

# Automated Analysis of Room Performance

Michael Novak

June 5, 2012

# Contents

<b>A Data Visualization</b>	<b>2</b>
A.1 Data . . . . .	2
A.2 Power & Cooling . . . . .	3
A.3 Chillers . . . . .	3
A.4 Data Mining . . . . .	4
<b>B Tables for Per-Node Energy &amp; Cooling Metrics</b>	<b>5</b>
<b>C Low-Density Workload Metrics</b>	<b>8</b>
<b>D Low-Density Workload : Chiller Clustering on KW</b>	<b>13</b>
<b>E Low-Density Workload : Chiller Clustering on Loads</b>	<b>16</b>
<b>F Low-Density Workload : Chiller Clustering on COP</b>	<b>19</b>
<b>G Low-Density Workload : Chiller Clustering on Chilled Water-Temperature Delta</b>	<b>22</b>
<b>H Low-Density Workload : Chiller Clustering on Condenser Water-Temperature Delta</b>	<b>25</b>
<b>I High-Density Workload Chiller Metrics</b>	<b>28</b>
<b>J High-Density Workload : Chiller Clustering on KW</b>	<b>47</b>
<b>K High-Density Workload : Chiller Clustering on Loads</b>	<b>63</b>
<b>L High-Density Workload : Chiller Clustering on COP</b>	<b>79</b>
<b>M High-Density Workload : Chiller Clustering on Chilled Water-Temperature Delta</b>	<b>95</b>
<b>N High-Density Workload : Chiller Clustering on Condenser Water-Temperature Delta</b>	<b>111</b>

## Appendix A

# Data Visualization

I've prototyped an analysis suite in Haskell (see [analysis.hs](#)) which produces quantitative visualizations of various energy related metrics concerning the given RAWDATA, described below. A temporal data-mining technique is used to produce a novel visualization of cluster overlays on the time-series data for the Chiller metrics, in an attempt to discover ‘motifs’ (inspired by work found in [3]).

### A.1 Data

- Postmortem data gotten from `/u/karavan/Public` at `rita.cat.pdx.edu`
- 2011-05-05—The Low Density Workload—`LD_A1_56p_2ppn_28n_IO-BASIC_even_RAWDATA`
- 2011-04-25—The High Density Workload—`HD_A1_224p_8ppn_28n_RAWDATA`
- This data seems to correspond to the experiments in [2].
- [2, p. 436]

In the HD schedules, the 224 processes ran on 28 nodes (eight processes per node) all housed in a single rack.

- [2, p. 436]

In the low density LD schedules, the 224 processes executed on 112 nodes, with two processes per node, and the processes were spread across racks B1, B2, B3, and B4.

- [2, p. 436]

Low Density Even Distribution – In this set, we used racks B1, B2, B3, and B4; and we scheduled two MPI tasks per node, using all of the nodes in all four racks.

- [2, p. 436]

The nodes are connected via a DDR InfiniBand 1-layer fat tree; one rack (A2) contains the networking equipment and seven racks (A1, A3–4, B1–4) are for the compute nodes.

- [2, p. 437]

*Power.* We collect power per rack, at 10 second intervals. This is converted by FRED to kWh.

- [2, p. 437]

*Cooling.* Each spray-cooled rack has a Thermal Management Unit (TMU) which contains pumps, a liquid-to-liquid heat exchanger, and control electronics.

- [2, p. 436]

All of the power and cooling data measured by FRED [Fundamental Research in Energy efficient Data centers, an analysis software tool developed at PNNL] sensors is collected into a central FRED database, using an independent data network. This is significant because the room environment data collection does not perturb the running application, and the data itself does not drive up the scaling requirements for the application performance measurement tool.

- The application and system level data for each trial (t01–03) are in the trial directories: t1, t2, t3 (we don't really need this information).

## A.2 Power & Cooling

Tables in Appendix B show power consumption, in kWh (7.63¢ per kWh, in Oregon), for the racks used in the LD and HD trials. Note: the data is badly corrupted by faulty sensor readings; especially for node-level temperature readings for CPUs and air, which gave negative, and ludicrously high, temperature values—these false readings had to be filtered from the true readings. For CPU temperature the filtering range was  $72 < \text{temp} < 150$ ; for Node air temperature the filtering range was  $0 < \text{temp} < 40$ . So the average temperatures do not include every node in every rack; see the node counts.

The figures in Appendix C include TMU utilization: the degree of cooling which the TMU provided, captured by the water-temperature-delta metric; and the mass flow rate of water, captured by the manifold pressure metric. TMU utilization metrics were collected by FRED at 10 second intervals; so, for simplicity, each trial's time series starts at 0 and is incremented accordingly.

The TMU utilization metrics for the HD dataset were erroneous. Hence the ‘motif’ visualization experiments (in the Figures) focus only on Chiller metrics.

## A.3 Chillers

Within the cooling infrastructure, most of the energy is spent on chillers, which refrigerate the coolant—water, in our case—used to extract heat from the equipment in the data center. The following metrics, derived from [3], are displayed in the Figures below. Chiller utilization measurements were collected by FRED at 30 second intervals; so, for simplicity, each trial's time series (in the Figures) starts at 0 and is incremented accordingly. Note: only three chiller units ( $C_1, C_2, C_4$ ) were used in the LD trials, and only two ( $C_1, C_4$ ) were used for the HD trials—as evidenced by KW consumption.

- **IT cooling load.** This is the amount of heat that is generated (and thus needs to be dissipated) at a data center. It is approximately equivalent to the power consumed by the equipment since almost all of it is dissipated as heat. It is commonly specified in kilowatts (KW).
- **COP.** The coefficient of performance (COP) of a chiller unit indicates how efficiently the unit provides cooling, and, is defined as the ratio between the cooling provided and the power consumed, i.e.,

$$COP_i = \frac{L_i}{P_i}$$

where  $L_i$  is the cooling load on the  $i$ th chiller unit and  $P_i$  is the power consumed by it.

- **Chiller utilization.** Chiller utilization depends on the degree of cooling provided; i.e., the difference between the inlet and outlet water temperatures (see CHILLER WATER-TEMP DELTA and CONDENSER WATER-TEMP DELTA in the Figures below).

## A.4 Data Mining

If only we had access to more data...

- It would be nice if FRED measurements were stored in a NoSQL graph database. A NoSQL database would be much faster than PostgreSQL. And having the data structured as a graph seems like it would make the data easier to navigate.
- The temporal data-mining technique of overlaying clusters on the time series, described in [3, 4], was tested on Chiller data. Though, it was difficult to find motifs at such a fine granularity, with our limited data.
- [4, p. 34:7]

Motifs are repetitive patterns of occurrence in time-series data. In understanding multivariate time-series data about chiller utilizations, we seek to identify motifs that underly how different chillers are involved in meeting the varying demand posed by data centers. We would like to identify regions of time-series progression that demonstrate better/improved sustainability measures than others.

- [3, pp. 1308–1309]

A multivariate time series  $T = \langle t_1, \dots, t_m \rangle$  is an ordered set of real-valued vectors of a particular variable. Each real-valued vector  $t_i$  captures the utilizations across all the chiller units.

- You look at the time series to detect motifs, then see if they are captured by clustering.
- [4, p. 34:12]

First, the time information is stripped from the data and clustering is performed with number of clusters,  $k = 5$ . The cluster transitions are overlaid in the plot. These transitions are used to encode the multivariate numeric data into symbolic form and serve as the input to frequent episode mining. One episode is discovered which occurs five times and this episode is unpacked into the original data and overlaid on the dataset as shown. This serves as an example of a motif that we embedded and were able to uncover.

[4, p. 34:6] High amplitude and frequent variations in utilization due to varying load or some failure condition result in decreased lifespan, and, thus, need to be minimized.

- Algorithms can be developed for processing multivariate time-series data to characterize sustainability measures of the patterns mined.

For clustering, I'm using ELKI (release 0.4.1 [1]). The algorithms being used are:  $k$ -means and expectation maximum (EM). I've labelled the input data in such a way that the time-series information is retained after clustering; hence the cluster transitions can be overlaid within the time series across the three trials. A Haskell script formats metric data and feeds it to ELKI; ELKI produces clustering files; Haskell takes the clustering files and generates gnuplot scripts, which are then rendered by gnuplot. Meaningful analysis might be carried out with more data (e.g. [4, pp. 34:14–34:16 (see Tables I–V)]), and a more advanced data-mining infrastructure could be built (e.g. the CAMAS framework in [4, p. 34:8 (see Fig 5.)]).

## Appendix B

### Tables for Per-Node Energy & Cooling Metrics

## Low-Density Workload

---

PowerUnit	PowerKWH	A1	A3	A4	B1	B2	B3	B4
<b>t01</b>		1.28	1.03	1.07	1.11	1.17	1.31	1.27
<b>t02</b>		1.28	1.03	1.06	1.11	1.17	1.31	1.27
<b>t03</b>		1.30	1.05	1.09	1.13	1.19	1.33	1.35
Total	PowerUnit	1	1	1	1	1	1	1

Total kWh increase.

CPU	Temp	A1	A3	A4	B1	B2	B3	B4
<b>t01</b>		90.49	82.88	82.94	99.91	90.40	101.47	108.81
<b>t02</b>		90.49	82.88	82.94	99.91	90.40	101.47	108.81
<b>t03</b>		90.49	82.88	82.94	99.91	90.40	101.47	108.81
Total	CPU	37	40	4	5	6	4	5

Average Per-Node, Per-CPU, CPU Tempurature Average for Each Rack (within  $72 < \text{Temp} < 150$ )

CPU	Temp	A1	A3	A4	B1	B2	B3	B4
<b>t01</b>		92.61	141.70	85.69	127.22	92.47	112.55	114.63
<b>t02</b>		92.61	141.70	85.69	127.22	92.47	112.55	114.63
<b>t03</b>		92.61	141.70	85.69	127.22	92.47	112.55	114.63
Total	CPU	37	40	4	5	6	4	5

Maximum Per-Node, Per-CPU, CPU Tempurature Maximum for Each Rack (within  $72 < \text{Temp} < 150$ )

NodeAir	Delta	A1	A3	A4	B1	B2	B3	B4
<b>t01</b>		26.10	24.44	26.30	25.51	24.55	23.51	26.39
<b>t02</b>		26.10	24.44	26.30	25.51	24.55	23.51	26.39
<b>t03</b>		26.10	24.44	26.30	25.51	24.55	23.51	26.39
Total	NodeAir	24	24	22	25	23	23	16

Average Per-Node Air Temperature Delta for Each Rack (within  $0 < \Delta\text{Temp} < 40$ )

## High-Density Workload

---

PowerUnit	PowerKWH	A1	A3	A4	B1	B2	B3	B4
<b>t01</b>		13.35	9.89	10.24	10.73	11.12	13.07	14.34
<b>t02</b>		6.87	4.25	4.41	4.56	4.86	5.69	6.14
<b>t03</b>		18.90	12.08	12.48	12.95	13.73	16.13	17.51
Total PowerUnit		1	1	1	1	1	1	1

Total kWh increase.

CPU	Temp	A1	A3	A4	B1	B2	B3	B4
<b>t01</b>		97.18	83.52	81.71	100.15	89.51	94.54	110.43
<b>t02</b>		104.83	83.99	82.30	100.44	89.75	94.22	111.05
<b>t03</b>		116.73	83.89	82.26	100.42	89.68	97.33	111.66
Total CPU		37	41	4	5	6	4	5

Average Per-Node, Per-CPU, CPU Tempurature Average for Each Rack (within  $72 < \text{Temp} < 150$ )

CPU	Temp	A1	A3	A4	B1	B2	B3	B4
<b>t01</b>		107.68	141.97	85.05	127.94	91.73	106.14	120.02
<b>t02</b>		126.13	142.13	85.20	127.94	91.86	106.93	120.95
<b>t03</b>		126.13	142.13	85.20	127.76	91.86	108.96	120.95
Total CPU		37	41	4	5	6	4	5

Maximum Per-Node, Per-CPU, CPU Tempurature Maximum for Each Rack (within  $72 < \text{Temp} < 150$ )

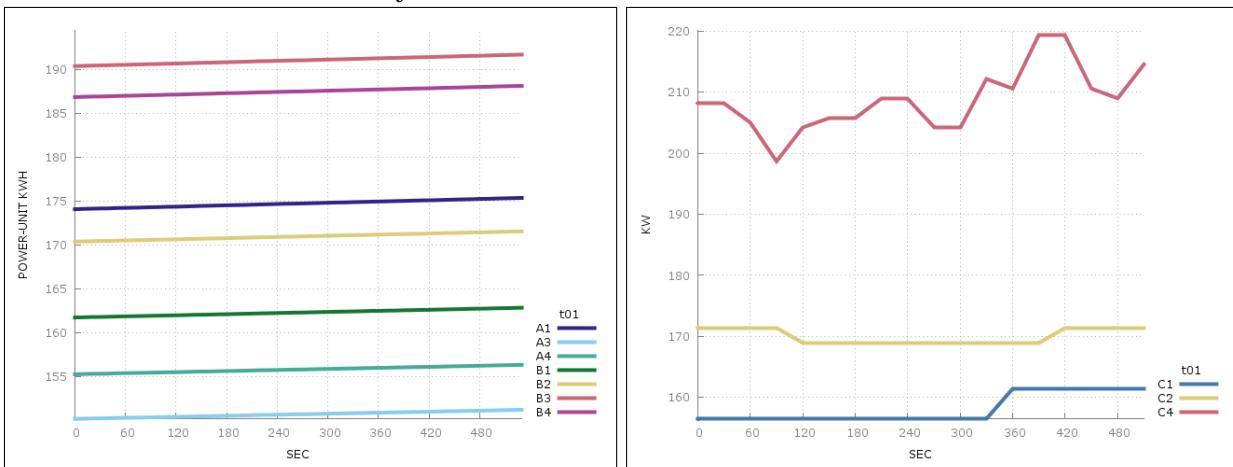
NodeAir	Delta	A1	A3	A4	B1	B2	B3	B4
<b>t01</b>		26.80	26.20	26.62	24.52	25.28	24.37	26.24
<b>t02</b>		27.43	26.06	26.44	24.76	25.28	24.43	26.92
<b>t03</b>		29.16	25.87	26.66	24.16	25.30	24.38	27.17
Total NodeAir		23	23	21	25	23	23	15

Average Per-Node Air Temperature Delta for Each Rack (within  $0 < \Delta\text{Temp} < 40$ )

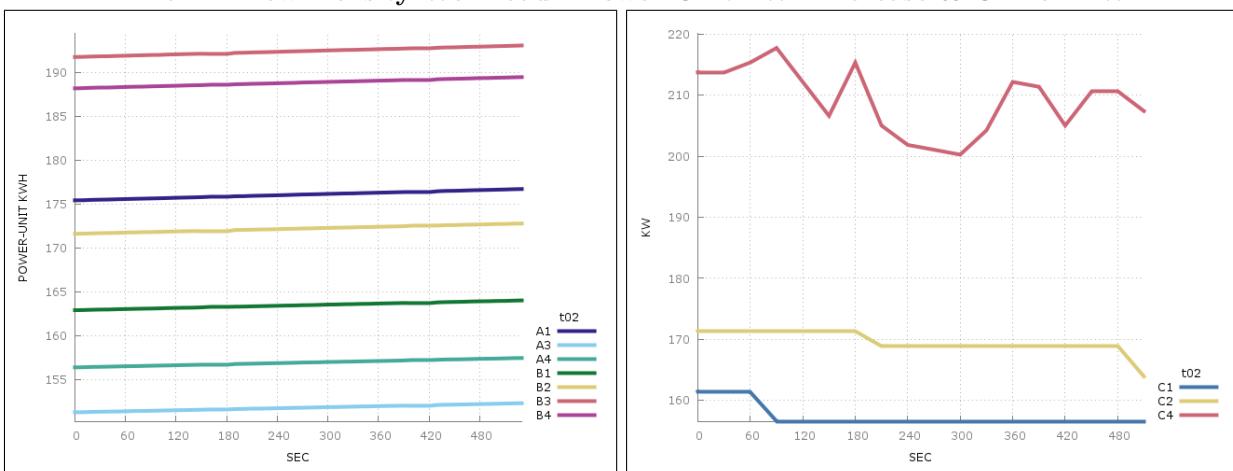
## Appendix C

### Low-Density Workload Metrics

### Trial 1—Low-Density Workload—Power-Unit kWh Increase & Chiller KW



### Trial 2—Low-Density Workload—Power-Unit kWh Increase & Chiller KW



### Trial 3—Low-Density Workload—Power-Unit kWh Increase & Chiller KW

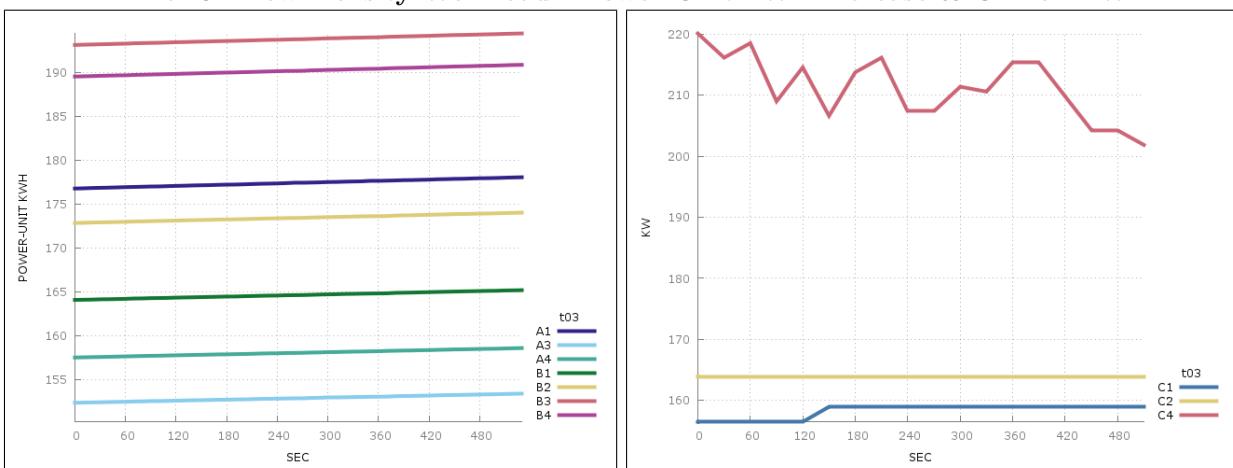
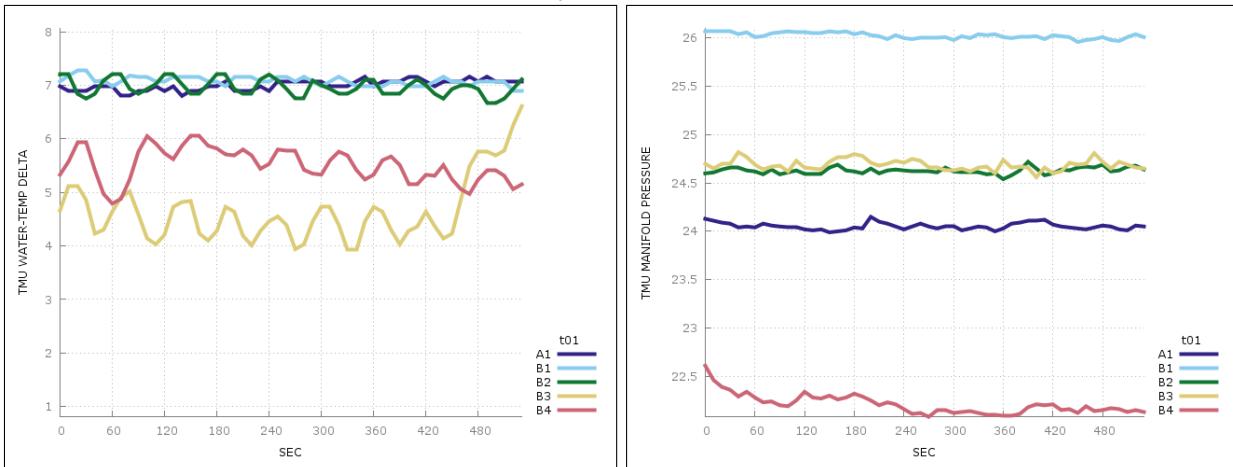
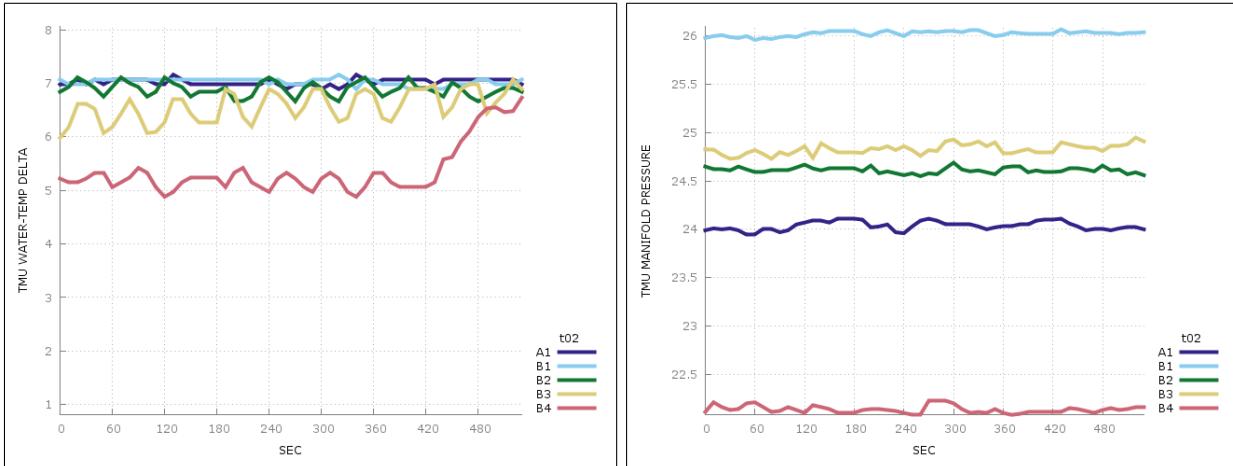


Figure C.1: The Power-Unit kWh increase (left), and the IT cooling load specified in kilowatts (left) for the Chillers in use.

### Trial 1—Low-Density Workload—TMU Utilization



### Trial 2—Low-Density Workload—TMU Utilization



### Trial 3—Low-Density Workload—TMU Utilization

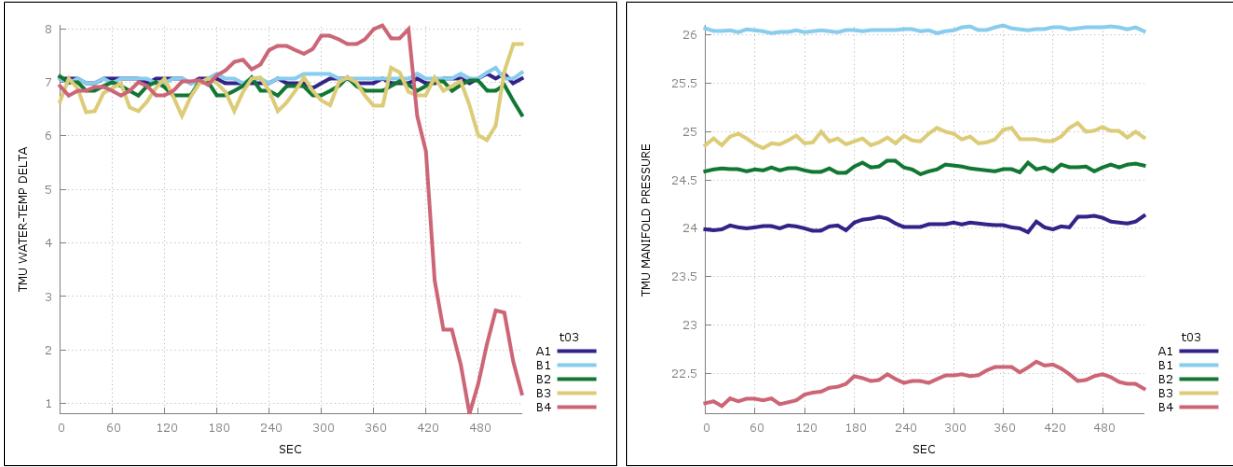
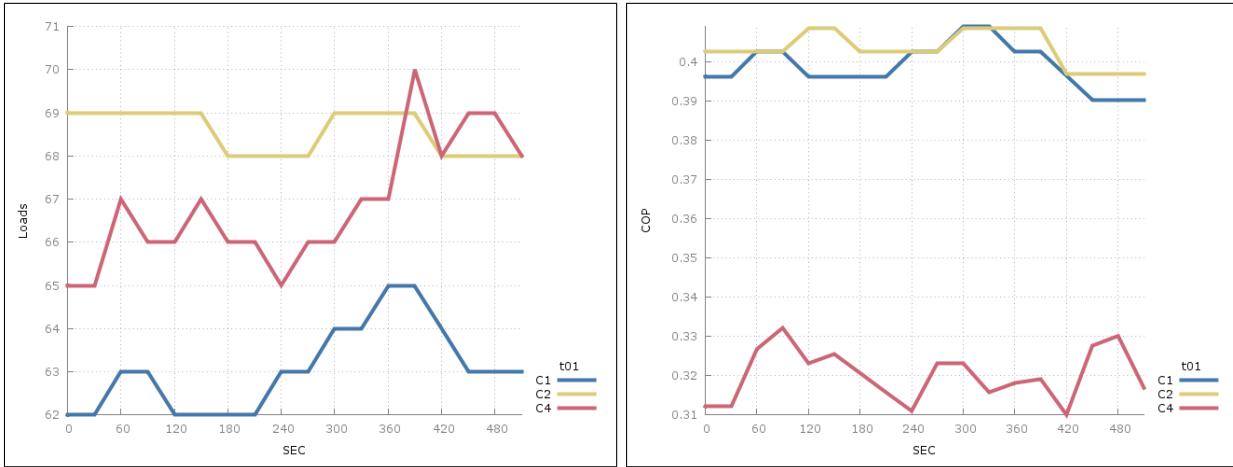
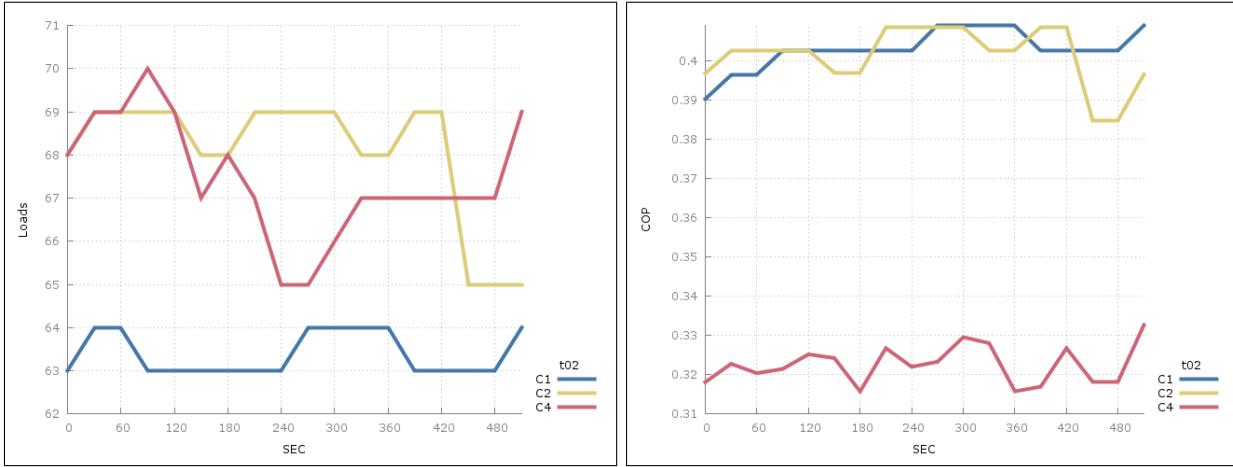


Figure C.2: TMU utilization. The water temperature delta (WTD), which is obtained by subtracting inlet from outlet temperatures, and the pressure of the hot/cold liquid distribution manifold (right).

### Trial 1—Low-Density Workload—Chiller Utilization



### Trial 2—Low-Density Workload—Chiller Utilization



### Trial 3—Low-Density Workload—Chiller Utilization

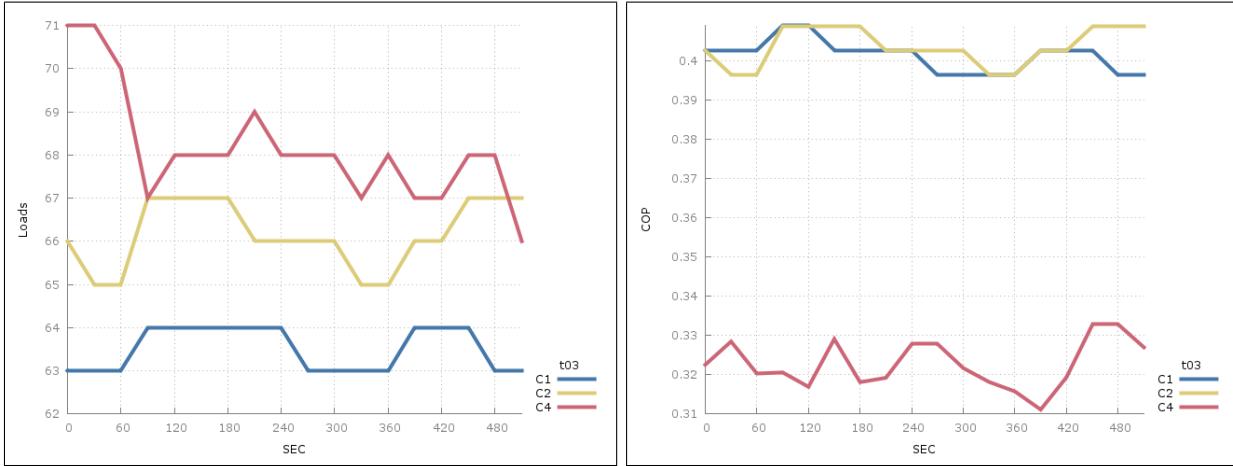
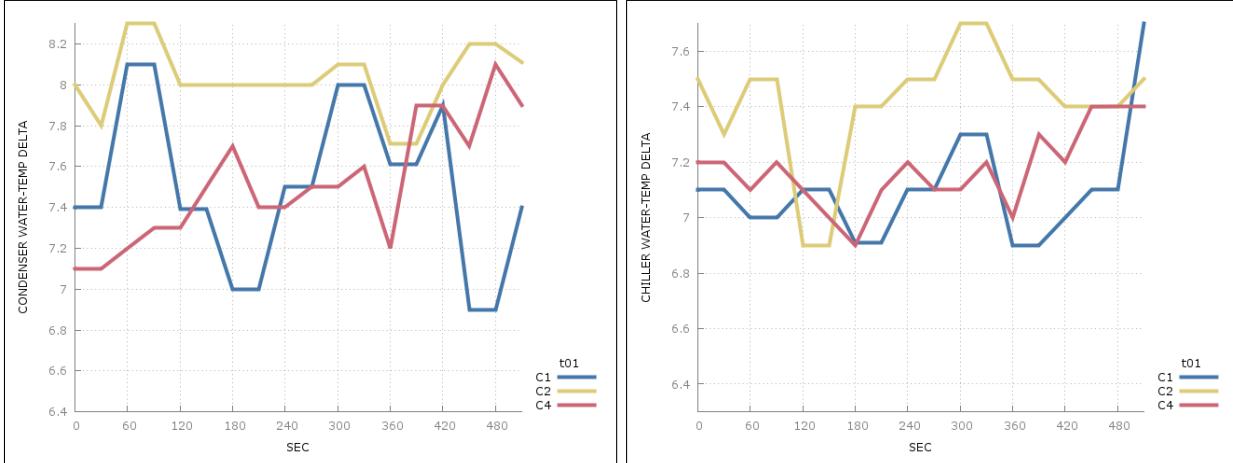
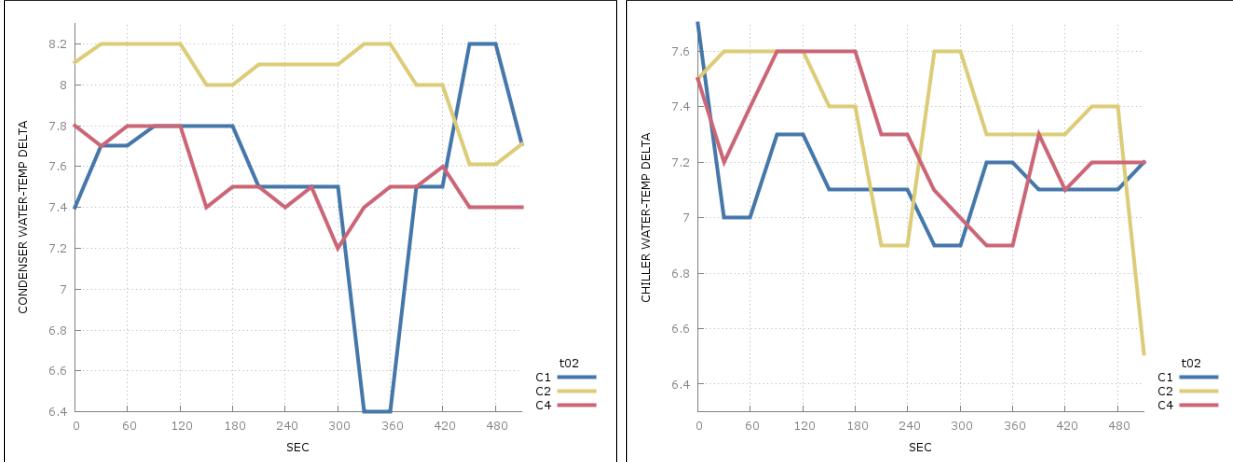


Figure C.3: Chiller Loads (left) and Chiller coefficient of performance (COP, right).

### Trial 1—Low-Density Workload—Chiller Utilization



### Trial 2—Low-Density Workload—Chiller Utilization



### Trial 3—Low-Density Workload—Chiller Utilization

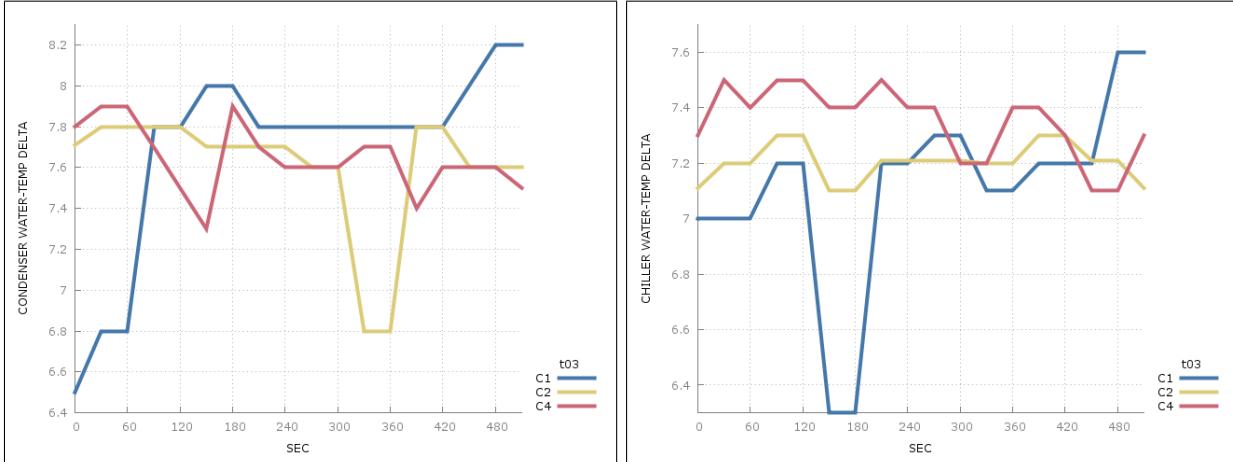
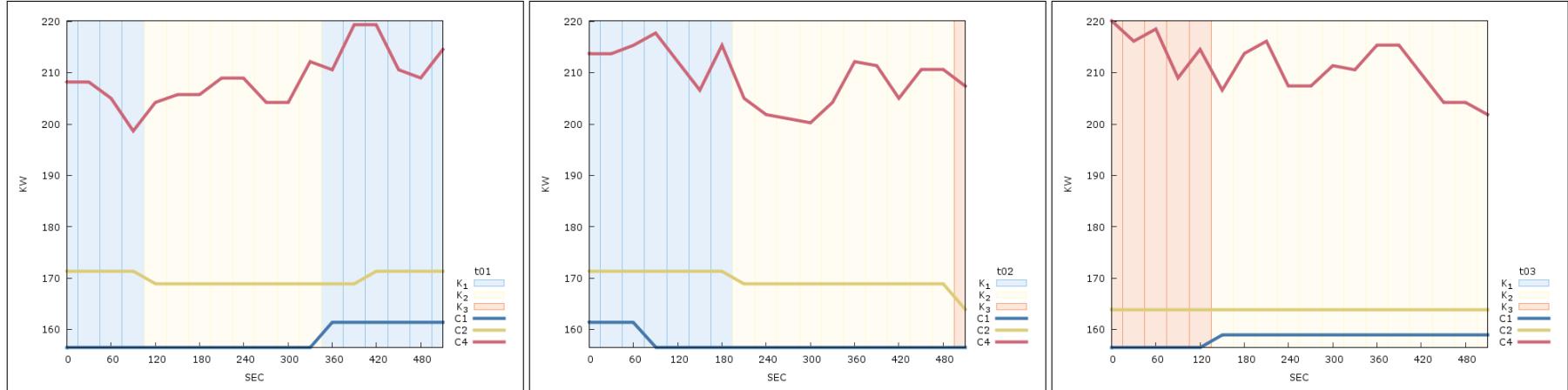


Figure C.4: Chiller utilization. The condenser water-temperature delta ( $LCWT - ECWT$ , left), and the Chiller water-temperature delta ( $ECHWT - LCHWT$ , right).

## Appendix D

# Low-Density Workload : Chiller Clustering on KW

### EM Clustering with $k = 3$



### K-Means Clustering with $k = 5$

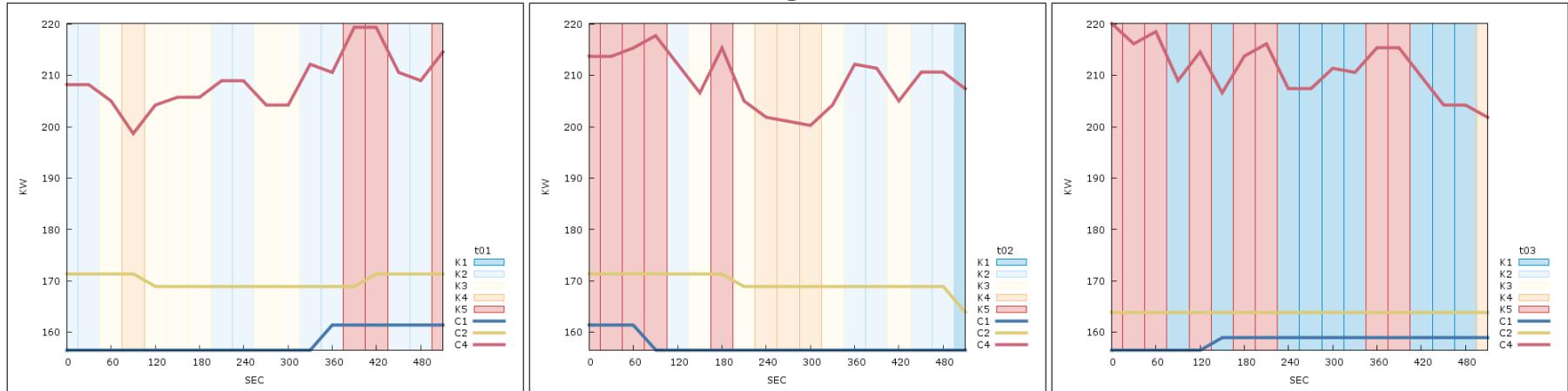
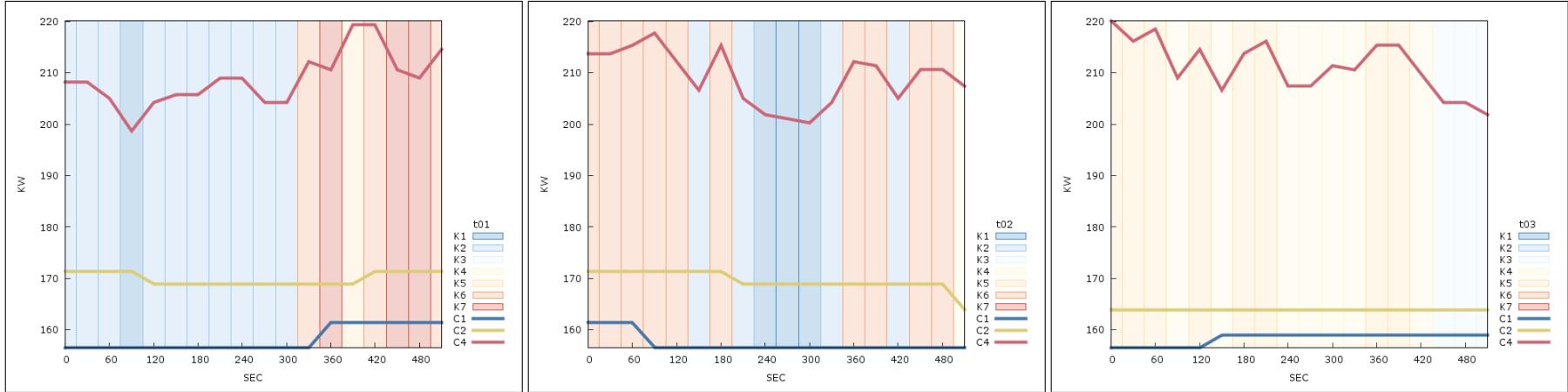


Figure D.1: Low-Density Workload—Chiller KW

### K-Means Clustering with $k = 7$



### K-Means Clustering with $k = 9$

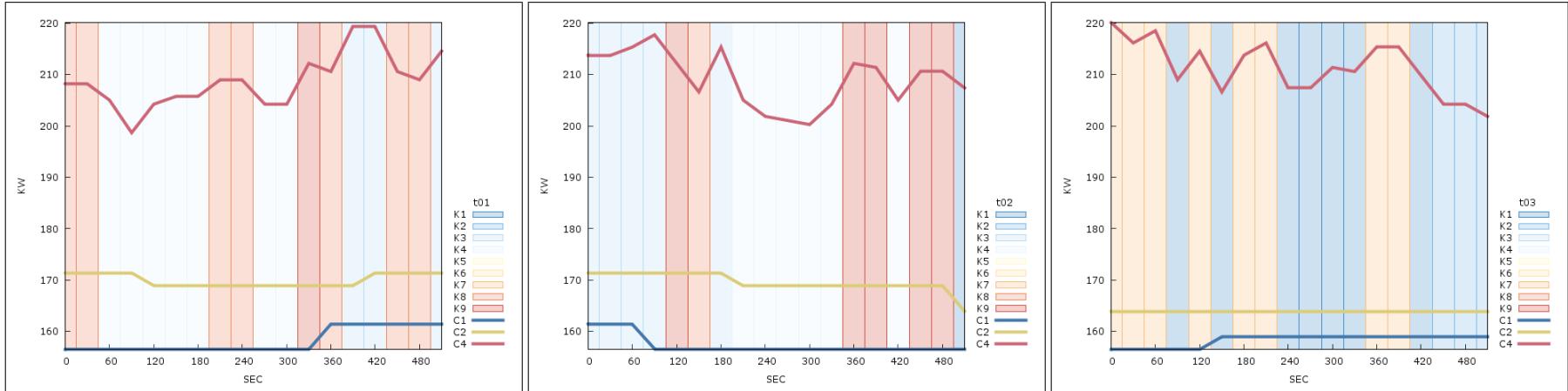
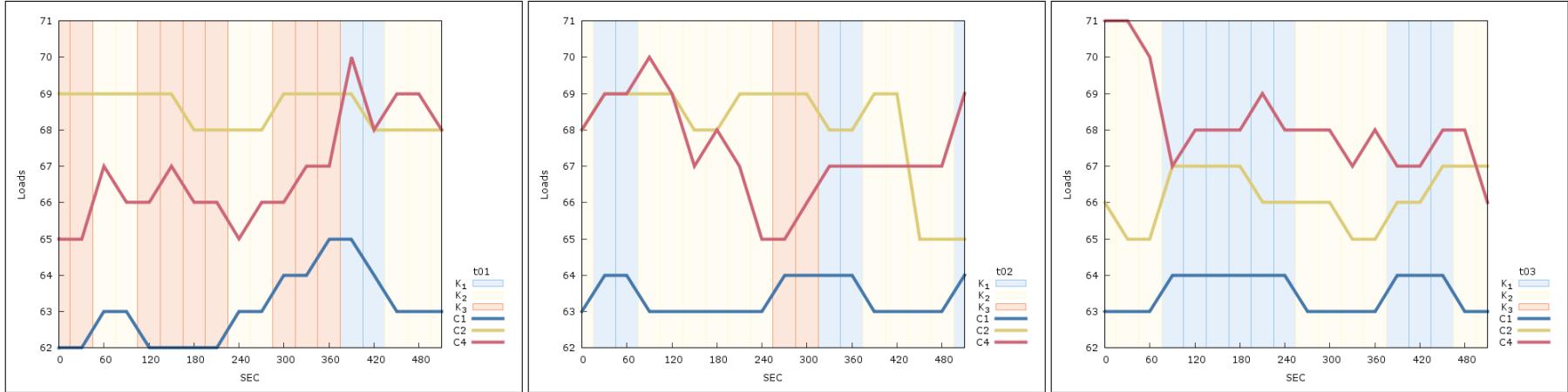


Figure D.2: Low-Density Workload—Chiller KW

## Appendix E

# Low-Density Workload : Chiller Clustering on Loads

### EM Clustering with $k = 3$



### K-Means Clustering with $k = 5$

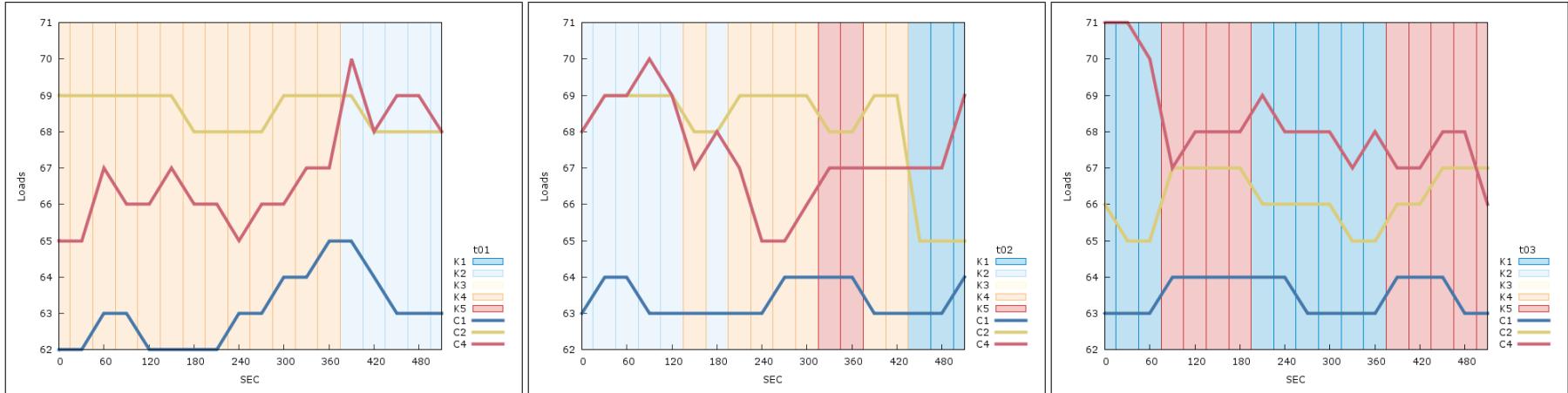
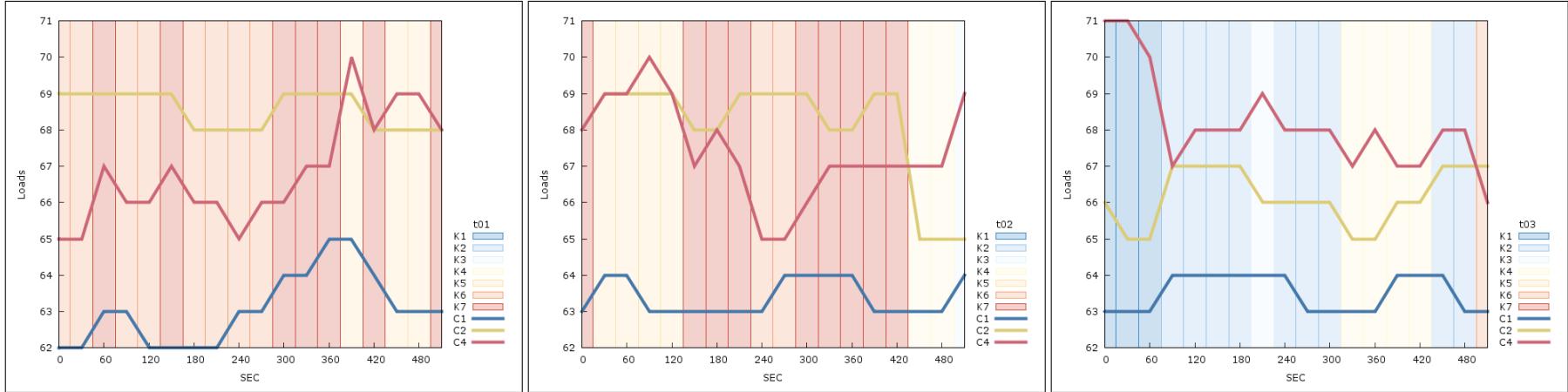


Figure E.1: Low-Density Workload—Chiller Loads

### K-Means Clustering with $k = 7$



### K-Means Clustering with $k = 9$

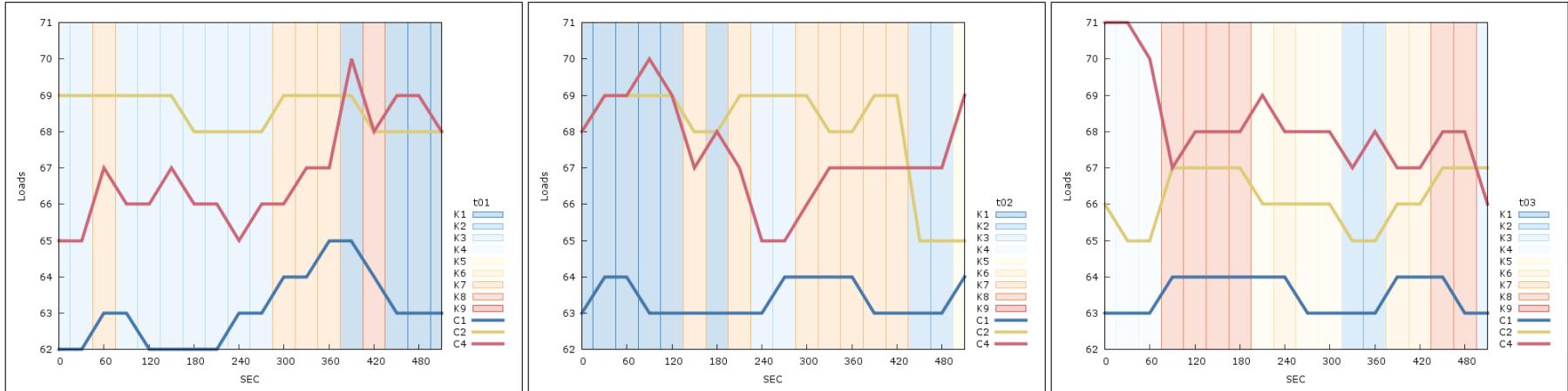
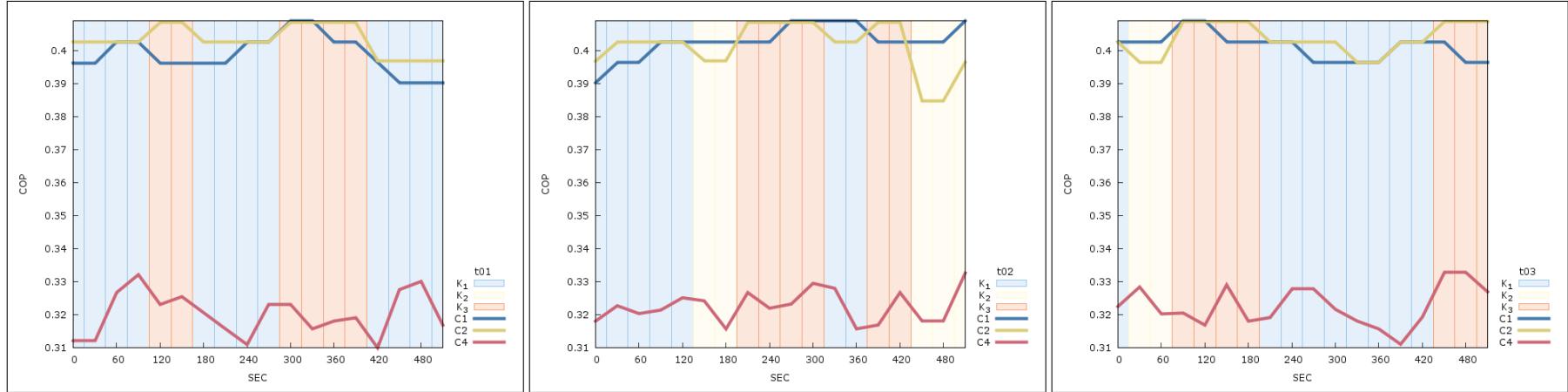


Figure E.2: Low-Density Workload—Chiller Loads

## Appendix F

### Low-Density Workload : Chiller Clustering on COP

### EM Clustering with $k = 3$



### K-Means Clustering with $k = 5$

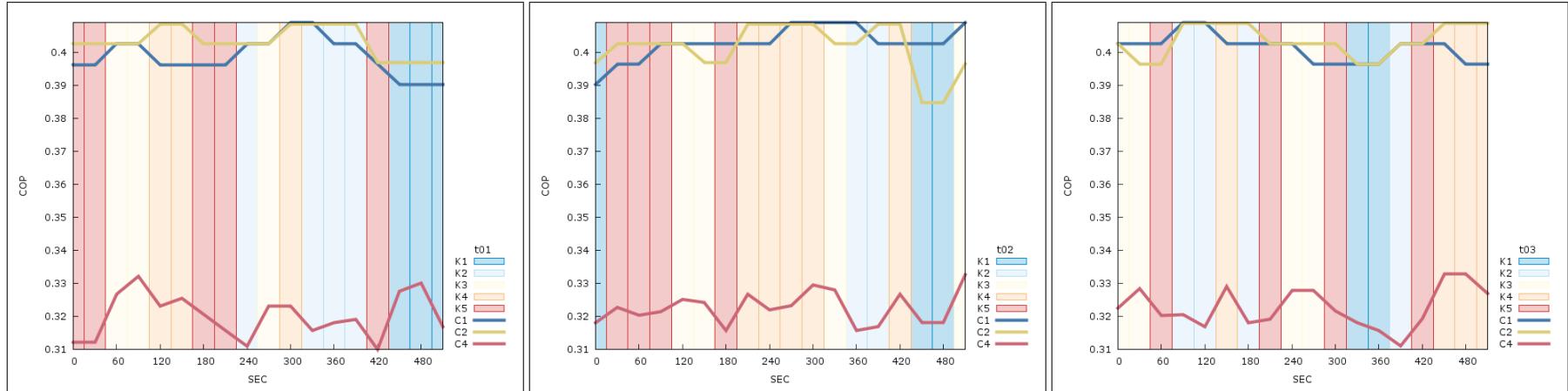
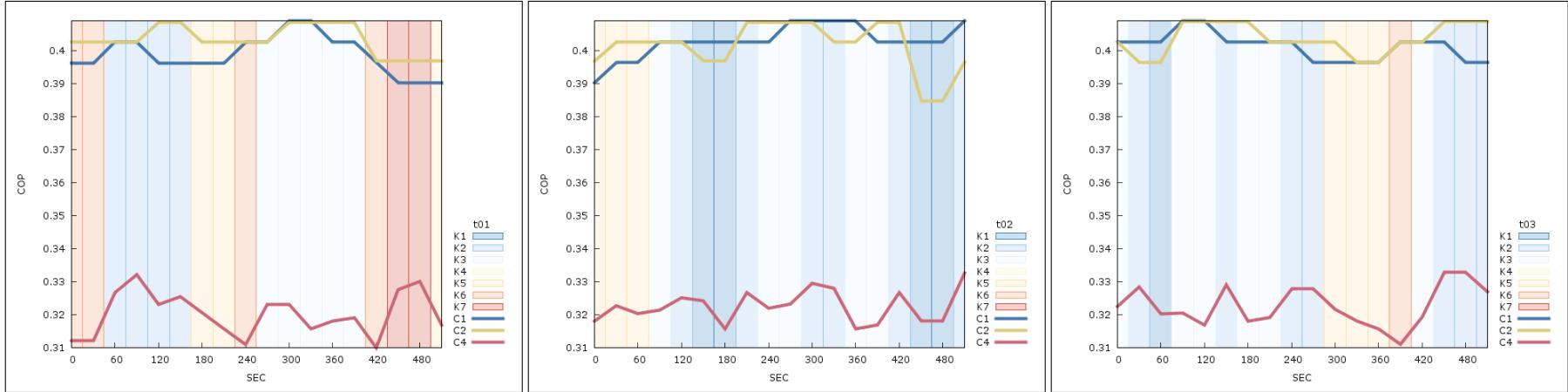


Figure F.1: Low-Density Workload—Chiller COP

### K-Means Clustering with $k = 7$



### K-Means Clustering with $k = 9$

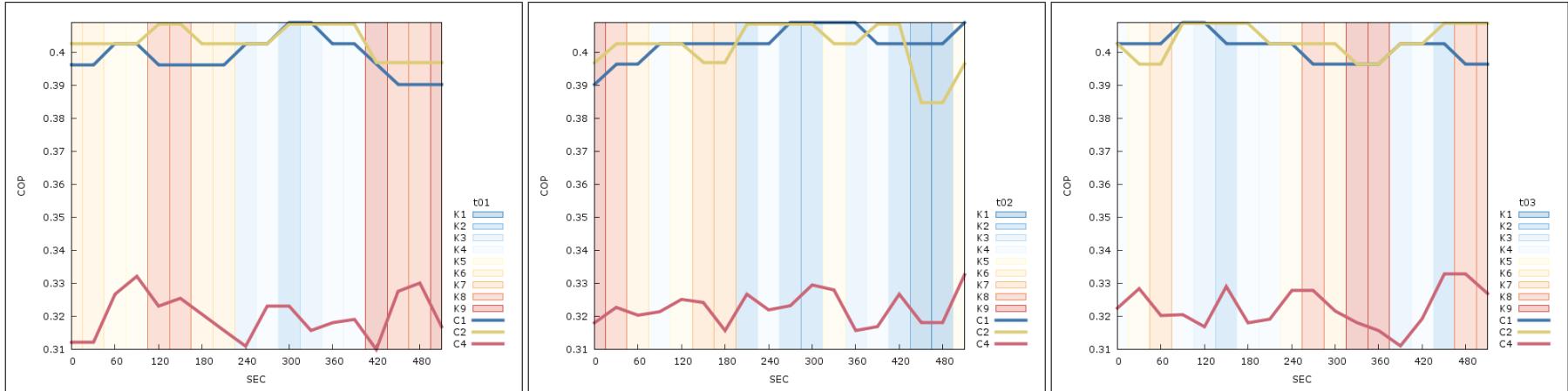
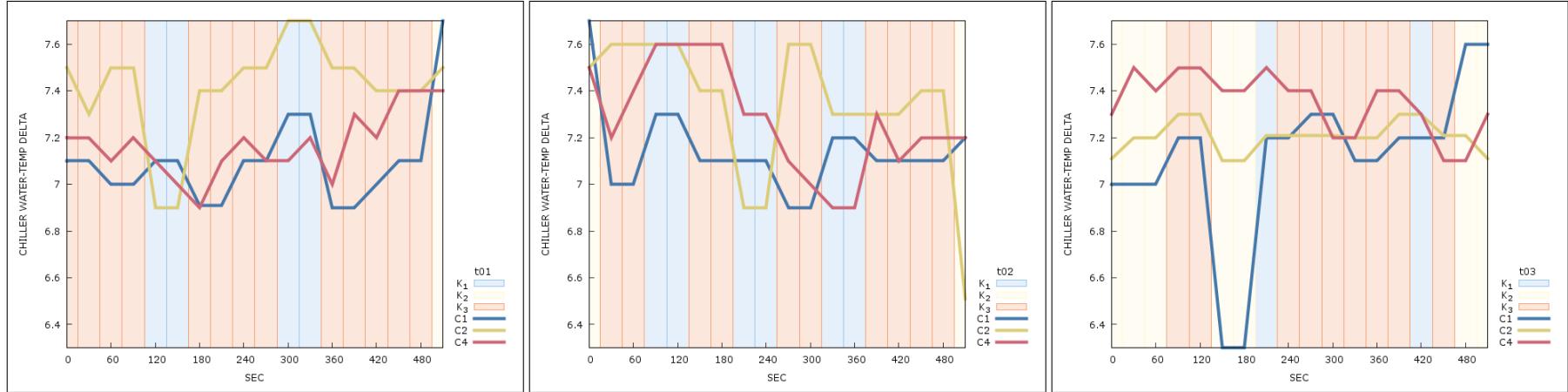


Figure F.2: Low-Density Workload—Chiller COP

## Appendix G

# Low-Density Workload : Chiller Clustering on Chilled Water-Temperature Delta

### EM Clustering with $k = 3$



### K-Means Clustering with $k = 5$

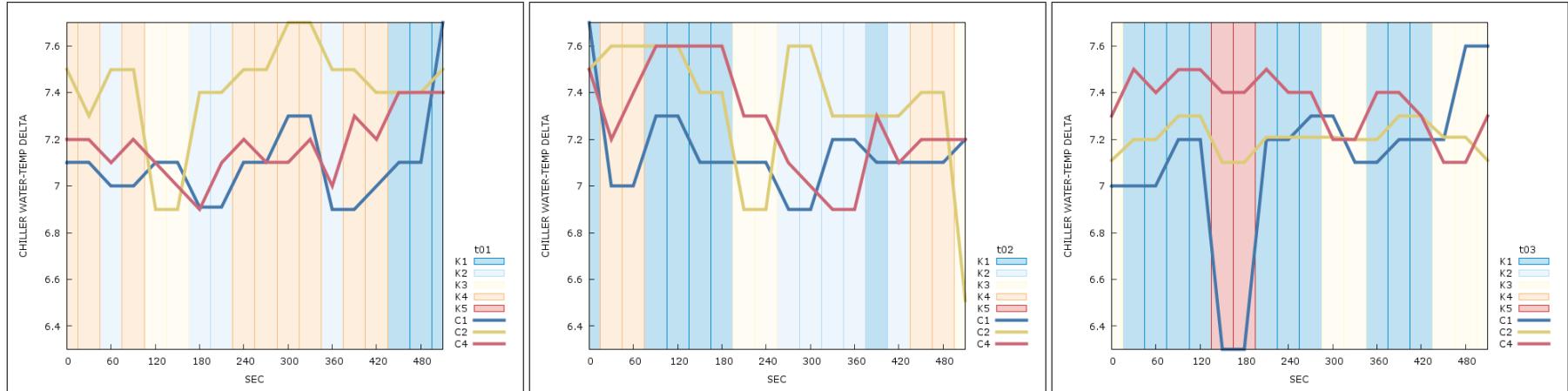
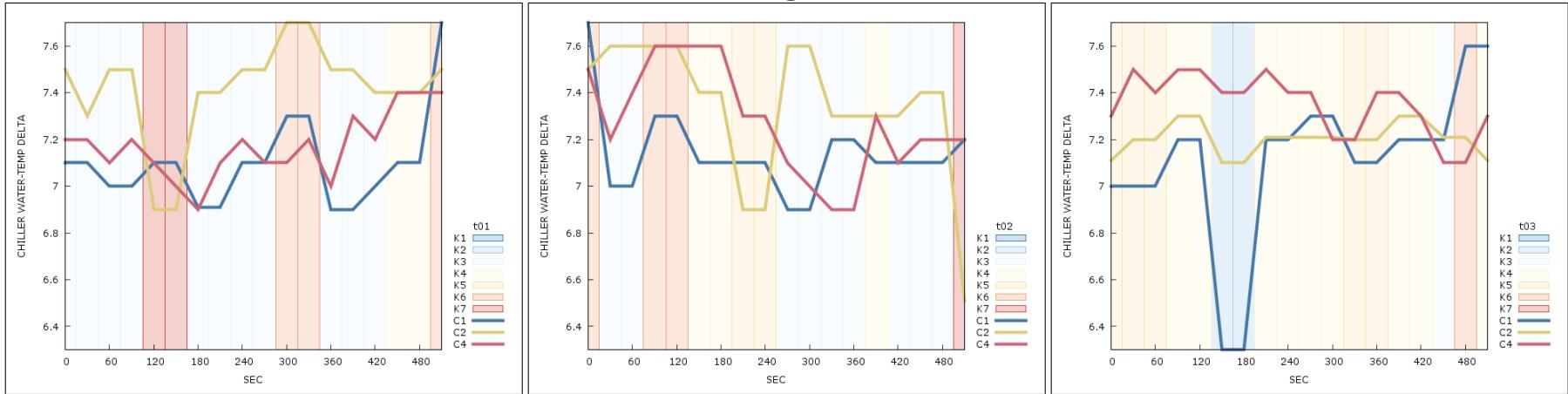


Figure G.1: Low-Density Workload—Chiller Cilled Water-Temperature Delta

### K-Means Clustering with $k = 7$



### K-Means Clustering with $k = 9$

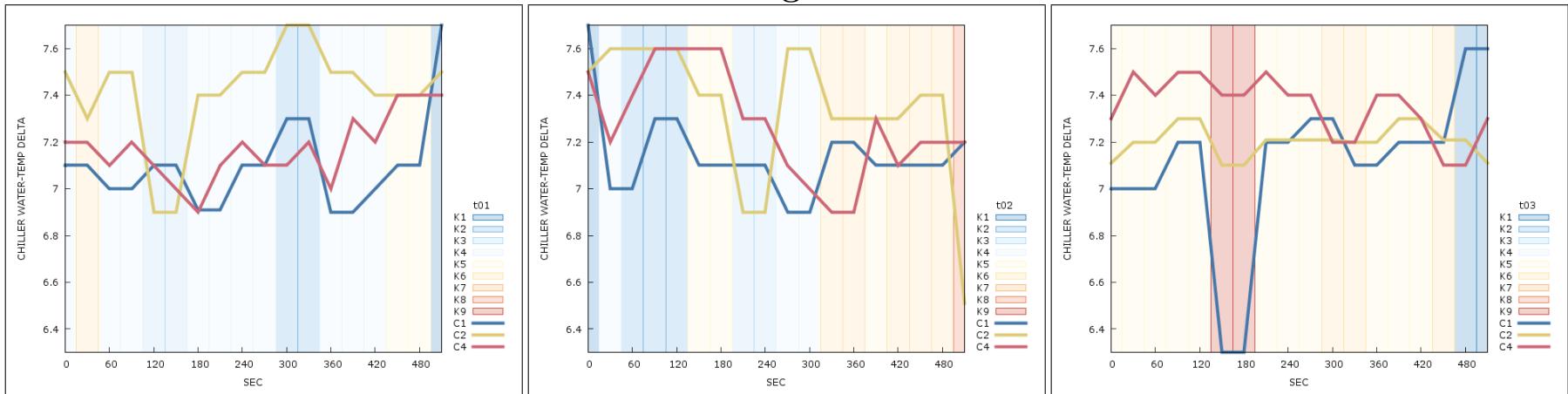
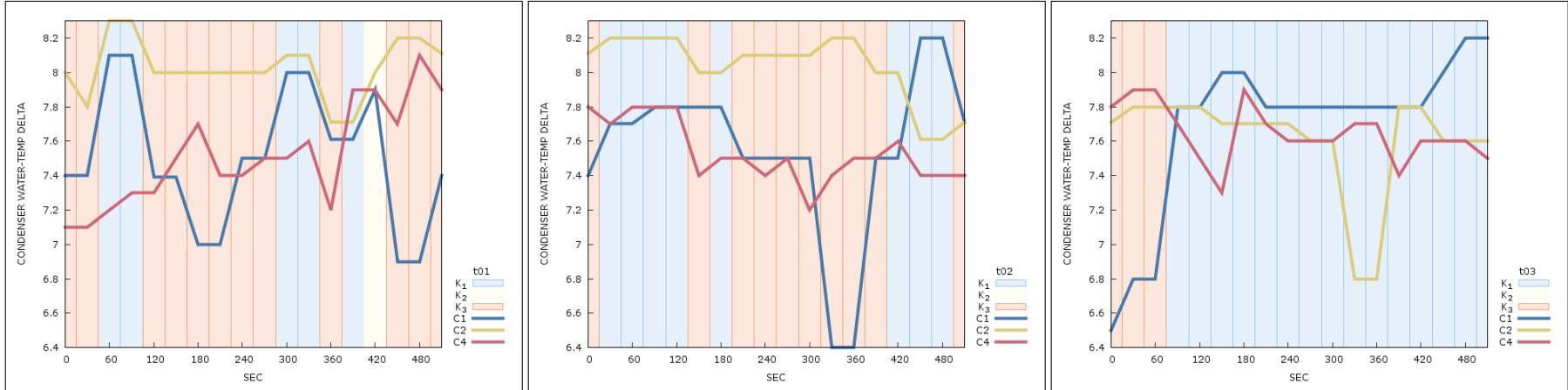


Figure G.2: Low-Density Workload—Chiller Chilled Water-Temperature Delta

## Appendix H

# Low-Density Workload : Chiller Clustering on Condenser Water-Temperature Delta

### EM Clustering with $k = 3$



### K-Means Clustering with $k = 5$

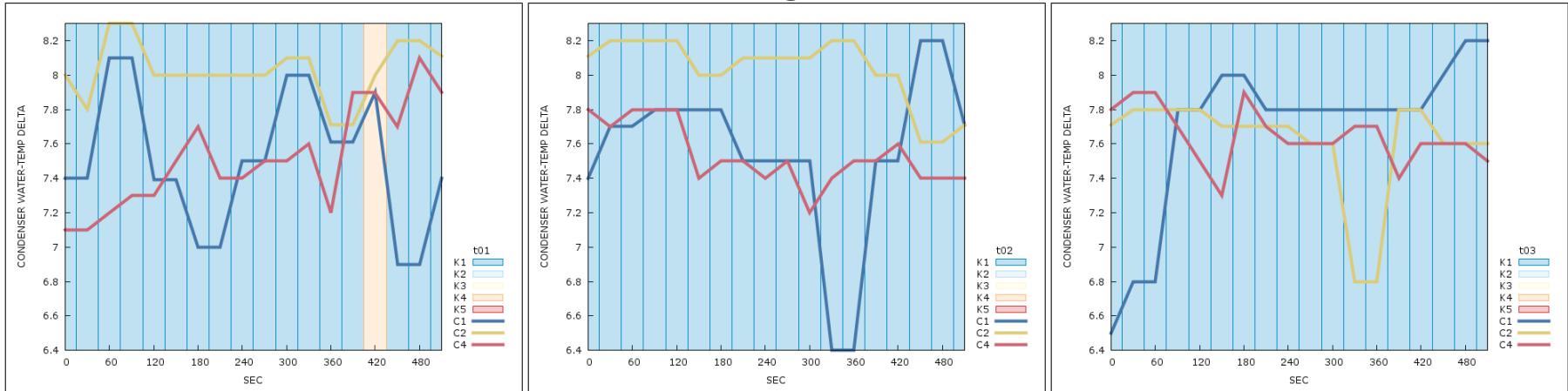
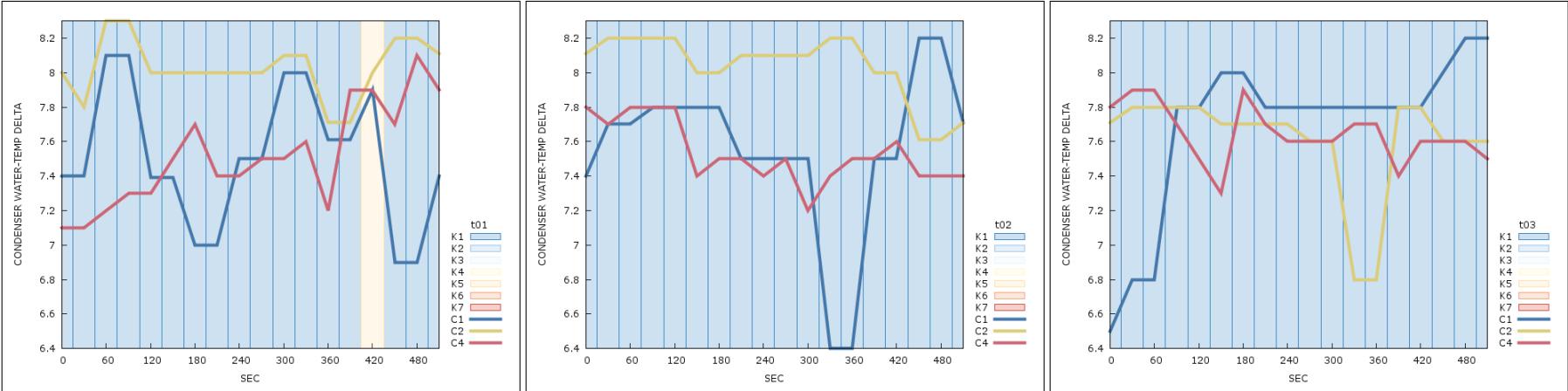


Figure H.1: Low-Density Workload—Chiller Condenser Water-Temperature Delta

### K-Means Clustering with $k = 7$



### K-Means Clustering with $k = 9$

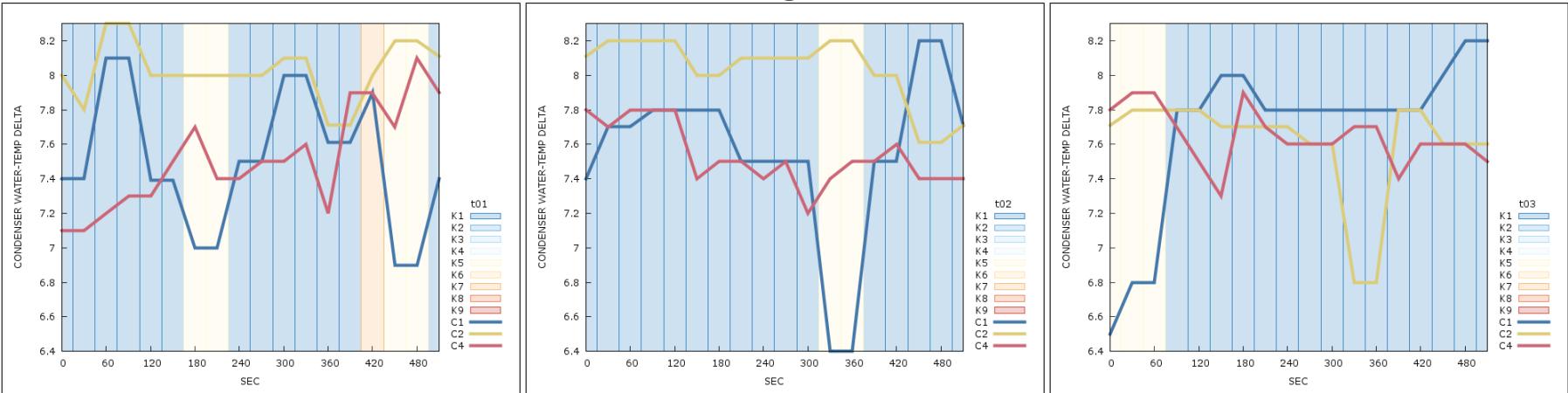


Figure H.2: Low-Density Workload—Chiller Condenser Water-Temperature Delta

## Appendix I

# High-Density Workload Chiller Metrics

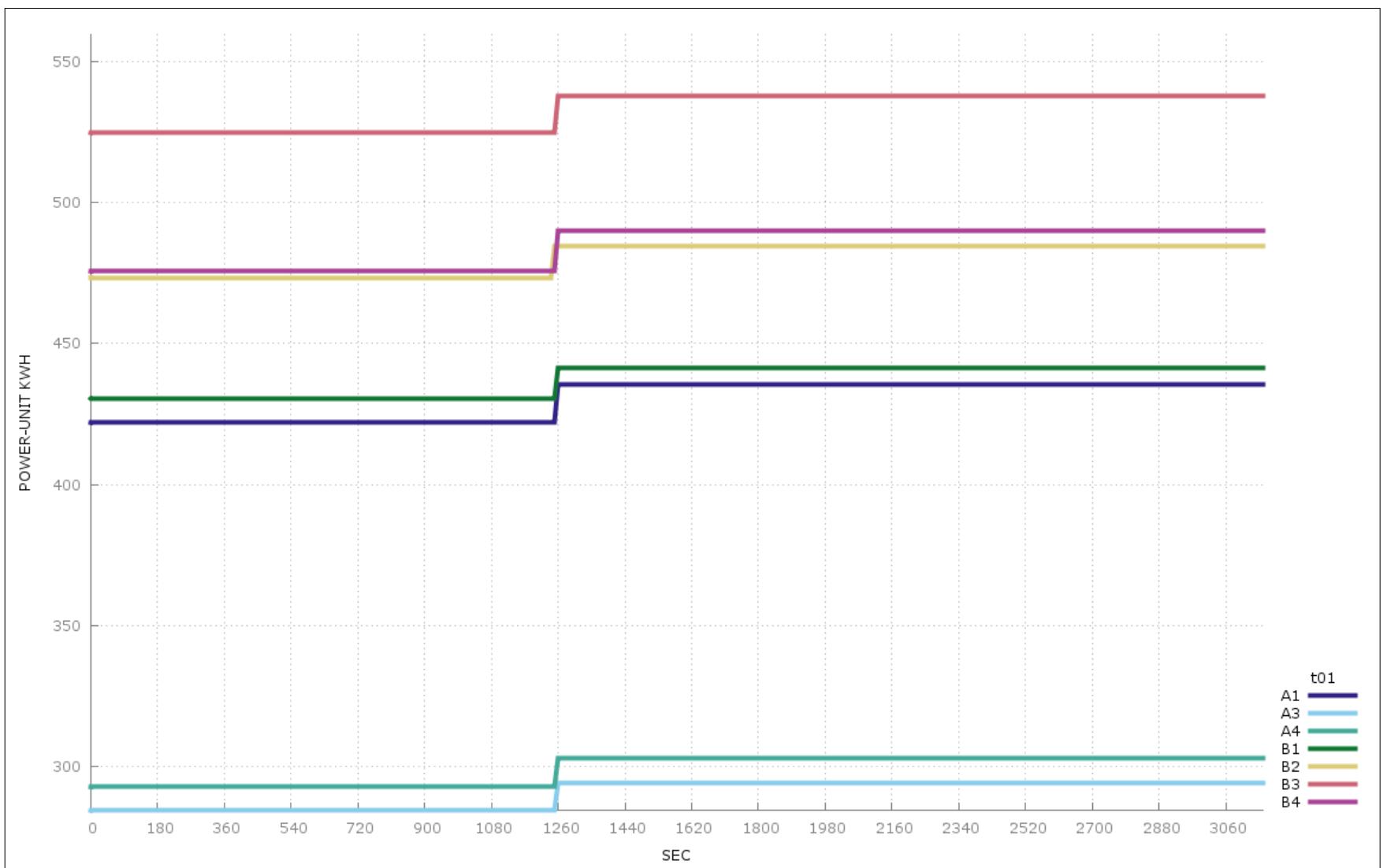


Figure I.1: Trial 1—High-Density Workload—kWh Increase

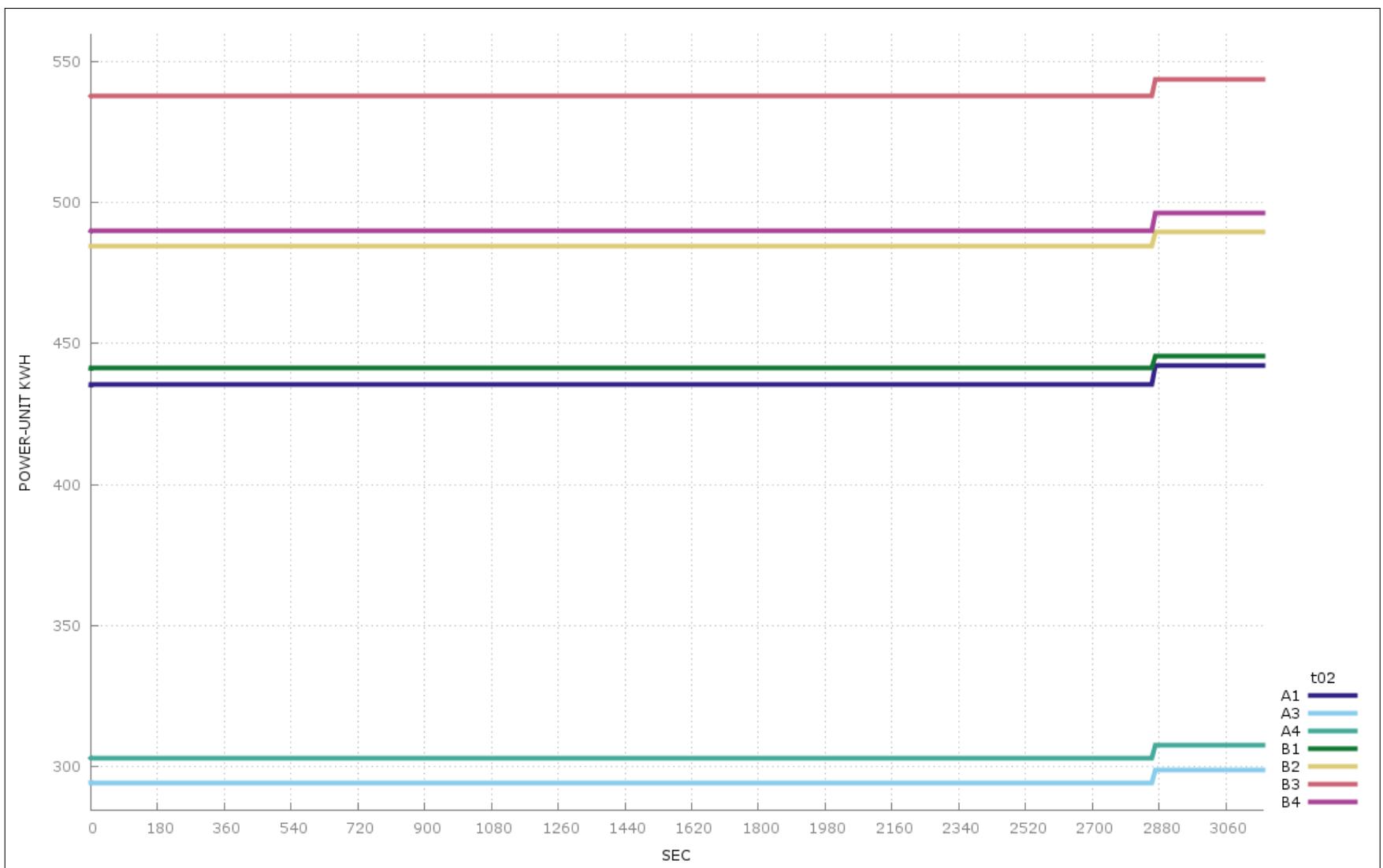


Figure I.2: Trial 2—High-Density Workload—kWh Increase

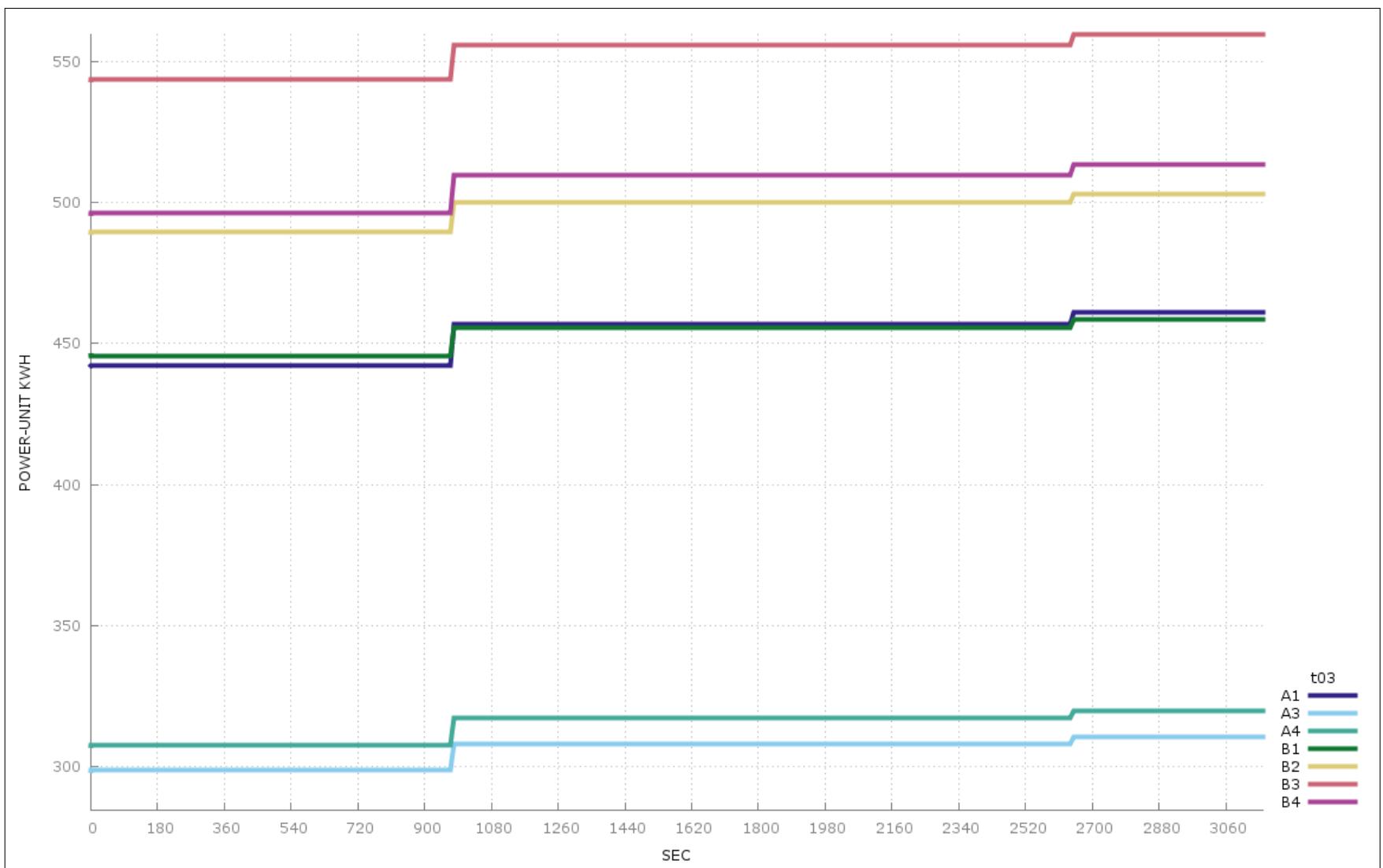


Figure I.3: Trial 3—High-Density Workload—kWh Increase



Figure I.4: Trial 1—High-Density Workload—Chiller KW

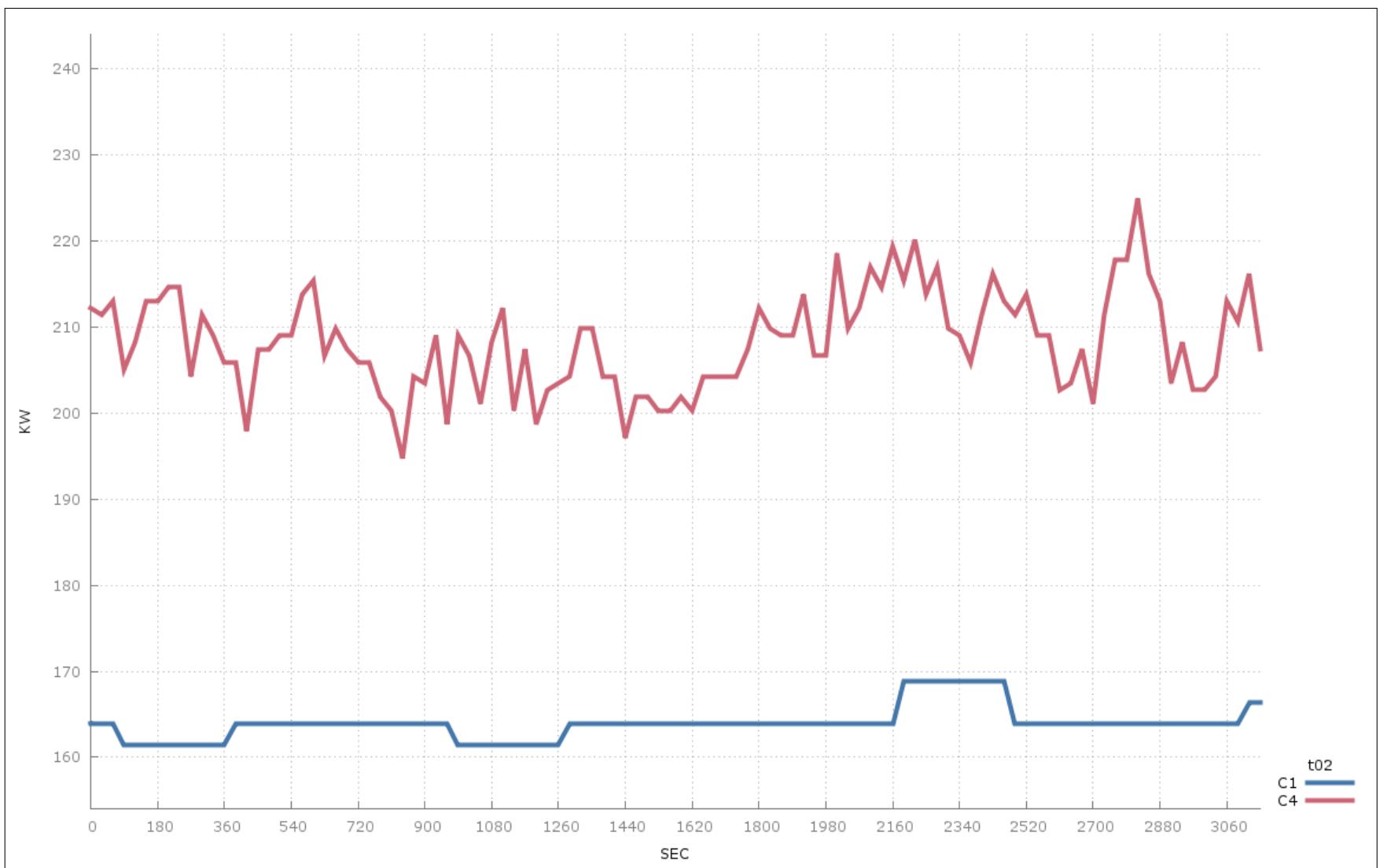


Figure I.5: Trial 2—High-Density Workload—Chiller KW

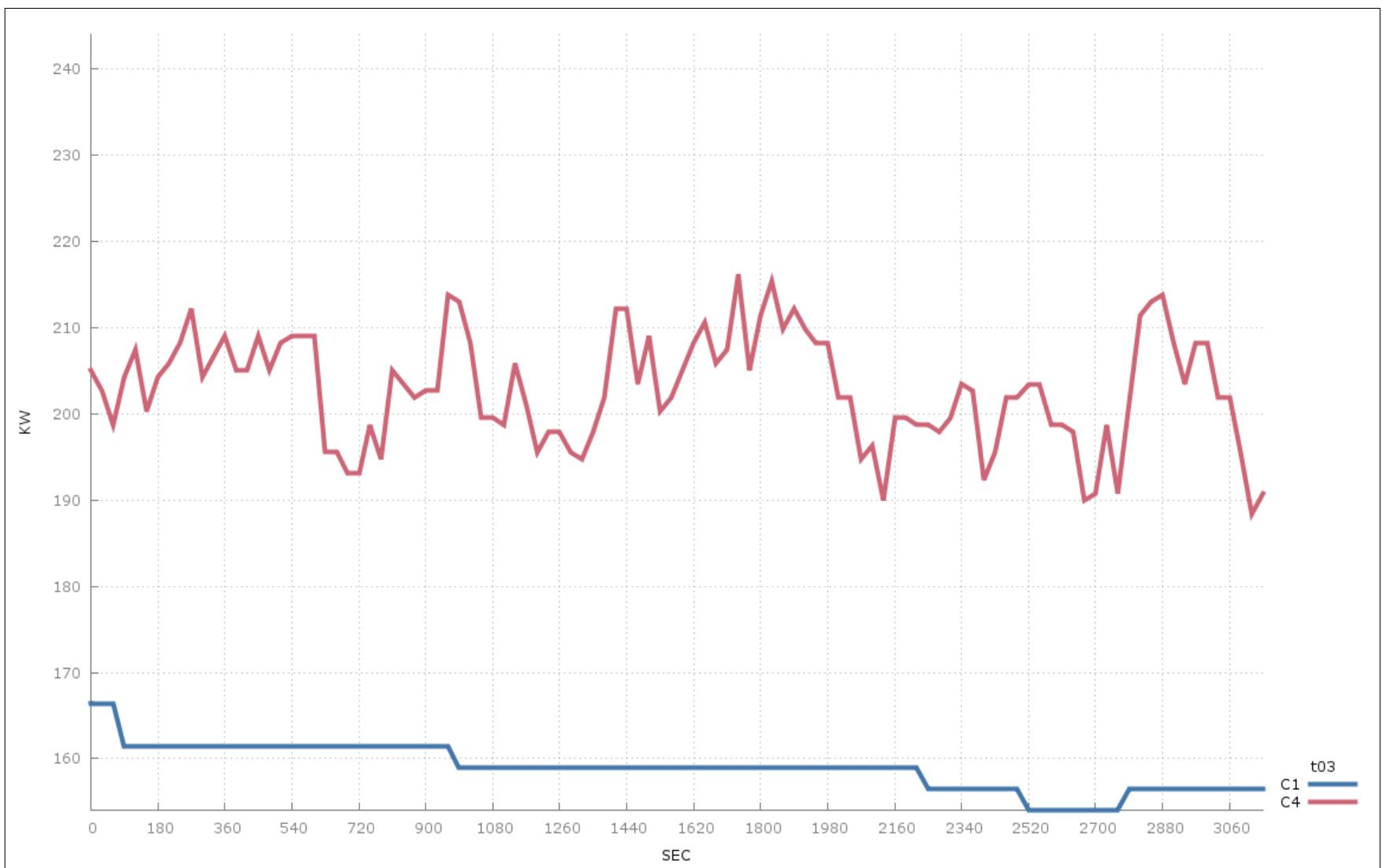


Figure I.6: Trial 3—High-Density Workload—Chiller KW

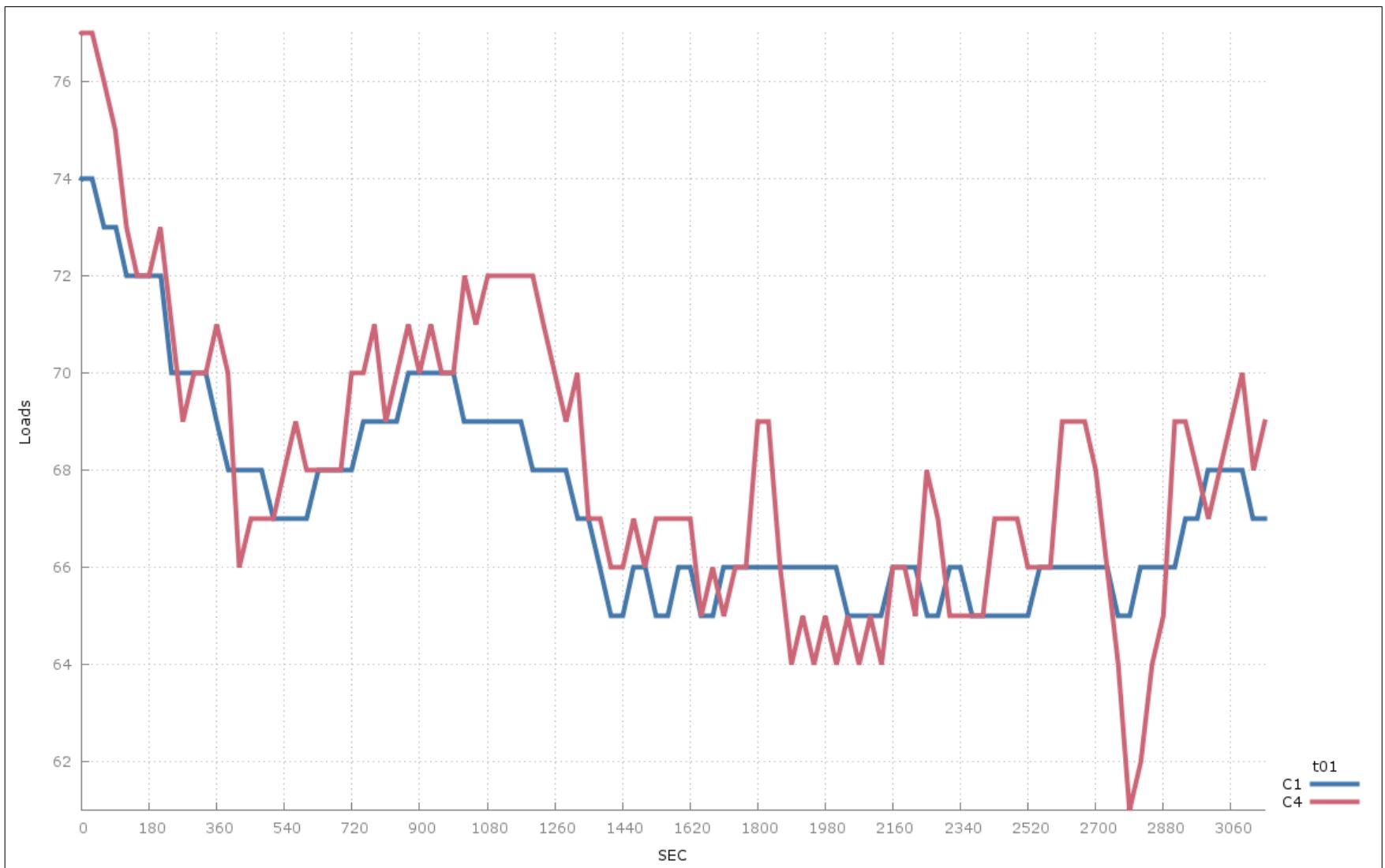


Figure I.7: Trial 1—High-Density Workload—Chiller Loads

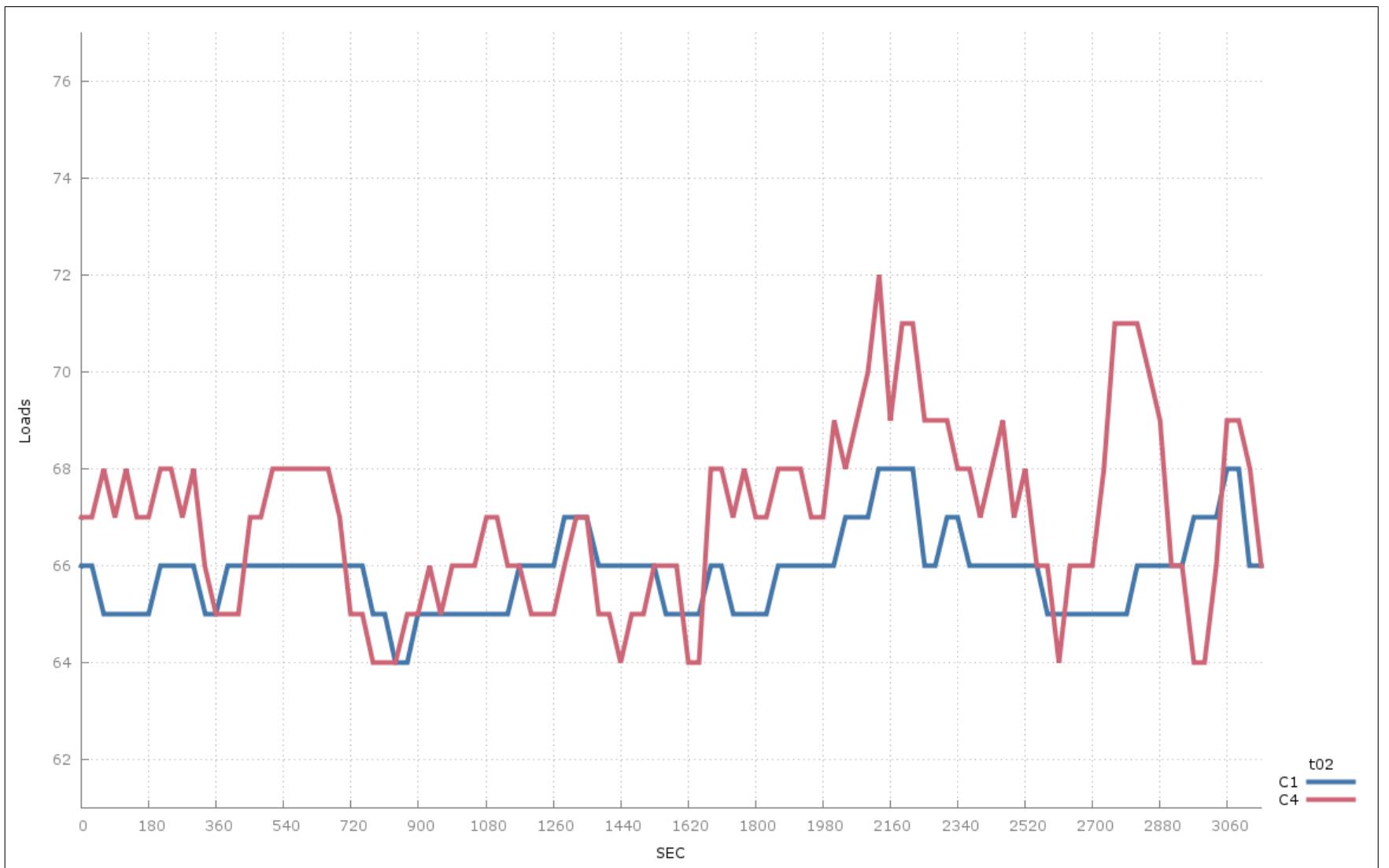


Figure I.8: Trial 2—High-Density Workload—Chiller Loads

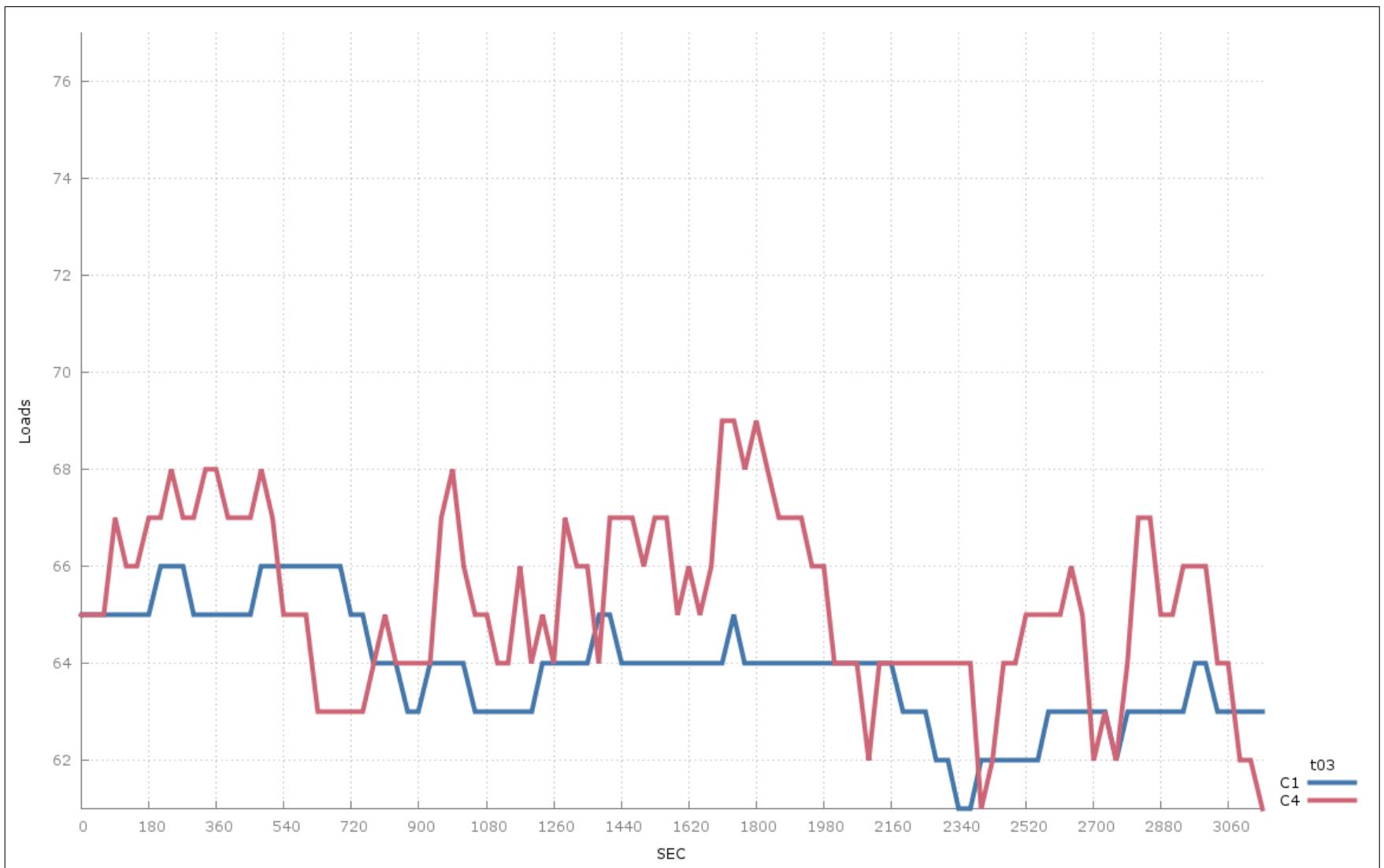


Figure I.9: Trial 3—High-Density Workload—Chiller Loads

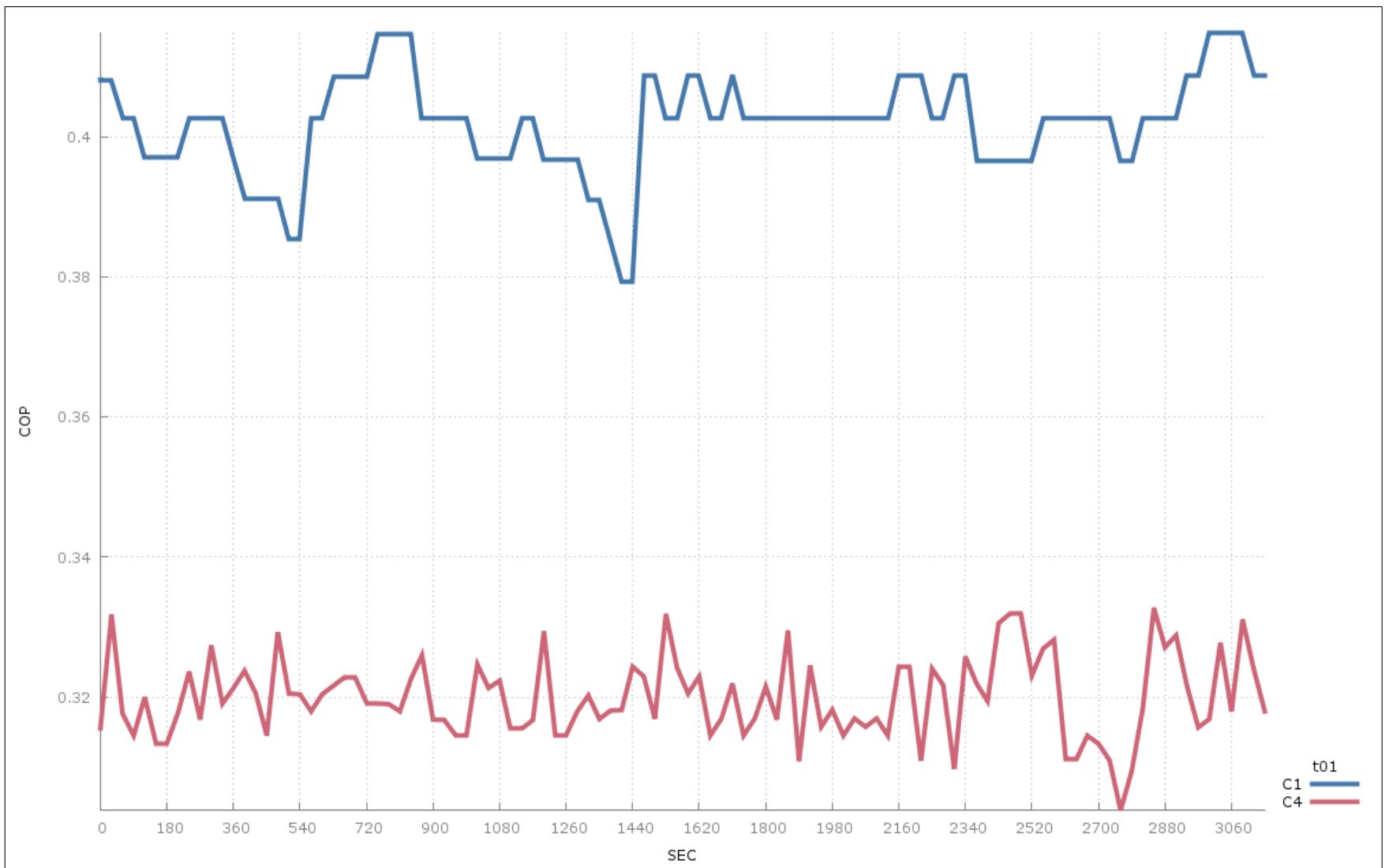


Figure I.10: Trial 1—High-Density Workload—Chiller COP

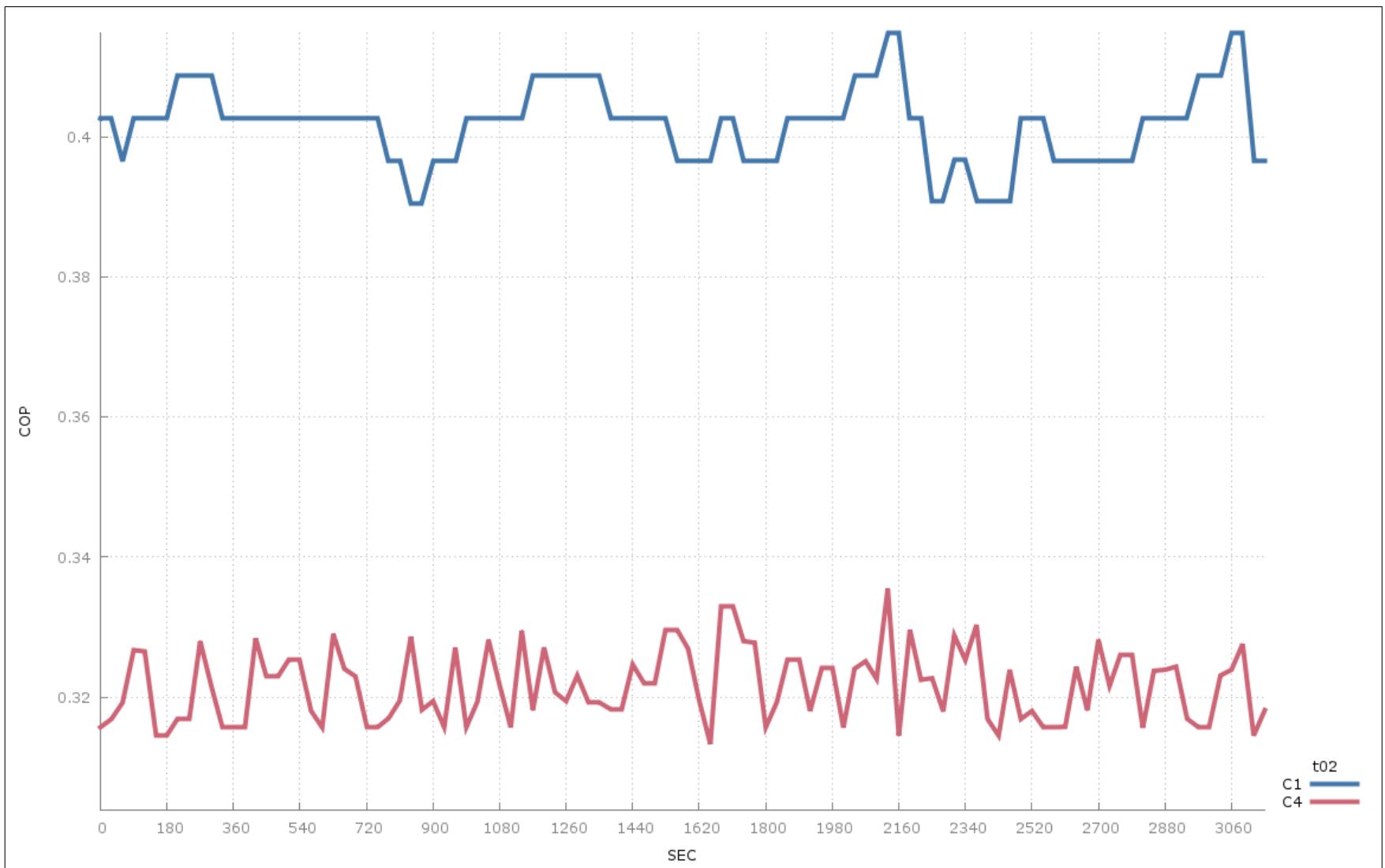


Figure I.11: Trial 2—High-Density Workload—Chiller COP

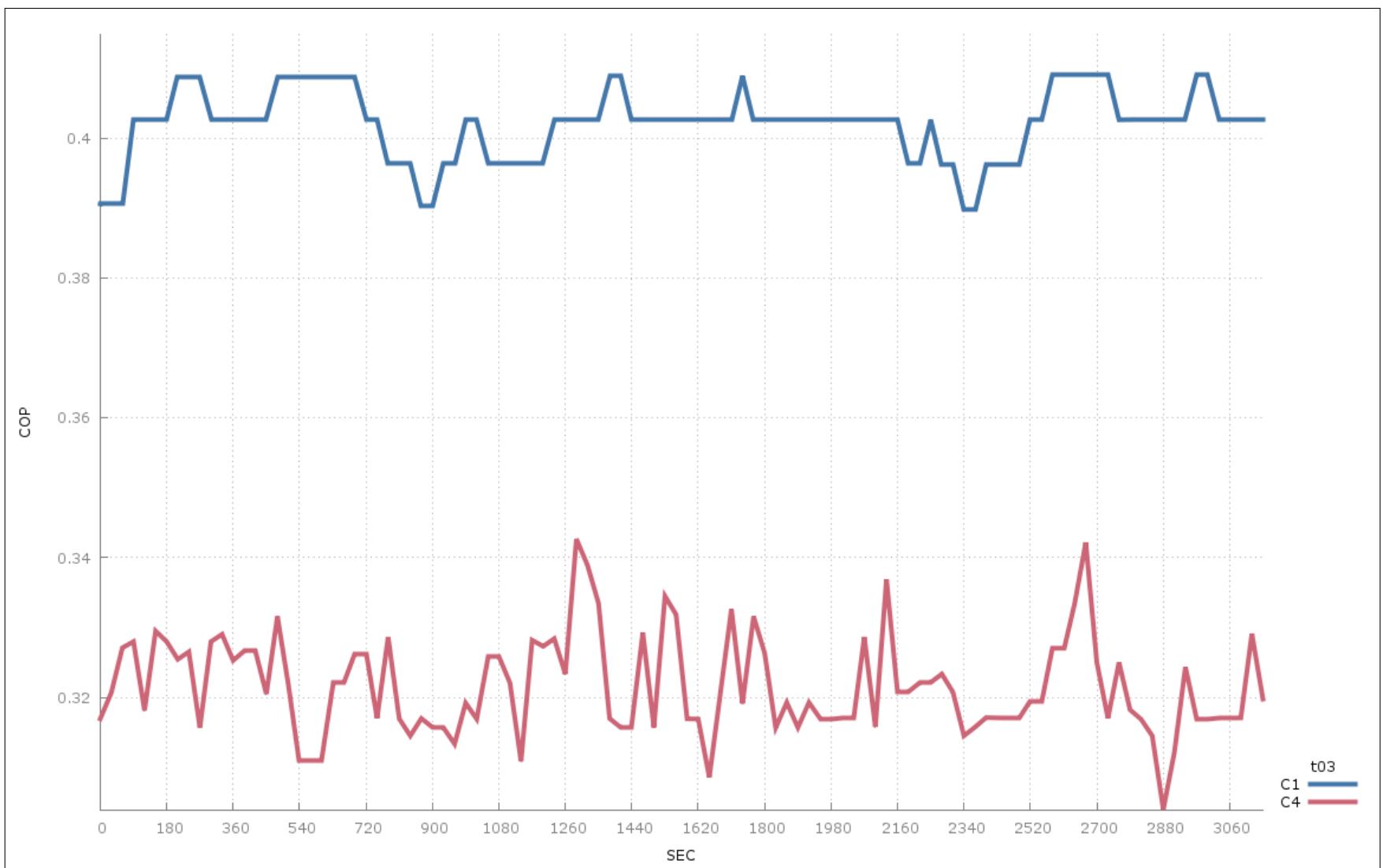


Figure I.12: Trial 3—High-Density Workload—Chiller COP

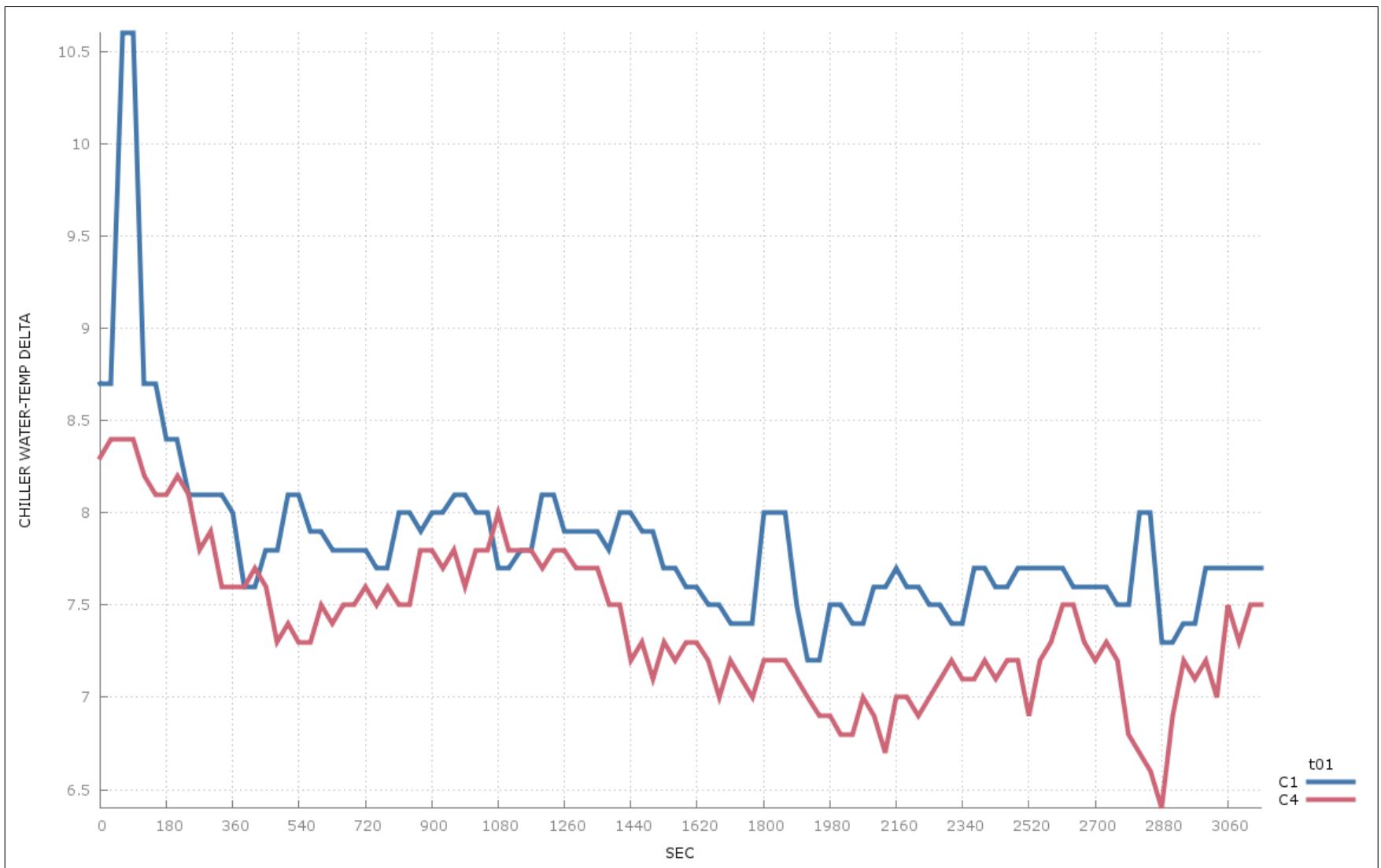


Figure I.13: Trial 1—High-Density Workload—Chiller Chilled Water-Temperature Delta

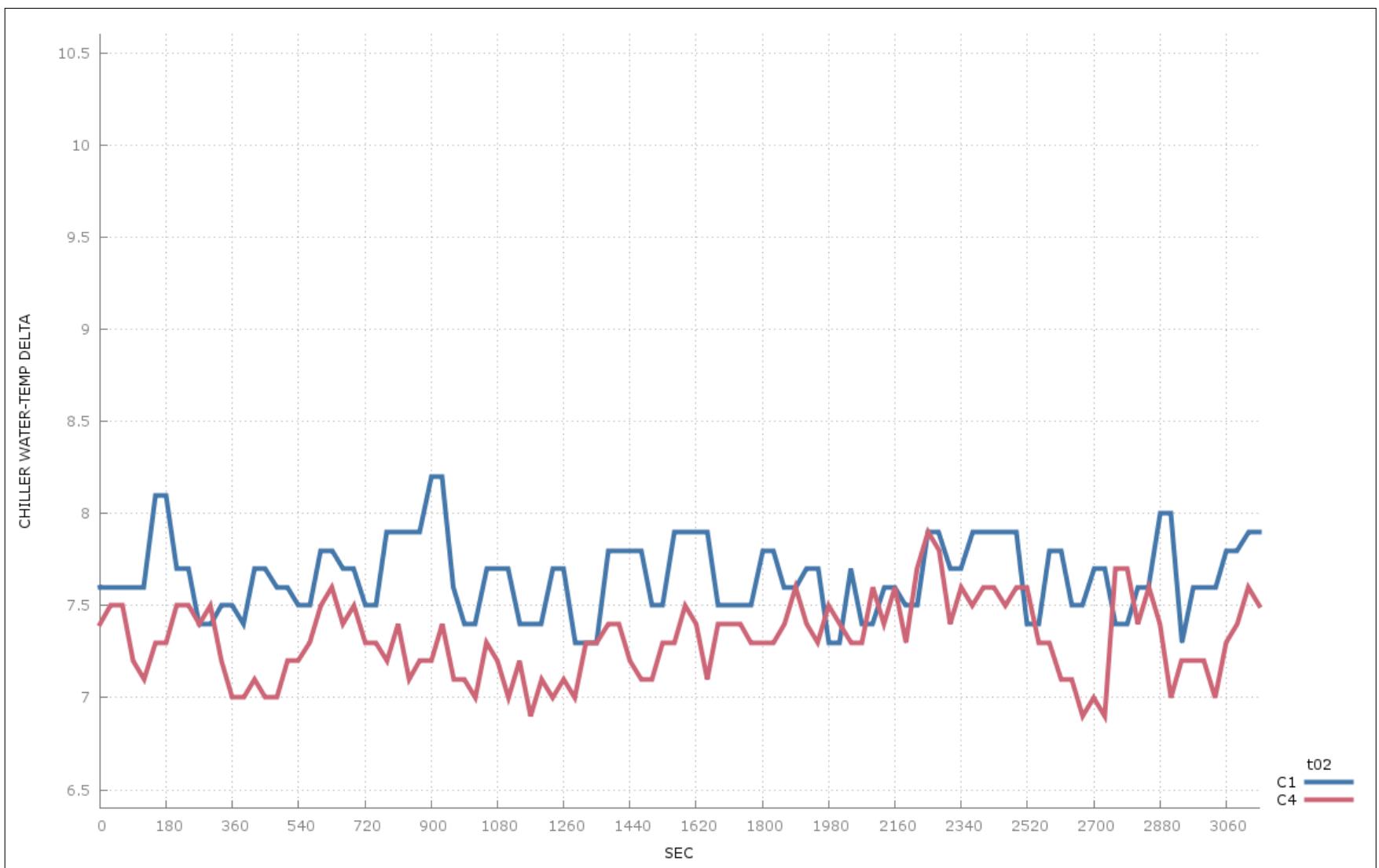


Figure I.14: Trial 2—High-Density Workload—Chiller Chilled Water-Temperature Delta

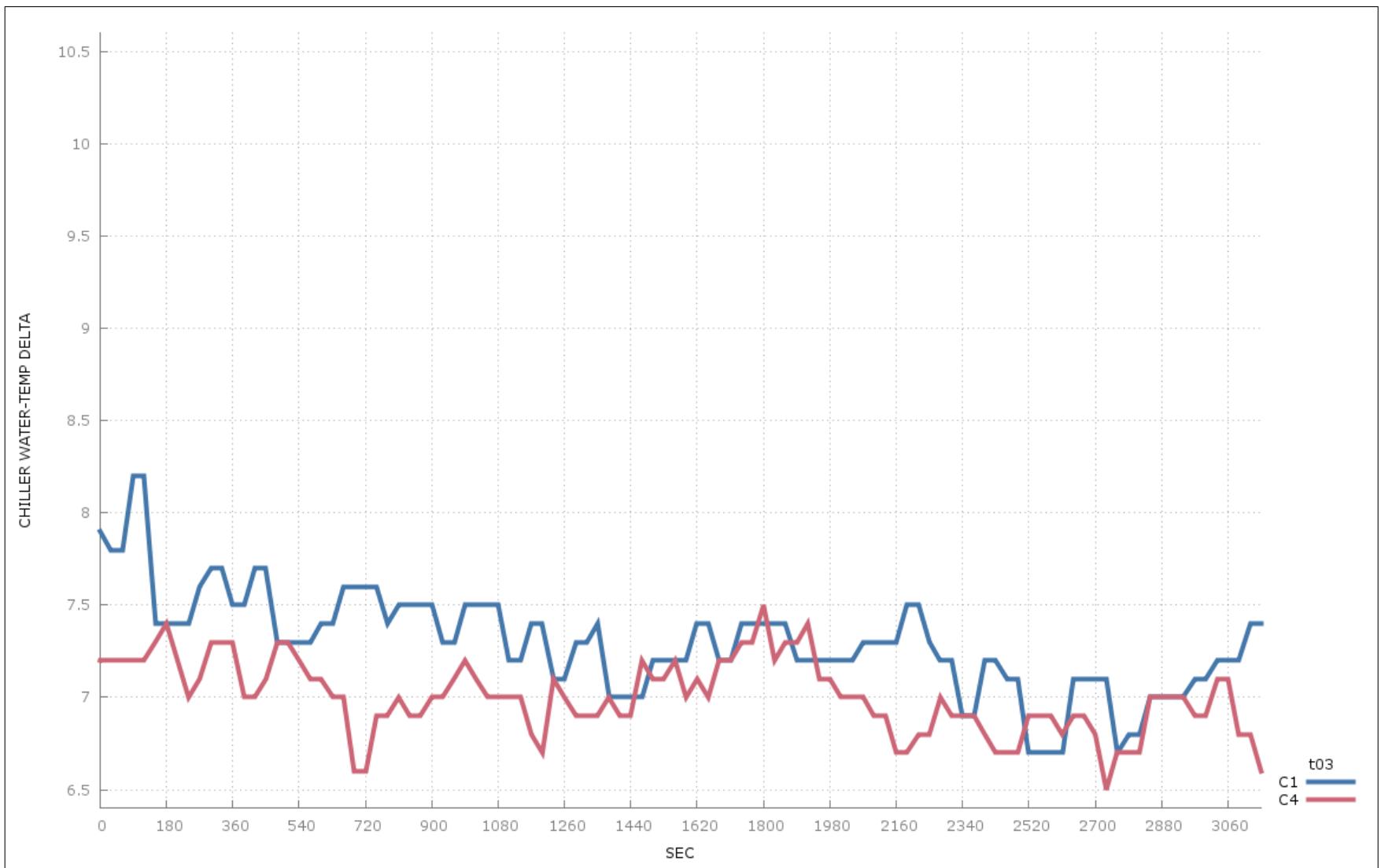


Figure I.15: Trial 3—High-Density Workload—Chiller Chilled Water-Temperature Delta

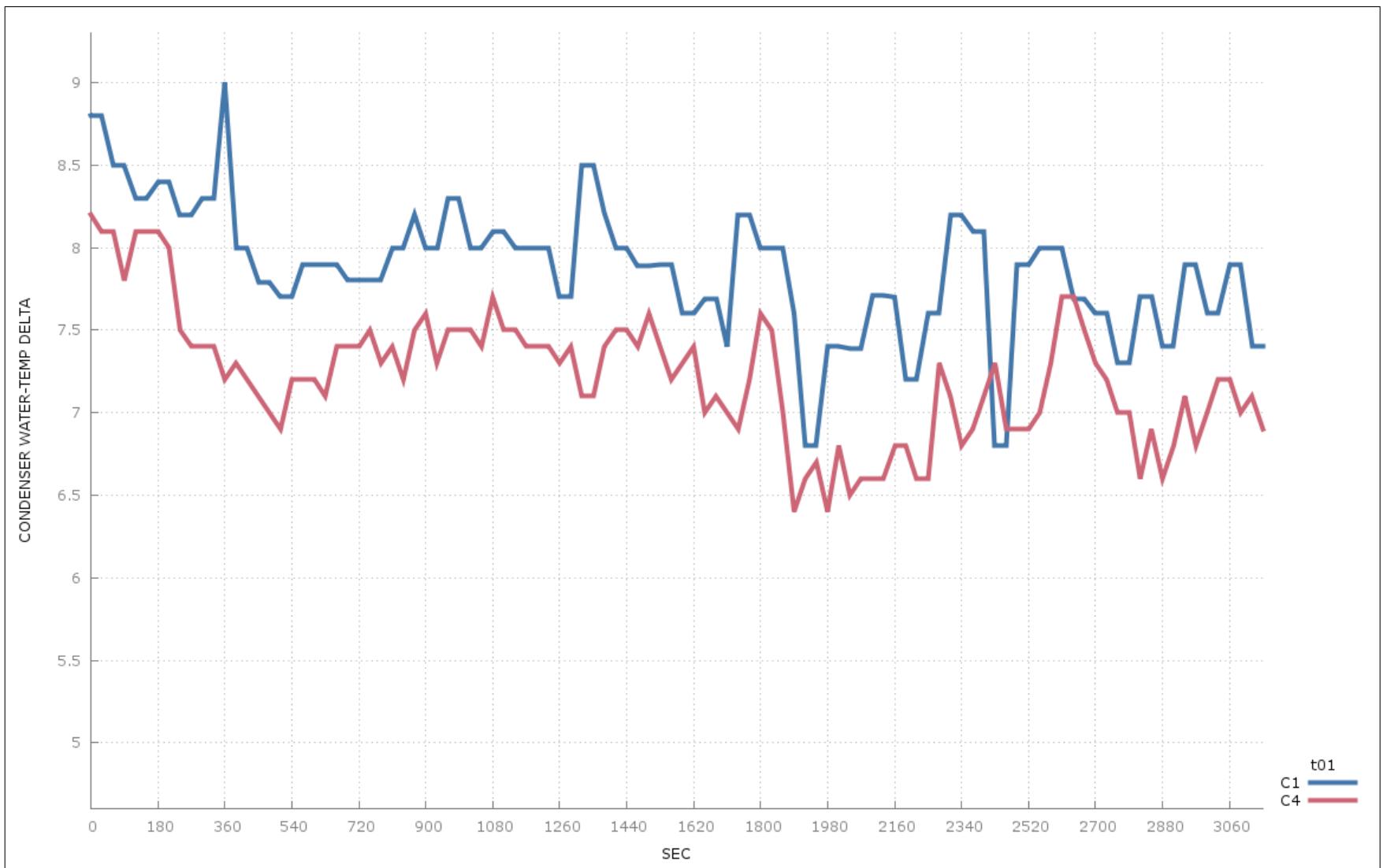


Figure I.16: Trial 1—High-Density Workload—Chiller Condenser Water-Temperature Delta



Figure I.17: Trial 2—High-Density Workload—Chiller Condenser Water-Temperature Delta

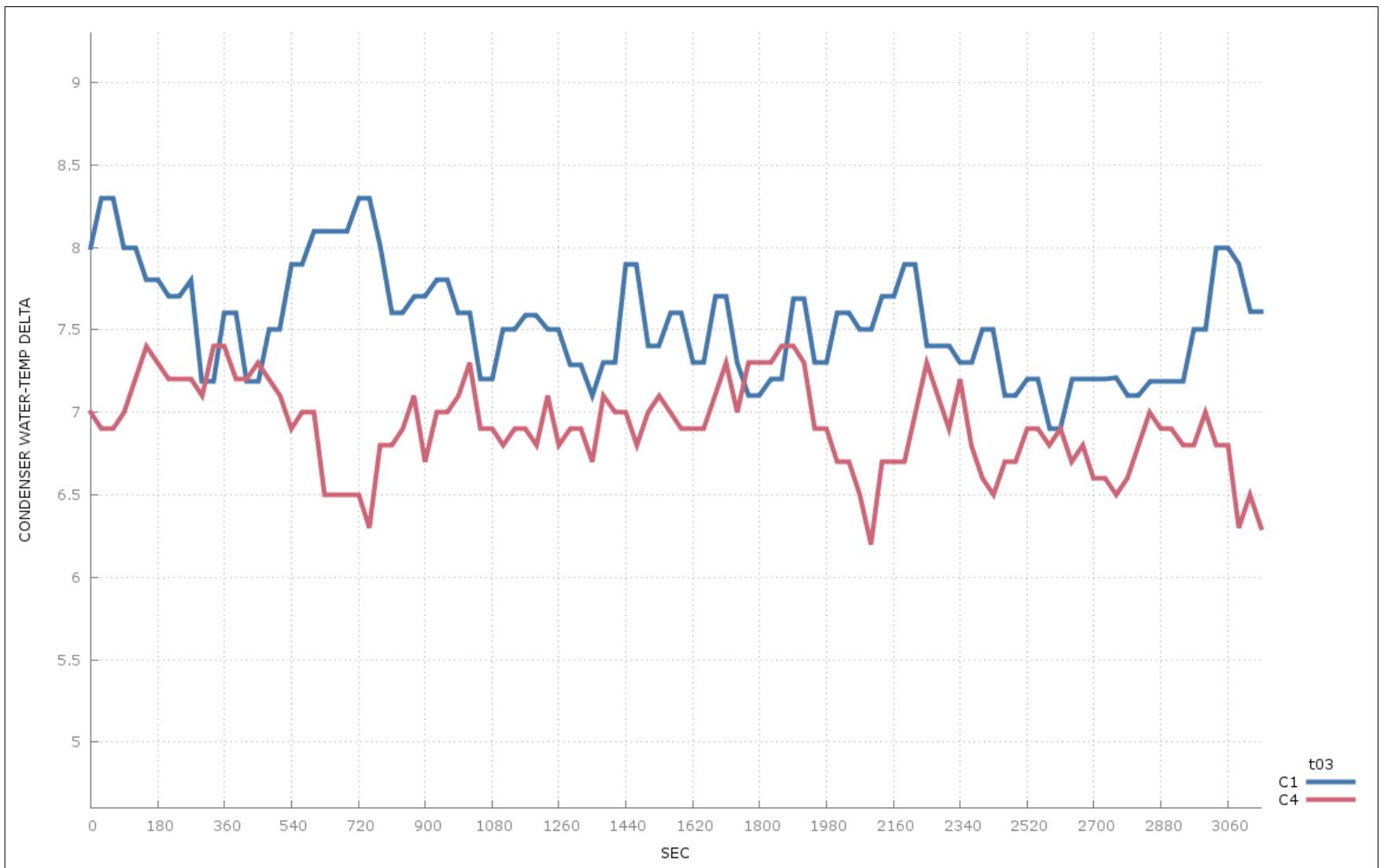


Figure I.18: Trial 3—High-Density Workload—Chiller Condenser Water-Temperature Delta

## Appendix J

# High-Density Workload : Chiller Clustering on KW

### Trial 1 : Chiller Clustering on KW

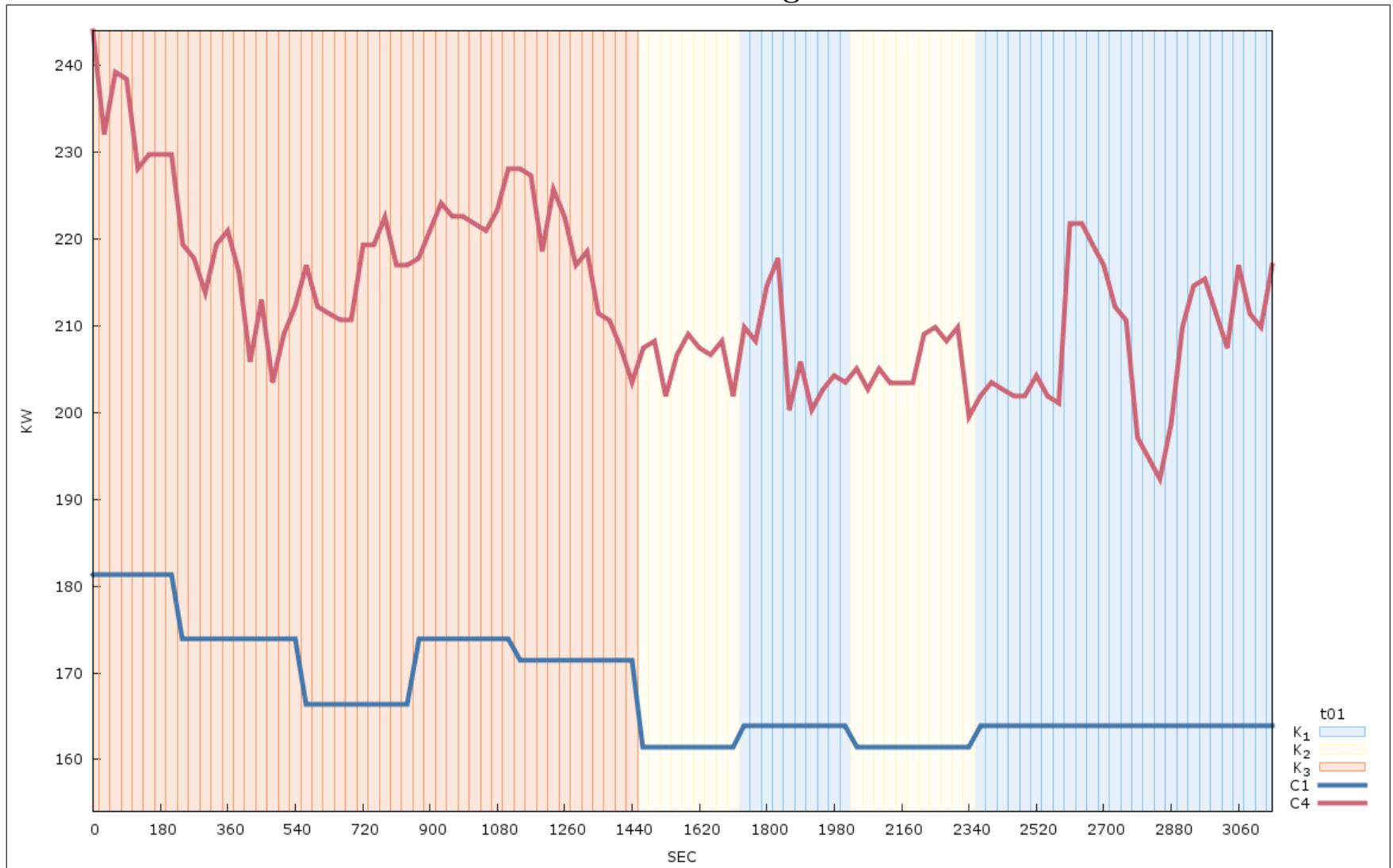


Figure J.1: EM Clustering with  $k = 3$

### Trial 2 : Chiller Clustering on KW

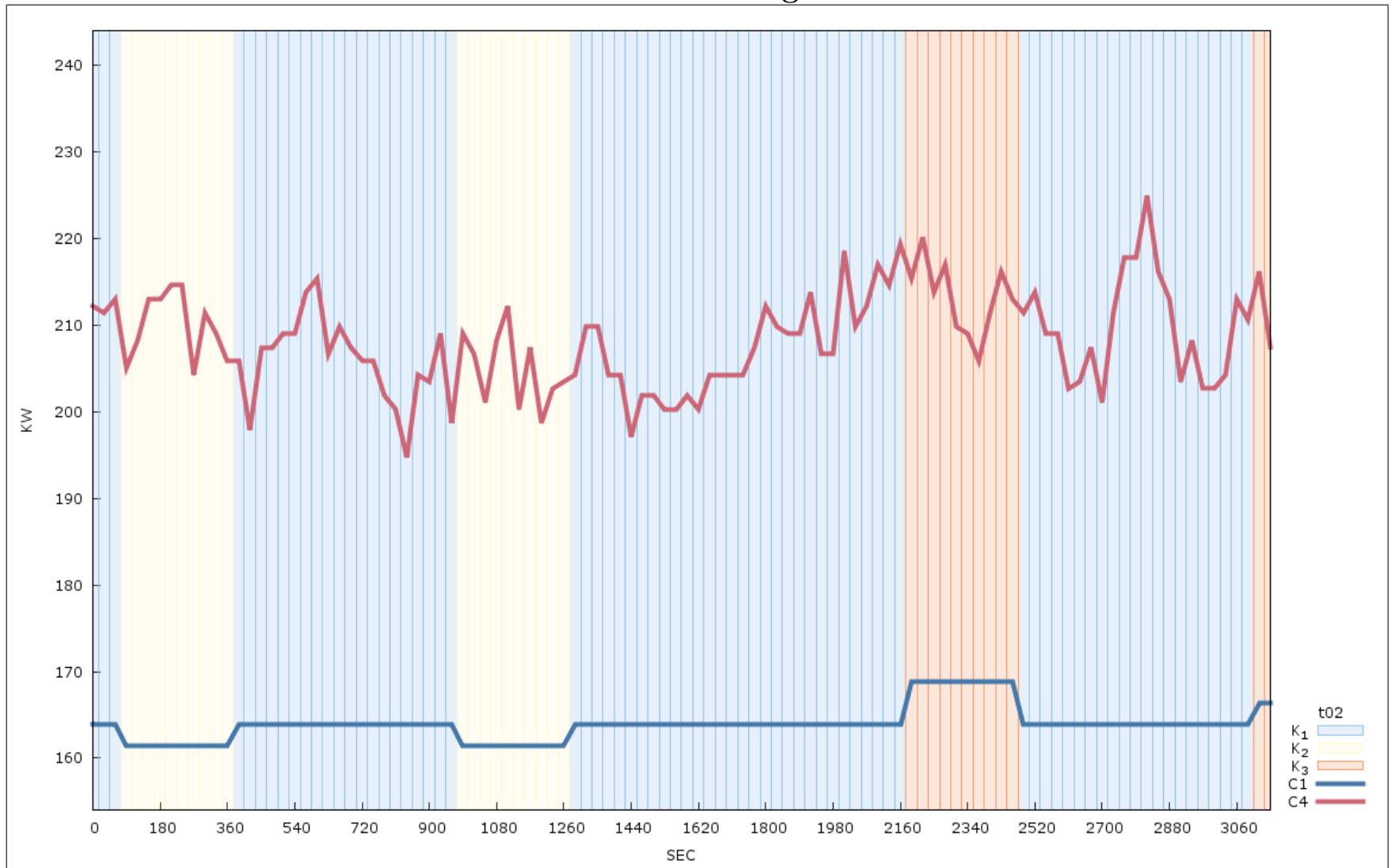


Figure J.2: EM Clustering with  $k = 3$

### Trial 3 : Chiller Clustering on KW

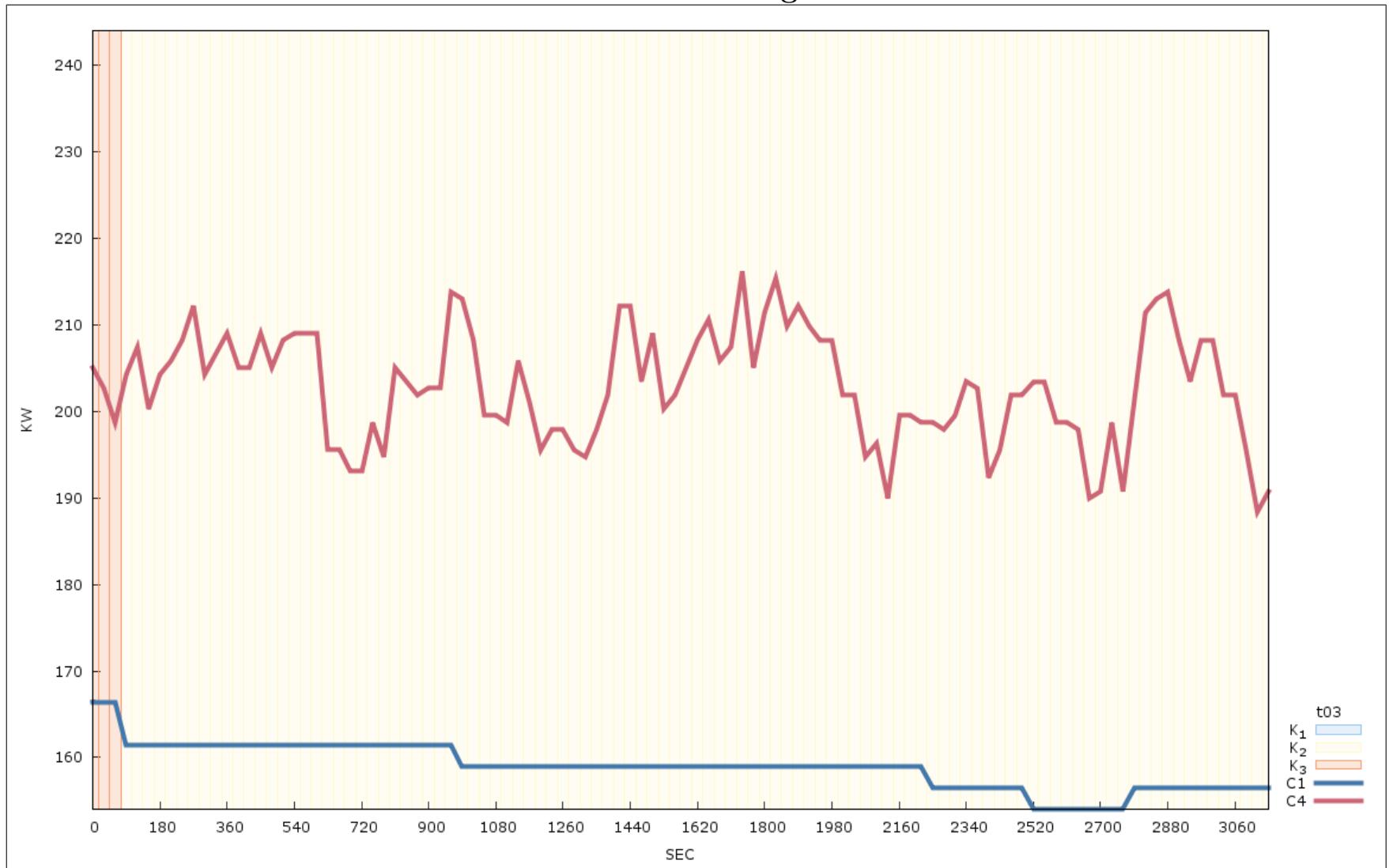


Figure J.3: EM Clustering with  $k = 3$

### Trial 1 : Chiller Clustering on KW

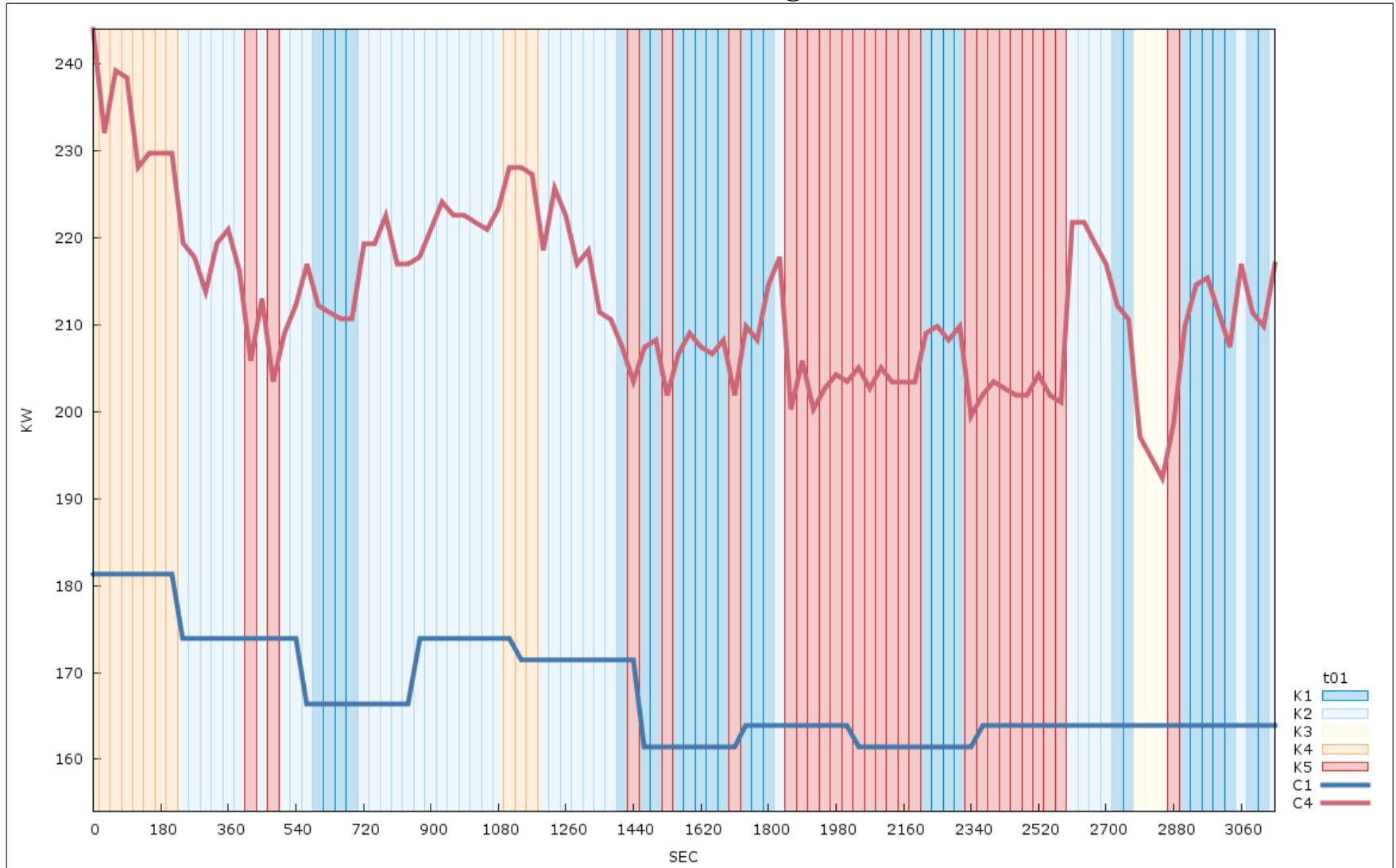


Figure J.4: K-Means Clustering with  $k = 5$

### Trial 2 : Chiller Clustering on KW

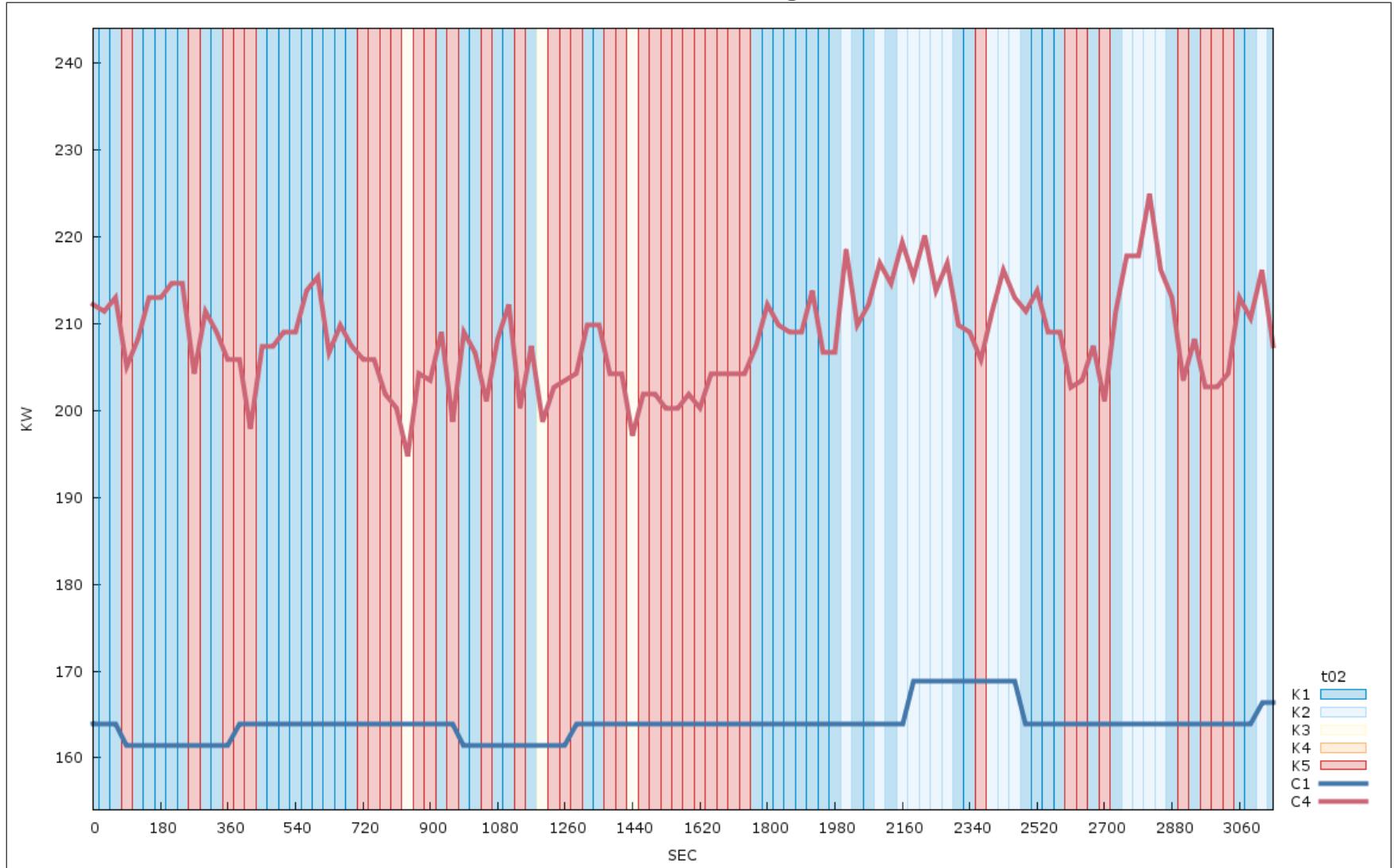


Figure J.5: K-Means Clustering with  $k = 5$

### Trial 3 : Chiller Clustering on KW

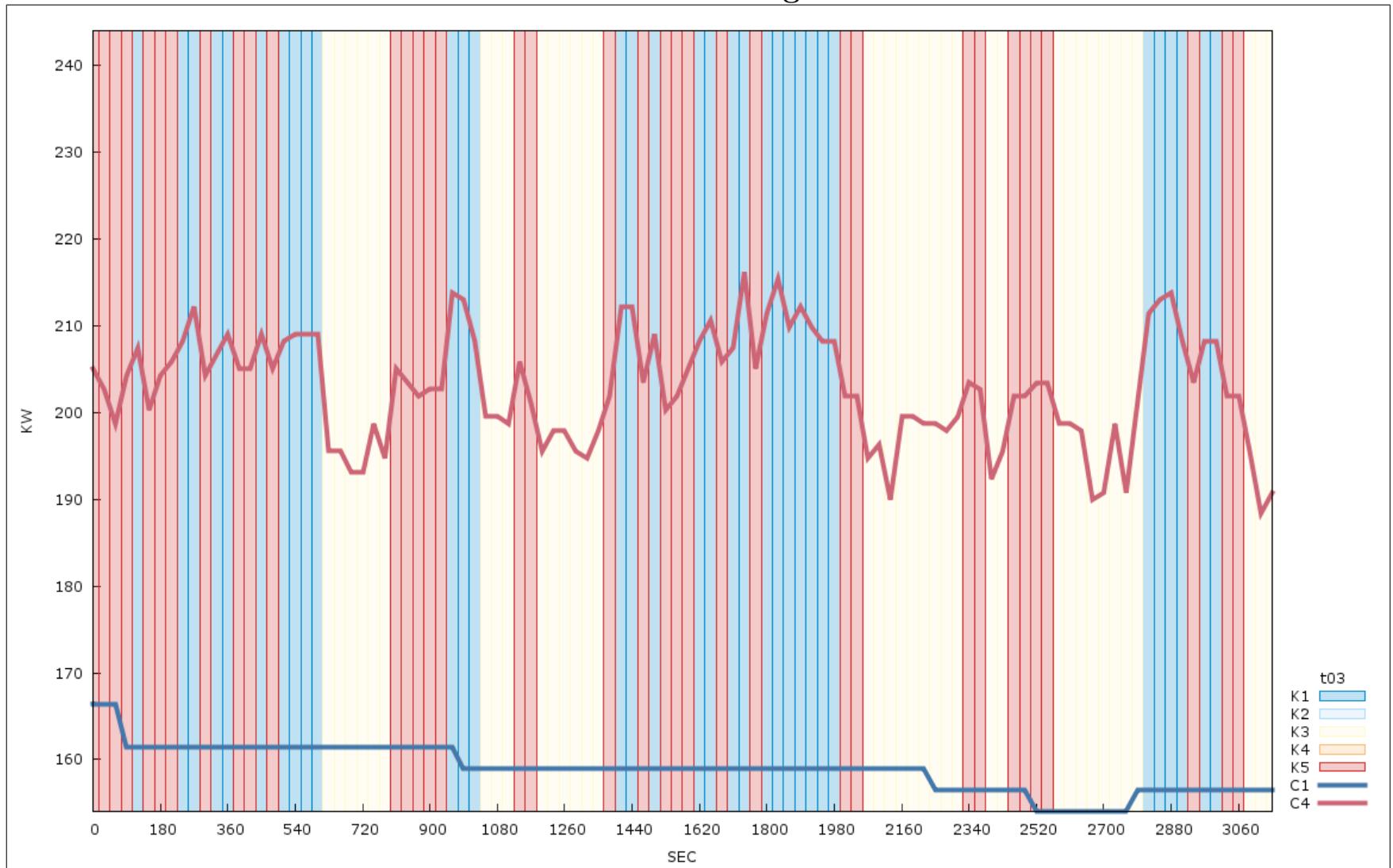


Figure J.6: K-Means Clustering with  $k = 5$

### Trial 1 : Chiller Clustering on KW

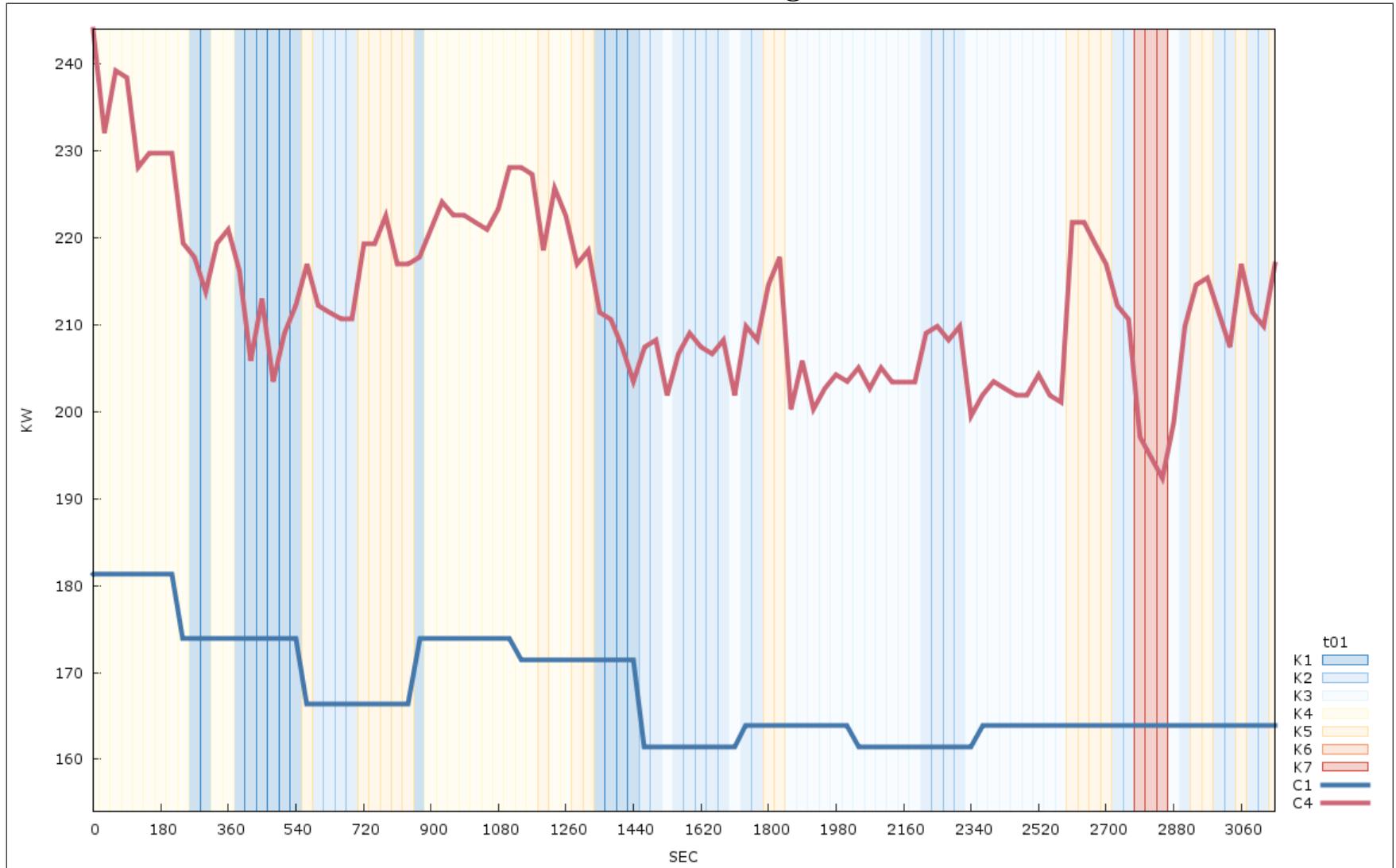


Figure J.7: K-Means Clustering with  $k = 7$

## Trial 2 : Chiller Clustering on KW

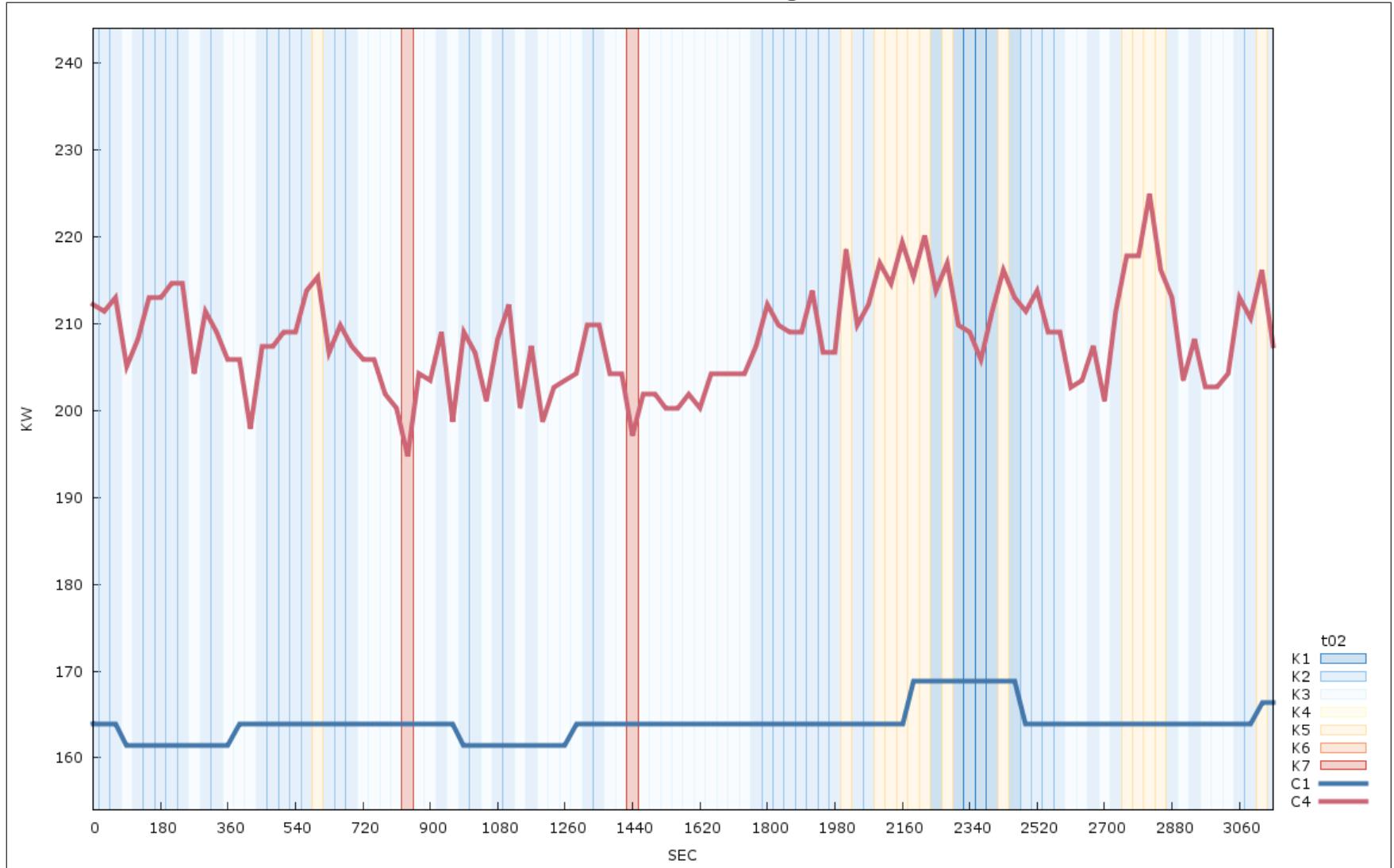


Figure J.8: K-Means Clustering with  $k = 7$

### Trial 3 : Chiller Clustering on KW

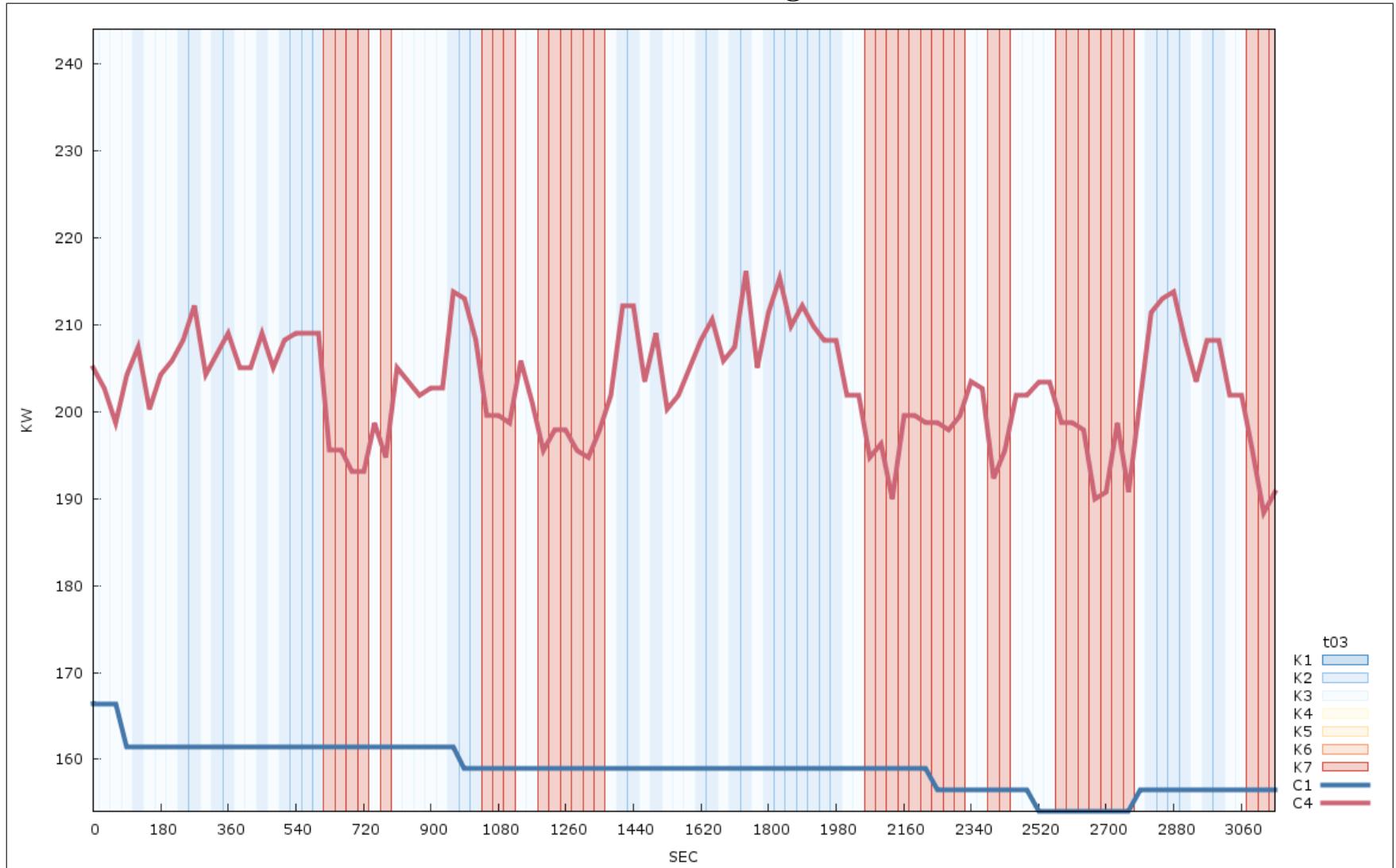


Figure J.9: K-Means Clustering with  $k = 7$

### Trial 1 : Chiller Clustering on KW

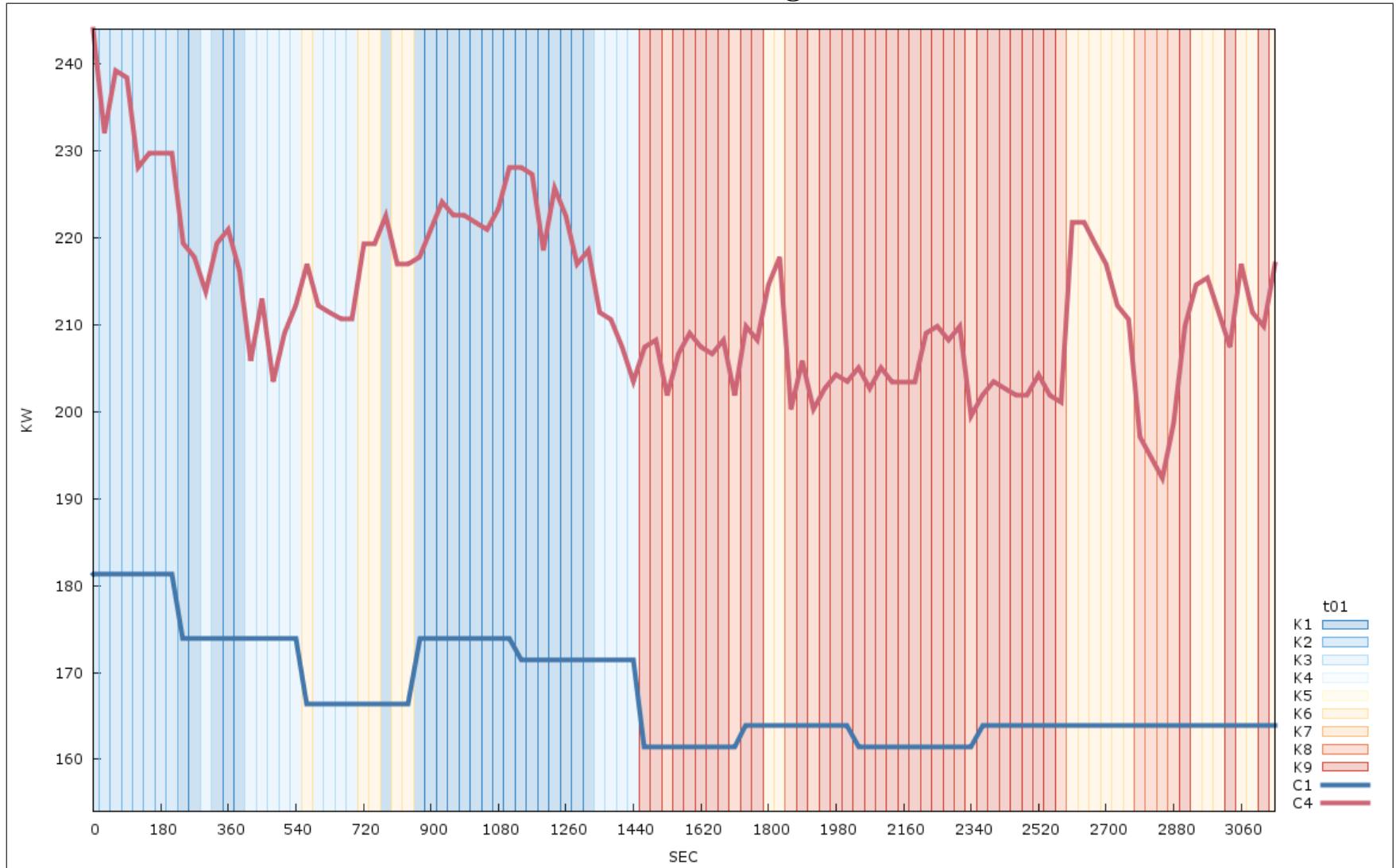


Figure J.10: K-Means Clustering with  $k = 9$

## Trial 2 : Chiller Clustering on KW

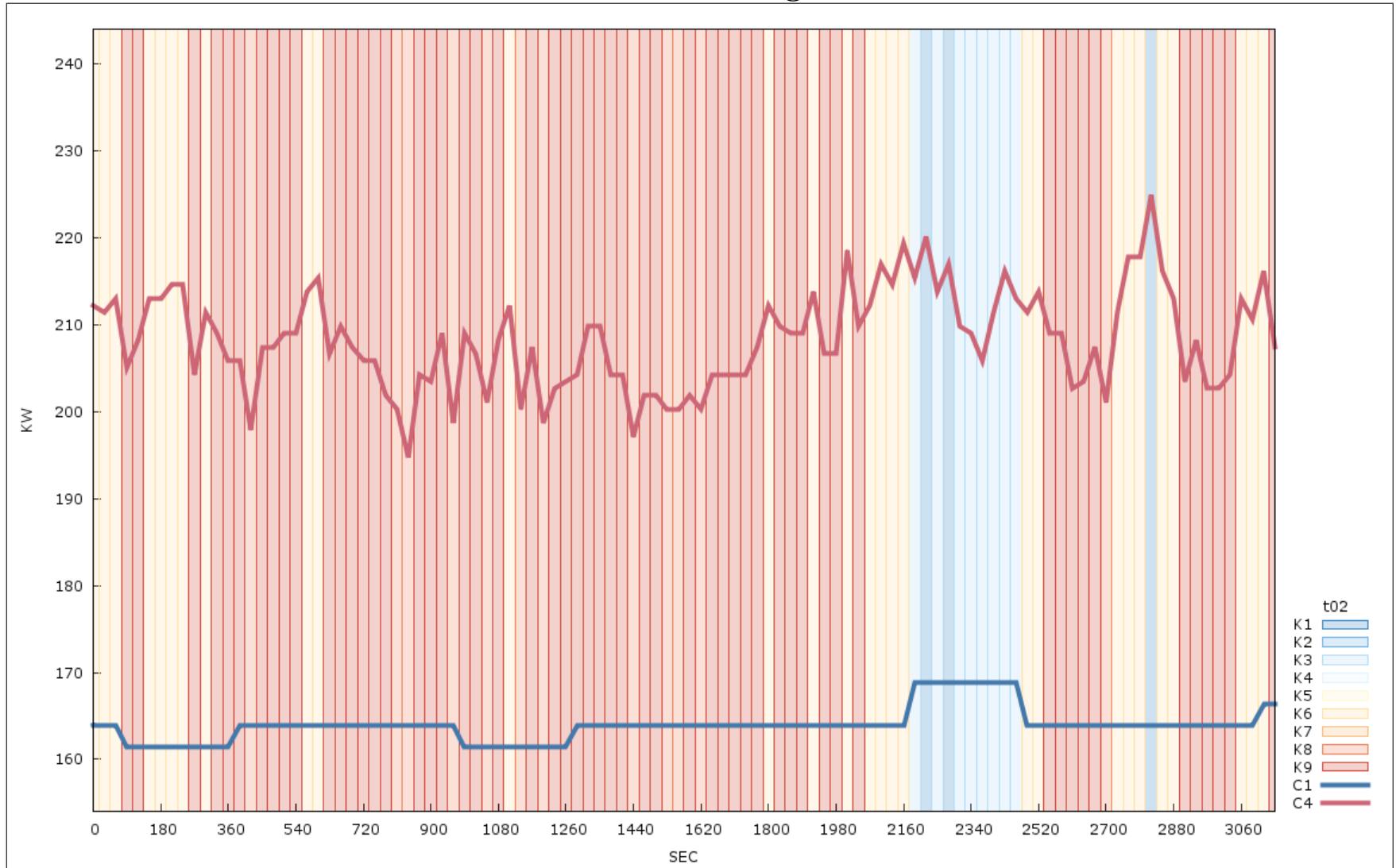


Figure J.11: K-Means Clustering with  $k = 9$

### Trial 3 : Chiller Clustering on KW



Figure J.12: K-Means Clustering with  $k = 9$

### Trial 1 : Chiller Clustering on KW

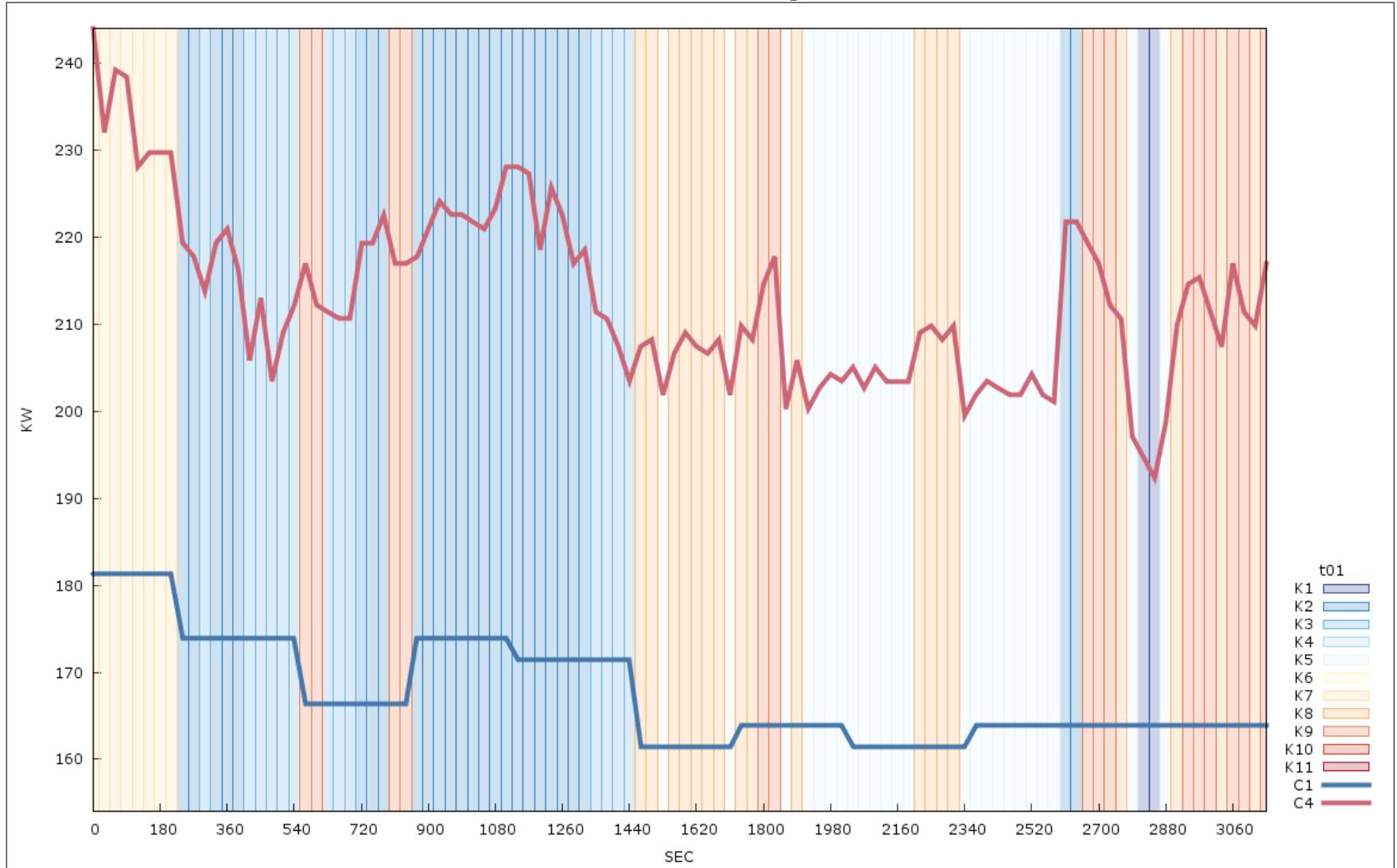


Figure J.13: K-Means Clustering with  $k = 11$

### Trial 2 : Chiller Clustering on KW

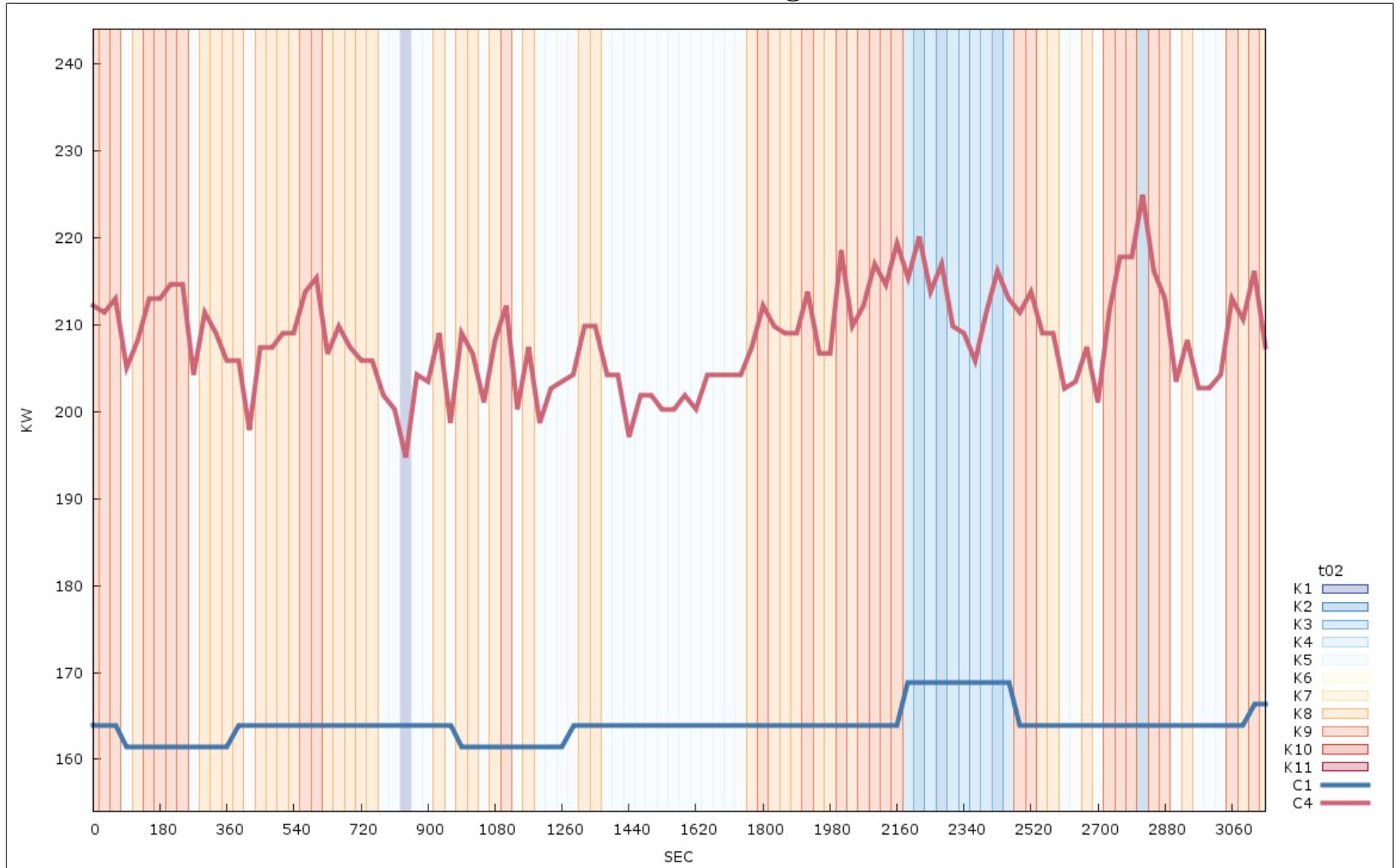


Figure J.14: K-Means Clustering with  $k = 11$

### Trial 3 : Chiller Clustering on KW

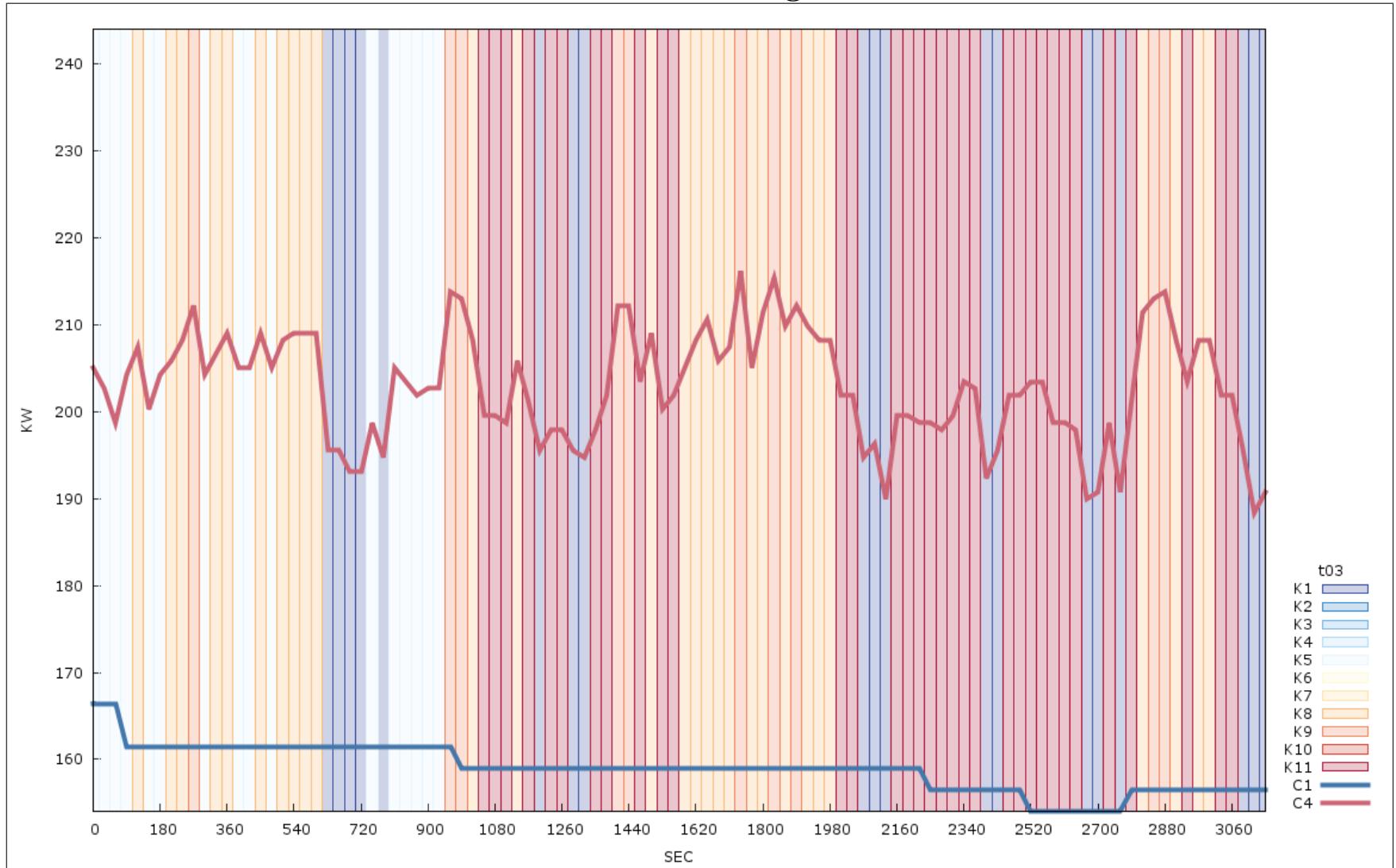


Figure J.15: K-Means Clustering with  $k = 11$

## Appendix K

# High-Density Workload : Chiller Clustering on Loads

### Trial 1 : Chiller Clustering on Loads

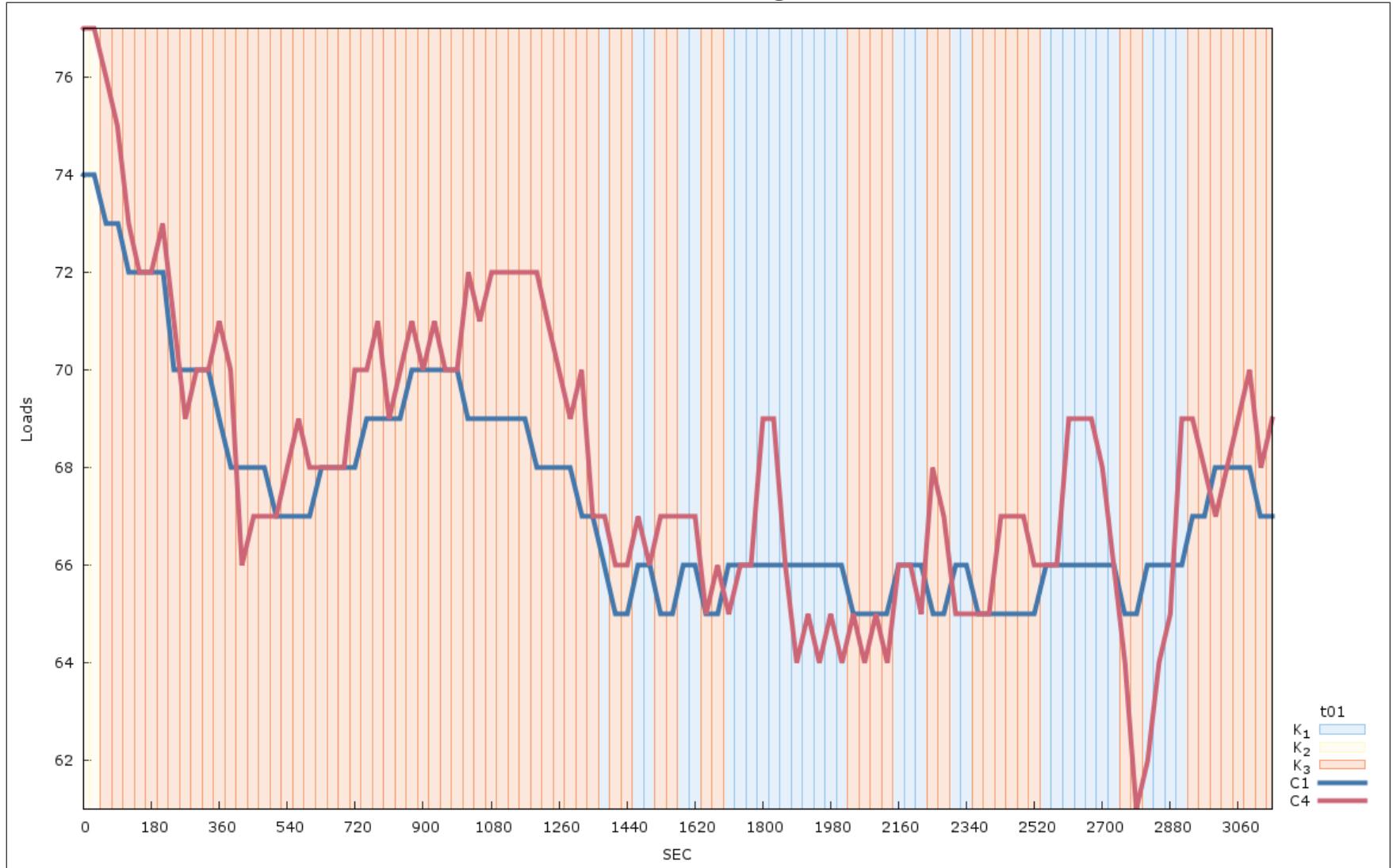


Figure K.1: EM Clustering with  $k = 3$

## Trial 2 : Chiller Clustering on Loads

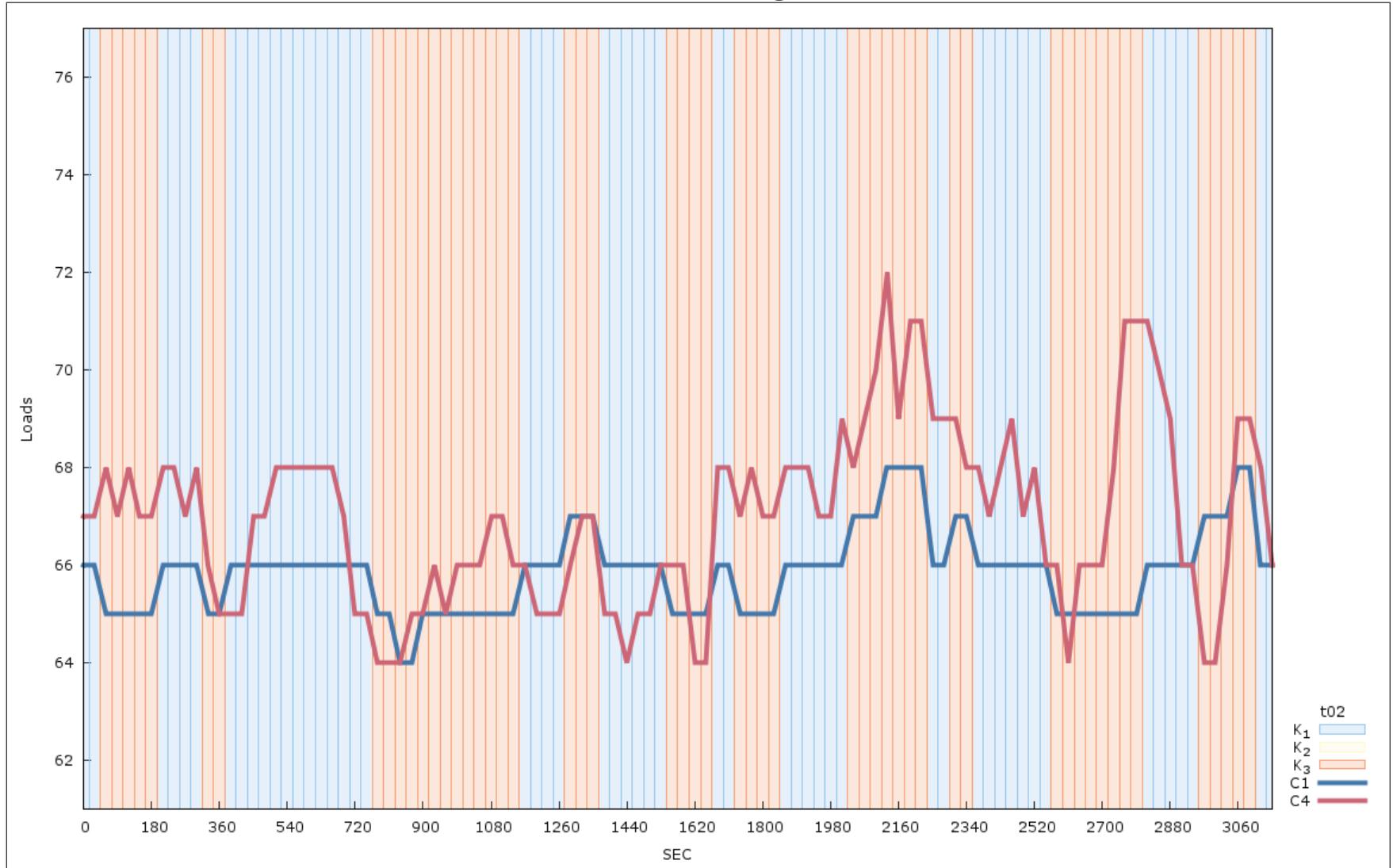


Figure K.2: EM Clustering with  $k = 3$

### Trial 3 : Chiller Clustering on Loads

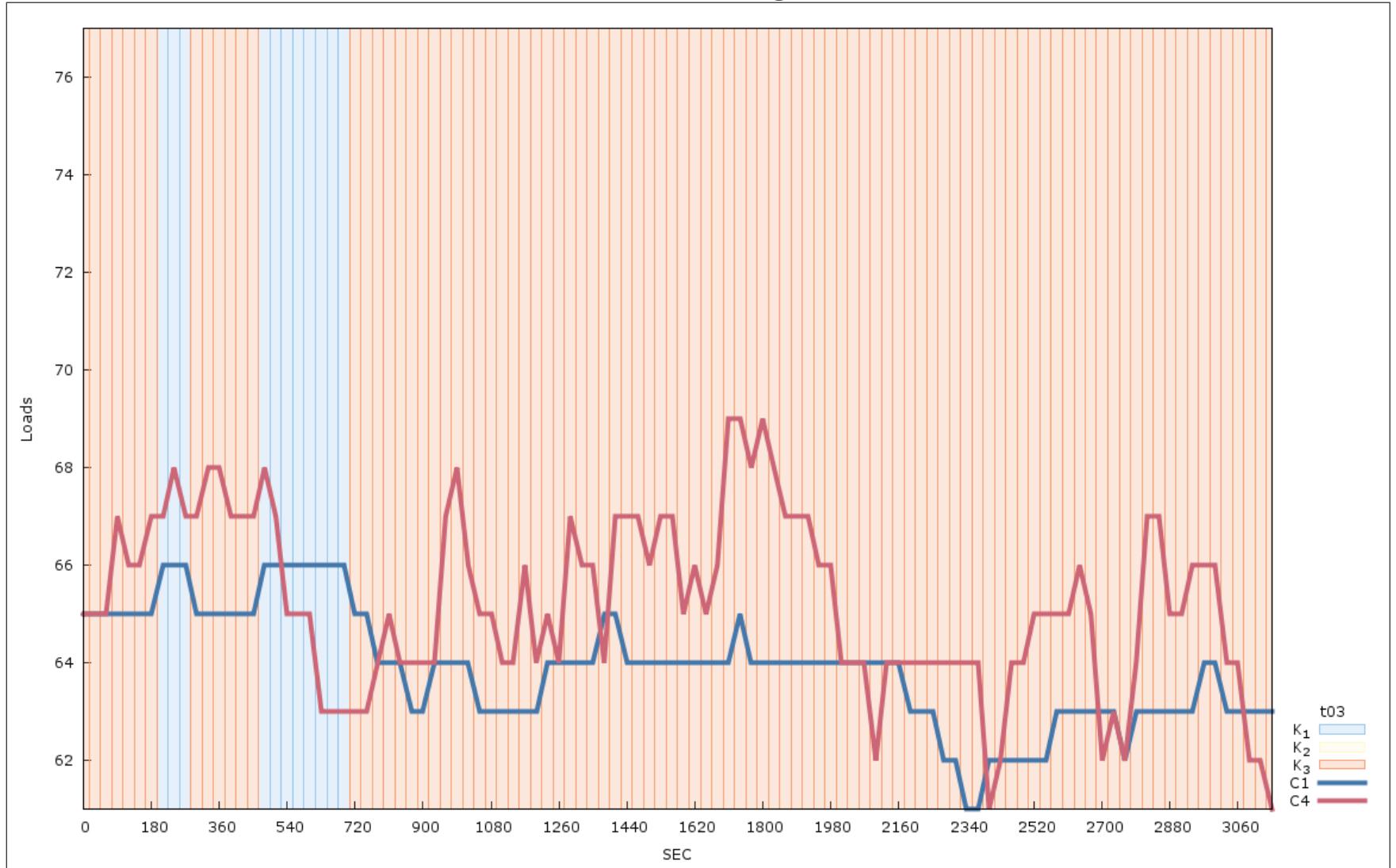


Figure K.3: EM Clustering with  $k = 3$

## Trial 1 : Chiller Clustering on Loads

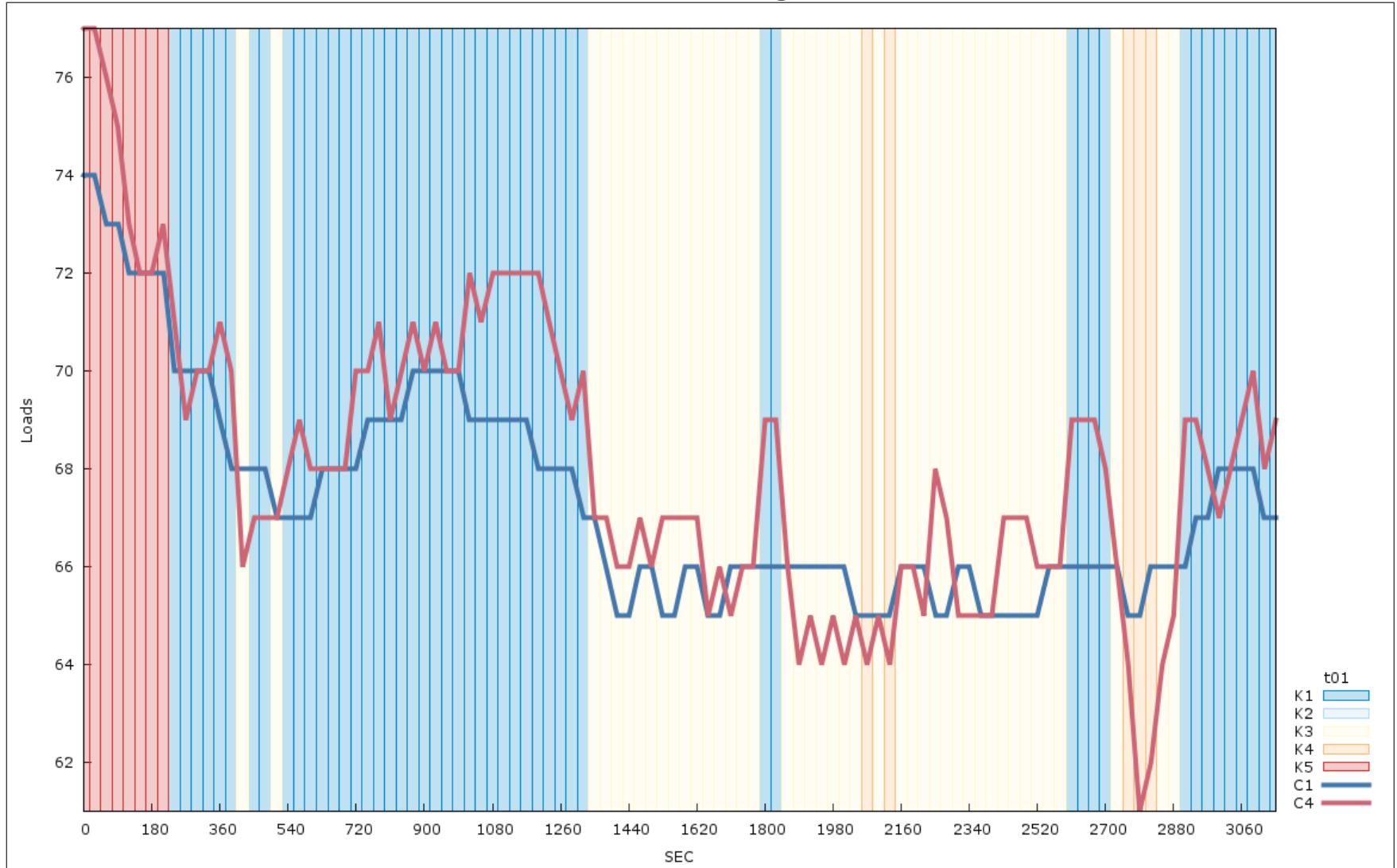


Figure K.4: K-Means Clustering with  $k = 5$

## Trial 2 : Chiller Clustering on Loads

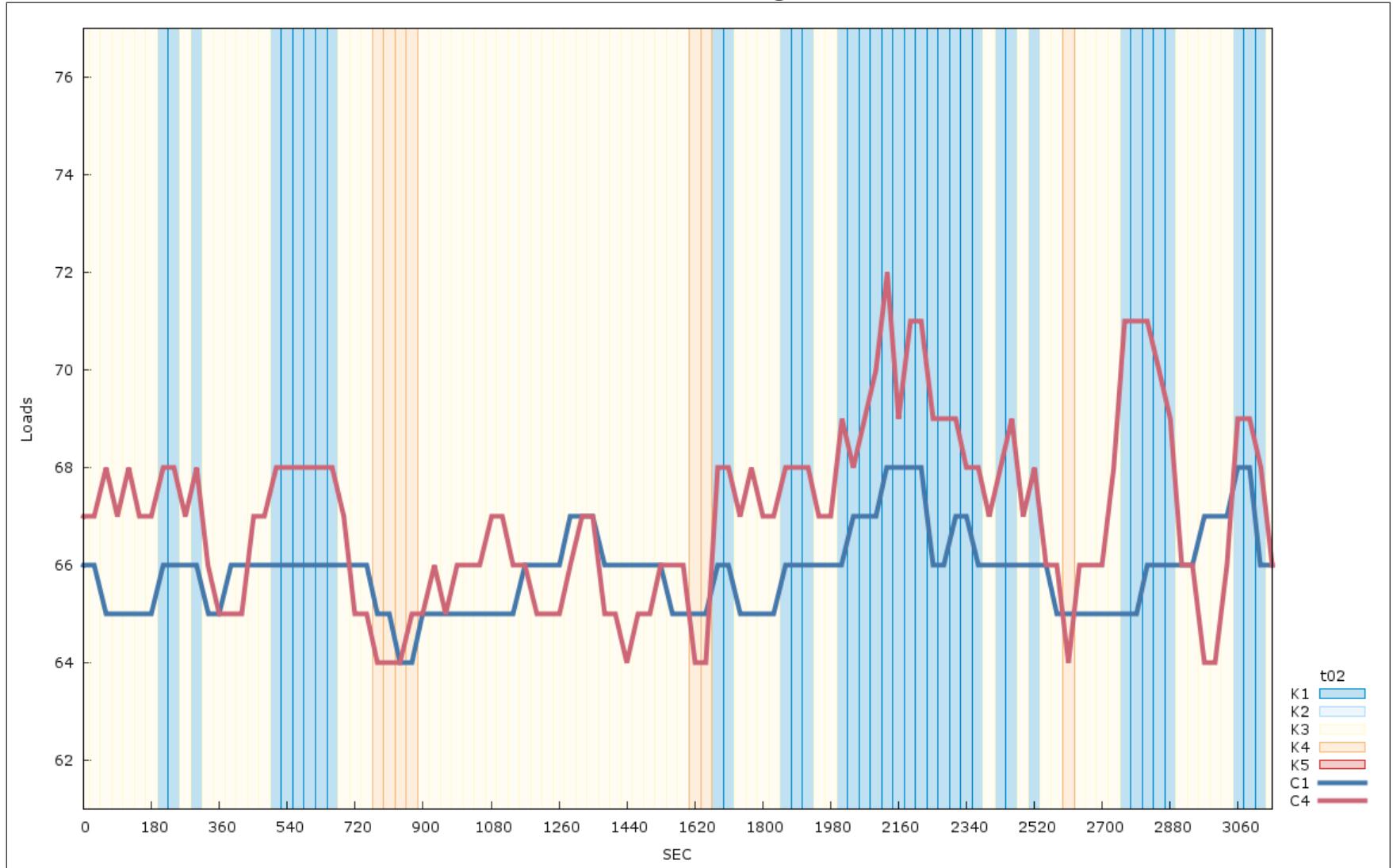


Figure K.5: K-Means Clustering with  $k = 5$

### Trial 3 : Chiller Clustering on Loads

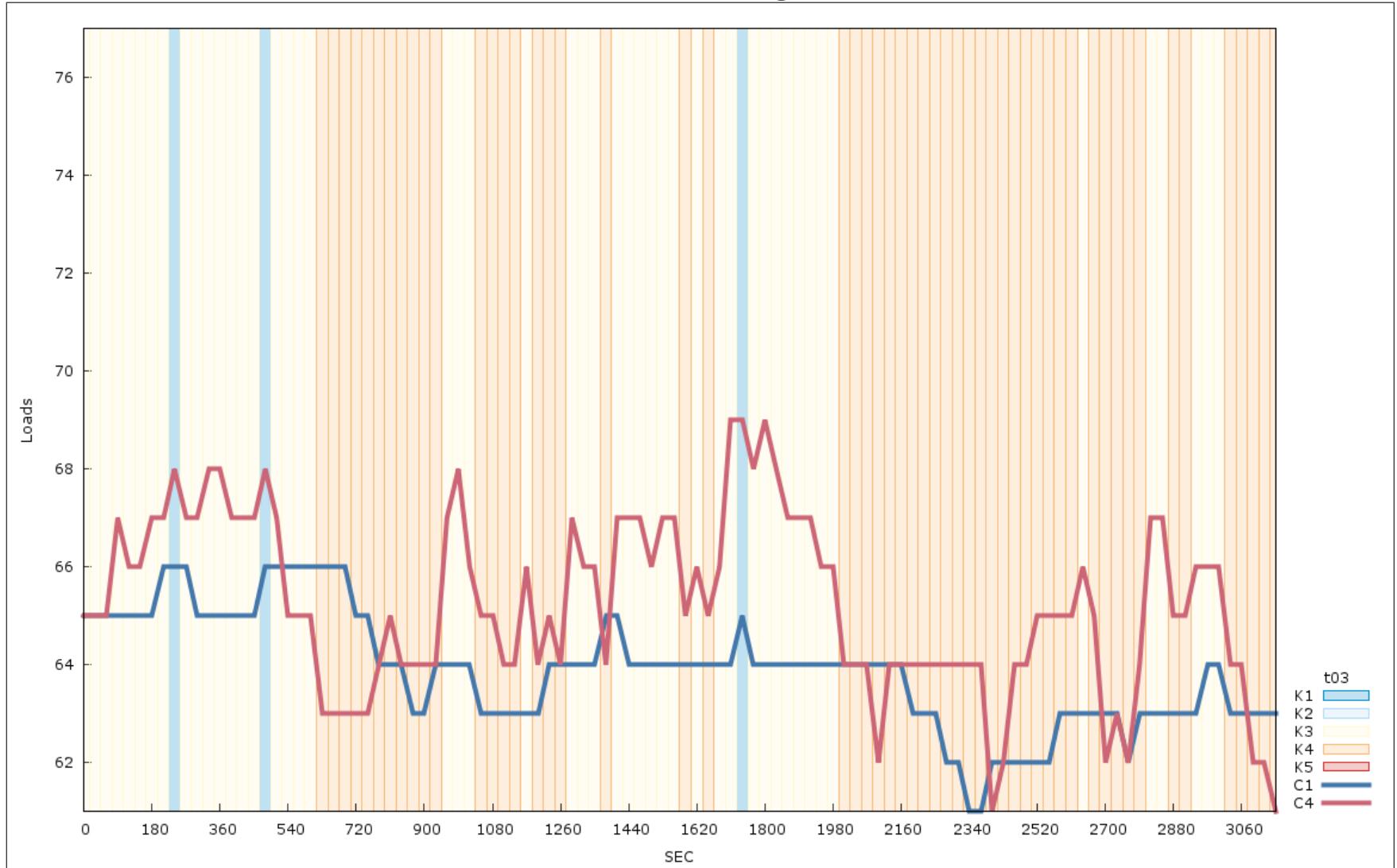


Figure K.6: K-Means Clustering with  $k = 5$

### Trial 1 : Chiller Clustering on Loads

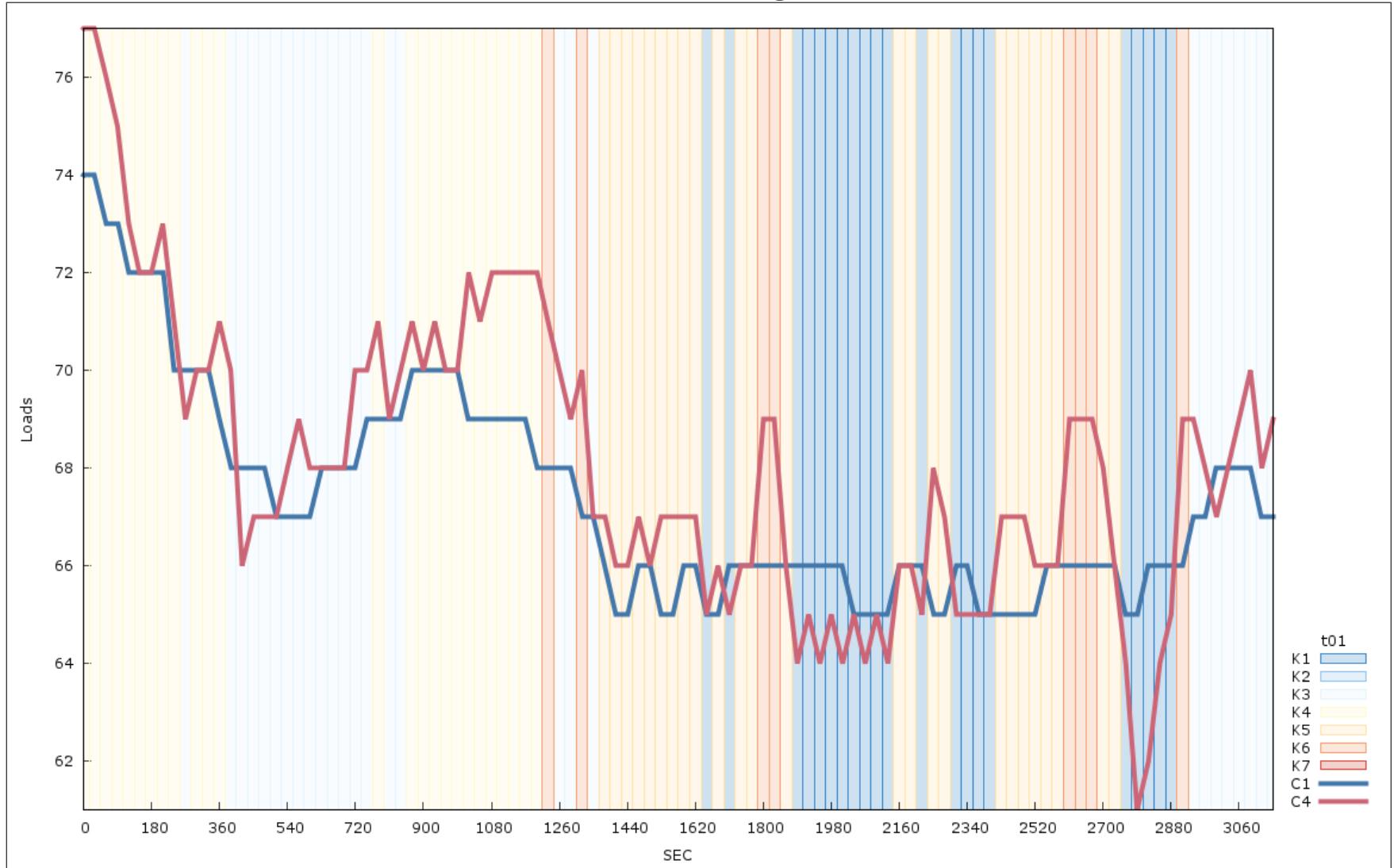


Figure K.7: K-Means Clustering with  $k = 7$

## Trial 2 : Chiller Clustering on Loads

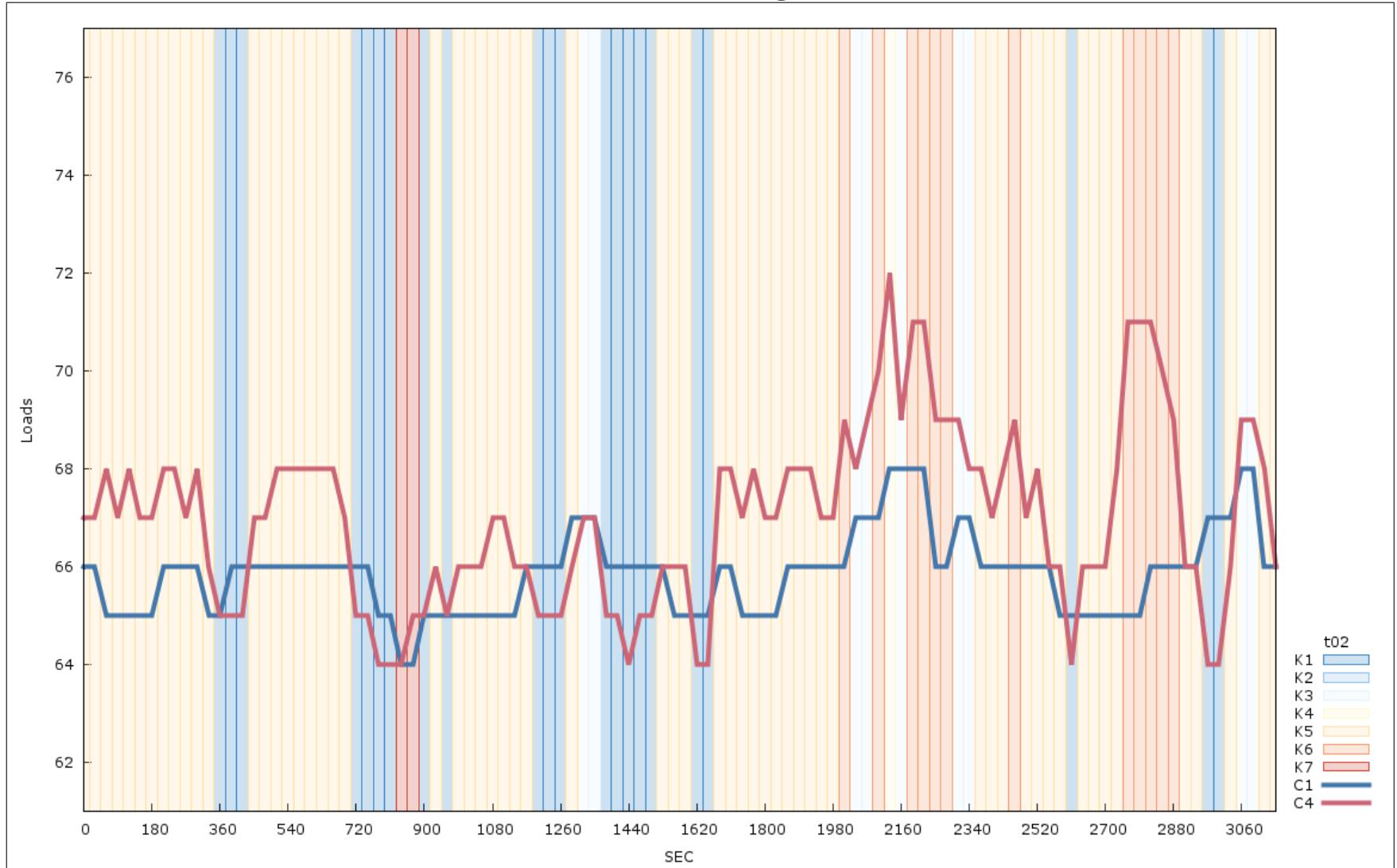


Figure K.8: K-Means Clustering with  $k = 7$

### Trial 3 : Chiller Clustering on Loads

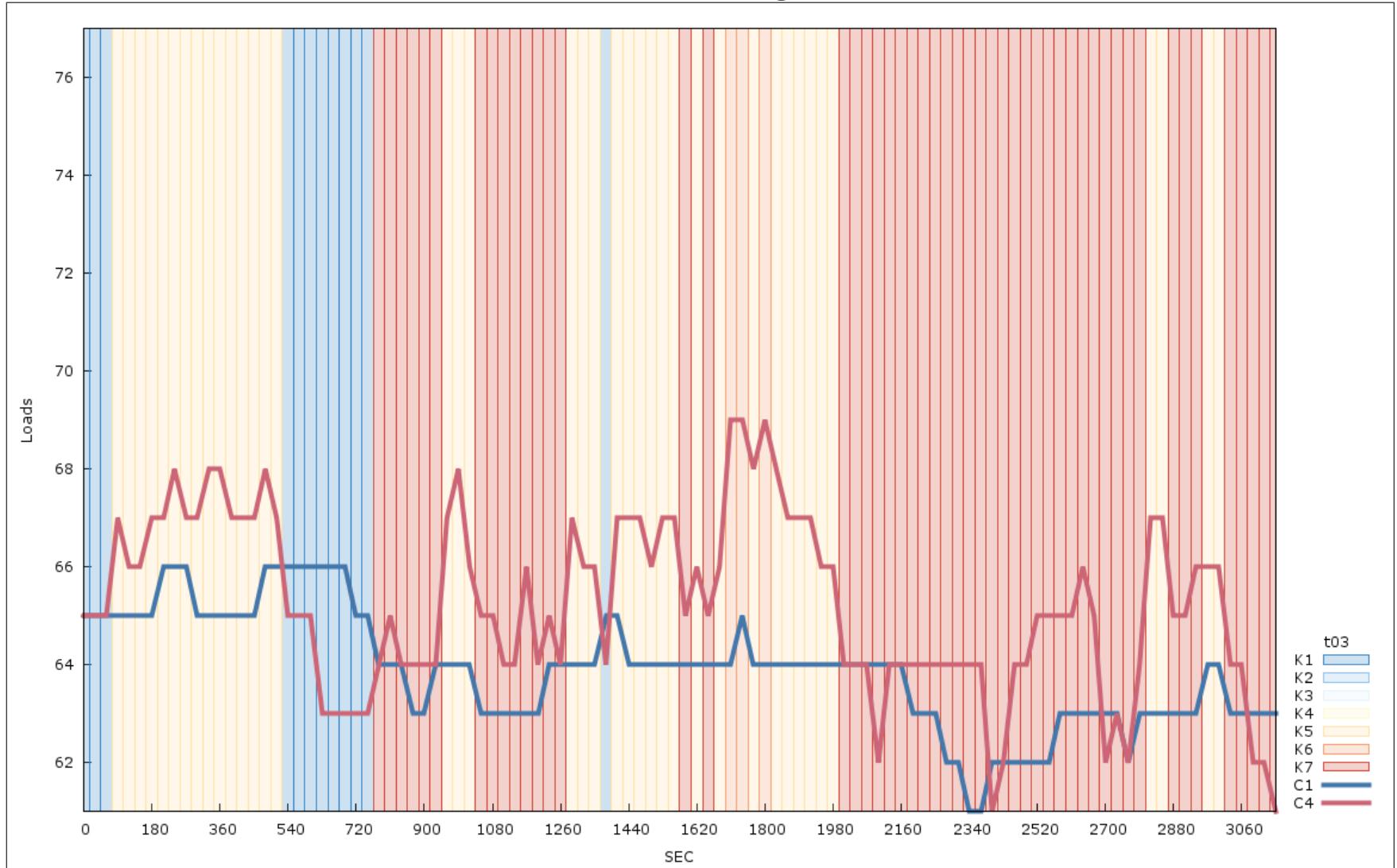


Figure K.9: K-Means Clustering with  $k = 7$

### Trial 1 : Chiller Clustering on Loads

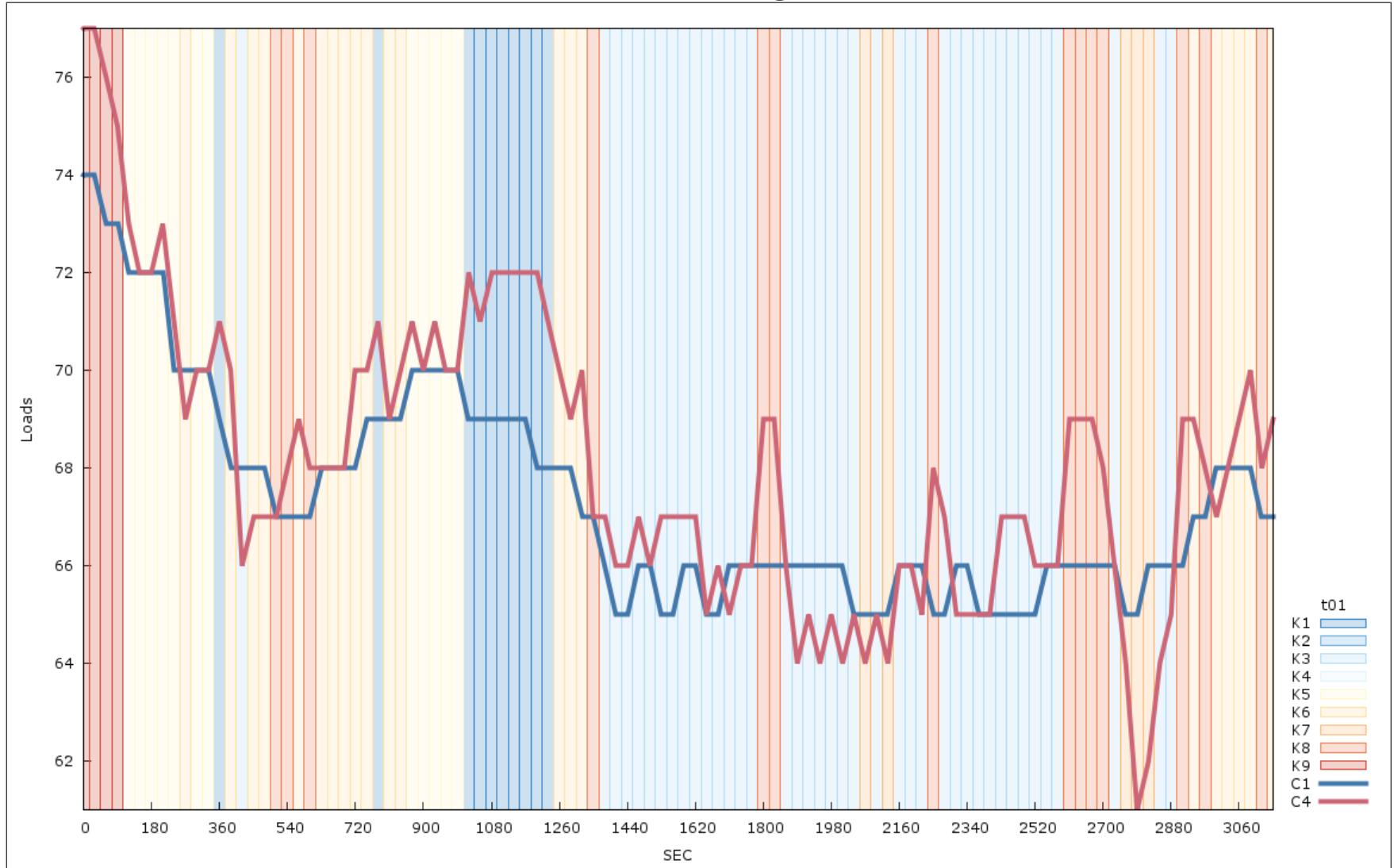


Figure K.10: K-Means Clustering with  $k = 9$

## Trial 2 : Chiller Clustering on Loads

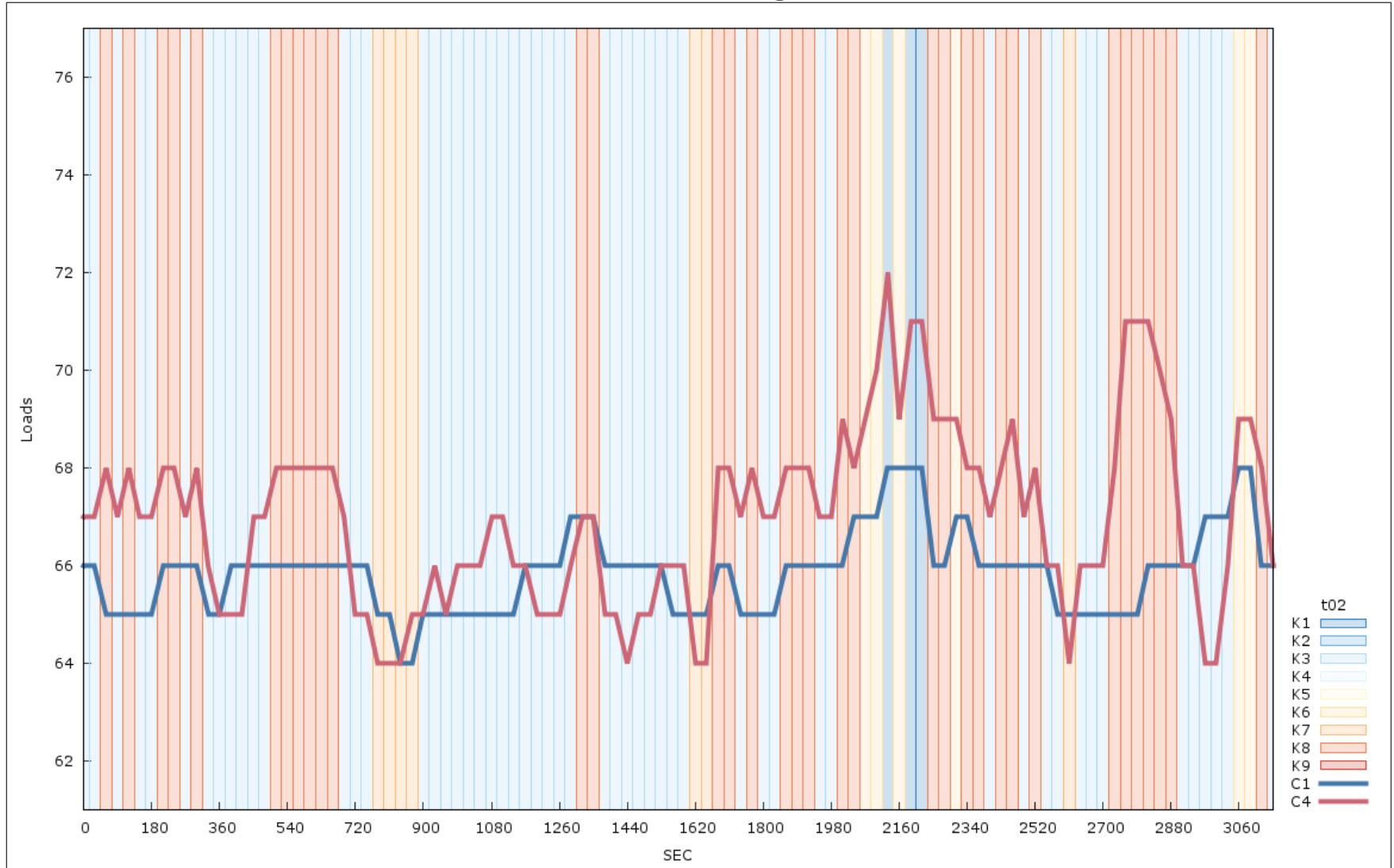


Figure K.11: K-Means Clustering with  $k = 9$

### Trial 3 : Chiller Clustering on Loads

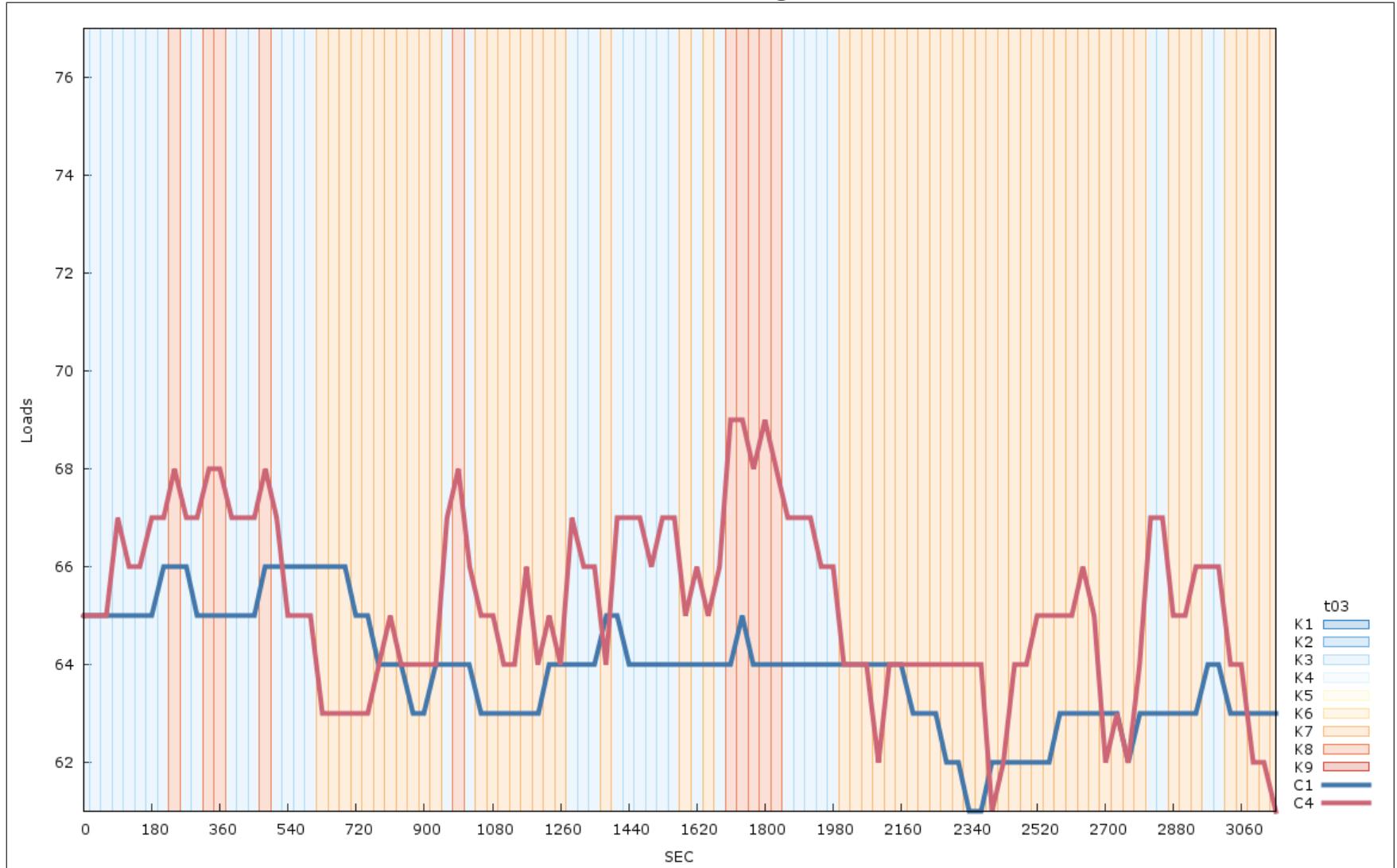


Figure K.12: K-Means Clustering with  $k = 9$

### Trial 1 : Chiller Clustering on Loads

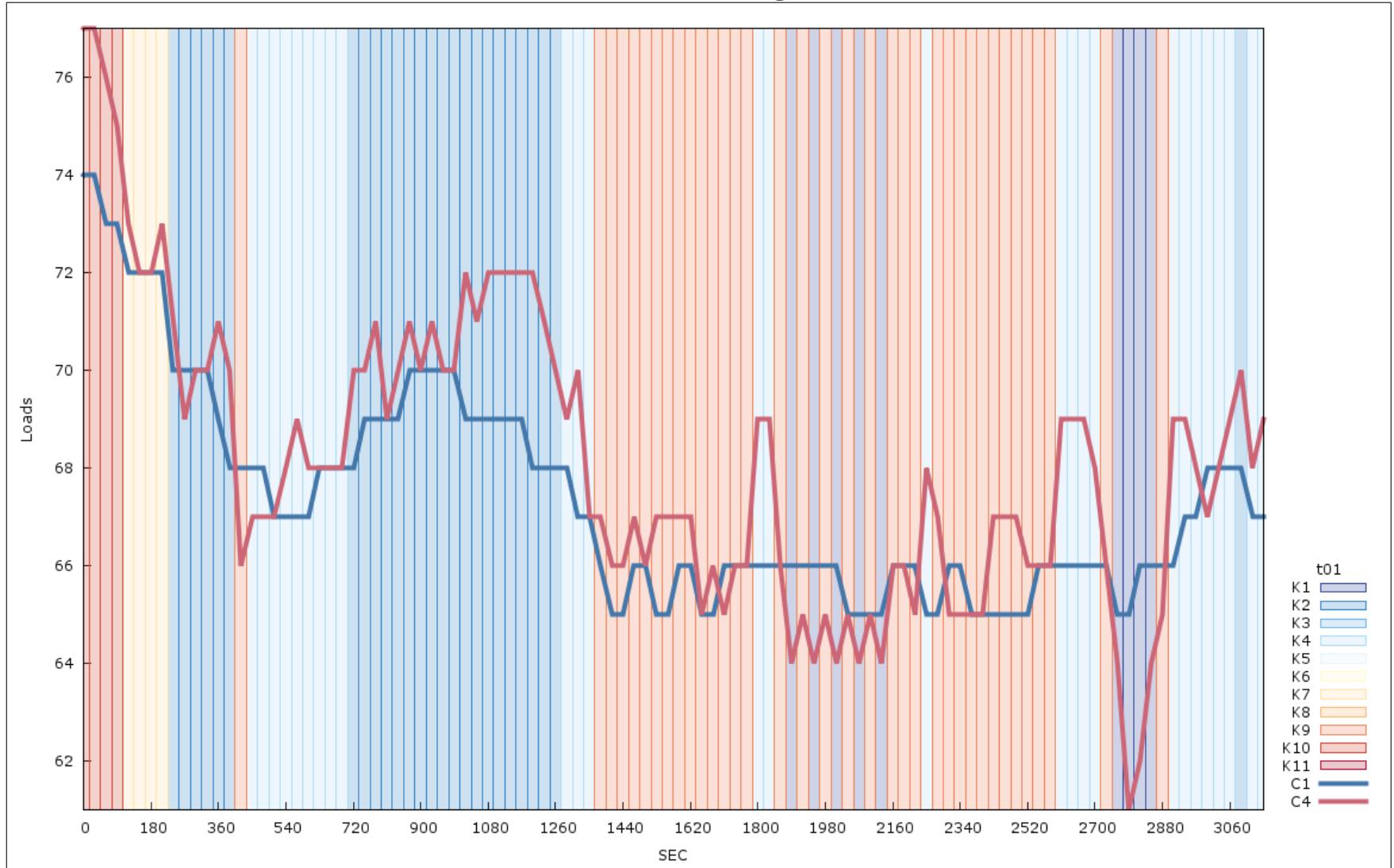


Figure K.13: K-Means Clustering with  $k = 11$

## Trial 2 : Chiller Clustering on Loads

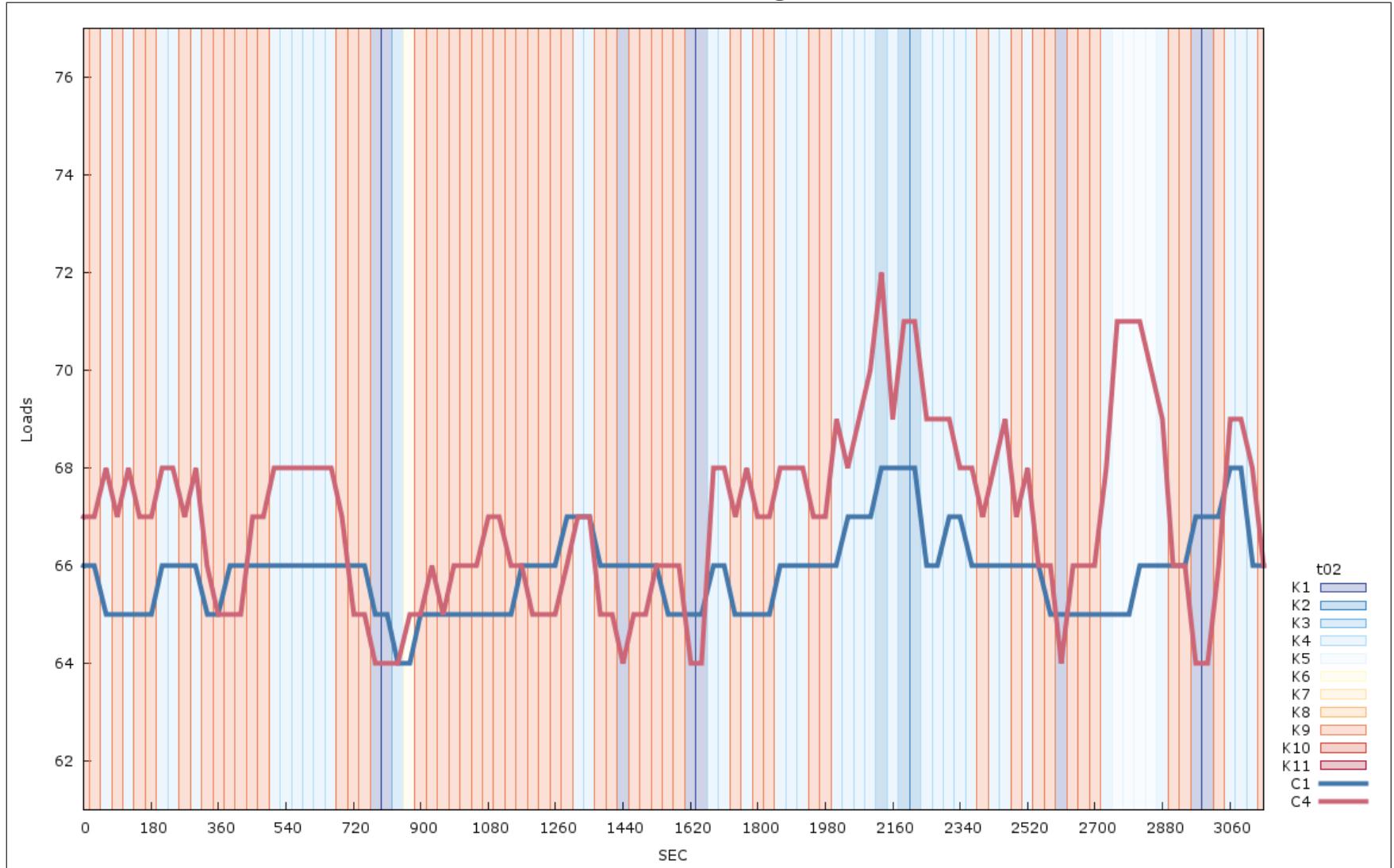


Figure K.14: K-Means Clustering with  $k = 11$

### Trial 3 : Chiller Clustering on Loads

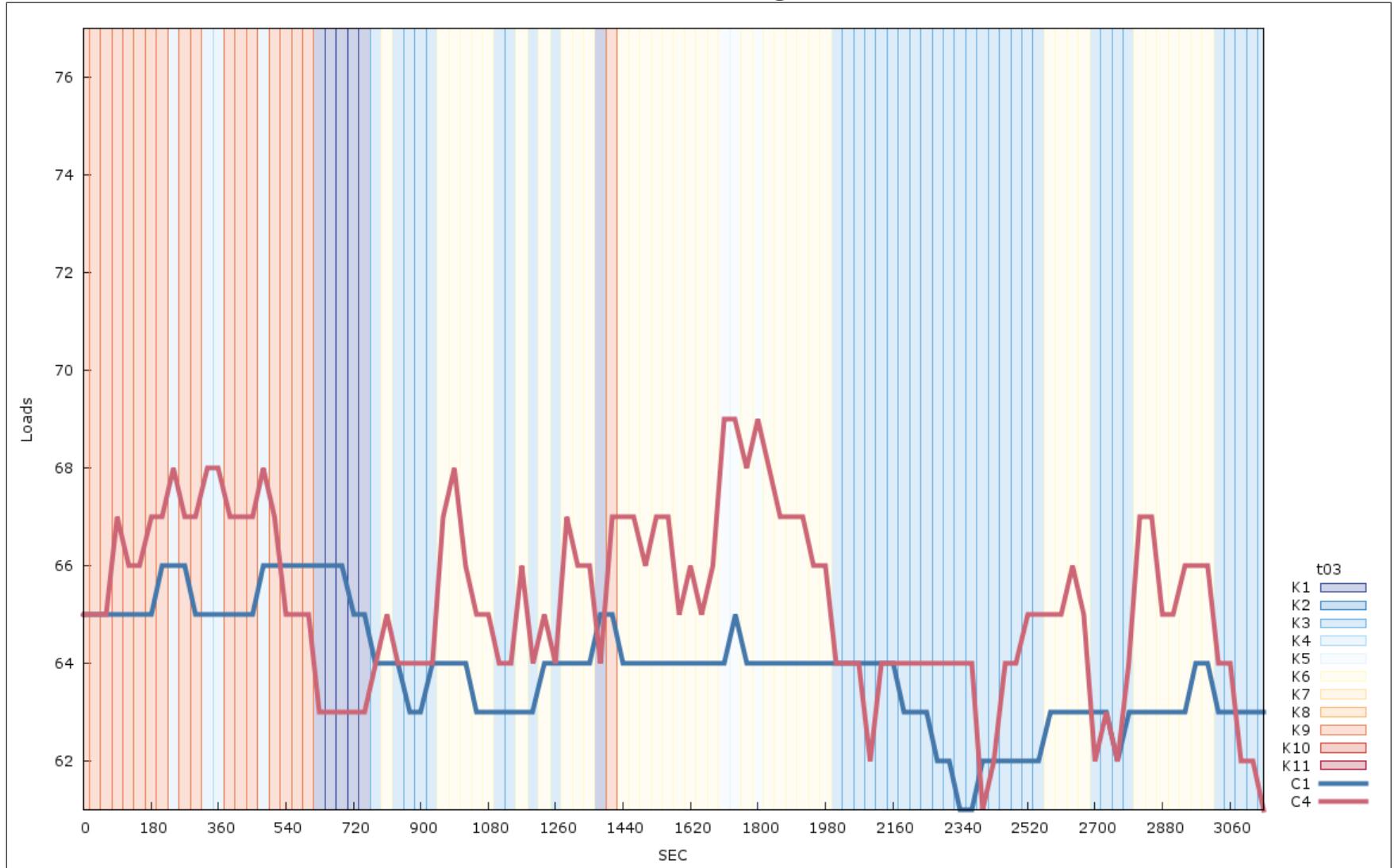


Figure K.15: K-Means Clustering with  $k = 11$

## Appendix L

### High-Density Workload : Chiller Clustering on COP

### Trial 1 : Chiller Clustering on COP

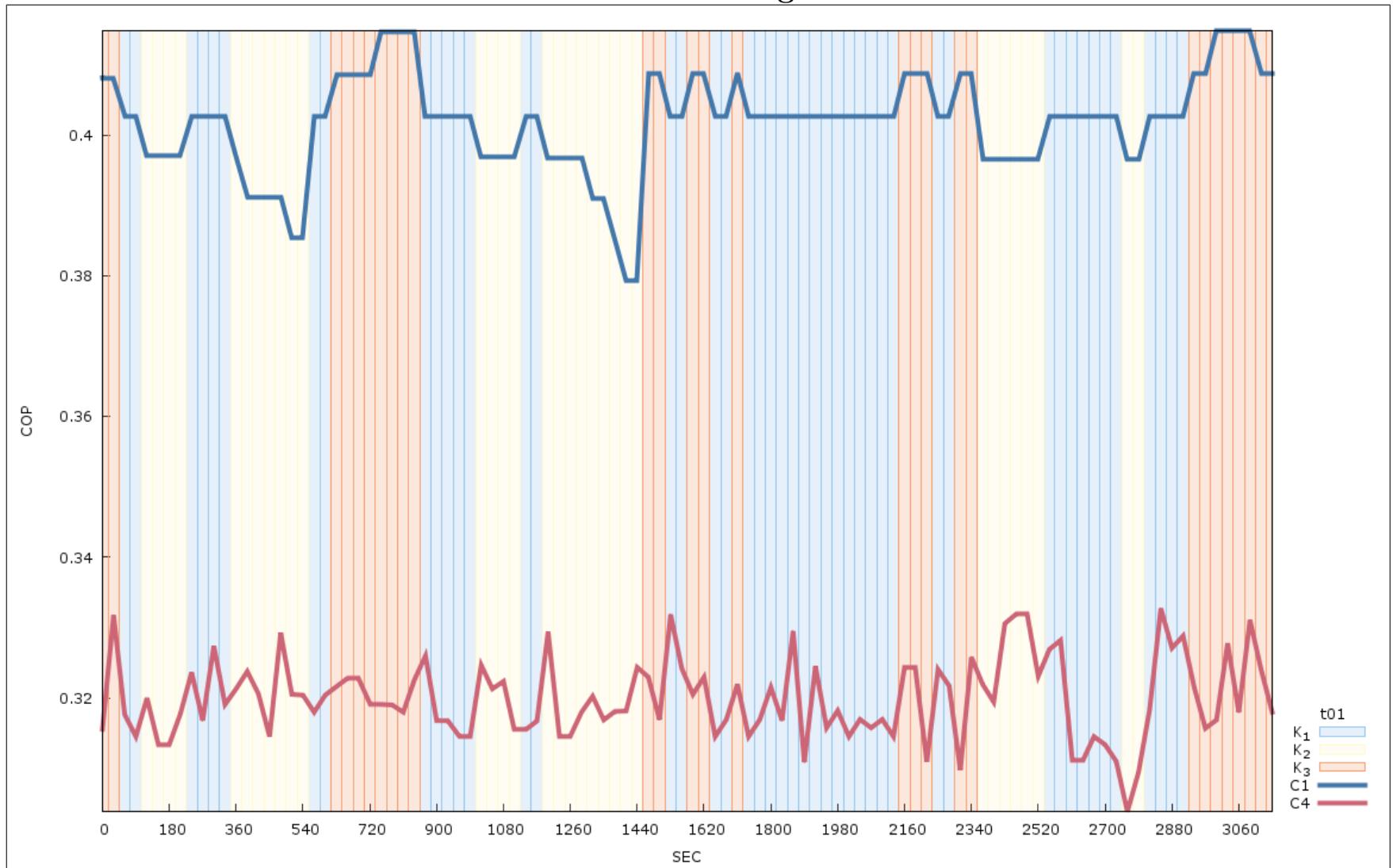


Figure L.1: EM Clustering with  $k = 3$

### Trial 2 : Chiller Clustering on COP

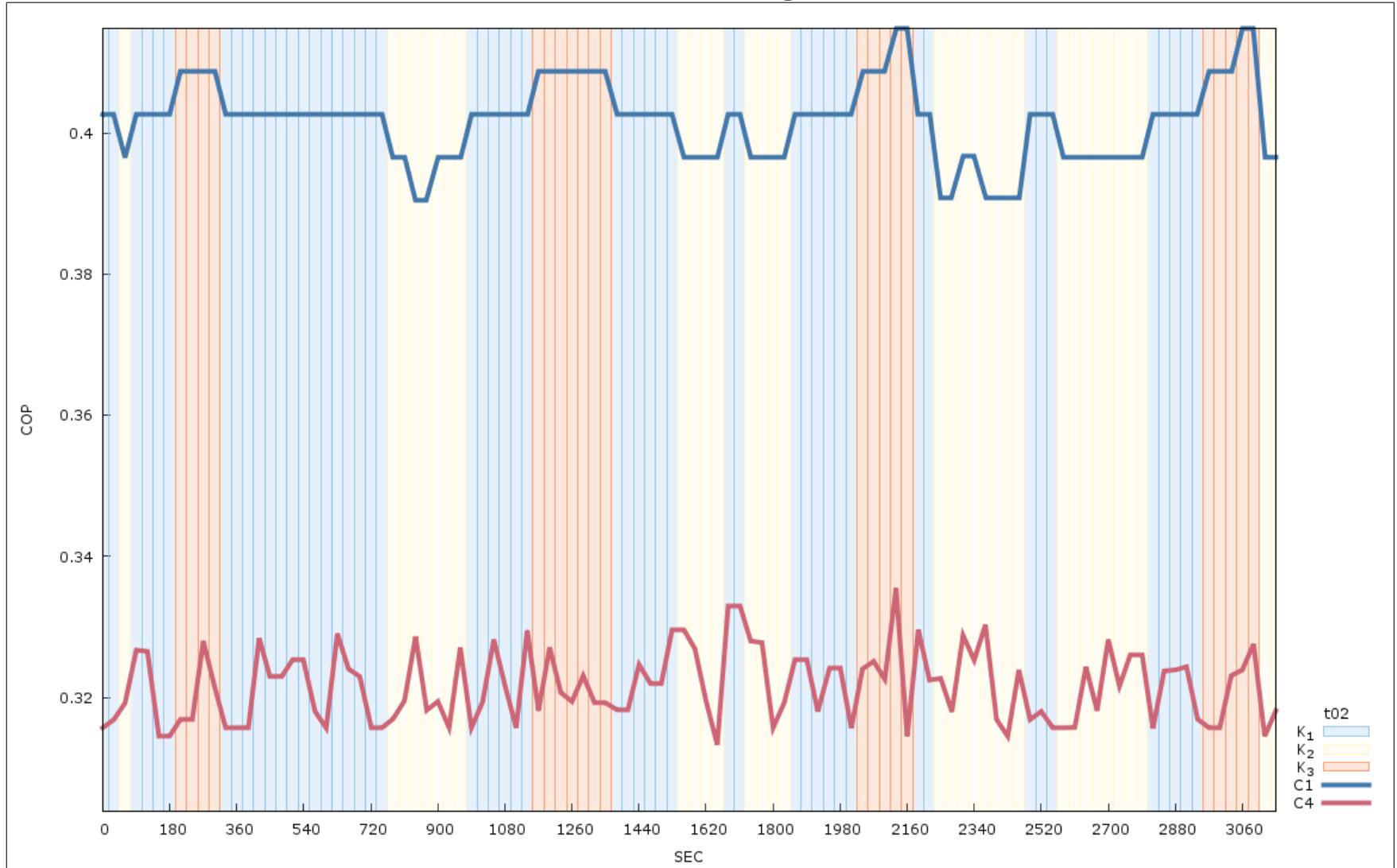


Figure L.2: EM Clustering with  $k = 3$

### Trial 3 : Chiller Clustering on COP



Figure L.3: EM Clustering with  $k = 3$

### Trial 1 : Chiller Clustering on COP

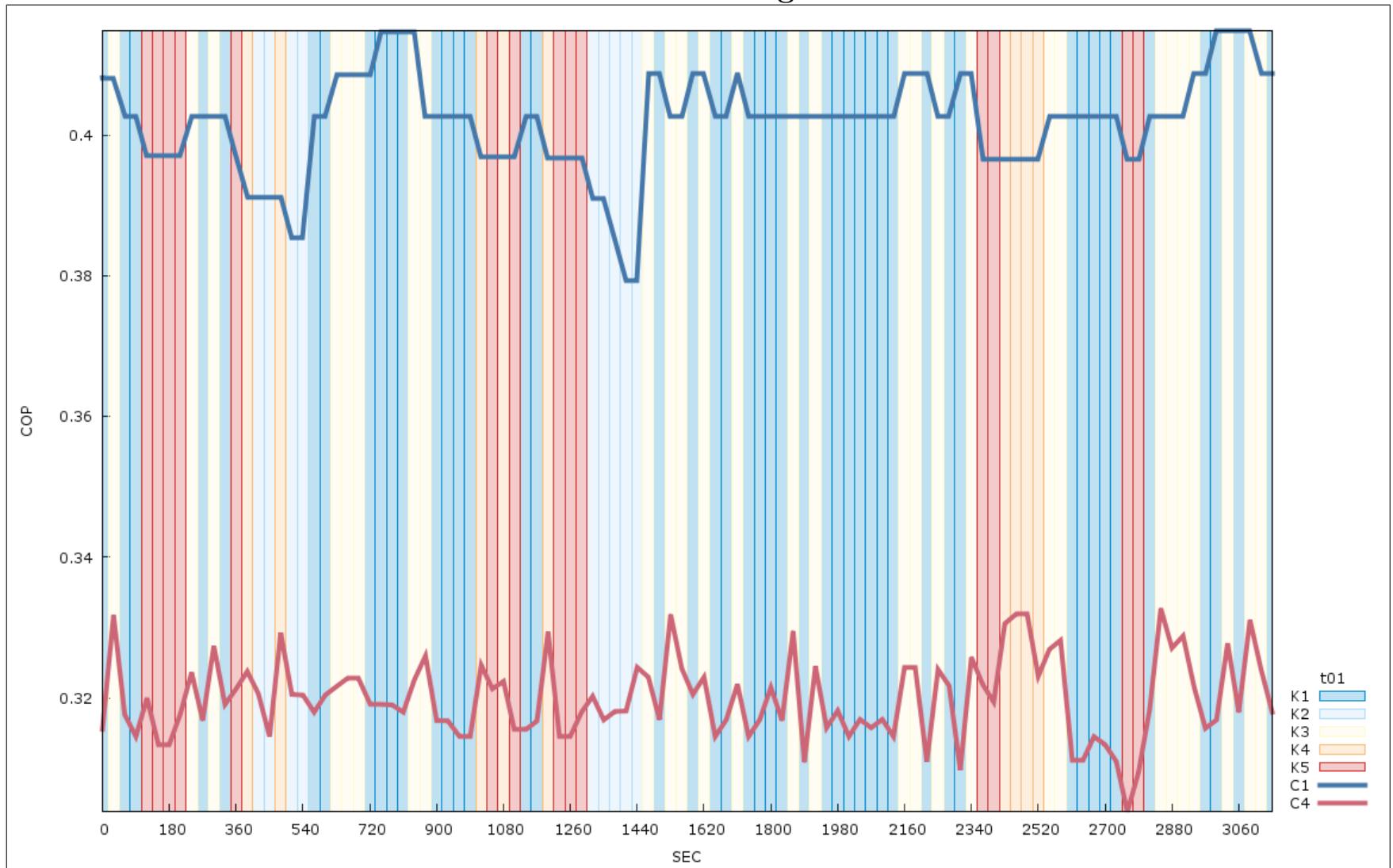


Figure L.4: K-Means Clustering with  $k = 5$

### Trial 2 : Chiller Clustering on COP

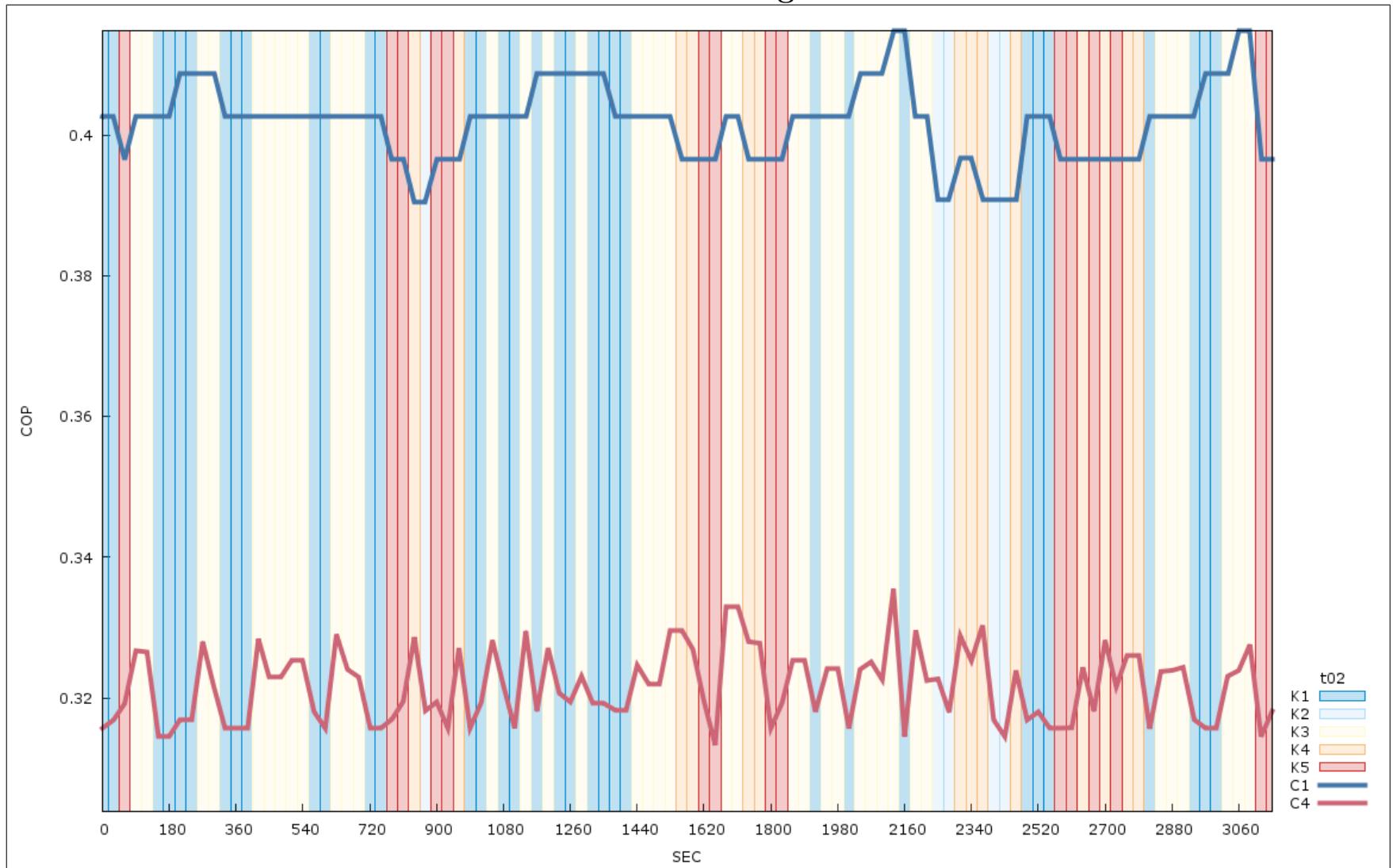


Figure L.5: K-Means Clustering with  $k = 5$

### Trial 3 : Chiller Clustering on COP

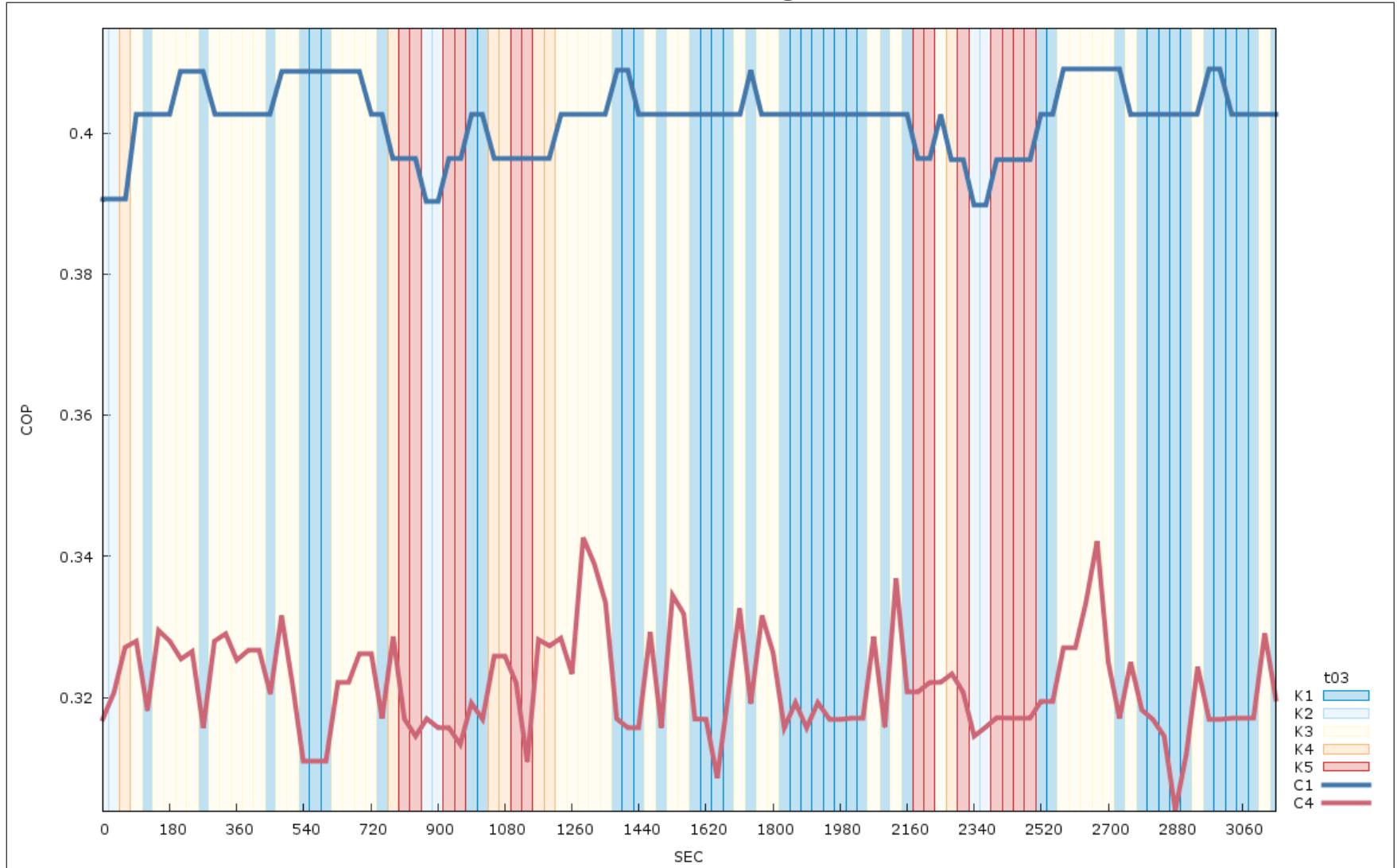


Figure L.6: K-Means Clustering with  $k = 5$

### Trial 1 : Chiller Clustering on COP

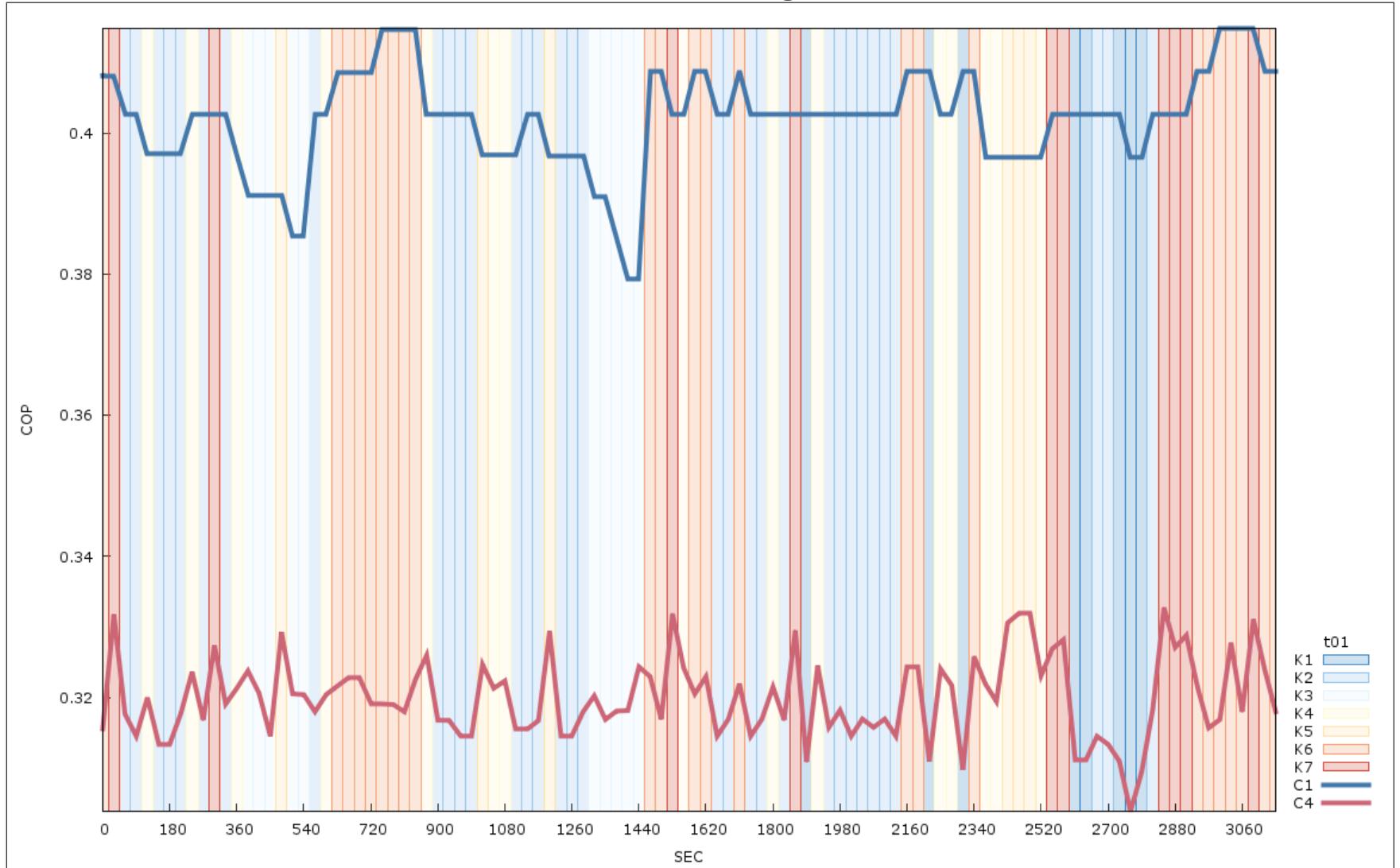


Figure L.7: K-Means Clustering with  $k = 7$

### Trial 2 : Chiller Clustering on COP



Figure L.8: K-Means Clustering with  $k = 7$

### Trial 3 : Chiller Clustering on COP

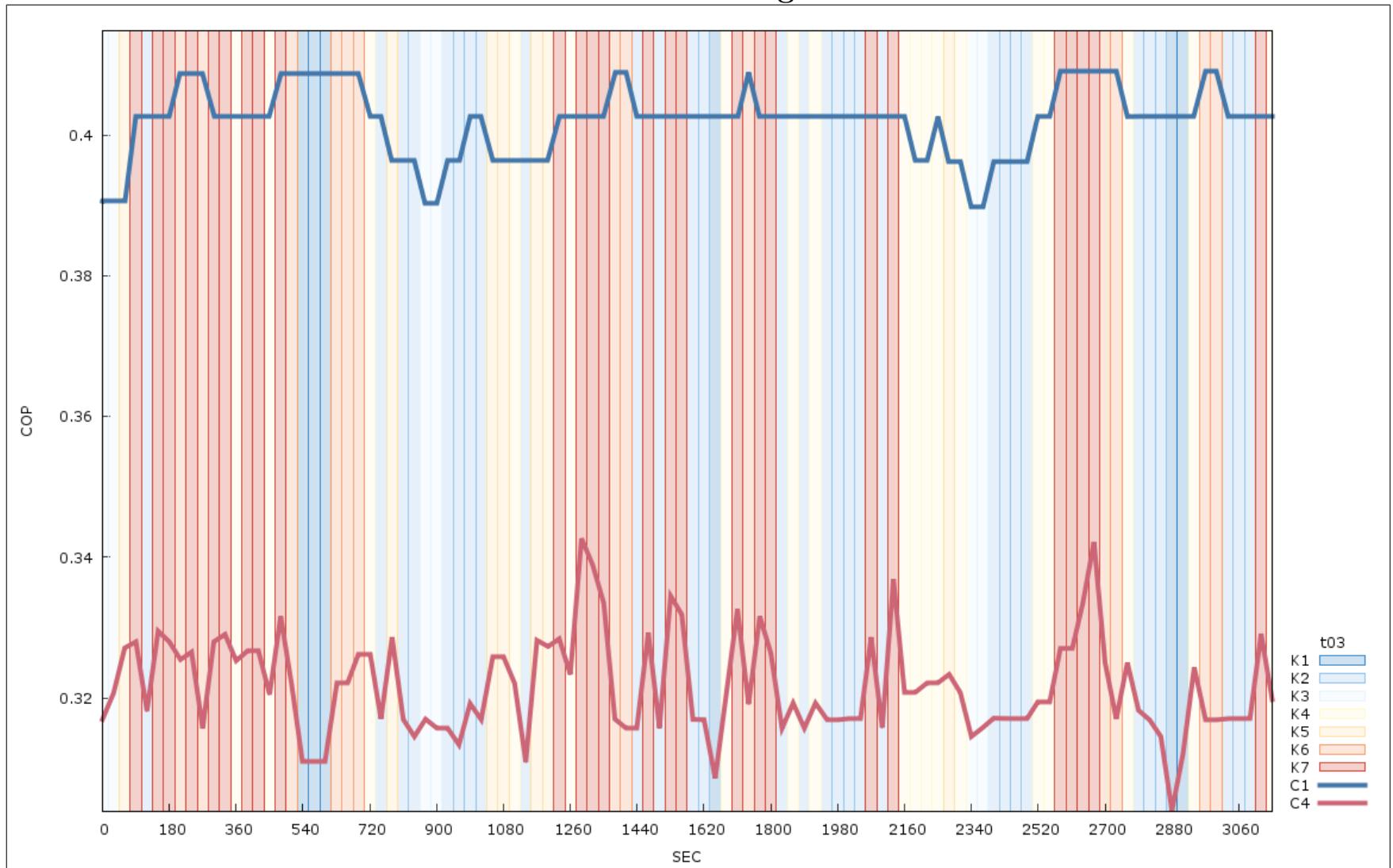


Figure L.9: K-Means Clustering with  $k = 7$

### Trial 1 : Chiller Clustering on COP

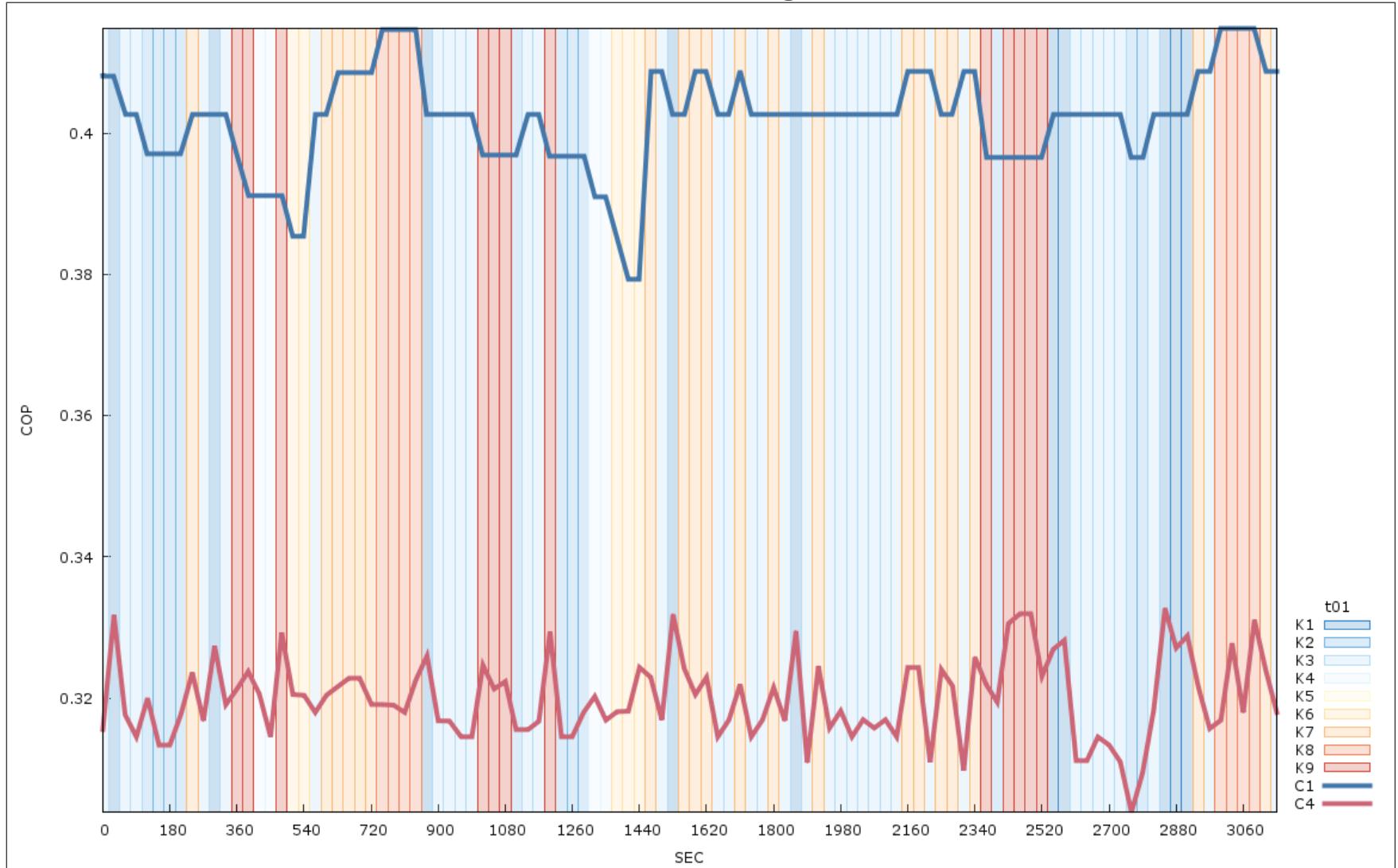


Figure L.10: K-Means Clustering with  $k = 9$

### Trial 2 : Chiller Clustering on COP

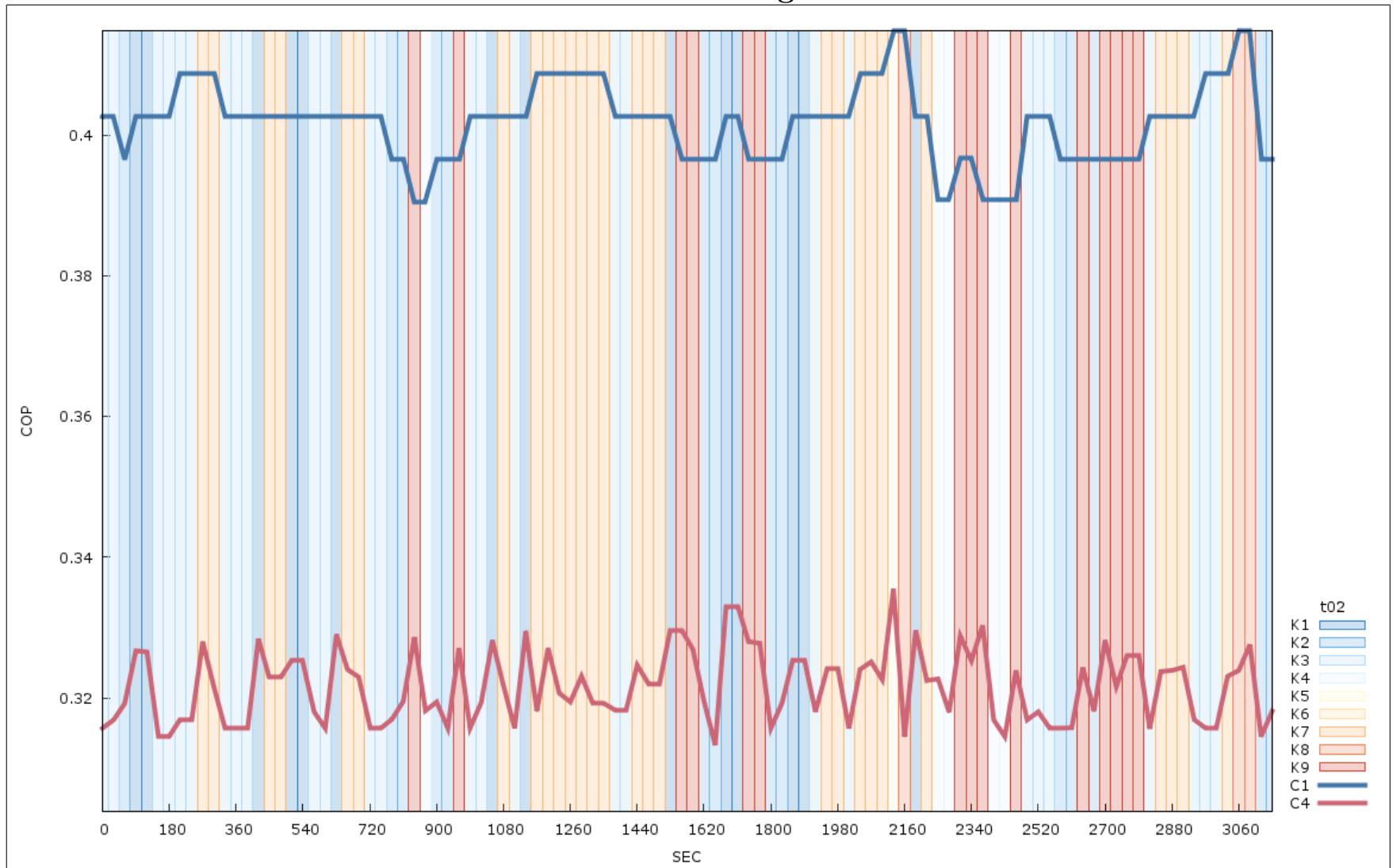


Figure L.11: K-Means Clustering with  $k = 9$

### Trial 3 : Chiller Clustering on COP

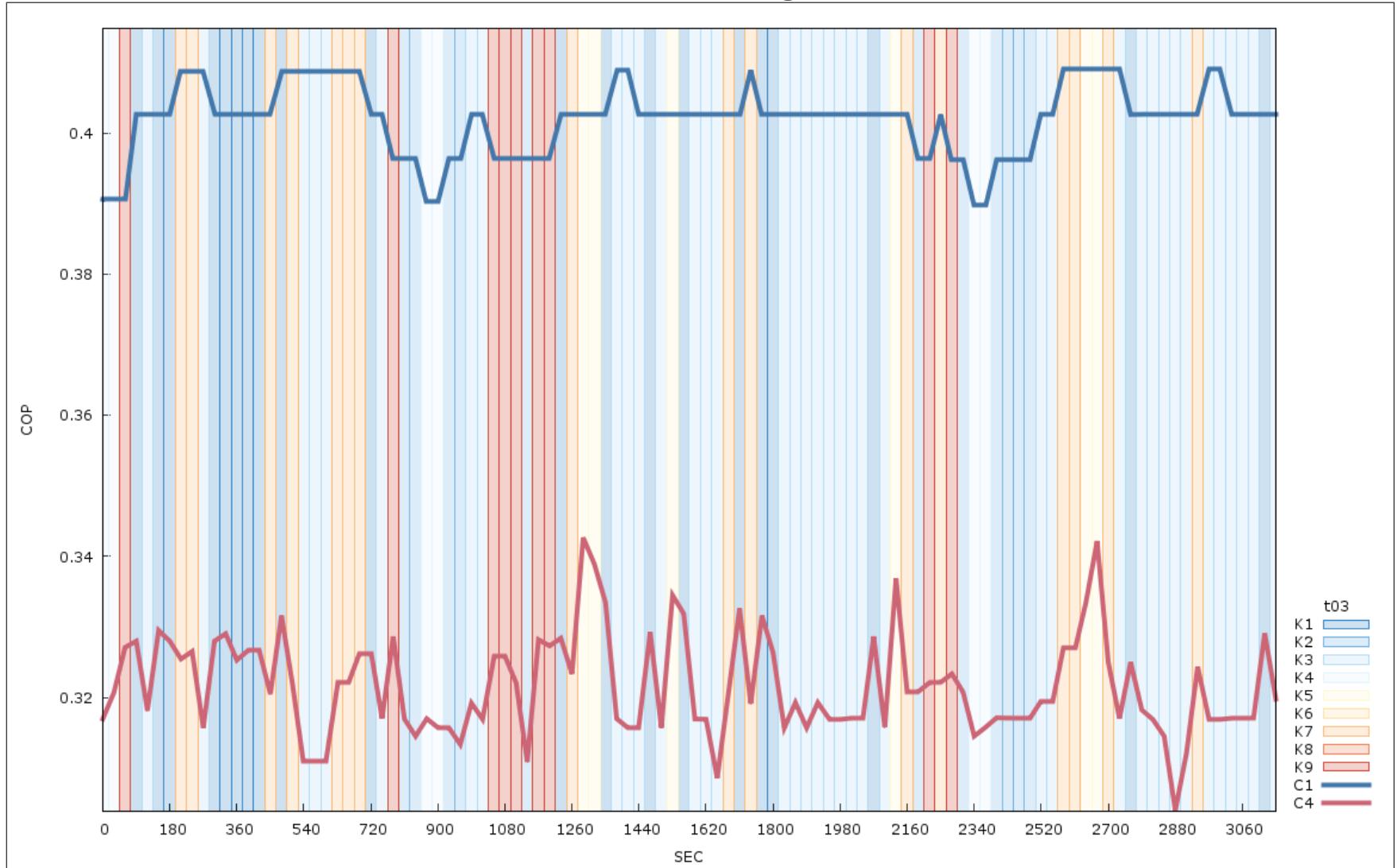


Figure L.12: K-Means Clustering with  $k = 9$

### Trial 1 : Chiller Clustering on COP

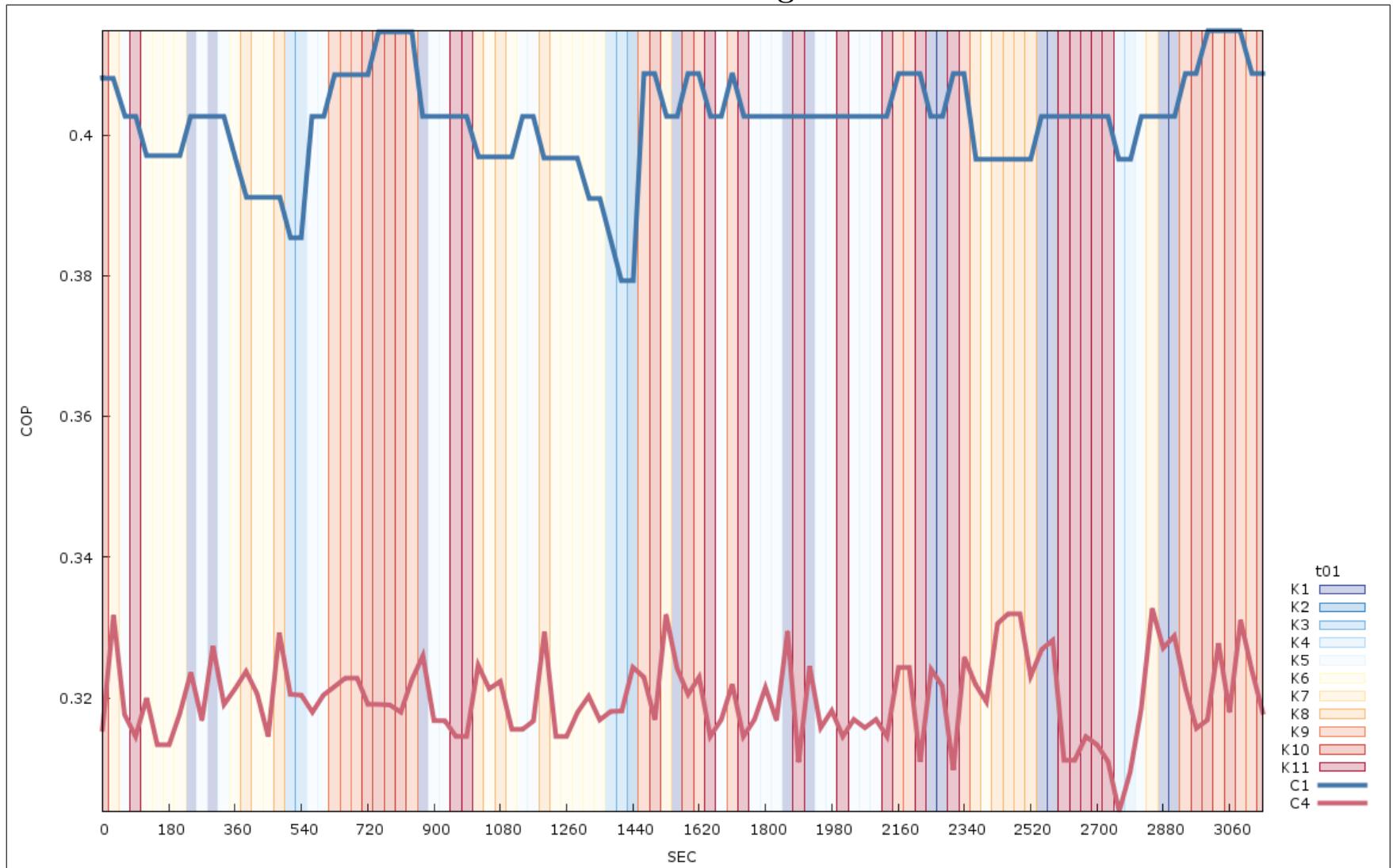


Figure L.13: K-Means Clustering with  $k = 11$

### Trial 2 : Chiller Clustering on COP

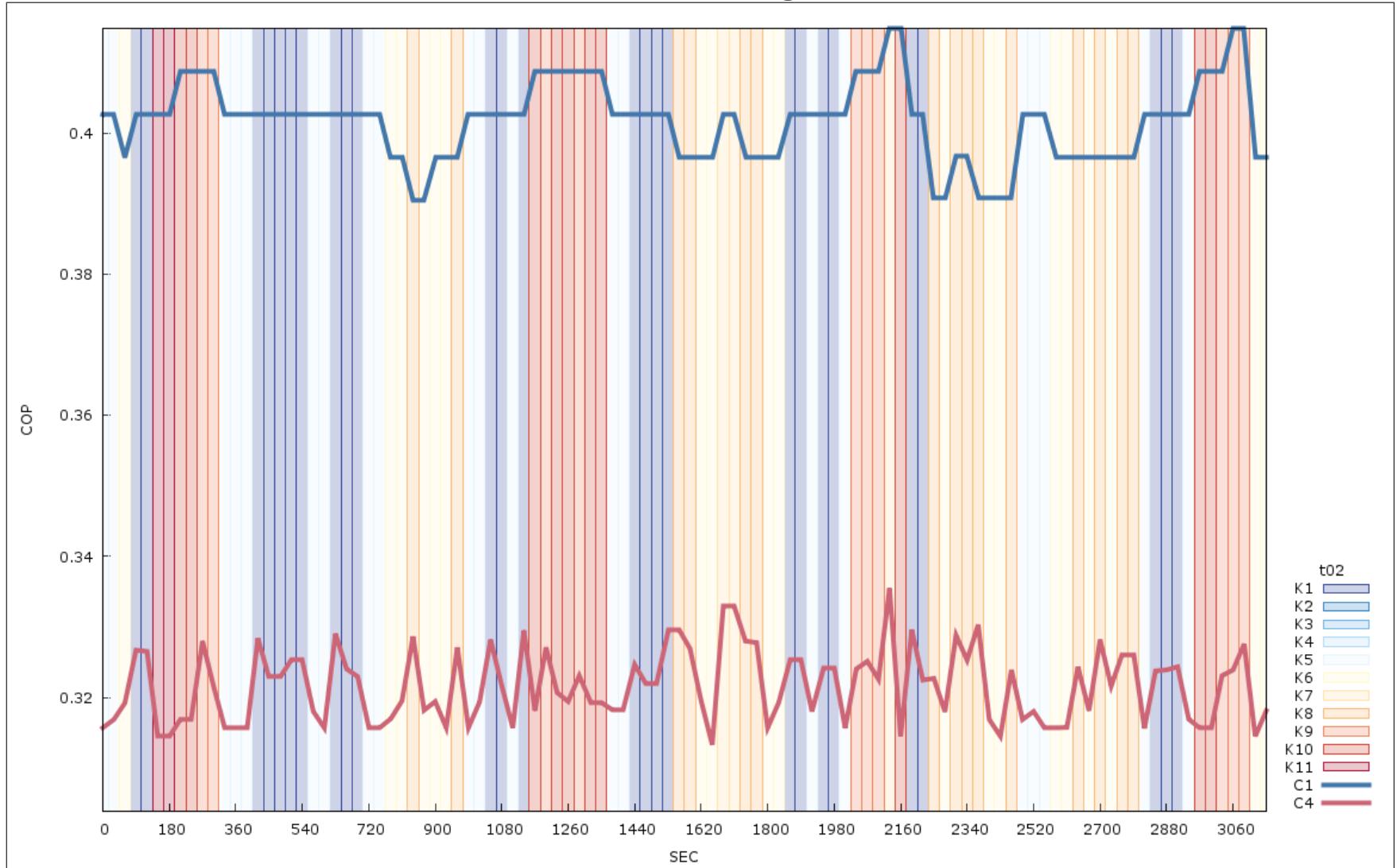


Figure L.14: K-Means Clustering with  $k = 11$

### Trial 3 : Chiller Clustering on COP

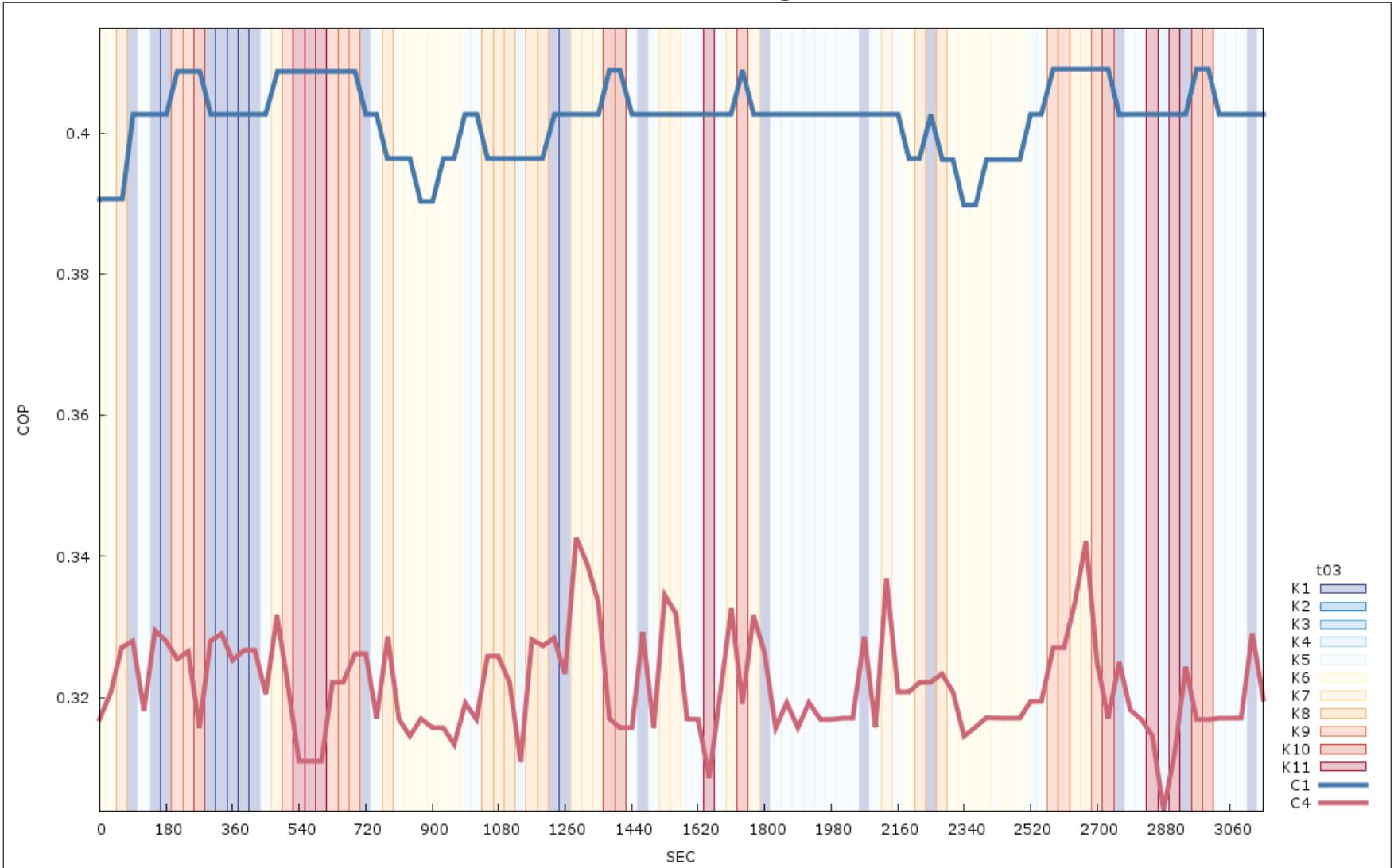


Figure L.15: K-Means Clustering with  $k = 11$

## Appendix M

# High-Density Workload : Chiller Clustering on Chilled Water-Temperature Delta

## Trial 1 : Chiller Clustering on Chilled Water-Temperature Delta

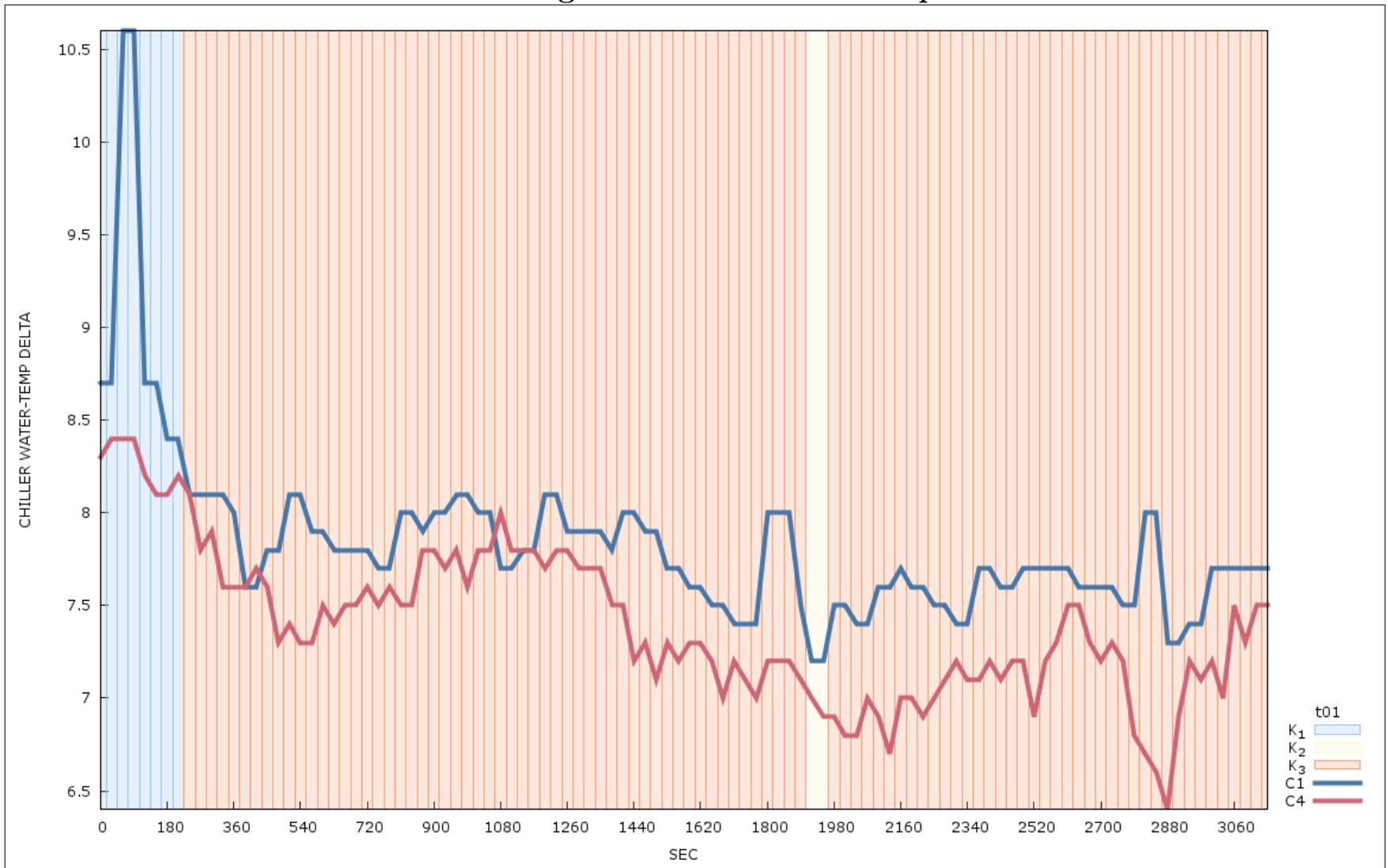


Figure M.1: EM Clustering with  $k = 3$

## Trial 2 : Chiller Clustering on Chilled Water-Temperature Delta

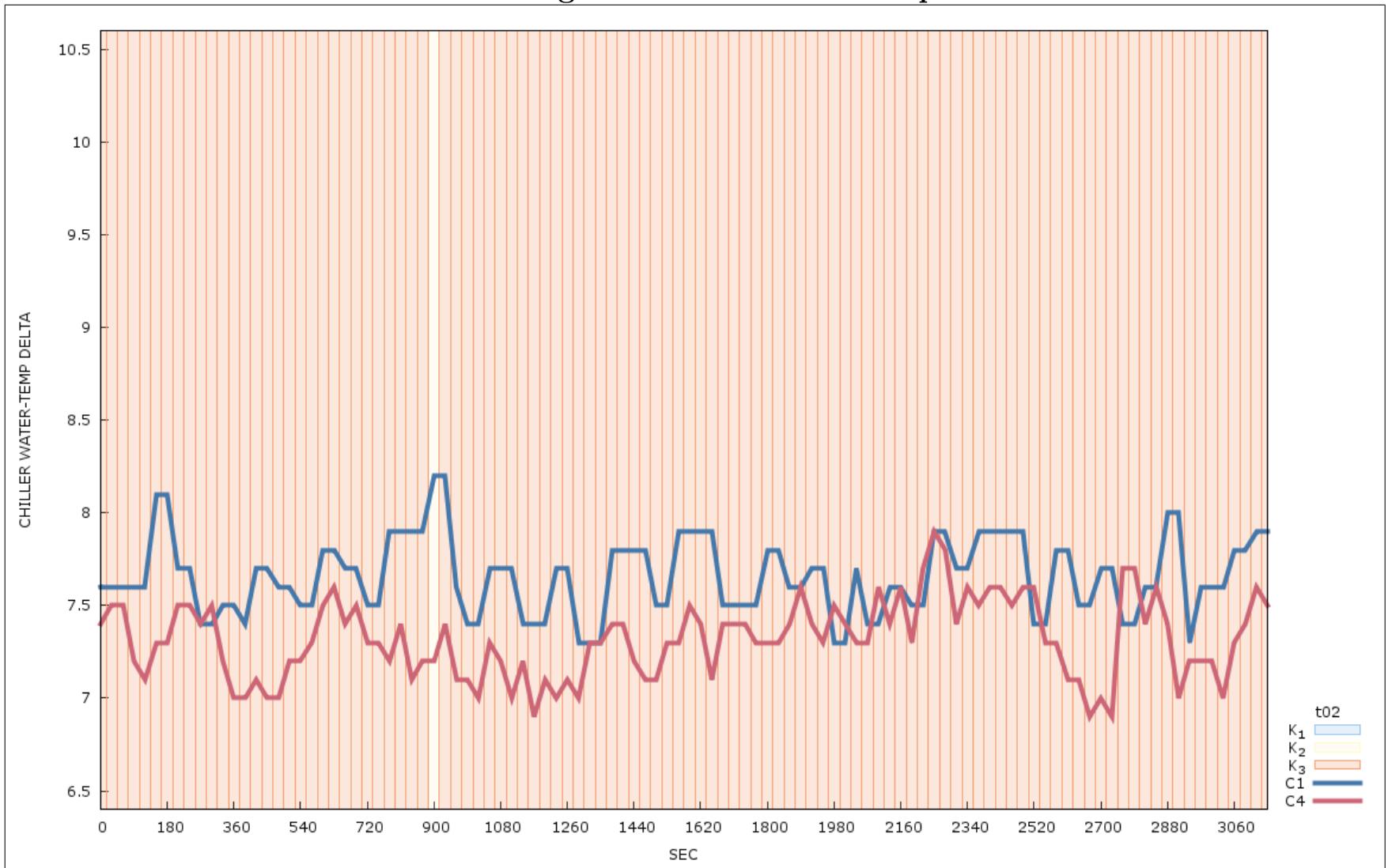


Figure M.2: EM Clustering with  $k = 3$

### Trial 3 : Chiller Clustering on Chilled Water-Temperature Delta

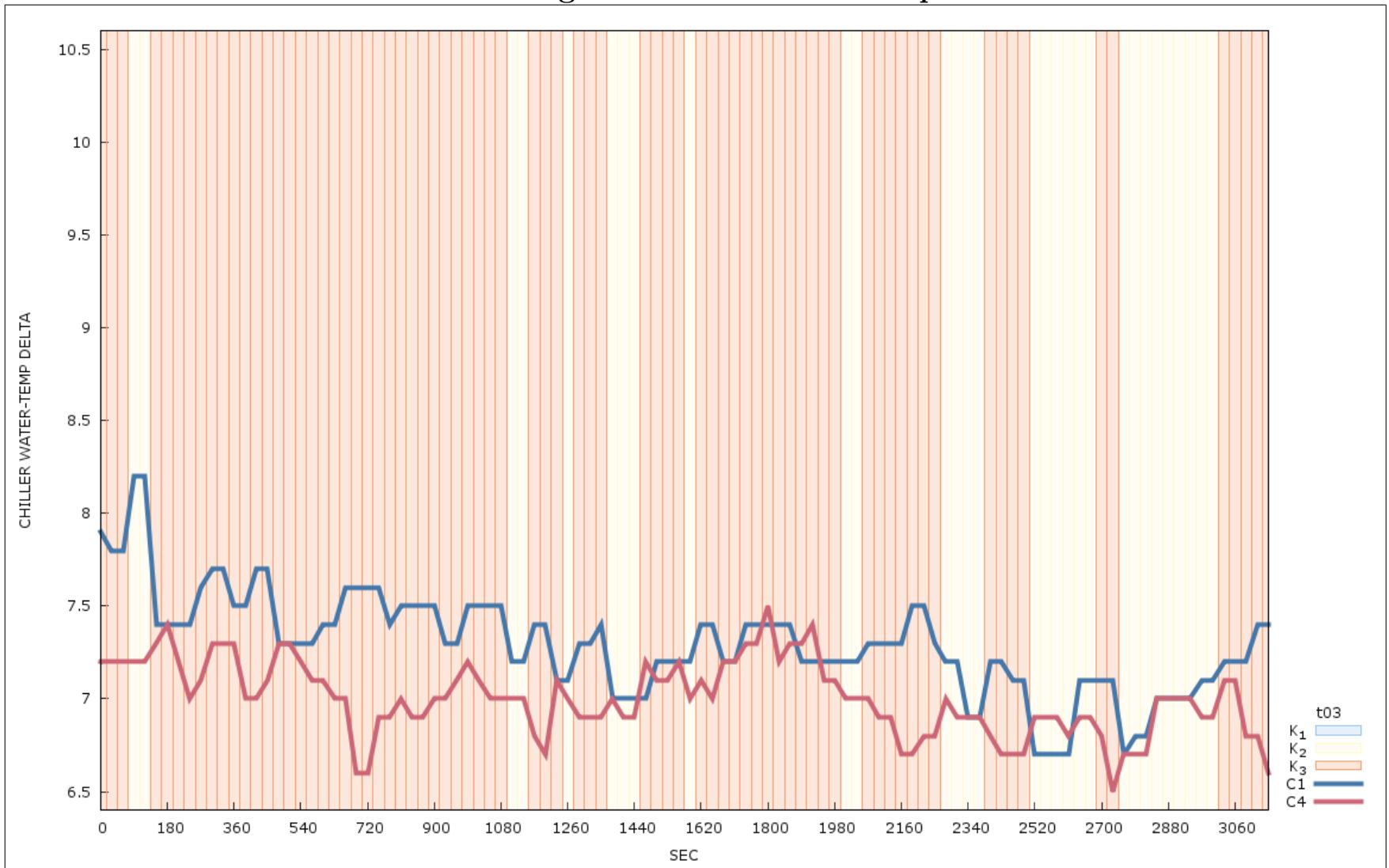


Figure M.3: EM Clustering with  $k = 3$

## Trial 1 : Chiller Clustering on Chilled Water-Temperature Delta

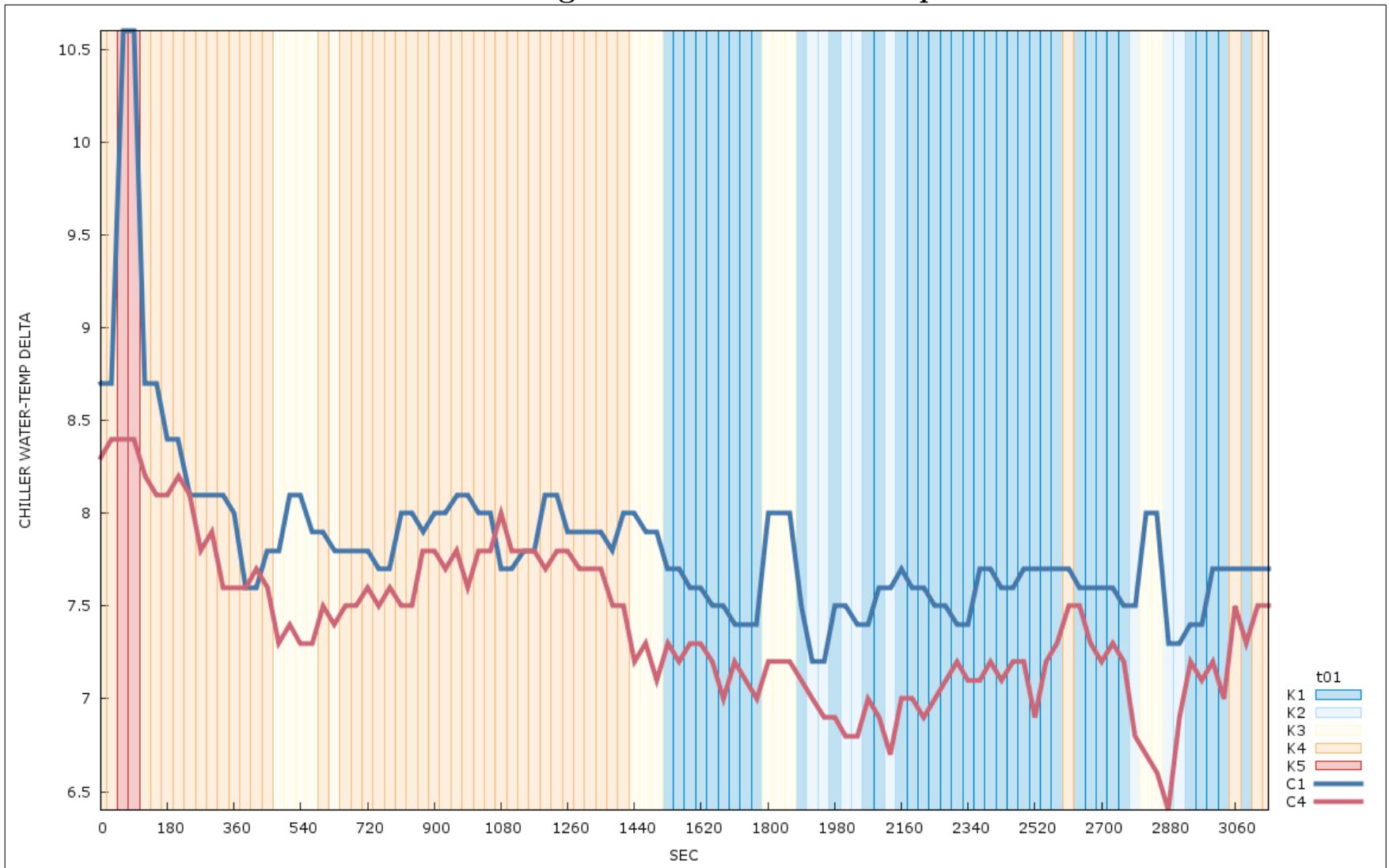


Figure M.4: K-Means Clustering with  $k = 5$

## Trial 2 : Chiller Clustering on Chilled Water-Temperature Delta

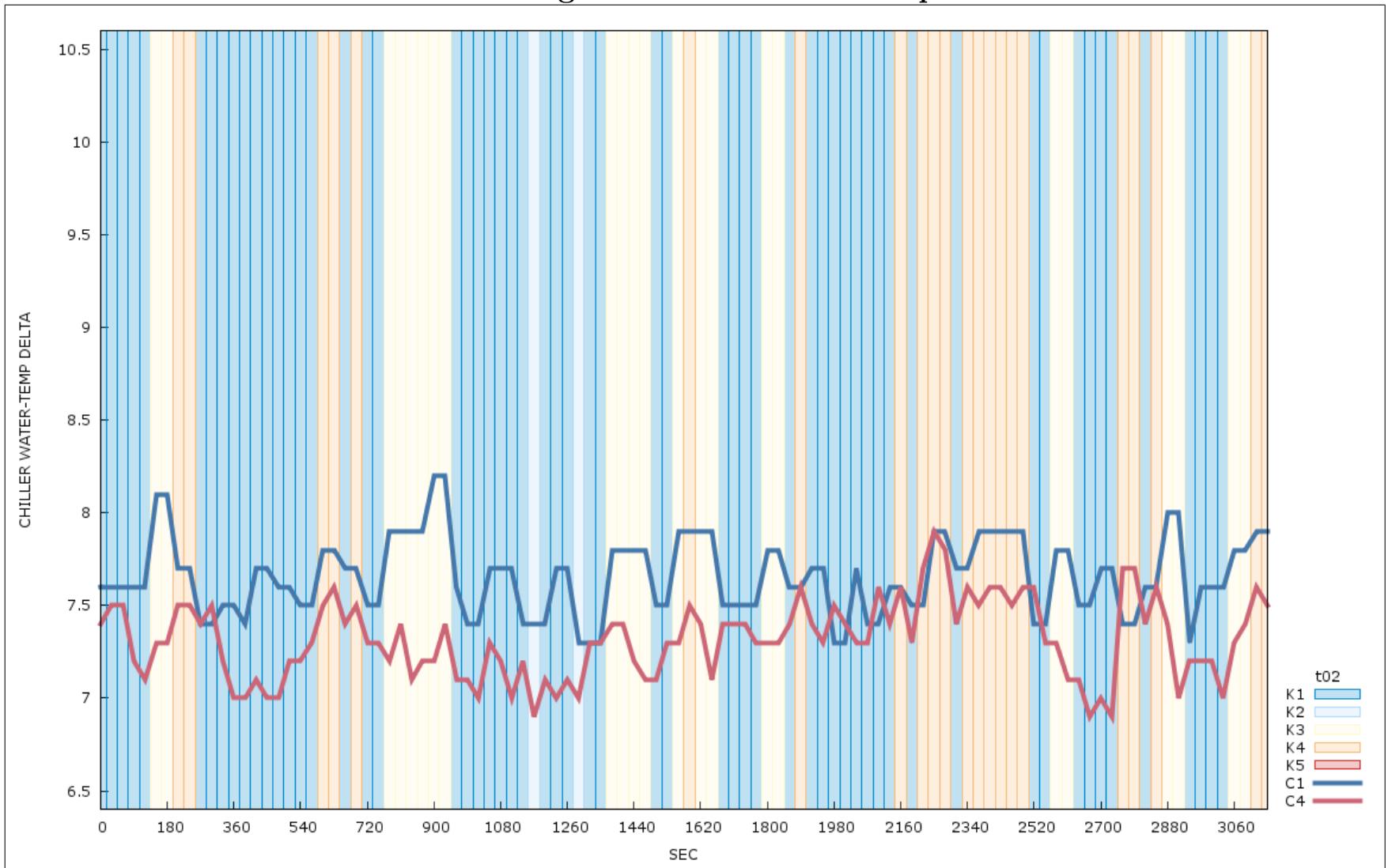


Figure M.5: K-Means Clustering with  $k = 5$

### Trial 3 : Chiller Clustering on Chilled Water-Temperature Delta

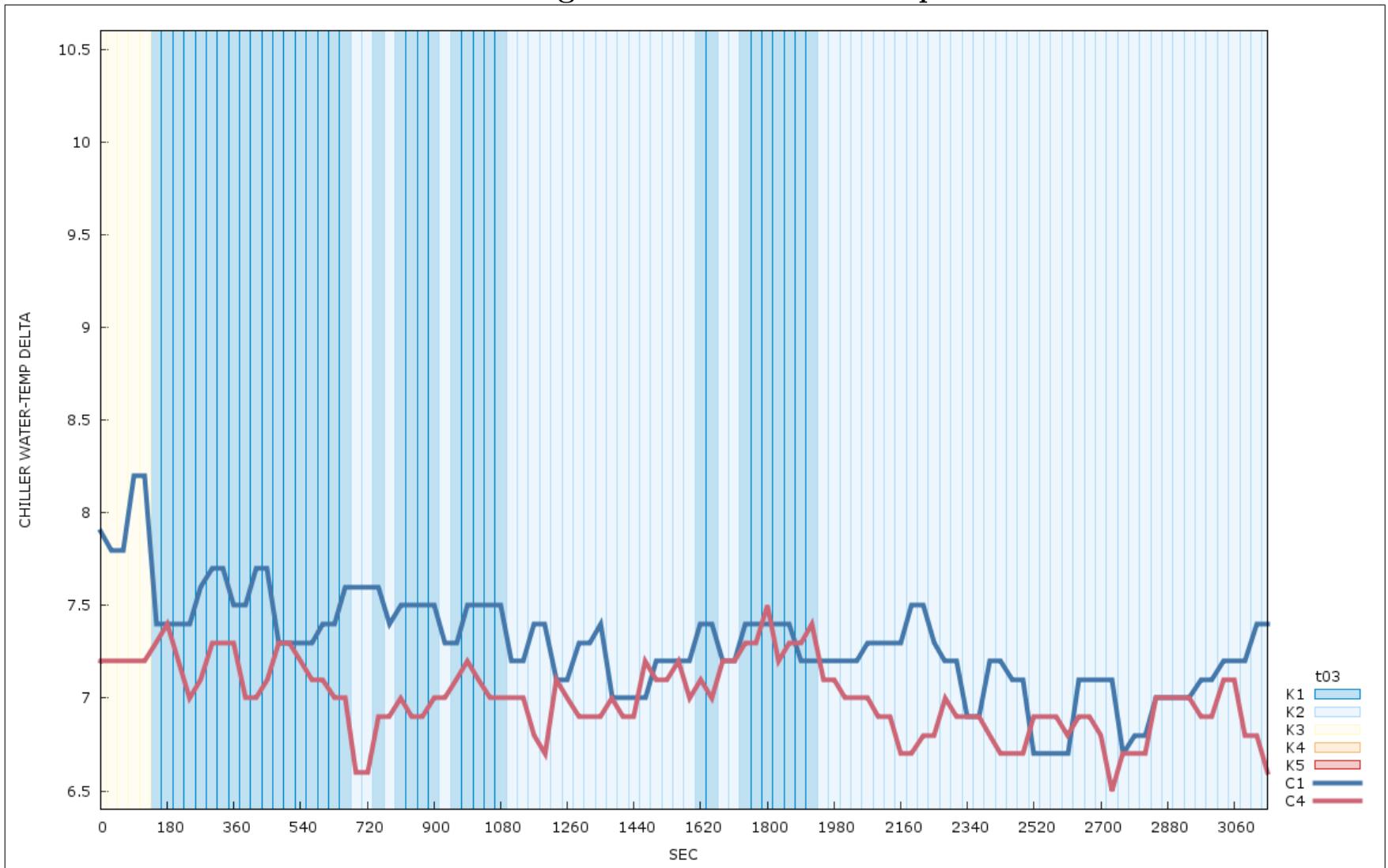


Figure M.6: K-Means Clustering with  $k = 5$

## Trial 1 : Chiller Clustering on Chilled Water-Temperature Delta

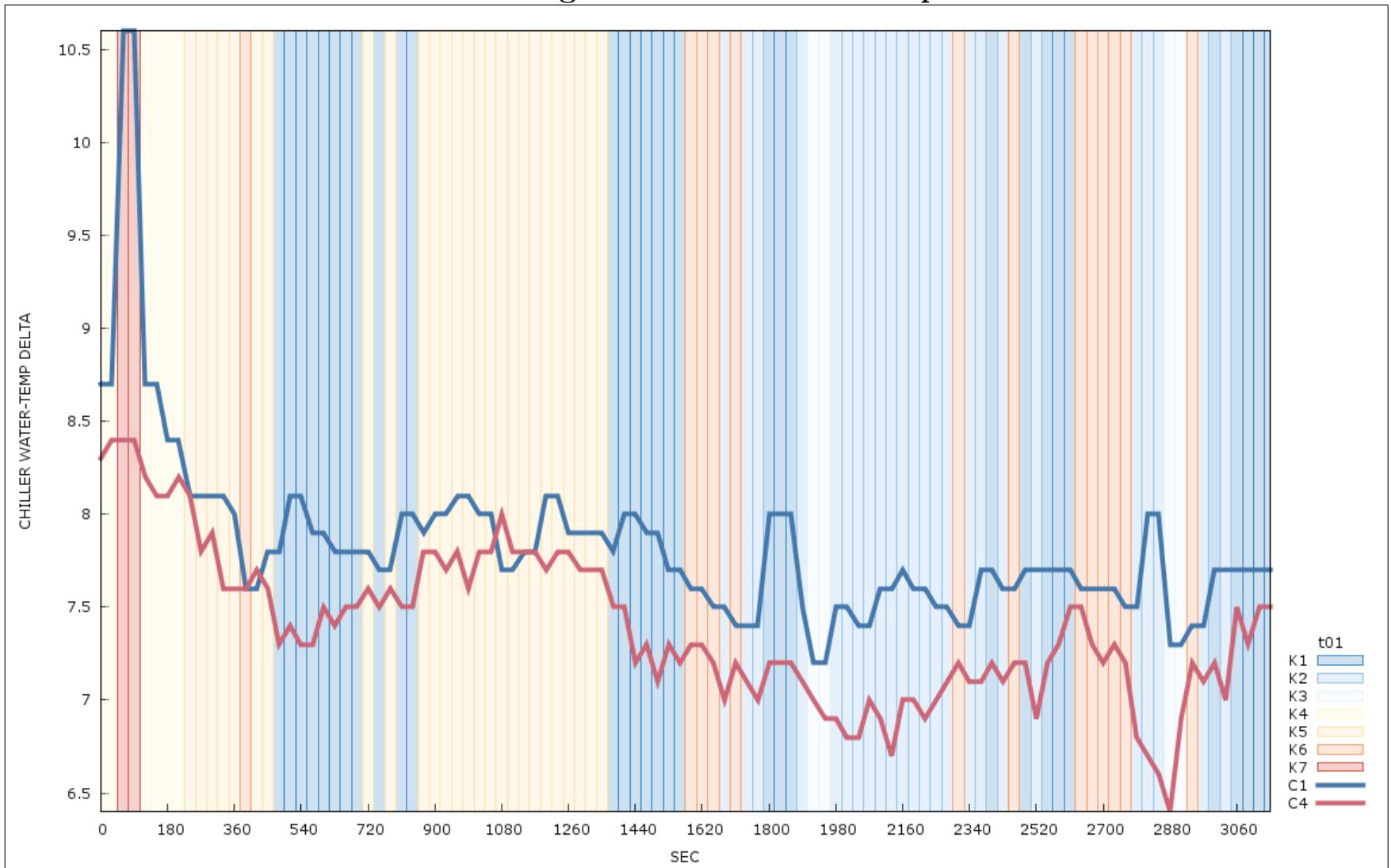


Figure M.7: K-Means Clustering with  $k = 7$

## Trial 2 : Chiller Clustering on Chilled Water-Temperature Delta

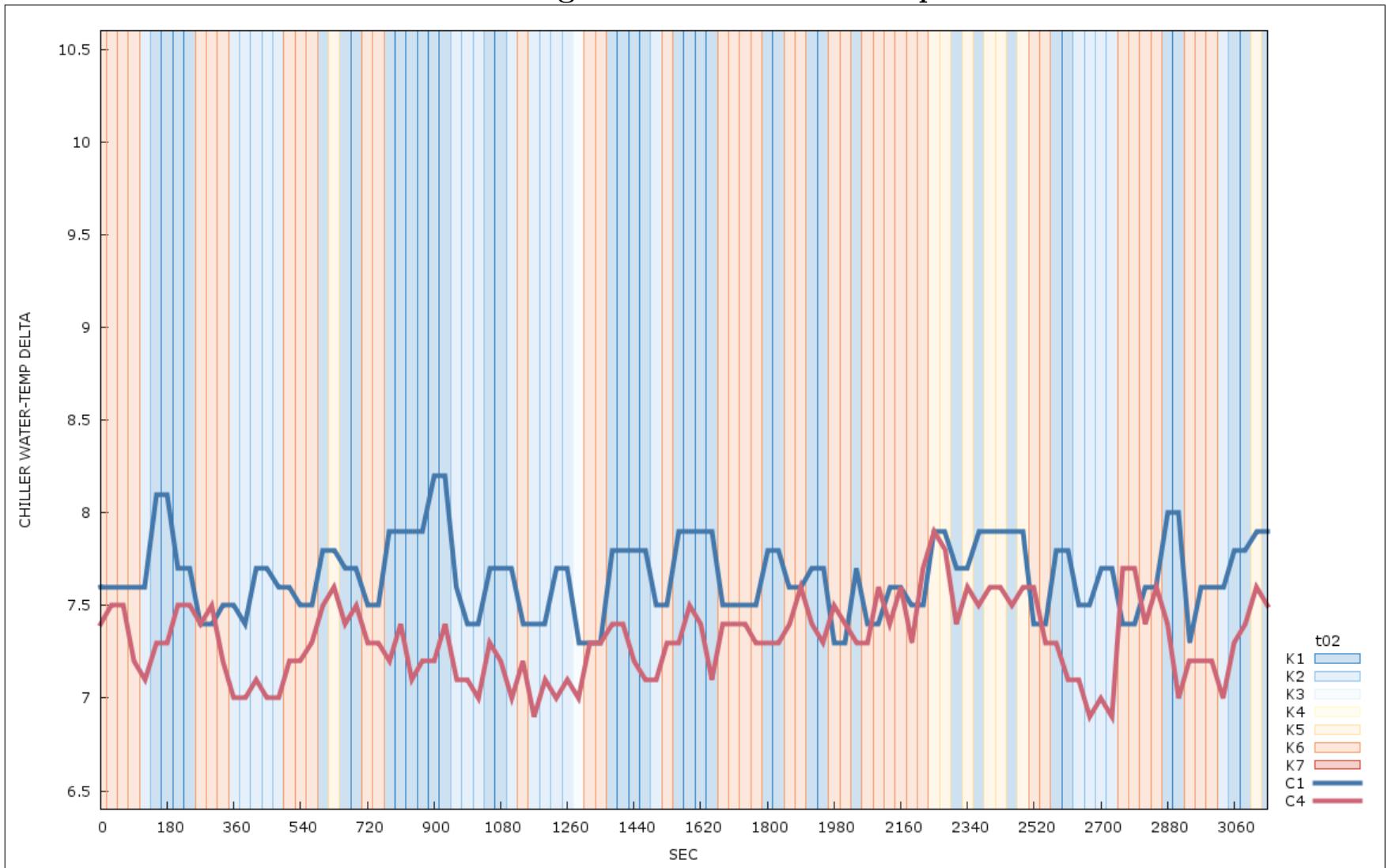


Figure M.8: K-Means Clustering with  $k = 7$

### Trial 3 : Chiller Clustering on Chilled Water-Temperature Delta

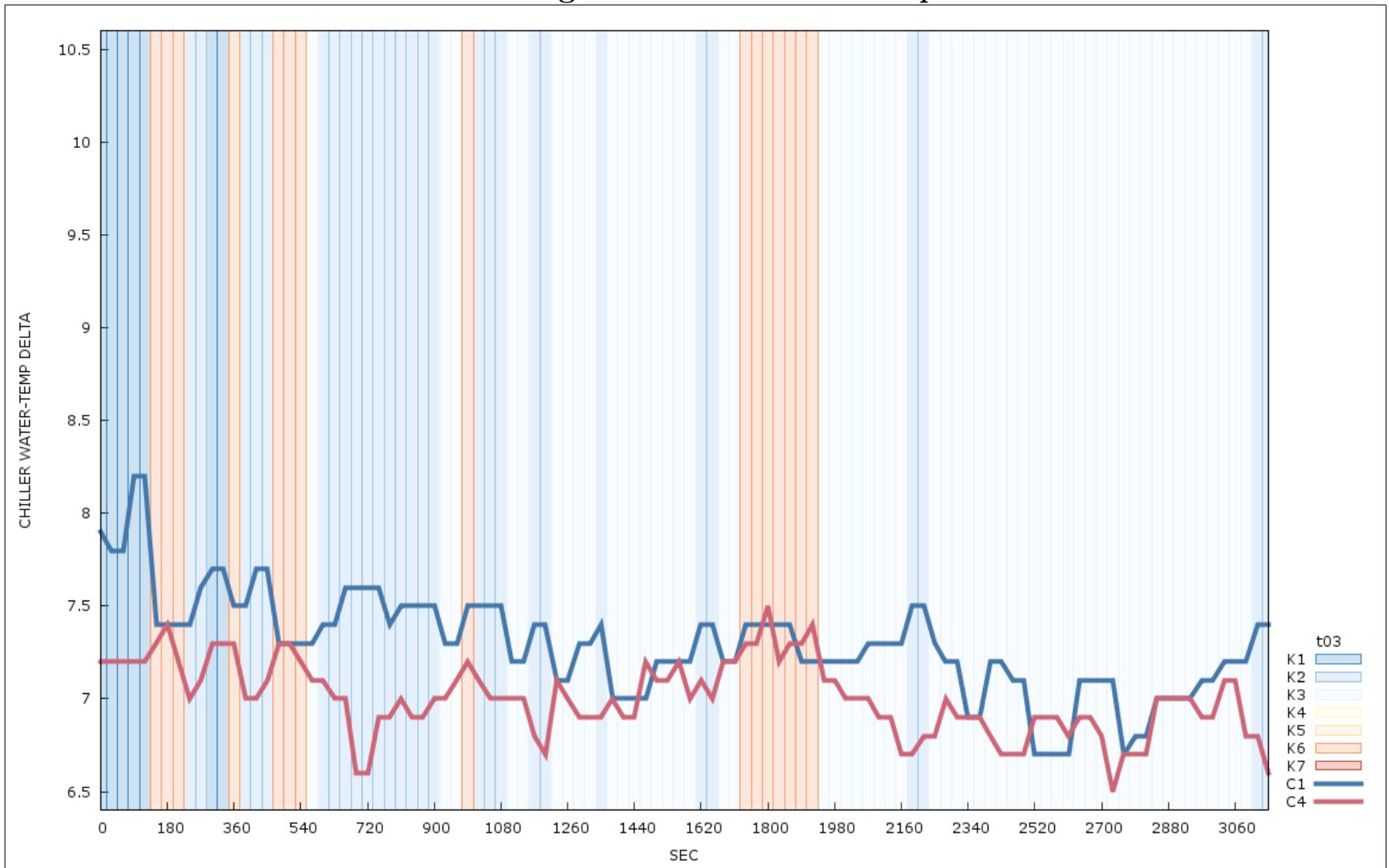


Figure M.9: K-Means Clustering with  $k = 7$

## Trial 1 : Chiller Clustering on Chilled Water-Temperature Delta

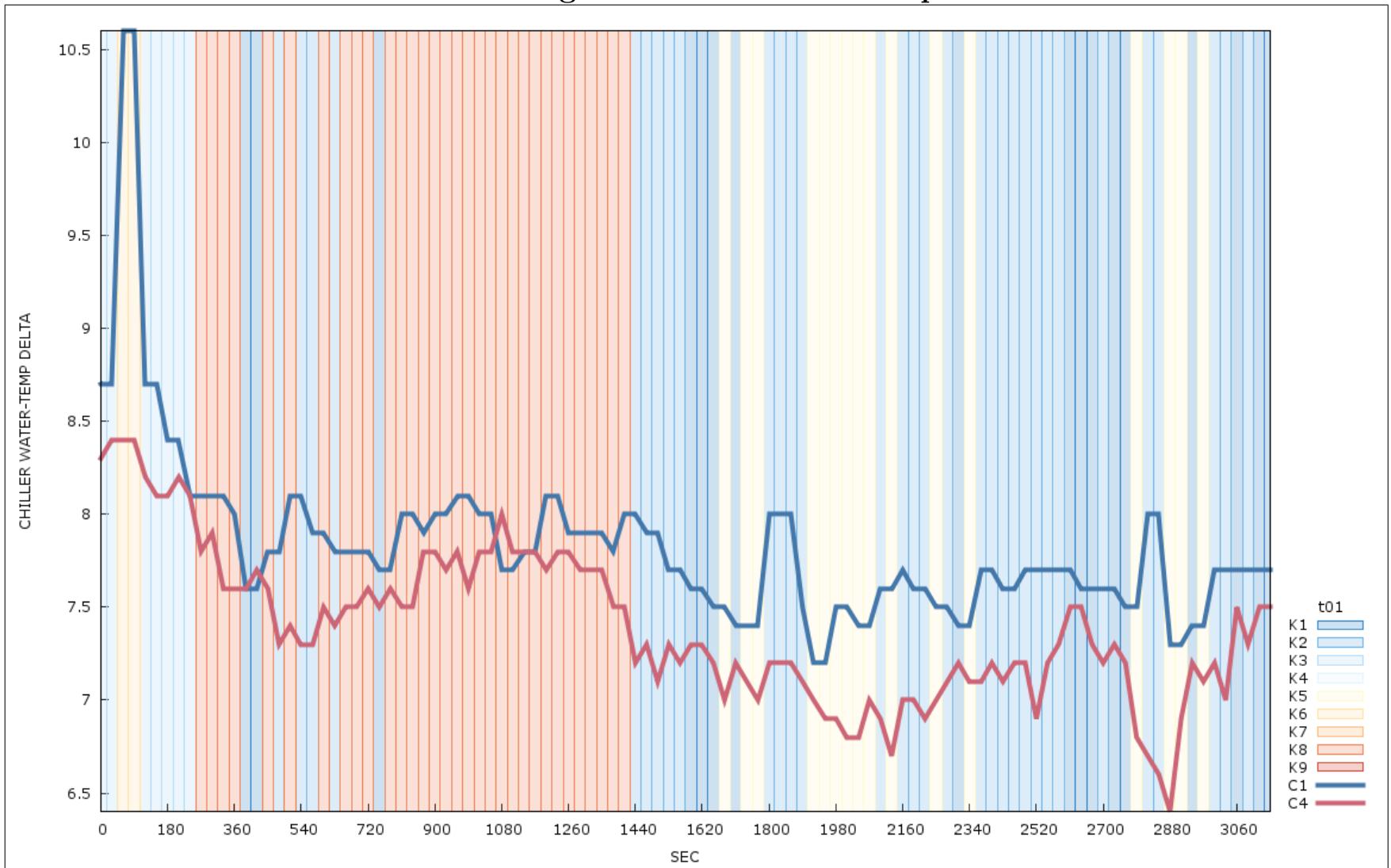


Figure M.10: K-Means Clustering with  $k = 9$

## Trial 2 : Chiller Clustering on Chilled Water-Temperature Delta

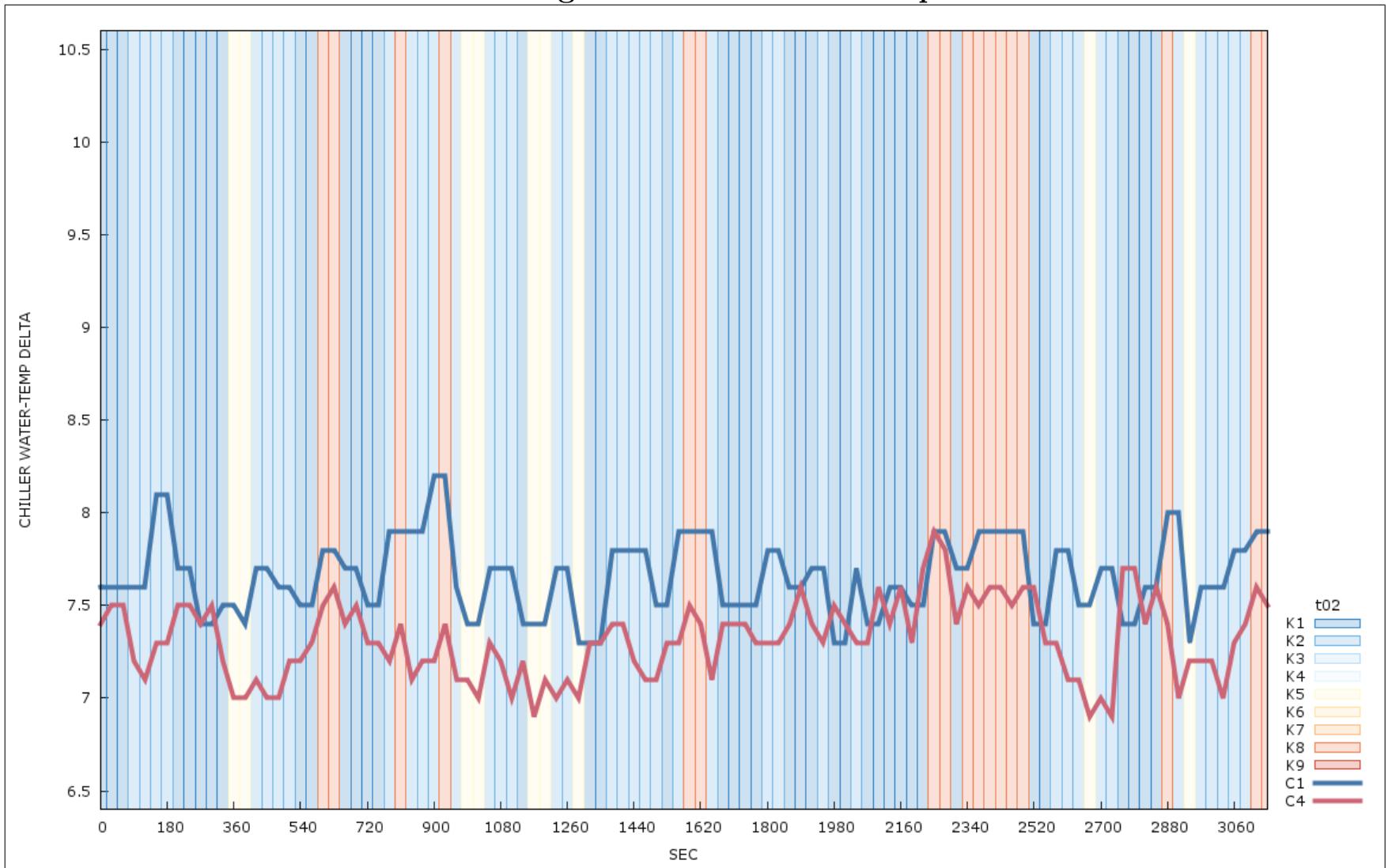


Figure M.11: K-Means Clustering with  $k = 9$

### Trial 3 : Chiller Clustering on Chilled Water-Temperature Delta

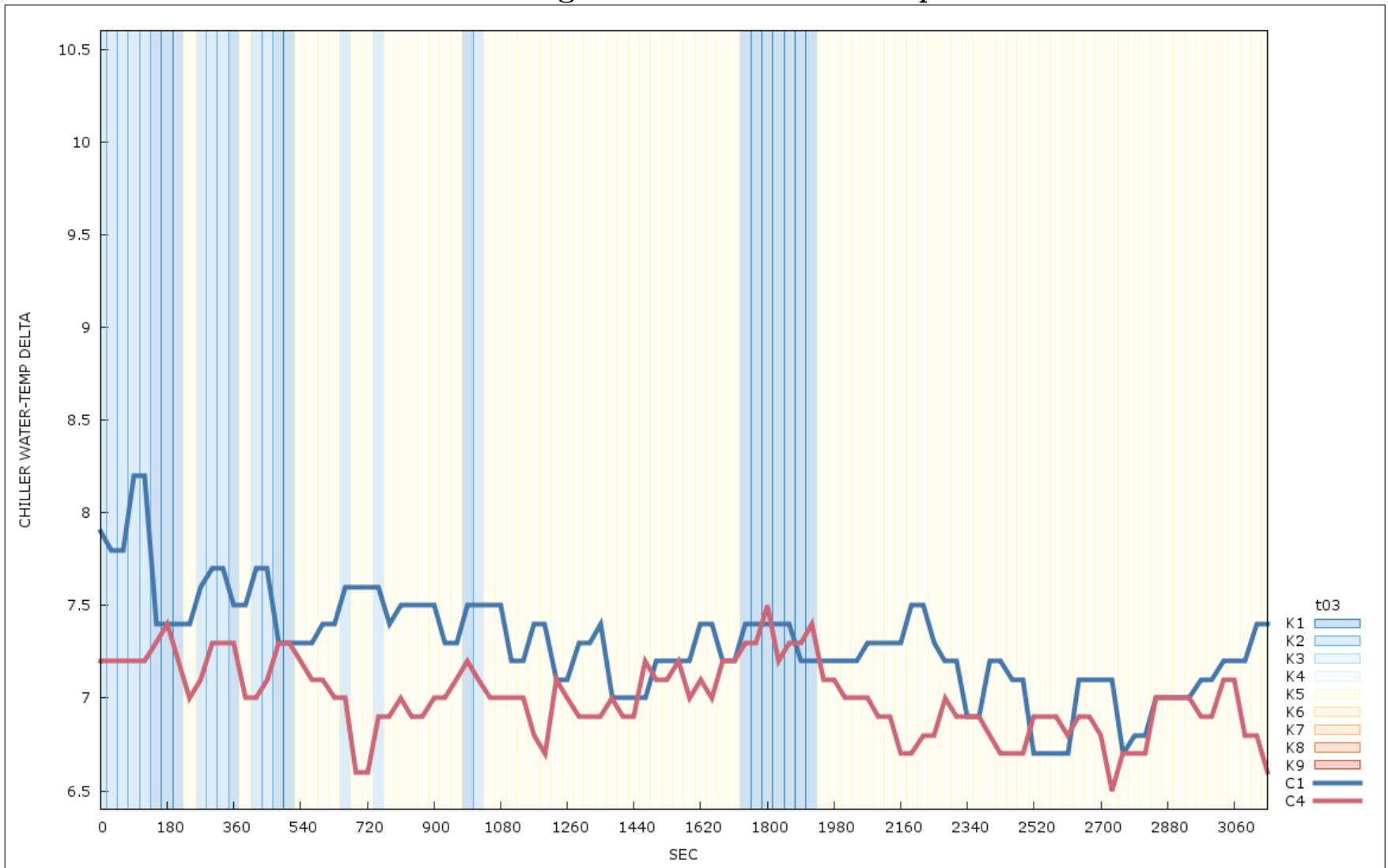


Figure M.12: K-Means Clustering with  $k = 9$

## Trial 1 : Chiller Clustering on Chilled Water-Temperature Delta

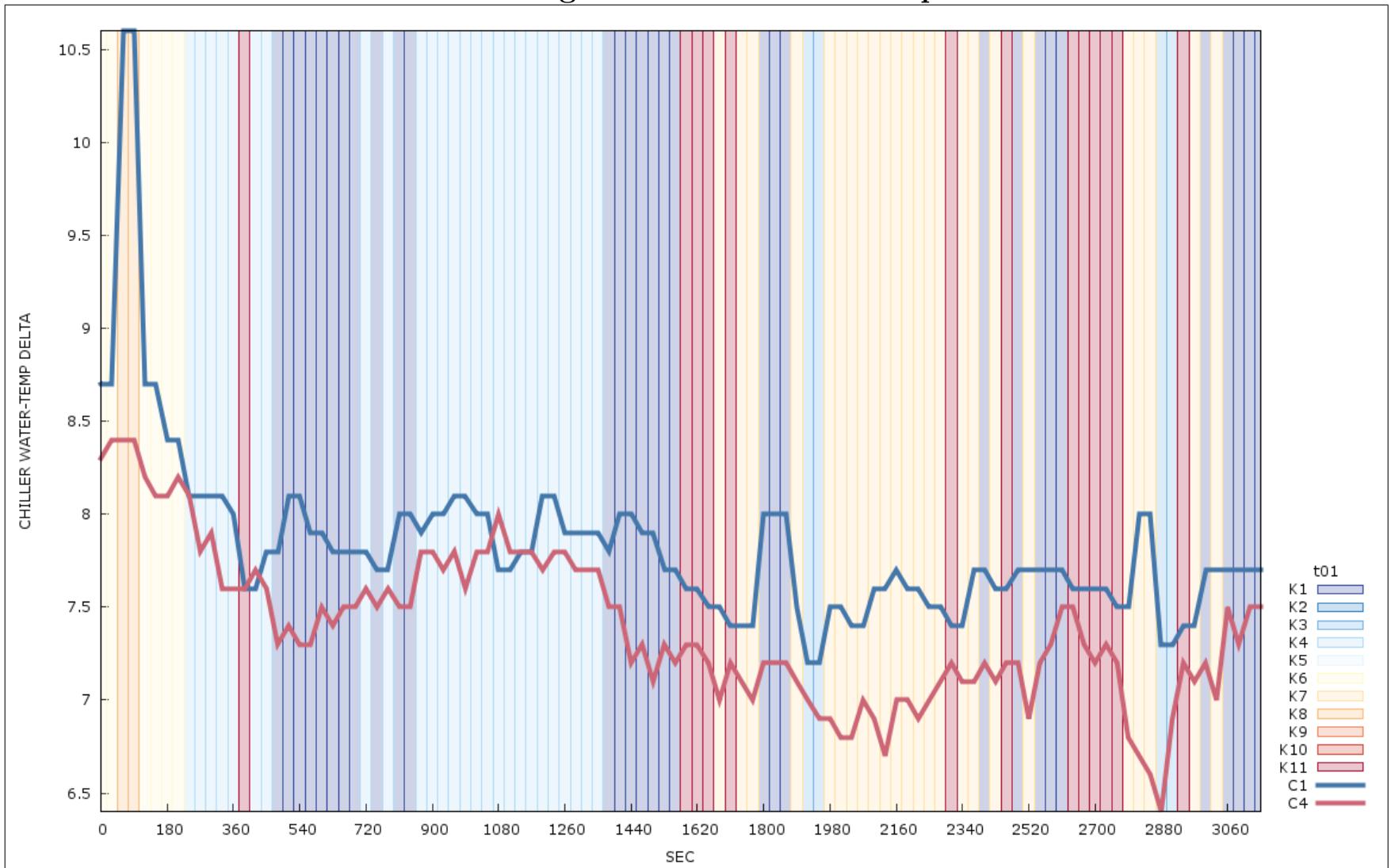


Figure M.13: K-Means Clustering with  $k = 11$

## Trial 2 : Chiller Clustering on Chilled Water-Temperature Delta

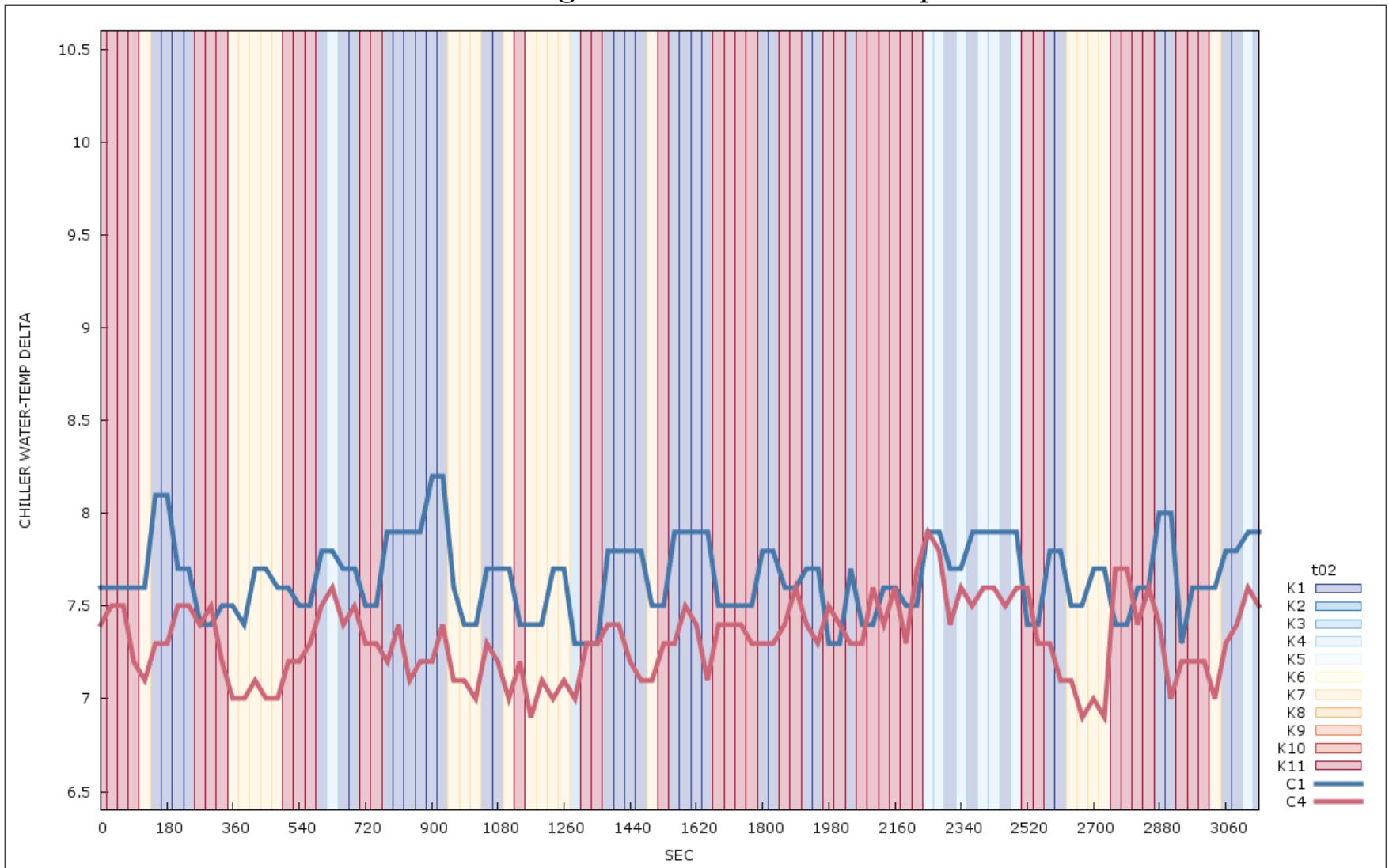


Figure M.14: K-Means Clustering with  $k = 11$

### Trial 3 : Chiller Clustering on Chilled Water-Temperature Delta

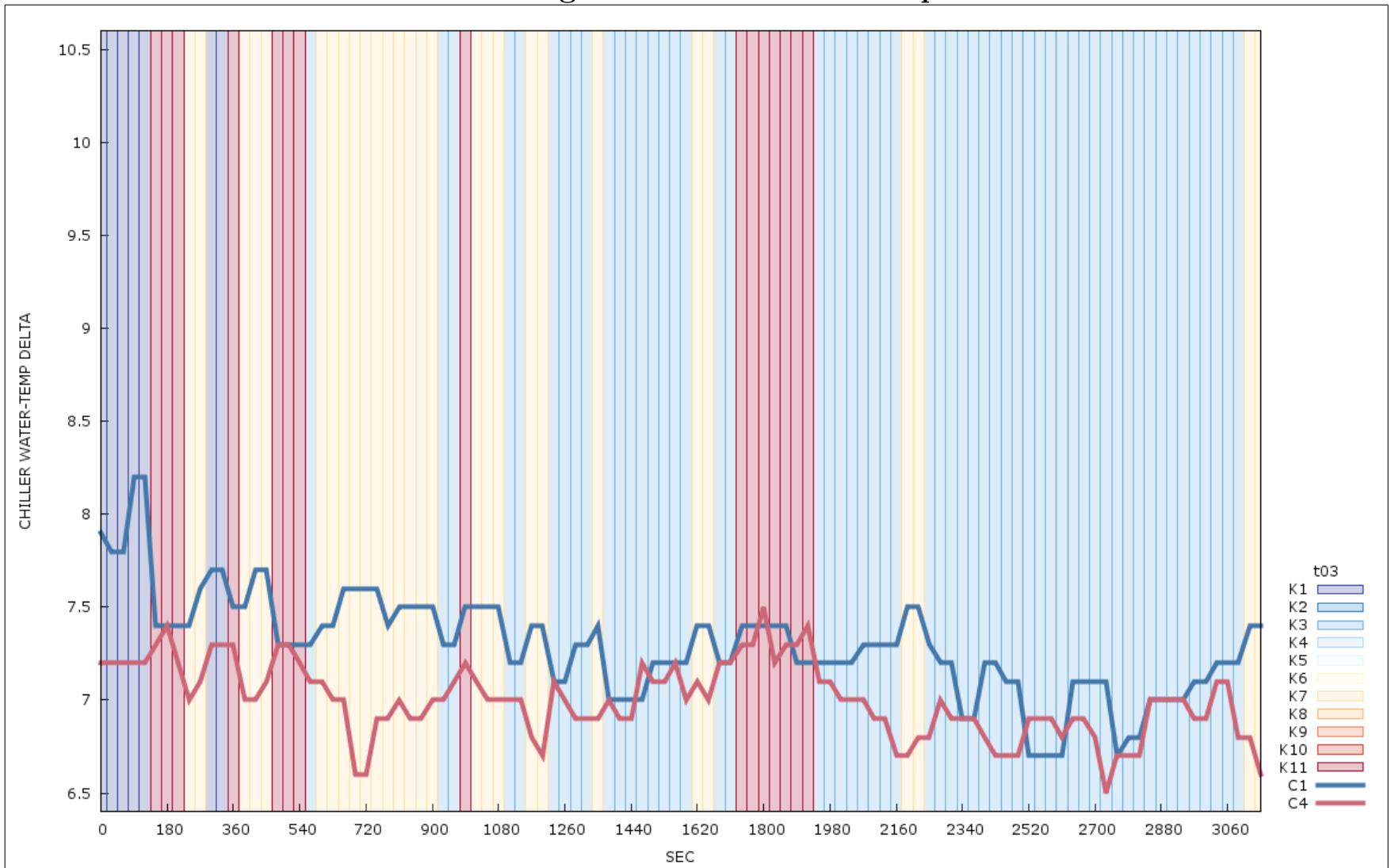


Figure M.15: K-Means Clustering with  $k = 11$

## Appendix N

# High-Density Workload : Chiller Clustering on Condenser Water-Temperature Delta

## Trial 1 : Chiller Clustering on Condenser Water-Temperature Delta

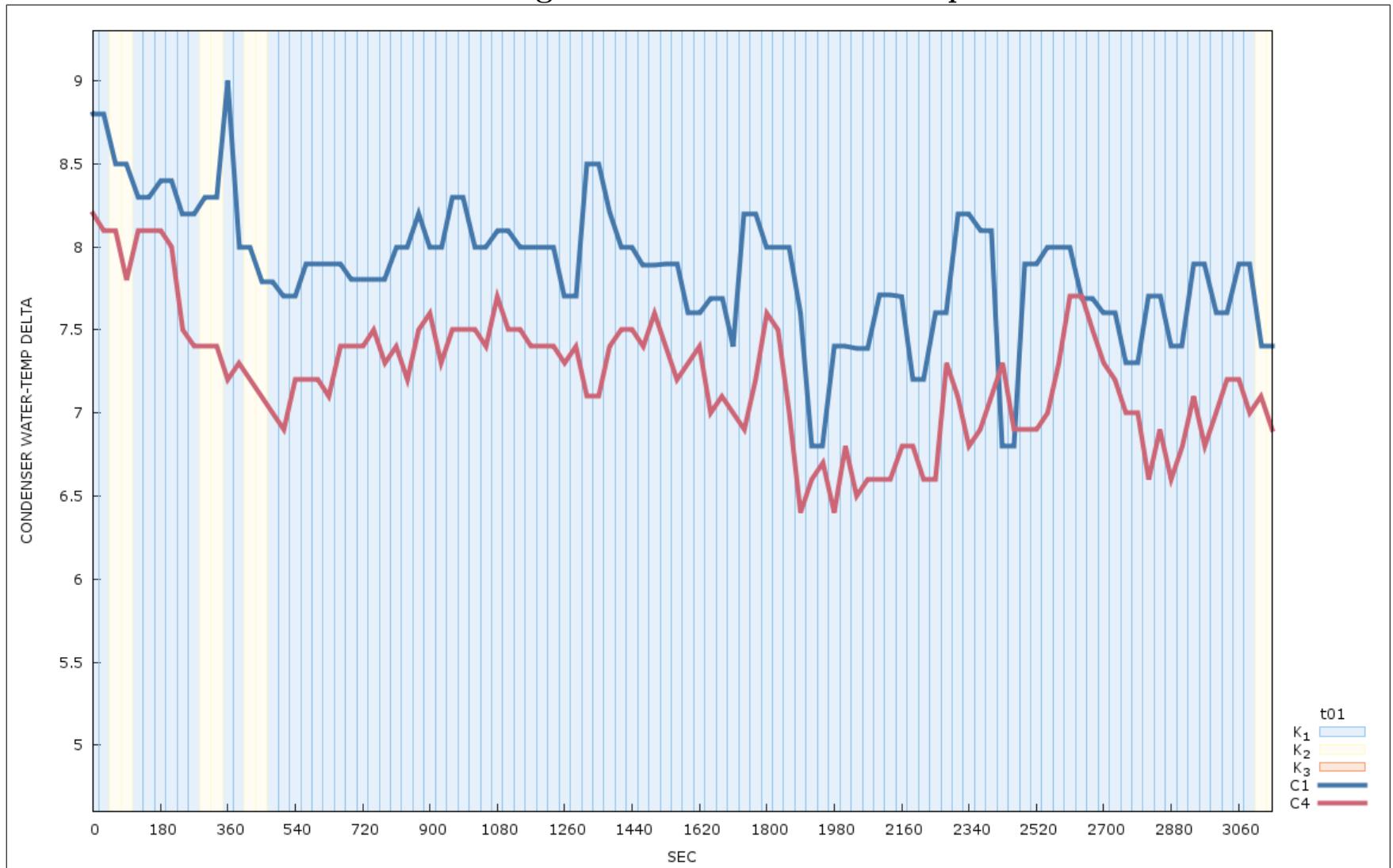


Figure N.1: EM Clustering with  $k = 3$

## Trial 2 : Chiller Clustering on Condenser Water-Temperature Delta

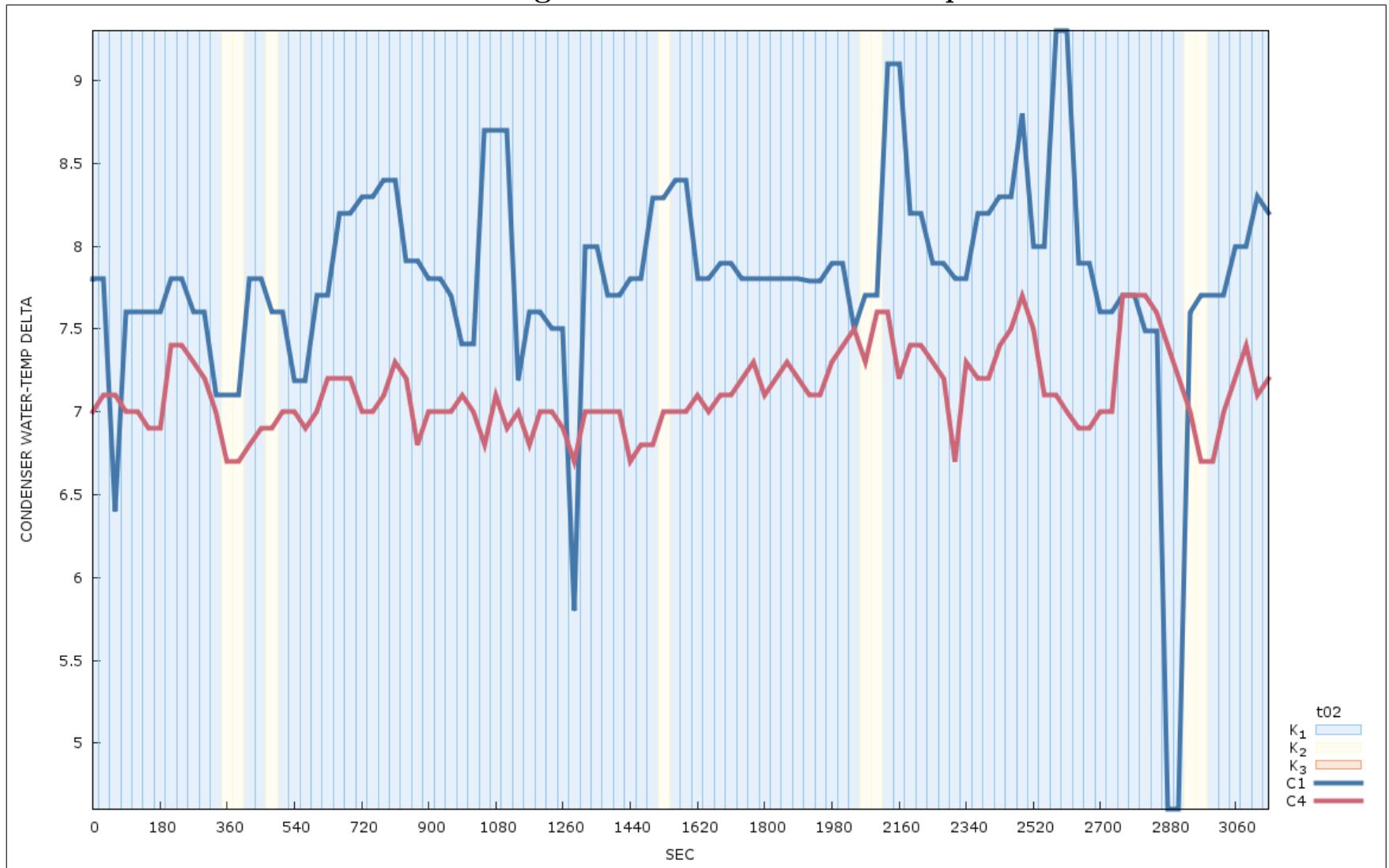


Figure N.2: EM Clustering with  $k = 3$

### Trial 3 : Chiller Clustering on Condenser Water-Temperature Delta

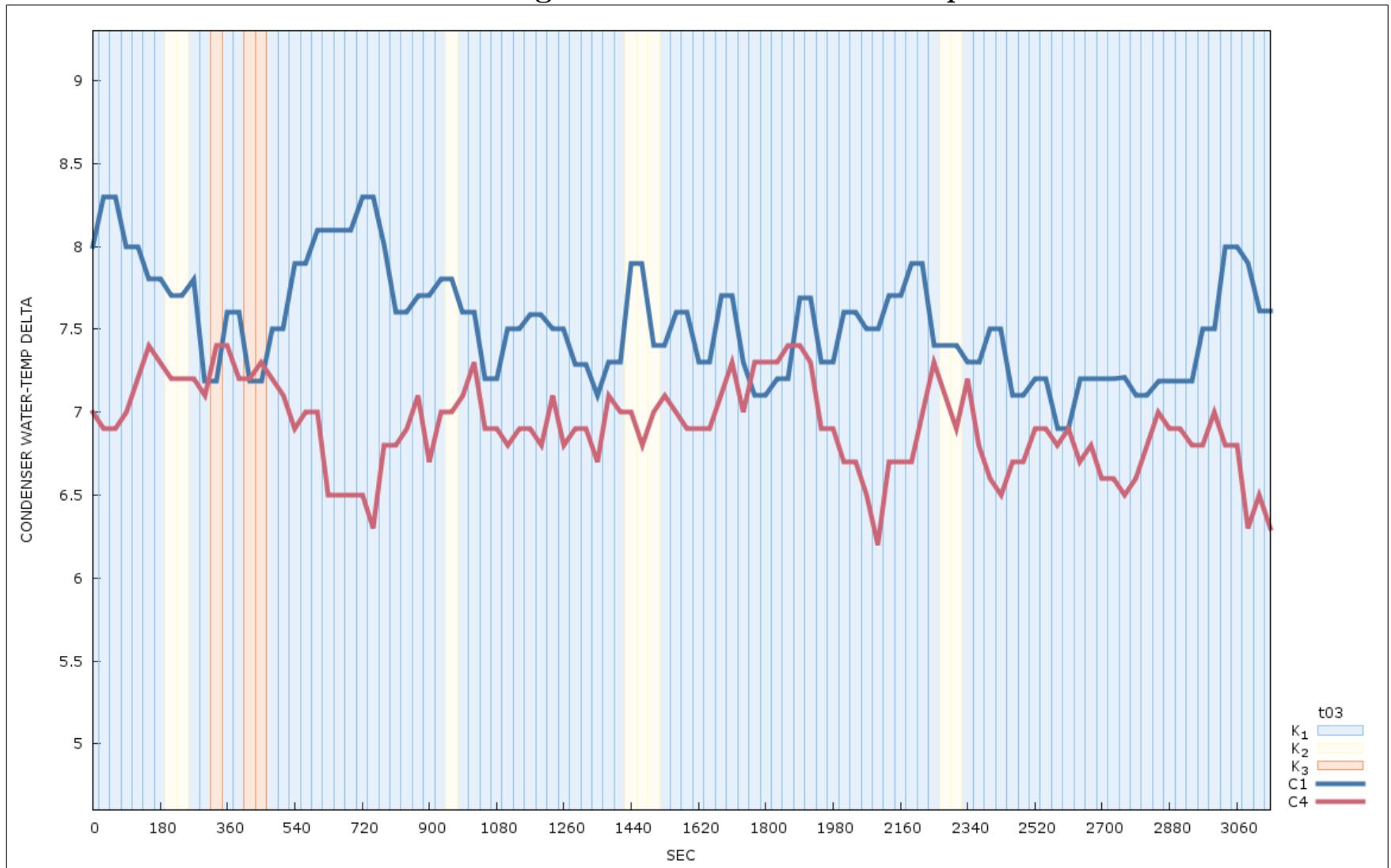


Figure N.3: EM Clustering with  $k = 3$

## Trial 1 : Chiller Clustering on Condenser Water-Temperature Delta

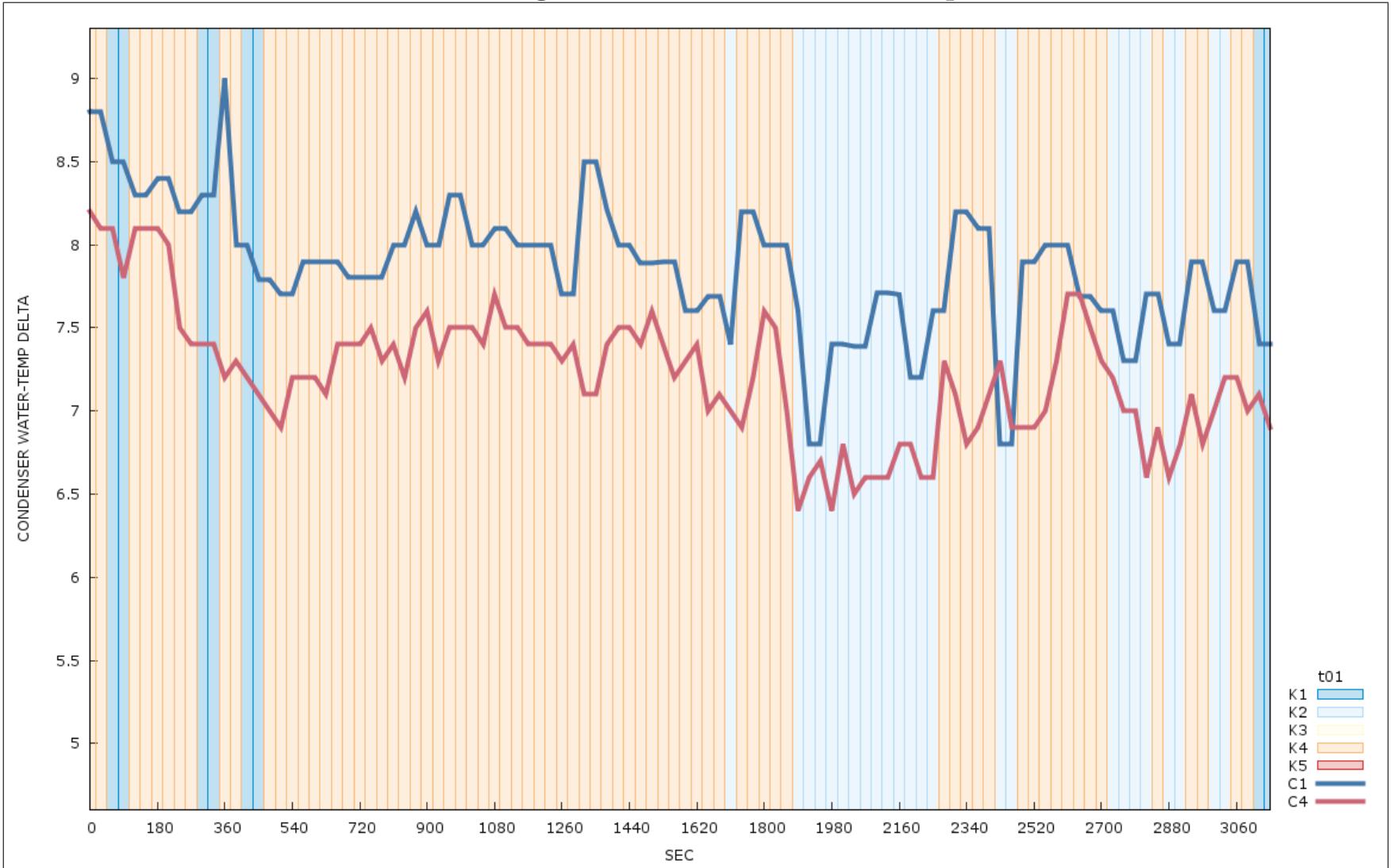


Figure N.4: K-Means Clustering with  $k = 5$

## Trial 2 : Chiller Clustering on Condenser Water-Temperature Delta

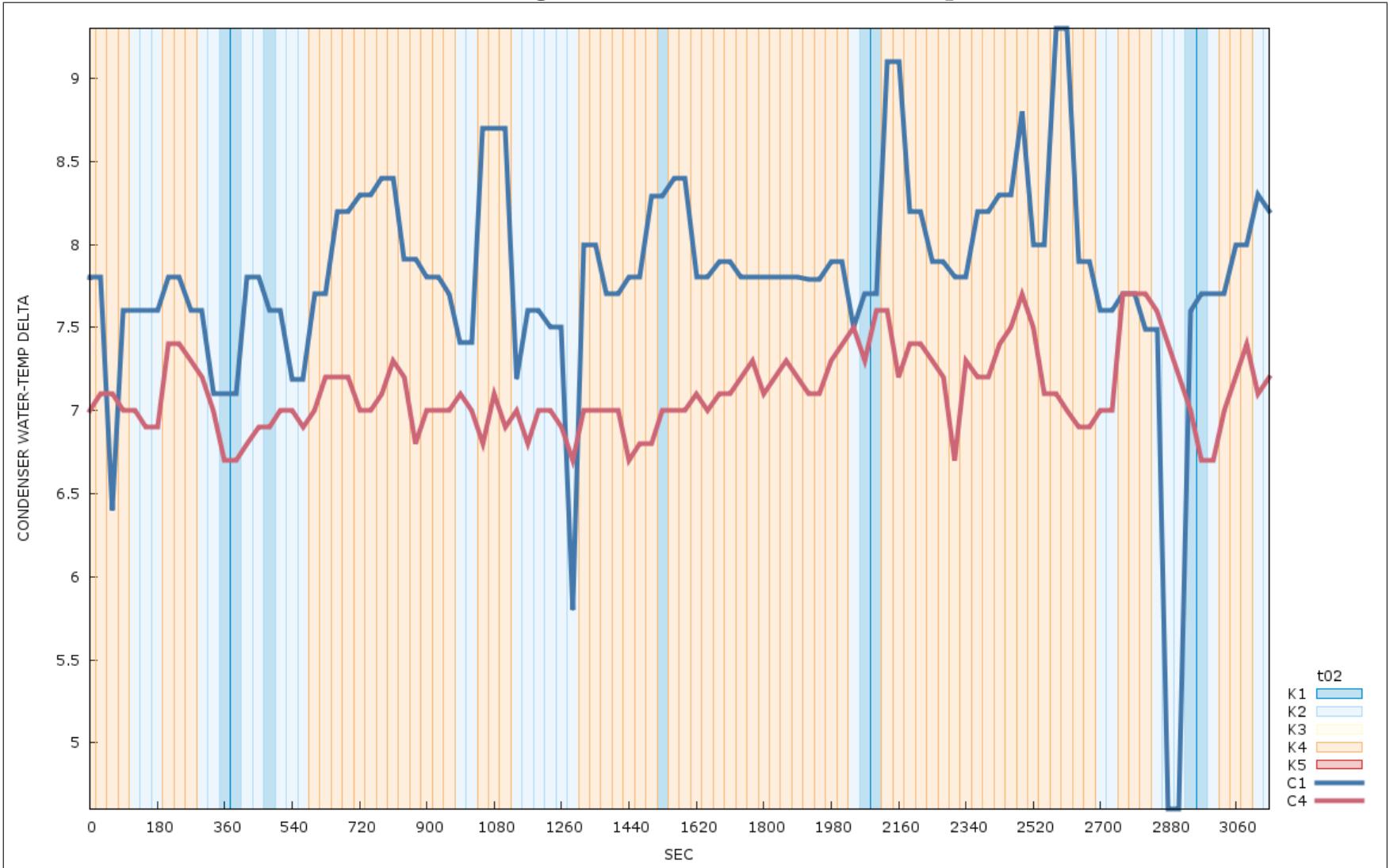


Figure N.5: K-Means Clustering with  $k = 5$

### Trial 3 : Chiller Clustering on Condenser Water-Temperature Delta

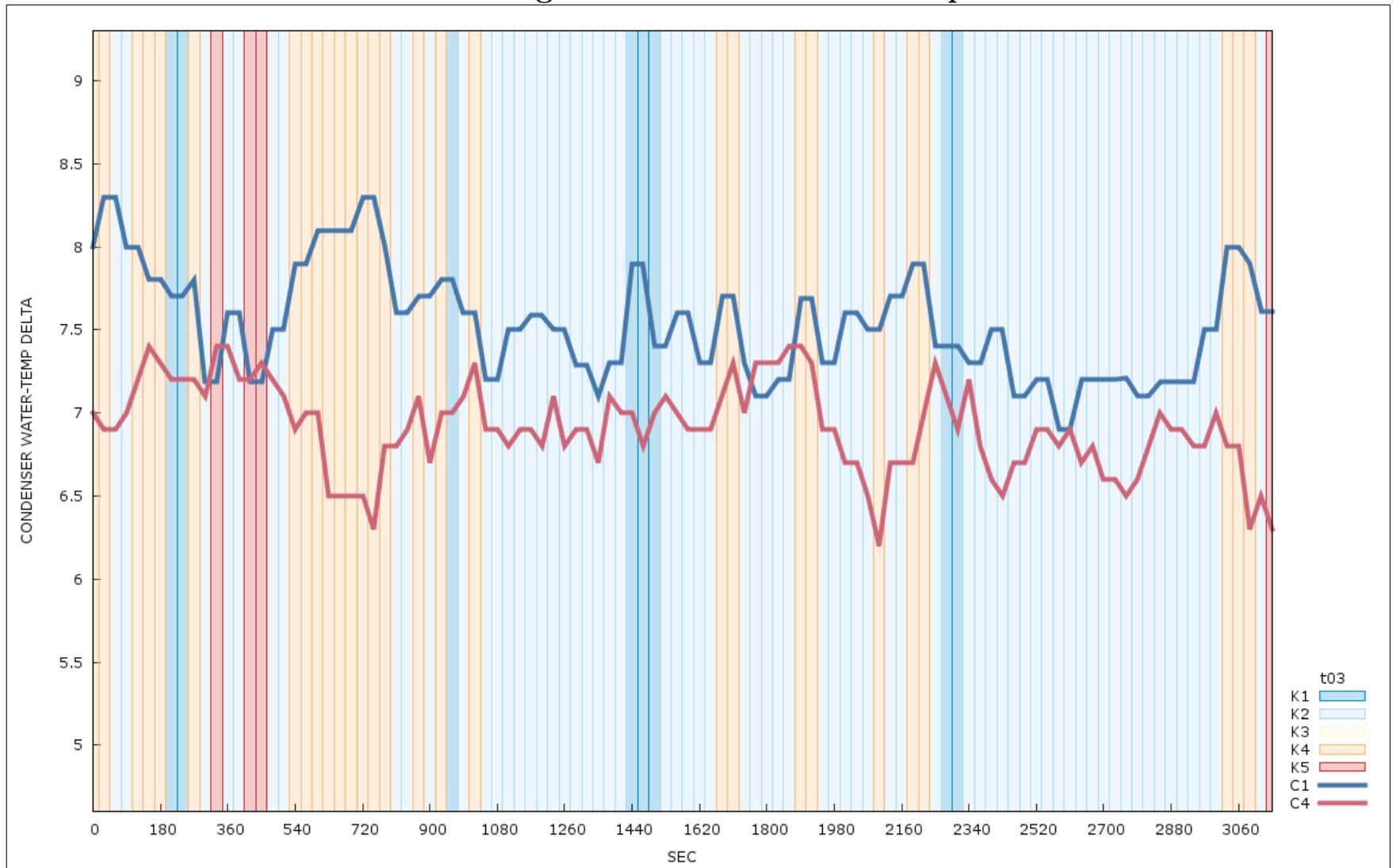


Figure N.6: K-Means Clustering with  $k = 5$

## Trial 1 : Chiller Clustering on Condenser Water-Temperature Delta

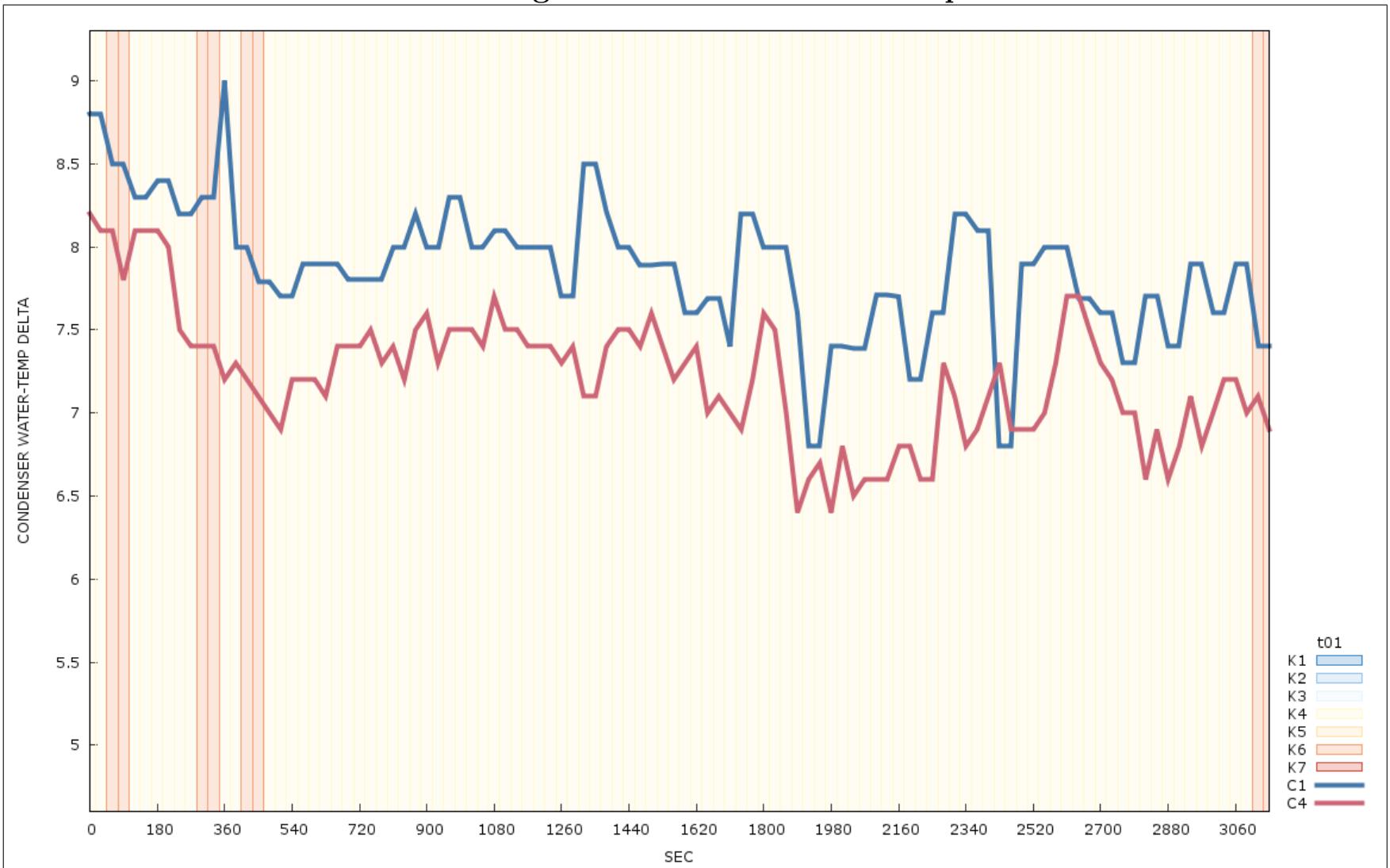


Figure N.7: K-Means Clustering with  $k = 7$

## Trial 2 : Chiller Clustering on Condenser Water-Temperature Delta



Figure N.8: K-Means Clustering with  $k = 7$

### Trial 3 : Chiller Clustering on Condenser Water-Temperature Delta

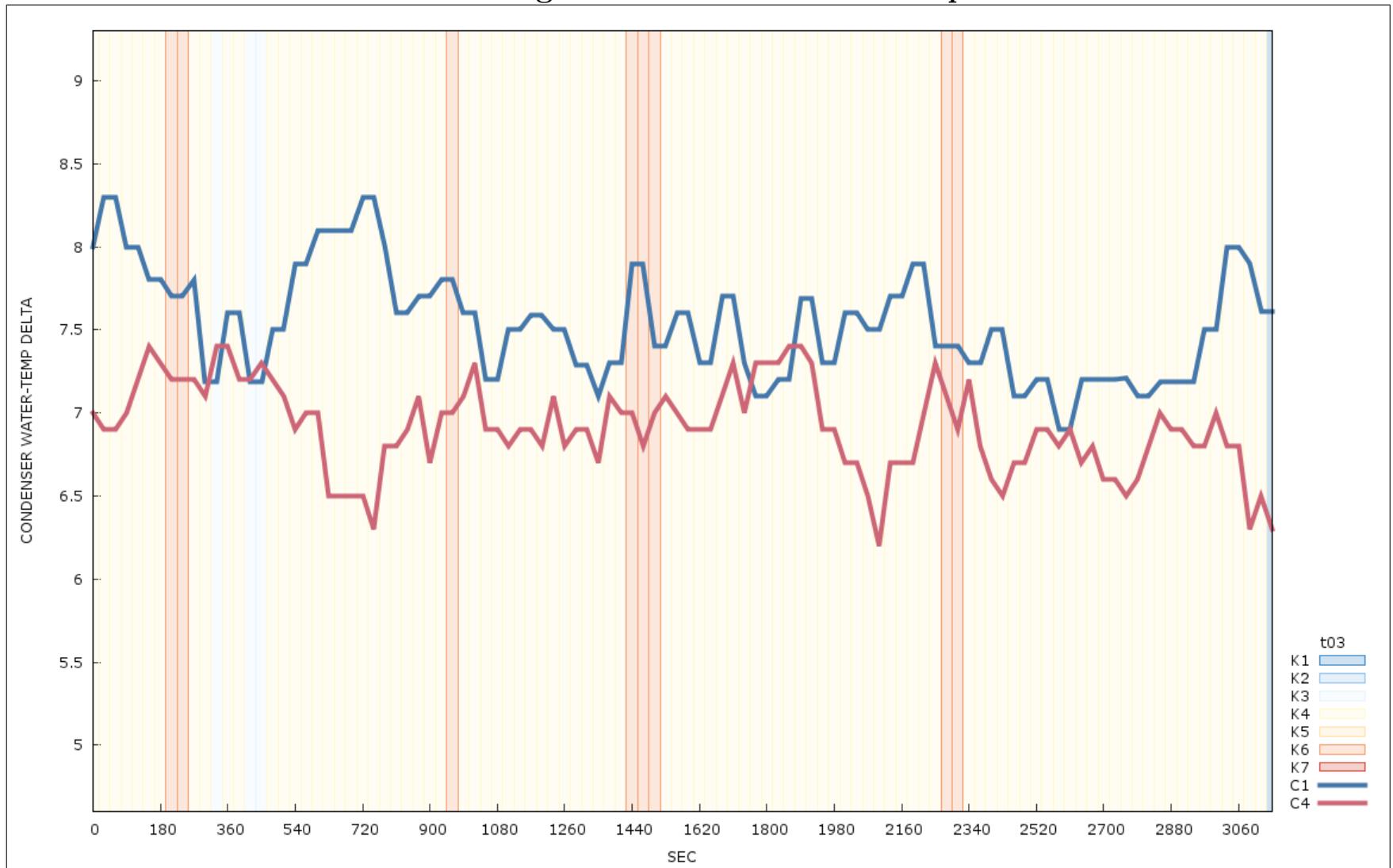


Figure N.9: K-Means Clustering with  $k = 7$

## Trial 1 : Chiller Clustering on Condenser Water-Temperature Delta

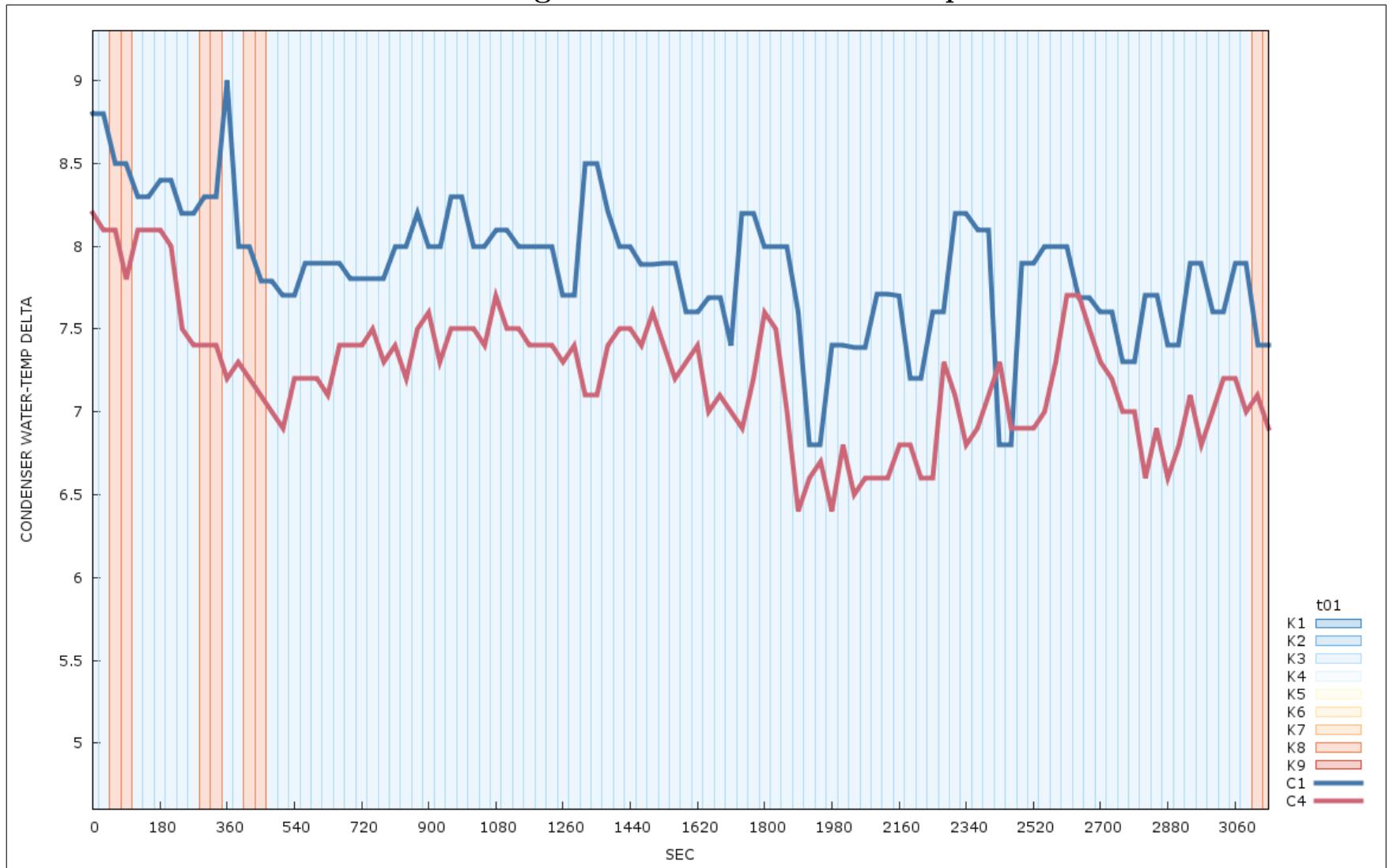


Figure N.10: K-Means Clustering with  $k = 9$

## Trial 2 : Chiller Clustering on Condenser Water-Temperature Delta



Figure N.11: K-Means Clustering with  $k = 9$

### Trial 3 : Chiller Clustering on Condenser Water-Temperature Delta

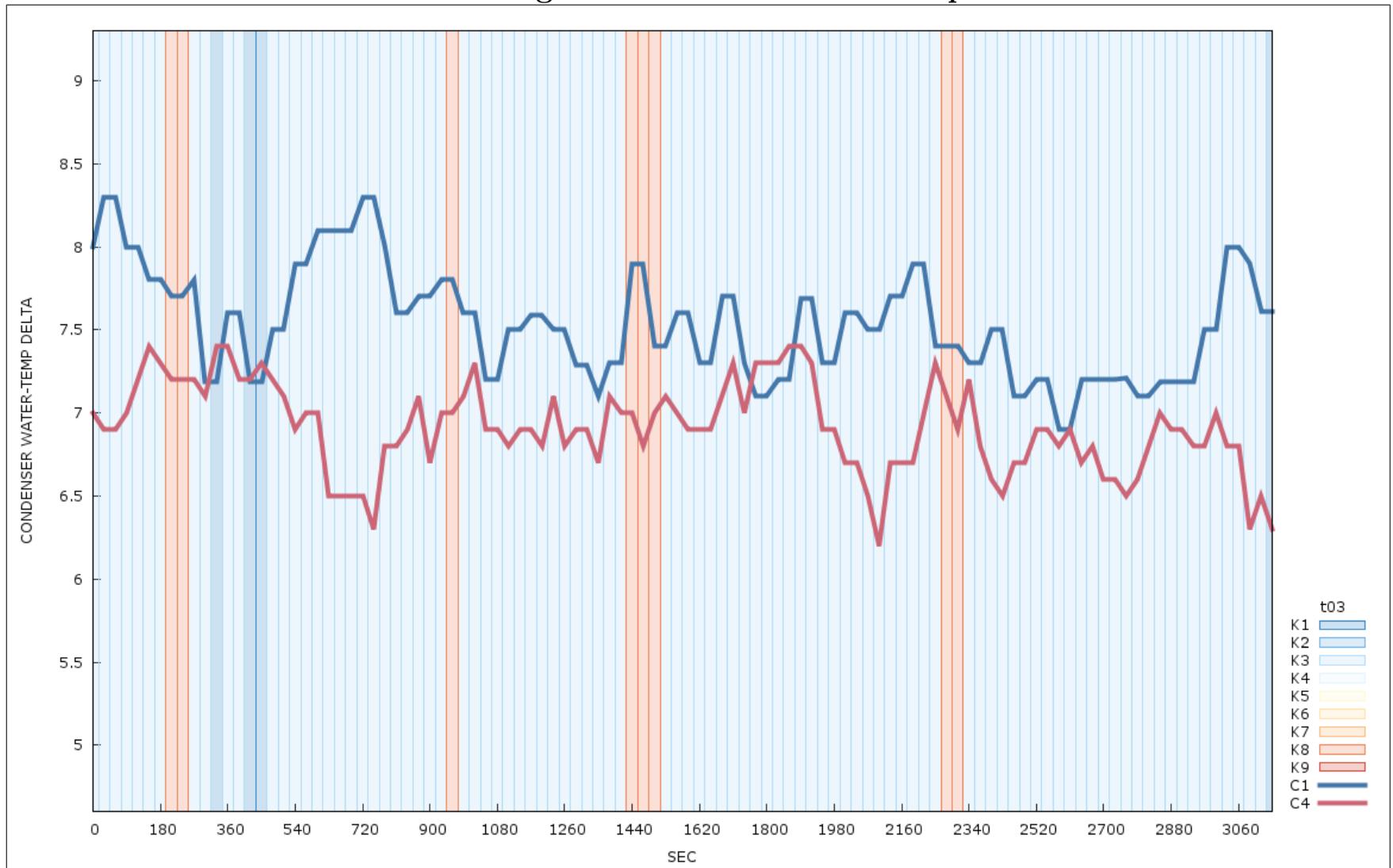


Figure N.12: K-Means Clustering with  $k = 9$

## Trial 1 : Chiller Clustering on Condenser Water-Temperature Delta

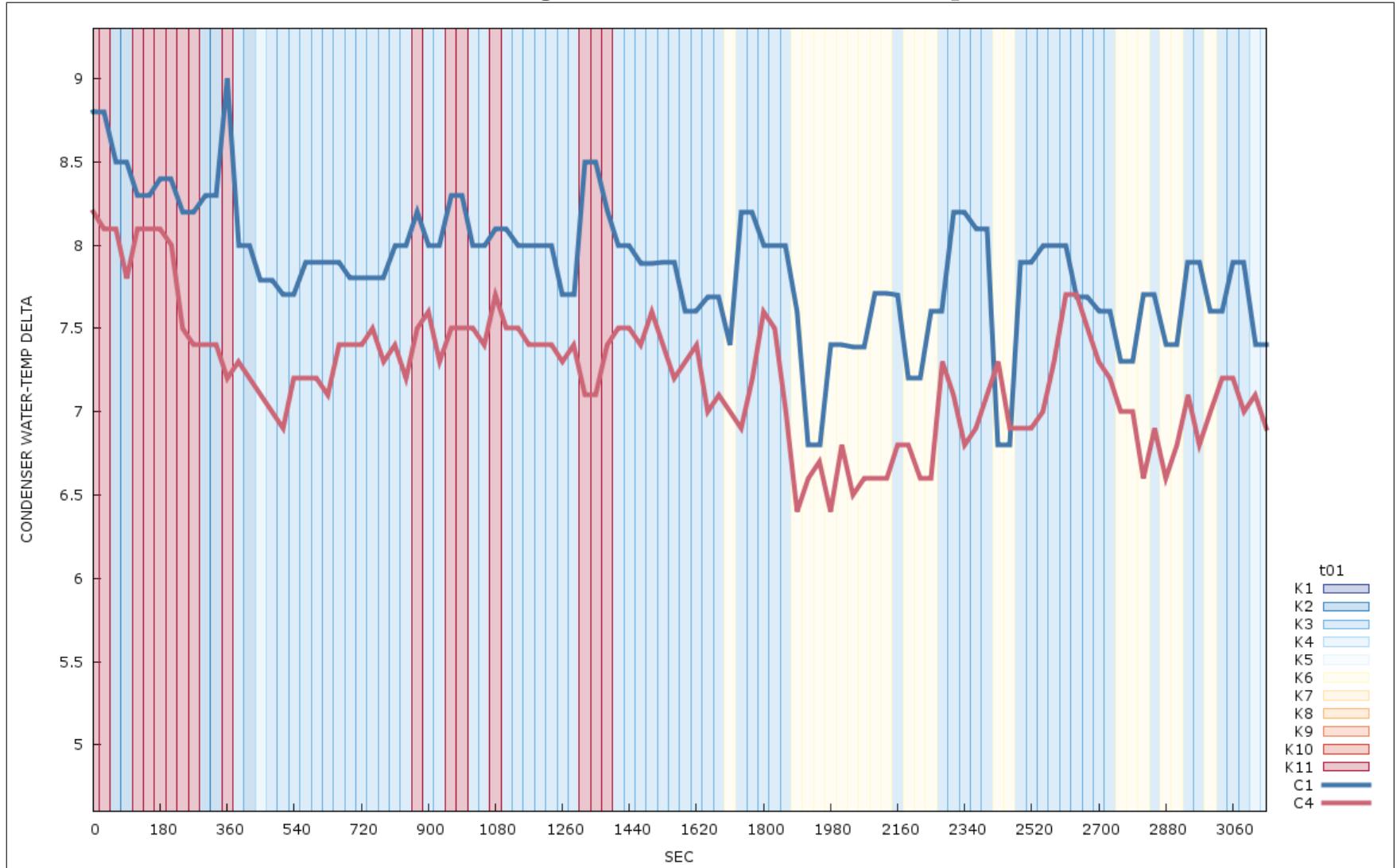


Figure N.13: K-Means Clustering with  $k = 11$

## Trial 2 : Chiller Clustering on Condenser Water-Temperature Delta

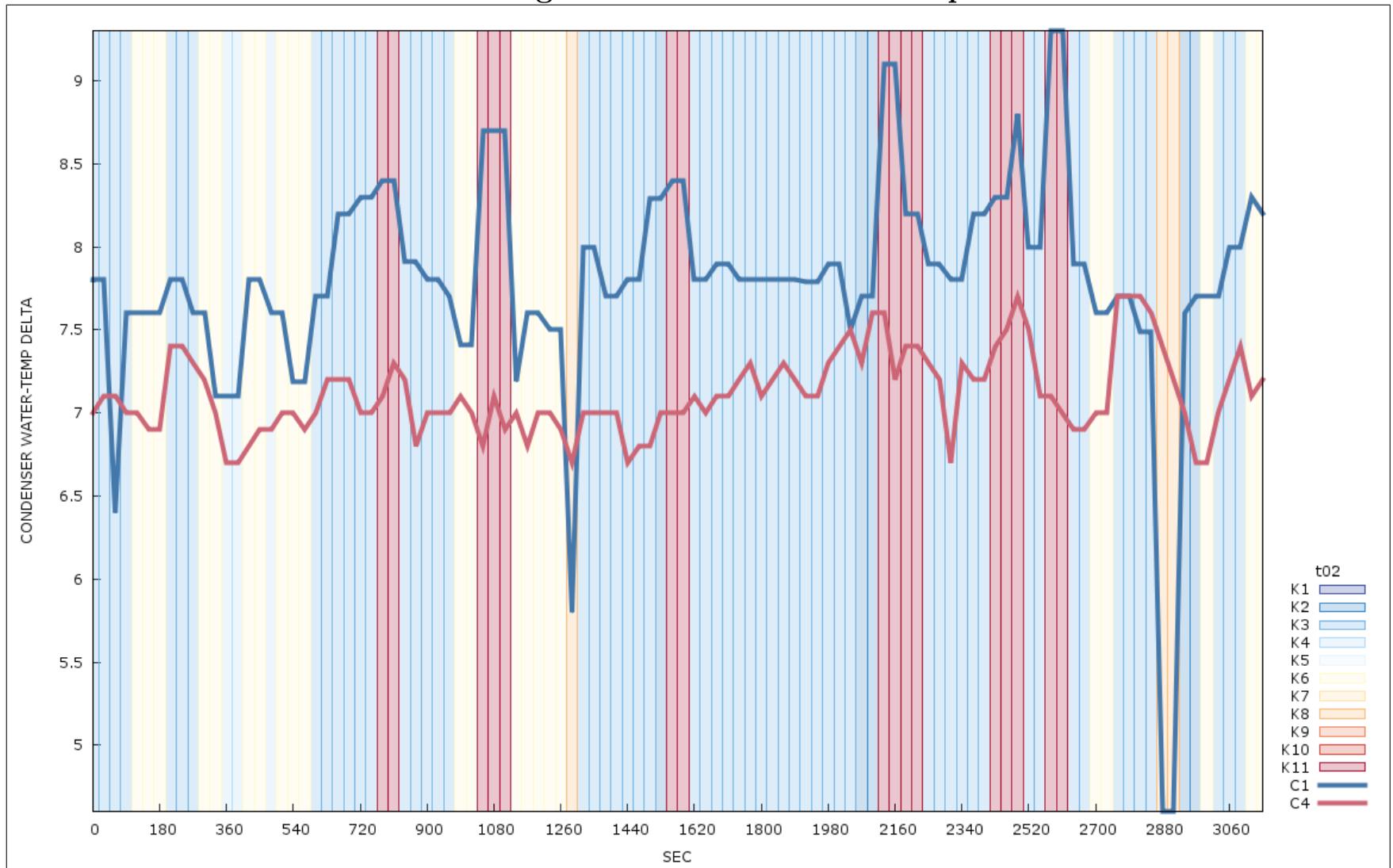


Figure N.14: K-Means Clustering with  $k = 11$

### Trial 3 : Chiller Clustering on Condenser Water-Temperature Delta

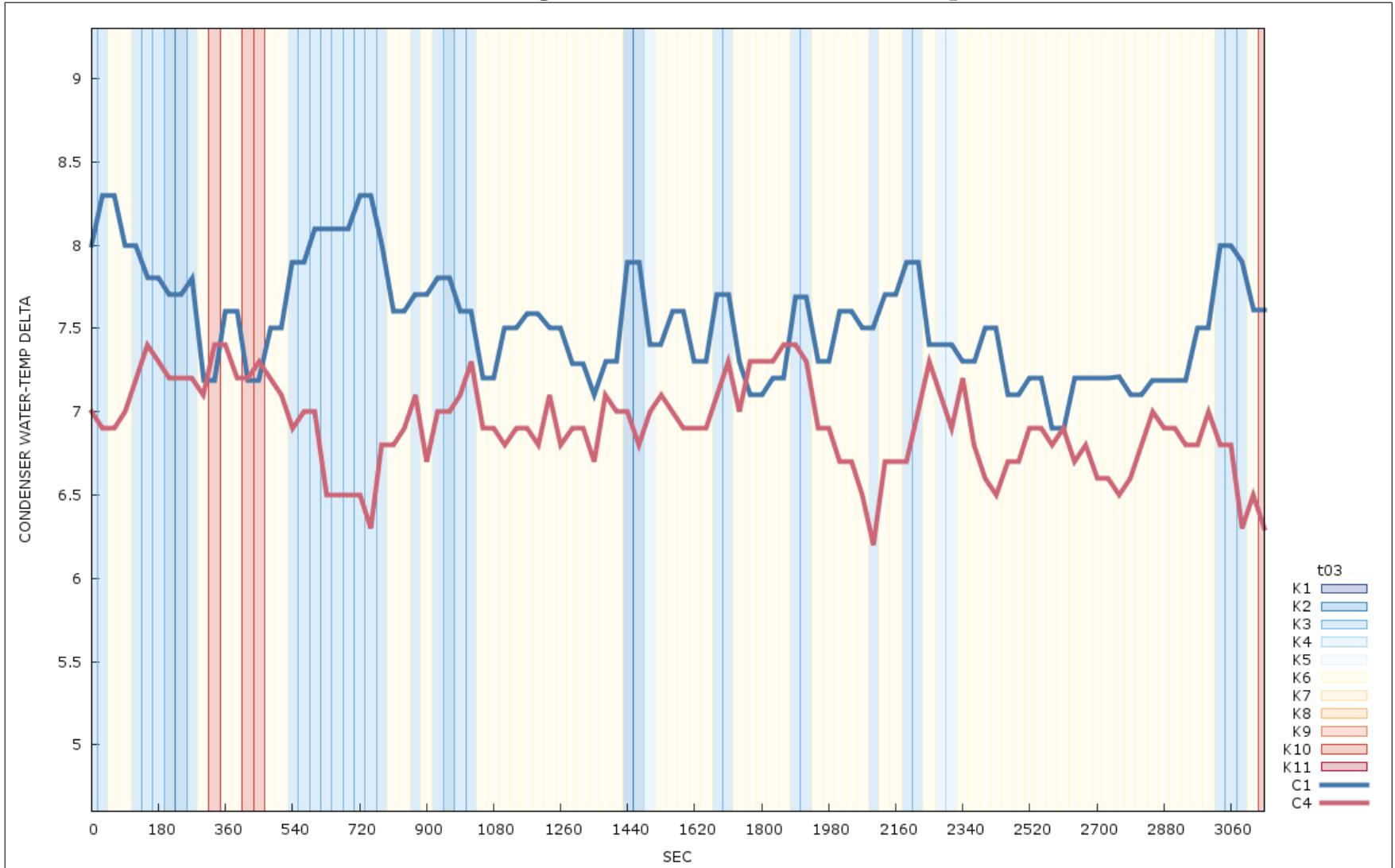


Figure N.15: K-Means Clustering with  $k = 11$

# Bibliography

- [1] Elke Achtert, Ahmed Hettab, Hans-Peter Kriegel, Erich Schubert, and Arthur Zimek. Spatial outlier detection: data, algorithms, visualizations. In *Proceedings of the 12th international conference on Advances in spatial and temporal databases*, SSTD'11, pages 512–516, Berlin, Heidelberg, 2011. Springer-Verlag.
- [2] Rashawn L. Knapp, Karen L. Karavanic, Sriram Krishnamoorthy, and Andres Marquez. Power- and cooling-aware parallel performance diagnosis. In *Parallel and Distributed Computing and Systems (PDCS 2011)*, Dallas, USA, December 2011.
- [3] Debprakash Patnaik, Manish Marwah, Ratnesh Sharma, and Naren Ramakrishnan. Sustainable operation and management of data center chillers using temporal data mining. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, KDD '09, pages 1305–1314, New York, NY, USA, 2009. ACM.
- [4] Debprakash Patnaik, Manish Marwah, Ratnesh K. Sharma, and Naren Ramakrishnan. Temporal data mining approaches for sustainable chiller management in data centers. *ACM Trans. Intell. Syst. Technol.*, 2(4):34:1–34:29, July 2011.