Dynamic-Phasor Data-Driven Modeling of Grid-Forming Battery Inverters under Unbalanced Conditions

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***Abstract*—Simulation environments are crucial tools for evaluating power system dynamics and stability prior to real-world implementation. Conventional phasor domain (RMS) and Electromagnetic Transient (EMT) simulations face a trade-off between computational efficiency and model accuracy. The Dynamic Phasor (DP) theory offers an intermediate alternative, representing harmonic content and unbalances with lower computational cost than EMT models. Meanwhile, Data-Driven (DD) modeling has emerged as a promising approach for directly capturing system behavior from input–output data, especially in modern power systems and energy storage systems. This paper proposes a hybrid approach combining DP theory and DD modeling to develop a parametrized, interpretable, and computationally efficient DP model. A Grid-Forming (GFM) battery inverter connected to an infinite bus is modeled using the subspace identification method (N4SID) in the DP domain to represent an unbalanced condition. The proposed DD-DP-based model closely matches EMT simulation results, demonstrating its potential for accurate and efficient power system representation.**

***Index Terms*—Data-Driven Modeling, Dynamic Phasor, Grid-Forming Inverter, Energy Storage System, Subspace Identification**

I. Introduction

Simulation environments provide representative insights into power system behavior, which are essential for analyzing stability and making informed decisions during the control design process before the systems are implemented in real-world operation, particularly for inverter-based resources and energy storage systems [1]. Currently, the most widely used simulation environments rely on RMS and EMT simulations. RMS simulations employ phasor analysis, assuming the system has reached steady state, whereas EMT simulations solve full differential equations to capture detailed waveform dynamics. Although EMT models can represent complete harmonic content and system unbalances, they are significantly more computationally demanding than RMS models.

To overcome the limitations of both approaches, the Dynamic Phasor (DP) theory has gained increasing attention. DP models can represent user-defined harmonic components and system unbalances, offering a robust framework for analyzing system behavior in greater detail than RMS models while remaining computationally lighter than EMT simulations [2]. Dynamic Phasor modeling is an emerging tool to model power electronics converters, which act as a control interface with an energy storage system. Specifically, Grid-Forming (GFM) has been modeled using the DP technique in [3], [4] to demonstrate its capability to produce an accurate and computationally efficient model. However, considering additional harmonics increases model complexity. Thus, a key challenge is to develop modeling approaches that incorporate higher-order harmonics and retain DP's representational accuracy while maintaining computational efficiency comparable to that of RMS methods. Also, to obtain a DP model, detailed knowledge of the system is required, which may not always be available.

Data-driven (DD) modeling also has emerged as a promising solution for various power system applications, ranging from control design to system identification. The main advantage of DD approaches lies in their ability to derive mathematical models directly from input–output data, without requiring detailed system knowledge [5]. The DD technique has also been used to model GFM inverters in [5]. Primarily, datasets in DQ representations are used in [5] and assume that the system is in a balanced condition. Data-driven methods using DQ cannot represent unbalanced dynamics in systems, as unbalanced dynamics caused by negative sequence appear as 120Hz oscillations in DQ. So, this paper proposes a hybrid approach that integrates DP theory and DD modeling to obtain an interpretable, parametrized, and representative input-output system model of the GFM inverter.

To the author's knowledge, only one study has combined DP environments with DD modeling techniques for system representation [6]. This study produces a surrogate model of electric drive using the DD technique on DP datasets. The dataset used was extracted from a DP model rather than a detailed model. It fails to highlight the significant advantage of using the DP-DD technique.

The main objective of this paper is to develop a Data-driven model based on the DP dataset of a three-phase GFM battery

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inverter connected to an infinite bus, and to represent the inverter's dynamics when there is a slight imbalance in the infinite bus voltage. Subspace identification method (N4SID) is used in the DP domain to capture the GFM dynamics when each phase observes different voltage perturbations. The accuracy of the DD-based voltage dynamic response is then compared with EMT simulations, demonstrating promising results as a first step toward interpretable DD models enhanced by DP theory.

The remainder of the paper is organized as follows. Section II briefly describes the dynamic phasor modeling technique, the mathematical DP model of the GFM inverter, and the background on the subspace system identification technique. Section III describes the simulation setup. The results and analysis are presented in Section IV. Lastly, the conclusion is presented in Section V.

II. Background on DP Modeling and System Identification technique

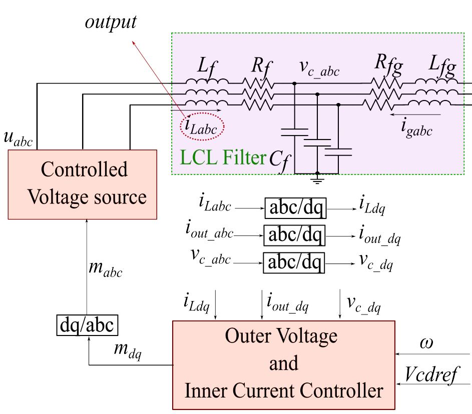

Fig. 1: Average model of GFM inverter connected to an infinite bus through a line impedance and LCL filter.

A. Dynamic Phasor Theory

The DPs of a time domain electrical signal $x(t)$ are represented by its Fourier coefficients. These Fourier coefficients are calculated over a moving time window as shown in (1) [2].

$$X_k(t) = \frac{1}{T}\int_{t-T}^{T} x(\tau)e^{-jk\omega_s\tau}d\tau = \langle x\rangle_k \tag{1}$$

$$x(t) = \sum_{k=-\infty}^{\infty} X_k(t)e^{jk\omega_s t} \tag{2}$$

where, T = length of the window and $\omega_s = \frac{2\pi}{T}$ is the fundamental frequency. $X_k(t)$ = $\langle x\rangle_k$ is the k^{th} Fourier coefficient which is a complex quantity. For a perfectly periodic signal, $\langle x\rangle_k$ is constant, whereas for nearly periodic signals during transients, $\langle x\rangle_k$ is time varying, which is also due to the sliding window calculation of the Fourier coefficient. The Fourier coefficients computed using a sliding window are referred to as *Dynamic Phasors* (DPs).

The real-valued signal $x(t)$ can be recomputed using the DPs as shown in (2). Although (2) shows an infinite number of DPs used during the reconstruction of $x(t)$, it can be approximated by a finite number of DPs as shown in (3).

$$x(t) \approx X_0 + 2Re\sum_{k\in K, k\neq 0} X_k(t)e^{jk\omega_s t} \tag{3}$$

where K is the set of selected DPs.

The significant properties of DP, which are widely used during modeling, are listed in [2]. When DPs of the ABC signals are calculated, the DPs of positive, negative, and zero sequence components are also preserved with it, which is represented by (4). This feature enables to model the system's unbalanced features using DP-ABC.

$$\begin{bmatrix}\langle x_a(t)\rangle_k\\ \langle x_b(t)\rangle_k\\ \langle x_c(t)\rangle_k\end{bmatrix} = \begin{bmatrix}1 & 1 & 1\\ 1 & \xi^2 & \xi\\ 1 & \xi & \xi^2\end{bmatrix}\begin{bmatrix}\langle x_0(t)\rangle_k\\ \langle x_+(t)\rangle_k\\ \langle x_-(t)\rangle_k\end{bmatrix} \tag{4}$$

where $\xi = \exp\frac{j2\pi}{3}$, $\langle x_+(t)\rangle_k, \langle x_-(t)\rangle_kand\langle x_0(t)\rangle_k$ are DPs of positive, negative, and zero sequence components.

B. DP Model of GFM

The properties of the DPs can be used to obtain the DP model of GFM. The equation defining the averaged model of GFM in Fig. 1 can be represented as:

$$L_f\frac{di_{Labc}}{dt} = u_{abc} - i_{Labc}R_f - v_{cabc} \tag{5}$$

$$L_g\frac{di_{gabc}}{dt} = v_{gabc} - i_{gabc}R_g - v_{cabc} \tag{6}$$

$$C_f\frac{dv_{cabc}}{dt} = i_{Labc} + i_{gabc} \tag{7}$$

where, $R_g = R_{fg} + R_{line}$ and $L_g = L_{fg} + L_{line}$.

The averaged model equation can be modified to obtain the DP model of GFM as shown below:

$$L_f\left(\frac{d\langle i_L\rangle_k}{dt} + j\omega k\langle i_L\rangle_k\right) = \langle u\rangle_k - R_f\langle i_L\rangle_k - \langle v_c\rangle_k \tag{8}$$

$$L_g\left(\frac{d\langle i_g\rangle_k}{dt} + j\omega k\langle i_g\rangle_k\right) = \langle v_g\rangle_k - R_g\langle i_g\rangle_k - \langle v_c\rangle_k \tag{9}$$

$$C_f\left(\frac{d\langle v_c\rangle_k}{dt} + j\omega k\langle v_c\rangle_k\right) = \langle i_L\rangle_k + \langle i_g\rangle_k. \tag{10}$$

For simplicity, x_{abc} is denoted as x in the above equations. The equations above represent only the LCL filter dynamics; the mathematical model also includes interactions with the controllers. The interaction between the model and the controller can be efficiently modeled if the DP of ABC signals can be well mapped to that of DQ signals.

The mathematical derivation for an extensive system would be cumbersome using DP, as the number of equations grows with the number of harmonics required. Also, to derive a DP model, we need detailed knowledge of the system. The system parameters may not be readily available for detailed modeling. So, a data-driven technique can be used in conjunction with DP models to parameterize them.

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C. System identification of DP model of GFM

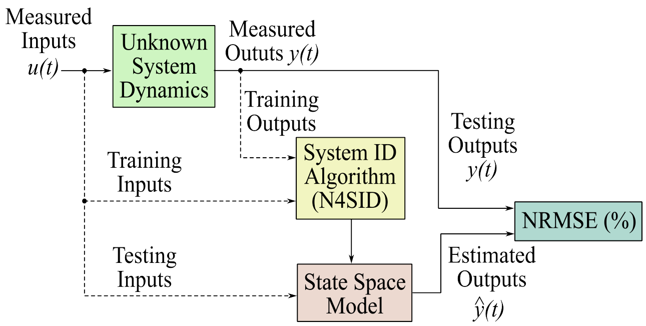

Fig. 2: Representation of system identification using input-output dataset [5].

System identification is the process of estimating system parameters from input and output datasets. This process is implemented without detailed knowledge of the system or its control structure. Fig. 2 shows the typical representation of the system identification process. The input and output measurements are fed to the system identification algorithm, which fits the model. The model is tested on a test dataset, and the normalized root-mean-square error (NRMSE) is calculated between the true and predicted measurements.

Subspace methodology, such as the N4SID algorithm, is the identification technique employed in this work to obtain a state-space model of the GFM inverter using the system´s DP measurements.

This methodology avoids local minima, unlike gradient-based techniques that minimize non-convex cost functions. This way, N4SID yields an interpretable model in the state-space domain by automatically generating the (A, B, C, D) [7].The N4SID algorithm relies on matrix decompositions that naturally preserve the multi-input multi-output (MIMO) structure of the system [7]. This property is particularly advantageous for the present work, in which DP theory will be employed to obtain the real and imaginary parts of the input and output data and to construct the state-space model for the GFM converter.

The most widely used tool to implement N4SID subspace system identification is the MATLAB System Identification Toolbox. This paper uses the same approach to perform parameterization.

D. Accuracy Comparison Technique

This paper compares the accuracy of the identified model using the subspace modeling technique with the EMT model. NRMSE is used to facilitate the comparison. The formula for NRMSE is shown below [8].

$$NRMSE = \frac{||\hat{y}(t) - y(t)||_2}{\sqrt{N}(\max(y(t)) - \min(y(t)))} \times 100\% \quad (11)$$

where $||.||_2$ is defined as the Euclidean norm, $\hat{y}(t)$ refers to estimates, $y(t)$ refers to true values, and N refers to the number of data points.

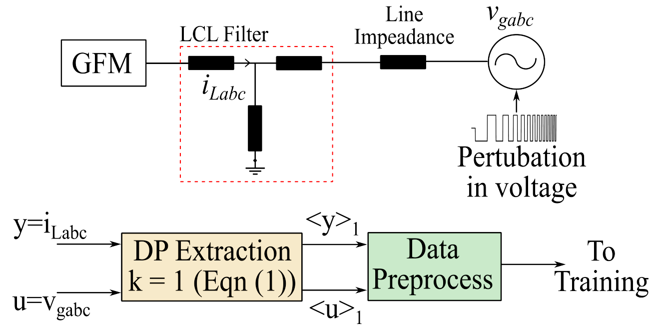

Fig. 3: Simulation setup for data collection and training to obtain a state space model

TABLE I: Summary of Simulation Parameters

Parameter	Value
R_f	0.01 Ω
L_f	2.988×10^{-5} H
C_f	6.2679×10^{-4} F
R_{fg}	0.01 Ω
L_{fg}	2.58×10^{-6} H
R_{line}	4.232×10^{-4} Ω
L_{line}	4.49×10^{-5} H
Base Voltage	460 V
Base Power	1 MVA

III. Simulation Setup

Fig. 3 illustrates the simulation setup used for input–output data collection to parameterize the DP model of the GFM inverter. An averaged GFM inverter connected to an infinite bus is employed in MATLAB/Simulink for dataset generation. The inverter parameters are summarized in Table I. A logarithmic square chirp signal was used to perturb the amplitude of each phase at infinite bus voltage. The frequency of the perturbation signal varied from 0.2Hz to 3Hz, and the amplitude was 0.1pu. The perturbation was applied around 1pu magnitude at each phase. Although the same perturbation signal was applied to all the phases, a 1-second delay was added at phase B perturbation and a 2-second delay at phase C to create unbalanced dynamics. Applying uneven perturbations to each phase enables the model to learn the coupling dynamics among phases, thereby capturing uneven transient behaviors across them. The model output corresponds to the inverter current.

Both input and output datasets were collected in the *abc* domain and subsequently processed to extract their DPs using (1). The simulation step size was set to 1×10^{-4} s, and the fundamental frequency for the DP computation was 60 Hz. The model was simulated for 15 s, after which the DPs of the input and output signals were extracted. Due to the sliding-window implementation, a delay of T seconds appears in the dataset; this delay was compensated for, and the data were detrended to remove the mean components. Finally, the N4SID algorithm from MATLAB's System Identification Toolbox was employed to obtain a state-space model from the preprocessed input–output dataset.

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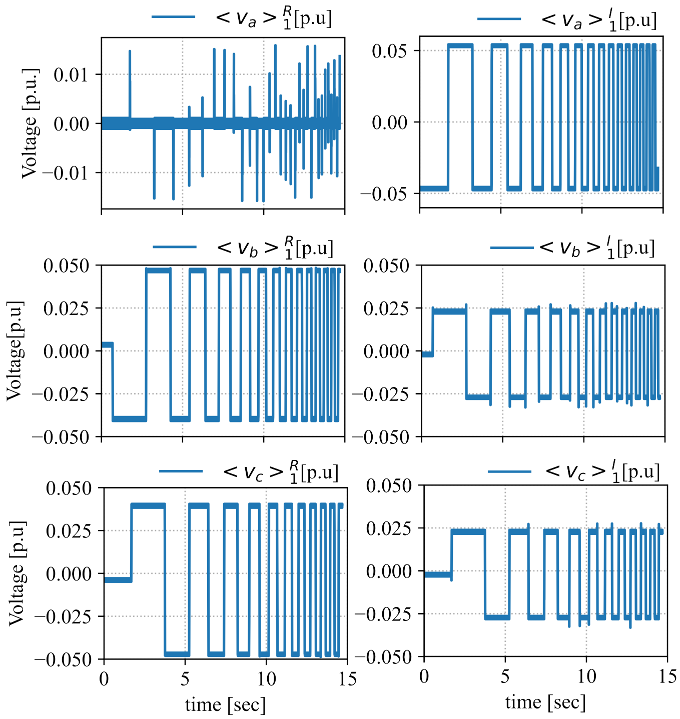

Fig. 4: DPs of infinite bus voltage when its amplitude is perturbed with a logarithmic square chirp signal

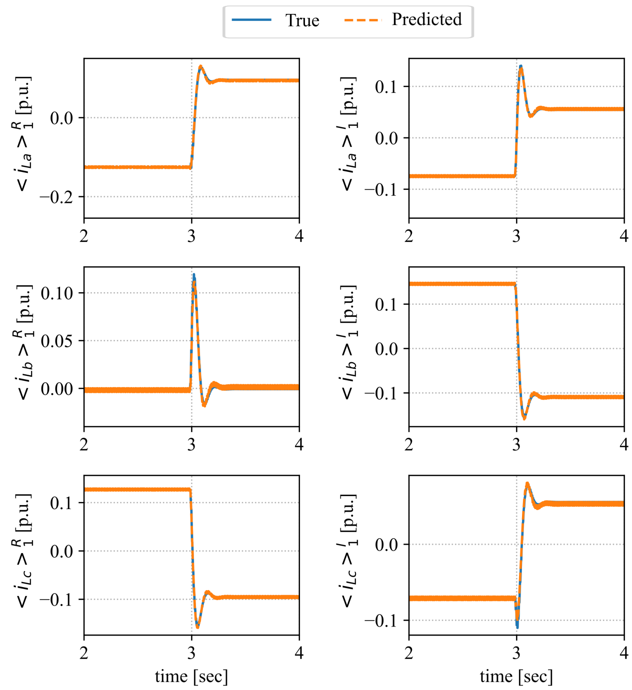

Fig. 5: True and Predicted Current from the inverter when all phases of infinite bus voltage were stepped up by 0.05pu at 3 s.

IV. Results and Discussion

Fig. 4 represents the DPs of the input data used for training purposes. Since DPs of input and output datasets were used, the identified model is a MIMO system with six inputs and six outputs (the DP of each phase has its own real and imaginary part). Only the first harmonic of the DP was considered, as this paper aims to capture the unbalanced dynamics of the GFM in the DP-ABC domain. The model was trained on orders ranging from 1 to 18, and the best-fitting order was selected as 18. The model was tested with 25 step changes between -0.1 and 0.1 pu at each phase, and it showed nearly identical accuracy across all step changes, highlighting its robustness across varying test cases. However, only one set of changes is shown in figure. 5, 6, and 7. Additionally, the validation of these test sequences was performed using the ControlSystems.jl library in Julia. The model was also validated with two different initial conditions, as explained below.

- Case I: Balanced operating point with balanced dynamics
  To test the model for a balanced case, a step change of 0.05 pu is applied to the voltage of all the phases at 3 seconds. Initially, all phases are at the same operating points, i.e., 1 pu. Fig. 5 represents how well the actual output matches the predicted output for the balanced condition, and NRMSE is also tabulated in the Table. II.
- Case II: Balanced operating point with unbalanced dynamics
  Fig. 6 represents the validation of the model at a random step change in voltage amplitude at each phase. Phase A is applied with a 0.08 pu voltage step at 3 seconds, phase B with a -0.08 pu step at 4 seconds, and phase C with a 0.04 pu step at 5 seconds. Initially, all phases were at 1pu voltage before the step changes. Each phase exhibits distinct dynamics at different time steps, which the identified state-space model captures very accurately. When only phase A experienced a step change at 3 seconds, the dynamics of Phases B and C were affected by coupling between the phases, as captured by the identified model. The NRMSE for this uneven dynamic scenario is tabulated in Table II.
- Case III: Unbalanced operating point with unbalanced dynamic change
  Fig. 7 represents the validation of the model at a random step change in voltage amplitude at each phase when the phases were initially at different operating points. Phase A is applied with a 0.08 pu voltage step at 3 seconds, phase B with a -0.08 pu step at 4 seconds, and phase C with a 0.04 pu step at 5 seconds. Initially, phase A was operating at 0.98 pu, phase B at 1 pu, and phase C at 0.96 pu. Each phase exhibits distinct dynamics at different time steps, which the identified state-space model captures very accurately. The NRMSE for this uneven dynamic scenario is tabulated in Table II.

The trained data-driven model accurately identifies GFM dynamics in both heavily unbalanced grid conditions and the dynamic modification of the unbalanced operating point.

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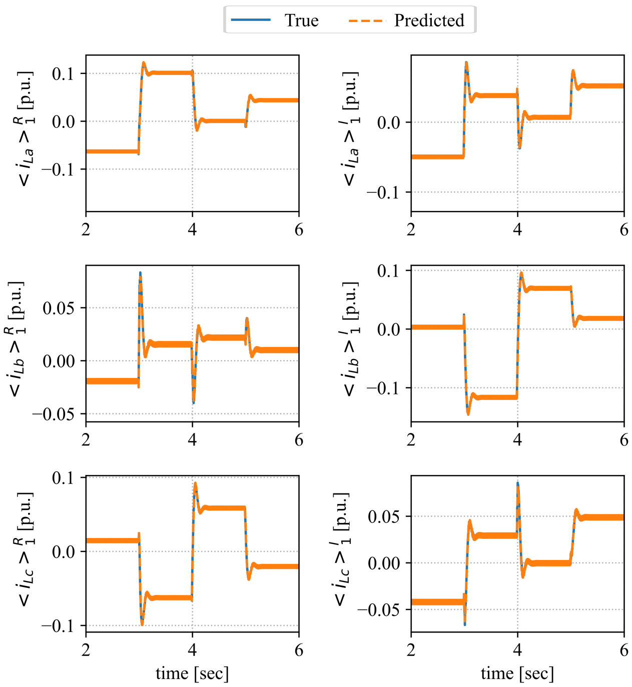

Fig. 6: True and Predicted Current from the inverter when Phase A of infinite bus voltage was stepped up by 0.08pu at 3 s, phase B stepped down by 0.08 pu at 4 s and phase C stepped up by 0.04 pu at 5 s. Initially, all phases were at the same operating points.

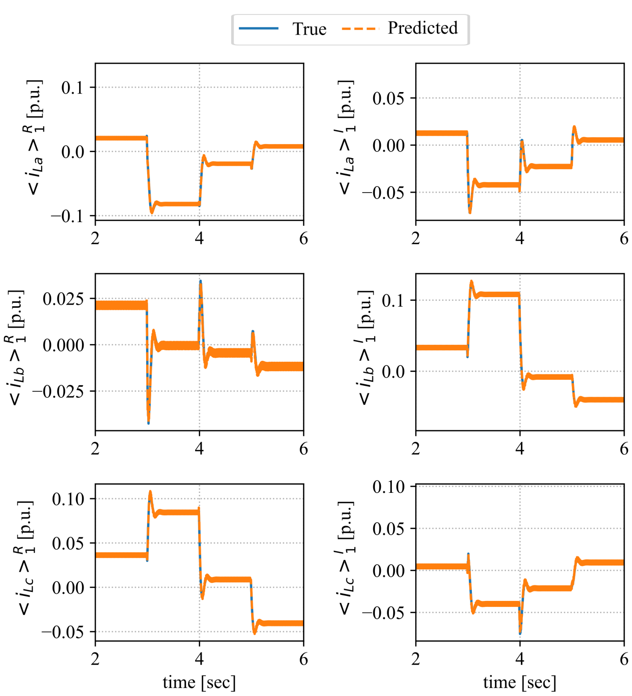

Fig. 7: True and Predicted Current from the inverter when Phase A of infinite bus voltage was stepped up by 0.08pu at 3 s, phase B stepped down by 0.08 pu at 4 s and phase C stepped up by 0.04 pu at 5 s. Initially, each phase was at a different operating point

V. Conclusion and Future Work

This paper evaluates the capability of a system-identified model of the GFM inverter in the DP domain to capture both balanced and unbalanced dynamics. This approach leverages both DD and DP modeling techniques to parameterize a DP model through subspace identification. It enabled a compact, efficient, and computationally tractable model that does not require any system information. This type of model can be beneficial for studying the system dynamics and stability to ensure a reliable power supply. The cross-platform validation with various test cases, including unbalanced initial conditions and unbalanced dynamic changes, emphasizes the robustness and precise identification of the underlying DP dynamics. This demonstrates the performance of DD modeling in representing complex DP systems, including unbalanced dynamics. In the future, the DP-DD technique can be utilized to model various power system components, capturing harmonic impacts and operating over a wide range of operating points.

TABLE II: NRMSE for Balanced and Unbalanced Dynamics

	Balanced Operating Points		**Unbalanced Operating Points**
	Balanced	**UnBalanced**	**Unbalanced**
$\langle i_{La}\rangle_1^R$	0.68 %	0.79 %	0.768 %
$\langle i_{La}\rangle_1^I$	0.70 %	1.017 %	0.957 %
$\langle i_{Lb}\rangle_1^R$	1.29 %	1.18 %	1.954 %
$\langle i_{Lb}\rangle_1^I$	0.60 %	0.735 %	0.991 %
$\langle i_{Lc}\rangle_1^R$	0.40 %	0.768 %	0.963 %
$\langle i_{Lc}\rangle_1^I$	1.13 %	1.12 %	1.184 %

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