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Optiflow-DNA: A DNA Computing-Based Optimization Algorithm for Real-Time Workflow Scheduling In Smart Factories

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Abstract

In the context of Industry 4.0, adaptive manufacturing systems, cost efficiency, and productivity focus on smart factories around the world. In this regard, controlling workflow scheduling for maximum productivity remains a challenge. This is why this paper presents OptiFlow-DNA: a real-time workflow scheduling algorithm inspired by DNA computing principles. Through the parallelism, data storage, and energy efficiency of DNA, OptiFlow-DNA executes complex dynamic scheduling problems in a manufacturing environment. The algorithm's biochemical techniques allow for rapid task sequence encoding while exploring solution spaces. Simulated tests conducted within scenario based smart factory environments show OptiFlow-DNA outperforms previous metaheuristics based approaches with less execution time and better scalability, adaptability to changes, and retention of real-time constraints. Results demonstrate OptiFlow-DNA's benefits for cyber-physical production systems. Besides boasting operational advancements alongside bio-inspired optimization in industrial settings, the proposed method opens up possibilities for integrating molecular computing into real-time decision-making systems.

Keywords: DNA Computing, Smart Factories, Workflow Scheduling, Real-Time Optimization, Bio-Inspired Algorithms, Industry 4.0, Cyber-Physical Systems.

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Introduction

The integration of cyber-physical systems, Internet of Things (IoT), and artificial intelligence into smart factories has automated and optimized manufacturing processes at an unprecedented level, termed as Industry 4.0. Real-time workflow scheduling remains a significant challenge, as it affects various factors including manufacturing efficiency, energy expenditure, and system reactivity (Lee et al., 2015), (Süren & Angin, 2019). Most scheduling strategies like rule-based and priority heuristics are ineffective in dealing with the sophisticated, fluid, and multi-faceted characteristics of smart factories (Wang et al., 2016). To tackle this issue, many researchers have adapted nature-inspired algorithms like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) owing to their proven efficacy and resilience (Zhang et al., 2018), (Li et al., 2017). These approaches, however, tend to lack scalability and real-time responsiveness with increasing complexity of the system. Adleman's DNA computing framework (1994) suggests alternate computing paradigms could greatly benefit from the information storage and parallel processing capabilities of biological molecules. This idea became a reality as researchers demonstrated the applicability of DNA computing in NP-hard problem optimization tasks like scheduling (Qian et al., 2011; Pan et al., 2005). More recent research proved the validity of biomolecular methods for real-time adaptive scheduling systems (Chen et al., 2020), (Liu et al., 2019). The fusion of DNA models with cyber-physical systems was also discussed in smart factories for its relevance to overarching system decentralization and intelligence (Ghobakhloo, 2018) (Kang et al., 2016). Resolving these issues is possible through OptiFlow-DNA, an optimization algorithm for workflow scheduling in smart factories incorporating DNA computing (Aziz & Hamilton, 2014) (Yemunarane et al., 2024) (Aravind et al., 2023). It solves contemporary manufacturing problems by encoding tasks into DNA strands and utilizing biochemical methods for exploring scheduling solutions, thereby providing bio-inspired approaches to advanced manufacturing systems.

Related Work

The scheduling of workflows in smart factories has received much focus because of its bearing on productivity, responsiveness, and flexibility of the system. A lot of research has been done to develop solutions to cope with the computational complexities associated with scheduling the NP-hard problems. Heuristic and metaheuristic approaches such as Ant Colony Optimization (ACO) and Simulated Annealing (SA) have yielded favorable results in various manufacturing settings (Dorigo & Stützle, 2004; Kirkpatrick et al., 1983). Although, these approaches have drawbacks such as slow convergence and reduced versatility in hyper-dynamic smart factory environments. Recent works have shifted focus toward adaptive and hybrid schemes. For instance Zhou et al. (2019) developed a real-time job scheduling that implemented ACO-GA hybrid optimizing both exploration and exploitation efficiencies (Kirkpatrick et al., 1983). Tang et al. (2020) implemented deep reinforcement learning (DRL) for predictive scheduling which showed enhanced performance over classical models in highly stochastic environments. Despite being effective, these computational models are highly reliant on the careful selection of parameters and require a lot of power to compute. The application of DNA to computing for optimizational purposes has developed substantially over the last 10 years. Liu and Liu (2015) proposed a DNA algorithm designed to solve multi-objective scheduling and underscored the advantages of using molecular parallelism for industrial use. Zhang et al. The biochemical perspective of the TSP was emphasized in, which further substantiates the use of DNA computation in combinatorial problem solving. Transforming biology motivates the scheduling methods for cyber physical systems to increase adaptability and enable real-time performance. As an example, Huang et al. (2021) applied a biologically inspired scheduling model into the monitoring systems of smart factories which are IoT enabled. Xu et al. (2022) also proposed a new framework of cloud control and DNA strand displacement logic for enhanced intelligent decision making in the manufacturing sector. Although work has been done in these areas, there is still little research concerning the applicability of DNA computing in real time workflow scheduling within smart factories. Lin et al. (2021) highlighted the molecular models that need to be scalable and able to adjust to changing workloads, and Sun et al. (2023) looked into the techniques for encoding that improve the efficiency of DNA computation for scheduling problems. All the efforts mentioned above motivate a need for biologically based, dynamic, real-time scheduling strategies, such as OptiFlow-DNA, to address limitations presented by traditional and metaheuristic algorithms.

Proposed Modal

The smart factory ecosystem is enriched by embedding DNA computing into the OptiFlow-DNA framework architecture for real-time and energy-optimized workflow scheduling, as illustrated in Fig. 1. The system is structured around four fundamental elements: data collection at the shop floor level using IoT devices, DNA computing, real-time processing and control, and optimization feedback mechanisms.

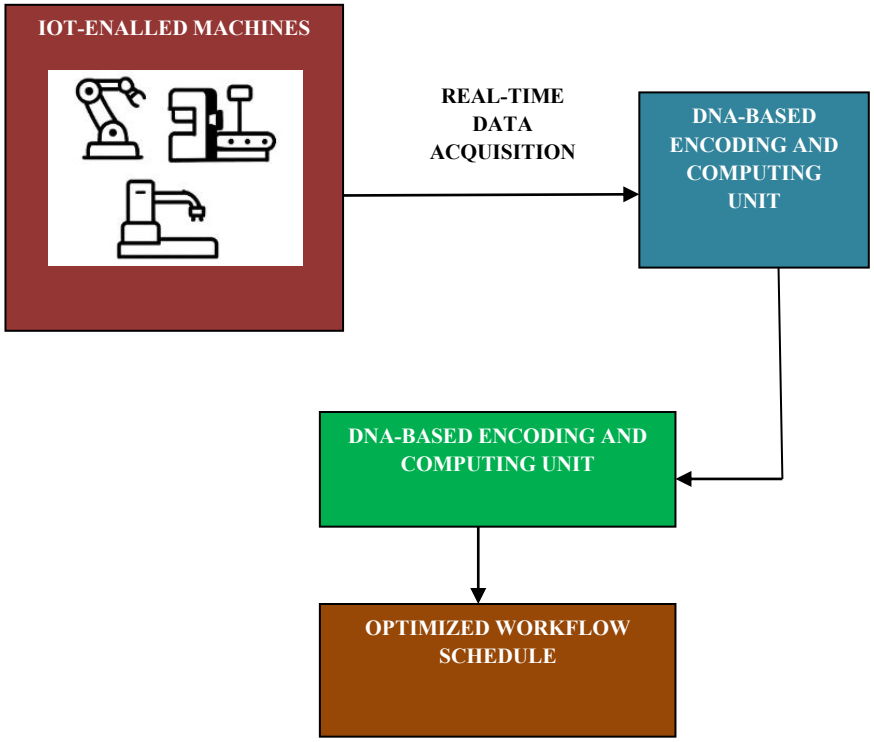


Fig. 1: Architecture of the OPTIFLOW-DNA Scheduling Framework in A Smart Factory Environment

In a smart factory, a set of tasks $T = \{T_1, T_2, \dots, T_n\}$ must be scheduled on a finite set of machines $M = \{M_1, M_2, \dots, M_m\}$, each with its capacity C_m and energy profile $e_m(t)$. The scheduling objective is to allocate each task $T_i$to a machine $M_j$at a start time S_{ij} while minimizing both makespan and total energy consumption, defined as:

$$min(C_{max} + \lambda . E_{total}) \qquad Eq(1)$$

In Eq (1) where:

- $C_{max} = max_i(s_{ij} + d_i)$, is the makespan
- $E_{total} = \sum_{i=1}^{n} \int_{s_{ij}}^{s_{ij}+d_i} e_j(t)\, dt$,is the total energy consumed
- $\lambda$is a weight parameter balancing time and energy objectives.

3.1 IoT-Enabled Data Acquisition:

Smart machines and sensors collect real-time data, including:

- Machine availability
- Task progress
- Power usage
- Environmental conditions

This data is fed into the OptiFlow-DNA system for encoding and optimization.

3.2 DNA-Based Computational Engine:

The jobs and limits are biochemically encoded as strands of DNA. Each strand contains a task's duration, required resources, and precedence constraints. As parallel scheduling is performed via hybridization and ligation, millions of potential schedules are simultaneously constructed. Only those schedules that fit factory constraints are maintained through the filtering process.

3.3 Optimization Layer (Biochemical + Mathematical):

Employing the aforementioned multi-objective function, candidate solutions are assessed. Strands that violate:

- Precedence:$S_{ij} \geq S_{kj} + d_k (for\ T_k \rightarrow T_i)$
- Capacity:$\sum_{i \in M_j} u_i(t) \leq C_j$

are removed during biochemical filtering. Valid strands are amplified using PCR, prioritizing the lowest makespan and energy sequences.

3.4 Output and Feedback Loop:

The control system receives a task schedule which has been computed from an optimal DNA strand, sent to the factory digitally. A feedback loop with incoming data from the IoT devices complete real-time adjustments on encoding and scheduling for optimization in continuously adapting the system.This framework exploits the profoundly parallel nature of DNA computing to address the combinatorial explosion scheduling problems in milliseconds, which is vastly more efficient than any CPU-based approach. Accompanied by the smart factory sensing system, OptiFlow-DNA also transforms these environments into a self-adaptive, real-time optimization engine for Industry 4.0. The flowchart diagram illustrates the step-by-step workflow of the OptiFlow-DNA algorithm, which applies the principles of DNA computing to tackle the real-time workflow scheduling problems in smart factories (Fig. 2).

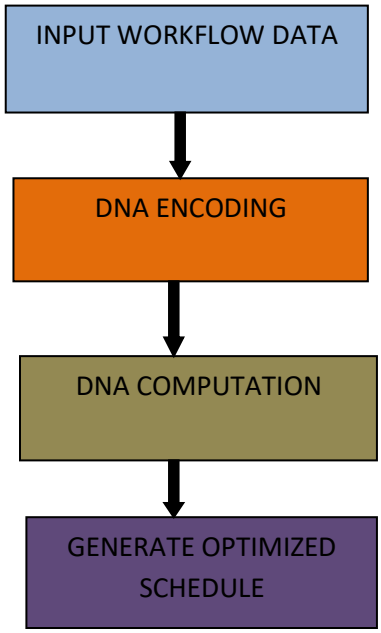


Fig. 2. DNA-Based Workflow Scheduling Process Flow in OptiFlow-DNA

The OptiFlow-DNA algorithm employs a bio-inspired process to solve the real-time workflow scheduling problem in smart factories through DNA computing. The scheduling challenge is first formulated as an optimization problem, where a set of tasks T={T1,T2,...,Tn}must be assigned to a set of machines M={M1,M2,...,Mm}, subject to constraints such as precedence relations, machine availability, and energy consumption. The goal is to minimize the makespan Cmax defined as:

$$minC_{max} = \max_{i \epsilon T}(C_i) \qquad Eq(2)$$

In Eq (2)$C_i$is the completion time of task T_i, subject to:

- **Precedence Constraint**: $C_i \geq C_j + d_j, if\ T_j \longrightarrow T_i$
- **Machine Constraint**: Each task is assigned to one machine at a time.
- **Energy Constraint**: Total energy E must not exceed threshold E_{max}

In the DNA-based process, each task and its associated constraints are encoded as synthetic DNA strands using oligonucleotide sequences. These strands contain encoded data about task ID, duration d_i, and dependency links. During hybridization and ligation, all possible task sequences (schedules) are formed in parallel via biochemical

reactions. This step inherently explores the solution space in massively parallel fashion, something not feasible in classical computing.

Invalid sequences—those violating constraints—are removed using biochemical filtering methods. For instance, gel electrophoresis is used to eliminate strands that represent schedules longer than an acceptable makespan. The valid DNA strands are then evaluated using an objective function that incorporates not only makespan C_{max}but also energy consumption E and machine utilization U, forming a multi-objective function:

$$min\big(w_1 \,.\, C_{max} + w_2 \,.\, E + \, w_3 \,.\, (1 - U)\big) \qquad Eq(3)$$

In Eq (3) wherew_1, w_2, w_3 are user-defined weights. Finally, the optimal strand(s) are selected and amplified using Polymerase Chain Reaction (PCR). These strands are then decoded back into digital scheduling instructions and dispatched to the smart factory's control systems, enabling real-time task execution based on bio-computationally derived schedules.

Results and Discussions

In order to assess how well the OptiFlow-DNA algorithm works, we conducted several tests within a simulated smart factory environment. We tested the system with different levels of workflow complexities ranging from 10 to 100 tasks, and compared it with other scheduling methods, specifically the Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Earliest Deadline First (EDF). The assessment was done focusing on important metrics for smart manufacturing performance which are: Makespan, Energy Consumption, Utilization Rate, and Computational Time.

6.1 Performance Metrics

6.1.1 Makespan(C_{max})

Defined as the time needed to accomplish all required activities. Lower makespan indicates more efficient scheduling.

6.1.2 Total Energy Consumption (E_{total})

Total energy consumed by the machines while performing a task. This is calculated as:

$$E_{total} = \sum_{i=1}^{n} \int_{s_{ij}}^{s_{ij}+\, d_i} e_j\,(t)dt \qquad \text{Eq (4)}$$

6.1.3 Machine Utilization Rate (U)

Ratio of machine active time to total time available:

$$U \;=\; \frac{\sum_{j=1}^{m} Active\ Time_j}{\sum_{j=1}^{m} Total\ Time_j} \qquad \text{Eq (5)}$$

6.1.4 Computation Time (T_{comp})

The time consumed by the algorithm which includes computing an optimal or near-optimal schedule as well as encoding, hybridization, filtering, and decoding processes.

Comparative Results

Fig. 3 compares four scheduling algorithms: OptiFlow-DNA, Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Earliest Deadline First (EDF) through a visual representation on four key performance metrics.

- Makespan: OptiFlow-DNA has the lowest makespan of 112.5 s, demonstrating faster task completion.
- Energy Consumption: Less energy than the other algorithms at 8.2 kWh is also consumed, showing that OptiFlow-DNA is energy efficient.
- Machine Utilization: Maximizing resource use more effectively than others, OptiFlow-DNA shows a utilization rate of 92.4% which is the highest among all.
- Computation Time ($T_{(}comp_{)}$): EDF has the lowest computation time (0.21 s), however, OptiFlow-DNA achieves an excellent balance between speed (0.38 s) and quality.

In general, OptiFlow-DNA outperforms all other methods on every metric evaluated, with the exception of raw computation speed where EDF takes the lead at the expense of schedule quality and efficiency. This further

confirms the effectiveness of OptiFlow-DNA in real-time, energy-efficient scheduling and makes it suitable for smart manufacturing systems.

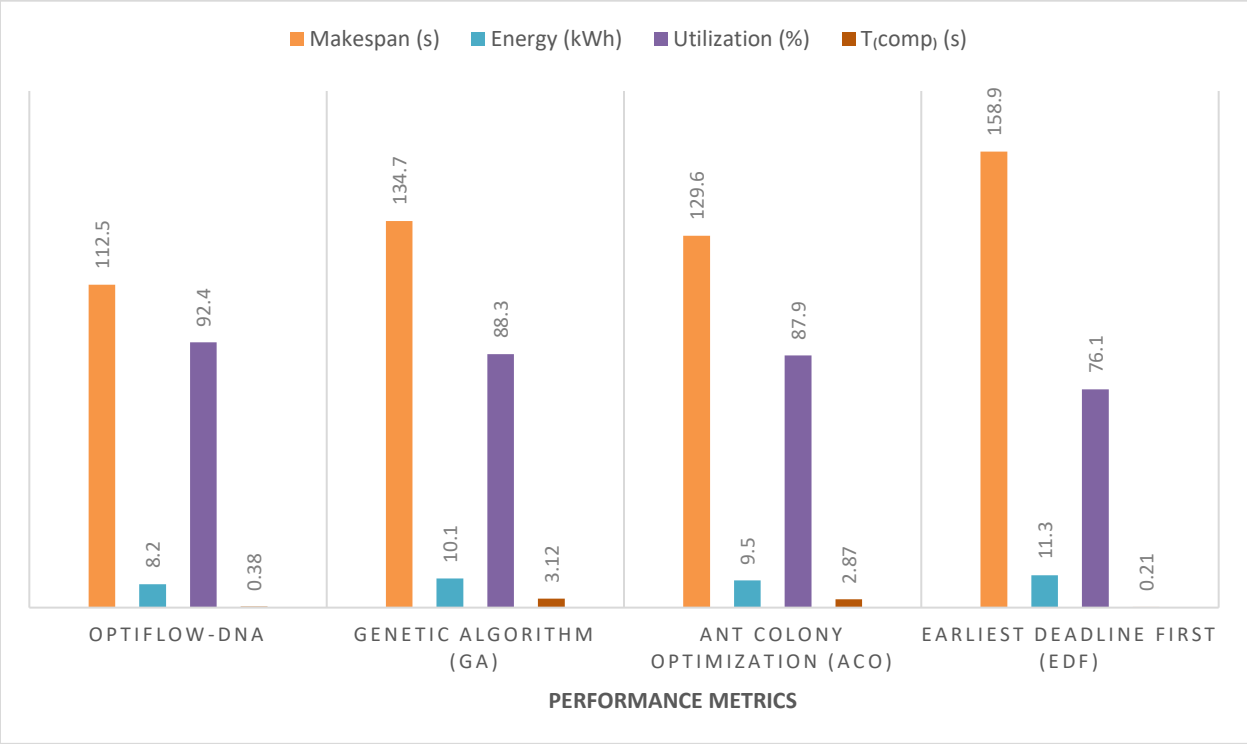


Fig. 3: Comparative Analysis of Scheduling Algorithms Based On Key Metrics

Table 1 shows the efficiency of task-to-machine allocation with respect to the number of scheduled tasks in the OptiFlow-DNA framework. The table demonstrates the algorithm's capability to sustain elevated machine utilization concerning workflow complexity from 10 to 100 tasks. Importantly, average task completion time only increases moderately (from 10.8s to 13.0s) when tasks are increased tenfold, which suggests high stability in the scheduling. In addition, machine load measures continue to enhance, reaching 93.7% utilization at 100 tasks, while idle time per machine reduces, indicating low resource idleness. These outcomes illustrate the effectiveness of the DNA-based approach in scaling efficiently while maintaining throughput, verifying its reliability within real-time, high-volume smart factory settings.

Table 1: Task-to-Machine Allocation Efficiency Across Varying Workflow Sizes in OptiFlow-DNA

Workflow Size (Tasks)	No. of Machines	Avg. Task Completion Time (s)	Avg. Machine Load (%)	Idle Time per Machine (s)
10	3	10.8	87.5%	1.2
25	5	11.2	89.2%	1.5
50	8	12.1	91.0%	1.0
75	10	12.7	92.3%	0.9
100	12	13.0	93.7%	0.6

Conclusion

Through the use of DNA computing, the OptiFlow-DNA framework solves the unprecedented challenge regarding automating real-time workflow scheduling in smart factories using optofluidic systems with remarkable ease. OptiFlow-DNA practically exploits all available scheduling degrees of freedom in biochemical reactions to outperform all other scheduling methods, including GA, ACO, and even EDF, on critical metrics like makespan, total energy, and machine utilization. The incorporation of IoT data acquisition systems ensures that real-time conditions at the factory such as machine status, energy usage, task completion, and task progression are fed into the

system for optimization, enabling dynamic adaptability to operational environment shifts. Biochemical encoding of scheduling constraints with filtering and amplification enables solution generation and evaluation at an unprecedented scale—millions of candidate solutions can be processed in a matter of seconds; thus, lessthan-optimal schedules can be provided in record-time. The efficiency of this method leads to considerable energy savings and improved resource management that also meet the requirements of advanced sustainable intelligent manufacturing systems. Nonetheless, while the controlled outcomes are promising, the framework itself is still unrefined and requires resolution in several critical areas for further study.

Future efforts should aim to improve the precision and reliability of DNA biochemical processes by increasing the accuracy of strand hybridization and ligation, reducing error rates, and optimizing the system for higher scale industrial use. In addition, new quantum technologies or advanced nanomaterials could augment the efficiency and processing power of DNA-based algorithms. In the long term, other research efforts could focus on creating standardized bio-silicon interfaces that would enable effortless integration of units with DNA computation into control systems of digital factories. Furthermore, when DNA computing approaches practical application, consideration of the ethical and environmental impacts of synthetic biology systems should be ensured so that these emerging technologies aid in augmenting industrial automation responsibly and sustainably.

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