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A LEARNING CONTROL TECHNIQUE TO INCREASE THE FREQUENCY OF SERVO-HYDRAULIC TESTING MACHINES

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Abstract. *For a given material resistance and magnitudes of alternate and mean stresses, the fatigue life depends essentially on the number of applied load cycles on the tested material. For this reason, working with a materials testing machine at high frequencies brings advantages of time and cost reduction, without altering the results. To achieve such frequencies, it is necessary to use an efficient control system. The present work shows learning control techniques developed and implemented in a materials testing machine, allowing the application of constant or variable amplitude loads at high frequencies. The proposed methodology consists of implementing a bang-bang type control to restrict the system servo-valve to permanently work at its extreme limits of operation, always completely opened in either direction. As the servo-valve works at its operating limits, the learning algorithm tries to obtain the optimal instants for the valve reversions, associating them to a non-dimensional variable, stored in a specific table. The learning law constantly updates the table values during the test execution, improving the system response. The experimental validation of this method is performed in a 100kN servo-hydraulic testing machine. A control system is especially developed to operate the machine, with a real time control software implemented in a CompactRIO computational system. The experimental results show that the test frequency can be significantly increased with the proposed learning control technique.*
Keywords*: frequency increase, learning control, bang-bang control, servo-hydraulic system*

1. INTRODUCTION

Hydraulic systems are widely used in industrial systems in applications such as automated plants, robotics, motion simulators, metal processing plants, mineral exploration, presses, heavy machinery and materials fatigue test systems (Merritt, 1967). In general, hydraulic systems are used in applications where relatively high forces, torques and accelerations are required. Machinery used in materials fatigue testing is based on servo-hydraulic systems, to provide useful information about the material's life in service by applying load cycles. The applied load may be repeated millions of times in typical frequencies up to one hundred times per second for metals. To achieve these frequencies, relatively high in a typical fatigue test, it is necessary to have an efficient control system.

In traditional control methods, all information from the process is known in advance, deterministically described (Doebelin, 1976). If the initial information is unknown, a controller may be designed able to estimate the information during the operation. This information could be used for future control decisions, a process known as learning control. The literature related to the control of servo-hydraulic systems presents many developments applied to industrial manipulators that are used to perform repetitive tasks (Sun and Chiu, 1999). One of these works is based on Lyapunov controller, where the adaptive law was also proposed to remove uncertainties of the hydraulic parameters (Sirouspour and Salcudean, 2000). A second work uses a non-linear controller that presents a better performance in both simulations and experiments than the results obtained using the proportional-derivative controller (Jelali and Kroll, 2003). Another work uses a robust controller and disturbance rejection for servo-hydraulic systems (Ching Lu and Wen Chen, 1993). In this case, the results of simulations and experiments showed that this controller has the ability to maintain the accuracy of the system in the presence of very large variations of the plant parameters and/or external disturbancies.

In the present work, a learning control technique is developed to increase the frequency of the applied load cycles in fatigue tests. An experimental control system is developed and applied to a fatigue test machine in order to assess and evaluate the performance of the proposed methodology.

2. LEARNING CONTROL

The learning process can be seen as a problem of estimation or successive approximations of unknown quantities or unknown function (King-Sun, 1970). In this case, the unknown quantities that are estimated or learned by the controller are parameters that are governed by the control laws.

The block diagram shown in Fig. 1 represents the learning control process. In each cycle, the system uses the information of the variables U_{IJ} stored in the memory to control the system through feedback. The errors measured at each cycle are used to update the parameters U_{IJ} through a learning law. The learning law is applied only at the end of each learning cycle k, which updates the values $U_{IJ}(k)$ with $U_{IJ}(k+1)$ based on the errors e(k). In the present application in fatigue testing, each learning cycle is associated with each reversal of the controlled parameter, e.g. in the peaks and valleys of the applied force history.

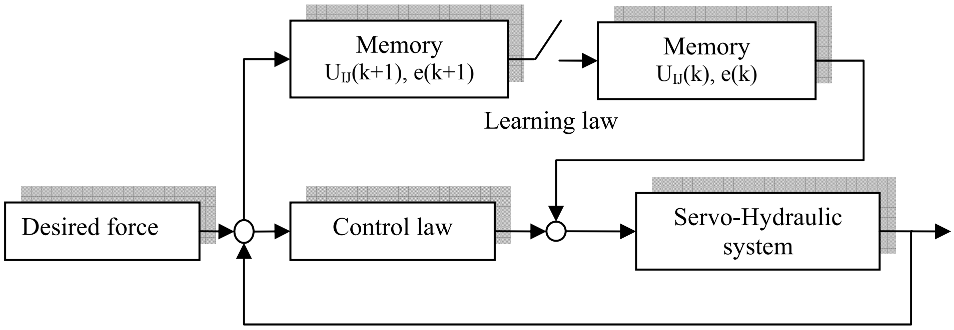

Figure 1. Block diagram of the learning control

The learning control methodology presented in this work aims to maintain the servo valve working in its extreme operation limits, keeping the valve most of the time in the fully open position in either one or other direction. This type of control is known as bang-bang (O' Brien, 2006). Due to the system dynamics, the servo valve reversion instants must happen before the peaks and valleys of the desired force or stress.

This instant of reversion is represented by a non-dimensional variable U_{IJ}, which is defined as the fraction of the peak-valley (or valley-peak) path where the valve should be reverted. For instance, when controlling a force cycle from 10 to 110kN, a value $U_{IJ} = 0.8$ would be equivalent to reversing the valve when 80% of the path between 10 and 110kN has passed, i.e., when the measured force is equal to 10 + 0.8×(110–10) = 90kN. In this same example, when returning from 110 to 10kN, the same value $U_{IJ} = 0.8$ would be equivalent to reversing the valve at 110 – 0.8×(110–10) = 30kN.

This U_{IJ} is a parameter that depends on several factors such as the amplitude and mean value of the applied load, and it is also influenced by dead zones caused in some cases by slacks in the test specimen fixtures. The objective of the proposed approach is to learn the values of U_{IJ} as a function of the load amplitude, mean, and direction (either from peak to valley or from valley to peak).

2.1. Learning Tables

Figure 2 shows a table that stores non-dimensional numbers $U_{i,j}$ (with the indexes in lowercase) associated with the learning process. These numbers are the discrete values of U_{IJ} for several combinations of load amplitude and mean. The columns show the values of the gamma (twice the amplitude) of the physical variable to be controlled, while the rows show the minimum value of the peak-valley half-cycle. Note that this table can be divided into two parts, one associated to when the system is going from a valley to a peak, and another when it is going to a valley. In order to join both tables, the concept of negative gamma is used, which indicates the transition from a peak to a valley.

Therefore, $U_{i,j}$ is defined as an element associated with the row i (minimum value "min_i") and the column j (associated with the gamma "$gama_j$"). For a loading with a minimum value min_i and gamma equal to $gama_j$, then $U_{IJ} = U_{i,j}$. If the minimum and gamma values are between two consecutive values in the table, $min_i < min < min_{i+1}$ and $gama_j < gama < gama_{j+1}$, then U_{IJ} is obtained by interpolation (see Figure 3):

$$U_{IJ} = a + (b-a)\cdot\frac{(gama - gama_j)}{\left(gama_{j+1} - gama_j\right)} \tag{1}$$

where

$$a = U_{i,j} + (U_{i+1,j} - U_{i,j})\cdot\frac{(min - min_i)}{\left(min_{i+1} - min_i\right)} \tag{2}$$

$$b = U_{i,j+1} + (U_{i+1,j+1} - U_{i,j+1})\cdot\frac{(min - min_i)}{\left(min_{i+1} - min_i\right)} \tag{3}$$

Columns (gamma)

Lines (minimum)

	-25	-15	-5	5	15	25
-25	0,9810	0,9602	0,8795	0,8016	0,8712	0,9475
-15	0,9688	0,9415	U_{ij}	0,8245	0,9005	0,9516
-5	0,9520	0,9230	0,8456	0,8429	0,9406	0,9712
15	0,9256	0,8910	0,7415	0,9038	0,9668	0,9856
25	0,9086	0,8723	0,6879	0,9312	0,9765	0,9901

Figure 2. Learning table

Columns (gamma)

Lines (minimum)

			$gama_j$	$gama_{j+1}$	
	0,8595	0,8364	0,8153	0,9314	0,9650
min_i	0,8143	0,7923	$U_{i,j}$	$U_{i,j+1}$	0,9736
min_{i+1}	0,7640	0,7289	$U_{i+1,j}$	$U_{i+1,j+1}$	0,9812
	0,7128	0,6935	0,9216	0,9715	0,9878
	0,6550	0,6320	0,9418	0,9835	0,9934

Figure 3. Procedure for interpolation when the values of gamma and minimum are between two cells

Once calculated the value of U_{IJ} from Eqs. (1-3), the servo valve reversal point can be calculated from

$$reversal = \begin{cases} min + U_{IJ} \cdot gama & (\textit{from}\ \text{valley to peak}) \\ (min + gama) - U_{IJ} \cdot gama & (\textit{from}\ \text{peak to valley}) \end{cases} \tag{4}$$

2.2. Learning Law

The learning law governs how the $U_{i,j}$ values are updated after each load reversion in the test. Thus, the new value of U_{IJ} is calculated using the error between the measured peak (or valley) x and the desired peak (or valley) x_d

$$e = \frac{x_d - x}{x_d - x'} \tag{5}$$

where x' is the valley or peak measured in last reversion. Note that the defined error is dimensionless, and that x can be any variable to be controlled in the tests, such as applied force, test specimen deformation or hydraulic piston displacement.

In the case where x and x_d are peaks, x' will be a valley, and the difference (x_d – x') will be positive. Thus, if there is an undershoot in this event, then x < x_d, resulting in e > 0. In the same way, if an overshoot happens, then e < 0.

On the other hand, if x and x_d are valleys, then x' will be a peak, and the difference (x_d – x') will be negative. In the case of an undershoot when the loading decreases, then x > x_d, and therefore e > 0. Similarly, for an overshoot, e < 0.

As a result, positive errors are always associated to undershoots, while negative ones to overshoots, no matter if the transition is from a valley to a peak or from a peak to a valley. Clearly, if an overshoot happens, then the approach is to reverse the valve sooner in future similar events, which implies in decreasing U_{IJ} for that combination of (*min*, *gama*). On the other hand, in the case of an undershoot, it would be necessary to increase U_{IJ}.

Assuming that any undershoots or overshoots will remain below 100%, then −1 < e < 1, and a learning law can be proposed:

$$U_{IJ} := U_{IJ} \cdot (1+e) \tag{6}$$

The above learning law does not need adjustable gains. It is associated with an increment of U_{IJ} by a factor (1+e) in the case of an undershoot (e > 0), and a decrease in its value for an overshoot (e < 0). It is possible to introduce a gain to multiply the error in equation (6), in order to tune the learning rate. Nevertheless, a unitary gain was enough in this work to achieve a stable and fast learning law.

Since the learning table only stores discrete values of U_{IJ}, then the values $U_{i,j}$, $U_{i,j+1}$, $U_{i+1,j}$, $U_{i+1,j+1}$ that generated U_{IJ}(min,gama) by interpolation must also be updated according to the learning law, where min_i < min < min_{i+1} and also $gama_j$ < gama < $gama_{j+1}$. This update process is also made using weight factors, i.e., the neighboring cell closer to U_{IJ} shall be updated in a greater degree than the other three neighbor cells. This process is easily implemented with the learning law

$$U_{i,j} := U_{i,j} \cdot \left[1+(1-\alpha)\cdot(1-\beta)\cdot e\right] \tag{7}$$

$$U_{i,j+1} := U_{i,j+1} \cdot \left[1+(1-\alpha)\cdot\beta\cdot e\right] \tag{8}$$

$$U_{i+1,j} := U_{i+1,j} \cdot \left[1+\alpha\cdot(1-\beta)\cdot e\right] \tag{9}$$

$$U_{i+1,j+1} := U_{i+1,j+1} \cdot \left[1+\alpha\cdot\beta\cdot e\right] \tag{10}$$

where

$$\alpha = \frac{min - min_i}{min_{i+1} - min_i},\ 0<\alpha<1 \tag{11}$$

$$\beta = \frac{gama - gama_j}{gama_{j+1} - gama_j},\ 0<\beta<1 \tag{12}$$

Note that Eqs. (2-3) may be rewritten in terms of α and β as follows

$$U_{IJ} := U_{i,j}\cdot(1-\alpha)\cdot(1-\beta) + U_{i+1,j}\cdot\alpha\cdot(1-\beta) + U_{i,j+1}\cdot(1-\alpha)\cdot\beta + U_{i+1,j+1}\cdot\alpha\cdot\beta \tag{13}$$

3. SIMULATIONS

Simulations of the control system applied to a servo-hydraulic testing machine were performed in MATLAB. The simulation includes the modeling of a 100kN servo-hydraulic machine, including detailed models for the servo-valve (Viersma, 1980; Thayer, 1965). The system model is too lengthy to be included in this work, however its full description can be seen in Alva (2008).

The simulations for the servo-hydraulic machine, performed for constant and variable amplitude load histories, show excellent results for the proposed learning control law. Figures 4 and 5 show how the controller learns by changing the location of the reversion points of servo valve at each load cycle. The learning process starts assuming U_{IJ} equal to 0.5 for any value of (min, gama).

As shown in Fig. 6, the learning process also presents good results for variable amplitude histories. In this example, three blocks with different (min, gama) values need to be applied to the specimen. In the first block, the learning process takes about 5 to 6 cycles to converge. The second block also needs 6 blocks to converge, because its (min, gama) is very different from the one from the first block, updating a very different section of the learning table. But the learning in the third block converges in only 2 cycles, because it could benefit from the updated U_{ij} values learned from the second block, which had similar (min, gama) values.

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Note also from Fig. 6 that the frequency of the system response depends on the desired amplitude. The blocks 1 and 3, which have the same amplitude [10 – (–10)]/2 = [30 – 10]/2 = 10kN, result in a higher frequency than block 2, with a lower amplitude [25 – 10]/2 = 7.5kN. This variable frequency is not an issue in fatigue testing, because the fatigue life of most materials under room temperature depends only on the load amplitude and mean, not on its frequency. These frequencies, on the other hand, are the highest achieveable for a given system and load history, since the servo-valves are always operating at their operational limits and their reversion has been optimized due to the learning law.

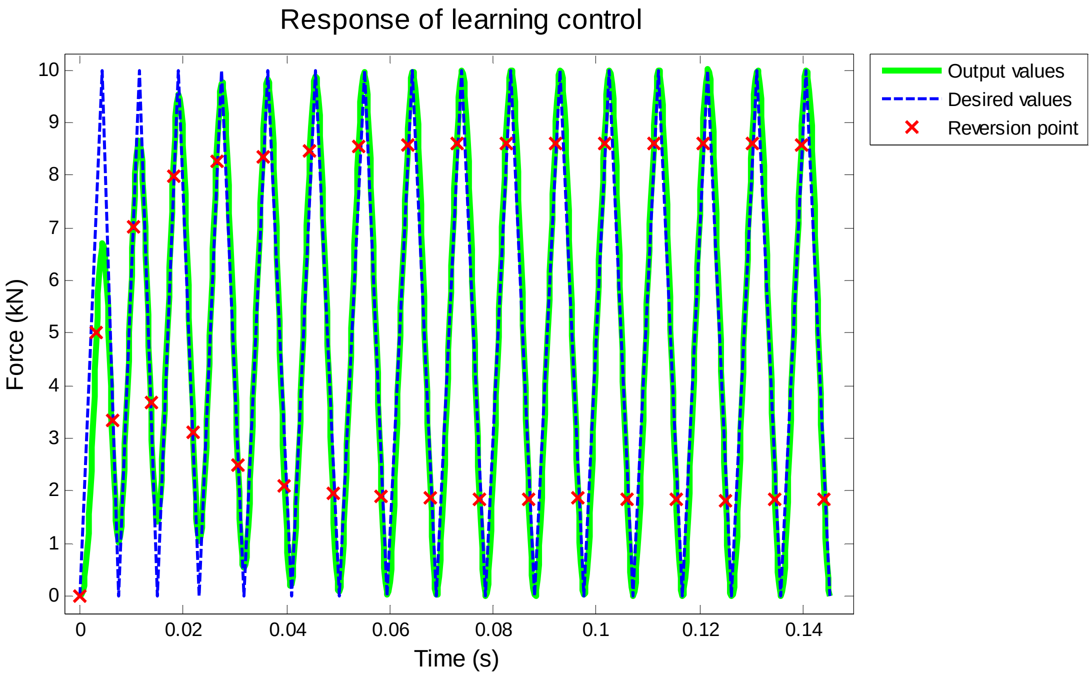

Figure 4. Learning control responses for a constant amplitude history from 0 to 10kN

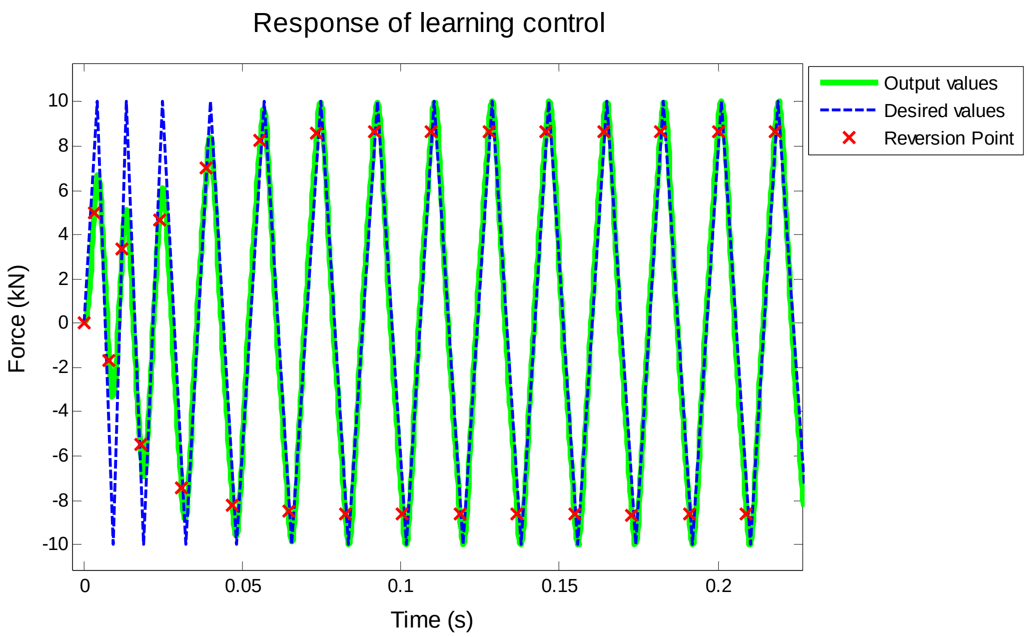

Figure 5. Learning control responses for a constant amplitude history from –10 to 10kN

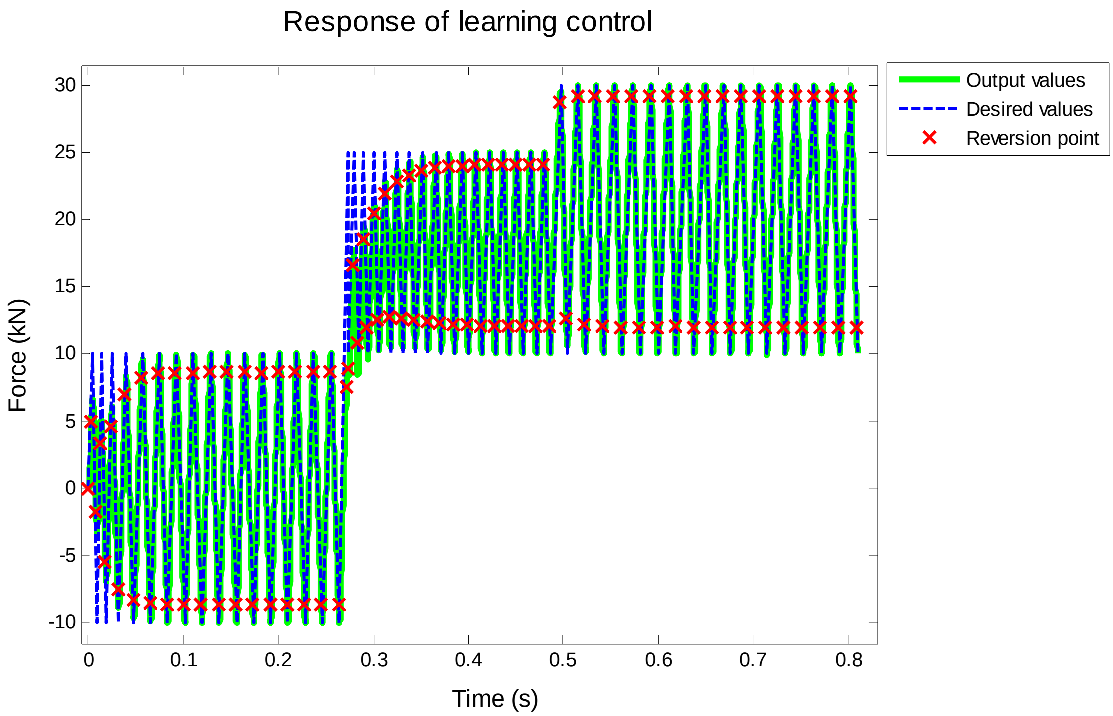

Figure 6. Learning control responses for a variable amplitude input

4. EXPERIMENTS

The proposed methodology is applied to a fatigue test machine INSTRON model 8501, with a servo valve MOOG D562 and with a current signal command of ±40 mA. The piston from this machine can generate forces up to 100 kN with a displacement amplitude of ±50 mm (from a central position). The fatigue test machine has a force sensor to control force histories, and a LVDT for displacement commands. A strain gage or clip gage attached to the test specimen also allows the control of a deformation history. The hydraulic fluid is supplied by a hydraulic pump at the pressure of 190 bar.

The learning control is implemented in a CompactRIO cRIO9004 computational system, from National Instruments. This system includes modules for analog outputs (NI9263), analog inputs, and an exciter module for strain gages (NI9237), see Figure 7.

The tests are run for zero mean loads and force amplitudes of 10 kN, 20 kN, 30 kN and 40 kN, all of them using ±20mA of current in the servo valve. The tests are performed using εN test specimens made of steel with 12mm in diameter in its thinnest section.

Figure 8 compares the performance of the proposed learning control using lower ±20mA currents and the traditional one from the Instron controller using ±40mA, for the servo-hydraulic machine under several load amplitudes. It is possible to observe a better performance of the learning control for low amplitudes and an equal performance for high amplitudes, even though the learning control only needs half the current. The traditional control is only able to outcome the proposed learning control when it is allowed to use currents beyond 40mA in the servo-valve (overdrive).

It is expected that using a current of ±40mA in the proposed learning control process it will be possible to obtain even better results. Learning control with currents beyond 40mA (overdrive) will also be investigated in future work.

5. CONCLUSIONS

In this work, it was shown that it is possible to increase the work frequency of a fatigue test machine using a learning control technique applied to servo-hydraulic systems. Both the bang-bang control and proposed learning laws do not need adjustable gains, simplifying their implementation. The proposed control system was simulated and applied to a fatigue testing machine, implemented in a CompactRIO system. The results showed that the proposed control is capable to generate frequencies higher than those obtained with the original controller using lower currents for the servo valve triggering.

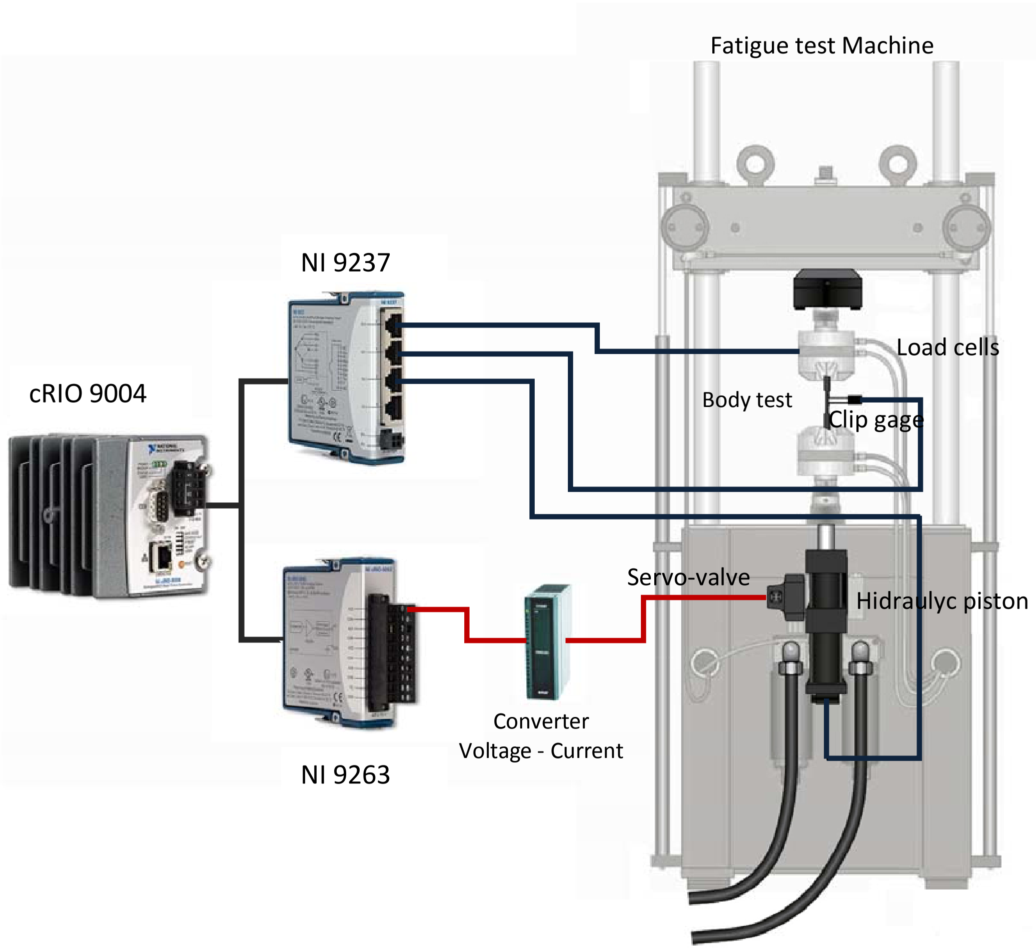

Figure 7. Experimental system

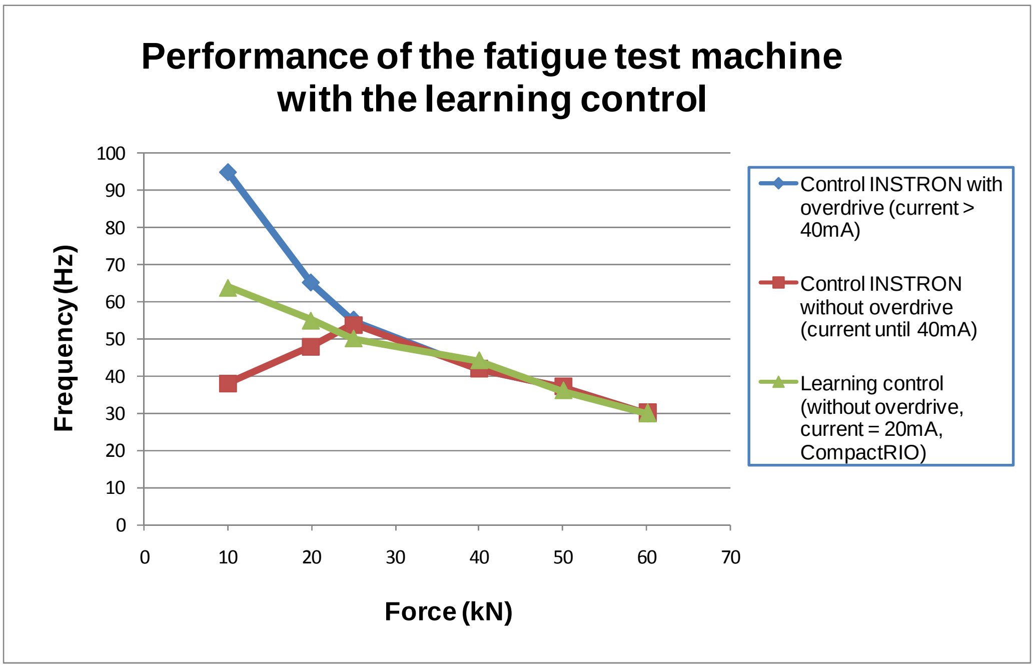

Figure 8. Performance comparison between the proposed learning control limited to ±20mA with the traditional Instron Controller at or beyond 40mA limits

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