ECOLE DOCTORALE IAEM LORRAINE

UNIVERSITÉ DE LORRAINE

Bootstrap-IOHMM to Manage the RUL for Rescheduling Maintenance Time-window of a System Considering Operating Conditions

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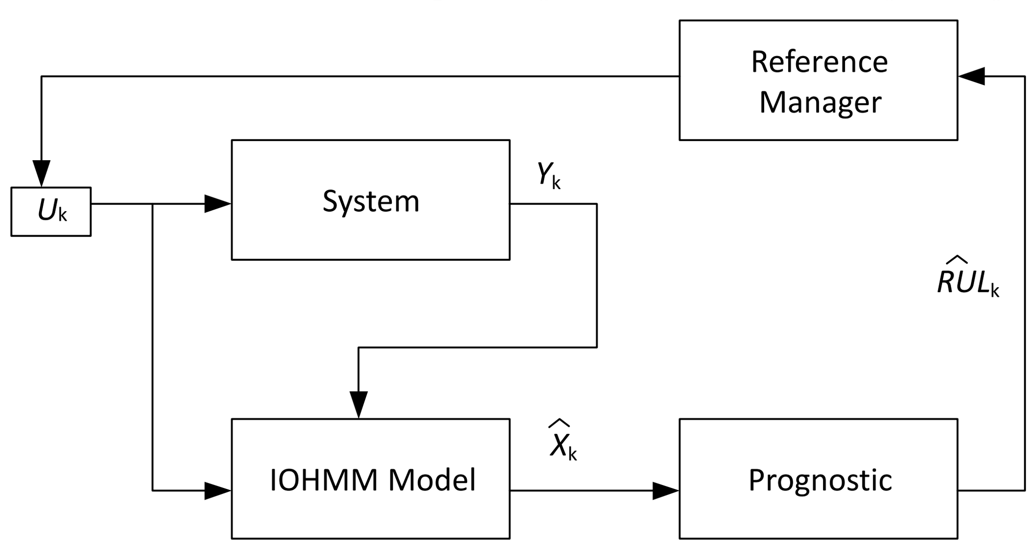
Thesis Objective (1)

The objective is to manage the remaining useful life (RUL) of the system by controlling its future operating conditions.

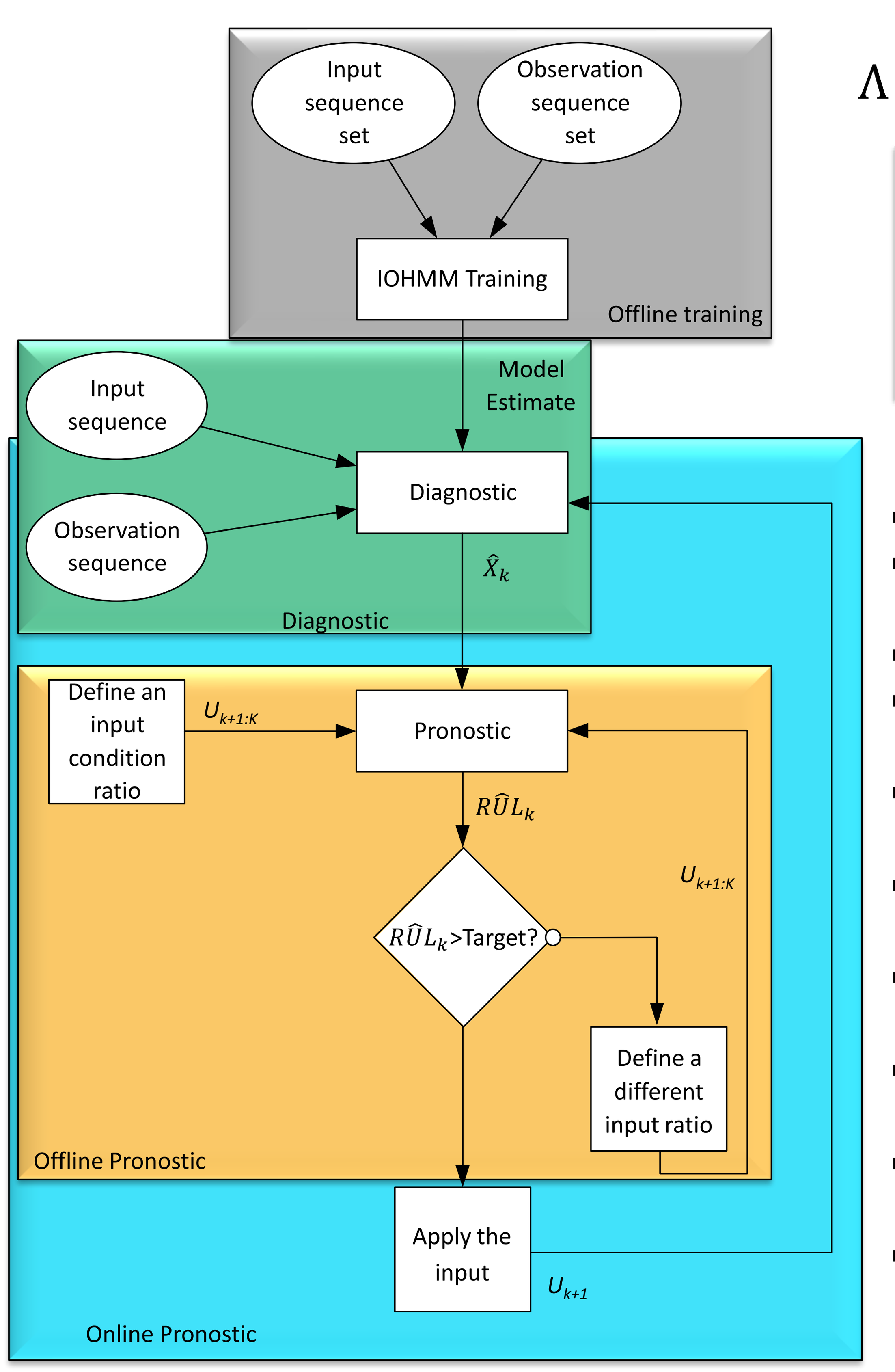
- The input-output hidden Markov model (IOHMM) diagnostic system health state $\hat{X}_k$ at time k when any new measurement (Y_k) come from output Y and then prognostic the system $R\hat{U}L_k$ according to the estimated health state ($\hat{X}_k$) of the system.
- After that, the $R\hat{U}L_k$ is taken into account through the reference manager which applies a proposed technique and decides the next operating condition that should get the given/target RUL of the system.



Controlling the operating condition based on the estimated RUL

- X is health state
- $\hat{X}_k$ is estimated health state at time k
- U_k is vector of input controls
- Y_k is vector of observation output
- $R\hat{U}L_k$ is estimated remaining useful life

IOHMM Process Flow Diagram (2)



$$\Lambda = (A^N, B^M, \pi)$$

$$A^N = P(X_k|X_{k-1}, U_{k-1})$$

$$B^M = P(Y_k^M|X_k)$$

$$\pi = P(X_1)$$

- A^N is transition matrices
- N is number of transition matrices
- B^M is emission matrices
- M is number of emission matrices.
- π is initial state distribution
- $\hat{X}_k$ is estimated health state at time k
- U_{k+1} is vector of next input control at time k
- Y_k^M is vector of observation outputs Y^M
- $R\hat{U}L_k$ is estimated remaining useful life
- "Target" is a given RUL

Key Issues of the Thesis (3)

- Learning IOHMM models of system health based on data sequences
- Prognosis of system health and managing the remaining useful life
- Qualify model confidence

[Mention: This thesis is under a contract of "Contrat Doctoral"]

The Forward-Backward Algorithm (FBA) (4)

This is an inference algorithm for IOHMMs which computes the posterior distribution of all hidden states given the sequence of observations

- Forward recursion, $\alpha(X_k) = \sum_{X_{k-1}=s_1}^{N} \alpha(X_{k-1}) P(X_k|X_{k-1}, U_{k-1}) P({Y^q}_k|X_k)$
- Backward recursion, $\beta(X_k) = \sum_{X_{k+1}=s_1}^{N} \beta(X_{k+1}) P(X_{k+1}|X_k, U_k) P({Y^q}_{k+1}|X_{k+1})$
- The evaluation, $P(Y_k^q|\Lambda) = \sum_{i=1}^{N} \alpha_i(X_k)\, \beta_i(X_k)\,; \forall k$

where Λ is the given model, N is the number of hidden states and k is the time instant

The Baum Welch: EM Estimation of Parameters

The Baum Welch algorithm uses the FBA algorithm to estimate parameters of the model Λ.

- State transition Probability, $\varepsilon_k(i,j) = \frac{\alpha_i(X_k).a^p(U_k)_{ij}.{b^q}_{jk}.\beta_j(X_{k+1})}{P(Y_{1:k}^q|\Lambda)}$
- Update transition parameters, $\hat{a}^p{}_{ij} = \frac{\sum_{k=1}^{K-1} \varepsilon_k(i,j).\, 1_{X_k(U_k=p)}}{\sum_{k=1}^{K-1}\ \omega_k(j).1_{X_k(U_k=p)}}$, where $1_{X_k(U_k=p)} = \begin{cases}1 \text{ if } X_k(U_k=p)\\ 0 \text{ others}\end{cases}$
- Update emission parameters, $\hat{b}^q{}_{jk} = \frac{\sum_{k=1}^{K}\ \omega_k(j).1_{{Y^q}_k=v_m}}{\sum_{k=1}^{K}\ \omega_k(j)}$, where $1_{{Y^q}_k=v_m} = \begin{cases}1 \text{ if } {Y^q}_k=v_m\\ 0 \text{ others}\end{cases}$

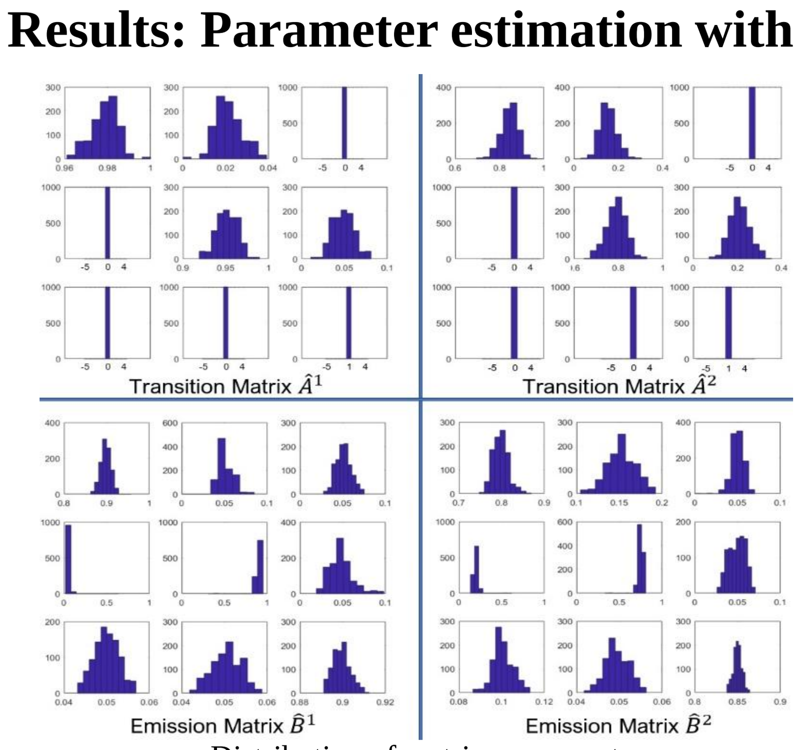
The Viterbi Equation

The Viterbi algorithm is used for computing diagnosis of the system

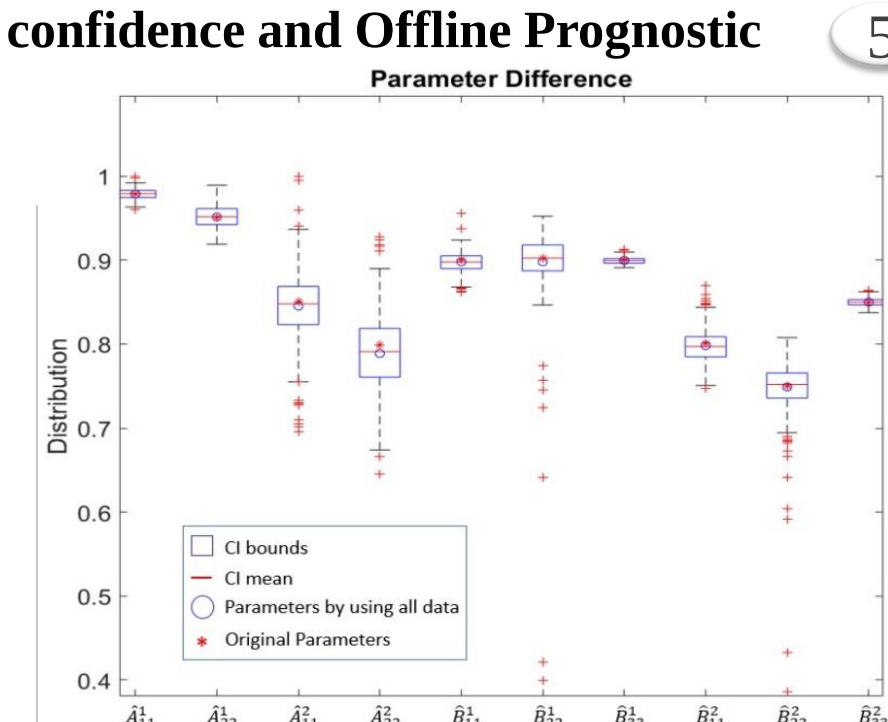
- Forward recursion, $\gamma(X_k) = max_{(X_{k-1})} P({Y^q}_k|X_k) P(X_k|X_{k-1}U_{k-1}) \gamma(X_{k-1})$
- Backward recursion, $\delta(X_k) = P({Y^q}_{k+1}|X_{k+1}) + max_{(X_{k+1})}\{\delta(X_{k+1}) + P(X_{k+1}|X_k, U_k)\}$

[Note: These algorithms are adapted from HMM to IOHMM in current developments of the thesis]

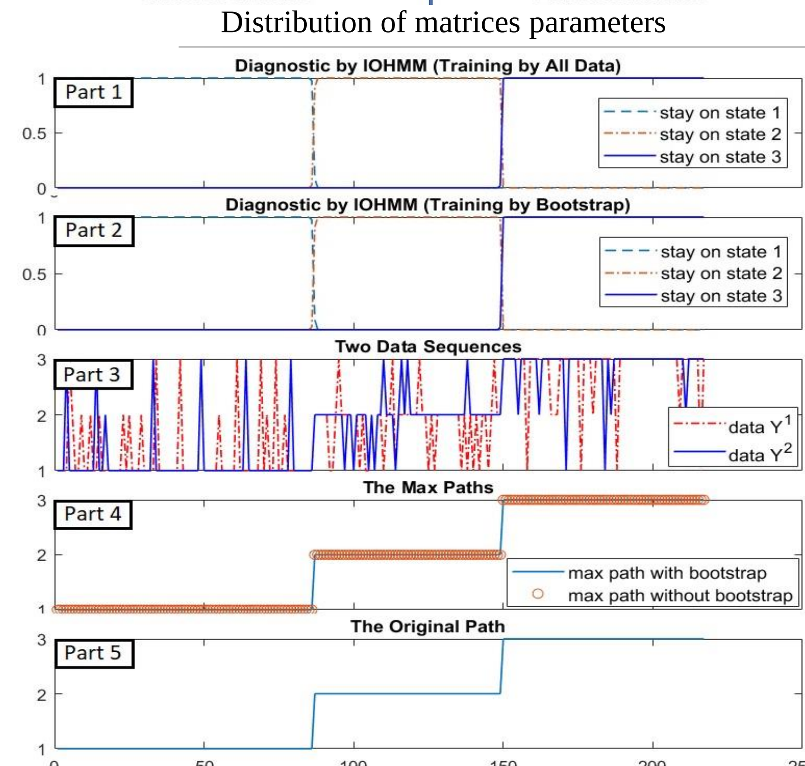
Results: Parameter estimation with confidence and Offline Prognostic (5)



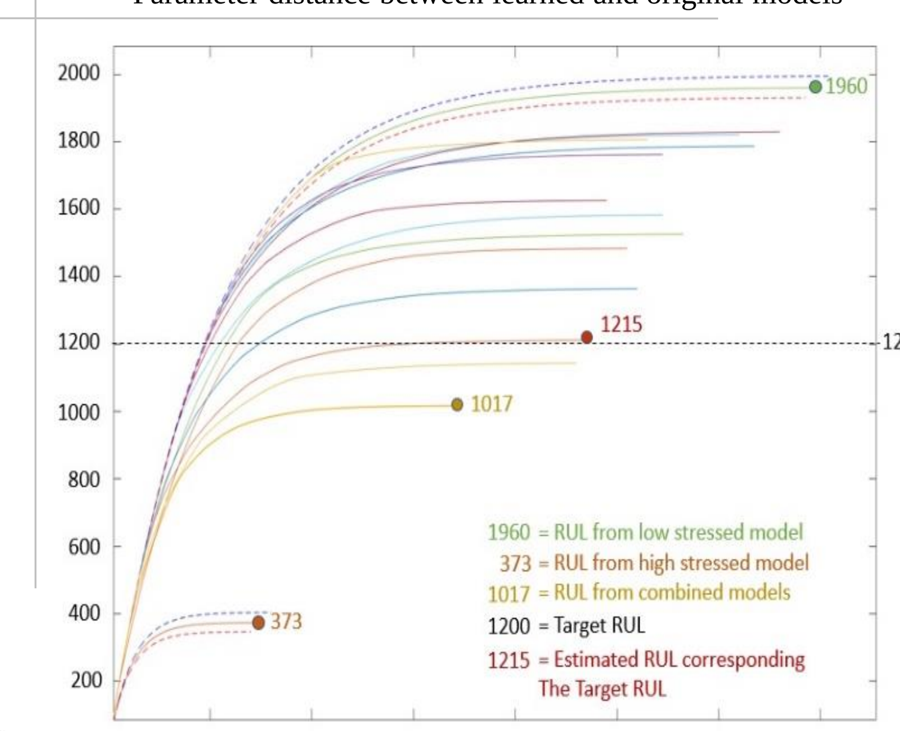
Distribution of matrices parameters



Parameter distance between learned and original models



Offline Diagnostic over the time from start to end



Different RULs using different operating conditions

Conclusion (6)

- This poster presents the thesis objectives and the key issues
- It presents the developments carried out in the implementation of IOHMM parameter learning, diagnostic and prognostic application
- Finally, the learning methodology and the results are projected.

Publications (7)

Journals:

1. **Shahin K I**, Simon C, Weber P, IOHMM in Prognostic of Complex Systems Under Multiple Operating Conditions. (***to be submitted***)
2. **Shahin K I**, Simon C, Weber P, Bootstrap-IOHMM to Manage the RUL Considering Operating Conditions. (***In progress***)
3. **Shahin K I**, Simon C, Weber P, Estimating Remaining Useful Life of Flow Distribution System. (***In progress***)

Conferences:

1. **Shahin K I**, Simon, C. and Weber, P., June. Input-output hidden Markov model for diagnosis of complex system. 13th International Conference, *CIGI QUALITA 2019*, Canada.
2. **Shahin K I**, Simon, C. and Weber, P., September. Estimating IOHMM parameters to compute remaining useful life of system. *29th European Safety and Reliability Conference*, Germany.
3. **Shahin K I**, Simon C, Weber P, Input-Output Hidden Markov Model to Manage the Remaining Useful Life of System by Tuning the Operating Conditions, *IFAC 2020*, Berlin, Germany. (**Submitted**)
4. **Shahin K I**, Simon C, Weber P, Bootstrap Confidence Interval on IOHMM Parameters for System Health Diagnostic Under Multiple Operating Conditions, *IFAC 2020*, Berlin, Germany. (**Submitted**)
5. **Shahin K I**, Simon C, Weber P, Managing Online RUL of System for Rescheduling Maintenance Time-window at Given Operating Conditions, *30th European Safety and Reliability Conference*, Italy. (**Submitted**)
6. **Shahin K I**, Simon C, Weber P, Prognostic of Flow Distribution System at Given Operating Conditions by Using IOHMM, *30th European Safety and Reliability Conference*, Italy. (**Submitted**)
7. **Shahin K I**, Simon C, Weber P, Input Output Hidden Markov Model for System Health Diagnostic Considering the Missing Data, *30th European Safety and Reliability Conference*, Italy. (**Submitted**)

References (8)

1. Kumar, A., Chinnam, R.B. and Tseng, F., 2019. An HMM and polynomial regression based approach for remaining useful life and health state estimation of cutting tools. *Computers & Industrial Engineering*, *128*, pp.1008-1014.
2. Bengio, Y. and Frasconi, P., 1995. An input output HMM architecture. In *Advances in neural information processing systems* (pp. 427-434).