An Integrated Voltage Optimization Approach For Industrial Loads

by

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Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.
Adarsh Madhavan.

Abstract

Although Voltage Varying (VV) strategies like Conservation Voltage Reduction (CVR) are widely used by utilities to reduce the overall energy consumption and peak power demand of distribution feeders, it is aberrant among industrial customers. This research proposes a Voltage Varying (VV) strategy for industrial customers that takes into account their complex characteristics and unique set of constraints. Unlike VV strategies for Local Distribution Companies (LDC), those for an industrial customers are far more complex, and require specific load modelling and process estimation to infer the optimal operating voltage for the industrial load.

The proposed VV technique referred to as Voltage Optimization (VO), is a generic and comprehensive framework that seeks to reduce the energy consumption of the industrial load vis-ã-vis the bus voltage. It utilizes a Neural Network (NN) model of the industrial load, trained using historical operating data, to estimate the real power consumption of the load, based on the bus voltage and overall plant process. This load model, is incorporated into the proposed VO model, whose objective is the minimization of the energy drawn from the substation and the switching operations of Load Tap Changers (LTC). The proposed VO framework is tested on load models developed using simulated and real data. Results suggest that the proposed technique can be successfully implemented by industrial customers or plant operators to improve their energy savings, in comparison to existing VV techniques.

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I would like to thank Daniel Olivares for his guidance, support and friendship which made it possible for me to navigate and comprehend the complex world of optimization. I would also like to thank my friend Mariano Arriaga Marin for patiently listening to my ideas.

Finally, and most importantly, I would like to thank my parents, Madhavan and Deepa, who laid the very foundations that I stand on, and my younger brother, Atulya, and my uncle, Dinendra, who inspired me to pursue graduate studies.

Dedication

To my parents and younger brother.

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List of Acronyms

VV Voltage Varying

CVR Conservation Voltage Reduction

VVO Volt-VAR Optimization

VO Voltage Optimization

NN Neural Network

OPF Optimal Power Flow

FFNN Feed Forward Neural Network

MSE Mean Square Error

ZIP Constant Impedance (Z), Constant Current (I), Constant Power (P)

CSA Canadian Standards Association

ANSI American National Standards Institute

LDC Local Distribution Companies

LTC Load Tapchanger Transformer

EOL End of Line

MINLP Mixed Integer Non Linear Programming

GAMS General Algebraic Modelling System

AMPL A Mathematical Programming Language

NEMA National Electrical Manufacturers Association

MC Monte Carlo

PLC Programmable Logic Control

PNL Pacific Northwest Laboratories

AMI Advanced Metering Infrastructure

DR Demand Response

VVC Volt VAR Control

VVMS Volt VAR Management System

Nomenclature

Sets

k	Number of neurons in the hidden layer
t	Time intervals

Parameters

α, β	Scalar weights of the objective function components
ψ_{max}	Maximum allowable slot change
a_1, a_3, a_5	Real power parameters of ZIP load model
a_2, a_4, a_6	Reactive power parameters of ZIP load model
b_h	Bias of the NN hidden layer
b_i	Bias of the NN input layer
b_o	Bias of the NN output layer
k_p, k_q	Load's active/reactive power voltage dependence, Real number
M	Number of tap changes between minimum and maximum transformer voltage
N_{tap}	Total number of tap changes

P_o	Nominal real power at V_o
Q_o	Nominal reactive power at V_o
R_a	Armature Resistance, p.u.
R_f	Rotor Resistance, p.u.
R_m	Core Resistance, p.u.
R_r	Rotor Resistance, p.u.
R_s	Stator Resistance, p.u.
S_{max}	Highest tap position
S_{min}	Lowest tap position
T	Total number of intervals in operating horizon
V_{min}	Lowest voltage of the tap, p.u.
V_o	Nominal voltage of the load
V_{step}	Voltage steps of the tap, p.u.
w_h^k	Weight of the NN hidden layer associated with the k^{th} neuron
w_{i1}	Weight of the NN input layer associated with first input
w_{i2}	Weight of the NN input layer associated with second input
w_o	Weight of the NN output layer
X_a	Armature Reactance, p.u.
X_{max}	Maximum process value of the training data, p.u.
X_{min}	Minimum process value of the training data, p.u.

X_m	Core Reactance, p.u.
X_r	Rotor Reactance, p.u.
X_s	Stator Reactance, p.u.

Variables

$\gamma_{dn,t}$	Negative change in tap position, at time t
$\gamma_{up,t}$	Positive change in tap position, at time t
F, n, x, y	Continuous Variables
P	Real power
Q	Reactive power
R_{adj}	Adjustable field resistance
s	Motor operating slip
$slot_t$	Tap position, integer variable at time t
V_f	Field Voltage
V_t	Plant voltage at time t, p.u.
X_t	Total plant process at time t, p.u.

Functions

$F(x, y)$	Function of x, y
$f_k(x, y)$	Activation function of hidden layer neurons
$P(V, X)$	Power consumed by the load, p.u.

Chapter 1

Introduction

1.1 Motivation

Stimulated by the oil embargo of 1973-74, several utilities operated their systems at lower than the nominal feeder voltage levels to reduce the energy consumption at the load end, and hence to bring about fuel savings [3]. Based on this, it was postulated that permanent voltage reductions might conserve substantial amounts of fuel. This permanent reduction of voltage to reduce energy consumption is called Conservation Voltage Reduction (CVR). Although a controversial idea at first, it is now generally accepted that CVR is a successful method that utilities can use to lower the energy consumption in their systems [4]. Like utilities, industrial loads have some level of dependence on voltage because of the presence of motor and impedance loads. This dependence on voltage can be exploited by using a Voltage Varying (VV) strategy to reduce the overall energy consumption. This research proposes a VV strategy for industrial customers triggered by the recent advances in plant automation and smart grid technologies, and followed by the success of VV strategies in utilities.

1.1.1 Plant Automation and Smart Grid

Automation and control of industrial plants is a fairly well established field in electrical engineering. Automatic systems for industrial plants used to be based on electromechanical relay logic for a number of years and were considered standard practice for the industry. Within the last two decades, Programmable Logic Control (PLC) and microprocessor-based controllers have become cost effective, accessible and sufficiently reliable to be suitable for operation in a industrial plant environment, and are now considered the norm in industrial plants. The automation of control and data logging functions has relieved the plant operator from spending too much time scheduling, planning, monitoring and supervising plant operation. The maintenance time for the plant has also been reduced. Graphical user interfaces, data historian, sequence of events, trending, and reduced plant operation and cycle cost are the main benefits that these systems offer.

Until recently, these systems were only of interest to industrial plant operators and other industrial customers. Due to the increasing energy demand and the move toward clean energy production, there has been a push to make the existing power grid more efficient. The existing grid is currently feeding large energy demand while using the same equipment and systems installed decades ago. Building new infrastructure to meet the energy demand is a fairly expensive and many-a-time an infeasible proposition. This has resulted in utilities considering the adoption of technologies and methodologies for control and automation of grid operation. In general terms, integrating these technologies and methodologies have led to what is now know as “smart grid”. International Energy Agency defines smart grid as “an electricity network that uses digital and other advanced technologies to monitor and manage the transport of electricity from all generation sources to meet the varying electricity demands of end users” [5].

The main features of the conventional grid as seen in Figure 1.1 are that the system’s generation is centralized and there are passive customers who only receive energy, with limited metering and energy storage in the grid. However, in the smart grid environment,

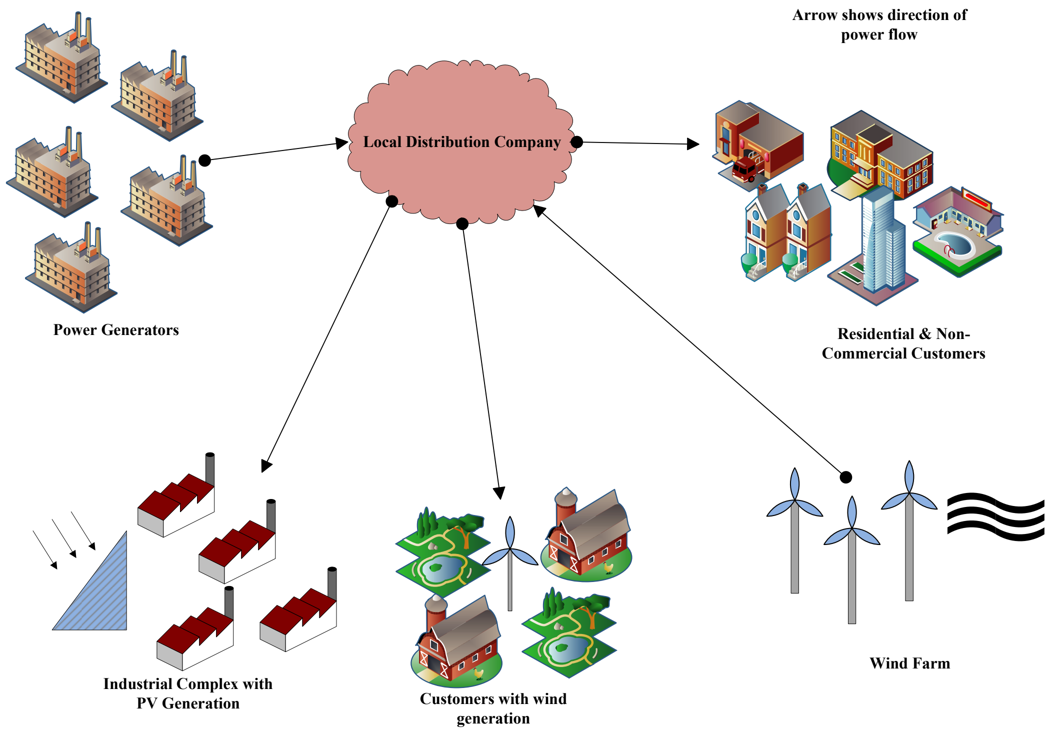


Figure 1.1: Conventional electricity grid.

Figure 1.2, the generation is decentralized and there are active customers who receive and send power back to the grid facilitated by an Advanced Metering Infrastructure (AMI).

Smart grids and their AMI allow end users to modify their demand during peak price periods and access. This is known as Demand Response (DR), which has been established to motivate changes in the customer's use of electricity. DR programs usually result in industrial customers curtailing loads or changing production to high-cost and high-margin products when the cost of electricity is high.

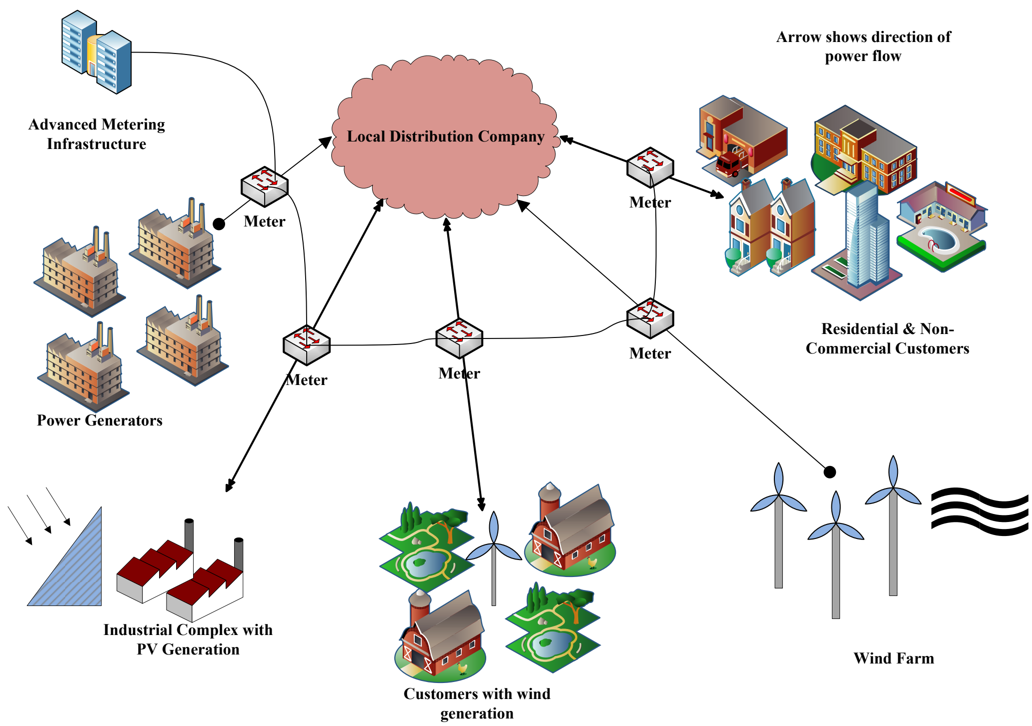


Figure 1.2: Smart grid environment.

1.1.2 VV Strategies in Utilities

VV strategies such as CVR were in use before smart grid technologies were introduced into the grid. The history and technical background of the CVR technique is discussed in detail in later sections. Since the CVR technique is more than three decades old, several studies can be found on its successful implementation by Local Distribution Companies (LDC). For example the Pacific Northwest Laboratories (PNL) report [1] on CVR demonstrates the ability to reduce long term energy consumption of distribution feeders using practical data. It is reported that CVR results in a peak load reduction and annual energy reduction in the range of 0.5%-4%, depending on the load. Furthermore, the report postulates a 3% energy savings, if CVR were to be implemented on a national scale. Furthermore, CVR was tested on twenty-four LDC feeders in different parts of the United States. The reported annual savings of each feeder is shown in Figure 1.3, where it is noted that the CVR technique is able to reduce energy consumption in most feeders by 1% to 2%. Applying CVR to the feeder tagged as F6 in Figure 1.3 increases the energy consumption by 4%, which this is identified to be due to the feeder losses increasing as the voltage decreases.

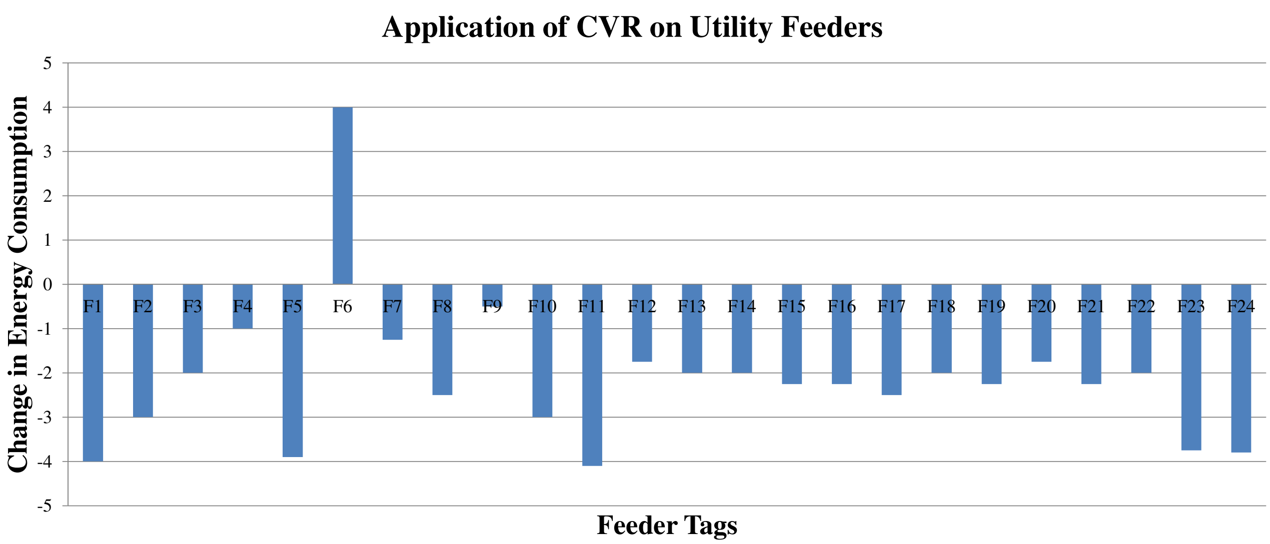


Figure 1.3: Change in energy consumption for each feeder on which CVR was tested [1].

With the advent of smart grid technologies, techniques such as CVR that control only voltage and use in-built system models have been replaced with more efficient techniques like Volt-VAR Optimization (VVO), which controls all reactive power resources and voltage using real time data. Hence VVO is a VV strategy that traditionally has been more attuned to LDCs rather than industrial customers. Furthermore, from a plant operator's perspective the load voltages are not constrained by the American National Standards Institute (ANSI) or Canadian Standards Association (CSA) requirements unlike LDCs, since the voltage constraints of industrial loads depend on the current and future plant processes, which are not adequately represented and modelled in the currently existing VVO systems.

1.1.3 Nature of End Loads

VV strategies such as CVR and VVO are well suited for most feeder loads. However, their VV strategies does not reduce energy usage for all loads, in fact, some loads may increase their energy usage when voltage is reduced [4]. This is because the behaviour of end loads, especially industrial loads, is not always intuitive under varying voltage [1]. Industrial loads generally have a complex behaviour between the input process, load voltage, efficiency and resultant power consumption. Previous studies [6] and [7] show that the application of CVR technique to industrial loads may reduce overall energy consumption. Many plant operators have already installed AMI and automation systems which give them significant control of their plant operation. Hence, an improved VV control strategy that takes into account the unique nature of an industrial load needs to be explored. This work examines the possibility of developing a VV strategy for industrial customers. In purview of what has been discussed so far, there is a motivation to investigate the following issues:

1. The behaviour of industrial loads under the influence of varying voltage.

2. Identify proper models for industrial loads.

3. Determine optimal load voltage profiles that minimize the energy consumption while meeting the operating constraints of the industrial load.

1.2 Literature Review

1.2.1 VV Strategies

A comprehensive analysis of CVR, as practised and applied in its early years, is reported in [3]. Voltage reduction was used for curtailing the instantaneous power demand of the system when it got close to the generation capacity. This was the last line of defence before load shedding would be resorted to. In order to test whether permanent voltage reduction resulted in permanent reduction of energy consumption, at least five utilities, LDCs and regulatory bodies implemented CVR during 1973-1980. It is important to note that during this period, CVR was not a "proven" technique; however, with certain studies that followed in the next decade, this perception changed.

From 1980 to 1990, several utilities implemented rather than tested CVR with varying degrees of success. North East Utilities in Connecticut implemented CVR using a line drop compensation method [8]. The economics of a permanent voltage reduction by compressing voltage limits to a narrower band was looked at, and a 1% total reduction in energy consumption was reported. This result was fortified by Commonwealth Edison reporting the exact same savings of 1% total reduction of energy by implementing CVR in Illinois [9]. A study by PNL indicates that region-wide implementation of CVR would result in significant level of energy savings in the Bonneville Power Administration system [10]. These studies led to several more utilities adopting CVR. Since then CVR, was accepted as an energy saving technique; however, it is difficult to implement CVR over a wide area without the danger of exposing some customers to unacceptable voltage conditions [4].

Just a few case studies of plant operators, industrial customers or VV equipment vendors implementing CVR techniques, to reduce energy consumption are reported in the literature [6], [7]. By applying CVR to an industrial complex, approximately 3% reduction in annual energy consumption is reported in [6]. While reporting successful implementation of CVR at industrial sites, the need for a better load modelling technique to evaluate and test VV strategies has been highlighted by CVR equipment vendors [7]. This is mainly because the modelling of industrial loads is a more complex exercise involving specific process estimation than for a distribution feeder, which is typically represented as aggregated load models. A precise load model is critical to ensure the proper design, implementation, and operation of power systems, especially due to the integration of smart grid technologies such as VO, DR, and energy storage. Although, Constant Impedance (Z), Constant Current (I), Constant Power (P) (ZIP) load models might be sufficient for system level voltage optimization, it does not capture the complex behaviour of an industrial load. To mitigate this, a multi-state load model for use in distribution system analysis is proposed in [11]. However, both these models are more attuned to the constraints faced by an LDC rather than plant operators, because the load is still represented as an aggregated model.

VVO is an improvement to the CVR technique that seeks to manage all reactive power resources in the system along with the LTC to achieve a desired objective. VVO is formulated in [12] as a multi-objective optimization problem that uses CVR techniques in addition to VAR optimization using shunt capacitors and reports the installation of a VVO scheme in the Ohio Area of USA. In [13], a multi-objective VVO, has been formulated and solved using combinatorial integer programming. As smart grid technologies like VVO become more prevalent in distribution systems the Optimal Power Flow (OPF) problem will become more complex. In order to minimize energy consumption, optimal use of capacitors and LTC need to be incorporated into the OPF problem. A modified version of the oOPF for an LDC, that integrates detailed models of the distribution system components in order to optimize its operation has been proposed in [14]. The modified OPF considers multiple operating objectives of the LDC such as minimizing energy consumption and LTC operation.

Besides the aforementioned cases of industrial customers using CVR, case studies of a VVO system being for a plant are discussed in [15]; in this case, the system was primarily being operated in CVR mode. Significant energy conservation of 3.72% with an annual energy savings of over 9,000 MWh per year, at full production capacity is reported. The mechanism of energy conservation when voltage is optimized in an industrial facility, and the measurement and verification method used to determine the actual savings is also detailed in [15]. Another case study of the same system installed in Murray State University is reported in [16]; a peak demand reduction of 4.4% and total energy savings of 4.8% is reported. In all cases, the VVO system was primarily being operated in CVR mode.

1.2.2 Load Models

In power systems, the solution to a problem and the corresponding deductions are extremely sensitive to the load model that is used to formulate the problem. For most power system simulations, simple load models such as the ZIP model or the static polynomial load model to represent the real system load characteristic are used. A majority of the research on VV techniques has been done using traditional ZIP models for loads or voltage dependant load representations of the form:

$$
\begin{aligned}
P &= P_o * (\frac{V}{V_o})^{k_p} \\
Q &= Q_o * (\frac{V}{V_o})^{k_q}
\end{aligned}
\tag{1.1}
$$

Aggregate load models, such as ZIP models, are used to mimic the equivalent-circuit or physical components of a group of loads connected to a single bus. The main purpose of this load model is to represent the changes in power demand of the modelled load as a function of voltage. This information is required for the analysis of system loading and operating conditions for the assessment of system performance in power system studies. Component-based aggregate load models are proposed in [17] based on measurements and statistical information on load structure and active/reactive power demands. Such models are of significant importance when evaluating VV strategies from the standpoint of an LDC. Aggregated load models are generally used for static power system analysis of distribution feeders; however, these are not well suited for dynamic analysis [18]. Techniques outlined in [18] can be used to improve the accuracy of the aggregated load model under dynamic conditions.

All VV studies mentioned so far use aggregated load models. From the perspective of an LDC this may suffice; however, from a power customers standpoint this poses a difficulty. Apart from the aforementioned work of [4], [1], and [7] suggesting that industrial loads cannot be modelled satisfactorily using aggregated load models for VV analysis, other studies have arrived at the same conclusion. Thus, in 1981, the Electric Power Research Institute commissioned the University of Texas at Arlington to test and study the effects of reduced voltage on the efficiency of important power system loads [19]. The study included end load devices such as television sets, microwave ovens, motors, heat pumps, air conditioners and distribution transformers. The report notes that the power consumption, efficiency and voltage dependence of end loads are complex and cannot be expressed by using (1.1) or a more complex aggregated load model. It is suggested in [20] that the LDC should consider operating their distribution circuits in the lower 5% of the permissible voltage band. Since only the lower 5% would be available for voltage regulation, operating with a reduced voltage band may require additional regulating facilities and/or equipment. These expenditures would have to be offset by the resulting benefits in order to justify installation of additional equipment.

1.3 Objectives

The main objective of this research is to develop a generic VV framework, from the perspective of industrial customers, to achieve optimal energy savings. The proposed framework, as shown in Figure 1.4, includes an NN module which uses historical load data of operational parameters to develop a generic load model of an industrial facility. This NN load model feeds into an optimization module that determines the optimal load voltage profile for achieving minimum energy consumption, while meeting process constraints. The Voltage Optimization (VO) model receives as input 24-hour ahead process forecast of the plant, in order to establish the optimal load voltage profile.

The proposed VO framework comprises the following parts (Figure 1.4):

1. Collect real load data of operational parameters such as voltage, real power, and process.
2. Build an NN load model using controlled variables (voltage and process) as inputs and responding variables (real power) as outputs.
3. Identify operational constraints of the load.
4. Formulate the VO problem using the load model and operational constraints to minimize energy or cost.
5. Based on the solution of the VO problem, determine the best VV strategy for the load.
6. Test the proposed VO model using various types of simulated and real industrial loads.

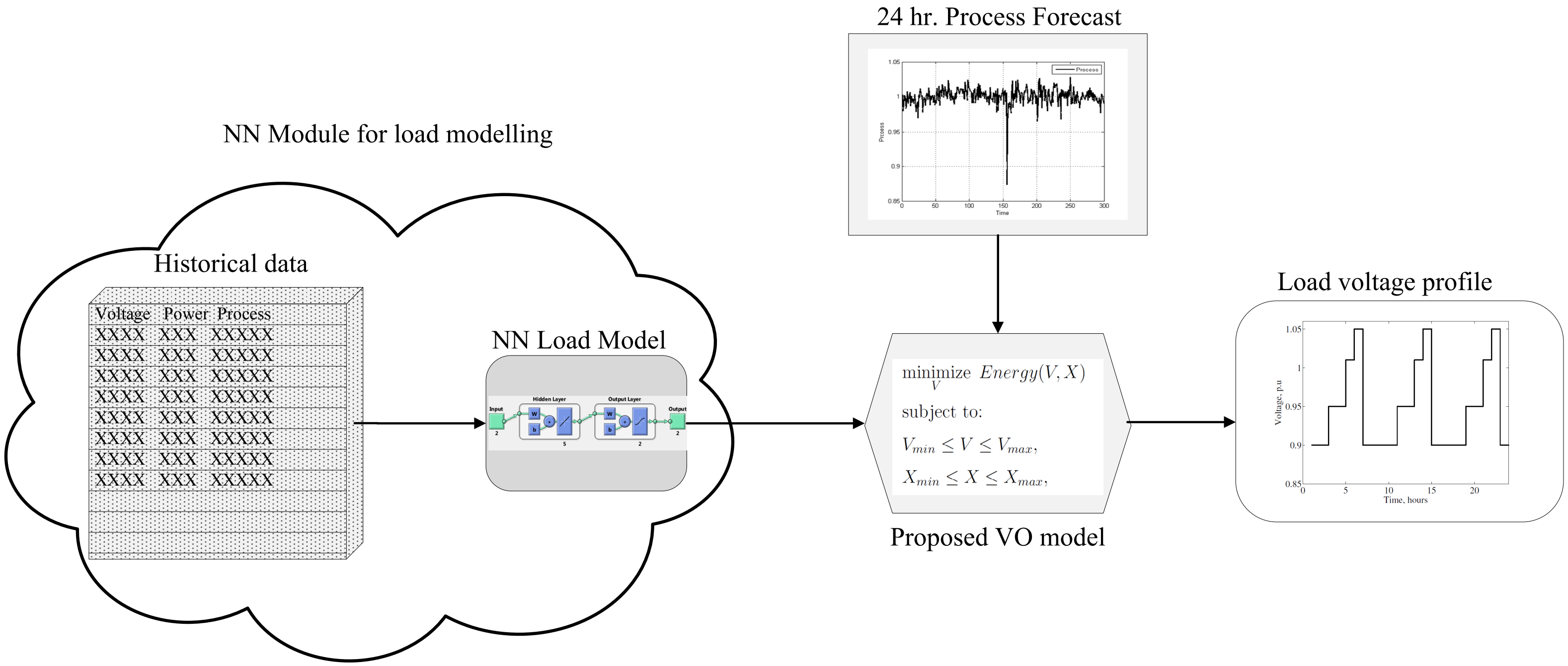


Figure 1.4: Schematic of the proposed VO framework

1.4 Organization

The thesis is organized as follows:

- Chapter 2: Background: This chapter discusses the implementation of existing VV strategies, followed by techniques and methodologies that have been used in this research. Load modelling techniques in VV studies are discussed, followed by a brief overview of optimization methods and Monte Carlo simulation methods, which are tools that have been used in this work. Important considerations from a plant operator perspective are also discussed.

- Chapter 3: Modelling Framework: In this chapter, the models used in this work are explained. Mainly two different models are presented: NN load model, and the VO model. The method used to incorporate the NN load model into the VO frame work is also explained.

- Chapter 4: Results and Analysis: The results of obtained from aforementioned models for various case studies are presented in this chapter. Three different modes of operation of an industrial load are considered: the base case, CVR and VO. The energy savings of using each method are presented and discussed. The significance of the results from a VV perspective is highlighted.

- Chapter 5: Conclusions: In this chapter, a brief summary of the thesis is presented, and conclusions from the research carried out are discussed. The main contributions of the work and scope for future work are also presented.

Chapter 2

Background

2.1 Implementing VV Strategies

In contrast to the common practice of setting the substation voltage at the maximum allowable level, CVR maintains the End of Line (EOL) voltage to the minimum allowable limit. This is accomplished primarily by using "R and X" (resistance and reactance) compensation, more commonly referred to as line drop compensation, to maintain the EOL voltage at a set value. All voltage regulators and LTC controllers today have the ability to implement line drop control. When implementing line drop control, the controllers use an internal model of the distribution feeder(s) fed by the substation, where the load is aggregated and the R and X values can be entered or adjusted in the controller. Controllers then regulate a control parameter which can be current, impedance or voltage. Based upon the control parameter, the voltage set-point at the LTC output is calculated so that the EOL voltage is held within ANSI or CSA standards, and the controller then adjusts the tap position accordingly.

The conventional method of line drop control used to implement CVR has some issues. The objectives of line drop control is to improve the voltage profiles over the feeders by decreasing the error between the measured EOL voltage and the actual EOL voltage. This yields an error bandwidth between the measured EOL voltage and the actual EOL voltage, which is the difference between the upper and lower acceptable voltage around the voltage set point. The is also a time delay associated with the dead band before the controller initiates a tap change. The bandwidth error and time delay result in the voltage set points of implementing CVR to be slightly amiss. There are various publications on improving these control aspects for an LTC. For example, a dead band control algorithm using a performance index of the LTC is proposed in [21] to reduce the number of tap changing operations and required time.

When pole mounted capacitors became available, LDCs started to install capacitors on the primary distribution feeders rather than at the substation. This was due to the benefits resulting from the placement of capacitors closer to the loads, such as improved voltage profile and loss reduction. Early work in this area is focused on optimally placing the capacitors and calculating the resulting loss reduction [22]. This has resulted in a significant amount of research into optimally operating the capacitors, LTCs, or both in order to meet various LDC objectives. These set of problem formulations are widely refereed to as VVO.

In the technical literature, VVO has also been referred to as Volt VAR Control (VVC) or Volt VAR Management System (VVMS). In the context of this work, VVO is a wide term that encompasses a broad spectrum of technologies that utilizes VVC [23]. Generally a VVO is formulated as a multi-objective optimization problem seeking to optimally control all reactive power assets and equipments such as the LTC. The objectives of VVO range from reducing system losses to minimizing voltage variation while reducing maintenance costs and operating costs. Additionally, it is desirable to attain the objective in the least possible number of control actions, thus minimizing the changes in LTC tap position.

Since the smart grid environment facilitates using real-time data to make these multi-objective optimization decisions, adding CVR as an additional objective to VVO is now begin explored. In [23], a specification of a such a VVMS that incorporates VVO and CVR is described in detail. Many aspects of the equipment and distribution system design are also explained.

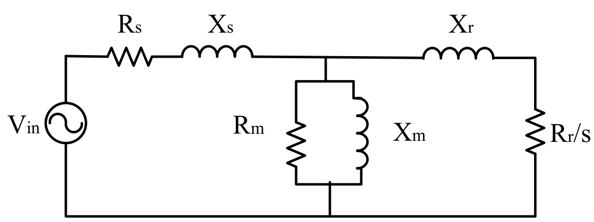
When considering differences in CVR with VVO, the most significant one is not the concept of VVO but rather its implementation. Conventional CVR implementation uses line drop control, which is an open-loop system with respect to the distribution feeders. Furthermore, tap changes are made based on current load and voltage as measured at the transformer or regulator. On the other hand, a VVO implementation in the smart grid paradigm, where in the system measures the actual EOL voltage in real time and feeds the data to the controller, allows for tap changes based on actual measured voltages.

2.2 Load Models

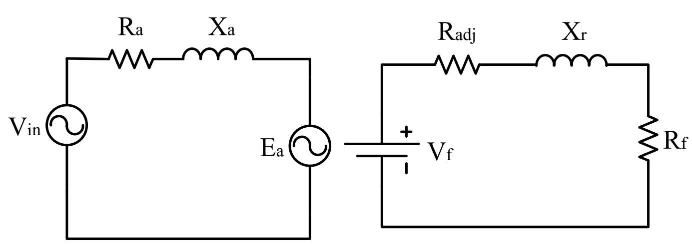
Load models are used extensively in power system analysis. Accurate load models are very important to ensure reliable operation of power systems. A static load model, usually a ZIP model, is commonly used. Developing a generic load model which would be flexible enough for all types of studies, from system planning to operation and control is not realistic. One step that can simplify this problem is to determine the extent of model detail required for the task at hand. If modelling is carried out at the individual load level, it needs more detailed representation, while modelling on an aggregate basis is sufficient from a bus stand-point. Choice of the load model must be governed by the intended application and computational constraints. The three types of load models of primary interest in this research are classical machine load models, aggregated load models, and NN models, which are described next.

2.2.1 Classical Machine Models

Although a classical machine model is not a generic load model, it is used to study the behaviour of some loads. This is usually the case if the machine accounts for a significant share of the power consumption. Classical machine models for induction and synchronous machine, as shown in Figure 2.1, are developed using standard machine name plate ratings and parameters for large motors. The model in Figure 2.1 is generally capable of representing a wide variety of induction motors; however, there are some induction motor types that need to be modelled differently, such as double cage or deep bar rotors.



a) Induction Machine



b) Synchronous Machine

Figure 2.1: Classical machine models

For large machines, it is not common for manufacturers to provide precise parameters for the components in Figure 2.1, and hence there are methods that can be used to estimate these parameters based on machine data. For example, an induction motor parameter estimation algorithm that is based on numerical techniques is presented in [24]; commonly available manufacturer name plate parameters are used as inputs to generate the remaining parameters of a three-phase induction motor model, for steady-state and quasi-steady-state analysis.

2.2.2 Aggregated Load Models

For most cases, at high voltage levels, power system loads are aggregated, and are commonplace for analysis and simulations. A commonly used aggregated load model is the ZIP model, which depends on the power relation to the voltage. The static characteristics of this model can be classified into constant power, constant current and constant impedance load. The ZIP load model is a polynomial model as follows:

$$\begin{aligned} P(V) &= P_o\left[a_1\left[\frac{V}{V_o}\right]^2 + a_3\left[\frac{V}{V_o}\right] + a_5\right] \\ Q(V) &= Q_o\left[a_2\left[\frac{V}{V_o}\right]^2 + a_4\left[\frac{V}{V_o}\right] + a_6\right] \end{aligned} \tag{2.1}$$

Parameters a_1 and a_2 determine how much of the load is constant impedance; parameters a_3 and a_4 determine how much of the load is constant current; and parameters a_5 and a_6 determine how much of the load is constant power.

Table 2.1: ZIP Load Models

Load Parameters for Real Power	a_1	a_3	a_5
Distribution Feeder (Mostly Residential) [25]	12.70	59.80	27.50
Distribution Feeder (Mostly Industrial) [25]	-6.10	21.20	84.90
End Load(Liquid Crystal Display Television) [1]	0.61	-0.54	-1.00

Some examples of ZIP load models for real power consumption are presented in Table 2.1. When the parameters of all machine components in the load are known, the parameters of the aggregate load models shown in (2.1) can be readily determined. If the parameters of separate loads are not known, deriving an aggregate load becomes more difficult. In [26], two power system load-identification techniques are proposed, and some theoretical and practical issues relevant to power system load modelling and identification are discussed; output error model based identification techniques are developed in the theoretical framework of stochastic system identification and then tested on real data.

If there are large rotating machines connected at a bus which has predominantly residential load, composite load models are developed. For example, models for paper mill and mining loads in Ontario's Northwest Region are proposed in [27], where two different models were added to the aggregated load model to generate a composite load model. The first model is a transfer function model which relates the power and reactive power outputs to input changes in voltage and frequency, and the second model is an induction motor machine model with shunt static load. Voltage is considered as an input to the model and the outputs are real and reactive power.

The only drawback of the methods discussed so far is that significant amount of data is required to create an accurate model. For example, in the load model development presented in [27], Hydro One had access to bus frequency, positive sequence voltage at the load bus, and real and reactive power on three feeders simultaneously at a rate of 20 samples per second of each quantity. Furthermore, acquisition of load response data during disturbances (system faults, inter-area swings, etc.), along with pre-disturbance data, is also necessary.

2.2.3 NN Load Models

The discussed load models are static or quasi-static. Complex P-V and Q-V equations have been used to generate dynamic load models [28]. In order to describe the dynamic behaviour of loads, NN load models have also been used. A neural network methodology for dealing with static and dynamic load modelling is presented in [28].

A NN is composed of a set of very simple processing elements called neurons. Each neuron operates on the input using an activation function. The topology of interconnection and rules employed by any NN are together called the paradigm of the network. A NN can be designed to have many different paradigms depending on the intent of the network [29]. The universal approximation theorem states that any arbitrary continuous function can be approximated closely by a multi-layer NN. This is valid only for a NN that uses a restricted class of activation functions such as the sigmoidal functions. A example of such an activation function is the following tansigmoid activation function:

$$\tanh(n) = \frac{e^n + e^{-n}}{e^n - e^{-n}} \tag{2.2}$$

The number of hidden layers can be increased to extract higher-order statistics [2].

There are two extreme topologies for NN [30]:

1. Feed Forward: Neurons are laid out in layers, and each subsequent layer has an interconnection from the preceding layer. Such a feed forward network can transform one pattern into another, which can be used for pattern detection or for associative memory.

2. Recurrent: The output of any layer may be fed back to its preceding layers. This net is sometimes called an attractor. It acts as a content addressable memory.

An example of an FFNN is shown in Figure 2.2. A common method used to train the FFNN is to iteratively adjust the network weights and biases to minimize a network performance function, such as the Mean Square Error (MSE) between the network outputs and the desired outputs. The gradient of the performance function is used to determine how to adjust all the weights and biases, using an updating technique known as back-propagation. This technique starts at the output layer and propagates the results backwards to the input layer [2]. The Levenberg-Marquardt algorithm is a very common method used to minimize the performance function based on its gradient; it has an adequate performance and is not affected by the accuracy required on the function approximation.

NN load models have more degrees of freedom compared to the load models discussed previously. A machine load model can represent the load if the load behaviour is dictated by the machine alone, which is not true for most cases. Using an NN load model allows

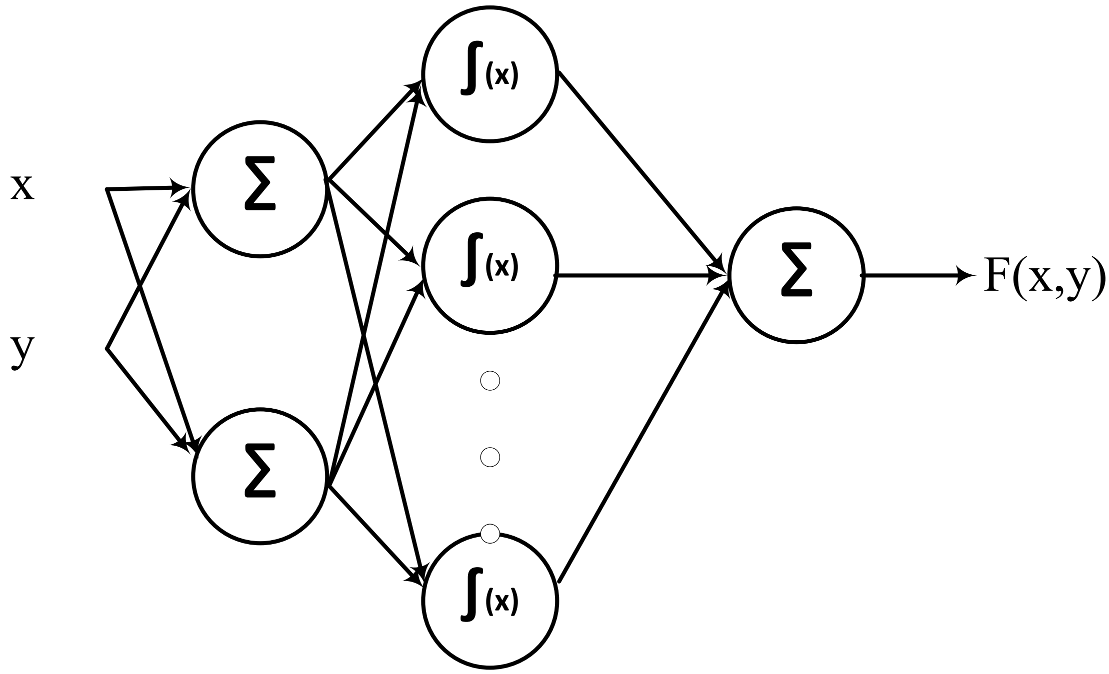


Figure 2.2: A typical topology of an FFNN [2]

inclusion of various variables of interest as inputs, while also allowing to represent multiple outputs.

2.3 Optimization in Power Systems

In power systems, the two basic optimization problems are economic load dispatch and the OPF. The OPF problem was introduced in the early 1960's by Carpentier [31]. This optimization problem is formulated as a non-linear programming problem. The voltage control or reactive power dispatch can also be formulated as an OPF. Reactive power and voltage control is typically associated with controlling LTC and capacitor banks so that daily energy losses are minimized, while satisfying operating constraints. Due to LTC and capacitor manufacturer restrictions and life expectancy, frequent switching operations of LTC and capacitor banks should be prevented. Thus, optimal reactive power and voltage control requires the solution of an optimization model with discrete or binary control variables. In [32], a new and efficient method to solve the optimal daily reactive power dispatch and voltage control problem in distribution systems, considering limits on the number of daily switching operations for capacitors and transformer LTC, is proposed. Since this problem combines continuous and discrete variables and non-linearities in the objective function and constraints it is a Mixed Integer Non Linear Programming (MINLP) problem. Typically MINLP problems are computationally intense. Various algorithms have been proposed to solve the aforementioned reactive power and voltage control optimization problem.

2.4 Monte Carlo Simulation

The name Monte Carlo (MC) simulations was first applied to a class of mathematical methods used in on the development of nuclear weapons in Los Almos in 1940 [33]. MC simulations depend on playing a game of chance whose outcome can be used to understand a phenomenon or pattern of interest. Many mathematicians argue that MC simulations will never be the method of choice but a method that can give rough estimates [33].

MC simulations can be split into two main categories: direct simulation of a naturally random system and addition of artificial randomness to a system. The latter is of more interest for engineering applications and is based on introducing random perturbations to inputs in order to test the sensitivity of the system variations to these inputs.

The behaviour of power systems depend on the load, which is stochastic in nature. Hence using deterministic data renders power systems analysis, at least to some extent, inaccurate. The uncertainty in system demand was first considered in a standard power flow problem using probabilistic techniques in the early 1970s [34]. With the introduction of electricity markets power flow problems have become more complex, resulting in stochastic methods like MC simulations being used frequently in power systems. Thus, in [35], an estimation method to account for uncertainties in the OPF problem in the context of deregulated electricity markets is presented, studying probability distributions of locational marginal prices.

2.5 VV Considerations For Large Industrial Loads

While implementing a VV strategy, care must be taken to ensure that voltage fluctuations and power quality are maintained within acceptable limits. This is especially true for an industrial load, since most loads in a plant are rotating machines, such as motors and pumps. Voltage fluctuations are usually caused by variations in the load, but using a VV strategy can cause the voltage swings to be even larger than intended. The National Electrical Manufacturers Association (NEMA) has set certain standards regarding operation of motors [36], which assist plant operators in the proper selection and use of motors and generators, stating that polyphase motors shall maintain operation at rated load when the voltage unbalance at the motor terminals does not exceed 1%. Furthermore, operation of a motor with above a 5% voltage fluctuation in a short time is not recommended, and will probably result in damage to the motor.

The relationship of the magnitude of the voltage fluctuation and the time span in which it occurs depends on the size of the motor. Since a plant operator has large motors, usually 1 MW or larger, it is not recommended to exceed the 1% limit for voltage fluctuation in a short period of time, since such a voltage fluctuation of 1% can cause a current swing of 6% to 10%. This may, in the long run cause the motor to produce excessive heat that shortens motor life and eventual burnout. In the short term, this may trip a circuit causing large economic loss to the plant.

Chapter 3

Modelling Framework

3.1 NN Load Model

As stated earlier, the objective of this work is to determine an optimal load voltage profile to achieve energy savings for the industrial customer. Hence, a generic load model that can be incorporated into the optimization engine is required. An NN that takes load voltage and process data as inputs and estimates the real power consumption as the output is developed in this work. Care must be taken to ensure that the NN load model can be incorporated into the proposed VO approach without unnecessarily increasing the computational burden; this can be done by selecting simple topologies for the NN and sacrificing some accuracy by limiting the number of neurons.

An FFNN is a simple and generic architecture that can be readily incorporated into the optimization model. Any FFNN can be algebraically modelled as a relation of the output F mapped to inputs x and y using the function $F(x, y)$, which depends on the weights and biases of the NN as follows:

$$F(x, y) = \sum_{i=1}^{k} \left[f_k((x * w_{i1} + y * w_{i2}) + b_i) * w_h^k \right] + b_h * w_o + b_o \tag{3.1}$$

where the tan-sigmoid function (2.2) is used here as the activation function f_k.

A technique of introducing input-output relations as an optimization model constraint using an NN representation is discussed in [37], for solving a security constrained optimal power flow problem. This technique is used here to incorporate the NN load model based in (3.1) into the proposed VO model.

3.2 Proposed Voltage Optimization Model

Once the NN model of the load is created, the next step is to integrate the load model into the optimization model. The optimization model, which is solved every 15 minutes using 24-hour forecasted process data, is used to determine the optimal load voltage profile that can minimize energy consumption while meeting the process constraints. The corresponding mathematical model is described next.

3.2.1 Objective Function

The objective function seeks to minimize two components: energy consumption of the load and LTC operation over the operating horizon.

LTC Operation The total number of changes in the LTC tap positions during the 24 hour operation is given by:

$$\sum_{t=1}^{T}[slot_{t+1} - slot_t] \tag{3.2}$$

Energy Consumption The following NN load model provides an estimate of the power consumption of the load based on process and load voltage data:

$$F(x,y) = \sum_{i=1}^{k} \left[f_k((V * w_{i1} + X * w_{i2}) + b_i) * w_h^k \right] + b_h * w_o + b_o \tag{3.3}$$

Depending on the location of the load, cost of electricity and the equipment maintenance cost, the value or weight associated with energy consumption of the load and LTC operation might be different. Hence, weighting factors of α and β are introduced to formulate an augmented objective function as follows:

$$J = \alpha * \sum_{t=1}^{T} P(V_t, X_t) + \beta * \sum_{t=1}^{T} [slot_{t+1} - slot_t] \tag{3.4}$$

$$\beta = 1 - \alpha \tag{3.5}$$

3.2.2 LTC Constraints

Only the secondary side of the transformer is considered in this work, and the grid is assumed to supply steady and reliable voltage. The main plant LTC has a maximum range $\pm 5\%$, with each slot position in the tap being 1.0%. Thus the LTC is modelled as follows:

$$S_{min} \leq slot_t \leq S_{max} \tag{3.6}$$

$$V_t = V_{min} + V_{step} * slot_t \tag{3.7}$$

where the integer variable $slot_t$ can only range between S_{min} and S_{max} (3.6), which are the lowest and the highest tap position of the LTC respectively. Since the LTC has a maximum range $\pm 5\%$, $S_{min} = 0$ and $S_{max} = 10$. The voltage at the load bus, which takes a discrete value, is given by (3.7).

It is not acceptable to vary the voltage of a large industrial load significantly [36]. Hence, the slot change across two consecutive time intervals is limited to ψ_{max} as follows:

$$-\psi_{max} \leq slot_{t+1} - slot_t \leq \psi_{max} \tag{3.8}$$

$$slot_{t+1} - slot_t \leq \gamma_{up,t} * M \tag{3.9}$$

$$slot_t - slot_{t-1} \leq \gamma_{dn,t} * M \tag{3.10}$$

$$\gamma_{up,t} + \gamma_{dn,t} \leq 1 \tag{3.11}$$

In order to capture the inter-hour LTC tap changes, the binary variables γ_{up} and γ_{dn} are used, where $\gamma_{up} = 1$ when the tap position moves up, while $\gamma_{dn} = 1$ when the tap position moves down. In order to ensure that γ_{up} and γ_{dn} does not occur simultaneously, (3.11) is used. The total number of tap changes in a 24-hour optimization horizon is limited to N_{tap} as follows:

$$\sum_{t=1}^{T} [\gamma_{up,t} + \gamma_{dn,t}] \leq N_{tap} \tag{3.12}$$

For the purpose of this work, it is assumed that $\psi_{max} = 1$; hence, (3.9) and (3.10) becomes redundant, and (3.8) can be replaced with:

$$\gamma_{up,t} - \gamma_{dn,t} = slot_{t+1} - slot_t \tag{3.13}$$

The VO model is thus formulated with the objective function (3.4), subject to the constraints given by (3.7), (3.6), (3.11), (3.12), (3.13). This is a MINLP problem that is solved here in the General Algebraic Modelling System (GAMS) environment using the $BARON$ solver [38].

Chapter 4

Results and Analysis

The following case studies are carried out to test the proposed VO framework:

- A single large induction motor on a bus using simulated data
- A single large synchronous motor on a bus using simulated data
- A industrial plant, as seen from the main plant transformer modelled using real data

4.1 FFNN Load Models

4.1.1 Motor Model Data

In order to generate the data to train the FFNN load model of the induction and synchronous motor, the classical machine models of Figure 2.1 are used [39]. Using these equivalent circuit representations of the motors and a set of input voltage and load, the machine model yields the total power consumption to create the training set for the FFNN model as illustrated in Figure 4.1. The machine models used here are based on the standard name plate ratings and parameters for large motors provided in Table 4.1 [39].

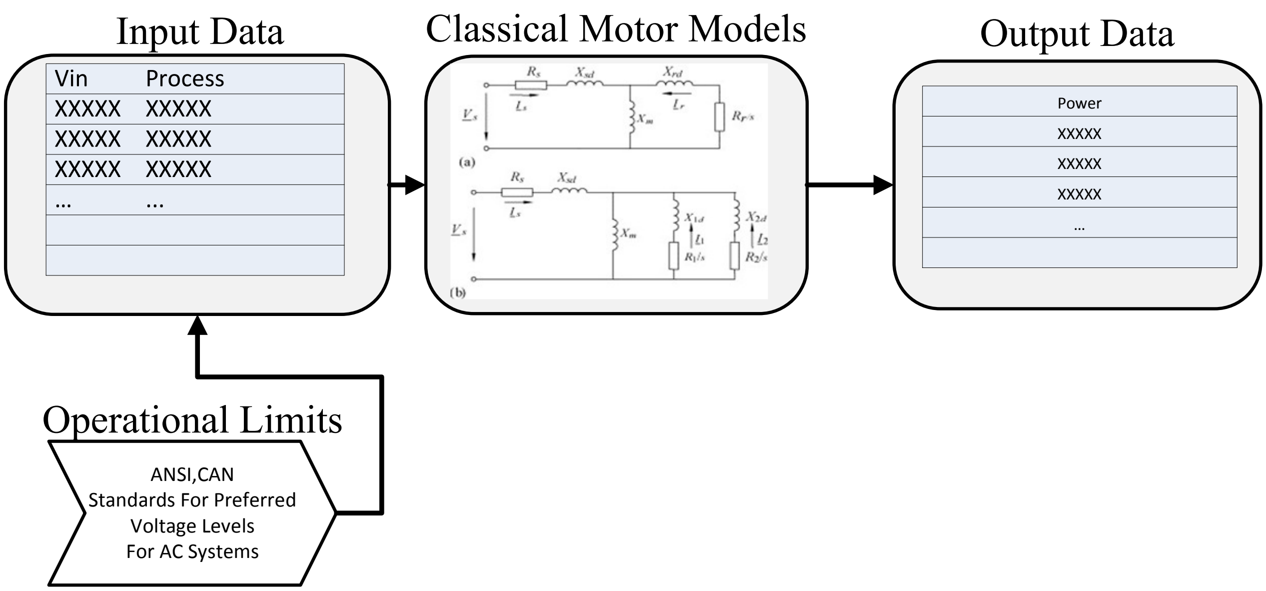


Figure 4.1: Procedure used to generate data for the FFNN load models.

4.1.2 Industrial Plant Data

The procedure to gather data for the FFNN-based load estimation model for the industrial plant was as follows: By using the main plant LTC, the voltage at the secondary side of the feeder transformer was varied as shown in Figure 4.2. The voltage was varied from 1.0 p.u to a higher value, and then dropped below 1.0 p.u after a fixed time interval. The total power consumption and the total plant process output were logged from the main plant meter, resulting in the data depicted in Figure 4.3 and Figure 4.4.

Using the raw data of voltage, process and power as metered from the site (Figure 4.2 to Figure 4.4), it is not possible to create an accurate FFNN load estimation model, for the VO purposes, which is a relatively slow process compared to the of fast transients observed. Therefore, using a rolling mean filter with a three minute window, the raw data was processed to eliminate the fast transients; the filtered data presented in Figure 4.5 shows that the general trend of the variables are not disturbed.

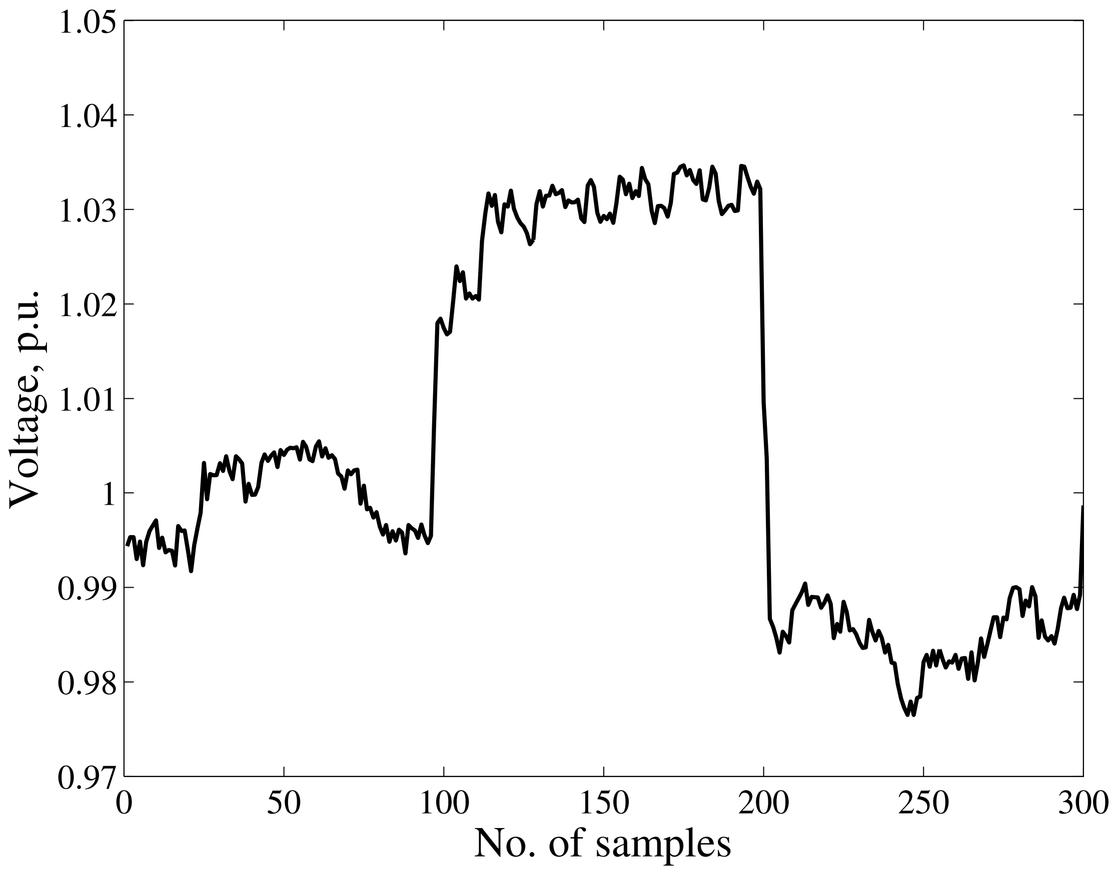


Figure 4.2: Varied voltage at the main plant substation.

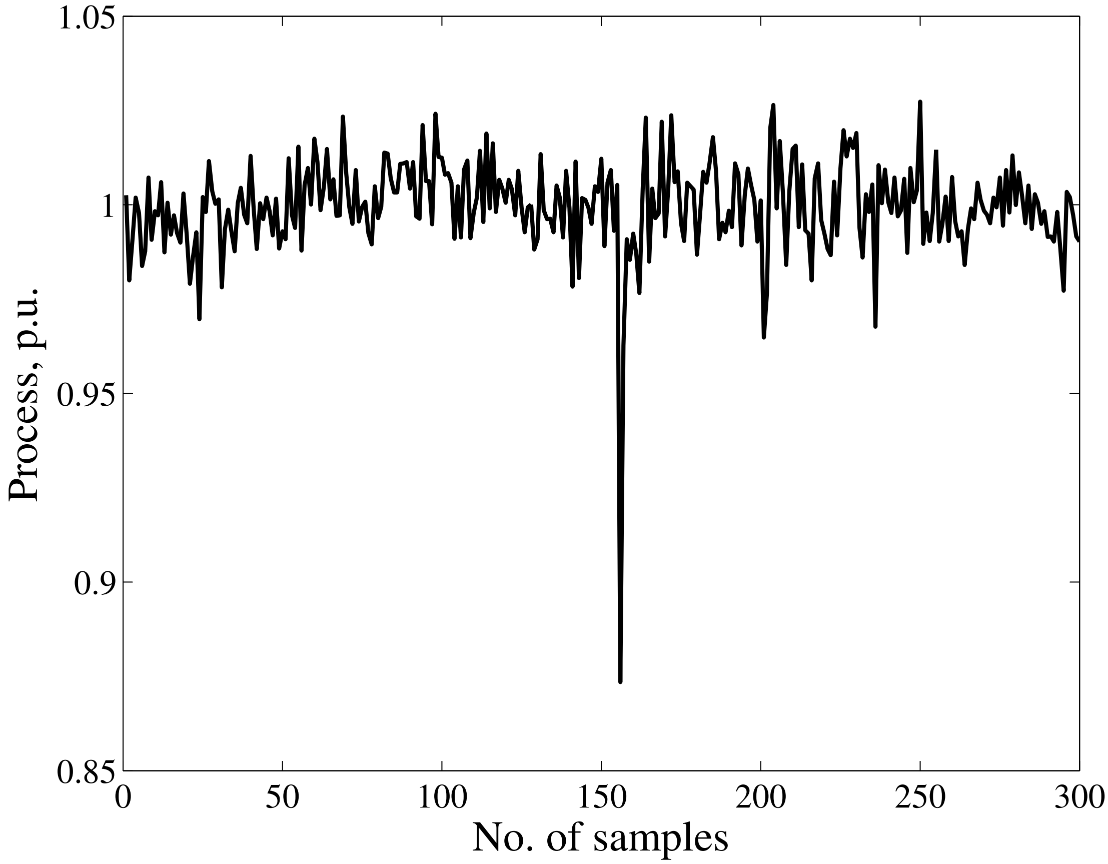


Figure 4.3: Overall plant process data as logged from the main plant meter.

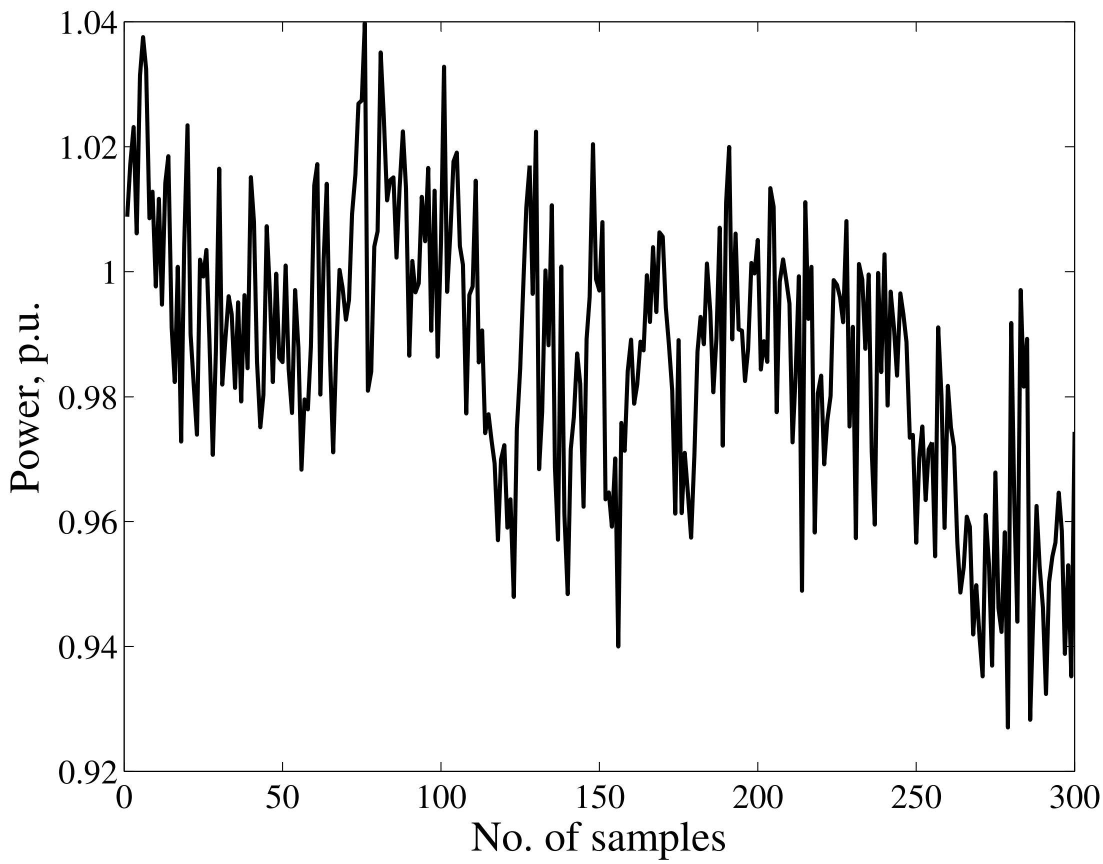


Figure 4.4: Total power consumption as logged from the main plant meter.

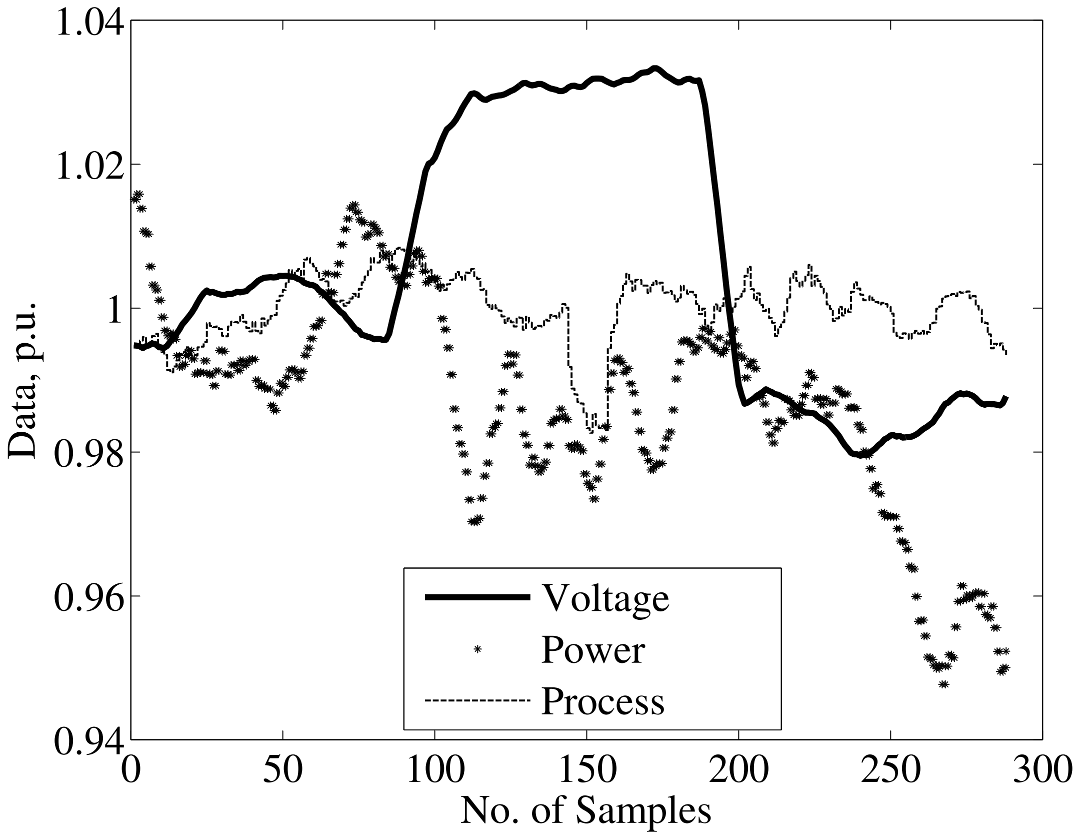


Figure 4.5: Filtered data used for training the NN load model.

Table 4.1: Motor Name Plate and Parameters

Induction Motor			
Name Plate	Rating	Parameter	Value (p.u)
V_{rated}	4300 V	R_s	0.461
ω	1170 rpm	R_r	0.258
P_{rated}	8000 HP	L_s	0.507
p	6	L_r	0.309
f	60 Hz	L_c	30.74
Synchronous Motor			
Name Plate	Rating	Parameter	Value
V_{rated}	6600	R_s	0.100
ω	1200	R_r	24.04
P_{rated}	12000	L_s	-
$P.F$	1.00	L_r	2.500
I_{rated}	1404	L_c	-

4.1.3 FFNN Load Model Training

The FFNN load models in this work comprise one neuron for both the input and output layers. The number of neurons in the hidden layer is decided by varying the number of neurons and using the MSE as a performance measure. The lowest number of neurons capable of estimating the real power consumption of the load with a reasonable degree of precision is chosen as shown in Table 4.2.

Table 4.2: FFNN Load Models

Model	Neurons In Hidden Layer	MSE
Induction Motor	3	$2.86 * 10^{-6}$
Synchronous Motor	3	$3.86 * 10^{-7}$
Industrial Load (Real Data)	7	$2.65 * 10^{-5}$

Since the behaviour of induction and synchronous motors while within the ANSI & CSA specifications, are fairly linear, increasing the number of layers is unnecessary. The data set is classified into training data (80%), testing data (20%) and validation data (20%).

The FFNN was trained in $MATLAB^{TM}$ using the Levenberg-Marquardt algorithm for back propagation.

4.2 Voltage Optimization

In order to evaluate the proposed VO framework, three different modes of operation for the loads are considered in this work:

- Base Case: Voltage is held constant at 1.0 p.u.
- CVR: Voltage is maintained at the lowest possible setting
- VO: Voltage is optimally varied based on the proposed VO

The power consumption of the two aforementioned VV techniques are compared with the Base Case to compute the energy savings. The Base Case and CVR are both implemented by maintaining the voltage at a constant position, regardless of the process. This renders the computation of energy consumption for CVR and the Base Case insensitive to the process forecast. Monte Carlo methods are subsequently used to compute the expected savings from the proposed VO model based on the process forecast.

4.2.1 Motor Loads Using Simulated Data

A 24-hour load process profile is generated by randomly varying the process within X_{max} and X_{min}. Large industrial motor loads may have two extreme kinds of process: a fairly constant or a highly varying process. For a constant process profile, $X_{max} = 1.05$ p.u. and $X_{min} = 0.95$ p.u. are used, and for a varying process profile the lower limit is altered to $X_{min} = 0.50$ p.u. Based on the ANSI and CSA standards, the lowest possible voltage to operate the induction and synchronous motor is 0.95 p.u.; hence, for CVR, the voltage is maintained at 0.95 p.u.

Figure 4.6 presents the voltage profiles for the three modes of operation for the single induction motor load discussed earlier. The voltage profile using the proposed VO model is initially 1.0 p.u., as per the initial conditions, converging to 0.95 p.u after a few time intervals. For five hundred different 24-hour process profiles, no difference in the optimal voltage profile and energy savings for each VV technique are observed. However, the energy savings are different depending on the process type, as seen in Table 4.3. Since the optimal voltage profile of the VO model remains at a constant level, the weighting factor α has no impact on the energy savings. Based on these results, it can be noted that the best VV strategy for a large induction motor is CVR, and the amount of energy savings depends on the process.

Figure 4.7 presents the voltage profiles for the three modes of operation for the single synchronous motor load discussed earlier. The voltage profile using the proposed VO model is initially 1.0 p.u. as per the initial conditions, converging to 1.05 p.u for five hundred different 24-hour process profiles. The energy savings accrued from the two VV techniques are shown in Table 4.3 and are independent of the process type. The weighting factor α has no effect on the energy savings, since the optimal voltage profile of the VO model remains at a constant level. It is interesting to note that for a synchronous motor, applying the CVR technique results in negative energy savings due to increased losses, and that voltage has negligible effect on the synchronous machine's torque-speed characteristic and consequently its real power consumption.

From the application of the proposed VO model on motor loads, it is noted that the VV techniques do impact the real power consumption of induction motors, but are ineffective for synchronous motors. The amount of energy savings for an induction motor load varies based on the process, which is not the case for a synchronous motor, as shown in Table 4.3. This is to be expected, since the torque-speed characteristic of an induction motor varies with terminal voltage, whereas, for a synchronous motor, this remains constant as the voltage changes, only affecting the pull-out torque. Note that a continuously varying

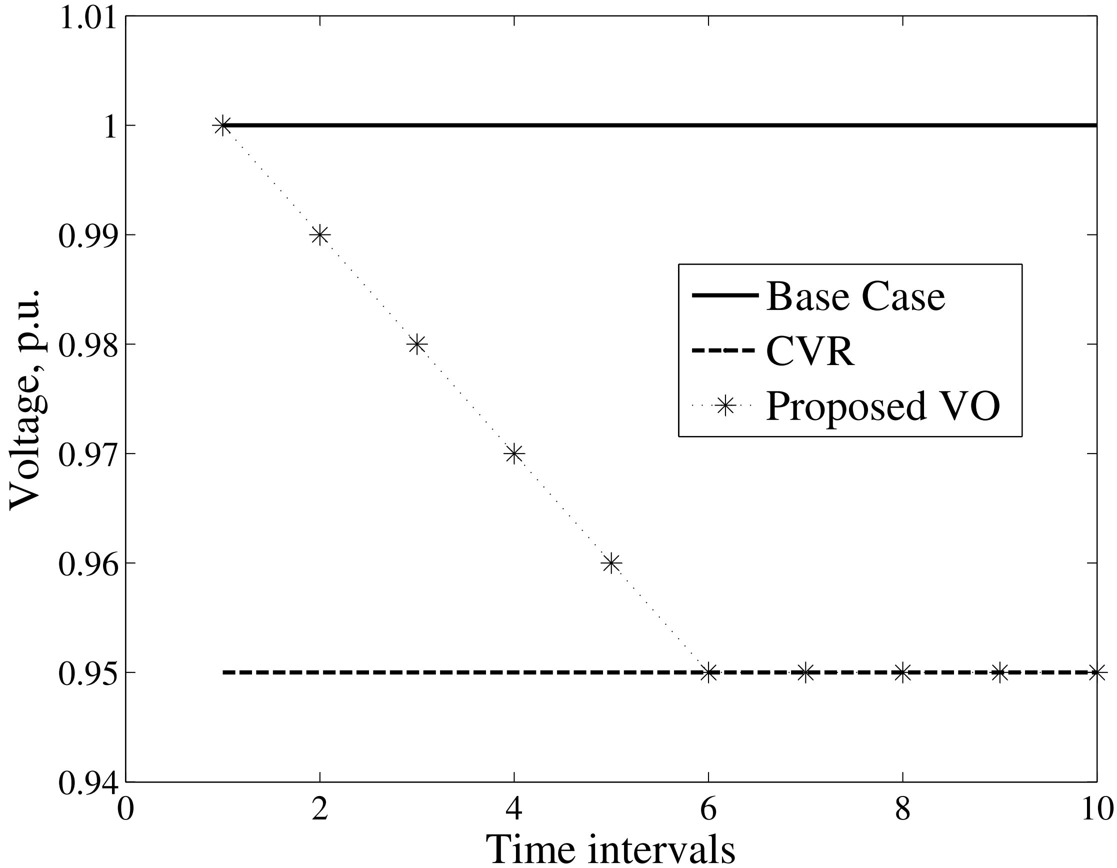


Figure 4.6: Voltage for the initial ten time intervals of fifteen minutes each for a single induction motor.

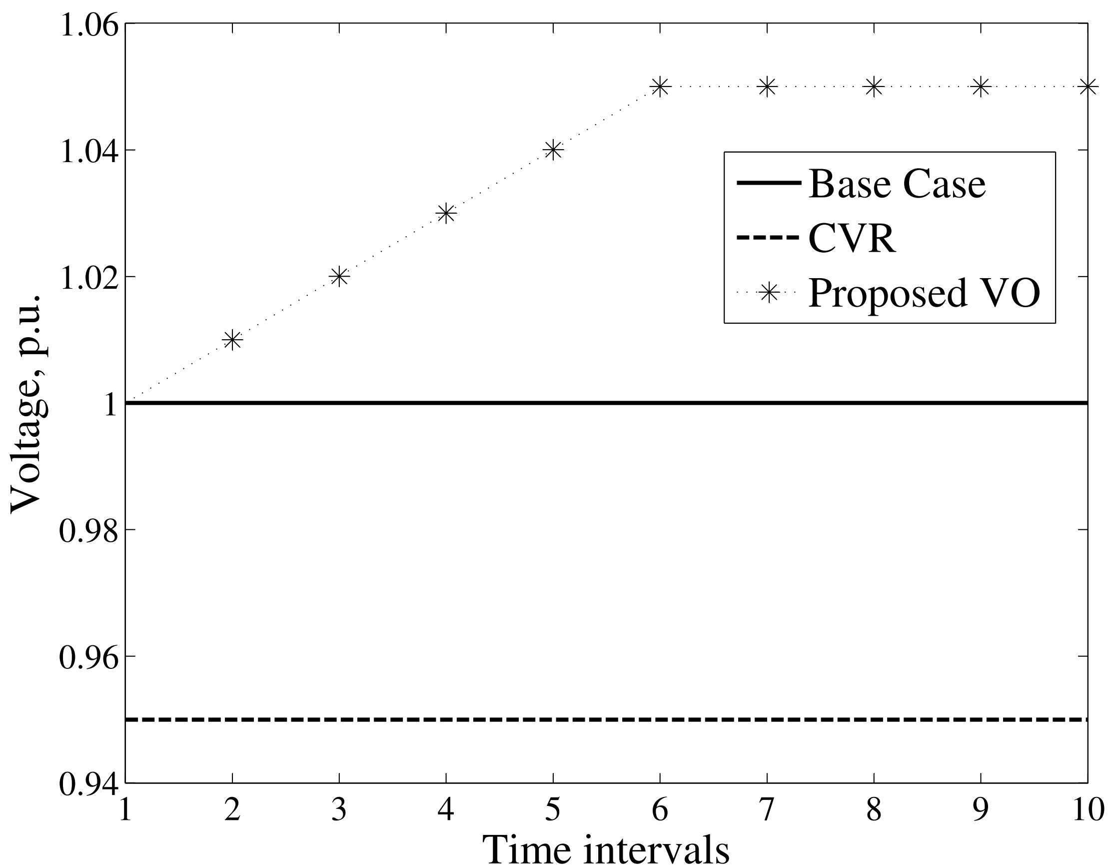


Figure 4.7: Voltage for the initial ten time intervals of fifteen minutes each for a single synchronous motor.

Table 4.3: Reduction in power consumption in motor loads for VV techniques

Process	Energy Reduction by CVR (%)	Energy Reduction by VO (%)
	Induction Motor	
Constant	1.46	1.46
Varying	0.90	0.90
	Synchronous Motor	
Constant	-0.15	0.15
Varying	-0.15	0.15

Table 4.4: Reduction in power consumption of real plant for VV techniques

Test Case	Plant Load	
	Energy Reduction by CVR (%)	Energy Reduction by VO (%)
Single 24-hour process profile	0.72	2.34
Monte Carlo simulation	0.80	2.29

optimal voltage profile is unnecessary, since the maximum or minimum operating voltage is the optimal load voltage in either case.

4.2.2 Real Plant Load

In this section, the proposed VO model is applied to an industrial plant load model. The process data over 24-hours is logged from the industrial plant and used as input to the proposed VO model. Figure 4.8 presents the voltage profiles for the three modes of operation for the industrial plant load. The energy savings are presented in Table 4.4, assuming the voltage to be in the narrow range 0.98 p.u. - 1.03 p.u., due to plant operator concerns, and $\alpha = 0.9$. Energy savings would be expected to change as the voltage range increases to 0.95 p.u. - 1.05 p.u.

In order to calculate the expected energy savings from VO, 500 unique 24-hour process profiles for the industrial plant are generated as inputs using the following approach:

- Step 1: Perturb the data around its original value using a normal distribution function

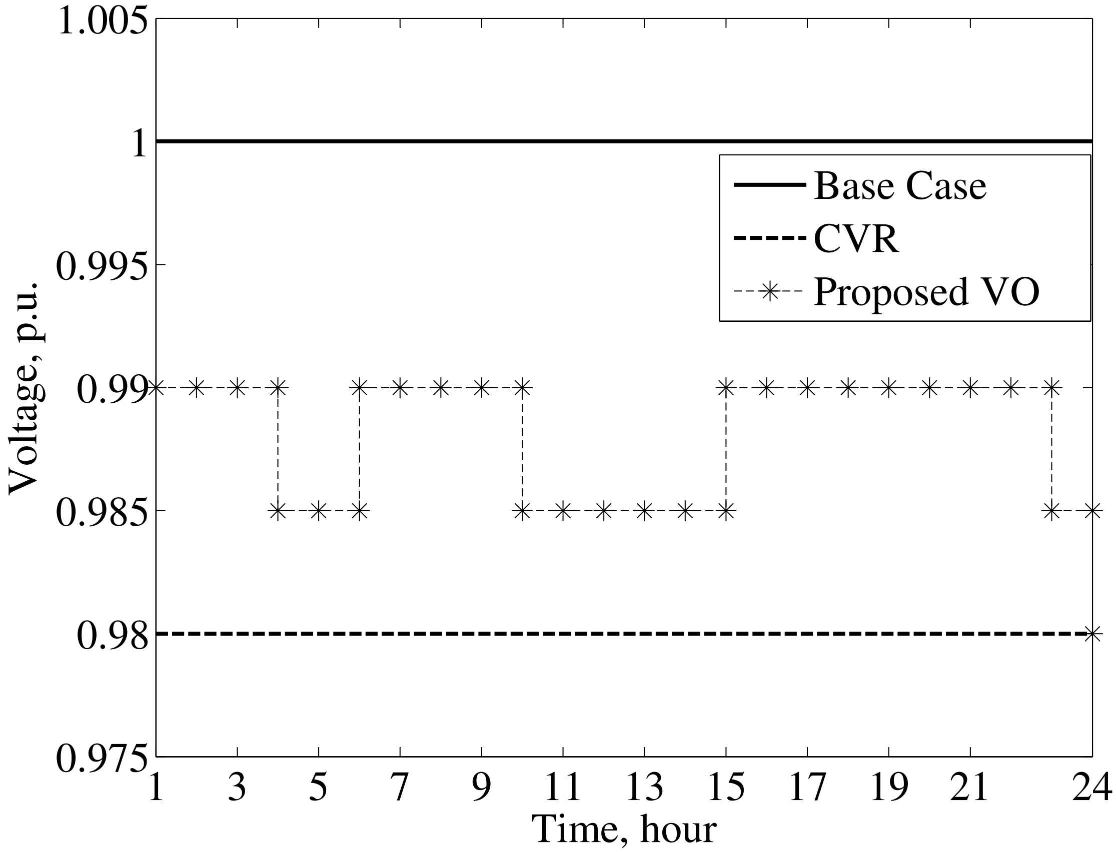


Figure 4.8: Voltage profiles of the real industrial plant load for each operating mode.

- Step 2: If the new data point is outside the operational limits, repeat Step 1.
- Step 3: Once a valid process data point is obtained, replace the old value with the new one.
- Step 4: Repeat Step 1 to Step 3 until the required number of different process profiles for 24-hours are obtained.

Carrying out MC simulations with the proposed VO model for the 500 process profiles, the expected savings converge as shown in Figure 4.9. In order to determine the effect of α on expected energy savings, MC simulations are run for different values of α until the expected savings converge as plotted in Figure 4.10.

Observe that when $\alpha = 0.6$, the tap operation remains fixed and the expected energy savings plateau at 1.02%, which is higher than what is obtained using the CVR technique.

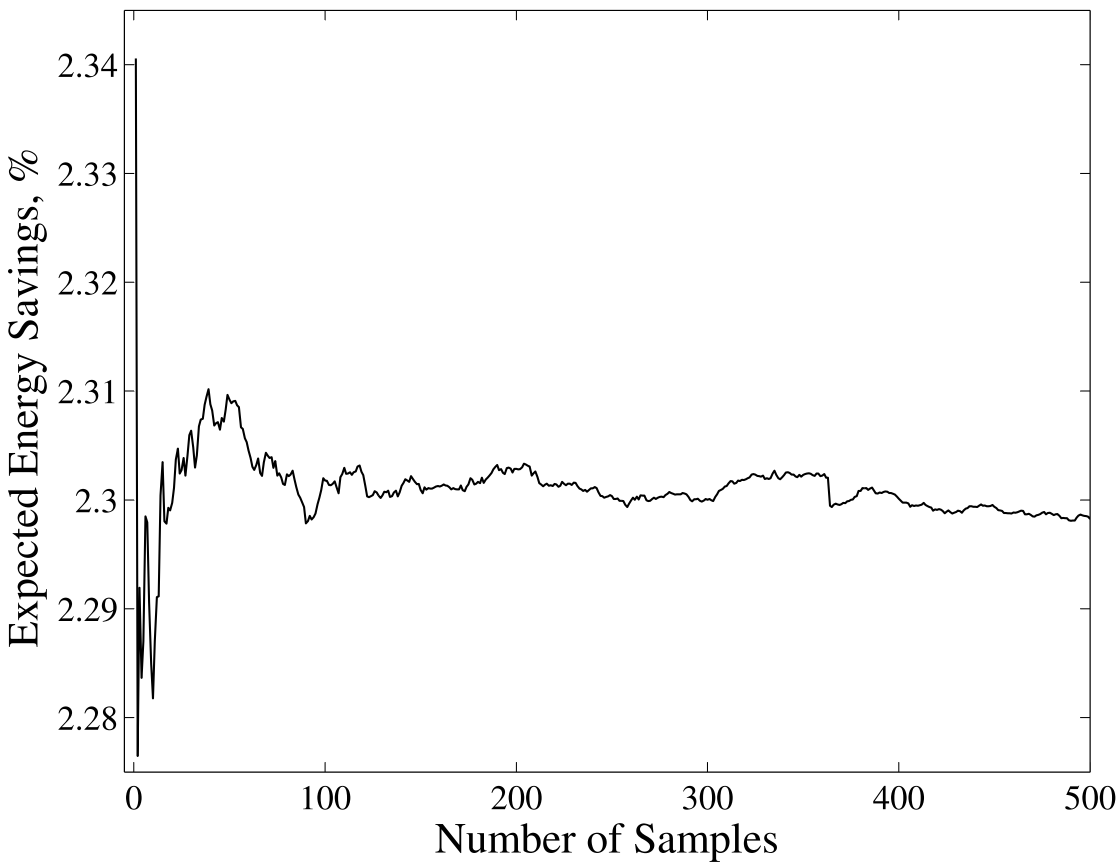


Figure 4.9: Expected savings in Monte Carlo simulations for the real plant model.

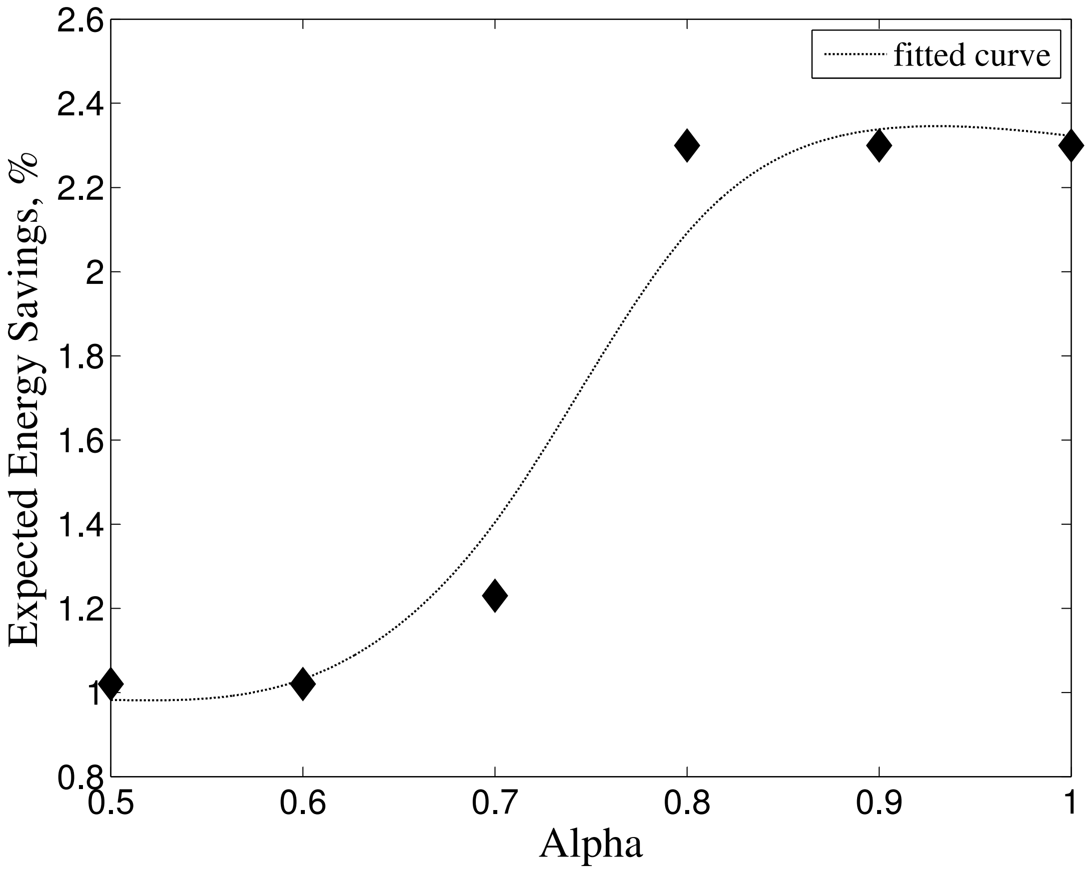


Figure 4.10: Effect of α on energy savings for the real plant model.

Chapter 5

Conclusions

5.1 Summary and Conclusions

In this work, a VV approach that can be used by industrial customers to reduce energy consumption was presented. The VO framework was developed and tested on load models created using simulated data and real data. Classical machine models were used to generate simulated load data, and the results suggest that VV techniques impact the real power consumption of the load; however, the VO framework is not necessary to decide the optimal voltage profile. The best VV strategy is the CVR for an induction motor load, while a synchronous motor load should be operated at the highest possible voltage.

The VO framework was then tested on the plant load model using real data. The plant load model showed characteristics of both an induction and synchronous motor, and the VO framework was able to take the unique constraints and nature of the load into account and provide a optimal voltage profile for the plant operator. The estimated energy savings suggest that VO framework is superior to the CVR technique when applied to an industrial load, even if the LTC is fixed.

This work is useful to the CVR and VVO equipment vendors and industrial customers. Incorporating the VO framework into the VV systems can boost the total energy savings of their customers. Many CVR and VVO systems use real-time data to decide on optimal voltage set points for the LTC, which tends to be the lowest operating voltage. Rather than maintaining the voltage at the lowest possible level, incorporating the proposed VO framework in their systems will enable them to take the process forecast and the relationship of power, on voltage and process into account to decide the optimal voltage set points for the plant LTC.

5.2 Contributions

The main contributions of this work are as follows:

1. Load model for industrial loads: Several studies have concluded that conventional load models are insufficient to study the effect of voltage on real power consumption for an industrial load, as demonstrated in this work. The proposed load modelling technique is able to factor in the complex nature of the industrial load in order to be used in system analyses. This load modelling method was validated using real data from an industrial plant.

2. VO approach for industrial loads: This work proposes a VV strategy that accounts for the industrial loads dependence on plant process as an alternative to existing VV strategies of CVR and VVO. The approach was tested using real data from an industrial plant.

5.3 Future Work

A possible vector of further research include developing a model predictive voltage supervisory controller for plant operation, based on the proposed models to decide the optimal plant voltage. Such a controller can be developed as a stand alone device to be easily incorporated into existing CVR and VVO equipment.

Further voltage perturbation studies on other industrial sites will result in more generalised strategies for industrial customers. This can be used to better refine the techniques developed here.

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