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Paper

Analysis of Enterprise Production and Transportation Collaborative Scheduling Algorithm in Intelligent Manufacturing Environment

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Intelligent manufacturing has garnered much interest from academia and business due to the current state of economic development worldwide. The two essential components of a manufacturing business are production and transportation. However, traditional production and transportation scheduling management is done independently, which lowers the efficiency of the system's operation. Collaborative production planning amongst geographically dispersed manufacturing facilities through transportation to customers for production order delivery. The scheduling method should use the fewest resources necessary to fulfill service requests. In order to solve this, a Hybridized(H) meta-heuristic strategy, Particle(P) swarm optimization, and Whale(W) optimization algorithm associated with Local(L) neighborhood search has been proposed for addressing the collaborative scheduling problem under different production and transportation enterprises in Intelligent Manufacturing Environment (HPWL-IME) based on multiple objective functions. The hybridized strategy strives to achieve optimal efficiency of resources while minimizing production time by arranging order production requests on machines in an enterprise optimally. The hybridized approach of the Particle(P) swarm optimization technique aims to effectively explore the solution space and identify potential production schedules and transportation routes. The whale optimization algorithm seeks to balance international exploration and regional exploitation, assisting in identifying promising areas and raising the standard of solutions for increased effectiveness. It considers several scheduling constraints, including machine accessibility, processing times, and customer demand requests with earlier due dates. Overall, the implemented HPWL-IME approach improves customers' delivery commitments by ensuring optimal transportation time, minimal makespan (ms) of production orders, and Average Relative Deviation Index (ARDI), Earliest Due Date Assignment (EDDA) rule, and achieving all objective functions with scheduling constraints for effective utilization of production and transportation.

Keywords : intelligent manufacturing, enterprise, production and transportation, collaborative scheduling, search optimization.

1. Introduction

Currently, nations all over the world are pushing for the transformation of intelligent manufacturing processes, and conventional production techniques are consistently undergoing intelligent modifications as a result of the ongoing development of society. The growth of the global marketplace and the variety of industrial needs make it challenging for a single enterprise to complete complicated or customized ventures. The issues above can be resolved effectively by collaboration between various businesses. An intelligent manufacturing procedure has the capacity for autonomy and controls over oneself production and transportation to build the product following the design parameters. Collaboration enables enterprises to cooperate on resources and activities to accomplish a clear and shared business goal related to production and transportation in an intelligent manufacturing environment. The swarm intelligence-based systems for scheduling have the potential to revolutionize the way manufacturing executives approach challenging scheduling problems by using the power of decentralized decision-making and combined intelligence. Implementing collaborative scheduling in enterprises increases the employee involvement ratio and improves productivity.

Intelligent manufacturing processes address the degrees of innovative and progressive cleverness to promote its development, its ability to be understood as a manufacturing system, and its ability to adapt to changing conditions without sacrificing goals [1]. Using novel communication and information technologies enhanced the connectivity and openness of intelligent manufacturing infrastructure, changing how information interacts, how the work is completed, and how work should be managed. For Intelligent Manufacturing (IM) and operations management, such developments call for cooperation, adaptability, communication, and autonomous and collaborative decision-making [2]. Thereby [3] created a novel intelligent manufacturing framework that emphasizes correct decisions through big data-driven evaluation in the industrial environment and real-time adaptive observation. But it has a limitation related to reliability and a big data field that indirectly affects production decision-making. Hence [4] created a platform that gathers distributed resources and implements a platform-based intelligent manufacturing environment to maximize the collaborative arrangement of resources across enterprise levels with multi-agent systems. Then [5] explored the

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strategies for implementing collaborative smart technology for manufacturing to increase the robustness and survival of supply chains for manufacturing and businesses to fend off big calamities with smart technologies IoT,5G, big data, and others to maintain the manufacturing sector's endurance and sustainability. [6] provided a range of digital designs of circuit break intelligent manufacturing processes, cost and quality efficiency, and environmental effects concerning the intelligent enterprise paradigm in the preproduction stage and offered dependable options for real the real world. In [7], the quality and total cost of the product in an enterprise could be impacted by the manufacturing unit's efficiency and the factory's overall production efficiency. The intelligent manufacturing facility can break down an order after receiving it from the user and transmit it to every component to set up specific duties.[8] offered a digital twin and blockchain technologies improved manufacturing service cooperation mechanism for the Industrial Internet platforms to solve the lack of physical and digital space contact and credibility issues during the establishment of the present manufacturing network platform-based production. Outlined an instantaneous collaborative scheduling approach based on online Cyber-Physical System for Production (CPPS) observation to tackle the issue of quick reaction repair of interruption in the rapid railroad wheelset manufacture.

Scheduling is crucial in intelligent manufacturing processes for reducing production expenses and raising consumer satisfaction [9]. The scheduling method should use the fewest resources necessary to meet the demand for services, such as scheduling the shortest task first and the earliest due date first [10]. An integrated discrete multifaceted imperial competition approach is suggested by [11] to minimize processing time consumption of energy and noise by building a multifaceted, dynamic job shop scheduling constraint paradigm bounded by job transportation time and learning impact. Likewise, [12] outlined an instantaneous collaborative scheduling approach based on the online cyber-physical system for production observation to deal with the issue of quick reaction repair of interruption in the rapid railroad wheelset manufacture. Additionally, an improved neighborhood-discrete Particle swarm algorithm features an extended neighborhood search strategy for the equipment production process. [13], addressed a hybrid flow shop scheduling challenge with a parallel machine in each stage to reduce the weighted sum of makespan and overall flow time while accounting for human factors. The limitation here is the weighted average of makespan, and the entire flow time is the only performance metric used in the study. In [14] analyzed an effective order-merging approach that combines a selection of orders of the same kind across the course of production while weighing the benefits of continuous processing. Although simple, this tactic could result in higher deviation rates, raising scheduling costs.[15] provided a thorough analysis of how prepared SMEs are in emerging nations to use the cutting-edge technology associated with Intelligent Industry version 4.0. These methods include cyber-physical systems, intelligent manufacturing systems, and other essential technology tools for enhancing connectivity and communication inside production and manufacturing processes. To strengthen the capacity of enterprises and transportation at various levels to handle all crucial aspects, [16] defined collaborative scheduling of intelligent manufacturing technologies ought to include 5G connection, cloud concepts in manufacturing, IoT for sensing, cutting-edge computing, big data analytics, and virtual reality.

The main innovations of this research work are as follows:

- To improve collaborative production and transportation scheduling in an IME, the hybridized solution blends three meta-heuristics approaches in an enhanced way with the earliest due date of production orders to satisfy customer requests.
- To enable complete service requests of customers, ensure minimal production time, and consider the fewest production resources effectively resource utilization, lowering costs and improving transportation efficiency.
- To emphasize optimal transportation routing for delivering production orders to customers quickly by employing maximum capacity of vehicles and delivery windows.
- To evaluate performance metrics like reduced make span, minimum ARDI, optimal transportation time, and EDDA rule for better production and transportation schedule.

The remaining sections of this manuscript are arranged as follows. Section 2 discusses the literature study on enterprise production and transportation scheduling collaboration-related techniques. Section 3 starts with objective formulation, constraints, and implementation of hybrid metaheuristic algorithms for an effective enterprise management environment in an intelligent way. Section 4 discusses the results and discussion of the proposed method with the state of art techniques. Finally, the research results are summarized in the conclusion, and future work is suggested in Section 5.

2. Relevant literature survey

Liu et al. [17] suggested a Collaborative and Intelligent Production system with Human Cyber Physical (HCP) fusion is built in the non-ferrous metals sector to realize HCP fusion and collaboration manufacturing, a knowledge-graph based HCP data integration system and a cyber-physical system driven HCP enterprise collaborative management model are explored. An investigation is conducted on a copper smelting and mining-based enterprise to improve autonomous decision-making with a supply and marketing integration process. The scalability and generalizability of the suggested approach to other non-ferrous metal businesses might be constrained.

Hayat et al. [18] addressed a variant of the enterprise production sector called permutation flow-shop scheduling challenges; particle swarm optimization was hybridized with Variable Neighbourhood Search and Simulated Annealing (pso-VNS2A). Through an internal comparison based on the outcomes of 120 different instances Taillard created with various production problem sizes, the effect of hybridization was confirmed with the improvement. The algorithm's robustness and noticeably better performance in maximizing the makespan are demonstrated by a reduced value of 0.48 for the mean relative performance differential value. Despite the improvement, the learning criteria influence the implemented study's efficiency by adjusting social factors and self-adjusting criteria.

Fu et al. [19] reviewed distributed scheduling issues in intelligent industrial systems, particularly using swarm intelligence and evolutionary algorithms. Consider the workload distribution between facilities and production costs in distributed manufacturing systems. Numerous parameters, lowering the lifespan, flow time and energy, delays, and energy usage, are involved in production scheduling issues. Additionally, reducing delay, which makes up 10% of incidents, has drawn attention due to its significant impact on customer satisfaction.

Xiong et al. [20] suggested using a DT-based Collaborative Scheduling (DTCST) technique for production and transportation. A three-phase CS model for production, shipping, and procurement was created to minimize the time needed for transportation in a flexible job-shop manufacturing environment. An enhanced genetic algorithm is used to solve the model, handling the genomic encoded and decoded information with the DT-based model capable of handling dynamic interference, such as critical entry of demands in time and actual time observation of the real-world setting. The outcomes show that the collaborative scheduling technique is beneficial throughout the scenario study and experimental results.

Mohammadi et al. [21] solved the integrated scheduling of production and transportation challenges, where production is expected to be carried out in a dynamic job-shop environment. The first goal function wanted to reduce the cost of production and distribution scheduling, while the second objective function was to reduce the weighted sum of on-time and late deliveries. A Hybridized Particle Swarm Optimisation (HPSO) approach is created to address the scheme for mid- and huge problems in an acceptable time frame after it was successfully optimally solved by a constraint method. The result showed a raise in customer happiness without significantly raising the system's overall operational costs, striking a balance between expenses and customer concerns.

For scheduling production and transportation routing, Liu et al. [22] taken into account to reduce the overall order balanced time to delivery with the specialization of jointly taking their interactions into account using an Enhanced Large Neighbourhood Search (ELNSs) approach is suggested with savings(s) technique. An initial solution is first constructed by a two-stage procedure the vehicle routing is established, and then, using the established vehicle routing, a specific rule for insertion and removal of heuristics is used to identify the best production order. The computational findings demonstrate that the suggested ELNS method outperforms the Genetic Algorithm (GA) and significantly improves the initial solution by about 50 s. The major shortcoming is not considering this integrated solution's lower and upper-bound constraints.

Lu et al. [23] Created a Hybridized Multi-verse Optimizer-Variable NS (HMOVNS) algorithm to quickly address the studied issue with a strong parallel-batching scheduling issue with fuzzy computation and delivery time that depends on the past sequence. The single machinery scheduling is optimized with structural properties of the corresponding enterprise issue in the intelligent manufacturing process. With this implementation, the hybrid meta-heuristic in various studies displays excellent outcomes, robustness, and computing time performance. The results showed that the computation time on average is 0.561s, the minimum standard deviation is 2.51%, and the relative percentage deviation is 6.461. The lack of study in determining the generality of the approach to various problem situations and industrial contexts.

Lan et al. [24] developed the production scheduling mechanism by using Simulated Annealing (SA) based on Artificial Intelligence (SA-AI). Thereby intelligent manufacturing units may assist businesses in rationally allocating resources and order sizes, and they can increase production efficiency while considering carbon-free production. Also introduced the particle group technique with the positions of the product throughout the lifecycle. It is important to take the necessary precautions to lessen any detrimental effects on populations, employees, and systems of society. The quickest running time was 59.141 seconds, the least energy was used (1035 J), and the quickest product processing cycle was 607.1 seconds.

Li et al. [25] proposed the Chaotic Whale Optimization Technique (CWOT) with chaos theory to optimize the WOA's parameters. First, to initialize the population in this study, combined with the Nawaz-Ensco-Ham (NEH2) Heuristic and largest-rank-value rules. To increase stability and speed of convergence, the chaos strategy is used, and the cross with reversal-insertion operator is used to improve the algorithm's search capabilities. Finally, the work sequence is optimized using the more effective local search technique to get an optimal makespan. Other benefits of CWA include less need for variable adjustment, quicker convergence with a minimal average error of 0.851, and increased stability of 85.71%. However, the method still needs more optimization and development due to its lack of research on broader dimensions.

Sang et al. [26] applied a collaborative, distributed, flexible job shop scheduling approach in an intelligent production process. The scheduling model's objectives optimize both the green and economic indicators simultaneously. A multidimensional many-objective memetic method is suggested to solve the problem effectively. This approach fuses the enhanced NSGA-III and searches local approaches. The neighborhood structure based on cooperative process and equipment adjustment centered on the critical path is built to efficiently extend the solution set space. It can create a schedule plan that is highly effective, energy-efficient, reduces consumption, and is highly flexible. The identified limitation in this study is the difficulty of achieving convergence, that is, finding the best solutions and variety encompassing the solution space.

It is clear from the literature review just mentioned that metaheuristics have improved our ability to handle difficult non-trivial situations in enterprise production. Furthermore, HPWL-IME has outperformed other techniques like SA, GA, CWOT, ACO, etc., when used with other heuristics taken for comparison, like DTCST, ELNSs, and HMOVNS with various performance metrics. The production and transportation scheduling module with various collaborative approaches uses balanced and optimized techniques analyzed for intelligent manufacturing processes with optimization algorithms.

3. Implementation of the Proposed technique

With limited resources, the collaborative scheduling challenge typically prioritizes client response times to improve customer service while reducing logistics costs. Utilizing resources more effectively and hastening the time it takes for firms to respond when making decisions together are two benefits of smart manufacturing. Although the globalization of manufacturing companies has brought forth numerous hurdles for intelligent manufacturing, including the lack of coordinating scheduling techniques to ensure the low latency requirement, manufacturing optimization issues frequently arise in complex production systems. Sequences created arbitrarily by a technique known as heuristic are the starting point of metaheuristic-based techniques, which repeats until a stopping requirement is met. These hybridized combinations of metaheuristic algorithms enhance the production process's overall effectiveness, productivity, and adaptability by considering the interrelated relationships and interactions among various processes, machines, humans, and other resources. Scheduling systems can adjust in real-time to changes in production circumstances, equipment availability, and client requirements thanks to swarm intelligence algorithms, which perform well in dynamic contexts. This flexibility shortens production lead times and improves customer responsiveness in an intelligent manufacturing environment. Enterprises must employ the scientific techniques or software created for logistics activities to be planned and executed in an organized manner. These techniques and programs improve the effectiveness and efficiency of transportation operations and offer significant benefits to administrators. Optimizing production schedules, enhancing on-time delivery performance, and raising overall manufacturing effectiveness are all facilitated by adding EDDA into an intelligent manufacturing approach.

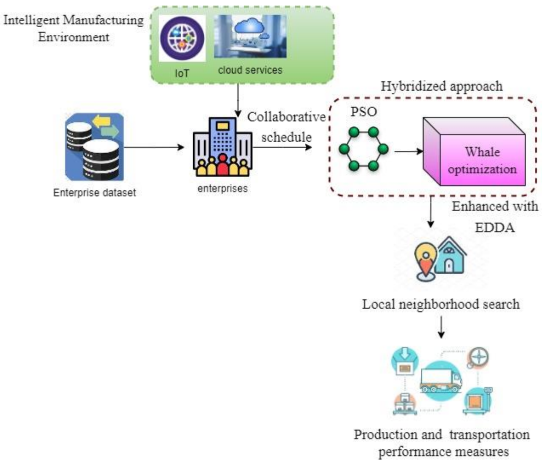

Figure 1. Implementation of the overall work of the proposed technique

As shown in Figure 1, coordinating enterprise production activity management and collaboration across all options is important. Pervasive understanding and interaction are the cornerstones of successful collaboration. In manufacturing, sensors and IoT devices are frequently utilized for monitoring and visualizing transportation and production procedures. New communication technologies make possible more effective and on-demand interactions amongst collaborative production entities. A starting point of possibilities, the initial population, is found by running the PSO algorithm hybridized to solve the problem. These solutions show potential production schedules and transportation routes. The PSO population's best solutions are then used as the beginning population for the WOA algorithm after the PSO algorithm has completed its rounds. With this initial population as a starting point, the WOA algorithm conducts more exploration and exploitation to sharpen and enhance the solutions.

3.1 Production stage

Before business mergers, acquisitions, and the construction of new factories, it is essential to carefully evaluate the transportation, coordination, collaboration, and other challenges that the development of several factories inevitably brings about. Deploying a cloud production platform across various plants is also crucial. The cloud platform ensures that several factories work together on supply and production. Always manufacturing is a subset of production denoted as manufacturing ⊆ production. In the production stage, an initial constraint focused on until the order that is being processed with constant production rate Ψ by machine is finished with the constraint of $t_{\mu+1,T2} - t_{\mu,T2} \geq 0$, the machine cannot make another new request given by C that represents the number of customers $C = \{1,2,3,\dots c\}$. Tasks cannot be completed faster due to overlapping between machines, and each variant is the same for every subsequent machine used for transportation purposes of scheduled tasks during delivery. Decision variables for scheduling a production process are listed as follows: The starting time t of each production task T is given as t ∈ T. The assignment of each production task within a time to a particular resource is called a machine in an enterprise as μ.

Scheduling Constraints:

Each production task in an overall production stage of an enterprise has given a particular weight with a specific constraint in which the T is given an order for processing time. t_p is calculated using Equation 1.

where $t(T_1) + t_p(T_1) \leq t(T_2)$ (1)

The resource constraints of a machine in a manufacturing environment and transportation stage are given as a constraint form: For each machine, the sum of t_p of the task assigned to a particular machine $t_p \in \mu \leq \alpha$, where the machine's total capacity is given as α. Similarly, the sum of transportation times of a particular route γ_d should not exceed the total capacity of the transportation route β is given as $\gamma \in T \leq \beta$. Completing production tasks T in an intelligent manufacturing environment typically necessitates the utilization of more than one machine. Each system's average time per work varies in enterprise production. Make span is the entire time required to execute all tasks needed in a production shift. Finding the order of tasks that will reduce the time needed is the purpose of the make-span calculation. The initial objective is to minimize the makespan with the constraints confirming that each production job is scheduled on one machine with the maximum load α.

min α such that $\sum_{x=1}^{\mu} ms_{T_y \in \mu_x}, y \in T \; and \; x \in \mu$, (2)

$\sum_{y=1}^{T} Q(x,y) ms_{T_y \in \mu_x} \leq ms, x \in \mu$ and $Q(x,y) \in \{0,1\}$. (3)

From the above equations, an objective function of production scheduling involves that the make-span (ms) of T is given using Equations 2 and 3 y represents the job mentioned in the production task T assigned to a particular machine x among total machines μ is labeled in a constraint $Q(x,y)$.

3.2 Transportation scheduling

It is possible to quickly decide on and modify a transportation schedule to accommodate decision variables and change orders based on customer demand. C_D in the production unit. The transportation routes γ for each production task to a destination place for delivery d is given in the form of $\gamma = \{\gamma_1, \gamma_2, \dots \gamma_d\}$ where $\gamma \in$ T. The customers or end users may reside at various locations geographically; hence, each production task's delivery and transportation time may vary based on the given constraints. The transportation time t_{ab} denotes delivery from one customer a to another one b or from one enterprise outlet to one customer for delivery may be represented as t_{ab,γ_d} within a transportation time in a particular route. The early delivery of the product is given as a e_d significant weight for processing the product request that is given as similar lateness of product delivery is given with specific weight as l_d. For each transportation. The vehicle used for transporting product deliveries leaves the enterprise at a time called departure time, represented as $\delta = \{1,2, \dots V\}$ with the same vehicle capable of delivering orders from many customers in a single round.

The second research idea is to schedule and allocate resources like vehicles δ to production scheduling activities such as distribution or delivery t_{ab} as efficiently and effectively as possible. Time-window limitations are also focused on that require each vehicle v to establish a connection with each customer at the time specified by that customer c and assume that a logistics enterprise is the only supplier in the transportation operation in the intelligent manufacturing environment. According to the number of orders, the enterprise delivers items to customers.

To attain the above-discussed patterns, the objective in this transportation scheduling of enterprise involves reducing the overall weighted timing of delivery, which requires synchronizing vehicle departure timings, taking into focus the amount of time the vehicles will take for production deliveries from an enterprise to end-users, and taking into account the unique weights or priority of various orders with the reduced transportation cost that is distributing the production materials from enterprise to customer.

Scheduling constraints with parameters update using Equation 4:

$$S_{ab,v}, Z_{r,v} = \begin{cases} 1, \; if \; v \; meets \; t_{ab} \wedge v \; loads \; O_r \\ 0, \; otherwise \end{cases} \tag{4}$$

Where the variable $S_{ab,v}$ denotes the transportation of a vehicle v takes a route γ from a to b.The parameter O_r denotes an order of products from multiple customers to an enterprise with its completion time of production given as ζ_{O_r} and the processing time of an order can be written as $O_{t_p} = C_D/\Psi$.The transportation schedule shown in Figure 2 includes the arrival time of v at customer c can be given as $\omega(v,c)$ with various δ and γ .The dotted lines from e_d to l_d denotes the early delivery of O_r before the scheduled date of delivery and late delivery of O_r to the customer after crossing the scheduled date because of unexpected circumstances like machine breakdown, transportation issues, etc. The solid line from a to b gives information about the transportation of O_r with an allocated processing time t_{ab} in a given possible delivery route. The trending line drawn towards b denotes that vehicle v among several δ with the correct departure time reaches the customer correctly. Beyond this objective function trend line the lateness of delivery to the customer occurs.

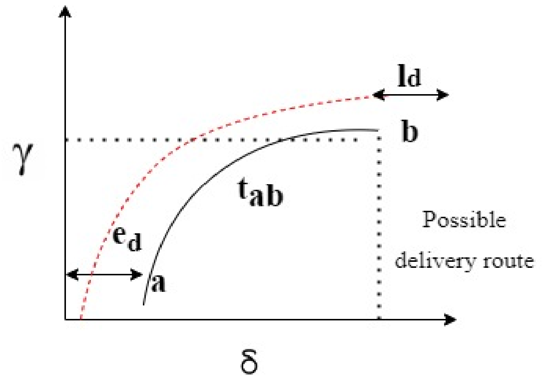

Figure.2 Vehicle transportation route with a time of delivery to customers

Objective functions:

$$\text{Min } \sum_{v=1toV} \sum_{c=1toC} \varphi(O_r)\omega(v,c).S_{ab,v} \tag{5}$$

$$\text{Subject to } \sum_{a=0}^{C} \sum_{b=1}^{C+1} O_{ab} \qquad where \; a,b = 1,,,,,,,C \tag{6}$$

The above equations 5 and 6 mentioned that the status of the order delivery O_r using V from customer a to b follows the sequential order, which means each order placed by a customer must follow the single previous and later delivery procedure in the production stage.

3.3 Hybridized metaheuristic algorithm implementation using PSO-WOA-based LNS in an improved way.

Intelligent manufacturing scheduling issues sometimes entail many goals, including lowering transportation time, shortening makes span times, minimizing average relative difference, total weighted delivery, and enhancing delivery effectiveness. Formulating the scheduling issue as a multi-objective optimization problem is the first step in the hybridization process.

3.3.1Particle swarm optimization algorithm for identifying the best solution:

Initially, the particle swarm optimization algorithm is implemented in a hybrid approach because it is a well-known optimization method that searches recursively over the solution space for the best solution, and it has been influenced by the social behavior of fish breeding and bird swarming. The algorithm uses particles to represent probable optimization issue solutions in a space with multiple dimensions. Each particle navigates the search space by altering its position in response to its own and neighbors' experiences. It is useful for addressing massive amounts and complicated collaborative scheduling problems because of its capacity to investigate the search space and converge on promising solutions for an enterprise. i)PSO can optimize the distribution of jobs across machines or resources for production scheduling, considering processing times for a minimal makespan of order completion and reduced ARDI. ii)PSO can optimize vehicle routes for scheduling transportation while considering variables like routing, time, and vehicle capability.

3.3.2Whale optimization algorithm for optimal scheduling of production tasks:

After applying the particle swarm optimization technique, the whale optimization technique is employed to refine the scheduling solutions further. It tries to efficiently search the solution space while gradually converging towards optimal solutions by simulating the social relationship among customers and enterprises and the hunting behavior of whales. The algorithm uses the process of exploration and exploitation to look for the best answers quickly. Scheduling and routing issues are just two optimization issues that this algorithm has successfully resolved in addition to the obtained best solution space of the previous step. This algorithm can optimize the job distribution among resources and the transportation routes while considering various restrictions and goals for production tasks and transportation schedules. This algorithm seeks to find competitive, high-quality solutions that satisfy the production and transportation scheduling problem's numerous objective functions and restrictions by striking a balance between exploration and exploitation.

3.3.3Local neighborhood search to initiate a localized solution

The enhanced way of local neighborhood search's label implies improvements and enhancements might include intelligent methods of manufacturing the search space, more effective neighborhood structures, and better methods for choosing the initial solution. The objective is to find enhancements that could result in a localized problem with an ideal solution. It evaluates neighboring solutions iteratively to determine their quality using the specified objective functions and restrictions. The system can make minor schedule adjustments while investigating the immediate area around the found answers. It aids in utilizing the regional framework of the search space and might find better solutions that the global optimization algorithms had not yet considered. The detailed explanation of Figure 3 is explained below in a step-by-step manner.

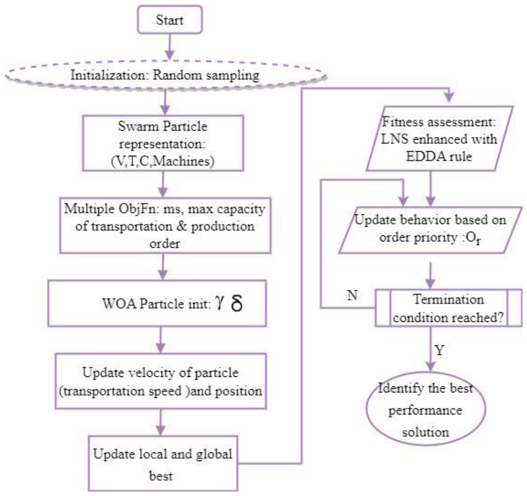

Figure 3. Workflow of the proposed hybridized approach

Step 1: Initialization: Considering customer requirements and resource constraints, a random sampling technique establishes a starting point for the production and transportation schedule. In this random sampling, each customer demand has been chosen randomly to satisfy their order request with a random route at initial.

Step 2: Particle Representation: Each particle should be represented as a potential remedy to the scheduling issue in the PSO algorithm. The position of the particle-like vehicle will be a list of production tasks T, specifying which jobs are sent to specific machines and transportation paths of travel.

Step 3: Setting up of Objective function:

Create a function with objective parameters to assess a particle's solution's quality. In this intelligent manufacturing scenario, the goal is probably to reduce the overall ms, considering both the process of production and transportation periods. The goal is to identify T associated with machine μ and route-transportation combinations that minimize the overall ms. At the very least, every member of the first population must be a viable candidate solution. Each transportation path in the original population must be viable. In this study, an individual is possible when the vehicle's maximum capacity and allotted trip time are met.

Step 4: Particle initialization:

Creating a particle population means the position update is initially scattered around the solution space. During optimization, a particle's velocity will serve as a representation of its direction of motion of the vehicle, which indirectly represents the transportation routing with δ_{vl} denotes the speed of the vehicle V among δ.

Step 5: Fitness Assessment: Based on the specified target function and considering the collaborative scheduling goals and limitations, assess the state of fitness of every single particle and whale. This involves evaluating the effectiveness of each solution in terms of actual transportation cost and penalty cost function of e_d and l_d of production orders, the efficiency of production, ms and $AVDI_S$ related to an enterprise. The solution algorithm subsequently explores the WOA space utilizing its search operating functions, such as encircling. The system's global search capabilities enable it to investigate various solutions effectively. New production schedules or sequences can be found through exploration, which could result in more effective resource allocation and shorter production times. The algorithm randomly distributes some operations to promote variety in the solutions investigated during the search phase. Exploitation tries to improve production schedules that have the potential to be more efficient in terms of both resource use and productivity. The algorithm maintains a record of the top solution so far. The algorithm intensifies its search for better-performing solutions with each iteration, attempting to outperform the current best option. Following the exploration stage of the WOA, the hybridized algorithm incorporates an enhanced strategy of LNS. The LNS concentrates on stepping up the search for potential solutions discovered by WOA.

Step 6: Update behavior:

Particles update the global optimal solution that is best positioned across the whole swarm of particles and their individual best solution identified up to the current production stage as they move across the solution space from the initialized position of machines and T. This cooperation enables the swarm to converge on superior solutions jointly.

At this point, the best solution found using the previous technique is also identical to the initial solution. The production order O_r the sequence is established using the EDDA rule, and then the objective value of the neighbor solution is calculated each time the vehicle routing is formed. Orders are planned according to their due dates. D_T tasks with lower or earlier due dates are prioritized to ensure prompt delivery. The improved local optimization approach is used to raise the caliber of the created neighbor solutions. The newly derived neighbor solution will win if it is superior to the best. Then arrange the O_r of each vehicle following the total of all vehicles' descending production order time frames. Recalculate each vehicle's V departure time and the sum of ordered-weighted delivery times by assuming that orders from a single order bundle in an enterprise are created sequentially and that each order's production sequence corresponds to its delivery sequence.

3.4 Pseudocode for calculating production order sequence:

Step:1 Initialize production order from customers O_r,α, C, β

Step:2 Calculate transportation route for particular customer C request with V

if $t_{\mu+1,T2} - t_{\mu,T2} \geq 0,\ t_p \in \mu \leq \alpha$

apply the EDDL rule using equation ()

else

identify possible route $\gamma \in T \leq \beta$

Calculate Transportation _time=dist(c,v,E)/Particle speed

$\zeta_{O_r} = O_r.t_p + (particles \times$departure time)

return ζ_{O_r}

The estimated overall delivery time for the orders is then determined. The scheduling of production orders within a manufacturing facility μ is called order production sequence. To maximize the utilization of resources, cut down on time spent setting up, shorten production times, and boost overall productivity, it entails deciding the sequence in which orders for production are completed. The objective is to develop an effective production flow and prompt product delivery to satisfy consumer demand.

Step 7: If $ctr = Maxitr$, the best optimal γ is achieved and optimum assignment of production task T to machines and transportation routes. With this proposed approach, the global best position indicates the optimal allocation of T to machines μ in an enterprise and transportation routes γ that minimizes the ms and delivery to the customer inefficiently and moves to the next step for termination condition. Else continue from step behavior update to identify the best possible production and transportation scheduling process.

Step 8: Termination criteria:

Terminate the hybridized optimization techniques involving swarm particle and humpback movement vehicle routing to stop the process if all machines μ involved in transporting order delivery to a customer from an enterprise. Otherwise, choose the next machine to opt for delivery and start from step 2.

4. Experimental study

This section presents the comparative analysis results for the proposed method using minimal makespan, reduced ARDI, transportation time, and EDDL metrics. The number of production tasks and the delivery time to customers varied in analyzing the metrics with various transportation routes. The data source related to enterprise survey is analyzed from multiple intelligent manufacturing environments to obtain the performance metrics results chosen from [27]. Here the input attributes involve customer size, machine count, order count, customer priority, transportation time to reach a customer, and an enterprise back. In this comparative analysis, the methods DTCST [20], ELNSs [22], and HMOVNS [23] are used alongside the proposed HPWL-IME method.

4.1 Identifying the objective function achievement with various scheduling constraints

Figure 4, the diagram shows the number of objective functions taken for efficient production and transportation collaborative scheduling constraints in an IME. The horizontal axis shows the scheduling constraints necessary to reach the multi-objective function is elaborated using equations 1 and 4 for production and transportation. Hence, the proposed algorithm follows a meta-heuristic optimization approach to satisfy objective criteria in complex environmental production and transportation problems.

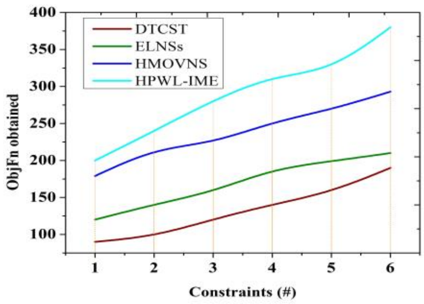

Figure.4 Analysis of ObjFn obtained in the enterprise production and transportation with scheduling constraints.

4.2 Average Relative Deviation Index for scheduling algorithm

As shown in Figure 5, the average relative deviation index ranges from 0 to 1, where the random population is identified from the input of the particle swarm optimization technique and finds the best possible solution for a particle with the maximum velocity of transportation speed to reach the customer with the highest priority order at first.

$$ARDI_S = \frac{1}{C} * \sum \left| \frac{(Est_{ms} - Obs_{ms\forall N}}{Est_{ms}} \right| * 100 \qquad (7)$$

From Equation 7, the variable C represents the total observations in the manufacturing scheduling-related criteria with the maximum count of iterations, Est_{ms} represents the actual make-span value, $Obs_{ms\forall N}$ represents the make-span value observed from all the N number of algorithms used for comparison.

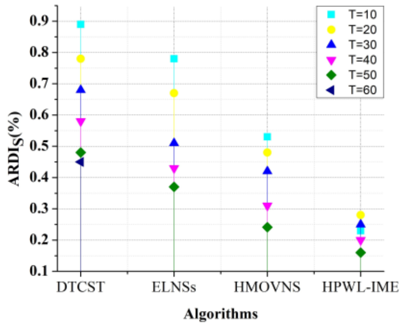

Figure.5 Analysis of AVDI based on production task

4.3 Calculation of makespan with an increasing number of production tasks

As depicted in Figure 6, the calculation of makespan is identified from the given objective function with the necessary input scheduling constraints of production tasks count taken from [28]. The multiple enterprises involved in an IME produce various T based on different customer needs that must be satisfied with the identification of local neighbor search properly. D_T and earlier completion time in addition to the t_p taken for arranging the order sequence. The makespan calculation from the initial objective function was achieved with the random sampling selection of machines from μ to complete the given production order in a minimal period. The proposed algorithm outperforms all existing approaches with minimum time spent completing the production process.

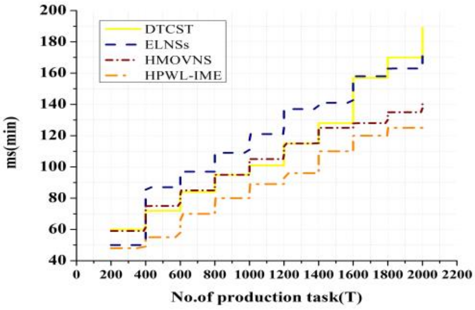

Figure.6 Calculation of ms for various T using different algorithms

4.4 Earliest Due Date Assignment (EDDA) rule:

Enterprises arrange jobs based on the earliest due date, and it prioritizes processing tasks T that have the earliest due dates, also known as due date assignment is calculated and shown in Table 1. The frequency of late jobs and the average tardiness among late jobs are used for evaluating manufacturing facility quality performance is calculated using Equation 8.

$$EDDA_L = \zeta_{O_r} - \mathrm{D}_T \tag{8}$$

Where the completion time of the production task is given as ζ_{O_r}, $EDDA_L$ represents the earliest due date assignment which defines the lateness of a task. The production task's /due date D_T, also known as the deadline, indicates when it must be finished within the production stage.

If the Lateness outcome L is positive, the production task T finished after its due date, resulting in lateness. A task or project was done earlier than expected if the delay or L result is negative, indicating an early completion. By effectively scheduling the tasks according to their D_T, utilizing the EDDA scheduling rule, the aim is to minimize the overall lateness by frequently identifying the scheduling constraints in the predecessor search process.

4.5 Transportation time:

The production orders' departure time and the particle movement velocity are two parameters that affect the distance traveled between production orders and customers. A particle's position corresponds to a certain order of consumer visits. Particles act as prospective solutions or pathways, searching for shorter, more efficient routes via the solution space. The particle placements (routes) are modified according to their velocities during every round of the proposed algorithm. Transportation times could change depending on the particle's new position, which varies based on the customer's order. O_r with weight update w. The program iteratively alters the particle's positions and speed to discover more efficient paths that reduce travel time. The optimal transportation route is represented by the best result attained after a specific number of iterations. Figure 7 identifies effective transportation routes that save travel time and raise the enterprise and transportation process's overall effectiveness.

Table-1 EDDA Rule sample calculation for various production tasks of an enterprise

T	Scheduled t_p(A)	D_T	Sort T based on min D_T	Arranged t_p (B)	ζ_{O_r}	Arrangement of D_T based on B	L
T1	20	36	T3	40	40	30	10
T2	35	32	T2	35	75	32	43
T3	40	30	T4	60	135	34	101
T4	60	34	T1	20	155	36	119

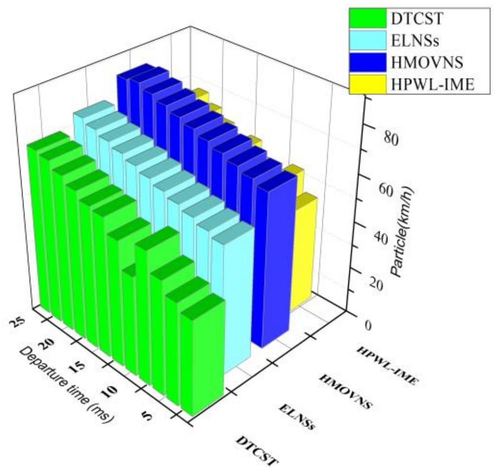

Figure. 7. Transportation time analysis based on varying departure time

5. Conclusion

Digital enterprises need intelligent manufacturing since simple technology is no longer enough to maintain ahead of customer demand. The proposed HPWL-IME approach efficiently and fairly optimizes production schedules and transportation routes by utilizing the advantages of each method. The hybridized technique makes it possible to explore the problem space effectively and find viable paths and timetables that could increase overall effectiveness. Balancing global exploration with local exploitation improves solutions for more efficacy. Different objectives and restrictions must be considered to meet consumer requests and reduce production time. The benefit of integrated meta-heuristic tactics results in better delivery commitments, a shorter manufacturing makespan, and more efficient transportation times. This method offers a considerable improvement in scheduling techniques for businesses in the quickly changing global economy, offering both academic significance and usefulness for implementing flexible, intelligent, and green manufacturing processes. The limitation faced in this proposed study is no one best approach simultaneously meets all of the scheduling problem's multiple objectives, such as minimizing makespan, transportation time with total weighted delivery, and minimal relative difference. The non-determined sorting and selection techniques may apply in the future to keep variety throughout the solution area and give decision-makers the freedom to select a well-balanced option that fits the enterprise's goals and scheduling constraints to take a decision.

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