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Smart grid adaptive energy conservation and optimization engine utilizing Particle Swarm Optimization and Fuzzification

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HIGHLIGHTS

- A novel energy conservation and optimization engine is proposed using smart grid functionalities.
- This paper presents an advanced Volt-VAR Optimization (VVO) solution using Particle Swarm Optimization algorithm.
- The energy conservation is achieved through Conservation Voltage Reduction as substantial subpart of VVO.
- To accurately weight the optimization engine sub-parts, Fuzzification technique is employed.
- 33-node test feeder is employed for a complete day in the presence of six different operating scenarios.

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ABSTRACT

This paper aims to present a novel smart grid adaptive energy conservation and optimization engine for smart distribution networks. The optimization engine presented in this paper tries to minimize distribution network loss, improve voltage profile of the system and minimize the operating cost of reactive power injection by switchable shunt Capacitor Banks using Advanced Metering Infrastructure data. Moreover, it performs Conservation Voltage Reduction (CVR) and minimizes transformer loss. To accurately weight the optimization engine objective function sub-parts, Fuzzification technique is employed in this paper. Particle Swarm Optimization (PSO) is applied as Volt-VAR Optimization (VVO) algorithm. Substantial benefits of the proposed energy conservation and optimization engine include but not limited to: adequate accuracy and speed, comprehensive objective function, capability of using AMI data as inputs, and ability to determine weighting factors according to the cost of each objective sub-part. To precisely test the applicability of proposed engine, 33-node distribution feeder is used as case study. The result analysis shows that the proposed approach could lead distribution grids to achieve higher levels of optimization and efficiency compared with conventional techniques.

1. Introduction

Nowadays, the advent and expansion of smart grid technologies have enabled the development of new energy efficiency improvement technologies for power distribution networks. The organic growth of this well-designed layer of intelligence over utility assets enables a range of smart grid's fundamental applications to emerge [1]. Faced with diverse technological, organizational, and business issues that adversely affect their bottom line, electric power utilities are contemplating immediate changes and/or upgrades of their technologies, business processes, and organization [2]. In recent years, many electric power utilities have upgraded and improved the operation of their distribution grids using smart grid technologies such as Energy Management System (EMS), Distribution Management System (DMS) and Substation Automation (SA). Some have improved their grid resolution by using technologies enabled by such components of smart grid as Advanced Metering Infrastructure (AMI). While electric power utilities continually move to integrate novel smart grid functionalities according to their road maps, applying smart grid components and technologies necessitate electric power utilities to seek new optimization and energy saving techniques that are in-line with their current implementation of smart grid technologies. Moreover, by increasing energy generation costs as well as electricity price in many countries,

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Nomenclature

$S^i_{l,t}$	apparent power loss (kVA)	φ_1, φ_2	acceleration constants in PSO
$P_{loss,l,t}$	active power loss of feeder-l at time-t (kW)	r_1, r_2	random values (between 0 and 1)
$Q_{loss,l,t}$	reactive power loss of feeder-l at time-t (kVAR)	$Loss$	loss
S	complex power (kVA)	dev	deviation of voltage
V	voltage magnitude (V)	$[B]$	branch current matrix
P	active power (kW)	$[BIBC]$	bus-injection to branch-current matrix
Q	reactive power (kVAR)	$[BCBV]$	branch-current to bus-voltage matrix
C	cost ($)	G, $Load$	generator, load
I	current (A)	X	position of particle
V_{base}	base voltage of system (V)	Min, Max	minimum, maximum
$S_{l,t}$	power limit of feeder-l at time-t	DG	distributed generation
V_{vel}	velocity of particle is PSO	END	last nodes of feeder
ρ	off-nominal turn ratio of OLTC and VR	CVR	conservation voltage reduction set
tap	tap unit	VR	voltage regulator
ΔV	voltage change	$Fuzzy$	Fuzzification factor
$P_{Trans\text{-}VR}$	active power loss of VR	c, k	capacitor bank, iteration
$\beta^i_{c,t}$	integer value for capacitor bank units	i, j	indices for buses
$\Delta q^i_{c,t}$	VAr value for each bank unit	I, J	indices for the last buses
$Q^i_{c,t}$	capacitor bank capacity	t, T	time interval, last time interval
$\alpha, \beta, \gamma, \delta$	weighting factors	l, L	feeder number, last feeder

distribution companies have to increasingly seek optimal loss minimization techniques based on smart grid distributed command and control topology. The primary concern of most electric power utilities is to find a cost-effective optimization solution for optimal operation of their existing grids.

One of the well-known distribution network energy optimization technique traditionally used by electric power utilities is Volt-VAR Optimization (VVO). Recent VVO solutions include an advanced optimization technique that optimizes voltage and/or reactive power (VAR) of a distribution network based on predetermined aggregated feeder load profile. This can be accomplished using Volt-VAR Control Components (VVCC) such as load tap changers (LTC) of transformer, Voltage Regulators (VRs), Capacitor Banks (CBs) and other existing Volt-VAR control actuators within distribution substations and/or along distribution feeders.

On the other hand, one of the well-known energy saving technique that has been taken into consideration by many utilities in the last two decades is "Conservation Voltage Regulation", "Conservation Voltage Reduction" or "CVR". ANSI C 84.1 standard [3] has defined the acceptable ranges of voltage at termination points (e.g. 114–126 V in North America). Based on that, CVR tries to decrease consumer's voltage levels into the lower limits of ANSI range, i.e. 114–120 V, to reduce energy consumption without expecting changes in customer's consumption behavior. As CVR control actuators such as LTCs and VRs could be categorized as Volt-VAR Control Components, and as CVR and VVO objectives are well-matched, many utilities suggest considering CVR as a part of VVO objective. With the emergence of smart grid technologies within distribution networks, and given their quasi real-time command & control capabilities, it is now conceivable to propose new smart grid adaptive VVO solutions that would be able to optimize distribution network more effectively.

In recent years, various noteworthy researches performed to study and develop new energy optimization solutions for distribution grids [4–14]. For instance, [12] presents a very interesting Honey-Bees Mating Optimization (HBMO) algorithm for multi-objective Volt-VAR control of distribution networks by considering Distributed Generators (DGs) but, it mainly focused on daily approach rather than a quasi-real-time approach. In another great study [13], a fuzzy adaptive Particle Swarm Optimization applied for VVO of distribution networks using DGs but this work focused only on daily scenarios. Some papers such as [14] investigated new approaches for real-time voltage control in automated distribution networks but they do not consider other VVO objectives such as loss reduction and energy conservation through CVR. Another applicable study [15] proved that Demand Response (DR) can boost system node voltages during peak hours which provide extra opportunity to perform VVO. However, it did not perform any VVO approach. Reactive power compensation issue studied in [16] to minimize active power loss of wind farms and to find set points of each wind turbine through Particle Swarm Optimization (PSO) algorithm. Although this study is practical, it did not cover all recent VVO objectives. Impact of Electric Vehicle (EV) penetration on recent AMI-based VVO solution studied in [17] by applying a real-time co-simulation monitoring platform that is comprised of measurement aggregator, VVO engine with Improved Genetic Algorithm (IGA) and control components modeled in a Real-time Digital Simulator (RTDS). The approach used in [17] is more applicable as its VVO objective function is closer to reality. However, this paper did not take voltage deviation minimization into account.

Some papers focused on the optimization technique [18–25] rather than smart grid adaptability of their solution. Several studies applied intelligent techniques such as Multi Agent System for their Volt-VAR Control [26–29] approach and some aimed to assess CVR plans but they assessed CVR separate from VVO [30–35]. Although some research papers have tried to address different aspects of Smart Grid and their specifications [27–31,34–40] before IEEE 2030 standard [40], it can be concluded that from literature survey that more theoretical work is needed to describe new practical Smart Grid-based VVO solution. In other words, there is a salient gap between conventional VVO and new Smart Grid adaptive VVO solutions. On the contrary, most VVO approaches studied by various utilities and/or literatures are Centralized such as [4–6,9,11–14,18–24]. In centralized VVO, the optimization and control processing system is placed in a central controller unit such as Distribution Management System (DMS) that is typically so called "Utility Back Office". The back office uses related measurement data taken from load premises (i.e. termination points) to find the best possible settings for Volt-VAR Control Components (VVCC) to achieve desired optimization and conservation aims. These optimal settings are then being sent to specified Volt-VAR control