) show the schematic diagrams of a common TM system in an EV [8] for the integrated and separate modes, respectively. For battery temperature control, the TM system includes three main types of controllable devices: a compressor, a radiator fan, and two electronic water pumps (EWPs) [25]. It also contains circulation loops by which air and the refrigerant in the integrated and separate modes, the coolant delivers and exchanges heat with the ambient (EWPs) [25]. It also contains circulation loops by which air and the refrigerant in the integrated and separate modes, the coolant delivers and exchanges heat with the ambient

The coolant temperature estimation.

The integrated mode is initiated when $T_b$ is maintained within a stable range and $T_{hi}$ is sufficiently low to cool down the battery (i.e., $T_{hi} \leq T_b$). Specifically, the EWPs operate with the same speed, so that the coolant flows into the battery module and then the power-electronics (PE) module with consistent $m_f$. At the low-temperature radiator (LTR), the coolant exchanges the heat collected from the battery and PE modules with the ambient air. The coolant, with low $T_{ro}$, then flows into the battery again. The radiator fan improves the rate of heat exchange between the coolant and ambient air, further reducing $T_{ro}$. On the other hand, the separate mode starts when $T_{ro}$ is higher than $T_b$, for example, due to the high ambient temperatures. The coolant loop is then divided into two, as shown in Fig. 1(b). Consequently, $T_b$ control is achieved by delivering the heat collected from the battery to the refrigerant at the chiller and then to the ambient air at the condenser. The compressor can operate not only to achieve air conditioning (AC) inside the vehicle but also to improve the efficiency of battery heat delivery [8]. This considerably reduces $T_b$, at the expense of increasing the total power consumption of the TM system.

#### B. ANN ARCHITECTURE AND TRAINING

For $T_b$ control, the TM system is divided into three subsystems with outputs of $m_f$, $T_{hi}$, and $T_b$, respectively. An ANN is then implemented to model each subsystem. For the ANN-based modeling, we adopt a nonlinear auto-regressive network with exogenous inputs (NARX), a type of dynamically driven recurrent ANN [26], considering the time-series vehicle data and network complexity. The ANN inputs include $X_C$, $X_E$, and $X_F$. The time-delayed values of $X_C$, $X_E$, and $X_F$ are also used as the inputs, as shown in Fig. 2, improving the modeling accuracy. The maximum time delays for the inputs are set to $d_c$, $d_e$, and $d_b$, respectively. The input data are normalized to values between $-1$ and 1, via a pre-processor, to facilitate the training process [27]. A post-processor is then required to reverse-transform the normal-ized output data $y'$ into the same unit as the original data $Y'$.

The training is performed with open feedback loops, so that the actual data on $X_F$ can be fed into the ANNs. During the training, the weighting coefficients and biases (i.e., $W_{ij}$, $HW_{ij}$, $LW_{ij}$, $b_{ij}$, $b_{hi}$, and $b_{bo}$ in Fig. 2) are determined for all input, hidden, and output neurons. Once the training is finished, ANN testing is conducted with closed feedback loops, so that the ANN-based models can be used for optimal TM system operation during a period of $N_t$ min, as discussed in Section III. The training and testing performances are evaluated using the normalized mean squared error (NMSE), $\epsilon_{NMSE}$ [26].

### Table 2. Details of the two operating modes of the TM system.

| TM system operation | Integrated mode | Separate mode |
|---------------------|----------------|---------------|
| Levels of $T_{bx}$, $T_{cy}$, and $T_b$ | low | high |
| Initiating conditions | $T_{ro} \leq T_b$ | $T_{ro} < T_{cy}$ |
| Devices for $T_b$ control | EWPs, fan | EWP, fan, compressor |

The table provides the details of the two operating modes of the TM system.
C. INTERCONNECTION OF INDIVIDUAL ANNS

The trained ANNs for the TM subsystems are interconnected in a specific order, as shown in Fig. 3, based on the physical configuration of the TM system. For the interconnection, the output of an ANN is used as the input and corresponding time-delayed inputs of another ANN. Specifically, since $m_f$ affects $T_{bi}$, the output $Y_{1t} = m_f t$ of NARX1 is fed into $X_{E,2t}$ of NARX2 for the period from $t$ to $t-d_e$ to calculate $Y_{2t} = T_{bi}$. Similarly, $T_b$ is influenced by $m_f$ and $T_{bi}$. Both $Y_{1t}$ and $Y_{2t}$ are then used for $X_{E,3t}$ of NARX3 to estimate $Y_{3t} = T_b$ during the same time period.

TABLE 3. Controllable inputs, environmental inputs, and outputs of the individual ANNs for the TM subsystems.

| Variables | NARX1 | NARX2 | NARX3 |
|-----------|-------|-------|-------|
| $Y$       | $m_f$ | $T_{bi}$ | $T_b$ |
| Integrated | $X_e$ | $F_p$ | $P_n$ | - |
|           | $t$   | $t$, $m_f$, $T_{bi}$, $V_{co}$, $T_{bo}$ | $t$, $T_{bo}$, $m_c$, $h_b$ | - |
| Separate  | $X_e$ | $F_p$ | $P_n$ | - |
|           | $t$   | $t$, $m_c$, $T_{bo}$, $AC$ | $t$, $T_{bo}$, $m_c$, $h_b$ | - |

D. ANN SELECTION FOR LEAST OVER-FITTING

Data volume and variability affect the performance of ANN training [28], implying a risk of over-fitting ANNs to limited sets of training data. Recently, various techniques [29] have been discussed to mitigate over-fitting, such as dropouts, ensemble learning, cross-validation, and early-stopping training. In this paper, a rather simple procedure is adopted, as shown in Fig. 4, where the hyper-parameters of each ANN are selected to minimize over-fitting. The hyper-parameter sets, shown in Table 4, are determined considering the trade-off between modeling accuracy and complexity. In other words, defining the sets with higher maximum and lower minimum limits will improve the modeling accuracy at the expense of increasing the complexity of the ANN architecture and thus the computational time to solve the optimization problem. This is discussed further in Section III. The hyper-parameter selection scheme is conducted as:

(Step 1) Implement an ANN for a subsystem with a combination $\pi$ of the numbers of hidden layers and neurons from set $\pi$, as shown in Table 4;
(Step 2) Train the ANN with the original input and output datasets $[X_0, Y_0]$;
(Step 3) For the $N_t$-min input and output datasets arbitrarily chosen from the testing datasets, select controllable or environmental inputs $X_0^t$ for $t = 1, \ldots, N_t$;
(Step 4) Acquire the outputs \( Y_{\pi,e} \) from the trained ANN for the incremental variation \( \epsilon \cdot \Delta X^i \) in the selected input \( X_0^i \) (i.e., \( X_{\pi,e} = X_0^i + \epsilon \cdot \Delta X^i \)) while increasing \( \epsilon \) from 1 to \( \epsilon_{\text{max}} \).

(Step 5) Calculate the evaluation index \( Q_{\pi,e} \) for the comparison between \( Y_0^i \) and \( Y_{\pi,e} \) as follows:

\[
Q_{\pi,e} = \pm \left( Y_{\pi,e} - Y_0^i \right) \frac{\left| \Delta X^i \right|}{\left| \Delta X^i \right|}, \quad \forall \epsilon, \forall \epsilon, \forall \pi, \forall \tau,
\]

(1)

with the positive sign when \( Y_{\pi,e} \) increases, as \( X_{\pi,e} \) increases, and the negative sign otherwise;

(Step 6) Repeat Steps 3–5 for all the \( N_{\pi} \)-min datasets in this paper, the total size of the datasets is approximately a tenth of that of the testing datasets); in the selected ANN using \( \pi \) with \( X_0 \) and \( Y_0 \).

(Step 7) Repeat Steps 1–6 for all the combinations of the hyper-parameter set \( \pi \);

(Step 8) Calculate \( Q_{\text{avg},\pi,e} \) and \( Q_{\text{avg},\pi} \) for \( t = 1, \ldots, N_{\pi} \) and \( \epsilon = 1, 2, \ldots, \epsilon_{\text{max}} \), based on the evaluation index \( Q_{\pi,e} \) estimated in Step 5, as follows:

\[
Q_{\text{avg},\pi,e} = \frac{1}{N_{\pi}} \sum_{t=1}^{N_{\pi}} Q_{\pi,e}, \quad \forall \epsilon, \forall \pi,
\]

(2)

\[
Q_{\text{avg},\pi} = \frac{1}{N_{\pi}} \sum_{\epsilon=1}^{\epsilon_{\text{max}}} \left( \frac{1}{N_{\pi} - 1} \sum_{t=1}^{N_{\pi}} \left[ Q_{\pi,e} - Q_{\text{avg},\pi,e} \right]^2 \right)^{1/2}, \quad \forall \pi,
\]

(3)

(Step 9) Select 40% of the combinations \( \pi \) that result in smaller values of \( Q_{\text{avg},\pi} \) than those for the rest of the combinations;

(Step 10) Select \( \pi \) for which the minimum value of \( Q_{\text{avg},\pi,e} \) is positive;

(Step 11) Select \( \pi \) for which \( \epsilon_{\text{NMSE}} \) for the original training dataset \([X_0, Y_0]\) is greater than or equal to 0.9;

(Step 12) Select \( \pi \) with the maximum value of \( Q_{\text{avg},\pi,e} \), or enlarging the size of \( \pi \) and starting from Step 1 for the case where no combination is left after Step 11;

(Step 13) Repeat Steps 1–12 for the next ANN-based subsystem model.

Using the proposed procedure, NARX1 has been implemented with a relatively simple architecture including one hidden layer and 16 neurons each for the integrated and separate modes. This results from the rather simple operating characteristics of the EWPs with respect to \( m_f \) and \( P_f \). The architecture of NARX2 is characterized by two hidden layers and four hidden neurons for the integrated mode, as well as two hidden layers and six neurons for the separate mode. Similarly, NARX3 has one hidden layer with 18 hidden neurons and one hidden layer with 30 hidden neurons for the integrated and separate modes, respectively. Note that alternate schemes to mitigate ANN over-fitting could also be integrated into the proposed SL-based strategy for optimal TM system operation.

III. OPTIMAL THERMAL MANAGEMENT SCHEDULING

A. EXPLICIT REPLICATION OF TRAINED ANNS

After the ANN-based TM system model is trained, as shown in Fig. 3, it is equivalently represented using an explicit set of piecewise linear equations that can be directly integrated into the optimization problem, discussed further in Section III-B. The piecewise linearization enables the optimization problem to be formulated with mixed-integer linear constraints and readily solved using an off-the-shelf MILP solver. Therefore, the piecewise linearization has been widely used in many applications, such as optimal control of vehicles [30] and power networks [31].

Specifically, (4) and (5) represent the pre-processing transformation to normalize the input data to values between \(-1 \) and \( 1 \); otherwise, the gradient used for back-propagation training is very small and, consequently, the ANN training becomes slow [27]. Due to the pre-processor, the reverse-transformation, represented in (6) and (7), for the post-processing is required to restore the normalized outputs to actual values with the original units, such as [KW] and [°C].

\[
2X_{i,s}' = \left( X_{i,s,\text{max}} - X_{i,s,\text{min}} \right) x_{i,s}' = X_{i,s,\text{min}} + 1, \quad i \in \{X_{C,s}, X_{F,s}\}, \quad \forall \epsilon, \forall s,
\]

(4)

\[
-1 \leq x_{i,s}' \leq 1, \quad i \in \{X_{C,s}, X_{F,s}\}, \quad \forall \epsilon, \forall s,
\]

(5)
The optimal TM scheduling is achieved by solving

\[
\arg \min_{P_{u}^{t}} J_{TM} = \sum_{t=1}^{N_{t}} \sum_{u=1}^{N_{C}} c_{fp}(P_{u}^{t}) + \sum_{t=1}^{N_{t}} c_{tf}(T_{b}^{t}),
\]  

subject to:

- Constraints on \(P_{u}^{t}\) and corresponding \(T_{b}^{t}\) for the ANNs:
  \[P_{u, \min} \leq P_{u}^{t} \leq P_{u, \max}, \quad u \in X_{C}, \quad \forall t,\]
  \[T_{b, \min} \leq T_{b}^{t} \leq T_{b, \max}, \quad \forall t,\]
  and (4)–(16).
- Constraints on the time-delayed inputs \(X_{i,s}^{t-r} \in X_{C,s}\) of the ANNs:
  \[X_{i,s}^{t-r} = X_{i,s}^{t-r} \in X_{C,s}, \quad i \in \{X_{C,s} \cup X_{E,s}\},\]
  \[X_{i,s}^{t-r} \cdot X_{i,s}^{t-r} = 0, \quad i \in \{X_{C,s} \cup X_{E,s}\},\]
  \[X_{i,s}^{t-r} \cdot X_{i,s}^{t-r} = 0, \quad \forall \in \{X_{C,s} \cup X_{E,s}\}, \quad \forall s,\]
  \[X_{i,s}^{t-r} \cdot X_{i,s}^{t-r} = 0, \quad \forall \in \{X_{C,s} \cup X_{E,s}\}, \quad \forall s,\]
  \[X_{i,s}^{t-r} \cdot X_{i,s}^{t-r} = 0, \quad \forall \in \{X_{C,s} \cup X_{E,s}\}, \quad \forall s,\]

- Constraints on the connections between the ANNs:
  \[X_{i,s}^{t-r} \cdot X_{i,s}^{t-r} = 0, \quad i \in \{X_{C,s} \cup X_{E,s}\}, \quad (s, s') \in \{(2, 1), (3, 1), (3, 2)\}.

The objective function (17) aims to minimize the total operating cost of the TM system, which consists of two terms. The first term indicates the \(N_{t}\)-min sum of the costs for the time-varying power inputs \(P_{u}^{t}\) of all the controllable devices: i.e., the EWPs, fan, and compressor. The second term represents the \(N_{t}\)-min sum of the costs incurred due to the variation in \(T_{b}^{t}\). Fig. 6(a) and (b) show the cost-power function \(f_{p}\) and the cost-temperature function \(f_{tf}\), respectively. In particular, \(f_{tf}\) is implemented based on [11], [13], and [14], with slight modifications, as:

\[
f_{tf}(T_{b}^{t}) = \alpha_{4}(T_{b}^{t})^{4} - \alpha_{3}(T_{b}^{t})^{3} + \alpha_{2}(T_{b}^{t})^{2} - \alpha_{1}(T_{b}^{t}) + \alpha_{0},
\]
where $a_{0-4}$ are set to 0.0001, 0.0026, 0.0310, 0.6210, and 15.0681, respectively. Note that for the application of an MILP solver, $f_2$ is piecewise linearized, as shown in Fig. 6(b). Moreover, $c_p$ and $c_T$ are used to impose the relative weights on the costs for the first and second terms, respectively.

Furthermore, the constraints (18) and (19) specify the limits of $P_u^t$ and $T_{bt}^t$, respectively, for all $u$ and $t$, ensuring the reliable operation of the TM system. The upper and lower limits can be determined from the specifications of the EV battery and the controllable devices (i.e., the EWP, fan, and compressor). Note that $T_{bt}^t$ is estimated for $P_u^t$ using the linearized ANN-based model (4)–(16) of the TM system.

In addition, (20)–(23) represent the constraints on the input neurons of the ANNs for the TM subsystems that receive the time-delayed data on $X_C$, $X_E$, and $X_F$. Specifically, (20) and (22) show that for the initial time period of the current scheduling, the input neurons receive the data on the optimal $X_C$ and $Y$ that were determined for $X_E$ during the previous scheduling time period. Constraints (21) and (23) are then applied to the input neurons for the rest of the current scheduling time period. The $N_f$-min-ahead forecasted data on $X_E$ and corresponding time-delayed data are also fed into the input neurons of the ANNs, as shown in (20) and (21).

Moreover, (24) represents the connections between the ANN-based subsystem models, as discussed in Section II-C. Specifically, the ANN output for the $s_{th}$ subsystem is fed into the input neuron for $X_E$ of the ANN for the $s_{th}$ subsystem. The output is also delivered to the input neurons for the time-delayed data on $X_E$ via (20) and (22). Note that the set of $(s, s')$ can be pre-determined using the physical configuration of the TM system, as discussed in Section II-B.

### IV. CASE STUDIES AND RESULTS

#### A. TEST CONDITIONS

The proposed SL-based strategy was tested for a TM system, characterized by the main specifications and operating data, shown in Table 5 and Fig. 7, respectively. The rated power inputs of the EWP, fan, and compressor were specified as 50 W, 250 W, and 4500 W, respectively, based on the operating data. The minimum power input of the EWP was determined to be 3.4 W for the continuous circulation of the coolant. Moreover, the minimum and maximum temperatures of the battery module were set to 8°C and 48°C, respectively, under normal driving conditions. Note that, as shown in Table 5, the proposed strategy does not require physics-based modeling parameters of the TM system, unlike the conventional strategies listed in Table 1.

Fig. 7 shows the operating data of the TM system, which were obtained during the normal driving conditions of a real EV, with repeated driving cycles consisting of the UDDS and HWFET schedule. The original data were measured with a sampling time of 5 s and then averaged over every 1 min interval to generate the datasets $[X_C^t, X_E^t, Y_C^t]$ for the ANN training and the optimal scheduling of the TM system operation. Consequently, optimal TM scheduling was achieved with a sampling time of 1 min. Specifically, Fig. 7(a)–(c) show the 10-min profiles of $X_C^t = [P_p^t, P_{fp}^t, P_{cp}^t]$. Fig. 7(d)–(f) represent the corresponding outputs $Y_C^t = [m_f^t, T_{bh}^t, T_{bt}^t, T_{pe}^t, AC]^t$ under the environmental conditions that were characterized mainly by $X_E^t = [t, V_{vs}^t, I_{ps}^t, T_{pe}^t, AC]$ shown in Fig. 7(g)–(j). Note that $T_{pe}^t$ and $AC^t$ affect the TM system operation for the integrated and separate modes, respectively. The variations in $P_{fp}^t$ and $P_{cp}^t$ were relatively large and continuous, whereas those in $P_p^t$ and $m_f^t$ were rather small and discretized. Moreover, for all the initial values of $T_{bh}^t=0$, the variations in $T_{bt}^t$ were small and continuous, mainly due to the large thermal capacity of the battery. Note that in several profiles, $T_{bh}^t$ changed with relatively large variations. It also can be seen that for the EV, $I_{ps}^t$ was mainly affected by $V_{vs}^t$, resulting in the similarity between the profiles of $I_{ps}^t$ and $V_{vs}^t$.

The total number of historical data $[X_C^t, X_E^t, Y_C^t]$ was 1009 and 10 with respect to time and objects, respectively, for the integrated mode. For the separate mode, it was estimated to be 2959 and 11 with respect to time and objects, respectively. The time-delayed data for the objects were not considered in the estimation. The training was conducted using approximately 80% and 90% of the total datasets for the integrated and separate modes, respectively. For the separate mode, the TM system operates with more controllable inputs, requiring more training data. The remaining datasets were used to test the performance of the TM system model.

Furthermore, Fig. 8(a) shows the 30-min profiles of $V_{vs}^t$ for the driving cycle of the UDDS followed by the HWFET schedule. Fig. 8(b) and (c) show the corresponding profiles of $I_{ps}^t$ and $T_{pe}^t$. The 30-min profiles of $V_{vs}^t$, $I_{ps}^t$, and $T_{pe}^t$ were used as the test conditions (or, equivalently, environmental inputs) for the optimal operation of the TM system. Note that

| Devices | Descriptions | Parameters | Values |
|---------|--------------|------------|--------|
| EWP     | rated power input | $P_{p_{max}} [W]$ | 50     |
|         | minimum power input | $P_{p_{min}} [W]$ | 3.4    |
| Fan     | rated power input | $P_{f_{max}} [W]$ | 250    |
|         | minimum power input | $P_{f_{min}} [W]$ | 0      |
| Compressor | rated power input | $P_{c_{max}} [W]$ | 4500   |
|         | minimum power input | $P_{c_{min}} [W]$ | 0      |
| Battery | maximum temperature | $T_{sb_{max}} [°C]$ | 48     |
|         | minimum temperature | $T_{sb_{min}} [°C]$ | 8      |
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FIGURE 7. Operating data of the test TM system: (a)–(c) power inputs of the EWP, fan, and compressor, (d)–(f) coolant flow rate, coolant temperature, and battery temperature, (g)–(j) vehicle speed, battery current, PE module temperature, and AC switch operating status.

in the original 5-s sampled data, the ramp rates of $I_{bt}$ were much larger than those of $V_{vt}$, due primarily to the large moment of inertia of the vehicle body. In the 1-min averaged data, the ramp rates of $I_{bt}$ became similar to those of $V_{vt}$, as shown in Fig. 8(b) and (c). In addition, for simplicity, it was assumed that the ambient temperature was constant at 20°C and 40°C for the integrated and separate modes, respectively [8], during the scheduling time period.

For the 30-min driving profile (i.e., $t_{dr, max} = 30$ min), $N_f$ was set to 10 min to reflect the time-varying conditions during EV driving more accurately. Therefore, the proposed scheduling strategy was iteratively performed with respect to time. The performance of the proposed strategy was then evaluated in comparison with that of a conventional, rule-based strategy [9], [32], where the EWPs, fan, and compressor operate based on the relative differences between the temperatures of the battery, coolant, and refrigerant. This rule-based strategy has been widely applied in practice, because it requires no physics-based modeling parameters, as in the proposed strategy.

For the proposed strategy, the optimization problem (4)–(25) was formulated using Matlab and solved with the library function of IBM ILOG CPLEX Optimizer [24], enabling both convergence to the optimal solution within reasonable computational time and measurement of the distance to the optimum. The case studies were conducted on a computer with 32 GB of memory, an Intel Core i7-7600k @ 3.80GHz CPU, and an NVIDIA GeForce GTX 1060 3GB.

B. ANN TRAINING AND TEST RESULTS

The individual ANNs for the TM subsystems were trained separately using the Matlab function [33]. Fig. 9(a)–(c) show the training results of the three NARXs with the outputs of $m_f$, $T_{bi}$, and $T_b$, respectively. The x- and y-axes represent the actual and predicted values, respectively, and the blue and green “×” marks represent the results for the integrated and separate modes, respectively. Each NARX successfully reflected the operation of each TM subsystem, leading $\epsilon_{NMSE}$ to be close to one, as shown in Table 6.

In addition, Fig. 9(d)–(f) show the testing results of the trained ANNs for the predictions on $m_f$, $T_{bi}$, and $T_b$, respectively. The test was performed after interconnecting the ANNs, as shown in Fig. 3. Table 6 also confirms the consistency between the actual and predicted data, indicating that the interconnected ANN successfully reflected the operating characteristics of the TM system for both the integrated and separate modes. This also ensures the feasibility and reliability of the optimal scheduling results, as discussed in Section IV-C. In particular, the ANN-based TM system model successfully reflected the variations in
$m_f$ during the EV driving, as shown in Fig. 9(d), although the variability of the training data on $m_f$ was rather limited. Fig. 9(e) shows that the $T_{bi}$ prediction performance was rather degraded particularly for the integrated mode. However, it did not significantly affect $T_b$, as shown in Fig. 9(f), due to the large thermal capacity of the battery. Fig. 9(e) and (f) show that $T_{bi}$ and $T_b$ remained higher in the separate mode than in the integrated mode, as discussed in Section II-A.

### TABLE 6. NMSEs for the individual ANNs and interconnected ANN.

| $e_{\text{NMSE}}$ | Integrated mode | Separate mode |
|-------------------|-----------------|---------------|
|                   | NARX$_1$        | NARX$_2$      | NARX$_3$      | NARX$_1$ | NARX$_2$ | NARX$_3$ |
| Training          | 1.000           | 0.996         | 1.000         | 0.999    | 0.990    | 0.999    |
| Testing           | 0.999           | 0.904         | 0.998         | 1.000    | 0.918    | 0.995    |

Additional case studies were performed without the proposed hyper-parameter selection scheme, shown in Fig. 4. Table 7 lists the values of $e_{\text{NMSE}}$ for the training and testing results in both operating modes. From the comparisons between Tables 6 and 7, it can be seen that for the testing, $e_{\text{NMSE}}$ in Table 7 were smaller than those in Table 6, whereas for the training, $e_{\text{NMSE}}$ in Table 7 are very similar to those in Table 6, with all values being close to one. This verifies that the hyper-parameter selection scheme is effective in mitigating the over-fitting of the ANNs, improving the generalizability of the ANN-based TM system model and hence the feasibility of the proposed SL-based scheduling strategy.

### TABLE 7. NMSEs for the individual ANNs and interconnected ANN without the hyper-parameter selection scheme, shown in Fig. 4.

| $e_{\text{NMSE}}$ | Integrated mode | Separate mode |
|-------------------|-----------------|---------------|
|                   | NARX$_1$        | NARX$_2$      | NARX$_3$      | NARX$_1$ | NARX$_2$ | NARX$_3$ |
| Training          | 0.999           | 0.996         | 1.000         | 0.999    | 0.990    | 0.999    |
| Testing           | 0.911           | 0.852         | 0.797         | 0.999    | 0.898    | 0.929    |

### C. OPTIMAL SCHEDULING RESULTS

1) INTEGRATED MODE

Fig. 10 shows the optimal schedule of the TM system operation for the proposed strategy (red line) in comparison with the rule-based schedule for the conventional strategy (blue line). Specifically, Fig. 10(a) and (b) present the profiles of $P_{pt}^i$ and $P_{fnt}^i$, respectively, and Fig. 10(c) and (d) depict the corresponding $T_{bi}^i$ and $T_b^i$, respectively. Note that $P_{pt}^i$ for the PE- and battery-side EWPs are the same for the integrated mode.

In the proposed strategy, the fan was mainly exploited to reduce $T_{bi}^i$, mitigating a rise in $T_b^i$ due to $I_b^i$, for $1 \text{ min} \leq t_{dr} \leq 4 \text{ min}$ and $11 \text{ min} \leq t_{dr} \leq 15 \text{ min}$. For $4 \text{ min} \leq t_{dr} \leq 10 \text{ min}$, the EWP increased $P_{pt}^i$ and hence $m_{f t}$ to improve the heat exchange between the coolant and ambient air at the LTR, so that $T_b^i$ remained almost constant. As $V_{vst}^i$ started increasing from $t_{dr}^i = 21 \text{ min}$, both the EWP and fan operated to prevent an abrupt increase in $T_{bi}^i$ particularly for $21 \text{ min} \leq t_{dr} \leq 22 \text{ min}$. For $t_{dr} \geq 24 \text{ min}$, $P_{pt}^i$ increased to almost $P_{p,max}$, while $P_{fnt}^i$ remained at zero. This is because as $V_{vst}^i$ increased, the intake air flow rate at the LTR increased, so the fan did not need to operate. Moreover, the EWP operated with the maximum levels of $P_{pt}^i$ and $m_{f t}$ to exploit more effectively the increased rate of the heat exchange at the LTR, which resulted from the increased air flow rate. This feature enabled considerable reduction of the total energy consumption $E_{ec}$, while still ensuring the control of $T_b$ at lower levels, compared to the conventional, rule-based strategy. Note that in the conventional strategy, $P_{pt}^i$ remained constant and, therefore, the control of $T_b^i$ heavily relied on the operation of the fan. Table 8 shows that for the proposed strategy, $E_{ec}$ was reduced by $48.5\%$, compared to $E_{ec}$ for the conventional strategy.
TABLE 8. Comparisons of the total energy consumptions for the proposed and conventional strategies in the integrated mode.

| Strategies | Total energy consumption, $E_{ec}$ [Wh] |
|------------|--------------------------------------|
|            | Two EWP | Fan | Compressor | Total  |
| Conventional | 19.30  | 104.43 |  | 123.73  |
| Proposed   | 13.62  | 50.13  |  | 63.75   |

2) SEPARATE MODE

Analogously, Fig. 11 shows the optimal operating schedule and rule-based schedule for the proposed and conventional strategies, respectively, when applied to the separate mode. Fig. 11(a)–(c) represent the profiles of $P_p$, $P_{fan}$, and $P_{cp}$, respectively, and Fig. 11(d)–(e) show the corresponding $m_f$, $T_{bit}$, and $T_{bt}$, respectively.

For the proposed strategy, the compressor operated with almost the maximum power input for 1 min $\leq t_{dr} \leq 5$ min, due to the relatively high $T_{bt}^i$ and $T_{bt}^f$ (see Fig. 11(c), (e), and (f)). Consequently, $T_{bt}^i$ and $T_{bt}^f$ were reduced for 5 min $\leq t_{dr} \leq 15$ min. The time delays were attributed to the large thermal capacity and hence slow time response of the battery. For $t_{dr} \geq 10$ min, $P_{cp}$ started changing dynamically and rather periodically with a period of approximately 5 min. The battery-side EWP was then controlled in coordination with the compressor, as shown in Fig. 11(a) and (d), which enabled the cooling rate supplied by the compressor to be delivered to the battery more effectively. In other words, the proposed strategy induced the pre-cooling and dynamic operation of the TM system, reducing $E_{ec}$ by 6.9%, compared to the conventional strategy (see Table 9). Moreover, $T_{bt}^i$ remained at lower levels with the proposed strategy than with the conventional strategy. Note that for the separate mode, the compressor operation increased $E_{ec}$ significantly and led to the large reduction of $T_{bt}^i$ in both the proposed and conventional strategies.

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For the proposed strategy, the compressor operated with almost the maximum power input for 1 min $\leq t_{dr} \leq 5$ min, due to the relatively high $T_{bt}^i$ and $T_{bt}^f$ (see Fig. 11(c), (e), and (f)). Consequently, $T_{bt}^i$ and $T_{bt}^f$ were reduced for 5 min $\leq t_{dr} \leq 15$ min. The time delays were attributed to the large thermal capacity and hence slow time response of the battery. For $t_{dr} \geq 10$ min, $P_{cp}$ started changing dynamically and rather periodically with a period of approximately 5 min. The battery-side EWP was then controlled in coordination with the compressor, as shown in Fig. 11(a) and (d), which enabled the cooling rate supplied by the compressor to be delivered to the battery more effectively. In other words, the proposed strategy induced the pre-cooling and dynamic operation of the TM system, reducing $E_{ec}$ by 6.9%, compared to the conventional strategy (see Table 9). Moreover, $T_{bt}^i$ remained at lower levels with the proposed strategy than with the conventional strategy. Note that for the separate mode, the compressor operation increased $E_{ec}$ significantly and led to the large reduction of $T_{bt}^i$ in both the proposed and conventional strategies.

TABLE 9. Comparisons of the total energy consumption for the proposed and conventional strategies in the separate mode.

| Strategies | Total energy consumption, $E_{ec}$ [Wh] |
|------------|--------------------------------------|
|            | Single EWP | Fan | Compressor | Total  |
| Conventional | 12.21  | 51.99 | 920.10 | 984.30  |
| Proposed   | 9.35  | 41.19 | 865.80 | 916.34  |

For $t_{dr} \geq 25$ min, the proposed strategy led to higher energy consumption than the conventional strategy, in which case the compressor turned off and the fan and EWP operated with almost constant, low power inputs. In other words, the ANNs could not reflect all of the operating conditions of the TM system, given the training datasets shown in Fig. 7. This implies that the performance of the proposed strategy can be further improved via the integration with online SL [34], which will be addressed in future work.

V. CONCLUSION

This paper proposed a new SL-based strategy for the optimal operation of the TM system in an EV, wherein the total energy consumption of the EWP, fan, and compressor was minimized while the battery temperature was maintained within an acceptable range. In the proposed strategy, the ANNs for the TM subsystem models were trained using data obtained for the normal conditions of the EV driving. The trained ANNs were interconnected based on the physical configuration of the TM system and equivalently represented using a set of explicit, piecewise linear equations that can be directly integrated into the optimal TM scheduling problem. Therefore, the off-the-shelf MILP solver can be readily applied to solve the problem. The case study results confirmed that the ANN-based model successfully reflected the operating characteristics of the TM system. Using the ANN-based model, coordination among the EWP, fan, and compressor was successfully achieved, reducing the total power consumption by 48.5% and 6.9% in the integrated and separate operating modes, respectively, compared to the conventional, rule-based strategy. The battery temperature was also regulated within the acceptable ranges.

Further work is still required particularly with regard to integrating the proposed strategy with online learning. After the proposed strategy has been initiated, the ANN-based model will be continuously trained online, as new data on the TM system operations start to be collected for various driving environments. This process will further improve the performance of the ANN-based model and hence the optimal TM scheduling strategy. Field tests using vehicle energy management systems are also required to further validate the performance of the proposed strategy in real driving environments with sensing errors and unexpected disturbances.

APPENDIX

A. EFFECTS OF WEIGHTS ON OPTIMAL SCHEDULING

Additional case studies were conducted to analyze the effects of $c_p$ and $c_T$ on the optimal operation of the TM system.
Table 10 shows the comparisons of the costs $f_p$ and $f_T$ for the total power consumption and corresponding battery temperature, respectively, in the integrated mode, when each of $c_p$ and $c_T$ became three times larger than the original values used in Section IV-C. Table 11 shows the analogous cost comparisons in the separate mode. Tables 10 and 11 clearly show the trade-off between $f_p$ and $f_T$ according to the relative magnitudes of $c_p$ and $c_T$ in both modes. It also can be seen that the changes in $c_p$ and $c_T$ led to larger variations in $f_p$ and $f_T$ for the separate mode than for the integrated mode, due to the compressor operation.

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