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Quasi real-time ZIP load modeling for Conservation Voltage Reduction of smart distribution networks using disaggregated AMI data

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ABSTRACT

This paper aims to investigate quasi real-time ZIP load models for new Smart Grid-based Volt-VAR Optimization (VVO) techniques. As recent VVO solutions are able to perform in quasi real-time using Advanced Metering Infrastructure (AMI) data, more accurate load modeling could give distribution network operators and/or planners more precise Conservation Voltage Regulation (CVR) and energy saving values at each operating time stage. Furthermore, more accurate load modeling of each quasi real-time stage could improve VVO efficiency. As type, amount and operating time of each residential appliance varies throughout a day, this paper aims to discover ZIP load model of each quasi real-time stage separately through disaggregated data (i.e. decomposing residential load consumption into home appliance consumptions). This paper shows that the energy conservation achieved by CVR operation through presented quasi real-time ZIP load modeling could lead AMI-based VVO solutions to higher level of accuracy and data resolution compared with conventional techniques. Therefore, this paper primarily introduces a new quasi real-time AMI-based VVO engine. Then, it investigates ZIP load model of each quasi real-time stage through statistical data to conserve energy consumption. To check the authenticity and the applicability of presented model in a whole system, 33-node distribution feeder is employed.

1. Introduction

With the advent of Smart Grid technologies, real-time operating systems and related capabilities such as Advanced Metering Infrastructure (AMI), Distribution Management Systems (DMS) and Energy Management Systems (EMS), the distribution networks are poised for adoption of higher levels of energy optimization and efficiency techniques. Hence, electric power utilities are increasingly eager to employ such technologies within their infrastructure and system operations. Many utilities have developed energy efficiency programs for buildings while others are looking for optimal energy management systems on the consumer side through utilization of new technologies such as EMS and AMI. AMI provides utilities with a two-way communication system to the meter, as well as the ability to modify customers' service-level parameters (Farhangi, 2010). Hence, utilities would be able to perform load management, revenue protection and even system optimization using AMI infrastructure and provisions. One of the most popular conventional distribution network optimization techniques is Volt-VAR Optimization (VVO). Basically, VVO intends to minimize distribution network losses and improve voltage profile of system nodes through Volt-VAR Control Components (VVCC) such as Switched Shunt Capacitor Banks (CBS), Voltage Regulators (VR) and On-load Tap-Changing Transformer (OLTC). New quasi real-time VVO solutions have now emerged based on Smart Grid technologies. Such quasi real-time VVOs are now able to optimize distribution networks through more sophisticated objective functions using AMI data as inputs. Typically, there are two well-known quasi real-time VVO techniques utilities aim to implement in their systems according to their grid topologies, features and future needs. The first quasi real-time VVO solution is "Centralized VVO" (Alencar de Souza & De Almeida, 2010; Auchariyamet & Sirisumrannukul, 2010; Dabic, Cheong, Peralta, & Acebedo, 2010; Diaz, Harnisch, Sanhueza, & Olivares, 2010; Electric Power Research Institute, 2011; Fakham, Colas, & Guillaud, 2011; Feltrin, Quinjano, & Mantovani, 2014; Huang, Xia, Kobayashi, & Xu, 2010; Hwang, Jeong, & Moon, 2013; Jauch, 2009; Keane, Hearne, Fallon, & Brooks, 2011; Krok & Genc, 2011; Lefebvre et al., 2008; Markushevich, 2011; Rahimi, Marinelli, & Silvestro, 2012; Roytelman, Wee, & Lugtu, 2009; Schneider & Weaver, 2014; Shah, Bose, & Srivastava, 2013; Shen & Baran, 2013; Singh, Tuffner, Fuller, & Schneider, 2011; Spatti, da Silva, Usida, & Flauzino, 2010; Svenda, Strezoski, Simendic, & Mijatovic, 2009; Uluski, 2010; Vaccaro, Velotto, &

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Zobaa, 2011) where the processing system is located in a central controller unit (e.g. Distribution Management System (DMS)) in the so called "Utility Back-Office". The DMS employs indispensable measurements taken from utility subscribers (i.e. termination points) supplied to it from either field collectors or directly from Metering Data Management System (MDMS), to determine the best feasible settings for field-bound VVO control components to achieve the desired optimization and energy conservation goals. These settings are then off-loaded to such assets through existing downstream pipes, such as Supervisory Control and Data Acquisition (SCADA) network. The main challenge of Centralized-VVO in meeting quasi real-time VVO requirements could be the communication channel's required bandwidth to support the immense amount of data which should be transferred from AMI to back-office, as well as the performance of downstream pipes from VVO to VVCCs at each quasi real-time stage.

The second quasi real-time AMI-based solution that can reside in medium voltage substation and optimize its downstream feeders is called "Decentralized VVO" (Fakham, Ahmidi, Colas, & Guillaud, 2010; Manbachi, Farhangi, Palizban, & Arzanpour, 2012; Manbachi, Nasri, et al., 2014; Solanki, Venkatesan, & Khushalani Solanki, 2012; Xiao et al., 2010). In this approach, VVO is able to capture its required quasi real-time inputs from its local AMI network and receive its general requirements (i.e. global system attributes) from control unit (e.g. DMS/SCADA) to optimize distribution network without creating communication pipe congestion due the AMI data (Manbachi, Nasri, et al., 2014; Manbachi et al., 2012).

One of the principal segments of recent quasi real-time AMI-based VVO techniques that has been explored in North America is "Conservation Voltage Reduction" or "Conservation Voltage Regulation" (CVR). CVR attempts to conserve the energy delivered at the termination point through maintaining the voltage level of residential loads within the lower limits of ANSI C-84.1 standard (e.g. between 114 and 120 V in North America) (ANSI, 1995). CVR has to perform its function without requiring any change in consumer's behavior or any damage to customer's appliances. Due to the fact that the not all customer loads are constant power, lowering voltage within the lower ANSI threshold could lead to energy conservation. Moreover, CVR reduces peak demand as well by saving generation capacity. As CVR could also operate with CBs, VRs and OLTCs, it can be considered as part of new quasi real-time VVO engines. It is proven that CVR's impact could be \$100 kW^{-1} and less than \$20/MW hour of network costs (Warner & Willoughby, 2013). Hence, CVR cost is less than other comparable energy sources.

It has to be stated that CVR concept diverges from that of Advanced Voltage Control (AVC) that is used for voltage control by applying voltage control relays (VCR's) or Load/line Drop Compensators (LDCs). It may well be conceivable for VVO to use AVC to achieve its objectives but no AVC techniques could perform VVO tasks such as loss minimization through VAR injection.

Several electric power utilities have already defined and implemented CVR projects for the energy conservation and/or peak demand reduction and achieved noteworthy results (Ajaja, 2011; Bettencourt & Malenfant, 2013; Dabic et al., 2010; Lefebvre et al., 2008). For instance, Canadian electric power utilities such as Hydro-Quebec (Lefebvre et al., 2008) implemented a voltage regulation and CVR plan in a project called CATVAR using remotely monitored transformers and capacitor banks. BC Hydro implemented a state-of-the-art DMS to provide a platform to create opportunities to implement leading advanced distribution applications, such as model-based Volt-VAR Optimization, and network reconfiguration (Dabic et al., 2010). Moreover, the target of using dynamic Volt-VAR control in one of Hydro-One projects (Bettencourt & Malenfant, 2013) was to utilize power electronic technologies and devices to keep voltage and reactive power within operational limits (Bettencourt & Malenfant, 2013). Different research studies have been done regarding CVR in distribution networks recently (Ajaja, 2011; Bettencourt & Malenfant, 2013; Dabic et al., 2010; Flethcher, 2009; Lefebvre et al., 2008; Paul & Jewell, 2014; Schneider, Tuffner, Fuller, & Singh, 2010; Sen & Keun Lee, 2014; Singh et al., 2011). Some of these studies such as (Schneider et al., 2010) stated that CVR provides peak load reduction and annual energy reduction of approximately 0.5–4% depending on the specific feeder (Schneider et al., 2010). Moreover, Paul & Jewell (2014) assess the impact of reducing voltage levels on distribution network generation and losses. As energy reduction percentage is highly dependent on load type and permutations, accurate load modeling for CVR is essential. One load modeling technique that considers load type and mix is "ZIP" load model. In this model, load is considered as a combination of three constant power (P-constant), constant current (I-constant) and constant Impedance (Z-constant) loads. Various research papers have investigated load modeling by ZIP coefficients (Bokhari et al., 2014; He, Habetler, Mousavi, & Kang, 2013; Higgins et al., 2014; Lu, Xie, Huang, Puyleart, & Yang, 2008; Quilumba, Lee, & Jativa-Ibarra, 2013; Quilumba, Lee, Huang, Wang, & Szabados, 2011; Rahim, Hashim, & Mohd Siam, 2013; Ranade, Ellis, & Mechenbier, 2001; Sortomme, Negash, Venkata, & Kirschen, 2013; Vignesh, Chakrabarti, & Srivastava, 2014) lately. For instance, (Sortomme et al., 2013) fully measured voltage responses of four different types of Electric Vehicles (EV) to find ZIP model of each EV. In order to determine ZIP coefficients of modern residential, commercial and industrial loads, (Bokhari et al., 2014) presented an experimental approach. It can be observed from literature survey that there has been insufficient works on finding accurate load models for new quasi real-time AMI-based VVO solutions. There are few papers which theoretically assessed CVR as a part of VVO engine in real-time operating conditions (Diaz-Aguiló et al., 2013; Fakham et al., 2010; Fakham et al., 2011; Manbachi et al., 2012; Manbachi, Nasri, et al., 2014; Nam et al., 2013; Spatti et al., 2010; Svenda et al., 2009; Tesfasilassie, Zarghami, Vaziri, & Rahimi, 2014). Even fewer works have been done regarding load modeling of new VVO engines (Diaz-Aguiló et al., 2013 October; Nam et al., 2013; Tesfasilassie et al., 2014). Despite the fact that the type, behavior and duration of operation of residential loads can vary from one quasi real-time stage (15-min) to another quasi real-time stage, only one ZIP coefficient set has been used for all operating time stages in almost all conventional studies. It is now conceivable to reach a more accurate load model for each quasi real-time stage using AMI as well as statistical data in order to perform more precise CVR in the presence of new ZIP load models. Quasi real-time load modeling could be achieved taking into account type, consumption value and duration of operation of each home appliance separately. This can be done through "Load Disaggregation" concept. Generally speaking, load disaggregation is an approach that enables disaggregation of total electricity consumption of a household into its contributing appliances. Typically, AMI infrastructure in existing smart grids use smart meters to capture consumer's data every 15 min. As smart meters show aggregated load consumed by each household, disaggregation techniques are still required to investigate the consumption profile of each home appliance separately, and to find accurate ZIP coefficients.

Diverse mathematical techniques have been presented for load disaggregation in recent year (Armel, Gupta, Shrimali, & Albert, 2013; Egarter, Bhuvana, & Elmenreich, 2015; Gonçalves, Ocneanu, & Bergés, 2012; Guo, Wang, & Kashani, 2015; Kelly, 2011; Makonin, Popowich, Bartramz, Gill, & Bajic, 2013; Parson, Ghosh, Weal, & Rogers, 2012; Perez, Cole, Baldea, & Edgar, 2014; Schoofs, Sintoni, O'Hare, & Ruzzelli, 2010; Xu & Milanović, 2015; Zoha, Gluhak, Imran, & Rajasegarar, 2012). One of the common mathematical disaggregation techniques is Non-Intrusive Load Monitoring (NILM) (Egarter et al., 2015; Gonçalves et al., 2012; Makonin et al., 2013; Parson et al., 2012; Perez et al., 2014; Zoha et al., 2012). Other mathematical approaches such as hidden Markov Model (Egarter et al., 2015; Parson et al., 2012) and Artificial Intelligence (Xu & Milanović, 2015) have studied load disaggregation as well. On the contrary, statistical data approach (Armel et al., 2013) proved to be applicable for load modeling. It is possible to speculate from (Armel et al., 2013) how appliance data can bring considerable benefits to load modeling, and how employing the statistical approach disaggregation algorithms combined with smart meter data would be an effective solution for getting appliance data. Moreover, it is possible to conclude from load disaggregation studies that most of the works have only considered a limited number of home appliances in their studies and they have not presented ZIP load models for different operating time stages for new AMI-based VVO solutions. Hence, the main content of this paper is to check the performance of a novel AMI-based VVO engine with CVR sub-part that is able to minimize distribution network loss cost, Volt-VAR Control Component operating costs and CVR cost to maximize energy saving values through quasi real-time ZIP load modeling. This paper introduces a new quasi real-time AMI-based VVO engine at first. Then, it investigates quasi real-time ZIP coefficients for load modeling of CVR as a part of new quasi real-time VVO engine. Next, VVO engine optimizes under-study distribution network at each quasi real-time stage through its load model. Presented model values could increase VVO engine's performance and improve the accuracy of conserved energy calculations in CVR study.

This paper is organized in five sections. After introductions in the first section, the second section describes a novel quasi real-time AMI-based VVO engine, its topology, objectives and constraints. ZIP load modeling of each quasi real-time stage according to load disaggregation of typical North American house consumption into consumption of existing appliances from statistical data approximation is explained in the third section of this paper. In order to test the validity of the system, 33-node distribution feeder (Baran & Wu, 1989) is studied in section four of the paper as a typical case study. The analysis result is given in this section, with the last section capturing the conclusions of this paper.

2. Quasi-real-time AMI-based Volt-VAR Optimization engine

This section presents the main structure and operation of quasi real-time AMI-based VVO and Volt-VAR control assets in smart distribution networks. Fig. 1 depicts the basic topology of a North American distribution feeder operating with AMI and quasi real-time VVO engine.

As seen in Fig. 1, different reactive power and voltage control components and actuators such as CBs, OLTC, VR and Distributed Generations (DG) exist that each could affect VVO performance in different ways. As mentioned before and according to embedded control and optimization structure of distribution networks, VVO engine can either be a part of DMS/SCADA in centralized control, or reside at the medium voltage substation in decentralized control. As immense amount of data has to be transferred from feeder termination points to VVO engine through AMI every 15 min (i.e. quasi real-time), VVO has to optimize distribution network using selected (required) data with Volt-VAR control components. Initial required data of an AMI-based VVO could be active/reactive power of loads and voltages of system buses. In order to optimize distribution network, quasi real-time AMI-based VVO uses the following objective function depicted in Eq. (1).

$$\begin{aligned} \text{Min} \quad \text{OF}_{\text{VVO},t} = & \left(\sum_{b=1}^{B}(\alpha \times C_{\text{loss},b,t})\right) + \left(\gamma \times C_{\text{VR,total},t}\right) \\ & + \left(\delta \times C_{\text{OLTC,total},t}\right) + \left(\varepsilon \times C_{\text{swCB,total},t}\right) \\ & + \left(\beta \times C_{\text{CVR,total},t}\right) \end{aligned} \tag{1}$$

Here, $\alpha, \beta, \gamma, \delta$ & ε are VVO sub-part's weighting factors. $C_{\text{VR,total},t}$, $C_{\text{CVR,total},t}$, $C_{\text{VR,total},t}$, $C_{\text{OLTC,total},t}$ and $C_{\text{swCB,total},t}$ are the cost of loss reduction by VVO, total operating cost of Conservation Voltage Reduction, total operating costs of VR, OLTC and switched shunt CBs of branch-b at time stage-t, respectively.

As Eq. (1) demonstrates, the main VVO objective function consists of three different sub-parts. The first sub-part is loss minimization of distribution network that attempts to minimize the loss of distribution feeders through CBs, OLTC and VRs regarding to Eqs. (2) and (3).

$$C_{\text{loss},t} = \sum_{b=1}^{B}(P_{\text{loss},b,t} \times \pi_t) \tag{2}$$

Here, $P_{\text{loss},b,t}$ and π_t are active power loss of branch-b at time stage-t and loss cost ($/kW) at time stage-$t$.

$$\sum_{b=1}^{B} P_{\text{loss},b,t} = \sum_{b=1}^{B} \left\{ \begin{array}{c} G_{b,t} \left(\begin{array}{c} \left(V_{i,t}\right)^2 + \left(V_{j,t}\right)^2 - \\ 2\left|V_{i,t}\right|\left|V_{j,t}\right| \cos\theta_{ij,t} \end{array} \right) \\ +G^0_{ij,t}(\varphi_{ij,t}V_{i,t})^2 + G^0_{ji,t}(\varphi_{ji,t}V_{i,t})^2 \end{array} \right\} \tag{3}$$

where, $b = i$–j. i and j are consecutive nodes. G is conductance vector of branch-b in per units, V is voltage of node, $\theta_{ij,t}$ is phase angle between node-i and j in time-t and $\varphi_{ij,t}$ is the turn ratio.

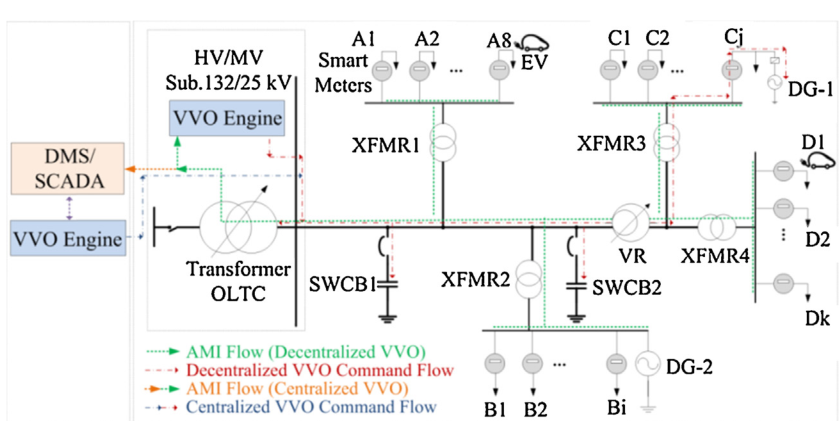

Fig. 1. Main topology of quasi real-time VVO and its flows in typical North American distribution feeder.

The second main VVO sub-part consists of CB, VR and OLTC operating cost minimization. In order to minimize CB, VR and OLTC operating costs, Eqs. (4)–(6) are applied.

$$C_{\mathrm{swCB,total},t} = \sum_{c \varepsilon C} C_c \times Q_{\mathrm{inj},c} = \sum_{c \varepsilon C} C_c \times \rho_c \times \Delta q_{\mathrm{inj},c} \tag{4}$$

$$C_{\mathrm{VR,total},t} = \sum_{r \varepsilon R} C_r \times I_{\mathrm{VR},r} \tag{5}$$

$$C_{\mathrm{OLTC,total},t} = \sum_{w \varepsilon W} C_w \times I_{\mathrm{OLTC},w} \tag{6}$$

where, C_c, $Q_{\mathrm{inj},c}$, ρ_c and $\Delta q_{\mathrm{inj},c}$ are, respectively, per kVAR cost of CB, injected reactive power (kVAR) to the system by CB-c, bank of CB-c and reactive power that bank injects to system. Moreover, C_r and C_w are operating costs of VR and OLTC ($/switching). $I_{\mathrm{VR},r}$ and $I_{\mathrm{OLTC},w}$ are the binary values for VR and OLTC switching action (1 means switching action and 0 otherwise).

Maximizing Energy conservation (or CVR Cost minimization) at termination points is the third important sub-part of an AMI-based VVO. As previously mentioned, accurate load modeling is necessary for an accurate CVR. Here, ZIP approach (combination of constant impedance, constant current and constant power) is used as well-known accurate load modeling. CVR operation can be clarified by Eq. (7).

$$\begin{aligned} C_{\mathrm{CVR,total},t} &= C_{\mathrm{saved\ \ energy}} \times \frac{1}{\Delta E_{\mathrm{energy\ \ consumption}}} \\ &= C_{\mathrm{saved\ \ energy}} \times \frac{1}{\mathrm{CVR}_f \times \Delta V} \end{aligned} \tag{7}$$

In order, $C_{\mathrm{saved\ energy}}$, $\Delta E_{\mathrm{energy\ consumption}}$, CVR_f and ΔV are cost of saved energy by CVR, energy load consumption through CVR, CVR Factor and Voltage Reduction in CVR.

Principal constraints of AMI-based VVO problem includes but not limited to: Active/Reactive Power Outputs of nodes, Distributed Generation Active/Reactive Power Constraints, Node Voltages Constraint (all node voltage must be within the ANSI band), Active/Reactive Power Balances based on Optimal Power Flow, Feeder thermal limit, CB, VR and OLTC number of switching (bank or tap) constraints. More details regarding constraints of an AMI-based VVO engine can be found in (Rahim et al., 2013) and (Manbachi, Farhangi, Palizban, & Arzanpour, 2013).

Therefore, as explained quasi real-time AMI-based VVO engine solves the optimization problem through its optimization technique (here, improved Genetic Algorithm is used as the algorithm programmed in MATLAB environment (Manbachi, Farhangi, Palizban, & Arzanpour, 2014)) at each quasi real-time stage. In next step, VVO engine sends control commands to VVCCs to optimize the distribution grid. As control commands could differ for each quasi real-time stage due to load type, amount and duration of operation, load modeling could affect quasi real-time AMI-based VVO efficiency. The next section investigates quasi real-time ZIP load modeling using disaggregation and statistical data in the presence of explained AMI-based VVO.

3. Quasi real-time ZIP load modeling for Conservation Voltage Reduction

This section investigates quasi real-time ZIP load models for CVR sub-part of new quasi real-time AMI-based VVO solution using historical disaggregated data.

3.1. ZIP load model for Conservation Voltage Reduction

As stated before, one of the most famed and most accurate techniques applied for load modeling in CVR studies is ZIP load model. As load model is not fully constant power, CVR can be performed to conserve energy at customer's premises. In order to determine the impact of each load model, it would be necessary to primarily study each of them:

- Constant power (P): In constant-P loads, demand would be constant regardless of voltage. Hence, if the load is fully constant power, decreasing voltage will increase network loss. In this scenario, CVR will not lead to energy conservation but rather increases the power loss of the grid, and therefore has negative impact on VVO engine sub-parts. Some important constant-P loads are induction motors, heat pumps, controlled power supplies, etc.
- Constant impedance (Z): Here, the demand would be proportional to voltage. Thus, by maintaining voltage within lower limits of ANSI band, network loss would slightly be increased by CVR sub-part, although VVO engine would be able to mitigate the impact and conserve energy. Some examples of constant-Z loads are incandescent light, resistive water heater, stovetop, oven, etc.
- Constant current (I): Here, demand would be proportional to voltage squared. Therefore, by reducing voltage level, CVR sub-part could conserve energy. Losses could even be decreased slightly. There are few constant-I devices such as welding units, smelting, florescent, some power electronics, etc.
- Different combination of the abovementioned loads can be observed in different times of a day in a residential building. It is possible to obtain active and reactive consumption of loads through Eqs. (8) and (9).

$$P = P_0 \left(Z_p \left(\frac{V}{V_0} \right)^2 + I_p \left(\frac{V}{V_0} \right) + P_p \right) \tag{8}$$

$$Q = Q_0 \left(Z_q \left(\frac{V}{V_0} \right)^2 + I_q \left(\frac{V}{V_0} \right) + P_q \right) \tag{9}$$

Here, P_0 and Q_0 are initial active (kW) and reactive power (kVAR) values. Moreover, V_0 is the initial voltage and V is the voltage of the system. Z_p, I_p and P_p are active power ZIP coefficients and Z_q, I_q and P_q are reactive power ZIP coefficients. Moreover, changes in energy consumption (ΔE) as well as voltage reduction (ΔV) can be found by Eqs. (10) and (11). By dividing Eqs. (10) and (11) CVR Factor (CVR_f) is gained which presents the ratio of energy consumption and voltage reduction (Eq. (12)). Typically, CVR factor is between 0.5 and 1.5 (Kennedy & Fletcher, 1991). Further studies such as EPRI in 2010 showed CVR Factor close to 0.8 (Awad, 2014).

$$\Delta E\% = \left(\frac{E_{\mathrm{base}} - E_{\mathrm{CVR}}}{E_{\mathrm{base}}} \right) \times 100 \tag{10}$$

$$\Delta V\% = \left(\frac{V_{\mathrm{base}} - V_{\mathrm{CVR}}}{V_{\mathrm{base}}} \right) \times 100 \tag{11}$$

$$\mathrm{CVR}_f = \frac{\Delta E}{\Delta V} \tag{12}$$

Here, E_{base} and V_{base} are initial energy and voltage, respectively. Then, E_{CVR} and V_{CVR} are system's energy and voltage after CVR. Due to the fact that the type, amount and duration of consumption vary throughout different times of a day, it is conceivable to define specific ZIP coefficients for each quasi real-time stage ($Z_{p-\mathrm{ele},i}$, $I_{p-\mathrm{ele},i}$, $I_{p-\mathrm{ele},i}$ for active power and $Z_{q-\mathrm{ele},i}$, $I_{q-\mathrm{ele},i}$, $P_{q-\mathrm{ele},i}$ for reactive power)

Table 1
Appliance classification for quasi real-time VVO study of this paper.

Appliance name	Items included	Impact factor (%)
Lighting	Incandescent lights, LED lamps, CFL bulbs	45, 10, 45
Cooking appliances	Oven and microwave	80, 20
Home entertainment	LCD TV, laptop charger, game console, PC	45, 10, 15, 30
Air conditioner	Window/wall mounted air conditioner	100
Dish washer	Conventional standard dish washer	100
Dryer	Clothes drier (35 loads per month)	100
Washing machine	Top load washing machine	100
Fridge	Standard refrigerator	100
Freezer	Deep chest freezer	100
Water heater	Mid-efficiency	100
Other appliances	Vacuum, fan, coffee maker	35.17, 6.7, 58.12

that could be shown by Eqs. (13) and (14).

$$P_t = \sum_{i=1}^{i=I} \left(P_{0-\text{ele},i,t} \times Z_{p-\text{ele},i} \left(\frac{V}{V_0} \right)^2 + I_{p-\text{ele},i} \left(\frac{V}{V_0} \right) + P_{p-\text{ele},i} \right) = \sum_{i=1}^{I} P_{\text{ele},i} \quad (13)$$

$$Q_t = \sum_{i=1}^{i=I} \left(Q_{0-\text{ele},i,t} \times Z_{q-\text{ele},i} \left(\frac{V}{V_0} \right)^2 + I_{q-\text{ele},i} \left(\frac{V}{V_0} \right) + P_{q-\text{ele},i} \right) = \sum_{i=1}^{I} Q_{\text{ele},i} \quad (14)$$

Here, P_t and Q_t are active and reactive power of each quasi real-time stage. Moreover, $P_{0-ele,i,t}$ and $Q_{0-ele,i,t}$ are initial active and reactive powers of each element at time stage-t that can be obtained as follows:

$$P_{0-\text{ele},i,t} = \frac{\text{APCR}_{\text{ele}}}{\sum \text{APCR}} \times P_{0,t} \quad (15)$$

$$Q_{0-\text{ele},i,t} = \frac{\text{RPCR}_{\text{ele}}}{\sum \text{RPCR}} \times Q_{0,t} \quad (16)$$

where ele denotes element (i.e. appliance), APCR is Active Power Consumption Ratio and RPCR is Reactive Power Consumption Ratio. In order to reach an adequate approximation of ZIP coefficient for each quasi real-time stage, it would be necessary to define type of loads, amount and style of their consumptions in detail for each appliance in a typical North American residential house.

3.2. *Load disaggregation for quasi real-time ZIP coefficients*

In order to find ZIP coefficients and model system loads accurately in quasi real-time, the following steps are respected in this study:

- Determining common home appliances for the study
- Determining type of appliances
- Approximate calculation of each appliance usage time and operating period
- Defining the impact factor of each appliance on VVO problem according to its energy consumption

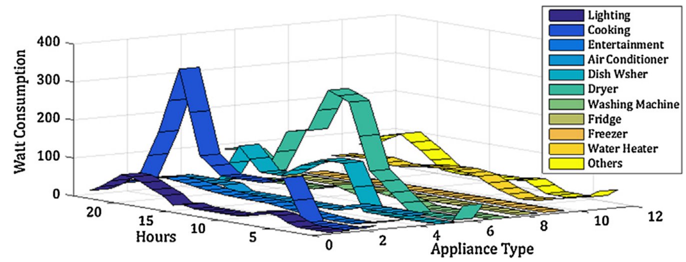

Fig. 2. Active Power consumptions of different appliances every four quasi real-time stage.

Accordingly, Table 1 represents typical appliance type, items and impact factors exerted in this study.

Impact factor percentage is defined as the percentage of consumption of an appliance item in a day compared to another appliance in the same appliance category. Knowing the impact factor could lead to a more accurate approximation of ZIP model of each appliance category. Hence, it is a totally different concept compared with CVR Factor. The impact factor percentages of Table 1 have been determined according to the consumption amount of each item within its category for a typical North American residential house. These impact factors are obtained based on consumption amount and time of usage of each item. As seen from Table 1, most conventional appliances of a residential building are considered in this study. Assessing statistical and historical data (Bokhari et al., 2014; EHACC, 2013; Higgins et al., 2014; Home energy consumption list; Hourly Load Profiles; Lu et al., 2008; OEERE; Quilumba et al., 2011; Sortomme et al., 2013; USDE, 2011), total active and reactive ZIP coefficients for each considered appliance shown in Table 1 are given in Table 2.

Now, using daily forecasted load profile and through statistical data (Awad, 2014; Bokhari et al., 2014; EHACC, 2013; Higgins et al., 2014; Home energy consumption list; Hourly Load Profiles; Kennedy & Fletcher, 1991; Lu et al., 2008; Quilumba et al., 2011; Sortomme et al., 2013), the time and duration of operation, as well as the active power consumption of each appliance is obtained. These are shown in Fig. 2. Voltage dependency of several typical domestic loads has been given in Higgins et al. (2014). Bokhari et al. (2014) presented equipment contribution weight and active/reactive ZIP model for different residential classes. ZIP model parameters of several tested appliances represented by (Lu et al., 2008). To find ZIP load model entertainment section, this paper extracted ZIP coefficients from (Quilumba et al., 2011) to assess electricity home appliance consumption, (EHACC, 2013) and (Home energy consumption list) used in this paper. Hourly load profile of residential load in different operating conditions can be found in (EHACC, 2013). The percentage of usage of different types of loads within a day was acquired from (USDE, 2011). Load data analysis accomplished by (OEERE) is the basis of the study in this paper. Normalized hourly load profiles of different load types in a typical residential home were used to categorize home appliances into different load types. This paper used operating factors of (OEERE) to find hourly consumption of each appliance separately. By dividing hourly consumption of each appliance from total hourly consumption of all appliances, hourly consumption factors of each appliance can be found using Eqs. (15) and (16) (Table 3). Multiplying the obtained time-stage consumption factors by the ZIP coefficient of each appliance, ZIP of that time-stage can be found. Explained method can be written as Eq. (17). Therefore, Table 4 presents active and reactive power ZIP coefficients for each four quasi real-time stage (hourly).

$$ZIP_{P.q,t} = \sum_{\text{ele}=1} \left(\text{Consumption Factor}_{p,q,\text{ele},t} \times \text{ZIP}_{p,q,\text{ele},t} \right)$$

Table 2
ZIP coefficients of different appliances in this study (Awad, 2014; Bokhari et al., 2014; Higgins et al., 2014; Home energy consumption list; Hourly Load Profiles; Lu et al., 2008; OEERE; Quilumba et al., 2011; Sortomme et al., 2013; USDE, 2011).

Item number	Appliance name	Z_p	I_p	P_p	Z_q	I_q	P_q
1	Lighting	0.634	−0.067	0.433	0.8125	−0.278	0.4655
2	Cooking appliances	0.738	0.928	0.096	13.304	−22.192	10.488
3	Home entertainment	−0.013	0.068	0.945	0.788	−0.6095	0.8215
4	Air conditioner	1.17	−1.83	1.66	15.68	−27.15	12.47
5	Dish washer	1	0	0	1	0	0
6	Dryer	1.02	0	−0.02	1.02	0	−0.02
7	Washing machine	0.5	0	0.5	0.5	0	0.5
8	Fridge	5.03	−8.48	4.45	17.44	−28.62	12.18
9	Freezer	5.03	−8.48	4.45	17.44	−28.62	12.18
10	Water heater	0.92	0.1	−0.02	0.15	0.86	−0.01
11	Other appliances	10.98	−16.86	8.88	35.03	−56.38	24.35

Table 3
Consumption factors of different appliances every four quasi real-time stage.

Time stage	Item #1	Item #2	Item #3	Item #4	Item #5	Item #6	Item #7	Item #8	Item #9	Item #10	Item #11
1	0.0202	0.0542	0.101	0.1397	0.0059	0.21	0	0.0249	0.027	0.1828	0.2347
2	0.0361	0	0.1017	0.2493	0	0	0	0.0435	0.048	0.274	0.2476
3	0.0427	0	0.0624	0.295	0	0	0	0.0502	0.057	0.251	0.242
4	0.052	0	0.0109	0.3593	0	0	0	0.0596	0.069	0.2165	0.2327
5	0.1451	0	0.0051	0.3344	0	0	0	0.0526	0.066	0.166	0.231
6	0.2667	0	0.0045	0.295	0	0	0	0.0452	0.059	0.1255	0.2038
7	0.1426	0.2737	0.0106	0.1408	0.006	0.1123	0	0.0216	0.028	0.0998	0.1642
8	0.0909	0.391	0.0152	0.0419	0.0043	0.1605	0	0.0154	0.02	0.0998	0.1607
9	0.0313	0.275	0.0202	0.0327	0.1704	0.195	0.02	0.0124	0.016	0.1115	0.1154
10	0.0172	0.1974	0.023	0.0265	0.2698	0.2082	0.033	0.0105	0.013	0.1193	0.0822
11	0.0141	0.1615	0.0259	0.0216	0.2207	0.3314	0.034	0.0088	0.01	0.1049	0.0673
12	0.012	0.1376	0.0281	0.0184	0.1881	0.4157	0.035	0.0079	0.008	0.0941	0.0554
13	0.0122	0.1395	0.0291	0.0187	0.1716	0.4413	0.023	0.008	0.008	0.0938	0.0542
14	0.0124	0.142	0.0303	0.019	0.1552	0.4654	0.012	0.0084	0.008	0.0939	0.0532
15	0.023	0.1902	0.034	0.0204	0.1352	0.399	0.025	0.0092	0.009	0.0954	0.0592
16	0.0146	0.2511	0.039	0.0224	0.1144	0.3292	0.042	0.0103	0.01	0.0973	0.0697
17	0.0433	0.3658	0.0349	0.0178	0.0909	0.254	0.019	0.0084	0.008	0.0713	0.0868
18	0.0507	0.4476	0.0326	0.015	0.0765	0.2041	0.004	0.0072	0.007	0.0561	0.0994
19	0.074	0.3634	0.0412	0.039	0.1242	0.1416	0.004	0.0076	0.007	0.0663	0.1312
20	0.0993	0.271	0.0533	0.0436	0.1852	0.0695	0.005	0.0083	0.008	0.0819	0.175
21	0.1183	0.1987	0.0672	0.0511	0.1282	0.1269	0.005	0.0098	0.01	0.0924	0.1921
22	0.1039	0.1016	0.0917	0.0653	0.05	0.2142	0.007	0.0125	0.013	0.1158	0.2256
23	0.0688	0.0905	0.095	0.0776	0.0297	0.2477	0.004	0.0145	0.015	0.1293	0.2279
24	0.034	0.0731	0.098	0.094	0.004	0.2917	0	0.0172	0.018	0.1467	0.2233

Table 4
Active and reactive power ZIP coefficients of different appliances every four quasi real-time stage.

Time stage	$Z_{p,t}$.	$I_{p,t}$	$P_{p,t}$	$Z_{q,t}$	$I_{q,t}$	$P_{q,t}$
1	2.2769	−3.0293	1.7523	9.8687	−15.901	7.0322
2	2.5037	−3.5939	2.0902	11.140	−18.202	8.0622
3	2.5588	−3.7063	2.1475	11.842	−19.432	8.5902
4	2.6303	−3.8575	2.2271	12.784	−21.087	9.3029
5	2.5773	−3.7645	2.1872	11.730	−19.243	8.5129
6	2.4106	−3.458	2.0474	10.315	−16.785	7.4699
7	1.7718	−2.0780	1.3062	9.5685	−15.433	6.8643
8	1.6048	−1.6801	1.0753	9.1615	−14.639	6.4774
9	1.4938	−1.3738	0.8800	4.7573	−6.8040	3.0466
10	1.3810	−1.0929	0.7119	3.2346	−4.1066	1.8720
11	1.3187	−0.9319	0.6132	3.0661	−3.8282	1.7621
12	1.2629	−0.7942	0.5313	2.8909	−3.5360	1.6451
13	1.2586	−0.7789	0.5202	3.0815	−3.8478	1.7663
14	1.2556	−0.7669	0.5113	3.3269	−4.2501	1.9231
15	1.2363	−0.7929	0.5565	3.5111	−4.6547	2.1435
16	1.2384	−0.859	0.6206	3.825	−5.2854	2.4604
17	1.2245	−0.8876	0.6631	4.8384	−7.0429	3.2045
18	1.2212	−0.9116	0.6904	5.7595	−8.6376	3.8781
19	1.4346	−1.3446	0.9099	5.5351	−8.2132	3.6782
20	1.7040	−1.8727	1.1687	5.2584	−7.6875	3.4291
21	1.8453	−2.1541	1.3088	5.9172	−8.8800	3.9628
22	2.0919	−2.6368	1.5449	7.3052	−11.365	5.0597
23	2.1339	−2.7121	1.5782	8.0885	−12.744	5.6551
24	2.1633	−2.7618	1.5985	9.1788	−14.669	6.4900

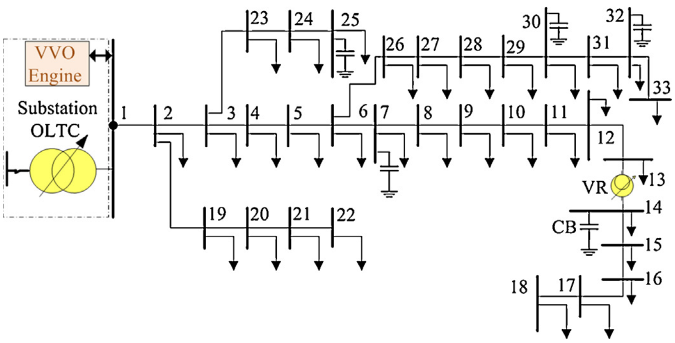

Fig. 3. Single line diagram of case study: 33-node distribution feeder.

This method is used to achieve ZIP coefficients for all 96 time stages in a day (i.e. for every 15 min). It has to be mentioned that the coefficients found here cannot fully show the exact load model in reality as many uncertainties, such as human factors or approximations such as the time and duration of usage, can affect load model coefficients. However, it is possible to state that quasi real-time load modeling could lead to more accurate VVO as its ZIP coefficients are changing in-line with VVO time stages compared to previous fixed load modeling where ZIP coefficients were considered constant throughout different operating time stages. The next section studies the performance of modeled ZIPs for quasi real-time stages in an AMI-based VVO using 33-node distribution feeder.

4. Case study and result analysis

A 33-node distribution feeder is employed to validate the presented quasi real-time load model compared with conventional load models in this section. As seen in Fig. 3, 33-node distribution network consists of one feeder with one OLTC with 16 tap steps on its medium voltage substation, a VR located between bus-13 and bus-14 and five 250 kVAR switched shunt CBs located at bus-7, bus-14, bus-25, bus-30 and bus-32. Each CB has five 50 kVAR banks. As the aim of this study is to find quasi real-time ZIP models for a typical North American consumer, the case study used typical residential houses for all consumers of 33-node distribution feeder. Here, VVO engine optimizes distribution feeder through seven different Volt-VAR control components according to Eq. (1) and VVO constraints. This grid is tested for a typical day in summer time in 96 quasi real-time stages (every 15 min). For each 15 min, AMI-based VVO optimizes distribution network by data captured from local AMI and load model presented in this paper, and sends optimal control strategies to each Volt-VAR control component of the system. Fig. 4 illustrates total loads of the case study in different quasi real-time stages of studied day. Table 5 compares the result of the objective function and energy conservation by CVR with two other conventional operating scenarios:

- Scenario-I: Offline VVO, when VVO is not performing in quasi real-time
- Scenario-II: VVO with constant ZIP coefficient, when only one ZIP set is used for all VVO time stages

Table 5
Initial results of VVO engine in comparison with Scenario-I and Scenario-II.

VVO engine results	Scenario-I	Scenario-II	This paper
Objective function ($)	29857.51	28727.23	28138.57
Time stage energy (kWh)	14995.22	14483.97	14227.94
Energy conservation (%)	–	3.4095	5.1168
Power loss (kW)	–	13103.15	12642.76
Voltage reduction for peak (time stage-60 to time stage-85 in %)	–	1.3209	1.7363

Fuzzification technique is used in order to find accurate weighting factors (α, β, γ, δ & ε) of each VVO objective sub-parts of this paper. For instance, in order to find the weighting factor of VVO loss-sub-part:

$$C_{\text{loss},b,t} = P_{\text{loss},b,t} \times \pi_t. \tag{18}$$

Here, $P_{\text{loss},b,t}$ is loss of branch-b at time stage-t (kW) and π_t is the value of loss ($/kW) which gives $C_{\text{loss},b,t}$ that is loss cost of branch-b at time stage-t ($). The Fuzzification loop within VVO algorithm for loss sub-part is as follows:

If $C_{\text{loss},b,t} < C_{\text{loss-min},b,t}$
$\alpha = 1$
Else if $C_{\text{loss},b,t} \geq C_{\text{loss-min},b,t} \&\& C_{\text{loss},b,t} \leq C_{\text{loss-max},b,t}$
$$\alpha = \frac{|C_{\text{loss},b,t} - C_{\text{loss-min},b,t}|}{C_{\text{loss-max},b,t} - C_{\text{loss-min},b,t}}$$
Else
$\alpha = 0$
end

This loop explains that weighting factor α will be equal to 0 when loss cost is more than maximum cost that grid operator intends to spend. This factor is equal to one when it is less than minim cost determined by grid operator and it is between 0 and 1 while loss cost is between minimum and maximum loss costs of the grid. Respectively, other weighting factors obtained for other sub-parts of VVO according to operating costs of VVCCs, and the value of saved energy. Fig. 5 compares loss values and Fig. 6 compares the value of consumed energy found by VVO engine of this paper (with quasi real-time load model) with Scenario-I and Scenario-II. As seen from Table 5, Figs. 5 and 6, the CVR and the objective function results are very close to each other in this paper and Scenario-II

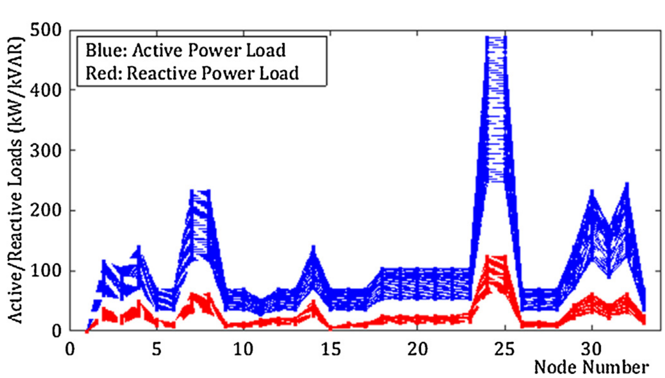

Fig. 4. Active and reactive power load variations in different quasi real-time stages.

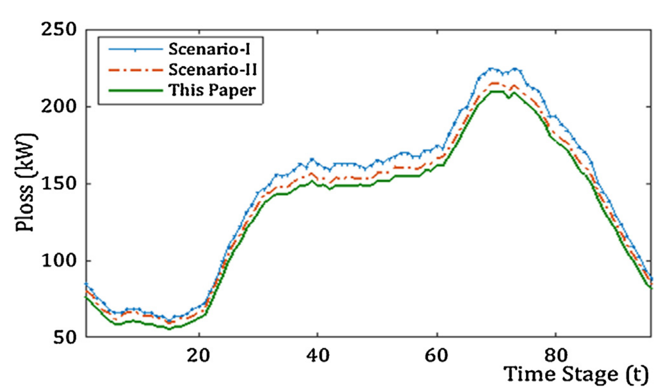

Fig. 5. Active power loss values for different quasi real-time stages in different operating scenarios.

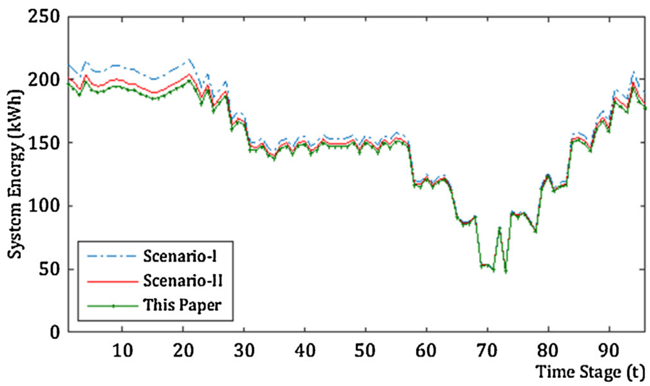

Fig. 6. Energy consumption values for different quasi real-time stages in different operating scenarios.

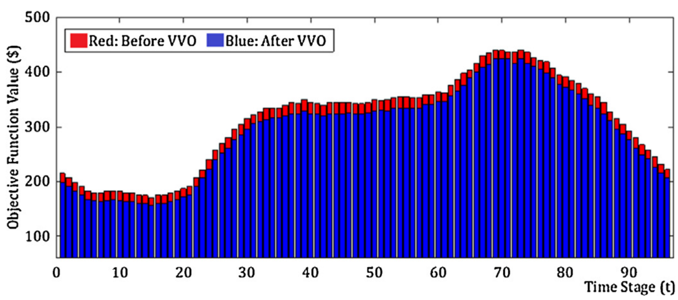

Fig. 7. Objective function values resulted by quasi real-time VVO engine.

but as presented load modeling is more accurate, it finds better solutions and obtains deeper results for CVR. In other words, VVO engine performs better by quasi real-time models presented in this paper rather than Scenario-II. It also led to better accuracy on computation of total conserved energy. It is possible to conclude that the approach presented in this paper would give quasi real-time VVO engines the opportunity to operate profoundly due to more detailed inputs that are given to the engine.

The results of the objective function of the case study are shown in Fig. 7. It can be observed that the objective function values were minimized at each and every quasi real-time stage. Fig. 8 represents Voltage Regulator performance and Fig. 9 gives CB amount and operating strategies at each quasi real-time stage. From VR operation, it can be concluded that VR is participating in CVR only in peak times by increasing its taps. Hence, most of CVR action performed by OLTC at the beginning of the feeder. Fig. 10 shows that the voltages of all nodes were being kept within the ANSI band. Therefore, it is concluded that quasi real-time modeling of loads through ZIP coefficients improved new AMI-based VVO performance and increased the accuracy of energy conservation computations in CVR sub-part of VVO.

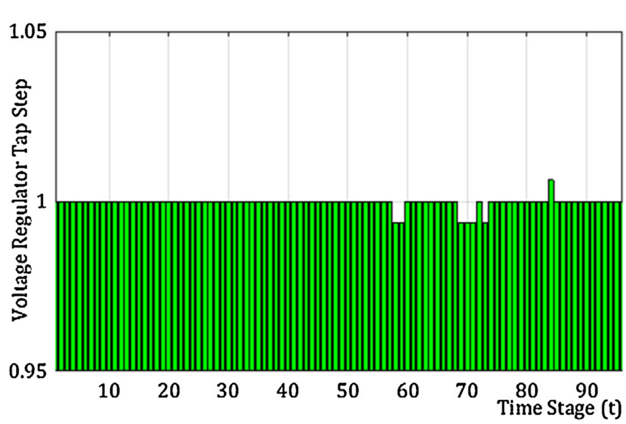

Fig. 8. Voltage regulator tap step results in quasi real-time stages.

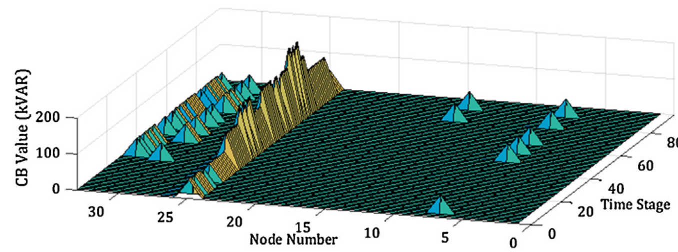

Fig. 9. Capacitor bank values and switching operations resulted by quasi real-time VVO engine.

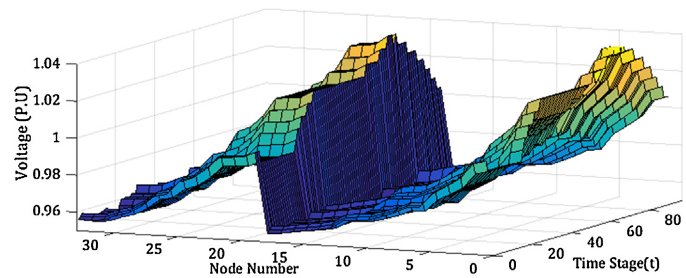

Fig. 10. Voltages of all nodes of distribution system in different quasi real-time stages.

5. Conclusions

This paper presented quasi real-time ZIP load model using load disaggregation and statistical data for energy conservation through CVR. The paper also showed the importance of Quasi real-time optimization techniques such as AMI-based VVO techniques, accurate quasi real-time load modeling through decomposition of total residential consumption to its appliance consumptions, defining appliance types, operational duration and time of use. The main advantage of the approach presented in this paper is its capability to improve VVO performance by using quasi real-time model of loads that are closer to reality compared with conventional load models. Hence, energy conservation is computed with more precision as well.

For this reason, this paper primarily introduced a new quasi real-time AMI-based VVO engine. Then, it explained load modeling concepts and ZIP coefficient calculation method for each quasi real-time stage. Afterwards, the performance of the whole system was checked in 33-node distribution network as case study and the results were compared with conventional load modeling approach.

It has to be mentioned that several factors such as type of day, calendar, weather patterns, seasonal variations, environmental conditions and geographical factors could affect load types and the amount of consumptions. Hence, in order to find more precise coefficients, it is possible to follow the same steps explained in this paper and find quasi real-time ZIP load models for other types of days (e.g. off-day) and/or other seasons. This point could necessitate further studies related to new adaptive load models quasi real-time VVO or CVR solutions. Furthermore, other techniques such as sensor placement can increase the accuracy of quasi real-time load models despite the fact that this technique could be costly. Hence, it is possible to categorize statistical methods used in this paper as the first steps for studying quasi real-time load modeling for novel CVR studies. New disaggregation methods could surely improve CVR (solely or as a part of VVO) performance. In conclusion, quasi real-time AMI-based VVO could reach higher degrees of accuracy and efficiency through more precise quasi real-time load modeling such as quasi real-time ZIP load modeling presented in this paper.

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