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International Refrigeration and Air Conditioning Conference

School of Mechanical Engineering

2016

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A Novice Method for Calibrating the Transient Model of an Automotive HVAC System

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ABSTRACT

A novice method for calibrating the transient model of an automotive HVAC system is presented in this paper. Transient models can be of great importance in the development process of automotive HVAC control algorithms, especially model based ones, as it saves both time and effort. However, the calibration process is usually difficult and relies heavily on experience due to the complexity of the model.

A set of customized measurement tools, which consists of several wireless temperature and humidity sensors and an OBD dongle, is used to capture time series data related to the HVAC system during normal driving. Parts of the time series data are then fed into an optimization algorithm to generate a cost function, which can be minimized when the measured data correspond to the simulation data generated by the transient model. A sensitivity analysis is also performed to find out which parameters in the HVAC transient model need to be optimized to calibrate the model. As the transient model is a physical network model which can be generally considered as a set of differential and algebraic equations, this presented method reduces the calibration process of a complex physical model into solving a common optimization problem. Therefore, various optimization algorithms and tools can be applied.

The method is developed and tested during the modeling process of an automotive HVAC system. The efficiency of the modelling process is improved while the calibration results fit better with the measured data.

1. INTRODUCTION

Typically, the development process of climate control algorithms in the automotive industry utilizes an empirically defined polynomial which is calibrated during several rounds of bench test and road test. This process was adapted from the old analog control time and has been successfully implemented since the beginning of electronic control era. In recent years, many new algorithms have shifted from the old polynomial method and adopted various modern concepts like set-forget, self-learning and model predictive control.

The efficiency of the development of new climate control algorithms can be greatly improved once utilizing a dynamic model of the physical system for algorithm validation or model predictive control (MPC) (Faruque & Vatanparvar (2016). This dynamic model acts as the virtual version of the physical system which needs to be controlled. Unfortunately, the model building process has been proved difficult as the break down and modelling process of a typical HVAC system can result in hundreds of physical parameters which needs to be experimentally or empirically determined. Various efforts have been made to solve this tuning problem (Garriga & Soroush, 2008), (Cairano & Bemporad, 2010). Moreover, there is little room left for the automotive manufacturer to do this calibration work as it fits neither in the manufacturer car development process nor the tire-1 supplier development process.

A novice model calibration method is proposed in this paper, which aims at simplifying the calibration process of automotive HVAC transient model. This method takes a set of time series data from normal road test as the inputs, and outputs a set of parameters which better describes the physical system (as shown in Figure 1). A brief case study is also included in the paper.

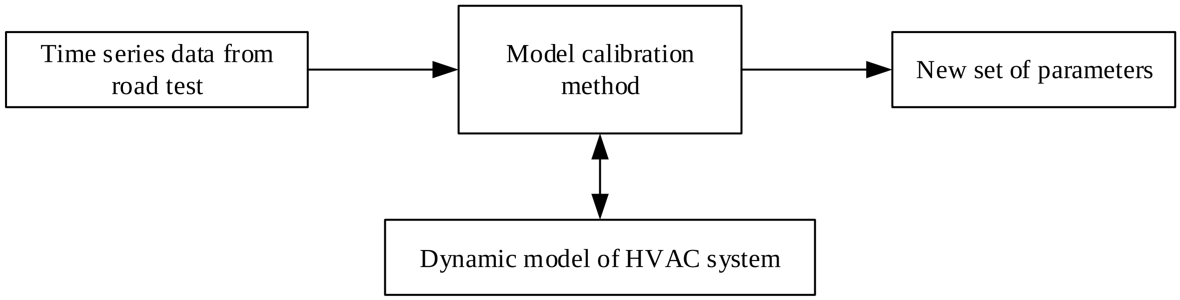

Figure 1: Overall structure of the method

2. TECHNOLOGY

2.1 Affecting factors

Various factors, such as the quality of the data, the quality of the model or the choice of the optimization algorithm, can affect the result of the auto-calibrating method.

The technology used in the automatic calibration method starts with the time series data, which come from various sources like common DAQ devices, manual logs, or something similar to the Bluetooth wireless DAQ system used in the following example. And the data can contain a huge amount of metadata such as the start time of the drive, the weather condition, the driver's action, etc. When using a wireless system, the signal strength can affect the data quality too. More things like the placement of sensors, the vibration of the vehicle can also have effect on the data. Therefore, a manual data preprocess which aims at checking and cleaning the data is always necessary before the start of the auto-calibration workflow.

The quality of the model can also affect the result of the technology (Avci, 2013). Usually, the model to be calibrated is a 1D-based multi-domain system model which can contain the thermal, two-phase and hydraulic physical domain. The thermal part is usually used to describe the thermal phenomenal which is void of fluid dynamics, while the two-phase part is used to describe the heat transfer process during the refrigerant phase change. However, there are also quite a few things which can only be described by experimentally determined correlations such as the wind-side heat transfer, the behavior of the throttle valve, etc. All these things together form a united physical model to describe the HVAC system, which is usually called the physical network. As a result, any part of the whole system can sabotage the result of the simulation.

The choice of the optimization method is also important. Because of the complexity of the physical network, the mathematical equation set to be optimized is always nonlinear and contains both dynamic and algebraic equations. Therefore, the choice of the optimization method can affect both the solvability of the optimization problem and the speed of the process.

2.2 Workflow

The workflow of the method generally contains three main steps as shown in Figure 2.

2.2.1 Preprocess. The preprocess step is quite important as it is the interface of the real world and the machine world. The data is fully defined not only by the data itself, but also by the timestamp of events and the metadata of each channel. Thus if without a specially developed DAQ system which has a good human machine interface, this job can cost quite a lot of human labor. The quality of the data is also to be determined as it is related to things like the mounting situation of sensor. Although the experiment operation standard inside an automotive company can partly guarantee the quality of the data, the remaining part of the quality needs to be achieved by a carefully designed preprocess step.

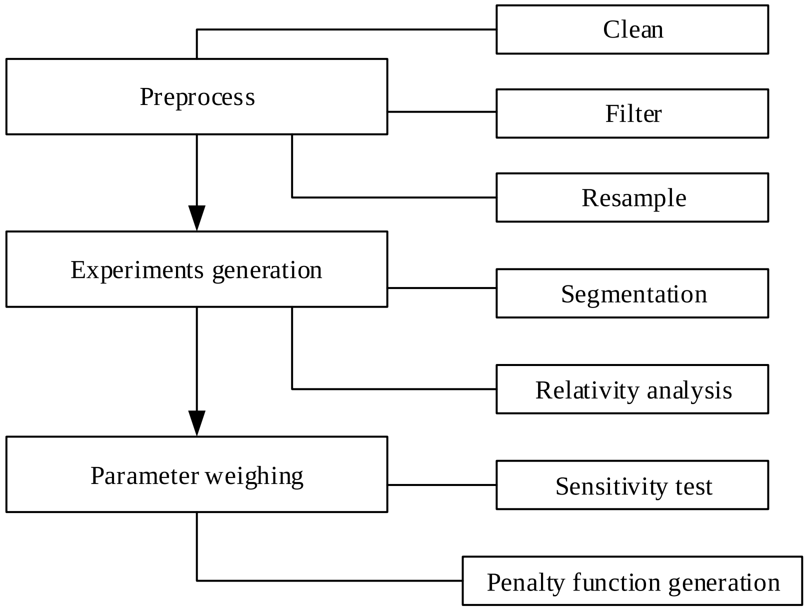

Figure 2: Workflow diagram

This data pre-process step usually contains three minor steps. Firstly, a data cleaning step needs to be done by eliminating abnormal points, deleting unnecessary dataset dimensions and correctly mapping the dataset columns to the real world meaning. Secondly, a filtering step can eliminate unnecessary information which lies on a frequency band not belonging to the modelled system. In addition, behaviors that are not modelled, such as the defrosting behavior of the evaporator, can also be filtered out. Thirdly, an additional resample step is taken to furtherly summarize time-domain information into characteristic points which can represent the signal well enough and save computational time. As thermal systems often have large inertia, the sampling interval can be extended to 30 seconds or even longer without feature loss..

2.2.2 Experiments generation. Typically, experiments need to be determined in advance. However, the experiments in this method are generated instead of pre-defined. This can benefit the calibration process of an automotive HVAC as it simplifies the usually long and costly experiments without setting a thorough and precise experiment plan. Instead, all experiments are carried out freely during the drivability test phase of an automotive development process. The test driver simply needs to operate the HVAC control panel as using a manually controlled one and the panel, together with the DAQ system, will log all the data. Experiments are generated after analyzing the logged data

The generation of experiments needs to be done in two steps. The first step is called time series segmentation, which aims at slicing the original long time series into short ones. The segmentation is based on two signals. One signal marks the beginning of a segment, which is always triggered by a sharp transition in control signal, such as the start of compressor, or the adjustment of blower speed. The other signal marks the end of a segment, which is determined by the relative steadiness of a working condition. This steady signal is usually triggered after about ten to twenty minutes following the start signal. Therefore, every segment generated by the experiments generation step can be taken as a step response to the control signal generated by the driver or the start of vehicle. There are also segmentation methods based on wavelet analysis (Rajagopalan & Ray, 2006), which can be carried out in a more automated manner.

The second step of the experiment generation process is called relativity analysis, which aims at analyzing which parameters in the model can be calibrated by the experiments generated in the former step. This step differs from any typical condenser calibration method as the testing conditions of the experiments are given instead of controlled. There are mainly two ways to finish this step. One way is to use the empirical method to decide what parameters in the model can be affected by a specific change in signal. For example, when the blower speed is changed, the parameters to be calibrated is usually the coefficients of the correlation which describes the air side heat transfer characteristic. Another way is to decide the relationship mathematically by analyzing the math equations with structure analysis methods to see which parameter becomes redundant with additional time series information feed in.

2.2.3 Parameter weighing. Different parameters have different influence on the output of the model. For example, 0.1cc in the displacement of compressor can mean quite different things compared with 0.1 in the volume efficiency of compressor. If they are treated the same in the optimization cost function, the optimization process will never converge as the change of 0.1 in volume efficiency can greatly change the output of model while 0.1cc in displacement can hardly be noticed. Therefore, a sensitivity test should be done to generate an adequate cost function for optimization.

There are generally two ways to carry out a sensitivity test, namely, the global way and the local way (Guenther (2013). The global sensitivity test utilizes the Monte Carlo method to test how the model reacts to different parameter changes while the local way simply changes one parameter and watch the change in output. Sometimes this local way can be computed in a mathematical manner by calculating the derivative of a parameter. A ranking can be given after the sensitivity test is done. The cost function can then be generated.

The model optimization can be started once the cost function is generated.

3. CASE STUDY

The HVAC system modelled here is an automotive HVAC system which is mounted on a medium sized SUV. The system includes a compressor, a condenser, a TXV, an evaporator system with evaporation temperature control for defrost purpose and a heater core for heating. As the whole system is quite complex and includes several different physical regimes (thermal, hydraulic, two-phase flow), the auto-calibration method is only applied to the condenser sub-model to simplify the case study. A series of sensors are installed on the HVAC and inside the cabin. All the data is acquired using a DAQ system which can log the data points with a 1 second interval.

Various commercial software platforms can be used to model the HVAC system. Although the GUI of each software platform may differ, they are all based on the same 1-D physical network simulation principle. The standard library of each platform may vary in abundance of parts and features, but they all provide basic thermal and two phase modelling capacity (Varun Kumar et al., 2014). With these model building platforms and carefully designed software interface to the DAQ system and the optimization software, the method described above can be carried out. Figure 3 shows the software structure used in this method.

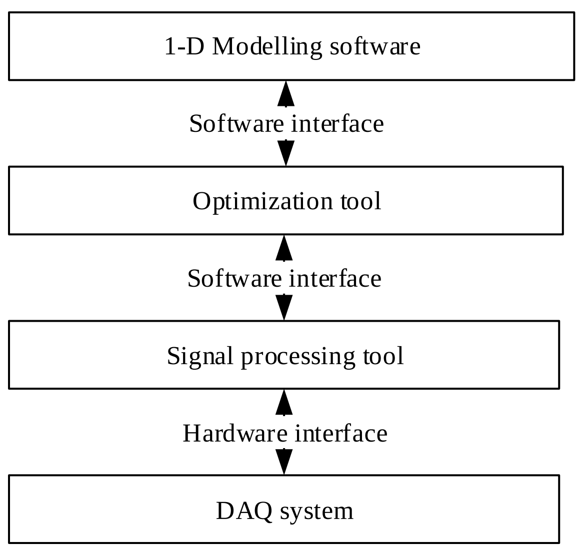

Figure 3: Software structure used in case study

3.1 Model Description

The condenser modelled here is a common parallel flow condenser. Typically, a finite volume method (FVM) with dozens of nodes can be used here to model the heat transfer behavior of the condenser. However, as the transient model has less requirement on the precision of the result, only three lumped nodes are used here, which can provide a balance between optimization efficiency and computational precision (He, Liu, & Asada, 1997).

Each finite volume here is governed by three balance equations, namely, the mass balance equation, the momentum balance equation, and the energy balance equation. As compressibility is not considered in this case study, the mass conservation equation is quite simple and omitted here. The momentum conservation equation is described in Equation (1). The energy balance equation is described in Equation (2).

$$p_A - p_B = \Delta p_{Loss} + \rho g \Delta z \tag{1}$$

Where p_A, p_B are the pressure at each end of the node, Δp_{Loss} is the pressure loss inside the node, ρ is the refrigerant density, g is the gravity coefficient, and Δz is the elevation change between nodes.

$$\frac{dE}{dt} = \emptyset_A + \emptyset_B + \emptyset_H - \dot{m} g \Delta z \tag{2}$$

Where E is the total energy inside the node, $\emptyset_A$, $\emptyset_B$ are the energy coming through the interface of adjacent nodes, $\emptyset_H$ is the energy flow through tube wall, $\dot{m}$ is the mass flow rate.

However, the most important work here is selecting the right correlation to calculate the micro-channel heat transfer coefficient. Kim, & Mudawar (2012) had done a famous work to describe the condensation in micro-channel tubes. Other information like the geometry and material information of the heat exchangers is also important in the calibration process. Table 1 describes the condenser used in the case study.

Table 1: Descriptions of condenser

Name	**Value**
Nominal working condition	Inlet pressure: 1.518MPa Outlet sub-cooling: 5°C Air side temperature:35°C Inlet superheat: 25°C Air flow: 5m/s
Capacity	13500W @ 5m/s
Flow type	Parallel flow, 4 passes, 15-9-7-R/D-5
Overall geometry dimension	613.5*360.8*H16
Tube type	Microchannel with rectangular port
Tube length	633.5L*36
Tube dimension and ports	16*1.8*16 ports，0.25t
Tube material	AL A1100-H112
Fin type	V-shape louver fin
Fin height	8mm
Fin thickness	0.08t
Fin material	Al A3003
nominal pressure drop	0.275Mpa

3.2 Preprocess

The preprocess step involves data cleaning, filtering and resampling. When the data was firstly transferred from the DAQ system, it has many error points which is caused by the loose connection of the DAQ system with the sensor. These error was first cleaned by applying several conditional filters which gives the data upper and lower limit.

Moreover, the original signal contains too much high frequency information that is not necessary in auto-calibration. A 60-300 points window FFT filter was used to eliminate all this high frequency information. Then a resampling step was taken. The result is shown in Figure 4.

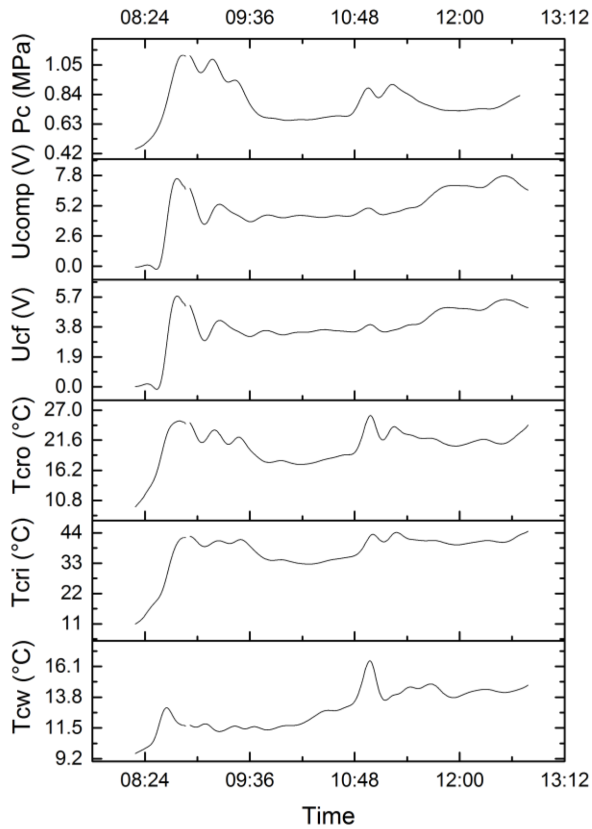

Figure 4: Preprocessed time series data

3.3 Experiments generation

According to the experiments generation method, one of the experiments can be generated as shown in Figure 5. In the generated experiment, the car is undergoing a cold start for about 20 minutes. The start signal is triggered by the rise in compressor voltage. At the end of this experiment, the condenser pressure and temperatures are reaching a stable status.

The data used in the generated experiment can be grouped into three categories, namely the input condition, the measured signal and the parameter to be adjusted. Tcw, Ucomp and Ucf are the input condition, while Tcri and Tcro are the measured signal. As the air-side flowrate of the condenser cannot be measured precisely on a driving vehicle due to room limit, the flowrate can only be calculated from the fan voltage (Ucf) and the car speed, which is maintained at about 50 km/h.

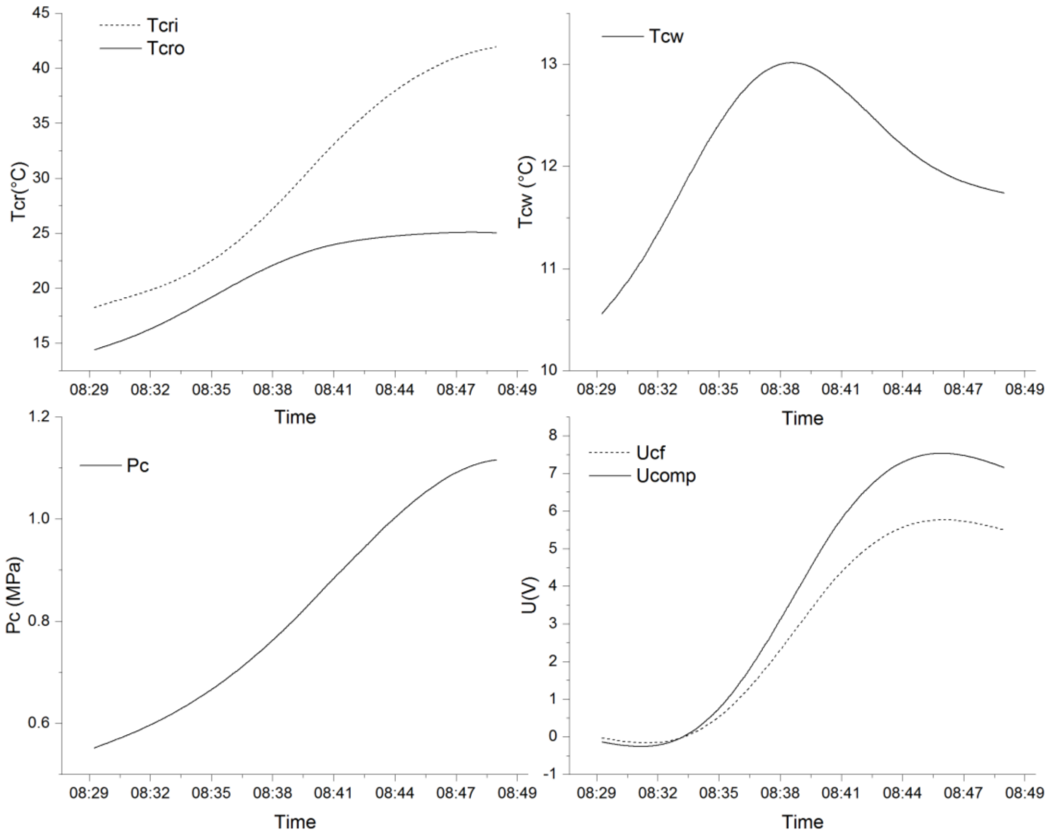

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Figure 5: Generated experiment example

The relativity analysis step is carried out after the experiments are generated. As the testing condition of the generated experiments are defined by the weather of the road test day and the driver's driving behavior, it is quite difficult to determine which parameters are related to a specific single generated experiment. However, from prior condenser calibration experience, several rules are summarized. One of the most important prior knowledge is that in parallel condensers, the refrigerant side heat transfer has little impact on the overall heat rejection while the air side heat transfer coefficient really matters. Another such knowledge is that the pressure drop inside the tube always needs to be calibrated using an additional coefficient. Therefore, the parameters related to this experiment are limited to the coefficients of air-side heat transfer correlation shown in Equation (3) and the pressure drop gain(kp).

$$Nu = aRe^{b}Pr^{c} \tag{3}$$

The overall heat rejection of the condenser is selected as the measured output of the analysis, while the parameters selected in the former step are taken as the input of the analysis. The relativity analysis result is shown in Figure 6. Some data seem to be missing from the figure because the absolute value of the partial derivatives at that perturbation level is too small to be noticed on the log-scaled axis. According to this analysis, the parameter c will be omitted in the final optimization search while a and b will be considered equally important. The pressure drop correction factor (kp) will be considered 1000 times less important than parameter a. All these weight information of the parameters will be considered in the algorithm for the efficiency of the optimization search.

3.4 Parameter Optimization

This part finishes the whole calibration process. Firstly, the sensitivity analysis should be done to create a more efficient cost function for the optimization engine. As the relativity analysis indicates, the condenser overall heat rejection is more related to the parameter "a" of the air-side heat transfer correlation than any other parameter. Thus the sensitivity analysis can use this parameter to analyze the sensitivity of model output. Figure 7 shows the derivatives of different output values of the model under different perturbation levels of parameter "a". It is clear that both Tcro and Tcri are 10 times more sensitive than Pc. This result will help create a more efficient cost function by setting smaller weight to the temperature outputs. The generated cost function is shown in Equation (4).

$$Cost = w_1 * abs(Tcri(t) - Tcri,e(t)) + w_2 * abs(Tcro(t) - Tcro,e(t)) + w_3 * abs(Pc(t) - Pc,e(t)) \quad (4)$$

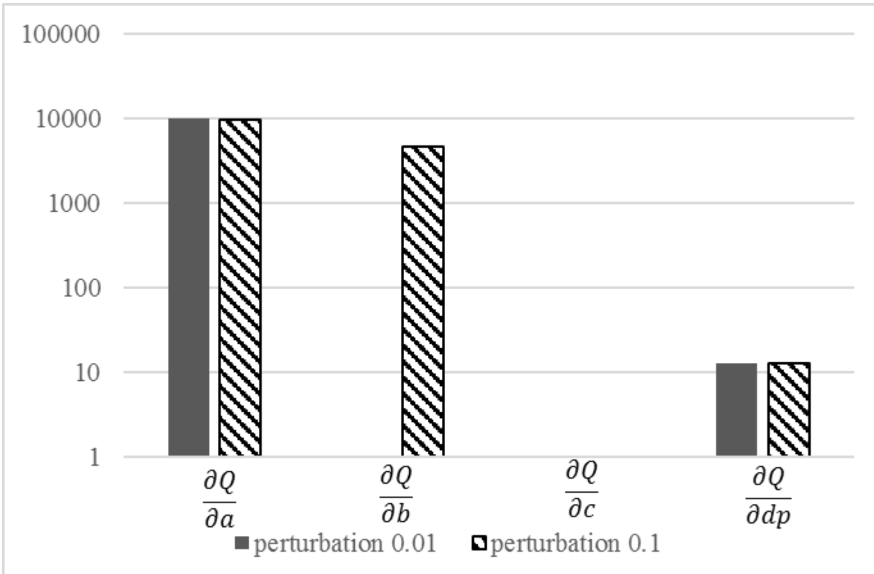

Figure 6: Relativitiy analysis result

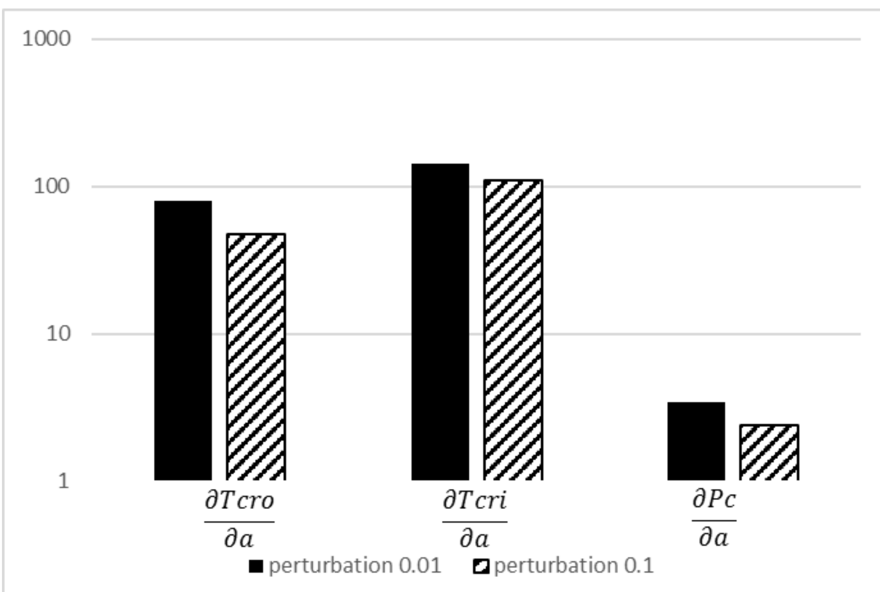

Figure 7: Sensitivity analysis result

As shown in Figure 8, the parameter values are adjusted during the estimation process automatically by the optimization algorithm. The result of the cost function is dynamically computed to determine the direction of optimization. The optimized model output is compared with the original one in the first three mini graphs in Figure 8. The optimization path is plotted in the fourth mini graph. The optimized result Tcri, Tcro are significantly closer to the generated experiment than the original result, while the pressure slightly drifted away.

During the optimization process, both sequential quadratic programming(SQP) algorithm and the genetic algorithm are tested. The SQP method is significantly faster than the genetic algorithm as it took only 1 step to finish the iteration. This is caused by the relatively stable nature of the model at this working condition.

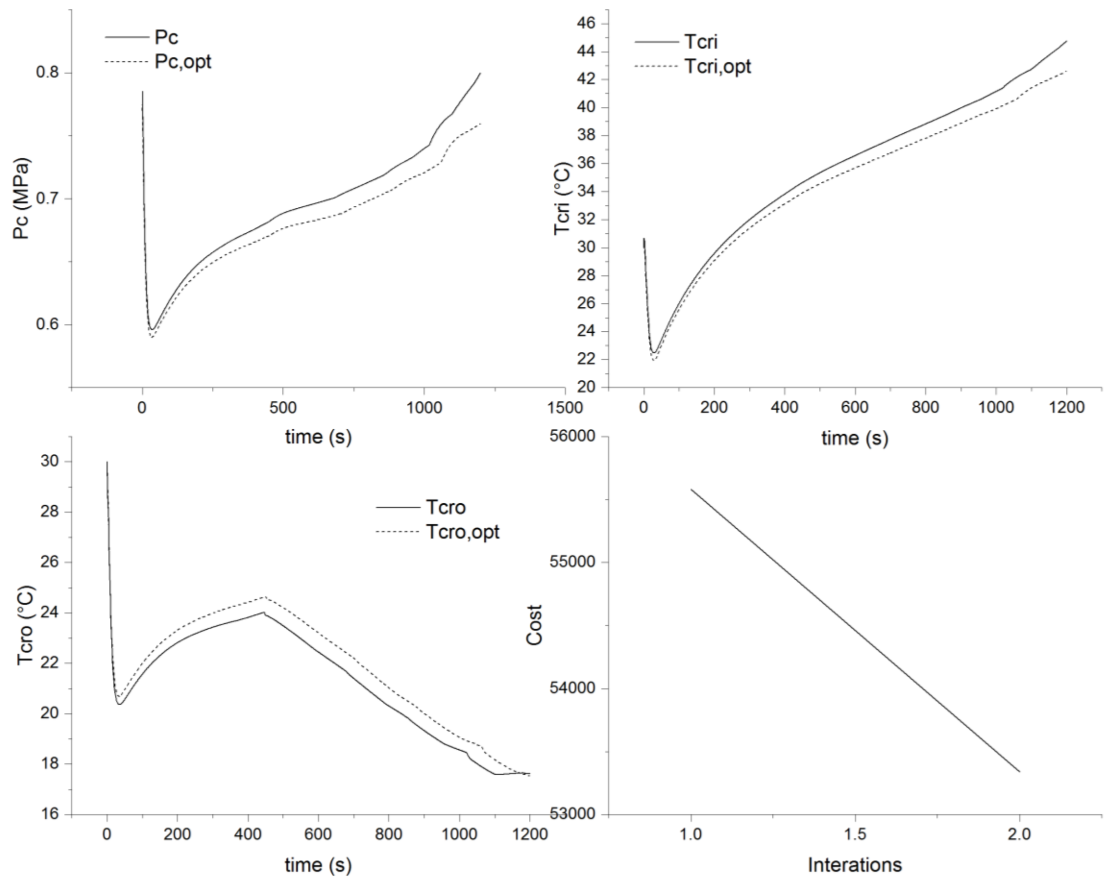

Figure 8: The optimization result

3.5 Problems in the case study

Problems can be found from the optimization result graph. As we can see from Figure 8, the condenser pressure drifted heavily from the real-world measured value. This drift comes from two sources. One is that the parameters in the condenser itself cannot fully determine the inlet pressure as it also depends on other parts in the vapor compression cycle. Another source of error is that the condenser model may not be correctly built to represent the working situation of the HVAC system mounted on a vehicle which is being started. Further analysis needs to be carried out to analyze this vehicle at this working condition.

The work is still in its preliminary phase and most steps taken in this method require experience from the engineer. However, in future works, artificial intelligence is planned to be involved and hopefully, can bring more automation to the method.

4. CONCLUSIONS

A novice method for calibrating the transient model of automotive HVAC system is provided in this paper. Most part of this paper describes this method and analyzes the key techniques needed to carry out this method. A preliminary case study is also provided in the paper, showing the possibility of calibrating an HVAC transient model without designing the experiment in advance. However, there is still much room for further research as both optimization and transient modelling techniques used in this paper need further analysis.

NOMENCLATURE

DAQ	Data acquisition	
T	Temperature	(°C)
TXV	Thermal expansion valve	
P	Pressure	(MPa)
U	Voltage	(V)
Nu	Nusselt number	
Pr	Prandtl number	
Re	Reynolds number	
w	weight	

Subscript

cri	condenser refrigerant inlet
cro	condenser refrigerant outlet
e	experimental
c	condenser
cf	condenser fan
cw	condenser wind
comp	compressor
opt	optimized

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ACKNOWLEDGEMENT

This work is sponsored by Anhui Jianghuai Automobile Co. Ltd.