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Coupled Design of High-Speed Motor Drive and Shaped Optimized Compressor Systems

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ABSTRACT

The heating, ventilation, air conditioning & refrigeration (HVAC&R) industry is undergoing the transmission from conventional high-Global Warming Potential (GWP) refrigerants to low-GWP refrigerants. Despite of the environmental benefits, the usage low-GWP fluids also yield to lower compressor volumetric capacities. This research aims at exploring the potential for meeting the capacity requirements while using low-GWP refrigerants by increasing the speed range of variable speed compressors. Running at higher speeds is particularly important during heating mode to provide greater capacity at low ambient temperatures. However, although promising, if such operation is considered without integrated design of the electric drive, the results are likely to be suboptimal. This is because that increasing the speed of an electric machine that is not tailored for a wide speed range will likely come at the expense of increased core and semiconductor losses. To meet this need, this study develops the coupled design of variable-speed compressors by two well-established tools. On the compressor side, the mechanistic compressor modeling tool positive displacement machine simulation package (PDSim) enables detailed design of the high-speed scroll compressor. A machine learning ANN model is also constructed as a light-weight alternative to the PDSim model. On the motor drive side, the multi-objective optimization toolbox electric driver optimization toolbox (EDOT) enables the rigorous multi-physics design of suitable motors. A method-of-moments engine then is used to test and validate the performance of the new designed high-speed compressor. This study takes R290 as the working fluid. Torque force, volumetric efficiency, and overall isentropic efficiency were recorded from PDSim results. Three corresponding optimized compressor-motor designs were selected among 150 design results. The height and radius of the new-designed compressor is around 20% and 15% less than that of the reference case, respectively. The volume of the new-designed compressor can be up 45% less than the reference case. While the power losses of the optimized cases are approximately equal to the reference case.

1. INTRODUCTION

In the recent years, the HVAC&R industry is facing challenges driven by regulatory changes (Department of Energy, 2021). While the industry is currently focused on transitioning to low-GWP refrigerants, these changes are suggestive of an inevitable transition to near zero-GWP or natural refrigerants to replace exiting hydrofluorocarbons (HFCs). The Department of Energy’s (DOE) recent phase-down proposal (Department of Energy, 2021) reinforces that this challenge needs to be addressed now. Optimized compressors are critical to meet energy efficiency requirements for air-conditioning and heat pumping units and are typically designed for a specific working fluid. This research project aims at exploring the potential for increasing the speed range of variable-speed hermetic compressors for heat pump applications to meet capacity requirements while using low-GWP fluids and inherently yield to lower volumetric capacities. Running at higher speeds is particularly important during heating mode to provide greater capacity at low ambient temperatures, while increasing the turn-down ratio is important for efficiency at low load conditions in both heating and cooling modes. Although promising, if such operation is considered without integrated design of the electric drive (motor/inverter), the results are likely to be suboptimal. This is because increasing the speed of an electric
There are numerous optimization studies in literature considering the modelling and design work for variable speed compressor and low-GWP fluid applications. However, very few of them consider the integrated optimization of the compressor and electric machines. Another drawback is that the proposed models are usually very specific to a certain case or type of compressor and electric machine. Bell et al. (2020) and Ziviani et al. (2020) proposed a comprehensive compressor modeling platform that can be applied to various types of positive displacement compressors and therefore empower the prototype design to different types of compressors. Horvath et al. (2019), Howard et al. (2017), and Howard et al. (2015) introduced and validated an application of modelling electric motors using Method of Momentum (MoM). Comparing to the Finite Element Analysis (FEA), in the MoM application only the active material is meshed. The MoM greatly reduces the number of unknowns with same level of accuracy. Therefore, it can enable a fast and comprehensive design of various types of electric machines. In these studies, the compressor and electric machine are modeled separately, where an integrated optimization method is still missing. Therefore, in this study, an integrated optimization method is proposed to develops the coupled design of variable-speed compressors by two well-established tools. The optimization results are validated utilizing the compressor specifications and performance map from the manufacturer.

2. INTEGRATED OPTIMIZATION MODELS

In this study, the proposed method integrates a series of optimization processes to ultimately obtain a new compressor design based on the specified boundary conditions. A comprehensive design space for the integrated-optimized compressor can be obtained.

![Figure 1: Working flow of the optimization process](image)

2.1. Overall optimization process

To simplify the whole optimization process and increase the usability of the optimization tool, the coupling between compressor model and the multi-objective optimization toolbox electric driver optimization toolbox (EDOT) is tackled firstly. To generate performance data of the compressor, a Python-based generalized framework entitled positive displacement machine simulation package (PDSim) is used (Bell et al. (2020) and Ziviani et al. (2020)). The motor model implemented in EDOT is developed in MATLAB and configured for the analysis and design of surface-mounted permanent magnet synchronous machines and associated drives. A schematic of the optimization process is demonstrated in Figure 1. The compressor model inputs include desired operation range, working fluid, rotating speed,
and displacement. The compressor model can compute the corresponding required shaft torque and rotating speed as outputs to the motor model. Based on the outputs of the compressor model, the motor model then conducts the multi-objective optimization and provides a Pareto-optimal front of possible designs for the electric drive. The compressor model and the EDOT models are further described in Section 2.2 and Section 2.3, respectively.

A commercially available scroll compressor is selected to verify the accuracy of the compressor model with available compressor performance data. Then, the PDSim sub-model and the EDOT sub-model are connected to run a one-way coupled simulation, which enabled a complete simulation and design of the entire compressor optimization process. Additionally, a case study of the selected scroll compressor is conducted to demonstrate the functionality of the overall modeling process. The motor mass and power losses are selected as the objective functions in EDOT. From the Pareto-optimal front, three local optimal results out of 150 possible designs are selected for further investigations.

2.2. Compressor model

The PDSim compressor model and a light-weight Artificial Neural Network (ANN) model are both implemented in this study with validation against the compressor map for different needs. The PDSim compressor model is considered for its high accuracy and capability of providing comprehensive solution space. But because the detailed compressor model implements comprehensive analytical methods as well as numerical methods, it has long run times and requires high computing power to achieve convergence. Therefore, to reduce the computational cost, a light-weight ANN compressor sub-model is constructed as an alternative. A comprehensive dataset of the target compressor is firstly generated by the detailed PDSim model with different combinations of initial parameters. The dataset is used to train the ANN model. The trained ANN model is then coupled with EDOT as a light-weight alternative to the PDSim model. The ANN and EDOT model are integrated into a complete and high-availability modeling platform. The PDSim model and the ANN model are introduced as following.

The PDSim-based compressor model is formulated on the governing equations of mass and energy conservation. By introducing the geometry parameters and other modeling aspects such as leakage flows, heat transfer correlations and friction losses, the same structure can be applied to any positive displacement machine. Detailed model descriptions and settings can be found in Ziviani et al. (2020).

ANN is a generalized black-box model for machine learning. In recent years, research on its application to compressor mapping have been investigated (Jie et al. 2020). It is inspired by the functions and connections of neurons in the human brain. The ANN model usually is built by an input layer, an output layer, and multiple layers in between, called hidden layers. Each neuron takes an input signal $x_i$ and a certain weight $w_i$. A bias $b_k$ function is added to the layer output after summing up the outputs from all neurons in a layer. An activation function is implemented to a certain layer to process the final outputs. A loss function is required to adjust the weights of each neuron in each layer to minimize the errors between the calculated outputs and the measured outputs.

In this model, the Feed-Forward backpropagation algorithm is used. The ANN model architecture is determined by a trial-error manually search process. The optimized ANN model has three hidden layers, with 20, 18, 18 neurons in each layer, respectively. Figure 2 shows the schematic of the optimized ANN model. The hyperbolic tangent function is used as the activation function and The Mean Absolute Error (MAE) function as the loss function. 60 points are collected throughout the entire compressor map. 15 and 45 points are fed to the ANN model as training and validation dataset, respectively. The $R^2$ value, mean absolute percentage error (MAPE), and Root Mean Square Error (RMSE) are taken as evaluation coefficients.
2.3. MoM-based electrical motor model (EDOT)

In this study, the electrical motor model is built in a MATLAB-based MoM toolbox called EDOT. It is configured for the analysis and design of surface-mount permanent magnet synchronous machines (PMSM) and their associated drives. For both surface and volume discretization, the MoM formulation derived in Howard et al. (2017) is used to establish the system of equations:

\[
[f_{B_{tot}M} - f_{BM}]M_{tan} = f_{BI}I_f + f_{BI_{PM}}I_{PM}
\]  

(1)

where \(M_{tan}\), the tangent component of magnetization field \(M\), represent the unknowns. The inputs to the MoM model are the free currents (i.e., currents due to conductors in the stator or rotor) and the currents used to represent the magnetization of permanent magnet materials, \(I_{PM}\). Specifically, the primary computational bottleneck in MoM field analyses is the population of the dense system matrix \([f_{B_{tot}M} - f_{BM}]\), thus it is desired to avoid computing it in its entirety. A method to limit the number of components that needs to be computed is derived and implemented for the case in which linear materials or nonlinear materials are used. This method, related to the discrete body of revolution (DBOR), is based upon techniques established within the computational electromagnetics community by Horvath et al. (2020). Details of its use in machines are provided in Horvath et al. (2019).

It is assumed the machine interfaces to a DC power supply through a standard 6-pulse inverter in which current is regulated. In addition, the Method of Moments toolbox (MoMT) utilizes a genetic algorithm to perform multi-objective optimization to minimize mass and loss. Genetic algorithm parameters inputs are used to specify the number of individual designs in a population and the number of generations to be evaluated. The losses calculated include the stator resistive loss, stator and rotor core loss, and conduction loss through the inverter devices. Switching loss of the inverter is not included.

3. MODEL VALIDATION

3.1. Validation of the PDSim model

A 3RT (10.55 kW) hermetic scroll compressor is selected as reference to verify the accuracy of the PDSim-based compressor model. It uses R290 as working fluid and has a displacement of 5.08 in\(^3\)/rev (83.3 cm\(^3\)/rev). The compressor rotating speed is 60 Hz. The PDSim scroll compressor model results are compared to the performance
map provided by the manufacturer. Figure 3(a) and Figure 3(b) summarize the mass flow rate and power consumption predictions and relative errors (RE) for each evaporating and condensing temperatures. Minimum tuning of the leakage flow coefficients and frictional losses is performed.

PDSim calculated 60 points of mass flow rate and power consumption of the compressor throughout the entire working condition range. The results were compared to the performance map. 83.3% of the predicted points have a RE value smaller than 0.1 for mass flow rate, 92% of which have a RE value smaller than 0.05. 10% of the predicted points are between 0.1 and 0.2. 6.7% of the predicted points have a RE value that are higher than or equal to 0.2 for mass flow rate. For compressor power consumption, 73.3% of the predicted points have a RE value lower than 0.1. 26.7% of the predicted points have a RE value that are between 0.1 and 0.2. None of the predicted points has a RE value higher than or equal to 0.2. The predictions with lower accuracy are located at the edge of the map. This is because the refrigerant is at the critical conditions at these points and has undesired property changes which can cause difficulty to achieve equilibrium steady state for the model and can easily disturb the results of compressor working condition. Overall, the PDSim model prediction is considered significantly accurate. Finally, the values of shaft torque needed for optimizing the motor efficiency are calculated using PDSim. The PDSim model computing time is affected by working conditions. In some extreme cases, for instance at the edge of the performance map, the computing time may take up to 30 minutes to converge for one data point.

![Mass Flow Rate Relative Error Map](image1)

(a) Mass flow rate relative error map.

![Power Relative Error Map](image2)

(b) Power relative error map.

**Figure 3:** Relative error mapping of mass flow rate and power.

### 3.2. Validation of the ANN model

The same compressor used in validation of the PDSim model is implemented here. The compressor specifications are coded into the ANN model with evaporating temperature, condensing temperature, rotating speed, and compressor displacement as input variables. The corresponding shaft torque and overall isentropic efficiency are treated as outputs. The ANN model is trained with 15-points training dataset and validated with the rest 45 points. The ANN model predictions versus true value from the performance map are plotted in Figure 4. The tendency lines are relatively linear. The R-square value, MAPE value, and RMSE value for shaft torque and overall isentropic efficiency is 99.9% and 98.2%, 1.1% and 3.1%, and 1.6% and 3.8% respectively. It can be seen from Figure 4(a) that all validation points for shaft torque fall within the 5% RE range of the true value. Figure 4(b) also shows good agreement between the predictions and the true value from performance map for the overall isentropic efficiency. The accuracy of the constructed ANN model is validated. As a black box model, the computing time for ANN is relatively stable. The optimized ANN model generally takes 20 to 40 seconds to converge, which is significantly shorter comparing to PDSim model.
Figure 4: Validation plots of the ANN model for shaft torque and overall isentropic efficiency.

3.3. Optimization framework

A comprehensive torque force map is calculated based on PDSim model for the all the working conditions of the selected scroll compressor from the validated detailed compressor model with R290 fluid, based on which a torque force profile is established. The maximum, mean, and minimum required power inputs are shown in Table 1. The compressor working schedule is arranged such that 33% of the total operating time is under maximum torque force, 34% of the time is under mean torque force, and 33% is under minimum torque force. The rotating speed of the compressor is set to be 90Hz and the compressor geometry is kept the same with 29.3 cm³. In response to the torque profiles created from the compressor model, the EDOT model then conducts a multi-objective optimization to the motor. Based on experience for optimization convergence, 500 populations and 500 generations are used. 18 degrees of freedom are established, and 12 design specifications are specified as shown in Table 2. The maximum and minimum values allowed are fixed as well as the type of increment method used for each gene. These are established from experience and industry standards for the motor torque required. The material of the stator, rotor, conductor, and magnet is established from a material index internal to EDOT.

Table 1: Power consumption working schedule

<table>
<thead>
<tr>
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<th>Maximum (33%)</th>
<th>Mean (34%)</th>
<th>Minimum (33%)</th>
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<tr>
<td>Power (kW)</td>
<td>5.89</td>
<td>3.63</td>
<td>1.39</td>
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Table 2: EDOT model design specifications

<table>
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<th>Design Specification</th>
<th>Value</th>
<th>Design Specification</th>
<th>Value</th>
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<tr>
<td>DC Voltage (V)</td>
<td>540</td>
<td>Shaft Radius (cm)</td>
<td>2</td>
</tr>
<tr>
<td>Switch Volt Drop (V)</td>
<td>2</td>
<td>Packing Factor (%)</td>
<td>50</td>
</tr>
<tr>
<td>Switch Resist (Ω)</td>
<td>0.002</td>
<td>End Winding Offset (cm)</td>
<td>1</td>
</tr>
<tr>
<td>Number of Rotor Positions</td>
<td>3</td>
<td>Max Tooth Aspect Ratio</td>
<td>10</td>
</tr>
<tr>
<td>Mass Limit (kg)</td>
<td>50</td>
<td>Slot Opening Factor</td>
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</tr>
<tr>
<td>Loss Limit (W)</td>
<td>10000</td>
<td>H Limit based on Hci (%)</td>
<td>75</td>
</tr>
</tbody>
</table>
4. RESULTS AND DISCUSSION

The Pareto-optimal front obtained for this study is shown in Figure 5. There are 150 optimized designs resulting in the EDOT model. Each cross represents a calculated design. A comprehensive list including mechanical features of each design such as volume, cross section radius, height, and mass as well as electric features of each design such as current, voltage, and electric losses, are provided by EDOT. Note that while the scheduling feature of the EDOT is employed to calculate weighted seasonal power loss, it is used merely as a proof of concept in this study due to the even distribution of time over the average, maximum, and maximum torque values of the 60 compressor operating points. The scheduling feature calculates mass for a motor capable of producing the maximum torque while the power loss is calculated from an average of the three torque values.

![Pareto-Optimal Front](image)

**Figure 5:** Pareto-optimal front of loss versus mass. Single loss computed by weighting operating point loss.

Three designs with masses 3kg, 3.5kg, and 4kg were chosen for comparison. The 3.5kg case is selected as it has the optimized balance between losses and motor mass. The 3kg case slightly inclined to reduce the mass on the basis of the 3.5kg case, and the 4kg case slightly more inclined to reduce power losses. The resulting PMSM machine radial cross-sections are illustrated in respectively. Figure 6(a) gives an example of the radial cross-section of the optimized outputs of 3kg case. The 3kg, 3.5kg, and 4kg design are labeled as “Optimal 1”, “Optimal 2” and “Optimal 3”, respectively. The comparison between each design associated with height and radius, volume, and power loss are shown in Figure 6 (b), Figure 6 (c), and Figure 6 (d). The comparison to the original scroll compressor is also included. Noticing that the selects scroll compressor is operated at 60Hz and is labeled as “Original” in the comparison. The 3 optimized designs all have smaller height and diameter than the two original designs of the compressor. The heights of the 3 optimized designs are approximately the same. 3kg design has the smallest radius but largest power loss and 4kg has the largest radius and the smallest power loss. This meets the fact that there is a trade-off between machine efficiency and mass since the total losses in the motor consist primarily of losses in the conductors, semiconductors and core, and the variation in losses in the Pareto-optimal front is mainly driven by resistive losses and to a lesser degree core losses. This implies that reducing losses in the Pareto-optimal front requires wires with a larger cross section that simultaneously weigh more and require more space, so they increase the required amount of stator steel. It is important to notice that stator steel accounts for most of the variation in weight in the machine, so increases in length or radius cause large increases in mass, which is proportional to the volume of the machine.

The solid volume of the 4kg design, which is the largest in the three optimized designs, is also around 30% smaller than the “Original” motor. Only the power loss of the optimized Design 1, which is the smallest among the three selected designs, is 5% higher than the original design. The two others optimized designs have a lower power loss.
than the original case for 4% and 9%, respectively. The results show that the EDOT model can simultaneously achieve lower volumes and higher efficiencies than the original design, although reductions in losses are more limited. The optimized designs are thus proven to have a compact volume while ensuring low power loss.

![PMSM Radial Cross-Section](image1)

(a) Mass 3kg cross section

![Height & Radius Comparison](image2)

(b) Height and radius comparison between designs

![Volume Comparison](image3)

(c) Volume comparison between designs.

![Loss Comparison](image4)

(d) Loss comparison between optimized designs.

**Figure 6:** Optimization results and comparisons.

Notably, cross-sections of PMSM created from the EDOT are each smaller in volume than the current motors. Although power losses of original scroll motors are unknown, the efficiency of these optimal designs can be calculated as a point of comparison. One limitation of the EDOT is that cost associated with construction or materials is not factored in the model. Although it is unlikely, while optimal designs are smaller, material cost may have increased. The cost associated with materials could be constrained to specific materials in further studies, however resulting volume may increase. Another limitation is that the EDOT does not include thermal analysis currently, taking this factor into account could improve the overall results and reduce total losses.
5. CONCLUSION

In this study, an integrated optimization method of compressor and high-speed electrical motor is proposed and validated. Through the optimization process of the integrated compressor-motor design, the overall volume of the compressor and the motor reduce significantly while ensuring the overall working efficiency. The compressor is designed to be a scroll compressor with low-GWP refrigerants as working fluid. The detailed compressor model is constructed using a Python-based compressor modeling package. The electric motor is optimized with a dedicated motor design toolbox, EDOT. An ANN model is established afterwards as a generalized black-box model for predicting the compressor torque force and overall isentropic efficiency. A scroll compressor is selected from commercially available product. The prediction accuracy of the detailed compressor model and the ANN model are validated by means of the performance map. A case study of the selected scroll compressor is then conducted as the demonstration of the proposed whole process optimization. Three optimized designs are selected among a final Pareto-optimal front. The comparison between the optimized designs and the original motors shows a significant reduction in volume up to 50% while achieving a similar power loss. The heights and radiuses of the optimized designs are all lower than the original motors. Only the power loss of the optimized Design 1, which is the smallest among the three selected designs, is 5% higher than the original design. The proposed coupled whole process optimization method is proved effective.

As the next step, a supervised optimizer can be implemented to close the loop in the compressor optimization process. The operating schedule of the compressor should also be adjusted to be more representative of the performance in heating or cooling mode. While optimizing the coupled compressor-drive assembly, the external optimizer can identify the trade-offs between compressor displacement and seasonal performance. With a desired set of inputs such as capacity, compressor displacement, and rotating speed, the combined model can optimize both the electric driver and the compressor chambers. The integrated optimization method is able to reduce the volume of the compressor while maintain the same or even increase the working performance.

NOMENCLATURE

<table>
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<th>Symbol</th>
<th>Description</th>
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<tr>
<td>I</td>
<td>Current</td>
<td>(A)</td>
</tr>
<tr>
<td>m</td>
<td>Mass</td>
<td>(kg)</td>
</tr>
<tr>
<td>M</td>
<td>Magnetization field</td>
<td>(T)</td>
</tr>
<tr>
<td>N</td>
<td>Rotation frequency</td>
<td>(rpm)</td>
</tr>
<tr>
<td>T</td>
<td>Temperature</td>
<td>(°F)</td>
</tr>
<tr>
<td>t</td>
<td>Time</td>
<td>(s)</td>
</tr>
<tr>
<td>V</td>
<td>Compressor displacement</td>
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<tr>
<td>P</td>
<td>Power</td>
<td>(W)</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Efficiency</td>
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<td>$\tau$</td>
<td>Torque force</td>
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<td>PDSim</td>
<td>Positive displacement machine simulation package</td>
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<td>EDOT</td>
<td>Electric driver optimization toolbox</td>
<td>(-)</td>
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<tr>
<td>MoM</td>
<td>Method of moments</td>
<td>(-)</td>
</tr>
<tr>
<td>MAE</td>
<td>Mean Absolute Error</td>
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<tr>
<td>MAPE</td>
<td>Mean Absolute Percentage Error</td>
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</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
<td>(-)</td>
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Subscripts

- **evap**: evaporating
- **cond**: condensing
- **tan**: tangent
- **tot**: total
- **i**: components
REFERENCE


ACKNOWLEDGEMENT

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