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PERFORMANCE OF INTEGRATED R744-PACKS PART 1 - COMPRESSOR MASS FLOW ESTIMATION BASED ON DATA-DRIVEN MODELS USING ANALYTICAL METHODS AND ACTUAL FIELD MEASUREMENTS

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ABSTRACT

Rising concerns for climate change impacts along with the new legislation aimed at lowering emissions indicates the inevitable transition in the cooling/heating industry towards a more energy-efficient solution with minimal environmental impact. Integrated refrigeration, air condition and heat recovery solutions by CO_2(R744) packs are efficient solutions to high energy demanding building (supermarkets and hotels). Proven performance enhancement of Multi Ejector Solution™ makes the R744 systems more energy efficient, especially in warm climates, compared to the most conventional synthetic refrigerant systems in food retail applications.

Pilot installation in the frame of MultiPACK, an EU funded project (Horizon 2020), provided a wide range of data, offering the possibility of evaluating the real performance of each ejector group: high pressure (HP), low pressure (LP) and liquid ejector (LE), by running the system in different operating modes. Analysis of the data indicated performance improvement of a system with ejector, on average a 35% lower energy consumption compared to baseline parallel compression R744 system without ejectors.

Availability of mass flow measurement, 5 Coriolis mass flow meters on this pilot, enabled the possibility of comparison of mass flow rate estimation based on data acquisition from compressors with actual measurement. Methods utilized include: Energy balance, volumetric displacement, manufacturer polynomials, and data-driven method. The comparison reveals the importance of compressor suction and discharge parameters for obtaining reliable results based on energy balance, volumetric displacement, manufacturer polynomials methods. The current study shows data-driven method performs well after enough training time with error bounded to 3% and 10 % on low and medium temperature level compressors, respectively.

Keywords: R744 (CO2); Ejectors, Compressors, Integrated systems, Refrigeration, Data-driven models, Energy saving

1. INTRODUCTION

In an operational supermarket, the instrumentation is usually a limited to set of sensors and measured parameters. Mass flow meters are usually not included in installations; however, the information of the mass flow rates is important for calculating the performance of the system and the performance of the individual components, i.e. compressors, ejectors, heat-exchangers and to evaluate the system performance i.e. determining the actual cooling and heating loads at the provided temperature levels.

The mass flow rates through a compressor can be calculated from the polynomial function the manufacturer is providing, or via methods based on energy balance in the system, Sawalha et al, (2017), and Piscopiello et at al. (2018), or the volumetric displacement of the compressor. Nowadays, with the wide utilization of data-driven models it is possible to train models that can predict with relatively high accuracy the requested parameters based on controlled/normal operation of the installation.

This paper presents the comparison between the methods of indirect calculation of compressors mass flow rates, with observed measurements from mass flow meters installed in the system. Additionally, the emphasis is given on the development and benefits of the data-driven model.

2. SYSTEM AND DATA AQUISITION

2.1. System description and layout

The system used in this study~~,~~ is one of the three demonstration sites under the Multipack project (Minetto 2019) and it is based on a parallel compression system and expansion work recovery with multi ejectors, as shown in Figure 1. The space heating and cooling of the supermarket is supplied by two direct CO_2 rooftop air handling units. The arrangement of the roof top units enables the dehumidification function as well.

Three semi-hermetic CO_2 compressors are installed at Medium Temperature (MT comp) level, three compressors at Low Temperature (LT comp) level, and four compressors are dedicated for intermediate temperature level (IT comp) (2). Inverter drives used to achieve smooth capacity for compressor control. There is one inventer in each temperature level, transforming one of the compressors to a variable speed compressor. The total installed electrical power for compressors and fans is 177 kW at dimensioning conditions (excluding air handling fans).

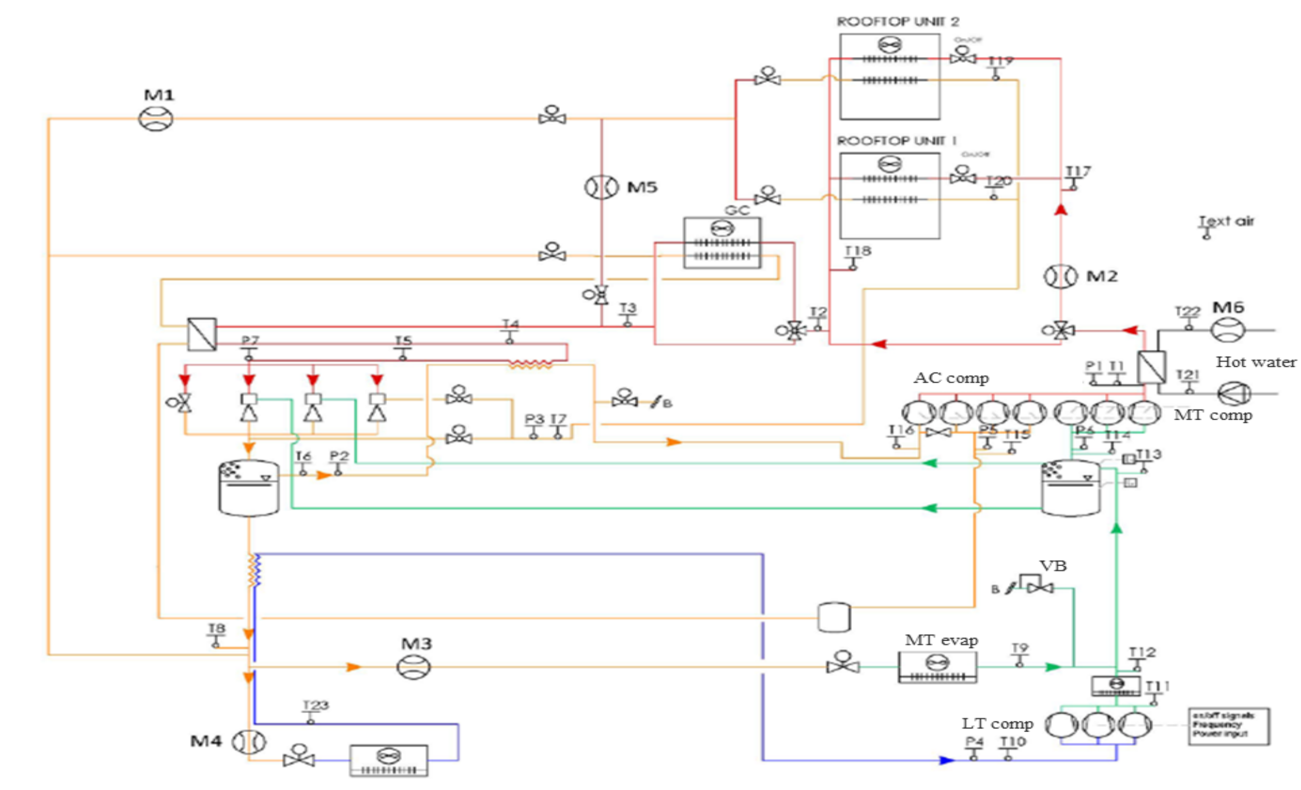

Figure 1 Integrated R744 system layout

The unit is operated as follows: at discharge of compressors at high pressure side, upon hot water request, CO_2 heat up water to 60 °C for domestic hot water application and the remaining heat is provided to roof top air handling unit (AHU) for space heating. During the summertime, excess heat of the CO_2 is rejected in the gas cooler (GC) to the ambient. In winter operation the GC is partially or completely bypassed. The expansion to intermediate pressure level in the range of 35 bar to 45 bar is done by means of multi ejector blocks or by electronically controlled high-pressure valves. The liquid receiver downstream of the ejectors separates the flash gas and liquid phase; the liquid enables stable charge variations in the circuit also provides a liquid head. The liquid CO_2 is subcooled by superheating LT evaporator outlet and sent to the LT, MT and AC evaporator. The LT load of the supermarket comprises of cabinets, freezing rooms, and an ice machine. The MT loads comprised of open and closed cabinets and cold rooms.

The supplied liquid CO_2 mass flow to the LT and MT evaporator is measured (Coriolis mass flow meter M4 and M3 respectively).The MT evaporators are controlled with a low minimum superheat (SH) setpoint, ALC mode, resulting to some liquid in the excite of the evaporators.

A separator in the suction line prevent MT evaporator liquid to move to the MT compressors. In the case of the liquid collection in the separator, a liquid ejector is activated to return it to the receiver. 2 high-pressure ejectors (HP) compress parts of the gas back to the liquid receiver and is thereby reduce the load on the MT compressors. The air conditioning (AC) function is provided either by liquid feed from receiver (M1 mass flow) or utilizing direct expansion (DX) downstream the GC (M5 mass flow). In the first case there is vapour compression by the mean two low pressure lift high entrainment ratio ejector (LP). The entire vapour of the AC evaporators enters the ejector and is lifted to the receiver pressure level. In the second case, the flash gas from AC operation is compressed by IT compressors. The models of compressors are as follows:

a. LT compressors: One 2KSL-1K (Operated as variable speed), two 2JSL-2K,
b. MT compressors: One 4HTC-20K (Operated as variable speed), Two 4FTC-30K
c. IT compressors: One 4MTE-10K (Varispeed series), One 4FTE-50K, Two 4FTC-30K

2.2. Data aquesition sytems

The instrumentation of the Multipack comprises ~~of~~ pressure, temperature, refrigerant, and water mass flow meters, compressor power consumption, and frequencies as described by Minnetto et al, (2019). Figure 1 shows the position of the sensors in the installation. Temperatures probes are type NTC 10 kΩ sensors indicated as T, having a declared precision is $\pm$0.5 °C at 25 °C and $\pm$1.0 K in the range -40 °C to +90 °C. Pressure transducers are type piezoresistive pressure transmitters and indicated as P, with accuracy ranging from $\pm$ 1 %FS for up to 60 bar and $\pm$ 4 %FS for 150 bar. Three-phase electric power meters measure total, low temperature, mediaum temperature and auxiliary power input (P_{TOT}, P_{LT}, P_{MT} and P_{IT} respectively with $\pm$ 0.5 %FS accuracy. The status of all compressors and the inverter frequency are also recorded. The liquid level in the liquid receiver is monitored in order to detect the status of the liquid ejectors.

Refrigerant mass flows meters are all Coriolis type with $\pm$ 1 % accuracy. M1 measures mass flow in air conditioning cooling mode with expansion work recovery and M5 with DX operation, respectively. M2 determines the hot CO_2 gas mass flow to the air handling unit in heating mode. M3 measure CO_2 mass flow to MT loads and M4 to the LT loads. The heat utilized for hot water production is measured by the magnetic mass flow meter M6, located on hot water side.

2.3. Data quality and challenges of field data

In order to ensure the reliability of data measurements, data logging has been done by 2 different sets of physical sensors. This enables the possibility to verify the data measurements and provide an indication of possible errors as the measurements for the same location are supposed to match. These 2 sources are:

a) Data from pack controller and system manager with temperature, pressure and power meters
b) Data logger with temperature, pressure, power meter, and Coriolis mass flow meters

3. COMPRESSORS MASS FLOW RATE ESTIMATION METHODS

The methods utilized for compressor mass flow estimation include: Energy balance over compressor assuming constant heat loss, volumetric displacement, manufacturer polynomials, and data-driven method. 5 Coriolis mass flow meters has been placed on the refrigerant side and calibrated to measure that enabled us to compare the methods and calculate the error.

3.1. Energy balance over compressor

In the system, all power consumptions by compressor groups are measured separately; furthermore, power consumption by fans, pumps, and lighting is recorded. Using the data on pressure and temperature in suction and discharge of each individual compressor and power consumption of compressors it is possible to estimate mass flow rate using energy balance by assuming a constant value for heat loss (Eq. 1), where:

$$\dot{m}_{hl} = \frac{E_{elec,comp} \cdot (1-\gamma_{hl})}{\Delta h_{comp}} \qquad \text{Eq. 1}$$

$\dot{m}_{hl}$, the mass flow estimation by energy balance over compressor [kg/s]
Δh_{comp}, the enthalpy variation over the suction and discharge of compressors [kJ/kg]
$E_{elec,comp}$, the electricity consumption by the compressor [kW]
γ_{hl}, the heat loss coefficient assuemed a value between the range of 3% to 10% suggested by Berglöf, 2005

3.2. Volumetric displacement

The volumetric displacement is based on the correlation between the volume passing through each compressor (Eq. 2) and is the function of inlet specific volume of refrigerant and the speed (frequency) of compressor, where:

$$\dot{m}_{vd} = \frac{\eta_{vol} \cdot (\dot{V}_{dis} \cdot R_{cap})}{3600.v_s} \qquad \text{Eq. 2}$$

$\dot{V}_{dis}$, the swept volume of compressors weighted average at maximum possible frequency [m³/s]
v_s, the refrigerant specific volume at the inlet of compressor [m³/kg]
R_{cap} is the running capacity of the compressor group and is a value between 0 and 1
The coeficients of volumentric efficiency of the compressor(η_{vol}), a and b, are fitted based on model from lab data measurements as previously used by Piscopiello et al, (2018), where:

$$\eta_{vol} = a + b(P_{disch}/P_{suc}) \qquad \text{Eq. 3}$$

P_{suc} and P_{disch} are suction and the discharge pressure of compressor [Pa]

3.3. Manufacturer polynomials

The compressor electric power consumption and mass flow can be estimated using manufaturer~~e~~ polynomial approximations. All compressors in the pilot are Bitzer (BITZER Software v6.15.2 rev2501) with estimations of certain parameters based on DIN EN 12900. Subcritical and transcritical modes are calculated based on the dedicated formula. In subcritical operation the polynomial function is dependent on the evaporation and the condensation temperature (ϑ_0 and ϑ_C respectively both in °C). (Eq. 4)

$$\mathrm{y_{i,sub}} = c_1 + c_2\vartheta_0 + c_3\vartheta_C + c_4\vartheta_0^2 + c_5\vartheta_0\vartheta_C + c_6\vartheta_C^2 + c_7\vartheta_0^3 + c_8\vartheta_0^2\vartheta_C + c_9\vartheta_0\vartheta_C^2 + c_{10}\vartheta_C^3 \qquad \text{Eq. 4}$$

The transcritical operation requires discharge pressures (P_H [bar]) on top of ϑ_0 and ϑ_C. (Eq. 5)

$$\mathrm{y_{i,tran}} = c_1 + c_2\vartheta_0 + c_3p_H + c_4\vartheta_0^2 + c_5\vartheta_0p_H + c_6p_H^2 + c_7\vartheta_0^3 + c_8\vartheta_0^2p_H + c_9\vartheta_0p_H^2 + c_{10}p_H^3 \qquad \text{Eq. 5}$$

For the LT compressors only, subcritical polynomial is required considering the operation pressures range. For each compressor group (LT, MT, AUX) one compressor with frequency inverted drive within the range of 30Hz–60Hz was used. The Bitezer software provides polynomials only for 50Hz therefore the frequencies in % from controller was corrected with a conversion factor as described by (Vindenes, 2018).

3.4. Direct measurement

5 Coriolis mass flow meters were placed on the inlet of evaporators directly measuring the mass flow to low temperature evaporators (M4), medium temperature evaporators (M3), air handling unit (M1 or M5 depending on the mode) and on heat recovery line (M2).

3.5. Data-driven method

Data-driven method has been utilized to satisfy following needs: a) to fill the gaps of data measurements; b) to estimate mass flow in IT using the model trained based on MT compressors; c) to enable later analysis on ejector performance; d) provide a more accurate model for mass flow estimation utilizing all data in disposal (Running capacity, pressure, temperature and power consumption) to potentially be used in other similar systems.

The detailed description of the data-driven model, also covering point b to d, is given in the second paper "Performance of integrated R744 packs Part 2-Ejectors performance, a comparison of Data-driven model from onsite measurements with rom model predictions" in this conference proceedings.

4. COMPRESSOR MASS FLOW RATE ESTIMATION BY DATA DRIVEN MODELING

The model used here is a grey-box model that utilizes all the relevant data at its disposal to estimate the mass flow rate. Apart from the usual data (Pressure, temperature, running capacity and power consumption); the model utilizes mass flow estimation from analytical mass flow estimation methods (energy balance using constant heat loss, volumetric displacement, and compressor manufacturer polynomials) to get an estimation of mass flow rate.

4.1. Data cleaning and synchronisation

The measurement from both sources contained some rows of “Not recorded” values that have removed from both data sets to keep times synchronized. One challenge that arises from dual sensors (control and measurement system) is the time synchronizing. A reference time was selected and an automated matching method was used for both synchronizing and date time conversion to seconds (t0 for all graphs is: ”17:00:00 11/07/2019”). Figure 2 shows and example of two dataset synchronization.

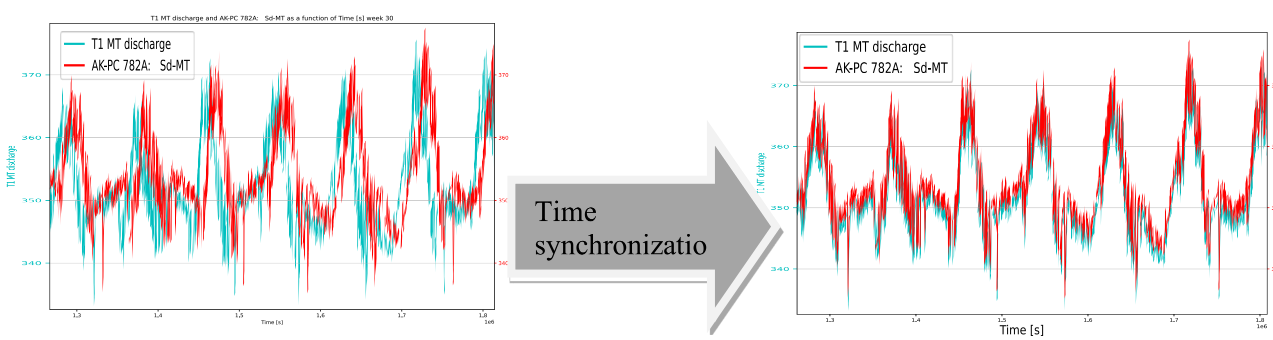

Figure 2 - Visualiation of time correction between different data sets

4.2. Data correlation

A common problem that arises when applying data-driven models is having two set of data with same sensor that represented in two or more columns (due to unit change or other calculations made in the controller). Finding a correlation between each pair of data enables spotting those kinds of redundancies and removing highly correlated data (duplicates or unit converted).

4.3. Train and test period selection (Train and test set)

In order to evaluate the model error, the data is devided to a training set and a train set; this enables the possibility to calculate coefficient of determination (R^2 score) for the model. That is well established method for assessing the performance of a model; with R2 score = 1 showing the model is perfectly correlated with measurement.

The training for LT mass flow rate estimation is with total disregard to ejector function in the system since there is no direct impact on LT operation from ejectors. For LT compressors, weeks 2-8 and 28-30 used for training, while 31-32 for testing and 33-35 is estimated by the model.

For MT compressors, weeks 2-8 (no ejectors running) and 30 used for training and week 33 used for test considering that only in these weeks we had the no ejector mode which follows Eq. 6. The trained model is then used to estimate MT and IT compressors mass flow rate weeks with Liquid & HP ejector.

$$\dot{m}_{MT_{Comp}} = \dot{m}_{MT_{Evap}} + \dot{m}_{LT_{Evap}} \qquad \text{Eq. 6}$$

4.4. Regression model selection

The linear_model regression library was used from the "sci-kit learn" machine learning tool for Python. There are multiple models available in the library and the two best performing ones in terms of R^2 score were: Multivariate Linear Regression and Bayesian Ridge. The Multivariate Linear Regression performed marginally better in the score and was used as the method for regression.

4.5. Variable selection

Selecting parameters for a data-driven model is one of the biggest challenges in the process. Analyticaly estimated values for compressor mass flow rate were added to the train/test/estimate set; these analytical methods were: 1. Energy balance over compressor 2. Volumetric displacement 3. Manufacturer polynomials

An automated process of selecting and removing variable to train/test data set was used to achieve the least R2_score with user supervision to verify. This step has been computationwise the most demanding since there are many combinations to select data that yields to best R^2 score.

The selected variable for LT compressor mass flow rate estimation: Mass flow rate calculated based on energy balance over the compressor, mass flow rate calculated based on manufacture polynomials, mass flow estimation based on volumetric displacement, power meters for the compressor group, running capacity of the compressor group.

The selected variable for MT compressor mass flow rate estimation: Mass flow rate calculated based on energy balance, power meters for the compressor group, suction pressure and temperature in compressor group.

5. DISCUSSION OF RESULTS

5.1. Data-Driven model test with new set of data

The data-driven model is put to test by the data it has not seen before to evaluate the accuracy. For training, testing, estimating the 180 data sample moving average has been used (the equivalent of 3 hours). Table 1 shows the R^2 score for LT and MT compressor group with all the method used vs the measurements from Coriolis mass flow meter for week without ejectors:

Table 1- Mass flow rate estimation and calculated values comparison vs direct measurement for LT compressor

	Energy balance	Volumetric	Manufacturer	Data driven	Direct

	over compressor	displaement	polynomials	model estimate	measurement
LT average weekly mass flow rate [kg/min]	0.038085	0.033121	0.033526	0.032291	0.032228
LT R^2 score	0.696838	0.939053	0.958228	0.978586	1
MT average weekly mass flow rate [kg/min]	0. 380856	0. 20303	0. 237937	0.207261	0. 206653
MT R^2 score	-4.176503	-1.060917	-1.114567	0.904348	1

5.1. Data-Driven model for estimating mass flow rate

The data driven models developed based on the data for weeks with no ejector were used to estimate mass flow rate for MT and IT compressor groups for weeks with ejectors that are discussed in detail in part 2 of the paper. In figure 3 and 4, the mass flow rate estimations and direct measurement has been depicted for LT and MT compressor group, respectively.

The caltulated mass flow rates in the MT and LT where compared with the measured values form M4 andM3 mass flow meters. The data-driven model is the one predicting more accurate for both compressor families. The energy balance model follows the fluctuation of the mass flow rates, but it overestimates the values for the MT and the LT compressors. The heat loses (assume to be 10%) in the model were probably underestimated for the MT compressors. The overestimation, hence, the heat loses is a subject of discharge temperature, as it appears to be less at LT level that MT. Further the correct positioning of the discharge temperature sensors may influence the results of the energy balance method.

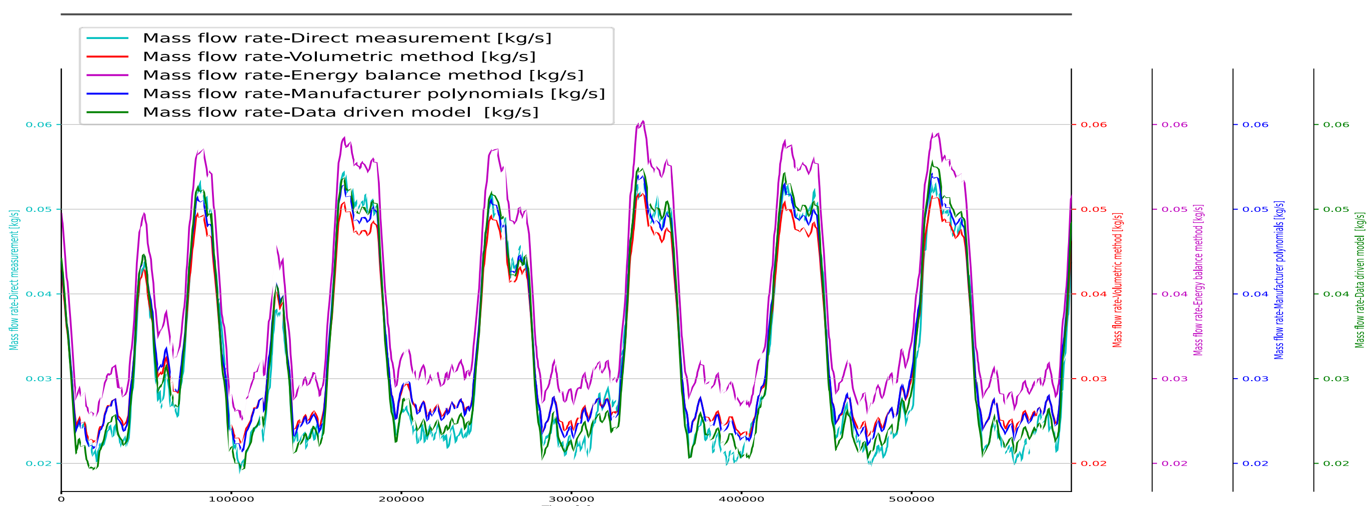

Figure 3 - Week 33 mass flow rate comparison from 4 estimation methods and direct measurement for LT level

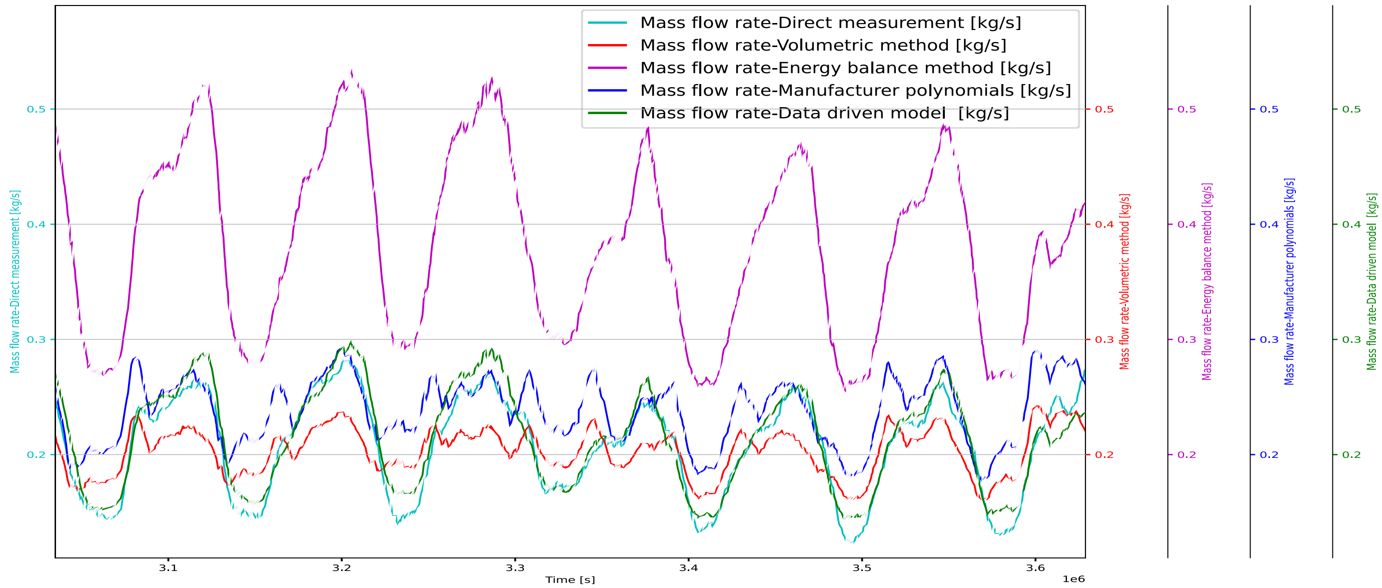

Figure 4 - Week 33 mass flow rate comparison from 4 estimation methods and direct measurement for MT level

Volometric efficiency and manufacturer polynimials appear to follow the same behaviour, though manufacturer polynomial curves are overestimating on the mean value. Data-driven on the other hand tend to follow the direct measurement for both LT and MT because it is utilizing on both analytical methods and fitting on the parameters. The mean value is also matching well with the measurement since all the constant values and effieceincies has been corrected by measured data. Figure 5 shows the devation of data-driven method from the measurement for both LT and MT compressors mass flow rate.

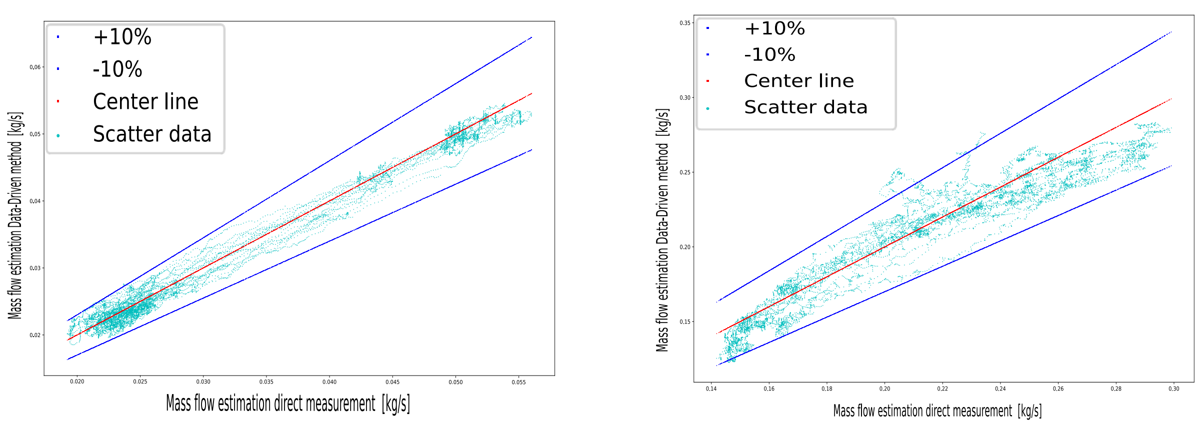

Figure 5 - Week 33 compressors mass flow rate devation of data-driven method estimation from the measurement for both LT(left) and MT(right)

6. CONCLUSIONS

From the analysis on the data it can be concluded that data-driven method is a potentially suitable approach for estimating mass flow meters and is possible to reduce the errors when trying to estimate system performance using mass flow rates. The 4 models evaluated in this paper led to following observations: For LT compressors all 4 models predict to a reasonable accuracy compared to the measuremnets. While, for MT compressors the models vary greatly on the accuracy compared to measurement: i)Energy balance approach shows high errors but has same trend as the measurement this indicates that it is possible to tune the energy balance cause it is an offset so with changing the coefficient (from 10%), also, the discharge temperature sensor may be asource of error which is in line with the estimating isentropic efficiency values; ii) The average value from the volumetric approach (3h average) is well matching the measuremnets but the exact value does not have good accuracy. iii) The manufacturer polynomials seem to follow the trend of volumetric approach with better accuracy with respect to the measurement, furthermore it provides well of the average value. iv) Data-driven method seems to perform best of the other methods both in accuracy and average value, the error is bounded to 10% for most of the data and seems to be reliable mthod.

The data-driven model is used in the 2nd part to estimate the entrainment ratio for CO2 ejectors:" PART 2 - EJECTORS PERFORMANCE, A COMPARISON OF DATA-DRIVEN MODEL FROM ONSITE MEASUREMENTS WITH ROM MODEL PREDICTIONS"

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NOMENCLATURE

p	pressure (kPa)	T	temperature (K)

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