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Characterizing Steady State Compressor Performance by Using Transient Test Data

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ABSTRACT

Compressor testing is an essential task to characterize compressor performance, but often requires significant time to be executed. This study suggests a method that could greatly reduce time needed for compressor testing by inferring steady state performance from transient data rather than waiting for true steady state conditions to be measured. The key finding is that the overall isentropic efficiency in transient operation is almost identical to its true steady state performance value after applying very simple data processing. The paper describes a simple data processing method that extracts steady-state performance from transient data. The proposed processing should not be understood as a general rule to all compressors, but as a positive result for this particular compressor and a first glimpse into the value of transient data for performance estimation.

1. INTRODUCTION

Prototype compressors are usually characterized by performing steady-state testing over an array of operating conditions. Different definitions of steady-state operation exist and most require at least 15 minutes of operation with no significant change in any measurement with time. The test matrix can prescribe the compressor speed, suction and discharge pressure, and suction superheat. The required time to collect one steady-state point of the array can take from 30 minutes up to 2 hours, highly dependent on the type of test stand, the desired operating conditions, and the experience of the testing personnel. Many studies explain the long testing time is a significant problem, both in R&D and catalogue data creation. The earliest work found (Gustafson et al., 1992) had an identical goal as set in this paper, but the approach was to set up a neural network and infer the most important operating conditions for steady-state data points from transient data. In particular for refrigeration compressors, other authors followed over the years, always seeking a testing time reduction using complex algorithms (Antonelo et al., 2018; Coral et al., 2019; Penz et al., 2012; Xu et al., 2019). Some of the aforementioned studies show good results, but the method proposed in this paper is fundamentally simpler in requiring only the removal and averaging of data by conditions. The conditions are to remove datapoints if the suction pressure falls below a certain threshold or if there is no superheat.

While targeting steady-state measurements during testing, the compressor is naturally exposed to varying suction and discharge pressures. This paper explores whether such transient data can reveal the same information as captured with time consuming, steady state measurements. Some data processing is required but limited to removing data points based on certain conditions and applying moving averages to transient data.

2. METHODOLOGY

2.1 General Approach

Steady-state measurements were collected on a positive displacement compressor by maintaining nine different operating conditions for 20 minutes. The data points over each 20-minute time window were averaged and stored as one steady-state point. The steady-state data points were compared with transient data from a single, 20-minute period operation covering a wide range of pressure ratios ($P_r = [5{,}35]$). The steady-state data was used as true data and the transient data was analyzed to understand which portions of the transient data align with the steady-state data.

2.2 Test Setup and Components

The compressor was an oil-free, variable-speed scroll prototype with an electric motor capacity of 800 W and a swept volume of 15.2 cm^3. For the experiment, the compressor was operated at $3900 \pm 20\ RPM$. A hot-gas bypass test stand was used for all measurements, which allowed relatively quick adjustments of suction and discharge pressures. In a hot-gas bypass test stand, the refrigerant is split after a discharge valve and a mass flow rate measurement. The hot gas is expanded to suction pressure directly via a bypass branch while the remainder of the flow is condensed and then expanded. The two branches are be mixed before the compressor suction line to reach a desired superheat. The superheat was controlled for the steady-state tests but not for the transient test data.

3. DATA

3.1 Steady-State Data

The target test matrix contained the evaporation pressures corresponding to the saturation temperatures of -35, -30, -25, -15 and -5 °C for two different discharge pressures corresponding to the saturation temperatures 30 and 40 °C at a speed of 3900 RPM and a suction superheat in the range $15 < \Delta T_{sup} < 25$. Only the operating condition (-5/30) could not be measured due to limited valve ranges on the test stand. Steady-state measurements and the overall isentropic efficiency ($\eta_{i,o}$) calculated are shown in Table 1 and the results are plotted in Figure 1 as a function of pressure ratio.

Table 1: 20-minute averaged steady-state data from the prototype compressor

T_{evap} [°C]	T_{cond} [°C]	ΔT_{sup} [K]	f [RPM]	$\dot{m}$ [g/s]	$\dot{W}$ [W]	P_r[−]	$\eta_{i,o}$ [−]
-34.4	30.6	15.1	3880	1.83	517	11.5	0.19
-30.1	29.4	20.8	3901	2.15	496	15.2	0.22
-25.1	31.9	23.5	3915	2.66	559	11.9	0.23
-14.7	30.2	24.6	3924	3.97	548	9.6	0.26
-34.9	39.7	18.2	3860	1.76	682	7.7	0.16
-29.8	39.8	16.8	3902	2.32	735	4.7	0.18
-24.8	40.5	21.7	3906	2.63	700	6.2	0.20
-14.9	40.0	23.4	3917	3.85	695	4.2	0.24
-5.3	40.1	22.2	3918	5.64	717	9.0	0.26

3.2 Transient Data

Transient data was collected to evaluate whether the steady-state performance could be reproduced. The compressor had been powered off for 1 hour and 45 minutes before starting this experiment. The compressor was restarted and used to charge the system, resulting in a runtime of approximately 10 minutes. The 20-minute period was defined to begin when the charging process was completed. The compressor frequency was between 3880 and 3920 RPM for the 20 minutes to match the steady-state compressor frequency. The sampling rate varied between 2 and 3 seconds. The pressure ratio and overall isentropic efficiency computed for each time step are displayed in Figure 2. The pressure ratio and efficiency varied greatly and quickly as the operator changed the metering valves of the test stand to cover a wide range of different pressure ratios.

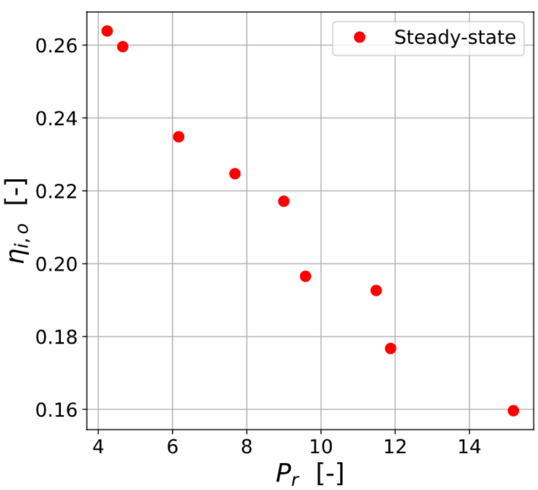


Figure 1: Steady state data

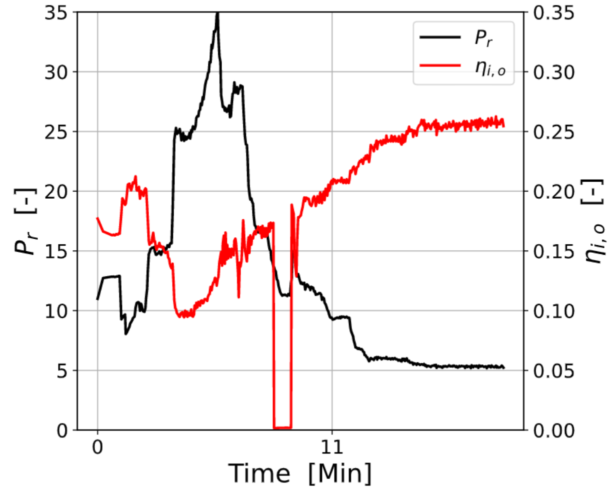


Figure 2: Transient data

4. PROCESSING

The isentropic efficiency from the transient data was plotted in Figure 3 as a function of pressure ratio (P_r) for all data samples collected by the data acquisition system (black) along with the steady-state data (red). Clearly, part of the transient data matches the steady state data, but other values are far off the linear behavior captured in the steady state data. A small group of points encircled in green is isolated from the data collected. The points did not have measured superheat making the computation of the isentropic efficiency (using property data of superheated refrigerant) not possible. The first step in processing transient data was therefore to eliminate any points that do not fulfill the criterion $\Delta T_{sup} \geq 1$ K.

A useful tool to understand the transient data is to flatten it, meaning that each data point becomes the average of a defined time window preceding it. This is sometimes also called a “rolling” or “moving” average. Figure 4 shows this result of flattening the data using 40 seconds for the moving average. As a result, the disorganized scatter plot becomes more of a line plot such that the time dependence of the collected points can be traced as indicated with the black arrows. A 54 second gap in the data acquisition is indicated with a dashed arrow and was due to stopping the code to update the output file. Points far away from one another capture quickly changing operating conditions while points close to each other have slowly changing operating conditions.

In a next step, the steady state data was overlaid over the flattened, transient data to evaluate the comparison. Varying degrees of data flattening, i.e. 10, 40 and 180 seconds were evaluated. Figure 5 shows the three different plots. With an increasing time-window for the moving average, the trend becomes clear and simple to understand. The moving average over 40 seconds was selected for the subsequent study because it gives a clear path by removing measurement fluctuations but does not remove significant information as occurred in the results shown in Figure 5 c), where the moving average window was 180 seconds. None of the three moving averages moved the transient data further away from the steady-state data. The best duration for the moving average could be a function of the compressor itself and should be revisited if this method is applied to other compressors.

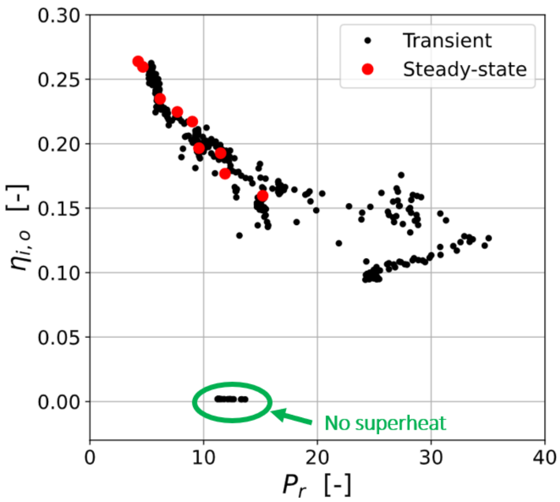


Figure 3: Overlay plot of transient and steady state data.

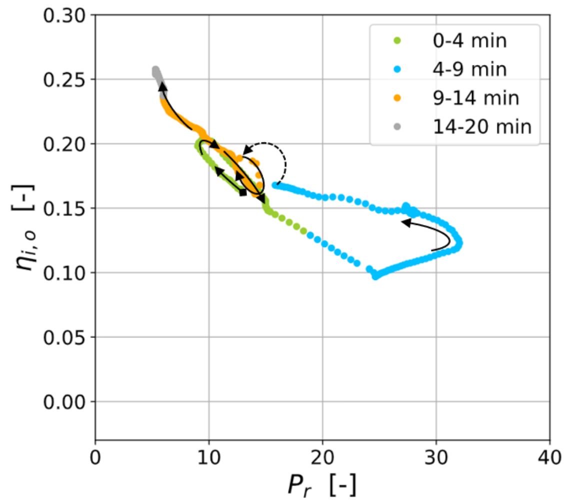
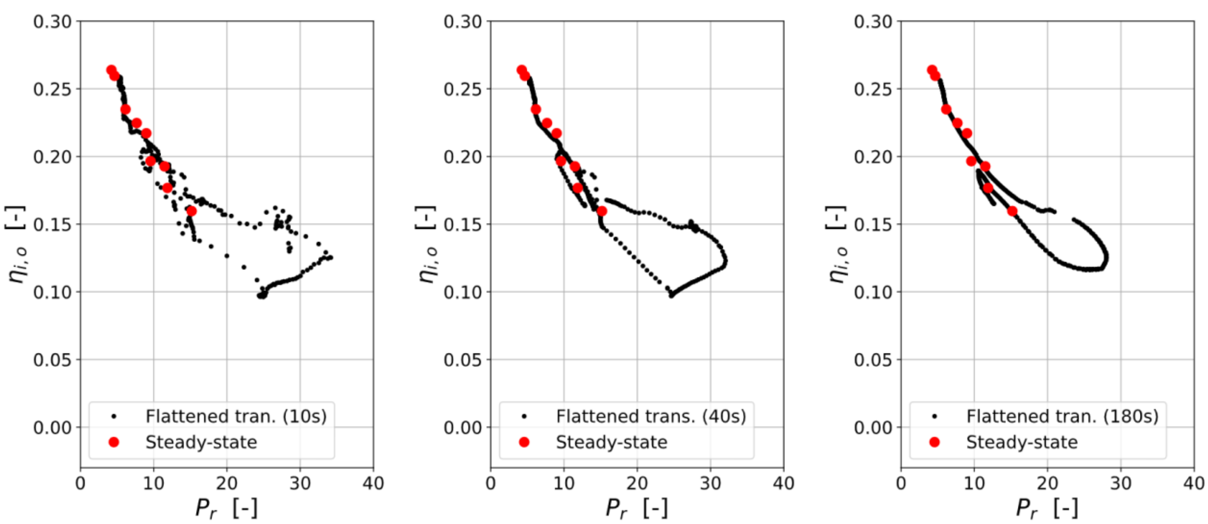


Figure 4: Flattened transient data with $\Delta T_{sup} \geq 1$ K.



a) Flattened over 10 seconds

b) Flattened over 40 seconds

c) Flattened over 180 seconds

Figure 5: Transient and steady-state data with varying degrees of flattening.

After applying the moving average, one section of the transient data still had a clear disagreement with the steady-state data. For $P_r > 15$ some data is in line with the linear trend of the steady state performance while other data shows a significantly higher efficiency at the same pressure ratio. By trial and error, it was found that the data points which are off the steady state trajectory all have very low suction pressures (below 50 kPa). Figure 6 visualizes this by using the evaporation temperature (saturation temperature corresponding to the suction pressure) as a third dimension.

The colored plot identifies that all data points away from the steady-state trajectory have evaporation temperatures of $T_{evap} < -40°C$. Since the design point of the prototype compressor is a suction pressure corresponding to $T_{evap} = -35°C$ and R134a is not typically used for $T_{evap} < -40°C$, the last processing step is to disregard data points that have an evaporation temperature below a certain threshold. Figure 7 a), b) and c) apply the thresholds -50°C, -40°C and -30°C. Clearly, -50°C leaves mismatching data while a -30°C threshold eliminates more data than needed to find a good match. It can be concluded that $T_{evap} > 40°C$ is a good criterion for this compressor and the refrigerant used. At the low suction pressures, the viscosity of R134a drops quickly and the mass flow rate of the compressor decreases below the design flow rate due to the low density, both justifying a lower bound on the suction pressure. Figure 8 shows the final result after three steps of data processing:

- Disregarding data with a superheat of less than 1 K
- Flattening data using a moving average over the last 40 seconds
- Disregarding any data with an evaporation temperature lower than -40$°C$

With the three filter rules applied, the transient performance in terms of isentropic efficiency matches the steady state performance very well. The results are significant because collecting the steady state data resembles a time-effort of several tens of hours, while the transient data was collected in 20 minutes.

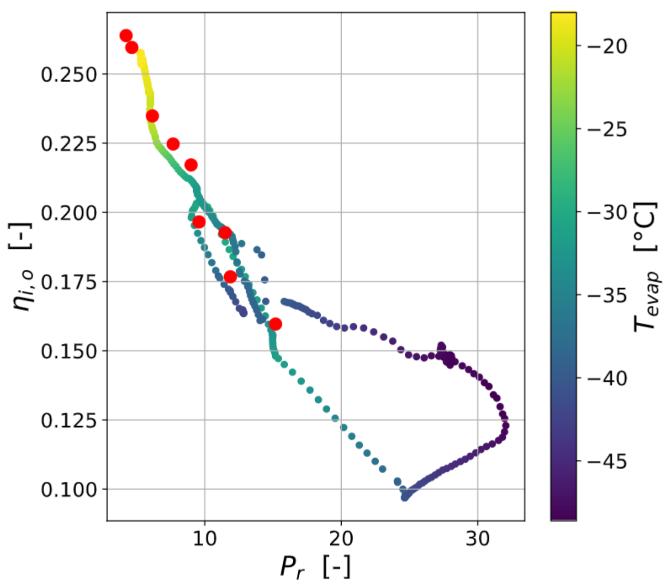
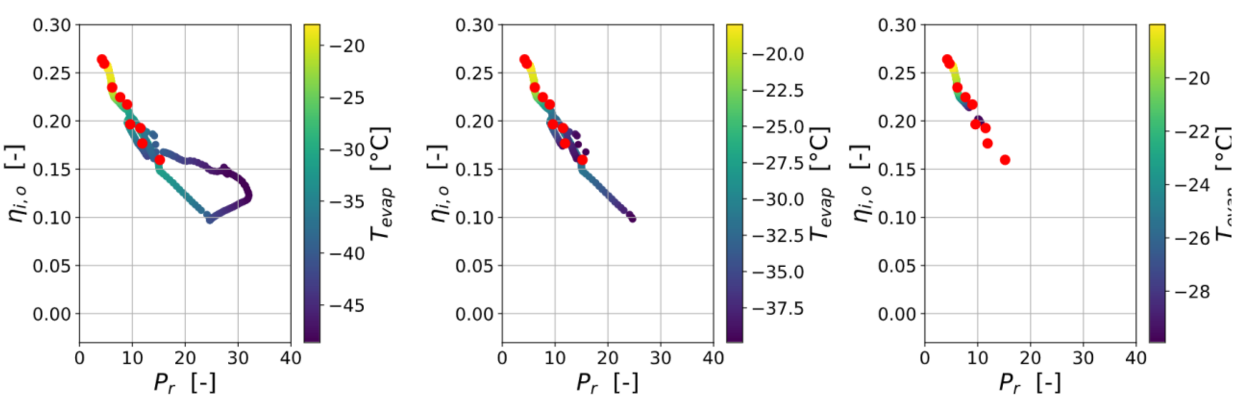


Figure 6: Overlay plot of transient and steady-state data with evaporation temperature as a third dimension for the transient data.



a) Data with $T_{evap} > -50°C$ b) Data with $T_{evap} > -40°C$ c) Data with $T_{evap} > -30°C$

Figure 7: Disregarding data points by varying evaporation temperature thresholds.

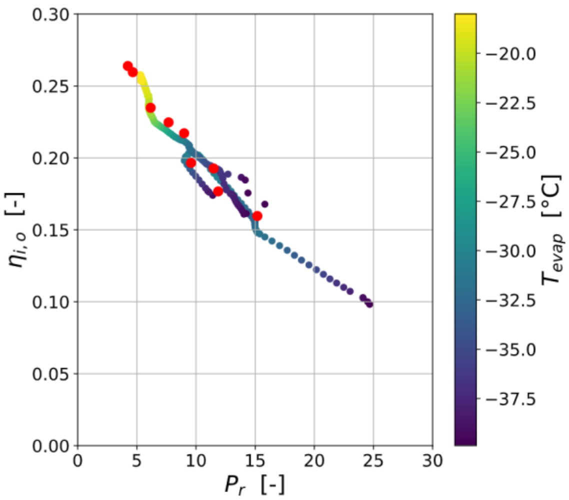


Figure 8: Steady-state and transient data after three steps of data processing.

5. DISCUSSION

The authors judge the processing steps as simple and possibly applicable to other compressor types and sizes. However, this cannot be directly inferred from this study and requires additional testing. For each compressor, a set of "true" steady-state and transient data is necessary to apply the same steps proposed in this paper and to locate additional processing steps to address disagreement.

Although the transient and steady-state data have similar ranges of pressure ratios, the operating conditions at which those pressure ratios were met are indeed different. Figure 9 shows this in a $T_{cond}\ vs.\ T_{evap}$ scatter plot. The steady state points match the array described in the "Steady-State Data" section. In comparison to that, the transient data is "all over the place" and approaches only the exact saturation suction and discharge temperatures of 2 steady state points (-30°C, 30°C) and (-30°C, -40°C).

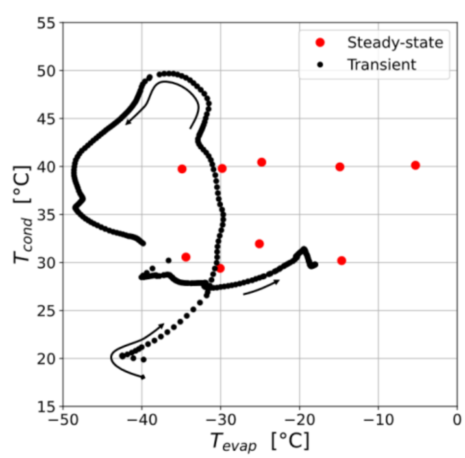


Figure 9: Comparison of the operating conditions of transient and steady state data.

The good agreement of steady state and transient measurements appears counterintuitive: During transient operation, the varying power inputs and efficiencies should result in different compressor temperatures, a process that is slow due to the high heat capacity of the metal parts. Only after the compressor is in thermal equilibrium is it expected that the correct isentropic efficiency would result from the measurements. However, the presented data in this paper shows a good match despite a very quickly changing isentropic efficiency.

Future work in the field should investigate whether the rules also apply to other performance criteria or whether additional criteria can be found. Of direct interest for compressor performance mapping are the volumetric efficiency and the heat rejection of the compressor to the ambient.

6. CONCLUSIONS

Simple data processing led to a good agreement of the isentropic efficiencies determined from 20 minutes of transient testing as compared to those determined from the testing of nine steady-state data points, each averaged over a 20-minute time period. The data processing disregarded data based on small superheat levels and extremely low evaporation temperatures and applied a moving average to smooth the transient data. The authors do not claim generalizability of the data processing steps, but believe that a larger study with different compressor sizes and types could reveal additional or other methods to find value in transient data and reduce the testing time needed to evaluate the performance of prototype compressors.

NOMENCLATURE

Symbol	Description	Unit
f	Compressor frequency	RPM
$\eta_{i,o}$	Overall isentropic efficiency $\eta_{i,o} = \dot{m}\left(h_{dis,s} - h_{suc}\right) / \dot{W}$	[-]
$\dot{m}$	Mass flow rate	[g/s]
P_r	Pressure ratio $P_r = P_{dis}/P_{suc}$	[-]
T_{evap}	Saturation temperature corresponding to suction pressure	[°C]
T_{cond}	Saturation temperature corresponding to discharge pressure	[°C]
ΔT_{sup}	Suction superheat	[K]
$\dot{W}$	Compressor power draw (measured after power supply before inverter)	[W]

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