BEUTH HOCHSCHULE
FÜR TECHNIK
BERLIN
University of Applied Sciences

Projekt-Labor: Automatisierungssysteme

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vorgelegt von

Emile Schons 903606

EDV.Nr.:123 456

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Gutachter
Gutachter1 Beuth Hochschule für Technik

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Abbildungsverzeichnis

Kapitel 1

Introduction

(4d) (mostly offline)
sudo apt install texlive-lang-german

1.1 Python Code within Latex

Python says “Hello we got it running finally!! YEahjjjjjjo ”

```
>>> x = 250
>>> x = x*2
>>> y = 5
```

The variable is $x = 500$ The Result of y*2 is $y = 5$

1.1.1 Integrated matplotlib inline with pythontex

1.2 why Kalman, why EKF????

Other methods are based on auto regressive exogenous (ARX) model or a combination of it and the Kalman Filter.

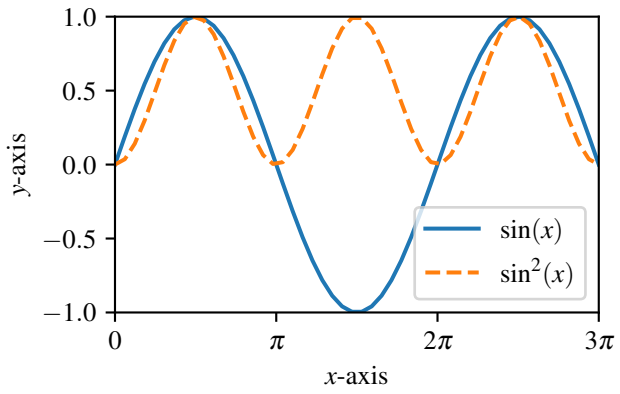
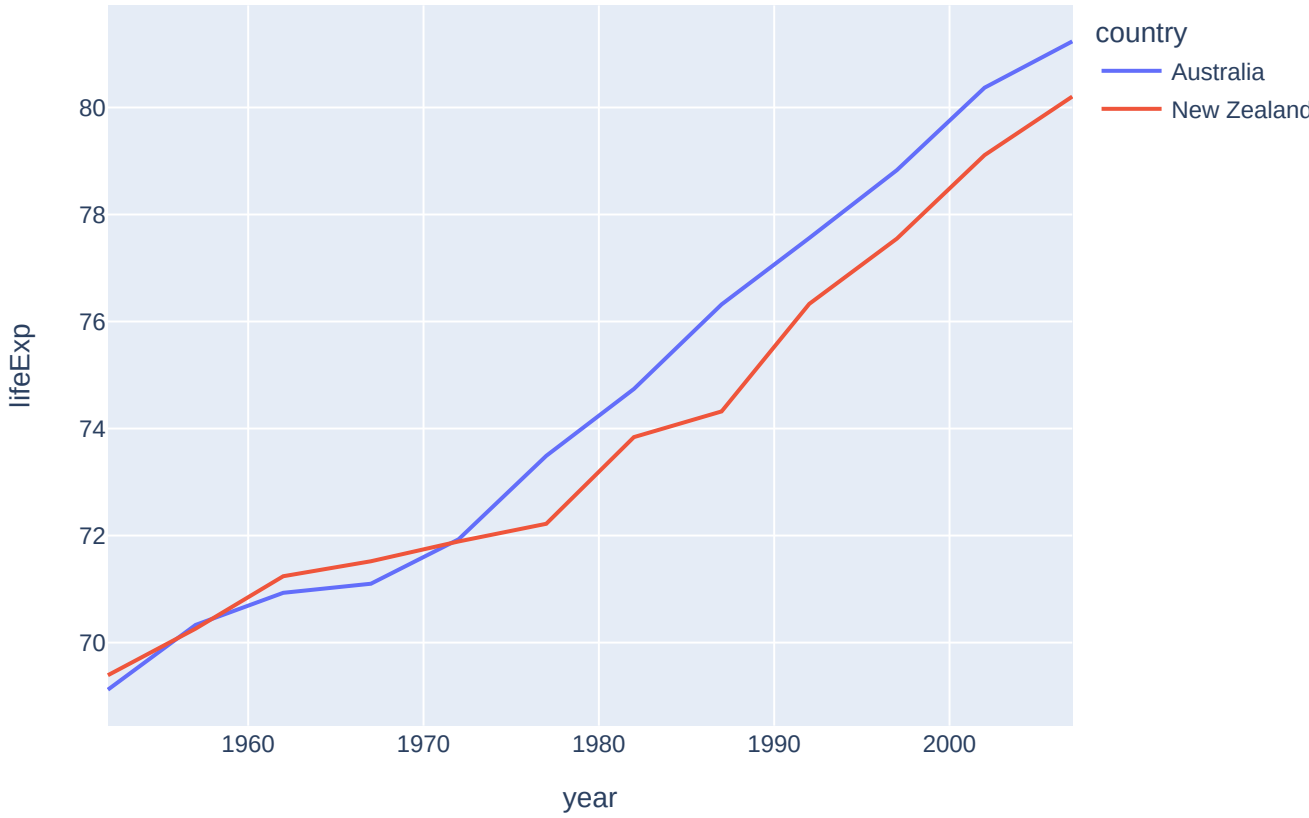


Abbildung 1.1: A plot created with PythonTeX and Matplotlib



Loading [MathJax]/extensions/MathMenu.js

Abbildung 1.2: A plot created with PythonTeX and Plotly

Kapitel 2

Implementation

2.1 Hardware Setup for validation

2.2 EKF Implementation

date: (4d)
To design an extended kalman filter algorithm three steps are necessary: 1.The control-input model and the observation model need to be well designed. 2.The constants inside the models expressed as matrixes need to be definied, which is as well known as parametrisation of the model. 3.The model needs to be implemented as code running on embedded systems.
The key to success for a good SoC is a good definition of both models and a good parametrisation. The implementation is independent of the use case and depends on the skills of the programmer, in his hands lies the optimization of the code. In case no FPU is available on the micro-controller unit (MCU) fix point arithmetic might be an option.
Particulary challenging is the parametrization, which is typically done offline [1] and required quite advanced equipment. Adaptive extend Kalman Filter is an option where the parameters are determined online, but still AEKF needs to be initialized with parameters not necessary fitting all batteries of a given chemistry (different capacities, different manufacturer). TODO It needs to be researched if it only affects the convergence time or if convergence is not reached at all? A further advantage of an adaptive filter is that the state of health (SOH) can be determined along the side. When simple observation and control-input models are used as in the okra kalman-soc algo, the parametrisation might be much easier? TODO to check if the only parameters OCV(SoC) data can be used generally or only on the batteries they have been measured on.
Offline parametrizatio:
Quote: Äs a result, many experimental pretests investigating the effects of the internal and external conditions of a battery on its parameters are required, since the accuracy of state estimation depends on the quality of the information regarding battery parameter changes"
"Therefore, some tests data must be available in advance to find the parameters of these models."[Hussein und Batarseh

Gregory Plett says: "Two possible approaches:

First, an algorithm might somehow adapt the parameter values of the model during operation to match presently observed current–voltage behaviors; but, this **must be done very carefully to avoid making the model unstable or physically nonmeaningful**.

[1] not done on the microcomtroller unit (MCU) the algorithm is deployed to, thus not on the system running the final algorithm. Offline means on more advanced hardware, which is not available in the final product. See `https://en.wikipedia.org/wiki/Online_model`

Alternately, a set of models could be pre-computed at different feasible aging points and the model from this set that most closely predicts presently observed current–voltage dynamics could be selected from the set. This second approach guarantees stable and physically meaningful models since all models in the pre-computed set meet these criteria. We propose such an approach here.-–https://www.sciencedirect.com/science/article/abs/pii/S2352152X18301385?viaIn order to have online first algo, the parametrization needs to be done online!.
As the OCV curve is non-linear the kalman filter can not be used.
state transition and observation models

2.2.1 Definition Mathematics Equations

TODO Make a diagram where you can see the input output and steps

Most general form of state observer equations:
$x_{k+1} = Ax_k + Bu_k$ (state observer equation)
$y_k = Cx_k + dDu_k$ (output equation)

$u_k \equiv i_k$ a control vector (input), defined as the measurement of current through the battery at time k.
$y_k \equiv v_k$ an observation (or measurement), defined as a voltage measurement of the battery at time k.
$A = I$ identity matrix f.i $I_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$
$B = \begin{bmatrix} -\frac{\Delta t}{Q_C} & 0 \\ 0 & 1 \end{bmatrix}$ is **the control-input model**, deduced from $f(\boldsymbol{x}_k, \boldsymbol{i}_k, \Delta t) = x_k - \frac{1}{Q_C}\int_0^{\Delta t} i_k \, dk$
$C = [0, -R_1, -R_2, ..., M] = H(x_k)$ and $H(x_k)$is the **observation model** , which maps the state space into the observed space and TODO understand the relationship to $h(x_k)$
$D = R_0$

Most general form of Kalman Filter equations:

$\boldsymbol{x}_{k+1} = f(\boldsymbol{x}_k, \boldsymbol{u}_k) + \boldsymbol{w}_k$ (State Space equation)
$\boldsymbol{z}_k = h(\boldsymbol{x}_k) + \boldsymbol{v}_k$ (Output equation)

$\hat{x}_{k+1} = (A - BK)\,\hat{x}_k + L\,(y_k - \hat{y}_k)$ (here u_k seems missing)

Predicted variables $\hat{y}_k$ and $\hat{x}_k$ are commonly denoted by a "hat"to distinguish them from y_k and $x(k)$ of the physical system. As the state of charge (SoC) denoted as $\hat{x}_k = SoC_k$ cannot be measured directly it is always a predicted variable, opposed to $y(k)$, which is the measured circuit voltage. Consequently $\hat{y}_k = v_k$ is the predicted circuit voltage also known as measurable output:
$\hat{y}_k = (C - DK)\,\hat{x}_k$
Input to the extend kalman filter (EKF) is current and voltage measurement and the period of time between these measurements. The initialization of the EKF outputs the initial estimate state of charge $x_{k|k=0}$ another input to the EKF.
System's dynamic model
The $f()$ function is defined as the $f(\boldsymbol{x}_k, \boldsymbol{i}_k, \Delta t) = x_k - \frac{1}{Q_C}\int_0^{\Delta t} i_k \, dk$ or more discrete $f(x_k, i_k, \Delta t) = x_k - \frac{\Delta t}{Q_C} i_k$, thus current measurement i_k The $h(\boldsymbol{x}_k)$ function is defined as the OCV lookup table. A general OCV lookup table for the battery chemistry can be used or for better results a specific OCV lookup established by offline measurements for the given battery should be used. To further improve the OCV prediction a correction of it can be performed by a equivalent circuit model (ECM) of the battery feeded by the current measurement used to predict the SoC:

$v_k = D\ OCV(z_k) + Cx_k + Di_k$ with $C = [0, -R_1, -R_2, ..., M]$ and $D = R_0$
-Measurement equation, input (measured voltage, OCV lookup table, current if the correction with a Enhanced Self-Correcting (ESC) Cell Model /ECM) -> output SOC) equation should be use standard letters: filterpy, wikipedia, gregoryPlett, Step by Step Guide
After having defined the observation and control-input model as matrices and described their meaning in case of SoC estimation we proceed to the functioning of the EKF, which is typically divided into to steps, Predict and Update.
In the **predict** step a future state of charge estimate $\hat{x}_{k+1}$ is predicted based on the current state of charge estimate $\hat{x}_k$ and the current i_k during the period Δt (between k and $k+1$) by calculating $\mathbf{\hat{x}_{k+1}} = \mathbf{A x_k} + \mathbf{B u_k}$ Moreover an estimate of the covariance $P_{k+1}x$ is calculated based on noise covariances Q_k and current P_k (wiki: a measure of the estimated uncertainty of the prediction of the system's state) $\mathbf{P}_{k+1} = \mathbf{B}_k \mathbf{P}_k \mathbf{B}_k^\intercal + \mathbf{Q}_k$
In the **update** step
$\mathbf{K}_k = \mathbf{P}_{k+1}\mathbf{H}_k^\intercal (H_k \mathbf{P}_{k+1} \mathbf{H}_k^{\intercal + \mathbf{R}_k)^{-1}}$ is the kalman gain, which weights whether the SoC based on the measurement of the circuit voltage v_k is more trusted than the SoC prediction based on current i_k
$\mathbf{\hat{x}}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)(\mathbf{\hat{x}}_{k+1}) + (\mathbf{K}_k)(\mathbf{H}_k \mathbf{\hat{x}}_k + \mathbf{v}_k)$ TODO update $\hat{x}_k$ because one can not now want one want to calculate

$\mathbf{P}_{k+1} = (\mathbf{I} - \mathbf{K}_{k+1}\mathbf{H}_{k+1})\,\mathbf{P}_k$ update of the covariance TODO is H_k the same as OCV?

$\mathbf{R_k}$ the covariance of the observation noise

Most general equation of extended kalman filter EKF:

$\mathbf{x}_k = f(\mathbf{x}_{k-1}, \mathbf{u}_k) + \mathbf{w}_k$ (state transition model)
$\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k$ (observation model)
f -> predicted state from the previous estimate
h -> compute the predicted measurement from the predicted state

Predict
$\hat{\boldsymbol{x}}_{k|k-1} = f(\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_k)$
$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_k \boldsymbol{P}_{k-1|k-1} \boldsymbol{F}_k^\top + \boldsymbol{Q}_k$

Update
$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - h(\hat{\boldsymbol{x}}_{k|k-1})$
$\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^\top + \boldsymbol{R}_k$
$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^\top \boldsymbol{S}_k^{-1}$
$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k \tilde{\boldsymbol{y}}_k$
$\boldsymbol{P}_{k|k} = (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k) \boldsymbol{P}_{k|k-1}$

2.3 Kalman-SoC

A Fork of Okra-Solar Algorithm.
Features:
-Works without the input of a Equivalent Circuit Model (ECM) specific to the physical battery, which would need to be parameterized doing advanced measurements during charging and discharging of the battery.
-Inputs: Current and Voltage Measurements and OCV Lookup Table

-Outputs: SoC in %Wh
TODO Discuss the Code Snippets? But Some Code in Appendix or reference Github Repo only?

Kapitel 3

Validation

1.1 has all the info how to integrate graphs here.
Discuss results. (4d)

Kapitel 4

Outlook

Promising articles and/or methods for online parameter estimation:

online parameter estimation from the ARX model [Tran et al. 2017]
[Xia et al. 2018] [Wang et al. 2021]

Anhang A

Angehängtes: Die Dateien des Pakets

Stylefile

Die Styledatei für diese Abschlussarbeit ist `bhtThesis.sty`, die in der Archivdatei vorliegt. Diese muss von LaTeX auffindbar sein, muss also in einem LaTeX bekannten Ordner liegen:

- Ubuntu-Linux: `$HOME/texmf/tex/latex/bhtThesis/bhtThesis.sty`
- MikTeX: `c:\localtexmf\tex\latex\bhtThesis/bhtThesis.sty`

Beispieldokument

Dieses Dokument befindet sich im Unterordner `tryout` des zip-files. Sie können diese Dateien in einen Ordner kopieren, in dem Sie schliesslich arbeiten werden. Die Dateien sind die folgenden

- `abstract_de.tex` Kurzfassung in deutscher Sprache
- `abstract_en.tex` Kurzfassung in englischer Sprache
- `anhang.tex` der Anhang
- `bhtThesis.bib` beinhaltet die zu zitierenden Literaturstellen und wird von bibTeXausgewertet
- `main.pdf` ist die Ausgabendatei mit der Druckvorlage
- `main.tex` beinhaltet das Hauptdokument
- `makefile` realsiert das automatische mehrfache Übersetzen, hierfür muss `make` auf dem System installiert sein.
- `myapalike.bst` beinhaltet die Formatierung für das Literaturverzeichnis
- `personalMacros.tex` kann einzelne, persönliche Macros beinhalten, die das Schreiben erleichtern
- `titelseiten.tex` realisiert alle Seiten bis zum Beginn des ersten Abschnittes
- Ordner `pictures`
  - `BHT-Logo-Basis.eps`
  - `BHT-Logo-Basis.pdf`
- Ordner `kapitel1`
  - `ch1.tex` Quelltext des Kapitel 1

    - Ordner `pictures`
        * `schaltbild.pdf`

- Ordner `kapitel2`
    - `ch2.tex` Quelltext des Kapitel 2
    - Ordner `pictures`
        * leer

Literaturverzeichnis

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[Wang et al. 2021] Wang, Y., Huang, F., Pan, B., Li, Y., und Liu, B., Augmented system model-based online collaborative determination of lead–acid battery states for energy management of vehicles. *Measurement and Control*, 54(1-2):88–101.

[Xia et al. 2018] Xia, B., Lao, Z., Zhang, R., Tian, Y., Chen, G., Sun, Z., Wang, W., Sun, W., Lai, Y., Wang, M., et al., Online parameter identification and state of charge estimation of lithium-ion batteries based on forgetting factor recursive least squares and nonlinear kalman filter. *Energies*, 11(1):3.