Chapter 1

INTRODUCTION.

"Control system modelling is the key ingredient of future simulation systems which will be applied in the pursuit of the so-called 'Intelligent Building.'" [Clarke 1987].

"The accurate modelling of control systems is important if the simulation of the environment inside buildings is to be realistic, and essential if simulation is to play a credible role in the design and comparative assessment of control system behaviour." [Dexter 1988].

1.1 CONTROL SYSTEMS SIMULATION: THE NEED.

The need for energy efficiency, both for economic and environmental reasons, has never been greater. The International Energy Agency [IEA 1994a] predicts that the global demand for primary energy will continue to grow at an average annual rate of 2.1 per cent and that, by 2010, the world will be consuming 48% more energy than it was in 1991. World GDP is also expected to be more than 70% higher in 2010 than in 1991. It is this underlying assumption of economic growth (especially in the developing world) which, more than any other factor, is the reason for the anticipated increase in energy demand. Moreover, excessive use of fossil fuels eventually brings about global problems such as acid rain, the greenhouse effect and thermal pollution as well as a shortage of non-renewable fuels [Masters 1991].

Consideration of energy in relation to the built environment throughout the world's developed countries, reveals that 20-40% of all delivered energy can be directly associated with buildings [IEA 1994a and 1994b] (Figure 1.1). Consequently, technologies suitable for buildings are going to make a significant contribution to reducing energy consumption. More specifically, by raising the efficiency of energy utilisation through improved automatic control techniques, it is possible to reduce the consumption of buildings in the UK by 10-30%, representing a saving of around 3 Mtce[†] per year, or several hundred million pounds [EEO 1987 and DTI 1994].

Technical progress has been made during recent years in the capabilities of heating, ventilation and air conditioning (HVAC) control equipment and building energy management systems (BEMS). Developments have been made in sensor technology, information transfer, actuators and the controller itself. However, optimisation of such complex technology can be elusive and expensive, and users require information from researchers on the use of BEMS, the performance to be expected and how to assess performance and compare different BEMS equipment. Evaluation will not be relevant, though, unless it takes into account the effect of BEMS functionality upon the managed facility as a whole. Factors as varied as operating cost, comfort, equipment wear, flexibility and behaviour in case of failure, must be integrated into the evaluation.

† Millions of tonnes of coal equivalent

Hence, both with respect to environmental impact and economics, the ability to make sensible and well based decisions regarding the choice and design of building control systems is of the utmost importance. Simulation offers an means of assessing the performance of alternative building control system strategies so that a desirable comfort level can be achieved with a minimum consumption of energy and optimisation of plant systems [Hanby 1989].

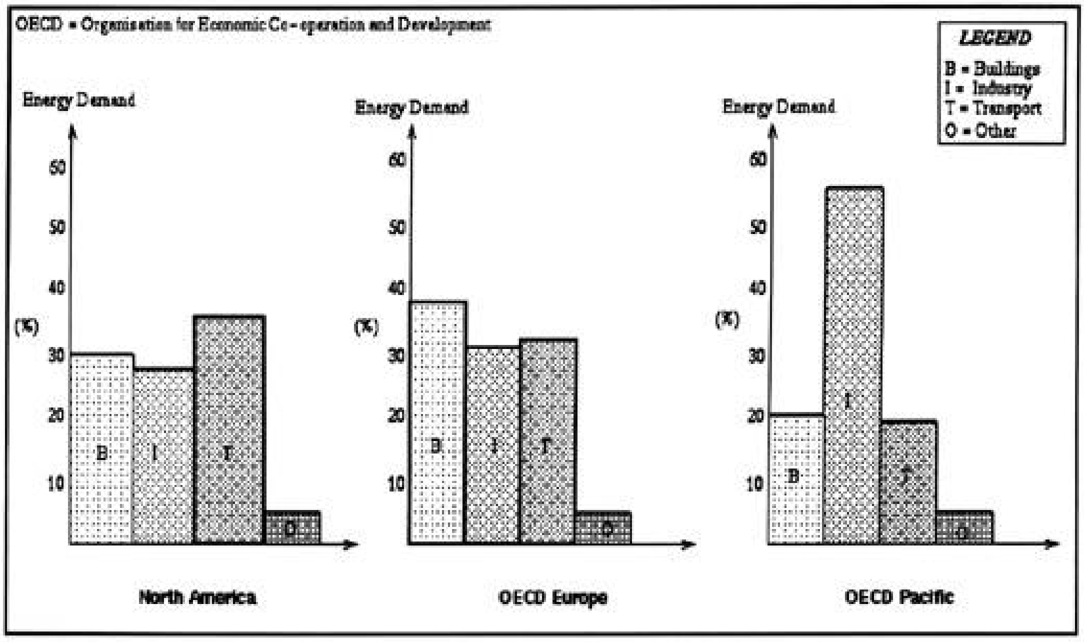

Figure 1.1 Sectoral energy demand 1993 [IEA 1994a].

1.2 SIMULATION: THE GOALS AND BENEFITS.

The terminology "simulation" may be regarded as the art of representing some aspects of the real world by numbers or symbols which may be easily manipulated to facilitate their study. Over the past 60 years, the field of simulation has undergone tremendous growth in its scope and capabilities. When once simulation was employed in the study of relatively simple systems, today hardly an industry or a discipline does not use simulation techniques extensively [Colella *et al* 1974]. The ability to handle complete systems has advanced to the point where global socio-economic systems are being investigated with such portentous variables as population, national resources and quality of life.

Tang [1985] described the goals of simulation as:-

- *predicting system performance under particular operating conditions;*
- *testing and evaluating a system or a particular subsystem;*
- *identifying those portions of the system that require further investigation;*

adding,

- *the activities of modelling, computer implementation and program utilisation may* *be regarded as the most important subprocesses within the overall process of simulation.*

Hensen [1991] described the main reasons as to why modelling and simulation have become indispensable engineering techniques (and in many cases replaced experimentation) as:-

- *economy and speed of analysis;*
- *prediction of systems which do not (at that time) exist;*
- *educational capabilities facilitate greater understanding of system processes;*

whilst also observing that,

- *simulation and experimentation are often complementary; experimentation to discover new unknown phenomena and/or for validation purposes; and simulation to understand interactions of the known components of a system.*

Thus, powerful, computer-based models have evolved over recent decades to assess cost, performance and visual impact issues in design; from life-cycle cost estimation at the design stage, through realistic visualisations of the design, to the comprehensive evaluations of building energy and environmental performance.

1.3 SIMULATION AND THE INTELLIGENT BUILDING.

The terminology "Intelligent Building" is formally defined by the Intelligent Buildings Institute (IBI) in Washington DC as:

'... one which integrates various systems (such as lighting, HVAC, voice and data communications and other building functions), to effectively manage resources in a coordinated mode to maximise occupant performance, operating cost-savings and flexibility. Various levels of intelligence are provided through interactive controls and communications devices driven by either central or distributed micro-chip intelligence and employing sensing devices and interactive distribution media.' [McLean 1991].

As many commercial and industrial buildings today contain one or more of these various systems, they can be considered to have some degree of intelligence. The intelligent building can therefore exist on a broad spectrum of capabilities. Thus, it is not a comparison between 'intelligent' buildings on the one hand and 'moronic' buildings on the other, but rather that all buildings exist on a continuum of capabilities ranging from the least to the most intelligent.

Although modern BEMS *can* be effective and offer considerable improvement in controlling buildings, hyperbolic claims of the capabilities of intelligent buildings based on such technology are often made. BEMS effectiveness is due principally to their data processing capabilities, not to characteristics of intelligence [Haves, 1992]. The building cannot be termed "intelligent" because the control systems are based upon algorithms which do not consider the implications of their actions on the whole building. Energy management is the lowest form of intelligence which can be given to a building and *automated building control* would, perhaps, be a more accurate definition.

Recent experience [Hartman 1988] has shown that there are impediments to increased performance of BEMS-based buildings and to them becoming truly intelligent. Traditionally, building control is based on steady state strategies. However, due to the rapidly changing outdoor and indoor environmental conditions, steady state control is neither effective nor efficient in the utilisation of energy for comfort conditioning. With the advent of direct digital control (DDC) techniques, most present day BEMS application software combines steady state with dynamic control strategies. Unfortunately these control strategies frequently work counter to one another, resulting in a conglomeration of routines that are too complicated to understand and monitor effectively. This provides neither efficiency nor comfort and succeeds only in 'optimising the irrelevant' [Bordass 1993].

Optimisation of energy conservation and comfort levels can best be achieved if the building's thermal performance, HVAC system sizing and control strategy are considered together within the building design process. However, buildings and their environmental control systems are complex (multi-dimensional and highly interactive) making this optimisation task non-trivial [Clarke 1985]. The design and layout of practical control systems varies dramatically owing to the diversity of design conditions which, in turn, are due to variations in climatic conditions, the type of space occupied, occupant behaviour and the relationship between building and plant. Deciding on the best control strategy or the optimum arrangement of design features is thus an extremely complex task and one which does not lend itself to simple paradigms and rules of thumb.

In order to *fully* exploit and optimise BEMS technology it is vital, as argued by Hensen [1991], that tools exist to allow the simulation and assessment of building control systems and that these tools be based on a *fully integrated simulation approach* in which the dynamic thermal interaction between building, plant and control system (under the influence of occupant behaviour and outdoor climate) is assessed. It is desirable that these simulation programs accommodate a large number of accurate, robust models of control system entities housed within a structure which allows flexibility of application. The integrity of the real world must be conserved within the computational medium because, if disregarded, will compromise simulation predictions and the related design decisions.

In addition to optimising BEMS control strategy at the design stage, simulation also has a crucial role in the *on-line optimisation* of future generation intelligent buildings. McLean [1991] *redefined* the intelligent building as comprising three elements which, when integrated together, make the building intelligent.

1. The controls of all the systems in a building, whilst retaining their own integral intelligence, are linked integrally to all others in the system.

2. The building has the ability to respond to any changes in the interior and/or external environment, necessitating the use of new building technologies.

3. The most important feature of a truly intelligent building will be the integration of 1 and 2 above by means of a dynamic simulation tool which can supervise the control system whilst coordinating the use of the building's 'dynamic' features to ensure optimum performance in terms of occupant comfort and energy consumption (Figure 1.2). The simulation program simulates the building in real time, being continually updated by sensor information. If some control action is requested, the control supervisor in rapid iterative mode predicts the consequences of various control strategies and selects the most efficient.

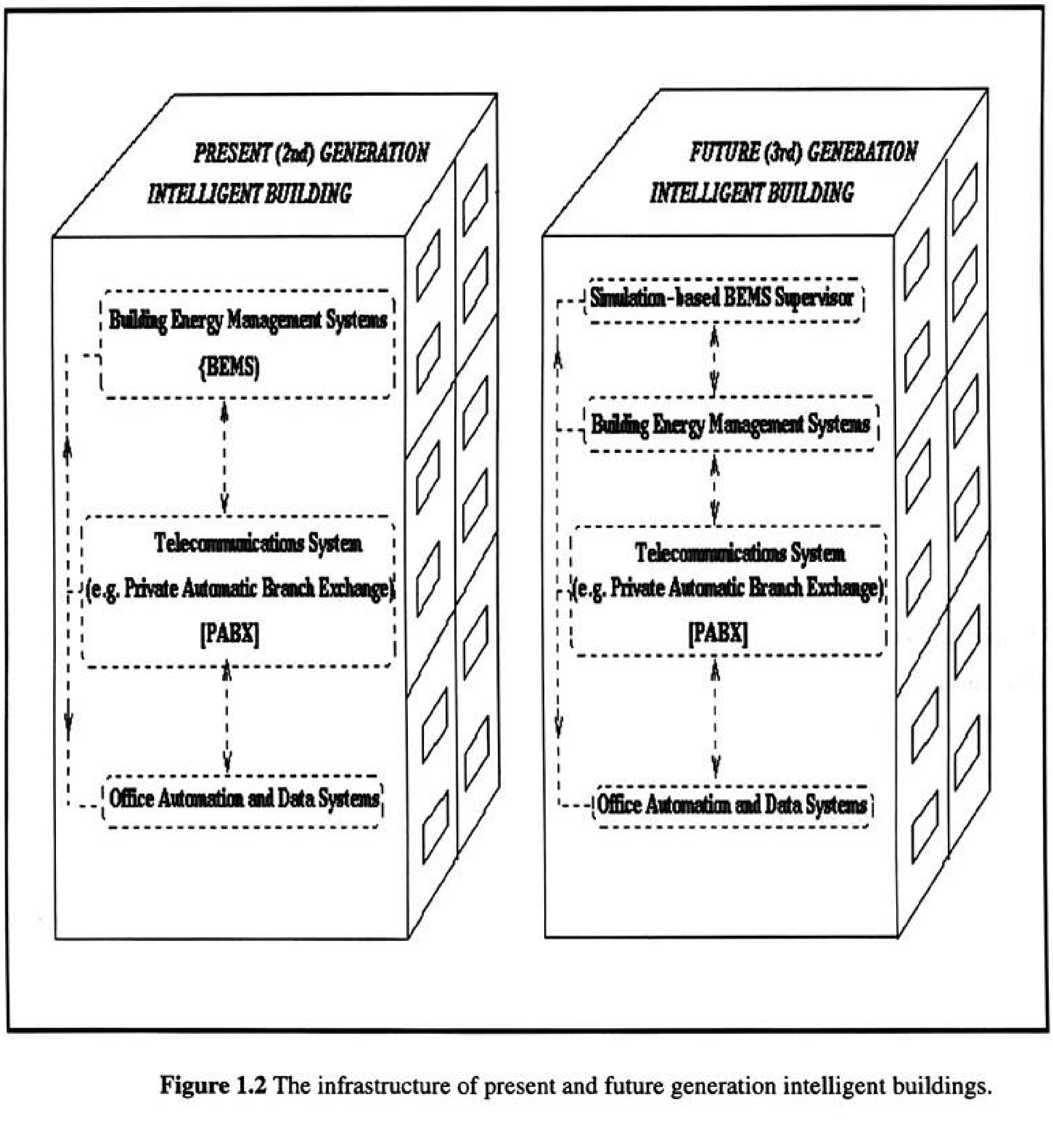

Figure 1.2 The infrastructure of present and future generation intelligent buildings.

1.4 OBJECTIVES AND OUTLINE OF THE PRESENT WORK.

1.4.1 Project objectives.

It was against the background outlined in the previous sections that the present research project commenced in 1992. The following visions of future simulation programs were observed:

- the diversity of real, practical control systems requires a comprehensive library of accurate, robust models of system entities;
- advances in computer technology will eventually allow a radical new approach to building controller design in which simulation will play an integral part. On-line, simulation tools - based on predictive-iterative techniques rather than empirical techniques - will allow control system optimisation and 'orchestration';
- in order to fully utilise an energy simulation model in such applications, a number of existing barriers and deficiencies in contemporary modelling techniques must be overcome so that a practical application to the simulation of combined building and HVAC systems can be attained and the intelligent building can become a reality.

Consequently, this research work has encompassed the following specific objectives:

- to identify and classify the control system entities extant in building control systems;
- to employ the resulting taxonomy of control system entities in the form of a general purpose control system simulation environment in order to improve the applicability and accuracy of the modelling, simulation and appraisal process;
- to implement, validate and verify the above when incorporated within the ESP-r program.

1.4.2 Thesis outline.

Chapter 2 of this thesis contains a review of the commonly occurring building control systems and discusses the theory underlying various approaches to system synthesis and design. Chapter 3 describes the ESP-r simulation environment which was employed as a test bed for assessing control modelling schema. Chapters 4, 5 and 6 identify the essential features and describes the structure and development of a control system taxonomy for systems simulation in terms of spatial, temporal and logical control system elements, respectively. Chapter 7 addresses the issue of validation of building control system modelling programs. Chapter 8 discusses applicability of the developed control modelling schema. Finally, Chapter 9 contains the conclusions drawn from the present project and indicates possible directions for further work.

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BUILDING ENVIRONMENTAL CONTROL SYSTEMS

The need for environmental control system simulation programs has been established in Chapter 1. The present Chapter details the main types of automatic building control system and reviews the modelling methods commonly adopted for their appraisal. This review highlights some of the disadvantages and shortcomings inherent in these methods, indicating that alternative approaches are required. It is concluded that such an approach should focus on expanding applicability of the system within multi-disciplinary building design environments.

2.1 INTRODUCTION TO ENVIRONMENTAL CONTROL SYSTEMS.

2.1.1 The need.

Environmental control is the control of temperature, moisture content, air quality, air circulation and lighting levels as required by occupants, processes, or equipment in the building space. Properly applied automatic controls ensure that correctly designed heating, ventilating and air conditioning (HVAC) and lighting installations will maintain a comfortable environment and perform economically under a wide range of indoor and outdoor conditions.

Limit controls ensure safe operation of HVAC equipment and prevent injury to building occupants and damage to the system. In the event of a fire, controlled air distribution can provide smoke-free evacuation passages and smoke detection in ducts can close dampers to prevent the spread of smoke and toxic gases.

It was not until the start of the twentieth century that automatic control was introduced. Since then, developments have been rapid with detailed analytical design methods evolving to meet the needs of increasing complexity in building structures, high construction costs and energy shortages.

2.1.2 Types of system.

2.1.2.1 Control system elements.

The premise of this thesis is that *all* building control systems - regardless of their exact make-up, function and operational characteristics - comprise the following elements:

- logical (e.g. controller intent);
- spatial (e.g. sensor location);
- temporal (e.g. time-and-event programs).

It is assumed that all systems can be assessed and categorised in terms of these three elements as depicted in Figure 2.1, thereby supporting the notion of a taxonomy of control system entities - a theme expanded upon in later chapters.

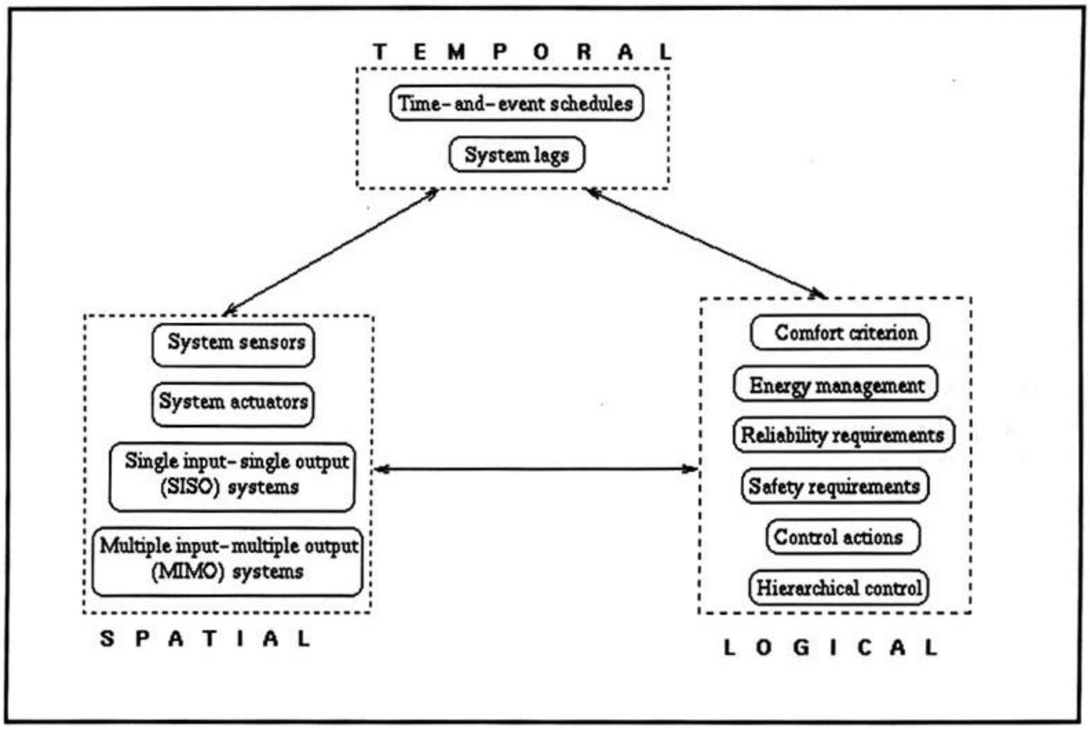

Figure 2.1 Building control systems: the main elements.

2.1.2.2 Automatic feedback control.

The most common type of building control system is that based on the principle of automatic feedback control. Such systems comprise one or more *control loops.* Basically, a control loop comprises three components: a sensor, a controller and an actuator (Figure 2.2). These elements serve the following purposes:

- *sensor:* to monitor the output from a given process;
- *controller:* to determine what action to take to maintain desired condition;
- *actuator:* the means by which corrective action may be initiated to bring about the desired condition.

In feedback control, the controller is error driven, i.e. the controller receives a continuous measurement of the difference between required and actual behaviour, and its output is some function of this error. The feedback principle works well provided that the available control actions do not encounter constraints that limit their magnitudes. For example, in the case of temperature control there will always be some limit on fuel flow rate.

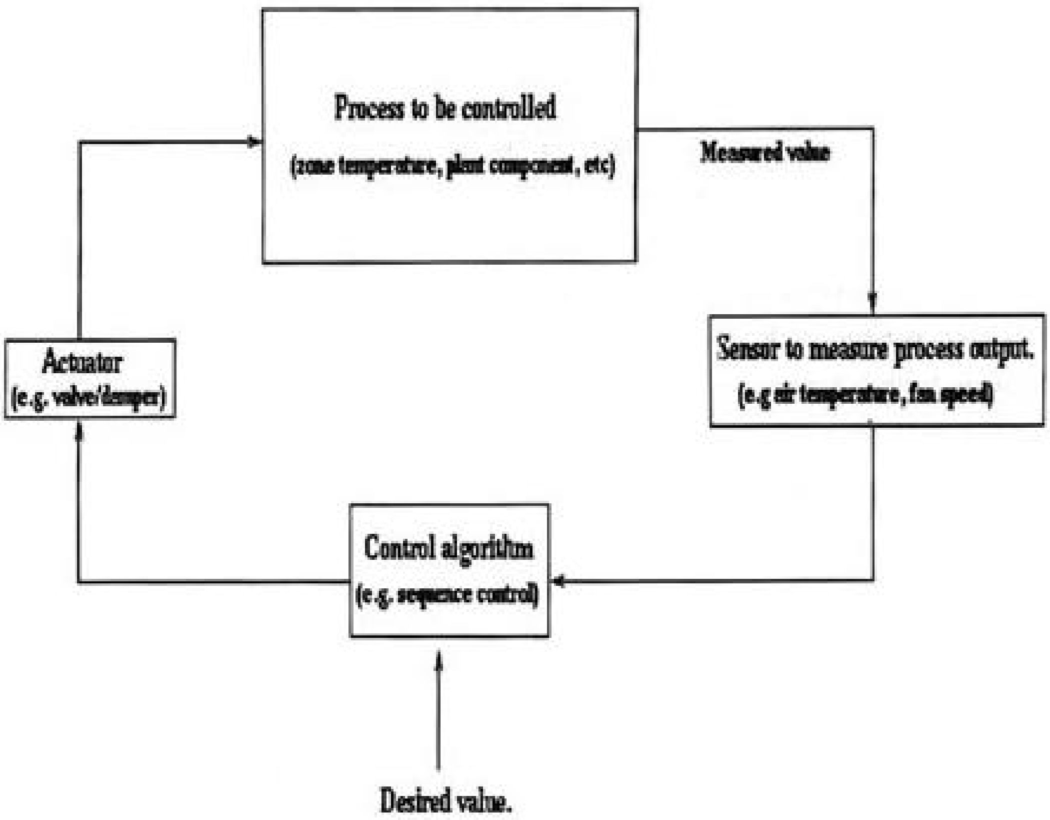

Figure 2.2 Block diagram of a control loop.

2.1.2.3 Alternatives to feedback control.

(1) *Preprogrammed control:* Here a recipe, strategy or sequence of control instructions is calculated in advance and is implemented with no account taken of system output signals.

(2) *Feedforward control:* Where all disturbances are assumed to be measured independently (not as a measure of received disturbances) and assumes control actions are accurately calculable with the aim of eliminating error before it can occur.

(3) *Predictive control:* Future conditions are predicted (using extrapolation algorithms or past records) and are used to allow the best possible positioning of the control system. It is often used in large delay systems where it can take a long time to bring in equipment; e.g, electrical generation systems.

2.1.3 Building energy management systems (BEMS).

In the nineteen fifties, it became apparent that there was a need to centralise the flow of information from increasingly large and complex technical systems in buildings. The first generation of BEMS were characterised by centralisation of information and remote control of technical installations (Figure 2.3(a)). In the nineteen sixties, with the trend of centralisation of company services, a flourishing economy and large-scale building programs in and around the cities, facilities such as air-conditioning, document transport systems, etc. were designed into new buildings. This increased the complexity of the control systems and led to selective data presentation systems which used the switching methods employed by telephone switchboards. The digital signals were no longer wired directly to the control panel but were collected in data gathering panels (DGP's) connected to the central panel. This resulted in reduced cabling requirements, whilst allowing flexible control signalling and selection strategies (Figure 2.3(b)). At the beginning of the nineteen seventies, developments in electronics led to digital switching techniques, facilitating digitalised analogue signals. Subsequently, the central control panel was replaced by a computer system. These systems were characterised by considerably increased processing speed and an increased number of data points.

The energy crisis of 1973 and the urgent need to reduce energy consumption led to a rapid increase in the installation of energy saving equipment controlled using so-called "energy management schemes" [Scheepers 1991]. These include night set-back, optimum start and event-sequenced strategies. Systems which previously used dedicated computer systems were altered so that standard mini-computers could be used as the central system (Figure 2.4(a)).

At this point, microprocessors were introduced into BEMS allowing intelligent substations to carry out some of the work previously done by the central station. As systems grew larger, they incorporated *distributed intelligence* where each zone/floor/building could have its own micro-computer. Since the early nineteen eighties, there has been many developments involving BEMS. Data processing is more widely distributed, resulting in increasingly distributed and autonomous substations. In addition, more functions, such as DDC (direct digital control) and PLC (programmable logic controllers) were added to the substations. Thus, the control functions previously carried out by means of analogue hardware, were now usually included in the substations.

The trend towards further distribution of tasks is not limited to substations in BEMS. The central station is also subject to the same evolution [Honeywell 1989]. The arrival of the personal computer and communications network systems have resulted in an increase in networked, less hierarchical BEMS. Such systems do not require a central computer as each operator station is itself a micro-computer. Combined hierarchical and network systems with the BEMS, included in an organisation's total buildings facilities management system, are also commonplace (Figure 2.4(b)).

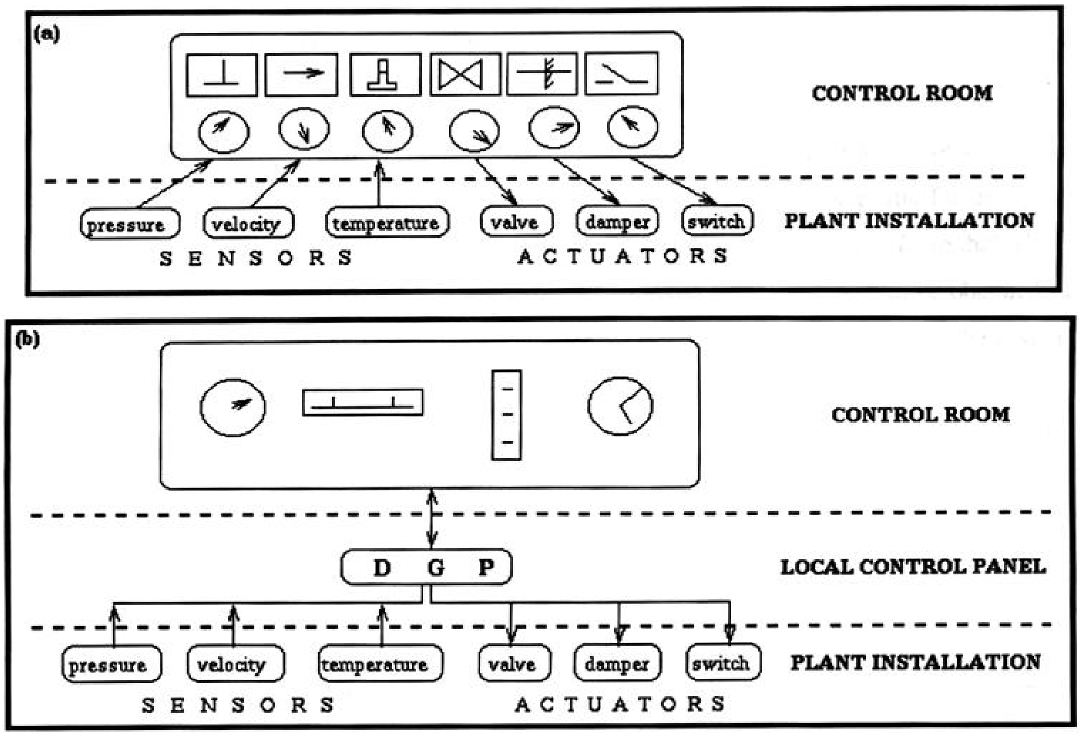

Figure 2.3 (a) Central control panel: **(b)** data gathering panels

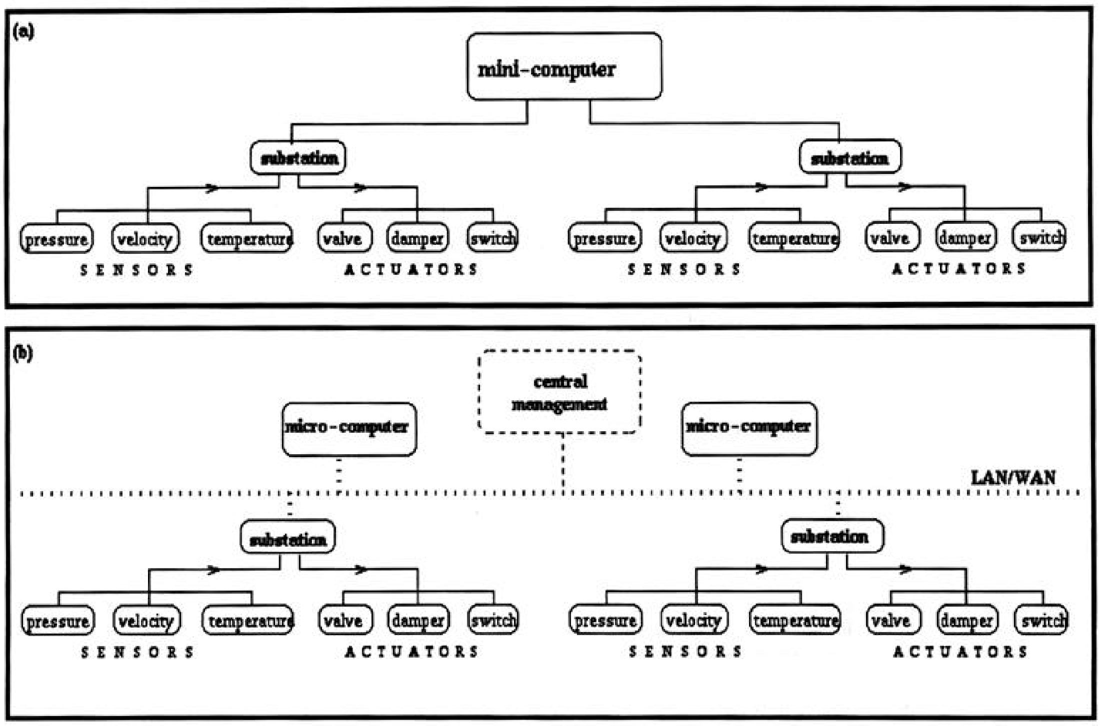

Figure 2.4 (a) Central computer system: **(b)** peer-to-peer network system

2.2 REVIEW OF CONTROL SYSTEMS MODELLING METHODS.

2.2.1 Classical linear feedback control theory.

2.2.1.1 Introduction.

Traditionally the approach to control system modelling is to establish a model of the process and then to combine this with a controller model to give some *overall* characteristic for the system (Figure 2.5). In feedback controller design the task is to establish a controller model D, so that when it is connected to process model G, a suitable overall characteristic for the system will be obtained. In this way, the controller artificially enhances the process characteristics in ways chosen by the designer in order to achieve some desired system performance. The following relationships are obtained:

$$\text{system output} = Gu, \tag{2.1}$$

$$\text{controller input} = e = v\text{-}y, \tag{2.2}$$

$$\text{controller output} = De. \tag{2.3}$$

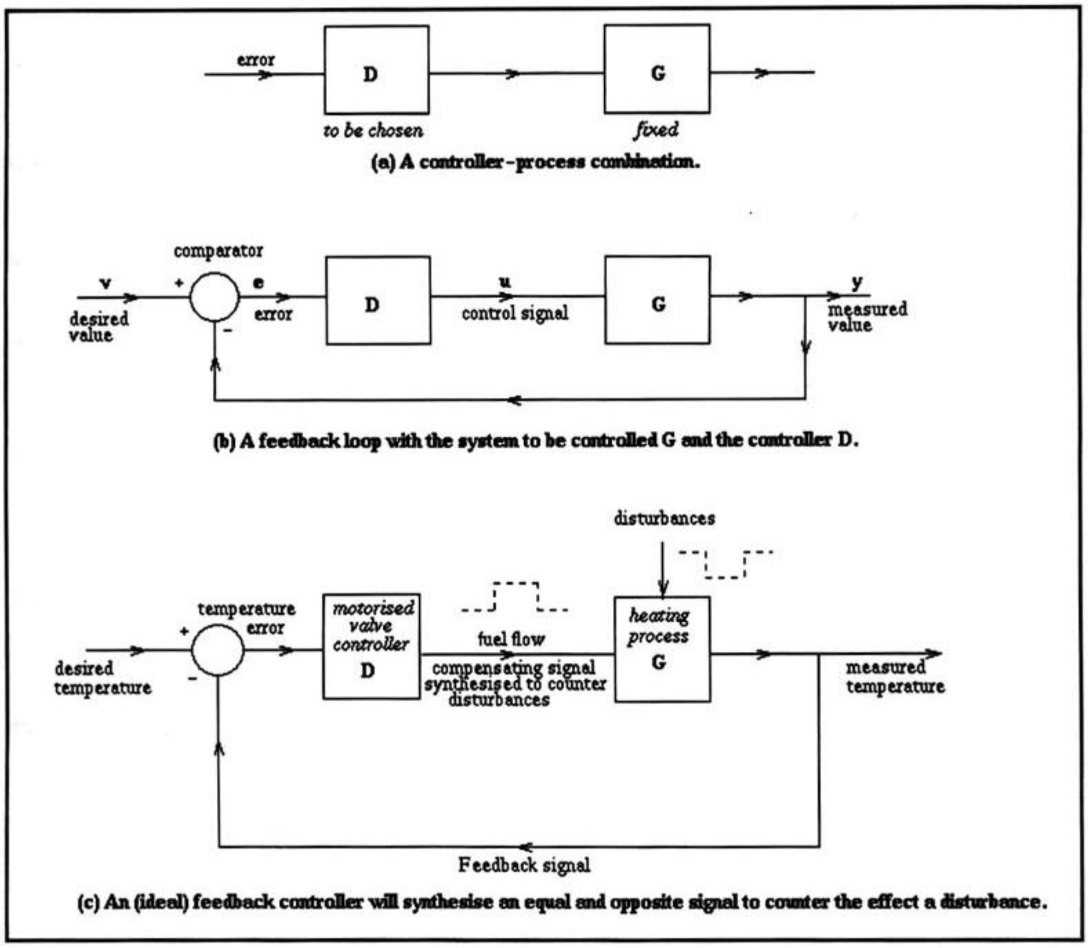

Figure 2.5 Feedback controller modelling.

If it is possible to synthesise the best possible actions continuously by some algorithm, then there is fully *automatic feedback control.* The success of the scheme depends on the disturbances being measurable and on the existence of an accurate quantitative understanding of the system to be controlled.

In order to determine whether or not the control action taken at the input will be successful, and to what extent it should be taken, control engineers must have some mathematical means of modelling the process under consideration. Typically, this is done by writing energy-balance differential equations for the components and applying the Laplace transform which converts the differential equation into an algebraic form so that a *transfer function* can be extracted [Liptak 1995]. Block diagram algebra is often deployed to help determine the overall transfer function for two or more coupled subsystems [Westphal 1995].

The transfer function of a dynamic system with input $u(t)$ and output $y(t)$ is defined to be the Laplace transform of $y(t)$ under the condition that $u(t)$ is a unit impulse applied at time t = 0; or more generally applicable in practice,

$$G(s) = y(s)/u(s) \tag{2.4}$$

where the complex variable $s = \sigma + j\omega$.

If $G(s)$ can be expressed as $G(s) = P(s)/Q(s)$ then the zeros are the roots of the equation $P(s) = 0$ while the poles are the roots of the equation $Q(s) = 0$. $Q(s)$ governs the nature of the system's response to initial conditions and hence also its stability; conversely, $P(s)$ affects the manner in which the system responds to external inputs.

2.2.1.2 Controller algorithm design.

There are two main approaches to controller algorithm design. The first approach is synthesis of D(s) in order to achieve a specified closed loop transfer function $H(s)$. The second approach is to use a gain plus compensator scheme.

It is assumed that there exists a desired hypothetical process with overall performance $H(s)$. From equations (2.1 to 2.4):

$$y(s) = G(s)D(s)[v(s) - y(s)] \tag{2.5}$$

and

$$y(s)/v(s) = \frac{G(s)D(s)}{1 + G(s)D(s)}. \tag{2.6}$$

Thus

$$D(s) = \frac{H(s)}{G(s)(1 - H(s))} \tag{2.7}$$

will set $y(s)/v(s)$ equal to $H(s)$, i.e. the specification of the overall system is converted into a closed loop transfer function $H(s)$ with $D(s)$ selected to make the synthesised configuration behave like the chosen hypothetical process $H(s)$.

However, as Leigh [1992] argues, not every $D(s)$ is synthesisable in practice, and even then care must be taken in defining $H(s)$ so as to avoid instability and over-sensitivity. There are usually difficulties encountered when specifying $H(s)$, since limits on attainable performance are set by the constraints in the process (e.g. system lags and plant capacity limits); constraints not all modelled by the (linear) operator $G(s)$, as elaborated later in this chapter.

An alternative strategy is to design a controller with element $D(s)$ having a pole-zero diagram of Figure 2.6 which will cancel the poles of $G(s)$ and produce the required pole positions. This technique is called *pole-placement*, and is elaborated by Towill [1970].

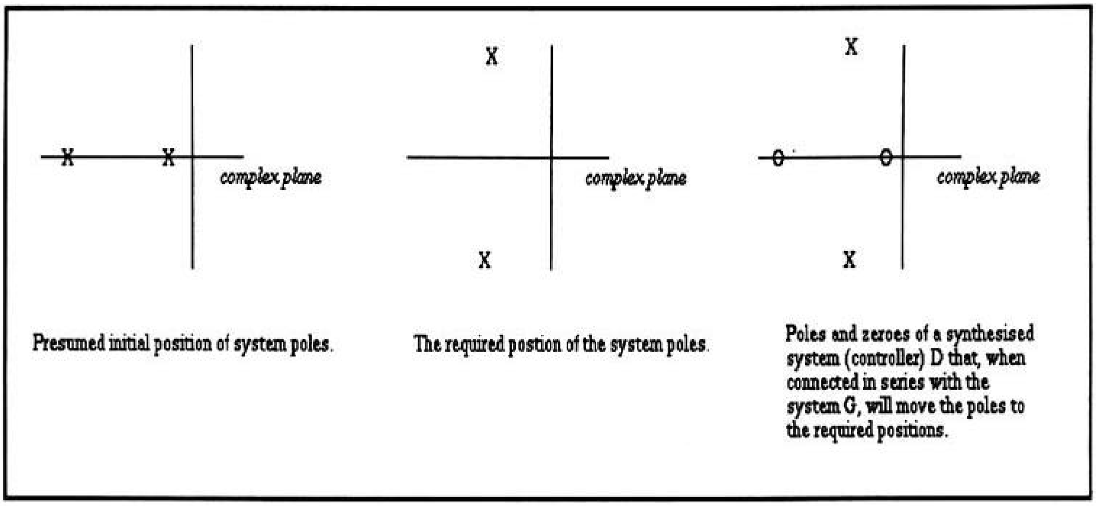

Figure 2.6 Pole-placement controller design technique.

2.2.1.3 Stability and performance appraisal.

The feedback control loop provides a means of close control; however, the existence of the loop brings the possibility of the potentially destructive phenomenon of instability. Usually performance is quoted in terms of the highest frequency that the control system can follow, when required to do so. All control loops tend to become unstable as higher and higher performance is sought. A system is stable so long as the output quantity can be controlled by the reference signal, i.e. a change in the reference signal results in a controlled change in the system output. Most systems become unstable as gains are increased in order to achieve high performance.

One commonly adopted approach to the determination of system stability is the Routh-Hurwitz procedure in which the poles are assessed to determine whether or not any lie in the right half plane thus indicating instability [Healey 1967]. It is possible, however, for a system equation to be on the borderline between stability and instability, a fact which does not emerge from the Routh-Hurwitz analysis. To have a method which indicates how near a system is to instability and which permits some assessment of the performance of a stable system, requires the observation of the movement of the characteristic equation roots as some parameter such as controller gain is varied - this is possible using the *Root Locus* method.

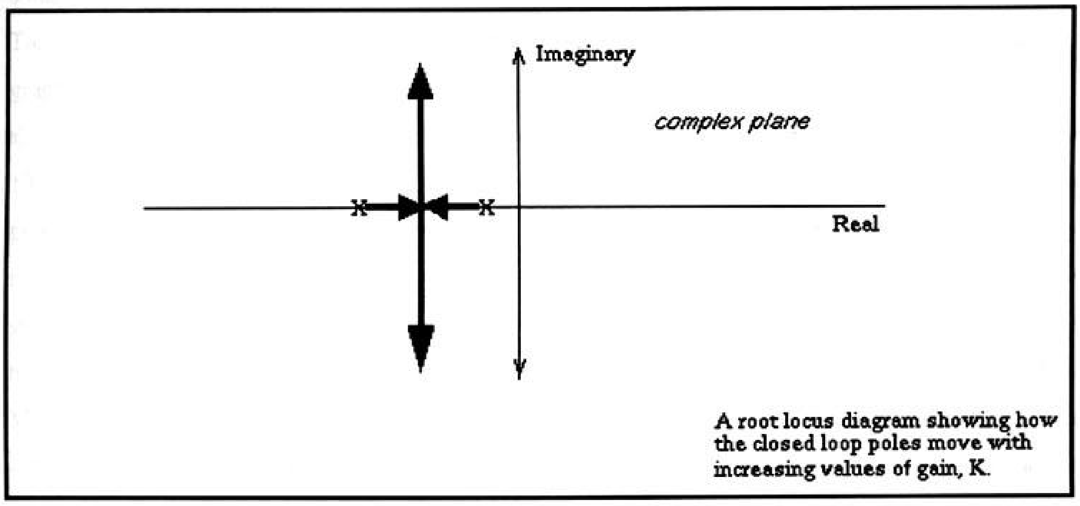

Figure 2.7 Root Locus plot.

For a polynomial equation with real coefficients, the roots will always be either real or occur in complex conjugate pairs. The Root Locus plot is the plot in the complex plane of the paths followed (loci) by the roots as a parameter of the equation varies, usually over the range zero to positive infinity (Figure 2.7). The parameter varied is usually the controller gain, *K*. With the aid of the Root Locus diagram, the value of *K* can be selected so that the closed loop poles are in desirable positions in the complex plane. In general, for a negative feedback control system with an overall forward-path transfer function *G(s)* and an overall feedback path function *H(s)*, the characteristic equation is:

$$G(s).\,H(s) + 1 = 0 \tag{2.8}$$

hence

$$G(s).\,H(s) = -1 \tag{2.9}$$

giving the two relations:-

Magnitude condition

$$|G(s).\,H(s)| = 1 \tag{2.10}$$

and *Angle condition*

$$arg[G(S).\,H(s)] = +/-\ 180^o \tag{2.11}$$

if *G(s)* is regarded as a complex function whose value is determined by the value of the complex variable, *s*.

From these two conditions a number of simple construction rules can be derived for sketching the loci of roots of a given equation [Westphal 1995].

As an alternative to the Routh-Hurwitz and Root Locus methods of analysis, it is possible to predict a control system's stability behaviour by examining its *open-loop sinusoidal frequency response* in terms of the relationship between the gain, phase shift and frequency. A number of sinusoidal changes are applied to the input with a constant amplitude but with an increasing frequency. The dynamic process gain and the phase shift are measured for each frequency and expressed in a graph (assuming all transient effects have died away - i.e. steady state response). Three ways of showing this relationship graphically are: the Nyquist plot, the Bode plot and the Nichols plot [Morris 1983] (Figure 2.8). The Nyquist Criterion is then used to draw conclusions about the significance of a given type of frequency response. The Nyquist Criterion states: if the magnitude of the frequency response of the open-loop transfer function is greater than unity when the phase lag is 180^o then the system is unstable. The Nyquist Criterion shares with the Root Locus method the ability to indicate how near the system is to being unstable. This can be quantified by the use of Phase Margin and Gain Margin. These are defined as follows for a stable system: *Phase Margin* is the difference between -180^o and the open-loop transfer function phase lag when the open-loop transfer function magnitude is unity; *Gain Margin* is the number of decibels to be added to the log-magnitude when the phase is -180^o to make the log-magnitude equal to zero. As a rough guide for building systems, a 5 dB Gain Margin *and* 40^o Phase Margin will generally be acceptable [Letherman 1981].

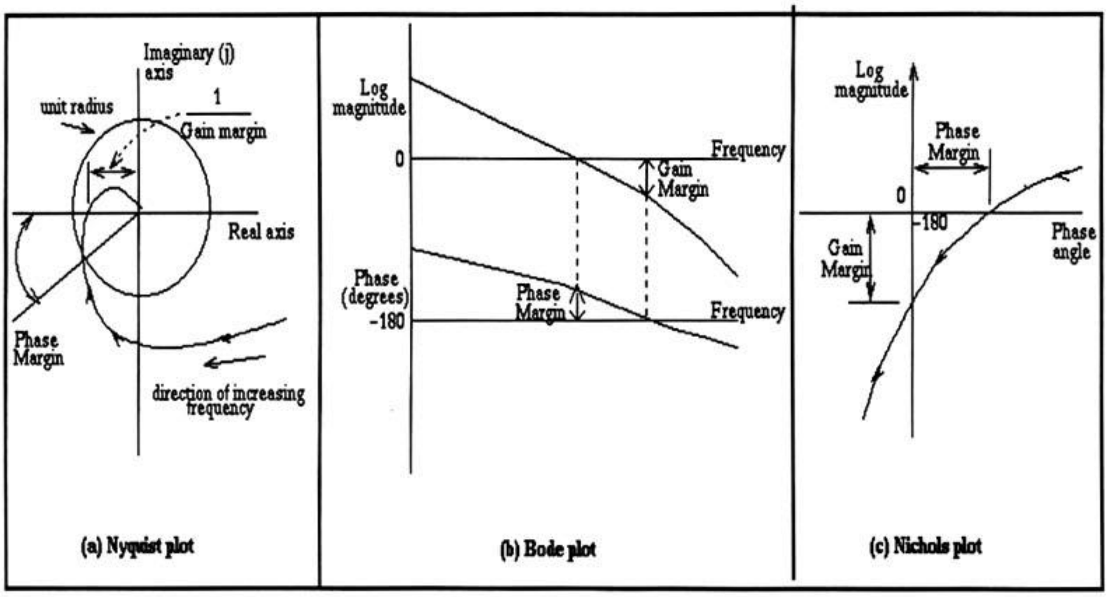

Figure 2.8 Phase and Gain Margins in Nyquist, Bode and Nichols plots.

Control design in the frequency domain typically consists of choosing a suitable compensator *D(s)*, and a gain *K* to obtain a closed loop system having high bandwidth. *D(s)* (containing frequency sensitive elements) is usually designed so that *G(s)* and *D(s)* taken together have a phase characteristic that reaches -180° at a much higher frequency than was the case for *G(s)* alone. The gain *K* (which affects only amplitude - it has no effect on the phase shift) is then chosen so that the necessary stability margin is obtained whilst allowing for variations in the real system. In this way, *D(s)* is being used to modify the phase characteristics of *G(s)* in such a way that a high gain *K* can be used without incurring stability problems.

The Nyquist, Bode and Nichols plots clearly show at which frequencies actions taken can still be effective. If the frequency of the input value is so great that the process gain becomes small and the phases shift approaches 180°, the process cannot be controlled by taking corrective actions at the input. Thus other courses of action will have to be taken in order to stabilise the output. These may be control methods such as feed-forward control, but usually it will be necessary to change the process itself in order to obtain a different dynamic process gain. Thus, by using these plots, it can be determined at which frequency of changes at the input the process will be self-stabilising, can be stabilised, or cannot be stabilised.

2.2.2 Modern control theory.

2.2.2.1 Optimal control.

So far, the techniques described have used simple optimisation techniques, such as obtaining maximum phase margin from a system by adjusting compensating network parameters. It is, however, possible to consider the introduction of a performance index directly involving system error, (i.e. the difference between system input and system output) which is often what is really required to be kept small and perhaps even be minimised in a mathematical sense. The concept of a performance index, or *cost function,* as the integral of some function of the system error, is then used to determine either system parameters or control inputs, or both, to minimise this error. Even the simplest optimal control design of a control system for some (building) process Σ requires a scalar-valued cost function $J(x,u,..)$ that realistically quantifies all the building process factors of importance. (For example, in a building heating process, J might map variables such as deviation from a set point, a comfort index and energy loss into a single number which, when minimised, ensures optimal control profitability of the process). Given the equations (model) of the process, Σ, and the cost function, J, optimal control theory then attempts to establish a control policy $u(k)$, $k = 0,.....n$ which will achieve given control objectives and simultaneously minimise (and, in some cases, maximise) the cost function J.

The classical mathematical tool for solution of optimisation problems is the *calculus of variations.* However, this method cannot deal with discontinuities and thus cannot be applied in many practical control situations [Sagan 1969]. *Pontryagin's Maximum Principle* or *Bellman's dynamic programming method* then need to be used [Bryson and Ho 1975]. These methods all yield open-loop optimisation strategies since they all specify $u_{optimal}$ for all t in the time interval of interest. Since, pragmatically, it is more usual to implement closed-loop optimisation, these strategies need to be converted to a closed loop algorithm. Provided that a quadratic cost function (i.e. with J restricted to be simply a weighted sum of squares of its arguments) is adopted and the process equations are linear, the conversion is always possible by solution of the *Riccati equation*. Since the performance of the design is judged with respect to J, nothing else matters in the optimisation and so it is important to formulate the objectives correctly. In practice the choice of J is always an extremely difficult one - a compromise always has to be reached between relevance and mathematical tractability in the search for a well-specified cost function. Also, implementation often requires massive real-time computation.

2.2.2.2 Adaptive, learning and self-organising control systems.

Often, control systems must be designed to operate in an environment such that the dynamics of the system or the inputs to the system are either incompletely known and/or change characteristics in an unpredictable way. Thus the design of a control system which will perform well in the face of many uncertainties is an attractive possibility. The primary objective of *adaptive, learning* or *self organising control* is to reduce uncertainties concerning knowledge of the environment and systems dynamics, and to alter controller performance in an on-line or real time fashion in order to continually ensure satisfactory system operation and further seek better performance.

Most adaptive systems can be classified as either *performance adaptive,* in which observations of the input and output of the controller are made and the parameters of the controller adjusted by composing the input-output performance of the system with a reference standard; or *parameter adaptive,* in which control system parameters are identified by observing control system input-output relations, and control system compensators modified in an on-line fashion in accordance with these changes (Figure 2.9). These topics are reviewed by Sage [1978].

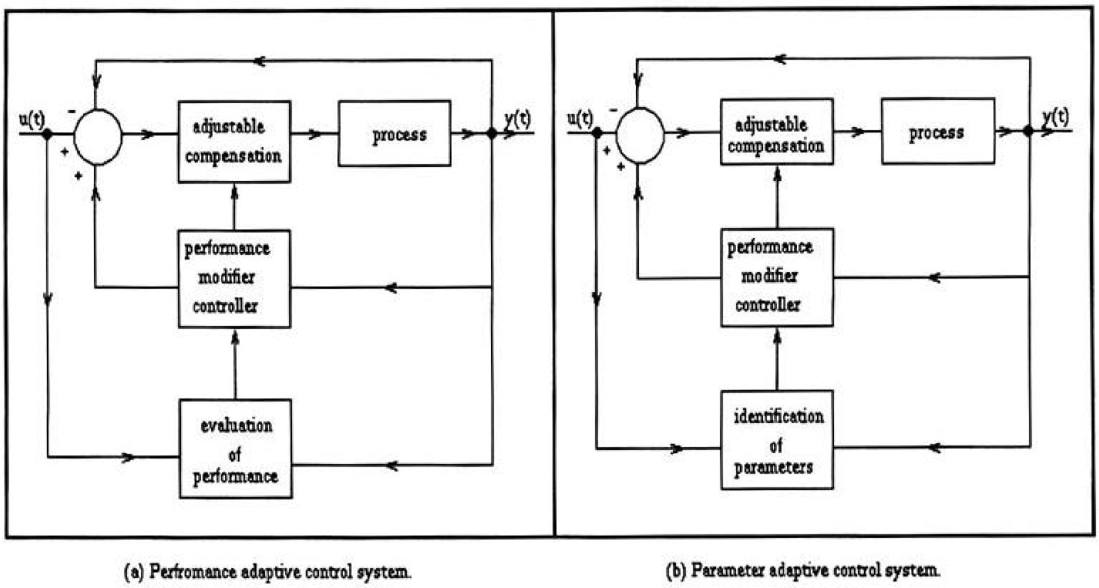

Figure 2.9 Approaches to adaptive control.

2.2.2.3 Non-linear systems.

The mathematical description of a dynamic system can be embodied in a differential equation such as:

$$a\ddot{\theta}(t) + b\dot{\theta}(t) + c\theta(t) = f(t) \tag{2.12}$$

and such a system would be described as linear if the coefficients a, b and c are not affected by the values of the dependent variable θ(t) or of the independent variable f(t). Most of the control systems design and analysis tools operate only on linear models: matrix and vector methods, transform methods, block diagram algebra, frequency response methods, poles and zeros and root loci are inapplicable [Leigh 1992]. Thus efforts are usually made to replace a non-linear system with a corresponding linear system model.

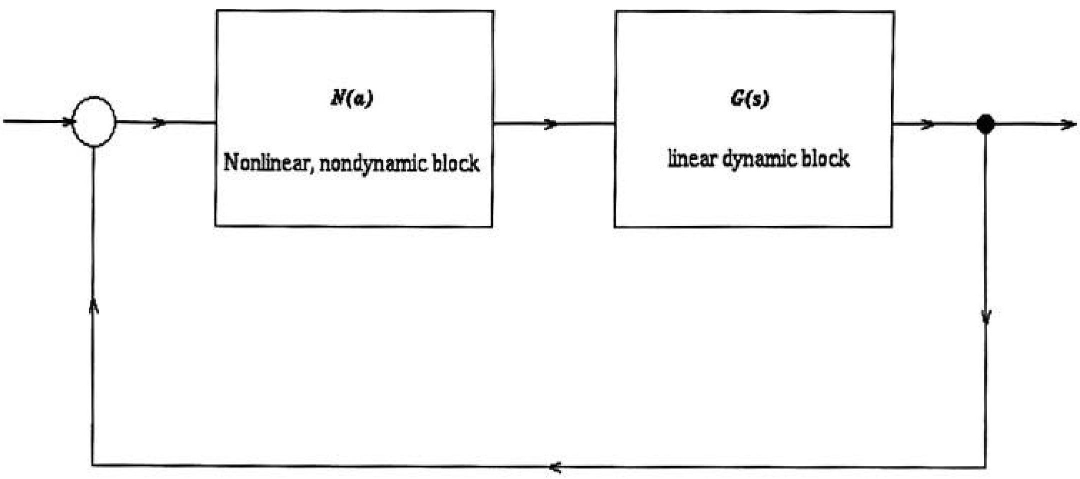

Figure 2.10 Control loop structure for Describing Function method.

This can be considered as an attempt to extend the concept of the linear transfer function to use in non-linear systems. For a linear transfer function with a sinusoidal input of unit amplitude $\sin(\omega t)$ the output will be a sine wave $A(\omega)\sin(\omega t + \phi)$. The transfer function introduces an amplification $A(\omega)$ and phase shift ϕ(t) both of which may in general be dependent on frequency ω but not on the amplitude. The difficulty in extending this concept to the non-linear systems is that the output waveform for such systems are not in general sinusoidal, and in certain cases may not be of the same frequency as the input wave.

There is an extensive literature on the topic of the control of non-linear systems [Letherman 1981]. Methods commonly adopted in the analysis of such systems include: the Step Response method, the Describing Function method and Tsypkin's method. The Describing Function method, for example, is a linearisation method in which sinusoidal analysis proceeds by the expedient of neglecting harmonics generated by non-linearities. Thus the approximation consists in working only with the fundamental of any waveform generated. The method assumes a system in which the linear and non-linear components can be separated, as shown in Figure 2.10 where $G(s)$ is the Laplace transfer function of the linear part of the system, and N represents the non-linear part. For example, N could be the input/output characteristic of the relay or thermostat. The method consists of deriving two loci in the complex plane, one for the non-linear element $N(a)$ and one for the dynamic element $G(s)$. The first locus is a function of amplitude only and the second is a function of frequency only. The describing function method then indicates whether stable oscillations will occur at the intersection of loci.

2.2.2.4 State space approach.

The classical transfer function based techniques described earlier can only permit the design and analysis of the complete input/output description. The advantages of the state space approach over the classical methods are that greater insight into the internal behaviour of the system is possible, as well as the ability to analyse individual sections of the overall system.

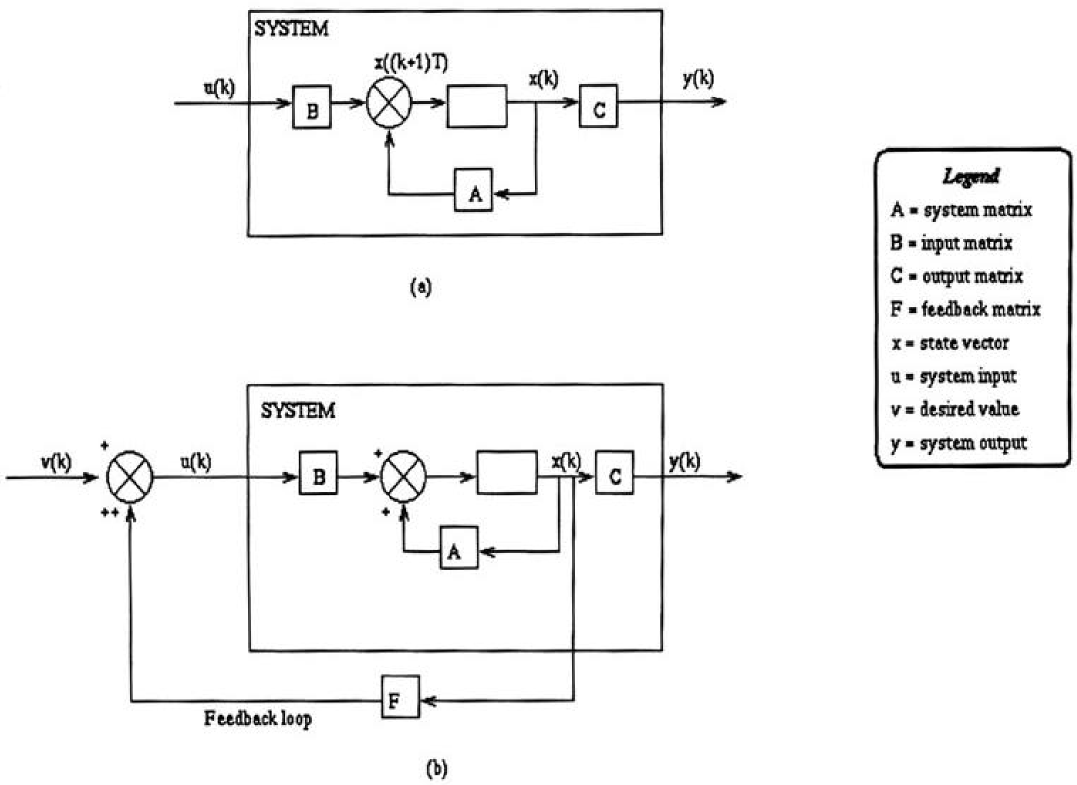

Figure 2.11 State-space modelling.

A state space is defined as a N dimensional space with axes of state variables. Therefore, any state can be represented by a point in the state vector of dimension equal to the order of the system. The selection of state variables is not unique, i.e. those considered as a *minimum set of variables determining the state of the dynamic systems*. For the solution of the state equations, many tools such as linear algebra, vector matrix and numerical methods can be used to analyse the dynamics of the system and optimal control problems. The transfer function may be transformed into an equivalent state space form by the use of classical programming techniques (e.g. the so-called *direct programming* technique [Virk 1991]).

Compensation in state space design.

The system is typically described by a system vector differentiation of the form:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$

$$\mathbf{y} = \mathbf{C}\mathbf{x} \tag{2.13}$$

where $\mathbf{x}(t)$ (the *state* vector) is $n \times 1$, $\mathbf{u}(t)$ (the *input* vector) is $m \times 1$, $\mathbf{y}(t)$ (the *output* vector) is $r \times 1$, A (the *system* matrix) is $n \times n$, B (the *input* matrix) is $n \times m$ and C (the *output* matrix) is $r \times n$.

The A matrix gives rise to the eigenvalues (poles) of the system which define the dynamic behaviour. The classical feedback compensation techniques can be extended to the state-space by the introduction of control loops that generate the input by a linear combination of the state x (Figure 2.11). If the systems is *controllable,* a feedback matrix, F can be designed such that the closed-loop poles are at any desired position. The state-space design methods rely on the complete state vector being available for feedback purposes, which in practice is not the case. This problem is overcome by employing a *state observer (estimator)* that is constructed (assuming the system is *observable)* using knowledge of the A, B, C system matrices. A whole armoury of estimation techniques, under the generic name *Kalman filter,* are available for this purpose [Kalman *et al* 1969]. Using the principle of separation, this state estimate can be used as if it were the real state vector in the design process.

2.2.2.5 Digital control systems.

So far, the discussion has focused on the use of Laplace transforms to solve *differential equations,* where the functions are analogue and continuous in time. However, the ubiquity of the digital computer both as a systems analysis and design tool as well as a component in control systems has led to the need for alternative mathematical approaches. Many other modern control systems, including BEMS, use microprocessors which operate on information obtained at discrete time points, denoted sampling points, sampled data systems or digital control systems (Figure 2.12).

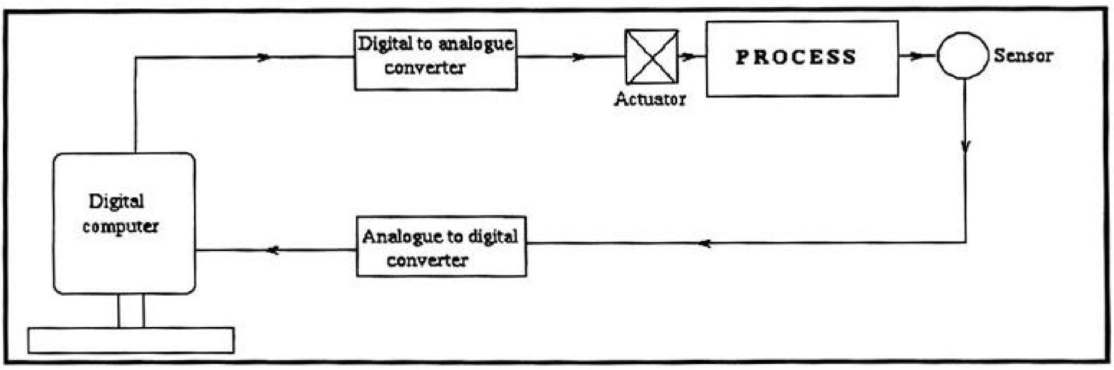

Figure 2.12 Digital control system.

For these systems *difference equations* rather than differential equations, and *z-transform* rather than the Laplace transform are used [Isermann 1981]. Essentially, all the design practices for continuous time systems have a discrete time equivalent. For example, frequency response analysis of discrete-time systems is carried out on the so-called ω-plane, which is equivalent to the s-plane for systems continuous in time [Ogata 1987]. The importance of discrete-time algorithms lies in the fact that they are directly realisable in a digital computer controller.

2.2.3 Numerical methods.

The classical and modern control design methods described above are based on sophisticated mathematical procedures resulting from several decades of research and development activity, with proven track records in many control engineering applications, e.g. food, manufacturing and chemical process industries [Newell and Lee 1989]. However, these analytical methods have limi applicability to many building/plant/control processes which have *time-dependent* thermal propert and highly non-linear characteristics not *all* of which are modelled by the (linear) operator $G(s)$ which assumes time-invariant properties. Factors accepted as contributing to building system non-linearity include [Kelly 1988, Virk *et al* 1990]:

- low valve authority and high valve hysteresis;
- HVAC systems operate over loads that can vary from 0% to 100% over a time period of a few hours causing large time delays;
- discontinuities result from on/off cycling;
- plant are sequenced from one controlled device to another (e.g. cooling coil valve, damper, heating coil valve);
- buildings are multi-variable in nature, since many inputs (climatic conditions, casual gains, heater/chiller flux, etc.) affect the many outputs (temperature, relative humidity, air flow rates, etc.);
- buildings are subject to stochastic effects such as fluctuations in occupancy levels, ventilation rate variations and climatic changes.

Also, as the complexity of the object system increases, as in the case of building and plant processes, analytical control strategies based on *controller-process* models often become infeasible:

- the model-building (identification) process becomes increasingly elaborate, iterative, error-prone and time-consuming;
- the collection of algorithms of system identification (based on methods of statistics, experiment design and multivariable-function optimisation) often loses a lot of its strength, power and applicability;
- this complexity can be due, for example, to non-linearities of the type mentioned previously.

Numerical methods, on the other hand, offer powerful techniques for the solution of many of the problem types insolvable by analytical techniques [Kup 1972]. With regard to building environmental control systems, numerical methods offer the following advantages:

- the modelling of *time-dependent, non-linear* characteristics of building systems not accounted for by the classical and modern control modelling approaches outlined earlier, is facilitated;
- it is possible to eliminate the need for separate controller and process models and elaborate identification procedures [Clarke 1985];
- numerical modelling methods are ideally suited to digital computing systems.

2.2.4 Computer based simulation programs.

The earliest computer simulations of building control systems were carried out using analogue computing techniques [Nelson 1965, Magnussen 1970]. Since the early 1970's, however, digital computing techniques have predominated [Ayres and Stamper 1995], the digital computer programs being based on the modelling methods outlined earlier [Winkelmann 1988]. In comparison to those for the building-side issues, the range of computer based modelling and simulation approaches for environmental control systems is much greater. Hensen [1993] reviewing current computer based building environmental systems simulation program types, classified them in terms of abstraction levels, characteristics and application (Figure 2.13), ranging from a purely conceptual representation of plant and control systems through to an explicit, subcomponent modelling level.

2.3 AREAS FOR DEVELOPMENT.

2.3.1 Issues to be addressed.

A recent review of the control options available in building energy simulation programs [Hitchin 1991], indicates the following typical program inadequacies:-

- control element dynamic response is often neglected;
- no mechanisms exist for the modelling of multiple input, multiple output (MIMO) systems;
- there is an inability to deal with multi-level, hierarchical systems;
- models for many microprocessor based controller strategies are omitted;
- no provision is made for *simulation-based controller design*, which would facilitate innovative control design strategies and on-line supervision of BEMS.

Accepting that these inadequacies exist, extending the modelling facilities and applicability of simulation programs are therefore the two main issues to be addressed in this work.

2.3.2 Accuracy of modelling.

The premise of this project is that the issue of modelling accuracy is of the utmost importance and, if disregarded, will greatly influence simulation predictions and, ultimately, the design and operation conditions, whilst also severely limiting model applicability.

LEVEL		TYPE
A	Room processes only; ideal plant	Conceptual
B	System wise in terms of (real) systems like VAV, WCH, etc.	
C	Component wise in terms of duct, fan, pump, pipe, etc.	
D	Subcomponent level in terms of energy balance, flow balance, etc.	Explicit

Figure 2.13 Categories of building systems simulation programs [Hensen 1993].

The contention is that the accuracy of building control system modelling in the transient domain can only be increased and optimised if *all* relevant aspects, features and characteristics of real systems are taken into account during the modelling process. This requires tools that adopt a *fully integrated* approach, which considers all energy flow paths and the interaction of control systems with fabric, flow, plant and power systems. Lebrun *(et al)* [1985] observed that a full *dynamic* model of the building is necessary to obtain realistic simulation results, adding that the scattering of real control laws among the different zones necessitates the use of a *multi-zone* simulation model (capable of handling physical processes such as inter-zone convective couplings) if the control engineer is to have a means of establishing optimal control of the HVAC system.

2.3.3 Extending applicability.

Although building control requirements are not severe by standards in the process control industries, problems arise when trying to predict the performance of building control systems and assess the effect of the quality of control on system operation, energy consumption or comfort. Many of the available design and appraisal simulation tools based on the modelling methods described earlier are not domain-specific; in those that are, the control theory/models/algorithms are often contained and presented in a manner which is entirely foreign to many members of the building design team, such as architects. Such simulation tools are therefore often not adequate or employable for the building control system appraisal task in hand.

Applications of building control system simulators may be classified into three broad categories:

- *initial building design appraisal,* where control specification may be very basic and simple;
- *practical system design* necessitating more rigorous specification for purposes of operating characteristics, commissioning, operator training, etc;
- *ambitious and highly conceptualised control schema* involved in control systems

research programs.

It is evident that the potential of simulation in all three areas has hitherto not been fully realised. This is a key issue facing the energy modelling community.

2.3.4 A control systems modelling and simulation environment.

If the applicability of modelling tools is to be increased and the full potential of control systems simulation realised and utilised in the pursuit of the intelligent building, there are many additional and desirable features with which programs must be equipped, including:-

- improved user interfaces and problem definition procedures;
- advanced sensor and actuator modelling capabilities;
- installation of optimal, adaptive and artificial intelligence control algorithms;
- hierarchical control strategy modelling capability;
- time-step controllers which allow simulation-based predictive-iterative control schema to be modelled both for design purposes and also - hitherto not implemented - for on-line optimisation of practical BEMS.

An attempt must therefore be made to formally identify and classify *all* those elements and characteristics extant in real control systems, which require to be considered during the modelling process and subsequently included in simulation programs. The resulting taxonomy of building control system entities can then be used to guide the modelling development process and thus aid the quest for a comprehensive building controls system modelling facility.

The conceptual development of a taxonomy of control systems entities in terms of system logical, spatial and temporal elements, together with associated modelling schema is detailed in Chapters 4,5 and 6. Such schema, however, require a simulation environment which satisfies the twin criteria of modelling accuracy and also provides initially a test bed and subsequently a vehicle for their widespread application. Such an environment is the subject of Chapter 3.

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BUILDING CONTROL SYSTEMS: THE TEMPORAL ELEMENT

This Chapter outlines methods and techniques designed to improve the accuracy and flexibility of modelling the temporal element of building control systems. Numerical schema developed and subsequently installed in ESP-r are presented.

5.1 INTRODUCTION.

The temporal elements of building control system simulation may be classified as depicted in Figure 5.1. Two main classes of elements exist, namely, simulation time-clock parameters and time-dependent system component design/operating characteristics. The former includes time-schedules and simulation time clock and time step manipulation features necessary for inclusion in a control modelling facility; the latter includes time-delays (both designed and operational), and also time-dependent control (sub)system definition and specification. These elements are now considered in turn.

5.2 TIME CO-ORDINATED MULTI-FUNCTIONAL CAPABILITY.

5.2.1 Time-and-event scheduling.

Practical BEMS control strategies are based on time schedules which can range in duration from a matter of seconds (e.g. start-up sequences) to a year or more (e.g. holiday shut downs). Similarly, in a software modelling environment, control strategies (typically complex and hierarchical in nature) imposed on the simulation must be co-ordinated and synchronised with the simulation time-clock and matched to the simulation time-steps. The entire simulation period then requires to be broken down in terms of control day types and control periods within these day types (Figure 5.2). Day *types* include weekdays, weekends, holidays, and seasons. Day *periods* include morning, afternoon, evening, night, working hours, periods of occupancy, etc. The techniques used to ensure the necessary time-coordination and synchronisation will differ according to the nature of the program, e.g. sequential or simultaneous.

In a modularised, numerical based, simultaneous program such as ESP-r, each subsystem (building, plant, flow, etc) has a capability for varying the frequency of matrix inversion in accordance with the dynamics of the individual subsystems. Thus, in order to harmonise the constituent control systems participating in the simulation, at each simulation time-step, the following factors must be established:

- which control subsystems are currently active?
- for each active control subsystem, how many control functions are operating?
- what are the time schedules in terms of control day types and control day periods?

- what is the nature of each active control function, as regards sensor location and quantity, controller type, and actuator location and quantity?
- what control system triggered time-step controllers are currently active, and what is the priority logic?

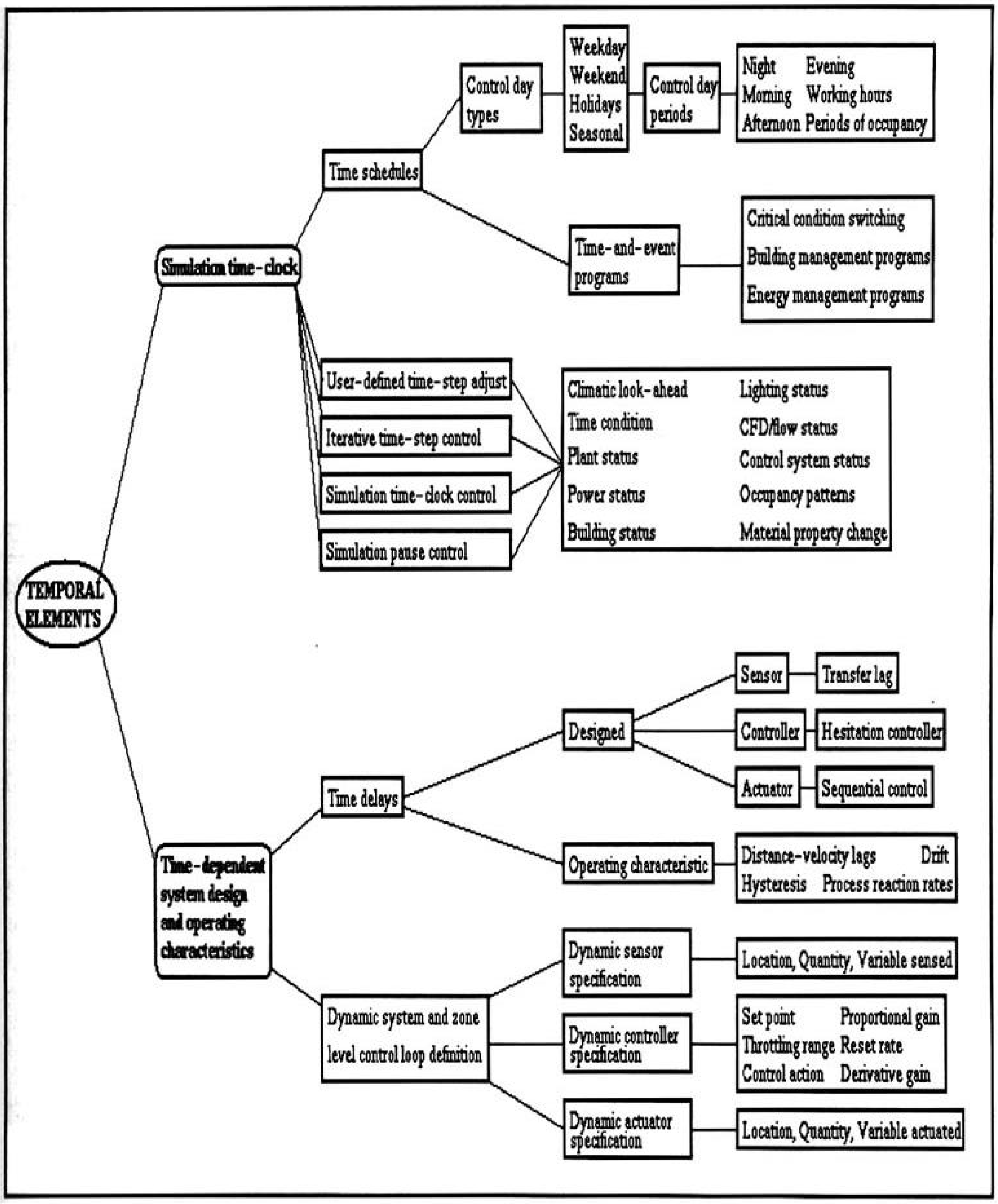
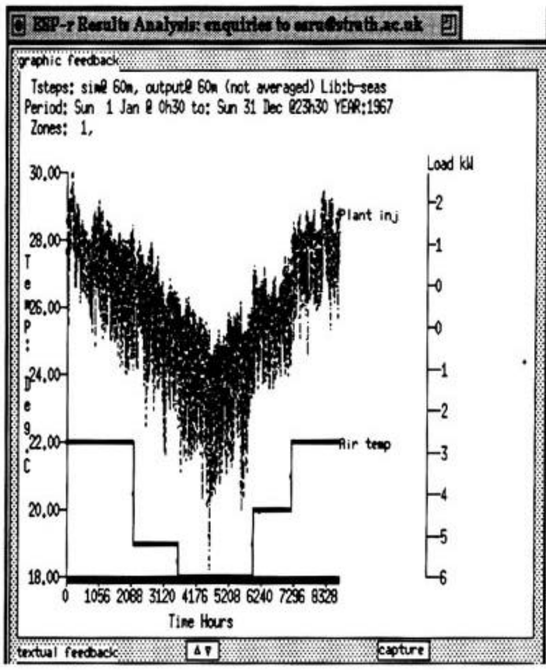
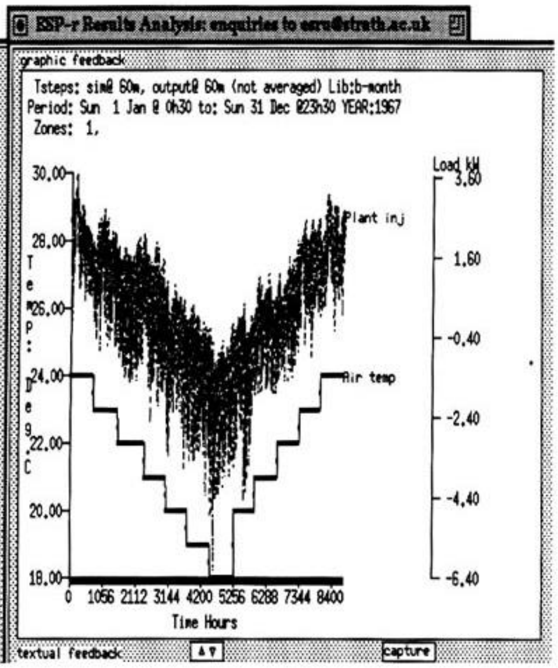


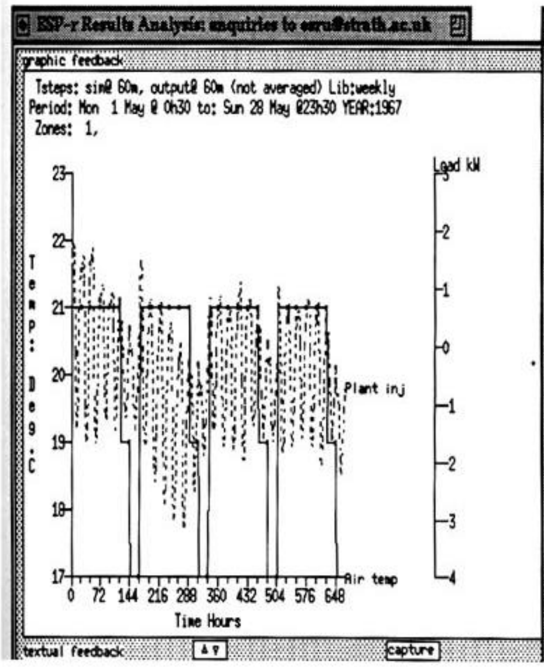
Figure 5.1 Building control systems modelling: the temporal element.



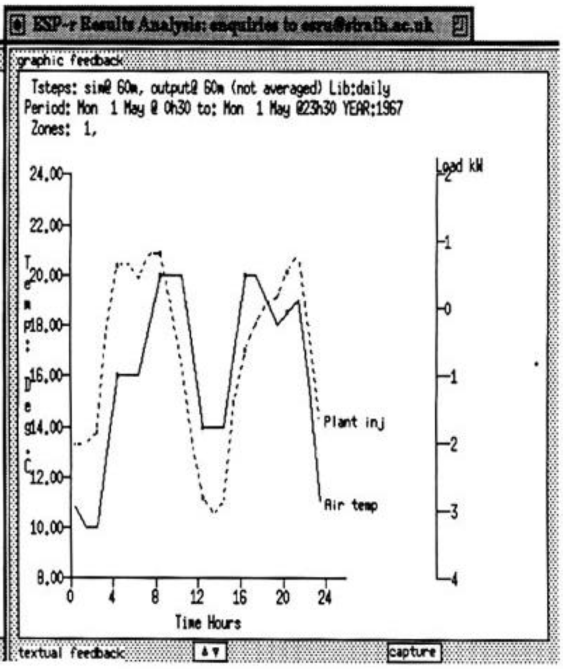
(a) Seasonly



(b) Monthly



(c) Weekly



(d) Daily

Figure 5.2 Control time schedules.

Within ESP-r, as described in Section 3.4.1. this information is held in the *system control configuration file* and is made available for control subsystem processing at each simulation time-step.

5.2.2 Dynamically reconfigurable control system definition.

The control system definition procedure described above provides flexibility of control system specification prior to commencement of simulation. This may be extended to include *conditional* time-varying control system definition features such as the dynamic re-specification of:

- sensor/actuator location;
- sensed/actuated variable;
- sensor/actuator quantity;
- controller type;
- controller defining data;
- control day types and day periods.

The time and conditional re-specification of control system parameters can be applied to all control subsystems.

As described in Section 3.4, control system specification affects the subsystem matrix topology and/or topography, and altering control specification at some juncture in the simulation process will dynamically alter the type of numerical solution processes invoked. It is necessary, therefore, for the case of building-side control, where the control point determines the solver type employed, to apply the conditional re-specification logic at each building-side simulation time-step *prior* to matrix set-up and formulation. For other control subsystems, the conditional logic is applied - at each subsystem time-step - at the start of the control executive subroutines.

In practical systems, such re-specification of temporal elements is typically done on the basis of a limited range of system parameters (e.g temperature levels) and often only carried out under critical conditions which would otherwise lead to so-called 'catastrophic failure' [Honeywell, 1989]. Simulation, on the other hand, need not be thus restricted; re-specification of temporal elements may be carried out, at any simulation time-step, according to prescribed conditional logic, based on, say, any one or more of those sensed conditions listed in Table 3.1.

Consider, for example, a compensation scheme in which the building-side control period start times are dynamically re-specified as a function of the external climate conditions in an attempt to decrease the plant switch-on time. Figure 5.3 shows such a scheme for a single zone (with coupled flow and plant networks), where the control period start times are amended according to external climate conditions. The control schedule is initially specified prior to simulation commencement. In the case of conditional re-specification then, if at the original start time for control periods 2 and 3 (06.00 hours and 19.00 hours, respectively), the external dry bulb temperature *AND* ambient relative humidity exceed predefined limits (16 °C and 50% respectively), the control schedule changes to that shown in Figure 5.3(b), where the start time for *control period* 2 is retarded to 08.00 hours and that for *control period 3* is brought forward to 1600 hours. Thus, in dynamic re-specification mode, the upper set point (20 °C) is (conditionally) active for a shorter period of time than for the original case. The results for such a strategy are shown on Figure 5.4.

Conditional re-specification of a plant-side control loop output is depicted in Figure 5.5, where the control loop actuator output for a single zone test case is amended according to the rate of change of the sensed condition in order to capture the system dynamics. Here, the conditional logic is that the loop actuator's maximum and minimum values change from 1500 W and 300 W respectively, to 2000 W and 500 W respectively, in the event of the rate of change of the supply air dry bulb temperature exceeding the user-specified value of 0.1 °C in a given plant-side time-step.

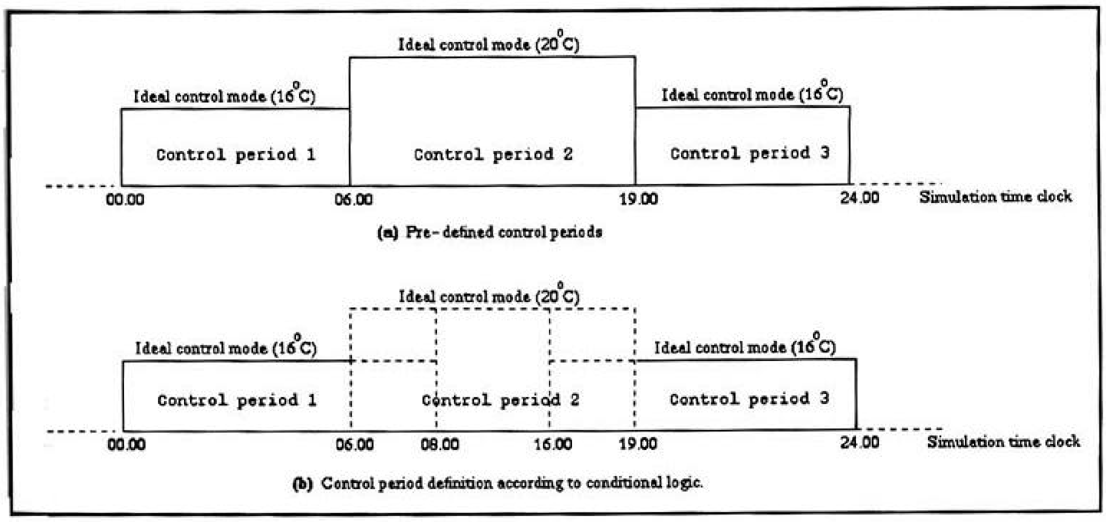
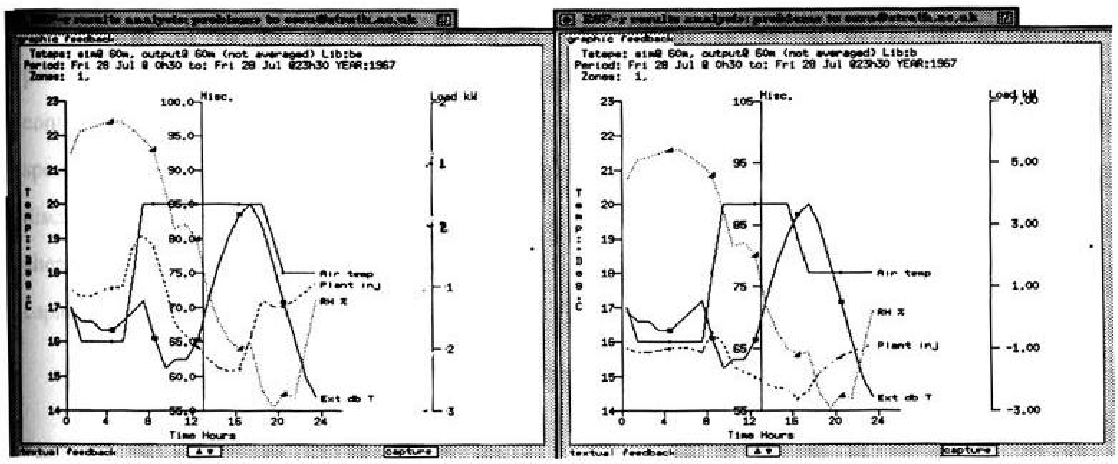


Figure 5.3 Dynamic re-specification of control period: control schedule



(a) Control period pre-defined **(b)** Control period dynamically respecified

Figure 5.4 Dynamic re-specification of control period; sample results set

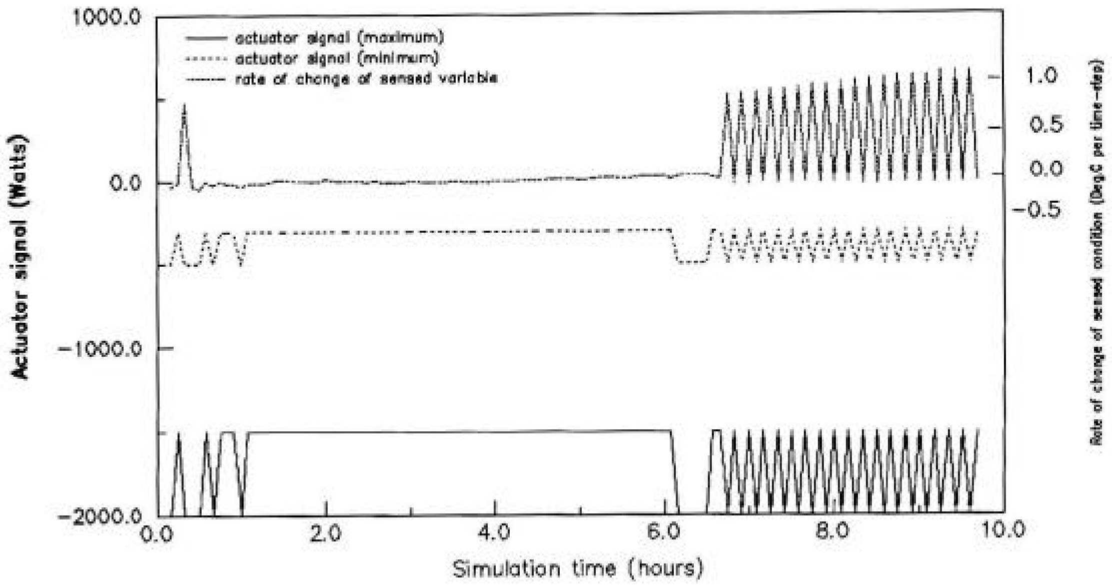


Figure 5.5 Dynamic re-specification of controller output: sample results set

5.3 SIMULATION TIME-STEP MANIPULATION.

5.3.1 General considerations.

Detailed energy simulation programs must have some means of allowing for the variability of the characteristic time-variation within building elements, e.g. foundation slab conduction varies in terms of weeks; the building fabric varies typically in terms of hours; plant components in terms of minutes; and the transients associated with control systems can have characteristic times of seconds [Winklemann and Clarke 1986]. Numerical methods for integrating differential equations representing heat and mass balance within buildings may require iterative or time-step reduction techniques for the successful modelling of control system dynamics, particularly those of a non-linear nature as commonly found in building control systems. Time-step reduction for the whole simulation period can often have the disadvantages of excessive results file size and computation time. Time-step control techniques, which adjust the time-step throughout the simulation according to some user-specified criterion, can help to overcome these problems. Simulation time-step manipulation in a discrete, simultaneous environment based on manual time-step reduction, boundary condition look-ahead and plant component time-constant, is described in detail by Aasem [1993]. Time-step control capabilities based on control simulation parameters (e.g those listed in Table 3.1) are now described.

These time-step controllers do one or more of the following:

- directly modify the simulation time-step;
- impose iteration on the solution at the same time-step;
- reposition the simulation time-clock to any simulation time-step.
- pause the simulation time-clock to allow control system interrogation and re-design.

5.3.2 TSCON_6: Automatic reset time-step controller.†

This controller (Figure 5.6) can be used where the transient effects introduced because of some control feature becoming active are to be minimised. For example, at simulation commencement, a user may specify one or more sensors to sense variables which are expected to fluctuate rapidly at some point(s) during the simulation (e.g. wind speed). Alternatively/additionally, a user may nominate control loops deemed to have particularly significant dynamic characteristics, e.g. those comprising PID controllers. In the event of any of the nominated sensors and/or control loops being active at any given time-step, the building-side simulation time-step is reset to the user-specified value.

The following control system elements can be used to determine the simulation time-step:

- active sensors;
- rate of change of sensed variable;
- active actuators;
- rate of change of actuated variable;
- active control laws;
- active control loops;
- deviation from set point.

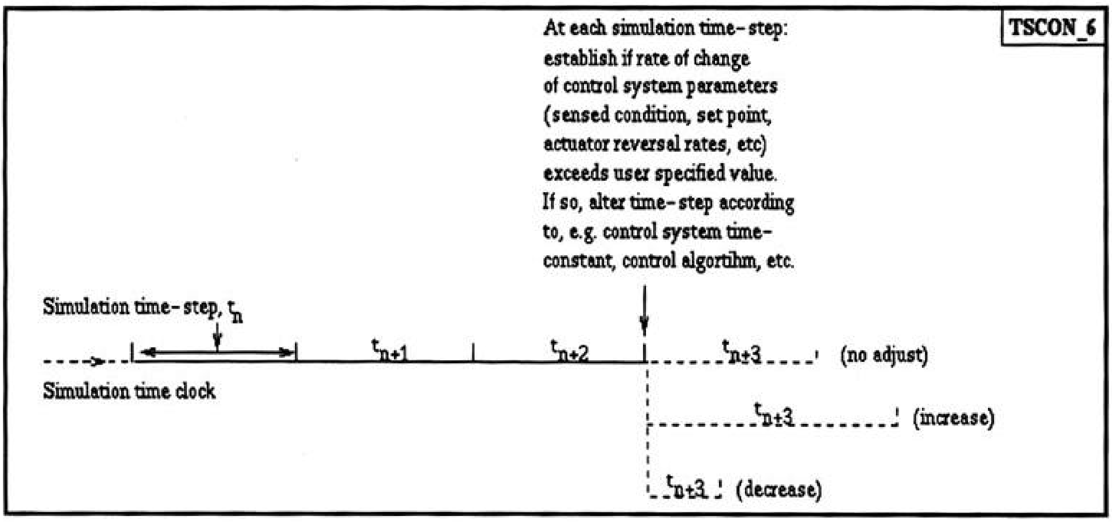


Figure 5.6 TSCON_6: Automatic time-step reset controller.

† Time-step controllers TSCON_1-5 were installed prior to project commencement.

5.3.3 TSCON_7: Control system based iterative time-step controller.

The rate of change of one or more control system variables (e.g. those listed above for the *TSCON_6*) can be evaluated and, if greater than the user-specified threshold value, the time-step is halved (Figure 5.7). This process is repeated until either the rate of change condition is satisfied or the maximum number of repetitions specified by the user is reached. The new time-step is subsequently used in the numerical solution. More than one system variable can be specified. In this case, time-step reduction will occur if the above condition is not satisfied by any control variable.

This type of controller is suitable for situations where the rate of change of a control variable is relatively large, such as in the case of controller set point changes in some cascade control applications. A rigorous investigation of control system stability over a range of simulation time-steps is thus enabled.

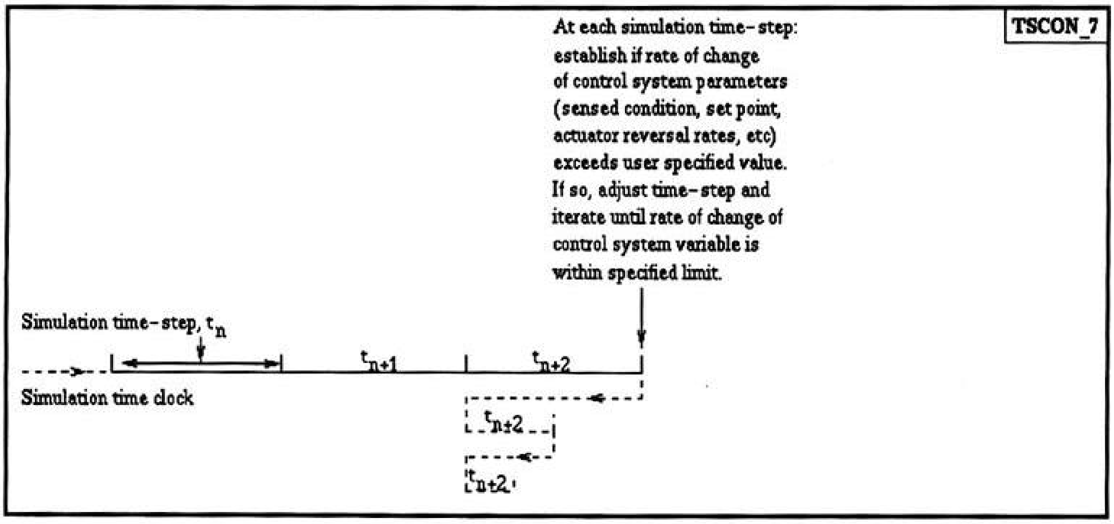


Figure 5.7 TSCON_7: Iterative time-step reset controller.

5.3.4 TSCON_8: Simulation time-clock reset to time-step controller.

This time-step controller resets the simulation time-clock to *any* previous simulation time-step on the basis of any simulated control system parameter. After reset, the simulation time-step can remain the same or may be adjusted. Such a time-step controller is necessary for the BEMS system-level modelling techniques described in Section 6.4.2. It is also required for the ESAC (Energy Simulation Assisted Control) predictive-iterative control strategies such as determination of optimum start times, load shedding schedules, etc, described in Section 6.6. Two methods of achieving simulation time-clock manipulation in discrete time programs are now described.

The first method (Figure 5.8(a)) involves saving all relevant simulation parameters at the time-step to which the simulation time clock is to be reset. Aasem [1993] details the procedure of saving all time-dependent state variables in ESP-r to allow the system matrix equation coefficient set-up for the time-step in consideration to be identical to that at a previous pass.

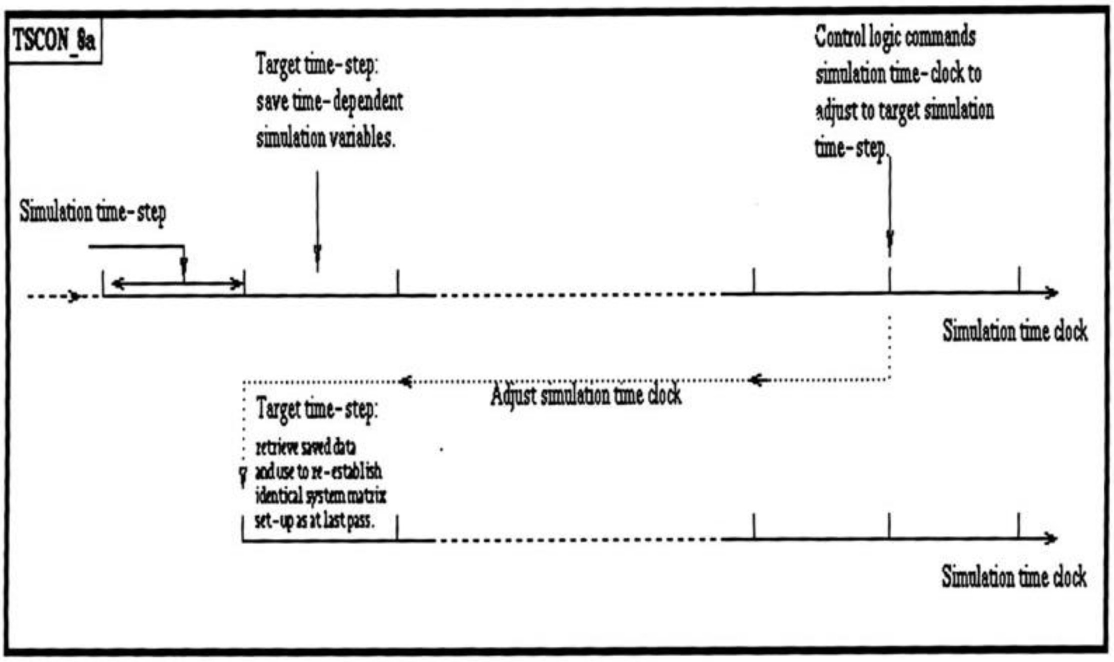


Figure 5.8(a) TSCON_8: Simulation time-clock reset controller (data save).

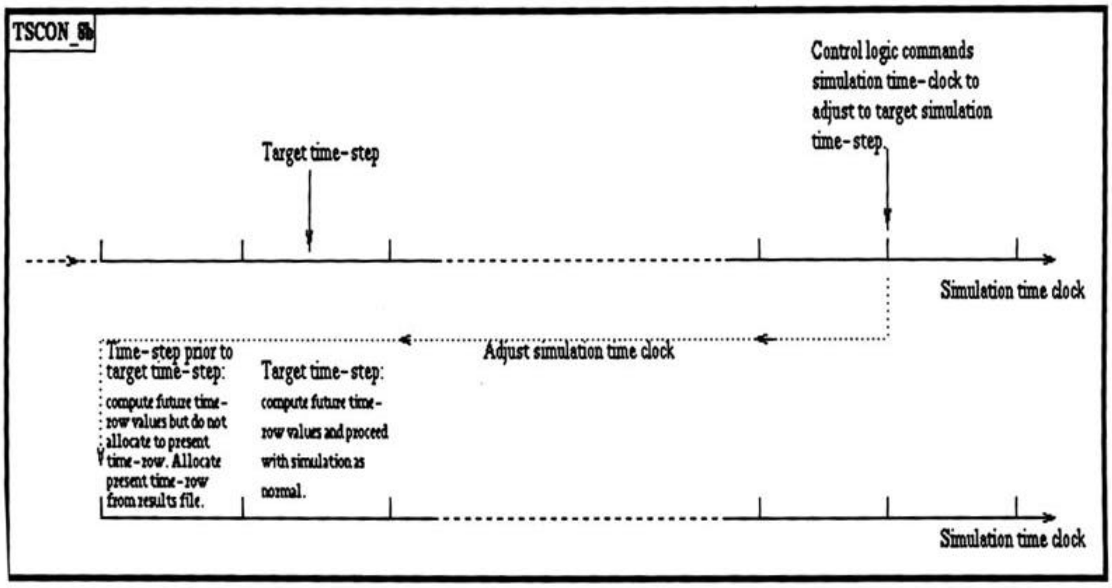


Figure 5.8(b) TSCON_8: Simulation time-clock reset controller (no data save).

The time-step controller is invoked at a command from one or more logic (controller) elements. The simulation time-clock is then adjusted to the desired time-step at which data was saved, the data retrieved, and the simulation recommenced. The data may be saved in memory or, alternatively, saved to an external file.

The second method of simulation time-clock control (Figure 5.8(b)) involves no saving of simulation time-dependent data. The technique involves the following steps:

(1) The time-step controller is invoked at a command from one or more logic elements (controller).

(2) The simulation time-clock is reset to the time-step immediately *preceding* the target time-step, as opposed to the target time-step itself.

(3) In processing this time-step, the computed future time-row values will be erroneous since the present time-row values do not apply to this time-step, but rather to the time-step prior to simulation time-step adjustment.

(4) The time-step is processed as normal with the exception that, at the end of the time-step, the (erroneous) future time-row values are *not* set to present-row time-step values for the next time-step. Instead, present-row time-step values for the next time-step are read and allocated from the results file (calculated at this time-step at the previous pass).

(5) The target time-step is then processed and the results allocated as normal, with the future time-row values being computed on the basis of correct present time-row values.

The time-step preceding the target time-step can therefore be thought of as a 'dummy' time-step to allow the allocation of the correct present time-row values.

With this approach, software requirements are not as demanding as with the save/retrieve strategy discussed earlier, involving only an extra (dummy) simulation time-step. Clearly, though, the approach adopted will be program-dependent.

5.3.5 TSCON_9: Simulation pause time-step controller.

Simulation-assisted control system design efficiency may be improved if some means can be provided of speeding up the 're-definition and re-run' process. Haves and Dexter [1989] describe a method whereby the simulated control system may be retuned *without* restarting the simulation. It is possible to incorporate automated re-run into the ESP-r simulation process by means of *UNIX Shell Script programs* [Kernighan and Pike 1984]. However, it is not always necessary to re-simulate the *entire* period; often, the preferred option is to *pause* the simulation time clock, adjust the desired control system parameters, and then proceed to simulate from this time-step.

The *TSCON_9* time-step controller acts to temporarily pause the simulation time clock to allow alteration of system control function parameters such as throttling range, set point, controller gains, etc, (Figure 5.9). The simulation time clock is paused by user command. Once the simulation clock is paused, a parameterised UNIX Shell Script program - contained within an external file - is invoked which then processes parameters in accordance with some user-defined control algorithm. At each pause, the user may alter parameters and/or the algorithm itself. Updated parameters are subsequently passed back to the simulation program and the simulation recommences from the time-step at which it was paused.

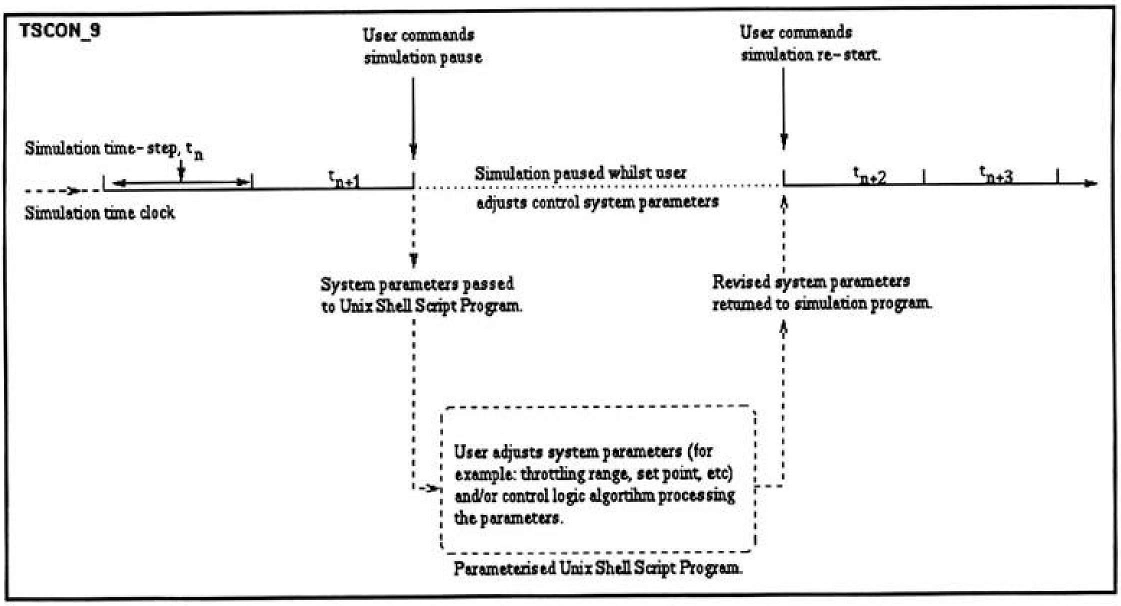


Figure 5.9 TSCON_9: Simulation pause time-step controller.

The simulation time-clock may be paused at any time-step during the simulation and as often as desired, according to the monitored simulation results. In this way, interactive graphics tools are combined with computer-assisted methods to facilitate comparative assessment of control performance and commissioning of control system networks. It is also possible to maintain a log of the different control strategies invoked, by appending the system control configuration file at each pause-adjust, thus allowing the simulation to be entirely reproducible.

The simulation time clock and time-step techniques described above will be utilised in Chapter 6 to facilitate *energy simulation assisted control* strategies. For the present, however, consider a single zone subjected to the building-side control schedules depicted in Figures 5.10-5.12. *TSCON_6* is active in the first case, and *TSCON_7* is active in the second. Figure 5.13 shows the resulting temperature and plant injection/extraction profiles for these time-step control regimes.

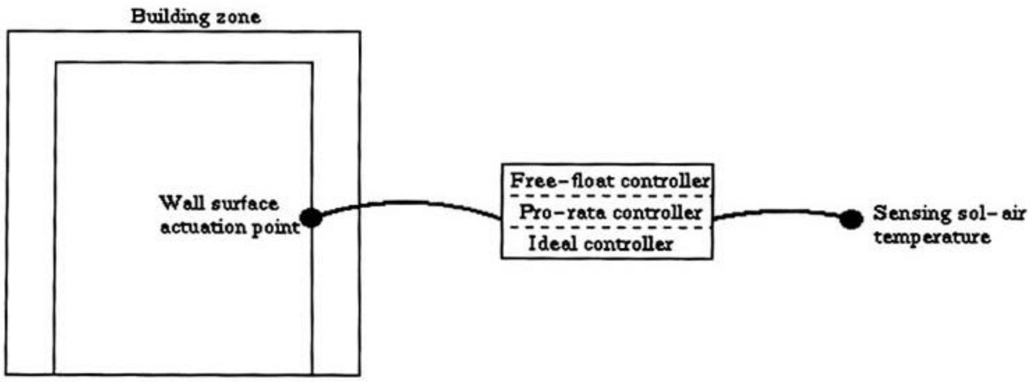


Figure 5.10 Control loop for time-step control test case.

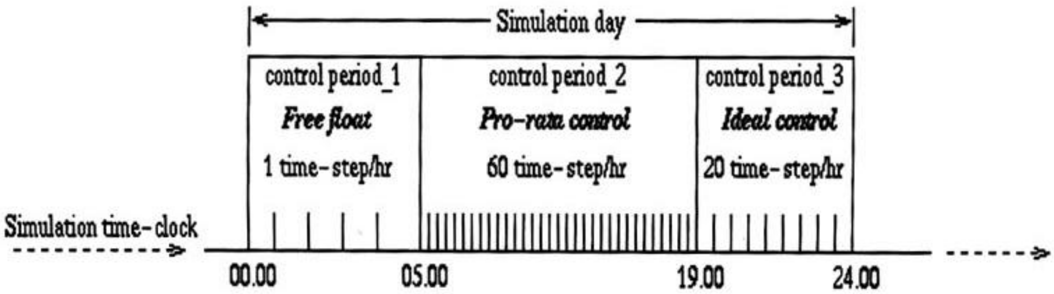


Figure 5.11 Time-step control schedule according to active control law (TSCON_6).

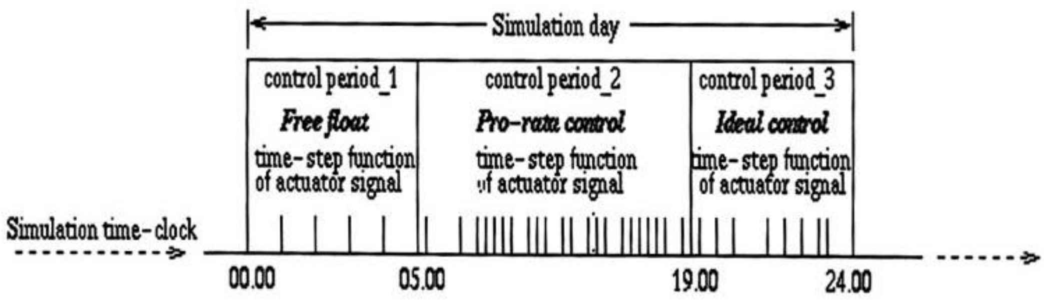
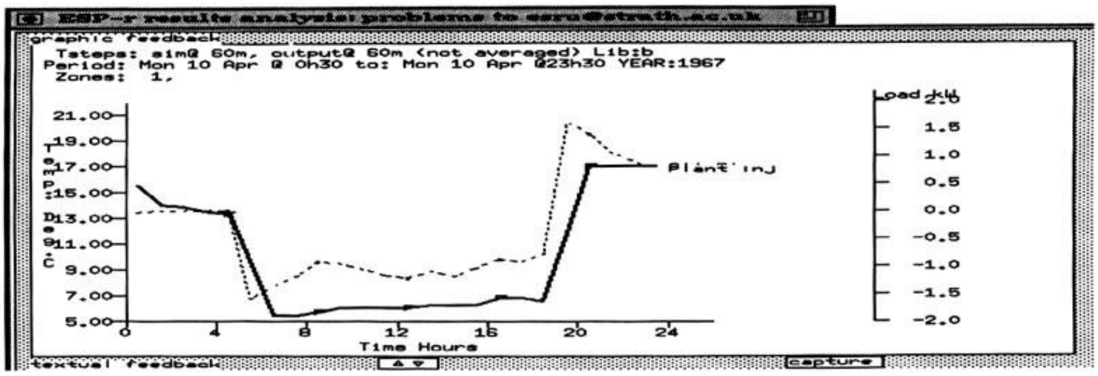
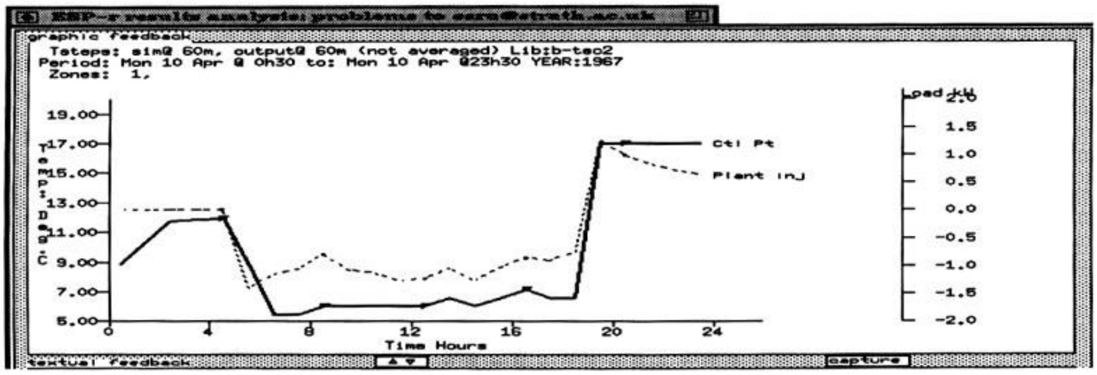


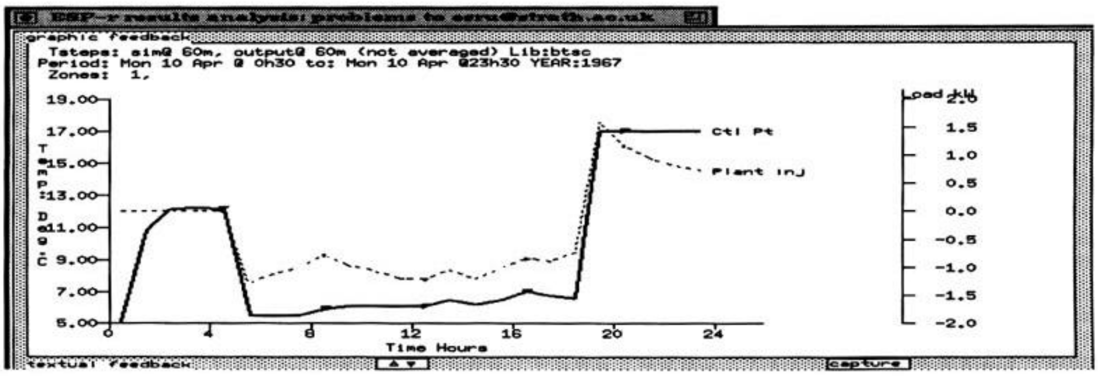
Figure 5.12 Time-step control schedule according to active actuator signal (TSCON_7).



(a) No time-step control



(b) Time-step control on active control law



(c) Time-step control on actuator signal

Figure 5.13 Simulation time-step control according to control system parameters.

5.4 TIME-VARYING OPERATIONAL CHARACTERISTICS.

5.4.1 Scope.

Time delays, time lags and time-varying characteristics within building control systems may be classified as either designed or operational (Figure 5.1). Delays designed into the system in order to bring about some desired controlled condition include sensor signal transfer delay, hesitation control action and final control element (actuator) sequential delay. Operational characteristics include dead time (e.g. due to transportation delay), lag (e.g. due to sensor thermal response) and drift. Techniques for superimposing realistic time delay and time lag characteristics on the simulated sensed/actuator variable signal are now discussed.

5.4.2. Modelling sensor time lags.

First order lags in temperature sensors are typically modelled by assuming the sensor dynamic response may be described by the following differential equation:

$$\tau \frac{dy}{dt} + y = u \tag{5.1}$$

where τ is the sensor time constant (ratio of thermal capacitance of sensor to thermal conductance for heat transfer to the surrounding fluid) y is the sensor output, u is the sensor input and t is time. This equation gives the time lag associated solely with the thermal response of the sensing element itself. Typically, this will be small compared to the deadtime introduced into the control loop due to the transport delay upstream of the sensing element.

The solution to Equation 5.1 for a given time-step is:

$$y_t = u_{t-\Delta t} - (u_{t-\Delta t} - y_{t-\Delta t})e^{-\frac{\Delta t}{\tau}} \tag{5.2}$$

where Δ t is the simulation time-step, $y_{t-\Delta t}$ is the sensor output at the beginning of the time-step and $u_{t-\Delta t}$ is the input at the beginning of the time-step.

5.4.3. Modelling control system time delays.

Time-delays affecting system response rates can be included by the incorporation of a *software memory facility* so that any control action can be delayed until some later simulation time-step, with current action resulting from some previous sensor/controller/actuator status. The length of delay, and thus the number of (sub)system simulation time-steps that the variable is being delayed by, may be user-specified prior to simulation commencement or, more accurately, computed according to some active controller algorithm (e.g. *hesitation relay control* where the controller output is delayed until some system state is reached).

Such a modelling scheme enables the following modelling features:

- each control subsystem (i.e. building, flow, plant, etc.) has an independent time delay processing capability, due to ESP-r's modular structure which allows different frequencies of matrix inversion;

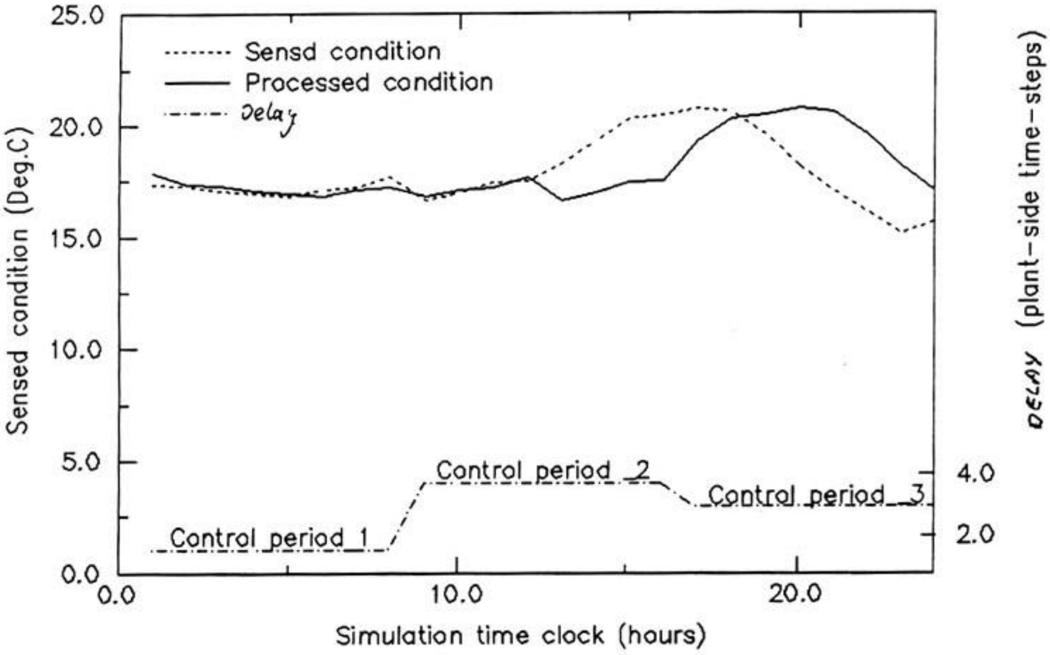


Figure 5.14 Fixed sensor time delay

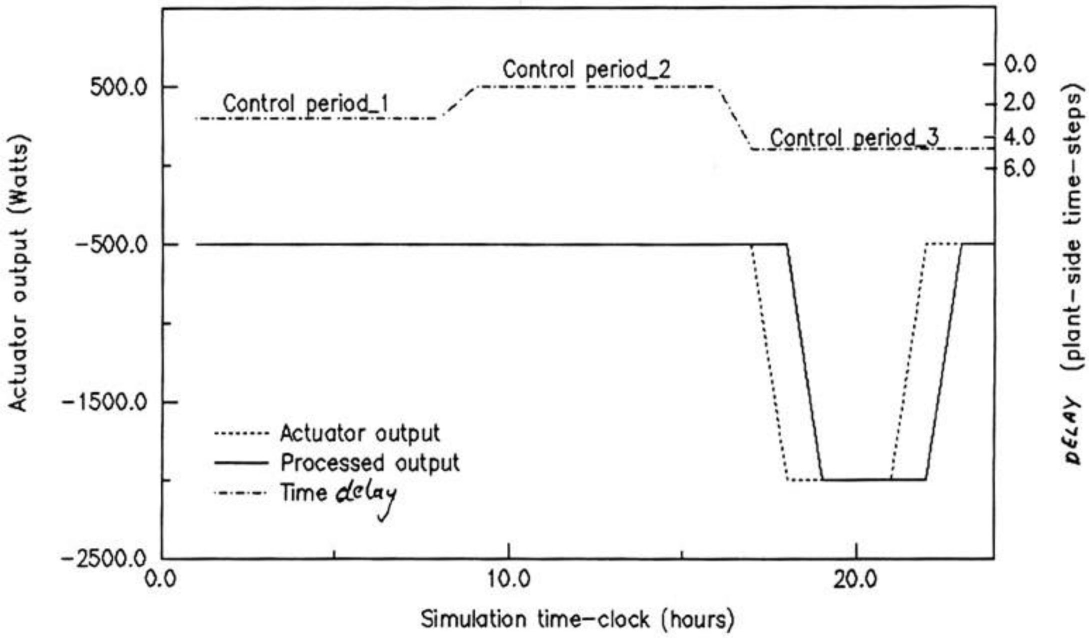


Figure 5.15 Fixed actuator time delay

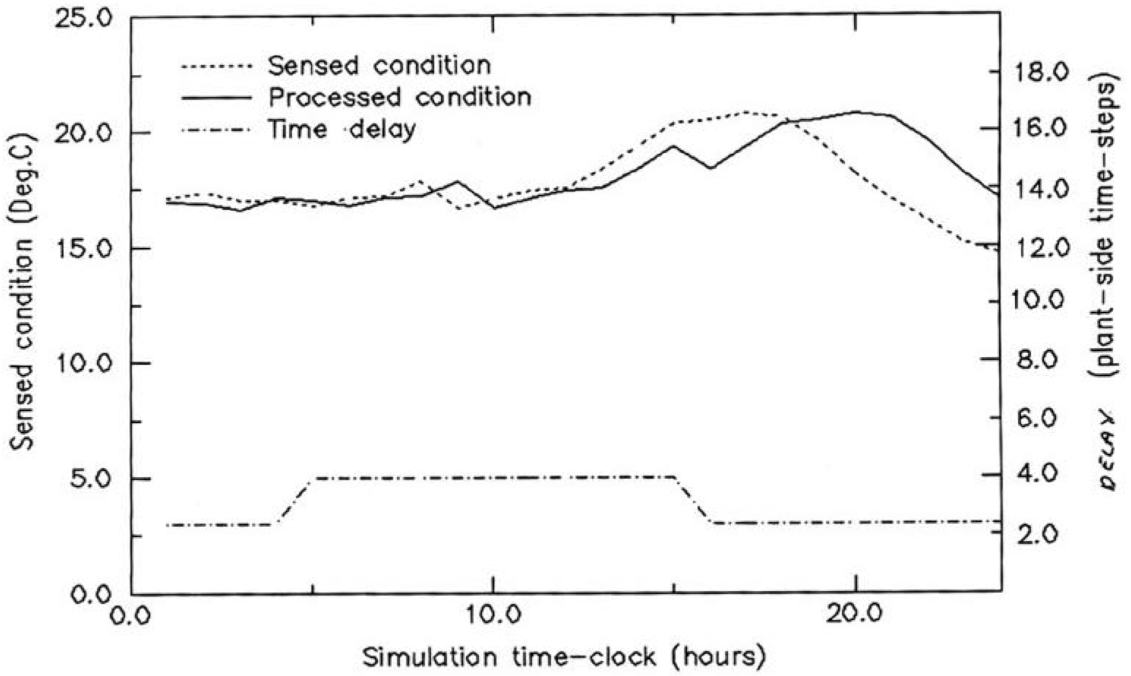


Figure 5.16 Variable sensor time delay

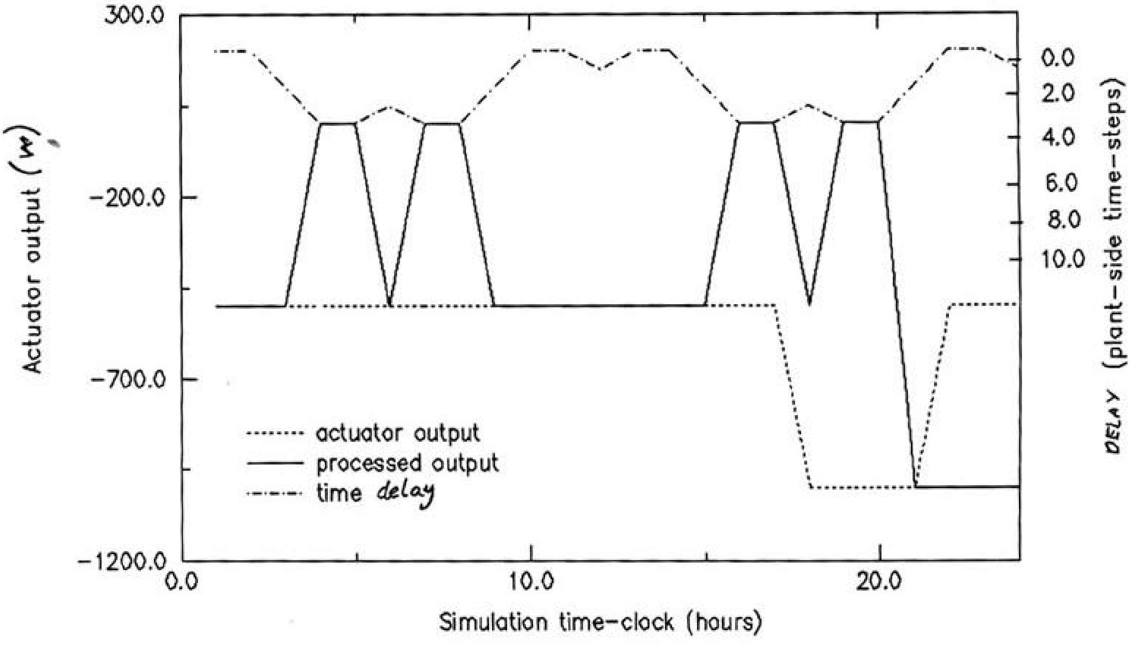


Figure 5.17 Variable actuator time delay