Prognostics-aware multi-robot route planning to extend the lifetime

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Abstract

In the transition to Industry 4.0, manufacturing systems need more intelligent devices that are capable of automation. Prognostic-aware robotic systems are one of the key components of automation in manufacturing. Furthermore, prognostics-aware route planning is essential for the success of multi-robot teams during long-term and uninterrupted operations, while also extending robot lifetime and reducing maintenance costs. In this study, a Prognostics-aware Multi-Robot Route Planning (P-MRRP) algorithm is proposed for extending the lifetime of the robot team. In the P-MRRP algorithm, first, routes are obtained from the Route Set Construction algorithm, and the most reliable set of routes is selected by calculating the Probability of Route Completion (PoRC) according to the reliability of the robot team. The proposed algorithm also considers the effect of load on robots during the route. In this study, the reliability of the robot is updated considering the travelled distances and loads of the robot between pickup and delivery nodes. The results of the P-MRRP algorithm are compared with the results of classical MRRP, which reveals that the lifetime of a mobile robot team can be extended using the P-MRRP algorithm.

Keywords: Lifetime extension; performance evaluation; prognostics-aware multi-robot route planning; reliability; remaining useful life.

1. Introduction

Autonomous robots are useful instruments that can overcome the physical inadequacies of humans and perform monotonous and high-precision repetitive manufacturing tasks in smart factories (Kapanoglu *et al.,* 2012). Smart factories will require more autonomous capabilities with the progress of Industry 4.0 (Oztemel & Gursev, 2020). Long-term repetitive operations performed by a team of autonomous robots require further development of automation capabilities in intelligent manufacturing systems (Villani *et al.,* 2018). Factory level autonomy with robot health management is necessary for intelligent manufacturing with almost no human intervention, which provides reduced maintenance costs, enhanced safety for humans, uninterrupted operations and more (Hossain & Muhammad, 2016). Enhanced autonomy can be achieved by considering the reliability (i.e., remaining useful life) (Kishorilal & Mukhopadhyay, 2018) of the autonomous robots during route planning. Reliability is an important metric for reducing the risk of failures for the team of robots.

The Prognostics-aware Multi-Robot Route Planning (P-MRRP) algorithm can be used to increase the lifetime of the mobile robot teams by considering reliability. Prognostics-aware planning aims to integrate the prognostics health information and the knowledge about the future operating conditions into the process of selecting subsequent actions for the system. Prognostics information can be used to predict the reliability of the system, and thus, promote the efficiency and lifetime of autonomous operations (Shah *et al.,* 2020). Estimation of the reliability has been conducted to suppress the possible faults of robotic systems and increase their success (Hossain & Muhammad, 2016).

In the literature, there are a few route planning studies for single mobile robotic systems that focus on increasing the lifetime or health management of the system. Mimlitz *et al.* (Mimlitz *et al.,* 2016) present a Goal-Oriented, Risk Attitude-Driven Reward Optimization (GORADRO) method that increases lifetime efficiency. GORADRO uses the local area and internal prognostics and health management (PHM) information to determine system health and potential localized risks for planning routes. LeSage and Longoria (LeSage & Longoria, 2015) measure the single mission feasibility for the mobile robotic system and present a sequential method for forecasting the mission feasibility for the mobile robotic system operating in risky environments. The method makes use of the marginal predictions required to permit Bayesian correlation estimation and improved process characterization. On the other hand, newly developed robots utilize health diagnostics for detecting possible faults inside the robot. In one study (Balaban *et al.,* 2013), a mobile robot platform is developed specifically for testing in failure scenarios. Different failure modes are examined for electrical, mechanical, and power subsystems of the mobile robot. In addition to the mobile robot, a software simulator has been developed for the validation of Prognostics-enabled Decision-making (PDM) algorithms. In another study (Sweet *et al.,* 2014), the hardware platform is designed to inject the predefined failure modes to the mobile robot's electrical power subsystem. The PDM algorithms were adapted to the hardware platform, including the development of a new route planner that replans the route based on faults in the mobile robot.

The previous studies typically consider a single-robot planning problem. However, a multi-robot route planning system appears to be more effective and adaptive to accomplish various complex tasks (Arai *et al.,* 2002). There are a few studies regarding the performance of the system that is required for the given mission. One study presents the Active Mission Success Estimation algorithm, which estimates real-time risks during a space mission by functional modelling and risk analysis techniques based on PHM information (Short *et al.,* 2018). The ASME algorithm provides a quick and effective estimation of current mission success, and projections of possible total mission success based on potential decisions. Another report proposes a method for developing safety indicators for the missions of Autonomous Marine Systems (AMS) (Thieme & Utne, 2017). The results of safety indicators reflect safety in the AMS mission and can help in planning. Additionally, a mission execution decision-making approach is proposed based on the correlation between mission requirements and the health of the system (Geng *et al.,* 2016). This approach transforms the inherent health into mission health and conducts correlation analysis, which provides quantitative implications for decision-making during the given mission. However, there is no study that measures the performance of the robot team for the given mission. In a study among the first few articles on MRRP considering the reliability of the robot team, the Route Set Construction (RSC) and Route Set Analysis (RAS) algorithms are proposed (Yayan & Yazici, 2019). The RSC algorithm is responsible for constructing route sets, and the RAS algorithm analyses route sets while considering the reliability and PoRC for each route set. Although the effect of the robot reliabilities on planned routes are shown, route planning and lifetime analysis are not given for extending the lifetime.

In the current study, a Prognostics-aware Multi-Robot Route Planning (P-MRRP) algorithm is proposed for increasing the number of completed tasks during the lifetime of the robot team. In route planning of the robot team, the Vehicle Routing Problem with Backhauls (VRPB) (Deif & Bodin, 1984, Koç & Laporte, 2018), which is one of the most common problems for in-plant logistics of autonomous vehicles, is considered. Routes are obtained using the Simulated Annealing (SA) algorithm (Van Laarhoven & Aarts, 1987) for the minimum distance objective function and minimum energy objective function. Furthermore, routes are generated for various load combinations of robots in the team. Thus, the proposed P-MRRP algorithm is analysed considering the effect of load. Moreover, the Prognostics-aware Lifetime Analysis (PLA) algorithm is proposed to analyse the lifetime extension of P-MRRP and classical MRRP algorithm for both the loaded and unloaded cases. The PoRC is calculated for each route on the route set, and the most reliable route set is selected. The hazard rate of components and the initial reliability of the robots are used in PoRC calculations. The results showed that the number of routes during the lifetime of the robot team is increased using the proposed P-MRRP algorithm. To the best of our knowledge, there are no previous reports that utilize prognostics-aware MRRP to increase the lifetime of a robot team by considering the loads of robots during tasks.

Definitions and preliminary descriptions are given in the following section. The P-MRRP algorithm is introduced in the third section, and the test results are given in the fourth section. The last section includes the conclusion and future works.

2. Definitions and preliminaries

The lifetime of the robot team may be increased if the team can know the health status of each robot and make task assignment decisions accordingly. Thus, it is necessary to consider the effects of reliability on the decision-making results in sustainable autonomous operations for the robot team (Fudzin & Majid, 2015). System Health Management (SHM) of a robot depends on prognostics technology and can be supported by diagnostics and health-based planning for a fully autonomous system. In the context of SHM, the end-of-life, availability, and reliability of systems and components can be predicted (Okoh *et al.,* 2014).

Prognostics are the data that forecast when a component or system doesn't satisfy desired operations. Using this prognostics knowledge, the system can make more appropriate decisions, like changing the component before it fails, prolonging component life by load reduction or task switching, and optimally plan or replan a route. In this study, the reliability is used for informing the P-MRRP problem. The PoRC is calculated considering the reliability value of each robot in the team.

Reliability is the probability that a piece of equipment operating under specified conditions can perform satisfactorily for a given period (Dhillon, 2015). The reliability takes values between 0 and 1. Reliability models involve descriptions of how the hazard rate changes over time. The exponential distribution model, with only one unknown parameter, is the simplest and most common model. Additionally, the exponential model exhibits a constant failure rate property. Due to this property, the exponential model is the perfect model for most of the components and systems that are used. Therefore, in this study, an exponential distribution alias bathtub curve is used as a reliability model for analysis. The bathtub curve has three distinct regions such as the infant mortality, useful life, and wear-out phases. There are formulations required in the analysis of a robotic system's reliability, which are shown below.

Mobile robots have many critical modules and components, including communication, sensor, battery, and mobility components. These components are used for the reliability estimation of mobile robots. The reliability of the whole system is analysed with its components. First, all components' reliabilities are calculated separately. Then, the reliability of the system is calculated as a combination of all components' reliability. For the calculation of reliability G and hazard rate of components, the usage time of components t and system architecture (series or parallel) must be known. It is assumed that the whole robot has a series configuration and constant hazard rate ht (failure/hour) according to the reliability model, which is based on the bathtub curve model for unloaded cases.

Equation (1) and (2) for $G_k(t)$, $k=1...m$ shows how a robot reliability is calculated in the series configuration. The reliability of a robot in a robot team can be calculated using the following Equation (1). In Equation (1), t denotes usage time, and λ denotes the hazard rate of the robot, which is equal to the summation of the hazard rates of each component.

$$G_k(t) = e^{-\lambda t} \tag{1}$$

The hazard rate of a robot with multiple components can be calculated according to Equation (2).

$$\lambda = \sum_{q=1}^{c} \lambda_q \tag{2}$$

Notably, it is assumed that each component in a robot is assumed to be in a series configuration. On the other hand, if there are multiple robots in a team, then the reliability of a robot team can be calculated using Equation (3).

$$G_s(t) = G_1(t)G_2(t)\ldots..G_c(t) = \prod_{q=1}^{c} G_k(t) \tag{3}$$

$G_s(t)$ denotes robot team reliability, which is equal to the product of each robot's reliabilities in Equation (3). In this study, reliability is updated using Equation (4).

$$G_{s\_new} = G_{s\_old}e^{-\lambda t} \tag{4}$$

G_{s_new} denotes updated reliability, G_{s_old} denotes the reliability of previous situation, and the rest of the formula is necessary to calculate new reliability values G_{s_new} according to the usage time *t* and hazard rate λ.

Moreover, we are dealing with the mobility component of the mobile robot and we are calculating the reliability of the robot using the hazard rate of the mobility component. The hazard rate depends on several conditions, and one of them is the load on the bearing in the mobility component. In this study, we analyse the effects of load on the reliability of the mobility component by estimating the reliability of the bearings (Medjaher *et al.,* 2012). Bearings are the most critical sub-component of the mobility system in the mobile robot. In this study, the customized hazard rate is used for estimating the reliability of the bearing in the robot's mobility module. Although the reliability estimation of the bearing with a constant initial hazard rate is assumed for robots in every route analysis, the hazard rate changes according to the load and returns to the initial value. The relationship between the hazard rate and the load is shown in Equation (5). In this study, the robot's utilize ball bearings. In the literature, when ball bearings are used, the power should be selected as "3" in Equation (5) (Shanker & Kumar, 2020):

$$\lambda_{load} = \lambda_0(\frac{P}{P_0})^3 \tag{5}$$

In Equation (5), λ_0 denotes the initial hazard rate, and λ_{load} denotes the hazard rate that occurs when the robot is loaded. *P* indicates the load carried by the robot, and P_0 indicates the robot's load capacity. Equations (5) and (6) are used for analysing the load effect on the robot's reliability.

$$G_{s\_new} = G_{s\_old}e^{-\lambda_{load}t} \tag{6}$$

In Equation (7), G_s and d_{total} are the reliability of robot team and total distance traversed by the robot team for a given route, respectively. In this study, the time is assumed to be proportional to the travelled distance. The PoRC for all tasks $PoRC_s$ for the robot team is calculated using Equation (7).

$$PoRC_s = {G_{s\_new}}^{d_{total}} \tag{7}$$

Reliability of robotic systems can be analysed in terms of the components of the systems. According to the literature, Equation (1) can be used for the calculation of the hazard rate of any robot or component, and then the robot's reliability can be calculated using Equation (2). The reliability of the robot team can be calculated using Equation (3). Overall, the reliability of the robot team can be updated using Equation (4). If the effect of carrying a load is considered, then the reliability of the robot team could be updated using Equations (5) and (6). Equation (7) can be used for the calculation of PoRC for any given mission.

3. Proposed Prognostics-aware multi-robot route planning algorithm

In the factories, the transportation of all materials, parts, and finished products by robots are usually repeated actions. Transportation of empty vehicles is called deadheading, and the corresponding distance is denoted by deadhead distances (meters), which can be translated to an increase in cost. To reduce the deadheading, after delivery activities, the vehicle visits the pickup points and picks up finished products at these points to transport them to the depot. This process is called backhauling (Dolgui & Proth, 2010). For this type of repetitive task, P-MRRP becomes particularly useful. Although there are various studies in this area, reliability-based multi-robot route planning is not considered in the literature, as mentioned before. The proposed P-MRRP algorithm focuses on extending the lifetime of the robot team by considering the reliability and loads of the robots. In this study, the reliability of the robot is updated considering both the travelled distances for the assigned route and the load of the robot between pickup and delivery nodes. Moreover, the lifetime extension of the robot team can be analysed using the proposed PLA algorithm. In the following subsections, the proposed P-MRRP algorithm and its sub-algorithms are discussed. The route planning algorithm (SA) is used to construct the route sets for pickup and delivery (P/D) problems. The PLA is used to analyse the lifetime of the robot team while considering the PoRC value.

3.1 Proposed prognostics-aware multi-robot route planning algorithm

P-MRRP algorithm is proposed to increase the number of completed tasks during the lifetime of the robot team. P-MRRP algorithm could be used with any route planning algorithm and could help to solve any vehicle routing problem considering the lifetime extension of the robot team. In this case study, the SA algorithm is used for RSC as given in Section 3.2. Steps of the P-MRRP algorithm are given in Algorithm 1.

It is assumed that the robots know positions of nodes x_i, y_i, *i=1,...,n*, required time to complete task at nodes $t_i, i = 1, \ldots, n$, weight of loads at nodes w_i, *i=1,...,n*, relative distances d_{ij} between nodes, and connections of the nodes. And robot positions x_k, y_k, *k=1,...,m*, initial reliability G_k, *k=1,...,m* of each robot, hazard rates of components λ_q, *q=1...c*, nominal load capacity P_k, *k=1...m*, nominal speed S_k, *k=1...m*, virtual capacity V_{k_cap} have been known in advance. E_{ij} indicates consumption of energy for the travelling from node *i* to node *j*, and E_i, *for i=1,...,n*, indicates required energy in performing its task at the specified node. Robots R_k, *k=1,...,m* have limited capacity of E_{k_cap}, *k=1,...,m*, according to route plannig algorithm for constructing all the possible route combinations of robot team and case study environment.

Algorithm 1. Prognostics-aware Multi-Robot Route Planning (P-MRRP) Algorithm.

Initialization Phase:

Step 1;Get all the information about environment and robots *n*, (x_i, y_i), d_{ij}, t_i, w_i, E_i;*for i* $\neq$ *j and i, j = 1, ..., n, m*, (x_k, y_k), E_{k_cap};*for k = 1, ..., m*, ΔV_{cap}, update distance matrix *D*,

Step 2;Run route planner algorithm for the robot team using pre-determined virtual capacities $V_{k\_cap} \in V_{cap}$ *for k = 1, ..., m*, and save each constructed tour R_{k_tour} and total traversed distances d_{k_total} to the route set *H*.

Main Phase:

Step 1;Set *r* = 1

Step 2;Get initial reliability of robots G_k *for k = 1, ..., m*, hazard rates of components belong to robots λ_q,*for q = 1...c*

Step 3;Calculate $PoRC_s(r)$ using Equation (7). Note that the reliability of the robots is updated using Equation (4) or (6) at each node of their tour.

Step 4;IF $r < p^m$ set *r* = *r* + *1* GOTO Step – 2 ELSE GOTO Step – 5

Step 5;Find the most reliable route set index $R_{k\_tour} = H(\hat{r}, :)$

In the initialization phase of the P-MRRP algorithm, a route set *H* is constructed for the given problem environment. To realize this, in the first step of the algorithm, the traversed distances d_{ij} and required energies E_{ij} for the robots between all pairs of nodes are calculated. In the second step, a virtual capacity set V_{cap} is determined considering the objective functions of the route planning algorithm that is given in the next subsection. Note that, the user may also consider workload balancing issues for selecting V_{cap} for each of the robots in the team. For this study, the SA algorithm is used to find route sets considering all possible variations of robots regarding the V_{cap}.

In the P-MRRP algorithm, the most reliable route set is selected among route set *H*. In the second step of the main part, the initial reliability G_k values of robots and hazard rates of components λ_l belong to robots are obtained. Note that, these values are kept the same for every route set of *H*. Then, $PoRC_s$ value is calculated for the system using Equation (7). In this step, a variable reliability and hazard rate are used to calculate reliability for a given route. For a given robot, after completing a sub-route (i.e., arrived at a node of the route) the robot's initial hazard rate λ_l, l = *1 ... c* and reliability values G_k are updated using Equation (4) or (6), and these values are used for the remaining sub-route of the main route. In Equation (6), the value of reliability is updated also considering carried load if it exists. Therefore, these approaches not only consider travelling issues but also carried a load. The algorithm repeats $PoRC_s(r)$ calculation until $r := p^m$. In the last step of the P-MRRP algorithm the most reliable route set is selected considering the values of $PoRC_s$. The P-MRRP algorithm can be used to determine the most reliable route set for a given robot team.

To analyse the effect of the algorithm on the lifetime extension following the PLA algorithm is proposed in Section 3.3.

3.2 Route planning algorithm

P/D problems are common problems of in-plant transportation. VRPBs where all deliveries have to be made for each route before the first pickup is one of the possible variants considered in intralogistics (Koç & Laporte, 2018). The VRPB was introduced by Deif and Bodin (Deif & Bodin, 1984). VRPBs increase efficiency by limiting the number of meters that is driven with an empty vehicle after all deliveries have been made should be balanced with preceding pickups on every route (Goetschalckx, 2011). Routing of robots and scheduling of P/D tasks are established using a metaheuristic algorithm, the SA algorithm. The conventional routing and scheduling problem is known as a combinational optimization problem, which is an NP-hard problem and cannot be solved by existing exact algorithms in a reasonable time. Therefore, metaheuristic algorithms are generally used to solve these kinds of problems (Sarıçiçek *et al.,* 2022). The SA algorithm is one of them. It is widely used and its performance is proven in the literature (Wu & Chen, 2003).

In our industrial environment (Figure 1), there are 12 workstations which have P/D points. Robots take the parts from the raw material warehouse (depot 1) to the workstations, which request P/D tasks. They also take the products or semi-products from the pickup points and deliver them to the finished products warehouse (depot 2).

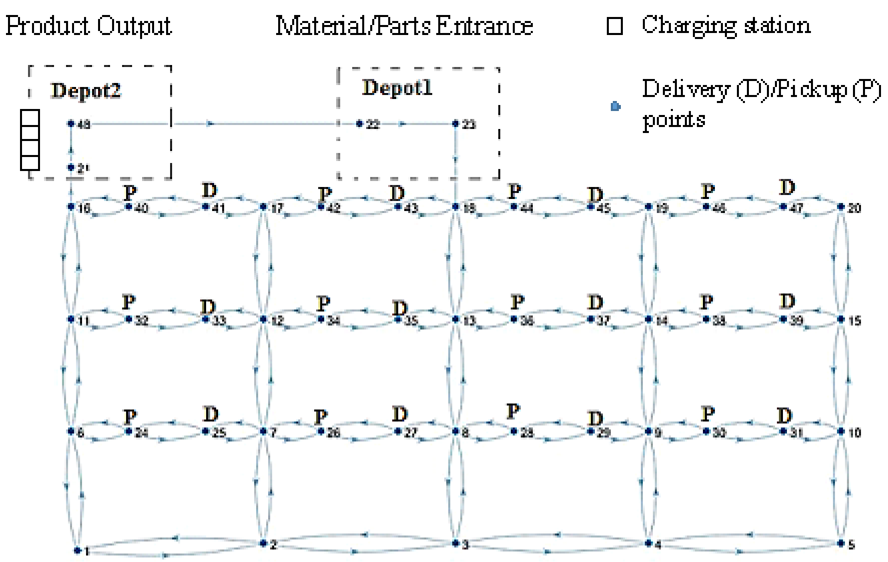


Fig. 1. The graph of the factory environment

Table 1. An example of the P/D task list.

Number of Items	P/D Point number	Type of the task (P/D)	Item	Weight (kg)
1 Item	25	Delivery	C	20
1 Item	27	Delivery	E	20
1 Item	29	Delivery	E	20
1 Item	31	Delivery	D	20
...	...	...	...	...
1 Item	30	Pickup	F	20
1 Item	32	Pickup	D	20
1 Item	34	Pickup	E	20
1 Item	36	Pickup	A	20
...	...	...	...	...

Table 2. Details of the Example Route Plan

Robot (Virtual Capacity (kg))	Robot 1 (40)	Robot 2 (40)	Robot 3 (80)	Robot 4 (80)
	Point (Weight)	Point (Weight)	Point (Weight)	Point (Weight)
Delivery tasks	43 (20) 41 (20) - -	35 (20) 33 (20) - -	25 (20) 27 (20) 29 (20) 31 (20)	45 (20) 37 (20) 39 (20) 47 (20)
Pickup tasks	42 (20) 40 (20) - -	34 (20) 32 (20) - -	30 (20) 28 (20) 26 (20) 24 (20)	46 (20) 38 (20) 36 (20) 44 (20)

The P/D requests for workstations are listed in Table 1. The task scheduling and route planning are established using a path planning algorithm.

In Figure 2, the number (-1) is a delimiter of the routes. According to the solution, the robot assigned to the first route leaves depot 1 and brings the requested part to points 43 and 41, then goes to points 42 and 40 to take the load/product and to bring them to the depot 2. The same process is implemented for route 2, 3 and 4. Each route is assigned to a robot in Figure 2. Therefore, four routes are assigned to four robots.

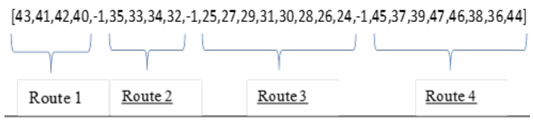


Fig. 2. An example for route plan

In Table 2, the details of the example route plan are shown. Virtual capacity is used for generating all possible route sets of a given environment and the robot team. For example, in this plan, the virtual capacities for the loads of four robots are 40, 40, 80 and 80 kg. Furthermore, pickup and delivery tasks are given in Table 2.

In the route planning algorithm,

i, j: index for nodes,

k: index for robots,

d_{ij}: distance between node *i* and *j*,

ρ^*: energy spent when the robot is full-load,

ρ_0: energy spent when the robot is no-load,

Table 3. The comparison of costs for two solutions

	Minimum Distance Objective Function SA		
Robot #	*Energy(kg*m)*	*Distance(m)*	*Time(s)*
4	787840	4774	33.7
	Minimum Energy Objective Function SA		
Robot #	*Energy(kg*m)*	*Distance(m)*	*Time(s)*
4	785760	4898	34.9

RC: robot capacity,
decision variables
x_{ijk}: 1; robot *k* moves from node i to node j, 0; otherwise
and
y_{ijk}: load from node i to node j with robot k.
Objective functions for selecting routes are shown in Equations (8) and (9).
Objective function 1: Minimum distance;

$$Min\ z1 = \sum_{k\in K}\sum_{i\in V}\sum_{j\in V}(d_{ij}x_{ijk}) \tag{8}$$

Objective function 2: Minimum energy;

$$Min\ z2 = \sum_{k\in K}\sum_{i\in V}\sum_{j\in V} d_{ij}(\rho_0 x_{ijk} + \alpha y_{ijk}) \tag{9}$$

$$where\ \alpha = (\rho * -\rho 0)/RC \tag{10}$$

The first objective function in Equation (8) is necessary to minimize the total distance travelled. In Equation (9), minimization of energy depends on the transported load and the travelled distance between nodes. Based on the number of robots, their starting positions, and the P/D requests, the assignment of requests and appropriate routes for the robots are obtained to minimize the total energy consumed by robots. Objective functions directly affect the lifetime of the robot team by selecting the tasks for the robots. Thus, objective function selection is critically important in the lifetime of the robot team.

In Table 3, trade-offs between costs for the minimum distance objective function and the minimum energy objective function can be seen. The total distance travelled and total energy consumption are calculated as 4744 m and 787840 kg × m using the minimum distance model, respectively. On the other hand, the values are 4898 m and 785760 kg × m for the minimum energy model, respectively.

3.3 Prognostics-aware Lifetime Analysis (PLA) algorithm

The PLA algorithm can be used for long-term reliability analysis of a routing strategy with different performance measures. The steps of the algorithm are given in Algorithm 2.

Algorithm 2. Prognostics-aware Lifetime Analysis (PLA) Algorithm
Step 1. GET a user-specified threshold for PoRC ($PoRC_{th}$) value and robot reliability values
Step 2. RUN the P-MRRP algorithm or classical MRRP algorithm for the defined mission
Step 3. For the routes, calculate $PoRC_s$ and update robot reliability values
Step 4. IF $PoRC_s < PoRC_{th}$ terminate the algorithm otherwise GOTO Step – 2

In the first step of the PLA algorithm, a user-specific $PoRC_{th}$ value that defines termination condition, and actual robot reliability values, are obtained. In the second step, a route set is constructed using the determined performance measure. In this step, the P-MRRP algorithm or classical MRRP algorithm can be used. In the third step, the PoRC values are calculated for the robot team and the

Table 4. Test Setup Values

λ_l, *for l = 1...c*	$5.07e^{-004}$
S_k, *for k = 1...m*	*4.32 km/h*
P_k, *for k = 1...m*	*200 kg*
$PoRC_{th}$	*0.1*

reliability values are updated considering the nature of the mission (i.e., travelled times, carried loads). If $PoRC_s < PoRC_{th}$, then the algorithm recalls the MRRP algorithms, otherwise it terminates. Thus, the PLA algorithm can be used to assign the number of sequential missions for a given environment and robot team. In this way, the lifetime extension characteristics of any MRRP algorithm, including P-MRRP, can be determined.

4. Test results

The proposed approach is tested in the simulation environment in Figure 2, which includes 48 nodes. Figure 3 gives the configuration space in the GAZEBOSim environment. Initially, all the robots are assumed to be at node 21 of depot 2 (Figure 3).

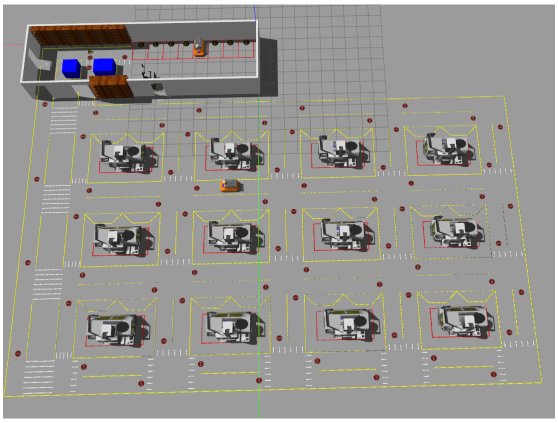


Fig. 3. Gazebo simulation case study environment

The hazard rates of the robot components λ_l, *l = 1...c*, nominal speed of robots S_k, *k = 1...m*, nominal load capacity of robots P_k, *k = 1...m*, and user-specified threshold value for $PoRC_{th}$ are given in Table 4. Initially, all parameters of the robots in the team are assumed to be identical to each other. In this study, the autonomous mobile robot's (IMTGD, 2021) datasheet is used as a base while configuring the test setup values.

Tests are conducted with a specially developed GUI, which is shown in Figure 4. In this GUI, the number of robots in the team, load case selection, PoRC or reliability threshold type and value can be selected. Via the GUI, the user can select the threshold type as reliability or PoRC. This means that the algorithm will stop after reaching the threshold for the reliability or PoRC value of the robot team. After reaching the threshold value, the algorithm creates a report that contains the number of completed tasks during the lifetime of the robot team. Furthermore, robots in the robot team can be configured according to the initial hazard rate value, initial reliability value, robot maximum speed value and nominal capacity value for each robot.

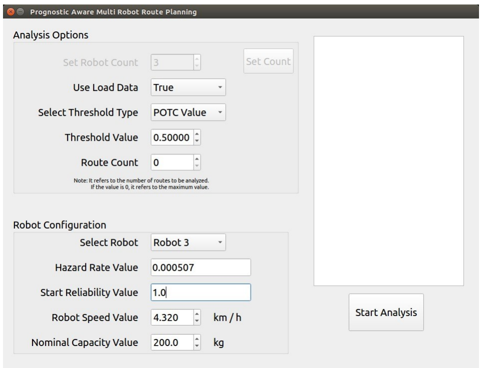


Fig. 4. P-MRRP test GUI

The reliability of a robot team is highly related to the number of completed tasks during the operation time. The P-MRRP algorithm chooses routes for the robot team according to the PoRC values. After that, the proposed PLA algorithm is applied for the lifetime analysis of the robot team using the P-MRRP algorithm. In this algorithm, the PoRC values are calculated, and the reliability values are updated considering the nature of the mission (i.e., travelled times, carried loads) for the robot team. The PLA algorithm continues to recall the MRRP algorithm as long as $PoRC_s < PoRC_{th}$, otherwise it terminates. In the analysis, it is assumed that the user-specific value of $PoRC_{th}$ that defines the termination condition is set to 0.1.

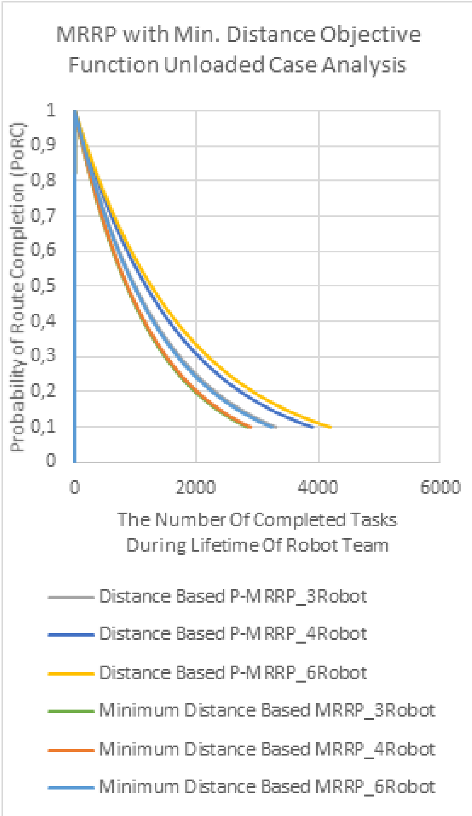
Furthermore, routes are obtained using two different objective functions. The energy minimization or the distance minimization objective function is selected for creating route sets. The lifetime analysis results of the proposed P-MRRP algorithm and classical MRRP are compared in terms of both load and unload cases, and energy and distance-based objective functions. Notably, the classical MRRP-based route sets are not changed in the lifetime of the robot team, i.e., the shortest distance route does not change. Besides that, these route sets are created for 3, 4 and 6 robot team combinations. In the following, firstly, MRRP with minimum distance objective function studies are analysed. Later, MRRP with minimum energy objective function studies are given. Lastly, MRRP with prognostics-aware algorithm results are compared among themselves, and the results are commented on.

4.1 MRRP with minimum distance objective function

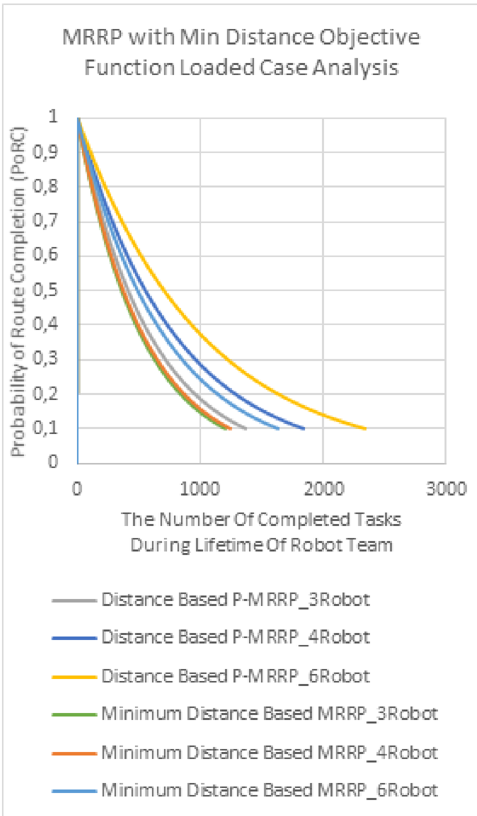
First, the analysis is conducted for the route set of MRRP with minimum distance objective function. In this analysis, it's assumed that robots are homogeneous and have the same reliability value $G_k = 1.0$ $k = 1, \ldots, m$ and the loaded and unloaded cases are considered and configurations are given in Table 4. A comparison among the conducted tests are given in Table 5. In Table 5, the number of completed tasks during the lifetime of the robot team is given according to robot team combination, load case and objective function of route planning. The PLA comparison of the P-MRRP and classical MRRP for different robot team combinations (3, 4, 6 robots) is realized. Unloaded and loaded cases of MRRP with distance objective function-based route set are given in Figure (5a) and Figure (5b) respectively. As demonstrated in Table 5 and Figure 5, the robot team with the P-MRRP algorithm has completed more tasks than classical MRRP algorithms with minimum distance-based MRRP during the lifetime of the robot team.

Table 5. Lifetime Analysis for MRRP with Minimum Distance Objective Function

Load Case	***Robot Team***	***Objective function of Route planning***	***The num of comp. tasks during lifetime of robot team***
Loaded	3 Robots	Distance based P-MRRP	1367
		Minimum Distance Based MRRP	1204
	4 Robots	Distance based P-MRRP	1836
		Minimum Distance Based MRRP	1244
	6 Robots	Distance based P-MRRP	2332
		Minimum Distance Based MRRP	1634
Unloaded	3 Robots	Distance based P-MRRP	3302
		Minimum Distance Based MRRP	2836
	4 Robots	Distance based P-MRRP	3899
		Minimum Distance Based MRRP	2882
	6 Robots	Distance based P-MRRP	4192
		Minimum Distance Based MRRP	3236

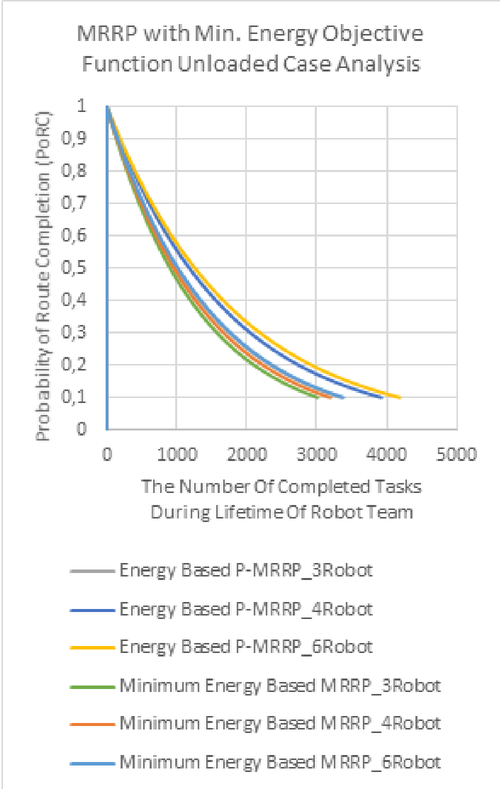


(a)Unloaded

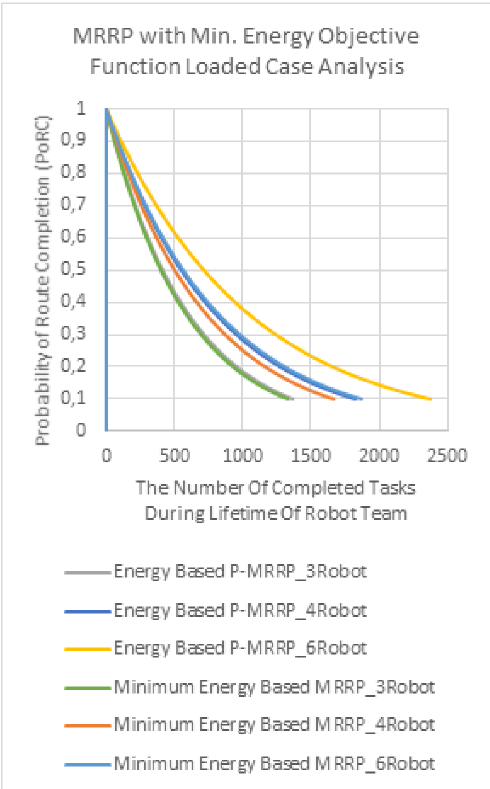


(b)Loaded

Fig. 5. Lifetime analysis for MRRP with minimum distance objective function



(a)Unloaded



(b)Loaded

Fig. 6. Lifetime analysis for MRRP with minimum energy objective function

In Figure 5 (a) and (b), the load effect can be seen clearly. In the loaded case, the completed tasks of

Table 6. Lifetime Analysis for MRRP with Minimum Energy Objective Function

Load Case	*Robot Team*	*Objective function of Route planning*	*The num of comp. tasks during lifetime of robot team*
Loaded	3 Robots	Energy based P-MRRP	1563
		Minimum Energy Based MRRP	1331
	4 Robots	Energy based P-MRRP	1826
		Minimum Energy Based MRRP	1667
	6 Robots	Energy based P-MRRP	2375
		Minimum Energy Based MRRP	1871
Unloaded	3 Robots	Energy based P-MRRP	3349
		Minimum Energy Based MRRP	3010
	4 Robots	Energy based P-MRRP	3920
		Minimum Energy Based MRRP	3189
	6 Robots	Energy based P-MRRP	4182
		Minimum Energy Based MRRP	3380

the robot team are approximately half of the unloaded case without distinction of robot team combination. Moreover, as shown in Figure 5 (a) and (b), as the number of robots in the robot team increases, the number of completed tasks during the lifetime also increases.

4.2 MRRP with minimum energy objective function

Second, analysis is conducted for the route set of MRRP with energy objective function. In this analysis, all configurations and test scenarios are the same as in Section 4.1. In Table 6, lifetime analysis results of MRRP with minimum energy objective function are given.

The comparison of Tables 5 and 6 show that the MRRP algorithm with minimum energy objective function completes slightly more than the MRRP algorithm with minimum distance-based objective function. This means that MRRP with the minimum energy objective function route set is more suitable for lifetime extension than MRRP with the minimum distance objective function route set.

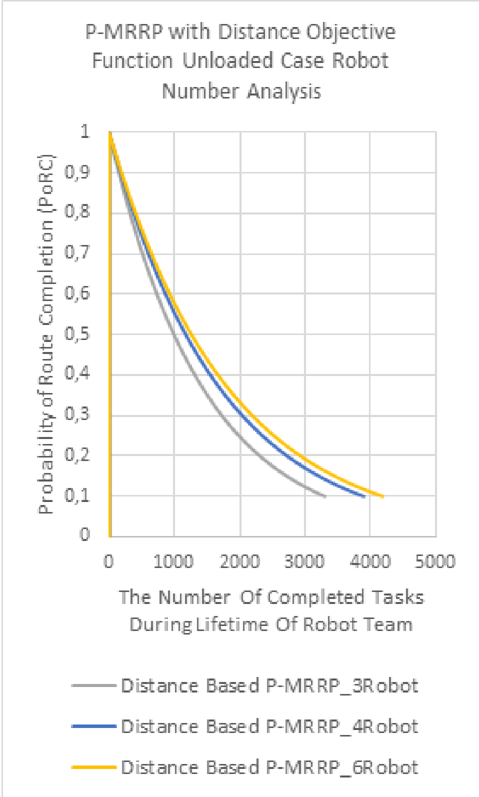
When the unloaded case is compared with that loaded one in Figure 6, the load effect in the number of completed tasks during the lifetime of the robot team could be seen. Besides, the number of robots in the team is another crucial factor in extending the lifetime of the robot team.

4.3 MRRP with the Prognostics-aware algorithm

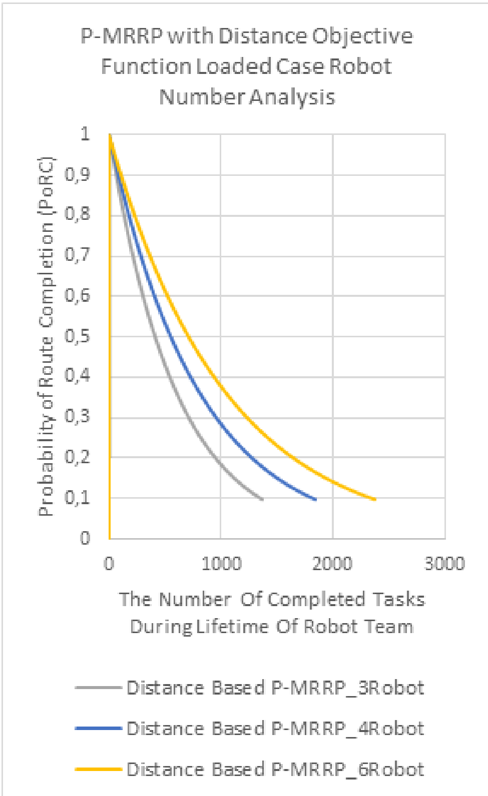
P-MRRP algorithm results are analysed depending on the number of robots in the team. In Tables 5 and 6, P-MRRP algorithm test results for a different number of robots can be analysed.

The lifetime of the robot team is extended when the number of robots is increased in the P-MRRP algorithm for the loaded and unloaded cases. For example, the difference between three robots and four robots in terms of the number of completed tasks is approximately 500 tasks for the loaded case and 600 tasks for the unloaded case. The situation is roughly the same for a four-robot team and six-robot team, with 500 tasks for the loaded case and 300 tasks for the unloaded case.

From Table 6, the P-MRRP algorithm analysis with energy objective function route set is shown. The lifetime is extended according to the number of robots in the team.

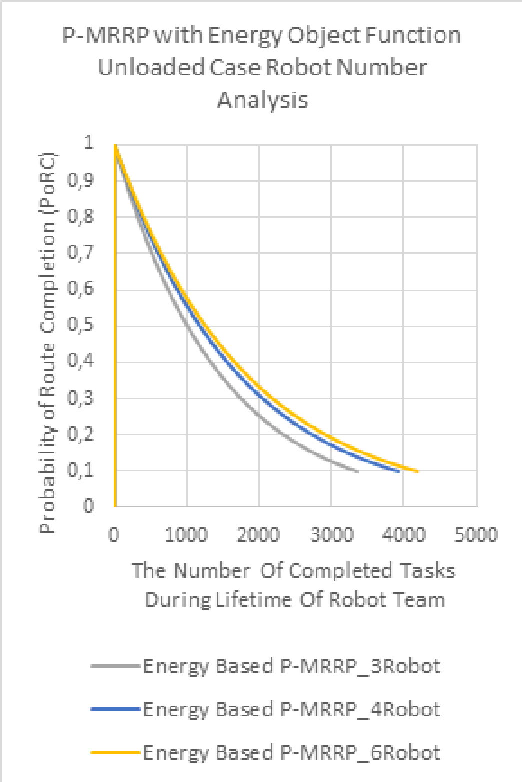


(a)Unloaded

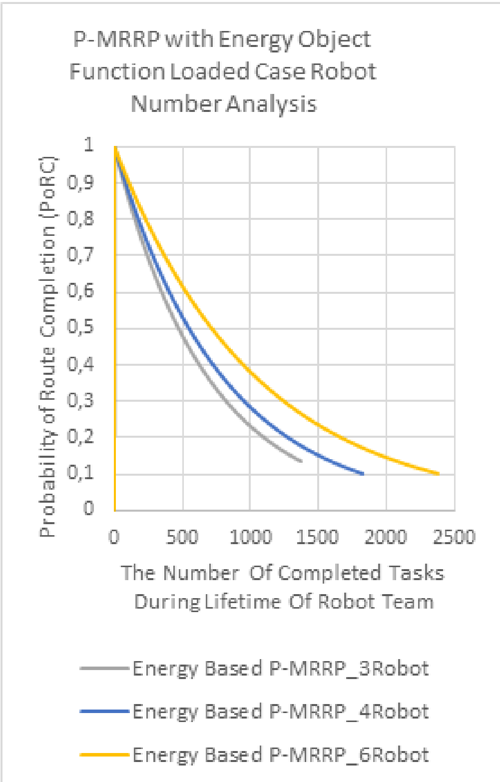


(b)Loaded

Fig. 7. Robot Number Analysis for P-MRRP with Minimum Distance Objective Function



(a)Unloaded



(b)Loaded

Fig. 8. Robot Number Analysis for P-MRRP with Energy Objective Function

In Figure 8, comparing the unloaded case with the loaded one, the number of completed tasks during the lifetime of the robot team is approximately similar to the minimum energy objective function-based route set test results (see Figure 7). However, the minimum energy objective function-based route set has a higher number of completed tasks than the minimum distance objective function-based route set cases. On the other hand, the route planning strategy is very important for the robot team when loaded and unloaded cases are compared, and the load effect is clearly seen for the lifetime of the robot team. Significantly, the experiments show that the P-MRRP algorithm is capable of extending the lifetime of the system.

5. Conclusion

In Industry 4.0 era, long-term repetitive operations are an important application of autonomous multi-robot teams in manufacturing facilities. The transportation of parts to the workstations from the depot and transportation of the finished products to the depot are repetitive tasks that affect the lifetime of autonomous robots. The lifetime of the robot team is increased if the team can know the reliability values of each robot in the team and plan routes accordingly. In this study, a P-MRRP algorithm is proposed for extending the lifetime of the robot team. Using reliability-based route planning enables long-term autonomous operations of the robot team. Moreover, the P-MRRP algorithm can consider the carried loads of robots in the environment, and the PLA algorithm results show the extension of robot lifetime by comparing P-MRRP with the classical MRRP (specifically, their minimum distance and energy objective functions) in loaded and unloaded scenarios. The proposed P-MRRP algorithm outperforms the classical MRRP algorithm, especially in the loaded case. The P-MRRP algorithm can be used for lifetime planning, reduction of the maintenance cost, sustaining autonomy and more. Therefore, it is preferable for fully autonomous systems considering long-term strategic planning. In the future, the reliability analysis of robots will be extended to include other components such as communication, sensors, batteries and electronics. Furthermore, the optimum number of robots could be estimated with the P-MRRP algorithm for the given test environments.

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