A DECISION MODEL FOR PRODUCTION LOGISTICS PLANNING CONSIDERING ELECTRIC VEHICLE USAGE

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ABSTRACT

Logistics in production involves the movement of materials/parts to the workstation to ensure an efficient and effective production process. This study is motivated by the practices of production logistics within a manufacturing company and aims to minimize delays and total costs in transferring materials/parts to the workstation by utilizing electric vehicles (EV). The problem is formulated as an EV multi-period routing problem (EV-MPVRP), taking into account factors such as vehicle capacity, limited operation time, restricted distance, and charging time for EV. The results demonstrate that the proposed method effectively reduces delays and costs associated with the movement of materials/parts. Additionally, incorporating inventory into the production plan can lead to a decrease in both travel distance and charging time.

Keywords: *Production Logistics, Inventory Routing Problem, Electric Vehicle, Optimization*

1.0 INTRODUCTION

In today's highly competitive manufacturing environment, the ability to coordinate internal flows of materials, information, and resources is increasingly critical to operational performance. The term of Production Logistics which refer to internal logistics or production internal logistics is the function within operations management that plans, controls, and executes the flow of materials, information, and resources inside the production system. The objective of Production Logistics can be wide from inventory, storage and transportation costs minimization, lead times reduction, and flexibility and productivity enhancement [1] [2].

Production logistics is critical to managing the internal flow of materials/parts within manufacturing systems. Several research highlight how technological advancements, particularly those aligned with Industry 4.0, are transforming production logistics into more intelligent and efficient systems. Technologies like RFID, digital twins, cyber-physical systems, and other Industry 4.0 tools improve visibility, traceability, and decision-making across supply chains, leading to cost reductions and enhanced customer service [3][4][5]. Another important issue in production logistics is related to green and environmental friendly production logistics. The focus in this issue is to minimize energy to transform materials/parts into desired products while still mange to achieve the target [6].

In the current manufacturing landscape, mass customizations, shortened product life cycles, and higher customer service expectations have made production logistics planning

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a challenging problem. This research is motivated by production activities in an automotive spare parts manufacturing company based in West Java, Indonesia. This company produces several spare parts to supply a main automotive manufacturer. One of the related problems is the delay which occurs in the movement flow of materials/parts in the production floors. According to the internal production department, there are 13%-15% delays in the production target caused by inefficient materials/parts movement.

Currently, the materials/parts are transported from the internal storage area to each workstation using an electric tow train system as material handling equipment (MHE). A similar transportation method is used to move finished goods to the internal final storage. Since it is an EV, it will require a charging time, which could be take some time compared to a regular combustion engine vehicle. Each material or part is placed in the pallet, and the MHE will move the pallet to the workstation. Each workstation has a limited temporary storage area to temporarily store materials/parts before the production process if necessary. An illustration of the production layout is displayed in Figure 1.

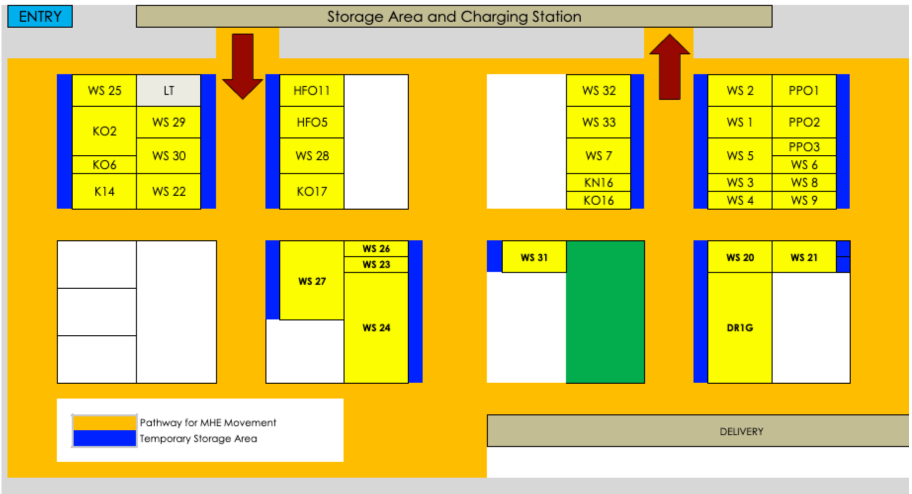


Figure 1. Illustration of the production layout

In classic production logistics research, the main focus in the objective function is to minimize the tardiness or makespan to eliminate penalty [7] [8]. Efficiency in terms of total distance or cost is considered after producing timely and less penalized solutions. In the era of sustainable and agile manufacturing, cost efficiency can be considered an important aspect for manufacturers. Several studies consider the temporary inventory of materials/parts stored in the workstation to achieve cost efficiency [9] [10]. The consideration of inventory storage in each workstation can maximize the utilization of MHE; thus, it may reduce the distance traveled.

Another option to enhance cost efficiency is through the usage of EV. Current research in production logistics concentrates on the transportation of MHE through EV [11] [12]. The usage of EV instead of internal combustion engine (ICE) in the production plan is justified due to cost efficiency, low emission, safety, and also promotes green initiatives in the manufacturing company. Several studies aim to minimize energy consumption in the objective function [13][14][12]. Although electric MHE has its benefits in terms of cost, the recharging mechanism remains a challenge to solve. Several electric MHE have the technology to swap batteries to maintain their movements. However, recharging, which is time-consuming, continues to be a challenge for electric MHE that do not have battery swap technology.

Throughout the study, we extend current production logistics research by considering the use of EV as MHE and its recharging requirement for non-batteryswappable MHE. This paper proposes an optimization model to plan electric MHE routing while considering the recharge trip to the recharging area. Additionally, inventory storage at each workstation during the planning periods is considered to further minimize travel distances and reduce MHE energy consumption.

This paper's contribution is as follows: Our study introduces a novel method for planning electric MHE routes to transport materials/parts within the production plant, taking into account inventory considerations for each planning period. We develop a Mixed Integer Linear Programming (MILP) model to solve the problem. Our model's results can effectively address instances based on real-world problems. An interesting insight related to considering temporary inventory storage at each workstation is provided.

The remainder of this paper is organized as follows. Section 1 will discuss the background, importance, and contribution of this study. Problem description and formulation are presented in section 2. We report the numerical experiments and computational results in Section 3. Finally, discussion and conclusion, as well as future works, are presented in Section 4.

1.1 Literature Review

In this subsection, we review several studies related to production logistics in general. Production logistics research direction can be categorized into two interesting topics. First is related to technological usage to improve efficiency and performance. It utilizes machine learning, deep learning, digital twins, etc. to help minimize resources and maximize the performance [15]. In the other direction, energy preservation and environmental issues are the focus [13][14]. A literature review for environmentally friendly production logistics can be found in [6], [16].

The literature review section is divided into two subsections. Reviews on production logistics scheduling and routing are presented in the first subsection since this study proposes an optimization model for production logistics scheduling and routing. Since this study proposed a multi-period routing problem, several studies related to multi-period routing problems are reviewed. In the last paragraph, the contribution of this paper will be stated.

1.1.1 Production logistics scheduling and routing

A study proposes an innovative approach to address dynamic part feeding scheduling problems (DPFSP) in automobile mixed-model assembly lines using automatic guided vehicle (AGV) as MHE [7]. This strategy combines fuzzy logic with neural networks by integrating self-organizing maps (SOM) and fuzzy C-means clustering (FCM) into a hybrid dynamic scheduling algorithm (SOM-FCM-DS). This hybrid approach effectively handles the uncertainty and dynamic disturbances common in assembly line environments. Based on the result, this method enhances scheduling adaptability and efficiency amid disturbances in mixed-model assembly lines.

Green Vehicle Routing Problem with Simultaneous Pickup and Delivery and Time Windows (GVRPSPDTW) to plan AGV's operation was studied by [14]. A mathematical model was developed to minimize the total energy consumption of AGVs, considering factors such as load, driving distance, travel time, and standby energy usage. This study also proposes a hybrid algorithm combining Differential Evolution (DE) and Large Neighborhood Search (LNS) with adaptive scaling and a squirrel migration operator to enhance solution quality and search efficiency.

The AGV scheduling problem to accommodate the interdependencies between operations and AGV availability is studied by [8]. This study formulates the joint scheduling problem in hybrid flow shops, considering limited AGVs for material transport and integration between machine operations and AGV availability. This research optimizes multiple objectives, including minimizing the make span (overall completion time), reducing the AGV operation time, and balancing machine workloads, thereby improving production efficiency and resource utilization. A hierarchical learning-based swarm optimization algorithm is proposed as a novel method to solve this multi-objective scheduling problem efficiently. The algorithm incorporates learning mechanisms to enhance the swarm optimizer's ability to explore the solution space and converge on high-quality solutions.

A generalized vehicle routing problem to solve MHE routing for production planning while preventing blocking in an aisle was proposed by [17]. A pixel-based grid framework is utilized to enable precise detection of blocking two trains. A blocking detection and avoidance algorithm is introduced to detect vehicle conflicts systematically and resolve them through avoidance strategies, ensuring conflict-free MHE routing in narrow aisles. To solve large problems, a simulated annealing (SA) heuristic with problem-specific neighborhood operators is developed to optimize MHE routes efficiently. This metaheuristic approach balances exploration and exploitation to identify high-quality routing solutions given blocking constraints.

MHE routing optimization is studied by [11]. Their study addresses the combined problem of optimizing MHE dispatch schedules and planning conflict-free routes simultaneously, aiming to minimize total energy consumption and transportation expenses in complex mixed-model assembly lines. The study incorporates well-known shortest path algorithms within this grid framework, which enable accurate distance calculations between workstations and facilitate more efficient route planning. A metaheuristic such as simulated annealing (SA) is combined with the routing and conflict management framework to optimize MHE dispatching and routing decisions effectively.

A mathematical formula for scheduling MHE (small transport vehicles) that deliver parts from decentralized storage areas was proposed by [9]. This study formulates the problem as a pick-up and delivery scheduling problem with fixed routes for the two trains operating within constrained factory shop floors, where routing options are typically limited. This study makes a significant contribution by providing a comprehensive mathematical model and practical scheduling algorithms for efficient in-plant part delivery logistics, optimizing the critical feeding of automotive assembly lines under space, demand, and operation constraints.

Another optimization study for scheduling the MHE has also been proposed by [8]. This study proposes a mathematical optimization model that simultaneously considers the routing paths, delivery schedules, and loading capacities of the MHE to optimize the overall parts supply process. The model accounts for constraints such as fixed routes, time windows for deliveries, and varying demand at multiple assembly stations, reflecting realistic production conditions.

A study addresses the challenge of efficiently supplying parts to mixed-model assembly lines using MHE and supermarket systems in automotive manufacturing was available in [10]. The study focuses on three interconnected problems: MHE routing, scheduling, and loading, aiming to optimize the delivery schedule, route, and loading plan for a single MHE that transports parts from a supermarket to workstation buffers. The results demonstrates that integrating supermarket systems with MHE can significantly improve part feeding efficiency, especially in environments with high product variety and complex assembly requirements.

An EV scheduling model as a multi-depot EV scheduling problem (MDEVSP), aimed at managing a fleet of EV that serve various production-related transport tasks while starting and ending at assigned depots was studied by [12]. This study considers charging time as a function of battery state and power constraints, which is important for planning feasible routes and schedules, ensuring that vehicles cover all assigned service trips within time windows, maintaining battery energy within allowed limits at all times, and undergoing sufficient charging at stations before continuing tasks.

1.1.1 Multi-periods routing problem

In this subsection, we review several pieces of research related to the multi-period routing problem. Classification for the the periodic routing problem can be found in [18].

A column generation heuristic approach to solve multi-period vehicle routing was introduced by [19]. The authors propose a two-phase heuristic approach combining column generation for allocation of visits and an ant colony optimization metaheuristic for routing. The objective is to optimize regional compactness of routes to specialize routes in restricted geographical areas and to minimize costs while respecting vehicle capacity and customer constraints.

A bi-objective mathematical model to solve the the multi-product, multi-period inventory routing problem (IRP) was proposed by [20]. The problem incorporates a green transportation approach that explicitly considers both minimizing transportation expenses and reducing greenhouse gas (GHG) emissions. A key feature is the transshipment option, where vehicles can deliver products either directly from suppliers or from temporary storage locations created by previous deliveries to other suppliers, thus optimizing routes and reducing total travel distances.

A hybrid optimization algorithm for the periodic vehicle routing problem (PVRP), which extends the classical vehicle routing problem by scheduling routes over multiple days on a planning horizon was presented by [21]. Each customer must be visited a specified number of times according to the allowed combinations of visit days, while also adhering to constraints on vehicle capacity and fleet size. This study proposed a set-covering-like integer linear programming formulation solved via column generation, which iteratively generates and refines route columns using an iterated local search algorithm.

A vehicle routing problem where the workload associated with a set of delivery requests must be distributed over multiple periods, respecting a limited load capacity per period was studied by [22]. The problem aims to plan deliveries over a sequence of periods while adhering to constraints on the total workload for each period to avoid overloads and inefficiencies. The authors develop mathematical models and solution methods to balance the workload across the given planning horizon, ensuring that vehicle load and period capacity limits are not exceeded.

A study to address the tactical planning challenges in the management of India's public distribution system (PDS) food grain supply chain was proposed by [23]. The authors develop a mixed-integer, nonlinear programming (MINLP) model aimed at minimizing the overall cost, which includes transportation, storage, and operational expenses over a multi-period planning horizon. The authors propose an improved metaheuristic algorithm called the Improved Max-Min Ant System (IMMAS), inspired by ant colony optimization, to efficiently find high-quality solutions. The validity of IMMAS is benchmarked against the standard Max-Min Ant System (MMAS).

A multi-period vehicle routing problem (VRP) in the context of a hygiene services company which has different service frequency requirements, e.g., some must be visited weekly, bi-weekly, or monthly was proposed by [24]. The authors decompose the planning horizon into weekly and daily subproblems. A hybrid adaptive large neighborhood search (ALNS) metaheuristic was proposed to generate efficient routes.

A study proposed a modified adaptive genetic algorithm to solve the multi-product, multi-period inventory routing problem (IRP) involving a supplier, multiple customers, and a fleet of heterogeneous vehicles is available in [25]. The problem focuses on determining delivery schedules and vehicle routing to satisfy customer demands over time while minimizing total operational costs, including transportation, inventory holding, and routing expenses. A unique feature of the proposed algorithm is the ability to adaptively modify crossover and mutation rates based on the evolution of fitness values during the search process to balance diversification and intensification.

Table 1. Summary of previous related research

		Research															This Study
		[13]	[14]	[7]	[8]	[17]	[11]	[9]	[10]	[12]	[19]	[20]	[21]	[22]	[23]	[25]	
Obj. Func	Tardiness / Makespan	X		X	X	X	X										
	Transportation Cost			X					X	X	X	X	X	X	X	X	X
	Inventory Cost			X				X	X			X			X	X	X
	Energy Consumption	X	X				X										X
Cons.	Capacity and Routing	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	Overlap or Conflict				X	X	X										
	Time Window	X	X	X			X			X			X	X			X
	Inventory							X	X			X			X	X	X
	Multiperiod							X	X	X	X	X	X		X	X	X
	Charging																X
Sol. Method.	Math. Model	X			X	X	X	X	X	X	X	X	X	X	X	X	X
	Metaheuristic Algorithm	X		X	X	X	X	X	X		X		X		X	X	

The related literature and the work of this paper are concluded in Table 1 that shows the summary of the literature review based on several key components. The literature review covers crucial research in the field of production logistics and scheduling, and multi-period routing problem.

In the production logistics and scheduling subsection, several research related to the term green and/or energy consumption have not considered multiperiod planning and/or inventory. The closest research that can be found is the electric MHE routing and scheduling study, which is done by [12]. Although our case shares a similar problem of transporting materials/parts to the workstation using EV, the major dissimilarity is the consideration of inventory in each workstation to minimize the travelling distance and energy consumption. In this study, we introduce the inventory consideration as one of the alternative solution to reduce the cost. In addition, our study add charging mechanism that allow the MHE to charge and maintain its energy in the planning process.

Based on the review for the multi-period routing problem, several studies proposed a model and heuristic algorithm to solve the multi-period routing problem and even consider inventory in each period [23] [25]. However, the consideration of using EV is still limited in multi-period routing problem study. Our study considers the use of EV as the MHE in the production area, as well as the planning of EV charging mechanism.

To sum up the contribution of this research, our study develops of an optimization model to solve multi-period production logistics scheduling and routing using EV as MHE to minimize the transportation and inventory cost. This study overcome the limitation of the previous study which are not consider the usage of EV in the production floor as well as the charging mechanism, and the use of inventory in each period to maximize MHE utilization and the reduce the movement. This model can be classified as an EV multi-period vehicle routing problem (EV-MPVRP).

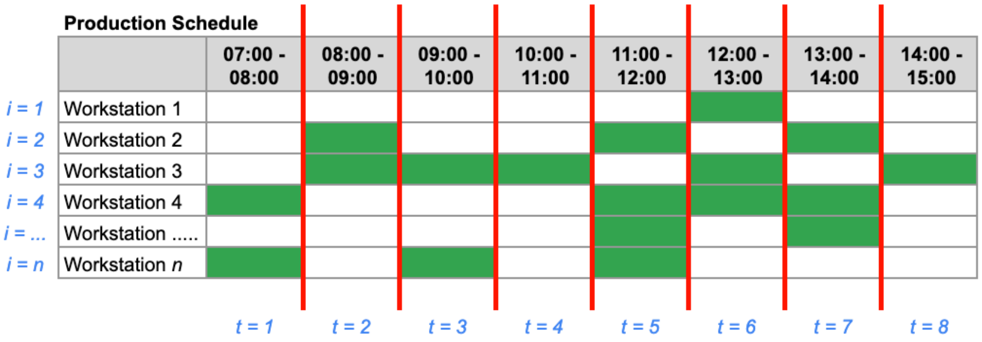
2.0 EXPERIMENTAL PROCEDURE

2.1 Problem Description and Model Formulation

In the production plant, electric tow train system, acting as MHE, manages the movement of materials/parts. According to the production schedules, each workstation has a demand for materials/parts for the production process. Each workstation provides limited temporary storage for the materials/parts before their use in production.

The MHE will transport the materials/parts from the storage area to the workstations. MHE will have a maximum load capacity and maximum distance covered before it needs recharging. When needed, MHE can be recharged using the charging facility, which is available at the depot.

Since the problem is bound to the production schedule, which is outside of this study's scope, it is modeled as a multiperiod routing problem, where periods represent an hour's time. The study will divide the production schedule into hourly segments and plan the towing movement accordingly. Therefore, there will be an hourly maximum planning horizon for each period. As for the charging mechanism, MHE can be charged after it finishes transporting the materials/parts to workstations in each period if needed. The total travel time to move materials/parts and the charging time will not exceed one hour, which is the maximum allowed time in each period. An illustration of problem formulation is available in Figure 2.



Production Schedule

		07:00 - 08:00	08:00 - 09:00	09:00 - 10:00	10:00 - 11:00	11:00 - 12:00	12:00 - 13:00	13:00 - 14:00	14:00 - 15:00
$i = 1$	Workstation 1						🟩		
$i = 2$	Workstation 2		🟩			🟩		🟩	
$i = 3$	Workstation 3		🟩	🟩	🟩		🟩		🟩
$i = 4$	Workstation 4	🟩				🟩	🟩	🟩	
$i = ...$	Workstation					🟩		🟩	
$i = n$	Workstation *n*	🟩		🟩		🟩			
		$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$	$t = 7$	$t = 8$

Figure 2. Problem Formulation Illustration

In this study, the problem is formulated as a mixed-linear integer model. The problem itself can be categorized as a multi-period routing problem with EV and inventory considerations. Consider a graph $G = (V, A)$ where $V = v_0, v_1, \dots, v_n$ is a set of vertex represents the depot, charging station, and workstations and $A = \{(v_i, v_j): v_i, v_j \in N, i \neq j\}$ is the set of arc. Depot and charging station which is denoted as v_0 are located at the same location. A workstation, which is neither a depot nor a charging station, has a non-negative demand for materials/parts, as well as a temporary storage area for storing these materials/parts that are waiting for production, with a specified maximum quantity I_{max}.

A set of arc A is associated with travel distance D_{ij} and travel time T_{ij}. For each period $p, p \in P$, a set of MHE F will transport materials/parts to workstations. Each MHE limits its maximum load capacity Q^f and maximum distance B before it needs to be recharged. MHE can be recharged when needed with O conversion rate from distance to kWh and each kWh charged cost C. The whole operations are bounded by a maximum service L.

This study defines three decision variables. First decision variables x_{ijp}^{f}which have value 1 if the MHE f transport a materials/parts from workstation i to workstation j at period p, otherwise 0. The second decision variables q_{ip}^{f}, decides the load carried by MHE f to workstation i at period p. The last decision variable is related to the MHE charging decision c_{p}^{f}, denoting recharging needed in distance for MHE v at period p. The complete description of sets, parameters, and variables are shown below.

2.2 Mathematical Model

Indexes, Sets and Parameters

$\mathrm{i, j, k}$	Indexes of depot, charging stations, and workstations
f	Indexes of MHE
p	Indexes of periods
N	Number of workstations, node 0, is the charging station and depot.
F	Number of MHE
P	Number of periods
D_{ij}	Distance between workstations i to j
S	Speed of MHE
G_{ip}	Materials/parts needed for each workstation i at the period p
Q^{f}	Maximum load capacity of MHE f
I_{max}	Maximum inventory for all workstations
C	Electricity cost for charging MHE per kWh
O	Conversion rate from distance to kWh
L	Maximum time of service per period
H	Holding cost per unit per period
B	Maximum distance of MHE before charging
Z	Sufficiently large number

Variables

x_{ijp}^{f}	Binary variables indicating workstations i and j are visited consecutively using a MHE f.
q_{ip}^{f}	Load carried by MHE f to workstation i at period p
c_{p}^{f}	Charging distance needed for MHE f at period p
u_{ip}^{f}	Accumulated time/distance of MHE f in workstation i at period p
z_{ip}^{f}	Binary variables indicating the MHE f visits the workstation i at period p
v_{i}^{p}	Inventory at workstation i period p
d_{p}^{f}	Total distance for MHE f at period p
c_{p}^{f}	Charging distance needed for MHE f at period p

The objective of this model (1) is to minimize the electricity costs associated with using the MHE to transport materials/parts from the storage area to each workstation, and inventory holding cost per period. A conversion parameter exists to translate the distance into the amount of electricity required, measured in kWh.

$$\min \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{f=0}^{F}\sum_{p=0}^{P} x_{ijp}^{f} D_{ij} O C + \sum_{i=0}^{N}\sum_{p=0}^{P} v_{i}^{p} H \tag{1}$$

The constraints of this model are described in constraints (2) to (15) below.

$$\sum_{i=0}^{N}\sum_{f=0}^{F} x_{ijp}^{f} - z_{jp}^{f} = 0 \qquad \forall j = 1,..,N-1; f = 0,..,F; p = 1,..,P \tag{2}$$

$$\sum_{j=0}^{N}\sum_{f=0}^{F} x_{ijp}^{f} - z_{ip}^{f} = 0 \qquad \forall i = 1,..,N-1; f = 0,..,F; p = 1,..,P \tag{3}$$

$$\sum_{i=0}^{N} x_{ikp}^{f} - \sum_{j=0}^{N} x_{kjp}^{f} = 0 \qquad \forall k = 1,..,N; f = 0,..,F; p = 1,..,P \tag{4}$$

$$\sum_{i=0}^{N} x_{0ip}^{f} - z_{0p}^{f} = 0 \qquad \forall f = 0,..,F; p = 1,..,P \tag{5}$$

$$\sum_{i=0}^{N} q_{ip}^{f} \le Q^{f} \qquad \forall f = 0,..,F; p = 1,..,P \tag{6}$$

$$q_{ip}^{f} \le z_{ip}^{f} Z \qquad \forall i = 0,..,N; f = 0,..,F; p = 1,..,P \tag{7}$$

$$u_{ip}^{f} \le N + 1 \qquad \forall i = 1,..,N; f = 0,..,F; p = 1,..,P \tag{8}$$

$$u_{jp}^{f} \ge u_{ip}^{f} + 1 + \left(x_{ijp}^{f} - 1\right)(N + 1) \qquad \forall i = 0,..,N; j = 1,..,N; f = 0,..,F; p = 1,..,P \tag{9}$$

$$v_{i}^{0} = 0 \qquad \forall i = 1,..,N-1 \tag{10}$$

$$v_{i}^{p} = v_{i}^{p-1} + \sum_{f=0}^{F} q_{ip}^{f} - G_{ip} \qquad \forall i = 1,..,N-1; p = 1,..,P \tag{11}$$

$$v_{i}^{p} \le I_{max} \qquad \forall i = 0,..,N-1; p = 0,..,P \tag{12}$$

$$d_{p}^{f} = \sum_{i=0}^{N}\sum_{j=0}^{N} D_{ij} x_{ijp}^{f} \qquad \forall f = 0,..,F; p = 0,..,P \tag{13}$$

$$\left(\sum_{s=0}^{p} d_{s}^{f}\right) - c_{p-1}^{f} \le B \qquad \forall f = 0,..,F; p = 1,..,P \tag{14}$$

$$\frac{d_{p}^{f}}{S} + \frac{c_{p-1}^{f} F}{S} \le L \qquad \forall f = 0,..,F; p = 1,..,P \tag{15}$$

Constraints (2) and (3) ensure that the MHE visits the workstation and leaves if needed in each period. Constraint (4) defines flow conservation of each MHE. Each MHE can only be used once in a period that is defined in constraint (5). Constraint (6) prevents the load of each MHE from exceeding its maximum load. Constraint (7) defines the load that needs to be carried by the MHE in each period. Constraints (8) and (9) determine sub-route elimination constraints. The quantity of inventory in each workstation and period is defined in constraints (10)-(12).

Constraint (13) determines the total distance covered by a MHE per period. The accumulation distance covered for every consecutive period is accumulated, and it cannot exceed the maximum distance of the MHE before charging. Variables define the charging distance needed before the battery of the MHE runs out. Constraint (14) makes sure the MHE will have an empty battery while transporting materials/parts to each workstation per period. Lastly, constraint (15) prevents total transporting time and charging time per period from exceeding the maximum time periods.

2.2 Numerical Experiments

The proposed mathematical model will be solved using the Gurobi solver, which is available with an academic license. Numerical experiments will be performed using Python codes to achieve optimal results. All computational experiments will be executed on a desktop-class computer featuring an AMD 5950X processor with 16 cores and 32 threads, along with 16 GB of DDR5 RAM.

Our study conducts a numerical experiment based on the real data obtained from our object. The information includes the locations of workstations, the depot or charging station, production demand, MHE specifications, and other relevant details. Travel distances D_{ij}, is obtained based on the real layout of the production floor, and materials/parts demand G_{ip}, per period are also obtained from the real daily production plan. The movement of MHE is organized during each 8-hour shift ($P = 8$). At present, only one MHE is available for delivering materials/parts to the workstations ($F = 1$). In Table 1, we summarize the parameters related to the problem.

Table 2. Parameter Setting

Parameter	Values
Number of workstation (N)	20
Number of towtrain(F)	1
Number of periods (P)	8
Speed of MHE (S)	8 km/h
Distance between workstations (D_{ij})	0.36 - 197 meter
Materials/Parts needed of each workstation (G_{ip})	409 - 1.038 kg
Maximum load capacity of MHE (Q^f)	6 tons
Maximum inventory level in every workstation (I_{max})	500 units
Electricity cost for charging MHE per kWh (C)	Rp 498
Conversion from distance to kWh (O)	0.75 kWh/km
Maximum time of service per periods (L)	60 mins
Holding cost per period (H)	Rp 50
Maximum distance of MHE before charging (B)	10 km
Sufficient large number (Z)	99999

3.0 RESULTS AND DISCUSSION

3.1 Illustration of the MHE routes

This section evaluates the proposed model to minimize material/part movement between workstations and the depot. The results of MHE routes, load utility, total distance, and charging indication per period in each period are presented in Table 3 and Table 4. The problem set consists of only 10 workstations and 8 periods.

Table 3. MHE routes for scenarios where temporary inventory storage is not available

Periods	Routes	Load Utility	Distance	Charging
1	0 > 2 > 1 > 8 > 10 > 6 > 4 > 0	47.88%	253.88	
2	0 > 7 > 3 > 9 > 10 > 6 > 4 > 1 > 0	54.87%	245.58	
3	0 > 2 > 4 > 3 > 5 > 0	31.87%	45.4	
4	0 > 8 > 6 > 9 > 5 > 3 > 7 > 2 > 1 > 0	60.65%	185.4	
5	0 > 2 > 4 > 7 > 3 > 8 > 10 > 9 > 0	54.02%	253.88	Yes
6	0 > 2 > 7 > 8 > 10 > 6 > 4 > 0	48.57%	253.88	Yes
7	0 > 2 > 1 > 3 > 10 > 6 > 4 > 0	50.28%	253.88	Yes
8	0 > 1 > 2 > 7 > 8 > 3 > 0	41.75%	169.34	

Table 4. MHE routes for scenarios where temporary inventory storage is available

Periods	Routes	Load Utility	Distance	Charging
1	0 > 5 > 8 > 10 > 6 > 9 > 4 > 1 > 2 > 0	86.87%	253.88	
2	0 > 7 > 3 > 4 > 0	39.58%	26.42	

3	0 > 2 > 1 > 0	21.80%	13.66	
4	0 > 7 > 9 > 6 > 10 > 8 > 5 > 3 > 4 > 0	93.32%	240.22	
5	0 > 2 > 0	15.88%	13.66	
6	0 > 7 > 8 > 6 > 10 > 4 > 0	40.40%	240.22	Yes
7	0 > 4 > 10 > 6 > 3 > 2 > 1 > 0	66.82%	253.88	Yes
8	0 > 7 > 3 > 8 > 0	25.22%	155.68	

Based on the results, temporary storage availability in each workstation can create significant improvements. Total route lengths are reduced for 38.71% when temporary storage is available compared to when it is not. The charging time is also reduced because of total route length saving. This efficiency enhances productivity and minimizes energy consumption across the workstations. On average, there is a 30% saving in charging time.

The availability of temporary storage allows the MHE to maximize its capacity in certain periods. However, the average utilization remains the same. The MHE will carry more than its period's demand and create an inventory to satisfy the demand for the next period. As a consequence, it reduces the traveling distance and workstation visits for the next periods.

3.2 Numerical Experiment Results

In this study, we conduct extensive numerical experiments involving various problem settings. Each problem set is executed with a runtime limitation of two hours. Optimal results are indicated by an asterisk (*) preceding the number. Table 5 displays the results of the numerical experiments. We categorize these results based on the availability of temporary storage. There are three problem sets (S), each with different configurations of workstation numbers (N) and available MHE units (V). In each category, we evaluate the objective function, total distance traveled, and total charging time. For the category with no inventory storage available, optimal results are achieved for all instances. Conversely, the MIP Gap is reported in the category with available inventory storage due to suboptimal results in several instances. Additionally, we provide the gaps for the objective function (Obj. Func.), total distance (Dist.), and total charging time (Charg.).

Table 5. Computational Results for

S	**N**	**V**	**No Inventory Storage**			**Available Inventory Storage**					**Gap**		
			Obj. Func.	**Total Dist.**	**Charg.**	**Obj. Func.**	**MIP Gap**	**Total Dist.**	**Charg.**	**Total Inv.**	**Obj. Func.**	**Dist.**	**Charg.**
1	10	1	680,696.28	1661.24	0.9	464,989.07	*	1197.62	0	8,839	31.69%	27.91%	100.00%
1	15	1	769,790.97	1753.36	1.72	499,395.89	0.1	1289.74	0	8,839	35.13%	26.44%	100.00%
1	20	1	870,523.92	1851.96	2.68	672,173.90	0.4	1629.7	0.73	7,519	22.79%	12.00%	72.76%
2	10	1	547,311.96	1465.36	0	524,013.24	*	1365.84	0	6,936	4.26%	6.79%	0.00%
2	15	1	894,711.78	1883.12	2.87	852,436.49	0.4	1839.74	2.38	3,166	4.73%	2.30%	17.07%
2	20	1	1,236,538.98	2127.78	6.62	1,167,636.76	0.6	2069.82	5.8	3,743	5.57%	2.72%	12.39%
3	10	1	679,889.52	1660.16	0.9	503,605.63	*	1318.58	0	5,558	25.93%	20.58%	100.00%
3	15	1	1,168,576.92	2111.42	5.69	1,135,513.02	0.5	2078.74	5.3	2,778	2.83%	1.55%	6.85%
3	20	1	1,430,445.24	2311.74	8.5	1,399,307.17	0.6	2284.42	8.11	2,288	2.18%	1.18%	4.59%
1	10	2	620,473.14	1661.24	0	464,989.07	*	1197.62	0	8,839	25.06%	27.91%	0.00%
1	15	2	654,879.96	1753.36	0	499,395.89	0.3	1289.74	0	8,839	23.74%	26.44%	0.00%
1	20	2	691,707.06	1851.96	0	565,112.19	0.4	1475.54	0	6,999	18.30%	20.33%	0.00%

S	N	V	No Inventory Storage			Available Inventory Storage					Gap		
			Obj. Func.	**Total Dist.**	**Charg.**	**Obj. Func.**	**MIP Gap**	**Total Dist.**	**Charg.**	**Total Inv.**	**Obj. Func.**	**Dist.**	**Charg.**
2	10	2	547,311.96	1465.36	0	524,013.24	*	1365.84	0	6,936	4.26%	6.79%	0.00%
2	15	2	703,345.32	1883.12	0	689,352.88	0.3	1826.08	0	3,656	1.99%	3.03%	0.00%
2	20	2	794,725.83	2127.78	0	780,393.77	0.6	2069.82	0	3,658	1.80%	2.72%	0.00%
3	10	2	620,069.76	1660.16	0	503,605.63	*	1318.58	0	5,558	18.78%	20.58%	0.00%
3	15	2	788,615.37	2111.42	0	781,965.38	0.4	2084.1	0	2,288	0.84%	1.29%	0.00%
3	20	2	863,434.89	2311.74	0	856,784.91	0.6	2279.06	0	2,778	0.77%	1.41%	0.00%

Based on the results presented in Table 5, the objective function for minimizing total cost can be derived for all instances ranging from 1% to 35%. This finding points out the importance of temporary storage availability for inventory. It is important to note that these improvements are based on suboptimal results from instances where storage is available, suggesting that the potential for improvement could be greater. One significant finding is the reduction in the total distance traveled. By storing inventory for the next hour's production, the total distance can decrease by an average of 11.76%, with a range varying from 4.87% to 51%, depending on the specific problem instances. Consequently, the load utility of MHE can be maximized by transporting the next period's load. This approach will reduce the number of visits to workstations in the subsequent period and ultimately lead to a decrease in total travel distance.

During the movement of materials/parts, MHE needs to recharge to continue its operations before the battery depletes. The availability of inventory stored in each workstation results in an average reduction of 22.98% in charging time. With less travel distance and workstation visit reduction, energy consumption can be preserved by a minimum of 4.59% to as much as 100%, depending on the problem sets, indicating both energy savings and cost reductions.

In the current setting, only one MHE is available for delivering materials/parts to the workstations. However, in our numerical experiment, we explore the impact of varying the number of available MHE to obtain additional results. Introducing an extra MHE can lead to overall cost reductions. Our findings indicate an average reduction of 20.27% in total costs when two MHE are available in a scenario where no inventory is stored. In contrast, the benefit of having additional MHE in a scenario with inventory storage available is reduced to 15.33%. With multiple MHE units, the delivery of materials/parts can be divided, allowing for shorter trips for each MHE below the MHE battery capacity; thus, it won't need to recharge.

3.3 Impact of Temporary Inventory Storage Size

One parameter that can lead to significant improvement is the availability of temporary inventory storage at each workstation which refer to parameter I_{max} in the mathematical model. In the current condition, there is small inventory storage available that can covered up to 500 units of materials/parts in each workstations. We exercise the contribution of temporary inventory storage by changing the size of storage capacity in the comparison of having no available storage. Figure 3 shows the gap in terms of objective function, total distance and total charging time.

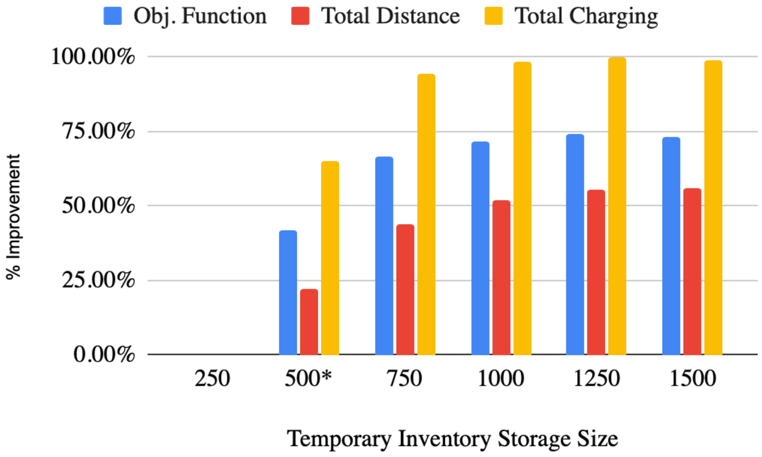


Figure 3. Impact of Various Inventory Storage Capacity

Based on the results shown in Figure 3, available inventory storage can lead to a 41.47% reduction in the objective function and a 21.87% decrease in total distance. Generally, further enhancements are observed when the storage size is increased. For example, an additional 50% increase in storage size can result in a 37% improvement in total cost within the objective function. These enhancements can contribute to greater savings in terms of the objective function, total distance, and total charging time. Notably, there is a turning point where increasing the storage size beyond twice its original capacity becomes unnecessary.

Another interesting finding is that reducing the storage size contributes to no reduction in total distance traveled or total charging time. This suggests that maintaining a specific inventory size is crucial, as it creates a significant additional load to transport, which in turn minimizes workstation visits in later periods, ultimately reducing both total distance traveled and charging time.

In accordance with the total distance traveled, temporary storage availability can also increases the efficiency of charging time. The gap between having available inventory storage and having no available storage can reach up 64.94% in average at the current setting. This effect may become even more pronounced when the storage size is increased as it can reach up to 94%.

The availability of temporary storage can greatly affect the efficiency of operational activity, as it will create significant cost reduction. In addition to availability, storage size is also an important aspect to be considered. A minimum storage size is necessary to achieve cost improvements; however, excessively large storage can be counterproductive, leading to increased investment costs with only marginal reductions in expenses. Moreover, storage availability and size will also influence the production layout and space utilization, leading to increased costs. Investing in a racking system and MHE at the workstation, along with addressing special safety considerations, can result in substantial expenses. Exploring the trade-offs between investing in temporary storage and achieving operational cost savings could be a valuable area for further study.

4.0 CONCLUSION

This paper studies a production logistics plan by creating a routing system that employs EV as MHE. An MILP mathematical model is proposed to optimize the route of the EV MHE. By splitting the production schedule into hourly periods, this study formulates a multi-period routing model that allows an inventory to be carried in each period. Given the constraints associated with EV, the MHE's recharge time is considered at the end of each route within the period.

To address this routing challenge, the study utilizes the Gurobi mathematical solver, a widely recognized tool for optimization. Based on the numerical experiments, utilizing temporary inventory storage at each workstation can lead to a significant reduction in total traveling time and energy consumption. During each period, the MHE is permitted to transport materials/parts that exceed the current workstation's demand, allowing for the use of this surplus as inventory for the subsequent period, creating travel distance and workstation visit reduction.

The size of temporary storage is also important aspect in addition to its availability. A minimum size of temporary storage is necessary to achieve savings in travel distance and energy consumption. However, these factors can also affect the production layout and space utilization, which may result in increased investment and operational costs.

The methodology in this study has limitations. At present, it can only solve the problem optimally for small instances. If the number of workstations increases, a heuristic algorithm will be necessary. Exploring metaheuristic algorithms could be a promising avenue for future research.

In this study, battery energy consumption is treated as being linearly related to the distance traveled. However, it is worth noting that the energy consumption may also follow a non-linear function due to the various characteristics of MHE and its battery type. Additionally, a more comprehensive energy calculation could influence the efficiency of production logistics operations.

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