Research Article

The Application of Wireless Network Technology in the Capacity Building of Anhui Industry Associations Based on the Characteristics of Big Data

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Recent advances of wireless networks and communication technologies, integrated into the considerable development in the field of environmental policies and public participation, have resulted in the development of wireless network-enabled big data environment in the capacity building of Anhui industry association. At the same time, effective task scheduling in the cloud server based big data environment is essential to schedule the tasks accurately and rapidly. There are thousands of jobs to be executed by the resources available on cloud data centers to achieve minimum time, high performance, and the proper utilization of CPU and resources. The necessity to fulfill user requirements is the main reason of having studies for optimizing the cloud computing of big data in terms of latency, bandwidth, execution time, and resource utilization. Therefore, this work presents a crow search optimization-based task scheduling scheme (CSO-TSS) for capacity building of Anhui industry association on wireless network-enabled big data environment. The proposed CSO-TSS technique mainly intends to schedule the tasks exist in the wireless network-enabled big data environment. Besides, the CSO-TSS technique is executed on a MapReduce environment in order to proficiently handle the big data. In addition, the CSO-TSS technique derives an objective function intending to maximize resource utilization and minimize execution time of the tasks. For examining the improved task scheduling performance of the CSO-TSS technique, a wide range of simulations were carried out and the results are investigated under several aspects. The comparative result analysis stated the better outcomes of the CSO-TSS technique over the recent approaches in terms of different measures.

1. Introduction

To achieve a truly digital economy, digital knowledge and information must be transferred efficiently through modern information networks. The use of ICT as a driving factor for efficiency improvement and structural optimization must be exploited effectively [1]. This year’s China Network Security and Information Work Conference was a resounding success. In order to boost digital industrialization and develop China’s digital economy, country’s macroeconomic environment should be considered [2]. It is vital to assess and account for the digital economy in order to improve digital economy development management and encourage digital economy development [3]. Instead of using traditional methodologies, a new statistical index system must be developed to account for the digital economy’s distinct characteristics. There is no single metric for the digital economy, both domestically and internationally [4]. The primary focus of the digital economy growth measurement study is qualitative description. A quantitative strategy to gauge the digital economy cannot be provided by researchers who just focus on the creation of the digital economy’s assessment index system. There is also a lack of quantitative research that goes beyond the use of simple descriptive statistics and the structural equation model [5]. It is impossible to accurately assess the current condition of China’s digital economic develop-
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ment due to a lack of objective, comprehensive, and systematic quantitative study results. The era of the Internet has come to an end [6]. There are three main indicators and 20 auxiliary indicators in Anhui Province’s digital economy indicator system based on the China White Paper: industry digitization, information infrastructure, and digital industrialization. The efficiency coefficient approach was used to generate the indicator values for each of Anhui Province’s 16 cities, depending on their relative importance [7]. Data and policy recommendations for the expansion of the digital economy are then presented in relation to the specific indicator systems in question. Here is a breakdown of what follows: This chapter covers all aspects of the weight design, construction, and analysis of every indication system. A brief overview and viewpoint on the economy of Anhui Province is also provided, as is data on several of the province’s cities [8]. In this study, the organizational capacity of Anhui industry associations has been analysed using wireless technology with artificial intelligence.

2. Related Studies

As a result, the European Union has placed a high priority on the development of the digital economy and the collection of data. The European Commission (DESI) has released a report and an index on the EU’s digital economy [9]. Progress in the digital economy of the EU as assessed by the DESI is a composite index. The index takes into account 31 secondary factors. Broadband accessibility, human capital, Internet applications, and the use of digital technology are all factors to consider in EU countries. Economic metrics (such as GDP and productivity level) and the growth effect of digitization across industries were recommended by the World Economic Forum (WEF) has published the network readiness index (NRI) for the leading countries and regions in the global information sector and their ranks, experience, and practices [11]. The focus of this research is primarily on the basis, development, and influence of the digital economy in China’s digital economy index has shown how essential the national plan and the current digital economy development trend are, as well as how rapidly different organizations, corporations, and local governments have responded to it since it was first announced in 2017. It was launched in 2017. In addition, this suggests that China has been tardy in adopting digital economic assessment methods in constructing economy. Many options are available to begin with. Organizations around the world use the same methods to evaluate their employees [14]. The focus of this research is primarily on the basis, development, and influence of the digital economy [15]. Various institutions and their roles in China’s digital economy are reflected in the country’s ranking. Big data innovation and application are the remaining two pillars. For the purpose of constructing the enterprise-led design index, data from a wide range of resources can be combined. Agriculture and the environment are increasingly at odds because of the rising global population and the tightening of environmental regulations. Famine, water scarcity, and pollution are only a few of the many problems that threaten agriculture’s long-term viability. Approximately, 135 million people were considered food insecure by the World Food Program’s 2019 Food Crisis Report. According to the Food and Agriculture Organization of the United Nations, water scarcity will affect more than 3.2 billion people in 2020. Using current technologies and service models to promote sustainable farming practices is so crucial [16]. Due to population growth, water scarcity, and climate change, it is becoming increasingly difficult for regional agriculture to maintain its long-term profitability. Relevant data must be used to accurately and fairly assess the agriculture industry’s structure and competitiveness, and policy suggestions tailored to the local environment must be developed [17]. In today’s volatile and dynamic world, knowledge generates significant resources and gives a competitive advantage. In the last two decades, absorptive capacity (ACAP) has emerged as a critical concept due to the availability of external knowledge resources. There has been a number of academic and empirical research into the ability of organizations to absorb knowledge in light of the work done on absorptive capacity [18]. For just a few examples, industrial organizations, organizational learning, strategic management, and innovation management can all benefit from ACAP’s adaptability. Organizational decisions about how resources should be allocated are a primary concern for DL. A variety of terms have been used to describe current thinking, including “mind-sets,” “interconnected choices,” and “strategic frames” [19]. The research is backed by
absorption, which is based on the ability to absorb and the current rationale. The researcher defines dominant logic as an administrative tool for making business decisions at various stages of an organization’s activities. In a transition economy, current logic can be put to the test. In environments with limited resources, the dominant logic is subjected to further tests in order to assess its intangible resource potential and significance. According to recent findings, competitive advantage is primarily derived from intangible resources. They are more difficult to replicate and more difficult to deal with in the market than tangible or physical resources, which makes dealing with these resources more complex [20]. Few empirical studies have examined the link between intangible resources and the success of businesses. This study focused on the application of wireless network technology in the capacity building of Anhui industry associations using artificial intelligence.

3. Materials and Methods

In this work, a new CSO-TSS technique has been developed for capacity building of Anhui industry association on wireless network-enabled big data environment. The proposed CSO-TSS technique mainly schedules the tasks exist in the wireless network-enabled big data environment. Moreover, the CSO-TSS technique is executed on a MapReduce environment in order to proficiently handle the big data. Furthermore, the CSO-TSS technique derives an objective function intending to maximize resource utilization and minimize execution time of the tasks.

3.1. MapReduce. It is commonly employed for processing large scale data. It is an effective distributed scheduling approach. “Map” and “reduce” are the two fundamental computing units of the MapReduce method [21, 22]. Huge data is cut into unrelated blocks through Map program and scheduled to different computers for processing, achieve distributed computing. Next, the outcomes from this computer are outputted and summarized through Reduce program [23]. The big data structure is shown in Figure 1.

3.2. Overview of CSO Algorithm. The crow is observed as the smartest creature amongst birds. Its huge brain is compared with its body size. According to a brain-to-body relative, their brain has marginally lesser than human. The proof of the smartness of crows is several. It is demonstrated that self-awareness from mirror testing is talent for generating tools. The crow is memorizing faces and alerting one another about the threats [24]. Also, it uses tools and shares data from difficult manners and remembered their confidential food place. It can monitor and track where the birds saved their food in secret place. If the crow ensured robbery, then it alerts the hiding spot for abstaining in victim. Essentially, it uses their skill of being a thief for speculating the activity of robbers and is decided the most secured manner for defending their food in stolen. The criteria of CSA are [25]

(i) The crow exists as a group

(ii) The crow preserves in mind the place of their confidential places

(iii) The crow follows one other to do theft

(iv) The crow secured their hideouts from being stolen by probabilities

Most probably, there is $N$ dimension environment containing many crows. Entire crows are $C$ and the place of crows $u$ at time (iteration) $\text{iter}$ from the searching space (SS) has been defined as the vector,

$$V_u^{\text{iter}}(p = 1, 2, \cdots, C; \text{iter} = 1, 2, \cdots) \text{iter}_\text{max},$$

Whereas $V_u^{\text{iter}} = [V_u^{1, \text{iter}}, V_u^{2, \text{iter}}, \cdots, V_u^{\text{iter}_\text{max}}]$, and $\text{iter}_\text{max}$ indicates the iterations with maximal counts. All the crows memorize the confidential place where it is kept. In the iteration, confidential place of the crows $u$ has been demonstrated as $s_u^{\text{iter}}$. During the memory of all the crows, the place of its optimum experiences has been stored. The crows begin searching for an optimum source from the environment.

Assume such iteration that the crow $v$ requires to move their confidential location, $s_v^{\text{iter}}$. In this iteration, the crow $u$ definite for tracing crows $v$ to confidential place of crows $v$. During this phase, 2 events occur.

Event1: The crow $v$ has no concept that crow $u$ is tracking it. Thus, the crow $u$ has reached to confidential place of crows $v$. During this phase, a novel location of crows $u$ has developed as

$$V_u^{\text{iter}+1} = V_u^{\text{iter}} + k_j \times (fll_u^{\text{iter}} \times (s_u^{\text{iter}} - V_u^{\text{iter}})),$$

where $k_j$ stands for the arbitrary number with uniform distributing amongst zero and one, and $fll_u^{\text{iter}}$ refers to the flight length of crows $u$ at iteration. The minimal value of $fll$ outcomes from local search and maximal value leads to global searching.

Event2: the crow $v$ identifies that crow $u$ has been tracked. Therefore, for defending their confidential location in theft, the crow $v$ implies the deceive crow $u$ by moving
Therefore, events 1 and 2 are explained as

\[ V_{u, \text{iter}+1} = \begin{cases} V_{u, \text{iter}} + k_j \times f u_{\text{iter}} \times (S_{u, \text{iter}} - V_{u, \text{iter}})k_j \geq A W P_{v, \text{iter}} \\ \text{a random location otherwise} \end{cases} \]

where \( A W P_{v, \text{iter}} \) refers to the probability of awareness of crows \( v \) at iteration.

3.3. Process Involved in CSO-TSS Technique. The core of CSO-TSS technique is to assign \( n \) independent tasks to \( m \) heterogeneous accessible resources; thus, the overall task execution time is minimized and resource is completely exploited. It has a heterogeneous environment, largescale, decentralized, and feature includes scalability. In a distributed scheme, \( n \) subtask \( Task = \{ T_1, T_2, \ldots, T_n \} \) is allocated to \( m \) processor \( C = \{ C_1, C_2, \ldots, C_m \} \).\( R_j \) characterizes the maximal resource quantity of the processor \( C_j \), \( R = \{ R_1, R_2, \ldots, R_m \} \) denotes the maximal resource quantity set of processor, and the amount of resources needed for the task implementation is \( H = \{ H_1, H_2, \ldots, H \} \) designates. \( T_j = \sum_i X_{ij} = t_i / v_j \) characterizes the amount of execution time of each task scheduled on processor \( j \), whereas \( t_i \) signifies the implementation time of task \( i \) on the slower processor and \( v_j \) embodies the processing speed of processor \( j \).

\[ f(X) = \min \left( A \sum_{j=1}^{m} t^i_j + B \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{p=1}^{m} \sum_{q=1}^{m} \omega_{ijpq} X_{ij} X_{pq} \right), \] (4)

\[ \sum_{j=1}^{m} X_{ij} = 1, i = 1, 2, \ldots, n, \] (5)

\[ \sum_{i=1}^{m} H_j X_{ij} \leq R_j, j = 1, 2, \ldots, m. \] (6)

In which \( A \) and \( B(A + B = 1) \) indicate the relative significance of the overall execution time and transmission cost in the objective function, and \( \omega_{ijpq} \) indicates the task \( i \) scheduled on processor \( j \) and the task \( p \) implemented on processor \( q \). For calculating the processing time needed for all the tasks on a distinct VM, implementation time matrix can be determined by

\[ T = \begin{bmatrix} time_{11} & time_{12} & \ldots & time_{1m} \\ time_{21} & time_{22} & \ldots & time_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ time_{n1} & time_{n2} & \ldots & time_{nm} \end{bmatrix}. \] (7)
Here, \( time_{ij} \) indicates the implementation time needed to the VM \( v_j \) for processing the task \( t_i \), and \( time_{ij} = \frac{M I_j}{M I P S_j} \). The predictable time for performing \( n \) tasks on \( m \) virtual resource is represented as \( E \), where \( E \) indicates an \( n \times m \) matrix. \( E_{ij} \) shows the time needed for \( T_i \) for running in the VM, \( E_{ij} = e_{ij} + t_{ij} \). Next, the VM implements the task execution time as \( E_j \). As the task allocated to VM resources is concurrently implemented, the implementation time needed for each task is the maximal value in the array \( E \) characterized as

\[
E_{total} = \sum_{i \in Task_j} e_{ij} + \sum_{i \in Task_j} t_{ij}. \tag{8}
\]

In which, \( Task_j \) denotes the set of tasks to be implemented on the VM. The matrix \( x[i][j] \) is determined based on the matching relationships among the VM and the task indicates either the task \( t_i \) is allocated to the VM \( v_j \), as follows:

\[
x[i][j] = \begin{cases} 
1, & \text{is assigned to } V_j \\
0, & \text{otherwise}
\end{cases}. \tag{9}
\]

The implementation efficacy of the VM is estimated by evaluating the overall implementation time of the task execution.

### 4. Performance Validation

The performance validation of the CSO-TSS technique is carried out under distinct number of tasks. Table 1 and Figure 2 inspect the make span time (MST) examination of the CSO-TSS technique with existing methods [26] under scenario 1. The results indicated that the CSO-TSS technique has accomplished effective results with least MST under all tasks.

For instance, with 10 tasks, the CSO-TSS technique has obtained lower MST of 1.60 min whereas the Languid particle swarm optimization (L-PSO), Task-Based System Load Balancing PSO, and Dynamic Load Balancing Algorithm (DLBA) techniques have attained higher MST of 7.60 min, 5.60 min, and 2.88 min, respectively. In addition, with 50 tasks, the CSO-TSS technique has attained minimal MST

### Table 3: RU analysis of CSO-TSS model on scenario 1.

<table>
<thead>
<tr>
<th>No. of tasks</th>
<th>L-PSO</th>
<th>TBSLB-PSO</th>
<th>DLBA</th>
<th>Proposed model</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.750</td>
<td>0.757</td>
<td>0.757</td>
<td>0.776</td>
</tr>
<tr>
<td>20</td>
<td>0.848</td>
<td>0.858</td>
<td>0.858</td>
<td>0.867</td>
</tr>
<tr>
<td>30</td>
<td>0.966</td>
<td>0.979</td>
<td>0.998</td>
<td>1.017</td>
</tr>
<tr>
<td>40</td>
<td>0.979</td>
<td>1.000</td>
<td>1.011</td>
<td>1.026</td>
</tr>
<tr>
<td>50</td>
<td>0.987</td>
<td>1.001</td>
<td>1.019</td>
<td>1.034</td>
</tr>
</tbody>
</table>

### Table 4: RU analysis of CSO-TSS model on scenario 2.

<table>
<thead>
<tr>
<th>No. of tasks</th>
<th>L-PSO</th>
<th>TBSLB-PSO</th>
<th>DLBA</th>
<th>Proposed model</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.500</td>
<td>0.502</td>
<td>0.507</td>
<td>0.513</td>
</tr>
<tr>
<td>20</td>
<td>0.568</td>
<td>0.571</td>
<td>0.573</td>
<td>0.580</td>
</tr>
<tr>
<td>30</td>
<td>0.578</td>
<td>0.583</td>
<td>0.590</td>
<td>0.599</td>
</tr>
<tr>
<td>40</td>
<td>0.585</td>
<td>0.594</td>
<td>0.600</td>
<td>0.612</td>
</tr>
<tr>
<td>50</td>
<td>0.589</td>
<td>0.596</td>
<td>0.605</td>
<td>0.613</td>
</tr>
</tbody>
</table>
of 10.88 min whereas the L-PSO, TBSLB-PSO, and DLBA techniques have obtained maximum MST of 33.18 min, 25.18 min, and 15.60 min, respectively.

Table 2 and Figure 3 review the MST examination of the CSO-TSS technique under scenario 2. The results designated that the CSO-TSS technique has accomplished operative results with minimum MST under all tasks. For instance, with 10 tasks, the CSO-TSS technique has obtained lower MST of 0.57 min whereas the L-PSO, TBSLB-PSO, and DLBA techniques have attained higher MST of 3.83 min, 2.67 min, and 1.67 min, respectively. Furthermore, with 50 tasks, the CSO-TSS technique has reached minimal MST of 8.33 min whereas the L-PSO, TBSLB-PSO, and DLBA techniques have gained maximum MST of 19.58 min, 14.92 min, and 9.50 min, respectively.

Table 3 and Figure 4 demonstrate the resource utilization (RU) examination of the CSO-TSS technique with recent methods under scenario 1. The experimental results depicted that the CSO-TSS technique has obtained improved outcome with the higher RU under all tasks. For instance, with 10 tasks, the CSO-TSS technique has resulted to increased RU of 0.776 whereas the L-PSO, TBSLB-PSO, and DLBA techniques have reached lower RU of 0.750, 0.757, and 0.757, respectively. In line with that, with 50 tasks, the CSO-TSS technique has accomplished raised RU of 1.034 whereas the L-PSO, TBSLB-PSO, and DLBA techniques have resulted to reduced RU of 0.987, 1.001, and 1.019, respectively.

Table 4 and Figure 5 validate the resource utilization (RU) examination of the CSO-TSS technique with recent methods under scenario 2. The experimental results portrayed that the CSO-TSS technique has obtained improved outcome with the higher RU under all tasks. For instance, with 10 tasks, the CSO-TSS technique has resulted to amplified RU of 0.513 whereas the L-PSO, TBSLB-PSO, and DLBA techniques have reached lesser RU of 0.500, 0.502, and 0.507, respectively. Along with that, with 50 tasks, the CSO-TSS technique has accomplished raised RU of 0.613 whereas the L-PSO, TBSLB-PSO, and DLBA techniques have resulted to reduced RU of 0.589, 0.596, and 0.605, respectively.

After examining the above result and discussion, it is evident that the CSO-TSS technique has the capability of outperforming the other methods on distinct scenarios and measures.

5. Conclusions

In this study, the Anhui industry association has developed a wireless network-enabled big data environment as a result of recent advancements in wireless networks and communication technologies, which have been combined with significant development in environmental policies and public participation. The cloud server-based big data environment necessitates effective task scheduling in order to schedule tasks accurately and quickly. To help the Anhui industry association build its capacity in a big data, wireless network-enabled environment, this study presents a task scheduling scheme based on crow search optimization (CSO-TSS). It is the primary goal of the proposed CSO-TSS technique to schedule tasks in the wireless network-enabled big data environment. CSO-TSS is also implemented in a MapReduce environment to handle large datasets effectively. With this technique, an objective function is generated that aims to maximise resource utilization while also cutting down on task execution time. The improved task scheduling performance of the CSO-TSS technique was examined in a variety of ways through a wide range of simulations. The proposed CSO-TSS method has outperformed well than the existing methods.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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