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An evolutionary approach to robot scheduling in protected cultivation systems for uninterrupted and maximization of working time

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An evolutionary approach to robot scheduling in protected cultivation systems for uninterrupted and maximization of working time

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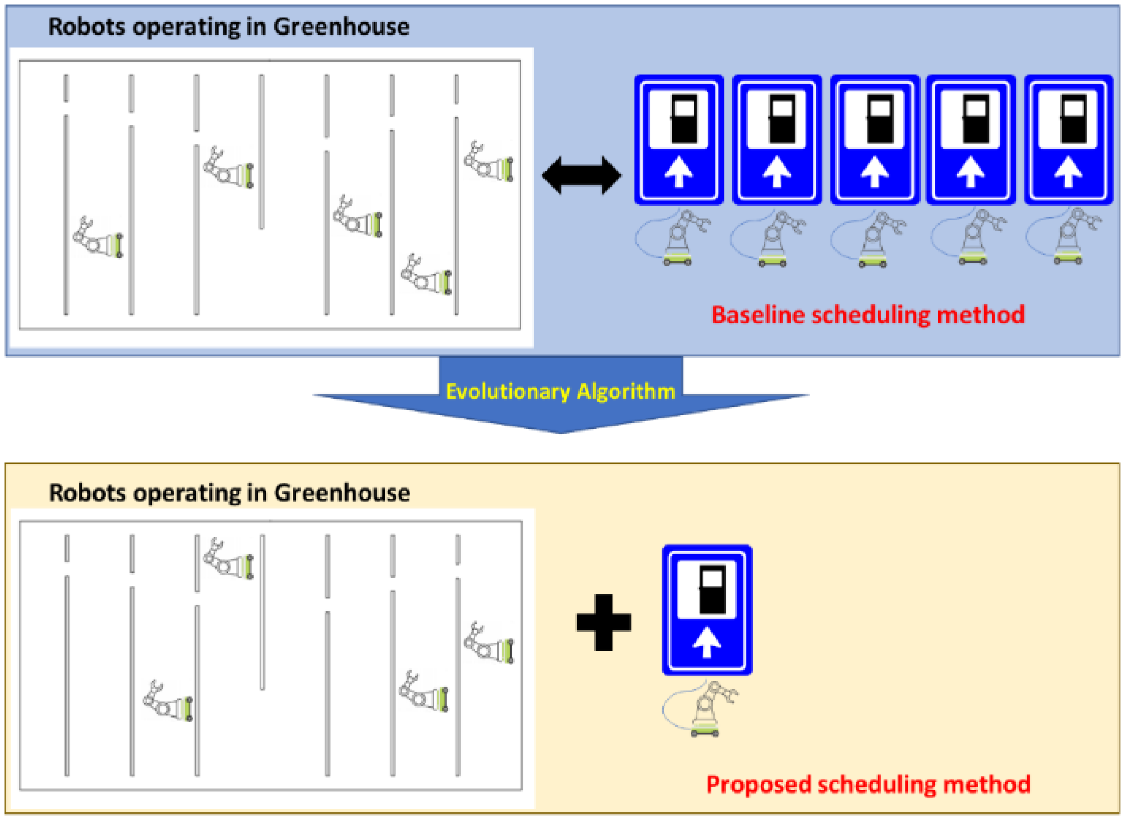
Abstract

The protected cultivation system, an alternative to open field cultivation provides opportunities such as year-round crop production and improved food security especially during disasters as well as ease in automation. However, protected cultivation is limited by the hazardous work environments and skilled labor shortages thus necessitating robotic applications. Robots are mostly battery-powered, requiring regular charges depending on the task. In a multi-robot system, due to the limitation on the availability of charging infrastructure and uneven discharge rates of the robots depending on the task, it is very difficult to predict when the robots would require charging. Therefore, to maximize the continuous work time of the robots, optimal scheduling is required. Consequently, we propose a novel system for efficiently utilizing mobile robotic systems in protected cultivation by developing a scheduling system that will maximize work time and minimize concentrated energy demand. We formulated the robot scheduling problem to regularly evaluate battery charge state and optimally send the robot to the charging station. This problem was solved using an evolutionary algorithm. We considered: a) the number of available robots; b) number of charging stations; c) required work hours; d) robot battery capacity; e) robot battery charge and discharge rates; and f) the number of continuous discharge time instances. All parameters could be set to user preference. The applicability of the proposed method was demonstrated with experimental simulations using MATLAB under different cases and scenarios. These cases and scenarios demonstrated that our proposed system maximized worktime by a significant percentage and minimized the required power to charge the batteries in all situations.

Keywords: Energy demand; Food security; Greenhouse; Robot battery; State of battery charge



Graphical Abstract

1. Introduction

Protected cultivation systems such as greenhouses and plant factories for growing plants in controlled environments are becoming popular recently. Cultivating in these systems has numerous benefits to the grower and global food security due to increased productivity and availability of food year-round regardless of the climatic conditions (Jensen et al., 1995, Khan et al., 2011). This is even becoming more pertinent during disasters such as the recent COVID 19 global pandemic outbreak caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (Wu et al., 2020) where movement is restricted due to fears of rapid spread of the virus. Invariably, farm labor and trade would be substantially affected. Furthermore, the Food and Agriculture Organization of the United Nation (FAO) has warned of impending starvation and malnutrition in many countries across the globe (FAO, 2020) . This is even more so because of the climate of many countries in temperate regions or the non-availability of land for growing essential foods with short shelf-lives such as vegetables. These make countries rely heavily on imports to meet demand of some essential foods. The FAO suggested coherent and robust plans for global food systems as a solution for disasters that restrict movement of people and goods (FAO, 2020) . Protected systems where the climate can be controlled such as greenhouse and plant factories provide a solution to these issues, by allowing the use of autonomous robotic growing systems that require limited or no physical presence. Regardless of external factors like temperature, relative humidity, wind speed and rainfall, plants in protected cultivation systems can be grown in relatively safer conditions in which essential macro and micro requirements are provided. This increases productivity while ensuring year supply of essential foods.

It is much easier to implement automation in protected systems compared to the open field with many disturbances such as lighting conditions, rain, etc. (Roldán et al., 2018). However, growing crops in a protected cultivation system has some drawbacks. For example, the use of pesticides in protected systems is much more complicated compared to open-field cultivation where there is adequate circulation of air. Other conditions like elevated temperatures and relative humidity required for optimal plant growth could also cause long-term health complications for human workers (Arundel et al., 1986, Basu, 2009). Apart from the adverse impact to the health of the workers, protected systems require repetitive tasks like harvesting and transportation which are also cumbersome and cause fatigue to the human workforce. Due to the high capital investments required in protected cultivation, optimal growing conditions and skilled labor is required for an economically viable and sustainable system. Farmers are also facing the challenge of producing more food from less land in a sustainable way to meet the demand of the predicted 9.8 billion human population expected by 2050 (King, 2017). With the global shortage of skilled labor especially in developed countries due to migration of young people from farming rural communities to urban areas, (Cai et al., 2006, Hertz et al., 2013), most growers are increasingly seeking to employ robotics in cultivation. In (Future Farming, 2019), the increased use of robots in greenhouses to mitigate labor shortage was recorded in the Netherlands.

Consequently, robotic companies have keyed into developing robots for tasks in protected cultivation systems. These include inspection and treatment of plants (Acaccia et al., 2003), recognition and cutting system for sweet-pepper picking (Kitamura et al., 2005), autonomous spraying of pesticides in greenhouses (Sammons et al., 2005) and greenhouse operation (Mandow et al., 1996). According to Verified Market Research, the agricultural robot market is expected to reach $11.58 billion by 2025 (Verified Market Research, 2020) .

Using robots in protected cultivation requires optimal implementation for best results. This led to different studies such as navigation techniques for mobile robots in greenhouse (González et al., 2009), path tracking of mobile robots in greenhouses controlled by slide mode variable structure (Niu et al., 2013), ultrasonic sensors for determining position and orientation of mobile robots in a greenhouse (Masoudi et al., 2010), and vision-based localization in greenhouses using a daisy-chaining approach (Mehta et al., 2008). However, there are limited studies considering rapid utilization of robots to save time, thereby lowering operation costs. Consequently, in our earlier study (Uyeh et al., 2019), we proposed efficient navigation in a greenhouse by optimizing the layout system. We developed a system to find optimal points on each bed to create an access path that would enable a reduction in the total travel time from all points in the greenhouse to the base point. The system allowed: (a) specifying bed size; (b) inputting greenhouse size; (c) specifying required space for inter-bed and rotary robot navigation; and (d) indicating base point for starting and terminating navigation.

Just like in electric vehicles (EV), robots in protected cultivation are mostly battery powered. An EV's charging scheduling strategy based on photovoltaic output prediction was proposed in (Wei et al., 2017), while (Yang et al., 2013) proposed a system to minimize the waiting times of EVs by charge scheduling on highways. Other studies includes optimal routing and charge scheduling of EVs (Barco et al., 2017), EV's charging scheduling problem derived from a charging station designed to be installed in community parking (García-Álvarez et al., 2018) , delay-optimal charging scheduling of EVs with multiple charging stations (Zhang et al., 2013), and determining an optimal vehicle schedule given a set of trips (Niekerk et al., 2017).

However, in protected cultivation, the battery power consumption of robots depend on tasks and environmental conditions like temperature and relative humidity (Smart et al., 1999, Hu et al., 2004) making it difficult to predict at what point the robot would need charge. For example, a harvesting robot took between 18 and 25 seconds to harvest a ripe fruit (Shamshiri et al., 2018). The battery usage and consumption in harvesting robots can be separated into three main sections as sensing (i.e., fruit recognition), planning (i.e., hand-and-eye coordination) and acting (i.e., end-effector mechanism for fruit grasping) (Murphy, 2019). Duration of each task will vary among models of robots. Furthermore, with the frequent improvement in technologies related to greenhouse robotics, it can be challenging to predict the required number of robots needed to complete a task without a scheduling system. Without scheduling, usage of robots in protected cultivation systems involve using the battery to a drainage point (baseline algorithm) and charging all robots together. This has drawbacks such as: a) same time robots charge means high power consumption and this could result in higher costs of power and transformers (Darabi et al., 2011, He et al., 2018); b) non continuation in operation in the protected system especially in a task where two different types of robots with different battery capacities are involved (for example, the harvesting and transportation tasks). The working time of robots in a protected system mainly depends on battery status of the robots and speed to complete a task. If a greenhouse is small and the available robots can finish a task in one charge-discharge cycle, then scheduling of robots is not essential. However, in large commercial greenhouses that are commonly found in most countries, the scheduling of robots is beneficial, and can reduce operational costs.

In general, optimal scheduling is required to reduce the cost of operation or to satisfy the needs of the application. Other well-known applications of scheduling includes, travelling sales man problem, swarm robots scheduling, UAV scheduling, path planning (Jin et al., 2006, Peters et al., 2018), electric vehicles charge and discharge scheduling (Yao et al., 2017), and agricultural robot scheduling (Ahsan et al., 2019) which was limited to seedling and more of sequencing.

Various scheduling techniques employed for mobile robots primarily focused on task-based scheduling. In previous studies, various scheduling problems were solved using integer linear programming (Tiotsop et al., 2020) (Cheng et al., 2019), and dynamic programming (Jin et al., 2006). Optimal scheduling problems arising in different real-world activities have been solved using classical search and optimization algorithms including linear programming methods. The difficulties often faced in solving such problems are the dimensionality of the search space, and integer restriction of the decision variables (Deb et al., 2003). For the past few decades, optimal scheduling problems have also been solved by using various nontraditional methods such as simulated annealing (Kirkpatrick et al., 1983), genetic algorithms (Goldberg, 2006), and tabu search (Glover et al., 1998). Genetic algorithm optimization has good search capabilities for stochastic operators, are flexible with easy tunable parameters according to the type of the problem. In the current study, we solved the scheduling of robots in protected systems using the binary genetic algorithmic approach (Goldberg, 2006).

The scheduling of available robots in a protected cultivation system to accomplish a task (harvesting, spraying or transportation) is complex and differs from EVs where the approximate distance a charge can cover, and information of charging stations are known.

In this study focusing on protected cultivation, the objectives were to develop a system to determine: a) the optimal number of charging stations required in respect to number of robots; b) the optimal number of robots required to meet a target worktime or task; c) compute the available work hours in relation to the number of robots and battery charge and discharge rates; and d) frequently (every 15 minutes) evaluate the charge status of each robot and determine the optimal time to dispatch it for charging.

2. Problem formulation and proposed method:

This study focused on scheduling robots to maximize working time to complete a given task in a protected cultivation system by assuming the following scenarios: a) all the robots were identical with similar battery capacity; and b) robots have different battery capacities. As mentioned earlier, the total time a robot can operate, depends on the battery capacity and its task-based discharge characteristics. Depending on usage, the batteries require charge at the time when the current battery state of charge (SOC) falls below the minimum limit to complete the task. Consequently, the proposed system has the capabilities to be adjusted to user preference.

We assumed all robots had same charge/discharge limits i.e., the minimum allowable SOC for a robot's battery was 5% and the maximum allowable SOC was 100%. When the battery of a robot reached the minimum discharge limit, it went for charging. When the robot is performing a task and active, it was considered as '1' and not working condition or charging was considered as '0'. This scheduling problem can be considered as combinatorial and nondeterministic polynomial time hard (NP-hard).

Due to the high temperature and relative humidity in protected cultivation systems, it is usually recommended that charging stations should be located outside. The location of the charging station has a direct relationship to the minimum SOC the robot should have to be triggered to go for a charge. The number of robots that can be simultaneously charged at the same time depends on the charging infrastructure or the number of charging slots available. In addition, depending on the charging infrastructure and number of robots, it may not be possible to fully charge all the robots before the start of a new workday. Therefore, the initial SOC of the robots may be different. In addition, a limitation on the minimum continuous time instances a robot undergoes discharge (working) between two consecutive charging instances has been considered and can be specified by the user.

The objective of the problem was to minimize the charge time of robots i.e., maximizing the worktime of each robot so that the overall worktime to complete a given task was reduced. The scheduling constraints that were needed to be satisfied were: a) maintain minimum battery level; b) ensure maximum charge limit; c) dispatch only the maximum number of robots allowed for charging at any one time; and d) execute the minimum continuous instances of discharge (T_{dis}).

The objective functions modelled for the current scheduling problem consisted of the parameters related to battery characteristics and initial battery SOCs. The different charge and discharge characteristics of batteries usually depend on the usage, type of battery, operating temperature, and their charge and discharge rates. The discharge time of the robot's battery may depend on the state of the crop or availability of crop.

Major parameters that affect the scheduling process are:

1. number of robots (*N*)
2. number of charging stations (*m*)
3. state of charge of the robot (SOC)
4. minimum duration the robot needs to continuously work before going for charge (T_{dis}) = 1,2 and 3.

The objective function of maximizing the working time of robots is given in Equation (1) subject to Equations (2), (3) and (4).

$$Maximize\left(\sum_{t=1}^{T}\sum_{n=1}^{N} S_n^t\right) \quad (1)$$

Subjected to

$$n_c^t \leq m \quad (2)$$

$$\theta_{min} \leq SOC_n^t \leq \theta_{max} \quad (3)$$

$$\sum_{n=1}^{N}\sum_{i=1}^{|Z_n|}[Z_n(b_i) - Z_n\,(a_i) - 1 \geq T_{dis}] \quad (4)$$

where *N* is number of robots, *m* is number of charging stations; *T* is the total number of scheduling instances for the given task and time (*T* = 24/48/72 for 6/12/18 hours, respectively for one scheduling instance of 15 minutes), *t* is time index for evaluating SOC, S_n^t is state of robot *n* at time index *t*, state vector =$[S_n^1, S_n^2, S_n^3, \ldots\ldots S_n^{24}]$, SOC_n^t is battery

SOC of robot n at time t, n_c^t is number of robots that need charging at time t, θ_{min} is the minimum discharge limit of battery, and θ_{max} is maximum charge limit of battery. $Z_n = \left\{(a, b) \in T, S_n^a = S_n^b = 0 \; \& \; \prod_{j=a+1}^{b-1} S_n^j = 1\right\}$ is a set of ordered pairs (a, b), a and b are integers that represents the time instances as demonstrated in Figure 1.

In Figure 1, the vector (Z_n) represents a prospective schedule of robot n, where 0 and 1 represent the charging and discharging (working) states of robot, respectively. $Z_n = \{(a_1, b_1)\ (a_2, b_2)\ (a_3, b_3)\}$ and ordered pair (a_i, b_i) gives information on the number of continuous working time instances (1's) between two charging time instances (0's).

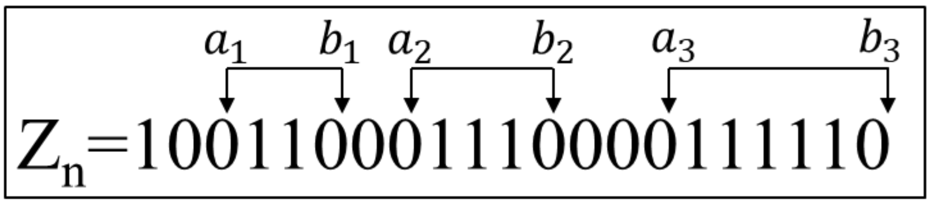


Figure 1. Prospective scheduling vector of robot *n*

An additional continuity constraint (Equation 4) is included to satisfy the smooth charge or discharge operation for robots by considering a user-specified input (T_{dis}). Since the size of the protected system and the dynamics of robots (speed and accelerations) varies among growers, and type of robots, respectively, two constraints (Equations 3 and 4) were formulated and implemented to incorporate the dynamics with robot utilization. The constraint related to the minimum state of charge (SOC) (Equation 3) prompts the robot to go for a charge when the SOC is below a preset threshold. For example, in (Arad et al., 2020), the authors developed a first-of-its-kind commercial sweet pepper harvesting robot with varying durations to carry out sub-tasks such as platform movement, fruit and obstacle localizations, fruit harvesting, etc. Based on these, it is difficult to estimate at what point the robot would need to charge and efficiently plan its travel. Equation 4 (continuous discharge time instances (T_{dis})) constraints the robot to work for a minimum amount of time (T_{dis}) between two charging instances. In other words, once in a charging state, the robot continues to remain in a charging state until its SOC reaches a level that is enough to work for at least T_{dis} scheduling instances.

Between two charging instances, the minimum working time of a robot should be at least T_{dis}. The speed, acceleration, and task of the robot have a direct relationship with the discharge rate of the robot battery. Consequently, depending on the size of the protected system, the robot should continuously have sufficient power (SOC) to travel for events such as harvesting, spraying, charging, discharge of products, pesticide refilling, etc. Further, if the T_{dis} is not implemented, then a robot scheduled to be charged would return to work immediately after SOC reaches the preset minimum threshold (θ_{min}). However, the robot would be forced to go back to charging after a short period of work, which would not be efficient especially in large commercial protected cultivation systems. Consequently, when charging, it should gain enough power to perform work for at least the set T_{dis}. This would help save time for the robot to travel a long distance to charge and return to carry out a negligible amount of work and expend another long time to travel back for a charge. The inbuilt navigation system of robots especially in protected cultivation systems helps the robot estimate the distance from its position to where it needs to travel for tasks or charge (Arad et al., 2020). In our previous study (Uyeh et al., 2019), we developed a layout system for rapid robot navigation in a protected cultivation system. This was because, unlike other situations where path planning could be implemented, the scenario in a protected cultivation system is complex since the location of the tasks the robots need to carry out is constantly unknown and the usage of the battery varies in tasks to be performed each day. This is because mobile robots in protected cultivation system are required to navigate down every aisle to perform a task, and it is difficult to predict at which point the robot will need to return to the start point, to offload or refill for transportation and spraying schedules, respectively or battery charges. For efficient navigation, a layout with access paths that would enable a reduction in the total travel time from any point to the base point would be required. The developed system in this study could ensure maximization of total work time in a protected cultivation system, and avert situations where robots are waiting to charge.

The modeling for SOC estimation for every scheduling interval with battery characteristics, (i) fixed rate of charge /discharge, and (ii) variable charge/discharge depending on efficiency of charge/discharge are given in Equations (5) and (6)

i) Robots with Fixed charge and discharge rate:

$$SOC_n^t = SOC_n^{t-1} + \left(\theta_{Charge} \times (1 - S_n^t)\right) - \left(\theta_{discharge} \times (S_n^t)\right) \tag{5}$$

ii) Robots with variable charge and discharge rates:

$$SOC_n^t = SOC_n^{t-1} + \left(\frac{\eta_n^c \times p_n^{c,\max} \times T_s}{B_n^{cap}} \times (1 - S_n^t)\right) - \left(\frac{p_n^{d,\max} \times T_s}{B_n^{cap} \times \eta_n^d} \times (S_n^t)\right) \tag{6}$$

Where: S_n^t is state of robot '*n*' at time 't' and 't – 1' (0 = charging; 1 = working); SOC_n^t and SOC_n^{t-1} is the state of charge of robot '*n*' at time '*t*' and '*t*-1'; B_n^{cap} is battery capacity of robot '*n*'; η_n^c *and* η_n^d are the efficiencies of charge and discharge of robot '*n*' battery which varies with temperature; $P_n^{c,max}$ *and* $P_n^{d,max}$ are the maximum allowable charge and discharge rates of robot 'n' battery and $T_s =$ is the sampling time of 0.25 (that is: 15 min = 25%)

The Battery parameters such as η_n^c and η_n^d, $p_n^{c,max}$ and $p_n^{d,max}$ are directly affected by the working time of the batteries. These parameters depend on the type of battery and the environmental conditions where it is used. Therefore, in this study, we considered the variation in efficiencies of charge and discharge of batteries.

2.1. Search algorithm

Genetic Algorithm (GA) is a stochastic population-based optimization algorithm based on Darwin's theory of evolution (Beasley et al., 1993, Mirjalili, 2019). In GA, a group of prospective solutions to the optimization problem referred to as population, evolve over the iterations to converge to the optimal solution of the optimization problem defined by an objective function (Equation 1) and a set of constraints (Equations 2 ~ 4). The population evolves by producing new solutions, referred to as offspring population, by exploiting the information present in the population. The offspring population is produced from the parent population through variation operators referred to as mutation and crossover. Mutation produces a new solution by the perturbation of an existing solution. Crossover produces one or two different individuals by combining the information present in two different solutions of the population (Mallipeddi et al., 2011). Further, the solutions in the parent and offspring populations compete to enter the next generation which is determined through the selection operator. The goal of the selection operator is to promote solutions that better suit the environment defined by the objective and constraint functions of the optimization problem to future generations. In other words, the population dynamics follow the basic rule of evolution "survival of the fittest". The process of producing new solutions from the current population of solutions and enforcing selection repetitively forces the population to converge to an optimal solution.

In summary, the major steps in GA are a) initialization of population; b) the individuals in the population evolve over a given number of generations through operations such as mutation, crossover, and selection. The parameters of GA are fine-tuned depending on the problem. Consequently, we coded and fine-tuned these parameters (initial population, the maximum number of generations which is also a termination criterion, probability of mutation, and crossover rates) and evaluated the populations (solutions) on the objective function in Equation 1 which was to maximize the working time of the robots subjected to Equations 2 to 4. The process is repeated (iterations) until the stopping criteria are met which is the maximum number of generations.

The flow chart of the GA used as search algorithm to solve the problem is given in Figure 2. Primarily, N_p chromosomes are initialized. Each chromosome has D genes (dimensions) and are initialized randomly with '0' or '1'. Until the termination criteria are met, each chromosome is evaluated on the objective function. Selection, crossover, and mutation are performed during each iteration. The optimal solution obtained represents the best schedule for the robots, which also gives the individual operation times of robots for the given charge/discharge characteristics.

The proposed scheduling problem was solved using the binary GA. Roulette Wheel based selection between single, double, and uniform crossover and binary mutation were used. The implementation was done in MATLAB 2019® (Mathworks, 2019), with 64-bit Windows 10, 3.4 GHz CPU and 24 GB RAM.

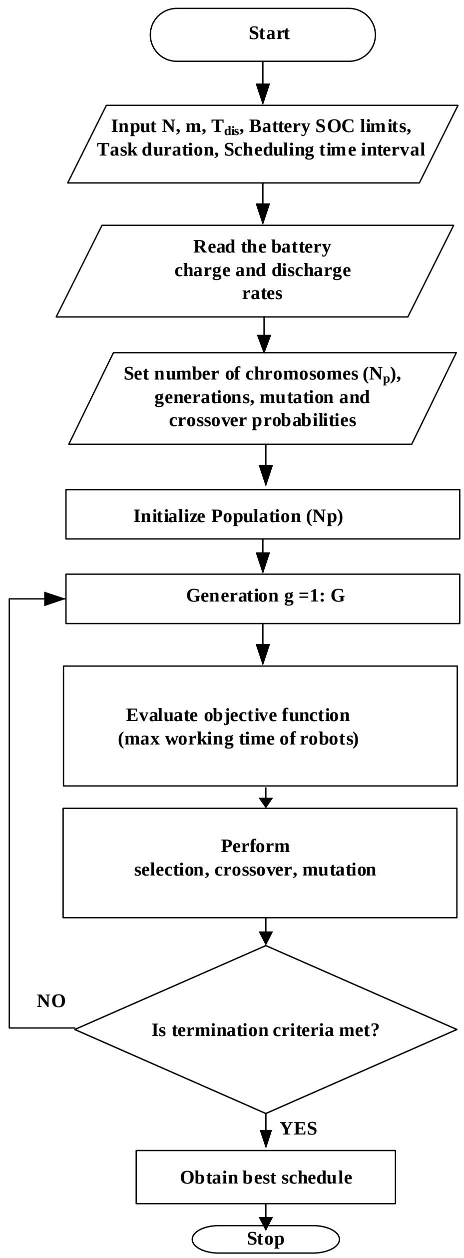


Figure 2. Flowchart of the search genetic algorithm

The parameters of the optimization algorithm were set as:

a. Population size (NP): 500
b. Maximum number of generations (termination criteria): 500
c. Probability of crossover (Pc): 1.0 and
d. Mutation and Crossover rates: 0.8 and 0.3, respectively.

3. Experimental design and simulations

Simulations were performed to demonstrate the applicability of the proposed method to schedule robots in a protected cultivation system. Two Cases of robot scheduling (Cases 1 and 2) were considered. These Cases were designed to investigate when all the robots start a workday with a 100% level of battery charge (Case 1) and random levels of battery charge (Case 2). These two Cases were evaluated in four Scenarios (Scenarios 1, 2, 3, and 4) to investigate different capacities of batteries.

a. Battery characteristics

Two different types of battery characteristics and variations with 1) 100% SOC, and 2) random levels of SOC. The batteries considered in this study were classified based on their efficiencies (Battery-University, 2017, Eftekhari, 2017). Their efficiencies were as follows: efficiency of charge = 0.9, efficiency of discharge = 0.99 and efficiency of charge = 0.8, efficiency of discharge = 0.6. Batteries with 100% SOC and random levels of SOC were selected to investigate what would happen when a grower has a shorter workday and resources to fully charge the batteries and when the workday is long and no time to fully charge the batteries before the start of another workday, respectively.

b. Power requirement for charging batteries

Scenarios for the given two cases of initial SOCs of robots.

i) Fixed rate of charge and discharge of 5% for each scheduling instance t. (i.e., for 15min)
ii) Variable rates of charge/discharge that depend on efficiencies of charge/discharge of robot batteries.
iii) Number of robots (*N* = 5, 10 or 15),
iv) Number of charging stations
v) Initial SOCs of batteries
vi) Instances for discharge (T_{dis}: 1 to 3).

For the two cases (Cases 1 and 2), the initial SOCs used in the experimental simulations are presented in Table 2. We considered 6, 12 and 18 hours as total operation hours. However, any duration and number of robots could be entered by the user for scheduling. The charge and discharge of robots were evaluated for every instance of scheduling with time frame of 15 minutes. Therefore, the total number of scheduling instances required were T = 24, 48 and 72. The power required for charging during the task for one scheduling instance can depend on the scenario and initial SOCs of robots. The calculation of power for charging a single instance for each robot is given below.

For the 5 robots, the power needed to charge for one scheduling instance can be calculated as follow:

Scenario 1: for each scheduling instance (t) the power required to charge θ_{charge} =5% (fixed) of an 8-kW robot battery is, P_{req} = 8 kW × 5/100 = 0.4 kW

For Scenarios 2, 3 & 4, the rate of charge was calculated using the part of the Equation (7) and (8).

$$\text{i.e.,} \quad \theta_{Charge} = \frac{\eta_n^c \times p_n^{c,max} \times T_S}{B_n^{cap}} \tag{7}$$

$$\eta_n^c = \begin{cases} 0.9, & for\ Scenario\ 2\ and\ 3 \\ 0.8, & for\ Scenario\ 4 \end{cases} \tag{8}$$

From the above settings $\theta_{Charge} = 4.5\%$ for Scenario 2 and 3 and $\theta_{charge} = 4\%$ for Scenario 4. The power required to charge a robot's battery depends on the battery's capacity. In Scenario 2, the robot batteries with capacity of 8 kW are used. In Scenarios 3 and 4, robots with 8, 16, and 48 kW are used.

In Scenario 2, for each one scheduling instance (t), the power required to charge, $\theta_{charge} = 4.5\%$ of an 8-kW robot battery was P_{req} = 0.36 kW.

In Scenario 3, for each one scheduling instance (t) the power required to charge θ_{charge}, 4.5% of 8-, 16-, and 48-kW robot batteries (P_{req}) were 0.36 kW, 0.72 kW, and 2.16 kW, respectively

In Scenario 4, for each one scheduling instance (t) the power required (P_{req}) to charge θ_{charge}, 4 % of 8-, 16-, and 48-kW robot batteries were 0.32 kW, 0.64 kW, and 1.92 kW, respectively. The power required for scheduling at different scenarios are given in Table 1.

Table 1. Power required to charge robot batteries with different characteristics for one scheduling instance

Robot	Scenario 1 $\theta_{charge} = 5\%$		Scenario 2 $\theta_{charge} = 4.5\%$		Scenario 3 $\theta_{charge} = 4.5\%$		Scenario 4 $\theta_{charge} = 4\%$	
N	B_n^{cap} (kW)	P$_{req}$ (kW)	B_n^{cap} (kW)	P$_{req}$ (kW)	B_n^{cap} (kW)	P$_{req}$ (kW)	B_n^{cap} (kW)	P$_{req}$ (kW)
1	8	0.4	8	0.36	8	0.36	8	0.32
2	8	0.4	8	0.36	8	0.36	8	0.32
3	8	0.4	8	0.36	16	0.72	16	0.64
4	8	0.4	8	0.36	16	0.72	16	0.64
5	8	0.4	8	0.36	48	2.16	48	1.92

c. Scenarios to evaluate battery capacities

The efficiency of the proposed algorithm was shown with the following scenarios for the two cases of initial SOCs of robots.

Scenario #1: Robots with fixed rates of charge and discharge = 5%

Scenario #2: Robots with same capacities (8 kW) (efficiency of charge = 0.9, efficiency of discharge = 0.99)

Scenario #3: Robots with different capacities (efficiency of charge = 0.9, efficiency of discharge = 0.99)

Scenario #4: Robots with different capacities (efficiency of charge = 0.8, efficiency of discharge = 0.6)

The scenarios included different battery capacities, charge, and discharge efficiencies.

In Scenario 1, the robot will charge and discharge 5% of its battery if it is charging or working for a duration of 15-minutes (one scheduling interval). The state of operation was represented with ’0’ and ‘1’ for charging and working, respectively.

In Scenarios 2, 3, and 4, as described by equation (7), we considered variable charge and discharge patterns that were dependent on the efficiency of charge and discharge, maximum allowable charge, and discharge ($\eta cn\ \eta dn\ pc, maxn$) of robot batteries.

In Scenario 2, we assumed the robots had an equal battery capacity of 8 kW each.

In Scenarios 3 & 4, we performed the simulations with variable standard battery capacities (Yao et al., 2017).

The battery percentage increase for every 15 minutes (single instance) is 5%. However, we considered scenarios where the battery starts aging or the batteries of other robots do not have similar efficiencies resulting in less charge percentages such as 4.5% and 4% for a single instance.

The selection of the capacities and initial SOC considered for 5, 10 and 15 robots in this study are shown in Table 2.

Table 2. Experimental design using two different initial states of charge of robots and random battery capacities

Robots No.	Battery capacities (kW)			Initial state of charge (%)					
				Case 1			Case 2		
	5 robots	10 robots	15 robots	5 robots	10 robots	15 robots	5 robots	10 robots	15 robots
1	8	8	8	100	100	100	100	100	100
2	8	8	8	100	100	100	75	90	85
3	16	16	16	100	100	100	50	80	80
4	16	16	16	100	100	100	25	70	75
5	48	17	17	100	100	100	5	60	70
6		17	17		100	100		50	65
7		18	18		100	100		40	60
8		18	18		100	100		30	55
9		30	20		100	100		20	50
10		48	25		100	100		10	45
11			30			100			40
12			35			100			35
13			40			100			30
14			45			100			25
15			48			100			20

To demonstrate improvement of our proposed method for scheduling the robots, we performed simulations using a base line algorithm where the robots charge and discharge pattern was well-known. The robot works until the battery discharges completely and sent for full charge (i.e., 100% SOC).

4. Simulation results

This study considered two Cases of robot scheduling (Cases 1 and 2). These Cases were designed to investigate when all the robots start a workday with 100% level of battery charge (Case 1) and random levels of battery charge (Case 2). Furthermore, four Scenarios (Scenarios 1, 2, 3, and 4) were considered to investigate different capacities of batteries.

4.1. **Scheduling of robots in protected cultivation system**

a. Scheduling of robots in protected cultivation system with baseline algorithm

In a commercial protected cultivation system, the work time of the robots would not be optimal because of the charge needs of the robots. Additionally, a greater number of robots may need charging at the same time and consequently, the variable cost of the protected system will increase from power initialization and increase in the cost of installing the required number of charging stations. A baseline scheduling system is described in Figure 3.

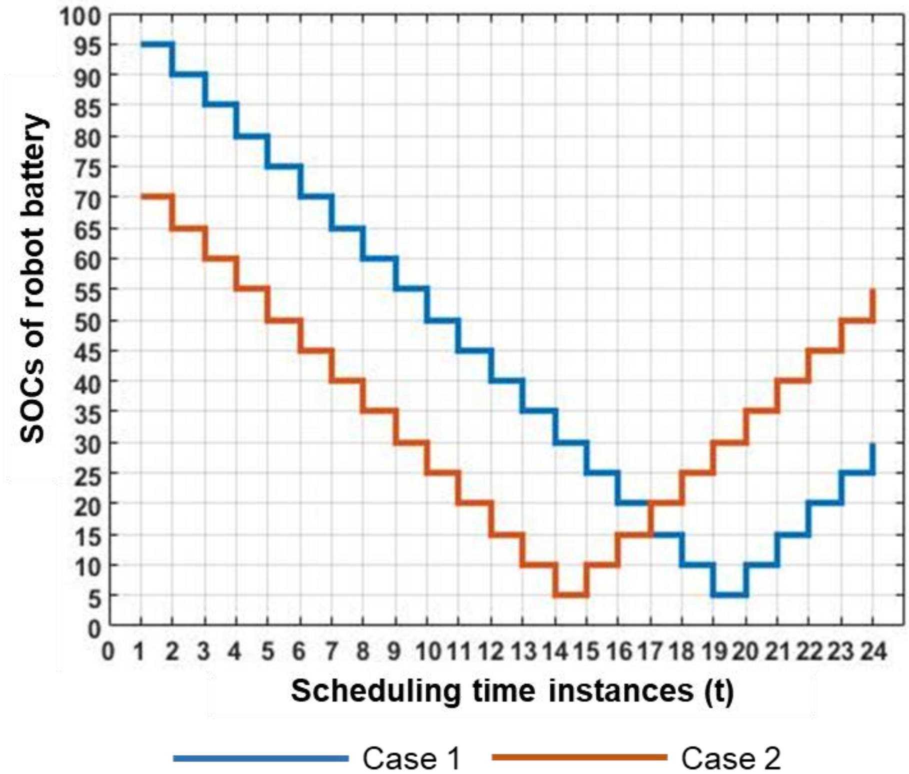
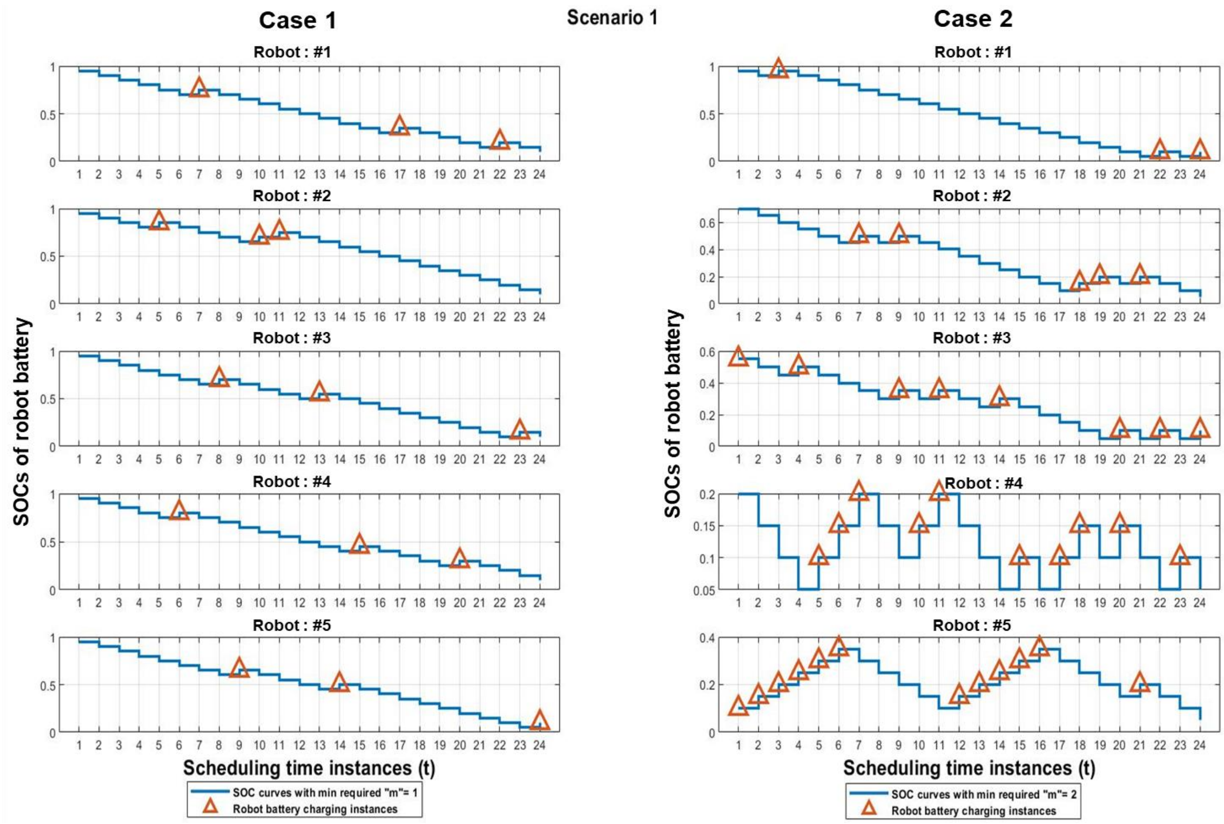


Figure 3. Robot discharge and charge curves using a baseline algorithm

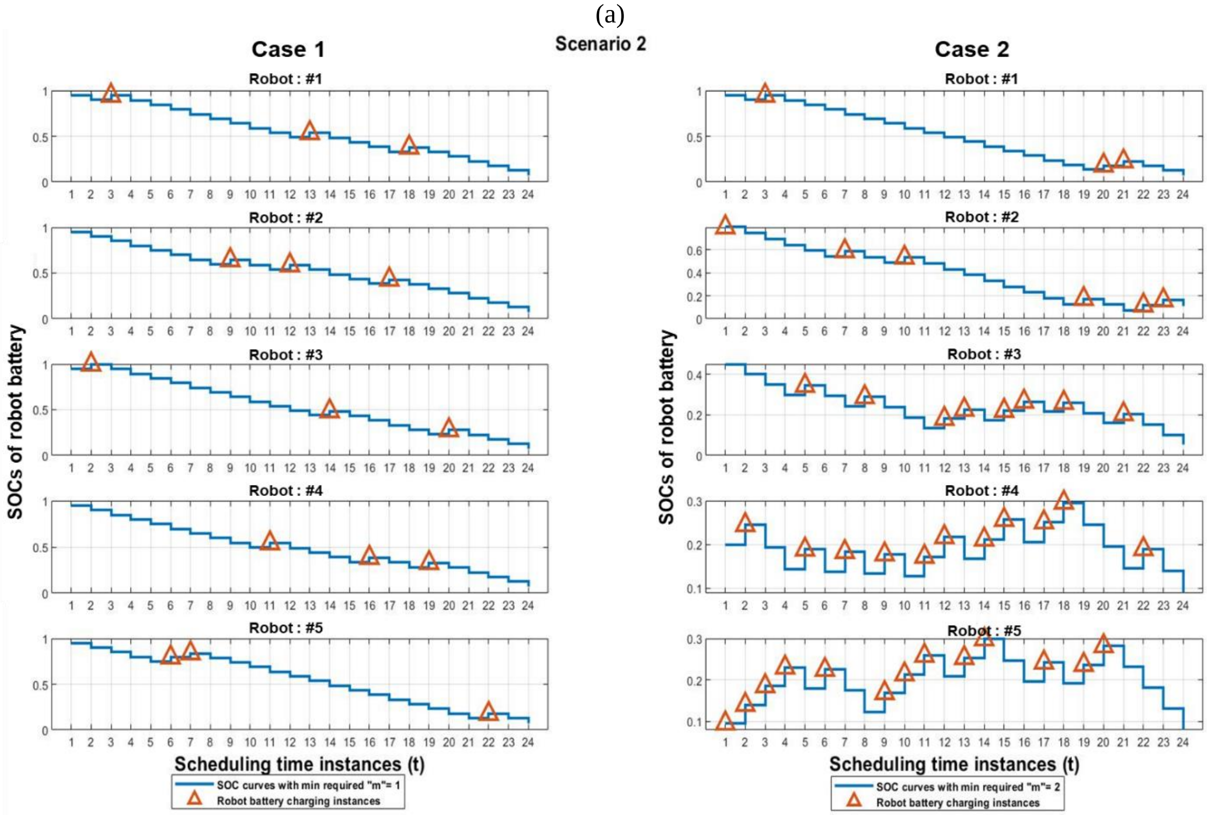
Other drawbacks of a conventional scheduling using a baseline algorithm is a disruption in operation. For example, the harvesting task requires both the harvesting and transportation robots to be simultaneously working. Without an efficient scheduling system, it is most likely for at least one of the robots to run out of charge. An example can be seen considering a scenario of fixed charge and discharge rate of 5% (Scenario 1) for five robots with different initial charge levels (Case 1 and Case 2). In this case, robots 1 to 5 have initial charges of 100% in Case 1, whereas 100, 75, 50, 25, 5 for Case 2. For Case 1, each robot works for the first 19 instances and the total working scheduling instances of all the robots are 95. After that, all the robots will undergo charging as their battery SOC would be less than the minimum allowable limit. Thus, the robots will require battery charge at the same time where the number of stations equals that of the robots or one at a time. This will lead to high power requirement and or delay in finishing a given task.

b. Scheduling of robots in protected cultivation system with single instance for battery discharge (T_{dis} =1)

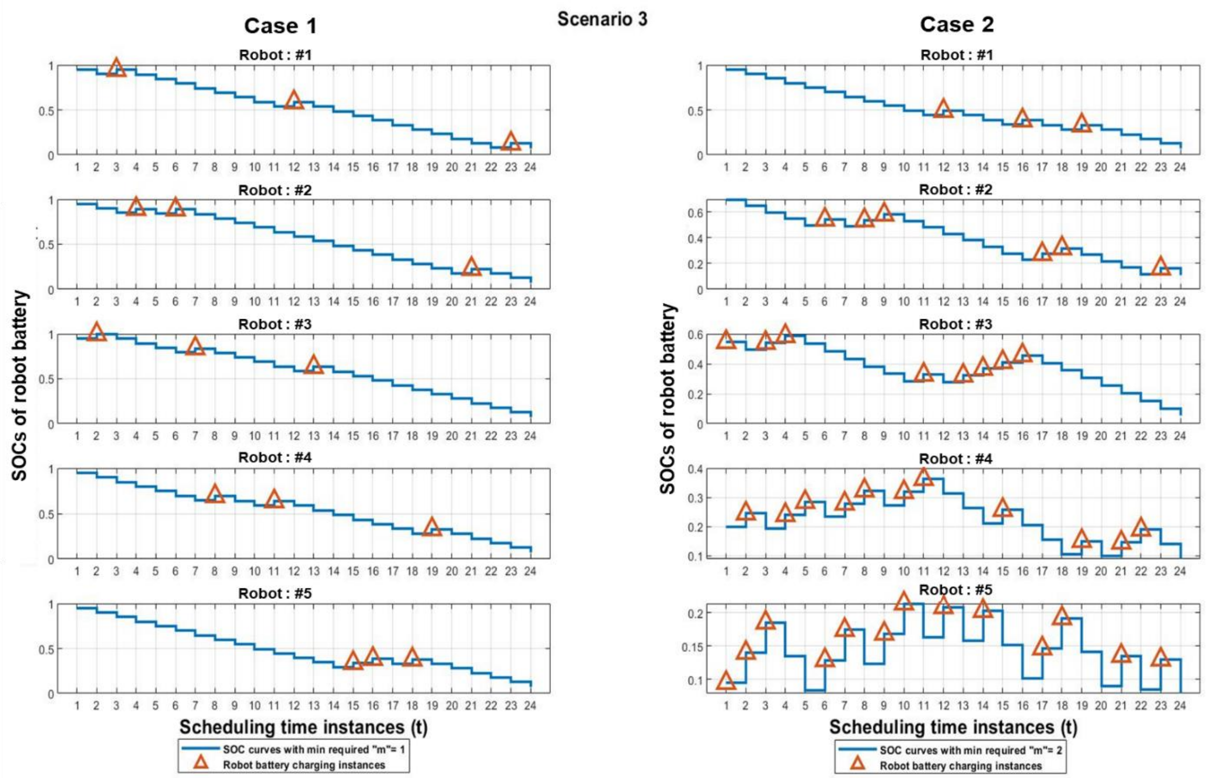
The battery discharge and charge curves are presented in Figure 4a, b, c, and d for Scenarios 1, 2, 3 and 4, respectively for 5 robots. In Scenario 1 where robots had fixed rates of charge and discharge of 5%, there were more robots continuously working at Case 1 compared to Case 2 showing the positive impact of initial full charge. A similar trend was observed in Scenarios 2, 3 and 4 despite differences in their battery capacities and efficiencies. A further analysis of the optimal number of charging stations required for the different cases and scenarios are shown in Table 3. We observed here that the scenarios did not have considerable impact on the number of charging stations required compared to cases and number of robots. Despite the scenarios differing significantly, the number of stations were the same for five robots in Scenario 1, 2 and 3 and increased by an extra charging station in Scenario 4. However, as the number of robots increased to 10, the optimal number of charging stations remained the same in Scenario 1, 2 and 3 but drastically increased by 150% to 5 in Scenario 4 (Table 3). With a further increase in number of robots, all scenarios in Case 1 recorded different increases in the number of charging stations. In Case 2, a similar trend in the optimal number of charging stations required at the different scenarios was observed. Scenarios 1, 2 and 3 had similar numbers of optimal charging stations compared to Scenario 4 (Table 3) for 5, 10, and 15 robots with only a charging station increased at 5 robots and 50% at 10 robots which was much lower compared to Case 1. This could be because Scenarios 1, 2, and 3 had a higher charge capacity of 4.5% and above compared to Scenario 4 with 4%. Further, Scenario 4 here showed 80% increase in the required optimal number of charging stations from Scenarios 1 to 3. Our analyses showed that the efficiency of charge and discharge of the batteries contributed significantly to the optimal number of charging stations required in optimally scheduling at single instance of battery discharge (T_{dis}=1).


Scenario 1
Case 1
Case 2
Robot : #1
Robot : #2
Robot : #3
Robot : #4
Robot : #5
SOCs of robot battery
Scheduling time instances (t)
SOC curves with min required "m"= 1
Robot battery charging instances
SOC curves with min required "m"= 2
Robot battery charging instances

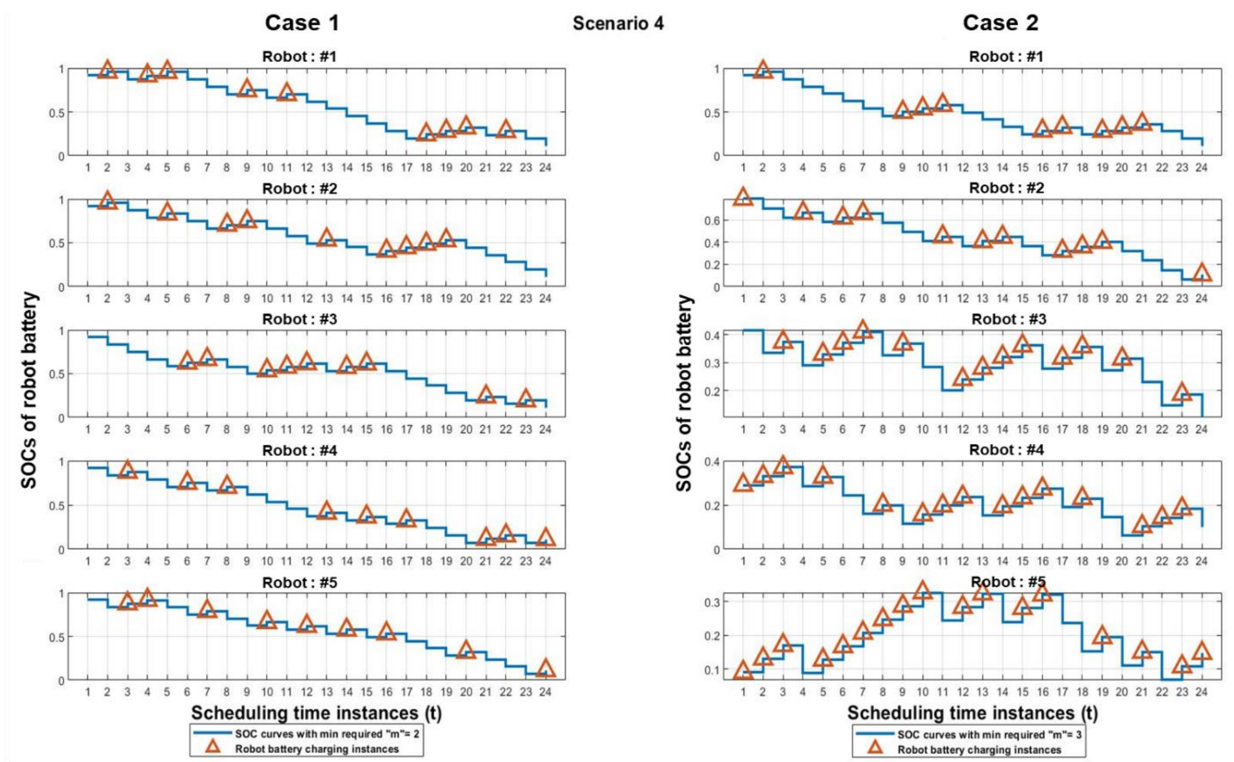
(a)


Scenario 2
Case 1
Case 2
Robot : #1
Robot : #2
Robot : #3
Robot : #4
Robot : #5
SOCs of robot battery
Scheduling time instances (t)
SOC curves with min required "m"= 1
Robot battery charging instances
SOC curves with min required "m"= 2
Robot battery charging instances

(b)



(c)



(d)

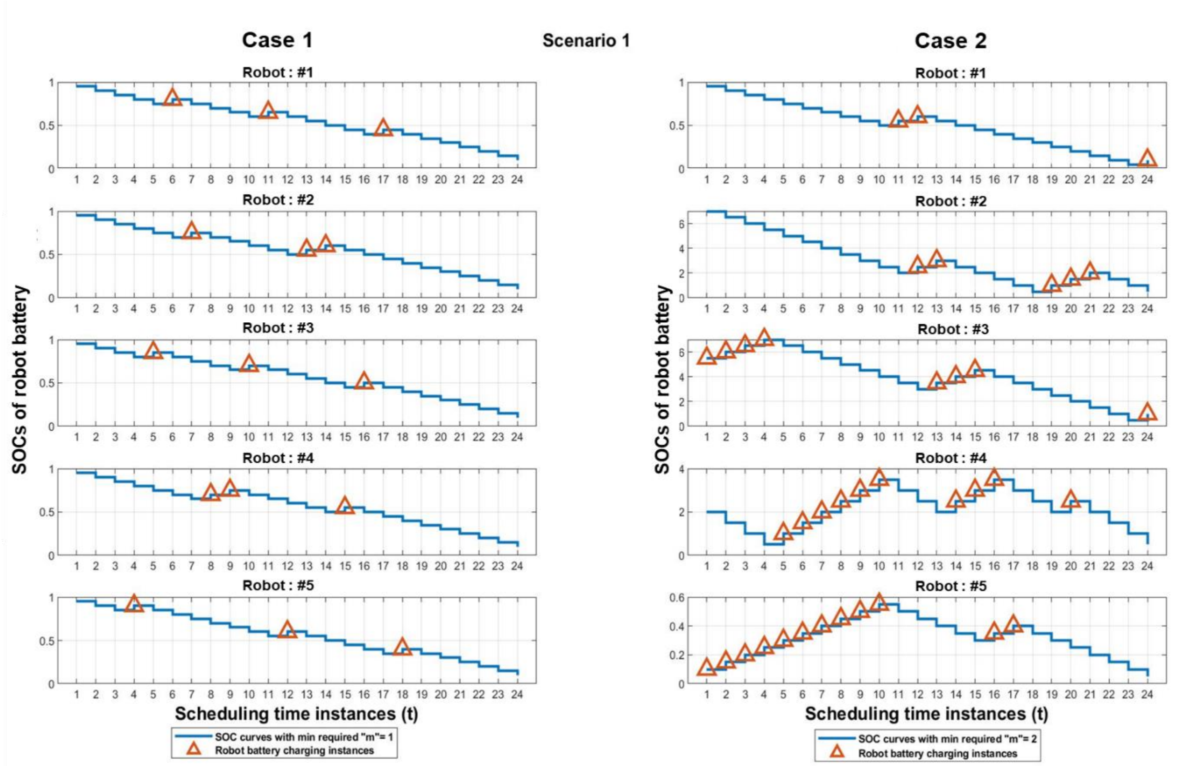
Figure 4. Battery SOC curves and robot charges (Δ) for individual robots with required optimal (minimum) number of charging stations (*m*) for Cases 1 and 2 at T_{dis}=1; Scenario 1 (a); Scenario 2 (b); Scenario 3 (c) and Scenario 4 (d)

Table 3. Optimal number of charging stations required for scheduling 6 hours (24 Instances) task

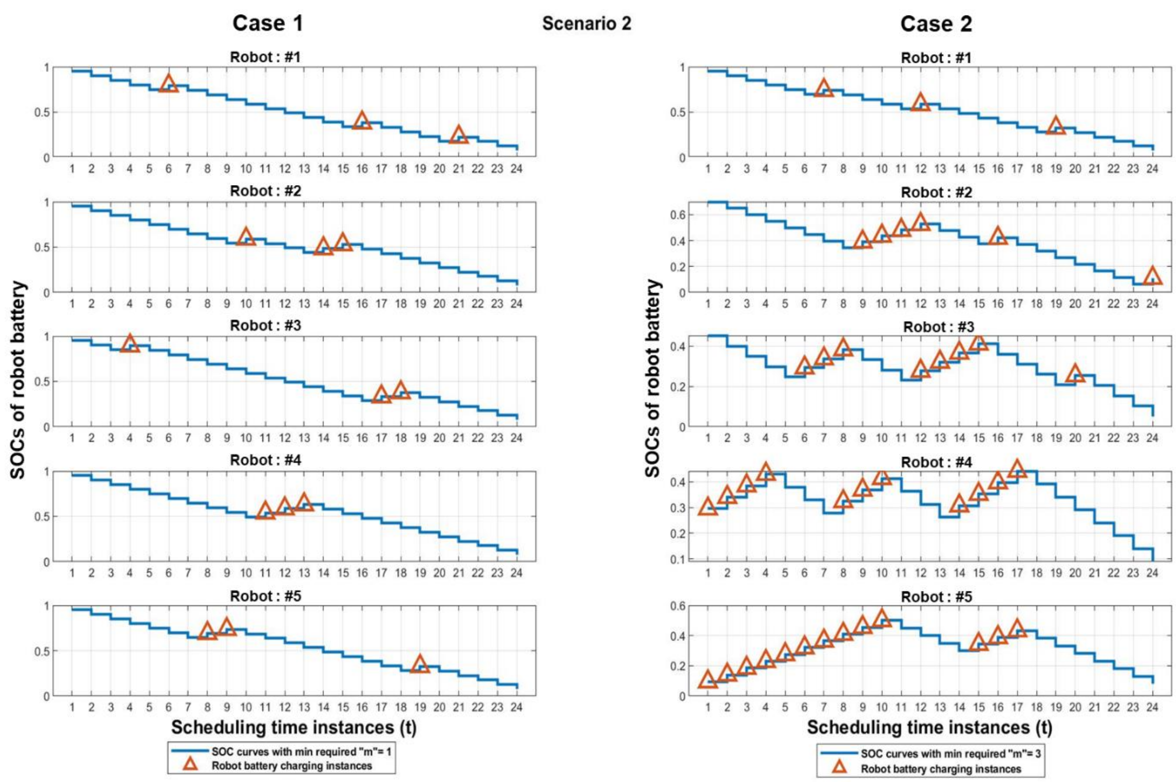
	Optimal (minimum) number of charging stations required when T_{dis}=1								
	Scenario 1			Scenario 2 & Scenario 3			Scenario 4		
Initial SOCs	5 robots	10 robots	15 robots	5 robots	10 robots	15 robots	5 robots	10 robots	15 robots
Case 1	1	2	3	1	2	4	2	5	7, (>6)
Case 2	2	4	5	2	4	5	3	6	9, (>6)

c. Scheduling of robots in protected cultivation system with T_{dis} > 2

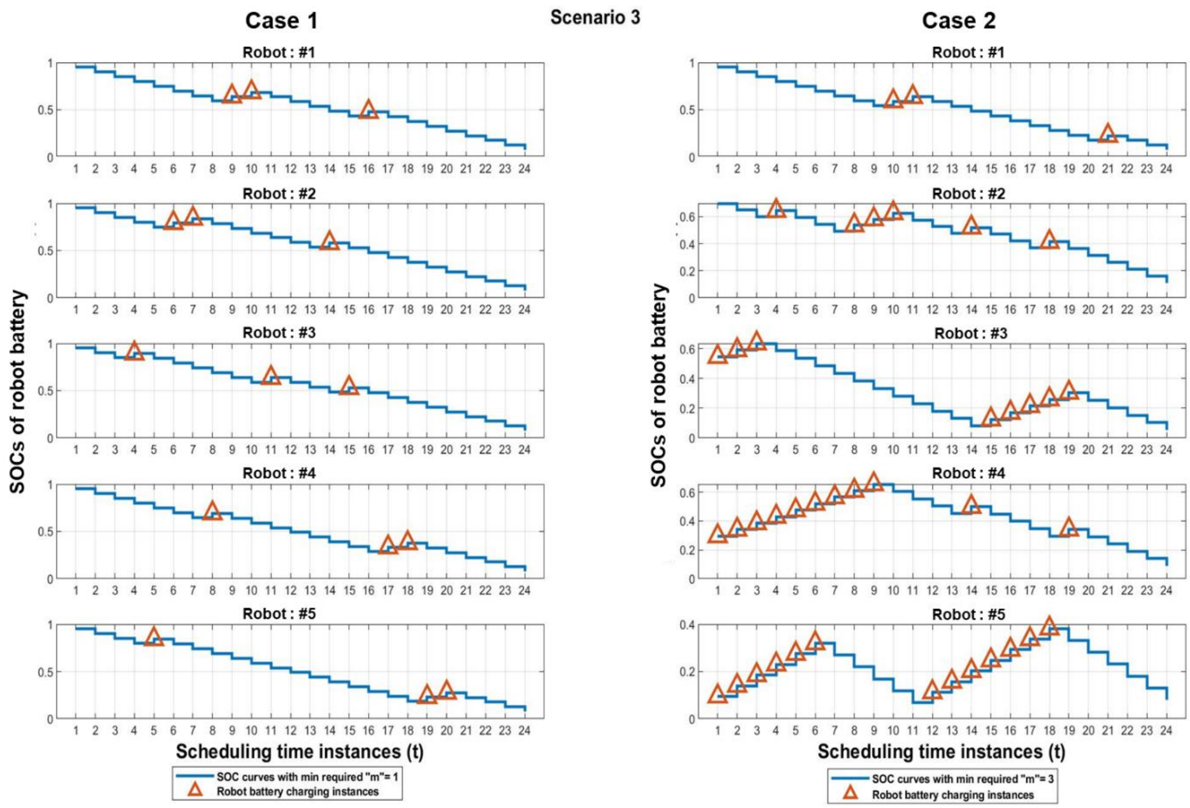
Individual working states of robots, battery SOC and robot charge and discharge curves are presented in Figure 5 for scheduling at three instances of discharge (T_{dis}=3) for 5 robots. We discussed the results of only three continuous instances of discharge here and presented a complete analysis in the subsection below. Although there was a different trend in the optimal number of charging stations between single instance of battery continuous discharge (T_{dis}=1) and three instances of battery continuous discharge (T_{dis}=3), we observed a similar trend of the impact of the initial battery SOC on the working state of the robots. In Scenario 1 where the robots had fixed rates of charge and discharge of 5%, there were also more continuously working of robots in Case 1 compared to Case 2 (Figure 5). A similar trend was observed in the other scenarios even with disparity in their battery capacities and efficiencies. However, as mentioned above, the number of instances affected the optimal number of charging stations (Table 4). In scheduling with three continuous instances of battery discharge before charge, a distinct pattern was recorded for the optimal number of charging stations in all scenarios. This is presented in Table 4. The first three scenarios in this instance of battery continuous discharge at Case 1 recorded similar optimal number of charging stations at 5 robots just like in the scheduling of the single instance of continuous discharge (T_{dis} = 1). A similar optimal number of charging stations required in 10 robots for Scenarios 1 and 2 and a reduction by one in Scenario 3 and 100% increase from Scenarios 1 and 2 to Scenario 4 were observed. A further 200% increase in the number of optimal charging stations from Scenario 3 to 4 were recorded. The scenarios also differed in the optimal number of charging stations for 15 robots with a 100% increase from the least number of charging stations (Scenarios 2 and 3) to the highest (Scenario 4). In Case 2, there were some similarities in between the two cases but a high number of optimal stations required at 15 robots for Scenario 4. In this instance of battery discharge (T_{dis}= 3), it was difficult to conclude on what exactly affected the optimal number of charging stations, suggesting that when the complexity of constraints increases, predictions will be challenging without enough scheduling simulations.


Case 1
Scenario 1
Case 2
Robot : #1
Robot : #2
Robot : #3
Robot : #4
Robot : #5
SOCs of robot battery
Scheduling time instances (t)
SOC curves with min required "m"= 1
Robot battery charging instances
SOC curves with min required "m"= 2
Robot battery charging instances

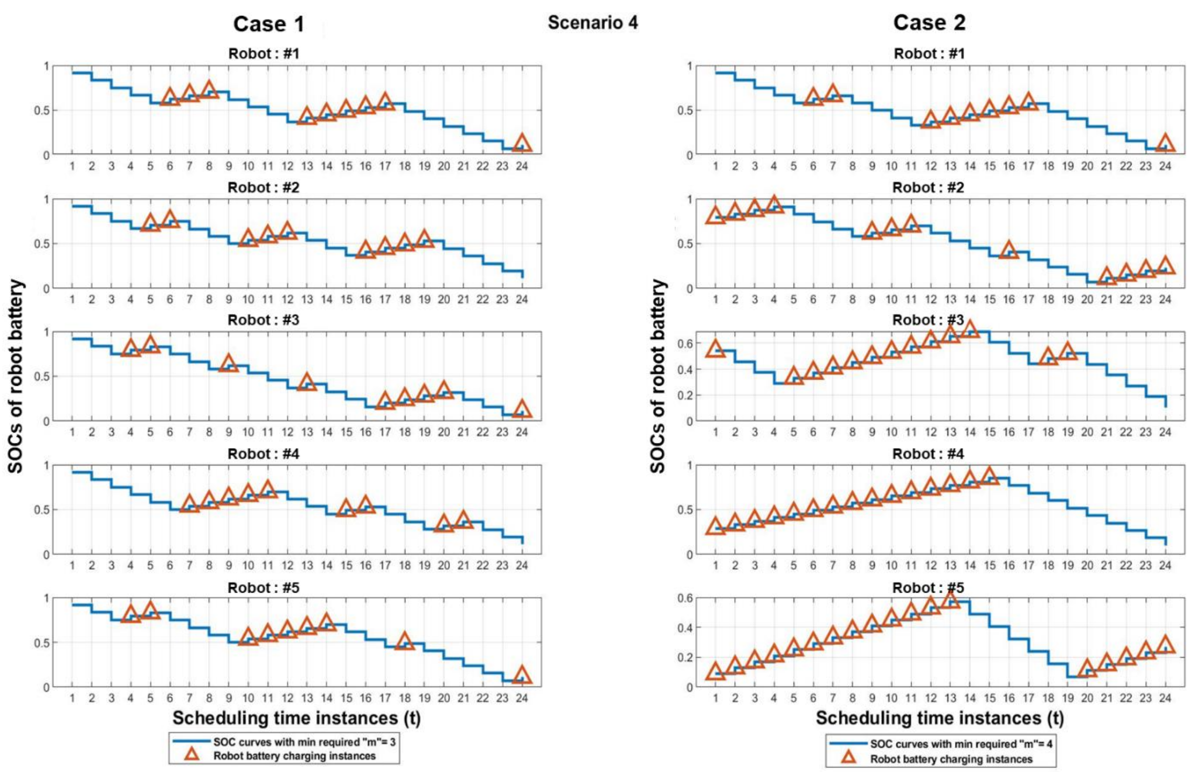
(a)


Case 1
Scenario 2
Case 2
Robot : #1
Robot : #2
Robot : #3
Robot : #4
Robot : #5
SOCs of robot battery
Scheduling time instances (t)
SOC curves with min required "m"= 1
Robot battery charging instances
SOC curves with min required "m"= 3
Robot battery charging instances

(b)



(c)



(d)

Figure 5. Battery SOC curves and robot charges (Δ) for individual robot with required optimal (minimum) number of charging stations (*m*) for Cases 1 and 2 at T_{dis}=3; Scenario 1 (a); Scenario 2 (b); Scenario 3 (c) and Scenario 4 (d)

Table 4. Optimal number of charging stations required for scheduling 6 hours task (24 Instances) and T_{dis} = 3

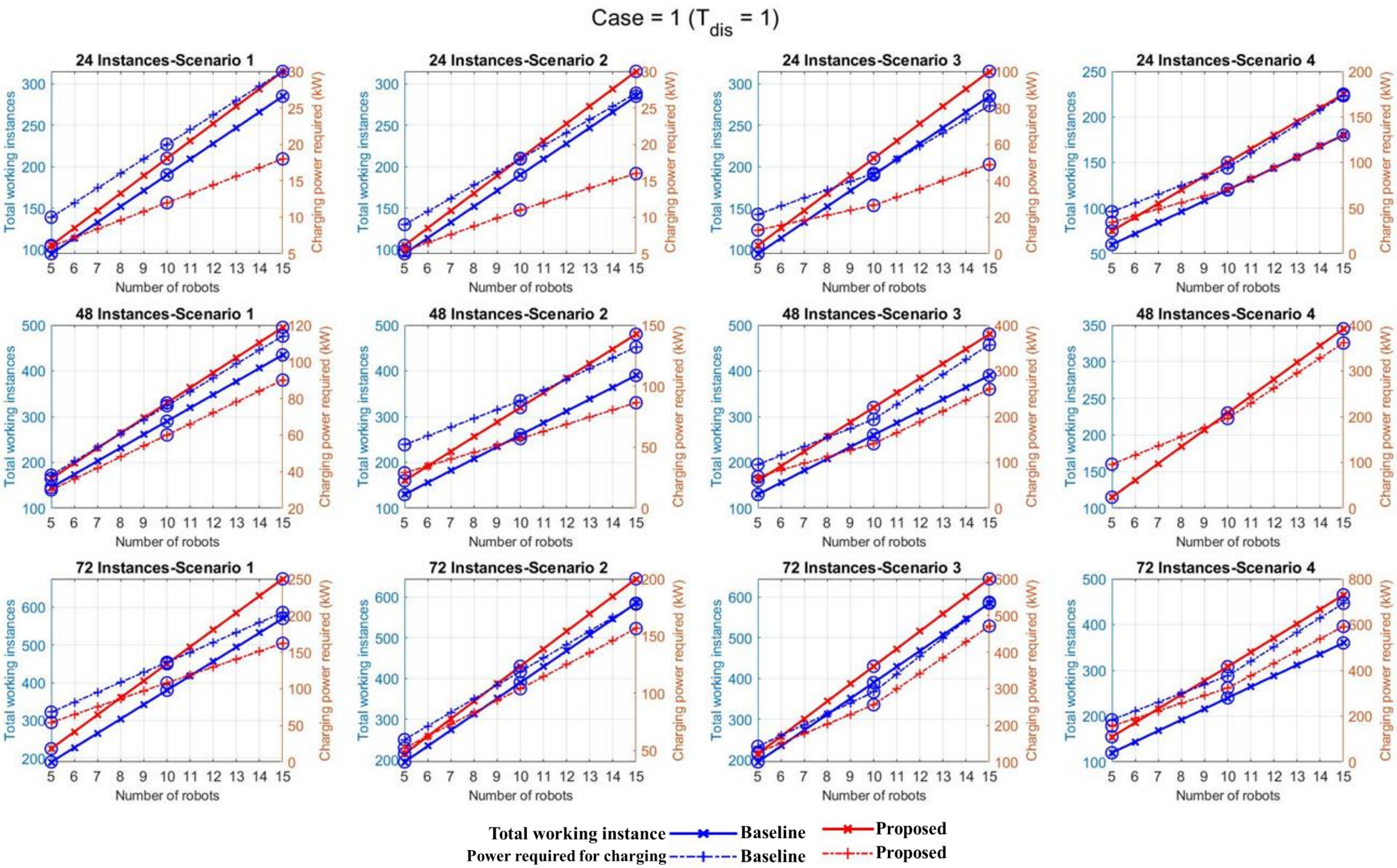
	Optimal (Minimum) number of charging stations required when T_{dis} = 3											
	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
Initial SOCs	N=5	N=10	N=15	N=5	N=10	N=15	N=5	N=10	N=15	N=5	N=10	N=15
Case 1	1	3	5	1	3	4	1	2	4	3	6	8
Case 2	2	5	7	3	5	8	3	6	8	4	7	Infeasible For <10

4.2.1. Total robot working time, number of robots and required charging power for Case 1

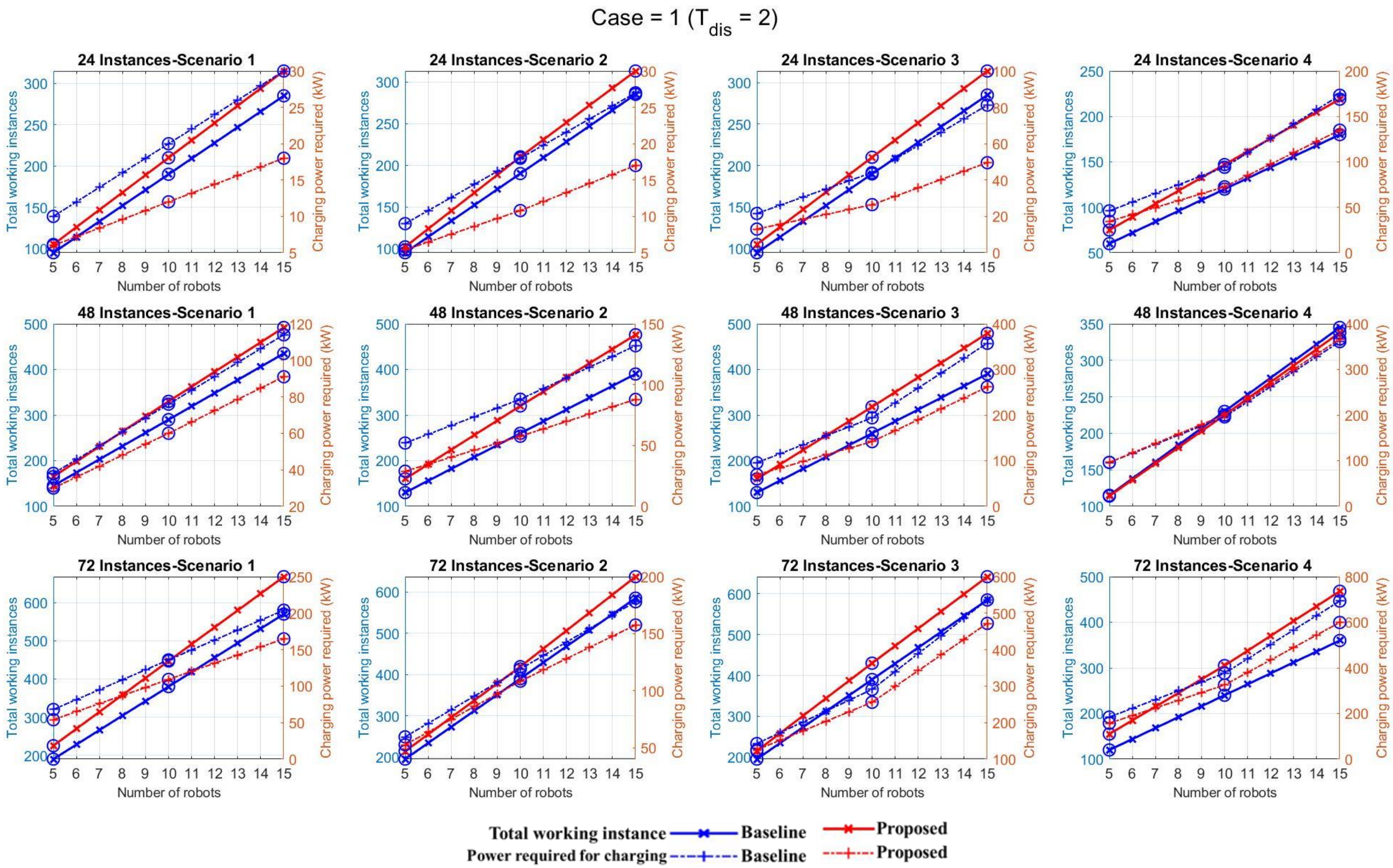
In evaluating the total working time, required charging power and number of robots between baseline algorithm and our proposed method for Case 1 in a single instance of battery discharge, various observations were made. This further necessitates scheduling in protected cultivation system. In all instances of scheduling (24, 48 and 72 Instances) our proposed method provided better solutions. In 24 Instances, scheduling instances of single instance of battery continuous discharge (T_{dis}=1) (Figure 6a), about 15% increase was recorded in the total working instances at 15 robots and about 11% and 2% at 10 and 5 robots, respectively. A similar trend was seen at all cases indicating that as the number of robots increases, especially in commercial protected cultivation systems, the worktime of the robot would be drastically increased. This trend was seen at all the scheduling of scenarios and instances in Case 1, single instance of battery continuous discharge (T_{dis}=1) with as much as about 66% increase recorded at 72 Instance-Scenario 4.

In the power required to charge the batteries, 40% decrease was recorded between the proposed method and baseline algorithm at 15 robots, 43% and 64% for 10 and 5 robots, respectively. Significant decrease in the power required to charge the batteries were observed in all the instances and scenarios in scheduling at Case 1, single instance of battery continuous discharge (T_{dis}=1). This will save costs for initialization and installation of a bigger transformer.

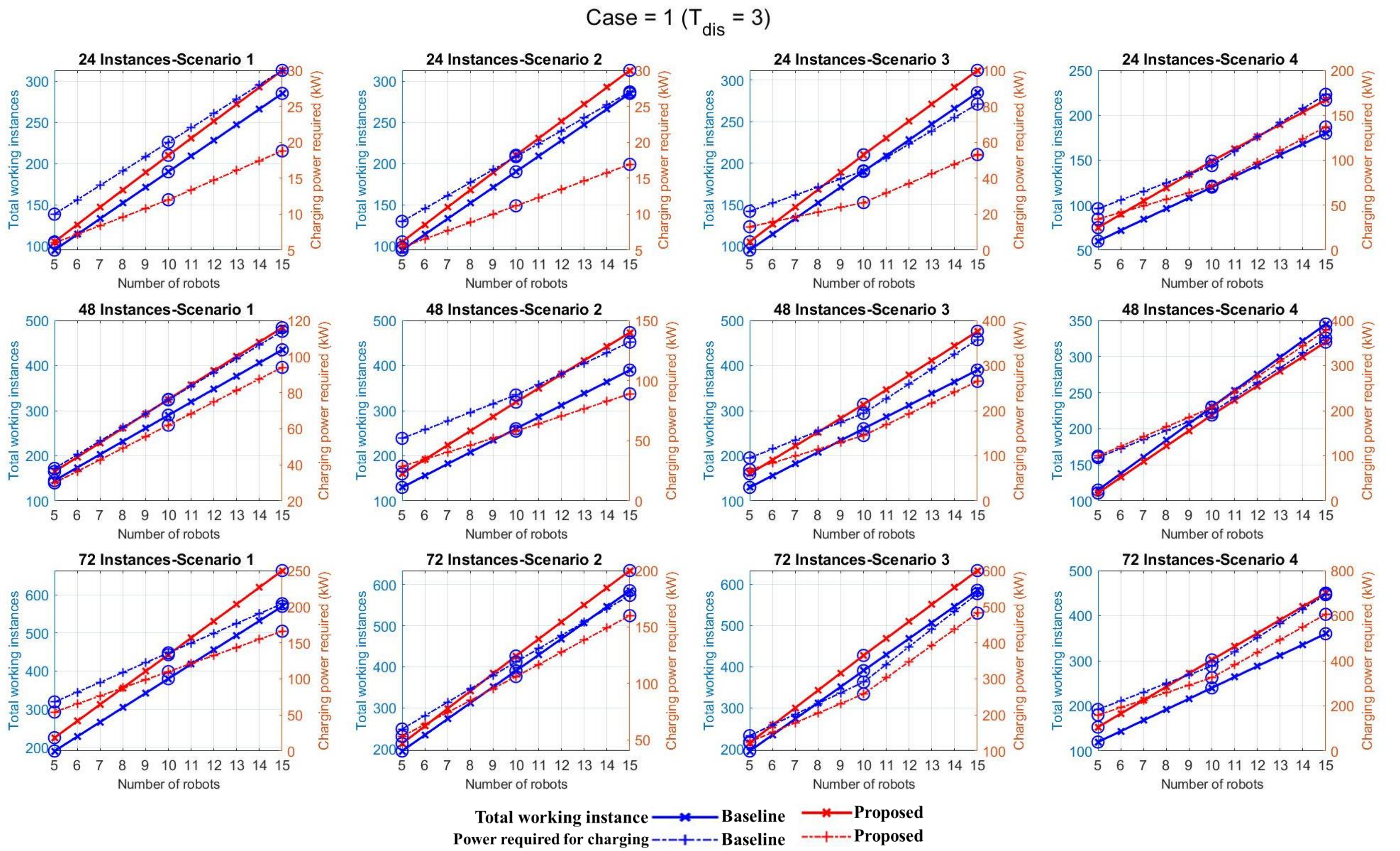
In two and three instance scheduling of battery continuous discharge (T_{dis} = 2 and 3) (Figure 6b and c), there was no significant improvement in total working time and charging power required in some scenarios like 48 Instances-scenario for both two and three instances of battery continuous discharge (T_{dis} = 2 and 3), and 24 Instances-Scenario 2 for two instances of battery continuous discharge (T_{dis}= 2). However, there was recorded improvement in all other scenarios with drastic reduction in the power required to charge the batteries at 15 robots of 24 Instances-Scenario 1 in two instance of battery continuous discharge (T_{dis}= 2) where about 43% reduction was obtained. A similar percentage reduction was also recorded in single and three instances of battery continuous discharge (T_{dis}= 1 and 3) in this case. Here, we learnt that all factors which include battery SOC, battery efficiencies, worktime and instances of battery discharge have impact on the percentage improvements that would be recorded for increasing worktime and that for reducing required charge power.


Case = 1 (T_{dis} = 1)
24 Instances-Scenario 1
24 Instances-Scenario 2
24 Instances-Scenario 3
24 Instances-Scenario 4
48 Instances-Scenario 1
48 Instances-Scenario 2
48 Instances-Scenario 3
48 Instances-Scenario 4
72 Instances-Scenario 1
72 Instances-Scenario 2
72 Instances-Scenario 3
72 Instances-Scenario 4
Total working instances
Charging power required (kW)
Number of robots
Total working instance
Power required for charging
Baseline
Proposed

(a)


Case = 1 (T dis = 2)
24 Instances-Scenario 1
24 Instances-Scenario 2
24 Instances-Scenario 3
24 Instances-Scenario 4
48 Instances-Scenario 1
48 Instances-Scenario 2
48 Instances-Scenario 3
48 Instances-Scenario 4
72 Instances-Scenario 1
72 Instances-Scenario 2
72 Instances-Scenario 3
72 Instances-Scenario 4
Total working instances
Charging power required (kW)
Number of robots
Total working instance
Power required for charging
Baseline
Proposed

(b)



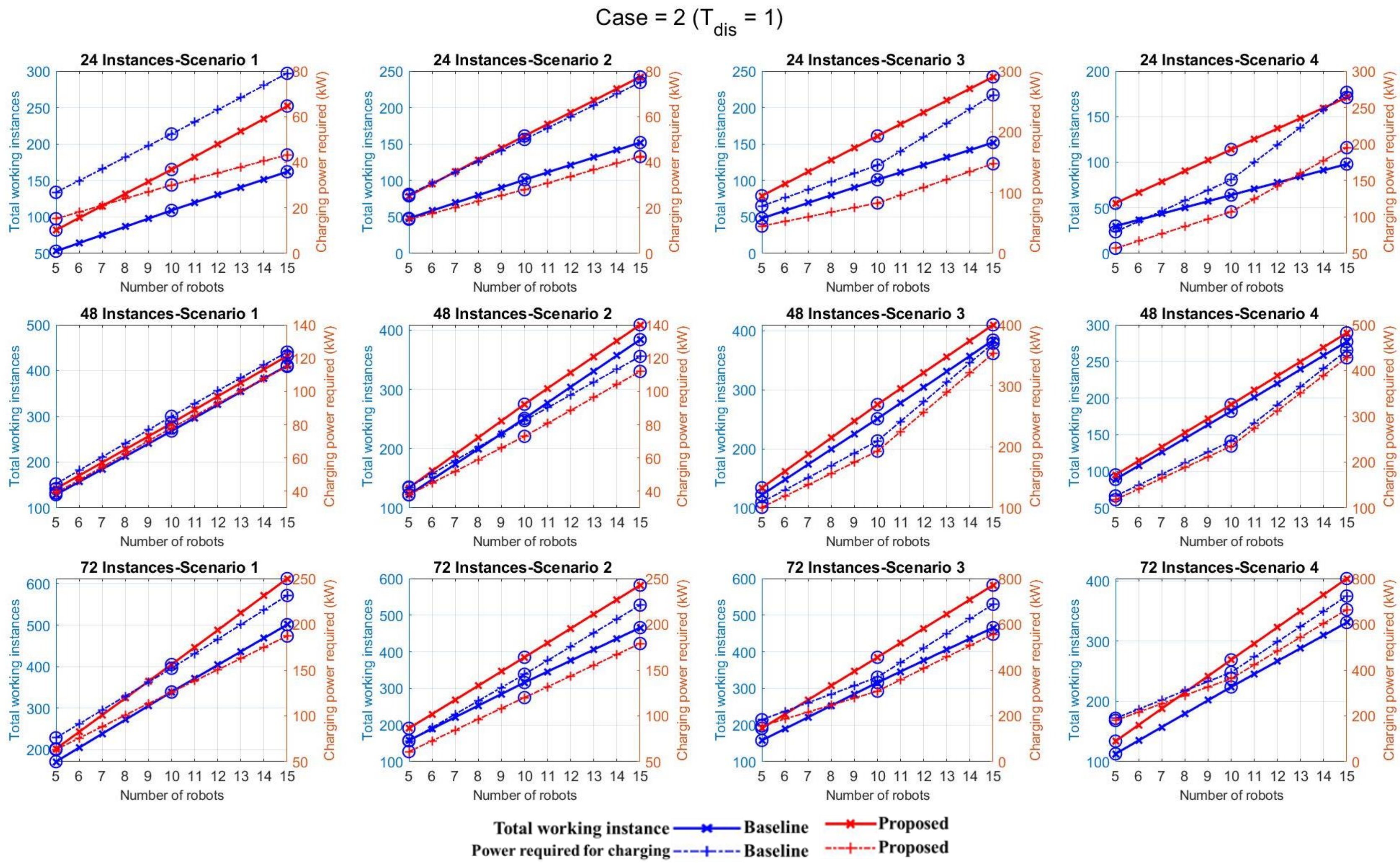
(c)

Figure 6. Total working instances and power requirements for scheduling robots at various scenarios for baseline algorithm and proposed method for Case 1; $T_{dis} = 1$ (a); $T_{dis} = 2$ (b); and $T_{dis} = 3$ (c)

4.2.2. Total robot working time, number of robots and required charging power for Case 2

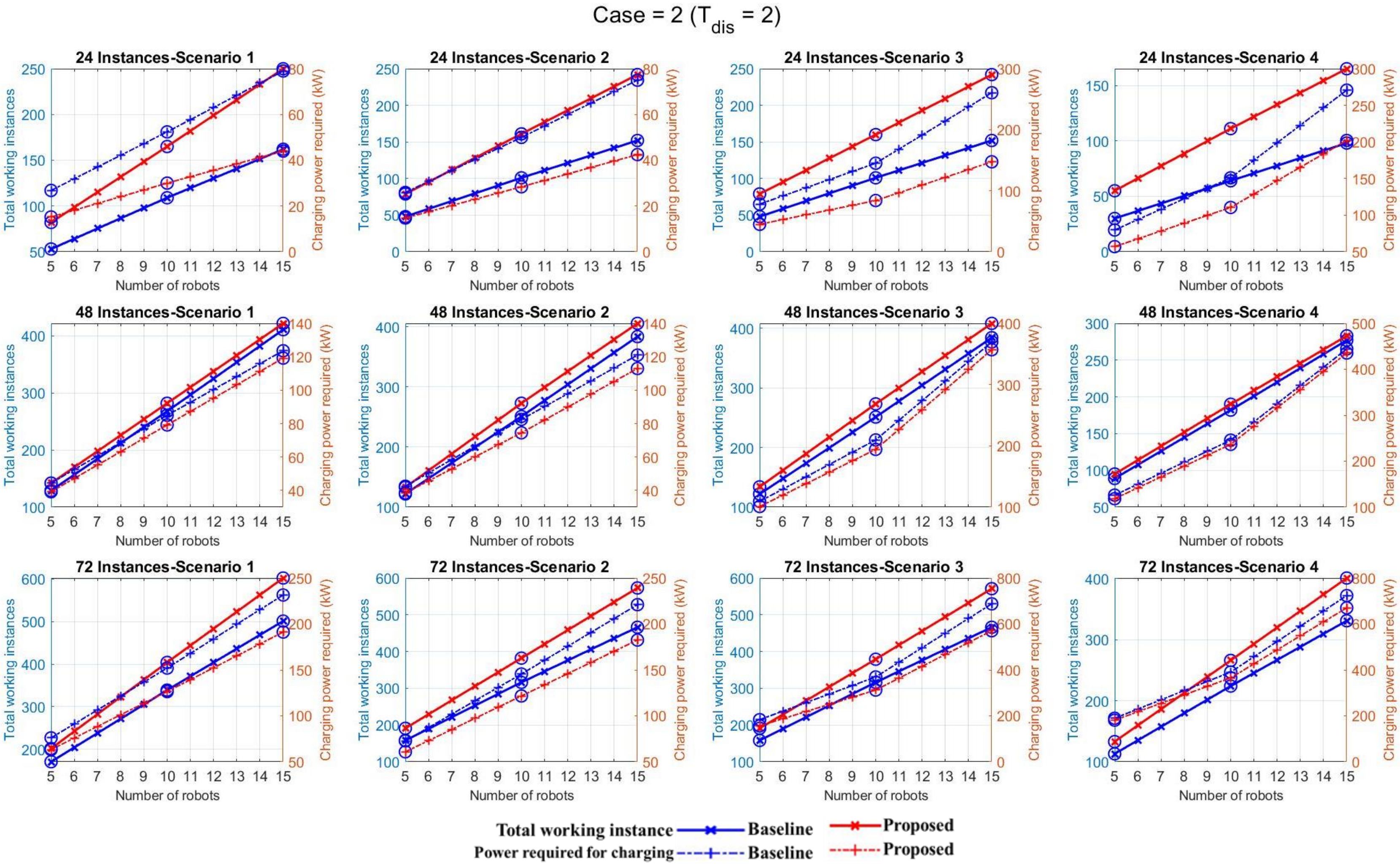
In Case 2, with the SOC of the robots varying, the improvements in total work time varied between instances, scenarios and minimum continuous discharge instances (T_{dis}). Unlike Case 1, the scenarios with more improvement in total working instances and reduction in power requirement differed. In this case, more worktime improvement was recorded in 5 robots 24 Instances-Scenario 1, 2, 3 and 4 with an improvement of about 69%, 108%, 72% and 100%, respectively (Figure 7a). A similar trend was observed regardless of the minimum continuous discharge scenarios (T_{dis} = 2 and 3) (Figure 7b and c) at 24 Instances with other instances at 48 and 72 not showing such improvement. This clearly shows that since the batteries in Case 2 had different SOC, a scheduling for a shorter work instance would result in more improvements. Furthermore, even though there was no significant difference in the improvements in the total working instances in the two and three continuous discharge scenarios (T_{dis} = 2 and 3), in both Case 1 and 2, the more the continuous battery discharge scenario, the more benefit it will be in real life. This is because, in a practical protected cultivation system as discussed earlier, the charging stations are usually situated outside because of the high temperature and humidity content inside the protected cultivation facility. Consequently, higher minimum discharge scenarios will benefit from the time saved in travelling to and from the charging station.

For the power required to charge the battery in this case, we also observed more reductions in required power to charge the batteries at the 24 Instances in all the scenarios at all the minimum discharge scenarios (T_{dis} = 1 to 3). About 43% power reduction was recorded in 24 Instances Scenarios 1 and 2. About 46% and 37% reduction in power required to charge the batteries were recorded in Scenarios 3 and 4. These percentage reductions were obtained in the 15 robots scheduling which also was the scheduling with the most significant reduction. A similar trend was recorded in the two and three continuous discharge scenarios (T_{dis} = 2 and 3). All scenarios and instances showed the proposed method outdid the baseline algorithm.



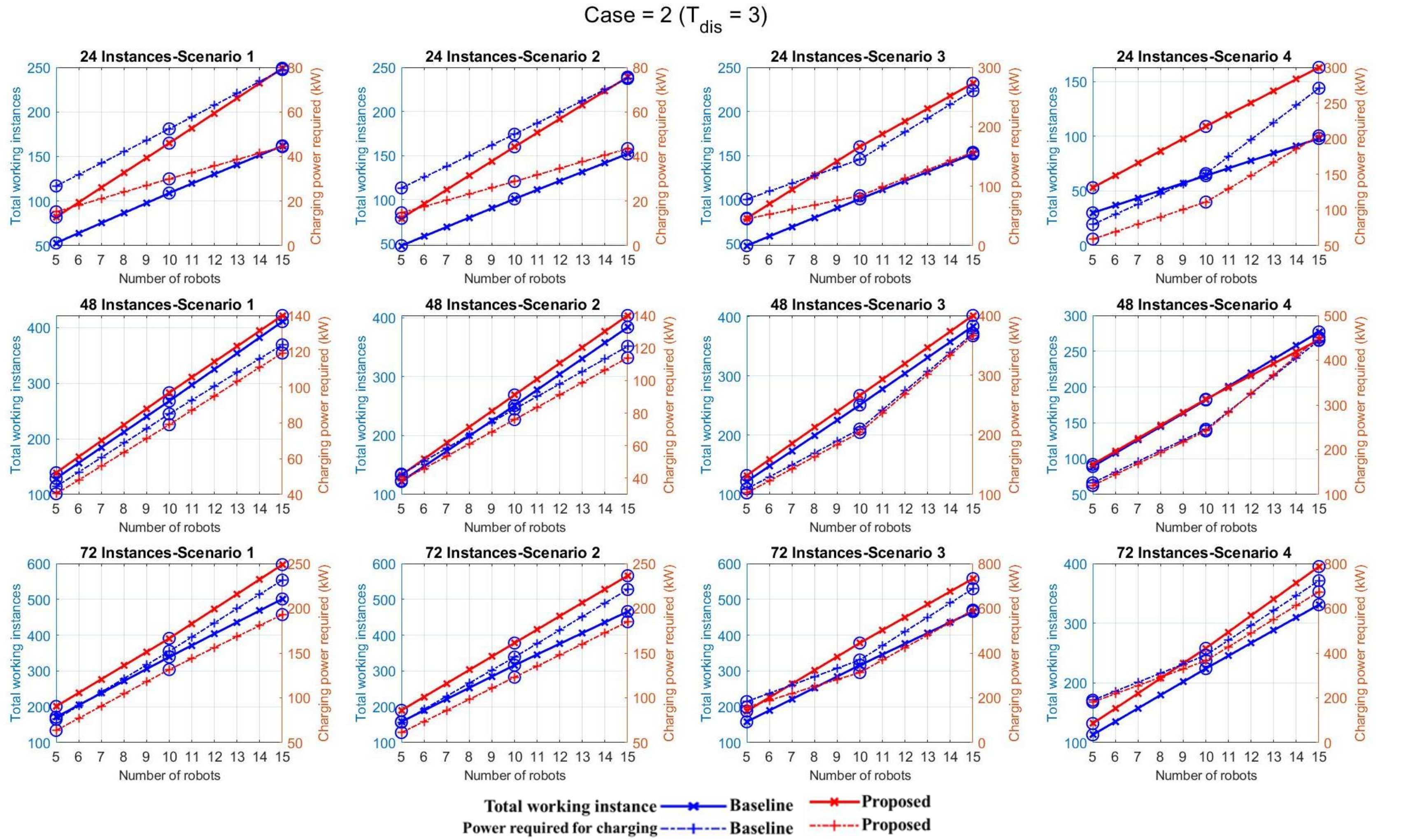
Case = 2 (T_{dis} = 1)
24 Instances-Scenario 1
24 Instances-Scenario 2
24 Instances-Scenario 3
24 Instances-Scenario 4
48 Instances-Scenario 1
48 Instances-Scenario 2
48 Instances-Scenario 3
48 Instances-Scenario 4
72 Instances-Scenario 1
72 Instances-Scenario 2
72 Instances-Scenario 3
72 Instances-Scenario 4
Total working instances
Charging power required (kW)
Number of robots
Total working instance
Baseline
Proposed
Power required for charging
Baseline
Proposed

(a)



Case = 2 (T_dis = 2)
24 Instances-Scenario 1
24 Instances-Scenario 2
24 Instances-Scenario 3
24 Instances-Scenario 4
48 Instances-Scenario 1
48 Instances-Scenario 2
48 Instances-Scenario 3
48 Instances-Scenario 4
72 Instances-Scenario 1
72 Instances-Scenario 2
72 Instances-Scenario 3
72 Instances-Scenario 4
Total working instances
Charging power required (kW)
Number of robots
Total working instance
Baseline
Proposed
Power required for charging
Baseline
Proposed

(b)



(c)

Figure 7. Total working instances and power requirements for scheduling robots at various scenarios for baseline algorithm and proposed method for Case 2; $T_{dis} = 1$ (a); $T_{dis} = 2$ (b); and $T_{dis} = 3$ (c)

5. Conclusion

We developed a system for optimal scheduling of robots in a protected cultivation system such as greenhouses to maximize work time and support uninterrupted operation. We observed that the number of working hours of a robot depended on its initial charge and had a direct impact on the optimal number of charging stations required. Also, the speed of the robot and the size of the protected cultivation system had a direct relationship to the minimum SOC the robot battery needs to have at every given time. Therefore, to account for that, we incorporate a constraint the imposes the minimum SOC on the robot. Furthermore, the more continuous instances of discharge (T_{dis}) the robots need to work before going to charge would benefit growers in saving time spent from frequent travels to and from the charging station in large commercial protected systems when the charging location is located outside. However, in small systems, the T_{dis} would not have a significant impact on extending the work hours and the robot should be allowed to go to charge at any time. This is because the reduction in robot travel time for charges would no longer be a factor. Overall, we recorded improvements in robot work time and reduction in charge power and stations required in the proposed method as robot numbers increased compared to the conventional baseline algorithm.

Acknowledgement

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Author contributions

DDU: Conceptualization, Methodology, Investigation, Formal analysis, Data Curation, Visualization, and Writing-original draft. TP and RM: Methodology, Investigation, Software, Data Curation, Visualization, and Writing. TPark and YH: Validation, Resources, Writing - review & editing, Supervision and Funding acquisition. SW, SL and JL: Methodology, validation, Funding acquisition and Project administration.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Author contributions

DDU: Conceptualization, Methodology, Investigation, Formal analysis, Data Curation, Visualization, and Writing-original draft. TP and RM: Methodology, Investigation, Software, Data Curation, Visualization, and Writing. TPark and YH: Validation, Resources, Writing - review & editing, Supervision and Funding acquisition. SW, SL and JL: Methodology, validation, Funding acquisition and Project administration.