4. Results

The most relevant results of the analysis are shown and organized in this chapter as follows. As a first step, the number of states of the model is decided. Then, a model selection is performed for the given dataset in order to find which model is the most appropriate one, and which parameter should have a switching effect in the model. An analysis of residuals is carried out with the graphical in a later section as a means to validate the models. Next, the results of a non-parametric analysis are presented, and a comparison between Markov switching autoregressive model and the non-parametric analysis are made. The last two sections report the results of predicting a state of the new observations in each dataset, and a usage of a predict function using a simulated data.

4.1. States

To estimate the set of necessary parameters, an *MSwM*[1] package in R is used. More details about the package can be found in Appendix B.

A complete linear Markov switching autoregressive model in this thesis framework is defined as

$$\begin{aligned} y_t =& \beta_{0,S_t} + \beta_{RrcConnectionSetupComplete,S_t} X_{RrcConnectionSetupComplete,t} \\ & + \beta_{Paging,S_t} X_{Paging,t} + \beta_{X2HandoverRequest,S_t} X_{X2HandoverRequest,t} \\ & + \beta_{DuProdName,S_t} X_{DuProdName,t} + \beta_{Fdd/Tdd,S_t} X_{Fdd/Tdd,t} \\ & + \beta_{NumCells,S_t} X_{NumCells,t} + \phi_{1,S_t} y_{t-1} + \varepsilon_{S_t} \end{aligned} \tag{4.1}$$

Markov switching autoregressive model is performed for each dataset with every parameter in the model has switching effects i.e., the coefficients can take on different values in different periods. The estimation is made under the assumptions of two or three states $S_t \in S$, where $S = 1, 2, .., k$ and $k = 2$ or 3. These two numbers come from a hypothesis that the state of the CPU utilization might have two states (Normal and Bad, Normal and Good, Bad and Good) or three states (Normal, Bad, and Good). During the estimation, a normality assumption is also applied to the distribution of residuals.

[1]https://cran.r-project.org/web/packages/MSwM/index.html

Before performing the Markov switching autoregressive model, a standard linear regression model is fitted to the dataset first. It is found that one coefficient in the dataset of software release L16A is not defined because of singularity. Hence, DuProdName variable is dropped from Equation 4.1. BICs from fitting the Markov switching autoregressive model are shown in Table 4.1.

Table 4.1.: BIC of the model with two and three states. The left column gives the different datasets.

Software release	BIC	
	$k = 2$	$k = 3$
L16A	439.677	417.682
L16B	1,763.507	1,797.259
L17A	1,189.061	1,199.075

For the software release L16A, BIC suggests that the three-state Markov switching autoregressive model gives a better fit in comparison to the two-state model. Figure 4.1 presents that the Markov chain remains in State 1 for an extensive period of time before it switches to State 2. When the chain is in State 2, it stays there only a short time and then quickly moves back to State 1. There are a few switches between these two states in Figure 4.1. On the other hand, it is visible that there are more switches between states in Figure 4.2. One noticeable thing is that State 2 in the two-state model seems to be defined as State 1 in the three-state model instead. Moreover, the periods of State 1, which has a rather long duration, in the two-state model now contain plenty of switches between states in the three-state model.

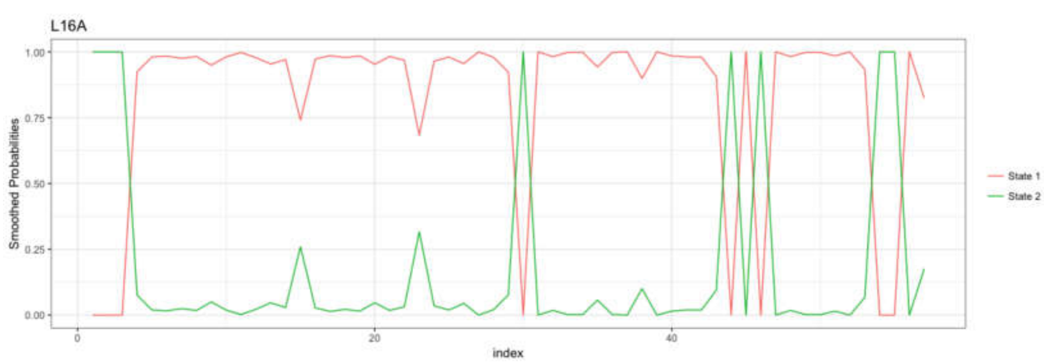

Figure 4.1.: The smoothed probabilities of the software release L16A with two-state model

According to Table 4.1, the Markov switching autoregressive models with two states for the remaining two software releases, L16B and L17A, yield better results in favor of lower BICs.

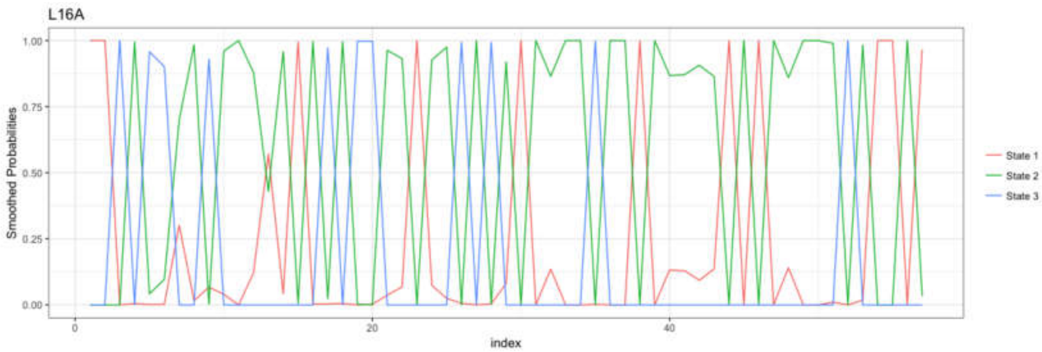

Figure 4.2.: The smoothed probabilities of the software release L16A with three-state model

In Figure 4.3, the Markov chain has several periods where it switches back and forth between the two states of the software release L16B. The durations of being in State 2 have a longer length compare with the durations of staying in State 1. Although the chain temporarily stays in State 1, it remains in this state for a few moments in the middle of the time period (observation 91-99 and 101-114) before turning to State 2. Apparently, there are more switches between states in the three-state model, especially in the beginning, middle, and at the end of the period. Figure 4.4 shows that the chain remains in State 3 over a considerable period as can be seen throughout observation 15-39, 42-67, and 140-170.

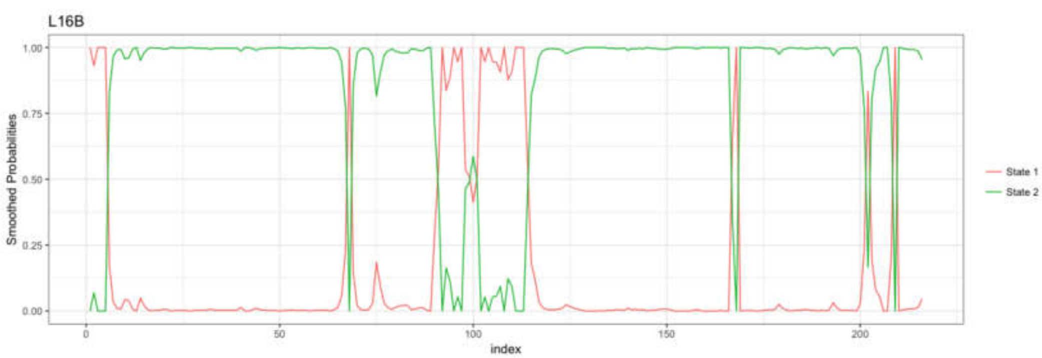

Figure 4.3.: The smoothed probabilities of the software release L16B with two-state model

There are a number of switches between states in the two-state model of the software release L17A. In Figure 4.5, when the Markov chain is in State 1, it continues to stay in its state for a while before leaving to State 2. Furthermore, it can be seen that the chain has a fairly short duration for being in State 2. After the chain visits State 2, it instantly switches back to State 1. Figure 4.6 presents the chain which has many switches between State 1 and State 2 in the first half of the time period. The chain for the three-state model stays in State 2 significantly long duration. From the plot,

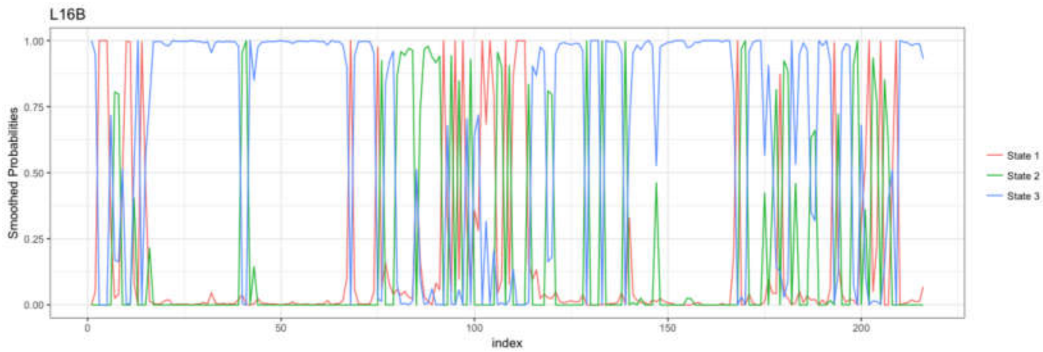

Figure 4.4.: The smoothed probabilities of the software release L16B with three-state model

it begins from observation 104 until 129 which is the end of the period.

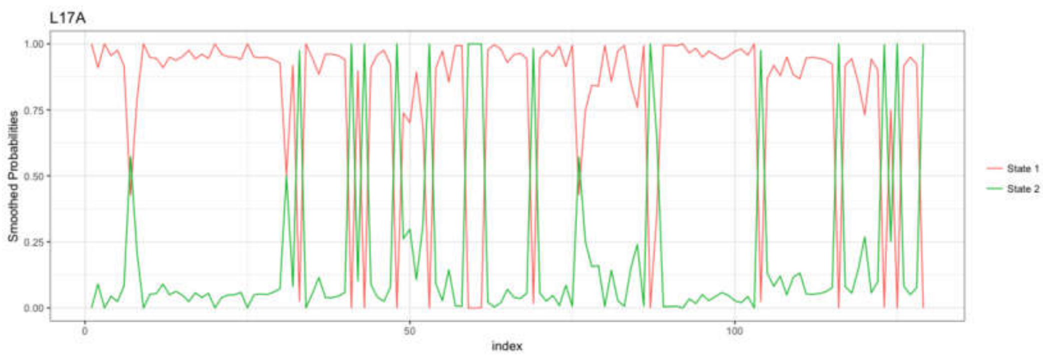

Figure 4.5.: The smoothed probabilities of the software release L17A with three-state model

The outputs from the models along with plots provide more interpretable results when defining the model with three states in the software release L16B and L17A. In regards to this, the three-state models for each software release are further analyzed in the thesis.

4.2. Switching coefficients

The fitted Markov switching autoregressive models in sec. 4.1 only have state-dependent parameters i.e., coefficients of the regression with switching effects. Apparently, each coefficient can have either a switching or non-switching effect. A hypothesis for the switching/non-switching coefficients is that the variables considered as the test environment are possible to have non-switching effects. Markov switching autoregressive models are applied to each dataset again, but this time all combinations