Reaction-Drift Model for Switching Transients in \( \text{Pr}_{0.7}\text{Ca}_{0.3}\text{MnO}_3 \)-Based Resistive RAM

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Abstract—\( \text{Pr}_{0.7}\text{Ca}_{0.3}\text{MnO}_3 \) (PCMO)-based resistive RAM (RRAM) shows promising memory properties like nonvolatility, low variability, multiple resistance states, and scalability. From a modeling perspective, the charge carrier dc current modeling of PCMO RRAM by drift-diffusion (DD) in the presence of fixed oxygen ion vacancy traps and self-heating (SH) in Technology Computer Aided Design (TCAD) (but without oxygen ionic transport) was able to explain the experimentally observed space charge limited conduction (SCLC) characteristics, prior to resistive switching. Further, transient analysis using DD+SH model was able to reproduce the experimentally observed fast current increase at \( \sim 100 \text{ ns} \) timescale, prior to resistive switching. However, a complete quantitative transient current transport plus resistive switching model requires the inclusion of ionic transport. We propose a reaction-drift (RD) model for oxygen ion vacancy-related trap density variation, which is combined with the DD+SH model. Earlier, we have shown that the Set transient consists of three stages and Reset transient consists of four stages experimentally. In this work, the DD+SH+RD model is able to reproduce the entire transient behavior over 10 ns–1 s range in timescale for both the Set and Reset operations for different applied biases and ambient temperatures. Remarkably, a universal Reset experimental behavior, \( \log(I) = (m \times \log(f)) \) where \( m \approx −1/10 \) is reproduced in simulations. This model is the first model for PCMO RRAMs to significantly reproduce transient Set/Reset behavior. This model establishes the presence of SH and ionic-drift limited resistive switching as primary physical phenomena in these RRAMs.

Index Terms—Ion-migration, \( \text{Pr}_{0.7}\text{Ca}_{0.3}\text{MnO}_3 \) (PCMO), Reset/Set, resistive RAM (RRAM), transient current.

I. INTRODUCTION

Pr\(_{0.7}\text{Ca}_{0.3}\text{MnO}_3 \) (PCMO) is used in a nonfilamentary resistive switching memory device [resistive RAM (RRAM)].

It is attractive due to better variability and multilevel resistance states [1], [2]. A forming-less operation is observed in PCMO [3], [4], which simplifies the memory controller. The device is a W/PCMO/Pt, that is, a metal–oxide–metal structure fabricated on an SiO\(_2\)/Si substrate. The PCMO film (60 nm) is deposited using a room temperature pulsed laser deposition followed by annealing at 650 °C. The top contact (W) size is \( \sim 1 \mu \text{m} \). The detailed fabrication methods are explained earlier in [5]. From a perspective of the mechanism, in PCMO-based RRAM, the extent of understanding is depicted well in the literature. To explain the experimental dc IV characteristics, space charge limited conduction (SCLC) mechanism has been invoked for current transport [6]–[8]. Resistance is modulated by trap-density-consistent with trap SCLC [9]. We have presented a simple trap density extraction methodology based on trap SCLC model to correlate trap density change with resistance switching [10]. Furthermore, a Technology Computer Aided Design (TCAD) model consisting of drift-diffusion (DD)-based holes transport in p-type semiconductor with self-heating (SH) (but without ionic transport) to model SCLC current is able to replicate dc IV characteristics at lower bias, that is, prior to onset of resistive switching for a range of ambient temperatures (25 °C–125 °C) [11]. The inclusion of SH enabled the replication of nonlinear behavior, earlier erroneously attributed to trap-filled limit [9]. The signature of SH was further confirmed by fast (sub-100 ns) transient switching behavior [5]. Transient TCAD modeling was able to match the experimental current transient prior to the onset of resistance switching.

The switching phenomena in filamentary RRAMs like HfO\(_2\)-based RRAMs and the corresponding quantitative modeling of the steady-state and transient measurements has received widespread attention from researchers [12]–[24]. The switching mechanisms in uniform switching (bulk conduction) RRAMs has also been explored extensively [25]–[41]. The effects of top electrode properties [37] and an interface layer formation during switching [31] have also been demonstrated. Although there is a large amount of experimental data available for switching in these films, a quantitative model for the current transients in uniform switching RRAMs involving ion dynamics is still lacking. A qualitative explanation of resistive switching in PCMO-based RRAM is as follows. Resistive switching in PCMO-based RRAM is related to the transport of oxygen ion (or equivalently oxygen vacancies) [42]–[45]. Reversible ionic transport occurs by reversing bias polarity to drift ions to and from a reactive electrode (i.e., an oxygen source/sink) via lattice substitutions to modulate oxygen...
model and hence, it cannot account for resistive switching. Experimentally for Set stage S3, ionic motion leads to a current increase, which increases Joule heating in the device (i.e., SH) to further increase ionic motion. Thus, a positive feedback mechanism is set up to create a sudden sharp increase in current to compliance [see Fig. 1(a)]. The ionic transport, indicated by the ionic drift velocity \( v_{\text{drift}} \) at a given temperature and electric field, is given by Mott–Gurney Equation [49]

\[
v_{\text{drift}} = a \exp \left( \frac{E_m}{k_B T} \right) \cdot \sinh \left( \frac{\xi}{\zeta_0} \right)
\]

(1)

where \( a \) is the hopping distance, \( f \) is the escape frequency, \( \zeta = V_{\text{applied}}/L_{\text{film}} \) is the electric field, \( \zeta_0 = 2k_B T/qa \) is the characteristic electric field, \( E_m \) is the activation barrier, \( k_B \) is Boltzmann’s constant, and \( T \) is the absolute device temperature. Ionic motion timescale is essentially the timescale at which this \( v_{\text{drift}} \) produces significant ionic motion compared to present trap density. As the current is measured in log scale from 10 ns to 1 s, the positive feedback is observed as a sudden sharp take off in current toward compliance when the measurement timescale matches the ionic motion timescale for a given applied bias (stage S3). As bias is reduced, we observe an exponentially longer timescale in saturation (stage S2) to abrupt current take-off (stage S3), that is, occurrence of ionic motion. This is qualitatively consistent with (1). Essentially, lower field and lower current cause lower heating and consequently lower temperature. Lower electric field (\( \zeta \)) and temperature (\( T \)) will reduce \( v_{\text{drift}} \) to increase timescale for equivalent ionic transport distance exponentially as shown in (1). To validate this qualitative explanation, a quantitative model based on numerical simulations is presented in this article.

The Reset transient phenomenon has three different applied voltage regimes [Fig. 1(b)]—low, medium, and high. The high bias has a fast increase (stage R1) and then fast decrease in current (stage R2) followed by a time-independent current (stage R3). For intermediate bias, the high bias behavior is observed, but the constant current (stage R3) is higher. Eventually, when the measurement timescale matches the ionic motion timescale, the constant current starts to reduce to follow the “universal” curve with the time exponent \( \log(I) - \log(t) \) plot of approximately \( -1/10 \) (stage R4). The low bias shows initial current increase (stage R1) followed by the “universal” current transient curve with the time exponent of \( -1/10 \) (stage R4). We first model this specific “universal” behavior. To begin, we show that a universal power law dependence is possible in an isothermal case where ionic transport increases trap density and hence reduces current—similar to negative bias temperature instability (NBTI) analysis in MOSFETs [50], [51]. However, this universal power law derived using isothermal assumption has an inaccurate (i.e., larger than observed “\(-1/10\)”) time exponent. Inclusion of SH in the device rectifies this error as discussed later.

For Reset, an increase in hole trap density \( N_T \) reduces current, \( I_{\text{trap.SCLC}} \) as given by

\[
I_{\text{trap.SCLC}} \sim \frac{I_{\text{trap.free}}}{N_T} \exp \left( \frac{E_T - E_V}{k_B T} \right) \times \frac{1}{N_T}
\]

(2)

where \( I_{\text{trap.free}} \) is the trap-free SCLC current, \( N_T \) is the hole trap density, \( N_V \) is the hole effective density of states, \( E_T \) and \( E_V \) are the trap energy and valence band, respectively.
is the trap energy level, and $E_V$ is the valence band edge. We assume two concurrent processes.

1) The applied bias attracts the anions throughout the PCMO bulk toward the reactive electrode ($W$) and the ionic/vacancy motion occurs in a substitutional manner (see Fig. 2).

2) The anions at the W-PCMO interface observe a sink and undergo redox activity to create a source of new vacancies/trap.

To create positive traps at the interface, a substitutional unit element ($O_{lattice} = O^+_O$) produces an anion ($O^{−}$) with $n$ charges and a vacancy that yields $n$ hole traps ($h^+_T$) per anion (3). This reaction is a reversible process and the equilibrium is largely toward the left in the bulk. However, at the interface, this anion sinks at the reactive electrode (redox reaction) and any excess electrons escape through the contact (4).

$$O^+_O \rightleftharpoons O^{−} + n\cdot h^+_T$$

$$W + x\cdot O^{−} \rightleftharpoons WO_x + xne^−. \quad (4)$$

The oxygen ionic species that forms with the highest probability would be the doubly charged $O^{2−}$ anion leaving behind a newly formed oxygen vacancy at the interface (5)

$$O^+_O \rightleftharpoons O^{2−} + n\cdot h^+_T$$

but we work with general $n$ traps per anion situation going forward. The newly formed vacancies can drift into the bulk via substitutions under applied electric field as governed by (1). We assume first-order chemical kinetics for each reactant in (3). We also assume that the entire process is drift limited, that is, the reaction (3) is essentially close to equilibrium, which means the forward and backward reaction rates are approximately equal

$$\frac{d[\text{h}_T]}{dt} = \frac{d[O^{−}]}{dt} = k_F[O_{lattice}] - k_R[O^{−}][\text{h}_T]^n \approx 0 \quad (6)$$

constant $= k_F[O_{lattice}] \approx k_R[O^{−}][\text{h}_T]^n \quad (7)$

$$[O^{−}] \approx \frac{k_{eq}[\text{h}_T]^n}{k_{eq} + k_{eq}[\text{h}_T]^n} \quad (8)$$

where $k_{eq} = k_F[O_{lattice}]/k_R$. This is a constant because $[O_{lattice}]$ is almost constant for small extent of reaction, and $k_F$ and $k_R$ are also constants under isothermal condition. The motion of generated vacancy defects into the system is equivalent to motion of anions in the bulk out of the system, that is, substitutional hopping of ions through vacancy defects. The total ionic concentration leaving PCMO is $[O^{−}]$ concentration of ions drifting a small distance $l = v_{\text{drift}} \times dt$. For simplicity, we assume a uniform change in concentration, given by

$$\frac{d[O^{−}]}{dt} = \frac{[O^{−}]v_{\text{drift}}dt}{L} \quad (9)$$

$$\frac{d[O^{−}]}{dt} = \frac{v_{\text{drift}}[O^{−}]}{L} = n\frac{d[\text{h}_T]}{dt} \quad (10)$$

where $L = \text{PCMO film thickness}$. Using (8), we substitute out $[O^{−}]$ in (10) to construct a differential equation in the hole trap density, $[\text{h}_T]$,

$$\frac{d[\text{h}_T]}{dt} = \frac{k_{eq}[\text{h}_T]^n}{nL[\text{h}_T]^n}. \quad (11)$$

Integrating, we get the time evolution of hole trap density

$$[\text{h}_T] = (\frac{n + 1}{n} \times \frac{k_{eq}v_{\text{drift}}}{L})^{-\frac{1}{n-1}} t^{-\frac{1}{n}}. \quad (12)$$

Assuming $[\text{h}_T] = N_T$, that is, uniform trap density, then (2) gives

$$I_{\text{trap,SCLC}} \propto t^{-\frac{1}{n-1}}. \quad (13)$$

Thus, $n$ traps per anion $O^{−}$, based on RD model, would produce a time exponent $m = -1/(n+1)$. The experimental exponent of $\sim -1/10$ requires $n = 9$. It is indeed quite difficult that a single diffusing species of oxygen produces nine traps. The first possibility is an oxygen ion ($O^{2−}$), which produces $n = 2$ traps is widely reported which should produce an exponent of $m = -1/3$, much sharper than the observed $-1/10$. Next, a superoxide ion ($O_{2}^−$) should produce $n = 4$ traps. However, superoxide ions are unstable and only reported for surface diffusion and dissociation into $O^{2−}$ ions for bulk diffusion in solid oxide fuel cell (SOFC) electrode studies of LSMO [52]. Thus, for an isothermal case, it is highly unlikely to get $n = 9$.

Next, we show qualitatively that SH should reduce the magnitude of this time exponent. For Reset, the device starts in low resistance state (LRS). Upon application of bias, the current increases with SH (stage R1). Consequently, the temperature rises, and ion transport is initiated to increase trap density, which reduces the current (stage R2). First, in the case of high bias, a very high current is reached to enable a high temperature quickly. At high temperature, rapid ion transport occurs and saturates at a high value to reduce the current abruptly resulting in abrupt temperature drop too. Trap density and consequently current become time independent. Second, in the case of lower bias, a lower final current is reached (stage R1). Consequently, the temperature rises to a moderate level (lower than the high bias case), where ion transport increases trap density slowly to reduce the current (stage R4). The gentle current reduction will reduce the temperature gently, which will further reduce the ion transport. A negative feedback occurs due to temperature reduction, which will slow down ionic transport in time compared to the isothermal case. Naturally, the rate of current reduction will also slow down. Thus, the magnitude of power law exponent will reduce from the isothermal prediction of $1/3$. We will show that we can achieve the exponent of $m = -1/10$ using detailed
DD+SH+RD numerical simulations. Based on this model, we also show that high bias regime, that is, fast increase and then fast decrease of current followed by constant current is also realized. Furthermore, the intermediate bias regime, that is, initially high bias like behavior (stages R1 and R2), which results in a higher constant current will remain unchanged in time (stage R3) as the initial timescale of measurement is too fast for ionic transport at that intrinsic device temperature. However, at longer timescale of measurement when the timescale becomes comparable to the rate of ionic transport at that device temperature, then the transient current reduces again and merges with the “universal” curve of time exponent $m = -1/10$ (stage R4).

### III. Simulation Setup

In this section, we describe the time-dependent hole current transients simulation methodology for a fixed applied bias, ambient temperature, and starting trap density (low resistance state, low $N_T$-LRS or high resistance state, high $N_T$-HRS) (see Fig. 3). After the initialization in device temperature, $T$, trap density, $N_T$, and voltage ramp time, the detailed time evolution is performed in MATLAB at the fixed applied bias. For updating the trap density during simulation transient, the RD model based on Mott–Gurney ionic drift (1) and the ionic reaction kinetics explained in Section II are used (11). In addition, the device temperature is calculated as a function of the input power density and the thermal parameters. The hole current is obtained from a lookup table (LUT) of quasi-static simulations performed in Sentaurus TCAD for different fixed trap density values and isothermal device temperature values. The following sections explain the simulation steps in detail.

#### A. Assumptions

Before describing the time dynamics, it is essential to understand four assumptions involved.

1. Trap density is uniform across device (no spatial $N_T$ dependence).
2. Temperature is uniform across device (lumped or point-device model assumption).
3. Hole current response time is much faster than temperature or ionic RD response time.
4. The conduction is limited by the bulk trap density and not the interfacial oxide WOX.

It is true that ionic transport may lead to nonuniform trap density. Still, assumption 1) is reasonable because of two observations. First, we have earlier shown by simulations that asymmetry in trap spatial profile only weakly affects the largely symmetric IV characteristics [10]. Second, the experimental IV characteristics are essentially symmetric for positive versus negative bias before the onset of ionic transport, that is, Set/Reset [10]. Thus, a unique trap density is a reasonable approximation. For the assumption 2), detailed finite-element method (FEM) thermal simulations were performed for the device stack earlier [5], [11] to extract equivalent thermal capacitance and conductivity values for a lumped or point device model to be used in this work. Hence, assumption 2) is a useful simplification which allows capturing the temperature dependence in resistive switching without the simulation complexity of a more complete spatial Fourier heat equation. We have also ignored the capacitive response delays of the hole currents [assumption 3]), because first, holes have high mobility compared to ions due to significantly smaller mass. Second, the objective is to capture the long timescale transients governed by temperature and ionic RD phenomena and the hole response time is expected to be much shorter. It is assumed that the current conduction is limited by the bulk trap density in the much thicker PCMO layer (~60 nm) than the nonstoichiometric and ultrathin interface oxide (~5 nm), WOX [assumption 4)] [33], [53], [54]. In previous works [11], we have observed $I \propto V^2$ dependence which indicates space charge limited conduction in all the following states of the film: as-fabricated, Reset to HRS, and Set to LRS.

#### B. Initialization

The total time simulation has four variables: 1) external applied bias, $V(t)$, this is the input; 2) carrier current, $I(t)$; 3) trap density, $N_T(t)$; and 4) device temperature, $T(t)$. At $t = 0$, the start of the transient simulation, the current, and voltage are zero and the device is in one of LRS ($N_{T_0} \sim 10^{18}/\text{cm}^3$) or HRS ($N_{T_0} \sim 10^{20}/\text{cm}^3$) state. It is possible to extract the starting trap density, $N_{T_0}$ from a given resistance state as observed in experimental dc IV measurements [10]. The device is in equilibrium with the ambient temperature to begin with ($T = T_{amb}$).

#### C. Voltage Ramp

The input bias rises from 0 to $V_{app}$ in a short span of 20 ns (same as experiment). This timescale is much shorter to result in any significant change in trap density or device temperature. Hence, for this duration, these values are held at their initialized values and the hole current is updated in time from TCAD quasi-static simulation values corresponding to the voltage sweep values (0 to $V_{app}$).

#### D. Time Dynamics at Applied Bias

The time evolution that follows happens at a fixed external bias ($V_{app}$). In this duration, the current, temperature, and trap density evolution are interdependent. In Section II, the time dynamics of the trap density (11) was discussed using a RD model. The drift velocity of the oxygen ions follows the Mott–Gurney law and this velocity is utilized to evaluate the ionic reaction kinetics. As a whole, the RD model takes the present trap density and device temperature as inputs. The device temperature is a simple heat balance between input power and dissipation at any moment in time.
Since the hole response time is small compared to temperature and traps transients, a quasi-static LUT generated in TCAD for different $T$ and $N_T$ can be used immediately to calculate hole current at any instant in time.

1) Current Transport in TCAD: The current LUT is generated using quasi-static IV simulations in Sentaurus TCAD (see Fig. 4). In current transport, TCAD uses electron–hole DD formalism to compute current through the PCMO film ($L = 65$ nm) with the experimental top contact area ($1 \mu m^2$) at a fixed uniform trap density ($N_T$) and device ambient temperature ($T_{amb}$). The device is isothermally in equilibrium with ambient temperature ($T = T_{amb}$) and trap density does not evolve during TCAD current calculation. This is repeated for several $T_{amb}$ and $N_T$ values. Essentially, the TCAD model solves the Poisson, carrier continuity, and carrier statistics self-consistently in the presence of constant mobility, Auger, and Shockley–Read–Hall (SRH) recombination models. The TCAD solver uses silicon material parameters except for the ones specified in the TCAD section in Table I. The current values are stored for a fixed value of applied voltage as a function of $N_T$ and $T$. This constitutes an LUT for that applied bias to be used later in the MATLAB solver. We had earlier demonstrated excellent matching of temperature-dependent current transport in PCMO-based RRAM using trap SCLC model with SH [10] implemented in Sentaurus [11]. Furthermore, the dc model was extended to perform transient simulations where transient current for fast Set and Reset was modeled to show excellent match with experimental current transients before the on-set of ionic transport [5]. Our TCAD solver and material parameter files are hence calibrated to experimentally observed current conduction except the resistive switching phenomena for which we propose the RD model external to TCAD LUT generation in this work.

2) Thermal Model: For a single point device, the transient device temperature, $T$ can be described in terms of its thermal properties as

$$
\frac{(T - T_{amb})}{R_{th}} + c_v \frac{dT}{dt} = I \cdot V
$$

(14)

where $R_{th}$ is the thermal resistance of device ($R_{th} = (L/A\lambda)$), $L$ is the device conduction length, $A$ is the device area, and $\lambda$ = effective thermal conductivity of device), $T_{amb}$ is the ambient temperature, and $c_v$ is the heat capacitance ($c_v = c_o AL$, $c_o$ is the effective specific heat capacity of device). This device temperature affects the current conduction through the device by means of the LUT and affects the trap density based on the RD model discussed in Section II.

IV. RESULTS AND DISCUSSION

The self-consistent solver based on models and simulation setup described in Sections II and III is used to reproduce the experimental characteristics significantly (parameters used are listed in Table I) as discussed in the following sections.

A. Effect of $n$ on Reset Transient

The Reset transient for $n = 1, 2, 4$ is shown in Fig. 5. Essentially, without SH, we obtain a $m = -1/(n+1)$ time exponent. However, with SH, the magnitude of the time exponent is reduced. The RD model along with SH can thus be instrumental in predicting the transient Reset timescales for materials with different mobile ionic species.
B. Reset Simulations

The effect of bias on Reset simulations is shown in Fig. 6. At high bias, $T(t)$ increases quickly ($\sim 800$ K). $N_T$ rises fast and saturates [see Fig. 6(a)]. Accordingly, the three regimes are observed, that is, 1) current increases quickly and 2) then decreases quickly to 3) saturation state [see Fig. 6(b)]. At low bias, the temperature rises to $\sim 400$ K, the associated change in trap density is small too [see Fig. 6(c)]. Then a slow negative feedback between temperature and trap density occurs. Accordingly, two regimes in current transient is observed: 1) current increases and then 2) follows the universal time exponent [see Fig. 6(d)].

Fig. 7(a) compares simulated versus experimental $I(t)$ for a range of biases. Our model is able to reproduce the experimental behavior quite comprehensively. Small quantitative differences can be attributed to the various simplifying assumptions (Section III-A). Next, we simulate the effect of ambient temperature ($T_{amb}$). Our transient simulations are in excellent agreement for a range of $T_{amb}$ (i.e., 300–450 K). We observe that at high-bias [yellow–red curves in Fig. 7(a) and (b)], there is a saturation to indicate that higher bias does not produce faster switching beyond 100 ns timescale. Furthermore, at low bias, the switching timescale is also limited 10 ms. $T_{amb}$ does not strongly affect these levels. Simulations show excellent agreement with experiments [see Fig. 7(c)–(e)].

C. Set Simulations

The effect of bias on Set simulations is shown in Fig. 8. At high bias, the temperature [see Fig. 8(a)] and current [see Fig. 8(b)] rise sharply to compliance. $N_T(t)$ reduces quickly too [see Fig. 8(a)]. For low bias, temperature [see Fig. 8(c)] and the current [see Fig. 8(d)] increases and then saturates. Then $N_T(t)$ falls at a specific timescale when the current and accordingly the temperature rise sharply [see Fig. 8(c) and (d)] to compliance. Set simulations include a compliance current level ($\sim 10$ mA, as in measurements). Beyond compliance, the experiment shows compliance current as fixed (which is true) but with the desired voltage applied (which is not actual). The actual voltage is reduced appropriately to ensure current compliance. However, the actual voltage is not displayed in output by the instrumentation. In simulations as well, the output current is actual (compliance) but the voltage is still the set point not the reduced actual value. As Set time is defined as time to reach a critical current level below compliance, the experiment and simulations for $T$ or $N_T$ beyond compliance is not of interest in this study and are not valid beyond current reaches compliance (as indicated by dashed lines in Fig. 8).

Next, we show that the experimental Set transient is captured well by simulations at 300 K as seen in Fig. 9(a) and (b). A constant current (10 mA) for simulations and experiment is used to extract Set time as a function of applied bias for $T = 300$, 375, and 450 K in Fig. 9(c). At higher bias, Set time shows saturation and is essentially limited to 100 ns. At lower bias, there is a fast increase in Set time, which is essentially the voltage–time dilemma. This is in excellent agreement with simulations.

Furthermore, the $T_{amb}$ dependence on the Set behavior shows that the voltage–time dilemma at low bias responds to temperature. However, at high bias, the timescale of Set is still limited to 100 ns, which is temperature insensitive. These simulation results are also in excellent agreement with experiments [Fig. 9(c)]. This effect of ambient temperature on improving Write timescales at low biases is more pronounced for Set [see Fig. 9(c)] when compared to Reset [Fig. 7(c)–(e)]. We expect thermal design of RRAM to become an important consideration. Thermally insulating design for dc performance enhancement has been experimentally
demonstrated [55] but still remains to be seen for the transient performance. Furthermore, PCMO composition engineering has been performed to show tradeoff between speed and retention [56]. RD model captures the device temperature in comparison to the ambient temperature using effective thermal conductance and capacitance of the RRAM stack. We expect the results of switching times at different ambient temperatures in this work [see Fig. 9(c)] to translate to thermally efficient RRAM stacks operating at room temperature. We expect the predictions from this model to enable optimal composition design in addition to thermal design.

V. CONCLUSION

In this article, a RD model is proposed to include ion dynamics to a DD with SH-based model for hole transport. We demonstrate that the model can reproduce experimentally observed Set and Reset transient across a range of timescale (100 ns–1 s), Set/Reset bias, and ambient temperatures (300–450 K). Remarkably, a universal Reset behavior of (300–450 K). Remarkably, a universal Reset behavior of time-exponent $m \approx -1/10$ is replicated. The simulations are able to capture the difference between Set/Reset timescales versus Set/Reset voltages to explain the different voltage–time dilemma observed in Set vis-a-vis Reset. The ambient temperature shows a stronger effect for Set compared to Reset—which is captured well in simulations. Furthermore, the timescale for fast switching is limited to ~100 ns for Set and Reset—which is independent of ambient temperature is also captured. Thus, we present a simple point device model of Set/Reset in PCMO-based RRAM that can comprehensively reproduce timescale, bias, and temperature effects. Such models with further refinements will enable a detailed understanding of physical phenomena and design of PCMO-based RRAMs.

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