Neural Networks in Petrol Station Objects Calibration

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Abstract. The fuel tank autocalibration problem is an important issue in managing the amount of fuel stored in the tank. Current values are calculated basing on fuel sold (going out through nozzles - dispensing) and fuel pumped into the tank by a tanker (delivered). The difference in these values may point to different reasons - leakage, theft, or other errors. To pinpoint the cause it is important to rule out the case of wrong tank calibration, hence the tank autocalibration method is required. In this paper we present autocalibration method based on a neural networks algorithm, along with method's drawbacks and an alternative calibration method proposition.

Keywords: Autocalibration; Petrol Tanks Calibration; Neural Networks; Leak Detection; Inventory Reconciliation

1 Introduction

To evaluate the petrol inventory in petrol stations, daily inventory records are used. These records are needed to assess the current petrol level in tank and quantity of sold and bought petrol. This whole process is called the reconciliation process, and it is a basic method of detecting any abnormalities in petrol station operation, which can imply theft, leaks or technical problems with tank or petrol pumps.

Problem of data reconciliation is well researched and defined [13–15]. The reconciliation process can be performed in different cycles – the granularity (month, week, day or hour) is chosen basing on the needs of the specific case. The reconciliation process returns Var – defined as a variance or an error (equation 1).

$$Var = V_s - V_p - V_d \tag{1}$$

where:

- V_s – volume of fuel sold
- V_p – volume of fuel pumped out of the tank during sale
- V_d – volume of delivered fuel, the amount of fuel added to the tank's volume

The variance is interpreted as follows:

$$\begin{cases} Var < 0 \text{ leak or theft} \\ Var = 0 \text{ perfect} \\ Var > 0 \text{ fluid surplus} \end{cases} \tag{2}$$

The variance represents a single error during specific time period; however, to perform a long term analysis the Cumulative Variance (CV) is used. The CV is a sum of variances during considered time period. The CV at a time i can be denoted as (equation 3):

$$CV_i = CV_{i-1} + Var_i \tag{3}$$

In ideal situation variance equals zero, which means that the balance between dispensed, delivered and stored fuel is correct so there are no losses or gains. As mentioned before, the reconciliation process gives an insight in any abnormal changes in fuel quantity. Differences in theoretical inventory and real inventory can be a warning on serious problems like fuel leaks or spills, which are environmentally dangerous [4, 12]. Moreover, the problem may be caused by petrol theft, or that the petrol station infrastructure such as tanks, petrol pumps, and nozzles need maintenance.

Proper tank calibration gives also the exact data about the free space remaining in the tank and this allows for optimization of delivery process, refilling the tank in fully, not only partially. Because the storage, distribution, and management of fuel inventories are key issues in various industries, the proper tank calibration is a major problem in managing fuel tanks [5, 8, 16]. To exclude the petrol tank errors, the measurements of its condition should be precise and reliable. The tank calibration process may deliver this level of information assurance.

The proper tank calibration is a crucial problem in managing fuel tanks [3, 5, 8, 16]. The difference in bought/sold amount of fuel can mean serious problems like theft (especially by petrol truck drivers during delivery) or leaks. The latter are very important considering ecological issues. Also proper tank calibration gives the information on the exact amount of fuel that can be poured into the tank during delivery. Such prognosis could optimize delivery rates so that the fuel level in the tank after delivery is maximum, instead of it being filled only partial. Taking these facts into consideration it is crucial to assure tank proper calibration and the quality and precision of measurements to make them trustworthy.

The storage, distribution, and management of fuel inventories is a crucial matter in various industry branches. Therefore this paper presents the autocalibration system, that automatically calibrates tanks, to assure that measured petrol tank levels are accurate. Works carried out in this area are the subject of a project founded by the Polish Council of the National Centre for Research and Development within the DEMONSTRATOR+ program [1].

2 Tank Calibration

The tank usually has a cylindrical shape with a circular section, which stores the fuel (liquid). The level of fluid in the tank is measured using the internal probe. The initial measurements contain only height of fuel, which is strictly connected to the particular tank. Having the reconciliation process performed on volumes of fuel, measured fluid height is calculated to actual fluid volume in the tank. The dependence between fluid height (H) and fluid volume (V) is not linear and depends on various factors (e.g. tank shape, probe setting, temperature, tank pitch). Because of potential changes in these factors, the dependence of H and V factors can be variable. Changes to the tank structure or position, partial malformations have a direct impact on the relation between height H and volume V for particular tank and as a result they may introduce changes to this relation only in some height ranges.

The problem is modelled using the neural network N [6, 7, 9, 11], which is trained using tank's calibration table (CT). The calibration table represents relation between measured fuel height H and corresponding volume V. Initially, the CT table is created when the tank is emptied and it is being filled with precisely measured quantities of fuel e.g. 300 or 500 litres of petrol. After pouring each portion of petrol to the tank, the probe height readouts are recorded with the corresponding total volume values giving real and current height - volume ($H - V$) tank characteristics. After the petrol tank is filled to the certain height during petrol delivery, the petrol levels are diminishing respectfully to the sales quantity.

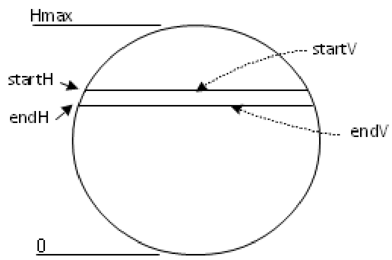

Fig. 1. Calculating quantity of sold petrol using the neural network

During normal working conditions the tank probe measures petrol level at the beginning of the sale $startH$ and at the end of the sale $endH$. At the same time the petrol pump registers quantity of sold petrol V_s. The neural network N

returns values $N(startH) = startV$ and $N(endH) = endV$, which are starting $startV$ and final volume of fluid in the tank ($endV$). The difference is $V_t = N(startH) - N(endH)$ (Fig. 1). The difference between V_t and V_s is denoted as E_t – model's error for a given reconciliation interval (transaction).

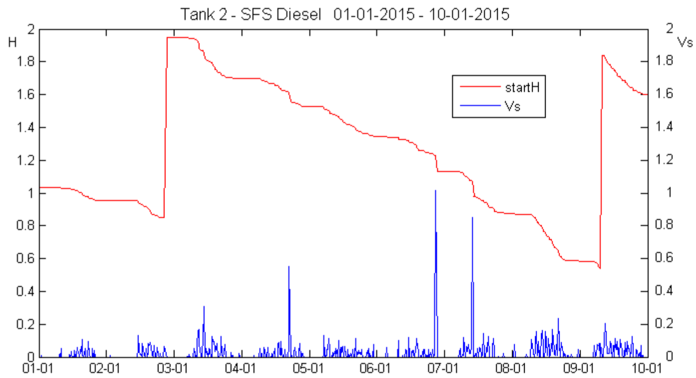

Fig. 2. Reconciliation intervals – a set of height changes in response to sold petrol volumes

Sequence of points in time, that correspond to fluid levels H after each performed dispensing transaction, creates a graphs representing process of emptying the tank. Together with V_s values, these data are used to assess the quality of the $H-V$ characteristic of the neural network. The process of refilling the petrol tank (delivery) initializes next sequence of H points representing record of next tank emptying processes (Fig. 2). Sequences of such records are used to train the network in order to minimize neural network related error.

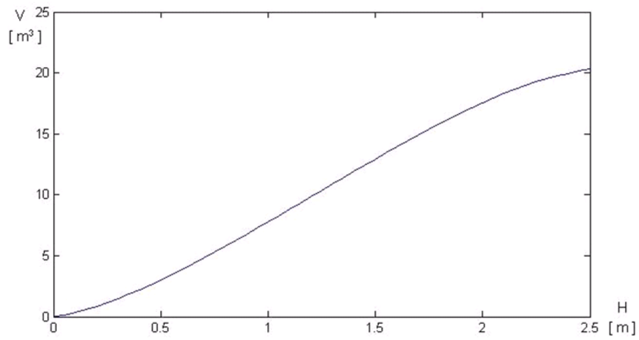

Fig. 3. Sample Calibration Curve

On fig. 3 the effect of neural networks processing is presented, i.e. the calibration curve.

The correct calibration curve is a crucial part of the whole reconciliation process. Errors in the calibration curve's shape can implicate errors in the reconciliation process. To minimize adverse effects of some random errors of neural networks utilization, proposed solution uses ensemble of 10 independent neural networks. Each of the separate networks is fed with the same training set, and the final result is an average value of all networks output in the ensemble.

3 Current method discussion

The current algorithm was implemented in the Matlab environment. The neural network input data are created basing on petrol tank data and contain:

- Output data from previous calibration (current neural network ensemble).
- Tables of a manual tank calibration, along with networks created on its basis that are not yet calibrated – used for comparison of current and future solutions.
- Set of height values $startH$ and $endH$.
- Set of volumes values $startV$ and $endV$, respectfully corresponding to heights $startH$ and $endH$. Basing on these values and the current network, the fluid level change in petrol tank is calculated – the sale V_s and delivery V_d. These values are compared with data from petrol pumps and nozzles and the errors E_t are calculated for each reconciliation interval.
- Set of temperatures in the tank $startTemperature$ and $endTemperature$ for values $startH$ and $endH$. These values are used for thermal tank compensation (rescaling results to selected reference temperature - the Temperature Model).

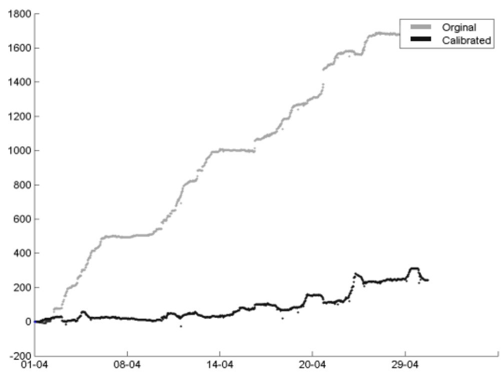

Fig. 4. Cumulative variance – an original (grey) and calibrated (black) [litres]

Using the current neural network, the data from a new data set are analysed and the MSEs (mean squared errors) are calculated. For a considered time interval, the data ranges of a length larger than minimal are marked, and the errors - differences between neural networks data and sales data in these ranges are checked to not exceed the threshold set by the user. The sets of data that meet these criteria are used as training sets.

Then, the neural network is fed with next training sets. The more sets are fed to the network the better the network results are (smaller errors) [2].

After the tank is calibrated basing on the best obtained network, the *CV* errors are recalculated. To assess the neural network, the *CV* graphs before and after calibration are compared (Fig. 4), and rating is calculated - the average weighted value of errors at certain tank height during tank working time period. Fig. 4 shows two cumulative variances. The upper curve (grey) is a result of the neural network calibration using the original calibration table. The lower curve (black) is a result of the calibration using new networks, fed with data from previous month. During this period, 300 cubic meters of fuel were sold and total percentage error (CV error/sold volume) were respectively 0.58% (grey) and 0.08% (black).

3.1 Problem of the Current Calibrating Solution

Currently proposed autocalibration method using neural networks ensemble improves the calibration of tanks in comparison to calibrating them using only the user given calibration curve. The process of the neural network learning is actually an algorithm which modifies the neural network to minimize errors for current data series. The *strengthening* of learning algorithm is minimal - to obtain more meaningful changes, many learning sets has to be processed. If the learning sets include only small part of tank height, the observed effect is local, outside of the considered fragment network errors can even increase - in conclusion obtained *CV* graph is worse for the whole tank The user delivered CTs consider only the "working" part of the tank - during manual calibration the tank is not fully filled - the actual tank height is larger than the one given in CTs. Similarly the nominal tank volume can differ from its actual volume. For some tanks the lack of official CTs was solved by tanks working data. In effect the starting neural networks created from CT table can differ from actual tank H-V characteristics, and encumbered with starting error. Although the use of autocalibration methods has improved the network efficiency (in comparison with the use of CTs), the improvement is often only by a fraction of percent while sometimes the results might be even worse. There are still some emerging issues that can be a source of potential problems:

- The above shown method of networks efficiency assessment is not entirely fault-less. For some tanks, the networks taught with previously obtained data give smaller error values (CV graph); however, they are rejected because of larger rating values.
- For some cases the efficiency of network learning is neglectable - network in-creased its efficiency by a fraction of percent.

- Lack of access to source data – databases are placed inside users infrastructure (petrol station). The database should be duplicated, updated at least daily and available for access when calibration is necessary. Currently data for calibration are incomplete, and because of "holes" in data the distortions are hard to pinpoint
- Lack of temporary database with repository of e.g. analysis results, methods comparison, hardware assessment.
- Change management process has to be addressed - information of all changes in user's hardware, algorithms, software has to be noted and available in calibration process.
- Neglecting errors and filtering them out causes the "holes" in data. Modifications of data structures in Matlab environment are quite difficult and time consuming. Data should be verified logically before processing e.g. deliveries and sales should be periodically balanced - if only sales data are taken into consideration it can lead to errors omitting and their accumulation.

3.2 New calibration methods

During research on above presented autocalibration methods and analysis of emerging problems an alternate autocalibration method was proposed. It is based on creating the neural network on data from theoretical tank model ($H - V$ dependence).

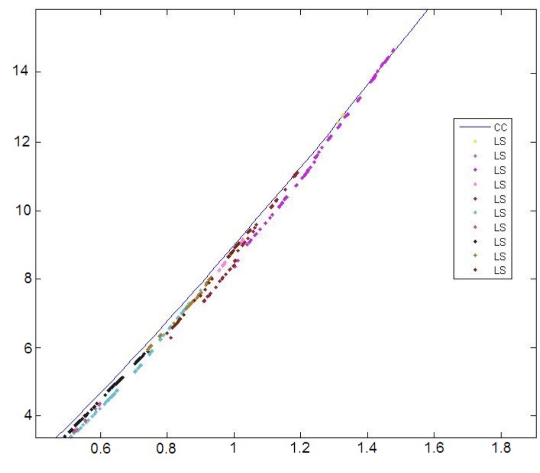

Fig. 5. Initial stage – comparison of learning sets LS and the tank $H-V$ characteristics (magnified)

Initially the $H - V$ curve (calibration curve) is compared with collection of learning sets LS points and model parameters (H and V) are selected to match the slope of the learning sets. After selecting the initial tank parameters (V,H) tank model is assessed by calculating the CV values. If the error grows the tank model parameters are changed ($Hmax$ or $Vmax$) until CV graph is flat and almost equals zero. In many cases after the initial setup of tank parameter further learning is not necessary (rating 0.6%-0.8%). The further training of the network requires data sets with low error threshold (below 100%) (Fig. 5).

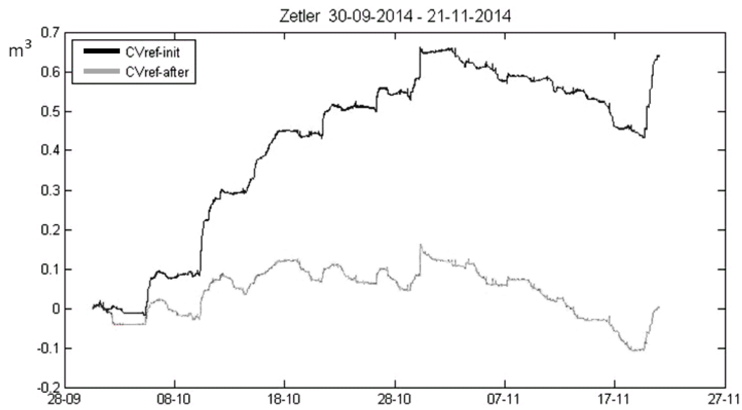

Fig. 6. CV curves obtained without neural network learning

After choosing the tank shape sometimes distortions appeared for extreme fluid levels (high and low). While there were small errors for middle values this can imply that the tanks shape is not a perfect cylinder e.g. more elliptic or flattened. This fact can be included by introducing more complex shapes of the theoretical tank. Below we present the effect of the new method that consists of two stages:

- choosing the theoretical model
- selecting the best obtainable model and neural network learning

Fig. 7 shows the result of algorithm operation on exemplary tank Zetler_725_2 with diesel stored. While magnified (fig. 5), the lean of the learning sets are observed to be different than the tank $H - V$ curve and the initial CV error increases by almost 0.7 m^3.

To straighten out (moving up) the tank $H - V$ line, the model volume has to be increased along with the ellipse eccentricity. Basing on the theoretical model a new network and new learning sets are created. Then the tank is calculated with new characteristics of learning sets until adequate CV error curve is obtained. In this case optimal model values are $V = 15.9$, $H = 1.9$, $m = 0.1$. Fig. 6 shows the CV curves without tank calibration (neural network learning). Fig. 7 shows the

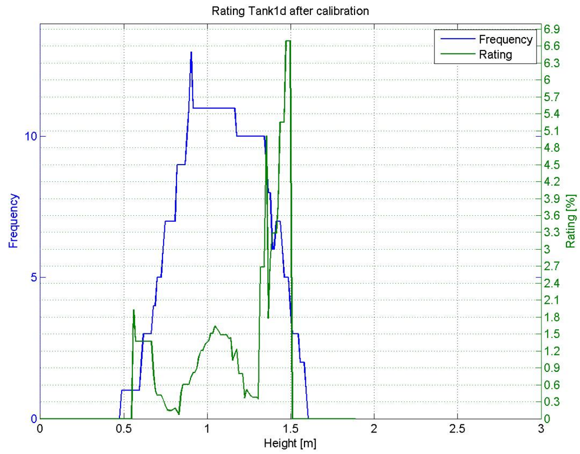

Fig. 7. Rating curves

rating graph. For heights 1.3m-1.6m a considerable error exists; however, overall rating (the mean value of the sum of the products of error for given height times the incidence of this height at the tank operation) equals 1.3717%, which can be further minimized with fixing the ellipse parameters.

4 Conclusions

In this paper the autocalibration of petrol tanks is presented. The adequately calibrated tank is needed to have a trustworthy data on actual petrol inventory, sales and deliveries. The proposed solution bases on the neural network ensemble, which considerably improves effect of the tank calibration comparing to the calibration based on the CT. While researching the original algorithm presented in section 3, the number of issues were raised (section 3.1).

Although the use of neural networks improves calibration correctness, there are some drawbacks that need to be addressed. While researching the original solution based on neural networks ensemble presented in section 3, the number of issues were raised (section 3.1). The alternative calibration solution was presented in 3.2. This calibration solution, is more intuitive than neural networks, and gives similar results in a faster and less complicated process. The simplification of calibration method improves further optimization and automatization of the whole process. Future work will focus on improving the neural network algorithm, and researching alternative methods of calibration.

One of the issue raised in section 3.1 concerned the data processing. In other works the authors research the architecture of a stream data warehouse that would significantly improve the processing of data and analysis performed in autocalibration system [5, 10].

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