Automation in Manufacturing

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Abstract

This paper is aimed at posing some of the problems in manufacturing automation. It will also refer the interested reader to some state-of-the-art solutions that have been proposed by several researchers in this area. The main scope of this paper is with regards to the control of manufacturing tools and their health monitoring for insuring high quality products.

1 Introduction

Manufacturing Automation is a key technology necessary for improving the quality and quantity of manufactured products. This technology is specially important in developing countries due to the shortage of skilled workers in those countries. Two key components of manufacturing automation will be touch in the following sections. First, a list and a brief description of modern manufacturing machines and their methods of operation are given. Then, a description of the special nature of control systems in the manufacturing domain is given with an overview of the available theory and technologies in this area. Third, a description of methods of ensuring the health of manufacturing machines is given. Several automatic techniques are available for detecting faults in different machine components and locating the immediate faulty areas. This is known as condition monitoring and it will be described for some widely used components.

2 Manufacturing Machines

Computer Numerical Control (CNC) machines, robots, surface milling machines, lathes and compressors are among hundreds of widely used machines in manufacturing. Every one of these tools is designed with the idea of repetition in mind. On an assembly line, each component repeats a task over and over again, most of the time without a break. The cost associated with manufacturing a piece is multiplied by hundreds and thousands of pieces manufactured at a site. These pieces could be related to automobiles, refrigerators, toys, paharmaceuticals, clothing, computers, etc. Precision has found more and more demand everyday for the past decade. Due to great amounts of competition in the line of manufacturing, unlike the past, only companies with the best products survive.

Due to the repetitive nature of manufacturing, most people working in these sites become more and more valuable for the creation of their product. This is due to the fact that they gain experience and their productivity increases with their experience. Unfortunately, one cannot say the same thing about most machines on the assembly line. They start wearing out and they hardly learn anything from their past experiences. For example consider a robot which is supposed to perform a simple pick and place task or an automatic lathe which is supposed to cut through and change the cross-section of a circular rod into an ellipse. Robot dynamics is highly nonlinear due to Coriolis and centrifugal forces, nonlinear bearing forces, and so on. Also, lathe cutting dynamics possesses a very dynamic nature mostly due to chatter problems. It is very realistic to assume that any system employed for controlling these processes will not be 100% accurate. However, the most unfortunate problem is that once a piece is done, these machines make the same mistakes with the second and the thousandth and, in short, every other piece on which they operate. An even worse problem is that after processing many pieces, these systems will experience wear in their bearings, gears, cutting tools and other components which makes them produce products of much lower quality.

In an optimal manufacturing process, it is desirable for the system to learn and improve its performance with experience. It is also desirable that any components of the system which are no longer performing optimally should be found and reported to the human supervisor in an automatic manner so that they could be replaced with a new piece. The next two sections touch these issues further and they provide some ways of achieving such optimality.

3 Control in Manufacturing

A wide class of controllers in this field employ pre-defined gains and do not take into consideration the nonlinear dynamics in these machines. [1, 2] These gains are based on linear approximations of these highly nonlinear systems and are tuned to different tasks manually. These tuning jobs usually take hours and sometimes days and during this time the machines are not operable. The result is that these machines are not utilized to their full potential in terms of speed and precision. With a more sophisticated control strategy, it is possible to compensate for the complicated effects of nonlinearities which have in the past been considered as mere disturbances in most systems. Several advanced schemes have been proposed for an improved performance, which would generate control actions to compensate for the aforementioned nonlinear dynamics. These include nonlinear feedback control [3], feed-forward control [1], resolved motion control [4, 5], sliding mode control [6] and adaptive control [7, 8, 9, 10, 11]. Neural network based control systems have also been used widely in application to manufacturing control. Neural networks are nonlinear systems by nature and they have been employed mostly to learn the inverse-dynamics of controlled systems such that they could be used as nonlinear controllers. [12] With better learning algorithms being developed recently, these controllers have become more practical. [13, 14]. Although these controllers perform better, they still repeat the same errors over and over again.

Two classes of newly developed control systems which are mostly geared toward manufacturing applications are called Repetitive and Learning control systems. A repetitive controller [15, 16] is designed for processes which operate in cycles. Repetitive controllers assume that there is continuity between the last point of a repetition and the first point of the next repetition. This statement translates to the assumption that the initial conditions of the system change slightly each time it undergoes a new repetition. The second class of controllers for repetitive systems, learning controllers [17, 18], assumes that the initial conditions are reset to the same value each time a new repetitions begins.

3.1 Learning Control

The most important assumption of Learning Controllers is that the initial conditions are reset to the same value at each repetition. Physically, this means that for robot trajectory control, for example, the robot should be homed into the same position before the task is repeated. This assumption is theoretically essential in the formulation of these controllers. One important feature of these controllers is that any disturbances with frequencies of exact integer multiples of the their frequency of operation are theoretically canceled. Different approaches have been used for the formulation of learning controllers. The most original approaches are the application of ideas from linear control theory, such as Proportional-Derivative (PD) [17] and Integral [18] controllers, to the repetition domain. Some have also applied fuzzy set theorems to solving this problem. [19]

A more recent approach comes from the application of several optimization techniques to the minimization of error functions generated by new formulations of the dynamics of repetitive systems. [20, 21] These techniques in some cases use adaptive methodologies as well. Another purely adaptive technique that has been used in conjunction with learning control is a Self-tuning Regulator with learning parameter estimation [17]. This formulation uses recursive least-squares parameter estimation in the repetition domain versus the conventional adaptive systems which do so in the time domain.

Within the optimization approaches, the generalized secant technique has shown promising results. It acts as an observer which would operate in conjunction with a conventional controller. Once it has sufficient data about the performance of the system, it changes the control strategy to reduce the error to its minimal value. This controller is very robust since it has shown to operate very well with systems of highly nonlinear nature. [20, 21]. Figure 1 shows the reduction in error caused by this learning controller after a few repetitions of control of a nonlinear robot arm.

Figure 1: Squares of the errors of the trajectory of the manipulator using the Generalized Secant Learning Controller with rejections

The Learning Self-tuning Regulator has also shown both in computer simulations and in experimental setups to be highly robust and to reduce the total error of systems by considerable amounts. [2] Figure 2 shows the nonlinear response of the Piezoelectric tool of a diamond cutting lathe. As apparent from the figure, this system has high degrees of hysteresis. The Learning Self-tuning regulator was experimentally added to the apparatus which was purchased with its own manufacturer-tuned PD controller. Figure 3 shows the desired trajectory in each repetition and Figure 4 shows the error of the output of the system using the original PD controller and the response of the Learning Self-tuning Regulator at the tenth repetition. Figure 5 shows a summary of the sums of squares of errors of the trajectories for the first ten repetitions of the task. As it is apparent from figure 5, the performance of the system is monotonically improved by using the Learning Self-tuning Regulator (LSTR).

Figure 2: Steady-state response of the Piezoelectric tool to input voltage 0-400V, signifying the hysteresis in its dynamics

Figure 3: Desired output for the Piezoelectric tool in each repetition

3.2 Repetitive Control

Repetitive controllers do not make the initial condition assumptions that learning controllers do. The theory behind repetitive control is very similar to learning control with the difference that some stability issues are solved for specific problems. These solutions allow the usage of learning controllers with certain amounts of drift in the initial conditions from one repetition to the next. [15, 16] However, some researchers have shown that a continuous drift in the initial conditions indefinitely, could cause some stability problems. [22]

Figure 4: Output error of the Piezoelectric tool for the first execution of the task using PD control and the tenth repetition using the LSTR

Figure 5: Sum of squares of the output errors of the Piezoelectric tool for the first execution of the task using PD control and the ten repetitions using the LSTR

4 Condition Monitoring of Manufacturing Components

Another important need of manufacturing systems is to be able to monitor different components automatically. Lots of research has been done in this area in the past decade. The health of components such as bearings could be monitored by placing inexpensive accelerometers on the body of the machine. Dynamic models of the bearings available in the machine are mathematically built. The vibration modes of the system are then computed and stored. By looking at the histogram of the vibration picked up through the accelerometer, one could find out if a defect exists. Knowing modes of vibration of different pieces of the bearing such as inner and outer races and the balls, one could evaluate the location of defects also. This apparatus is very inexpensive and it does not require any internal components. A personal computer is powerful enough to monitor several of these bearings. [23, 24, 25]

Cutting tools such as blades of surface milling machine or a lathe could also be monitor in a very inexpensive manner. Pieces of inexpensive piezoresistive or Piezoelectric foils could be place in the mountings of these blades. The voltage across these foils could be taken to a frequency modulator and be transferred using an infrared LED to an infrared receiver. This ensures the ability of free motion of the blade. The signal could then be demodulated and analyzed. Information such as the SPECTRUM, CEPSTRUM and Kurtosis of the signal could be analyzed for good, worn and bad blades and they could be classified using any linear or nonlinear classifier. In operational modes, a computer will sample the signal from a test blade and classify it based on the training data. The computer could then alarm a human supervisor on the status of worn blades or it could automatically shut down machines with broken blades. This could avoid possible ruining of workpieces which in some cases could be very expensive. [26]

Similar type of research has been done for monitoring compressors which could seriously malfunction and blow up in cases. Automatic monitoring systems could shut these systems down before they could cause any danger. In such cases, lives might be saved using these automatic monitors. [27] Research in health prognosis of gear pairs, screws and other components has also been done.

5 Conclusion

Usage these new technologies in control and monitoring of manufacturing processes could be very practical and valuable. Using these techniques, better quality products could be manufactured in addition to the increased speeds of production. The down-time of manufacturing processes is reduced extensively using condition monitoring techniques and the expertise of human workers could be used in much more useful ways. Perfect integration of the above techniques could amount to an optimal manufacturing process.

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