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Wellbore Model Inversion: Coupling of a Wellbore Simulator and an Inversion Software

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ABSTRACT

Modeling of two-phase fluid flow in a geothermal production well is one of the reservoir engineering techniques widely used to study well performance under different flowing conditions. As with other modeling techniques, it is a good practice to validate wellbore models by calibrating them against measured parameters such flowing temperature, pressure, velocity, and wellhead flow characteristics before it can be used for any prediction purposes. In this paper, an automated method of wellbore flow model calibration is demonstrated. The wellbore flow simulator Simgwel was used to model flow in a number of geothermal production wells and the inversion software PEST was coupled with the simulator to automate the calibration process. Reservoir pressure, feedzone enthalpies and productivities, and %NCG were identified as calibration parameters. The method proved to be very fast and effective when tested with several producing wells.

1. INTRODUCTION

Wellbore modeling is vital in the interpretation of the data gathered from down-hole surveys of geothermal wells.

In reservoir engineering, a well-calibrated wellbore model would help in decisions in maintaining wells, or proper reservoir management strategies that would make the geothermal field sustainable and profitable.

Manual calibration of a wellbore model can be time consuming depending on the available measured data from a geothermal steam field. For less experienced reservoir engineers, the combinations of parameters in a wellbore model to reproduce a specific behavior can be difficult. More often than not, as the number of parameters increase, the number of forward runs it takes to adequately calibrate a wellbore model also increases.

Energy Development Corporation uses Wellsim(DOS version) and Simgwel(McGuinness, 2013) as its main geothermal wellbore simulators. The latter is a GUI based simulator whose core is based on the research tool GWELL, but is completely rewritten in Fortran 95. Simgwel's current version is 9.09. Figure 1 shows some of the tabs in Simgwel's GUI.

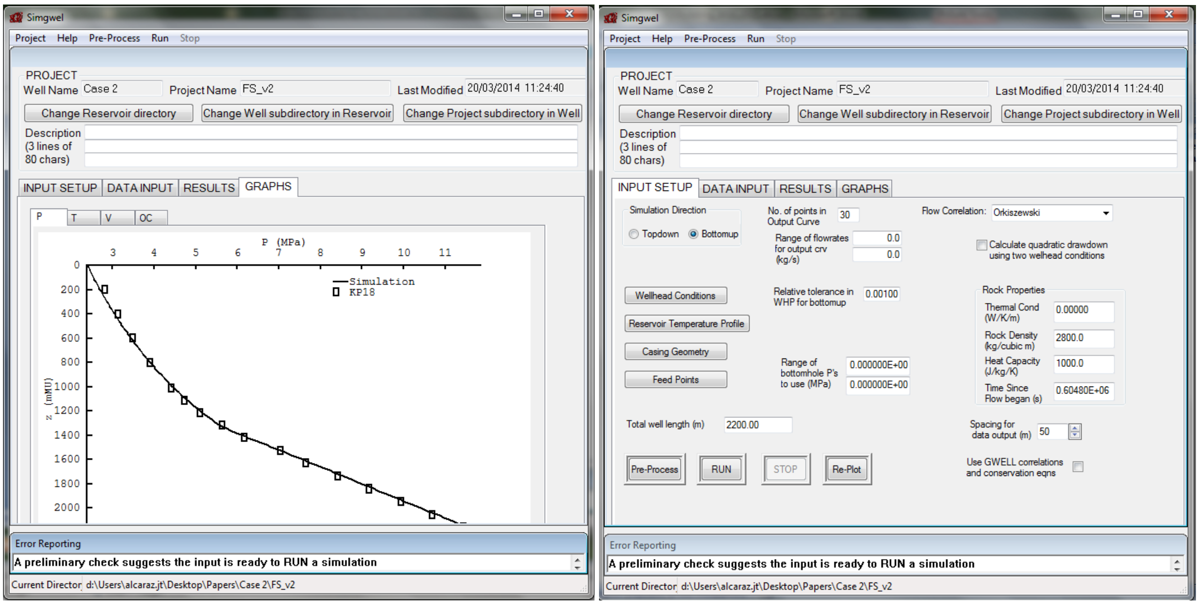

Figure 1: Left: Simgwel graphs tab showing simulated and measured pressures; Right: Simgwel input parameters tab

Inverse theory deals with finding the parameter solution set of a model from specified observation data. It has been widely used in different scientific and engineering applications because of its efficiency and speed, especially in complex systems. In the field of reservoir engineering, inversion software are extensively used to calibrate 3-dimensional heat and mass transfer models of large subsurface geothermal systems. Modern inverse modeling software also incorporate cloud computing in their procedures, further reducing computational restrictions of individual desktop and laptop computers. In this paper, an inverse modeling software, PEST (Doherty, 2005), was used to calibrate wellbore models that are simulated by Simgwel.

2. METHODOLOGY

2.1 Intermediate softwares

A combination of different programs was used to do the model inversion of a wellbore simulator. Aside from Simgwel and PEST, AutoIt3, Python and Microsoft Visual Basic for Applications (MS VBA) were used. Since Simgwel is GUI-based, a graphics based automation software was needed to automate keyboard strokes and mouse clicks. AutoIt3 is a free scripting software that does that job for Windows users. Moreover, its commands can be called and executed in Python by importing its COM interface. Python code was used in almost all the pre- and post-processes to couple PEST and Simgwel.

2.2 Control parameters and the objective function

The selection of parameters that are going to be optimized is critical in doing an inversion. Any of Simgwel's input parameters can be a calibration parameter in reducing the objective function. Too many parameters can take longer, making the inversion process inefficient. Then again, few parameters could lead to non-unique solutions giving non-sensible results.

The objective function on the other hand would consist of measured data that can be calculated by Simgwel, such as pressure, temperature and velocity profiles, mass output curves and enthalpy output curves.

2.3 Process flow

The process flow for the inverse model from pre-processing up to the inverse model is shown in Figure 2.

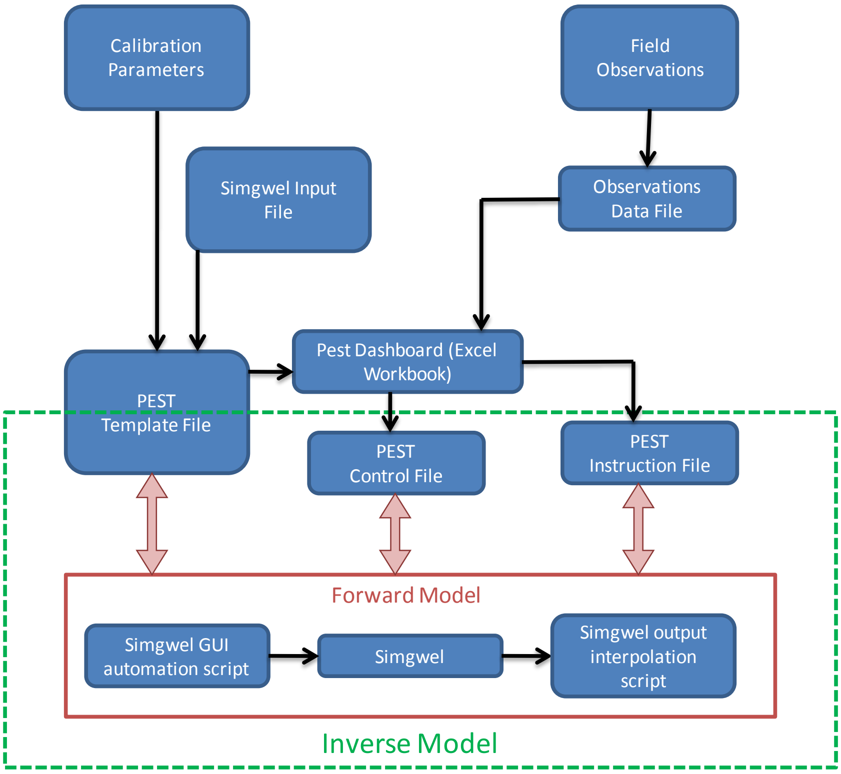

Figure 2: Process flow of inverse model.

2.3.1. <u>Preprocessing</u>

Depending on the data that is available, the observations file is filled up with data. Observations that can be used are flowing temperature, pressure and spinner profiles vs. depth, wellhead mass flow vs. wellhead pressure, and wellhead enthalpy vs. wellhead pressure. Initially, the user must also have a general idea of where the feed-zones are located by reviewing spinner data and completion test reports. By then, the user will have to determine the number of feedzones and their approximate locations inside the wellbore. Feedzone depth can still be a calibrating parameter to a certain extent if it is unclear due to lack of spinner data.

Well geometry must also be well defined. It can come from the deviation data that was recorded during drilling. Blockages and depositions can be represented by smaller radii casing. Moreover, it can be parameterized by making the casing radius a calibrating parameter.

When all the necessary calibration parameters are defined, the PEST template file can be created by editing and copying the Simgwel file. A sample is shown in Figure 3 below.

The PEST dashboard is an excel file where the user can design the pest control file. The pest control file is the main controller for the inverse model run. It contains the parameters, its initial values, its upper and lower limits, scale and many other options. It also has the observations compiled and the weight assigned to each observation. The PEST dashboard is designed using MS VBA such that it will automatically acquire the data from the Simgwel template file and the observations.csv file. It then reproduces the control parameters from the dashboard to a .pst file that is readable by PEST.

```
ptf #



   2  1  50  0.000000  0 T T T  0.000000  0.000000  42
   3
 "KP11 (1981)"  1
 "KT13 (1981)"  2
 "1981 BOM"  4
   2
   #whp          #  #mflowtot      #  #whenthalpy    #  1.000000047497451E-003  -1.00000000000000
  -999.000000000000  -999.000000000000  -999.000000000000  1.000000047497451E-003  -1.00000000000000
   1.000000047497451E-003   0.000000000000000   0.000000000000000
   2400.00000000000
   0.000000000000000
   2800.00000000000
   1000.00000000000
   604800.000000000
   2
  1056.000  #radius1     #  0.45720000E-04  0.2500000000E+02   90.0000      1056.000   47
  1344.000  #radius2     #  0.00000000E+00  0.2500000000E+02   90.0000      1344.000  104
   0
   3
   1100.00000000000  4  #pressure1     #  #enthalpy1     #  #mflow1         #  0.000000000000000  #ncg1               # -1.00000000000000
   1600.00000000000  4  #pressure2     #  #enthalpy2     #  #mflow2         #  0.000000000000000  #ncg2               # -1.00000000000000
   2400.00000000000  4  #pressure3     #  #enthalpy3     #  #mflow3         #  0.000000000000000  #ncg3               # -1.00000000000000
```

Figure 3: PEST template file for Simgwel

2.3.2. Forward Model

PEST needs to read the results of a forward model in order to optimize parameters. Simgwel certainly produces plenty of results, but only specific points are needed. Usually, an interpolation of data is done to properly transfer the results to the next iteration in the inversion algorithm. This is where the python interpolation script comes in. It basically gets the results from a single simulation and interpolates data based on the observations that the user defined. For example, it interpolates the simulated temperatures based on the depths of observed temperatures from a specified .csv file. The interpolation script does this for temperature, pressure and spinner profiles. Similarly, it also interpolates the simulated mass and enthalpy output curves based on wellhead pressures of the measured output data. Figure 4 below illustrates an example of the files involved in interpolation process.

Completing the forward model is the automation script that runs the Simgwel GUI. It is a combination of Python and AutoIt3 scripts. As the Simgwel executable is launched, the existing SGWinput text file is loaded. The Python script launches the application, starts the simulation and closes the application. The script also determines if there are errors encountered during the simulation or if the forward model does not run for a given parameter set.

SGWPlot.csv

"Depth (mMU)"	"P SIM (bara)"	"T SIM (deg C)"
0.00E+00	1.00E+01	1.80E+02
2.51E+01	1.02E+01	1.81E+02
5.03E+01	1.05E+01	1.82E+02
7.54E+01	1.08E+01	1.83E+02
1.01E+02	1.11E+01	1.84E+02
1.26E+02	1.14E+01	1.85E+02
1.51E+02	1.18E+01	1.87E+02
1.76E+02	1.21E+01	1.88E+02
2.01E+02	1.24E+01	1.89E+02
2.26E+02	1.27E+01	1.90E+02
2.51E+02	1.30E+01	1.91E+02

…

…

…

SGWobservations.csv

Depth	Pressure	Depth	Temperature
0	2	0	216
200	2.4	200	226
400	3.1	400	230
600	3.4	600	236
800	3.9	800	243
1000	4.5	900	247
		1000	251

SGWoutfile.dat

```
PRESSURE
         0.0         1.0002
       200.0  1.23797159905
       400.0  1.48234107356
       600.0  1.72305234686
       800.0  1.96887386635
      1000.0  2.22624687624
TEMPERATURE
         0.0         179.62
       200.0  189.046945107
       400.0  197.371677932
       600.0  204.572665076
       800.0  211.164574383
       900.0   214.31052506
      1000.0  217.405348189
```

Figure 4: Simulated output interpolation process

2.3.3. Inverse model

The forward model, PEST template file, PEST instruction file, PEST control file together acts as the inverse model. Parameter estimation was implemented using the Levenberg-Marquardt algorithm. It is usually better to try to get the model working and getting a similar profile compared to the measured data. This helps in setting the limits of the calibration parameters when setting-up the control file.

2.4 Test cases

Actual production wells and an artificial well were considered in this paper to demonstrate the coupling and performance of the wellbore simulator and inversion software. A total of three different observation sets were calibrated.

Case 1: Two feed model with output curve data

The first well, Well A, is assumed to be a two-feed well without any flowing survey data. Shut pressure and temperature profiles were measured before production. Measured data include only the equations that define the mass and enthalpy output curves. Well geometry was calculated from deviation survey reports.

Based from shut pressure data, the gradient of the shut pressure profile indicate liquid density for the production liner. In addition, the measured enthalpy output points dwell around 1300-1320 kJ/kg indicating a pure liquid to a low vapor fraction enthalpy at the feed zones. Thus, an initial assumption of saturated liquid enthalpy was simulated. Furthermore, the initial productivity indices for both feeds were set to 7.0 kg/s-MPa based from average values of nearby wells.

The parameter estimation process took 98 forward model runs to finish. It is noticed that there is a significant improvement in the output curve match. Moreover, the model cannot reproduce the enthalpy curve exactly but is still within the accepted error range of 50kJ/kg.

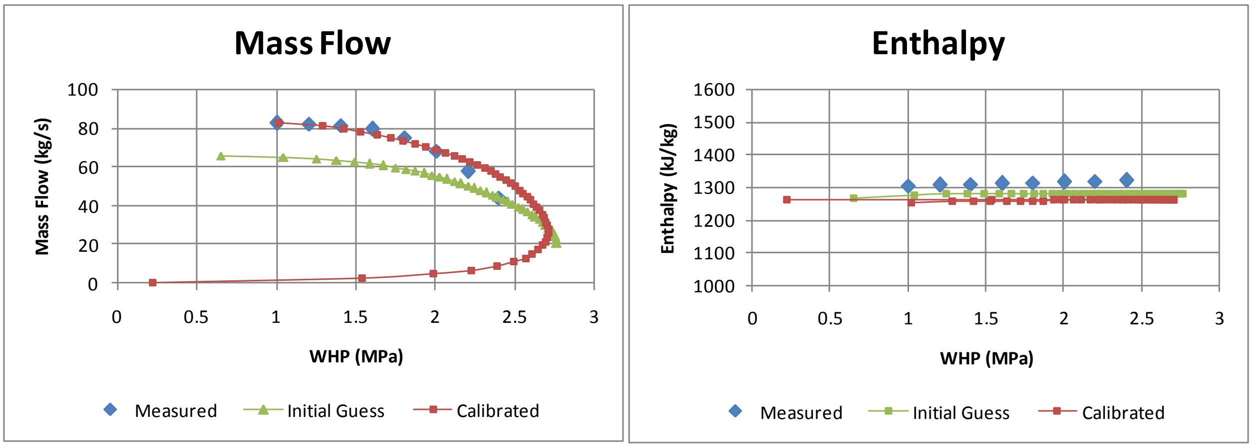

Figure 5: Well A measured, initial run and optimized mass flow and enthalpy output curves

Case 2: Three feed model with flowing profile and output curve data

More data is available for the second test well, Well B. Three permeable zones were inferred from initial well analysis by observing the shut temperature and pressure profiles. Flowing pressure and temperature profiles were measured at the early stages of production. Shut pressure was also measured before production. An output curve and enthalpy curve was measured during the medium-term discharge of the well.

Casing geometry was calculated using deviation survey reports. The feed zones of the wellbore model were set at 1320mMD, 1600mMD and 2200mMD. Judging from the slope of the pressure profile, the bottom two feeds would most likely be liquid. Initially, their enthalpies were assumed to be at saturated liquid conditions of its flowing temperature. It was also observed that the enthalpy curve range from 1200-1400 kJ/kg, so the shallow feed was initially assumed to have an enthalpy of 1400 kJ/kg. Lastly, the initial productivity values for all feed zones were assumed to be equal, each having a productivity index of 3.0 kg/s-MPa. Reservoir pressures were based from the shut flowing pressures. The measured data, simulated results of initial guess and the final results of optimization are plotted in figures 6 and 7.

Simulated pressure and temperature profiles match well with the measured data except for the location of the flash point, which was shallower than the actual data. However, the mass and enthalpy output curves needed to be improved.

PEST was used to improve the match using the methodology discussed in the previous chapter. Calibration parameters were the productivity index and the enthalpy of each of the three feed zones. Calibration successfully finished after 50 model runs. The results are also plotted in figures 6 and 7.

Case 3: Single feed model with flowing profile, spinner and output curve data

Artificial observations data was generated for Well C. The model is a single feed well with a total depth of 2200m. Its feedzone at the bottom has an enthalpy of 1100kJ/kg and a PI of 13.9 kg/MPa. The resulting simulated data using these parameters were obtained and made the observations data for the inversion process.

The model was initially run with an enthalpy of 1300kJ/kg and a PI of 5.5 kg/MPa. The model was successfully calibrated after 56 model calls. It reached the true solution with a maximum error of 4.4E-04 in the parameter set. Figures 8 and 9 show the results for Well C.

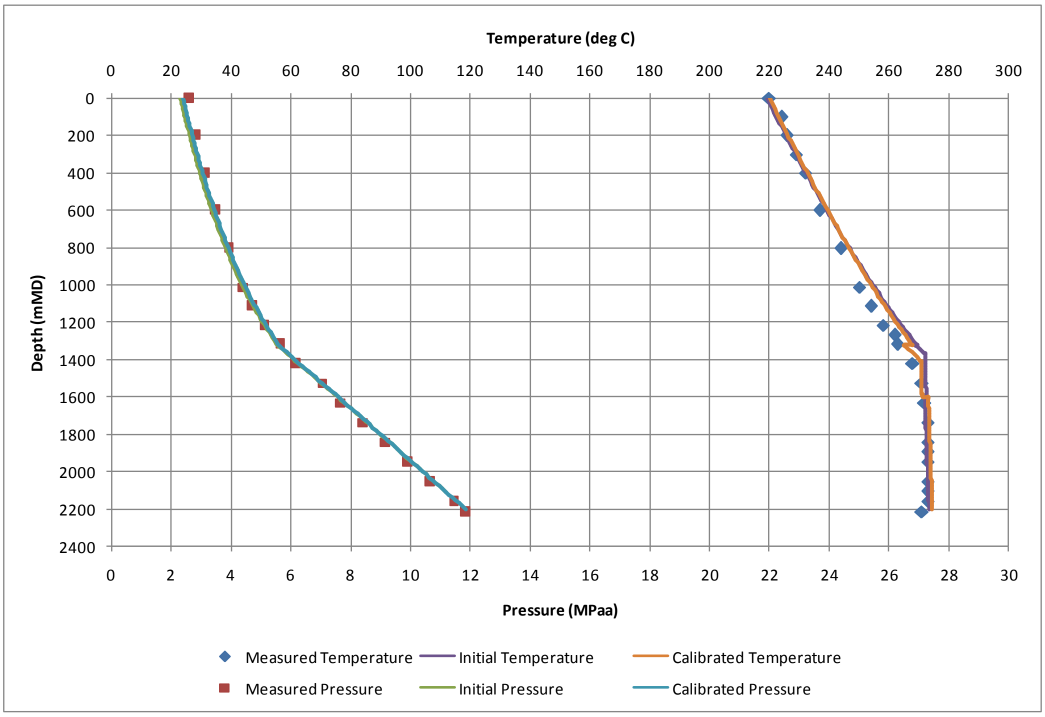

Figure 6: Well B measured, initial run and optimized pressure and temperature profiles

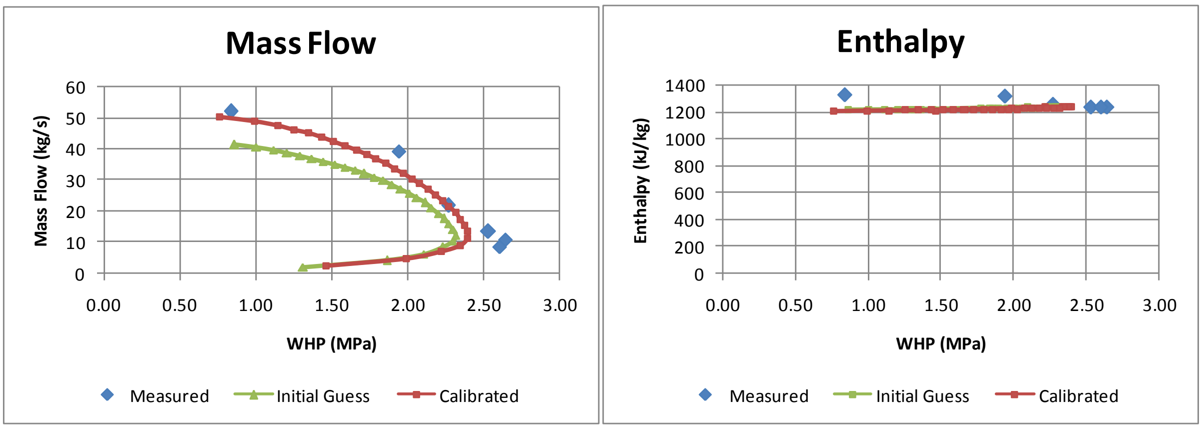

Figure 7: Well B measured, initial run and optimized mass flow and enthalpy output curves

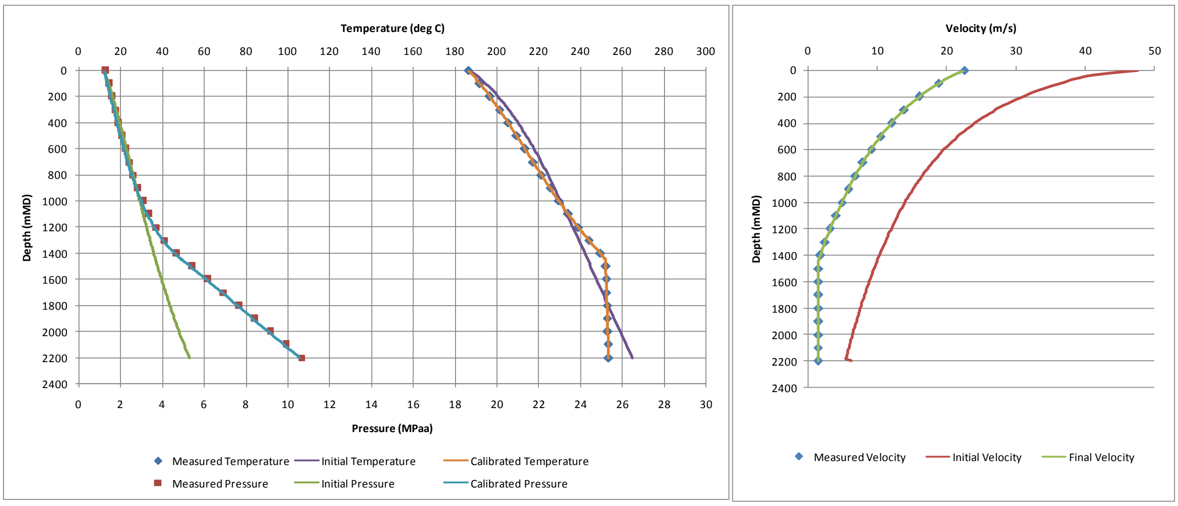

Figure 8: Well C measured, initial run and optimized temperature, pressure and velocity profiles

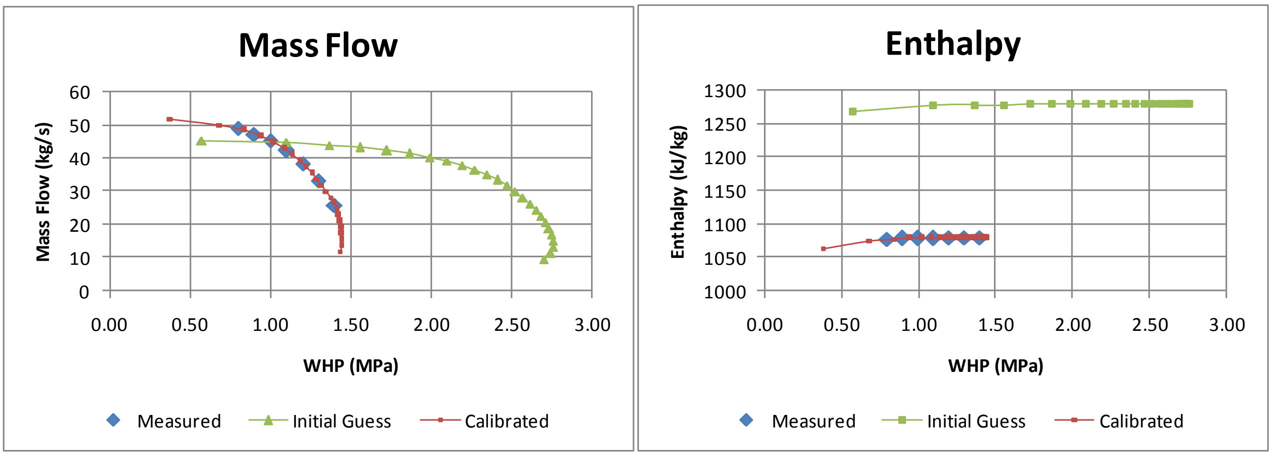

Figure 9: Well C initial run and optimized mass flow and enthalpy output curves

3. CONCLUSION

The inversion process for wellbore models proved to be effective in calibrating actual production wells. A test case also suggests that the algorithm can compute for the parameters used to reproduce artificially generated observation data.

Efficiency was significantly improved compared to manual calibration. Full automation of the process made it possible to calibrate multiple models using a single computer. However, in very simple wellbore models, manual calibration may be suitable and more efficient, given an individual's understanding of an actual production well. The total time for the inversion can be optimized by adjusting termination criteria in the pest control file (Doherty, 2005). Parameter bounds can also be refined by understanding the physical limitations of the flow in a well. It is best to choose the initial values for the parameter set with a careful study and review of reservoir properties near the study area.

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