HIDDEN MARKOV MODELS AND NEURAL NETWORKS FOR FAULT DETECTION IN DYNAMIC SYSTEMS

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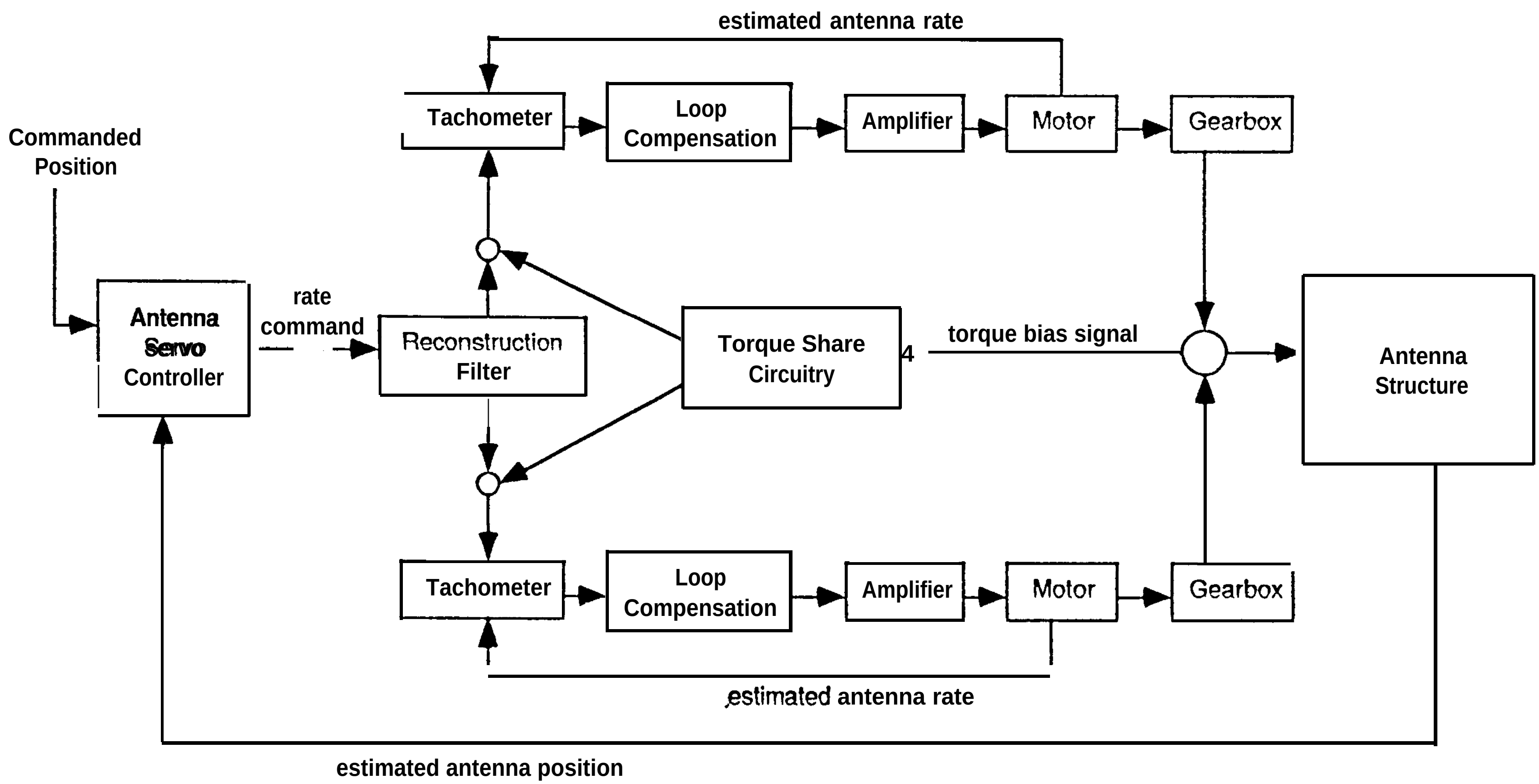
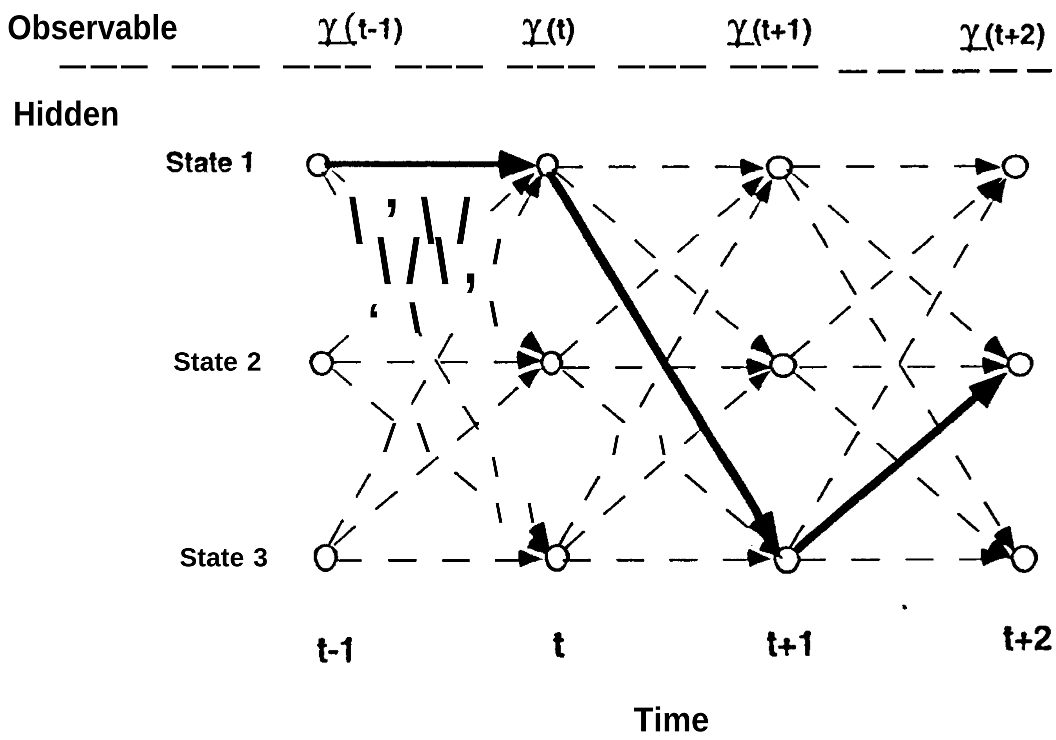
OVERVIEW

- **Neural Network + Hidden Markov models (HMMs):**
  - networks for discrimination and probability estimation
  - embedding networks in HMM's
  - application to fault detection (different from speech)
- **Application to Deep Space Network (DSN) Antenna Monitoring:**
  - online fault detection in large 34 meter ground antenna
  - discriminative vs. generative models for novelty detection
  - experiment al evaluation
- **Conclusions and Application Status**

34 meter Beam Waveguide Antenna Pointing System



HIDDEN MARKOV MODEL BASICS



- **Explicit Assumptions (first order):**

  1. Present state only depends on previous state.

  2. Observable are independent over time *given* the states.

BASIC HIDDEN MARKOV EQUATIONS

Let $\Phi_t \{\theta_t, \theta_{t-1}, \ldots, \theta_0\}$.

and $\Gamma_{t-k} = \{\theta_t, \theta_{t-1}, \ldots, \theta_{t-k+1}\}$.

- **Probability of Current State given Past Observed Data:**

$$p(\omega_j^t|\Phi_t) = \frac{1}{C_t} p(\theta_t|\omega_j^t) \sum_{i=1}^{m} a_{ij} p(\omega_i^{t-1}|\Phi_{t-1})$$

where

$$C_t = \sum_{j=1}^{m} \left[p(\theta_t|\omega_j^t) \sum_{i=1}^{m} a_{ij} p(\omega_i^{t-1}|\Phi_{t-1}) \right]$$

- **Probability of Past State given Observed Data to Present**

$$p(\omega_j^{t-k}|\Phi_t) = \frac{p(\omega_j^{t-k}|\Phi_{t-k}) p(\omega_j^{t-k}|\Gamma_{t-k})}{\sum_{i=1}^{m} p(\omega_i^{t-k}|\Phi_{t-k}) p(\omega_i^{t-k}|\Gamma_{t-k})}$$

NEURAL NETWORKS **FOR PROBABILITY ESTIMATION**

- **Theoretical Results:**
  - Theory shows that networks can approximate $p(\omega_i|\text{input}$ features)
  - Must use appropriate loss function: mean squared error or cross entropy
  - Results are asymptotic, assume global minimum in weight space.

- **Links with Conventional Statistics**
  - Feedforward networks can be considered a generalization of logistic regression: logistic nature of output is appropriate form for approximating posterior probability ies from exponential families.

- **Practical Consequences**
  - Practical results suggest that networks do a decent job of probability estimation.
  - Networks are better at probability estimation than competing non-parametric models (e.g., near-neighbor, decision tree methods).

HYBRID **HMM/NEURAL** NETWORK MODELS

- **Duality of Observed data term:**
  - Update equations are valid when terms are scaled by constants
  - By Bayes' rule can write:

$$p(\omega_j^t|\Phi_t) = \frac{1}{K_t}\frac{p(\omega_j^t|\theta^t)}{p(\omega_j)}\sum_{i=1}^{m} a_{ij}p(\omega_i^{t-1}|\Phi_{t-1})$$

- **Estimation of $p(\omega_j^t|\theta^t)$ terms:**
  - $p(\omega_j^t|\theta_t)$ = posterior probability of class j given inputs θ_t.
  - Train a feedforward network with MSE or GE loss functions.
  - Simple **12** input, **8** hidden units, **4** output units (normal+ 3 fault conditions) feedforward network trained using conjugate gradient descent.
  - Cross-validation indicated that network size was not important.

HYBRID HMM/NN FOR FAULT DETECTION

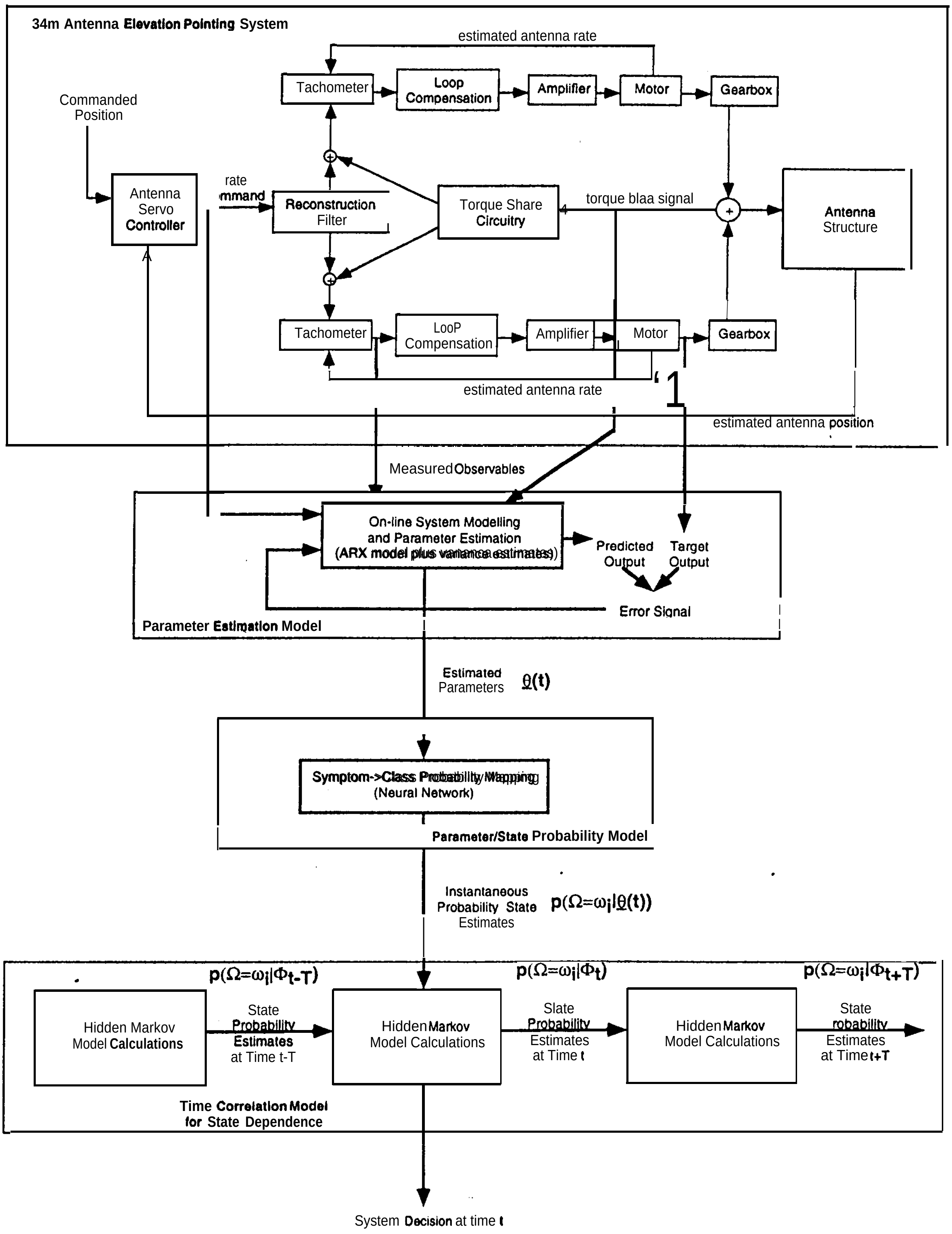
. **Key Ingredients:**

- States are known a priori, correspond to distinct physical states of system, e.g., normal, fault conditions.
- Observable-state conditional dependencies, $p(\omega_j^t|\theta_t)$ are learned by neural network from suit ably generated training data.
- HMM transition probabilities are a function of system MTBF and other long term charact erist its:

$$a_{11} = 1 - \frac{\tau}{\text{MTBF}}$$

- Only a single model is used: purpose is to infer "hidden" state sequence. i.e.,

estimate $p(\omega_j^t|\Phi_t)$


34m Antenna Elevation Pointing System
estimated antenna rate
Tachometer
Loop Compensation
Amplifier
Motor
Gearbox
Commanded Position
Antenna Servo Controller
rate
mmand
Reconstruction Filter
Torque Share Circuitry
torque blaa signal
Antenna Structure
Tachometer
LooP Compensation
Amplifier
Motor
Gearbox
estimated antenna rate
estimated antenna position
Measured Observables
On-line System Modelling and Parameter Estimation (ARX model plus variance estimates)
Predicted Output
Target Output
Error Signal
Parameter Estimation Model
Estimated Parameters θ(t)
Symptom->Class Probability Mapping (Neural Network)
Parameter/State Probability Model
Instantaneous Probability State Estimates p(Ω=ωi|θ(t))
p(Ω=ωi|Φt-T)
p(Ω=ωi|Φt)
p(Ω=ωi|Φt+T)
Hidden Markov Model Calculations
State Probability Estimates at Time t-T
Hidden Markov Model Calculations
Slate Probability Estimates at Time t
Hidden Markov Model Calculations
State robability Estimates at Time t+T
Time Correlation Model for State Dependence
System Decision at time t

SUMMARY OF EXPERIMENTAL RESULTS OBTAINED AT DSS-13 34M ANTENNA IN REAL-TIME UNDER NORMAL AND FAULT CONDITIONS

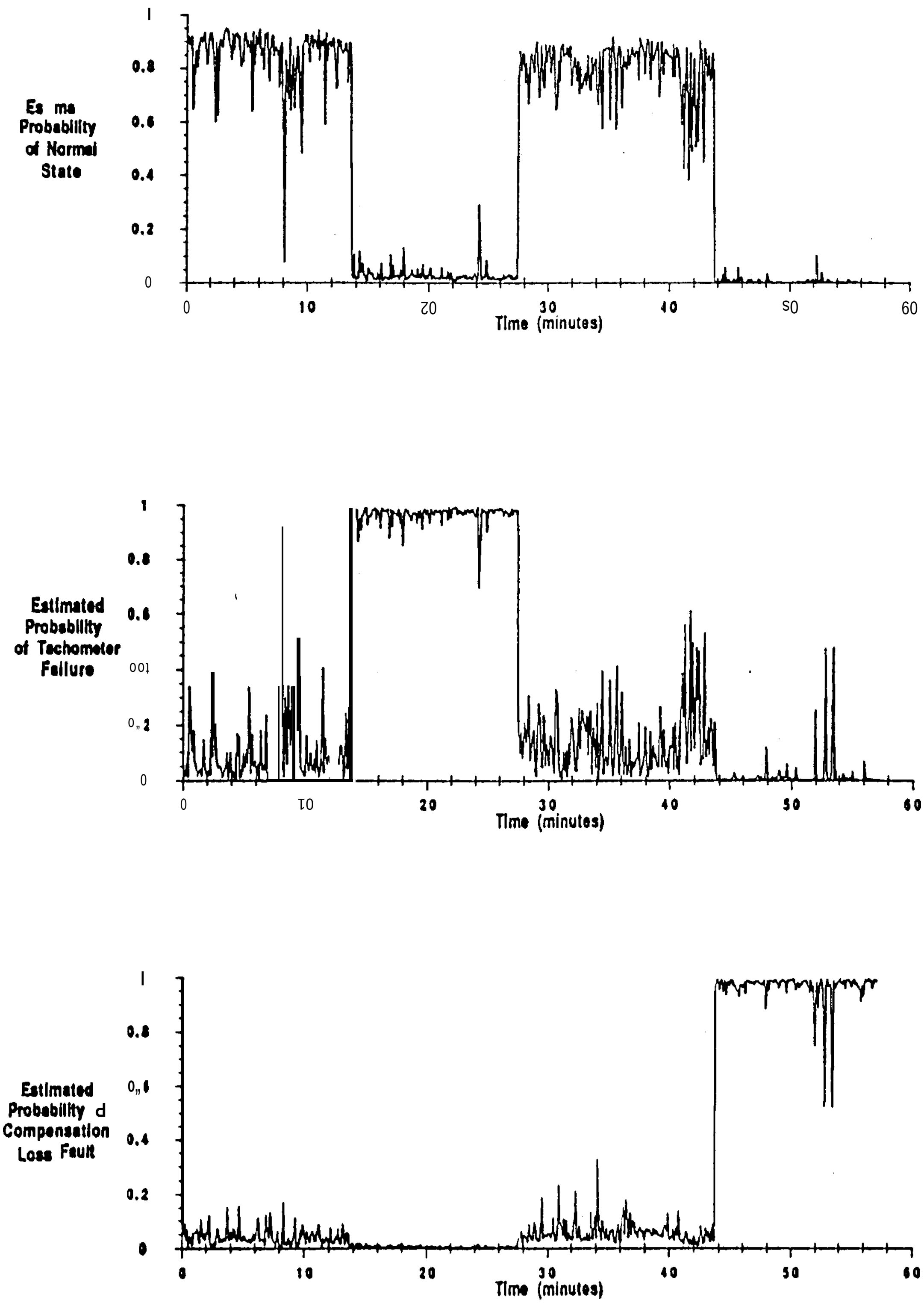
Class	Without Markov model		With Markov model	
	Gaussian	Neural	Gaussian	Neural
Normal Conditions	0.36	1.72	0.36	0.00
Tachometer Failure	27.78	0.00	2.38	0.00
Compensation Loss	34.21	0.00	43.16	0.00
All Classes	16.92	0.84	14.42	0.00

Percentage misclassifation rates for Gaussian and neural models both with and without Markov component.

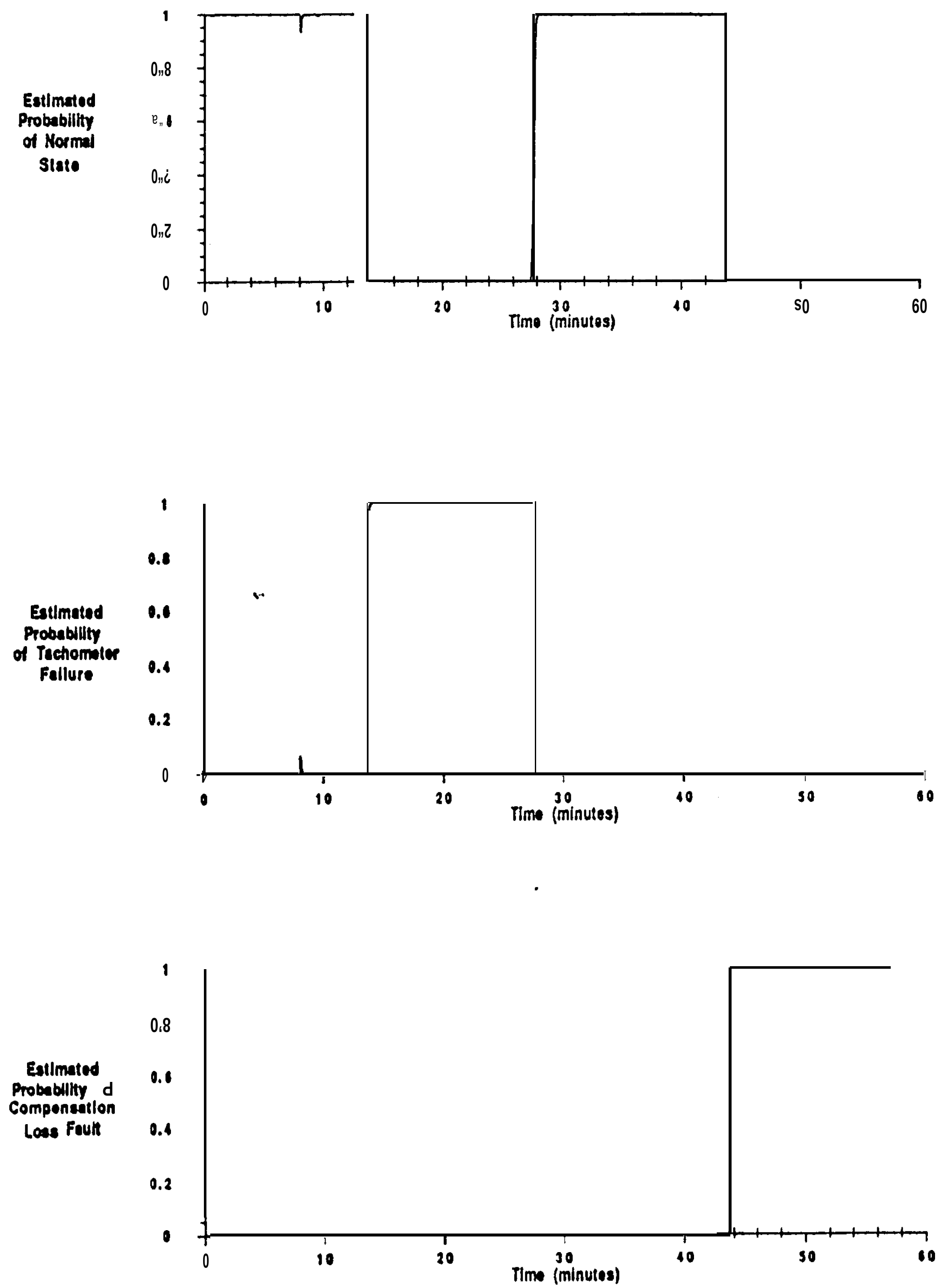
Class	Without Markov model		With Markov model	
	Gaussian	Neural	Gaussian	Neural
Normal Conditions	-2.44	-1.97	-2.46	-4.24
Tachometer Failure	-0.40	-3.52	-0.42	-4.22
Compensation Loss	-0.82	-3.48	-1.39	-4.71
All Classes	-0.87	-2.29	-1.02	-4.34

Logarithm of Mean Squared Error for Gaussian and neural models both with and without Markov component (more negative is better).

Without hidden Markov model



With hidden Markov model



DETECTING NOVEL STATES

- **Basic Problem**
  - In fault detection, it is highly likely that the set of known faults are *not exhaustive.*

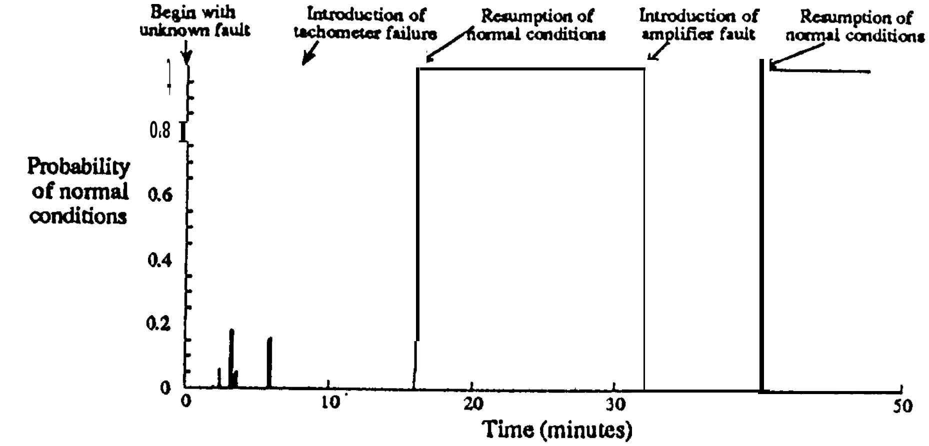
- **Solution**
  - Let ω_{m+1} be the "novel" state
  - Let $p_d(\omega_i\, x, \omega_{1,\ldots,m})$ be the discriminative probabilities among the m known states
  - If we can define, $p(x|\omega_{1,\ldots,m})$, $p(x\, \omega_{m+1})$, and $p(\omega_{m+1})$, then

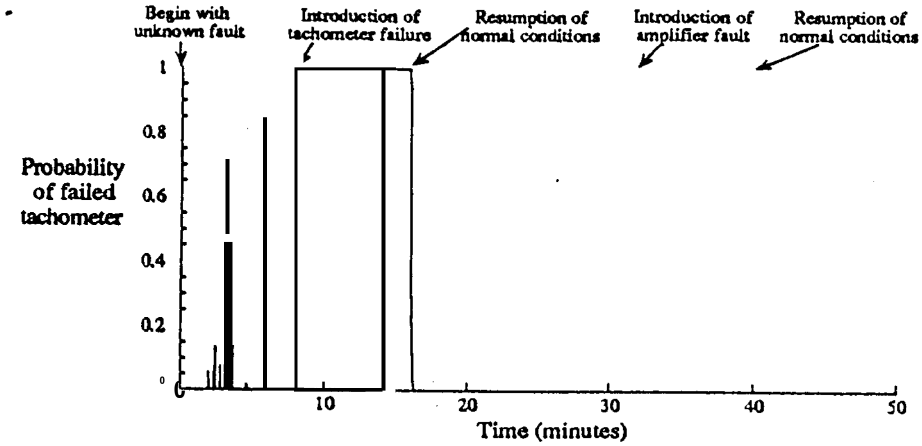
$$p(\omega_i|x) = p_d(\omega_i|x, \omega_{1,\ldots,m})p(\omega_{1,\ldots,m}|x)$$

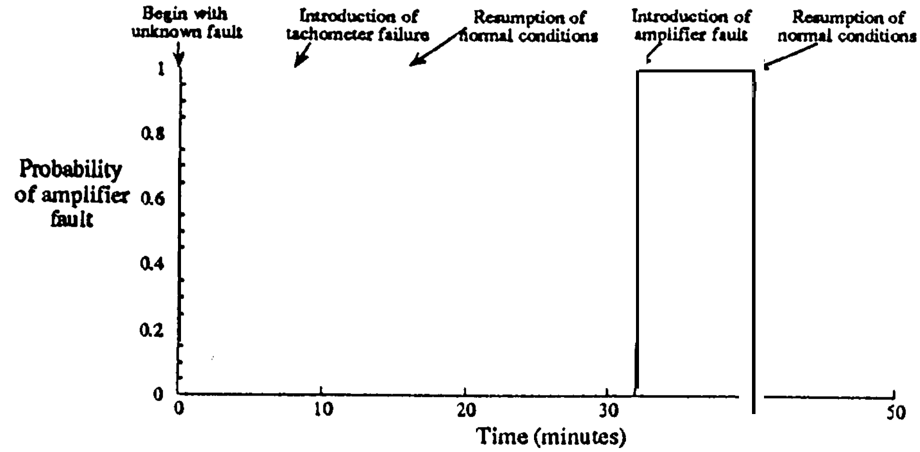
and

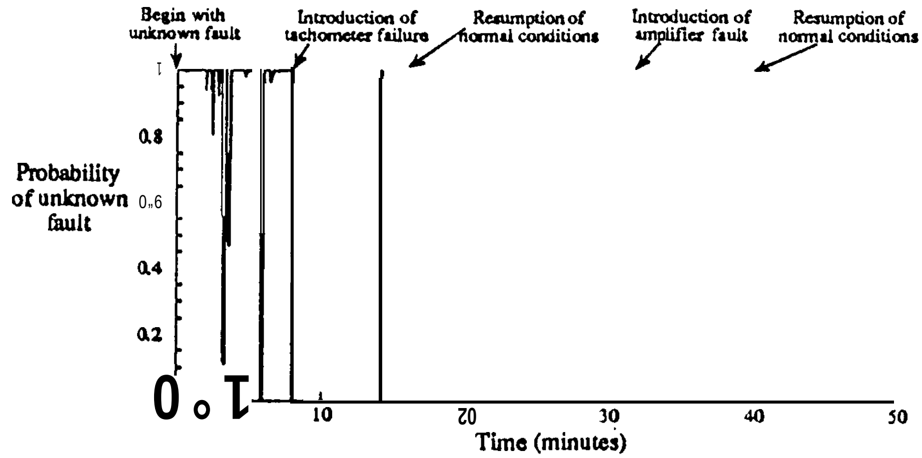
$$p(\omega_{m+1}|x) = 1 - p(\omega_{1,\ldots,m}|x)$$

  - $p(x\, \omega_{m+1})$ is determined a priori, e.g., a non-informative prior density.


Begin with unknown fault
Introduction of tachometer failure
Resumption of normal conditions
Introduction of amplifier fault
Resumption of normal conditions
Probability of normal conditions
Time (minutes)


Begin with unknown fault
Introduction of tachometer failure
Resumption of normal conditions
Introduction of amplifier fault
Resumption of normal conditions
Probability of failed tachometer
Time (minutes)


Begin with unknown fault
Introduction of tachometer failure
Resumption of normal conditions
Introduction of amplifier fault
Resumption of normal conditions
Probability of amplifier fault
Time (minutes)


Begin with unknown fault
Introduction of tachometer failure
Resumption of normal conditions
Introduction of amplifier fault
Resumption of normal conditions
Probability of unknown fault
Time (minutes)

CONCLUSION

- **Summary**
  - Neural networks plus HMMs can provide excellent detection and false alarm rate performance in fault detection applications
  - Modified models allow for novelty detection

- **Key Contribution of Neural Network Model:**
  - Excellent non-parametric discrimination capability
  - A good estimator of posterior state probabilities, even in high-dimensions, thus, can be embedded within overall probabilistic model (HMM).
  - Simple to implement compared to other non-parametric models.

- **Application Status:**
  - NN/HMM monitoring model is currently being integrated with the new DSN antenna controller software: will be online monitoring a new DSN 34m antenna (DSS-24) by July.