Decision Making for Dynamic Systems under Uncertainty: Predictions, Recomputations, and a Mobile Tool

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- Based on some knowledge of an unfolding phenomenon, **predicting** its behavior $\longrightarrow$ e.g., to allow preventive actions for instance
- **Enforcing some behavior**, when control of input or other parameters is possible, and/or recomputing parameters on the fly $\longrightarrow$ e.g., to address an unexpected event and still guarantee an acceptable outcome of the situation

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  - We’d like to be able to rely on such data.

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- **Reliability.**
  - Interval computations allow to carry guaranteed computations

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- How to conduct parameters' recomputations for unfolding dynamic phenomena?
- Is this usable in practice? Or do we need to harness a lot of computational power to make such decisions?

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- We assume that we have access to a ROM of such problem

BASE PROBLEMS

- Original **FOM** problem. We have:

$$F : \mathbb{R}^n \times \mathbb{R}^m \longrightarrow \mathbb{R}^n, \quad F : \; (x, \lambda) \mapsto F(x, \lambda)$$

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- **Reduced problem** (ROM). We now have:

$$F_\Phi:\mathbb{R}^p\times\mathbb{R}^m\longrightarrow\mathbb{R}^n,\quad F_\Phi:\ (\tilde{x},\lambda)\mapsto F(\Phi\cdot\tilde{x},\lambda),\quad \text{with: } p\ll n$$

  Knowing the value of λ, we could solve $F(\Phi\cdot\tilde{x},\lambda)=F_\lambda(\Phi\cdot\tilde{x})=0$, where $\tilde{x}\in\mathbb{R}^p$, and then we would recover x using $x=\Phi\cdot\tilde{x}$.

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In what follows, we illustrate our work on the Lotka-Volterra problem.

PREDICTIONS: LOTKA-VOLTERRA

Let's consider the following problem of predators and preys, defined by:

$$\frac{dv}{dt} = \theta_1 v(1-w) \quad \text{and} \quad \frac{dw}{dt} = \theta_2 w(v-1)$$

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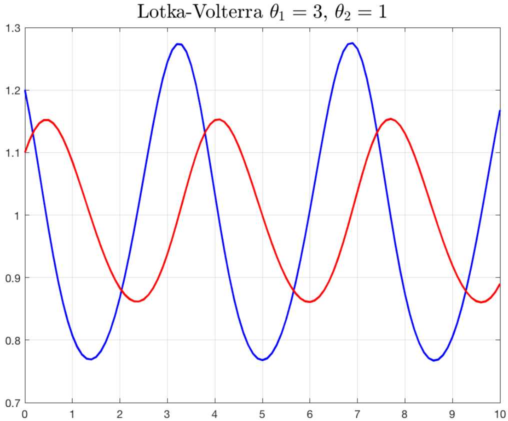

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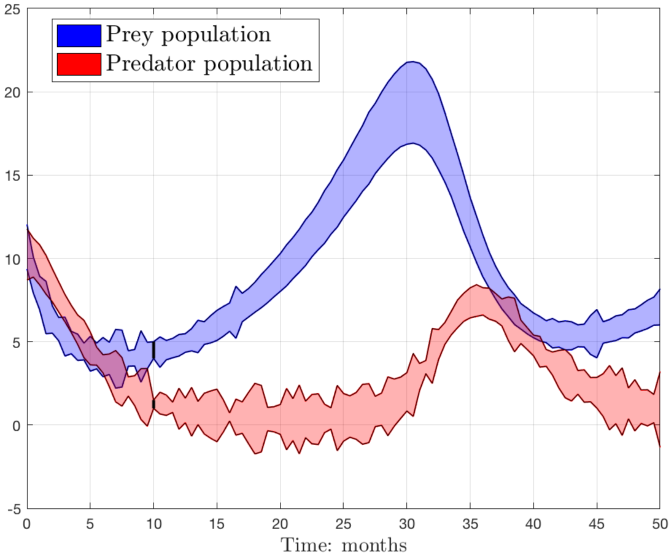

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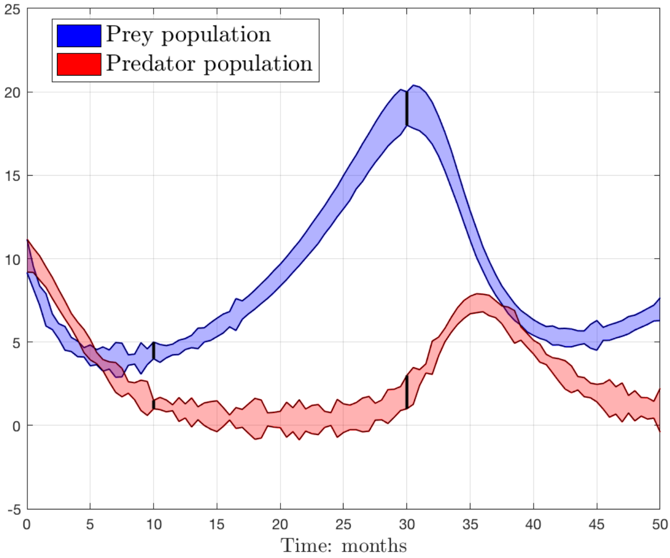

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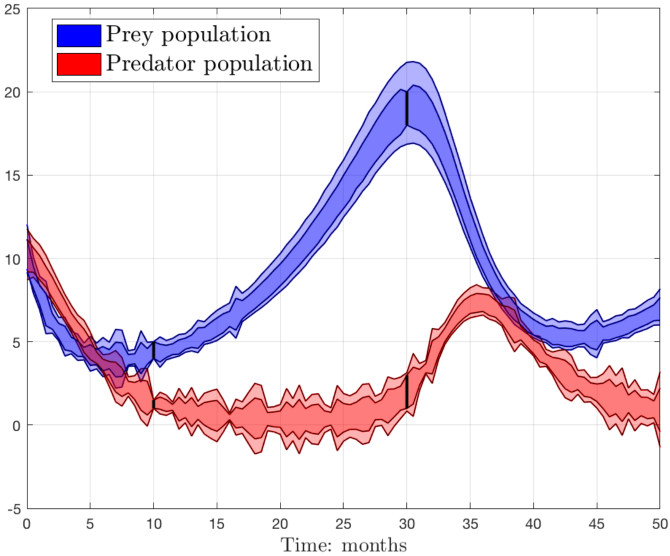

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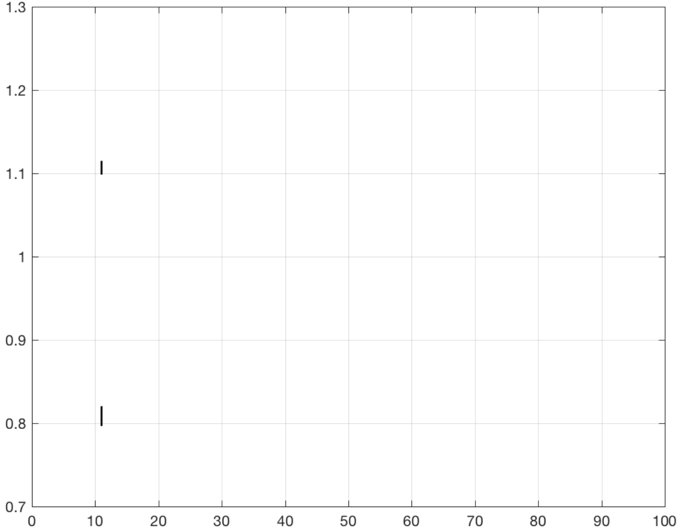

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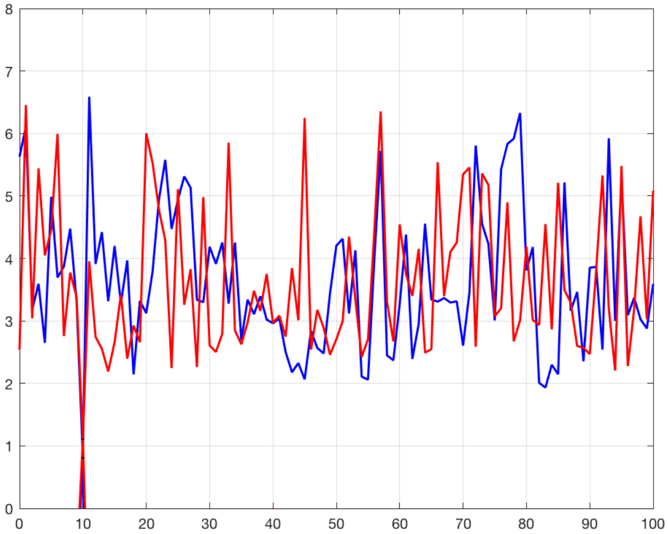

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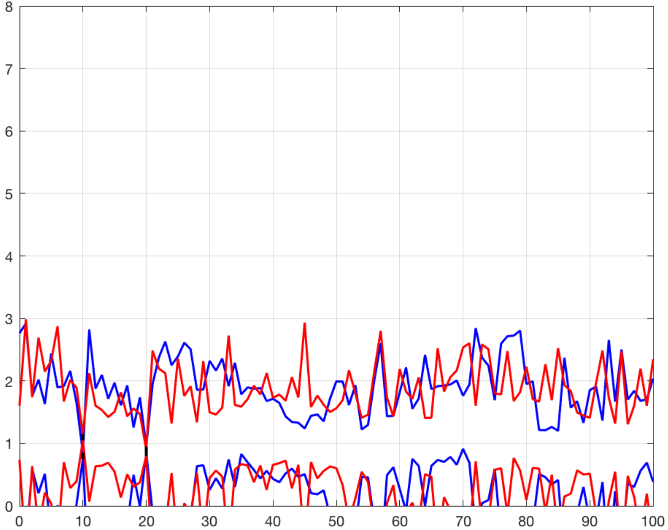

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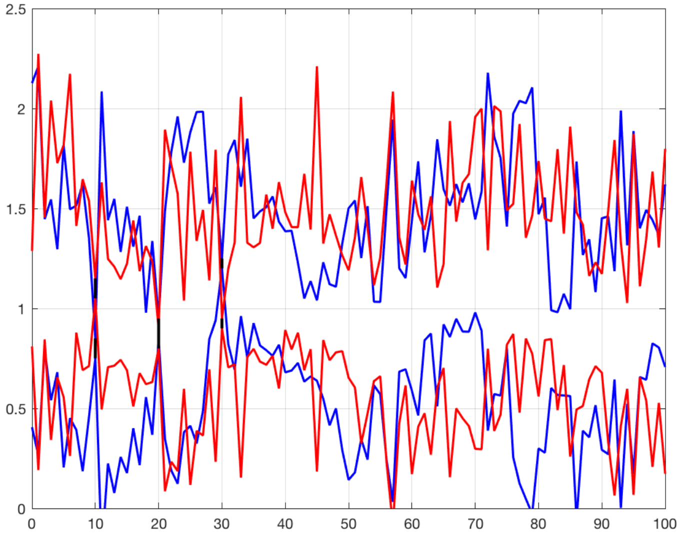

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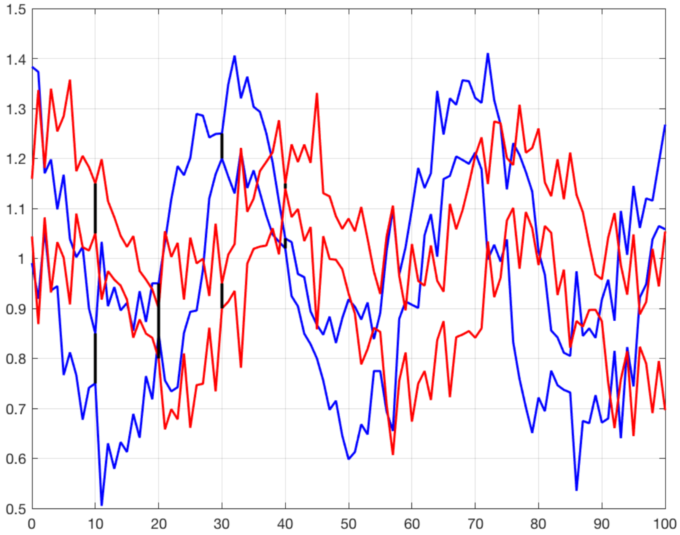

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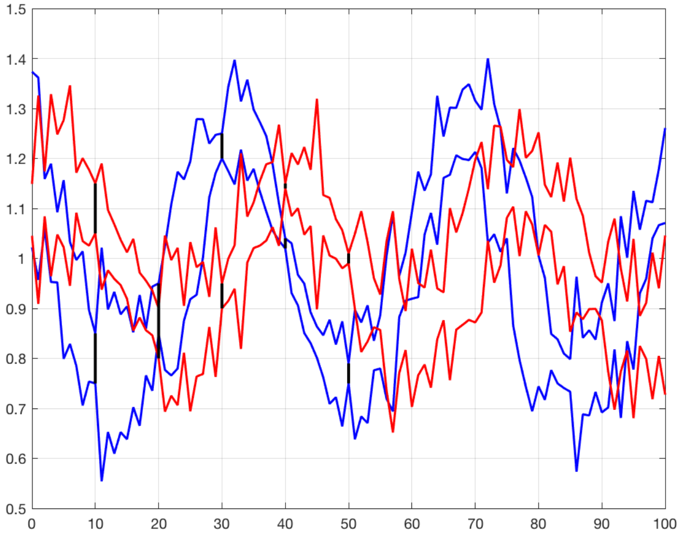

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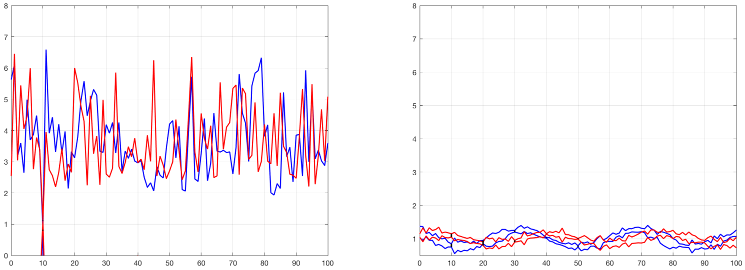

Left: one observation set and $\theta_1 = \theta_2 = [0, 6]$.
Right: five observation sets, $\theta_1 = [0.1875, 6]$ and $\theta_2 = [0, 4.6875]$

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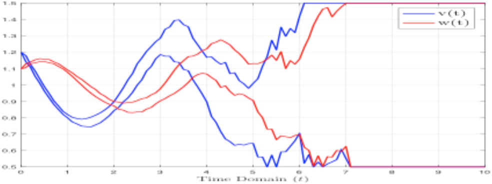

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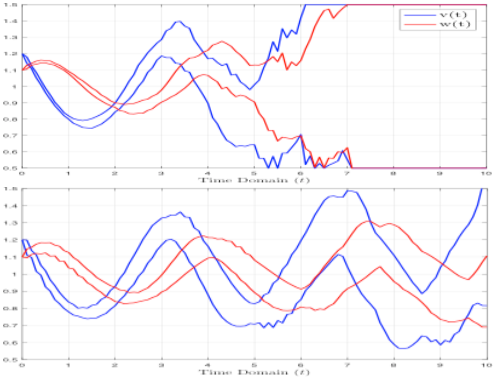

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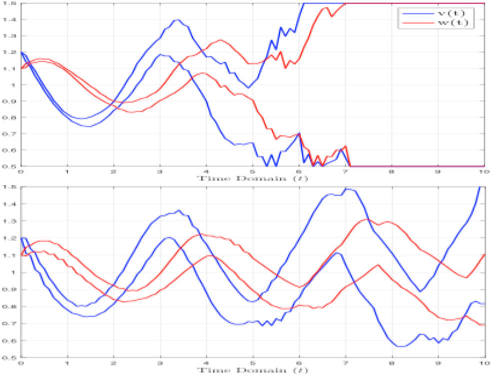

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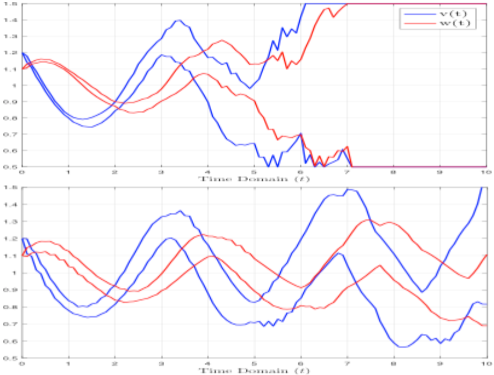

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This poses the question of the quality of the ROM: *should we consider local bases?*

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  - to handle outliers: *at best no solution, at worst erroneous ones*
  - to handle time horizon uncertainty

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- **What does it look like?**

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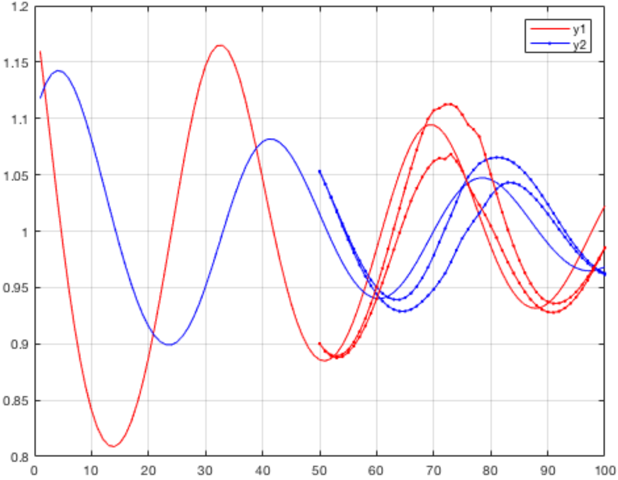

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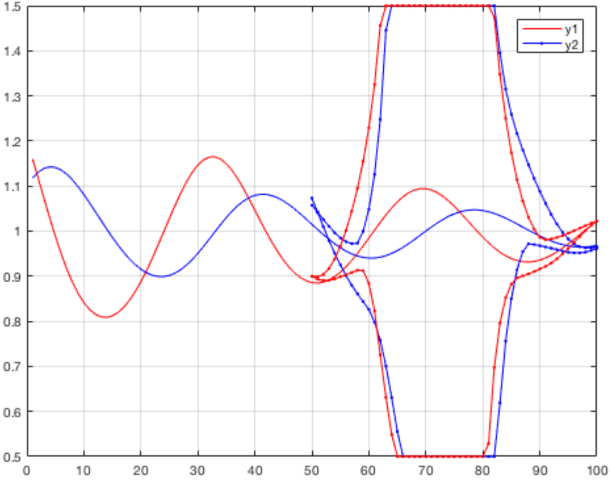

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Still using the Lokta-Volterra problem:

$$\begin{cases} y_1' = \theta_1 y_1 (1 - y_2) = \theta_1 y_1 - \theta_1 y_1 y_2, \\ y_2' = \theta_2 y_2 (y_2 - 1) = \theta_2 y_2 y_1 - \theta_2 y_2, \end{cases}$$

We choose: $y_1(0) = 1.2$, $\theta_1 = 2.95$, $y_2(0) = 1.1$, and $\theta_2 = 1.0$.

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$$\begin{cases} y_1' = \theta_1 y_1(1 - y_2) = \theta_1 y_1 - \theta_1 y_1 y_2, \\ y_2' = \theta_2 y_2(y_2 - 1) = \theta_2 y_2 y_1 - \theta_2 y_2, \end{cases}$$

We choose: $y_1(0) = 1.2$, $\theta_1 = 2.95$, $y_2(0) = 1.1$, and $\theta_2 = 1.0$.

But then we decide to alter the value of θ_1 to 1.5 at the 50^{th} time step, and we recompute θ_2 to enforce that y_1 and y_2 will converge to the same end point as in the initial problem at the 100^{th} time step.

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We obtained no solution despite $\theta_2 = [0, 5]$.

RECOMPUTING DYNAMIC SYSTEMS' PARAMETERS

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Some conclusions:

- We are able to (re-)compute parameters
- But we still have to take recomputation time into account when doing it "on the fly"
- **Future steps?** identify parameters that, even under uncertainty, guarantee a certain behavior. E.g., combustion problem in collaboration with Luis Bravo, ARL APG: what type of fuel mix? what geometry of the nozzle, etc.

DECISIONS UNDER UNCERTAINTY ON A MOBILE APP

- **Objective:** Show that we can handle uncertainty in ways we showed before on a computationally-limited device.

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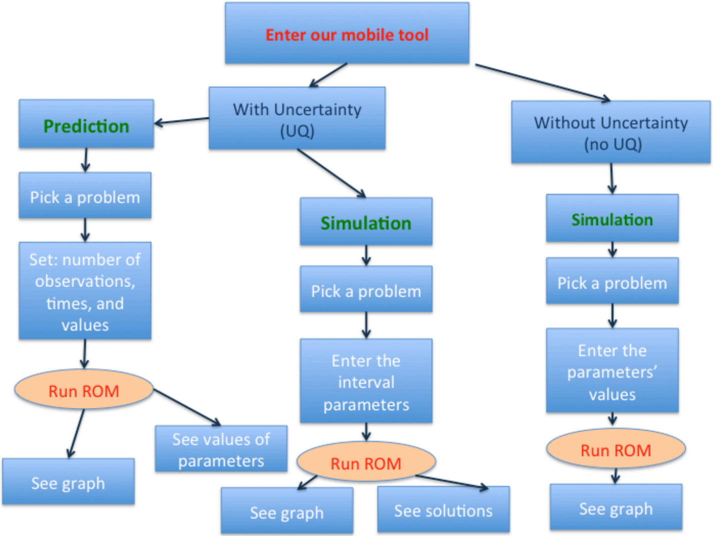
- **Objective:** Show that we can handle uncertainty in ways we showed before on a computationally-limited device. That was our **capstone** project.
- We implemented all techniques used before on an android device.
- Let's take a look at the intended use and functionalities of this app.
- *Note: this work was conducted with feedback from Simon Su, ARL APG*

OUR MOBILE TOOL



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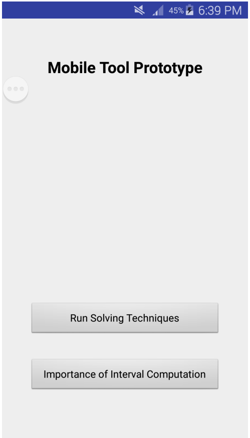

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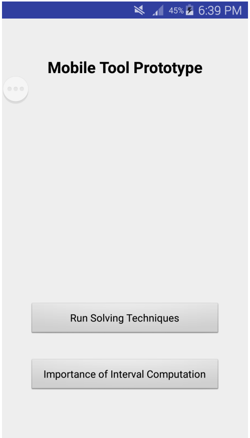

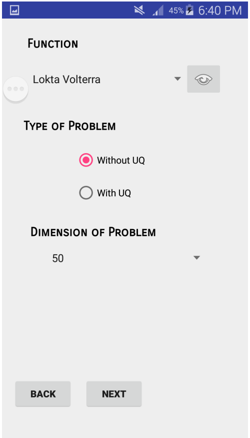

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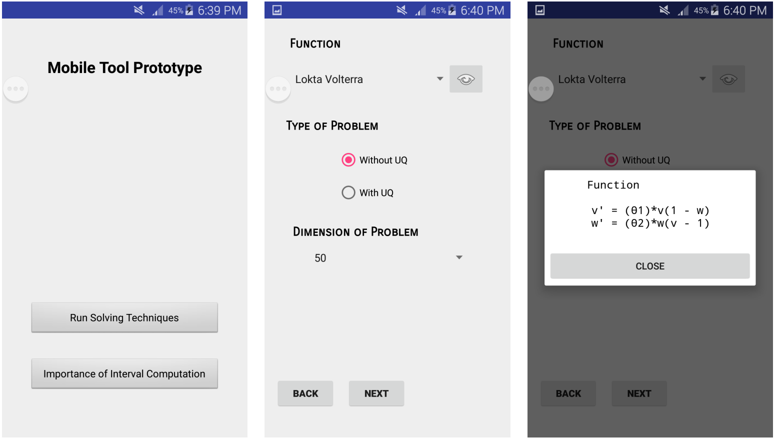
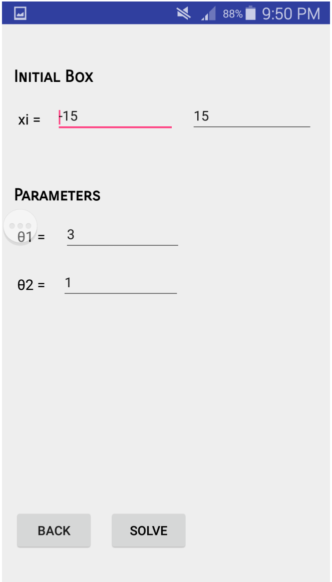


OUR MOBILE TOOL: SIMULATION W/O UQ



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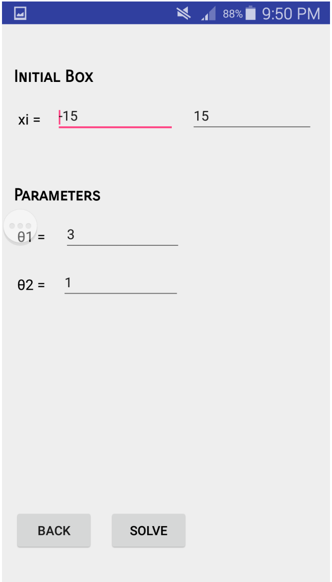

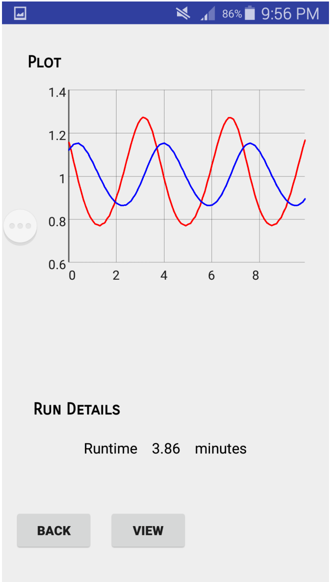

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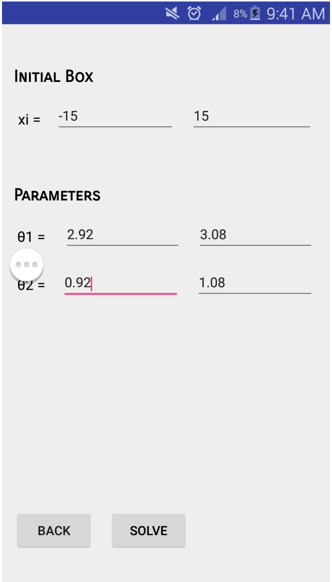

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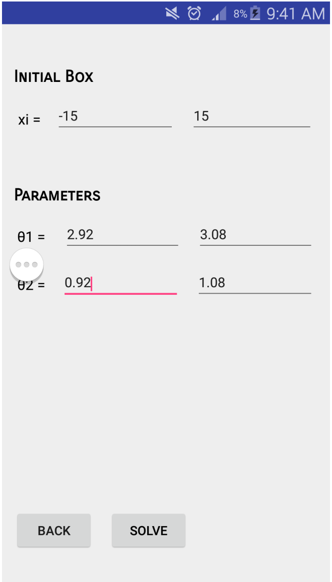
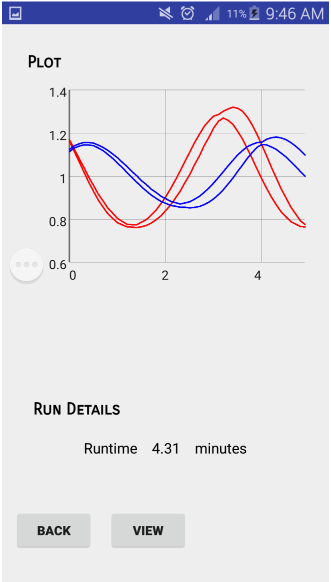
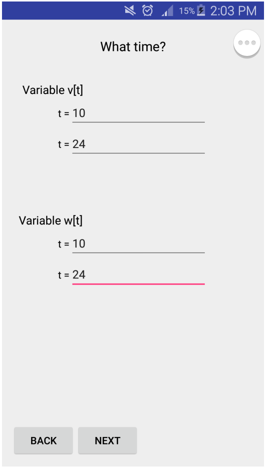




OUR MOBILE TOOL: PREDICTION (WITH UQ)



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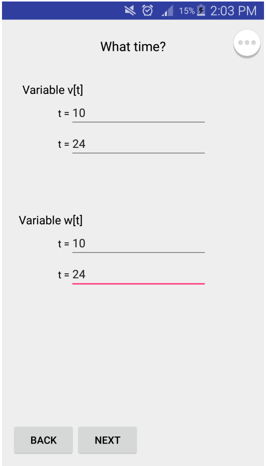

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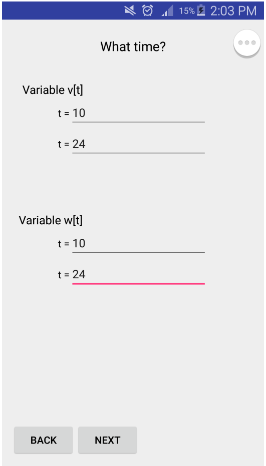

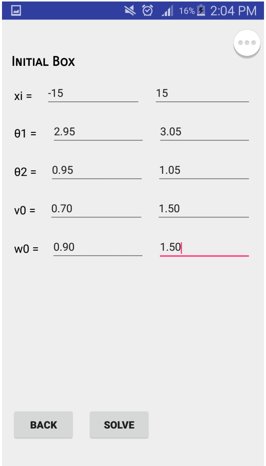

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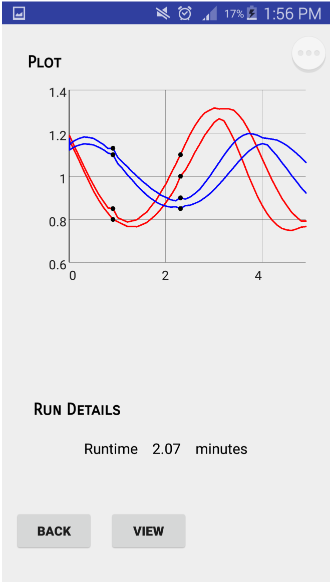

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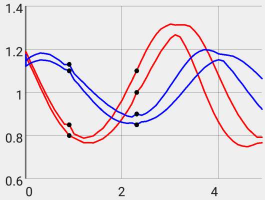
17% 1:56 PM

Plot



Run Details

Runtime 2.07 minutes

BACK VIEW

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BACK

Hull All Solutions

Output Detail

```
Solutions: 49
Function:
 v' = (θ1)*v(1 - w)
 w' = (θ2)*w(v - 1)
Initial Box
 xi = [-15.0,15.0]
 θ1 = [2.95,3.05]
 θ2 = [0.95,1.05] v0 = [0.7,1.5]
 w0 = [0.9,1.5]
Parameters

Box1
 v[1]=[1.16519418288,1.18857764561]
 v[2]=[1.11958081648,1.13946168551]
 v[3]=[1.07261493326,1.09261510602]
 v[4]=[1.02296678247,1.04530425043]
 v[5]=[0.97701077844,0.99959411163]
 v[6]=[0.93003025554,0.95792814917]
 v[7]=[0.89128378776,0.91740113855]
 v[8]=[0.85605902646,0.88430014653]
 v[9]=[0.82782711787,0.8522046992]
 v[10]=[0.8,0.85]
 v[11]=[0.78850809499,0.80756512129]
 v[12]=[0.77758528196,0.79677692846]
 v[13]=[0.7665912551,0.78737453682]
 v[14]=[0.76607292834,0.79233461908]
```

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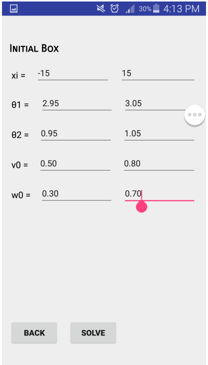

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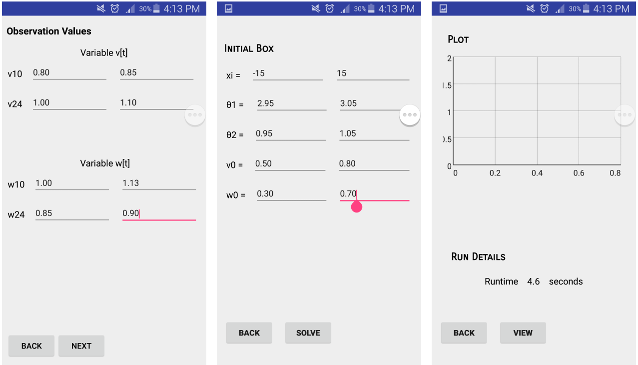

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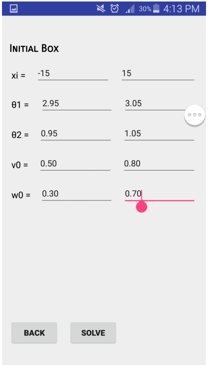

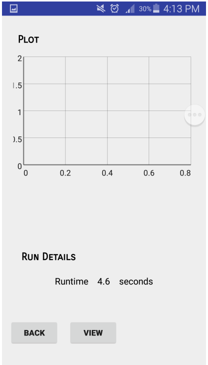

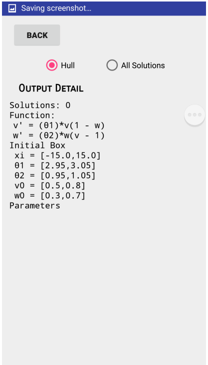

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- We can also easily:
  - expand it to handle larger problems: with a connection to a webserver and a powerful machine
  - to include recomputations: similar computations to predictions, but will need to handle time uncertainty

CONCLUSION

What we learned and demonstrated:

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The UTEP team also consists of: Miguel Argaez (Co-PI), HoracioFlorez (Post-doc at ARL ALC), Leobardo Valera (Ph.D. student at UTEP), Jesus Padilla and Phillip Hassoun (undergraduate students at UTEP).

PRODUCTS OF OUR WORK (SINCE 2014)

Conference papers: 16 + 2 in progress with Luis Bravo (ARL APG)

- among which 2 best student paper awards

Journal articles and chapters: 2 + 1 in progress

- Florez and Argaez, in Applied Mathematical Modelling (2017)
- Ceberio and Valera, in the Journal of Uncertain Systems (2016)

Invited presentations: 2

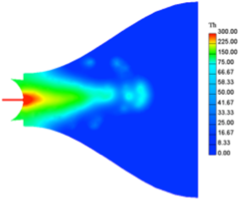
- Ceberio: Plenary talk at the International Conference SCAN'16 on Validated Computing
- Ceberio: Invited seminar at the University of Paris 6, Pierre and Marie Curie, in fall 2017

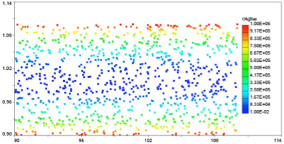
Mobile application for decisions with UQ

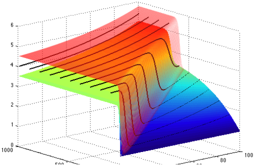
THANK YOU FOR YOUR ATTENTION

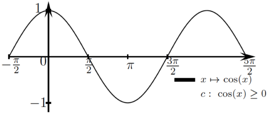
Any Questions?

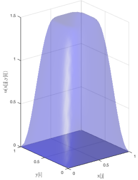
Below are illustrations of other parts of our work:

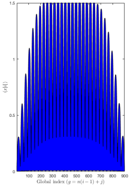


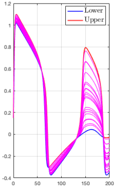


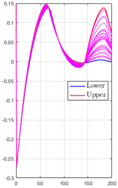












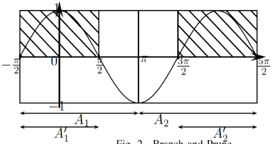


Fig. 2. Branch and Prune