MPC Based Navigation of an Omni-directional Mobile Robot under Single Actuator Failure

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***Abstract*—This paper presents the modeling and Model Predictive Controller (MPC) design for an omni-directional robot during a single actuator failure. A fault estimation method is used to identify the actuator failure, and thereby, the kinematic model of the mobile robot is reformulated to account for the fault. The controllability of the modified model during a single actuator failure is verified using Lie algebra. Finally, in the event of unforeseen combinations of single actuator failures, a Nonlinear MPC is designed for trajectory tracking and obstacle avoidance. Simulation results are used to demonstrate the robustness of the system to actuator failure.**

***Index Terms*—Omni-directional robot, Actuator failure, MPC**

I. INTRODUCTION

Autonomous Mobile Robots (AMR) have achieved increasing attention among researchers in recent decades owing to their applications in domains, such as manufacturing, military, and space exploration [1]. The omni-directional robot [2] is an AMR that can navigate in any direction by altering the velocity and direction of each wheel while maintaining its orientation. For efficient performance of an omni-directional robot in a constrained workspace, motion control algorithms for obstacle avoidance and robustness towards actuator failures is of utmost importance [4]. In this context, we envisage the application of control theory to build the mathematical model of the omni-directional robot in the presence of actuation faults.

Identification and isolation of actuation fault may be done using either hardware, or analytical redundancy [3]. In [4], [5] and [6], fault isolation is based on hardware redundancy whereas [7] addresses fault isolation employing an additional gear mechanism. Hardware redundancy and extra mechanisms to accommodate actuator failure are not always feasible due to cost constraints. This necessitates the deployment of a fault isolation approach based on analytical redundancy [8]. It is based on the idea that an actuator failure reformulates the system dynamics by introducing a fault parameter matrix, estimated using an Extended Kalman filter (EKF).

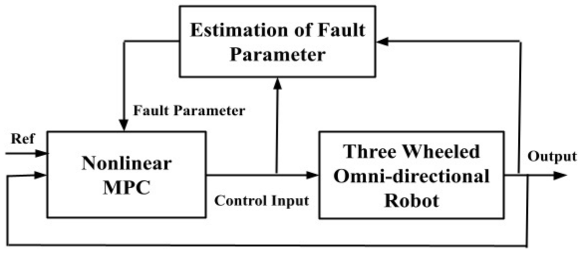


Figure 1. Overview of the proposed approach

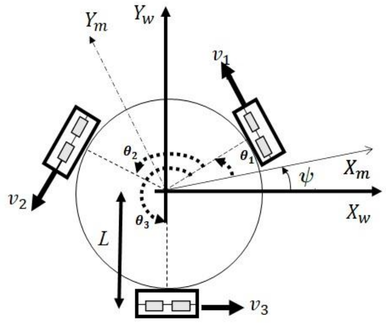


Figure 2. Omni-directional robot: kinematics

An NMPC is applied on this modified model to account for the actuation fault. Due to its capability to handle constraints, flexibility to changes in system dynamics, and application to nonlinear systems, NMPC is an effective tool for fault isolation [8], [9].

II. PROBLEM FORMULATION

The proposed approach is depicted in Fig. 1. In this work, a three-wheeled omni-directional robot is used in an application environment to follow the waypoints with and obstacle avoidance while we explore the case of single actuator failure during trajectory tracking. A fault estimation method is used to evaluate the fault parameter matrix at each time step, and thus the actuator failure is identified. When one of the actuators fails, a non-holonomic constraint is introduced, and the kinematic model is modified to account for the fault. Lie algebra [10] is used to prove the controllability of the modified nonlinear kinematic model of the omni-directional robot. Furthermore, we propose using an NMPC, whose model is updated based on the actuator failure and determines the

Manuscript received January 11, 2022; revised April 1, 2022.

doi: 10.18178/ijmerr.11.6.399-404

optimum solution in the presence of various actuation faults.

III. OMNI-DIRECTIONAL ROBOT

This section presents the description and kinematic model of the omni-directional mobile robot. The modified model during the actuator failure and the corresponding controllability also discussed. For an omni-directional mobile robot, the three omni wheels, separated by 120°, perform independent and simultaneous translational and rotational motions.

A. Kinematic Model

Kinematic model describes the geometric relationship between input and the system characteristics [11]. The kinematic model of the three-wheel omni-directional robot [12], [13] can be obtained as follows:

Global coordinate frame $[X_w, Y_w]$: The pose of the robot in global coordinate frame (see Fig. 2) is represented as:

$$q = \left[x_w \, y_w \, \varphi\right]^T \tag{1}$$

Moving coordinate frame $[X_m, Y_m]$: A moving coordinate frame, with same origin as the global coordinate frame, is attached to the robot. The pose of the robot in moving coordinate frame (see Fig. 2) is represented as:

$$q = \left[x_m \, y_m \, \varphi\right]^T \tag{2}$$

The transformation from global coordinate frame to moving coordinate frame is, $R\varphi$, defined as below:

$$R_\varphi = \begin{bmatrix} \cos(\varphi) & \sin(\varphi) & 0 \\ -\sin(\varphi) & \cos(\varphi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

The translational velocity of the mobile robot in global coordinate frame is $\sqrt{\dot{x}_w^2 + \dot{y}_w^2}$ and angular rate is $\dot{\varphi}$[11]. For $\theta_1 = 0$, the total velocity of wheel 1 is defined as:

$$v_1 = -\dot{x}_w \sin(\varphi) + \dot{y}_w \cos(\varphi) + L\dot{\varphi} \tag{4}$$

Where L is the radius of the mobile robot and φ is the global angle of first wheel. The first two terms of (4) represent the translational part and third terms represents the angular part. Similarly, the velocities of second and third wheel can be obtained.

$$v_2 = -\dot{x}_w \sin\left(\varphi + \theta_2\right) + \dot{y}_w \cos\left(\varphi + \theta_2\right) + L\dot{\varphi} \tag{5}$$

$$v_3 = -\dot{x}_w \sin\left(\varphi + \theta_3\right) + \dot{y}_w \cos\left(\varphi + \theta_3\right) + L\dot{\varphi}$$

Where $(\varphi + \theta_2)$ and $(\varphi + \theta_3)$ are the global angle of the second and third wheel, respectively. Hence, the inverse kinematics in global frame can be represented as:

$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} = \begin{bmatrix} -\sin(\varphi) & \cos(\varphi) & L \\ -\sin\left(\varphi + \theta_2\right) & \cos\left(\varphi + \theta_2\right) & L \\ -\sin\left(\varphi + \theta_3\right) & \cos\left(\varphi + \theta_3\right) & L \end{bmatrix} \begin{bmatrix} \dot{x}_w \\ \dot{y}_w \\ \dot{\varphi} \end{bmatrix} \tag{6}$$

$$v_w = S\dot{q} \tag{7}$$

Forward kinematics of the mobile robot can be obtained as:

$$\dot{q} = Jv_w \tag{8}$$

Where, $J=S^{-1}$.

Equation (8) holds for $\theta_2 = 120^\circ + \theta_1$; $\theta_3 = 240^\circ + \theta_1$. For $\theta_1 = 0$, it can be rewritten as:

$$\begin{bmatrix} \dot{x}_w \\ \dot{y}_w \\ \dot{\varphi} \end{bmatrix} = \left(\frac{2r}{3}\right) \begin{bmatrix} -\sin(\varphi) & -\sin\left(\varphi + \theta_2\right) & -\sin\left(\varphi + \theta_3\right) \\ \cos(\varphi) & \cos\left(\varphi + \theta_2\right) & \cos\left(\varphi + \theta_3\right) \\ \frac{1}{2L} & \frac{1}{2L} & \frac{1}{2L} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix} \tag{9}$$

Where r is the wheel radius and $\left[\omega_1 \; \omega_2 \; \omega_3\right]^T$ is the angular velocity vector of the robot. To obtain the wheel velocities in local coordinate, use $\dot{q}_m = R_\varphi \dot{q}$, where R_φ is given by (3).

B. Faults in Omni-directional Robot

Various faults occur in an omni-directional robot due to failure of sensors, batteries, and actuators, etc. [14]. We believe actuator failure to be a critical fault, as the wheel velocities may become unreliable for subsequent trajectory tracking. During normal operation (with no actuator failure), the wheels are controlled by three independent actuators, and there are no constraints between (x, y, θ). However, the failure of one of the actuators introduces a non-holonomic constraint, and hence the kinematic model cannot be stabilized by continuous static feedback [10]. In this work we present four modes of operation of the omni-directional robot based on the actuator failure: Mode 0: No actuator failure; Mode 1: Failure of first actuator; Mode 2: Failure of second actuator; and Mode 3: Failure of third actuator.

Modified kinematic model and controllability analysis during actuator failure: In this work, we use the Lie algebra concept to prove the controllability of the nonlinear system during actuator failure. Assume that owing to actuator failure, third wheel velocity (ω_3) is zero (Mode 3), and hence, the kinematic model is modified as follows [10]:

$$\begin{aligned} \dot{x}_w &= \left(\frac{2r}{3}\right)\left(-\sin(\varphi) * \omega_1 - \sin\left(\varphi + \theta_2\right) * \omega_2\right) \\ \dot{y}_w &= \left(\frac{2r}{3}\right)\left(\cos(\varphi) * \omega_1 + \cos\left(\varphi + \theta_2\right) * \omega_2\right) \\ \dot{\varphi} &= \left(\frac{2r}{3}\right)\left(\left(\frac{1}{2L}\right) * \omega_1 + \left(\frac{1}{2L}\right) * \omega_2\right) \end{aligned} \tag{10}$$

The states and inputs of the modified kinematic model for Mode 3 operations are $\left[x_w \; y_w \; \varphi\right]^T$ and $\left[\omega_1 \; \omega_2\right]^T$ respectively. Thus, (10) can be represented in matrix form:

$$\begin{bmatrix} \dot{x}_w \\ \dot{y}_w \\ \dot{\varphi} \end{bmatrix} = \left(\frac{2r}{3}\right) \begin{bmatrix} -\sin(\varphi) \\ \cos(\varphi) \\ \frac{1}{2L} \end{bmatrix} \omega_1 + \left(\frac{2r}{3}\right) \begin{bmatrix} -\sin(\varphi+\theta_2) \\ \cos(\varphi+\theta_2) \\ \frac{1}{2L} \end{bmatrix} \omega_2 \quad (11)$$

$$\dot{q} \stackrel{\text{def}}{=} X_1\omega_1 + X_2\omega_2 \quad (12)$$

The Lie algebraic rank condition (LARC) [10] is used to prove the controllability of the nonlinear system in (12). If the Lie bracket of $\mathbf{X_1}$ and $\mathbf{X_2}$ is linearly independent of the other two directions, then the control inputs can find a motion along the new direction. Lie bracket of $\mathbf{X_1}$ and $\mathbf{X_2}$ is defined as:

$$X_3 = [X_1\, X_2] = \frac{\partial X_1}{\partial q} X_2 + \frac{\partial X_2}{\partial q} X_1 = -\frac{r}{3L} \begin{bmatrix} \cos(\varphi) - \cos(\varphi+\theta_2) \\ \sin(\varphi) - \sin(\varphi+\theta_2) \\ 0 \end{bmatrix} \quad (13)$$

The nonlinear system fulfills the LARC requirement because the new direction, $\mathbf{X_3}$, is linearly independent of $\mathbf{X_1}$ and $\mathbf{X_2}$. The linear independence of [$\mathbf{X_1}$ $\mathbf{X_2}$ $\mathbf{X_3}$] demonstrates that the nonlinear system (12) can be controlled even when actuator fails. This ensures that, even if actuator fails in one direction, the available control inputs may still generate motion in the other missing directions. Hence,

$$span(\boldsymbol{X}_1(q), \boldsymbol{X}_2(q), \boldsymbol{X}_3(q)) \in \mathbb{R}^3, q \in S \quad (14)$$

Where manifold S is defined as:

$$S = \{q \stackrel{\text{def}}{=} (x_w, y_w, \psi) \in \mathbb{R}^3\} \quad (15)$$

IV. Control Design and Fault Parameter Estimation

Subsequent to modeling the nonlinear system for the omni-directional robot, we design an MPC controller. This section presents the design of a nonlinear MPC controller for the case of single actuator failure by fault parameter estimation technique.

MPC for Nonlinear System: The nonlinear system in (9) can be represented as:

$$\boldsymbol{q}(k+1) = f\big(\boldsymbol{q}(k), \boldsymbol{u}(k)\big) \quad (16)$$

Where $\mathbf{q}(k)$ and $\mathbf{u}(k)$ denote the state and input vector at a time step, k, respectively. The control sequence over the prediction horizon, N_p is given by:

$$\boldsymbol{U} = \{\boldsymbol{u}(k), \boldsymbol{u}(k+1), \ldots, \boldsymbol{u}(k+N_p-1)\} \quad (17)$$

In MPC, a cost function is minimized over a finite prediction horizon, and only the first control input, $\mathbf{u}(k)$ of the control sequence, $\boldsymbol{U}$ is applied to the system [9]. The standard cost function for the MPC [15] is given as:

$$J(U, q(k)) = \sum_{i=0}^{N_p-1} \{(q(k+i) - r)^T Q (q(k+i) - r) + u(k+i)^T R u(k+i)\} + \left(q(k+N_p) - r\right)^T Q_t \left(q(k+N_p) - r\right) \quad (18)$$

where $\mathbf{r}$ is the vector representing the reference state. Q, R, and Q_t are the positive definite weighting matrices for the states, control inputs and terminal state respectively.

The constraints of the state and the control input of the system are given by: $\boldsymbol{q}(k) \in \mathbb{X}$ and $\boldsymbol{u}(k) \in \mathbb{U}$. Similarly, the constraints of the terminal state, $\mathbb{X}_t$, over a set is denoted as: $\boldsymbol{q}(k+N_p) \in \mathbb{X}_t$ Where the set $\mathbb{X}$ includes the entire state space and set $\mathbb{U}$ consists of all the possible values of control input. The optimization problem solved over the finite horizon is given by:

$$\begin{aligned} &\boldsymbol{u}^*(k) = arg \min_{u(k)} \ldots \min_{u(k+N_p-1)} J(\boldsymbol{U}, \boldsymbol{x}(k)) \\ &st\ \forall\, i \in \{0, 1, \ldots, N_p - 1\} \\ &\quad \boldsymbol{q}(k+i+1) = f(\boldsymbol{q}(k+i), \boldsymbol{u}(k+i)) \\ &\boldsymbol{q}(k+i) \in \mathbb{X};\ \ \boldsymbol{u}(k+i) \in \mathbb{U};\ \ \boldsymbol{q}(k+N_p) \in \mathbb{X}_t \end{aligned} \quad (19)$$

The superscript * denotes the optimized value. The optimization problem (19) can be solved by a dynamic programming approach [16]. At each time step, k, MPC generates an optimized input, $\mathbf{u}^*(k)$ by solving the optimization problem given in (19).

A. Modified MPC during Actuator Failure

To model the actuation fault, the nonlinear system dynamics of the omni-directional robot given in (16) is modified [9], [17] as below:

$$\boldsymbol{q}(k+1) = f\big(\boldsymbol{q}(k), \boldsymbol{\gamma}(k)\boldsymbol{u}(k)\big) \quad (20)$$

Where $\boldsymbol{\gamma}(k)$ is the fault parameter matrix at time step, k. The value of $\boldsymbol{\gamma}(k)$ at each time step is estimated by identifying the actuator failure (refer subsection 1V-B). $\boldsymbol{\gamma}(k)$ is a diagonal matrix as shown below:

$$\boldsymbol{\gamma}(k) = diag\big(\gamma_j(k) \mid j = 1,2,3\big) \quad (21)$$

Where $\gamma_j(k)$ represents the failure of j^{th} actuator. Since we are not considering the partial failure of the actuator, $\gamma_j(k)$ can be either 0 or 1. $\gamma_j(k)=1$ represents a healthy actuator and $\gamma_j(k)=0$ represents a faulty actuator. Hence $\gamma(k)$ is a 3x3 identity matrix for a perfect omni-directional robot (Mode 0). The optimization problem for the nonlinear MPC owing to actuator failure can be reformulated as:

$$\begin{aligned} &\boldsymbol{u}^*(k) = arg \min_{u(k)} \ldots \min_{u(k+N_p-1)} J(U, \boldsymbol{x}(k)) \\ &st\ \forall\, i \in \{0, 1, \ldots, N_p - 1\} \\ &\quad q(k+i+1) = f(\boldsymbol{q}(k+i), \boldsymbol{\gamma}(k+i)\, \boldsymbol{u}(k+i)) \\ &\boldsymbol{q}(k+i) \in \mathbb{X};\ \ \boldsymbol{u}(k+i) \in \mathbb{U};\ \ \boldsymbol{q}(k+N_p) \in \mathbb{X}_t \end{aligned} \quad (22)$$

Where the cost function, $J(\mathbf{U},\mathbf{x}(k))$ is as shown in (18).

B. Estimation of Fault Parameter Matrix

Since the system under consideration is nonlinear, an EKF [19] based state estimator is employed to identify the actuator failure and thus to estimate the fault parameter matrix. **EKF:** The nonlinear model of the omni-directional robot in EKF [14] can be represented as:

$$\boldsymbol{q}(k+1) = f\big(\boldsymbol{q}(k), \boldsymbol{u}(k), \boldsymbol{w}(k)\big) \quad (23)$$

$$\boldsymbol{y}(k) = h\big(\boldsymbol{q}(k), \boldsymbol{v}(k)\big)$$

Where, **q**(k) is the state vector, **u**(k) is the input vector, **y**(k) is the output vector, $f(\cdot)$ and $h(\cdot)$ are nonlinear functions of state vector, and **w**(k) and **v**(k) are process and measurement disturbance vector used in the Kalman model respectively [14].

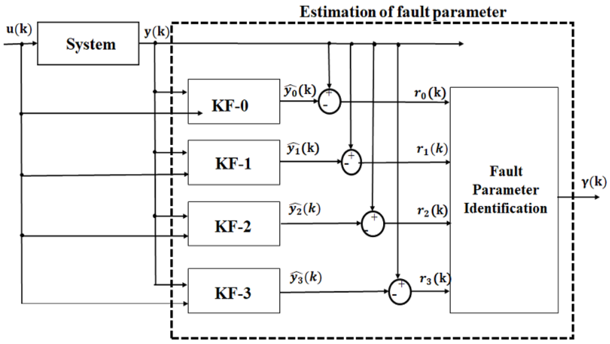


Figure 3. Estimation of fault parameter matrix

Estimation of Fault Parameter Matrix: In this work, we employ a bank of EKFs to estimate the fault parameter, each using a distinct model [20] as shown in Fig. 3.

KF-0 estimates the output, $\hat{y}_0(k)$ for the normal operating region (Mode 0), whereas, KF-j, j=1,2,3 estimates the output, $\hat{y}_j(k)$ for actuator failure modes, Mode j. The models of omni-directional robot for Kalman gain estimation under different actuator failure conditions were as detailed in Section III-A. The model for KF-0 is the standard nonlinear model of the omni-directional robot as in (23) whereas, the model for KF-j is the modified model with $\omega_j = 0$ in (23), which refers to the failure of jth actuator. At each instant of time, residual vector ($\boldsymbol{r}_j(k+1)$) can be obtained as:

$$\boldsymbol{r}_j(k+1) = \boldsymbol{y}(k+1) - \hat{\boldsymbol{y}}_j(k+1) \qquad (24)$$

Where **y**(k) is the measurement vector and $\hat{\boldsymbol{y}}_j(k)$ is the Kalman filter estimate at kth instant.

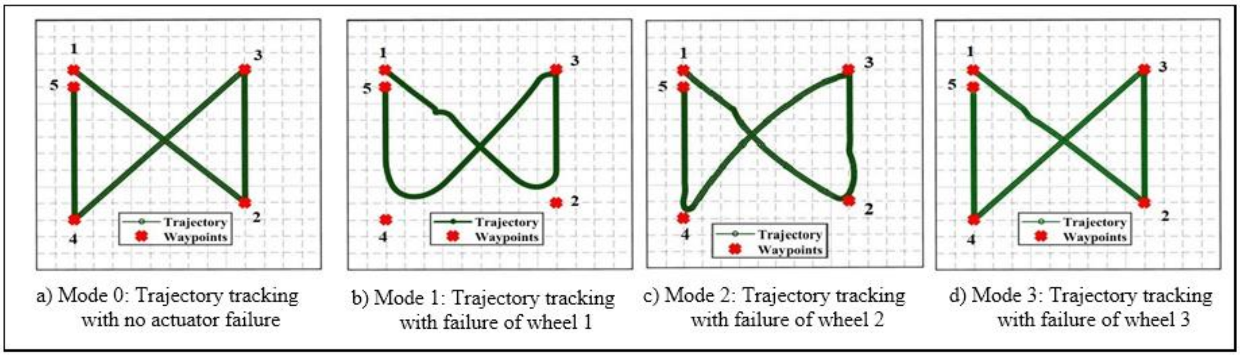
Fault parameter identification module as shown in Fig. 3 includes a hypothesis testing algorithm [18], [20], which utilizes the residuals obtained in (24) to assess the conditional probability and thus to estimate the fault parameter.

The probability that the jth actuator fails, p_{δ_j} assuming same fault probability for all actuators [14] is:

$$p_{\delta_j}(k+1) = \frac{p(y=y(k+1) \mid \delta_j, \vec{y}(k)) \cdot p_{\delta_j}(k)}{\sum_{i=0}^{3} p(y=y(k+1) \mid \delta_i, \vec{y}(k)) \cdot p_{\delta_i}(k)} \qquad (25)$$

Where $\vec{y}(k)$ is the sequence of final measurements defined as $\vec{y}(k) = [y_0, y_1, \ldots y_k]$ and $p(y = y(k+1) \mid \delta_j, \vec{y}(k))$ refers the probability that the system can attain measurement data $y = y(k+1)$ provided jth actuator fails, δ_j and last measurement in sequence is $\vec{y}(k)$.

At the instant of actuator failure (let jth actuator fail), the corresponding Kalman filter estimate of measurement vector ($\hat{\boldsymbol{y}}_j(k)$) and the actual measurement vector (y(k)) are very close to each other, resulting in a nearly zero residual vector ($r_j(k)$). As a result, the equivalent Kalman filter has a high conditional probability ($p_{\delta_j}(k)$), suggesting the best fit with the real system. The conditional probability indicates the relative correctness of the various models of the Kalman filter. Based on this, the fault parameter estimation module identifies the mode of operation (Mode j), and the corresponding fault parameter ($\gamma_j(k)$) is modified as zero, and the same is updated in NMPC as in (22).



a) Mode 0: Trajectory tracking with no actuator failure
b) Mode 1: Trajectory tracking with failure of wheel 1
c) Mode 2: Trajectory tracking with failure of wheel 2
d) Mode 3: Trajectory tracking with failure of wheel 3

Figure 4. Trajectory tracking of the omni-directional robot under actuator failure

V. Experimental Validation and Conclusion

In this section, we have presented a set of results to show the efficacy of the proposed approach. Fig. 4 shows the trajectory tracking of the omni-directional robot under actuator failure. The red cross marks in the same figure indicates the waypoints (numbered 1 to 5), which define the reference path, and the green line indicates the path of the robot. The wheel speed trajectory during different modes of operation is shown in Fig. 5 (a) to Fig. 5 (d). Fig. 5 (a) shows the case where there is no actuator failure, whereas Fig. 5 (b), Fig. 5 (c), and Fig. 5 (d) shows the case where first, second and third actuator fails respectively at some instant of time. To obtain the simulation results under actuator failure, a fault is induced at t=10s, and hence the wheel speed of the failed actuator drops to zero. The fault is identified by the EKF at t=15s since the corresponding residual reaches zero and conditional probability reaches maximum. The speed of the other wheels modifies accordingly for further trajectory tracking. The trajectory tracking with obstacle avoidance [4] together with actuator failure is shown in Fig. 6. The simulation results presented in this section validate the usefulness of the proposed approach. For the future work, we would like to derive necessary theory for formation control of omni-directional mobile robots in an application environment.

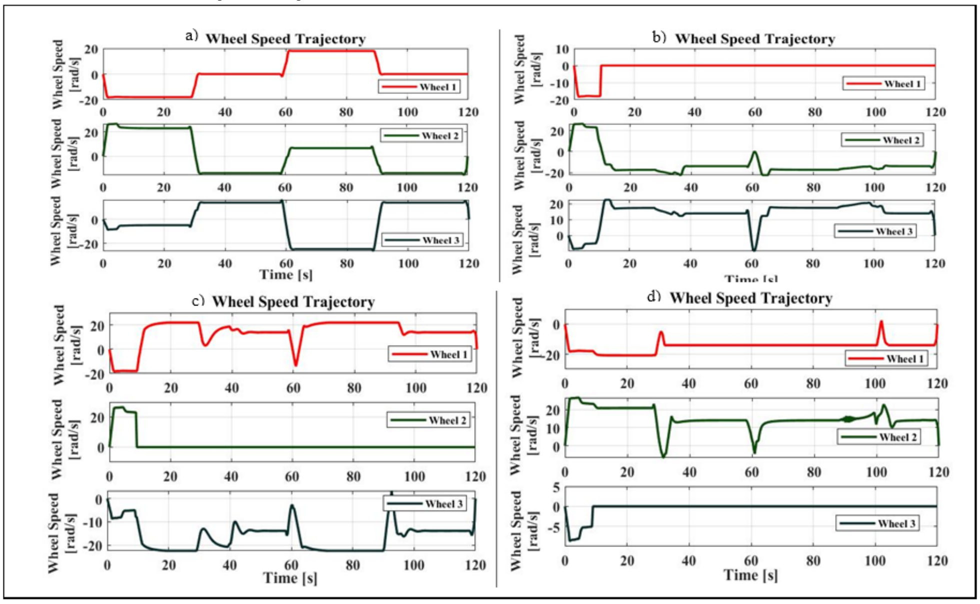


Figure 5. Wheel speed trajectory

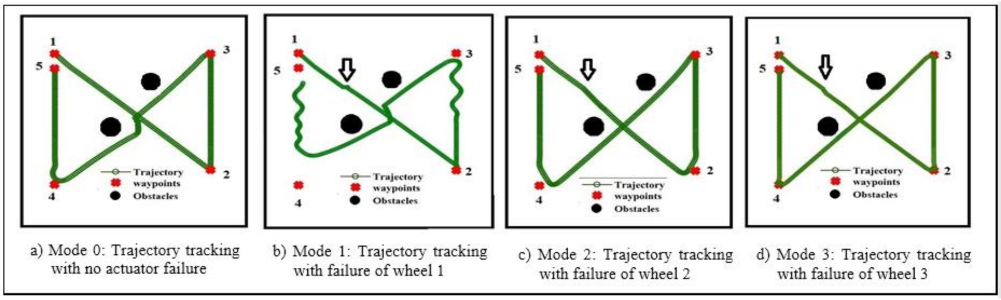


Figure 6. Trajectory tracking of omni-directional robot with obstacles

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Dinsha Vinod. Dr. PS Saikrishna supervised the research, supported in conducting experiments, and substantially reviewed and edited the manuscript. All authors read and approved the final manuscript.

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