

# The new dynamic synthesis control algorithm for the 1.3 GHz LCLS-II Cryomodule test at Fermilab

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**Abstract-**The 1.3GHz LCLS-II Cryomodule (CM) has 8 cavities and each cavity has 9 RF cells and a 50W heater. The 1.3GHz LCLS-II CM is 12.2-meter-long and contains a total 241.3 liters (equivalent liquid) of liquid helium, which is filling up by the 4KW@2.0K cryogenic plant at the Fermilab Cryomodule Test Facility (CMTF). A new dynamic synthesis PID control of 2K cryogenic control system is built to control the large time-lagged unstable CM cryogenic system, under different modes operations. A report on the results obtained from the dynamic synthesis control algorithm in the CMTF 1.3GHz CM test will be presented.

**Index:** large time lagged, unstable cryogenic control system, new dynamic synthesis control algorithm

## I. INTRODUCTION

The large volume cryomodules, high volumetric flow rate and high helium vapor velocity of the smaller Joule-Thomson (JT) valve contributed to some PID operational difficulties in its liquid level and pressure. Figure 1 is the cryomodule, Figure 2 shown the cryomodule layout, Figure 3 illustrates the cryomodule piping arrangement.



Figure 1. The 1.3GHz LCLS-II 12.2-meter-long SRF cryomodule made by Fermilab.

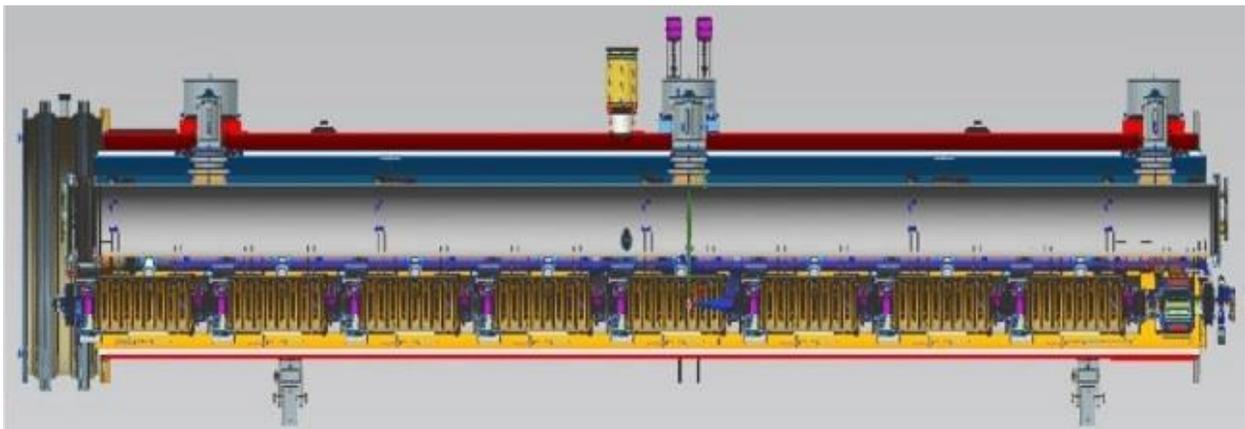


Figure 2. The 1.3GHz LCLS-II Cryomodule layout.

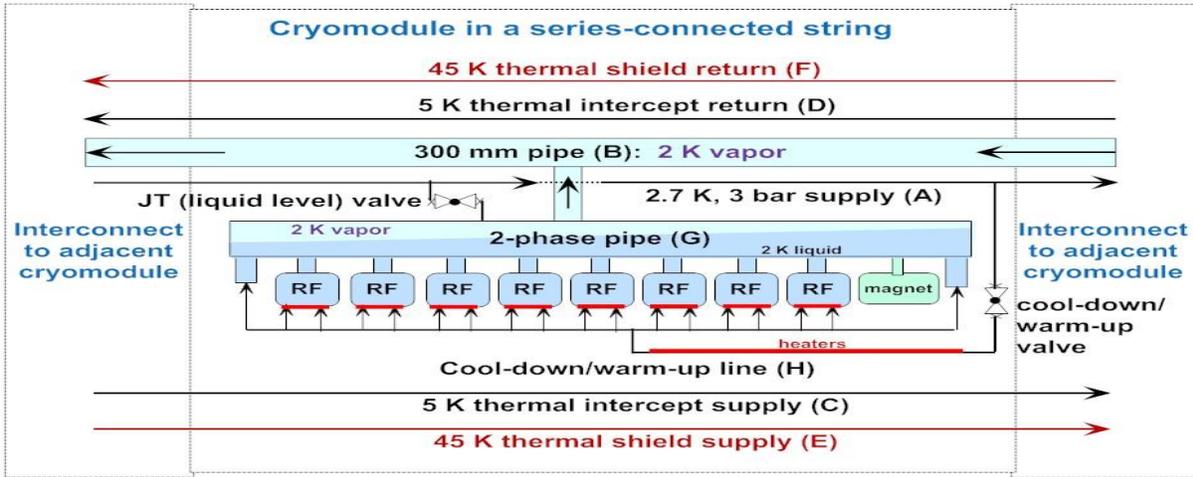


Figure 3. Cryomodule helium flow schematic.

The line A provides the approximately 3 bar pressures and 2.7 Kelvin liquid helium to the cryomodules. The JT DN5 valve (Cv + eq%) PID control provides range 0 to 10 g/s two phase helium (liquid and gas) from Line A to the 241.3 liters RF cavity helium vessels by maintaining a liquid level in the 2-phase pipe.

## II. THE LARGR TIME LAGGED SYSTEM USING COMMON PID CONTROL

Higher temperature liquid helium (LHe) into the JT expansion valve results in a significant fraction of the helium flow through the valve flashing immediately to vapor at the low pressure (31 mbar), 2 Kelvin, valve exit. Above 4.6K results in more than 45% of the flow just passing through the 2-phase pipe and out to the line B, 300mm gas return pipe, as vapor, but 2.7K results in just 20%. So, the liquid level in the 2-phase pipe respond will be very slow to JT position change under the common PID control as shown in Figure 4, and even worse when RF power operates at 80W maximum range or all heaters start to operate. Overall, the common PID Loop control system will result in the cryomodules cryogenic system to oscillation and take longer time to stabilize if could. The Figure 4 shown the time spent of the common PID loop control for 8 hours with constant heat load (89.5% set point).

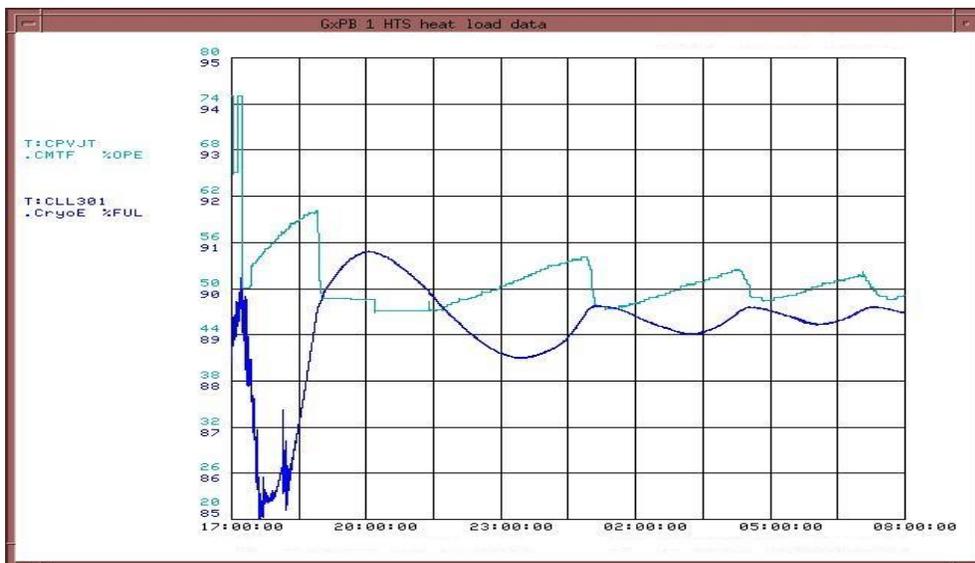


Figure 4. Common PID Loop control

### III. SYSTEM ANALYSIS AND NEW CONTROL ALGORITHM DESIGN

If balancing the cryogenic system with different preconditions, it is possible that they will respond differently for the same kind of control. For this reason, at least, the adaptive mechanisms are needed, capable of observing the reactions of the system and modifying their parameters to improve the given control algorithm.

The decisions taken by the control algorithm may depend upon the observation of various system responds. Creating a single control algorithm that contains this knowledge includes all of the possible system responses with the different combination of its settings is a highly complex task, if not impossible and may need considerably large number of data. We solve this problem by subdividing the control algorithm into several subdivision control algorithms. This gives us the possibility of describing the subdivision control behavior focusing on its specific parameters and using less number of data for each subdivision control. Then the new dynamic synthesis PID control algorithm for these subdivision control algorithms is added to create a real-time, on-line, large time-lagged control theory. To get the best control results, the fuzzy algorithm, the model predictive algorithm and the adaptive algorithm will dynamically combine into the dynamic synthesis control algorithm using the information of the subdivision control algorithms. This new dynamic synthesis control algorithm can automatically modify its synthesis control algorithm by observing the response of the cryogenic system in comparison to what is expected.

The new dynamic synthesis control algorithm is shown in Figure 5. It consists of the pre-estimated optimal algorithm control, the error subzone PID control and the weight arithmetic mean control.

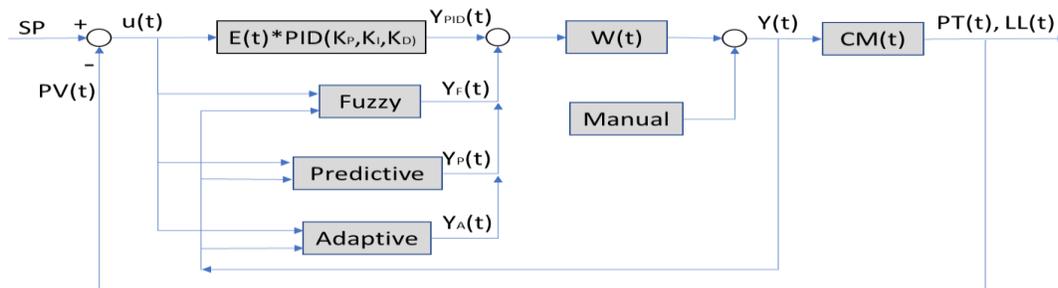


Figure 5. the new dynamic synthesis control algorithm block flow

Due to the slow liquid level response time of small JT valve changes. Three types of pre-estimated optimal algorithm controls are selected.

#### A. The fuzzy algorithm control $Y_F(t)$

The basic configuration of a fuzzy algorithm system shown in figure 6 is based on a fuzzification block gathering all the inputs of the system and its corresponding sets, a rule-base, an inference mechanism and defuzzification. To this configuration additional scaling factors were introduced to the inputs ( $x$ ) and output ( $Y$ ). This allows the easy configuration of the range of values covered by the fuzzy sets.

Because of the system lag time is usually more than several minutes to hours, and system control cycle is on the scale of hours. The ideal real-time control system should estimate its JT valve control partial true direction based on the fuzzy algorithm which could calculate current operated data.

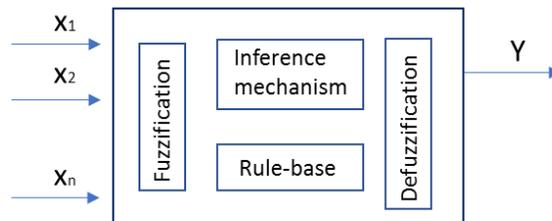


Fig. 6. Fuzzy controller architecture

If X is a collection of objects denoted by x, then a fuzzy set Y in X is defined as a set of order pairs:

$$Y = \{(x, \mu_Y(x) \mid x \in X\}$$

where  $\mu_Y(x)$  is called the membership function for the fuzzy set Y.

$$\text{Rule}^i : \text{if } (x1.\text{is}.A1_{ji}).\text{and}.(x2.\text{is}.A2_{ki}).\text{then}.(y.\text{is}.O_m^i)$$

Where:

$A1_j$  and  $A2_k$  is two of the fuzzy sets of the fuzzy partitions for x1 and x2.

$O_m^i$  is q one of the fuzzy set of the fuzzy partitions for Y.

The strength of the  $\text{Rule}^i$  is as strong as its mid component:

$$\mu_{O_m^i}(y) = \text{Mid}[\mu_{A1_{ji}}(x1), \mu_{A2_{ki}}(x2)]$$

Then Y for JT is,

$$Y_F(t) = \int_{-t}^{-t+N} N \mu_{O_m^i}(t) dt / T_f$$

where  $T_f = N * T$ ; T is JT control  $[-t, t_N]$  cycle time,  $N = 1, 2, 3, \dots$

#### B. The model predictive algorithm control $Y_p(t)$

To estimate the JT position better and faster control result when control condition setting has a suddenly change, for instant, the big RF power or heater watts setting change, the real-time control system should be able to predict its control direction and volume based on those data had been saved. The model predictive algorithm control is:

At each time t to solve the planning problem,

$$\text{Minimize } \sum_{\tau=t_0}^{t+T} l(x(\tau), u(\tau)) = Y(\tau),$$

subject to  $u(\tau) \in U, x(\tau) \in X, \tau = t, \dots, t + T$

$$x(\tau + 1) = Ax(\tau) + Bu(\tau), \tau = t, \dots, t + T - 1$$

$$x(t + T) = 0$$

With variables  $x(t + 1), \dots, x(t + T), u(t), \dots, u(t + T - 1)$

and data  $x(t), A, B, l, X, U$

call solution  $\tilde{x}(t + 1), \dots, \tilde{x}(t + T), \tilde{u}(t), \dots, \tilde{u}(t + T - 1)$

then take  $u(t) = \tilde{u}(t)$ , its feedback control  $u(t) = \phi_{mpc}(x(t))$

$$\phi_{mpc}(x(t)) = K_j x(t) + g_j, x(t) \in R_j$$

$R_1, \dots, R_N$  is polyhedral partition of X

and  $\phi_{mpc}$  (i.e.,  $K_j, g_j, R_j$ ) can be computed explicitly in off-line

So, the Y for JT predictive logic is:

$$\text{Minimize } \sum_{t=1}^N l(x(t), \phi_{mpc}(x(t))) = Y_p(t)$$

where,  $t$  is JT control ideal position  $[-t_1, t_0]$  period.

### C. The adaptive algorithm control $Y_A(t)$

At the beginning the previously defined fuzzy and model predictive control algorithms will not be optimally tuned for all the possible scenarios and specific event reactions. Therefore, an adaptive mechanism is needed capable of recognizing when a big unknown change must be made and how the control parameters should be modified. It is difficult to detect how the parameters should be changed in each control steps, this was solved by introducing a self-learning adaptive algorithm that can adjust its own parameters. This adaptive control algorithm uses the same inputs as the knowledge fuzzy base and model predictive control algorithms together with additional self-learning method that help to characterize a specific situation, e.g. refrigerator plant LHe supply disturbing, cavity heat load or RF power big change, etc. The adaptive algorithm control is:

$$Y_A(t) = (\text{Max} \sum_{i=0}^N \int_{t_0}^t Y(t-1) dt / T_i + \text{Min} \sum_{i=0}^N \int_{t_0}^t Y(t-1) dt / T_i) / N$$

where,  $T_i$  is one JT current control  $[t_0, t]$  period,  $N$  is 1,2, 3...,  $N[t_0, t]$  periods.

### D. The error subzone PID control $Y_{PID}(t)$

The CM will be operated on two type of modes, one is the subcritical mode, and another is the supercritical mode. those two modes will cause the significant different response of the JT valve opening. For each mode, the JT PID gains (PG, TI and DG) will be divided to three zone by its error of set point vs current control value and it will switch automatically among those six zones by the control logic.

$$Y_{PID}(t) = K_{p_j} u(t) + K_{I_j} \int u(t) dt + K_{D_j} \frac{du(t)}{dt}$$

Where  $j=1, \dots, 6$  based on  $e=1,2,3$ .

### E. The new dynamic synthesis control algorithm $Y(t)$

Finally, the new dynamic synthesis control algorithm  $Y(t)$  is divided by sub zones. There are:

a) When  $E1 < e < E2$ , then

$$Y(t) = \sum X_1 Y_{PID}(t) + X_2 Y_F(t) + X_3 Y_p(t) + X_4 Y_A(t)$$

where, weight arithmetic mean  $\sum_{i=1}^4 X_i = 1$ , and  $E1, E2$  are sub-zone.

b) When  $e > E2$ , then

$$Y(t) = Y_{PID}(t)$$

c) When  $e < E1$ , then

$$Y(t) = \sum (Y_{PID}(t) + X_f Y_F(t) + X_i Y_p(t) + X_a Y_A(t)) / 2$$

where, weight arithmetic mean  $\sum X_f + X_i + X_a = 1$

#### IV. REAL SYSTEM TEST RESULT AND ANALYSIS

To best description the dynamic synthesis control algorithm, two control configurations results were shown in here. The first one is the result of using the PID gains zones, fuzzy algorithm and model predictive algorithm directly. The second control refers to self-learning adaptive algorithm, it is the new dynamic synthesis control algorithm of the fuzzy, the predictive and the adaptive algorithm for the big time lagged cryogenic control system.

The real-time Synoptic remote control viewer is shown as Figure 7 as used on LCLS II CM. The CM was operating on stable 2K situation in the supercritical mode. The CM3 LL301 was fill up to 91.98% LHe, the PT8I2 was 35.2 psig, the RF power was 4.57W, and the heat loads were 35W. The PVJT was open at 68%, the PV82K was 38% opening and flow rate FT8A2 was 4.6 g/s.

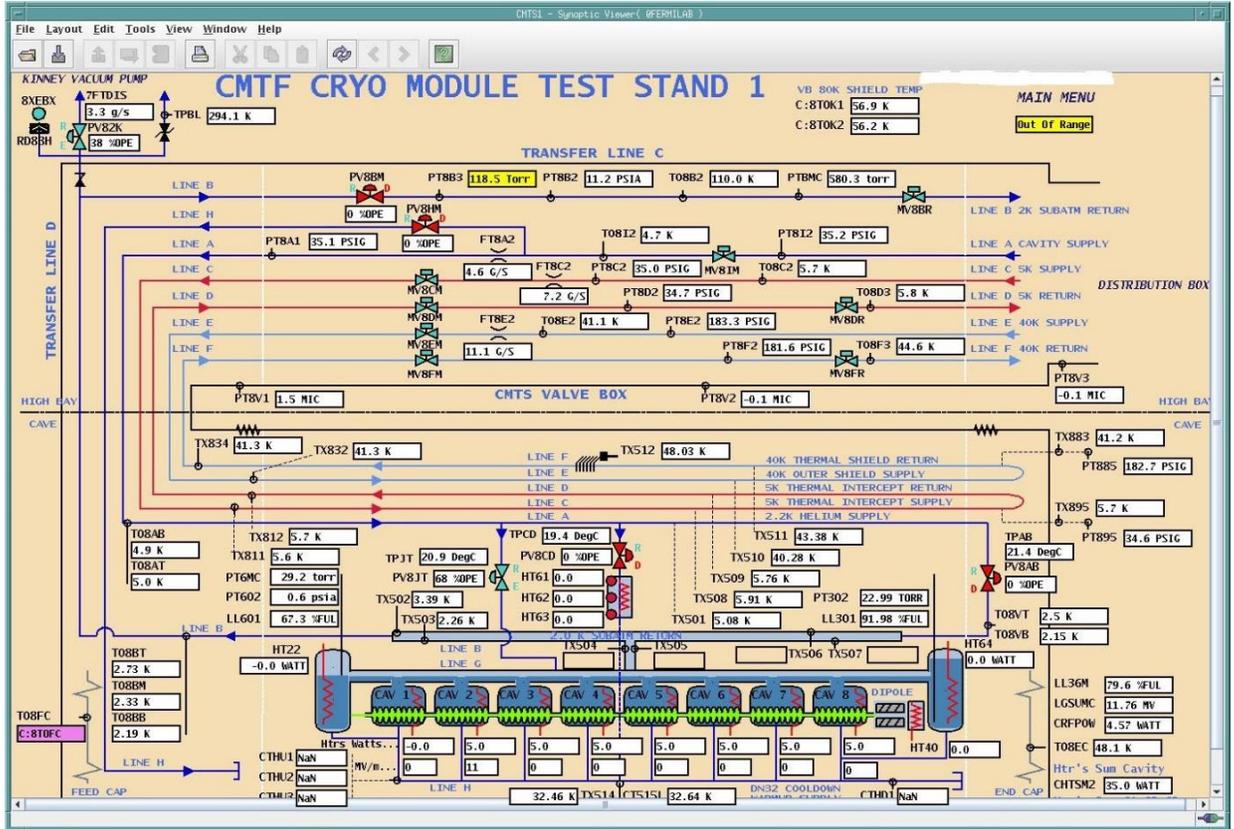


Figure 7. Real-time synoptic control view of LCLS-II CM3

A. The first control configuration result is here.

The CM cooldown result of fuzzy and model predictive algorithms combined control without big disturbance is shown in figure 8. The PVJT PID set point was 92%, the maximum position of PVJT was 90%, the PVJT PID error zone setting was +/-2%. The synthesis control algorithm result of fuzzy and model predictive algorithms is shown in Figure 8 and in Table 1.

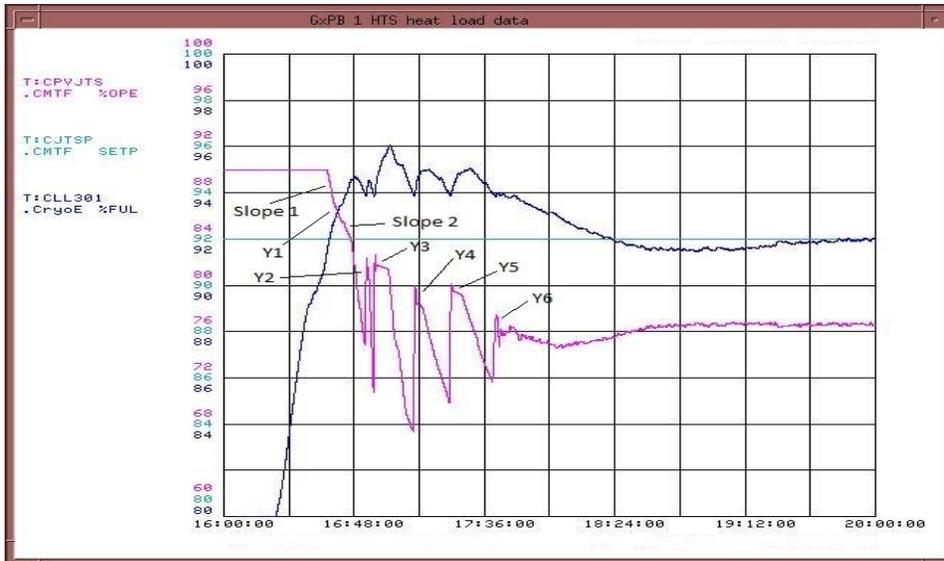


Fig. 8. The dynamic synthesis control algorithm of fuzzy and model predictive algorithms without big disturbance.

| LL301 | up to 90% | down to 94% |
|-------|-----------|-------------|-------------|-------------|-------------|-------------|
| Y     | Y1=86%    | Y2=82%      | Y3=82.5%    | Y4=79.9%    | Y5=80%      | Y6=77.5%    |

Table I

After cooling down CM procedure started, the LL301 LHe level climbed up finally while PVJT valve was kept in its maximum 90% position. When LL301 passed 90% critical point, 92%(SP) - 2%(error zone), the PVJT valve's dynamic synthesis algorithm control responded by set PVJT valve optimal number Y1 (86%) and valve position continuously down to 75%. The LL301 started to fall and finally reached another critical point 94%, 92%(SP) + 2%(error zone), the dynamic synthesis algorithm control set the new optimal number Y2 (82%). LL301 bumped up four times to become stable at 92% set point and synthesis algorithm control set Y3 (82.5%), Y4 (79.9%), Y5 (80%) and Y6 (77.5%) to match that bump ups. Total time spend to stable was two more hours, the slope of valve position curve was different based on the critical and non-critical area of LL301.

B. The second control configuration result is here.

The 2K CM3 suddenly sets an 80W heat load change, the result of the dynamic synthesis control algorithm of fuzzy, model predictive and adaptive algorithms is shown in Figure 9 and in Table 2. The PVJT PID set point was 90.5%, the PVJT PID error zone setting was +/-0.5%.

After the HTSM2 heat load was changed to zero from 80W, the dynamic synthesis control algorithm we developed set the optimal number Y1 (75%) to compensation the 80W power loss. So, the PVJT valve position could drop to around 75% quickly from 95% without waiting for LL301 up. When LL301 was down to 91% critical point again, the dynamic synthesis control algorithm set new calculated Y2 (69%), then, Y3(68%), Y4(67%) to Y7 (61%). The working time from Y1 to Y2 was two hours and Y6 to Y7 was one hour. Then, that 2K cryogenic system was stabilization.

Further improvements are still possible to make the synthesis algorithm more efficient. If the dynamics of the system is unknown and the volume of the liquid helium could be calculated through PVJT, some more optimal set number may be generated once the control has reached a certain state. An alternative is to reduces the LL301 oscillation more after a certain valve performance has been achieved. A second approach is to make the valve move more dynamically change according to the response of the system.

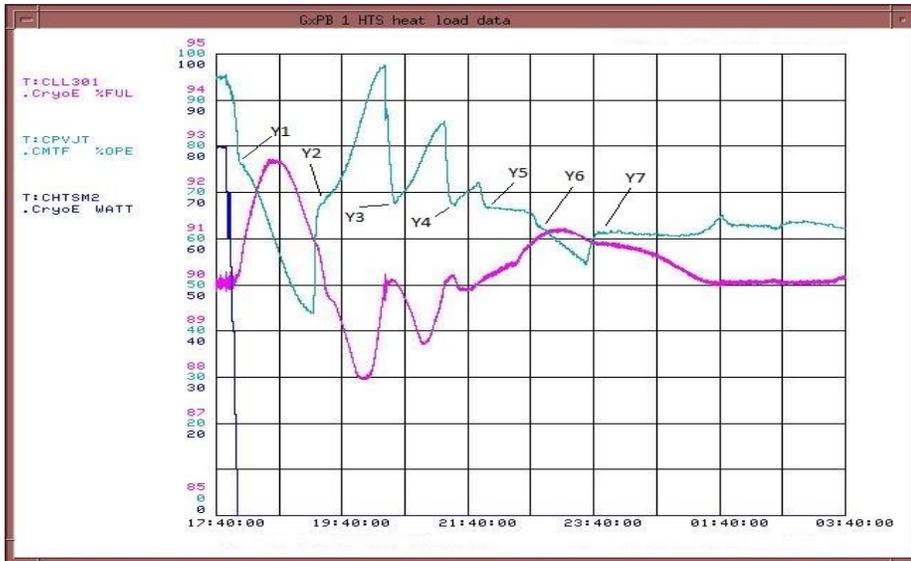


Figure 9. The heat load changed from 80W to 0 W

| Heat load | 80W to 0W |             |           |           |           |           |             |
|-----------|-----------|-------------|-----------|-----------|-----------|-----------|-------------|
| LL301     |           | Down to 91% | Up to 90% | Up to 90% | Up to 90% | Up to 91% | Down to 91% |
| Y         | Y1=75%    | Y2=69%      | Y3=68%    | Y4=67%    | Y5=66.5%  | Y6=62%    | Y7=61%      |

Table II

## V. CONCLUSION

The presented new dynamic synthesis control algorithm could control the large time-lagged cryogenic system very well even if it did not have previous knowledge on how to control the system. However, to assure best control for the stabilization, the 2K cryogenic system should start with previous knowledge of the system and be able to learn and adapt as quickly as possible by itself automatically.

The commenting from user at Jan 25, 2018. “Presented at the QAQC meeting and was again astonished by the basic assumption that the JLab people have about cavity frequency drift. They assume that the JT valve motors are going to be moving constantly because the cavities are going to be drifting in temperature and pressure, while I'm sitting here looking at plots of frequencies stable to 2 Hz over 8 hours. Certainly, a credit to all of you guys”.

## VI. Acknowledgments

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