IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 18, 2020, accepted December 28, 2020, date of publication January 5, 2021, date of current version February 1, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3049237

A Greener Meta-Heuristics Scheduling Algorithm With Energized Optimization Dynamics by Deeper Intelligence Fusion

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This work was supported in part by the National Natural Science Foundation of China under Grant 61702248, Grant 61070017, and Grant 61272094; in part by the National High Technology Research and Development Program of China under Grant 2006AA01A113 and Grant 2012AA01A306; and in part by the Talent Introduction Project of Ludong University under Grant LB2016015.

ABSTRACT As is known to all, the heterogeneous green scheduling objects have the intelligent feedback related to the efficiencies corresponding to the schemes, which has been largely ignored in most existing studies. That is why the existing optimization dynamics in green meta-heuristics scheduling algorithms, generally appear underpowered and vulnerable in the face of the rapid extension from homogeneity to heterogeneity of scheduling objects. Then, with respecting and ingeniously leveraging hardware (i.e., heterogeneous scheduling objects) intelligence, an efficient meta-heuristics algorithm with re-energized majorization dynamics for heterogeneous greener scheduling (i.e., CA^r_FI(HS)), is proposed. The experimental results show that compared with the other meta-heuristics scheduling algorithms, CA^r_FI(HS) has obvious advantages in the overall performance and the solution quality, for both data intensive and computing intensive instances.

INDEX TERMS Greener, energized optimization dynamics, fusion intelligence, meta-heuristics algorithm, nonlinear heterogeneous scheduling.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Nowadays, fundamental saving energy or reducing emissions of the wide-area heterogeneous computing, represented by the virtual cloud, is the goal that is far from achieved [1]. In fact, the intelligent decision-making of the scheduling middleware is key, where green scheduling aims for the computing evolution from high performance to high efficiency. For green scheduling as the high-dimensional multi-objective optimization problems under the strong restriction in the real complex super-system, meta-heuristics algorithms like genetic algorithms and artificial immune algorithms, have been used [2], [3]. Although with many achievements in homogeneous scheduling, meta-heuristics algorithms are underperforming in the nonlinear heterogeneous green scheduling, with the balance conflict between convergence and distribution [4]–[6].

The associate editor coordinating the review of this manuscript and approving it for publication was Xiangtao Li.

Here, the optimization dynamic equation in the meta-heuristics algorithm, close to the scheduling QoS (Quality of Service) model, is constructed from various QoS metrics, such as some technology or economy indexes. However, most of the existing QoS metrics related to the energy-efficiencies, are quantified via fuzzy estimation [7], [8] or approximate linear mathematical models [9], [10]; even some other equations are only the "electricity-price optimizers" [11], [12].

Then, in the face of the rapid extension from homogeneity to heterogeneity of computing resources, the existing optimization dynamics in meta-heuristics scheduling algorithms, generally appear underpowered and vulnerable [13], [14].

In fact, distinguished from homogeneous scheduling, heterogeneous objects have hardware intelligence [15], [16]. To be exact, derived from hardware intelligence, there are some inevitable and logical relationships between every candidate scheduling scheme and the physical feedback; and nonlinearity and heterogeneity of the allocated resources mean a big discrepancy in the dynamic effects between different scheduling schemes, such as the energy-efficiencies related.

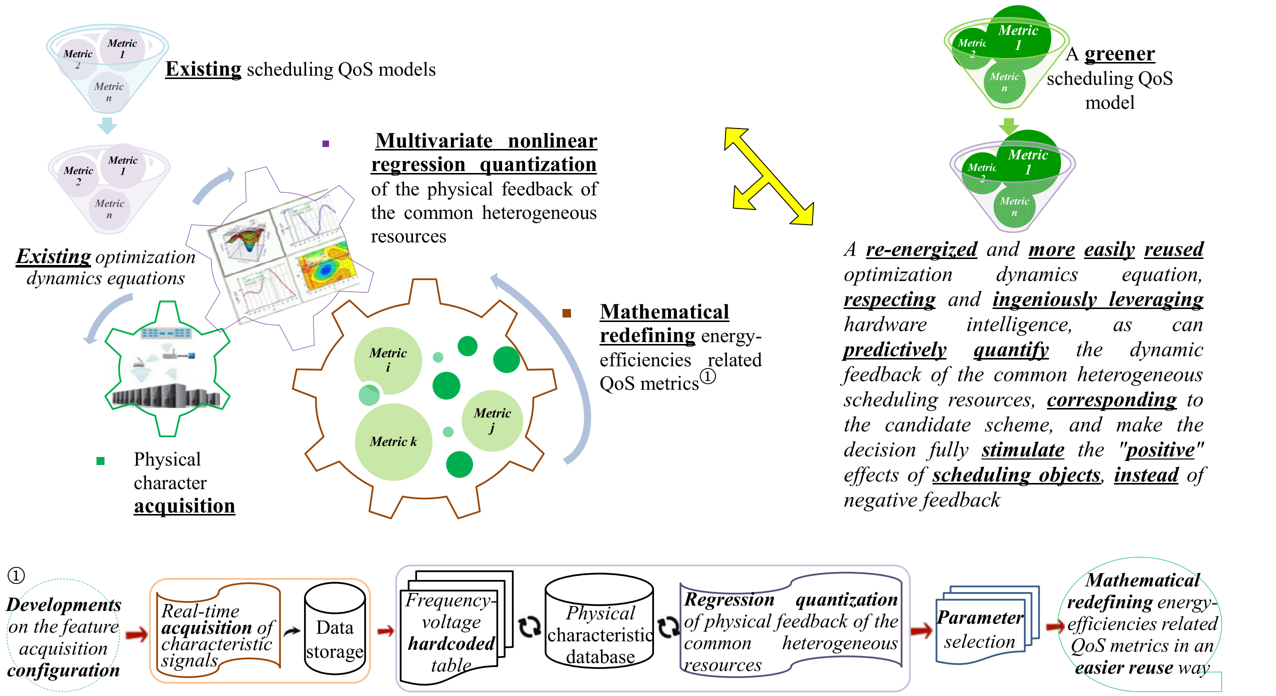

FIGURE 1. The technical route to energize the optimization dynamics of meta-heuristics scheduling algorithms.

Therefore, our idea is to energize the optimization dynamics of meta-heuristics scheduling algorithms in the green direction with respecting and ingeniously leveraging hardware intelligence, and then make the soft decision fully stimulate the "positive" effects of heterogeneous objects, instead of negative feedback.

Then, an efficient meta-heuristics algorithm for greener heterogeneous scheduling driven by deeper fusion of hardware and software intelligence, is proposed, i.e., CA^r_FI(HS).

B. OUTLINING

The rest of the paper is organized as follows: Section 2 outlines the related work. In Section 3, an efficient meta-heuristics algorithm, i.e., CA^r_FI(HS), is presented. Performance evaluations and the analyses of the algorithms are discussed in Section 4. Section 5 concludes the paper with a summary and future work.

II. RELATED WORK

Systematically, the computing evolution from high-performance to high-efficiency, partly benefits from hardware modes and methods.

One of the growing trends is heterogeneous multicore/many-core systems in accelerating super-scale scientific computing. This trend is due to the greatly improved throughput for higher efficiencies, however, the rapid increase of the power density narrowing the bottleneck of chip cooling [17].

There is another upward trend, as is the intellectualization of the hardware. Involving circuit or microelectronic level, there are many landmark achievements, such as DPM (Dynamic Power Management) and DVFS (Dynamic Voltage Frequency Scaling) [18].

However, there is a considerable green space that cannot be touched by physics regulation although with hardware intelligence, such as DPM and DVFS.

① DVFS and DPM can make a minimum number of components active; however, CMOS (Complementary-symmetry Metal Oxide Semiconductor) circuits even at idle states can bring approximately 60% of the energy consumption at full load to cloud nodes.

② For the heterogeneous processors corresponding to different frequency-voltage levels, there is an extreme dispersion in power consumption even at the same working frequency, which means that the cloud efficiency largely depends on the scheduling middleware.

Actually, the scheduling middleware including the model and algorithm is to make decisions on the mapping between computing services and the hardware cloud, with some QoS (Quality of Service) metrics satisfied. Further, the energy-aware scheduling is to minimize the energy consumption of the cloud services, without affecting the performance. In essence, the energy-aware scheduling is NP-Complete problem of high-dimensional multi-objective optimization with strong constraints.

Some works related to energy-aware homogeneous scheduling have gained results; however, there still are many limitations for the software methods of heterogeneous green scheduling.

① Many explorations turn to virtual management upgrading, using Gaussian process regression method, multi-dimensional packing mode or integer programming strategy;

TABLE 1. The theory developments of the algorithm design in this paper based on GHSA_di [2].

①	Focusing on the **software and hardware bidirectional fusion of highly intelligent driver**, the greener algorithm is addressed in this paper, i.e., **CA^r_FI(HS)**, while in [31], the algorithm **incarnating deep integration of hardware-software energy regulation principles** for heterogeneous scheduling, i.e., **GHSA_di**[31], was proposed.
②	The **parameters** involved and shown in **Table II** in **Section 3.A** in this paper, are **easier to obtain**, **more representative** and **as few as possible**, which is **more suitable** for the real-time, dynamic and particularity of heterogeneous scheduling deployment stage, and is obtained by means of exploring the explicit and implicit relationships of nonlinear circuit characteristics.
③	The **reuse** of QoS definitions in the dynamic equation of **CA^r_FI(HS)** in **Section 3.A** in this paper is **much easier**.
④	The technical route to energize the optimization dynamics of **CA^r_FI(HS)** is **firstly** given as **Figure 1** in **Section 3.A** in this paper, including the predictive quantification the dynamic feedback of the common heterogeneous resources, corresponding to the candidate scheme, and mathematical redefinition the energy-efficiencies related QoS metrics in an easier reuse way.
⑤	Based on three dimensional matrices encoding in **Section 3.B** in this paper, evolutionary operator-definitions in **Section 3.C**, such as individual selection, crossover, mutation and clone, are described in detail for the **first** time.

however, due to the information asymmetry, these fuzzy decisions have little effect on saving energy in the dynamical adjusting virtual clusters [19], [20].

② Based on the volatility of the electricity price in the world time-zones, some discoveries get the scheduling sequence of clusters in different time-zones via the large deviation principle or Markov decision. They are electricity-price-optimizers, which significantly decrease the maintenance costs, but cannot fundamentally reduce energy-consumption [11], [12].

③ Derived from empirical statistics or linear models, most of the energy-consumption estimates generally lack accuracy or timeliness, when facing the dynamic randomicity of real-time tasks and the heterogeneity extension of cloud platforms [9], [10].

In recent years, with high intelligence, strong robustness and good optimization ability, heuristics or meta-heuristics algorithms have been attempted to solve cloud scheduling problems; this kind of technology simulates Darwin's "survival of the fittest" theory of natural evolution or biological immunity [21]–[28]. And there are many achievements of the meta-heuristics algorithms applied in the homogeneous scheduling.

In [28], the green problem was regarded as the Distributed Assembly Blocking Flow-shop Scheduling, abbreviated as DABFSP, and the metaheuristic algorithm is applied to it; for DABFSP [28], all processed jobs are assembled into a series of products on an assembly machine and even there are no intermediate buffers between any adjacent machines. In [29], a clustering-based meta-heuristics algorithm, i.e., MaOEA/C, was suggested for many-objective optimization problems; MaOEA/C [29] balanced the diversity and convergence by classifying the population into a number of clusters. In [30], the parallel branch and bound algorithm was presented, i.e., MBB, for the optimality of the multi-objective flexible job shop scheduling problem; MBB [30] made use of NSGA-II algorithm to initialize the upper bound and incorporated a grid representation of the solution space; and according to the optimal Pareto front of MBB [30], it is useful for the scientific community.

In [2], the algorithm incarnating deep integration of hardware-software energy regulation principles for heterogeneous scheduling, i.e., GHSA_di [2], was proposed. In a word, literature [2] belongs to the preliminary work of this paper; and this paper is its further expansion and extension, no matter the radiation breadth, theoretical depth, difficulty in tackling key problems or innovation height, which are listed in **Table 1**.

III. AN EFFICIENT NONLINEAR HETEROGENEOUS GREEN SCHEDULING ALGORITHM

A. THE ENERGIZED OPTIMIZATION DYNAMICS EQUATION

The technical route is given as **Figure 1**, including the predictive quantification the dynamic feedback of the common heterogeneous resources, corresponding to the candidate scheme, and mathematical redefinition the energy-efficiencies related QoS metrics in an easier reuse way.

Definition 1 (Dynamic Power Consumption (in W)): Several frequencies of CPU functioning are allowed on every node. Indeed, there are great differences in dynamic power consumption (in W) between distinguished processor types based on energy heterogeneity even at the same working frequency.

TABLE 2. The related variables of meta-heuristics dynamic equation and their representative meanings.

Symbol	Description
o	Processor type based on energy heterogeneity
φ_γ^o	Current working frequency of Processor $o \in N^+$
v^o	The coefficient of the processor load at Frequency φ_γ^o
$\tau_{full}(\varphi_\gamma^o)$	The power consumption (in W) of the processor with full load running at Frequency φ_γ^o by manual intervention
$\tau_{idle}(\varphi_\gamma^o)$	The power consumption (in W) of the processor with no load running at Frequency φ_γ^o by manual intervention
$\tau(\varphi_\gamma^o)$	The power consumption (in W) of the processor running at Frequency φ_γ^o
η_o^θ	The number of the different DVFS levels for the processor type $o \in N^+$ based on energy heterogeneity
η_ρ	The number of the clusters
η_ω^ρ	The number of computing nodes in Cluster $\rho \in N^+$
ΔT_γ^o	Execution time of Processor $o \in N^+$ at Frequency φ_γ^o
$\eta_\varpi^{\rho\omega}$	The number of virtual machines running on Node $\rho_\omega \in R^+$
ξ^ϖ	The instruction number (in million)
$\varepsilon_{\varphi_\gamma^o}^{\varpi,\rho\omega}$	The capacity of each virtual machine (for example, in terms of million instructions per second (MIPS))
$\delta_O^{\rho_\omega}$	The maximum CPU capacity allowed of Node $\rho_\omega \in R^+$
ϕ	The candidate solution of the meta-heuristics scheduling algorithm, i.e., candidate scheduling scheme
$CMP\_E(\phi)$	The dynamic energy consumption (in Wh) of all nodes powering on
$RESP\_T(\phi)$	The execution time of the virtual machines (VMs)
$SCAL\_R(\phi)$	The available computing power without new nodes
$HW\_REL(\phi)$	The average number of VMs deployed in per used node
$No\_VM(\phi)$	The number of the temporary migrated virtual machine
Λ_i	The weight factor of the QoS metric
$\psi(\phi)$	The dynamic equation of the meta-heuristics scheduling algorithm

By the above multivariate-regression methods, for the processor type based on energy heterogeneity (denoted by $o \in N^+$) at Frequency φ_γ^O, the dynamic power consumption (in W) is given by **Eq. (1)**.

$$\tau(\varphi_\gamma^O) = v^o(\tau_{full}(\varphi_\gamma^O) - \tau_{idle}(\varphi_\gamma^O)) + \tau_{idle}(\varphi_\gamma^O) \quad (1)$$

Definition 2 (Dynamic Energy Consumption (in Wh)): For the processor type based on energy heterogeneity (denoted by $o \in N^+$) at Frequency φ_γ^O, the dynamic energy consumption (in Wh) is the product of power values (in W) and execution time (denoted by ΔT_γ^O).

Following that, the dynamic energy consumption (in Wh) of all nodes powering on, contains the different DVFS levels, where $\eta_O^\theta \in N^+$ is the number of levels for the processor type $o \in N^+$ based on energy heterogeneity.

This gives the dynamic energy consumption (in Wh) of all nodes powering on.

$$CMP\_E(\phi) = \sum\nolimits_{\rho=1}^{\eta_\rho} \sum\nolimits_{\omega=1}^{\eta_\omega^\rho} \sum\nolimits_{\gamma=1}^{\eta_O^\theta} (\tau(\varphi_\gamma^O) \times \Delta T_\gamma^O) \quad (2)$$

Definition 3 (Response Time): In same consideration of CPU capacity, the response time considered as the execution time of virtual machines (VMs), denoted by $RESP\_T(\phi)$, can be evaluated by the instruction-number (in million, denoted by ξ^ϖ, and the capacity of each virtual machine (for example, in terms of million instructions per second (MIPS)), denoted by $\varepsilon_{\varphi_\gamma^O}^{\varpi,\rho\omega}$.

Then, response time, denoted by $RESP\_T(\phi)$, can be expressed (in seconds) as **Eq. (3)**.

$$RESP\_T(\phi) = \max_{\rho=1}^{\eta_\rho} \max_{\omega=1}^{\eta_\omega^\rho} \max_{\varpi=1}^{\eta_\varpi^{\rho\omega}} (\xi^\varpi / \varepsilon_{\varphi_\gamma^O}^{\varpi,\rho\omega}) \quad (3)$$

Definition 4 (Scalability): One of the most important flexibility factors, represents the available computing power without new nodes, leading the cloud provider not to consolidate VMs on nodes for a certain amount of latent capacities in case of a peak load.

It can be evaluated based on the maximum CPU capacity allowed of Node $\rho_\omega \in R^+$, denoted by $\delta_O^{\rho_\omega}$, and the current CPU capacity allowed of Node $\rho_\omega \in R^+$.

Then, scalability, denoted by $SCAL\_R(\phi)$, can be expressed as **Eq. (4)**.

$$SCAL\_R(\phi)=\{\sum\nolimits_{\rho=1}^{\eta_\rho} \sum\nolimits_{\omega=1}^{\eta_\omega^\rho} (\delta_O^{\rho_\omega} - \varepsilon_{\varphi_\gamma^O}^{\varpi,\rho\omega})\}/(\sum\nolimits_{\rho=1}^{\eta_\rho} \eta_\omega^\rho) \quad (4)$$

Definition 5 (Robustness): One of the most important stability factors with resistance to host or network failure and malicious attacks, is interpreted as how many VMs should be transplanted if Node $\rho_\omega \in R^+$ fails.

In other words, it is the average number of VMs deployed in per used node, expressed as **Eq. (5)**.

$$HW\_REL(\phi) = (\sum\nolimits_{\rho=1}^{\eta_\rho} \sum\nolimits_{\omega=1}^{\eta_\omega^\rho} \eta_\varpi^{\rho_\omega})/(\sum\nolimits_{\rho=1}^{\eta_\rho} \eta_\omega^\rho) \quad (5)$$

Taken together, the QoS metrics are applied the fitness or affinity evaluation of chromosomes or antibodies in the following intelligent algorithms, defined as **Eq. (6)**, where Λ_i respectively represents the weight factor of the QoS indicator.

$$\begin{aligned}\psi(\phi) = \min_{\phi\in\Phi}[&\Lambda_1 \cdot CMP\_E(\phi) + \Lambda_2 \cdot RESP\_T(\phi) \\ &+ \Lambda_3 \cdot HW\_REL(\phi) - \Lambda_4 \cdot SCAL\_R(\phi) \\ &- \Lambda_5 \cdot No\_VM(\phi)]\end{aligned} \quad (6)$$

Following that, in order for adding the sufficient meta-heuristics dynamics to CA^r_FI(HS), the first three QoS metrics: $CMP\_E(\phi)$, $RESP\_T(\phi)$, and $HW\_REL(\phi)$ have to be minimized, as opposed to $SCAL\_R(\phi)$ and $No\_VM(\phi)$ that have to be maximized.

Another feature of the dynamics equation is the compromise coefficients of the QoS metric. Here, the compromise coefficients can be tailored due to preference for relevant indicators.

B. THREE-DIMENSIONAL ENCODING/DECODING OF THE BIONIC INDIVIDUALS

Definition 6 (Biomimetic Individual): A scheduling candidate scheme mapping among the tasks $\{\boldsymbol{Xi^r}(\boldsymbol{i} \in \{1,\ldots,\boldsymbol{m}\}, \boldsymbol{r} \in \mathrm{R}^+)\}$, the virtual machines $\{\boldsymbol{Yi^r}(\boldsymbol{i} \in \{1,\ldots,\boldsymbol{m}\}, \boldsymbol{r} \in \mathrm{R}^+)\}$ and the nodes $\{\boldsymbol{Zi^r}(\boldsymbol{i} \in \{1,\ldots,\boldsymbol{m}\}, \boldsymbol{r} \in \mathrm{R}^+)\}$, is regarded as a biomimetic individual $\boldsymbol{Ch_r}(\boldsymbol{r} \in \mathrm{R}^+)$.

Specifically, the gene feature $\{\boldsymbol{Gi^r}(\boldsymbol{i} \in \{1,\ldots,\boldsymbol{m}\}, \boldsymbol{r} \in \mathrm{R}^+)\}$ of $\boldsymbol{Ch_r}(\boldsymbol{r} \in \mathrm{R}^+)$ is expressed as the three-dimensional encoding, which represents the random task $\boldsymbol{Xi^r}(\boldsymbol{i} \in \{1,\ldots,\boldsymbol{m}\}, \boldsymbol{r} \in \mathrm{R}^+)$ is assigned to the virtual machine $\boldsymbol{Yi^r}(\boldsymbol{i} \in \{1,\ldots,\boldsymbol{m}\}, \boldsymbol{r} \in \mathrm{R}^+)$ of the computing node $\boldsymbol{Zi^r}(\boldsymbol{i} \in \{1,\ldots,\boldsymbol{m}\}, \boldsymbol{r} \in \mathrm{R}^+)$.

So the biomimetic individual $\boldsymbol{Ch_r}(\boldsymbol{r} \in \mathrm{R}^+)$ is encoded as three-dimensional matrices (see **Eq. (7)**and**Figure 2**).

$$\boldsymbol{Ch_r} = \begin{bmatrix} X_1^r & Y_1^r & Z_1^r \\ X_2^r & Y_2^r & Z_2^r \\ \vdots & \vdots & \vdots \\ X_i^r & Y_i^r & Z_i^r \\ \vdots & \vdots & \vdots \\ X_m^r & Y_m^r & Z_m^r \end{bmatrix} \tag{7}$$

C. EVOLUTIONARY OPERATOR-DEFINITIONS

Based on three dimensional matrices encoding in **Section 3.B**, genome evolution simulation includes the definition of intelligent operators, such as individual selection, crossover, mutation and clone.

According to the evolutionary dynamic information matrix defined in **Section 3.A**, the **CA$^\mathbf{r}$_FI(HS)** algorithm can directly select non inferior bionic individuals in the population, which greatly improves the efficiency of the algorithm.

Different strategies of gene crossover and mutation can help to maintain the diversity of population, and to cooperate or exchange information among bionic individuals.

Definition 7 (Crossover Operator): Crossover operator, denoted by $\otimes$, is dualistic, whose two operands $(\boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+})$ and $\boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+}))$ and results $(\{\boldsymbol{Ch_c}(\boldsymbol{c} \in \boldsymbol{R^+}), \boldsymbol{Ch_d}(\boldsymbol{d} \in \boldsymbol{R^+})\})$, respectively, represent the original and new biomimetic individuals (scheduling schemes).

In a random fashion, the original biomimetic individuals $(\boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+})$ and $\boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+}))$ are chosen and grouped together; and by the crossover point randomly generated, each original individual $(\boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+})$ or $\boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+}))$ can be divided into two genomes:

$\boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+}) = \{\{\boldsymbol{G_i^a}(\boldsymbol{i} = \{1\cdots\boldsymbol{\sigma}\}, \boldsymbol{a} \in \boldsymbol{R^+})\} \subset \boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+}), \{\boldsymbol{G_i^a}(\boldsymbol{i} = \{\boldsymbol{\sigma}+1\cdots\boldsymbol{m}\}, \boldsymbol{a} \in \boldsymbol{R^+})\} \subset \boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+})\}$ *and* $\boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+}) = \{\{\boldsymbol{G_i^b}(\boldsymbol{i} = \{1\cdots\boldsymbol{\sigma}\}, \boldsymbol{b} \in \boldsymbol{R^+})\} \subset \boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+}), \{\boldsymbol{G_i^b}(\boldsymbol{i} = \{\boldsymbol{\sigma}+1\cdots\boldsymbol{m}\}, \boldsymbol{b} \in \boldsymbol{R^+})\} \subset \boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+})\}$.

Then new individuals $(\{\boldsymbol{Ch_c}(\boldsymbol{c} \in \boldsymbol{R^+}), \boldsymbol{Ch_d}(\boldsymbol{d} \in \boldsymbol{R^+})\})$ are generated by crossover combinations of different individual genomes:

$\boldsymbol{Ch_c}(\boldsymbol{c} \in \boldsymbol{R^+}) = \{\{\boldsymbol{G_i^a}(\boldsymbol{i} = \{1\cdots\boldsymbol{\sigma}\}, \boldsymbol{a} \in \boldsymbol{R^+})\} \subset \boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+}), \{\boldsymbol{G_i^b}(\boldsymbol{i} = \{\boldsymbol{\sigma}+1\cdots\boldsymbol{m}\}, \boldsymbol{b} \in \boldsymbol{R^+})\} \subset \boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+})\}$ *and*

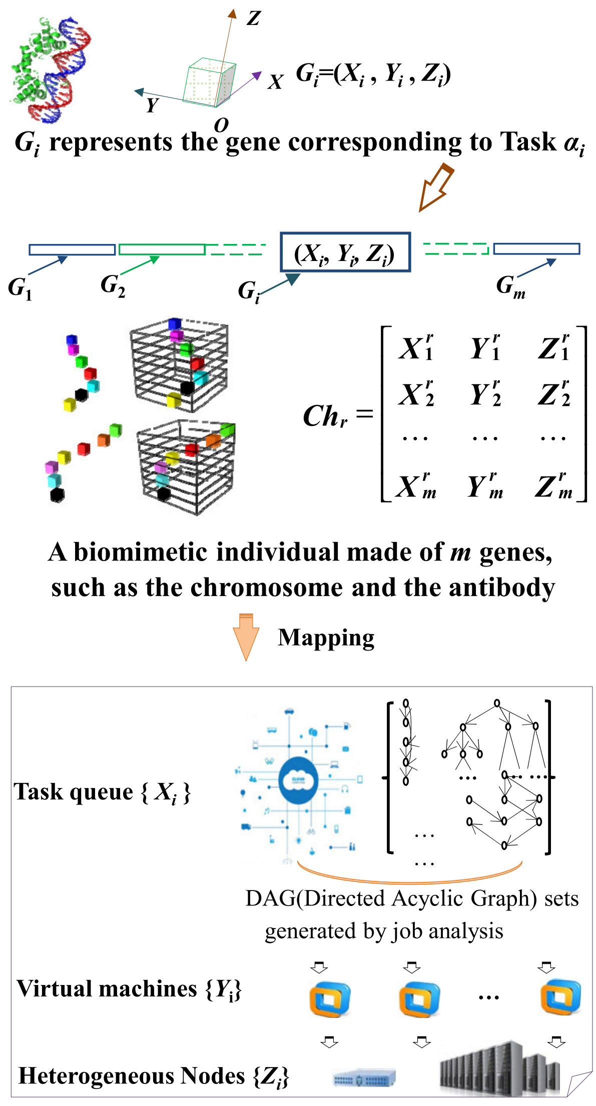

FIGURE 2. Three-dimensional encoding/decoding of the bionic individuals.

$\boldsymbol{Ch_d}(\boldsymbol{d} \in \boldsymbol{R^+}) = \{\{\boldsymbol{G_i^b}(\boldsymbol{i} = \{1\cdots\boldsymbol{\sigma}\}, \boldsymbol{b} \in \boldsymbol{R^+})\} \subset \boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+}), \{\boldsymbol{G_i^a}(\boldsymbol{i} = \{\boldsymbol{\sigma}+1\cdots\boldsymbol{m}\}, \boldsymbol{a} \in \boldsymbol{R^+})\} \subset \boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+})\}$.

*Following that, the crossover operation of $\boldsymbol{Ch_a}(\boldsymbol{a} \in \boldsymbol{R^+})$ and $\boldsymbol{Ch_b}(\boldsymbol{b} \in \boldsymbol{R^+})$ is given by **Eq.(8)**.*

$$\begin{bmatrix} X_1^a & Y_1^a & Z_1^a \\ \cdots & \cdots & \cdots \\ X_\sigma^a & Y_\sigma^a & Z_\sigma^a \\ \cdots & \cdots & \cdots \\ X_m^a & X_m^a & X_m^a \end{bmatrix} \otimes \begin{bmatrix} X_1^b & Y_1^b & Z_1^b \\ \cdots & \cdots & \cdots \\ X_\sigma^b & Y_\sigma^b & Z_\sigma^b \\ \cdots & \cdots & \cdots \\ X_m^b & X_m^b & X_m^b \end{bmatrix} = \left\{ \begin{bmatrix} X_1^a & Y_1^a & Z_1^a \\ \cdots & \cdots & \cdots \\ X_\sigma^b & Y_\sigma^b & Z_\sigma^b \\ \cdots & \cdots & \cdots \\ X_m^b & X_m^b & X_m^b \end{bmatrix}, \begin{bmatrix} X_1^b & Y_1^b & Z_1^b \\ \cdots & \cdots & \cdots \\ X_\sigma^a & Y_\sigma^a & Z_\sigma^a \\ \cdots & \cdots & \cdots \\ X_m^a & X_m^a & X_m^a \end{bmatrix} \right\} \tag{8}$$

Definition 8 (Mutation Operator): Mutation operator, denoted by $\odot$, is unary, whose operands $(\boldsymbol{Ch_p}(\boldsymbol{p} \in \boldsymbol{R^+}))$ and

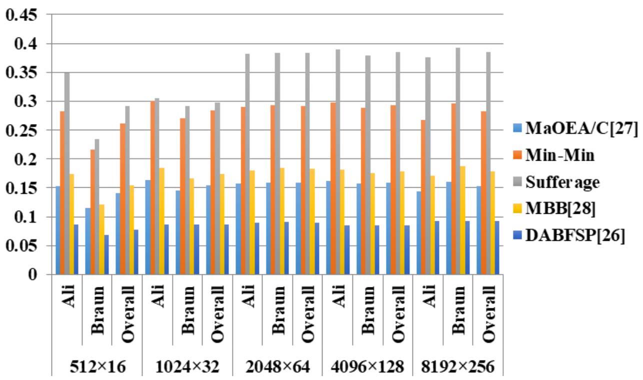

FIGURE 3. Averaged energy-efficiency improvements of the solution of CA^r_FI(HS) over the algorithms summarized for HCSP instances.

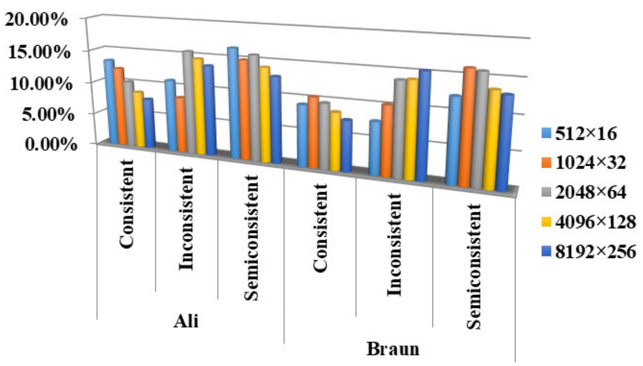

FIGURE 4. Improvements of CA^r_FI(HS) over the best deterministic heuristic results, regarding the consistency classification.

results ($Ch_q(q \in R^+)$), respectively, represent the original and new biomimetic individuals (scheduling schemes).

The original biomimetic individuals ($Ch_p(p \in R^+)$) is chosen with the mutation probability,0.28; and by the mutation point randomly generated, new individual ($Ch_q(q \in R^+)$) is automatically created with a mutation gene, denoted by $(X_\varsigma^q, Y_\varsigma^q, Z_\varsigma^q) \subset Ch_q(q \in R^+)$.

Then, the mutation operation of $Ch_p(p \in R^+)$ is given by ***Eq.(9)***.

$$\odot \begin{bmatrix} X_1^p & Y_1^p & Z_1^p \\ \cdots & \cdots & \cdots \\ X_\varsigma^p & Y_\varsigma^p & Z_\varsigma^p \\ \cdots & \cdots & \cdots \\ X_m^p & X_m^p & X_m^p \end{bmatrix} (Ch_p) = \begin{bmatrix} X_1^p & Y_1^p & Z_1^p \\ \cdots & \cdots & \cdots \\ X_\varsigma^q & Y_\varsigma^q & Z_\varsigma^q \\ \cdots & \cdots & \cdots \\ X_m^p & X_m^p & X_m^p \end{bmatrix} (Ch_q) \tag{9}$$

D. ALGORITHM DESCRIPTION

The main steps of the CA^r_FI(HS) algorithm are given as follows.

E. THE COMPLEXITY ANALYSIS OF THE ALGORITHM

Let's assume the size of the population is θ in each generation, and the variable dimension, the cloning multiples, constraint dimension, and the objective function dimension are, respectively, ***<001>***, ***£***,***<002>***, m.

Initialize the iteration (ι) and the subpopulation $\Xi(\iota) = \{Ch_1(\iota), Ch_2(\iota), \ldots, Ch_\epsilon(\iota), \ldots, Ch_\theta(\iota)\}$, each subpopulation of Θ individuals;
While ($\iota < \iota_{max}$) and (other termination criteria are not satisfied)
Do in parallel for each island /*Obtain coarse-grained model, one of parallel and distributed models */
$\iota = \iota + 1$;
Do in parallel /*Obtain master-slave model, another parallel model */
Evaluate genome fitness based on the dynamic equation (**Eq.(6)**) in the current subpopulation:
$\Gamma(Ch_r(\tau))(r \in R^+, Ch_r(\tau) \in \Xi(\tau))$;
Sort the individuals fitness: $\Gamma(Ch_r(\tau))(r \in R^+, Ch_r(\tau) \in \Xi(\tau))$,
and **save** the fittest individual Ch_{elite} (ι) in the external memory;
Perform local search strategies;
Perform gene operations, such as crossover and mutation defined as **Section 3.C**;
End Do in parallel
If $\iota = \tau$ (migration interval) **then**
Create Ψ_δ for the current subpopulation;
Send Ψ_δ to the neighboring subpopulation;
Receive Ψ_δ from the neighboring subpopulation;
Construct the founding subpopulation Ξ;
Select Θ individuals into Ξ;
Replace the subpopulation Ψ_δ with Ψ_δ^τ;
End If
End Do in parallel
End While
Output the best individual.

Complexity of calculating the genetic affinity value of the population: O(***£<001>θ***).

Complexity of cloning operation of the population: O(***<001>θ***).

Complexity of crossover operation of the population: O(***£<001>θ***/2).

Complexity of mutation operation of the population: O(***£<001>***θ).

Complexity of selecting the non-dominant solution set: $O((m+1)(<001>+1)\theta + \theta + m(<001>+1)^2\theta^2 + (m+1)(<001>+1)\theta \log_2((<001>+1)\theta))$.

Then, the time complexity of **CA^r_FI(HS)** algorithm is polynomial time.

Furthermore, because different definitions of evolution simulation in algorithms (CA^r_FI(HS) and GHSA_di[2]), there is the lower space complexity in CA^r_FI(HS).

IV. EXPERIMENT RESULTS AND DISCUSSION

Noteworthily, the large-scale nonlinear earthquake simulation software by the earth-system-science department of Tsinghua University and the high-performance-computing team of Shandong University, won 2017's ACM Gordon Bell

TABLE 3. Comparative makespan results: meta-heuristics for 512 × 16 HCSP instances.

Instance	GA	MA+TS	ACO+TS	PSO+TS	MBB[30]	MaOEA/C[29]	DABFSP[28]	CA^r_FI(HS)	t_B(ms)
u_c_hihi.0	**8050844.5**	**7530020.2**	**7700929.8**	**7497200.9**	**7448640.5**	**7461819.1**	**7381570.0**	**7218029.1**	**12**
u_c_hilo.0	**156249.2**	**153917.2**	**155334.8**	**154234.6**	**153263.3**	**153791.9**	**153105.4**	**144913.6**	**62**
u_c_lohi.0	**258756.8**	**245288.9**	**251360.2**	**244097.3**	**241672.7**	**241524.0**	**239260.0**	**231064.3**	**20**
u_c_lolo.0	**5272.3**	**5173.7**	**5218.2**	**5178.4**	**5155.0**	**5177.5**	**5147.9**	**5072.9**	**49**
u_i_hihi.0	**3104762.5**	**3058474.9**	**3186664.7**	**2947754.1**	**2957854.1**	**2952493.2**	**2938380.8**	**2833027.4**	**36**
u_i_hilo.0	**75816.1**	**75108.5**	**75856.6**	**73776.2**	**73692.9**	**73639.8**	**73387.0**	**71152.9**	**51**
u_i_lohi.0	**107500.7**	**105808.6**	**110620.8**	**102445.8**	**103865.7**	**102136.1**	**102050.6**	**99808.3**	**77**
u_i_lolo.0	**2614.4**	**2596.6**	**2624.2**	**2553.5**	**2552.1**	**2549.8**	**2541.4**	**2140.6**	**49**
u_s_hihi.0	**4566206**	**4321015.4**	**4424540.9**	**4162547.9**	**4168795.9**	**4198779.5**	**4103500.3**	**4031142.3**	**16**
u_s_hilo.0	**98519.4**	**97177.3**	**98283.7**	**96762**	**96180.9**	**96623.3**	**95787.4**	**93560.6**	**42**
u_s_lohi.0	**130616.5**	**127633**	**130014.5**	**123922**	**123407.4**	**123251.5**	**122083.3**	**120147.6**	**24**
u_s_lolo.0	**3583.4**	**3484.1**	**3522.1**	**3455.2**	**3450.5**	**3450.1**	**3433.5**	**3217.6**	**28**

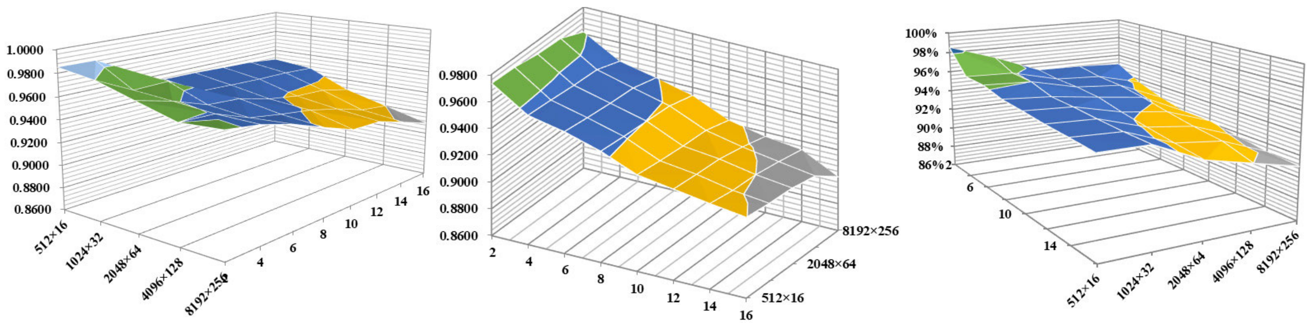

FIGURE 5. Mean values of the normalized energy-efficiency improvements of CA^r_FI(HS) over the algorithms.

Award in Denver, U.S.A. Specifically, the core algorithms that the high-performance-computing team of Shandong University was responsible for, were debugged and run just in this platform of National Supercomputing Center in Jinan, China.

A. SIMULATOR AND SIMULATION PARAMETERS

① The setting of relevant parameters of CA^r_FI(HS), such as the crossing-over rate and the mutation rate, linked with the execution time of the algorithm itself, has not specially involved in this paper, just with keeping the settings regular.

② For the compared algorithms like DABFSP [28], MaOEA/C [29] and MBB [30], the parameters are consistent with the corresponding references.

③ In the course of the heterogeneous scheduling experiment, 200 clusters with three common nodes based on energy heterogeneity ($\boldsymbol{o} \in \boldsymbol{N}^+$) are used.

④ For the computing/data intensive heterogeneous scheduling, the number of the virtual machines is 5000 and each application case is divided into 20000 tasks.

⑤ In further detail below, for the nodes with energy heterogeneity $\boldsymbol{o} = \mathbf{1}$, there is the highest energy efficiency when the disk and CPU/GPU utilization is respectively within certain ranges: [75%, 85%] and [80%, 95%]; in the same manner, for $\boldsymbol{o} = \mathbf{2}$, the ranges are [60%,70%] and [60%,75%], and for $\boldsymbol{o} = \mathbf{3}$, the ranges are [45%,55%] and [40%,55%].

⑥ The initial utilizations of CPU/GPU and hard disk before the scheduling are, respectively, [10%, 40%] and [10%, 40%].

B. THE SOLUTION QUALITY COMPARISONS

Fundamentally, for meta-heuristics algorithms of heterogeneous scheduling, there is the critical defect like the low solution quality, inextricably linked with green scheduling decision-making, as is to minimize the energy consumption of the hardware cloud to complete services, with not affecting the performance metrics.

In other words, the improvement in solution quality is essential.

In this subsection, twelve instances of heterogeneous scheduling proposed by [31] are used.

1) PERFORMANCE ESTIMATION

Table 3 presents the makespan values comparison of CA^r_FI(HS) against the best results previously found with diverse meta-heuristics techniques. The analysis of **Table 2** shows that CA^r_FI(HS) is able to compute better makespan values than the previous best-known solutions for all problem instances, such as GA, MA+TS, ACO+TS, PSO+TS,

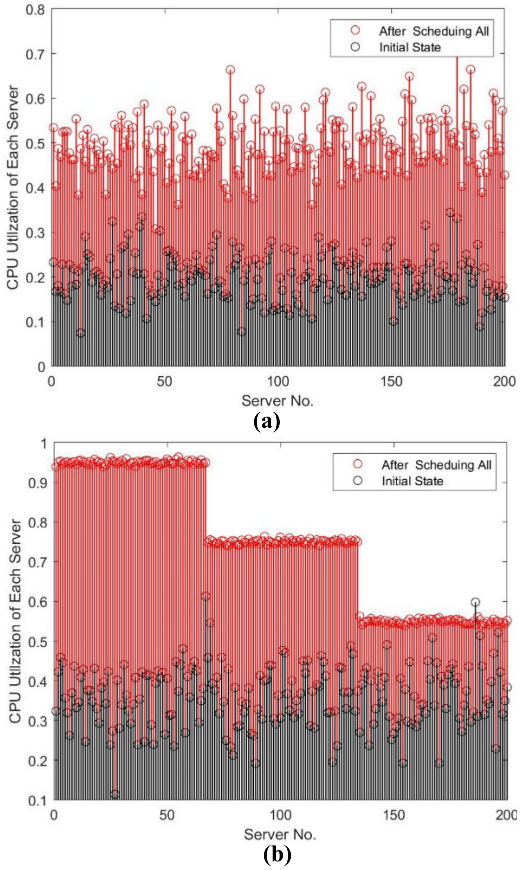

FIGURE 6. Comparison of CPU utilization after scheduling the computing intensive tasks by the different algorithms.

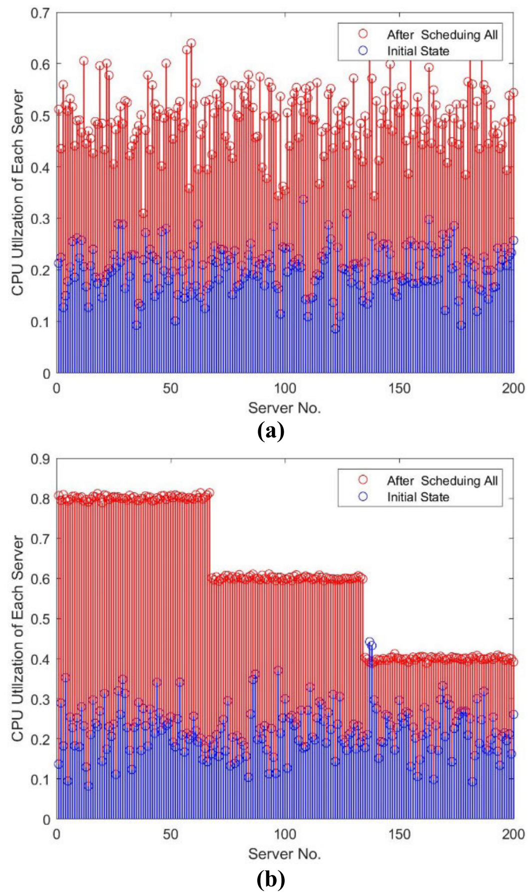

FIGURE 7. Comparison of CPU utilization after scheduling data intensive tasks by the different algorithms.

DABFSP [28], MaOEA/C [29] and MBB [30],which are the seven previous best methods for solving the HCSP instances.

It also presents the time required by CA^r_FI(HS) to reach the best-known(previous) makespan value(t_B, in milliseconds).

2) ENERGY-EFFICIENCY COMPARISON

Figure 3 summarizes the averaged energy-efficiency improvements of the solution of CA^r_FI(HS) over that of DABFSP [28], MaOEA/C [29], MBB [30], Min-Min and Sufferage, for each dimension and heterogeneity model.

Shown as **Figure 4**, the averaged energy-efficiency improvements over the best deterministic heuristic are always above 11% for semiconsistent instances, and above 7% for consistent instances. Lower improvement factors are obtained for small inconsistent instances, but the improvements significantly increase up to more than 13% for large inconsistent instances.

Mean values of the normalized energy-efficiency improvements achieved in 2828 independent executions of CA^r_FI(HS) are reported in **Figure 5** for consistent, inconsistent and semiconsistent instances for each problem dimension studied. The graphic shows that the normalized energy-consumption diminish when solving large-dimension problem instances. These results demonstrate CA^r_FI(HS) can steer the optimization-dynamics in the green direction in an efficient manner when using additional computational resources.

C. IMPACT OF ARTIFICIAL FUSION-INTELLIGENCE ON THE META-HEURISTICS ALGORITHM

In this subsection, the impact of respecting and ingeniously leveraging hardware (i.e., heterogeneous scheduling objects) intelligence on the energized optimization dynamics of the proposed meta-heuristics scheduling algorithm (CA^r_FI(HS)) is given, compared with DABFSP [28] that shows the approximate performance estimation of CA^r_FI(HS) through the overall investigates in the previous subsection.

By the two meta-heuristics scheduling algorithms: CA^r_FI(HS) and DABFSP [28], the utilization changes of CPU/GPU in 200 clusters after the scheduling, are shown in **Figure 6**.

From **Figure 6**(a), we can observe that for the computing intensive tasks, the CPU/GPU utilization of 200 clusters although with energy heterogeneity, cannot engender different responses after scheduling through DABFSP [28].

From **Figure 6**(b), we can see that the CPU/GPU utilization rates of 200 clusters are approximating 0.95,0.75 and

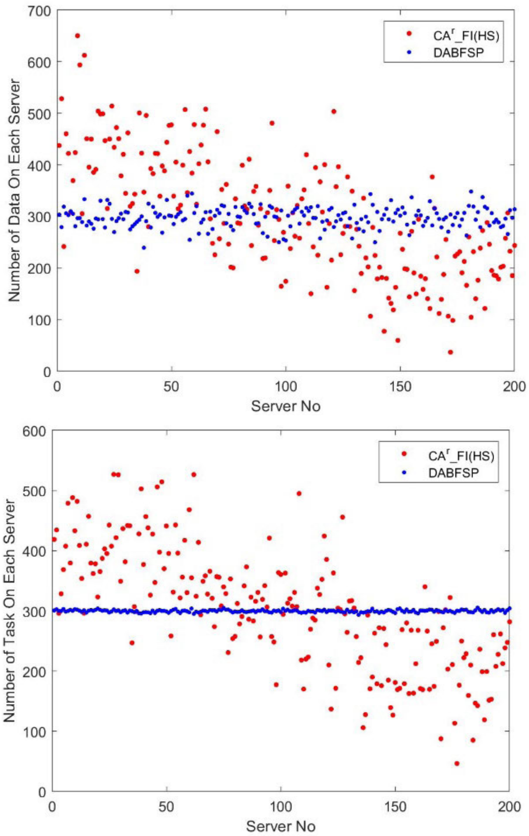

FIGURE 8. Data block deployment and task allocation on each cluster by the different algorithms.

0.55 after scheduling through CA^r_FI(HS), which are in the scope of the theoretical optimal values.

For data intensive tests, there exists the similar situation, shown as **Figure 7**. Then, it demonstrates that CA^r_FI(HS) has the advantages of reasonable deployment due to artificial fusion-intelligence.

Furthermore, detains about data block deployment and task allocation on each cluster via CA^r_FI(HS) and DABFSP [28] for the certain loads, are introduced in **Figure 8**. **Figure 8** has highlighted that CA^r_FI(HS) works not only according to load balancing, but also taking into account heterogeneous diversities of the many-core system in cloud for energy saving due to artificial fusion-intelligence.

V. CONCLUSION

In this paper, an efficient new meta-heuristics algorithm of heterogeneous greener scheduling driven by the deeper fusion of hardware(i.e., scheduling objects) and software intelligence, is proposed, i.e., CA^r_FI(HS); that is, with respecting and ingeniously leveraging hardware intelligence, our idea is to predictively quantify the dynamic feedback of the common heterogeneous resources, corresponding to the candidate scheme, and to mathematically redefine the energy-efficiencies related QoS metrics in an easier reuse way, so as to re-energize the optimization dynamics and then make the decision fully stimulate the "positive" effects of scheduling objects, instead of negative feedback.

Extensive experiments highlight that the algorithm CA^r_FI(HS) has the predictive quantification ability of the dynamic energy feedback of the candidate schemes. More importantly, they demonstrate that the hardware-software fusion intelligence of the algorithm CA^r_FI(HS), can make greener space extending in breadth and depth.

Main lines are already in progress and remain to be tackled as future work, including streamlining the definition of energy-efficiencies related QoS metrics, through the further improvements of experimental simulation and mathematical calculation.

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