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Distribution loss reduction: A genetic algorithm approach.

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Distribution Loss Reduction:

A Genetic Algorithm Approach

by

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A thesis

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Abstract

In this thesis two genetic algorithm methods are developed which may be applied to perform real-time, on-line control of the shunt capacitors and voltage regulators that are placed on a distribution system for the purpose of reducing distribution losses, while maintaining all bus voltages within ±5% of their nominal rated values. The first genetic algorithm method employs a penalty based fitness function, while the second genetic algorithm method employs a fuzzy logic based fitness function. Both methods are tested on a 30 bus distribution system under varying load conditions and the results obtained are compared with the global optimal solution which is obtained by performing an exhaustive search of the solution space using the penalty based fitness function as its objective function. The results of the penalty based method are quite close to those of the global optimal solutions for the load levels studied. The results of the fuzzy based method while not as good as those of the penalty based method are quite promising, and deserves further study. Both genetic algorithm methods were capable of arriving at a solution in less than 3 minutes and 30 seconds, and hence, would be suitable for real-time, on-line applications.

Dedication

This thesis is dedicated to:

my father, Edwin Morelli, for a lifetime of love and support, which, while not always spoken, was always understood. What has taken me six years of university to understand, you have always known.

Jesse, your love for life is an inspiration. You will always be close to my heart.

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Also, I would like to thank Dr. M.M.A. Salama of the University of Waterloo for his interest and discussions, and for acting as host to several meetings during the course of this research.

Thanks also to my wife, Evelyn, for her encouragement and support, and for always understanding the many times when I needed to be off alone during the course of this research.

To my mom, Henriette, for your encouragement and support throughout the years, I couldn't have made it this far without you.

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List of Abbreviations

Symbols:

B	Susceptance [S]
E	Source voltage [V]
G	Conductance [S]
I	Current [A]
P	Power [W]
Q	Reactive power [VAR] (inductive positive)
R	Resistance [Ω]
S	Apparent power [VA]
V	Voltage [V]
X	Reactance [Ω]
Y	Admittance [S]
Z	Impedance [Ω]
ϕ	Power factor angle [° or radians]
Δ	A small change in...

Subscripts:

C	Compensator
L	Load
R	Real or resistive component
S	Source
X	Imaginary or reactive component

Note: Boldface symbols denote complex quantities. The asterisk denotes the complex conjugate. Italic symbols denote magnitudes. Primed symbols represent the unprimed quantity after the effects of compensation are considered.

Chapter 1

Introduction

1.1   Background

The quality of service of a power system depends in part, on the correct voltage level being consistently available to the customer. In order to assure this, compensation is often needed on the distribution system.

Compensation may be performed for various reasons and by various methods. Choosing the most appropriate type and level of compensation necessary is important, as overcompensation can be as harmful to the system as under compensation. Once the appropriate type of compensation has been determined, a method of controlling the compensators under the varying load conditions of the system must be formulated.

1.2   Thesis Scope and Objectives

The objective for this thesis was to develop a fast technique for controlling the shunt capacitors and voltage regulators which are placed on a distribution system for the purpose of reducing the distribution losses, while maintaining the bus voltages within ±5% of their nominal rated values.   In order for the method developed to be useful in a practical distribution system an accurate model for the load, one taking the dynamic nature of the system into account, was required.   In addition, for any method to be applicable in practice requires that it be capable of consistently arriving at a high quality solution in a time of less than five minutes.   To accomplish this task, it was felt that artificial intelligence techniques such as genetic algorithms and fuzzy logic were ideally suited.

Successful accomplishment of the objective of this thesis required considerable preparation and preliminary work to be performed.   First, in order to properly formulate the problem, a thorough investigation of the previous research in the area was carried out, and the associated issues of system protection, load flow techniques and system planning were also examined.   As well, a thorough review of the theory of voltage and reactive power control, including compensation techniques was performed.   Once the problem was properly formulated, a study of artificial intelligence techniques in general was performed, and their previous application to functions of distribution system automation was studied in great detail. Next, a review of several programming platforms was conducted, resulting in the selection of Visual C++ Version 4.5.   The Gauss-Seidel load flow technique was implemented in VC++ and validated, and a realistic model for load variations was developed and implemented in VC++.   Finally a genetic algorithm for controlling the compensators placed on a test

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distribution system for the purpose of loss reduction, under the constraints of bus voltage limits was developed and implemented in VC++, and experimentation was carried out to demonstrate its validity.

1.3   Thesis Organization

Chapter 1 states the objective and serves as an introduction to this thesis. Chapter 2 presents the theory necessary to understand and meet the objective. It breaks the overall voltage and reactive power control problem into two subproblems: the placement problem and the control problem. In Chapter 3, the advancements made in the formulation of these subproblems and the modeling of the system was considered, along with a review of the methods developed by other researchers for solving these two subproblems using 'modern' techniques. Chapter 4, presents the system model and problem formulation adopted in this thesis and describes the solution methodology in detail. Chapter 5 presents and discusses the results obtained when this methodology was applied to a test distribution system. Finally, Chapter 6 provides concluding remarks and recommendations for future work.

Chapter 2

Voltage and Reactive Power Control

2.1 Introduction

In the past century, human civilizations have grown more and more dependant on electric power as a part of their daily lives. Since the early days of electricity, when it was used primarily for lighting purposes, a diverse range of applications have been developed. Electricity is used to light and heat homes, store personal records, to perform financial transactions, and perhaps in the not so distant future, even to power automobiles for general use. It is not surprising therefore, that consumers of electricity should demand a high degree of reliability and efficiency from their suppliers of electric power. Ensuring the reliability and efficiency of the electric power system is the primary goal of performing voltage and reactive power control in an electric power distribution system.

Voltage and reactive power control can be broken down into two main components,

namely:

a)   Power Factor Correction, and

b)   Voltage Regulation.

The first of these two components, power factor correction, deals with the efficiency with which electric power is distributed. The more efficient the distribution of electric power, the cheaper it is for both the supplier and the consumer. Power factor correction is one of the primary methods of reducing the power losses of electric power in the distribution system. The second component of voltage and reactive power control, voltage regulation, is performed in order to enhance the quality of service of the distribution system. That is, voltage regulation serves to improve the reliability of the system. The two components of voltage and reactive power control are described in greater detail below.

2.2   Power Factor Correction

Power factor correction is the practice of generating reactive power where it is consumed, rather than supplying it from a remote power station. The result of this is that the apparent power supplied to the load from the supply system, and hence, the total current supplied to the load, is reduced. This reduction in current corresponds to a reduction in the I^2R losses in the distribution lines, and hence, to an overall improvement in the efficiency of the distribution system. In addition to improving the efficiency, the reduction of distribution losses frees up system capacity, which may permit capital expenditures for system upgrades to be deferred.

In general, the onus for power factor correction is on the customer or end-user [2]. Typically, residential and commercial loads do not require much reactive power, and hence,

these types of loads generally do not require a power factor correction. Industrial loads, however, typically consume a considerable amount of inductive reactive power, and hence, they often require power factor correction. Furthermore, supply tariffs for industrial customers almost always penalizes low power factor loads. In Ontario for example, power-factors less than 0.9 incur a penalty [6]; it is therefore usually in the best financial interest of the industrial customers to perform power factor correction.

2.2.1 Compensation Theory for Power Factor Correction

Consider the single-phase system shown in Figure 2.1(a), having a load of admittance $Y_L = G_L + jB_L$ which is supplied from a voltage V. When V is taken to be the reference phasor, the resulting load current, I_L, is given by:

$$I_L = VY_L = V(G_L + jB_L) = VG_L + jVB_L = I_R + jI_X \qquad (2.1)$$

Hence, it is apparent that the load current consists of a real component, I_R, which is in phase with V, and a reactive component, I_X, which is in phase quadrature with V. The phasor diagram for an inductive load, which is the most common case, is given in Figure 2.1(b). In this case, the reactive current, I_X, is negative and the load current, I_L, is said to be lagging the voltage, V. The angle between the voltage and the load current is ϕ_L.

For the system shown in Figure 2.1(a), the apparent power, S_L, supplied to the load is given by:

$$S_L = VI_L^* = V^2G_L - jV^2B_L = P_L + Q_L \qquad (2.2)$$

Hence, it is clear that the apparent power has a real component, P_L, and a reactive

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component, Q_L. The real power, or active power as it is sometimes referred to, is the power which is capable of being converted into useful forms of energy such as heat, light and mechanical work. The reactive power, however, is incapable of doing useful work; none the less, its existence is an inherent requirement of the load. Consider for example an induction motor, in this case, the active power corresponds to the output power of the motor shaft plus all electrical and mechanical losses, such as those due to heating and air resistance, the reactive power on the other hand, represents the magnetizing power, which although it is not converted into useful energy, it is fundamental to the operation of the motor. The relationship between the real, reactive and apparent powers is shown in Figure 2.1(c). By convention, B_L is negative and Q_L is positive for inductive loads.

For the system shown in Figure 2.1(a), the current, I_S, supplied by the power system is equal to the current consumed by the load, i.e. $I_S = I_L$. Furthermore, from Figure 2.1(b) it is clear that the current supplied by the power system is larger than that which is necessary to supply only the real power required by the load by the factor:

$$\frac{I_L}{I_R} = \frac{1}{\cos \phi_L} \tag{2.3}$$

In addition, from Figure 2.1(c) the ratio of the active power to the apparent power is given by:

$$\cos \phi_L = \frac{P_L}{S_L} \tag{2.4}$$

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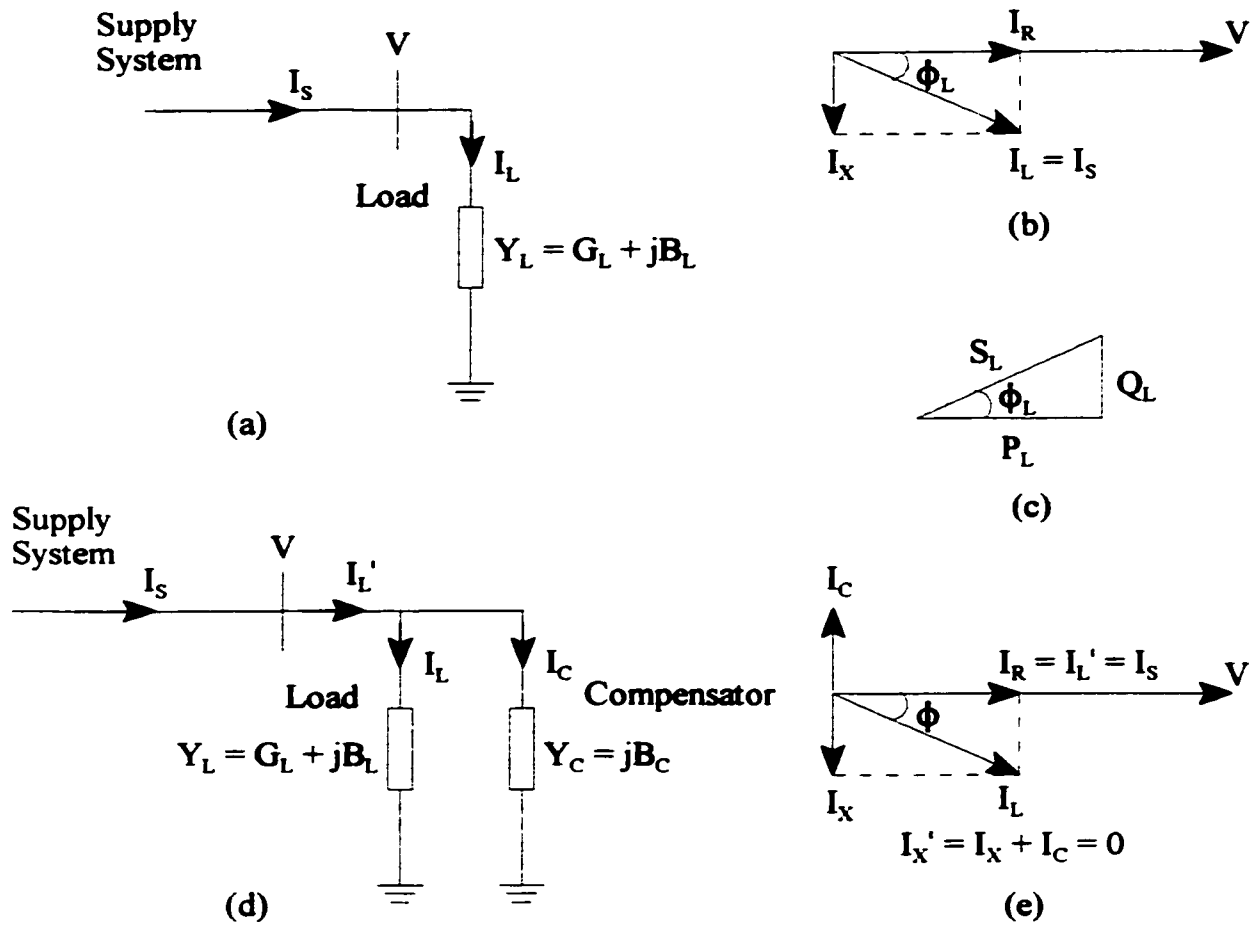
Figure 2.1 (a) through (e). Power factor correction. (a) Uncompensated system and corresponding phasor (b) and power (c) diagrams. (d) Compensated system and (e) corresponding phasor diagram.

Hence, the quantity, $\cos \phi_L$, is commonly referred to as the power factor, as it represents the fraction of the apparent power which can be converted into useful forms of energy.

As a result of the reactive power required by the load being supplied from the supply bus, the Joule losses in the distribution cables are increased from that when only the real power required by the load is supplied from the supply bus by the factor $1/\cos^2 \phi_L$. Consequently, it is desirable to keep the power factor near to unity. For poor power factor loads, $\cos \phi_L < 0.95$, compensation is generally employed in order to improve the power

factor. Compensation for this purpose is known as power factor correction. Power factor correction is performed by locally generating the reactive power required by the load, instead of supplying it through the distribution lines from the power system. In this way, the losses are reduced, and the entire distribution system operates more efficiently.

The method of power factor correction just outlined may be accomplished by connecting a compensator having a purely reactive admittance, $Y_C = -jB_L$, in parallel with the load, as is shown in Figure 2.1(d). As a result of this compensation, the current supplied by the power system becomes:

$$I_S = I_L' = I_L + I_C = V(G_L + jB_L) + V(-jB_L) = VG_L = I_R \qquad (2.5)$$

where I_C is the current drawn by the compensator and I_L' is the total current drawn by the load-compensator combination. In addition, the apparent power S_s supplied by the power system is:

$$S_S = VI_L'^* = V[V(G_L - jB_L) + V(jB_L)] = V^2G_L = P_L \qquad (2.6)$$

Note that the real and reactive power consumed by the compensator are respectively $P_C = 0$ and $Q_C = V^2B_L = -Q$, and keep in mind that by convention Q is positive for inductive loads. From Equation 2.5 it is apparent that the supply current of the compensated system is now in phase with V, and has the lowest possible magnitude which is capable of completely supplying only the active power requirement of the load. The phasor diagram for the compensated system is given in Figure 2.1(e).

For total compensation it is clear from Figure 2.1(c) that the reactive power rating of

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the compensator is related to the rated power of the load by:

$$Q_L = P_L \tan\phi_L \tag{2.7}$$

and to the rated apparent power by:

$$Q_L = S_L \sqrt{1 - \cos^2\phi_L} \tag{2.8}$$

The compensator rating per unit apparent power and per unit real power for complete compensation for various power factors are shown in Table 2.1. It is also possible to partially compensate the load. The degree of compensation which is required for a particular system depends on an economic trade-off between the capital cost of the compensator, which is proportional to its rating, and the cost of the power and energy losses over a period of time associated with supplying the reactive power required by the load through the distribution system. This trade-off has been considered extensively by many researchers and will be discussed further in Section 2.5. Consider for example, an uncompensated load having a power factor of 0.90, from Table 2.1 it is clear that in order to completely correct the power factor of this load a compensator with a rating of 0.436 per unit apparent power is required, while to correct the power factor to be no worse than 0.95 would only require a compensator with a rating of 0.124 per unit apparent power; this would translate into a considerable savings in the cost of the compensator employed.

Power Factor	Q_L/S_L	Q_L/P_L	$1/\cos^2 \phi_L$
1.0	0	0	1.00
0.95	0.312	0.329	1.11
0.90	0.436	0.484	1.23
0.85	0.527	0.620	1.38
0.80	0.600	0.750	1.56
0.70	0.714	1.020	2.04
0.60	0.800	1.333	2.78

Table 2.1. Rated reactive power of the compensator required for full compensation per unit rated apparent power of the load and power unit real power of the load for various power factors, and the corresponding factor by which the losses are increased.

Supply Bus   Load Bus

Z_S

Transmission Line

$Y_L = G_L + jB_L$
$S_L = P_L + jQ_L$

(a)

(b)

$Y_L = G_L + jB_L$
$S_L = P_L + jQ_L$

$Y_C = jB_C$
$S_C = jQ_C$

Load   Compensator

(c)

(d)
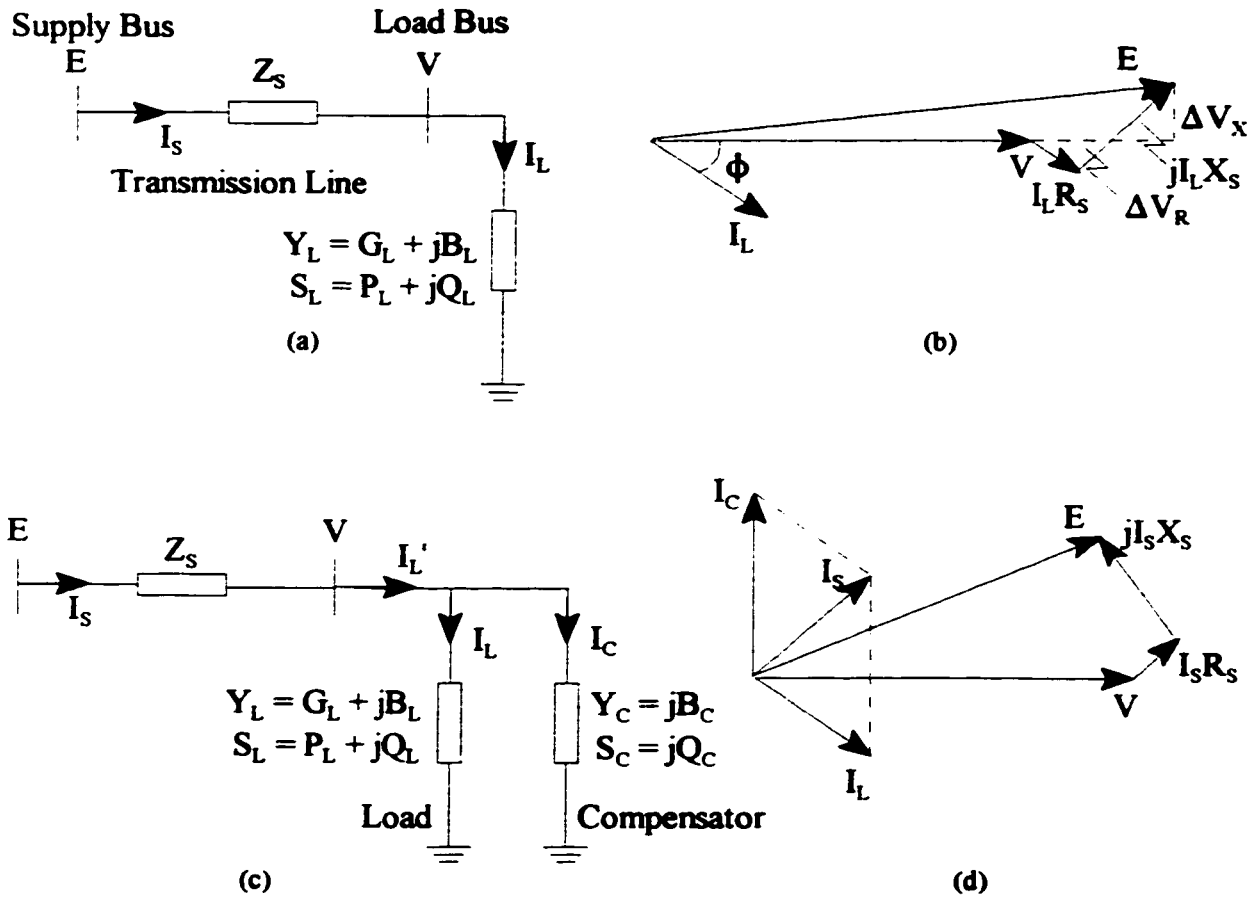
Figure 2.2 (a) through (d). Voltage Regulation. (a) Uncompensated system and (b) corresponding phasor diagram. (c) Compensated system and (d) corresponding phasor diagram.

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2.3   Voltage Regulation

In the previous section it was shown that the reactive power requirements of the load significantly affects the amount of supply current flowing through the distribution lines, and hence, the distribution losses. In this section it will be shown how this current also causes the variation, or regulation, of the voltage at the supply bus. In addition, the sensitivity of the supply bus voltage to the reactive power consumed at the load bus will be considered, and the theory of reactive power control for the purpose of voltage regulation will be considered.

The suppliers of electric power are required by statute to maintain the voltage of the system to be within ±3% and ±6% of the nominal rated value at each load point on the system for urban and rural customers respectively [2,3]. However, it will be shown that as a result of the impedance of the distribution lines which supply the current from the supply bus to the load bus, that there will be a voltage drop across this distribution line. Consequently, as the current increases in magnitude, so too does the voltage drop. It will be further shown that the voltage magnitude of the supply bus, relative to that of the load bus, can be controlled by employing a purely reactive compensator at the load bus.

2.3.1   Compensation Theory for Voltage Regulation

Voltage regulation is defined as being the proportional change in supply voltage magnitude associated with a defined change in load current [2]. By considering the single-phase distribution system shown in Figure 2.2(a), having a supply voltage E and a load voltage V, it is clear from the definition that the voltage regulation of this system is given by:

$$\frac{|E| - |V|}{|V|} = \frac{|E| - V}{V}$$

(2.9)

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where V is taken as the reference phasor.

The voltage change, ΔE, caused by the current, I_s, flowing through the distribution line having an impedance Z_s is shown in the phasor diagram of Figure 2.2(b), and is given by:

$$\Delta E = E - V = Z_s I_s \qquad (2.10)$$

From Equation 2.2 and the knowledge that $Z_s = R_s + jX_s$, and $I_s = I_L$, Equation 2.10 becomes:

Thus, it is clear that the voltage change has a component ΔV_R which is in phase with V and a component ΔV_X which is in phase quadrature with V. Furthermore, from Equation 2.11 it is evident that both the magnitude and phase of the supply voltage, relative to the load voltage, depend on both the real and the reactive power consumed by the load.

By adding a purely reactive compensator, i.e. $S_C = Q_C$, in parallel with the load it is possible to make the voltage regulation zero, that is, to make $|E| = |V|$. This is accomplished, by replacing the reactive power Q_L with the sum $Q_L' = Q_L + Q_C$, and choosing Q_C in such a way that the phasor ΔE is rotated until $|E| = |V|$. The phasor diagram for the compensated system is shown in Figure 2.2(c). It is evident from Equations 2.10 and 2.11 that:

$$|E|^2 = [V + \frac{R_S P_L + X_S Q_L'}{V}]^2 + [\frac{X_S P_L - R_S Q_L'}{V}]^2 \qquad (2.12)$$

Hence, the required value of $Q_C = Q_L' - Q_L$ can be found by solving this equation for Q_L' with $|E| = V$. The algebraic solution for Q_C is given in Section A of the Appendix. The important result here, however, is that no matter what the value of P_L, there is always a solution for Q_C.

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As a consequence, it can be concluded that a purely reactive compensator is capable of eliminating supply voltage variations caused by changes in the real and reactive power of the load. It should be pointed out that only the magnitude of the voltage is being controlled, its phase varies continuously with the load current.

2.4 Relationship Between Power Factor Correction and Voltage Regulation

Having shown that it is possible to use a purely reactive compensator either to reduce the reactive power supplied to the load by the power system to zero, or to reduce the voltage regulation to zero, it is important to determine the interrelation between these two processes. First, consider the case of a distribution system which is being compensated in such a way that the power factor of the load is unity. That being the case, Q_L in Equation 2.11 can be replaced with the sum $Q_L' = Q_L + Q_C = 0$. Hence the voltage change phasor, ΔE, becomes

$$\Delta E = \frac{R_S P_L + j X_S P_L}{V} = (R_S + j X_S)\frac{P_L}{V} \qquad (2.13)$$

which is clearly not under the control of the compensator. Therefore, it can be said that a purely reactive compensator cannot maintain both constant voltage and unity power-factor at the same time. Despite this, however, compensating for power factor does in general result in a reduction in the voltage regulation of the system.

Consider now, the case where the distribution system is being compensated in such a way that the voltage regulation is zero. In this case the current supplied by the distribution system to the load is given by Equation 2.6 as:

$$I_S = I_L' = \frac{P_L - j(Q_L + Q_C)}{V}$$ (2.14)

and its magnitude is given by:

$$I_S' = \sqrt{\frac{P_L^2 + (Q_L + Q_C)^2}{V^2}}$$ (2.15)

In contrast, the magnitude of the current without compensation is give by:

$$I_S = \sqrt{\frac{P_L^2 + Q_L^2}{V^2}}$$ (2.16)

Hence, it is clear that compensating the distribution system for the purpose of voltage regulation will result in a reduction of supply current, and hence, in a reduction of distribution losses, provided that $|Q_C| < |2Q_L|$ and that Q_C and Q_L be opposite in sign; otherwise, compensation will result in an increase in distribution losses. In fact, since the impedance of the distribution line is constant, it should be clear that whenever this condition is satisfied, that there will be both a reduction in losses and a reduction in voltage regulation, regardless of the purpose for which the compensation is being performed.

2.5 Factors to Consider

In developing the concepts of power factor correction and voltage regulation above, several simplifications were made; the distribution system was represented as a simple two bus system, the load was assumed to be constant with respect to time, and independent of

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voltage. Real distribution systems, however, may contain hundreds of busses. In this case, compensation at one bus will effect the level of compensation required at another bus. In addition, in order for a compensation scheme to be practical it must be economical. Hence, not every bus will require compensation. Typically this means that the system is compensated in such a way that the net power and energy losses are reduced while satisfying the constraint that the voltage at each bus be within ±6% of it nominal rated value as required by statute [2]. As a consequence, it is necessary to first determine which buses require compensation and which buses do not. This step is known as the placement problem. The placement problem not only requires a determination of where the compensators are to be placed, but also requires the type (fixed, switchable, or continuously variable) and rating of the compensators be determined. The placement problem has been considered extensively by many researchers. A good review of the more prominent techniques has been presented by Ng [4].

The practice of installing shunt capacitors in the distribution system is primarily of economic benefit, however, it does have the added advantage of improving the voltage profile of the system. Despite this, however, the cost of using shunt capacitors solely for the purpose of voltage regulation is often prohibitive. In this case it is often desirable to increase the voltage using a booster transformer. A booster transformer increases the voltage at an intermediate point along the distribution line rather than at the substation as with tap-changing transformers. The π-equivalent model of a typical booster transformer is given in Figure 2.3 [36,59]. Booster transformers give an in phase boost in the voltage just like the main tap-changing transformer at the substation. The booster transformer, however, has the advantage that its rating is only about 10% of that of a main transformer, as its rating is the product of

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the current and the injected voltage [2]. As with shunt capacitors, the number of booster

transformers to install ,their locations, and tap settings must be determined. This constitutes

another optimization problem which is closely coupled with the capacitor optimization

problem [4]. The voltage booster transformers are also often referred to as voltage

regulators, and from here on the two terms shall be used interchangeably.

A typical distribution system consists

of a combination of residential, commercial,

and industrial loads. Each of these types of

loads varies independently both with respect

to time and position. As a consequence, it is

necessary to develop a scheme to control the
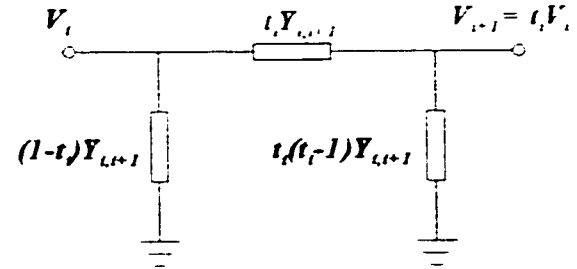
Figure 2.3. π-equivalent model of a voltage booster transformer [36,59].

compensators on the distribution system under varying load conditions so that the level of

compensation is always optimized. This is referred to as the control problem, and is the focus

of this thesis. The control problem consists of determining the optimal settings of the

compensators for any set of load conditions, and hence, for any instant in time. As a

consequence, the control scheme must be fast in order to be useful in practice. In the next

chapter both the placement and the control problems will be considered in greater detail, and

several 'modern' techniques developed by other researchers for solving these problems will

be discussed.

2.6   Summary

The two principle objectives of voltage and reactive power control, namely power-

factor correction and voltage regulation have been presented. It has been shown that a purely

reactive compensator is capable of fulfilling either of these objectives. It has also been shown, however, that the purely reactive compensator cannot maintain both constant voltage and unity power-factor at the same time. However, it was shown that regardless of the reason for the compensation, that both the losses and the regulation will be reduced provided that $|Q_C| < |2Q_L|$ and that Q_C and Q_L be opposite in sign.

While the concepts of voltage and reactive power control presented here were developed based on a simple two bus system, they are readily adapted to more realistic multi-bus systems. In addition, in most of the previous publications it was assumed that the characteristics of the load were constant. In general, however, this is not the case, as the load is a dynamic quantity. As a consequence, a compensation error occurs, and typically requires that the level of compensation provided by the compensators placed on the distribution system be capable of being varied over time. It is important therefore, to be able to quickly determine the correct level of compensation for any load conditions, and hence, for any instant in time. This process, known as the control problem, is quite complicated and has been studied by many researchers. The control problem is the focus of this thesis and will be considered further in the next chapter.

Chapter 3

Review of Previous Research

3.1   Introduction

As was mentioned in the previous chapter, the voltage and reactive power control problem consists of two subproblems: the placement problem and the control problem. The placement problem involves planning, and consists of determining the optimal location, size, type and number of compensators that are required for a distribution system, taking into account the cost of the compensators, the savings from energy and power loss reduction, as well as the bus voltage constraints. The control problem, in contrast, is an operational one, it involves determining the optimal compensator settings under varying load conditions, such that the power losses of the system are reduced, and the constraints of voltage are met. Both the placement and the control problems require that an accurate model of the load be used in order to arrive at meaningful solutions. The placement problem is a means of improving

the performance of the distribution system and can be performed off-line. In contrast, the control problem, must be performed on-line in order to be able to control the system in real-time; consequently, one requirement of any algorithm which performs the control problem is that it be fast.

In this chapter various methods for solving the placement and the control that have been proposed by other researchers will be discussed. In section 2, early research into both the placement and the control problems will be addressed, with particular attention being paid to the improvements made over the years in system modeling and problem formulation. In section 3, the 'modern' techniques for solving the placement and the control problems will be considered. The 'modern' techniques considered include those based on:

a) Fuzzy Logic and Fuzzy Sets,

b) Artificial Neural Networks;

c) Expert Systems, and

d) Genetic Algorithms.

3.2 Early Voltage and Reactive Power Control Research

The placement and control problems are very similar in nature, and the material available on the placement problem is much more abundant; in fact, many of the algorithms which were developed for the control problem are simply adaptations of those used for the placement problem. It is important, therefore, to have a thorough understanding of the placement problem before considering the control problem.

3.2.1 The Placement Problem

Perhaps the most important property of any method involving the determination of

the optimal placement or control of compensators on a distribution system is the model which is employed to represent the distribution system. In the early research into the optimal capacitor allocation problem by researchers such as Schmill [47], Neagle and Samson [48], Cook [49], Chang [50-52] and Bae [53], the distribution feeder was represented either as a uniform feeder having uniformly distributed loads, or as a uniform feeder having uniformly distributed loads along the feeder and a concentrated load at the end of the feeder. The assumption of a uniform feeder with uniformly distributed loads does not take into account the following features of a practical distribution feeder:

a)   Lateral branches,

b)   Loads are not uniformly distributed, and

c)   The conductors of the feeder sections are of varying length and varying cross-
       sectional area, and hence, each section of the line has a different impedance.

During 1980's, the model for the system became more realistic. In [55], Grainger and Lee developed a model which could represent a feeder having non-uniformly distributed loads. Then Salama and Chikhani, [64], presented a method for performing the capacitor placement problem which was not only capable of representing non-uniform load distributions, but could also represent a feeder having lateral branches.

Grainger et al, [59,60,61], and Salama et al., [71,72], have incorporated the problem of placing booster transformers on the system into their solution methodology for the capacitor placement problem. Both researchers accomplished this by decoupling their optimization methods into separate capacitor and booster transformer problems, and then solving the problem iteratively. However, as mentioned in Chapter 2, there is a voltage

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coupling between these two problems.

The improvements in system models were accompanied by improvements in commercially available computers. This development facilitated the solution of the more complex problem representation. As well, it made possible the development of fast techniques that were suitable for on-line application, and hence, for application to the control problem.

3.2.2 The Control Problem

In the early research into controlling the compensators on a distribution system only fixed compensators were considered. As the system models improved, researchers were able to consider switched compensators as well. Most of the research was consisted of dividing the load into discrete load levels of fixed duration, then solving the placement problem for each load level. Based on the results, a switching schedule would be compiled. This method, however, was unable to respond to dynamic changes in the load and often included simplifying assumptions such as all the load varying in the same proportion. Now, with the development of 'fast' computer systems and the availability of data from Supervisory Control And Data Acquisition (SCADA) systems, online decisions can be made which are based on the real-time condition of the distribution system.

The automation of electrical power distribution circuits has long been an active area of research, and has been achieved with varying degrees of success [81-88]. As the size of distribution systems continues to grow, so too does the computational difficulty associated with their control. As a result distribution engineers are finding it increasingly important to have computational tools at their disposal which are capable of handling such large-scale

problems. In order for the computational tools to be particularly useful, they must be capable of fast processing in real-time for on-line applications. Many of the computational tools which are currently being developed are based on Artificial Intelligence techniques. The use of these 'modern' techniques in solving both the placement and the control problems shall be discussed next. For a discussion of those methods which do not employ these 'modern' techniques, the reader is referred to [4].

3.3 "Modern" Techniques for Voltage and Reactive Power Control

"Modern" techniques for solving the voltage and reactive power problems include techniques based on fuzzy logic and fuzzy sets, expert systems, artificial neural networks and genetic algorithms. These techniques have been applied to both the placement and control subproblems of the voltage and reactive power problem and include references [10 - 28]. Each of these techniques will be discussed in detail, and their application by other researchers to the voltage and reactive power problems will be thoroughly examined.

3.3.1 Methods Based on Fuzzy Logic Systems

Fuzzy set theory and fuzzy logic was first introduced by Zadeh in 1965 [41]. Fuzzy logic makes it possible to generate precise solutions to a problem based on imprecise, uncertain or approximate information. Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth - truth values between completely true and completely false. A fuzzy set is a class of objects having a continuum of degrees of membership which are characterized by a membership function. The membership function assigns a degree of membership to each object. The degree of membership ranges

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from zero to one; zero represents non-membership and one represents complete membership.

The degree of membership can also be thought of as the degree of truth associated with an

object. In this case, the value zero would correspond to completely false, while the value one

would correspond to completely true. As an example, consider the following statement: the

load at a bus of a distribution feeder is heavy.

The question then becomes how light is

"light". Fuzzy sets are ideally suited to

answering such questions.

If X is a space of points, with a

generic element of X being denoted by x, then

X = {x}. A fuzzy set A in X, characterized

by the membership function $\mu_A(x)$, is defined

to be the set of ordered pairs, A = {x, $\mu_A(x)$

| x ∈ X and $\mu_A(x)$ ∈ [0,1]. Many of the

notions from ordinary sets, such as: empty,

inclusion, union, intersection and complement

also extend to fuzzy sets and will be defined

now. A fuzzy set is empty, A = { }, if and

only if $\mu(x)$ = 0 for all x ∈ X. Two fuzzy sets,

A and B, are equal, A = B, if and only if $\mu_A(x)$

= $\mu_B(x)$ for all x ∈ X. The compliment, Ā, of

a fuzzy set , A, is defined by $\mu_A(x)$ = 1 -
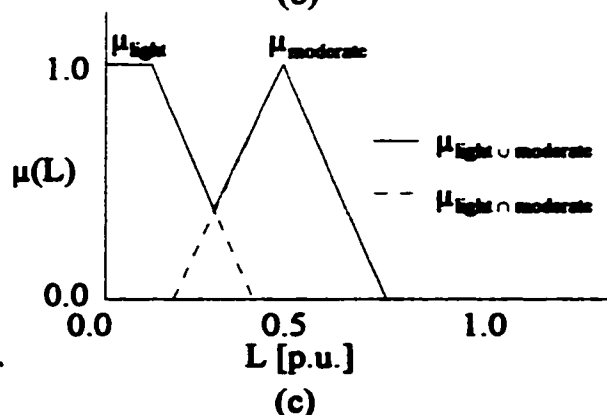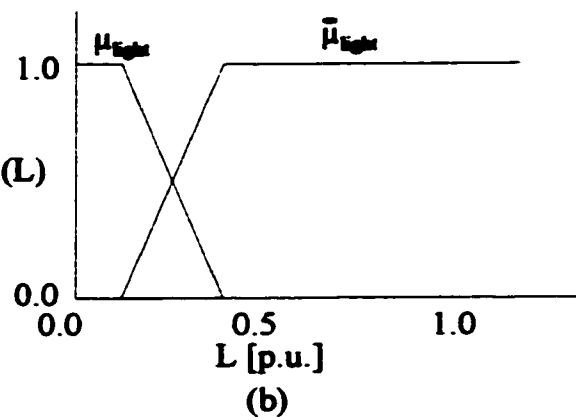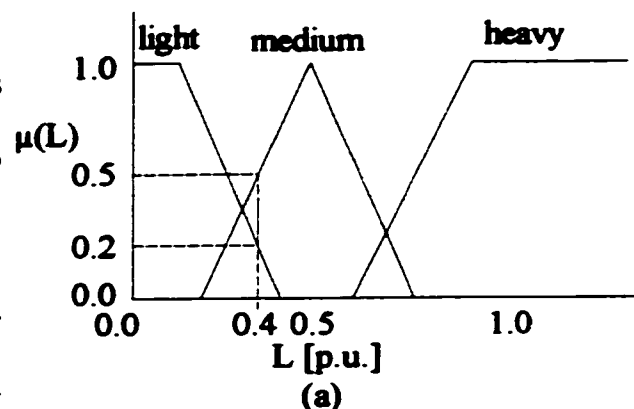
Figure 3.1. (a) Membership functions, (b) compliment and (c) intersection and union.

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$\mu_A(x)$. A is said to be a subset of B, A $\subset$ B, if and only if $\mu_A(x) \leq \mu_B(x)$. The union of A and B is a set C = A $\cup$ B, whose membership function $\mu_C(x)$ = max $[\mu_A(x), \mu_B(x)]$. The intersection of A and B is the fuzzy set C = A $\cap$ B, whose membership function is given by $\mu_C(x)$ = min $[\mu_A(x), \mu_B(x)]$.

To illustrate the concepts of fuzzy sets, consider again the example of the load, L, at a bus of a distribution feeder. The fuzzy sets light, moderate and heavy, can be defined by the membership functions μ_{light}, $\mu_{moderate}$ and μ_{high} respectively, as shown in Figure 3.1(a). From this it can be seen that a load of about 0.4 p.u. would be interpreted as belonging to the set light with a degree of 0.2, as belonging to the set moderate with a degree of about 0.5, and as not belonging at all to the set high [6]. Figure 3.1(b) illustrates the compliment of the fuzzy set light, and Figure 3.1(c) illustrates the notions of the union and intersection of the fuzzy sets light and moderate.

Fuzzy sets have been applied to a diverse range of power system applications [*find a ref summarizing fs apps in pwr sys]. Their suitability to the voltage and reactive power control problem has also been considered [10-12]. What follow is a review of their application in this area.

In [11], Tomsovic presents a fuzzy linear programming approach to the voltage and reactive power control problem for the purpose of voltage regulation. In his formulation, the steady state power flow equations are decoupled and linearized, and the voltage constraints are modeled by fuzzy sets. He considers multiple objective functions and tests his system using the IEEE 30-bus system under two cases. In the first case, there is a minor voltage violation, and in the second case there are severe voltage violations. He considers two sets

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of fuzzy objective for each case, and compares the results from the fuzzy linear programming method with those obtained using a standard linear programming approach. In the standard linear programming formulation, the objective was to minimize control adjustments while satisfying all constraints. The first set of fuzzy objectives consisted of giving a priority to the available controls as well as the objective of minimal control adjustment. Priority was translated into a cost function by assigning weights to each type of control, with reactive compensator injection and generator voltage control being given priority over on load tap changing transformer adjustment. It should be pointed out that no method of determining these weights was presented. A security consideration was added to the first set of fuzzy objectives to form the second set of objectives. This security objective expressed a preference for maintaining significant reactive power reserves for each generator. For both sets of objective functions, the fuzzy linear programming method sought to maximize a net savings function, which was defined by the intersection of the constraints with the objective functions. For the case of minor voltage violations, all three methods resulted in a solution which satisfied all voltage constraints in a single iteration. For the case of the serious voltage violations, however, the standard linear programming approach required several iterations while the fuzzy approaches only required a single iteration. In this simulation, the solution from the standard linear programming method required fewer control actions than either of the fuzzy methods. The ability of fuzzy based methods to make compromises between multiple conflicting objectives was well demonstrated under this situation, as the solution from the second fuzzy approach resulted in a smaller adjustment of generator at bus 8, compared with the solution from the first fuzzy method, by making a tap adjustment at bus

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26. This represents the compromise between the minimal control adjustment objective, the voltage constraints and the objective of maintaining reactive power reserves at the generators.

Abdul-Rahman and Shahidehpour, [10], present a fuzzy based linear programming approach to the voltage and reactive power control problem for the purpose of reducing losses under the limitation of voltage constraints. In their approach, the power losses in each section of the system are linearized about the current operating point with respect to the bus voltages, and represent the objective functions. The relationships between voltage increments, transformer tap positions and VAR sources (generator reactive power outputs and switchable capacitors) are derived and correlations between them are given by a modified Jacobian matrix. As a result of this formulation, inversion of the modified Jacobian matrix is not required, resulting in a considerable savings in computation time. Abdul-Rahman and Shahidehpour use fuzzy sets to model the linearized objective functions as well as the voltage constraints. They present membership functions for the objectives which are dependant on the current operating point of the system. The membership functions for the bus voltage constraints are defined such that slight voltage violations are allowed. They accomplish this with a membership function that for voltages between the crisp limits has a value of one, while bus voltages that exceed these limits have a value of satisfaction that decreases to zero at a pre-specified voltage increment. In the fuzzy environment the process of maximizing the objective functions while satisfying the constraints is equivalent to maximizing an overall membership function that is defined as the intersection of the fuzzy sets describing the objectives and the constraints. The overall solution of the problem represents a compromise between the objectives which try to push the voltages towards the extremes in order to

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minimize the losses and the constraints which seek to keep the voltages away from the extremes. Considering that the problem domain is convex, the formulation of n multiple objectives by decomposing the total losses of the system into its n additive parts seems to be unnecessary as it will lead to the same solution as the single objective of minimizing the total losses, provided that equal weights are assigned to all the individual objectives, as was the case in their work. The fuzzy based linear program approach was implemented and tested on the Ward and Hale 6-bus system as well as a modified IEEE 30-bus system. Their approach for the 6-bus system resulted in losses being about two percent lower than those obtained from a non-fuzzy based method. As well, the fuzzy based approach converged in five iterations, while the non-fuzzy method required seven iterations to converge, however, the computation time per iteration for the fuzzy case was about 0.38 seconds, while for the non-fuzzy method it was only about 0.33 seconds. For the 30-bus system, the fuzzy based approach resulted in losses being reduced by 12.9% as compared to the losses from a non-fuzzy approach, this can be explained by the fact that the fuzzy based approach resulted in the voltages at six of the buses exceeding their crisp limits. The fuzzy approach required 10 iterations with a time per iteration of 2.99 seconds, while the non-fuzzy method required 14 iterations with a time per iteration of 2.23 seconds. In each case, the fuzzy based linear programming approach was faster than the non-fuzzy based linear programming approach, as the non-fuzzy method required the inversion of the Jacobian matrix at each iteration, while the fuzzy based method did not. Overall, their results were quite promising.

Lu and Hsu, [12], present a fuzzy based dynamic programming approach to control an on load tap changing transformer and an on/off switchable capacitor at a distribution

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substation. The objective of their controller is to maintain the secondary bus voltage as close as possible to its nominal value, while keeping the power factor as close to unity as possible, under the constraint of keeping the number of switching actions of both the on load tap changing transformer and the capacitor to a minimum. In their approach they develop fuzzy membership functions for the voltage, power factor, number of tap changing transformer switching actions and the number of capacitor switching actions. Their objective becomes that of maximizing the sum of these objectives over a 24 hour period. They do not make use of fuzzy operators such as the intersection of fuzzy sets. Using forecasted load data, Lu and Hsu report that their fuzzy based approach results in an improvement both in the voltage at the secondary bus and the power factor at the substation. It should be pointed out that their algorithm employs a load model which represents the load as a combination of constant power, constant current and constant impedance loads, with the proportionality coefficients for both the real and the reactive power being taken from the annual report of the Taiwan Power Company for the substation under study.

3.3.2 Methods Based on Artificial Neural Networks

Artificial neural networks (ANNs) have been applied to a diverse range of power system applications [9,39]. Their suitability to the voltage and reactive power control problem has been well studied [15 - 22]. The details of ANNs will be presented next, as well as a review of their application to voltage and reactive power problems.

ANNs are low level, parallel distributed processing systems, which are modeled after the neurons in the human nervous system. ANNs consist of many loosely connected processing elements (PEs) which are linked by weights analogous to the biological synapse

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[43]. These weights are self adjusted by the ANN while it is being trained, hence, ANNs are capable of learning a relationship between complex input and output variables. The output of the each PE is determined by a transfer function, such as the sigmoid function, hyperbolic tangent or sine functions [6]. A PE is shown below in Figure 1.

Inputs   **Weights**

x_1 ——→ w_1

x_2 ——→ w_2

$\cdot$ $\cdot$

$\cdot$ $\cdot$

$\cdot$ $\cdot$

x_n ——→ w_n

Σ ——→ **Transfer Function** ——→ **Output**

Processing Element (P.E.)
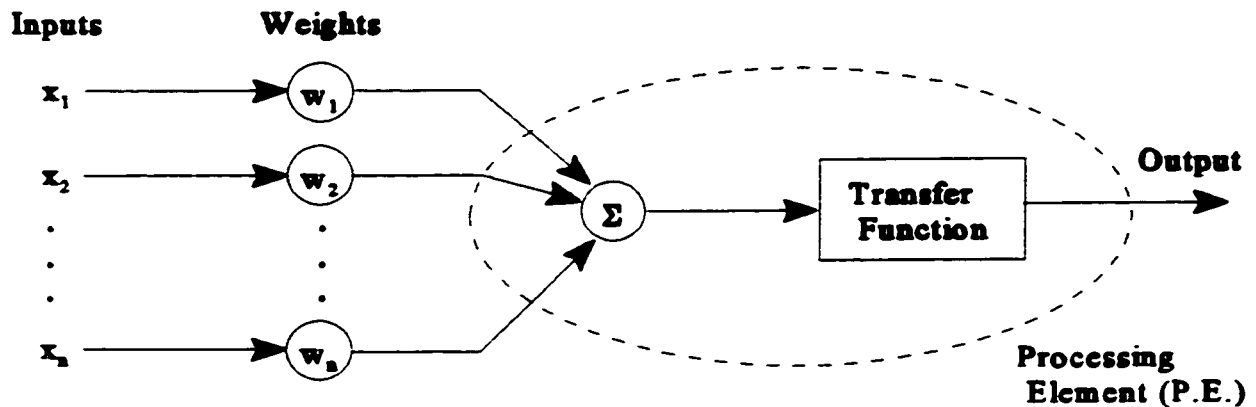
Figure 3.2. A Processing Element of an Artificial Neural Network.

In order to be useful, ANN must first be trained in order to minimize the error function to an acceptable value. Training is accomplished by adjusting the network weights using an algorithm such as the backpropagation algorithm [6]. One of the characteristic features of ANNs is its ability to adjust its own weights, for this reason the training of the ANN is similar to a learning process. Perhaps the most common method for the ANN to adjust its weights is through the use of the backpropagation algorithm. According to the backpropagation algorithm a global error function is associated with the network, usually it is the difference between the actual output of the ANN and the desired output. This error is attributed to all of the PEs, and is corrected by propagating it backwards through the network connections from one layer to the next, until the input layer is reached [6]. Hence, the name "backpropagation." As the error function passes through each of the PEs, the network

weights are adjusted appropriately. In effect, with the backpropagation algorithm, the input is forward propagated through the network connections until the output layer is reached, the error at the output is then determined, and is then propagated back through the network until the input layer is reached.

Depending upon the configuration of the interconnections between processing elements ANNs demonstrate various abilities including: classification, nonlinear mapping, optimization, feature extraction, and pattern recognition [43]. The four principle ANN architectures are [43]:

a) the layered feed-forward neural networks, such as the multi-layer perceptron,

b) the recurrent neural networks, such as the Hopfield network,

c) the laterally connected neural networks, such as the Kohonen network, and

d) the hybrid neural networks, such as the Counter-propagation network.

Irrespective of the particular architecture employed all neural networks consist of layers of neurons (processing elements), with each neuron in a given layer being connected to the input of every neuron in the next layer, as shown in Figure 3.3. As a result of being highly interconnected ANNs have the attributes of generalization, fault tolerance, and noise rejection [43]. In addition , due to their massive parallelism ANNs are not restricted by the bottle neck characteristic typical of von Neuman computers, i.e. sequential processing computers [15,43].
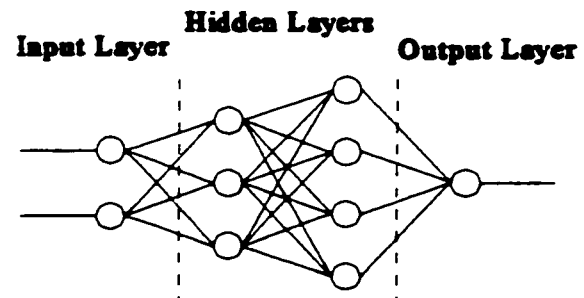
Figure 3.3. Interconnection of processing elements in an Artificial Neural Network.

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In [16], Kojima et al. present an ANN based controller for switching a capacitor bank installed on a distribution system. They used a recurrent neural network to learn the dynamics and inverse dynamics of a power system. Recurrent neural networks are inherently associated with the dynamics of the system because of their internal feedback loop, as well, sequential signal treatment is easier with recurrent neural networks than with other ANN configurations. They compare their ANN based controller to a conventional controller using a power system having 10 buses and 2 tap changing transformers and 5 static VAR compensators. In their approach, each compensator has a separate controller. Using simulated data their ANN controllers require a total training time of about 45 minutes on a Sun SPARC station 2. The objective of their controller is to improve the stability of the system and prevent voltage collapse by providing maintaining the voltage and reactive power at each bus as close as possible to their reference values. They report that their ANN based controller results in fewer useless switching actions and has RMSEs for both the voltage and the reactive power , with respect to their reference values, that are five times better than those obtained using conventional control on the same system.

Dash et al, [17] applied a three layer feed-forward neural network to a modified IEEE 30 bus system to evaluate the performance of two training algorithms (backpropagation and combined backpropagation-Cauchy's learning algorithm) in controlling the capacitors at selected buses [17]. The results of their tests show that while both algorithms produced satisfactory results, the combined backpropagation-Cauchy algorithm was more effective. They tested the system under two conditions for each training scheme. In the first case, the there were 12 inputs to the ANN, these were the P, Q and |V| at four buses which were

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chosen based on a sensitivity analysis. In the second case, there were 24 inputs to the ANN, these were the P, Q and |V| at the original four buses plus another four buses which were also chosen based on a sensitivity analysis of the system. The ability of their ANN to consistently perform well even when the net is faulty, and presented with noisy information was illustrated as their ANN controller produced consistent outputs even when presented with noisy inputs and faults as high as 20% in the network.

In [20], Hsu and Yang present a combined ANN dynamic programing solution to the capacitor scheduling problem for an eight bus distribution feeder of the Taiwan Power Company, having one on/off switched capacitor at each bus. They employ a Kohonen neural network structure to classify the daily load patterns into clusters, or groups, of similar load patterns. In their study, each daily load pattern is a 24 dimensional vector which consists of the substation load level measured at each hour during the day. Hsu and Yang make use of historical load data which was available for the feeder under study. Before clustering the load patterns, the optimal compensation scheme taking into account voltage constraints, the cost of the losses and of switching the capacitors for each load pattern, that is, the optimal on/off states of each capacitor for each hour, is calculated off-line. After classification, the compensation schemes for each cluster are averaged resulting in a 24 8-dimensional vectors where each element represents the state of a particular capacitor at the particular hour, and has a value from 0 to 1. As the load patterns in each cluster a very similar, their respective compensation schemes will also be quite similar, and hence, the elements will be very close to either 0 or to 1. The degree that each element is close to 0/1 indicates the degree of certainty that the capacitor represented by that element will be off/on. Those elements with

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a value that is either below some threshold or above some other threshold are assigned a 0/1 as appropriate. For those elements which are less certain, a second dynamic programming approach is used to decide their 0/1 (off/on) states. For a day in the future, the forecasted load pattern is then compared with each cluster and it is grouped with the most similar one, where the similarity is determined by the forecasted load patterns Euclidean distance from the various clusters. Once the forecasted load pattern is grouped, the appropriate compensation scheme is then chosen. The results obtained from their method were quite good, and for the small system studied, the ANN required about 10 minutes to be trained, and once trained, the capacitor schedule for a given load pattern could be determined in less than one minute. Their method however, does not consider voltage regulators, and requires that a large amount of historical data to train the ANN.

Santoso and Tan, [21], develop an expert system using a two-stage ANN in order to control, in real-time, the multi-tap capacitors which are installed on the distribution system having a nonconforming load profile. The goal of their expert system is to minimize the losses without violating any voltage constraints. They propose an expert system which employs several three layer feed-forward ANNs for both its knowledge base and for its inference engine. Their first stage of their control network predicts the load profile of the distribution system based on the input of P,Q, and |V| at certain buses, as well as from the current tap settings of the capacitors. The second stage of their control network then determines the optimal capacitor tap settings based on the load profile predicted by the first stage. They simulated their control system on a 30 bus distribution system which they further divided into six subsystems, with each subsystem having a first stage ANN to predict its load

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pattern. In addition, the aggregate load of each subsystem varied independently among four discrete load levels, while the real and reactive powers in each subsystem varied proportionally. Their test system had five capacitors which needed to be controlled, these capacitors were placed at fixed locations according to the method presented in [44] which takes into account the peak power demand, varying load profile, as well as the cost of the compensators. All of the ANNs in their study were trained using simulated data, and none required more than 200 seconds to be trained, resulting in a total training time of less than 25 minutes. Once trained, their expert system produced quite good results, and had an average solution time of 2.8 seconds. While their results are promising, they are for a rather small distribution system, and require that the system be subdivided into subsystems; such a division may not be obvious for a larger more realistic size system. As well, their algorithm does not consider the control of voltage regulators.

In [22], Gu and Rizy present an ANN based method for the combined control of capacitor banks and voltage regulators in a distribution system. They employ a three layer feed-forward ANN and the backpropagation training algorithm. The inputs to their ANN controller are the P,Q and |V| at select points of the distribution system, as well as the current tap settings. In addition, there is one output for each controlled device, that is, each output corresponds to a particular capacitor or voltage regulator. Their goal of their ANN based controller is to minimize the distribution losses under the constraint that the bus voltages are within ±5% of their rated values. They apply their ANN controller to the same 30-bus system as that presented in [21,61]. The location of the capacitors are the same as in [21], but their ratings are increased and a nine tap voltage regulator is added at bus 4 in order to satisfy the

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voltage constraints under maximum loading conditions. As well, Gu and Rizy only consider on/off switched capacitors, as opposed to four position capacitors as was considered in [21]. Their ANN was trained with simulated data on a Pentium 90 MHz based personal computer with a total training time on the order of minutes. Once trained their ANN based controller had a solution time of a few milliseconds! Obviously, the speed of their approach would be well suited for real-time, on-line application. Using simulated data, they performed Monte Carlo simulations, and report that their controller resulted in average energy losses that were only 0.19% higher than the true optimal energy losses for the system. Their method however, often results in slight voltage violations occurring at two of the thirty buses.

ANN based approaches have the advantage that they do not require algorithm or rule development, they do however require a large amount of accurate training data so that the ANN can learn to recognize the correct response to a particular input pattern. ANNs have proven themselves to be quite useful for applications in which the existing models do not have enough accuracy and where large amounts of historical data are available for training; an example of such an application is load forecasting. The applications of ANNs to the voltage and reactive power control problem offers the benefit of a fast solution, as time consuming load flows to not need to be performed. Despite this however, their applicability to the voltage and reactive control problem is limited by the following: a) a considerable amount of time is required for collecting accurate training data, the ANN must be trained for each distribution network to which it is applied, and any subsequent changes in the system must be accounted for. To date, ANNs have only been applied to small sized distribution systems. The author is only aware of one case in which ANNs were applied for the control of both

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switched capacitors and multi-tap voltage regulators under the constraint of bus voltages.

3.3.3 Methods Based on Expert Systems

Expert systems are computer programs that have knowledge in a particular, usually narrow, domain and are capable of solving problems which require that knowledge. For this reason, expert systems are often referred to as knowledge based systems. The aim of expert systems is to perform an intellectual task in a particular field by reproducing the reasoning behaviour of a human expert in that field [74]. Recently, the application of expert systems to various power system problems have been studied, [76,77]. Of particular interest here, is their suitability to voltage and reactive power control problems.

Expert systems consist of three main components, a knowledge base, an inference engine and a user interface. The knowledge base comprises the knowledge that is specific to the problem domain, and includes simple facts about the domain, rules that describe phenomena in the domain, and heuristics and methods for solving problems in the domain [14]. The former is generally contained within a database, while the later two normally form what is called a rule base. The inference engine is what drives the expert system, it applies the knowledge in the knowledge
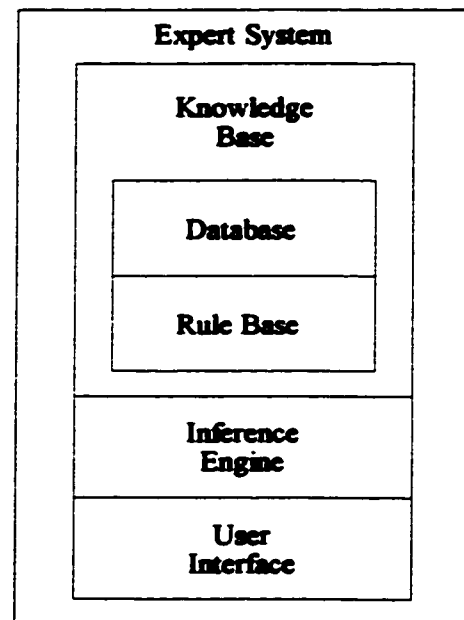
Figure 3.4. Block diagram of an Expert System.

base in order to solve a problem. In essence, the inference engine is capable of deducing (or inducing) facts or information from the knowledge base which have not been stored in it. The

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base which have not been stored in it. The user interface provides the communication between the expert system and the user. A block diagram of an expert system is shown in Figure 3.4. One of the most desirable characteristics of expert systems is their ability to justify, or explain, their line of reasoning to a human user. As a result of this characteristic, expert systems lend themselves very well to applications of assisting or training humans in a particular area of expertise. This is the primary role that expert systems have played in the area of voltage and reactive power control. What follows is a review of the research in which expert systems are applied to voltage and reactive power control problems.

In [13], Liu and Tomsovic present an expert system to assist in the decision making process of the voltage and reactive power control problem for the purpose of eliminating voltage violations. They provide theoretical justification for empirical rules, which their expert system applies in order generate the appropriate control actions to alleviate slight voltage violations. The controls considered are shunt capacitor, transformer tap changers and generator voltages. When the expert system deems the voltage problem to be severe, it formulates the problem so that an available application software package can be utilized. Their expert system was implemented in the production system language OPS5 developed by Carnegie-Mellon University [13]. They evaluated their expert system on a modified IEEE 30 bus system under various test scenarios with encouraging results. Liu and Tomsovic note that in order to develop an expert system for practical purposes would require a lot of research into areas such as methodologies to deal with large, complex systems and computational efficiency in real time environments.

Cheng, Malik and Hope, [14], develop an expert system for the control of voltage and

reactive power for the purpose of voltage regulation. Their expert system employs a methodology known as the sensitivity tree as part of its knowledge base. However, the sensitivity factors of the sensitivity tree must be determined for various operating configurations, and they may not be obvious. The control measures considered to overcome voltage violations are shunt capacitors, transformer tap changes and generator voltage adjustments. They implemented their expert system in the PROLOG language and evaluated it using a modified IEEE 30-bus system under various scenarios with promising results.

In [35], Yokoyama, Niimura and Nakanishi present an expert system for the purpose of voltage regulation. Unlike traditional expert systems, theirs employs fuzzy rules in its rule base. They define fuzzy membership functions for the bus voltages, the sensitivity of bus voltages to control action and the adjustable margin of each controller. They evaluated their fuzzy expert system on a modified IEEE 14-bus system, and compared the results obtained with those from a conventional expert system proposed by Liu and Tomsovic, [13]. They found that as a consequence of fuzzy modeling, the control actions determined by their expert system often results in coordinated control action, whereas, the traditional expert system tended to select only the controller with the highest sensitivity to correct voltage violations. Hence, their fuzzy expert system approach often resulted in more complex control action being taken, however, this also resulted in the distribution system being less vulnerable to further voltage violations as compared to when the conventional expert system was used. It should be pointed out, however, that their expert system did not consider the use of tap changing transformers and employed several simplifications to model the system, including a constant power model for the loads and a linear relationship for the sensitivity of the bus

voltages to the control action.

Salama et al., [71,72], develop an expert system for assisting the distribution planning engineer with the determination of the optimal locations, sizes and scheduling of shunt capacitors and the tap settings of voltage regulators. The objective of their expert system was to maintain the bus voltages within limits while reducing the peak power and energy losses. The knowledge base of their expert system was based on the methods of Grainger et al., [54,59-61], and Salama et al., [63,64]. Their expert system was implemented using an expert system shell, Nexpert Object, written in the C language by Neuron Data Inc. [72], on both a 33 MHz 80486DX and a 16 MHz 80386SX based computer. They tested their expert system on an IEEE 34 bus distribution system. The results obtained using their expert system were very close to those obtained by applying the method of [64] to the same system, under the same conditions. Salama et al. do not mention the time required by their expert system to arrive at a solution, however, as it employs an iterative procedure, it is not likely that it is suitable for real time applications.

The application of expert systems to voltage and reactive power problems is still in the early stages of development. To date, the approaches reported are primarily aimed at training or assisting the distribution engineer. In all of the expert systems based approaches just discussed, the authors do not mention the time required for their systems to arrive at a solution. As well, none of the researchers examined a system of realistic size. There is still much work that needs to be done in order to develop expert system based methods for solving voltage and reactive power control problems.

3.3.4 Methods Based on Genetic Algorithms

Genetic Algorithms (GAs) were developed by John Holland and his colleagues at the University of Michigan [42]. They are based upon the principles of natural selection and natural genetics. Genetic algorithms form a domain independent search and optimization technique which is inherently robust, and can be applied to a wide variety of problems where traditional solution methods are not available or provide unsatisfactory results. The physical processes involved include competition, selection, reproduction, and mutation.

Genetic algorithms are essentially a random search technique which is guided towards the optimal solution. In genetic algorithms each generation, t, consists of a population of n individuals, $P(t) = \{x_1^t, ..., x_n^t\}$, where each individual, x_i^t, represents a possible solution point in the search space. Each individual in the population is evaluated according to an objective function to determine its "fitness", hence, the objective function is often referred to as a fitness function, $f(x_i^t)$. The "better" individuals in the current generation, $P(t)$, are selected probabilistically to be parents for the next generation, $P(t+1)$. These parent individuals are paired off into mating pairs, and give rise to the offspring that comprise the new generation by the probabilistic application of genetic operators. In genetic algorithms the two most common operators are crossover and mutation. After several generations the population converges, and the best individual hopefully represents the optimum solution [6].

In genetic algorithms, as in natural genetics, each individual is characterized uniquely by its genetic makeup. In natural systems, one or more chromosomes combine to form the total genetic structure of an organism, with each chromosome being made up of many genes which may take on some number of values called alleles, As well, the position of a gene within

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a chromosome, its locus, is identified separately from its function. For example, an animal's eye colour gene may be described by its allele value, brown eyes, and its locus, position 10. In artificial systems, such as genetic algorithms, a chromosome is equivalent to a string which is comprised of features or detectors analogous to the genes in a biological system. The features in the artificial system may take on different values and may be located at different positions along the string. In natural genetics, the organism formed by the interaction of the genetic material with its environment is referred to as the phenotype, while in genetic algorithms, the structures decode to form a particular solution in the search space [38]. The designer of an artificial system has several options for coding the parameters of the system; this will be discussed in greater detail later on in this section. As well, it should be pointed out that as a result of their structure, genetic algorithms are particularly well suited to problems in which the control variables take on discrete values.

Genetic algorithms manipulate a population of individuals, solutions to a problem, by operating on an encoded representation of the solution. This encoded representation is equivalent to the genetic material of an individual organism in nature. Each individual has a fitness value associated with it. The fitness of an individual is determined by evaluating it according to some fitness (objective) function. As genetic algorithms use a fitness function they have the advantage of not requiring auxiliary information such as derivatives or gradients to be computed; such auxiliary information is often difficult and time consuming to compute, and often requires several unrealistic simplifications to be made to the representation of the problem. The fitness of an individual provides the means for comparing it with others members of the gene pool. The higher the fitness value of an individual, the higher its

representation in the population and the higher its chances of being selected to reproduce. This artificial version of natural selection, may be implemented according to any one of the following schemes [38]:

d) deterministic sampling,

e) remainder sampling without replacement,

f) stochastic sampling without replacement,

g) remainder sampling with replacement,

h) stochastic sampling with replacement, and
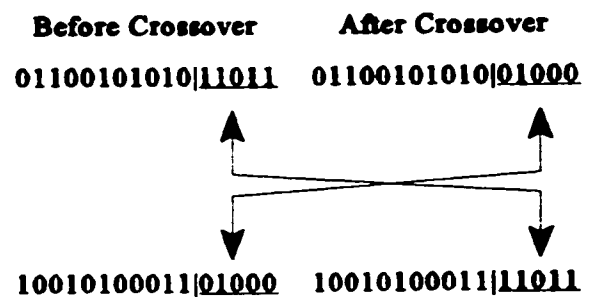
i) stochastic tournament (Wetzel ranking).

Regardless of which selection scheme is employed, only those individuals which are selected can contribute to the mating pool and reproduce.

By the use of a fitness function, genetic algorithms are able to focus in on higher payoff regions of the solution space. In fact, the number of strings in a given region increases at a rate that is proportional to the statistical estimate of the fitness of that region [42]. While a statistician would require many samples from all the possible regions to estimate the average fitness of each region, the genetic algorithm manages to accomplish this with far fewer strings and almost no computation. The reason for this remarkable ability lies in the fact that a single string belongs to all the regions in which any of its features appear. Consider the string 11101001; it is a member of the regions 11****** (where * indicates that a bits value is unspecified), 1******1, **101*** and so on. These regions are referred to as *similarity templates* or *schemata* [38]. The largest regions, those schemata which contain many unspecified bits, will typically be sampled by a large fraction of the strings in a population,

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thus, a genetic algorithm that manipulates a population of 100 strings actually samples a vastly larger number of schemata (approximately 100^3 [38]). This implicit parallelism is one of the principle advantages that GAs have over other search processes.

Once the competition and selection processes are completed and the mating pool is full, a new generation is formed by the probabilistic application of two operators to those individuals in the mating pool. These operators are crossover and mutation. Crossover is used to exchange portions of genetic material between mating string pairs. Mutation is the operation whereby new individuals are created by making small, random changes in the genetic coding of an individual.

Crossover combined with reproduction according to fitness is what give genetic algorithms the bulk of their processing power [38]. Crossover is a two step process. First, pairs of strings are picked at random from the mating pool for

Before Crossover   **After Crossover**

01100101010|11011   01100101010|01000

10010100011|01000   10010100011|11011

Figure 3.4. Crossover operation.

crossover. Then a random number in the range of [0,1] is generated; crossover for a mating pair only proceeds if the number generated is lower than the crossover rate which is specified at the start of the algorithm, otherwise, the two individuals are passed on to the next generation unaltered by the crossover process. If crossover is to occur for a mating pair, then a crossover point somewhere along the length of the strings is chosen at random, and all portions of the strings beyond the crossover point are exchanged to form new strings. The crossover operation is illustrated in Figure 3.4.

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Mutation plays a secondary role in genetic algorithms. It serves to recover lost genetic information. Consider for example a population in which the value of the feature (gene) in the 10th position of every individual has converged to '1'. It would be impossible therefore, for reproduction and crossover alone to ever generate a value other than '1' in that position in any individual. Mutation, however, would allow this to occur, thereby recovering lost genetic information. Mutation occurs after crossover by changing the value of a gene at a location along the string. Mutation at a location only proceeds if a randomly generated number in the range [0,1] is less than the mutation rate which is specified at the start of the algorithm. Mutation rates on the order of one mutation per thousand bit transfers have been shown to obtain good results [23,38].

One problem with genetic algorithms is that the user must specify the population size, as well as the crossover and mutation rates. Large populations increase the time required for the population to converge to the optimal solution but at the same time, increase the population's diversity and helps to prevent premature convergence, a topic to be discussed shortly. Studies have shown that the population size, crossover rate and mutation rate are closely related [23,38]. Small populations require relatively large crossover and mutation rates compared to those of larger populations [6,23,38].

One issue that often arises when genetic algorithms are applied to arbitrary problems is that the objective is more naturally stated as the minimization of some cost function rather than the maximization of some profit function [38]. When this occurs, the objective function must be mapped to fitness form. Several methods of accomplishing this are presented by Goldberg [38].

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Another issue involves the convergence rate of genetic algorithms. When the algorithm is first run, it is common to have a few extraordinary strings in a population of otherwise mediocre individuals. This often results in those individuals with the highest fitness generating a disproportionate number of offspring in the next generation, particularly when the population size is small. This is a main cause of premature convergence. In contrast, after many generations the population, while still being quite diverse, may contain individuals with approximately the same fitness levels. As a consequence, average members of the population contribute nearly the same number of offspring to the next generation as the best individuals. Thus, the driving force of the genetic algorithm, survival of the fittest, is lost. In both this situation and with premature convergence, fitness scaling can help. Goldberg describes in detail how fitness scaling may be performed [38].

As was mentioned earlier, there are numerous methods of coding the parameters of the problem to be optimized to the strings in a genetic algorithm. The coding may be binary or decimal, direct or mapped, to name but a few. However, regardless of the particular coding used there are two principle guidelines which should be followed when selecting the coding of the problem parameters into string format. They are the *principle of minimal alphabets*, and the *principle of meaningful building blocks* [38].

The principle of minimal alphabets states that one should choose the smallest possible alphabet that permits a natural expression of the problem. A simple example illustrates the reason behind this principle. Consider for example that we are trying to code the integers from 0 to 31. This may be accomplished by using a five digit binary coding or it may be accomplished by using a 32 character alphabet consisting of the 26 letter (A-Z) and 6 digits

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(1-6). The two coding methods are shown in Table 3.1.

Binary Coding	Nonbinary
00000	A
00001	B
:	:
11001	Z
11010	1
11011	2
:	:
11111	6

Table 3.1. Comparison of coding schemes.

In the binary case it is evident that there are similarities which may be exploited, however, with the 32-letter alphabet there are none. The principle of meaningful building blocks states that "the user should select a coding so that short, low-order schemata are relevant to the underlying problem and relatively unrelated to schemata over other fixed positions" [38].

One final issue that must be addressed before discussing the previous research applications of genetic algorithms to voltage and reactive power problems is that of how they deal with constraints. Constraints that cannot be violated may be implemented either by imposing penalties on individuals that violate them, or by creating decoders that avoid creating individuals that violate constraints. Each of these methods has advantages and disadvantages. If the problem domain is one in which the production of an individual that violates the constraints is likely, the genetic algorithm spends most of its time evaluating illegal individuals. As well, if the penalty imposed is quite high, when a legal individual is found the population may converge on it without finding better individuals as the paths to other legal individuals will likely require the production of illegal individuals as intermediate

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structures [5]. In contrast, if the penalty imposed is too low, the system may converge on individuals that violate constraints, but whose fitness is still higher than those which do not, because the objective function can be better satisfied by accepting the small penalty than by avoiding it [5]. The use of decoders to prevent individuals that violate constraints from being created frequently results in an algorithm that is too computation intensive to run efficiently [5].

During the 1990's there has been much interest into the suitability of genetic algorithms to various power system problems, [29,30,79,80], and to the voltage and reactive power problems in particular [23-28]. In [24], Ajjarapu and Albanna proposed the use of genetic algorithms to the capacitor placement problem. While they do not present an actual algorithm, they do get the ball rolling, so to speak, by discussing the suitability of GAs to the problem and suggesting a fitness function for the problem. This section will present the research which has been performed to date applying genetic algorithms to voltage and reactive power problems.

In [23], Haida and Akimoto propose a genetic algorithm for optimizing the voltage profile on a distribution system by controlling shunt capacitors. They evaluated their genetic algorithm using a simple seven bus system. Their genetic algorithm employed remainder stochastic sampling without replacement as its selection scheme, and sigma truncation scaling. The fitness function was the average of the bus voltage deviations from their nominal values, modified by penalty factors imposed for the violation of operational constraints. They considered the effects of changing the genetic algorithm of population size, crossover rate, mutation rate and coding type. They observed that there is a trade off between the population

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size and the mutation rate, that is, they found that the smaller the population size, the higher

the mutation rate that is required, and vice versa. As well, they found that crossover rates

between 0.6 and 0.8 did not significantly affect the performance of the GA. They observed

little difference between the use of gray coding and binary coding schemes. In their approach

there is one capacitor at each bus, and their ratings are encoded in the chromosomes.

However, the authors do not explain how the coding scheme corresponds to the actual VAR

ratings of the capacitors; as well, it seems unlikely that a practical distribution system would

have a multi-tap switched capacitor at every bus. They report that their GA resulted in better

solutions and in fewer iterations that other simple search methods. While Haida and Akimoto

acknowledge that their approach was tested on a small system and only considered capacitor

control, they suggest that it is an important first step on the way to developing

computationally efficient techniques for solving the voltage control problem.

Iba, [25], presents a method based on genetic algorithms for solving the voltage and

reactive power control problem. In his method, the distribution system is broken down into

subsystems, with each subsystem being evaluated according to four objective functions:

voltage violation, generator VAR violation, power loss, and the weighted sum of the three.

He proposes two genetic operators, interbreeding and manipulation to replace the operators

of crossover and mutation. According to his interbreeding scheme a new individual is formed

by applying the traditional stochastic selection rules to each subsystem in turn. His

manipulation operator consists of stochastically applying if-then rules to the strings. He

tested his algorithm using practical 51 and 224 bus systems. Using an HP9000/730 (76MIPS)

based computer his algorithm required 27 seconds to perform 17 generations and 93 seconds

to perform 80 generations for the 51 bus system with a population of 50 individuals, and 11:19 to perform 33 generations and 15:10 to perform 41 generations for the 224 bus system with a population of 100 individuals. The probability of his algorithm converging to a solution within 70 generations is 90%, however, it is possible that it will fail to converge within 80 generations. As well, the solution obtained is not always the global optimum. One advantage of GAs over other methods clearly illustrated by Iba's work is that the final generation consists not only of the best solution, but also of several quasi-optimal solutions. Iba, however, does not specify the loading conditions of the system, how the power flows were calculated, or how the compensators were placed on the system.

In [28], Pierre et al. present a genetic algorithm approach to the problem of placing shunt capacitors on a radial distribution system. Their algorithm uses as its fitness function the sum of the cost of real power losses and the cost of capacitors placed on the system. In formulating the problem they assume that the system is a balanced three phase system with time invariant loads. They do not consider energy losses in their formulation, and while they acknowledge the importance of bus voltage constraints, they do not include a mechanism for satisfying these constraints. They test their genetic algorithm on a simple ten bus system using a crossover rate of 0.6 and a mutation rate of 0.001. Their approach is successful in that it reduces the operating cost of the system; however, it results in capacitors being placed at every bus, something which is unlikely to ever occur in practice. As well, as every bus is considered as a candidate for capacitor placement, their approach would become computationally impractical if applied to a realistically sized system.

Sundharajan and Pahwa, [27], addressed the capacitor placement problem on a radial

distribution system by first applying a sensitivity analysis to determine candidate nodes, and then employing a genetic algorithm to determine the best size, type and location of capacitors from amongst the candidate locations. Their method considered the cost of both power and energy losses, as well as the cost of the capacitors. They divided the year into four load levels, with the bus loads being assumed to vary in proportion at each load level. They implemented their genetic algorithm using a software package GENESIS (GENEtic Search Implementation System) and a set of C programs. They applied their method to two test systems: a 30 bus system described in [61] and a 9 bus system. Using the 30 bus system their algorithm resulted in capacitors being placed at eight buses when a penalty for placement at more than five buses was applied. This resulted in an annual savings of $39404.61. Using the 9 bus system they studied the effects of the crossover and mutation rates on the performance of the system. They found that a crossover rate of 0.8 and a mutation rate of 0.003 yielded the best results when the population size was 50. In addition, it should be pointed out that they employed an elitist selection scheme in which the best individual in each generation was automatically contained in the next generation. While their results seem promising, there is still room for improvement as they do not consider the use of voltage regulators or operational constraints such as bus voltage violations. As well, the authors do not mention the processing time required by their algorithm.

Miu, Chiang and Darling, [26], considered the capacitor placement problem using a two stage approach. Their method also included the possibility of capacitor replacements. Like Sundharajan and Pahwa, [27], they employed a heuristic method to first determine candidate locations for placement or replacement of capacitors. They then applied a genetic

algorithm to optimally place and/or replace the capacitors on the distribution system. After a user specified number of generations, their GA was stopped, and the best two solutions were further evaluated using a heuristic method in order to improve upon the solutions locally. They tested their algorithm on an actual 292 bus feeder in the New York State Electric and Gas Corporation which already had 9 capacitors placed on it. In their study they used a population size of 50, a crossover rate of 0.7, and a mutation rate of 0.005. They found that their two stage approach always led to a better solution and in a shorter amount of time than by using either the GA or heuristic methods alone. For example, after 100 generations (3 hours and 20 minutes) their two stage approach resulted in the same solution that was returned by the genetic algorithm alone after 170 generations (5 hours and 40 minutes). The genetic algorithm portion of their system considers the cost of the power losses as well as the costs of placing and/or replacing the capacitors in its fitness function. As well, the operational constraints such as the bus voltage limits are implemented by imposing a penalty on those string which violate them. Although their results are quite promising, their method does not consider either the cost of energy losses or the use of voltage regulators.

While considerable progress has been made in applying genetic algorithms to the placement problem, little has been done in the way of solving the control problem. The success of genetic algorithms in solving the placement problem suggests that they could well be applied to the control problem. As well, the qualities of genetic algorithms seems to make them ideally suited to handling this problem, and deserves further investigation. This shall be the focus of the remainder of this thesis.

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3.4   Summary

Over the years many improvements have been made both in the manner in which voltage and reactive power problems are formulated and in the way the system is modeled. These improvements have been accompanied by improvements in the capabilities of microprocessors. Together these advancements have made it possible to develop fast techniques for real-time, online control of compensators placed on the distribution system. Many of the methods currently being studied are based on 'modern' techniques including: fuzzy logic and fuzzy sets, artificial neural networks, expert systems, and genetic algorithms. The use of these techniques developed by other researchers to solve both the placement and control problems has been discussed. The use of genetic algorithms to solve the control problem seems particularly promising. Evaluating their suitability to the control problem shall be the focus of the remainder of this thesis.

Chapter 4

Solution Methodology

4.1   Introduction

Based on the literature review presented in Chapter 3, genetic algorithms were thought to be quite applicable to the control problem. As a consequence, a method of solving the control problem for the purpose of reducing distribution system losses under the constraint of bus voltages using genetic algorithms was developed. In fact, two approaches were taken: one which employed a penalty based fitness function and the other which employed a fuzzy logic based fitness function. This chapter describes in detail these two genetic algorithm methodologies   As well as presenting the solution methodology, this chapter presents the system model and problem formulation adopted in this thesis.

4.2 System Modeling

In this thesis, the distribution system is assumed to be a balanced three phase system, and hence, a single phase representation can be used. The control devices consist of shunt capacitors and voltage regulators which are assumed to be already placed optimally on the system using a method such as that of Grainger and Civanlar, [59,60,61]. The distribution system is modeled using a π-equivalent representation.

4.2.1 Load Sensitivity to Voltage

Studies performed as part of the Athens Area Control Experiment, [8,92] demonstrated that while feeder losses are reduced following power factor corrections, that the system losses actually increase as a result of the improvement in voltage profile associated with the compensation. In fact, they observed that the increase in load actually exceeded the amount of the loss reduction, and consequently, the real power injected at the substation increased. They attributed the difference between the experimentally observed increase in the power injected at the substation and the expected reduction in power predicted by their simulation model to the use of a constant power representation for the loads. In order to account for this discrepancy, they proposed a model that represented each load as a parallel combination of constant power, constant current and constant impedance loads as shown in Figure 4.1.

Let $P_L(V)$ be the real power consumed by some load as a function of the applied voltage, V. Using a Taylor series expansion, $P_L(V)$ can be rewritten as:

$$P_L(V) = P_L(V_0) = P_L'(V_0)(V-V_0) + \frac{1}{2}P_L''(V_0)(V-V_0)^2 + HOT \qquad (4.1)$$

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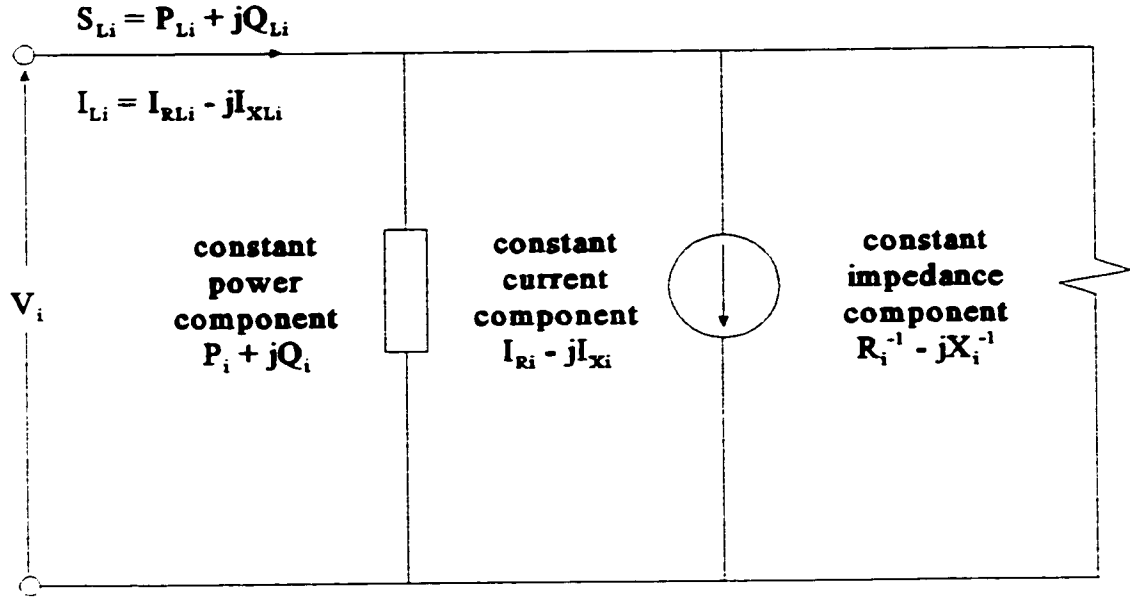
Figure 4.1. Voltage dependent model of the load at bus i.

where V_0 denotes the nominal voltage, and HOT stands for higher order terms. As distribution voltages are typically maintained within ±5% of their nominal values, an accurate approximation for $P_L(V)$ can be obtained by ignoring the HOT. Equation 4.1 then becomes:

$$P_L(V) = [P_L(V_0) - V_0 P_L'(V_0) + \frac{1}{2}V_0^2 P_L''(V_0)] + [P_L'(V_0) - V_0 P_L''(V_0)]V + [\frac{1}{2}P_L''(V_0)]V^2 \quad (4.2)$$

From this it is clear that if the nominal power, $P_L(V_0)$, and the first and second derivatives of the load with respect to voltage, $P'_L(V)$ and $P''_L(V)$, can be determined, then $P_L(V)$ can be represented as a quadratic polynomial in voltage. Using the following definitions for the coefficients:

$$P = P_L(V_0) - V_0 P_L'(V_0) + \frac{1}{2}V_0^2 P_L''(V_0)$$

$$I_r = P_L'(V_0) - V_0 P_L''(V_0) \qquad\qquad\qquad (4.3)$$

$$R^{-1} = \frac{1}{2}P_L''(V_0)$$

Equation 4.2 can be written as:

$$P_L(V) = P + I_r V + R^{-1} V^2 \qquad\qquad\qquad (4.4)$$

This can be interpreted as the real power consumed by a constant power sink, P, a constant current sink, I_r, and a constant resistance, R. Similar expressions can be obtained for the reactive power.

Without knowing the sensitivities of each load, it is difficult to determine its model parameters. By assuming that each load component (i.e. constant power, constant current, and constant impedance) contributes a given fraction of the total load at nominal voltage, the load model can be made to assume any voltage dependence by varying the component contribution parameters, ϵ_P, ϵ_{I_r}, and ϵ_R, that is:

$$P = \epsilon_P P_L(V_0)$$

$$I_r = \epsilon_{I_r} \frac{P_L(V_0)}{V_0} \qquad\qquad\qquad (4.5)$$

$$R^{-1} = \epsilon_R \frac{P_L(V_0)}{V_0^2}$$

where

$$\epsilon_P + \epsilon_{I_r} + \epsilon_R = 1 \qquad\qquad (4.6)$$

The disadvantage with this model is that the component contribution parameters must be specified by the distribution system engineer, and they may not be obvious.

In this thesis, a constant power model is used. This model is perhaps the most commonly used by researchers and utilities alike. While it may not be the most accurate model for a particular distribution system, it does produce the most conservative results when calculating line losses, and thus serves as a lower bound on the losses a utility might see in practice [6]. It should be pointed out that the above model could have been incorporated into this thesis by modifying the load flow portion of the program. However, without the specific operational experience necessary to determine the component contribution parameters, it would be quite difficult to offer a general-purpose load model, and hence the constant power model is used.

4.2.2 Load Flows

Load flow analysis is used to determine the apparent power and voltages at each bus in the distribution system under steady state conditions and has been described in many textbooks (for example, [90,91]). While there are several methods for performing load flow analysis the Gauss-Seidel technique and the Newton-Raphson techniques are perhaps the most common. Both methods can be carried out very quickly using modern computers, however, the Gauss-Seidel method is preferred for distribution systems as the low X/R ratios typical of distribution systems often leads to ill-conditioned Jacobian matrices which can cause the Newton-Raphson method to fail to converge [90]. As well, the Gauss-Seidel technique

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has the following advantages:

a)   it is relatively insensitive to the initial voltage estimates,

b)   it has reasonably small memory requirements, and

c)   it is simple to implement in a computer program.

Every possible solution in the control problem requires a load flow to be performed so that its merits can be assessed. As a result, for a large distribution system, even with the use of a fast computer, the time required to complete a load flow to evaluate every solution would be prohibitive. This is the main reason for not performing an exhaustive search. While the use of an optimization technique such as genetic algorithms does reduce the number of times that a load flow analysis must be performed, these load flows still consume most of the processing time required by the optimization technique. It is important therefore, to examine the issue.

Using the π-equivalent representation, the distribution system is characterized by a system of n nonlinear equations:

$$[I_{BUS}] = [Y_{BUS}][V_{BUS}] \qquad (4.7)$$

where n is the number of buses in the system, I_{BUS} is the bus current vector, Y_{BUS} is the bus admittance matrix, and V_{BUS} is the bus voltage vector [90]. The bus admittance matrix may be formed using a simple procedure. A diagonal element, Y_{ii}, is equal to the sum of the admittances connected to bus i, and an off-diagonal element, Y_{ij}, is equal to the negative of the admittance of the network element connecting bus i to bus j. It is clear that the bus admittance matrix is both symmetric and sparse, hence, the memory requirements can be

reduced by only storing nonzero elements of the $\frac{1}{2}n(n+1)$ elements as opposed to all n^2 elements.

From Equation 4.7 it is clear that the current at the ith bus is given by:

$$I_i = \sum_{j=1}^{n} Y_{ij}V_j = Y_{ii}V_i + \sum_{\substack{j=1 \\ j \neq i}}^{n} Y_{ij}V_j \qquad (4.8)$$

Solving this for V_i gives:

$$V_i = \frac{1}{Y_{ii}}(I_i - \sum_{\substack{j=1 \\ j \neq i}}^{n} Y_{ij}V_j) \qquad (4.9)$$

and recalling Equation 2.2

$$I_i = \frac{P_i - jQ_i}{V_i^*} \qquad (4.10)$$

Hence, Equation 4.9 becomes:

$$V_i = \frac{1}{Y_{ii}}(\frac{P_i - jQ_i}{V_i^*} - \sum_{\substack{j=1 \\ j \neq i}}^{n} Y_{ij}V_j) \qquad (4.11)$$

Equation 4.11 involves only the bus voltages and apparent powers as variables, and can be solved iteratively using the most recent estimates of the bus voltages until the change in bus voltages is smaller than some specified tolerance, ϵ. The iterative process employed to solve this system of equations is known as the Gauss-Seidel method, and forms the basis of the load

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flow analysis used in this thesis. It should be pointed out that equation 4.11 is only used for load buses (buses where the real and reactive power are specified), however, since distribution systems rarely contain generators this is sufficient. Using a similar procedure, an equation for generator buses can be developed.

In order to reduce the computing time, several calculations can be performed before the iterative procedure is initiated. These calculations only involve the constant quantities of the admittance matrix values and bus loads, and are given as follows:

$$A_i = \frac{(P_i - jQ_i)}{Y_{ii}} \qquad B_i = \frac{Y_{ij}}{Y_{ii}} \qquad \qquad (4.12)$$

Substitution of these quantities into Equation 4.11 gives:

$$V_i = \frac{A_i}{V_i^*} - \sum_{\substack{j=1 \\ j \neq i}}^{n} B_{ij} V_j \qquad \qquad (4.13)$$

A load flow algorithm based on Equations 4.12 and 4.13, and having a convergence tolerance, $\epsilon = 10^{-6}$, was implemented using Visual C++. This algorithm was verified by comparing the results obtained by it with those obtained by other researchers. Table 4.1 shows the results obtained using this algorithm for a distribution system consisting of three feeders with a total of 16 buses. Table 4.1 also shows the results presented by Civanlar et al., [89] for the same system. It is clear that the voltages are identical, except for minor differences in the phase angle of less than 1°.

It should be remembered that the Gauss-Seidel method is an iterative technique, and

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Feeder	Start Bus i	End Bus j	Section Data R_{ij} (p.u.)	X_{ij} (p.u.)	End Bus Load P_j (MW)	Q_j (MVAR)	End Bus Voltage V_j (p.u.)	End Bus Voltage V_j (p.u.)
							System Data From Civanlar et al. [89]	Load Flow Algorithm Results
1	1	4	0.075	0.1	2	1.6	0.991∠-0.370	0.991∠-0.370
"	4	5	0.08	0.11	3	0.4	0.988∠-0.544	0.988∠-0.544
"	4	6	0.09	0.18	2	-0.4	0.986∠-0.697	0.986∠-0.697
"	6	7	0.04	0.04	1.5	1.2	0.985∠-0.704	0.985∠-0.704
2	2	8	0.11	0.11	4	2.7	0.979∠-0.763	0.979∠-0.763
"	8	9	0.08	0.11	5	1.8	0.971∠-1.451	0.971∠-1.452
"	8	10	0.11	0.11	1	0.9	0.977∠-0.770	0.977∠-0.770
"	9	11	0.11	0.11	0.6	-0.5	0.971∠-1.525	0.971∠-1.526
"	9	12	0.08	0.11	4.5	-1.7	0.969∠-1.836	0.969∠-1.836
3	3	13	0.11	0.11	1	0.9	0.994∠-0.332	0.994∠-0.329
"	13	14	0.09	0.12	1	-1.1	0.995∠-0.459	0.995∠-0.456
"	13	15	0.08	0.11	1	0.9	0.992∠-0.527	0.992∠-0.523
"	15	16	0.04	0.04	2.1	-0.8	0.991∠-0.596	0.991∠-0.590
	5	11	0.04	0.04				
	10	14	0.04	0.04				
	7	16	0.09	0.12				

Table 4.1. Validation of Load Flow Algorithm

may require a considerable number of iterations to converge (or may even fail to converge) on a solution. To improve the time required for this technique to converge it is possible to make use of an acceleration factor. For larger systems (more that 50 buses) it may be preferable to use a faster method for performing load flow analysis such as that proposed by Rizy et al., [92]. However, for the system considered in this thesis it was felt that the Gauss-Seidel technique was sufficient as convergence and speed of convergence were not significant issues.

4.2.3 Load Variations with Time

It is well known that the loads on a power system are dynamic, that is, they vary over time. These variations may occur quite rapidly (during switching on or off of parts of the power system), or may take place more gradually, as in the case of daily load variations. It is these gradual changes due to load variations that are of interest in this thesis. System loads may be broadly grouped into three load categories: residential, commercial, and industrial. As well, the total load at a particular point in the distribution system may be some combination of these load types. The variation of each load type over the period of a year can be divided into three seasons during which the daily load profiles are quite similar [82]. These three seasons are: Summer, Winter, and Spring/Fall. Daily load profiles during each season can be further divided into four periods: weekday peak period, weekday off-peak period, weekend peak period, and weekend off-peak period [82]. Hence, the annual load variation of each of the three load types can be divided into twelve periods, and the load variation of the total load can be determined by the weighted sum of the three load types during each period, where the weights are determined from the proportion of each load type

at the load point.

In this thesis, the twelve period model was used. Using the load conversion factors presented by Abdel-Salam, [65], the load profile for each of the twelve periods was obtained. For the system studied in this thesis, the load at each bus was assumed to consist of 15% industrial load, 25% commercial load, and 60% residential load. To more realistically model the unpredictability of the loads, the load at each bus was multiplied my a uniformly distributed random number between 0.85 and 1.15. This technique also eliminates reliance on the unrealistic approximations used by many researchers that:

a)   the loads at every bus vary in the same proportion, and

b)   the reactive power consumed by the load is a fixed fraction of the real power consumed by the load.

While this technique for modeling the variation of loads over time is by no means accurate, it does provide a reasonable method for developing load profiles to evaluate the performance of the genetic algorithm developed in this thesis.

As a result of the daily load variations, the compensation must be changed periodically in order to maintain the system losses at their practical minimum levels. This is of course the goal of the control problem, and the aim of this thesis. Miller, [1], suggests that these adjustments can be made "infrequently" over a period of several minutes. Hence, in order to be useful, any algorithm which solves the control problem (including the one developed in this thesis) must be capable of arriving at a solution within a maximum of five minutes. Another factor which must be considered in deciding the frequency of adjusting the compensation level is the increased wear, and hence, increased maintenance and repair cost to equipment as a

result of more frequent switching operations. As well, the effect of transients caused by switching operations must be considered.

4.3 Problem Formulation

In this thesis, the objective is to apply a genetic algorithm to optimally control shunt capacitors and voltage regulators placed on a distribution system for the purpose of reducing losses, while satisfying the bus voltage constraints. To accomplish this task, the problem has to be formulated in such a way that the genetic algorithm can be applied. In this thesis a genetic algorithm was implemented in Visual C++ using the methods outlined by Goldberg, [38], for creating a genetic algorithm. This was discussed in detail in Chapter 3.

The genetic algorithm used in this thesis operated on a population of *popsize* individuals, where each individual corresponds to a point in the solution space. In this case, that means that each individual represents any possible combination of compensator settings. To accomplish this, each individual was coded as a string consisting of *genes* integer coded features, or genes, where *genes* is the number of compensators to be controlled. In this thesis, the value of each gene corresponds to the tap setting of the controlled device. For example, if the 3rd gene corresponds to a voltage booster that is placed at bus 23 of the distribution system, then if this gene had the value 7, this would correspond to the tap of that voltage booster being in its 7th position. In this way, the locations and ratings of each compensator for each of its possible switching positions is capable of being coded as an individual in the population of the genetic algorithm, and hence, the entire solution space can be effectively searched using this genetic algorithm approach.

In this thesis, the initial population of the genetic algorithm consisted of *popsize*

individuals which were randomly chosen from the solution space. As well, the genetic algorithm was allowed to proceed for *max_gens* generations before being terminated. At each generation, reproduction was performed using an elitist selection process, where the best individual in the generation was automatically added to the mating pool and the remaining *(popsize*-1) individuals were selected using the stochastic sampling with replacement technique as outlined in [38]. Once the mating pool was selected crossover was applied at a rate of *cross_rate* to form the new population. Finally, the mutation operator was applied as outlined in Chapter 3 at a rate of *mutation_rate*. In this thesis, the population size, the crossover rate and the mutation rate remained constant at every generation. As well, in order to alleviate possible convergence problems, linear scaling as described by Goldberg, [38], was employed throughout this thesis.

As the objective of this thesis is to minimize the distribution losses under varying load conditions while satisfying the constraints on the bus voltages, it was necessary to determine an objective function that was capable of accomplishing this. Mathematically the problem can be stated as follows:

$$
\min [P_{loss}] = \min [(P_s - P_d)] = \min [(P_0 - \sum_{i=1}^{n} P_i)]
$$
$$
such\ that\ V_{min} \le V_i \le V_{max}\ for\ i = 1..n
$$

(4.14)

where P_{loss} is the losses, $P_s = P_0$ is the power supplied by the substation, and P_d is the total power demanded by the bus loads, P_i. As mentioned in Chapter 3, however, genetic algorithms seek to maximize a fitness function, not to minimize one. Consequently, the problem is restated as that of maximizing the percent reduction in losses, that is:

$$\max[\% P_{loss}] = \max\left[\left(\frac{P_{loss_{bare}} - P_{loss}}{P_{loss_{bare}}}\right) * 100\%\right] \qquad (4.15)$$

where $P_{loss_{bare}}$ is simply the real power losses of the system without compensation, i.e. the bare system, and P_{loss} is given by Equation 4.14 and includes the constraints on the bus voltages. The problem is now stated in a form that is suitable for use with a genetic algorithm, except that it does not include a means for dealing with the bus voltage constraints. As was outlined in Chapter 3, the previous research applying genetic algorithms to the capacitor placement problem used a fitness function that was proportional to the total losses of the distribution system modified by a penalty that was applied for constraint violations. Initially, this was the approach adopted in this thesis, and was incorporated by reducing the objective function, Equation 4.15, by 10% for each constraint violation. Hence, the fitness function used becomes:

$$\max[0.9^k \cdot (\% P_{loss})] \qquad (4.16)$$

where $\% P_{loss}$ is the percent loss reduction given by Equation 4.15, and k is the number of buses having constraint violations.

Upon further consideration of the problem, it was thought that by using a fuzzy logic based approach for the fitness function, that the objective could be better achieved. With a fuzzy based approach, the task becomes that of maximizing the intersection between the fuzzy set describing the percent loss reduction and the fuzzy sets describing the bus voltage constraints. The fuzzy set for the bus voltage violations is shown in Figure 4.3(a) and that

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for the total losses is shown in Figure 4.3(b). In this thesis, the same fuzzy set was used to represent the voltage constraints at each bus, however, each bus could just as easily had its own fuzzy set associated with it. In this way, a compromise is made between solutions that improve the loss reduction by pushing the bus voltages to their extreme values, and the constraints which seek to keep the bus voltages away from their extremes. In this thesis, the constraints on the bus voltages was that they be within ±5% of their nominal values. As was pointed out in Chapter 3, this value is typical in much of the research into voltage and reactive power problems, however, the method used in this thesis, could easily have handled other values for constraints on the bus voltages including different constraints for different buses. The reader is referred to the Appendix for more details on the fuzzy fitness function.
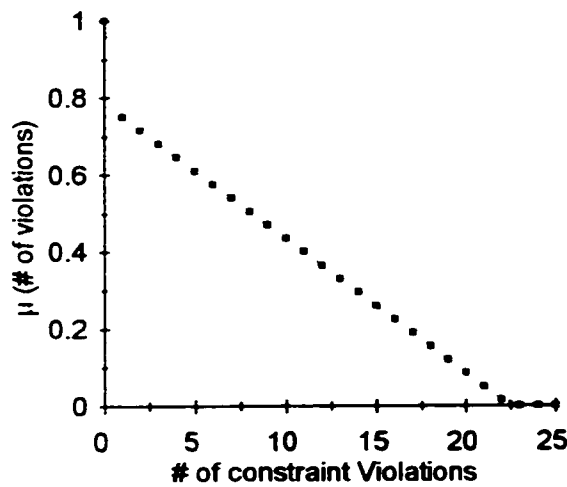
Figure 4.3(a). Membership function for the number of bus voltage violations.
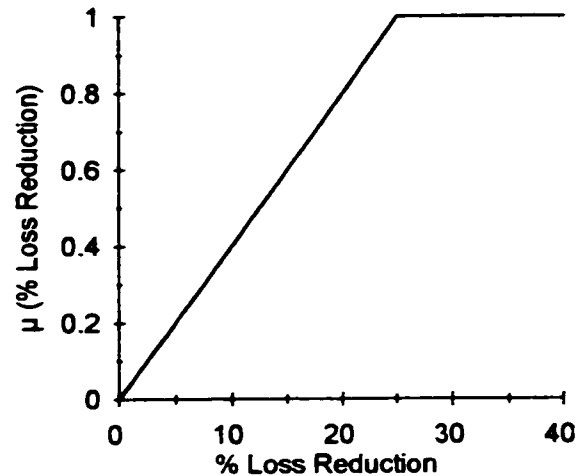
Figure 4.3(b). Membership function for the total percent loss reduction of the system.

4.4 Tests Performed

Having formulated the control problem in a manner that is suitable for solution by a genetic algorithm, the tests performed can now be described. In this thesis, all test were performed using the distribution system described in references [21,61]. This is a radial distribution system consisting of 30 load buses, with 6 lateral branches, and is shown in Figure 4.4. The system data is given in Table 4.2. The compensators that are to be controlled on this system have the maximum ratings and locations of those which were used by Gu and Rizy, [22], and consists of 5 switchable capacitors and 1 voltage regulator. The 5 switchable capacitors were initially placed on the system according to the method of Santoso and Tan, [44], and have the tap settings shown in Table 4.3. The voltage regulator is located at bus 4 and has nine tap positions which are distributed equally between 1.0 and 1.1 per unit.

For this test system the total number of compensators to be controlled is 6, and hence, *genes* is 6. As well, the total number of points in the solution space is $5^5 9^1 = 28125$. Obviously, even for this small test system, the time required for an exhaustive search to be performed would be prohibitive. In fact, to be useful the genetic algorithm approach developed in this thesis must be capable of arriving at a solution in less than 5 minutes, as was mentioned in Section 4.2.3. As a consequence, the method developed in this thesis must usefully process only a small fraction of the total 28125 possible solutions. This requires that the genetic algorithms used in this thesis operate on a small population, and that they are capable of converging in a reasonable number of generations. Throughout this thesis a population size of *popsize* = 20 individuals was used. This is quite small among genetic algorithms. As well, it will be shown in the next chapter that the genetic algorithms used here

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only require about 25 generations to converge. Hence, the genetic algorithm effectively searches only 20*25 = 500 points, or less than 2% of the total search space.

In this thesis, two groups of tests were performed. In the first group, the sensitivity of the solution to the values of the parameters of the genetic algorithm was investigated. In particular, the effect of variation of the mutation rate and the crossover rate on the performance of the genetic algorithm were studied. It is well known that the population size, the crossover rate, and the mutation rate are closely related, hence, in order for the genetic algorithm to perform well these parameters must first be determined. Since the population size is fixed, as was discussed above, it was only necessary to determine the appropriate mutation and crossover rates. This is the primary purpose of the first group of tests.

Making use of the results from the first group of tests, the second group of tests compared the performance of the genetic algorithm using the penalty based fitness function with the genetic algorithm using the fuzzy based fitness function. The results from the genetic algorithm were also compared with the result of an exhaustive search using the same objective function as the penalty based GA method. All tests in the second group were performed under the twelve loading conditions obtained from the method outlined in Section 4.2.3. Both groups of tests, and the results are discussed in greater detail in the next chapter.
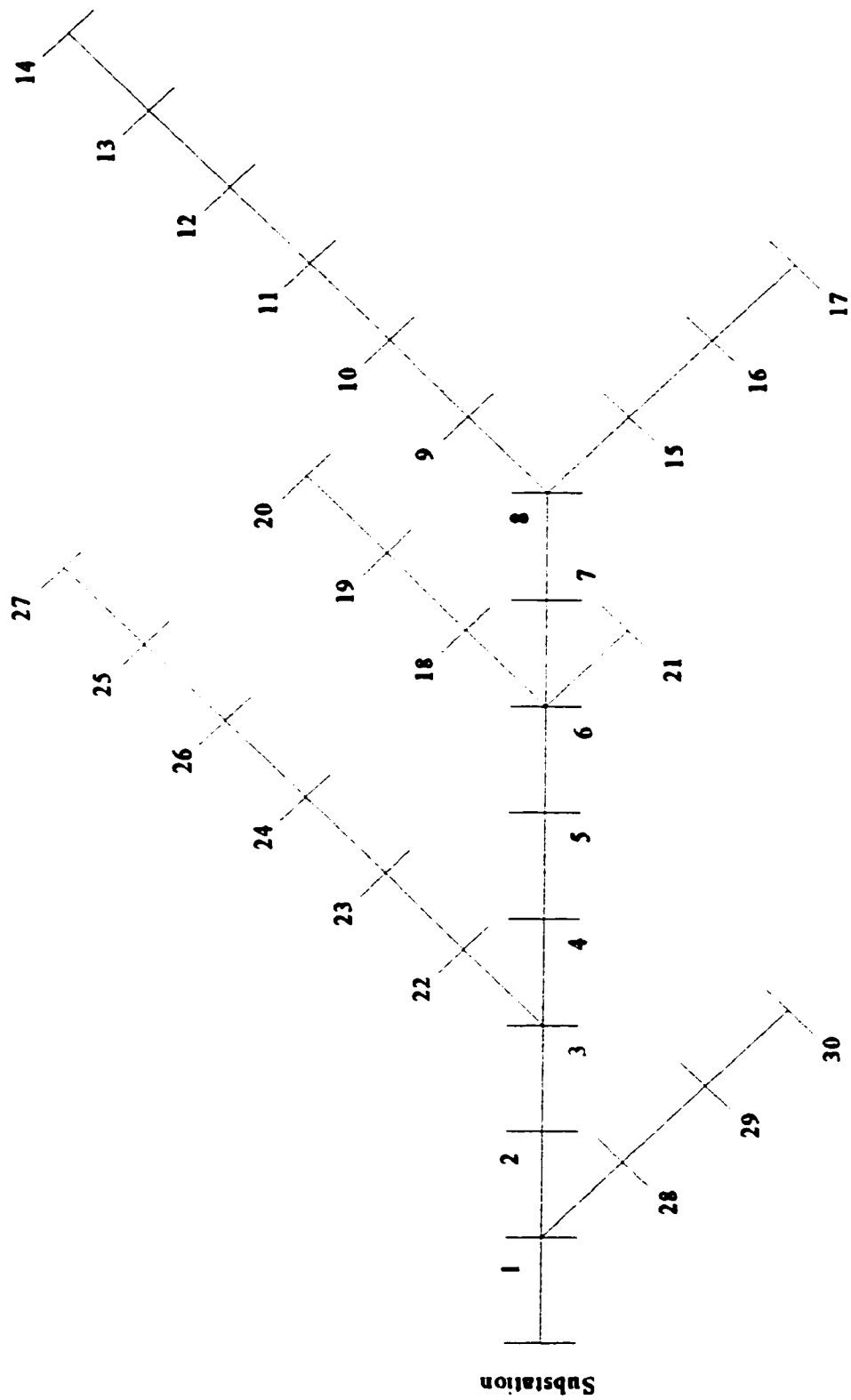
Figure 4.4. 30 bus distributions system [21].

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Bus	Bus	Branch Impedance		Maximum Load at Bus j	
i	j	r_{ij} (Ω)	x_{ij} (Ω)	P (kW)	Q (kVAR)
0	1	0.5096	1.7030	0	0
1	2	0.2191	0.0118	522	174
2	3	0.3485	0.3446	0	0
3	4	1.1750	1.0214	936	312
4	5	0.5530	0.4806	0	0
5	6	1.6625	0.9365	0	0
6	7	1.3506	0.7608	0	0
7	8	1.3506	0.7608	0	0
8	9	1.3259	0.7469	189	63
9	10	1.3259	0.7469	0	0
10	11	3.9709	2.2369	336	112
11	12	1.8549	1.0449	657	219
12	13	0.7557	0.4257	783	261
13	14	1.5389	0.8669	729	243
8	15	0.4572	0.4131	477	159
15	16	0.7282	0.4102	549	183
16	17	1.3053	0.7353	477	159
6	18	0.4838	0.4206	432	144
18	19	1.5898	1.3818	672	224
19	20	1.5389	0.8669	495	165
6	21	0.6048	0.5257	207	69
3	22	0.5639	0.5575	522	174
22	23	0.3432	0.3393	1917	639
23	24	0.5728	0.4979	0	0
24	25	1.4602	1.2692	1116	372
25	26	1.0627	0.9237	549	183
26	27	1.5114	0.8514	792	264
1	28	0.4659	0.0251	882	294
28	29	1.6351	0.9211	882	294
29	30	1.1143	0.6277	882	294

Table 4.2. System data for the 30 bus test system [21].

		Bus Location				
		13	15	19	23	25
Tap Position	0	0	0	0	0	0
	1	800	1000	400	1600	2000
	2	600	750	300	1200	1500
	3	400	500	200	800	1000
	4	200	250	100	400	500
		Capacitor Rating (kVAR)				

Table 4.3. Capacitor locations and ratings.

Chapter 5

Results and Discussion

5.1 Introduction

In this thesis, two groups of tests were performed. The first group of tests studied

the effect of the mutation rate and the crossover rate on the performance of the genetic

algorithm. The second group of tests compared the performance of three search methods:

the genetic algorithm using a penalty based fitness function, the genetic algorithm using a

fuzzy based fitness function, and an exhaustive search of the solution space. All tests were

performed using the 30 bus system described in Chapter 4.

5.2 Group One Tests - Genetic Parameters

In order to determine the optimal values of the crossover rate and the mutation rate

used in the genetic algorithm, a series of tests was performed. Using the penalty based fitness

function described in Section 4.3, the effect of varying the mutation rate and the crossover

rate on the performance of the genetic algorithm was able to be evaluated, and appropriate values were determined.

The first series of tests consisted of using a fixed crossover rate of 0.6 to determine the effect of the mutation rate on the performance of the genetic algorithm. Using this fixed crossover rate, four different mutation rates, 0.001, 0.003, 0.01 and 0.03 were considered. All four tests were performed under the same loading conditions using the 30 bus distribution system described in Chapter 4 . Because genetic algorithms are a probabilistic search method, each test was performed 5 times, and the average fitness of the population at each generation is plotted against the number of generations for each of the four mutation rates studied in Figures 5.1-5.4. Figure 5.5 shows the average results over the five tests for each of the four mutation rates studied. As the mutation rate increases, the search becomes more random and changes occur more frequently making it easier for the algorithm to escape from local optimums; on the other hand, with a low mutation rate changes take place in a comparatively smoother fashion, and hence, the algorithm is less able to escape from local optimum solutions. This is particularly true in small population genetic algorithms, as is the case here, because the population is so small that it requires a higher mutation rate to effectively search the solution space, as compared with a large population genetic algorithm. The inability of the genetic algorithm to escape from local optimal solutions is evident in Figures 5.1-5.4, as the mutation rate is increased, the genetic algorithm is able to more consistently arrive at good solutions, while for the lower mutation rates each trial results in a significantly different level of fitness. From Figure 5.5, it can be seen that a mutation rate of 0.03 gives a better performance than the others, hence, this value was used as the mutation rate in all the

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remaining tests.

Using, the fixed mutation rate of 0.03, the effect of the crossover rate was then studied. Tests using the same distribution system as the mutation rate tests were performed for four values of crossover rate: 0.4, 0.6, 0.8, 1.0. Again, each test was performed 5 times, and the average fitness of the population at each generation for each trial is shown in Figures 5.6-5.9. Figure 5.10 shows the average of the results over the five tests from each of the four crossover rates studied. A lower crossover rate corresponds to a lower exploration rate of the solution space and brings new structures into the population gradually. A higher crossover rate, in comparison, may eliminate high performance strings faster than selection can make improvements. This effect of the crossover rate on the convergence of the genetic algorithm is quite clear in Figures 5.6-5.10. Figure 5.10 indicates that a crossover rate of 1.0 performs slightly better than the other values tested, and hence, shall be used in all the remaining tests. As well, it is clear from Figures 5.9 and 5.10 that using the value of 1.0 for the crossover rate and 0.03 for the mutation rate always results in genetic algorithm converging in less than 25 generations, and hence *max_gens* is set at 25 for all the remaining tests described in this thesis.
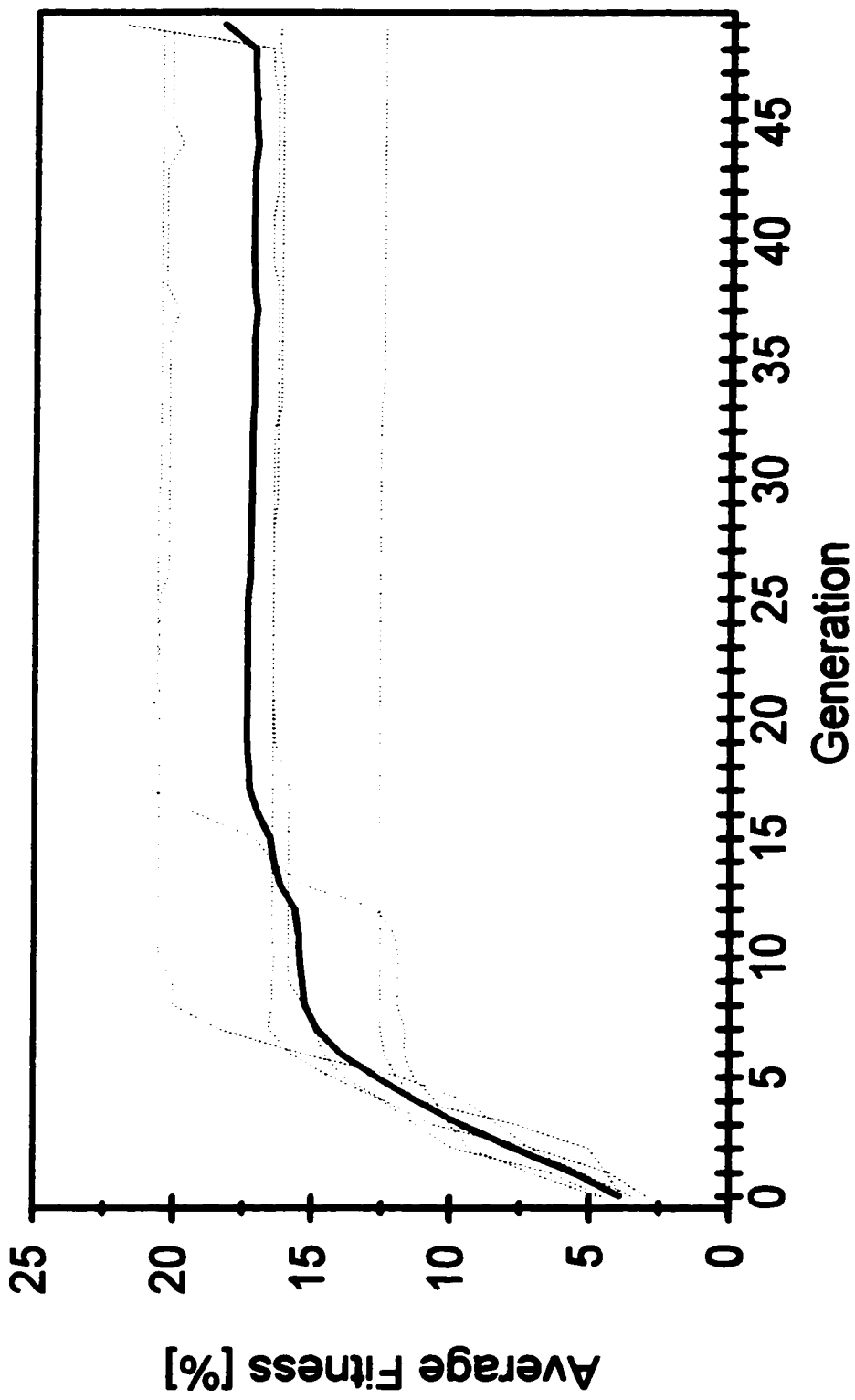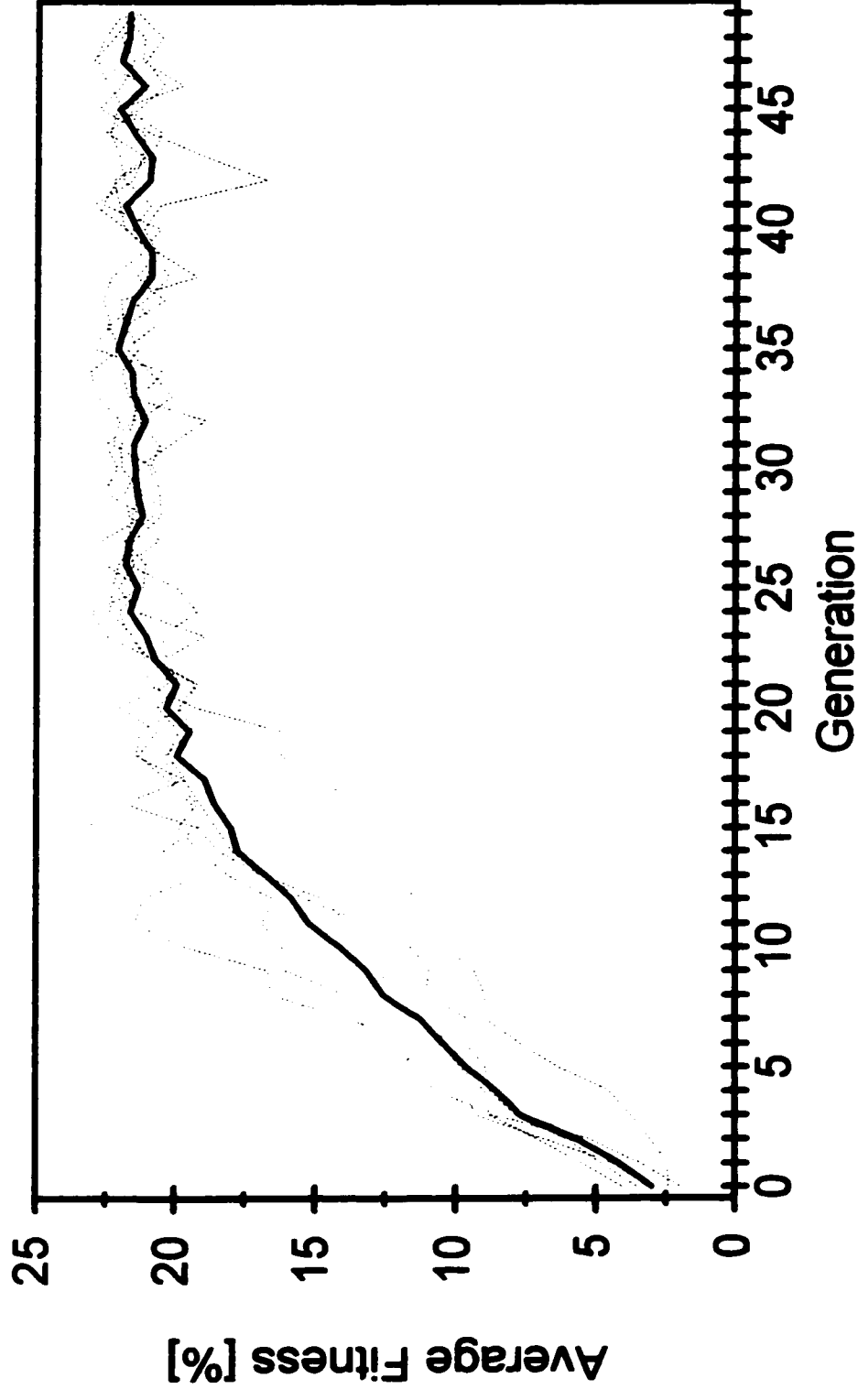
Figure 5.1. Average fitness of the population versus generation for each of the five trials (dashed lines), and the average fitness of the populations over the five trials versus generation (solid line) using a fixed crossover rate of 0.6 and a mutation rate of 0.001.
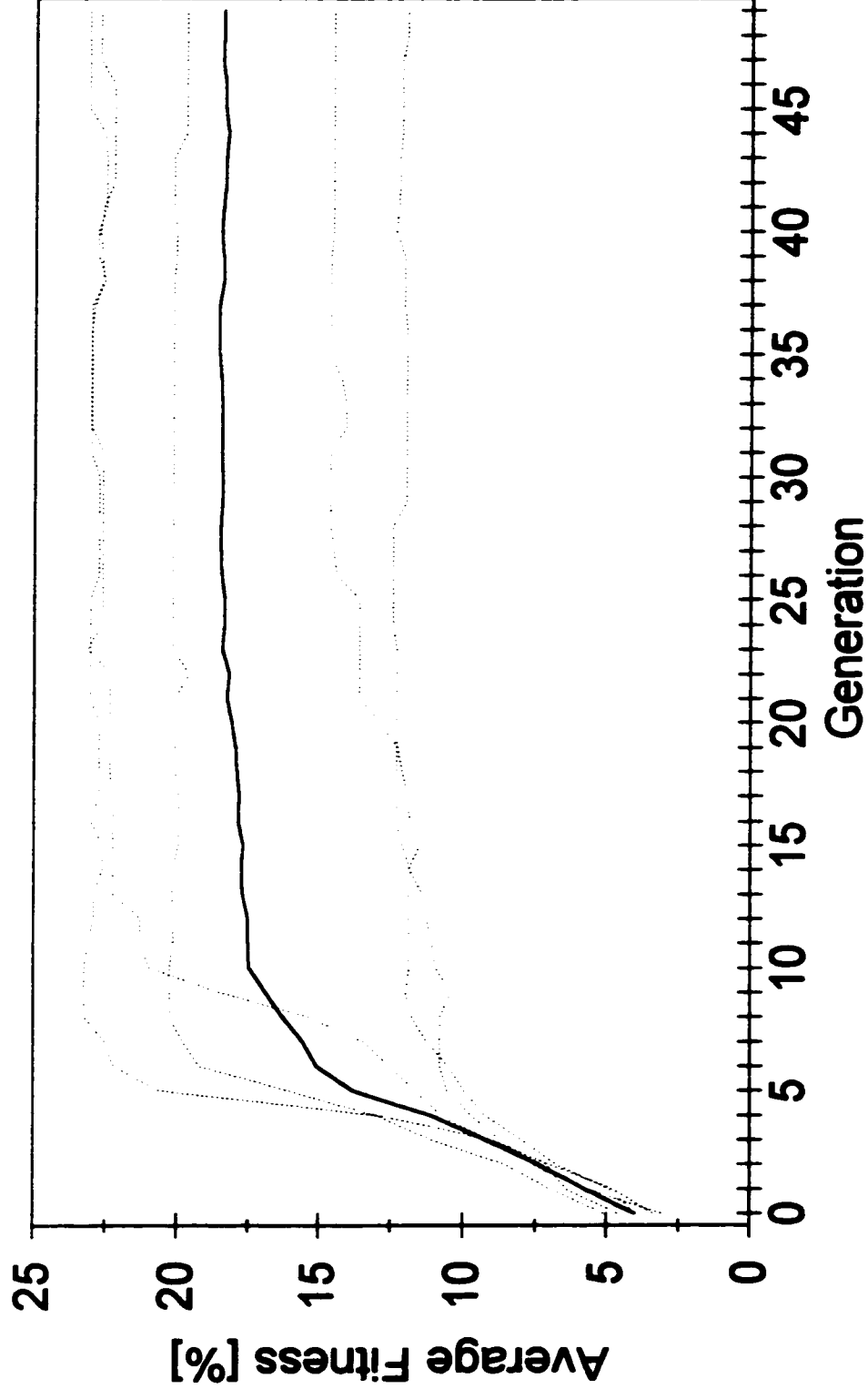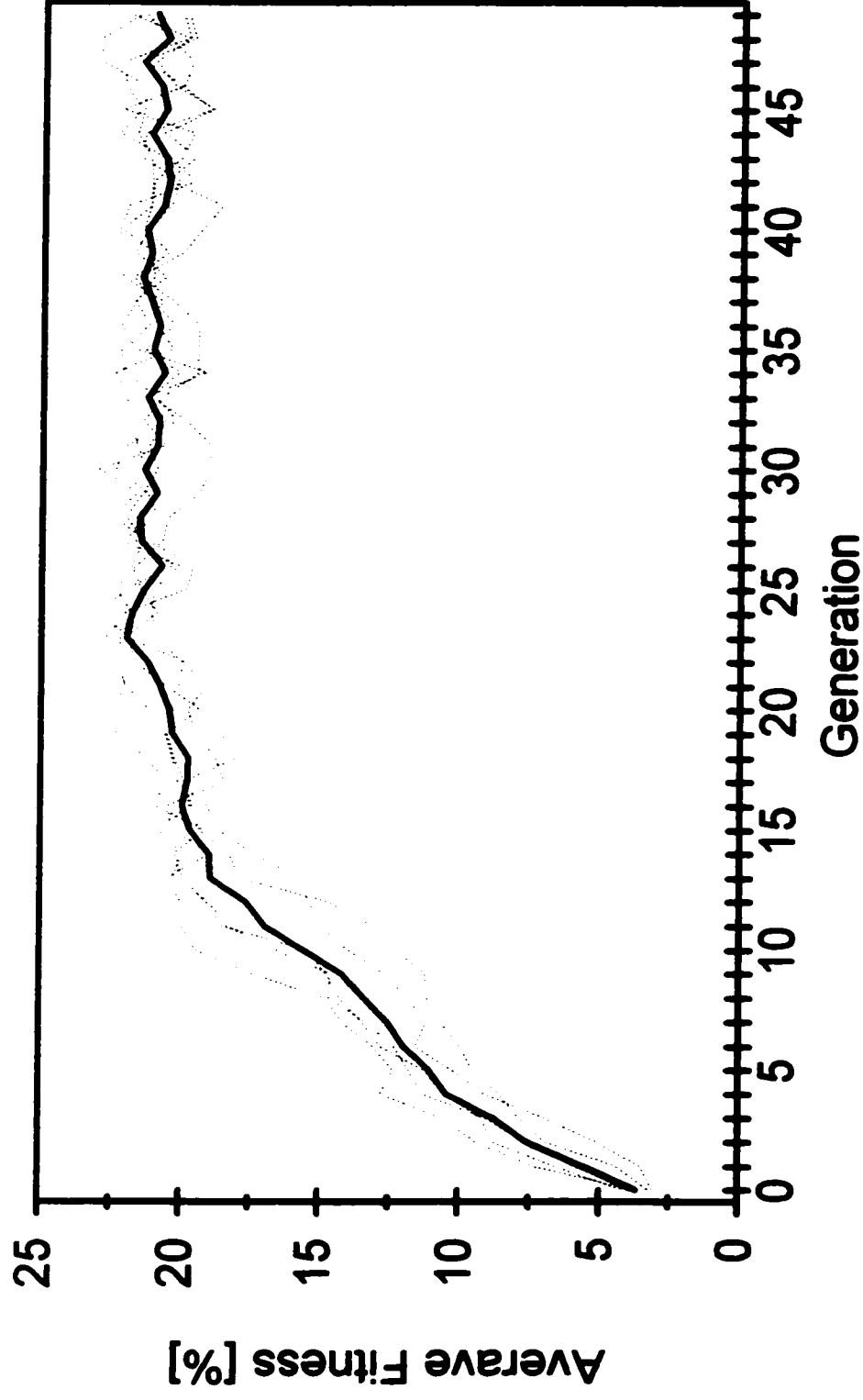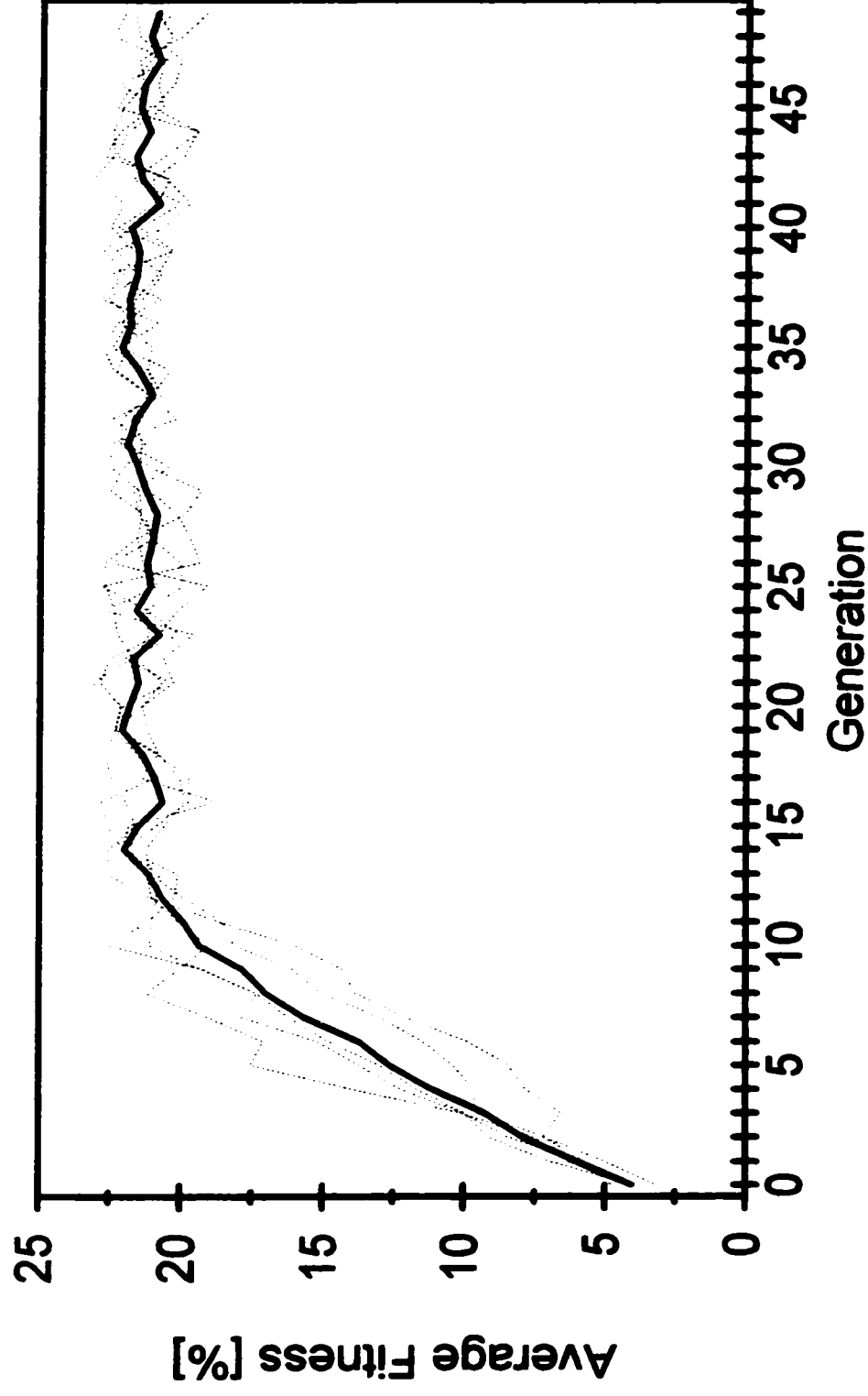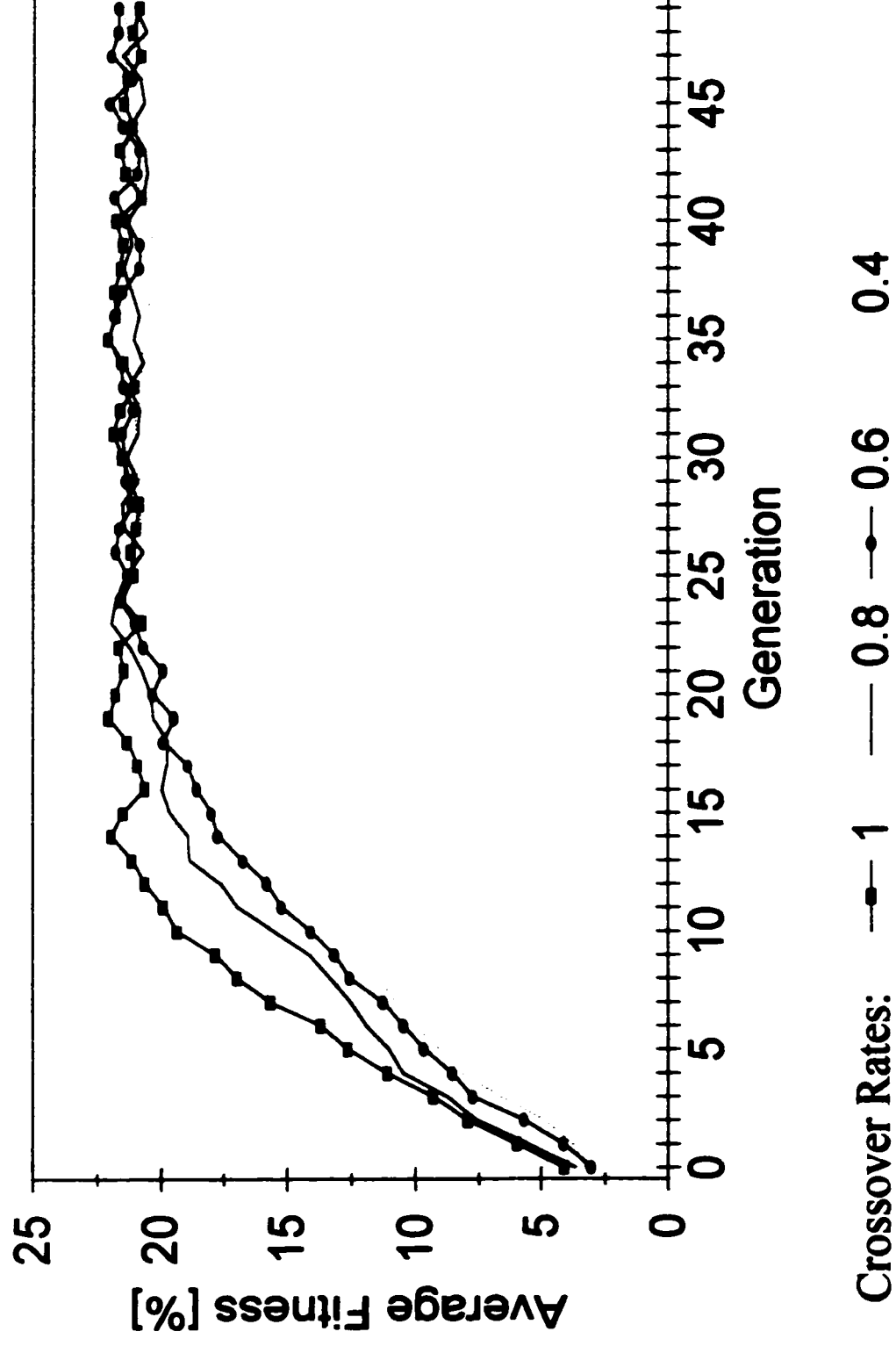
Figure 5.2. Average fitness of the population versus generation for each of the five trials (dashed lines), and the average fitness of the populations over the five trials versus generation (solid line) using a fixed crossover rate of 0.6 and a mutation rate of 0.003.
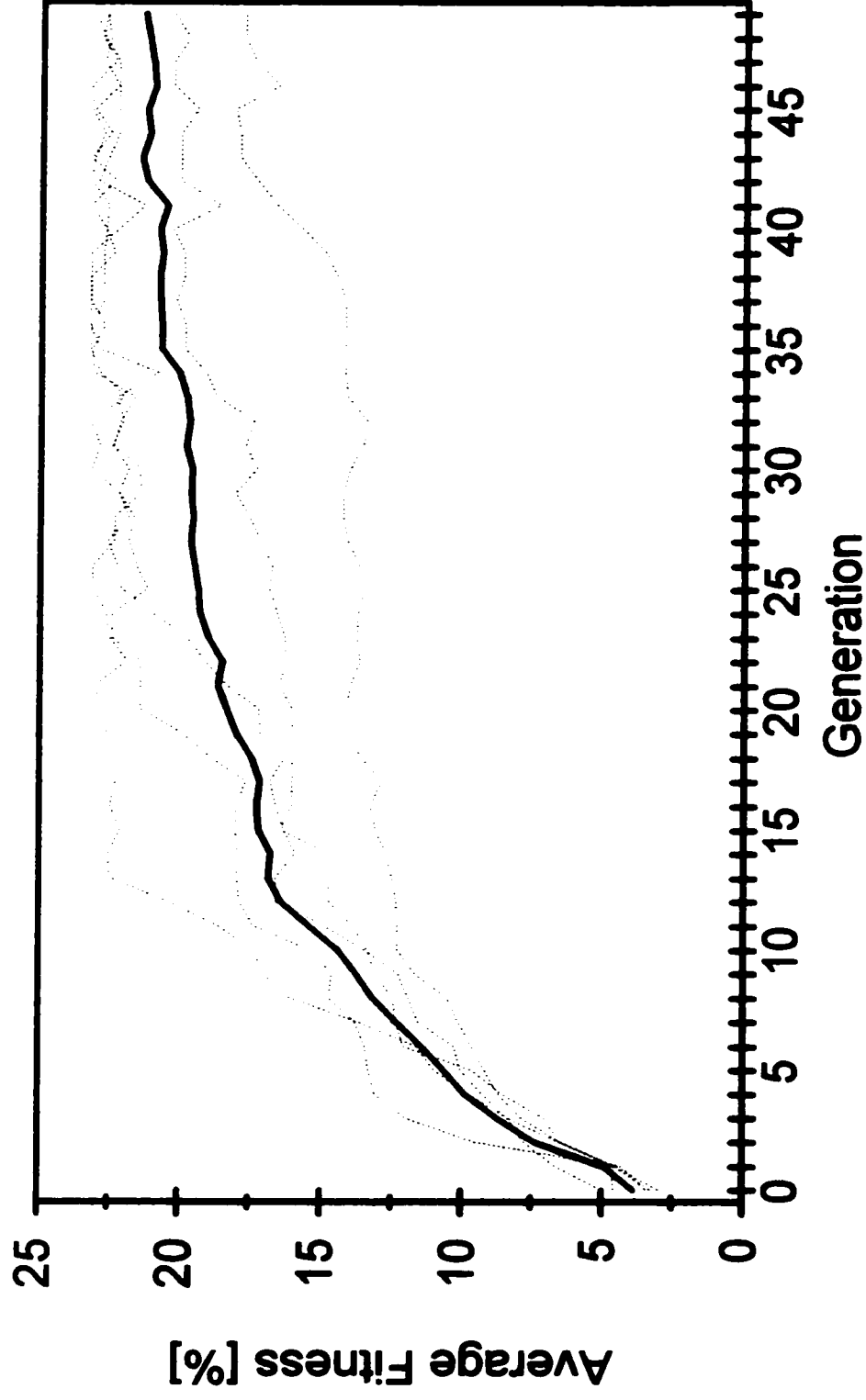
Figure 5.3. Average fitness of the population versus generation for each of the five trials (dashed lines), and the average fitness of the populations over the five trials versus generation (solid line) using a fixed crossover rate of 0.6 and a mutation rate of 0.01.
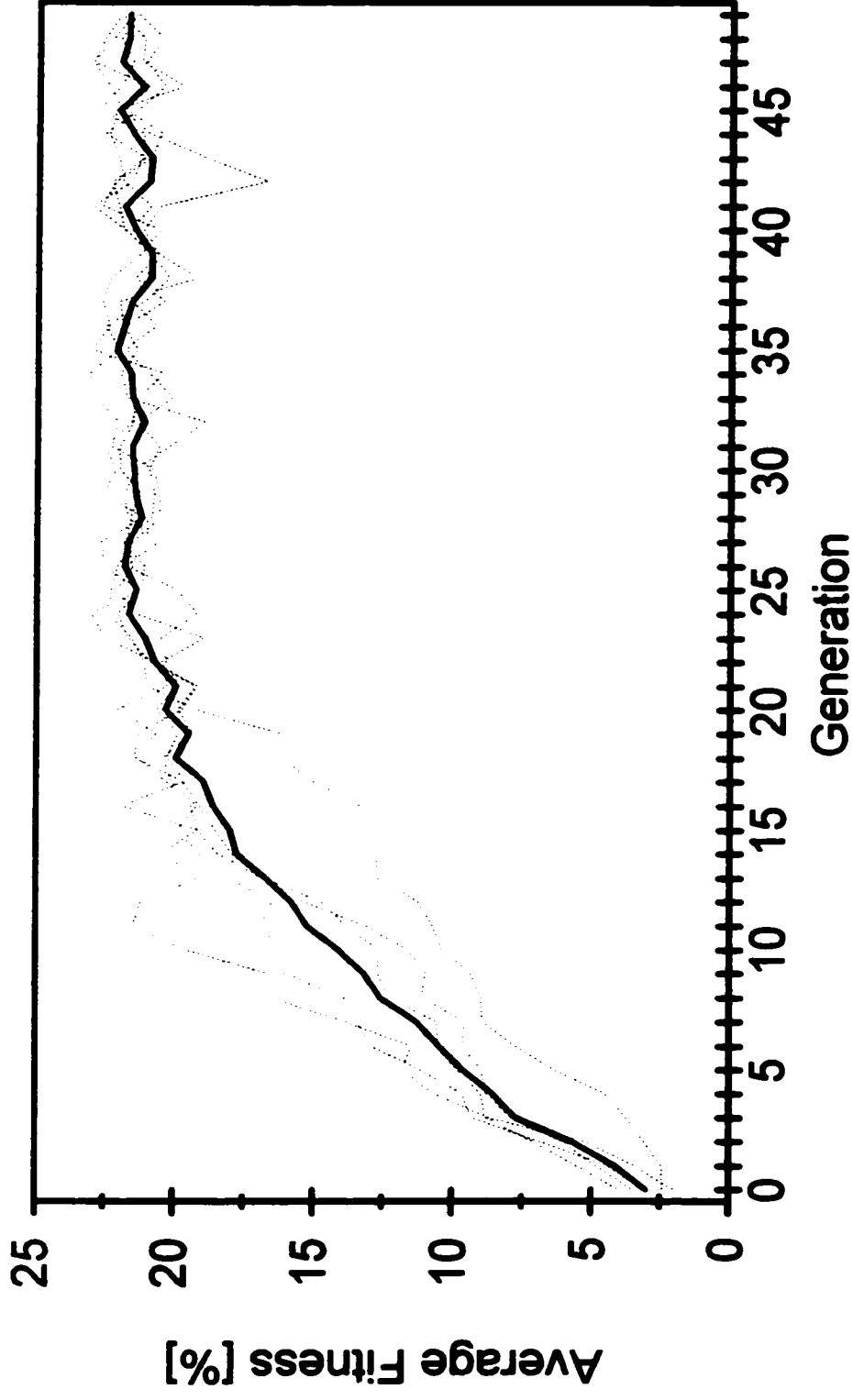
Figure 5.4. Average fitness of the population versus generation for each of the five trials (dashed lines), and the average fitness of the populations over the five trials versus generation (solid line) using a fixed crossover rate of 0.6 and a mutation rate of 0.03.
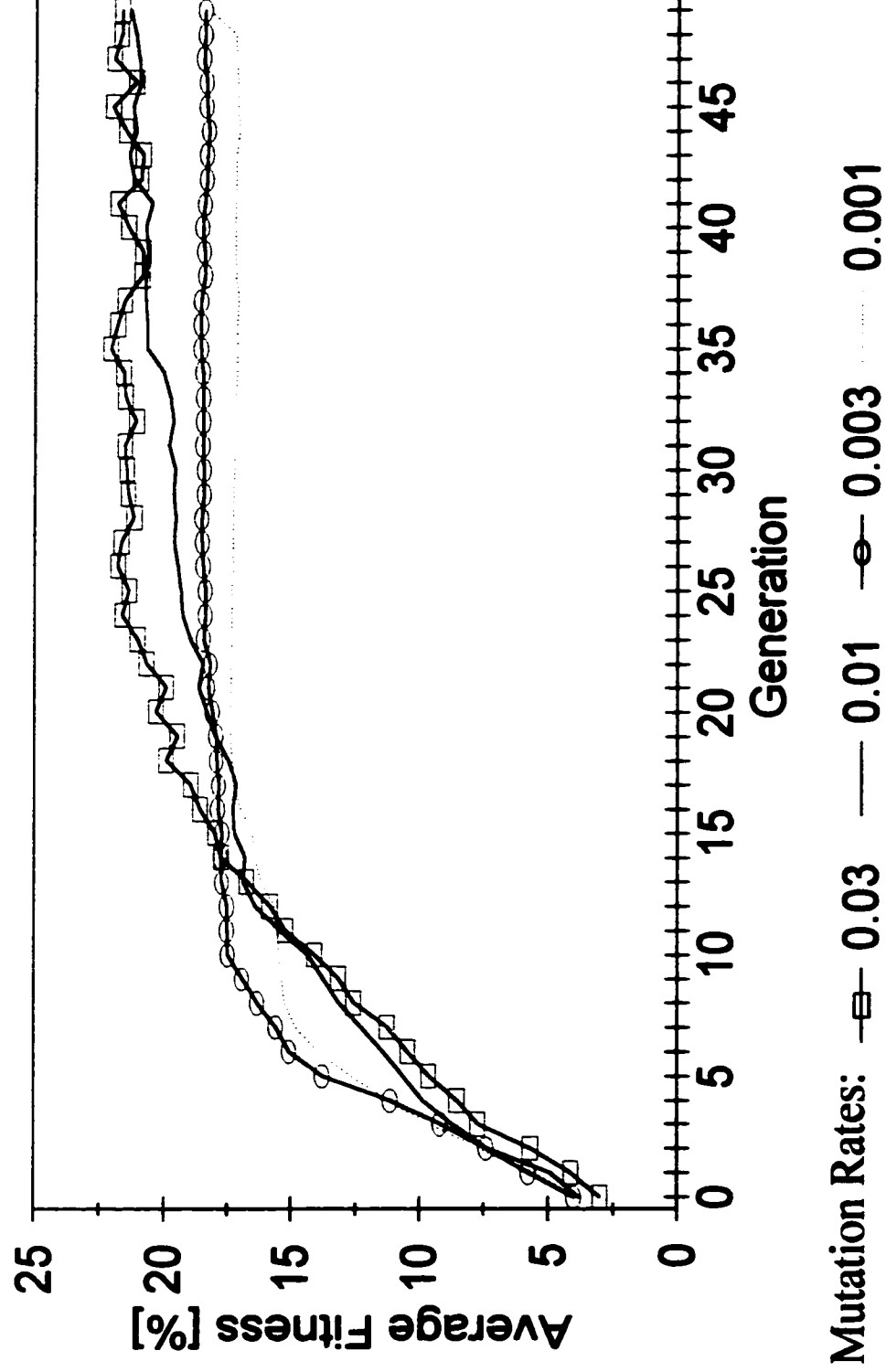
Figure 5.5. Average fitness of the populations over the five trials for a fixed crossover rate of 0.6 and various mutation rates.
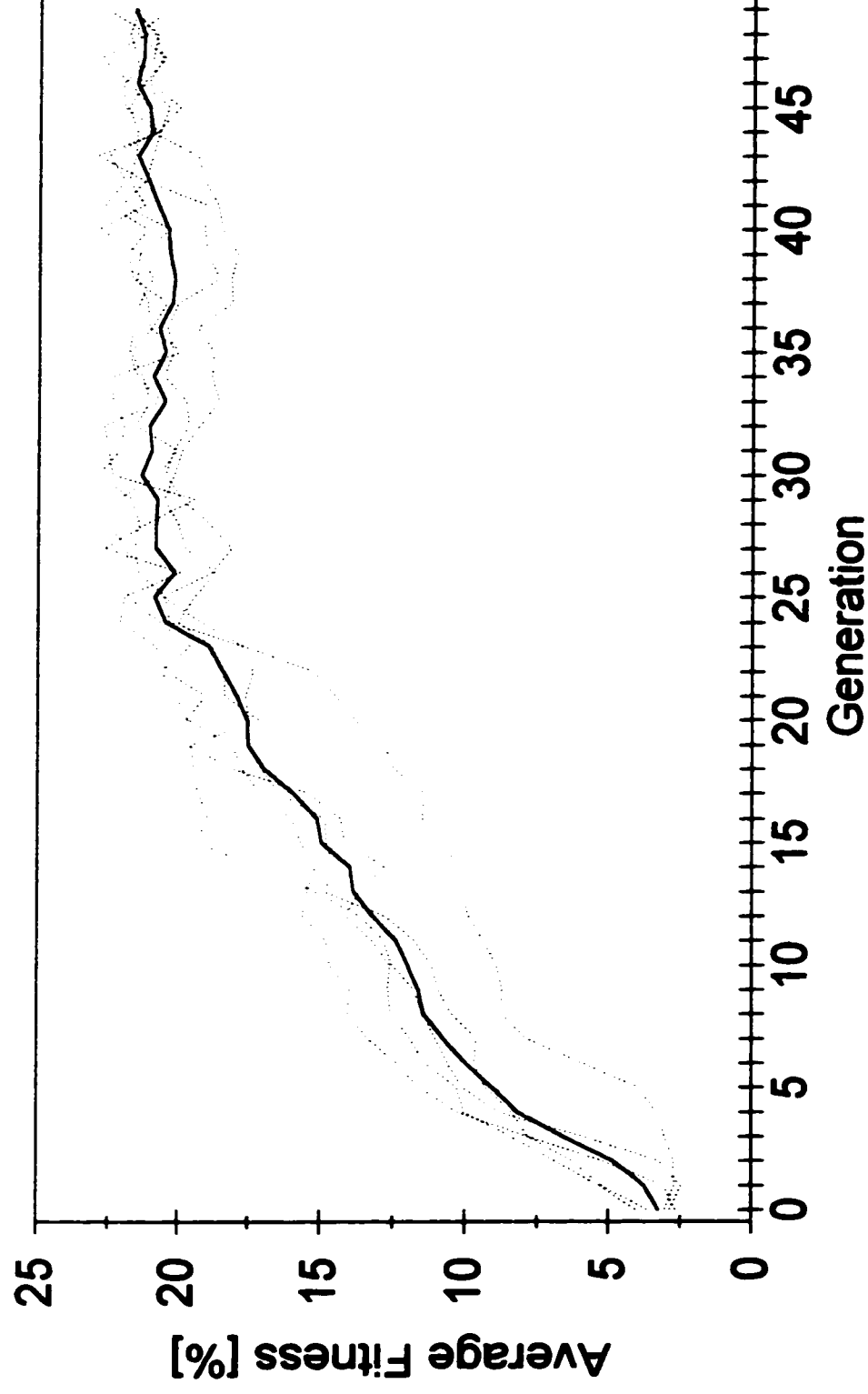
Figure 5.6. Average fitness of the population versus generation for each of the five trials (dashed lines), and the average fitness of the populations over the five trials versus generation (solid line) using a fixed mutation rate of 0.03 and a crossover rate of 0.4.

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Figure 5.7. Average fitness of the population versus generation for each of the five trials (dashed lines), and the average fitness of the populations over the five trials versus generation (solid line) using a fixed mutation rate of 0.03 and a crossover rate of 0.6.

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Figure 5.8. Average fitness of the population versus generation for each of the five trials (dashed lines), and the average fitness of the populations over the five trials versus generation (solid line) using a fixed mutation rate of 0.03 and a crossover rate of 0.8.

Figure 5.9. Average fitness of the population versus generation for each of the five trials (dashed lines), and the average fitness of the populations over the five trials versus generation (solid line) using a fixed mutation rate of 0.03 and a crossover rate of 1.0.

Figure 5.10. Average fitness of the populations over the five trials for a fixed mutation rate of 0.03 and various crossover rates.

5.3 Group Two Tests - Performance of the Genetic Algorithm

Having fixed all the parameters of the genetic algorithm, it can now be applied to the control problem. In this section the results of the genetic algorithm using both the penalty based fitness function and the fuzzy logic based fitness function are presented. As well, the performance of the genetic algorithm technique using these two fitness functions are compared to the global optimal as determined by performing an exhaustive search of the solution space using the penalty based objective function.

Using the method outlined in Chapter 4, twelve load profiles were generated. Each of the optimization methods were then tested using the same twelve load profiles. As genetic algorithms are a probabilistic search technique, three trials were performed for each of the twelve load level for both of the genetic algorithm approaches.

5.3.1 The Penalty Based Fitness Function

The results of the three trials using the genetic algorithm having a penalty based fitness function are shown in figures 5.11-5.23. Figure 5.11 shows the percent loss reduction for each of the three trials for each of the twelve periods. It is evident that the results from amongst the three trials at each load period are quite close, they differ by less than 1%. Although the results are not identical from trial to trial they are quite comparable. In fact, one of the beneficial features of the genetic algorithm approach is that the final solution consists not only of the best individual, but also contains other near optimal solutions. Figure 5.37 compares the results of the first trial using the genetic algorithm approach with an exhaustive search of the solution space for each of the twelve periods studied. From this it is clear that the results from the genetic algorithm using the penalty based fitness function are always

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slightly less than or equal to the global optimal solution. While the genetic algorithm is not guaranteed to find the global optimal, it does consistently find quite comparable near optimal solutions.

The voltage profile of the distribution system resulting from the compensation determined by the genetic algorithm with the penalty based fitness function for the three trials at each of the twelve periods studied are given in Figures 5.12-5.23. Upon examination of the voltage profiles, it is clear that all of the bus voltages are within the ±5% limits as required. In this respect the genetic algorithm using the penalty based fitness function was successful, as none of the final solutions resulted in constraint violations. Figures 5.38-5.49 compare the bus voltages obtained by the first trial of the genetic algorithm using the penalty based fitness function with those of the bare system and those of the distribution system when compensated according to the results of exhaustive search for each of the twelve periods studied. It should be mentioned that the bus voltage profile of the bare system for every load period violates the ±5% constraint at several buses. The ability of the genetic algorithm using the penalty based fitness function to consistently arrive at solutions which do not violate the voltage constraints is quite noteworthy. As was mentioned in Chapter 3, the method of implementing constraints in a genetic algorithm is quite important, this will be discussed further in the next section.

Table 5.1 shows a typical initial and final population of the genetic algorithm. From this it is evident that the genetic algorithm starts from a random population of individuals and converges to a final population that contains several optimal or near optimal solutions. Table 5.2 shows the total losses of the distribution system for the bare system, as well as for the

system after being compensated by each of the three methods. From this table, it can be seen that of the 36 trials performed using the penalty based fitness function, 7 resulted in the global optimal solution being found.

When evaluating the performance of the genetic algorithm approach it is important not only to consider the quality of solution, but also the time required to arrive at the solution. As was discussed earlier, in order to be useful any method of performing the control problem must be capable of arriving at a high quality solution in less than five minutes. The time required by the genetic algorithm using the penalty based fitness function was less than 3 minutes and 30 seconds in every case. This is quite acceptable. It should be pointed out that the time required by the genetic algorithm to arrive at a solution is primarily limited by the time required to perform a load flow analysis for the system. In this thesis the Gauss-Seidel technique was used as was discussed in Chapter 4. This method is not the fastest method available, however it was felt that for the system being studied here that this technique was sufficient. If this method were to be applied to a larger distribution system, consisting for example of several hundred buses, one of the faster load flow techniques might be required. The solution of the genetic algorithm is not sensitive to the load flow technique employed, providing that the technique yields accurate results.

5.3.1 The Fuzzy Logic Based Fitness Function

The results of the three trials for each of the twelve periods from the genetic algorithm using the fuzzy logic based fitness function are shown in figures 5.24-5.36. Figure 5.24 shows the percent loss reduction for the three trials for each of the twelve load periods studied. From this it is evident that the results from amongst the three trials at each load

period are quite similar. Although the results are not identical from trial to trial they are quite comparable. Again, this is evidence of one of the benefits of the genetic algorithm approach, that is, that the final solution consists not only of the best solution, but also contains several other near optimal solutions. Figure 5.37 compares the results of the first trial of the genetic algorithm approach using the fuzzy logic based fitness function with the results of an exhaustive search of the solution space for each of the twelve periods studied. From this it is clear that the results from the genetic algorithm using the penalty based fitness function are always close, or equal to the global optimal solution. Unlike the penalty based method, however, the fuzzy logic based method often results in a solution that has a higher percent loss reduction than the global optimal solution. In each instance that the losses were reduced further by the fuzzy logic based method than by the global optimal solution a voltage violation occurred at bus 5. This is the result of the trade off between solutions which tend to reduce losses and those which tend to keep the voltages away from their limits.

Figures 5.25-5.36 show the bus voltages for the three trials at each of the twelve load periods. Upon examining these figures it can be seen that in 11 out of the 36 trials (4 out of the 12 periods) performed, the genetic algorithm using the fuzzy logic based fitness function results in a voltage violation at bus 5. In each of these cases, the losses are reduced further by the genetic algorithm technique than by the global optimal solution which never violates voltage constraints. This is a result of the trade off performed by the fuzzy logic method between the number of bus voltage constraints and the percent loss reduction of the distribution system. This problem could be corrected by modifying the fuzzy objective functions for the number of constraint violations and the fuzzy objective function for the

percent loss reduction. Another way to resolve this problem would be to incorporate a more complicated fuzzy fitness function, perhaps one that sought to minimize the intersection between the total system losses and the number of constraint violations AND the degree of violation. The fuzzy fitness function used in this thesis was chosen for its similarity with the penalty based fitness function so that the two methods could be more easily compared. While the quality of the solution obtained by the genetic algorithm using the fuzzy logic based fitness function are not as good as those obtained by the genetic algorithm using the penalty based fitness function, they should not be discounted. As far as the author knows, this is the first time that a fuzzy based fitness function has employed to solve the control problem. The results from the fuzzy based method while not ideal are quite promising, and the idea deserves further study.

From Table 5.2 it can be seen that of the 36 trials performed using the fuzzy logic based fitness function, 3 were identical to the global optimal solution. The time required by the genetic algorithm using the fuzzy logic based fitness function was comparable to that required by the penalty based method, and never exceeded 3 minutes and 30 seconds. This is quite acceptable. It is worth mentioning that the time required to obtain the global optimal solution by performing an exhaustive search ranged from 2 hours and 45 minutes to 3 hours! This clearly illustrates the effectiveness of the genetic algorithm to quickly arrive at the optimal or near optimal solution.
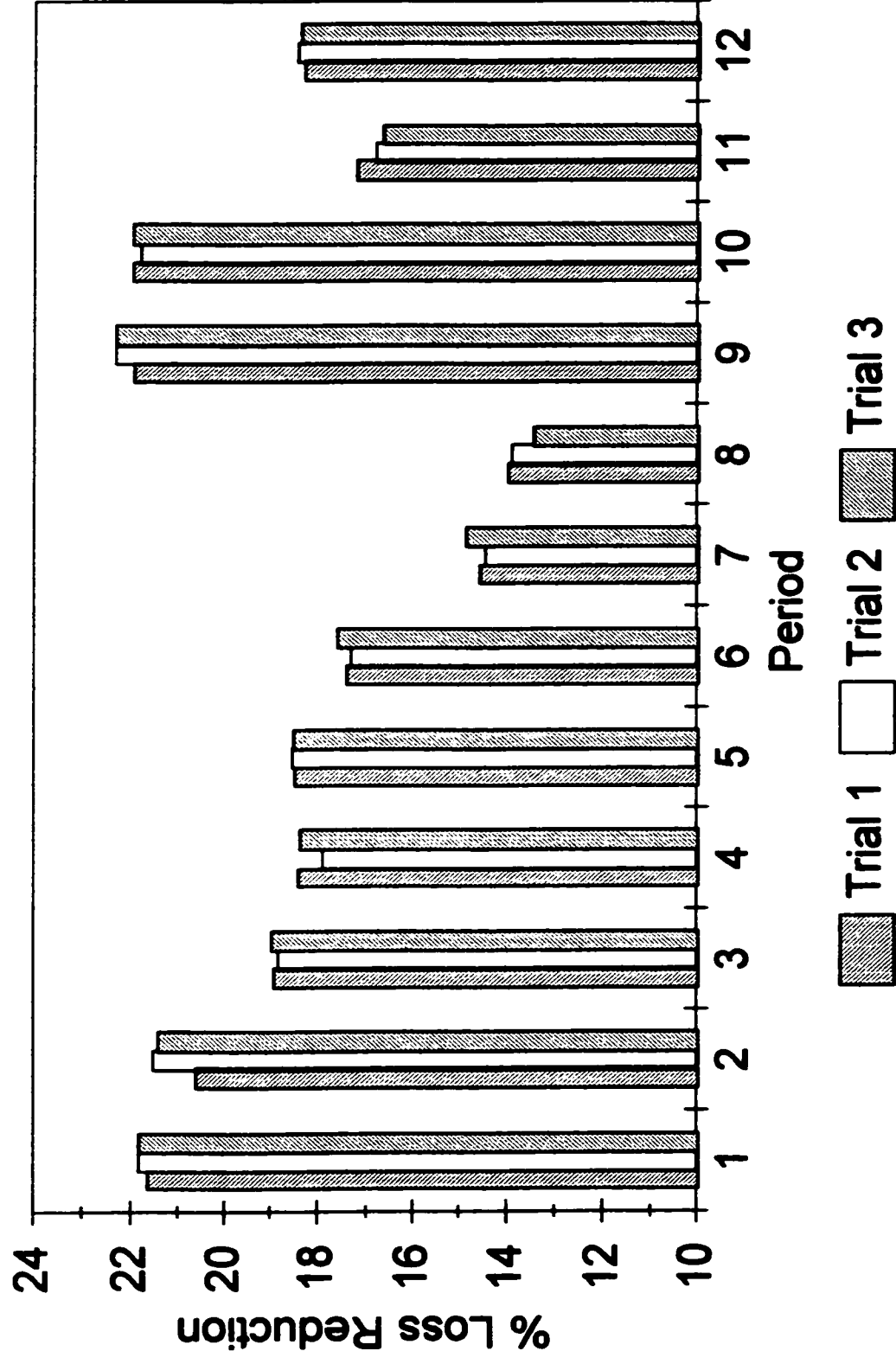
Figure 5.11. Percent loss reduction for the three trials using the penalty based fitness function for each of the twelve periods studied.
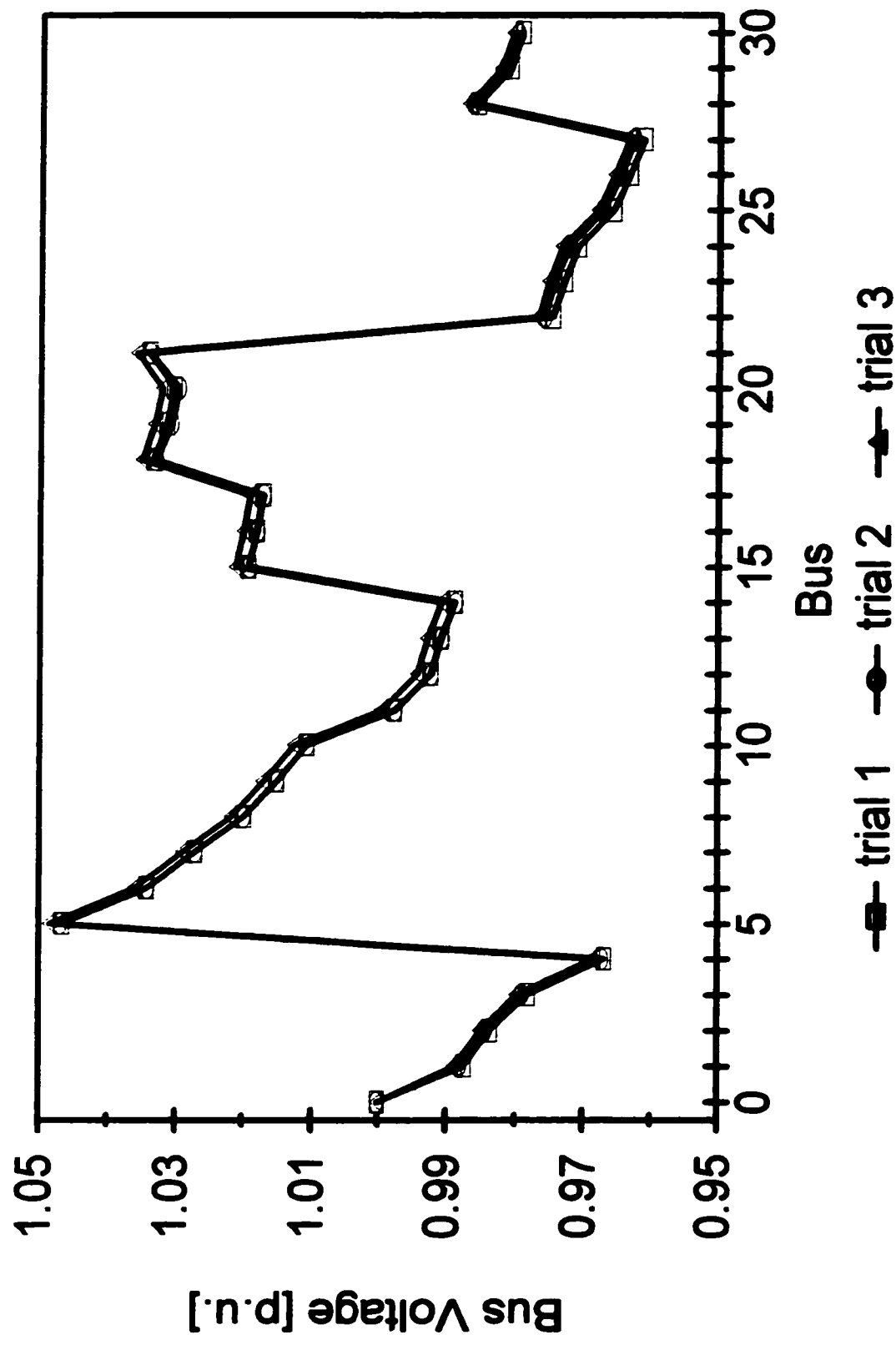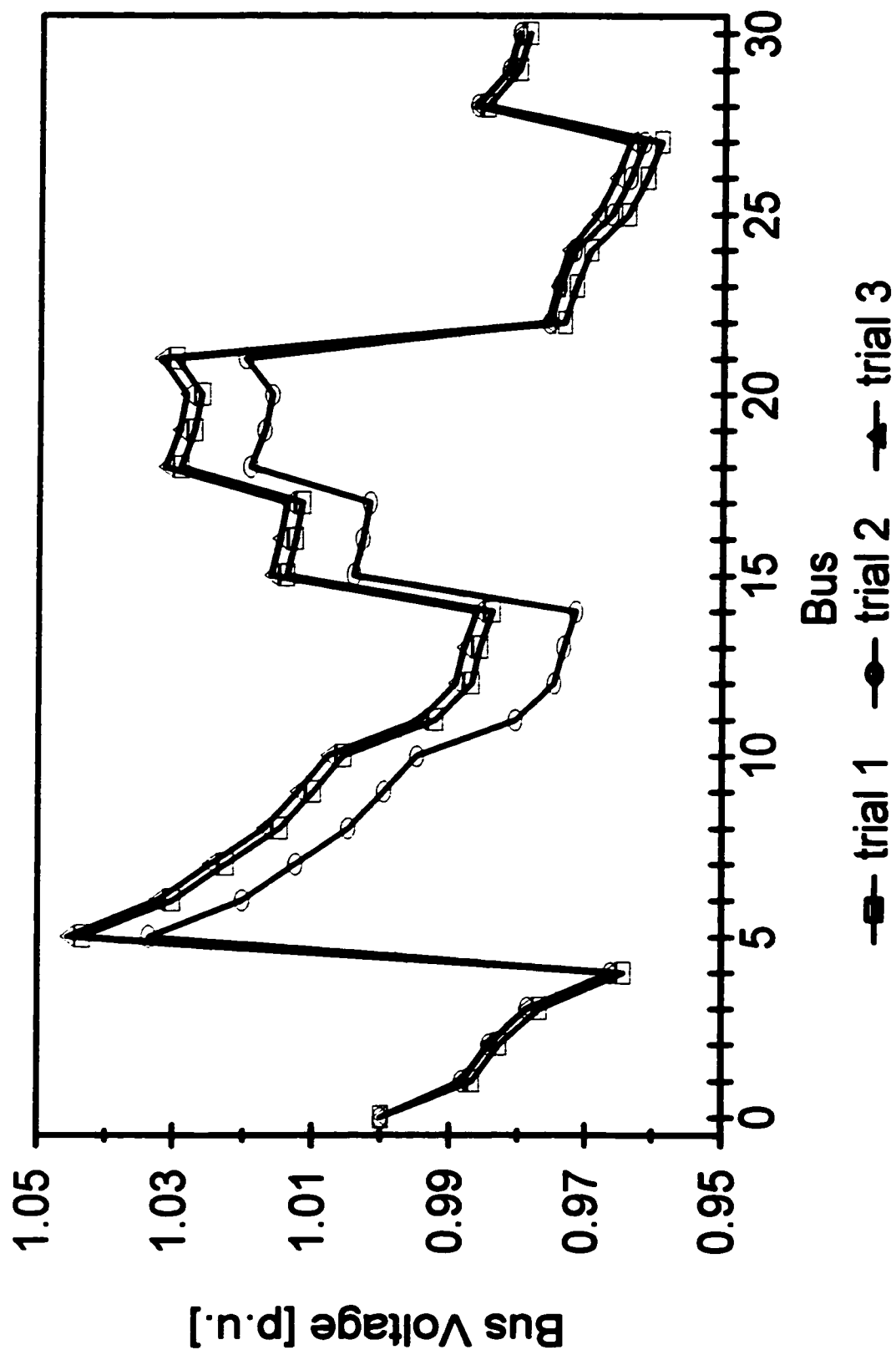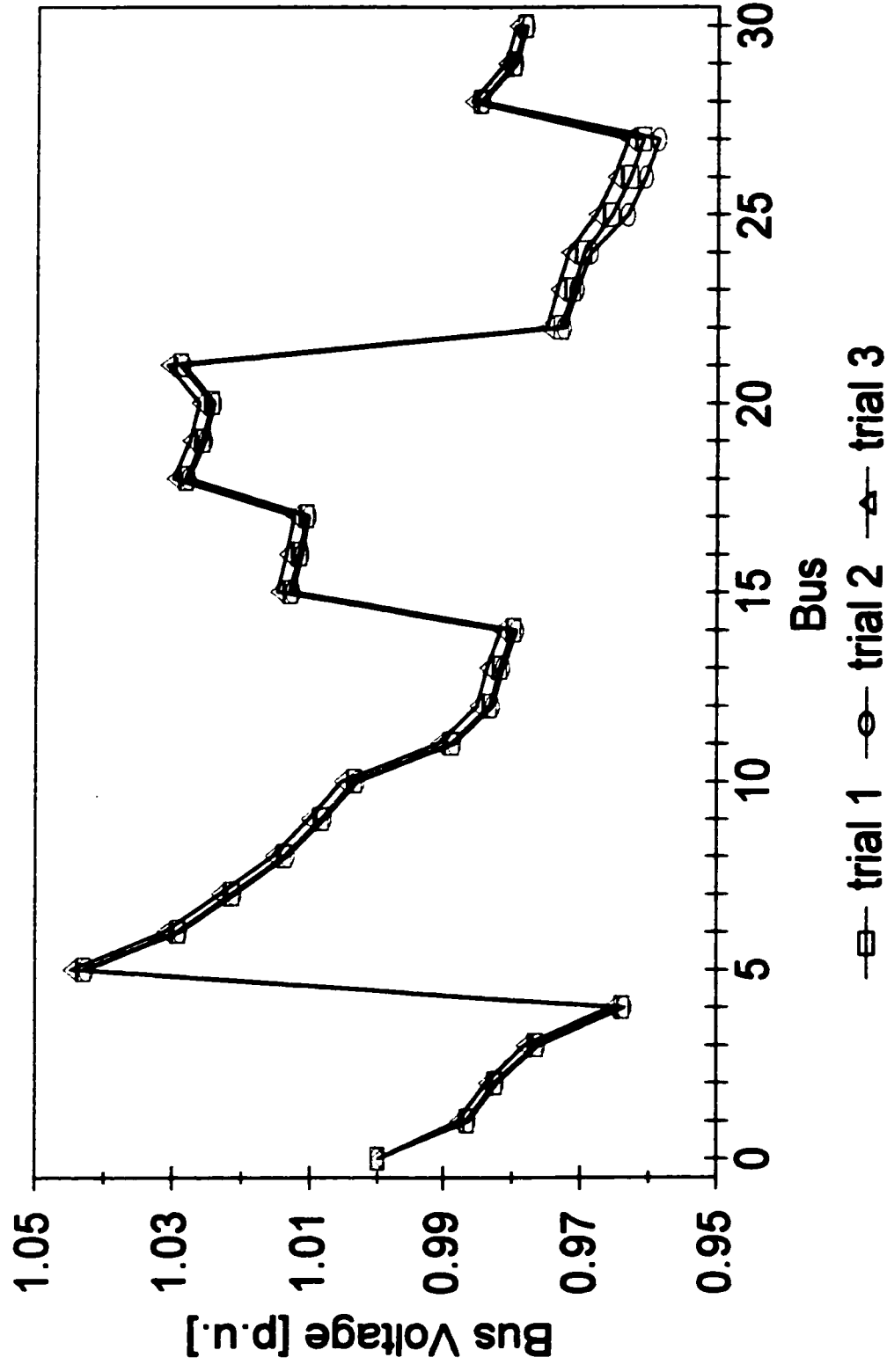
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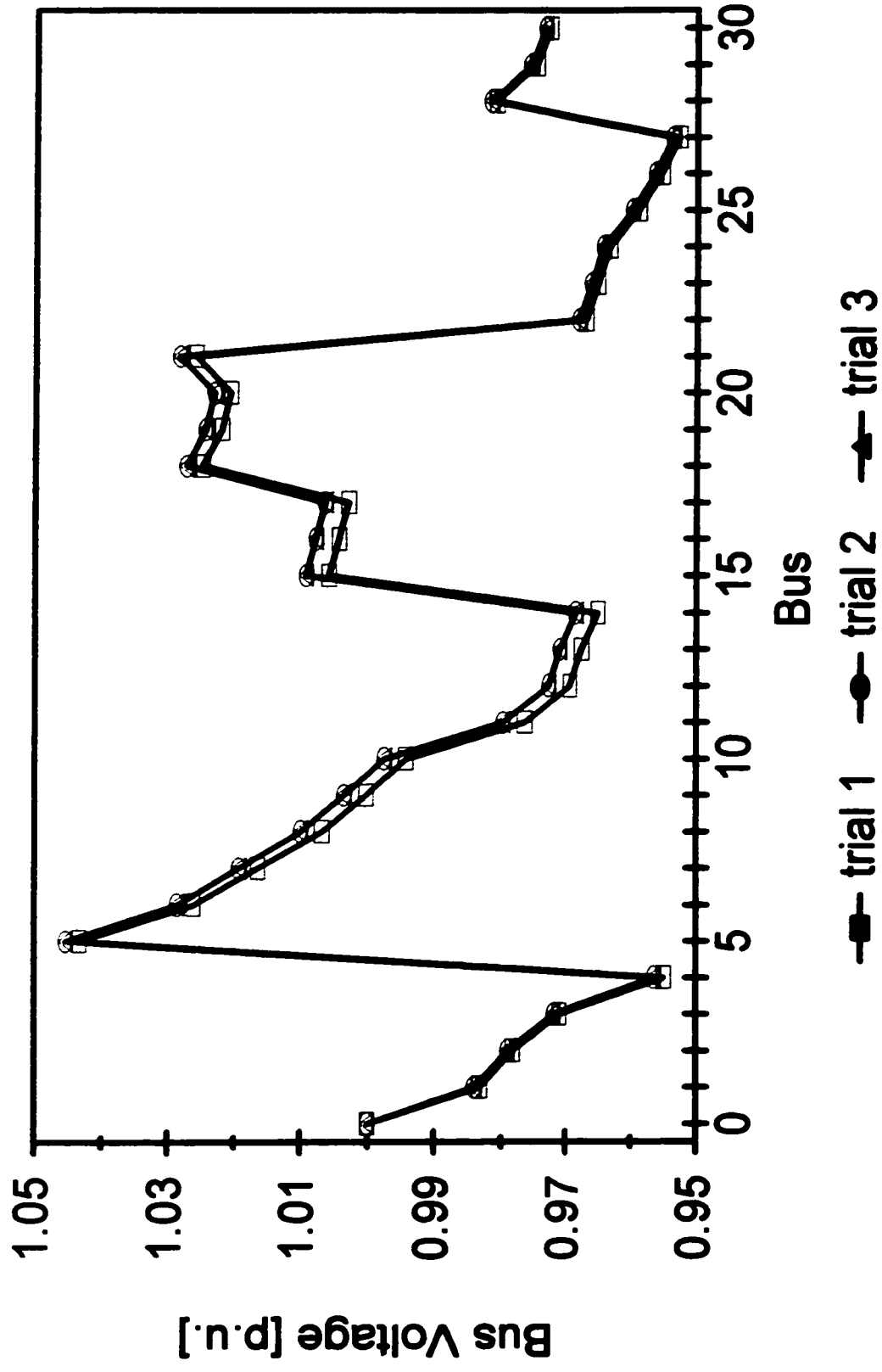
Figure 5.12. Voltage profile of the three period 1 trials for the genetic algorithm using the penalty based fitness function.
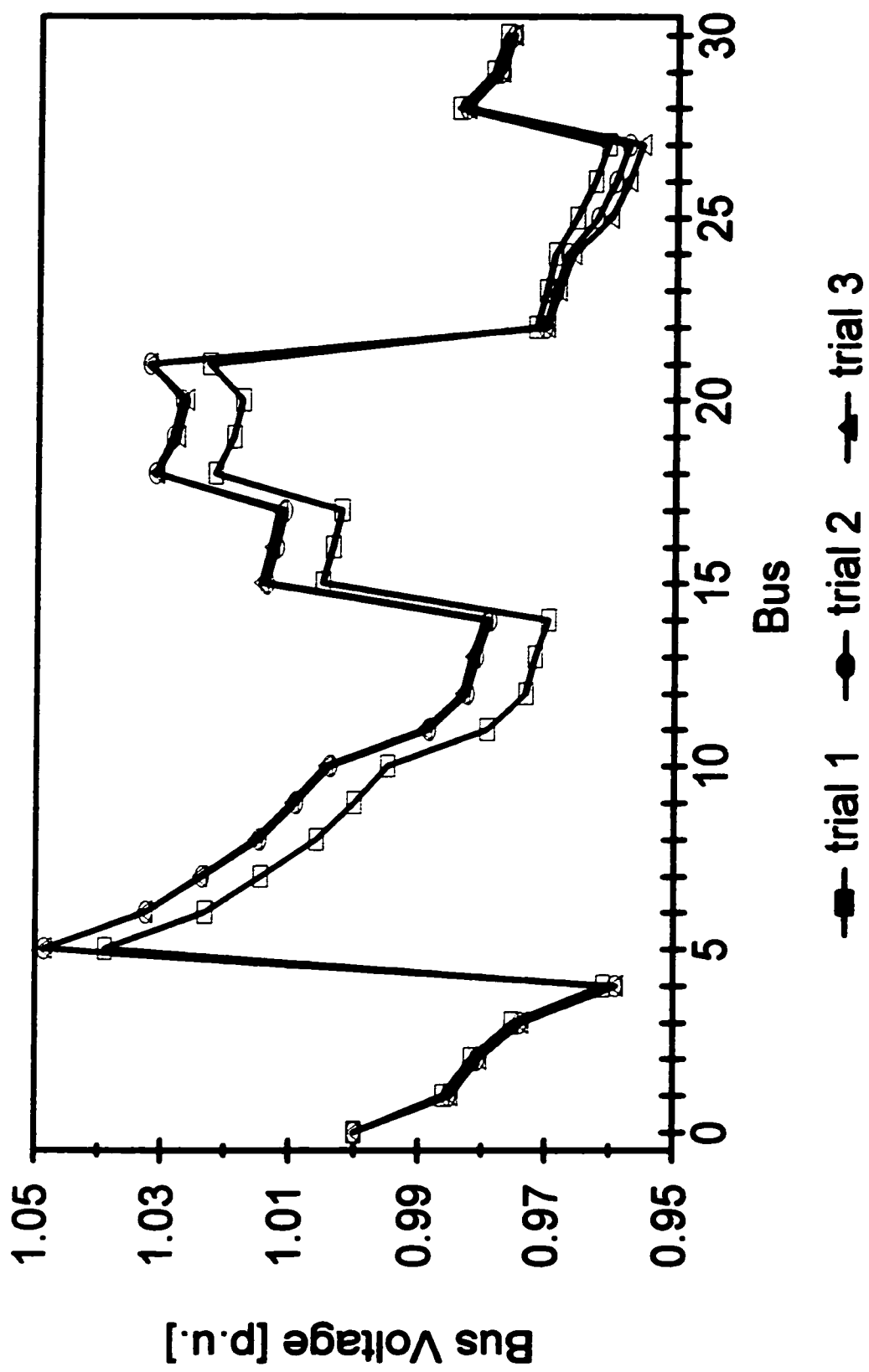
Figure 5.13. Voltage profile of the three period 2 trials for the genetic algorithm using the penalty based fitness function.
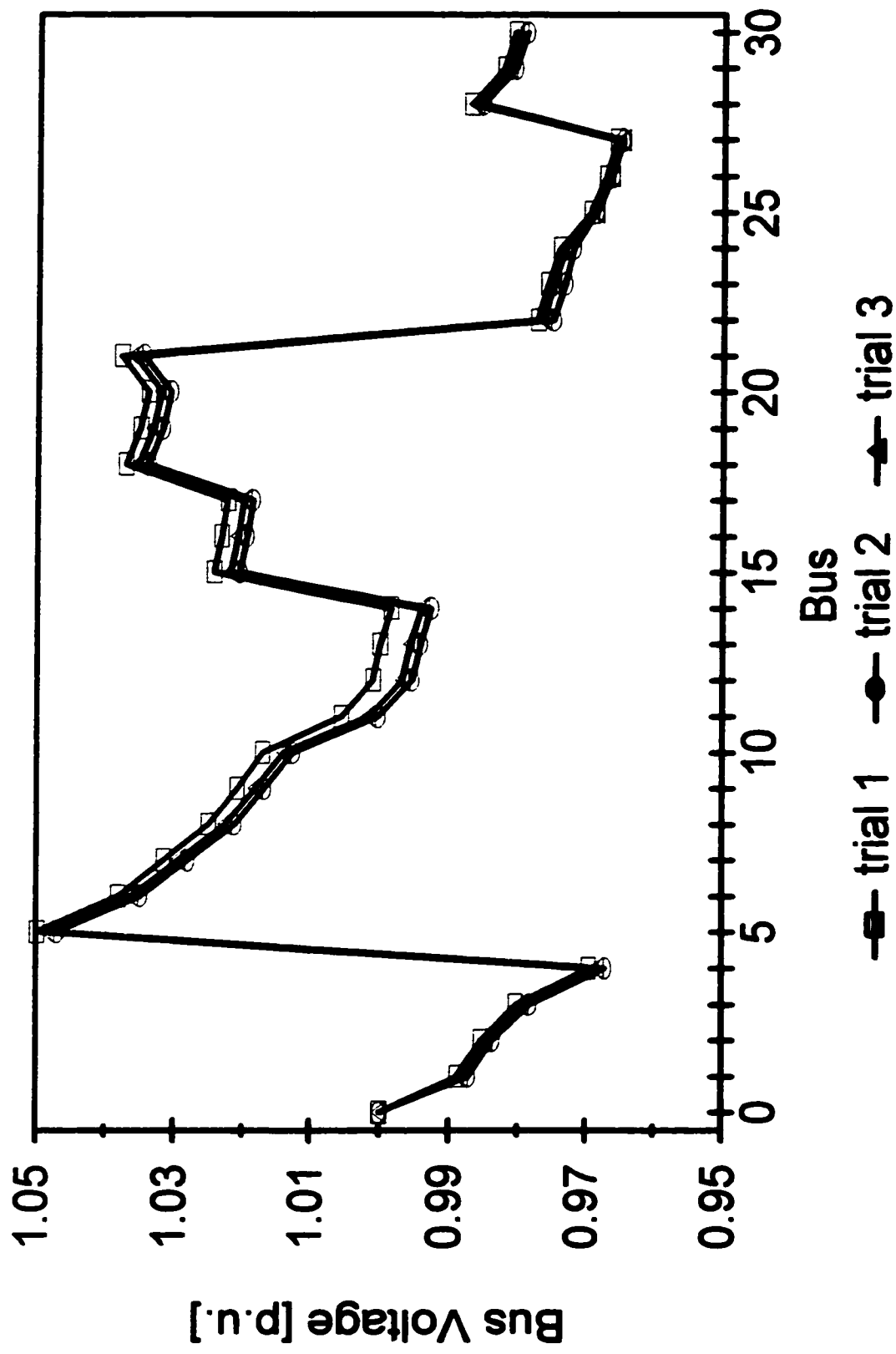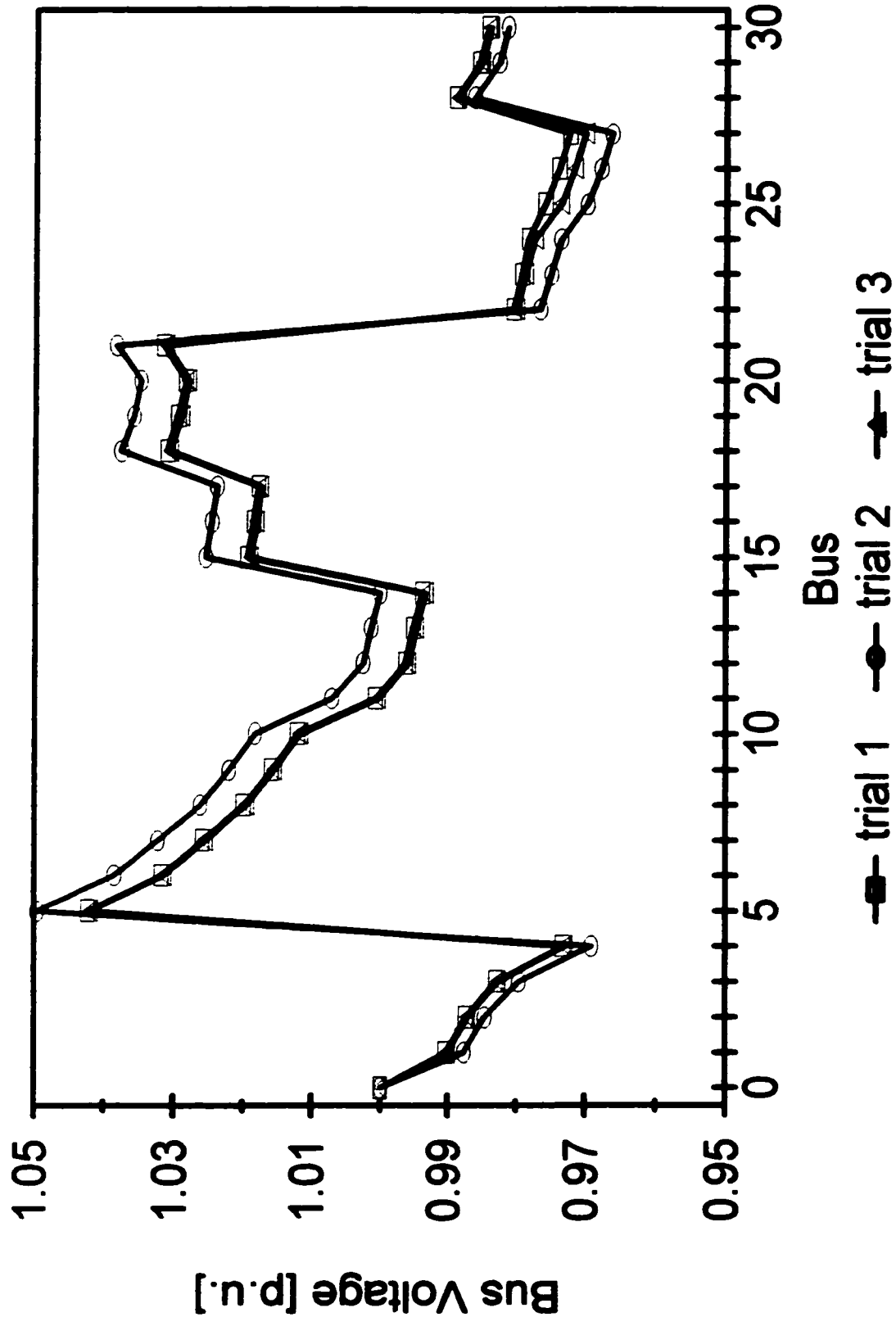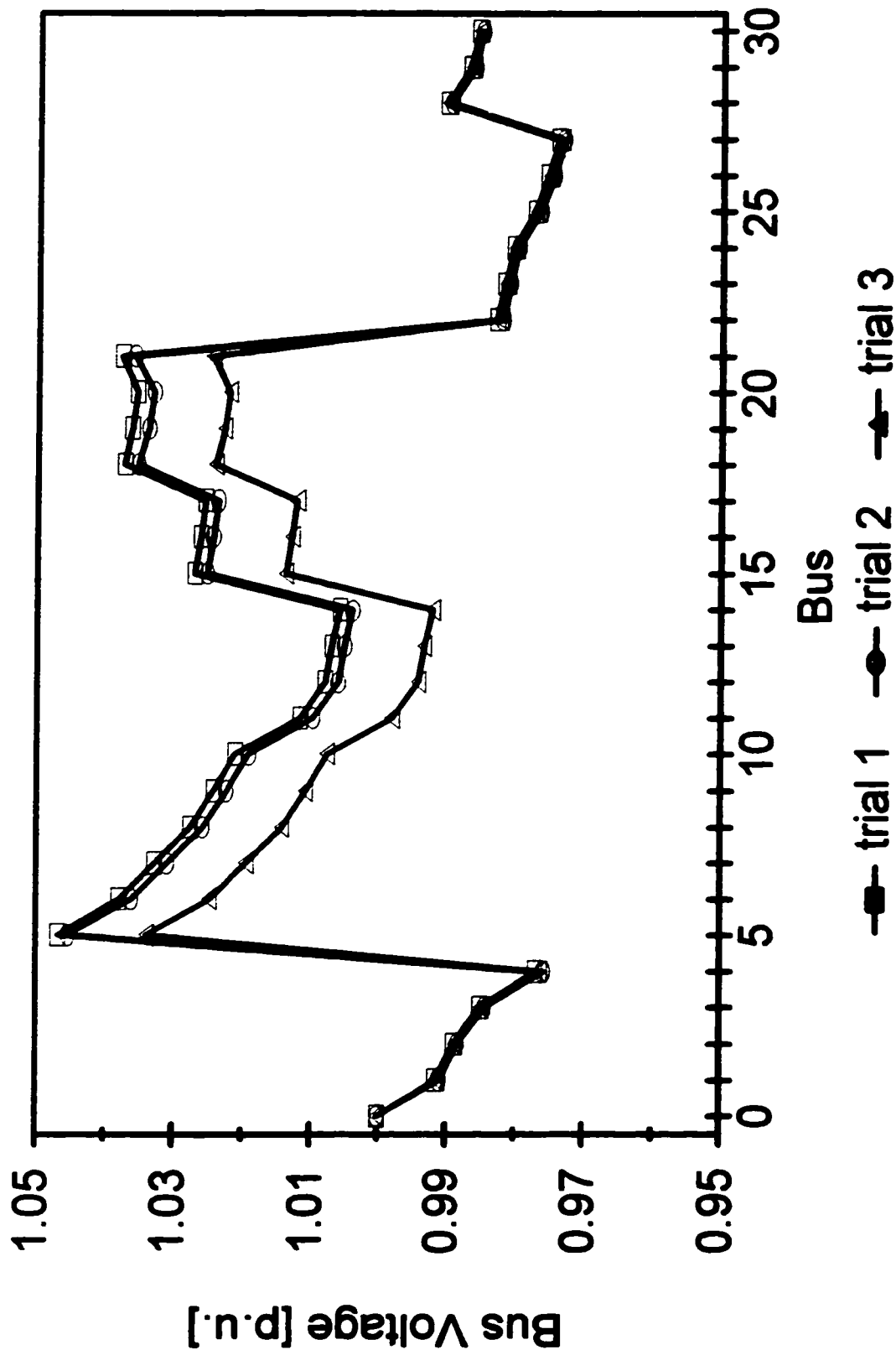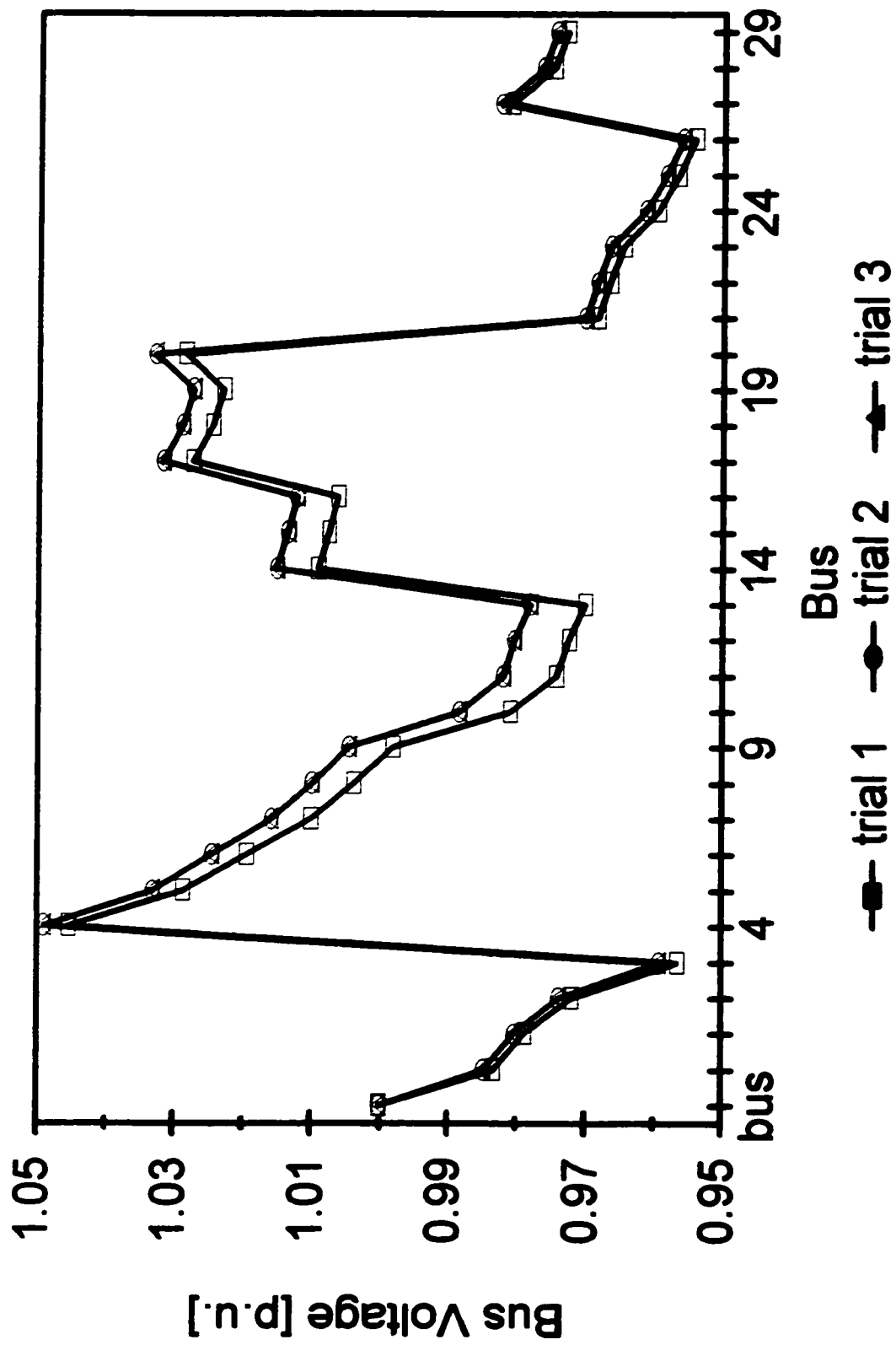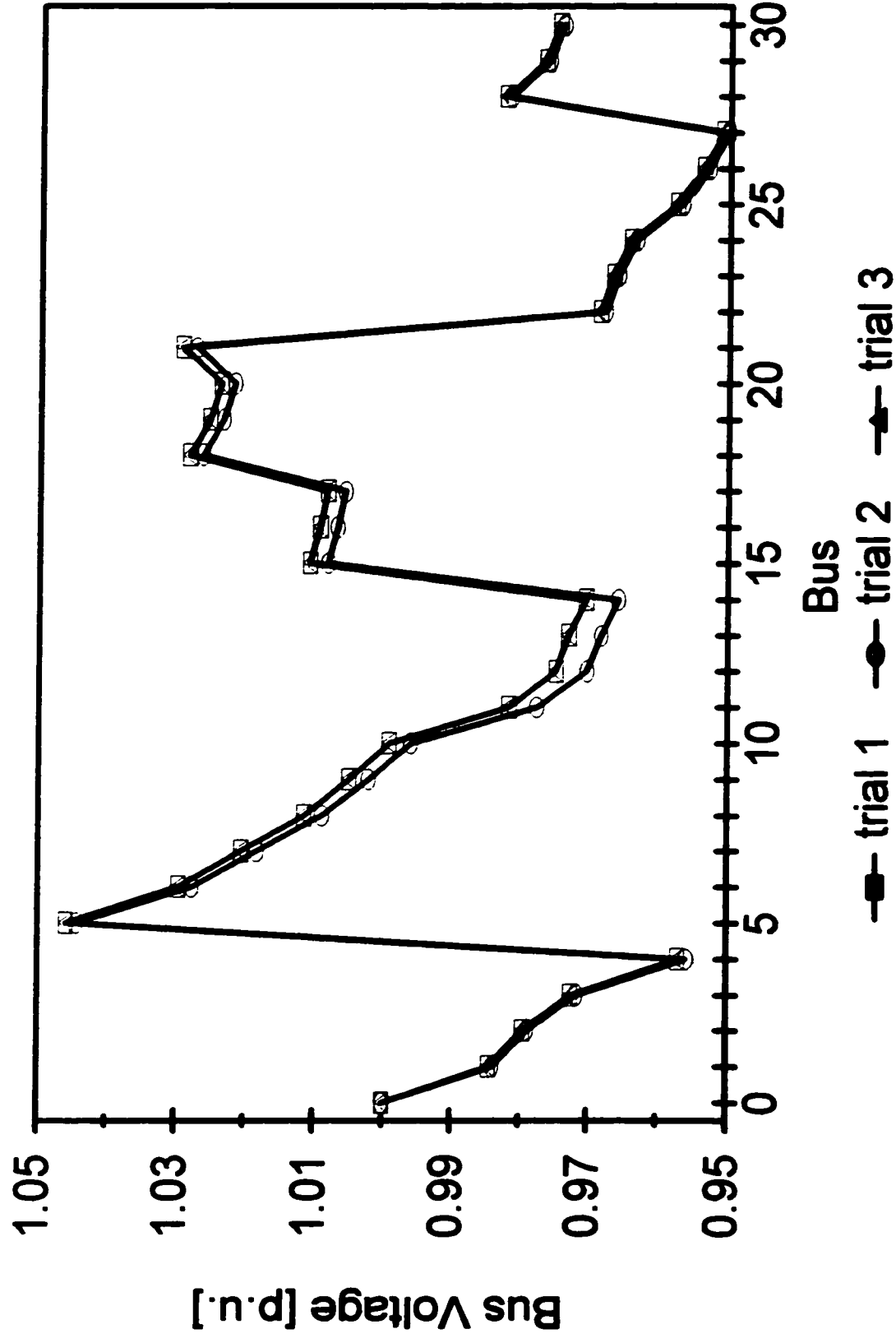
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Figure 5.14. Voltage profile of the three period 3 trials for the genetic algorithm using the penalty based fitness function.

Figure 5.15. Voltage profile of the three period 4 trials for the genetic algorithm using the penalty based fitness function.

Figure 5.16. Voltage profile of the three period 5 trials for the genetic algorithm using the penalty based fitness function.

Figure 5.17. Voltage profile of the three period 6 trials for the genetic algorithm using the penalty based fitness function.
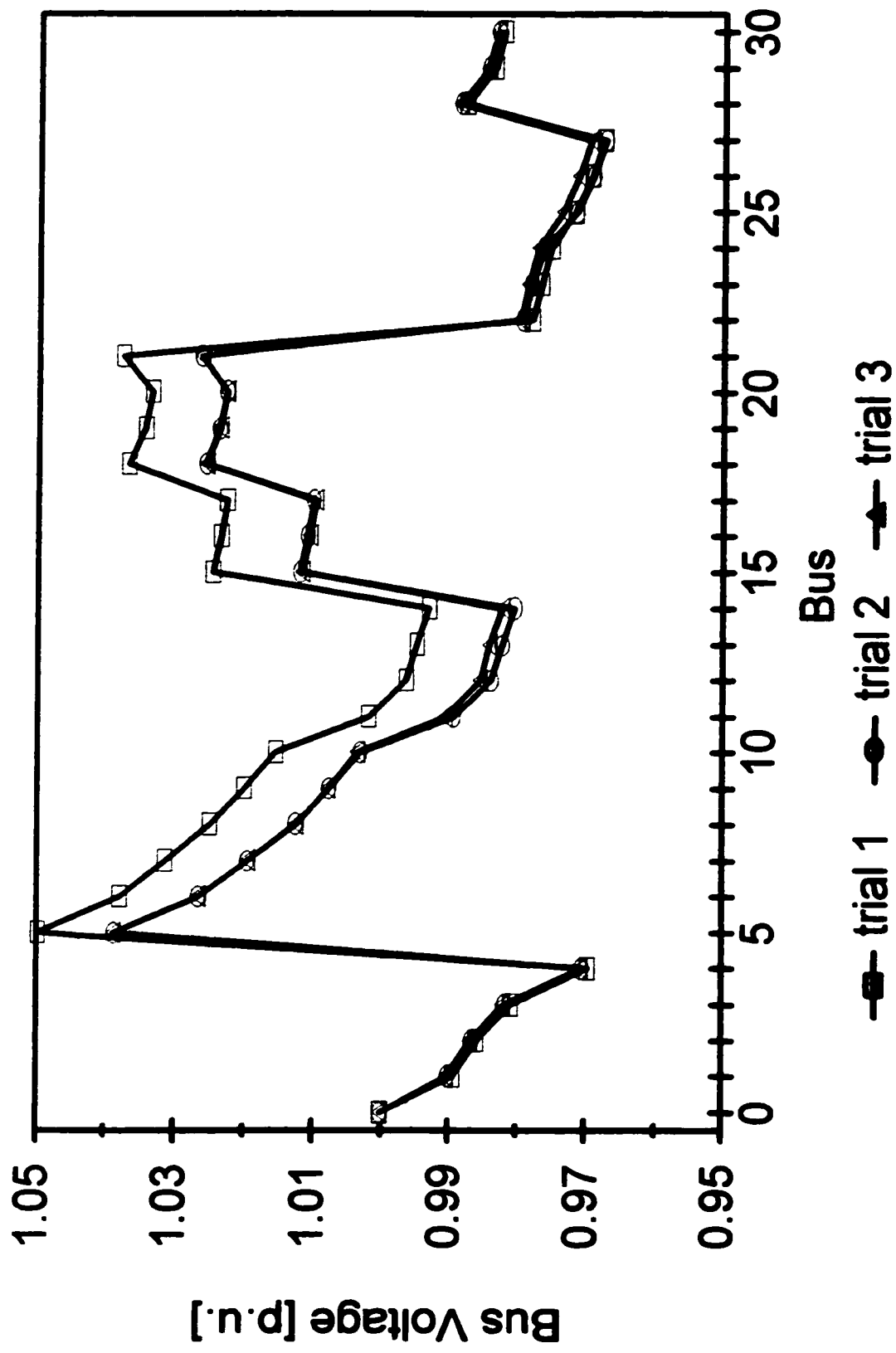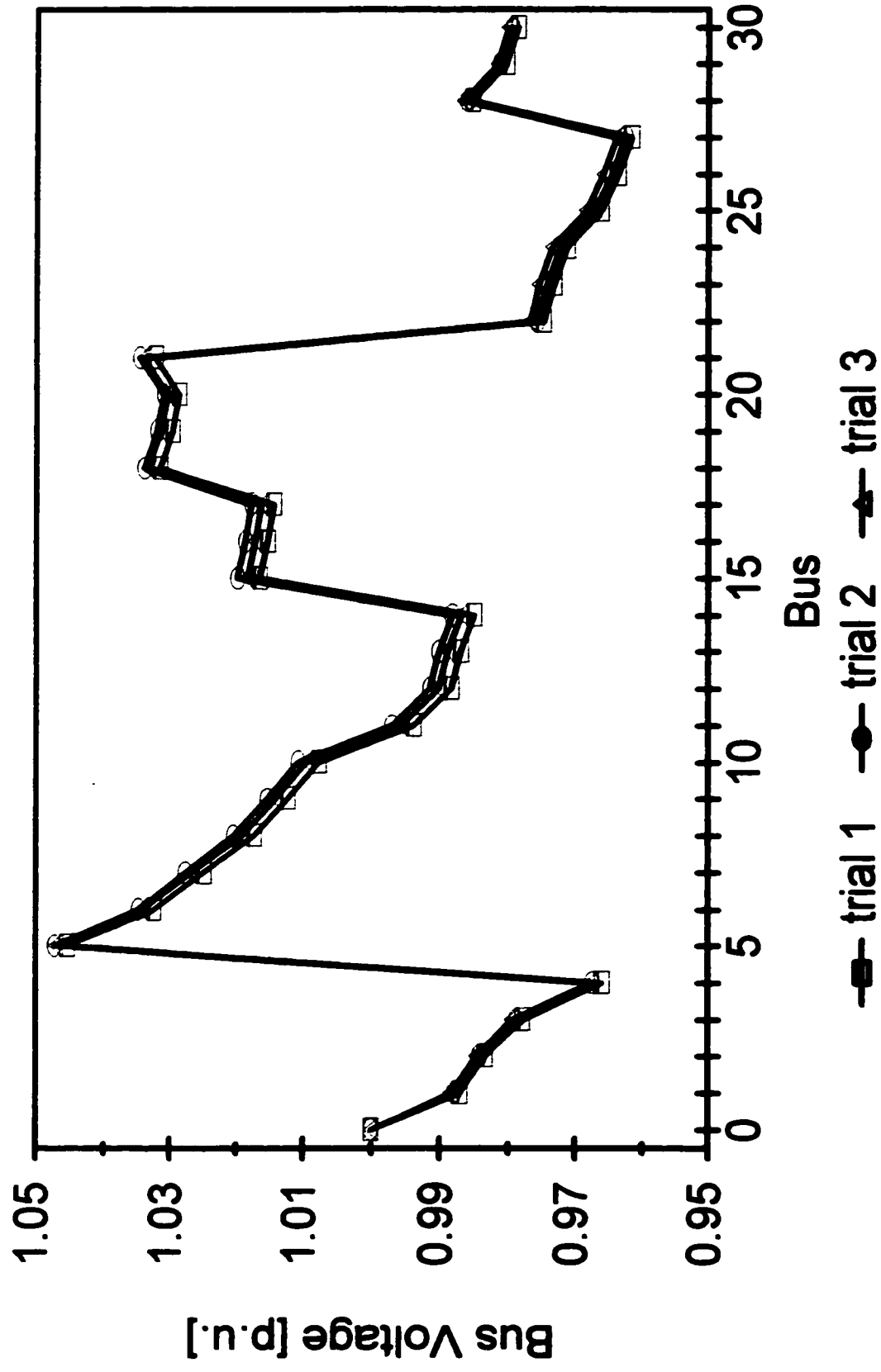
Figure 5.18. Voltage profile of the three period 7 trials for the genetic algorithm using the penalty based fitness function.

Figure 5.19. Voltage profile of the three period 8 trials for the genetic algorithm using the penalty based fitness function.

Figure 5.20. Voltage profile of the three period 9 trials for the genetic algorithm using the penalty based fitness function.

Figure 5.21. Voltage profile of the three period 10 trials for the genetic algorithm using the penalty based fitness function.

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Figure 5.22. Voltage profile of the three period 11 trials for the genetic algorithm using the penalty based fitness function.

Figure 5.23. Voltage profile of the three period 12 trials for the genetic algorithm using the penalty based fitness function.
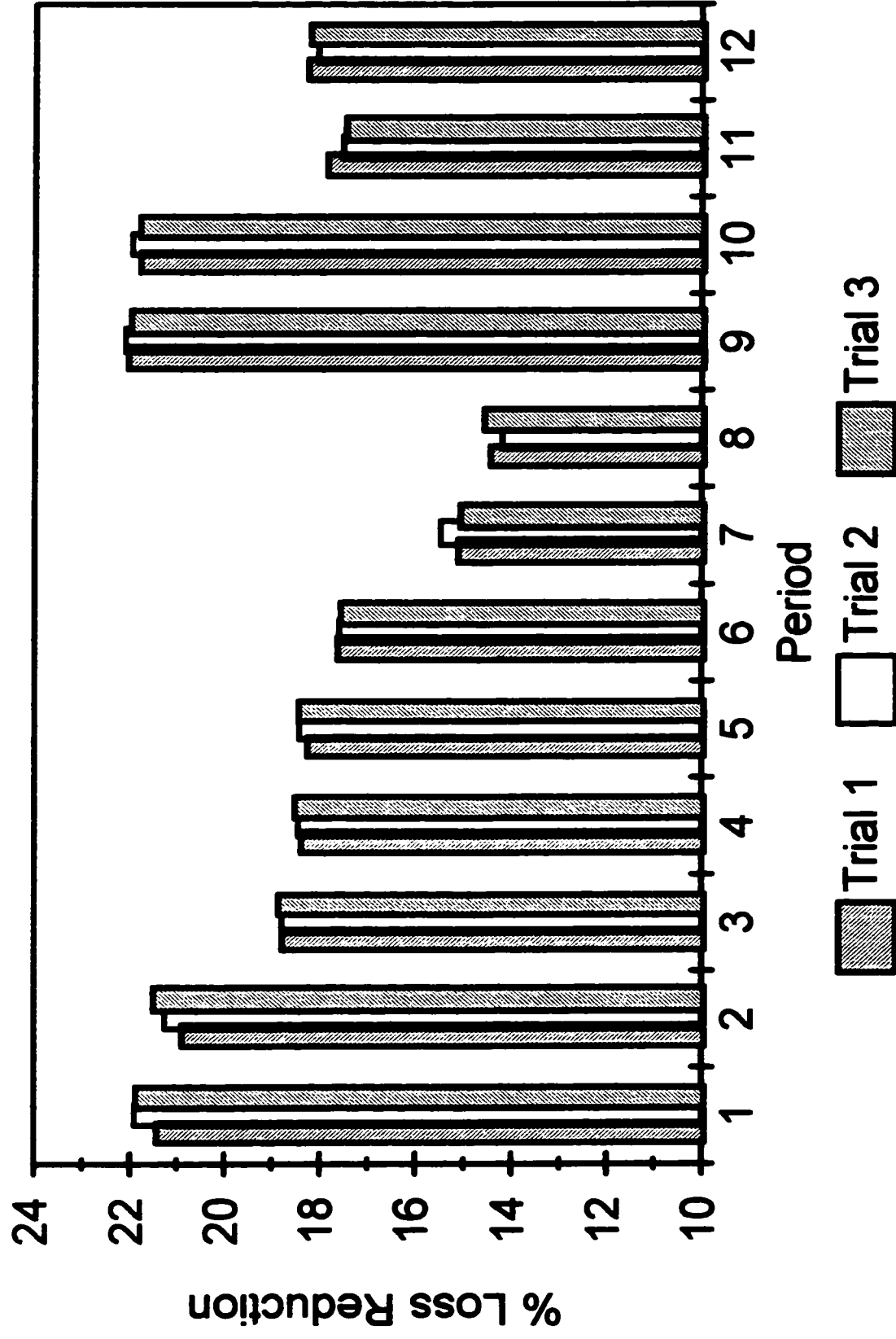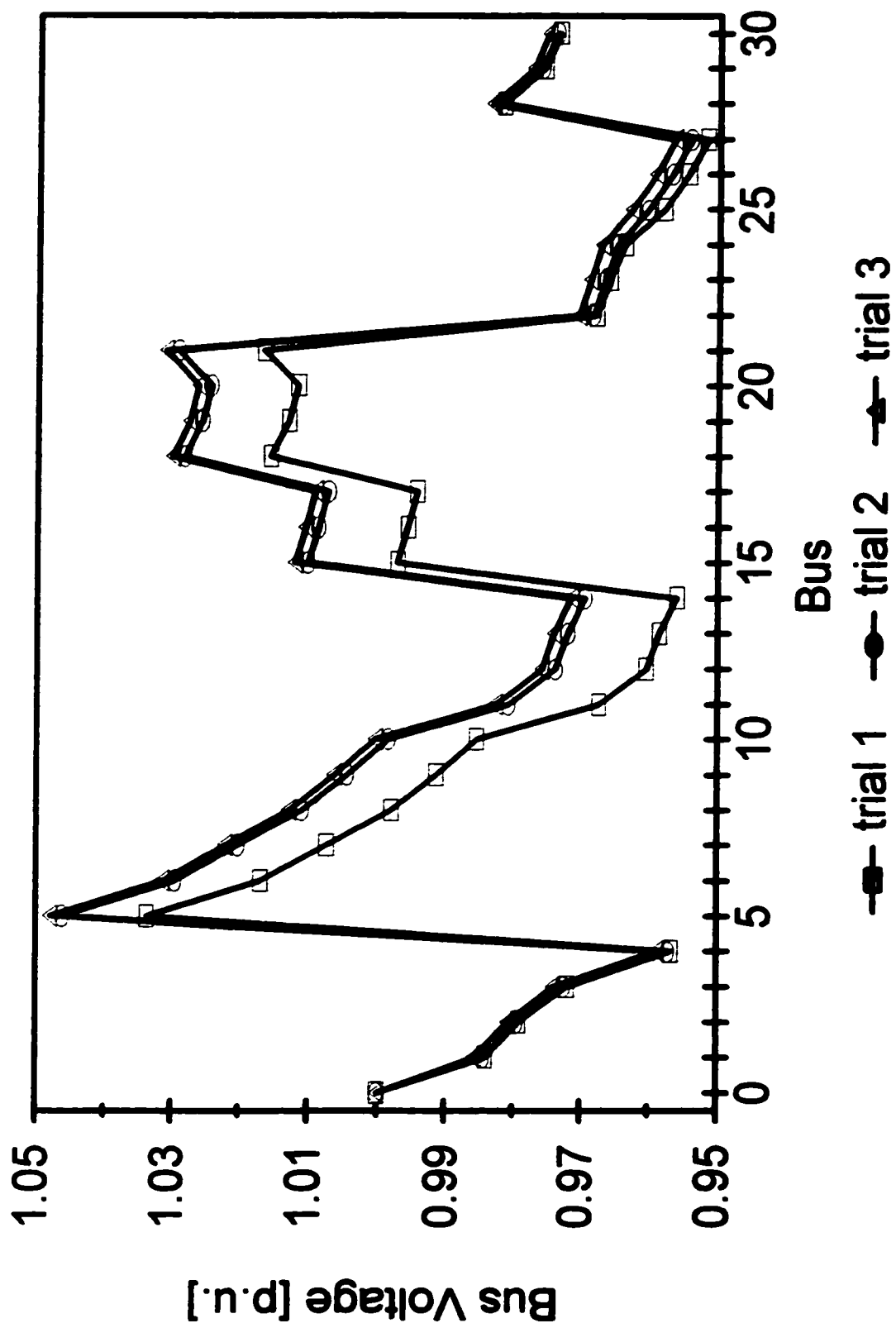
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Figure 5.24. Percent loss reduction for the three trials using the fuzzy based fitness function for each of the twelve periods studied.

Figure 5.25. Voltage profile of the three period 1 trials for the genetic algorithm using the fuzzy logic based fitness function.
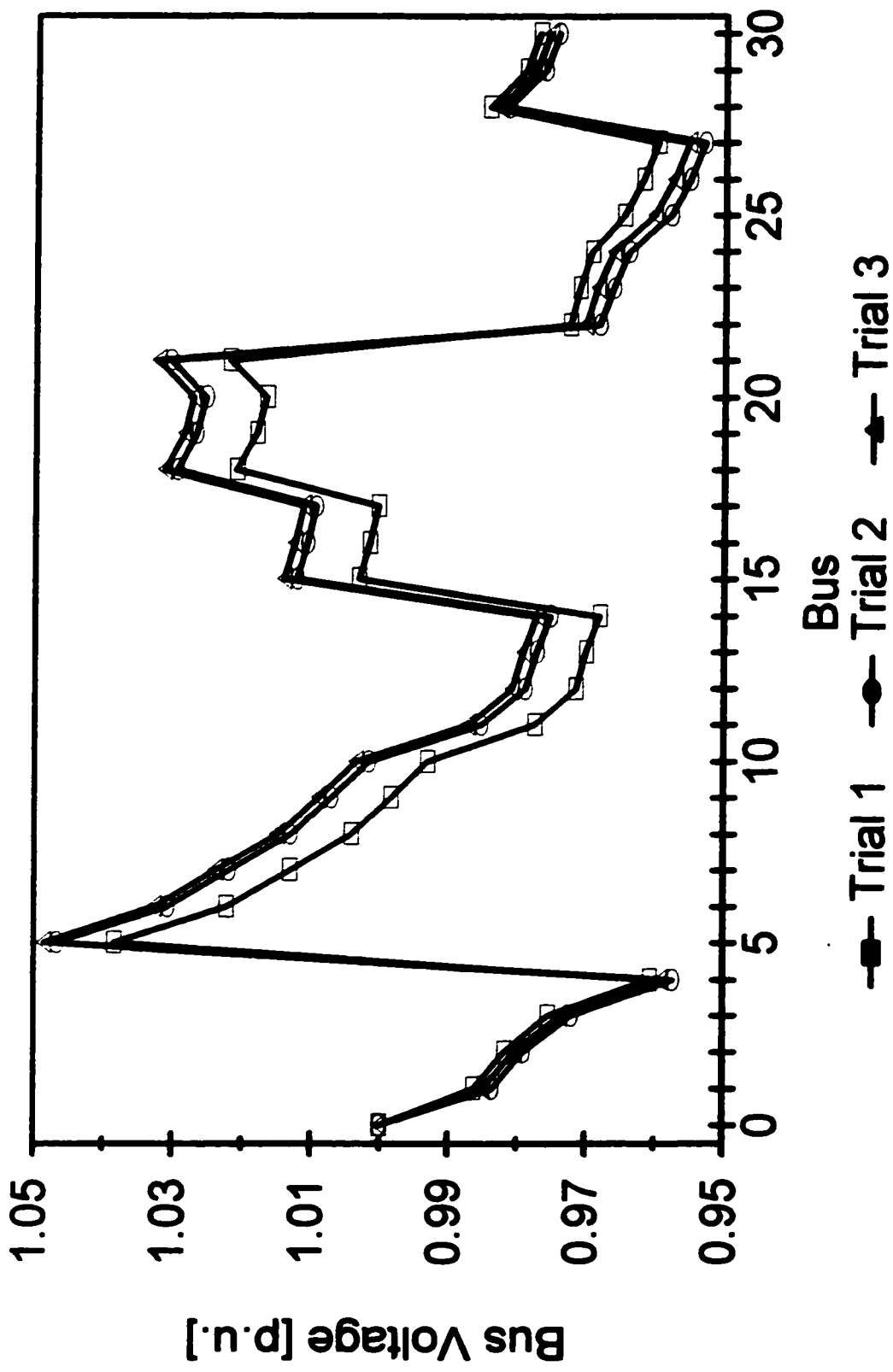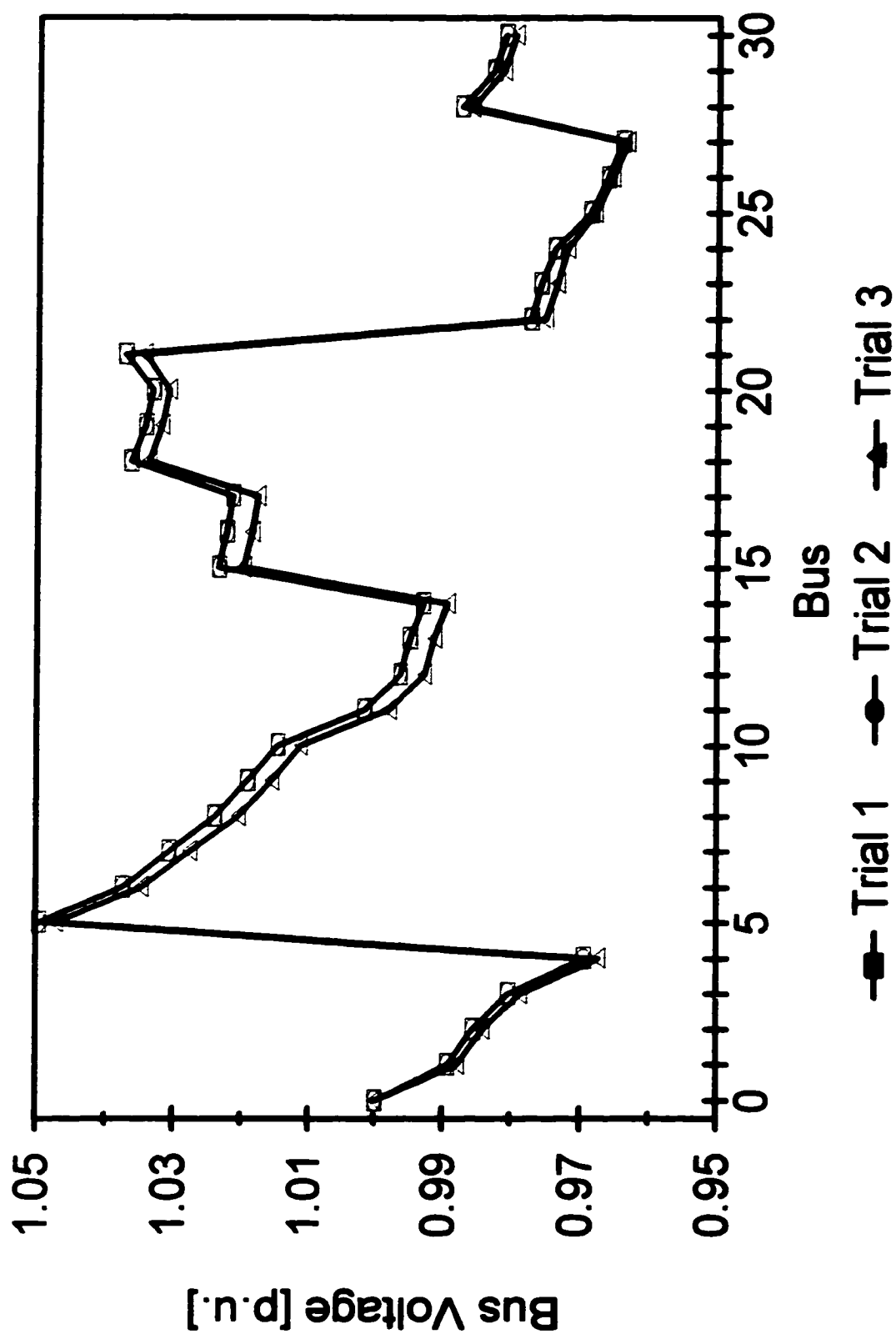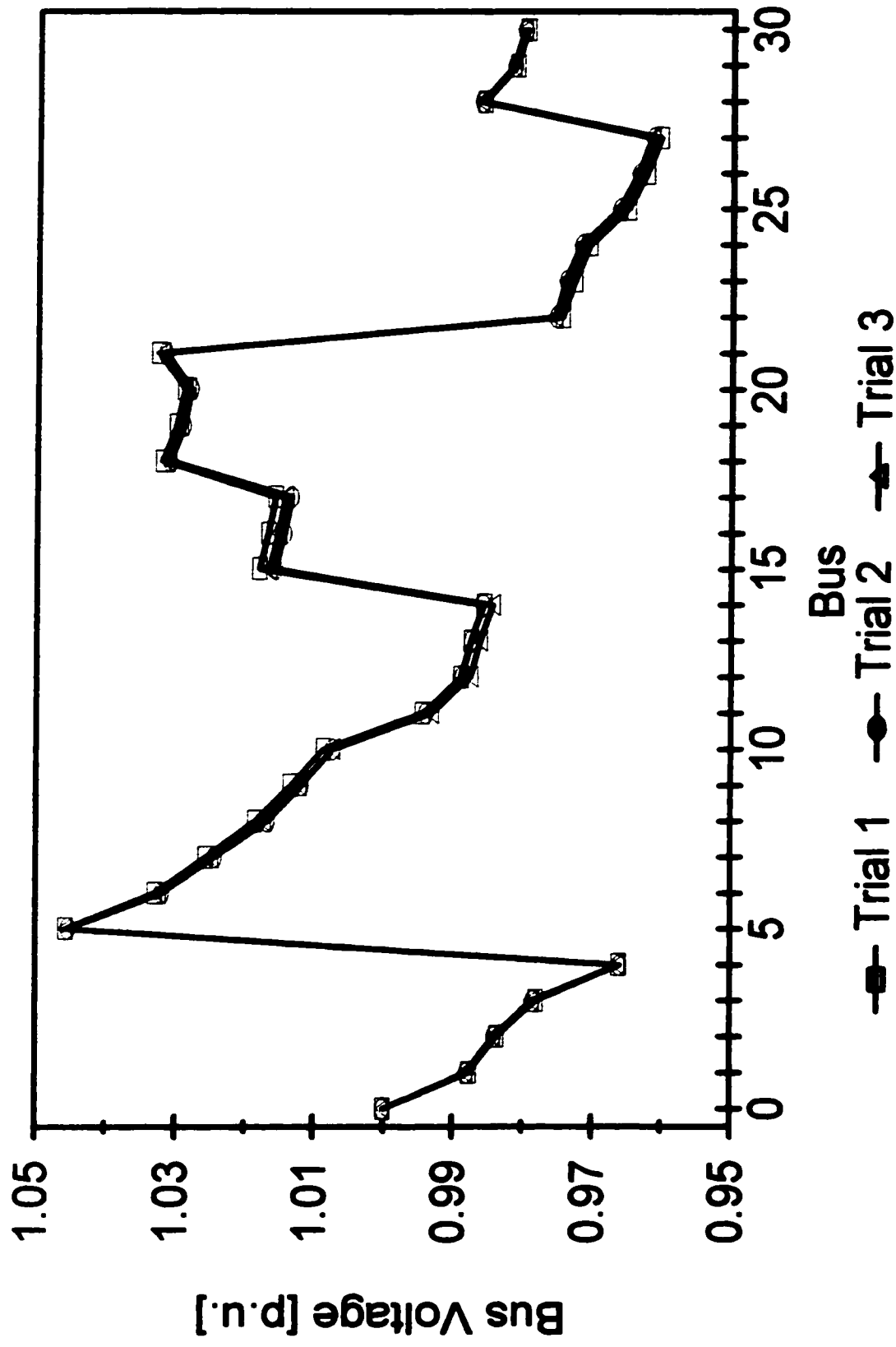
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Figure 5.26. Voltage profile of the three period 2 trials for the genetic algorithm using the fuzzy logic based fitness function.

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Figure 5.27. Voltage profile of the three period 3 trials for the genetic algorithm using the fuzzy logic based fitness function.

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Figure 5.28. Voltage profile of the three period 4 trials for the genetic algorithm using the fuzzy logic based fitness function.

Figure 5.29. Voltage profile of the three period 5 trials for the genetic algorithm using the fuzzy logic based fitness function.

Figure 5.30. Voltage profile of the three period 6 trials for the genetic algorithm using the fuzzy logic based fitness function.
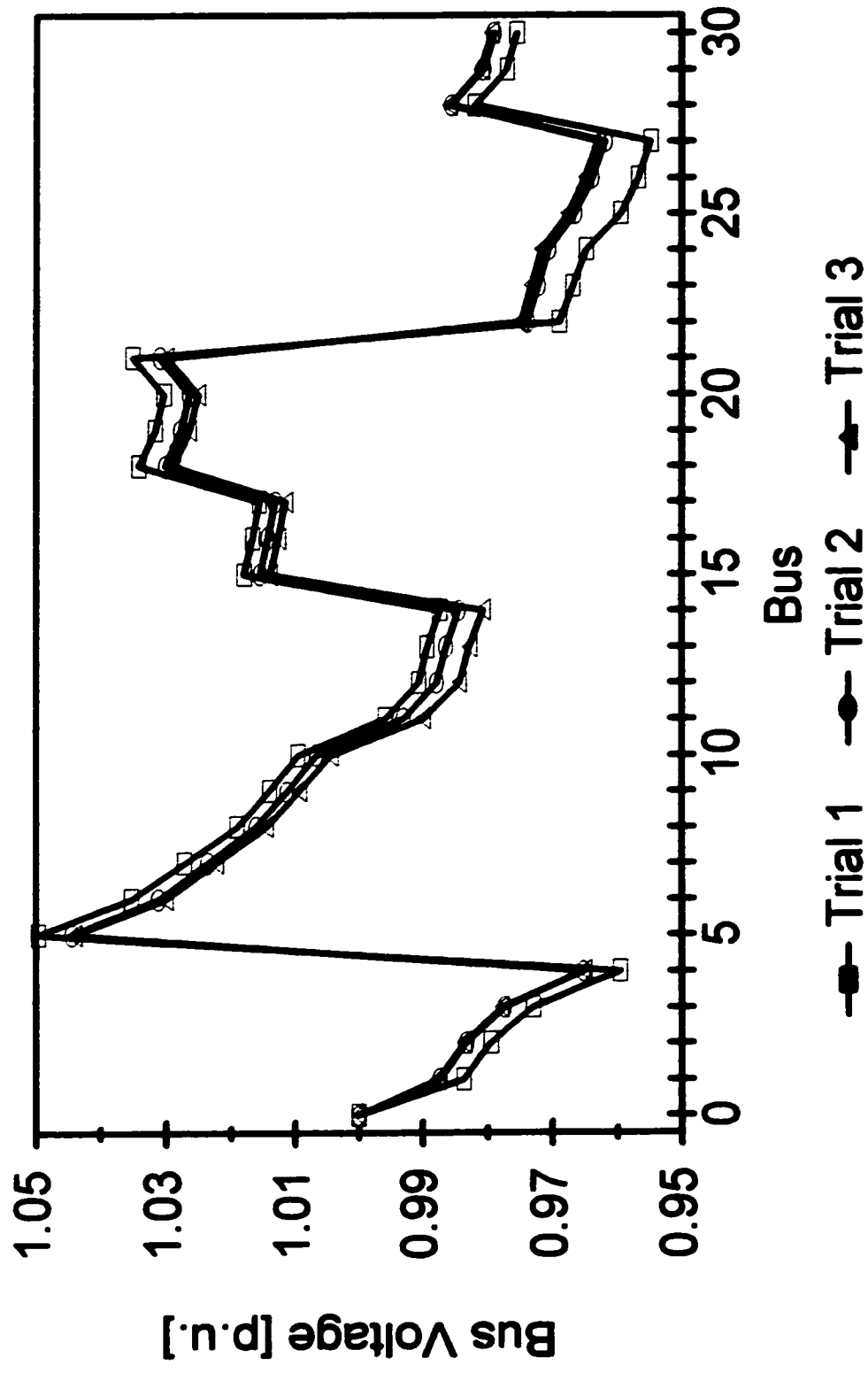
Figure 5.31. Voltage profile of the three period 7 trials for the genetic algorithm using the fuzzy logic based fitness function.

Figure 5.32. Voltage profile of the three period 8 trials for the genetic algorithm using the fuzzy logic based fitness function.
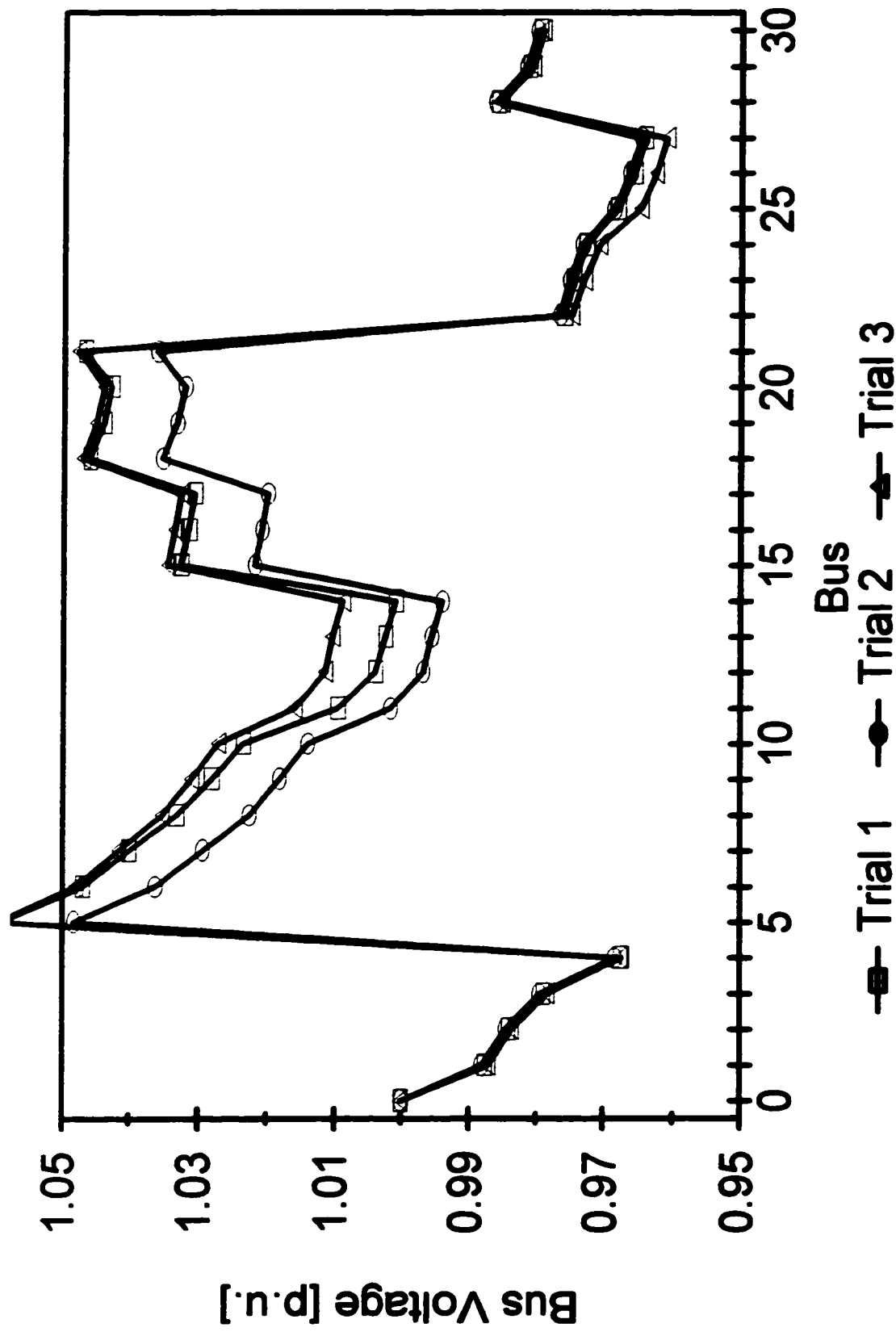
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Figure 5.33. Voltage profile of the three period 9 trials for the genetic algorithm using the fuzzy logic based fitness function.

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Figure 5.34. Voltage profile of the three period 10 trials for the genetic algorithm using the fuzzy logic based fitness function.

Figure 5.35. Voltage profile of the three period 11 trials for the genetic algorithm using the fuzzy logic based fitness function.
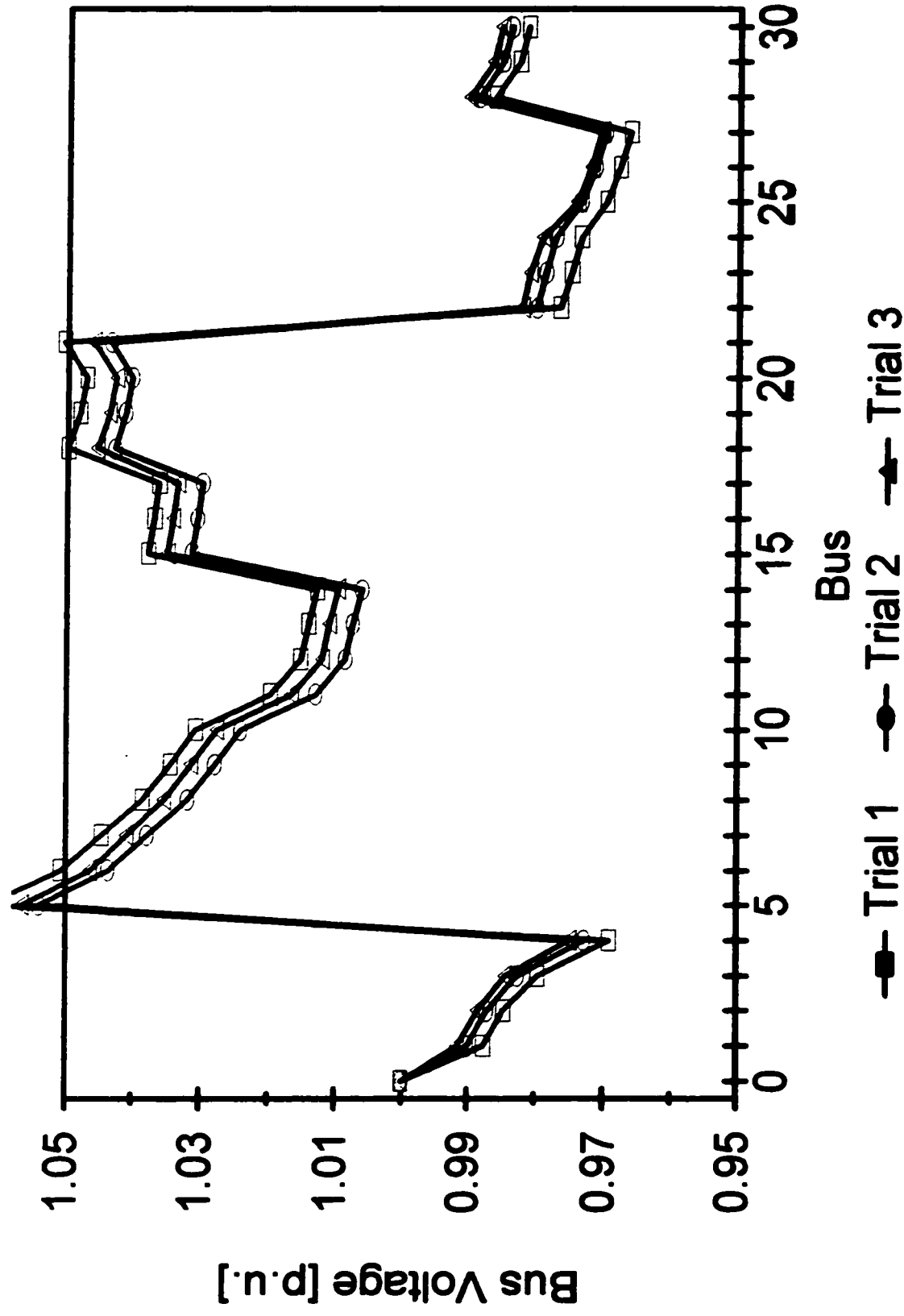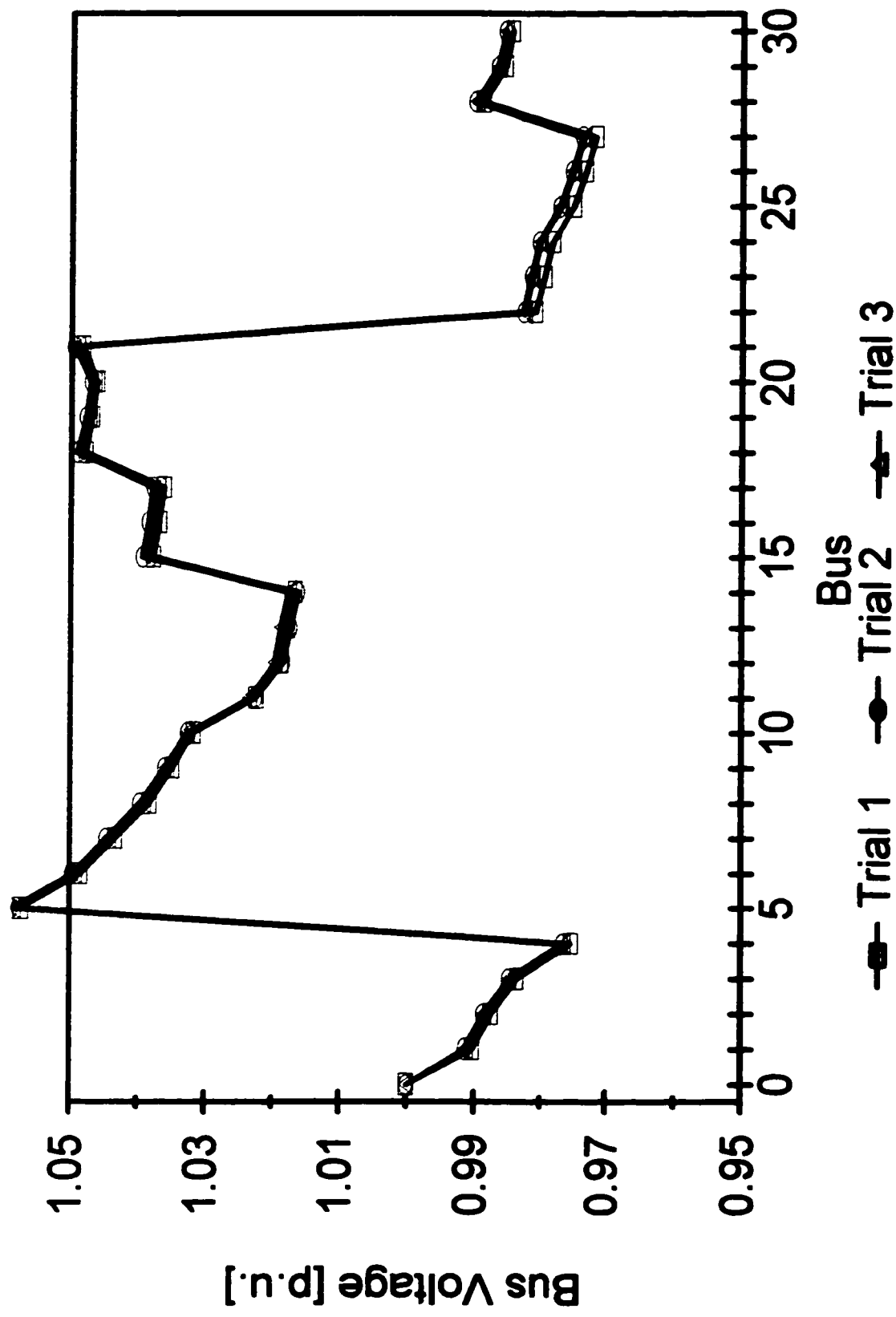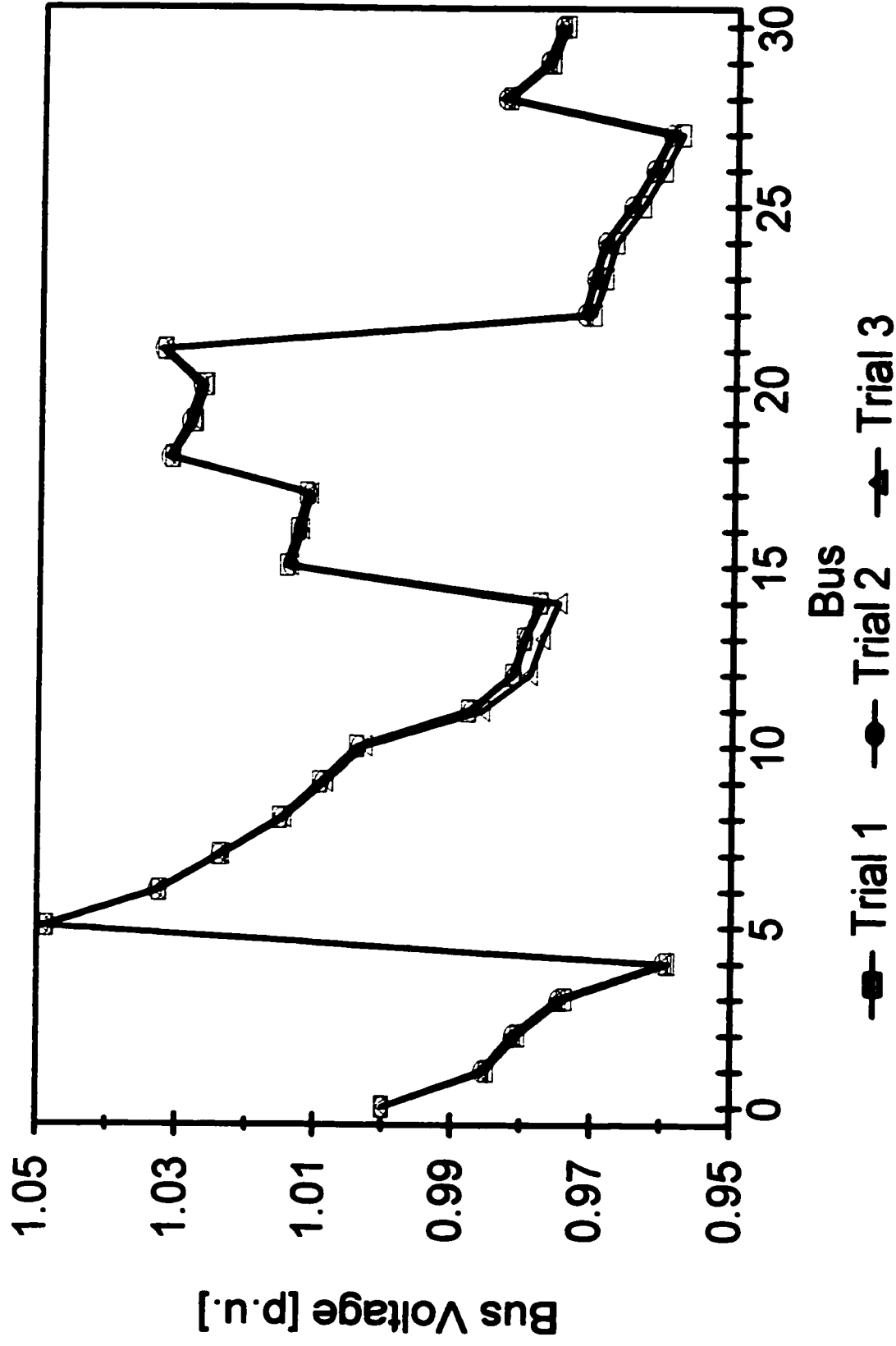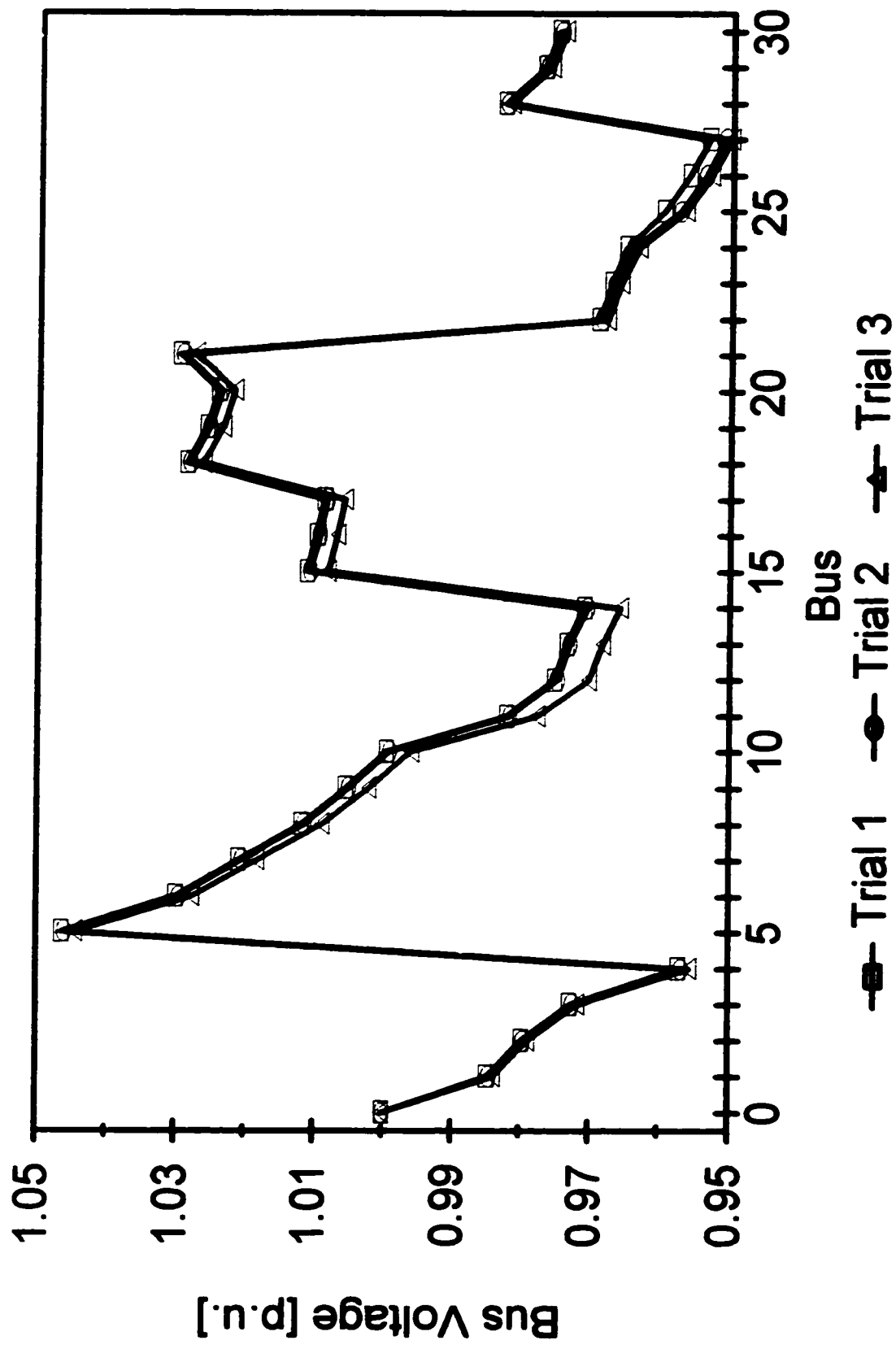
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Figure 5.36. Voltage profile of the three period 12 trials for the genetic algorithm using the fuzzy logic based fitness function.
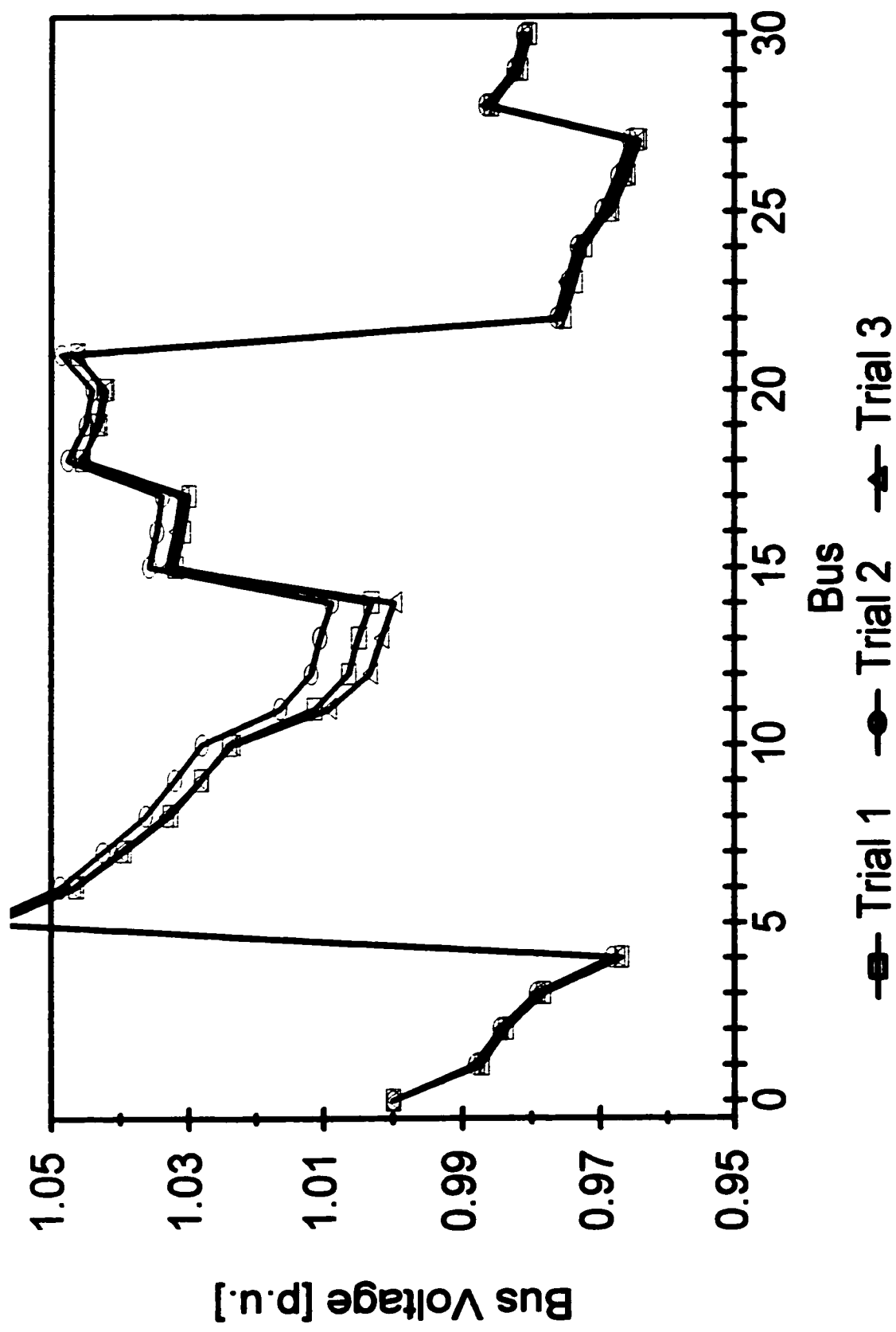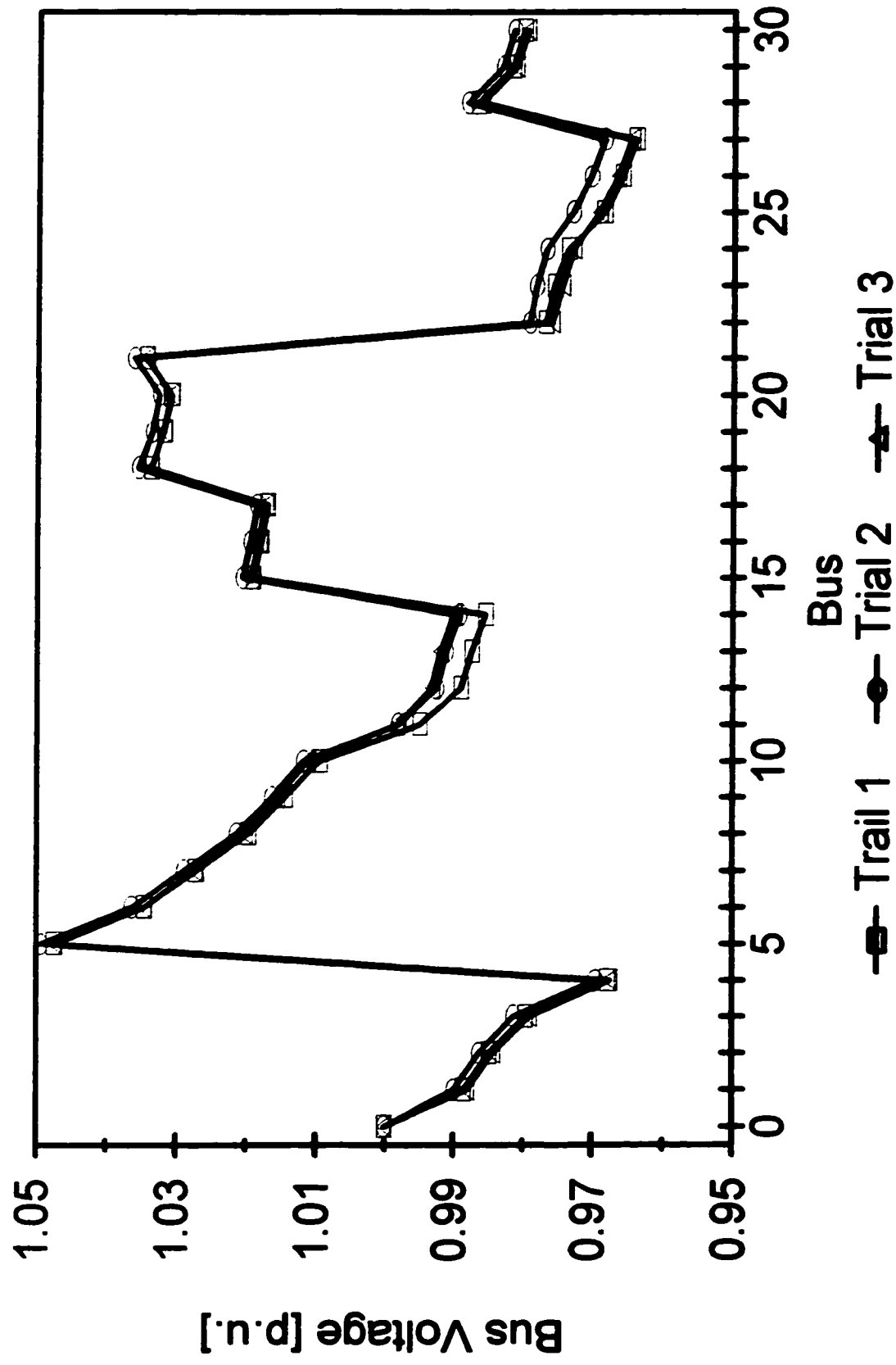
| Initial Population								Final Population							
Individual	Gene						Fitness	Individual	Gene						Fitness
	0	1	2	3	4	5			0	1	2	3	4	5	
0	2	0	4	2	3	0	1.309446	0	1	2	2	2	2	8	22.321495
1	2	1	4	0	3	3	3.121172	1	2	1	2	2	2	8	22.3201
2	1	1	1	3	3	3	5.287454	2	2	2	2	1	2	8	22.074173
3	1	1	0	0	0	8	9.863305	3	1	2	1	2	1	8	22.048069
4	2	2	2	4	0	5	5.340457	4	1	2	1	2	1	8	22.048069
5	2	2	0	3	3	7	9.624279	5	1	2	1	2	1	8	22.048069
6	1	3	2	0	2	2	2.211178	6	2	2	2	2	2	8	21.996813
7	1	2	2	0	0	2	1.397378	7	2	2	2	2	2	8	21.996813
8	1	2	1	3	3	0	2.131147	8	1	3	2	2	2	8	21.951493
9	2	3	2	1	1	1	2.911368	9	1	3	2	2	2	8	21.951493
10	2	0	0	2	0	5	2.984139	10	1	2	4	2	1	8	21.672761
11	0	0	4	3	4	7	3.773105	11	2	2	2	2	1	8	21.661911
12	4	1	2	2	1	7	14.625456	12	1	3	2	2	1	8	21.626364
13	4	0	1	1	2	3	3.195031	13	1	3	2	3	1	8	21.567608
14	1	0	4	1	1	8	19.921305	14	2	2	4	2	1	8	21.317852
15	0	0	0	4	3	0	0.379883	15	2	2	4	1	1	8	21.277664
16	2	3	2	3	2	2	2.771826	16	1	3	2	2	3	8	17.728657
17	2	1	4	2	2	8	22.023502	17	2	2	2	2	4	8	14.101933
18	4	3	3	3	3	0	1.266215	18	0	0	1	2	1	8	10.566348
19	4	2	3	0	3	8	7.904807	19	0	2	4	2	2	5	7.019491

Table 5.1. Typical initial and final populations of the GA taken from the first trial for period 1 using the penalty based fitness function.

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Period	#	Bare System Losses [p.u.]	Penalty-based GA Losses [p.u.]			Fuzzy-based GA Losses [p.u.]			Exhaustive Search Losses [p.u.]
			Trial 1	Trial 2	Trial 3	Trial 1	Trial 2	Trial 3	
Winter, Weekday, High	1	1.104553	0.865494	0.863512	0.863512	0.867830	0.862683	0.862921	0.860480
Winter, Weekday, Low	2	0.904555	0.718094	0.709903	0.710877	0.715557	0.712154	0.710079	0.709903
Winter, Weekend, High	3	0.598731	0.485455	0.486053	0.485189	0.486270	0.486270	0.485872	0.485189
Winter, Weekend, Low	4	0.664820	0.542521	0.545887	0.542837	0.542586	0.542167	0.541735	0.541735
Fall/Spring, Weekday, High	5	0.698830	0.569773	0.569400	0.569594	0.571293	0.570155	0.570016	0.568853
Fall/Spring, Weekday, Low	6	0.529081	0.437069	0.437616	0.436058	0.435878	0.436058	0.436184	0.436058
Fall/Spring, Weekend, High	7	0.378792	0.323640	0.324073	0.322591	0.321560	0.320197	0.321752	0.322591
Fall/Spring, Weekend, Low	8	0.295648	0.254372	0.254603	0.255943	0.252940	0.253683	0.252574	0.254372
Summer, Weekday, High	9	0.947993	0.740097	0.736459	0.736459	0.738994	0.738433	0.739549	0.736401
Summer, Weekday, Low	10	1.089043	0.849973	0.851724	0.849973	0.851811	0.849973	0.851724	0.849973
Summer, Weekend, High	11	0.529870	0.438785	0.440944	0.441683	0.435383	0.437085	0.437391	0.436785
Summer, Weekend, Low	12	0.601015	0.491112	0.490355	0.490710	0.491399	0.492666	0.491655	0.490364

Table 5.2. Total losses of the system during the twelve periods under study for the bare system and after solving the control problem.

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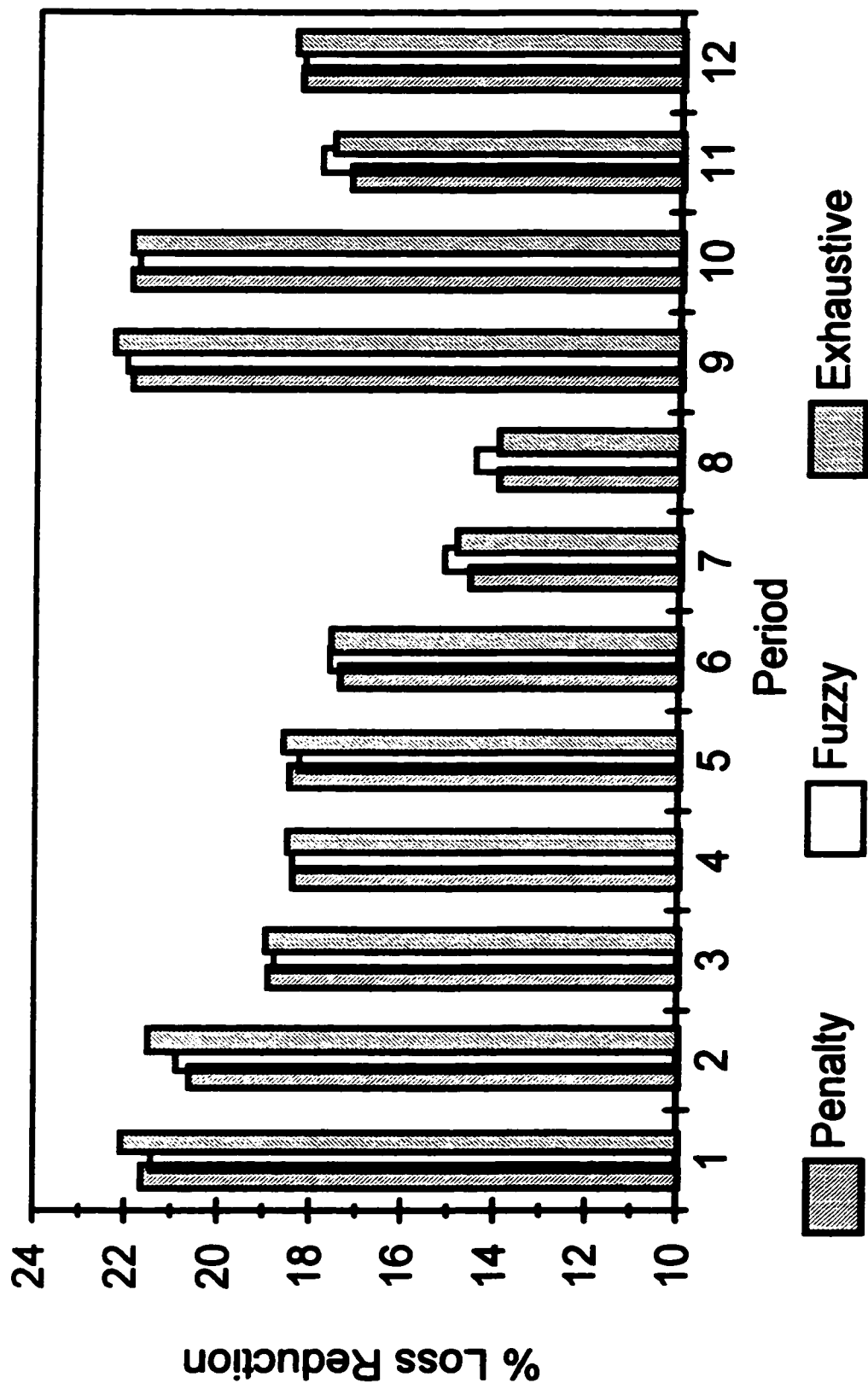
Figure 5.37. Percent loss reduction for each of the twelve periods based on the results of the first trial of the genetic algorithm using the penalty based fitness function, the first trial of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.

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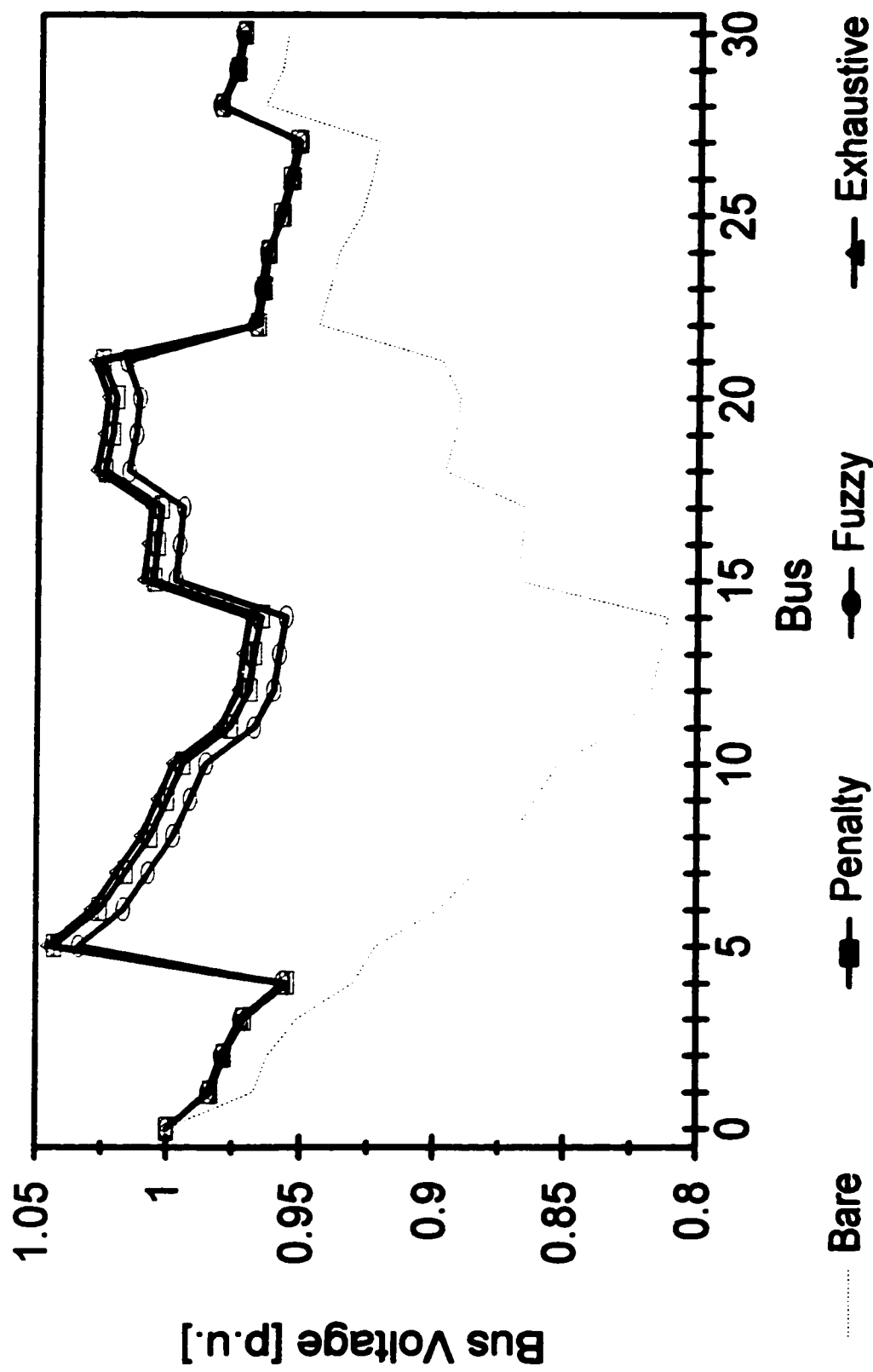
Figure 5.38. Voltage profile for period 1 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
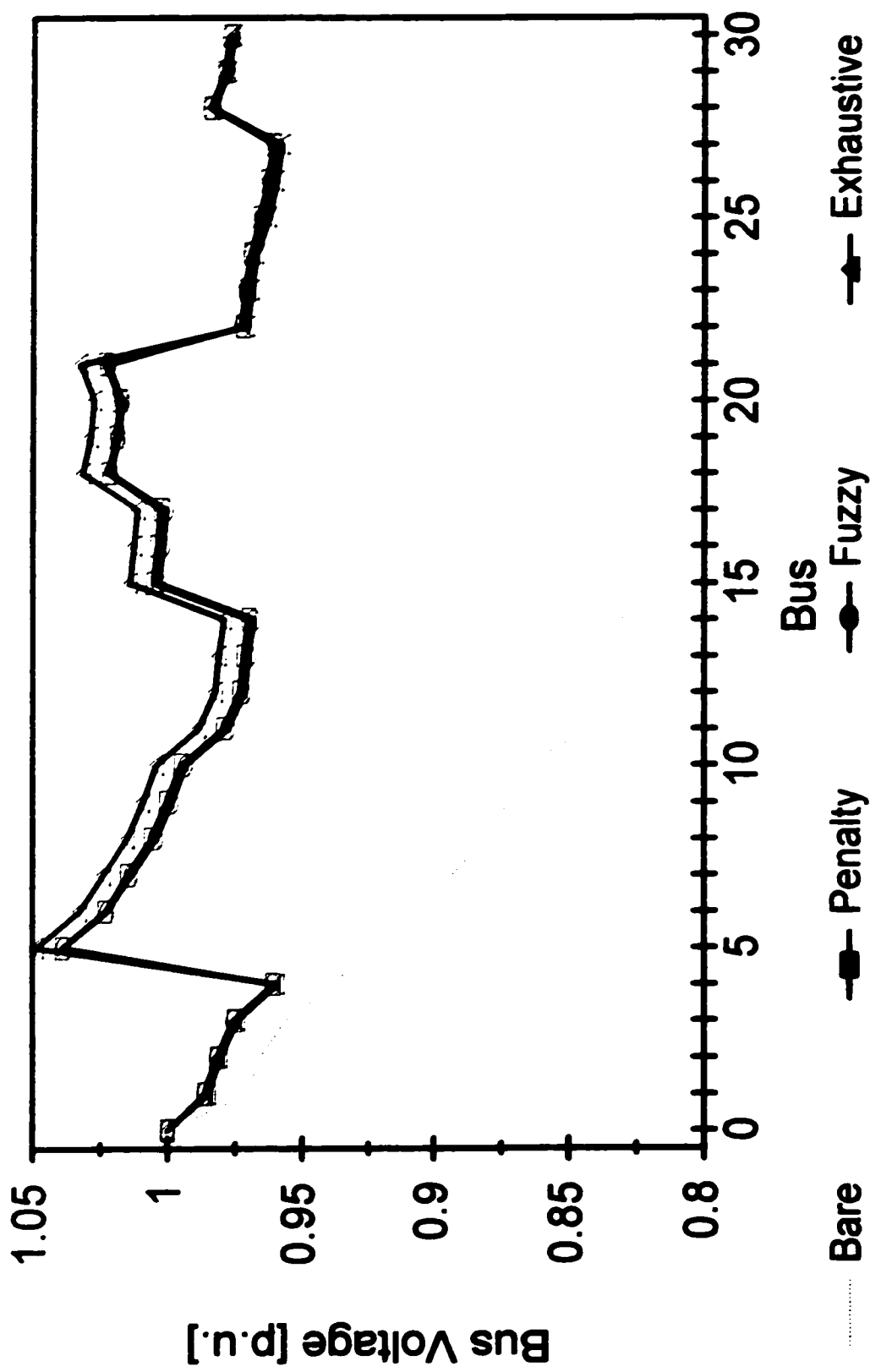
Figure 5.39. Voltage profile for period 2 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
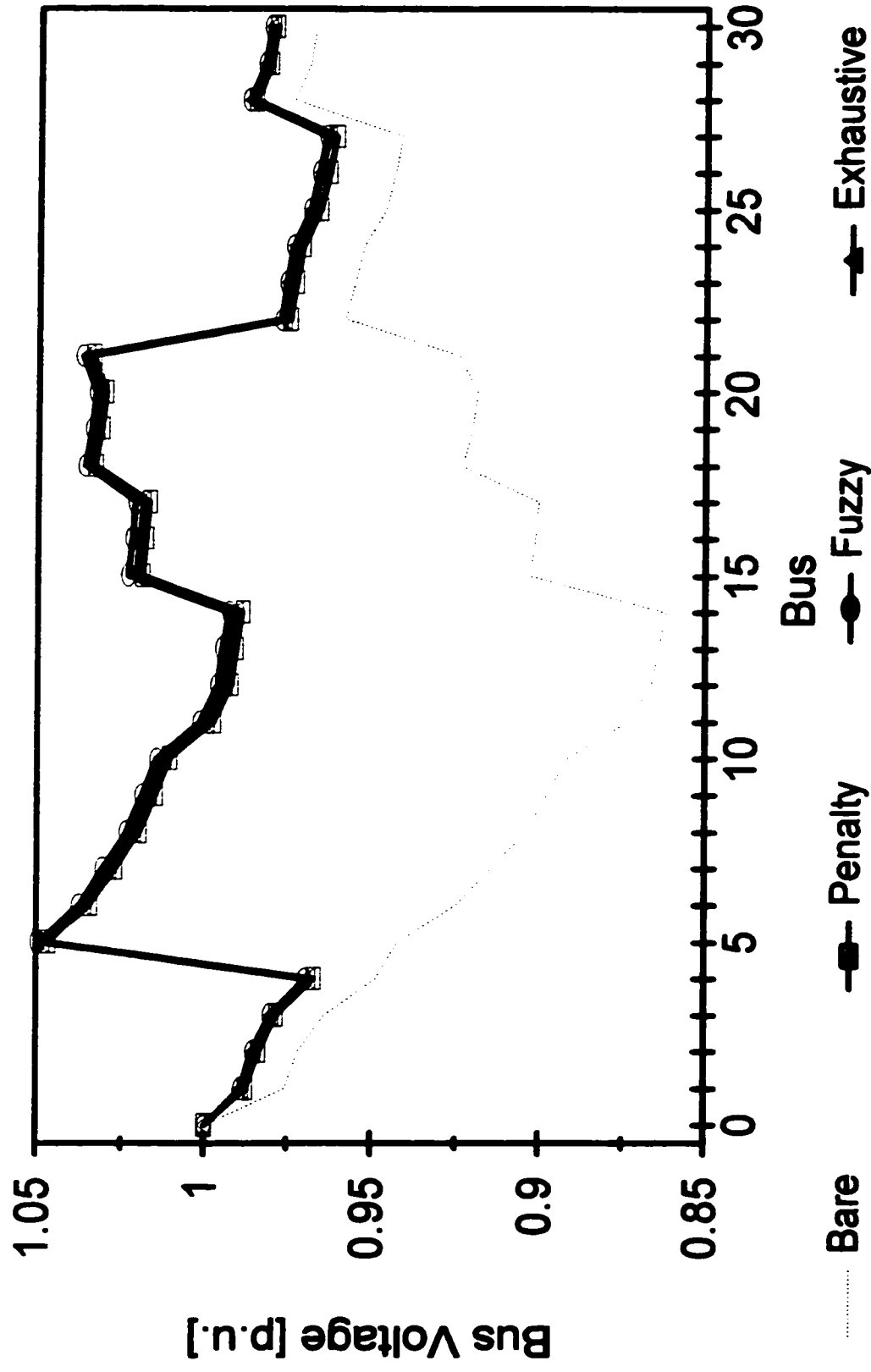
Figure 5.40. Voltage profile for period 3 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
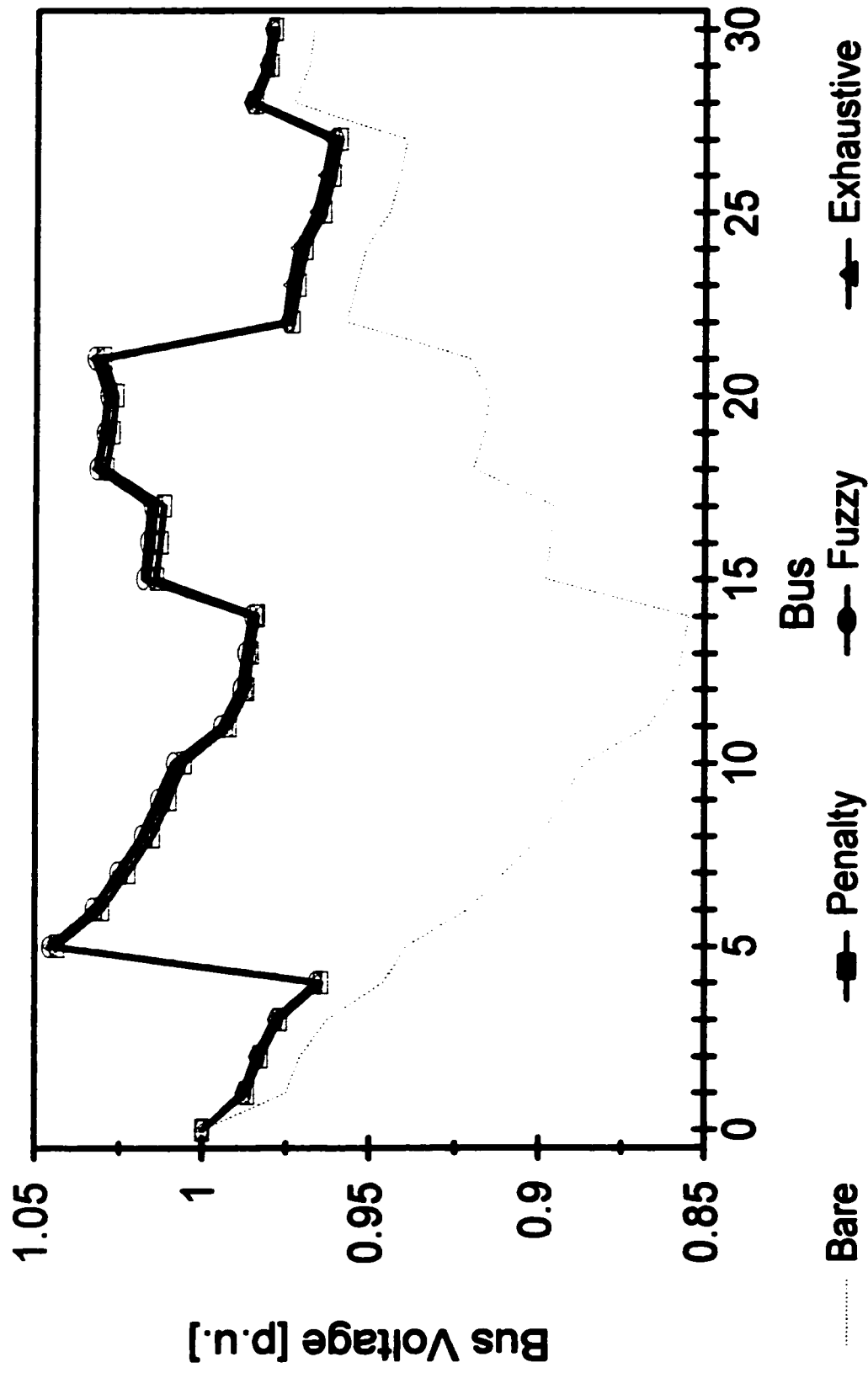
Figure 5.41. Voltage profile for period 4 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.

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Figure 5.42. Voltage profile for period 5 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.

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Figure 5.43. Voltage profile for period 6 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
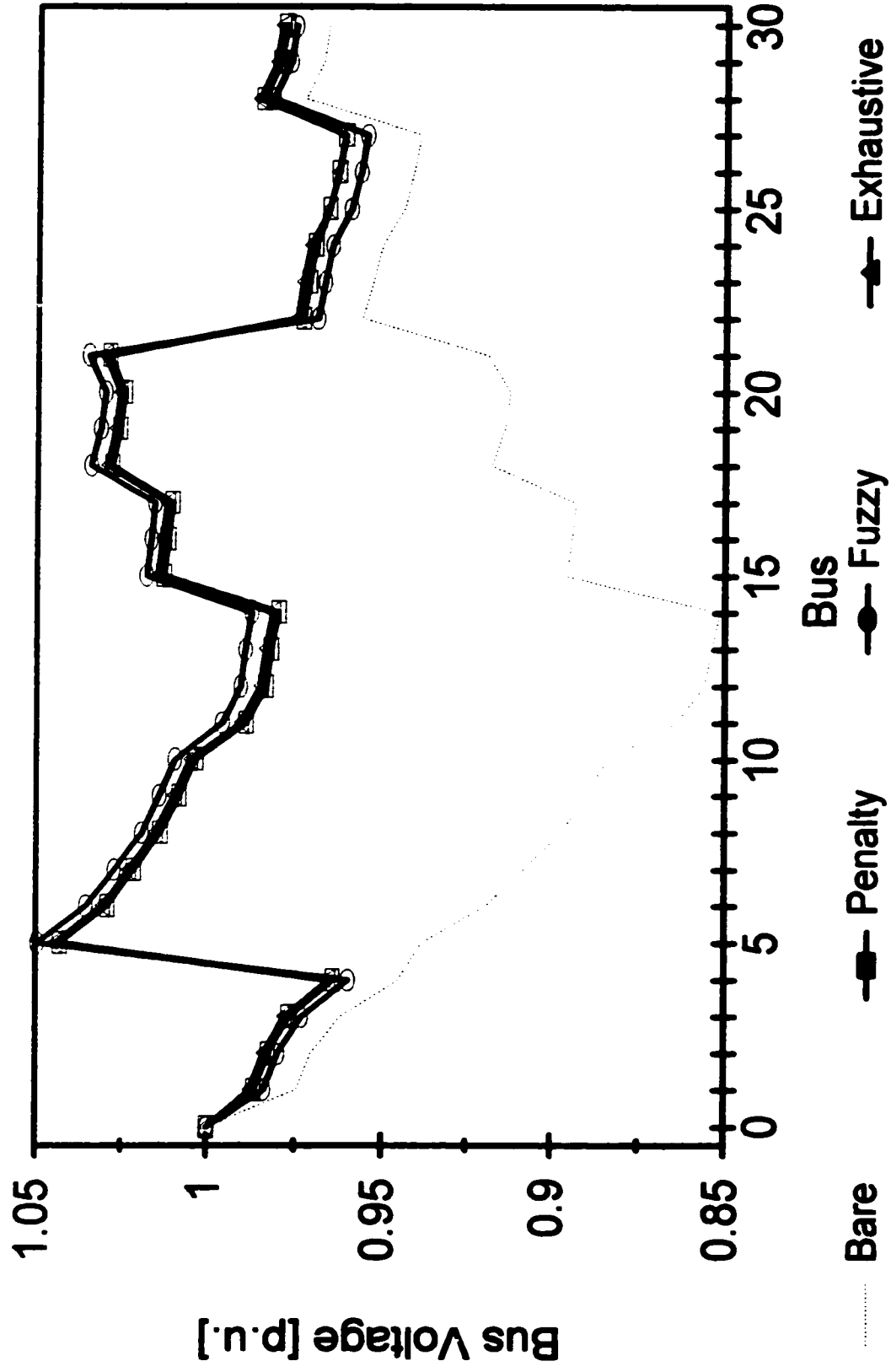
Figure 5.44. Voltage profile for period 7 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.

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Figure 5.45. Voltage profile for period 8 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
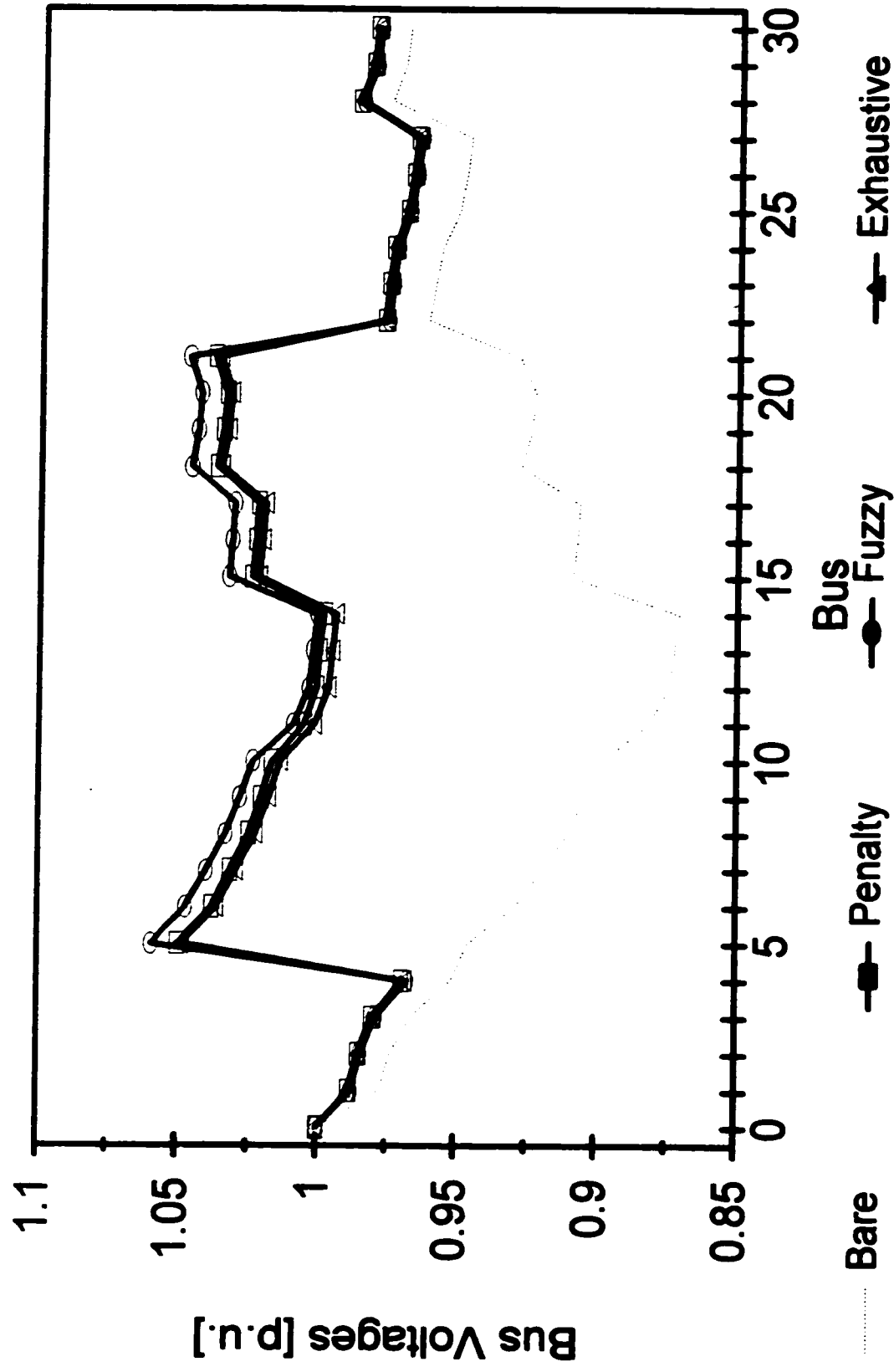
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Figure 5.46. Voltage profile for period 9 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
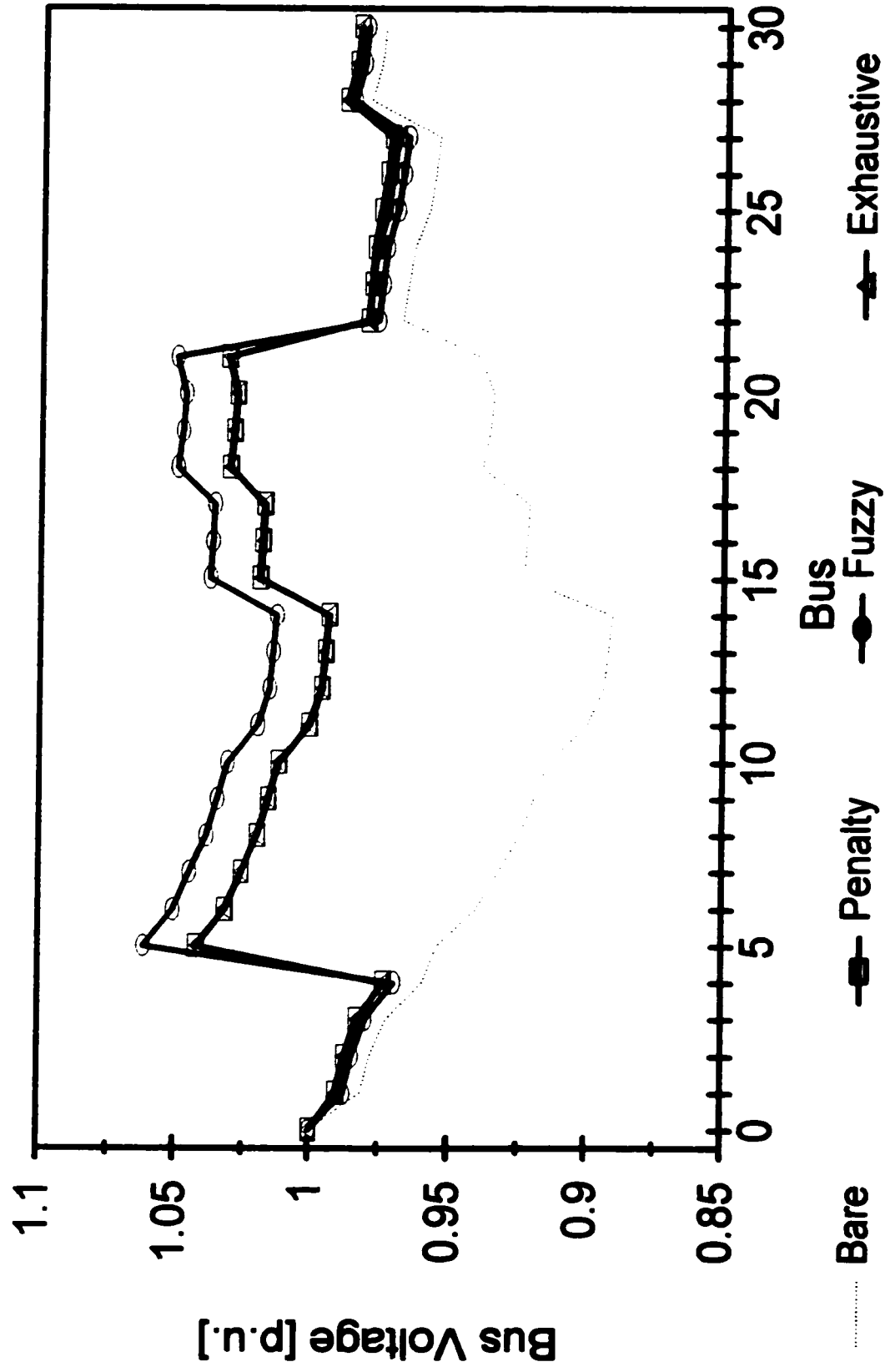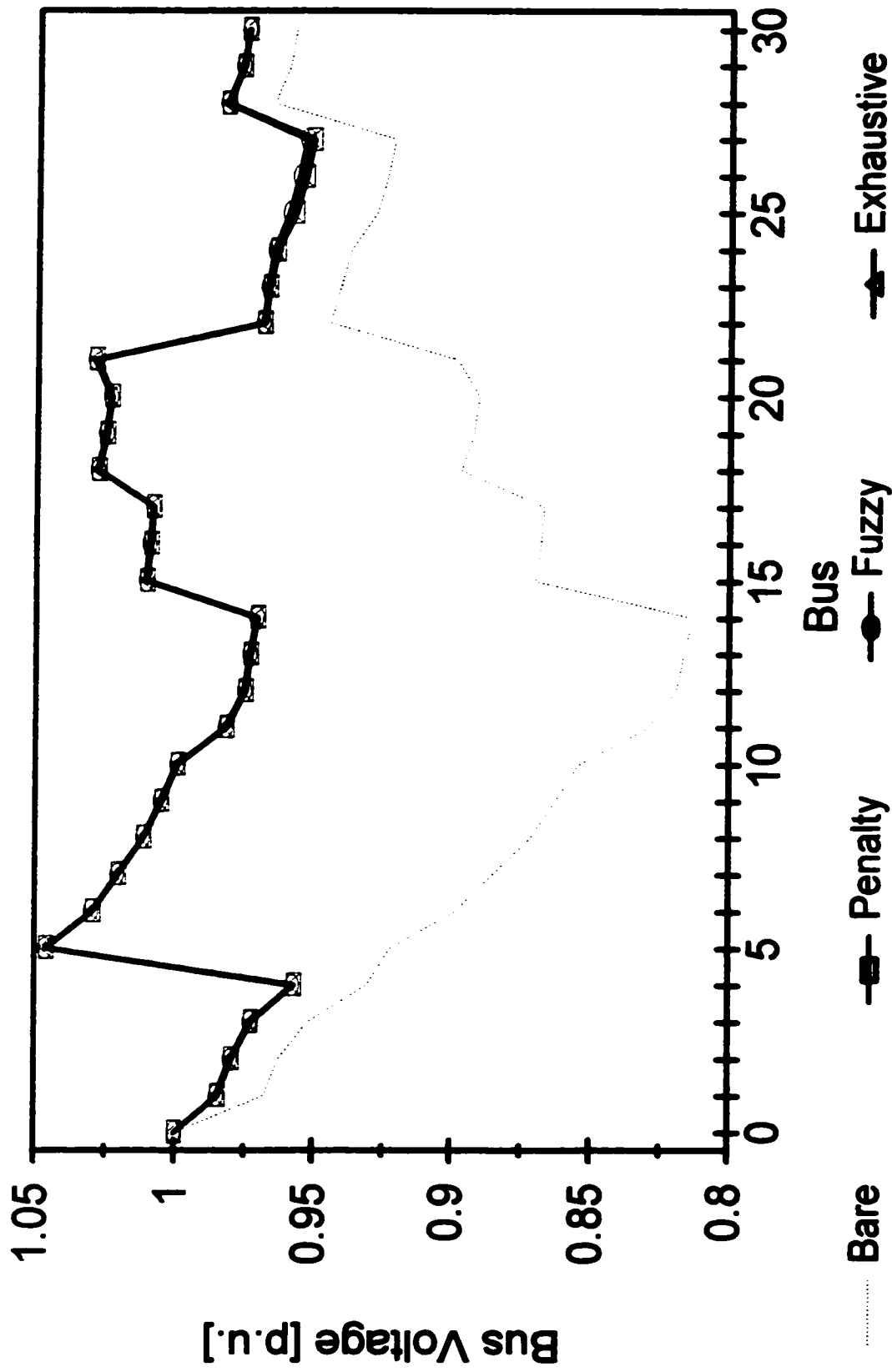
Figure 5.47. Voltage profile for period 10 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
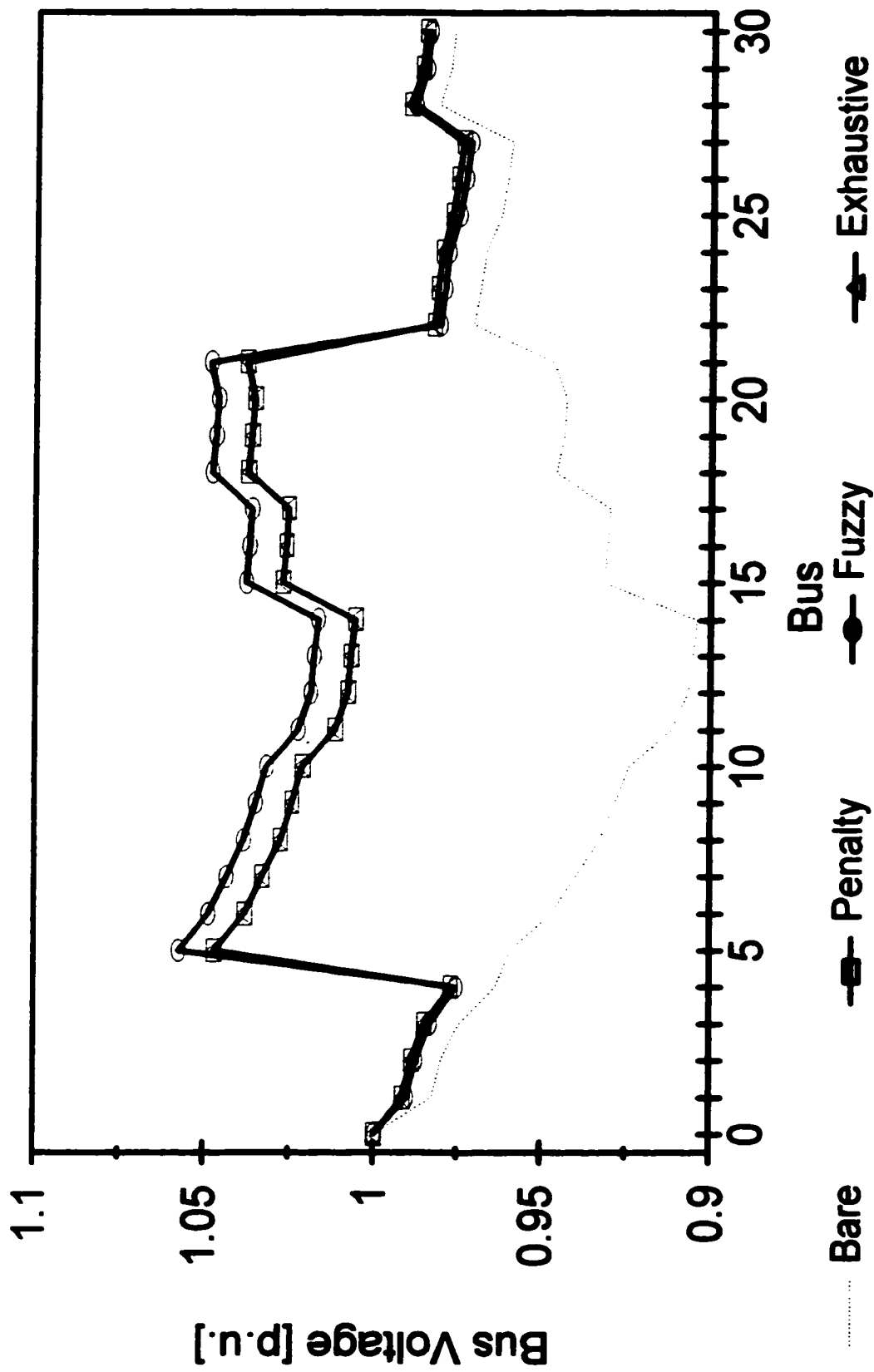
Figure 5.48. Voltage profile for period 11 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
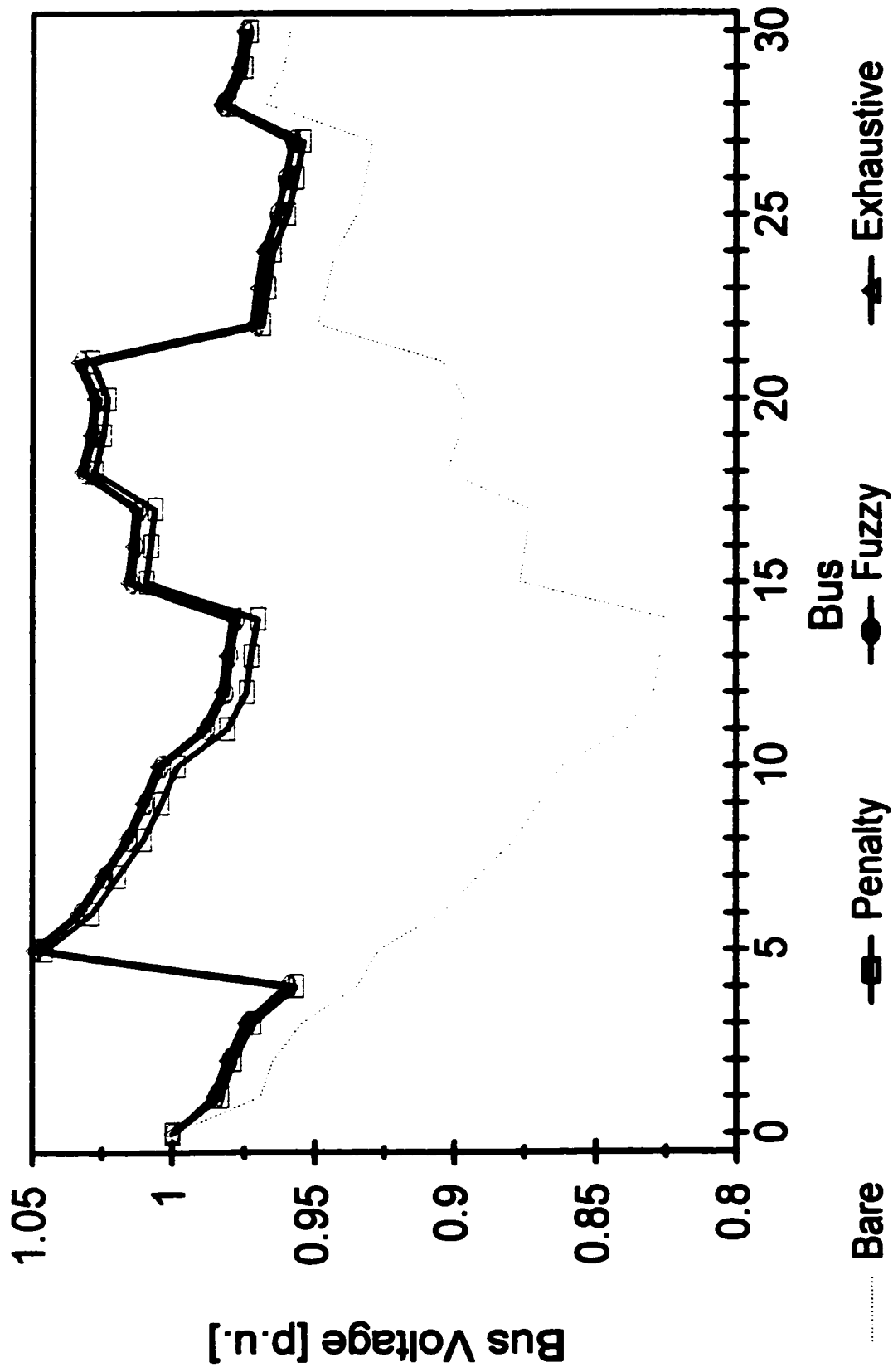
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Figure 5.49. Voltage profile for period 12 based on the results of trial one of the genetic algorithm using the penalty based fitness function, trial one of the genetic algorithm using the fuzzy logic based fitness function, and an exhaustive search of the solution space.
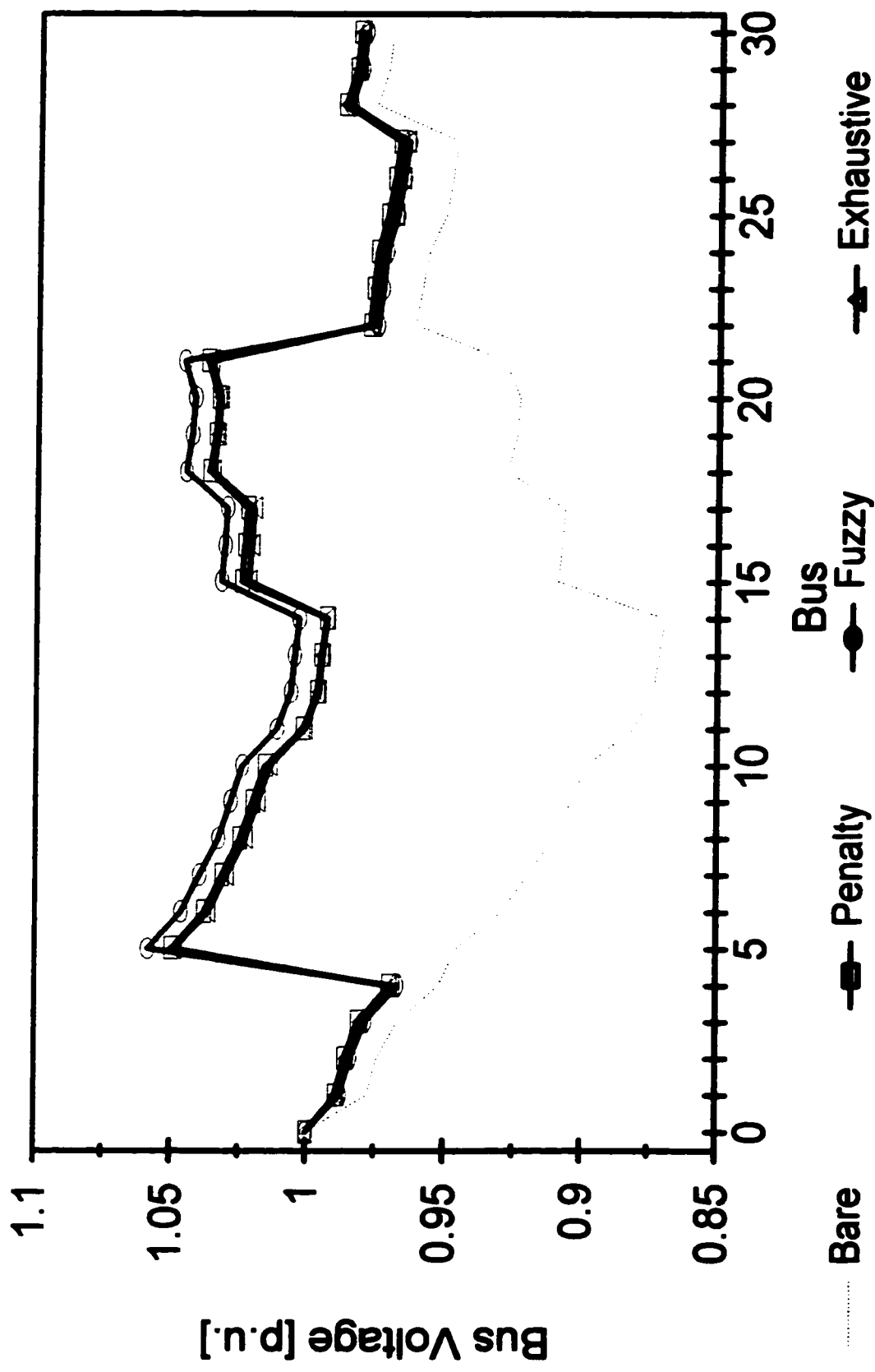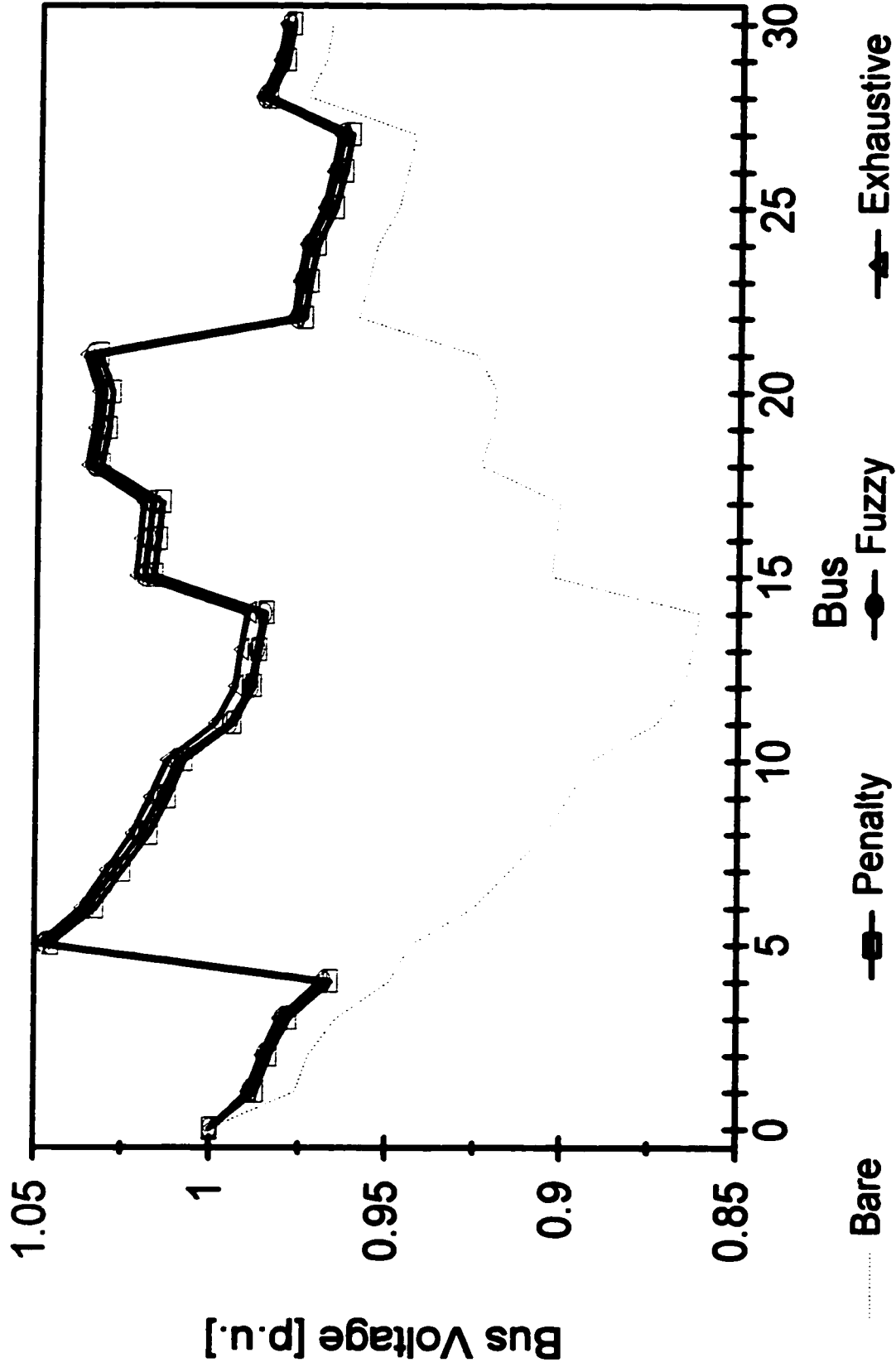
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Chapter 6

Conclusions and Recommendations

6.1   Conclusions

In this thesis, two genetic algorithm approaches have been applied to the problem of controlling shunt capacitors and voltage regulators for the purpose of reducing losses, while maintaining the bus voltages within ±5% of their nominal rated values. The first genetic algorithm approach used a penalty based fitness function, while the second genetic algorithm used a fuzzy logic based fitness function. The results obtained by the genetic algorithm methods were compared with the global optimal solution, which was obtained by performing an exhaustive search using the penalty based objective function.

The genetic algorithm method using the penalty based fitness function found the global optimal solution in 7 out of 36 trials, and near optimal solutions in the other 29 trials. In every case, the penalty based method resulted in the voltage constraints being satisfied at

all buses. The genetic algorithm method using the fuzzy logic based fitness function found the global optimal solution in 3 out of the 36 trials performed. However, in 11 of the trials the fuzzy based method results in a voltage violation at bus 5. In each of these 11 cases, the total losses of the distribution system were reduced further by the fuzzy based method than by the global optimal solution. This is a result of the trade-off performed by the fuzzy method between the number of voltage violations and the total losses, and could have been corrected by modifying the fuzzy objective functions or the fuzzy fitness function. The fuzzy fitness function used in this thesis was chosen because of its similarity with the penalty based fitness function. It should be remembered however, that the global optimal was determined using the penalty based fitness function, and hence, it is not surprising that the penalty based method would result in more occurrences of the global optimum than the fuzzy based method.

Both genetic algorithm methods had a solution time of less than 3 minutes and 30 seconds. This is well within the time limits for an algorithm to be useful for real-time, on-line application. The exhaustive search required from 2 hours and 45 minutes to 3 hours to determine the global optimal solution.

6.2 Recommendations for Future Research

In this thesis, all tests were performed on a 30 bus radial distribution system. While the size of this system is typical of the research into the control problem, it is far from realistic. A practical distribution system may consist of several hundred buses or more. The time required for the method developed in this thesis to arrive at a solution is largely dependant on the time required for a load flow to be performed, and hence, on the size of the distribution system. In this thesis the Gauss-Seidel technique was employed to perform the load flows.

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This method, however is far from being fast. In order for the method presented here to still be useful for real-time, on-line application to a more practical sized distribution system would require a much faster load flow technique. Since the genetic algorithms presented here are reasonably insensitive to the load flow technique employed it should not be too difficult to modify this method to accommodate a larger sized distribution system. A load flow technique based on an artificial neural network might be quite effective in this regard, and deserves study. As well, in this thesis, a constant power model was employed for the loads. However, for practical implementation, a more realistic model such as that described in Chapter 4 would likely be required; again an artificial neural network load flow approach might prove successful.

The results obtained by the genetic algorithm method using the fuzzy logic based fitness function, while not ideal were quite promising. As was mentioned, the fuzzy objective functions and the fuzzy fitness function was chosen because of their similarity to the penalty based fitness function. This choice was made to assist in comparing the two methods, however, another choice of fuzzy objective functions and fuzzy fitness function might yield better results. This certainly deserves further study.

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Appendix

With the penalty based method, the fitness function is reduced by 10% for each constraint violation. In order to obtain similar performance using a fuzzy logic based fitness function, two fuzzy sets are required. One set for the percent loss reduction, and another set for the number of constraint violations. One of the faults of both the penalty based method and the fuzzy logic based method is that they do not take into account the magnitude of the violations.

As with the penalty based method, it is desirable that the fuzzy logic based fitness function have a lower value for an individual that violates constraints, than the fitness function value of an individual with the same percent loss reduction and no constraint violations. The penalty based method accomplishes this by subtracting a percentage of the total fitness from the individual that violates the constraints. This method has the advantage that the final solution does not depend on the current operating condition (loading condition) of the system. This however is not the case with the fuzzy logic based fitness function. In order to obtain the desired performance using the fuzzy logic based method, the *min* operator is used, that is the fuzzy logic based fitness function is defined as the intersection between the fuzzy set for the number of constraint violations and the fuzzy set for the percent loss reduction. In this way the value of the fuzzy fitness function represents a trade off between individuals which seek to reduce losses by pushing the bus voltages to their limits, with those that endeavor to keep the number of constraint violations to a minimum.

The fuzzy sets for both the number of constraint violations and the percent loss reduction may be found in Figures 4.3(a) and 4.3(b) respectively. It is known based on the

results of the exhaustive search that the maximum optimum percent loss reduction is 22.3% and the minimum optimum percent loss reduction was 14.0%. Knowing this the membership function describing the percent loss reduction was formed. From the membership function describing the percent loss reduction, it is evident that the fitness value of the optimum solution varies between 0.892 and 0.560. In order to ensure that the fitness value of an individual having constraint violations is lower than an otherwise equivalent individual without constraint violations it is desirable to select the value of the membership function for the number of constraint violations as somewhat lower than these values. When values for the membership function for the number of constraint violations for a single constraint violation was chosen to be less than 0.5 the genetic algorithm had problems converging to the global solution as it was easily trapped in local optimal solutions. It was found that a value of 0.75 for the membership function for the number of constraint violations for a single violation yielded similar results to the penalty based method. As a result this is the value that was chosen. It should be pointed out, however, that as a result of this choice it is possible to obtain a final solution from the genetic algorithm using the fuzzy logic based fitness function that violates constraints at one or more buses. This was evident from the results presented in Chapter 5.

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