Advanced IoT Applications
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Lecture - 34
Calibration techniques for IoT air quality sensors

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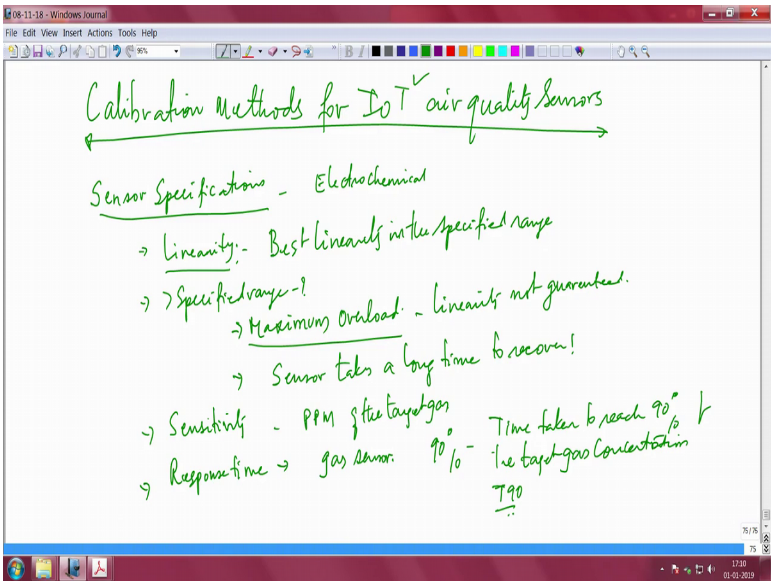

Alright. So, our goal is to look at calibration methods for IoT air quality sensors right you want to do this, but we may now be wondering why is it being done before we do any system building or any you know short very demonstration is being done, we are already looking at calibration methods. The reason why I am doing this prior to you know any system building exercise is only because this a very important topic number 1.

And, your electronics sensing system all that is all fine, but if you do not have a good calibration handle, it is of no use building anything with respect to air quality number that is a second reason. Third reason is this is purely algorithmic ok, it does not matter whether it is air equality or anything, whether you have data or not. Your, understand the algorithms which go behind calibration and as I said these are some of the latest topics in calibration. And, particularly applying statistical learning and machine learning techniques has taken the forefront.

And therefore, doing this is a module to get your field for the problem is really not out of the place. However, how good your data comes and how good the statistical learning and other machine learning techniques can be applied will largely depend on will be dependent on how good your data is right. Therefore, before we get into anything with respect to calibration method, let us understand what are these sensor sensors specifications? Ok.

Mainly specifications of sensors and I am just going to concentrate on electrochemical at the moment, you can make a bulleted list for the semiconductor sensors as well electrochemical. One of the first things that you have been looking at is linearity, because this is linearity, see this is a subject on instrumentation. Sensors and instrumentation there are some very common terms repeatability, linearity, resolution accur all accuracy all these terms are all part repeatability, all this things come part of any sensor specification. So, linearity is one such a specification first thing that occurs to you if you have a sensor you should say what is it is linearity is it a linear sensor right.

So, linearity is an important requirement. So, it is best shows linearity in a range. So, you do not define a sensors linearity over a full range never done that way. You define it over a range and you say between this PPM to that PPM or micrograms per meter cube depending on how you want to use different units, you define it over a range right. And, I flash to you ambient air quality range I also flash to you the exhaust vehicle exhaust you know range.

So, if they are linear in the range of measurement fantastic that is all you are interested in right. So, linearity is best linearity best linearity in the range, in the specified range, that is all you are looking for this is one specs. Second specification is if it is slightly beyond the range specified range. Now, if it is greater than specified range what will happen? Will the linearity, you know you know will be not guaranteed yes that is a point. We can also have a maximum so, this leads to another spec which is called maximum overload maximum overload.

And, so, maximum overload is linearity not guaranteed; linearity not guaranteed linearity is not so, it is inaccurate. And, and therefore, also another problem that will happen is if you work in this maximum overload situation sensor takes a long time to recover. This is important suppose he is doing a measurement and because it going beyond maximum over head or overload condition the sensor will have to recover from that condition.

So, the next view measurement results are going to be inaccurate, whatever is your learning technique be careful you should not over whelmed the sensor. You should not go beyond the maximum overload and go beyond the linearity region of the sensor.

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Ambient air quality:

Target Gas	Appx range
NO2	10-45ppb(max 200ppb)
NO	0-100ppb
O3	0-100ppb
NH3	0-200ppb
HC	<500ppb
PM2.5	65-70ug/m3
PM10	100-150ug/m3

Supposing it is meant for measuring, let us say typically let us take the ambient measurement. Let us take this chart ok. This is the range over which you want to make a this is not something I keep repeating a 100 times repeatedly, this is not the range that is acceptable for human breathing, this is from a sensor perspective, this is the range over which you want to make a measurement, sensor takes too long.

So, for example, if this is the measurement that you are doing and you suddenly realize that you have passed during testing phase a gas N O 2 gas, essentially over and above the 200 PPB range, which was guaranteed by the sensor, then it is going to get over whelmed. And, is going to take a long time for the sensor to come back and make a proper measurement.

Therefore, your calibration methods will work very good provided you take care of the basics of gathering good quality data proper data by adhering to these requirements.

So, maximum overload condition is an absolutely important requirement. Then the other one is sensitivity, the other one is sensitivity. It basically response to refers to the ppm parts per million of the target gas ok. Target gas this is pretty straight forward, you look at do not you have to look at what you want to measure what is the range over which you want to measure.

And, also ensure that your sensors are capable of measuring to that value, then there is something called response time ok, there is something called response time. Here it is response time of the gas sensor ok, number 1; it is the response time of the gas sensor. It should take say typically 90 percent of whatever you know the taken to reach 90 percent of the applied gas time. So, it is a time it is about response time right. So, time taken to reach 90 percent of the target gas concentration ok, gas concentration ok, concentration is typical of what is called T 90, that is T 90 means T 90 percent.

So, T 90 is what people talk about you pass 10 PPM 10 PPM of some gas the time it takes to reach 9 PPM ok. The not actually to reach the time it takes to read 9 PPM is what you are looking at 90 percent of the target gas concentration is very nice example, but response time is important T 90 response time.

So, you should ensure that whatever calibration methods that you are applying your input data quality is guaranteed and it is doing all this things.

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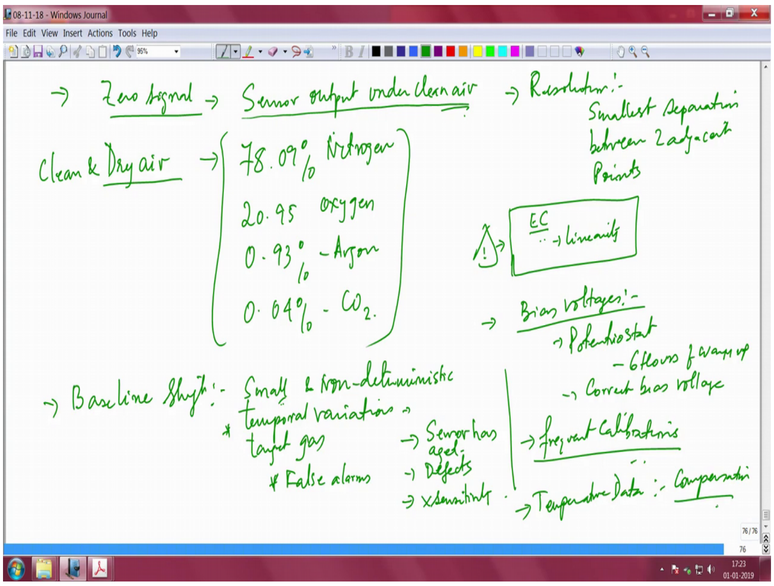

Then 0 signal 0 signal, even this becomes crucial when you are training your models using any of the analytical any of the statistical learning techniques ok. There should be no sensor output under clean air. Now, you will have to understand what is this clean air?

Is clean air at all your problem is you do not know what is clean air ok, where is your reference right. That is why they say clean air is also called I will say it clean and dry air. Typically people say clean and dry air, clean air or dry air, clean and dry air, I will call it clean and dry air, what is this air? This air is 78.09 percent of nitrogen right and 20.95 of 720 of oxygen, than 0.93 percent of argon. And, 0.04 percent of C O 2 ok, this is what it should be this is what you are expected to have clean and dry air, clean air this is clean air, this is what you should be breathing all the time right.

So, this essentially I hope this will add up to 100 percent and if any change occurs then you know essentially the other gases the partial pressure of other gases will increase creating uncomfortable feeling for humans. So, anything you do is it should not have any other pollutants under no pollutant condition, under clean air condition, you should get 0 output, then there is something called baseline shift. So, I have put one arrow here. I will put another arrow here they something called baseline shift ok.

So, this essentially is some sort of small drift and nondeterministic small and nondeterministic, nondeterministic temporal variations temporal variations right, when it is exposed to the target gas ok, when it is exposed to target gas. That means, it just does not you know indicate that a single value, but keeps drifting up and down a little bit under ideal conditions target gas, temporal variations even in the presence of the target gas ok.

It effects the ability to measure the gas accurately. So, if it is fluctuating too much you will have a problem. And so, you will have lot of false alarms, if it is well within the you know measurable range without too much of variations small extremely small, I would say extremely small it can be non-deterministic, but extremely small temporal variations of target in the presence of target gas no problem leave it. But, if it is too much you will have too many false alarms, then you have problems of then maybe the sensor is aged sensor has aged; that means, it has come to end of life ok, there are some manufacturing defects there are manufacturing defects and aging and so on.

Ah. Then perhaps it is having too much of cross sensitivity, because of it is age, it perhaps has developed a lot of cross sensitivity, interfering gases are too much, it has some problems in trying to work under ambient pressure ok. And, therefore, you may have to the only way out is frequent calibration.

So, your back to the same problem. Supposing you want to do if you want to do calibration methods, now your question will be you also have to account for what is the baseline drift that is coming into the system. So, that even that is accounted for and you know with ensure that you resolve this problem of baseline shift, then there is resolution ill put one more arrow here. Then, there is resolution well this definition is this quite simple straight forward whatever you knew well smallest separation essentially right, smallest separation between 2 adjacent points, between 2 adjacent points right.

And so, you should be able to say the gas sensor has a high resolution alright. And, so, better resolution not only from sensors perspective, but also from the instrument that is displaying the value. So, it should also be including that alright.

So, one good thing about electrochemical sensors, which I wanted to tell you is that EC sensors have good linearity. One of the major I would say positives of electrochemical, although they have limited shelf life and they have to be frequently replaced recalibrated and all that this perhaps is a very strong point they maintain linearity. However, the electrochemical sensors also suffers from the fact that they requires bias voltages, bias voltages will be required.

See this is one thing about gas sensors and measurements and so on. If, you look at electrochemical, if you look at the semiconductor sensors, they have typically initially you are to heat them for something that overnight and only then you have to start making a measurement. So, when you buy it of the pack it should not you cannot start using it directly I pass through the steps for you. And, you have to ensure that it is kept overnight and then only then it can actually start making a proper measurement.

Now, the issue is the there is a sensor the sensor part will have a heater and there will be a sensor output. So, heating is an input sensing is an output. Now, it turns out that you can not make a measurement if the heater is off the value is not going to not going to whatever you read is it going to be incorrect.

Therefore, if you do any energy power management strategy that you want to do so on and so forth. That is a bit hard because the heater should be on all the time if you want to do quick measurement of let us say N O 2 somewhere you are going, some road or somewhere you want to do exhaust ambient you want to do and you are in front of a traffic signal. You can not keep your the heater off you cannot surely with your semiconductor sensor the heater is to be on all the time. Maybe sensing can be kept off kept on you can read it.

People may actually may become as electronic engineers, we also know that you if you are not able to if you do not if you want to save power, you do not need to have a linear power supply which is connected to the heater. You can do switching right you can do pulsing you can pulse and therefore, save a lot of energy, because you will only be you know like a DC converter output will be just pulsing the power.

Now, here is the problem, that pulse power is also not acceptable to several of these air quality sensors. Therefore you are forced to keep a linear power supply, you are expected to keep a good DC, and keep the heater on all the time. So, again do not worry so, much about energy consumption power consumption and so on, because this is about betterment of life you must ensure that this has to be on all the time.

So, keep these things in mind when you do any system design. So, coming back to electrochemical it is a same issue here, you definitely need a bias voltage you basically need what is known as a potentiostat function correctly most often you will need to work like a potentiostat potentiostat ok, your essentially talking about potentiostat.

So, the biased requires a warm up time of about 6 hours also 6 hours of warm up, 6 hours of warm up and then you see ensure that it is stable enough, and then you start you apply the correct bias voltage, correct bias voltage has to be applied, you apply the correct bias voltage. And, then you stabilize the sensor right and after that you essentially start using it.

So, you read the data sheets of whichever sensors that you have shortlisted carefully to know what is the heat up time or the warm up time that is required both in the case of electrochemical as well as in the case of semiconductor sensors. Finally, there is another term, which you have to note, which is the temperature data, temperature data of any sensor.

And so, temperature dependence on gas output is an important parameter you may have to do temperature compensation of temperature is an important thing. And so, you will have to keep a note on that is I would say. So, before you go into any calibration methods understanding algorithms, think about the kind of sensors you are you have with you and the kind of you know specifications that you have lead.

So, that you collect good quality data and then move on from there in terms of trying to do calibration right. So, this is what I wanted to tell you before when even we go into any calibration method. Let us now get into some of the statistical learning techniques for calibration of these IoT sensors.

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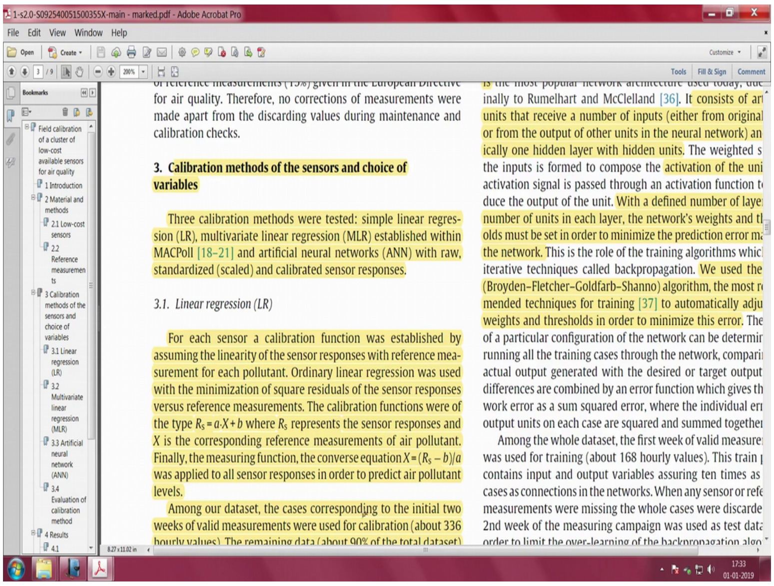
for air quality. Therefore, no corrections of measurements were made apart from the discarding values during maintenance and calibration checks.

3. Calibration methods of the sensors and choice of variables

Three calibration methods were tested: simple linear regression (LR), multivariate linear regression (MLR) established within MACPoll [18–21] and artificial neural networks (ANN) with raw, standardized (scaled) and calibrated sensor responses.

3.1. Linear regression (LR)

For each sensor a calibration function was established by assuming the linearity of the sensor responses with reference measurement for each pollutant. Ordinary linear regression was used with the minimization of square residuals of the sensor responses versus reference measurements. The calibration functions were of the type $R_S = a \cdot X + b$ where R_S represents the sensor responses and X is the corresponding reference measurements of air pollutant. Finally, the measuring function, the converse equation $X = (R_S - b)/a$ was applied to all sensor responses in order to predict air pollutant levels.

Among our dataset, the cases corresponding to the initial two weeks of valid measurements were used for calibration (about 336

inally to Rumelhart and McClelland [36]. It consists of ar
units that receive a number of inputs (either from original
or from the output of other units in the neural network) an
ically one hidden layer with hidden units. The weighted s
the inputs is formed to compose the activation of the uni
activation signal is passed through an activation function t
duce the output of the unit. With a defined number of laye
number of units in each layer, the network's weights and t
olds must be set in order to minimize the prediction error m
the network. This is the role of the training algorithms whic
iterative techniques called backpropagation. We used the
(Broyden–Fletcher–Goldfarb–Shanno) algorithm, the most r
mended techniques for training [37] to automatically adju
weights and thresholds in order to minimize this error. The
of a particular configuration of the network can be determi
running all the training cases through the network, compari
actual output generated with the desired or target output
differences are combined by an error function which gives th
work error as a sum squared error, where the individual er
output units on each case are squared and summed togethe
Among the whole dataset, the first week of valid measure
was used for training (about 168 hourly values). This train
contains input and output variables assuring ten times as
cases as connections in the networks. When any sensor or ref
measurements were missing the whole cases were discarde
2nd week of the measuring campaign was used as test dat

The simplest you can think of is the linear regression and you can see that in this book let me expand it so, that in this paper you will see that the linear regression is explained. Each sensor for each sensor calibration function was established by assuming the linearity of the sensor responses with the reference measurement for each pollutant.

Ordinary linear regression was used with the minimization of squares, square residuals of the sensor responses versus reference measurements. Ah. The calibration functions were of the type Rr s is equal to a dot x plus b where R s represents the sensor responses and x is the corresponding reference measurements of air pollutant. Finally, the measuring function the converse equation X is equal to R s minus b by a was applied to all sensor responses in order to predict air pollutant level. So, how do you get to this?

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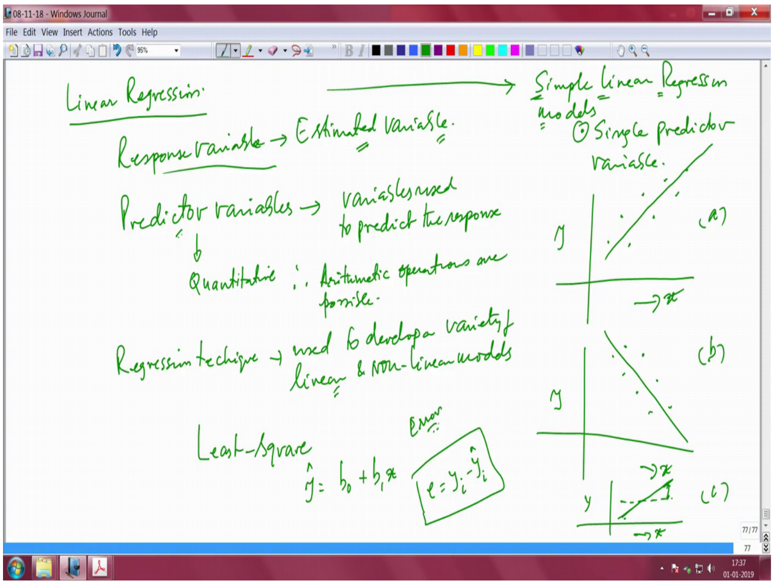

If you look up any text book on linear regression you will see some simple definitions I just wanted to quickly capture this. You basically have what is known as the response variable which is nothing, but the estimated variable of interest? In order to get to this estimated variable, you need what are known as predictor variables and this predictor variables are essentially quantitative by nature.

So, you could do you could perform several arithmetic operations on them multiply add divide and so on. These are essentially variables used to predict the response. So, the response variable comes from the predictor variable. And therefore, you use this regression techniques to develop these linear and non-linear models ok.

Now, if you take a single predictor, if you use a single predictor, you essentially call it simple linear regression model ok. And, that is a pretty straight forward I would say definition and if supposing you want to show, it is very intuitive x is there you have y, and supposing this is your these are your set of points ok. Essentially sensor measurements that you have done and you have a line like this or nothing to you have points like this is again x and this is y and you have a fit like this.

Either going down as x increases y is going down or the opposite as x increases y is also increasing both are extremely good regression models. But, if you have a crazy system which essentially is like this now, supposing I have x here and y you have points like this and you have fit like this ok. Then, you have errors right a lot of error is there in this points. So, essentially your measured value and your estimated values are all in correct. So, therefore, you would essentially say that there is a lot of error.

Now, even here if the how do you know sort of quantify this error, this is the problem. How do you know your model is good because it is nice to see visually that there is a line fitting and then the points are all closed by and perhaps everything is hunky dory in case a and case b, but in case c as you know the error is high, how do you do it mathematically? So, you need a metric which talks about these errors. In other words if you have a positive error the estimated response is less than the observed response and while the others are negative.

So, all those situations are taken care and ultimately you need a criteria, that criteria typically is the least square; least square criteria ok. In the least square criteria you basically have a mathematical definition for least square which says y hat is equal to b naught plus b 1 times x ok. Now, what is your error, error is essentially y i minus y hat of this I, this is your error this is your error e is error e is error very basic stuff I am just trying to give you in one go everything so, that you will be able to sort of piece things together.

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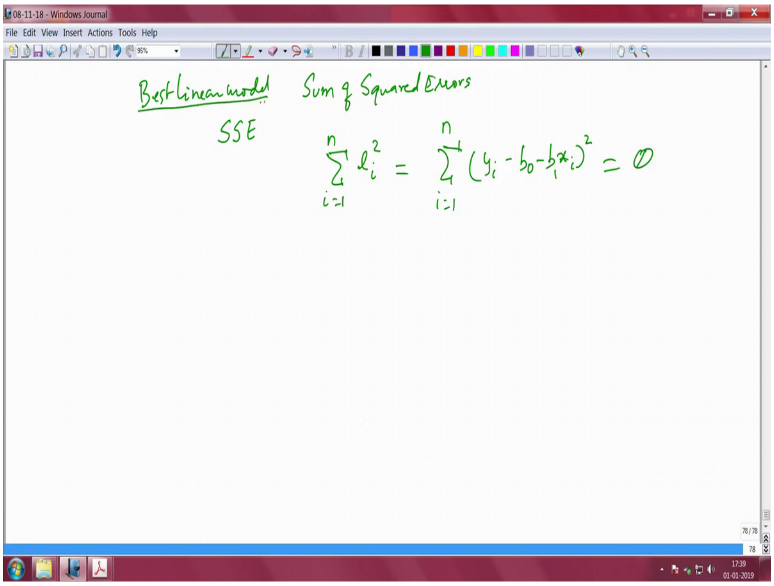

Now, when you talk about the best linear model best linear model, you look at sum of squares error ok, sum of squared errors sorry sum of squared, sum of squared errors ok. When you say sum of squared errors you have to put a sigma of what of e i and you have to do is square. And, what is I going from one to this n complete set of samples, the this is what you talk about SSE right is equal to sigma i going from 1 to n, you have y i minus b not plus minus b 1 i not b 1 b i sorry b 1 sorry b 1 x i it should be b 1 x i whole square ok. And you have the sigma here. So, it will take for all the samples ok.

This one should be equal to 0; that means, it is the best linear model. And, essentially this paper is talking about that only, this paper is saying essentially the same thing I want you to fit that understanding I showed you with this. So, that you exactly know what is it that you are trying to you know predict the how you are able to predict the air pollutant levels alright.

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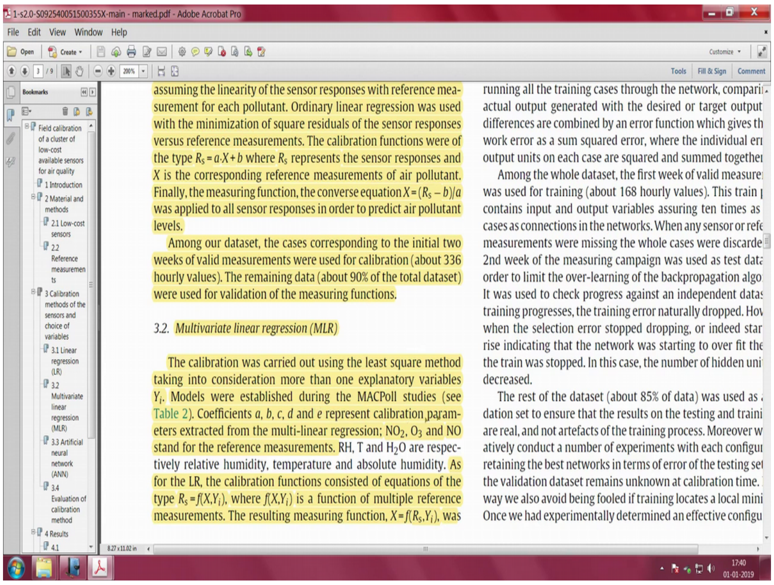

So, you have multivariate linear regression that is another way of calibration was carried out using linear square method. And, you have like LR the calibration function consisted of equations of types R s is equal to function of X comma Y i and is a function of multiple reference measurement.

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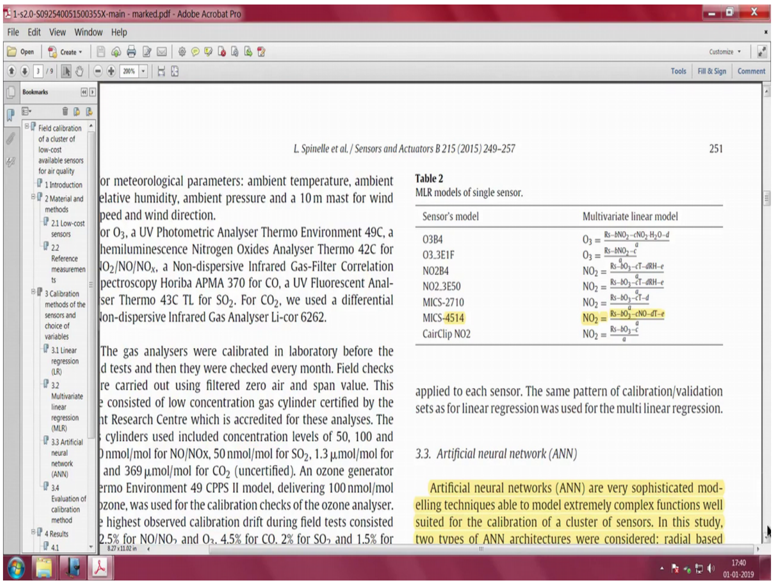
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or meteorological parameters: ambient temperature, ambient elative humidity, ambient pressure and a 10 m mast for wind peed and wind direction.

or O_3, a UV Photometric Analyser Thermo Environment 49C, a hemiluminescence Nitrogen Oxides Analyser Thermo 42C for O_2/NO/NO_x, a Non-dispersive Infrared Gas-Filter Correlation pectroscopy Horiba APMA 370 for CO, a UV Fluorescent Analser Thermo 43C TL for SO_2. For CO_2, we used a differential Non-dispersive Infrared Gas Analyser Li-cor 6262.

The gas analysers were calibrated in laboratory before the d tests and then they were checked every month. Field checks re carried out using filtered zero air and span value. This consisted of low concentration gas cylinder certified by the nt Research Centre which is accredited for these analyses. The cylinders used included concentration levels of 50, 100 and 0 nmol/mol for NO/NOx, 50 nmol/mol for SO_2, 1.3 µmol/mol for and 369 µmol/mol for CO_2 (uncertified). An ozone generator rmo Environment 49 CPPS II model, delivering 100 nmol/mol ozone, was used for the calibration checks of the ozone analyser. highest observed calibration drift during field tests consisted 2.5% for NO/NO_2 and O_3, 4.5% for CO, 2% for SO_2 and 1.5% for

Table 2
MLR models of single sensor.

Sensor's model	Multivariate linear model
O3B4	$O_3 = \frac{Rs - bNO_2 - cNO_2 \cdot H_2O - d}{a}$
O3_3E1F	$O_3 = \frac{Rs - bNO_2 - c}{a}$
NO2B4	$NO_2 = \frac{Rs - bO_3 - cT - dRH - e}{a}$
NO2_3E50	$NO_2 = \frac{Rs - bO_3 - cT - dRH - e}{a}$
MICS-2710	$NO_2 = \frac{Rs - bO_3 - cT - d}{a}$
MICS-4514	$NO_2 = \frac{Rs - bO_3 - cNO - dT - e}{a}$
CairClip NO2	$NO_2 = \frac{Rs - bO_3 - c}{a}$

applied to each sensor. The same pattern of calibration/validation sets as for linear regression was used for the multi linear regression.

3.3. *Artificial neural network (ANN)*

Artificial neural networks (ANN) are very sophisticated modelling techniques able to model extremely complex functions well suited for the calibration of a cluster of sensors. In this study, two types of ANN architectures were considered: radial based

And, then you have some numbers coming up. So, let me quickly want to this part and it is applied to each sensor. And so, that is another way of another technique for calibration. Then, you have the third technique which is the artificial neural network techniques; these are quiet sophisticated modeling techniques. And, you can see that the able to model extremely complex functions.

And, you essentially talk about radial basis function and functions and multilayer perceptron's essentially MLPS they are called, the radial based functions are not so, good it seems from this paper study. And, it appears that MLP multilayer perceptron seem to work very well, and the most popular architecture used today due to original people who invented this architectural system seems to give good performance results. So, they essential you are talk about a number of inputs either from original data or from output of other units in the neural network. And, you will have typically one hidden layer with several hidden units.

And, then the weighted sum of input is formed to compose the activation of the unit, and with the number of defined layers, and the number of units in each layer the network waits and thresholds must be said in order to minimize the prediction error made by the network. So, you use for training algorithm such as the back propagation, which is typically an algorithm called BFGS you can see here Broyden-Fletcher-Goldfarb-Shanno algorithm the most recommended techniques are all mentioned in another reference paper and to automatically adjust the weights and thresholds in order to minimize this errors.

So, essentially you are trying to again get back the closest value measured value, the measured value should be closest to what is the actual PPM value measured off by the sensor in it is linear region. So, all the objectives is essentially that, that you should be able to apply either statistical or this machine learning techniques in order to arrive at it.

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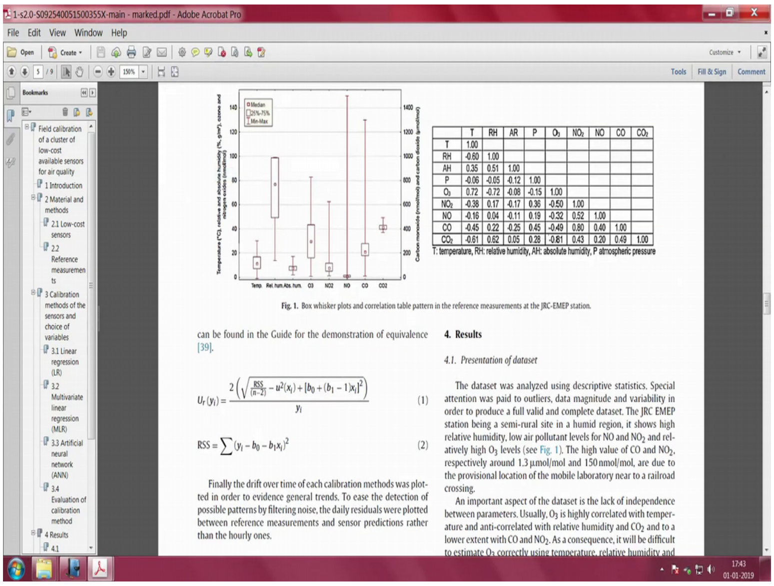

	T	RH	AR	P	O_3	NO_2	NO	CO	CO_2
T	1.00								
RH	-0.60	1.00							
AH	0.35	0.51	1.00						
P	-0.06	-0.05	-0.12	1.00					
O_3	0.72	-0.72	-0.08	-0.15	1.00				
NO_2	-0.38	0.17	-0.17	0.36	-0.50	1.00			
NO	-0.16	0.04	-0.11	0.19	-0.32	0.52	1.00		
CO	-0.45	0.22	-0.25	0.45	-0.49	0.80	0.40	1.00	
CO_2	-0.61	0.62	0.05	0.28	-0.81	0.43	0.20	0.49	1.00

T: temperature, RH: relative humidity, AH: absolute humidity, P atmospheric pressure

Fig. 1. Box whisker plots and correlation table pattern in the reference measurements at the JRC-EMEP station.

can be found in the Guide for the demonstration of equivalence [39].

$$U_r(y_i) = \frac{2\left(\sqrt{\frac{RSS}{(n-2)} - u^2(x_i) + [b_0 + (b_1 - 1)x_i]^2}\right)}{y_i} \quad (1)$$

$$RSS = \sum (y_i - b_0 - b_1 x_i)^2 \quad (2)$$

Finally the drift over time of each calibration methods was plotted in order to evidence general trends. To ease the detection of possible patterns by filtering noise, the daily residuals were plotted between reference measurements and sensor predictions rather than the hourly ones.

4. Results

4.1. Presentation of dataset

The dataset was analyzed using descriptive statistics. Special attention was paid to outliers, data magnitude and variability in order to produce a full valid and complete dataset. The JRC EMEP station being a semi-rural site in a humid region, it shows high relative humidity, low air pollutant levels for NO and NO_2 and relatively high O_3 levels (see Fig. 1). The high value of CO and NO_2, respectively around 1.3 µmol/mol and 150 nmol/mol, are due to the provisional location of the mobile laboratory near to a railroad crossing.

An important aspect of the dataset is the lack of independence between parameters. Usually, O_3 is highly correlated with temperature and anti-correlated with relative humidity and CO_2 and to a lower extent with CO and NO_2. As a consequence, it will be difficult to estimate O_3 correctly using temperature, relative humidity and

So, this paper if you read this paper you will get some idea on how one can apply these little techniques.

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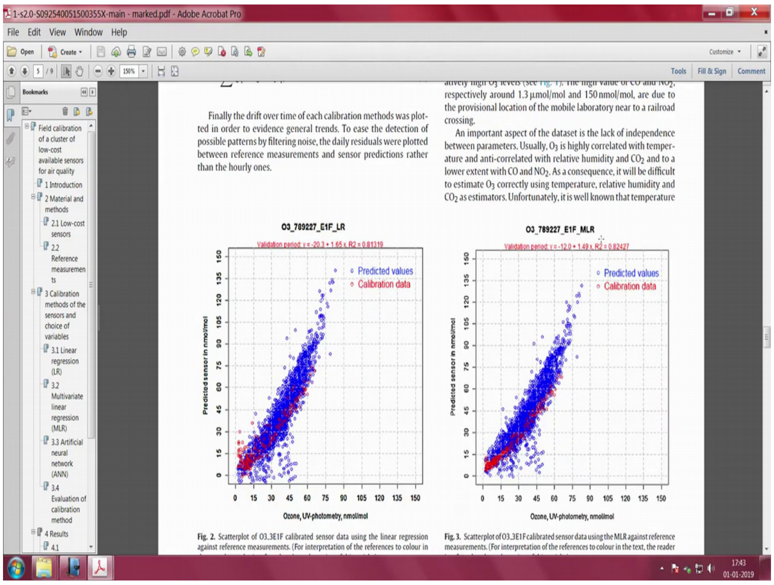
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Fig. 2. Scatterplot of O3.3E1F calibrated sensor data using the linear regression against reference measurements. (For interpretation of the references to colour in

Fig. 3. Scatterplot of O3.3E1F calibrated sensor data using the MLR against reference measurements. (For interpretation of the references to colour in the text, the reader

And, there is not much scope for us to spend more time than this, but you can see that there are you know predicted sensor values which are shown here in this results and they are trying to estimate as close as possible.

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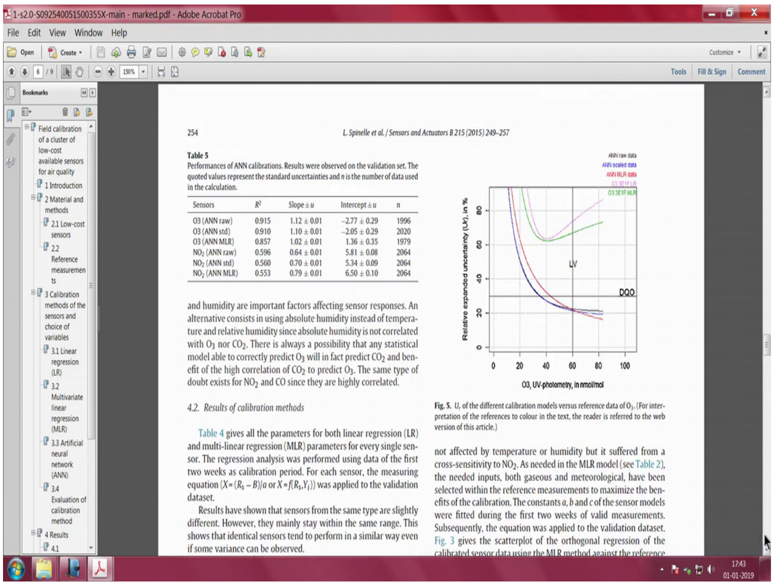
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Table 5
Performances of ANN calibrations. Results were observed on the validation set. The quoted values represent the standard uncertainties and *n* is the number of data used in the calculation.

Sensors	R^2	Slope ± *u*	Intercept ± *u*	*n*
O3 (ANN raw)	0.915	1.12 ± 0.01	−2.77 ± 0.29	1996
O3 (ANN std)	0.910	1.10 ± 0.01	−2.05 ± 0.29	2020
O3 (ANN MLR)	0.857	1.02 ± 0.01	1.36 ± 0.35	1979
NO_2 (ANN raw)	0.596	0.64 ± 0.01	5.81 ± 0.08	2064
NO_2 (ANN std)	0.560	0.70 ± 0.01	5.34 ± 0.09	2064
NO_2 (ANN MLR)	0.553	0.79 ± 0.01	6.50 ± 0.10	2064

and humidity are important factors affecting sensor responses. An alternative consists in using absolute humidity instead of temperature and relative humidity since absolute humidity is not correlated with O_3 nor CO_2. There is always a possibility that any statistical model able to correctly predict O_3 will in fact predict CO_2 and benefit of the high correlation of CO_2 to predict O_3. The same type of doubt exists for NO_2 and CO since they are highly correlated.

4.2. Results of calibration methods

Table 4 gives all the parameters for both linear regression (LR) and multi-linear regression (MLR) parameters for every single sensor. The regression analysis was performed using data of the first two weeks as calibration period. For each sensor, the measuring equation ($X = (R_S - B)/a$ or $X = f(R_S, Y_i)$) was applied to the validation dataset.

Results have shown that sensors from the same type are slightly different. However, they mainly stay within the same range. This shows that identical sensors tend to perform in a similar way even if some variance can be observed.

Fig. 5. U_r of the different calibration models versus reference data of O_3. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

not affected by temperature or humidity but it suffered from a cross-sensitivity to NO_2. As needed in the MLR model (see Table 2), the needed inputs, both gaseous and meteorological, have been selected within the reference measurements to maximize the benefits of the calibration. The constants *a*, *b* and *c* of the sensor models were fitted during the first two weeks of valid measurements. Subsequently, the equation was applied to the validation dataset. Fig. 3 gives the scatterplot of the orthogonal regression of the

And, they are trying to calibrate the sensor right. Because, if you read a voltage you should know from that voltage what exactly is the PPM; PPP levels and only then you know for sure that you are calibration is good.

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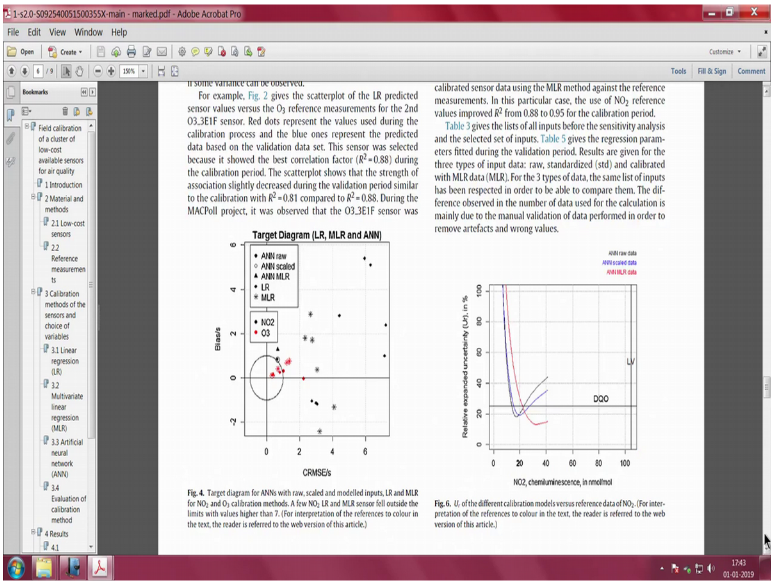

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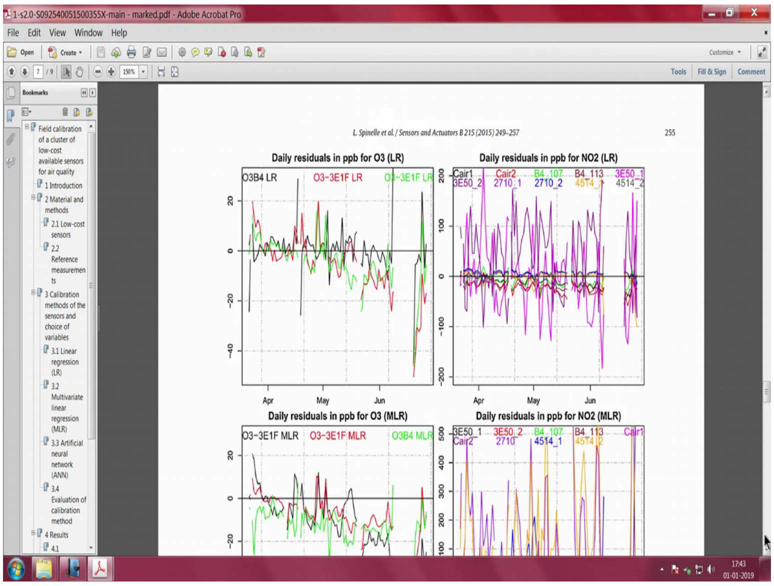

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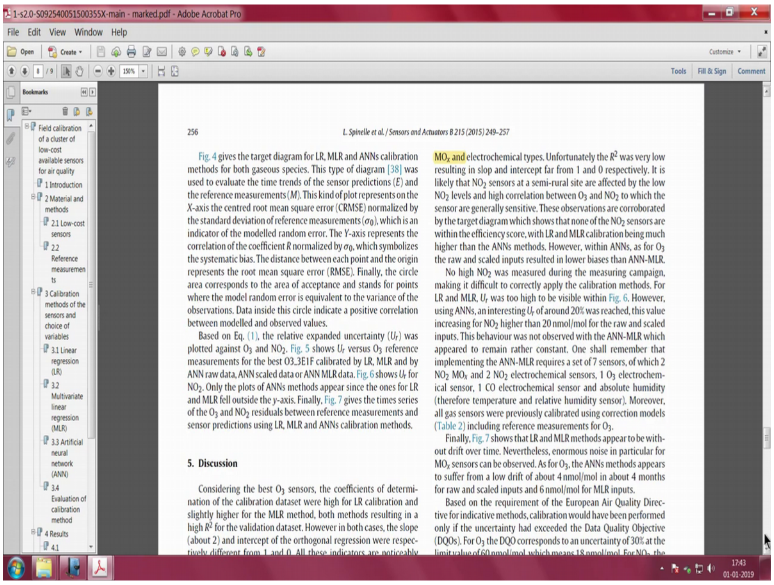
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Fig. 4 gives the target diagram for LR, MLR and ANNs calibration methods for both gaseous species. This type of diagram [38] was used to evaluate the time trends of the sensor predictions (E) and the reference measurements (M). This kind of plot represents on the X-axis the centred root mean square error (CRMSE) normalized by the standard deviation of reference measurements (σ_0), which is an indicator of the modelled random error. The Y-axis represents the correlation of the coefficient R normalized by σ_0, which symbolizes the systematic bias. The distance between each point and the origin represents the root mean square error (RMSE). Finally, the circle area corresponds to the area of acceptance and stands for points where the model random error is equivalent to the variance of the observations. Data inside this circle indicate a positive correlation between modelled and observed values.

Based on Eq. (1), the relative expanded uncertainty (U_r) was plotted against O_3 and NO_2. Fig. 5 shows U_r versus O_3 reference measurements for the best O3_3E1F calibrated by LR, MLR and by ANN raw data, ANN scaled data or ANN MLR data. Fig. 6 shows U_r for NO_2. Only the plots of ANNs methods appear since the ones for LR and MLR fell outside the y-axis. Finally, Fig. 7 gives the times series of the O_3 and NO_2 residuals between reference measurements and sensor predictions using LR, MLR and ANNs calibration methods.

5. Discussion

Considering the best O_3 sensors, the coefficients of determination of the calibration dataset were high for LR calibration and slightly higher for the MLR method, both methods resulting in a high R^2 for the validation dataset. However in both cases, the slope (about 2) and intercept of the orthogonal regression were respec-

MO_x and electrochemical types. Unfortunately the R^2 was very low resulting in slop and intercept far from 1 and 0 respectively. It is likely that NO_2 sensors at a semi-rural site are affected by the low NO_2 levels and high correlation between O_3 and NO_2 to which the sensor are generally sensitive. These observations are corroborated by the target diagram which shows that none of the NO_2 sensors are within the efficiency score, with LR and MLR calibration being much higher than the ANNs methods. However, within ANNs, as for O_3 the raw and scaled inputs resulted in lower biases than ANN-MLR.

No high NO_2 was measured during the measuring campaign, making it difficult to correctly apply the calibration methods. For LR and MLR, U_r was too high to be visible within Fig. 6. However, using ANNs, an interesting U_r of around 20% was reached, this value increasing for NO_2 higher than 20 nmol/mol for the raw and scaled inputs. This behaviour was not observed with the ANN-MLR which appeared to remain rather constant. One shall remember that implementing the ANN-MLR requires a set of 7 sensors, of which 2 NO_2 MO_x and 2 NO_2 electrochemical sensors, 1 O_3 electrochemical sensor, 1 CO electrochemical sensor and absolute humidity (therefore temperature and relative humidity sensor). Moreover, all gas sensors were previously calibrated using correction models (Table 2) including reference measurements for O_3.

Finally, Fig. 7 shows that LR and MLR methods appear to be without drift over time. Nevertheless, enormous noise in particular for MO_x sensors can be observed. As for O_3, the ANNs methods appears to suffer from a low drift of about 4 nmol/mol in about 4 months for raw and scaled inputs and 6 nmol/mol for MLR inputs.

Based on the requirement of the European Air Quality Directive for indicative methods, calibration would have been performed only if the uncertainty had exceeded the Data Quality Objective (DQOs). For O_3 the DQO corresponds to an uncertainty of 30% at the

So, I urge you to read this paper in detail and also to highlight to you that it is a very important technique for you to make a measurement.

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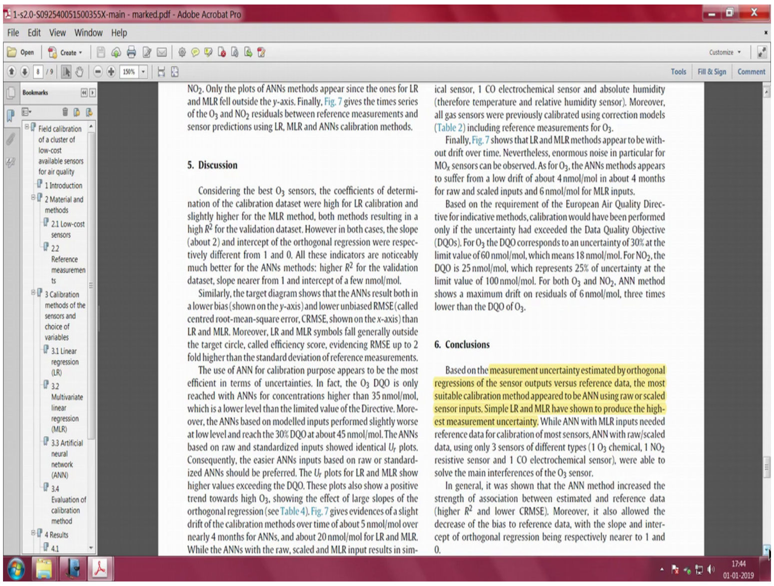
NO_2. Only the plots of ANNs methods appear since the ones for LR and MLR fell outside the y-axis. Finally, Fig. 7 gives the times series of the O_3 and NO_2 residuals between reference measurements and sensor predictions using LR, MLR and ANNs calibration methods.

5. Discussion

Considering the best O_3 sensors, the coefficients of determination of the calibration dataset were high for LR calibration and slightly higher for the MLR method, both methods resulting in a high R^2 for the validation dataset. However in both cases, the slope (about 2) and intercept of the orthogonal regression were respectively different from 1 and 0. All these indicators are noticeably much better for the ANNs methods: higher R^2 for the validation dataset, slope nearer from 1 and intercept of a few nmol/mol.

Similarly, the target diagram shows that the ANNs result both in a lower bias (shown on the y-axis) and lower unbiased RMSE (called centred root-mean-square error, CRMSE, shown on the x-axis) than LR and MLR. Moreover, LR and MLR symbols fall generally outside the target circle, called efficiency score, evidencing RMSE up to 2 fold higher than the standard deviation of reference measurements.

The use of ANN for calibration purpose appears to be the most efficient in terms of uncertainties. In fact, the O_3 DQO is only reached with ANNs for concentrations higher than 35 nmol/mol, which is a lower level than the limited value of the Directive. Moreover, the ANNs based on modelled inputs performed slightly worse at low level and reach the 30% DQO at about 45 nmol/mol. The ANNs based on raw and standardized inputs showed identical U_r plots. Consequently, the easier ANNs inputs based on raw or standardized ANNs should be preferred. The U_r plots for LR and MLR show higher values exceeding the DQO. These plots also show a positive trend towards high O_3, showing the effect of large slopes of the orthogonal regression (see Table 4). Fig. 7 gives evidences of a slight drift of the calibration methods over time of about 5 nmol/mol over nearly 4 months for ANNs, and about 20 nmol/mol for LR and MLR. While the ANNs with the raw, scaled and MLR input results in sim-

ical sensor, 1 CO electrochemical sensor and absolute humidity (therefore temperature and relative humidity sensor). Moreover, all gas sensors were previously calibrated using correction models (Table 2) including reference measurements for O_3.

Finally, Fig. 7 shows that LR and MLR methods appear to be without drift over time. Nevertheless, enormous noise in particular for MO_x sensors can be observed. As for O_3, the ANNs methods appears to suffer from a low drift of about 4 nmol/mol in about 4 months for raw and scaled inputs and 6 nmol/mol for MLR inputs.

Based on the requirement of the European Air Quality Directive for indicative methods, calibration would have been performed only if the uncertainty had exceeded the Data Quality Objective (DQOs). For O_3 the DQO corresponds to an uncertainty of 30% at the limit value of 60 nmol/mol, which means 18 nmol/mol. For NO_2, the DQO is 25 nmol/mol, which represents 25% of uncertainty at the limit value of 100 nmol/mol. For both O_3 and NO_2, ANN method shows a maximum drift on residuals of 6 nmol/mol, three times lower than the DQO of O_3.

6. Conclusions

Based on the measurement uncertainty estimated by orthogonal regressions of the sensor outputs versus reference data, the most suitable calibration method appeared to be ANN using raw or scaled sensor inputs. Simple LR and MLR have shown to produce the highest measurement uncertainty. While ANN with MLR inputs needed reference data for calibration of most sensors, ANN with raw/scaled data, using only 3 sensors of different types (1 O_3 chemical, 1 NO_2 resistive sensor and 1 CO electrochemical sensor), were able to solve the main interferences of the O_3 sensor.

In general, it was shown that the ANN method increased the strength of association between estimated and reference data (higher R^2 and lower CRMSE). Moreover, it also allowed the decrease of the bias to reference data, with the slope and intercept of orthogonal regression being respectively nearer to 1 and 0.

So, one thing that occurs is that measurement uncertainty estimated by orthogonal regulations of sensor output versus reference data ANN appears to you know be very good because L R and M L R have shown to produce high highest measurement uncertainty. So, therefore, moving in the direction of artificial neural networks to calibrate sensor perhaps is a good positive way to move on with air quality measurements.

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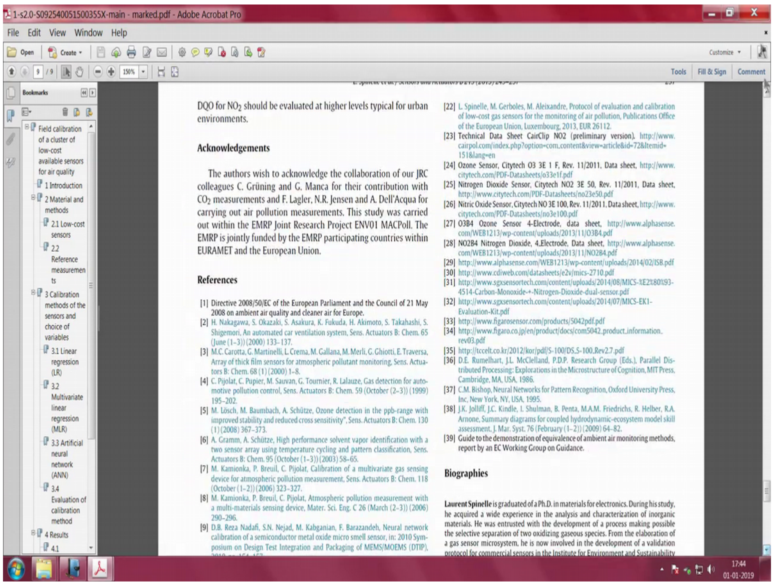

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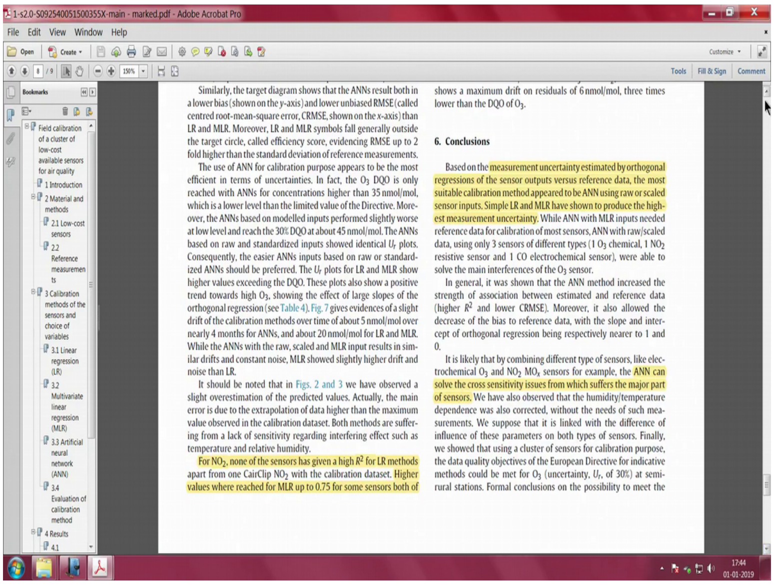

And, also this problem of cross sensitivity is an issue which is a problem for several sensors. And therefore, it is good for you too also check that the n and techniques can also solve this problem of cross sensitivity. So, I would say that it is a very important piece of paper that piece of work that you may want to ultimately understand.

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And, sort of use it in all your future endeavors for calibration of sensors.