



Signal and Image Processing Lab



Ultrasonic Water Meter Calibration by Deep Learning

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In collaboration with **ARAD**

Introduction

Calibration is an essential process in order to maintain the performance of a water meter

Dataset

• Expected data behavior

Results

• Average test results are:

- The calibration process consists of multiple stages each includes sampling calibration factors – 14 samples
- It is slow and expensive

Goals

- Shorten the calibration time using deep learning based methods
 - Predict calibration factors
 - Minimize the number of samples needed
 - Achieve the required error standard

Challenges

- High variance of the data
- Two different physical behaviors for data of different flow rates
- No suitable solutions in the literature



- Dataset given by Arad Technologies
 - Total of 94235 water meters samples



Flow rate [L\H]	Average [%]	Min [%]	Max [%]
12.8	3.754	3.2e-5	14.15
35	0.744	3.4e-5	10.21
57	0.669	2.6e-5	3.471
105	0.557	2.7e-5	2.779
525	0.364	2.5e-5	3.157
877.8	0.339	0	2.578
2500	0.347	8e-6	3.068
4000	0.375	0	3.055
5000	0.379	1.6e-5	2.945

• Error thresholds are:

- 1% for flow rate lower then 7[L\H]
- 0.5% for higher flow rates
- Red 1% or more above error threshold
- Orange 0.1%-0.3% above error threshold
- Yellow 0-0.1% above error threshold
- Green bellow threshold
- The columns represent error of prediction for each flow rate in %



- MLP neural network of two hidden layers
- Input dimension is the number of samples at a calibration process
- Outputs a single value
- Uses an ELU activation function
- Performance individually maximized

High variance characterize samples of low flow rates, and inconsistence with expected behaviour

Network Array

- Enables individual hyperparameter optimization
- Capable of handling different physical data behaviors



• The error is given by: $\frac{|K_{predicted} - K_{sampled}|}{K_{sampled}} \times 100$

Future Work

During the project we successfully predicted factor values while achieving required error bounds for higher flow rates, yet we have a difficulty handling samples from the lower range due to noisy data. We suggest further research should consider:

- Improve understanding of lower flow rate samples
- more complex deep learning network
- Architectural rethinking
- Different data interpretation and preprocessing
- Using samples of Reynolds number
- Different partition of data to train, test, validation
- Deeper literature survey

Reynolds Number

- Helps predicting the flow pattern of a fluid
- High Reynolds values (Re $>10^3$) tend to indicate chaotic flow
- Fluids with lower values flow more smoothly



- Each network in the array is an MLP network
- Given data is split for lower flow rates with lower Reynolds number, and higher with higher Reynolds values

Conclusions

- Partial success predicting Calibration factors
 - Using 5 points to predict 9
 - 5 points achieve error bounds
 - Better grasp of higher range behavior
- Network separation enables individual hyperparameter optimization
- Good running time
- Deeper literature survey is needed

