An Nonlinear Model Predictive Control Framework for Trajectory Planning of Skid-Steer Mobile Robots in Agricultural Environments

1st Katherine Aro
Universidad Católica del Norte (UCN)
Antofagasta, Chile
katherine.aro@alumnos.ucn.cl

2nd Ricardo Urvina
Universidad Católica del Norte (UCN)
Antofagasta, Chile
ricardo.urvina@alumnos.ucn.cl

3rd Nestor Nahuel Deniz
Universidad Técnica Federico Santa María (UTFSM)
Valparaíso, Chile
nestor.deniz@usm.cl

4th Oswaldo Menendez
Universidad Andrés Bello (UNAB)
Santiago, Chile
oswaldo.menendez@unab.cl

5th Jamshed Iqbal
University of Hull
United Kindom
j.iqbal@hull.ac.uk

6th Alvaro Prado
Universidad Católica del Norte (UCN)
Antofagasta, Chile
alvaro.prado@ucn.cl

***Abstract*—This work presents an integrated trajectory planning strategy with a motion control approach using a Nonlinear Model Predictive Control (NMPC) framework for Skid-Steer Mobile Robots (SSMRs) in agricultural scenarios. In a single control architecture, the proposed NMPC strategy is devoted to tracking trajectories while real-time re-planning pre-scheduled points in a given crop map against static/dynamic obstacles. A Real-Time Iteration scheme was adopted to ensure feasibility in the optimization process, even when meeting tightened constraints. A set of potential field functions is formulated to minimize tracking errors and control effort while maximizing the obstacle deviation. The benefits of the proposed strategy regarding performance, constraint satisfaction, and computational practicability were tested via simulations and field trials on a SSMR Husky A200. The results evidenced that prioritizing the robot position and obstacle speeds yielded a reduced tracking error and input effort by 45.3% and 40.8%, respectively, compared to results that only prioritized obstacle positions. Thus, prioritizing the obstacle model further mitigates the collision risks in the agricultural field.**

***Index Terms*—Trajectory planning, nonlinear model predictive control, obstacle avoidance, skid steer mobile robots, agricultural environment**

I. Introduction

The Food and Agriculture Organization (FAO) suggestions call for the agricultural sector to increase food production by the global demand, considering the projected demographic expansion by 2050 [1]. It is expected that the adoption of information technologies, automation and robotics in the agricultural processes enhances the efficiency of the manual operations to make of this activity safer, more productive, and more sustainable. Traditionally, human operations have been addressing the crop harvesting work; however, new technological developments are recently executing precision tasks such as autonomous pick and place, sort and packaging, or transportation [2]. In particular, it is required to assist mobility tasks for soil preparation, seeding, growing, product harvesting, and post-harvesting. Thus, the fundamental need for guided systems arises from the absence of automated mobility of agricultural products.

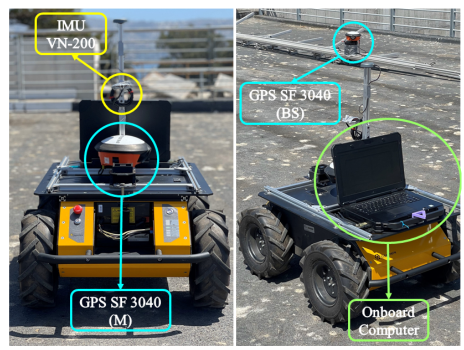

Fig. 1. Skid-Steer Mobile Robot (SSMR) intended to be used in tasks of agricultural work. This SSMR is a Husky-A200 robot equipped with an RTK-GNSS, an Inertial Measurement Unit (IMU), and inner encoders.

The autonomous navigation in agricultural scenarios is an issue yet to be tackled since the spatial distribution is usually arranged in unstructured or semi-structured environments, composed by farmers, restricted areas, or other obstacles limiting the machinery mobility [2]. Thus, this work is aimed at developing a trajectory planning approach integrated into a control strategy for autonomous service units, as those typical skid-steer robots from Fig. 1. In particular, the proposed control framework is intended here to real-time avoid static and dynamic obstacles in an agricultural scenario.

Planning and re-planning feasible trajectories are key points for safe guided control of autonomous vehicles. In particular, the real-time generation of trajectories is a challenge that requires simultaneous motion control under obstacle conditions, which usually demands trajectories non-kinematically compatible with the robot dynamics [3]. In the recent literature, conventional global or local path planning approaches are able to account for the obstacle avoidance problem with

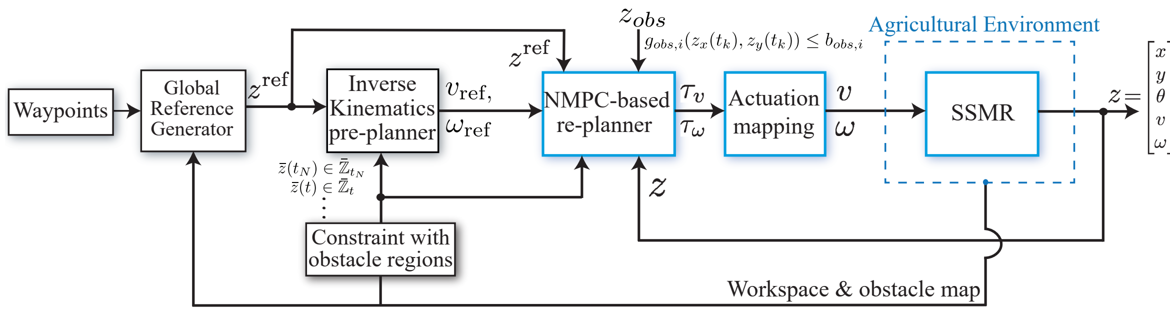

Fig. 2. General NMPC scheme of the integrated trajectory planning and motion control with obstacle avoidance for Skid-Steer Mobile Robots (SSMR).

methods such as A* [4], Rapidly-exploring Random Trees (RRT) built upon probabilistic search of samples [5], Artificial Potential Fields (APFs) derived from reactive virtual forces [6] or other geometrically-based and bio-inspired methods [7], [8]. The previous approaches are capable of generating feasible trajectories through post-process parameterization procedures based on speed profiles or time; however, most of them hardly take into account simultaneous real-time control adaptability and robustness against uncertain changes in the workspace.

Contrary to classical methods [9], the Nonlinear Model Predictive Control (NMPC) approach has emerged as a more attractive technology for vehicle guidance and motion control due to its ability to handle nonlinear models, soft constraints, and multiple control objectives [6], [10], [11]. For instance, in [12], an NMPC strategy was used to solve guidance problems with static obstacle avoidance for simulated robots. In [13], a fused trajectory planning and tracking strategy based on MPC with linearized models was proposed. However, the nonlinear dynamics was not exploited, resulting in robust performance losses when the robot deviates from obstacles. In a recent study by [2], a novel approach involving non-simultaneous path planning and control was designed to account only for headland turning constraints in obstacles-free farmlands.

The main contribution of this work is an integrated NMPC framework for motion planning and trajectory tracking control of Skid-Steer Mobile Robots (SSMRs). The architecture combines online obstacle avoidance capabilities and trajectory tracking to enable safe navigation in agricultural environments. To unify both perspectives, it was implemented a single centralized control scheme where re-planning and motion control objectives were simultaneously combined by a set of stage, terminal, and potential field cost functions subject to static and dynamic obstacle constraints. The optimization problem associated with the proposed NMPC approach is efficiently solved using the Real-Time Iteration (RTI) scheme, which is available in the `ACADO Toolkit` [14]. This scheme facilitates the instantaneous computation and application of the driveline torque actuation. The SSMR dynamics was represented by a unicycle-type dynamical model adapted from [15], whereas unexpected obstacles were characterized by regions bounded by logistics functions according to the workspace occupancy, positions, and speeds. Control performance, obstacle constraints fulfillment, and computational applicability were assessed in a custom-built agricultural environment within the robotic simulator CoppeliaSim [16]. Experimental field tests in an all-terrain Husky A200 robot showed promising results under real-time implementations.

The paper is organized as follows. The SSMR model is presented in Section II, and the proposed strategy is designed in Section III. In Section IV, the experimental setup is presented, as well as simulation and field results are discussed. Finally, the paper ends in Section V with conclusions and ongoing research from this work.

II. Motion model of the robot dynamics

In this Section, it is considered a unicycle-type Skid-steer Mobile Robot (SSMR) in a nonlinear state-space representation $\dot{z}(t) = f(z(t), u(t))$ with system states $z(t)$ and control input $u(t)$. This dynamical model is extended in order to include states of linear and angular speeds [15]. The purpose of this model is to incorporate nonholonomic conditions, concerning kinematic and dynamic characteristics into the planned trajectory and specifically the obstacle avoidance strategy. Briefly:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \\ \dot{v} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} v\cos\theta - \omega\sin\theta \\ v\sin\theta + \omega\cos\theta \\ \omega \\ \frac{\beta_3}{\beta_1}\omega^2 + \frac{\beta_4}{\beta_1}v^2 \\ \frac{\beta_5}{\beta_2}v\omega + \frac{\beta_6}{\beta_2}\omega \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \frac{1}{\beta_1} & 0 \\ 0 & \frac{1}{\beta_2} \end{bmatrix} \begin{bmatrix} \tau_v \\ \tau_\omega \end{bmatrix} \tag{1}$$

where x, y, and θ stand for the robot pose; v and ω represent linear and angular speeds, respectively. The system states are denoted by $z(t) = [x, y, \theta, v, \omega]^T$ and the control output by $u(t) = [\tau_v, \tau_\omega]^T$, where τ_v and τ_ω are traction and turning torques, respectively. In addition, $\beta = [\beta_1\ \beta_2\ \beta_3\ \beta_4\ \beta_5\ \beta_6]^T$ is a vector of model parameters, whose components are functions of structural parameters of the robot chassis such as mass, inertia, and geometric specifications [15].

III. Nonlinear model predictive control strategy for robot guidance

The proposed NMPC scheme for guided motion control is presented in Fig. 2. The proposed strategy requires a series of pre-scheduled waypoints, which represent harvesting points distributed along isles in farm crops. Assuming that these waypoints are distributed in a workspace map, a global-reference generation strategy computes a parameterized trajectory with constant linear speed. Using the robot pose,

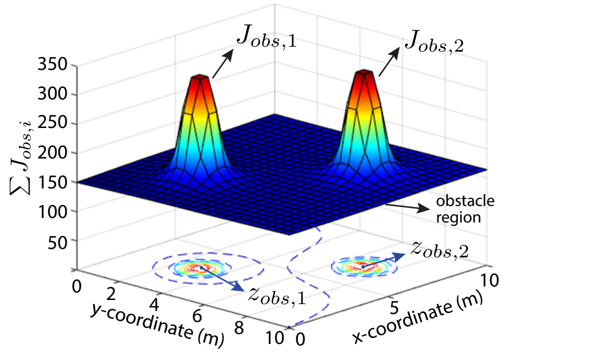

Fig. 3. Graphical representation of obstacle functions following APF insights.

an inverse kinematics pre-planner generates kinematics inputs (i.e., v_{ref} and ω_{ref}) subject to obstacle constraints, as follows:

$$\begin{aligned} v_{\text{ref}}(t) &= \sqrt{\dot{x}^2_{\text{ref}}(t) + \dot{y}^2_{\text{ref}}(t)}, \ (v_{\text{ref}} \neq 0 \text{ and constant}) \\ \omega_{\text{ref}}(t) &= \frac{\dot{x}_{\text{ref}}(t)\ddot{y}_{\text{ref}}(t) - \dot{y}_{\text{ref}}(t)\ddot{x}_{\text{ref}}(t)}{\dot{x}^2_{\text{ref}}(t) + \dot{y}^2_{\text{ref}}(t)} \end{aligned} \tag{2}$$

The obstacles are obtained from a workspace map (depicted in Fig. 4), in which re-sizeable regions are fixed to dynamic obstacle positions. These functions are intended to mostly cover the obstacle areas, although other shapes could be used instead. Once the reference and constraints are defined, an Optimization Problem (OP) associated with the proposed NMPC strategy is raised as follows:

$$\begin{aligned} \min_{u(\cdot)} \int_{t_k}^{t_k+t_{N-1}} & J(t, z(t), u(t))dt + J_N(t_{k+N}, z(t_{k+N})) \\ & + \sum_{i=1}^{n_o} J_{obs,i}(t_k, z(t_k), z_{obs,i}(t_k)) \\ \text{subject to :} \quad & \dot{z}(t) = f(z(t), u(t)) \\ & z_N(t_{k+N}) \in \mathbb{Z}_N \\ & z(t) \in \mathbb{Z}(t) \\ & u(t) \in \mathbb{U}(t) \\ & g_{obs,i}(z(t_k), z_{obs,i}(t_k)) \leq b_{obs,i}, \\ & \forall i \in [1, n_o], \text{ and } \forall t \in [t_k, t_k + t_{N-1}] \end{aligned} \tag{3}$$

with:

$$\begin{aligned} J(t, z, u) &= \left\| z^{\text{ref}}(t) - z(t) \right\|^2_Q + \left\| u^{\text{ref}}(t) - u(t) \right\|^2_R \\ J_N(t_{k+N}, z(t_{k+N})) &= \| z^{\text{ref}}(t_{k+N}) - z(t_{k+N})) \|^2_{P_N} \end{aligned}$$

where t_N denotes the time horizon for N predictions; Q and R are positive definite matrices that weight the control objectives associated with tracking errors and control input effort, respectively. Actually, the overall objectives are specified by the stage cost function $J(t, z, u)$ and an n_o set of differentiable logistic functions that stand for APF costs $J_{obs,i}(t, z, z_{obs})$. Unlike J, the cost functions $J_{obs,i}$ are included to prioritize regions occupied by obstacles that may arise in the workspace, as shown in Fig. 3. To ensure feasible constraint satisfaction at the final stage, the terminal constraint for J_N is specified by the set $\mathbb{Z}_N$. Note that achieving globally optimal responses are not guaranteed due to the non-convex nature of the OP caused

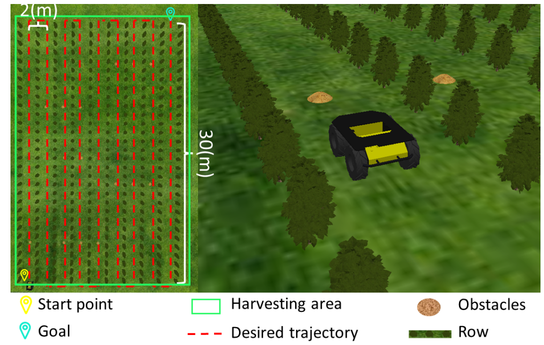

Fig. 4. Workspace map for guided navigation of the SSMR

.

by the nonlinear robot model and obstacle constraints. Within each obstacle function, the deviation region is attached to the obstacle position, whereas a coverage ratio $\rho_{obs,i}$ defines the obstacle boundary. The function $J_{obs,i}$ is given by:

$$J_{obs,i} = \frac{s_i}{1 + \exp[||z(t_k) - z_{obs,i}(t_k)||_2 - \rho_{obs,i}]} \tag{4}$$

where the parameter s_i is a tuning scalar denoting the proximity level and approaching speed at which the SSMR is capable of navigating close to a specific obstacle. Thus, s_i prioritizes the deviation between the robot and obstacle pose and speeds. In addition, a nonlinear representation $g_{obs,i}$ in (5) that best circumvents an obstacle is proposed here to ensure a feasibility condition in the OP (3), whereas the outer bound of $g_{obs,i}$ is set for each obstacle by $b_{obs,i} \in \mathbb{R}^{n_o}$. Thence,

$$g_{obs,i}(z(t_k), z_{obs,i}(t_k)) = s_i ||z(t_k) - z_{obs,i}(t_k)||^2 \tag{5}$$

The OP in (3) is solved following the receding horizon strategy, in which only the first component $u^*(t_k)$ from the resultant control sequence is applied [11]. Then, the OP is subsequently solved at the next sampling time updating the current initial condition of the system dynamics. Taking advantage of the Real-Time Iteration (RTI) scheme, the proposed controller was implemented iteratively using the ACADO toolkit [14].

IV. RESULTS

This Section presents the experimental setup and results of the proposed controllers. Waypoints in S-shaped reference trajectories were used in simulation trials, whereas rectangle-shaped trajectories in field tests, both at constant speed profiles and sampling time $T_s = 0.1(s)$. The guided control performance was assessed using cumulative values of tracking error C_{xy}, orientation error C_θ, operation time C_t, control input effort $C_{v\omega}$, and total cost C_{Tot} [16]. To compare performance while trading off tracking vs. obstacle avoidance, three case studies were considered: i) OP-NMPC with Obstacle Prioritization, ii) SP-NMPC with robot Speed Prioritization, and iii) PP-NMPC with Position Prioritization. The prioritization consists on balancing the cost function weights to provide more importance to such trade-offs, considering position or obstacle speeds. The NMPC weight matrices for simulations and field tests are shown in Table I.

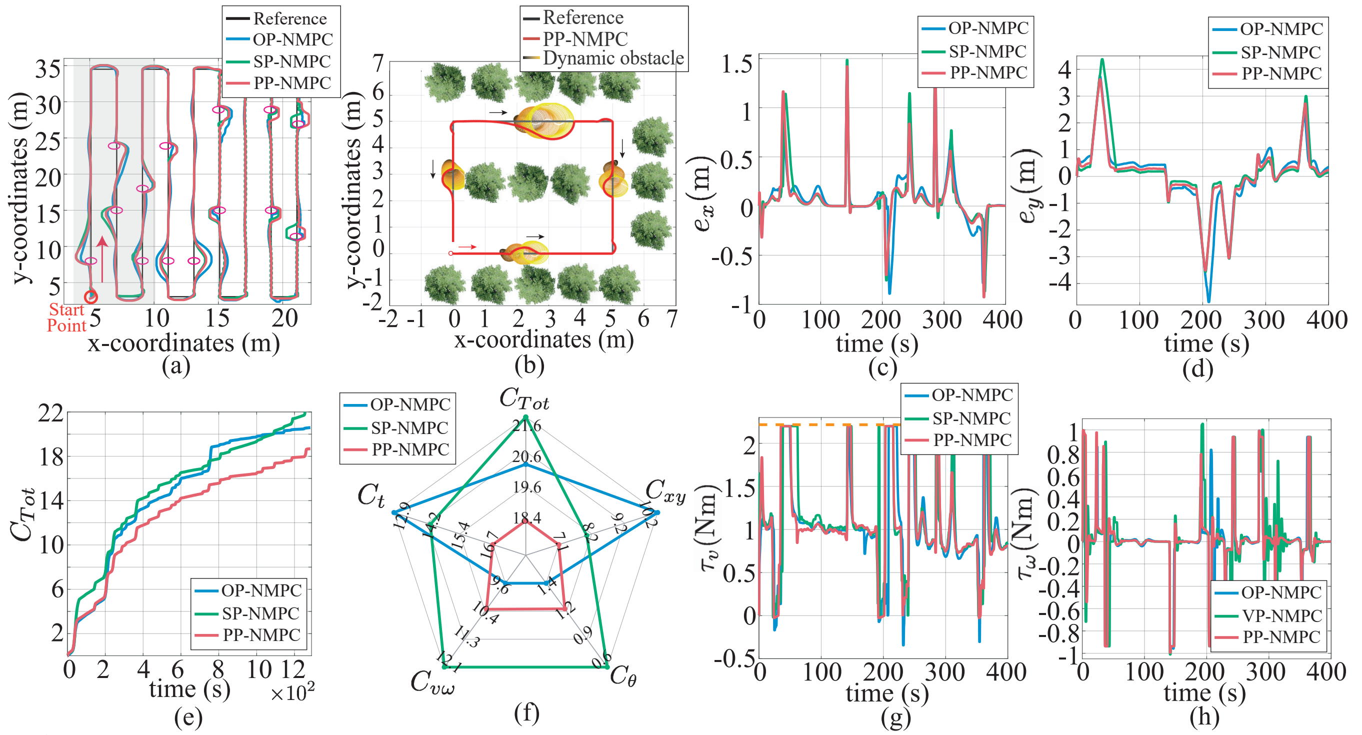

Fig. 5. Simulation results of motion control using the three case studies of NMPC. The S-shaped reference trajectories are subject to intermediate obstacles, as laid out on the simulated harvest workspace map. The tracking errors and control results were extracted from trials carried out on the depicted gray area.

TABLE I
WEIGHT MATRICES USED IN THE THREE CASE STUDIES

Approach	Q	R	P_N	s
OP-NMPC	diag(16,16,2,6,4)	diag(2,6)	diag(16,16,2)	$3I_{n_o}$
SP-NMPC	diag(16,16,3,6,4)	diag(6,4)	diag(16,16,3)	$3I_{n_o}$
PP-NMPC	diag(20,20,3,6,4)	diag(6,4)	diag(20,20,3)	$2I_{n_o}$

A. *Simulation setup and results*

This test was first carried out in an agricultural-type environment using CoppeliaSim [11] (see Fig. 4). It used a 335m trajectory, and each crop row (35m length) was separated by 2m aisles with structural and terrain obstacles. After several tests, it was identified that $N = 10$ predictions were suitable for safe obstacle avoidance at maximum speed. State and input constraints were set to $|v| \leq 0.7$ (m/s), $|\omega| \leq 1.2$ (rads/s), and $|\tau_v| \leq 2.2$ (Nm), $|\tau_\omega| \leq 1.6$ (Nm).

Figure 5 shows simulation results. The path drawn by the SSMR using the proposed controllers under static and dynamic obstacles is shown in Figs. 5a-b. A gray-shaded area encompassing five obstacles (pink circles) is highlighted for visualization purposes, in which the pose errors and control actions were further studied (see Figs. 5c-h). By inspection, it is shown that the three approaches were capable of avoiding obstacles; however, they achieved different control performances. For instance, the PP-NMPC approached lower cumulative tracking errors and operation time than OP-NMPC and SP-NMPC, as expected. Nevertheless, the position of the robot with PP-NMPC is much closer to the restricted region that inscribes the obstacles when compared to the other two controllers. This result is promising since the overall operation time with PP-NMPC was reduced by 22.7% with respect to SP-NMPC and 14.9% with OP-NMPC, being favorable in harvesting tasks. Compared to SP-NMPC, the PP-NMPC achieved a 15.8% decrease in the control effort. In addition, the PP-NMPC controller exhibited a lower cumulative total cost than those in SP-NMPC and OP-NMPC, reducing such costs by about 17.4% and 11.9%, respectively. By prioritizing robot and obstacle poses, a higher performance could be achieved than only prioritizing the obstacle position. In fact, the robot tends to deviate to the extent allowed by $J_{obs,i}$, which could also introduce new collision risks. Hence, an accurate obstacle characterization is crucial for guided motion control.

B. *Experimental setup and results*

This field test used a unicycle-type SSMR Husky A200. The robot was equipped with a laptop Intel® Core(TM) i7-10750H @2.6 GHz with 16GB of memory, an RTK-GNSS for relative positioning (SF-3040 base and mobile stations), an IMU sensor for orientation (VN-200), and encoders (see Fig. 1). A rectangle-shaped trajectory with obstacles was used to evaluate the performance of the previous three controllers. The states and control input constraints were those from the simulation trial.

Figure 6 shows experimental results. In particular, tracking errors were depicted in Figs. 6b-d, where the largest peak responses were produced using OP-NMPC, whereas the smallest ones were with PP-NMPC. This result was reasonable because ensuring obstacle avoidance was prioritized instead of tracking. Once the obstacle was successfully overcome, the tracking errors became almost zero promptly. Figure 6g-h illustrates the evolution of the total costs and their cumulative values. The PP-NMPC and SP-NMPC approached similar tracking errors with respect to OP-NMPC; however, it is observed that PP-NMPC and SP-NMPC achieved lower cumulative total costs

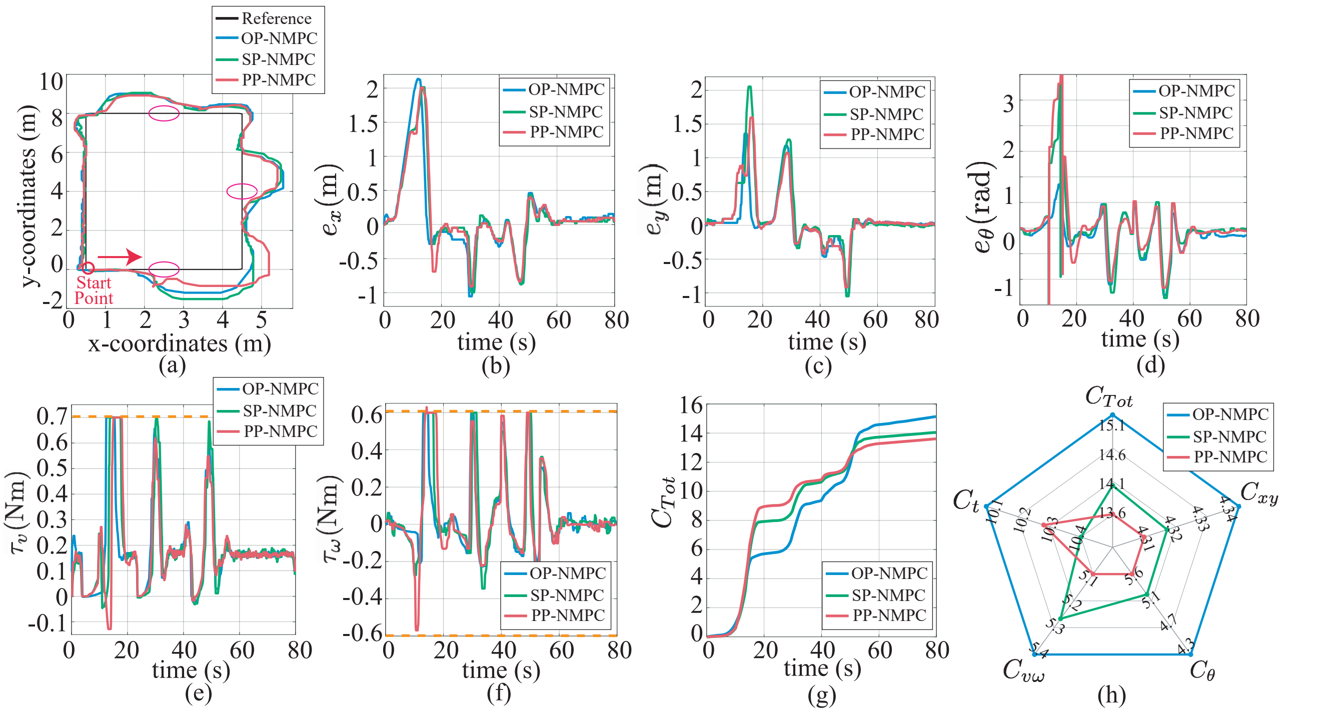

Fig. 6. Experimental results. It is shown traced rectangle-shaped trajectories with the three test NMPCs and the SSMR, prioritizing obstacle positions, speeds, and poses. Tracking errors and torque commands are presented. The evolution of C_{Tot} and cumulative performance metrics are also included

in a 45.3% and 40.8% than only considering prioritization on the obstacle position (i.e., OP-NMPC).

V. CONCLUSIONS

A combined Nonlinear Model Predictive Control (NMPC) and trajectory planning strategy was proposed, implemented, and validated for guided motion control of Skid-Steer Mobile Robots subject to static and dynamic obstacles in agricultural environments. The underlying optimization problem for NMPC included feasible obstacle constraints and a set of logistic functions associated with potential field costs used to avoid obstacles in the robot workspace. The experimental results successfully achieved a reduction in the cumulative tracking error and input effort by 45.3% and 40.8%, respectively, when prioritizing robot position and obstacle speeds instead of obstacle positions only. Ongoing research is aimed at studying further accurate obstacle characterization.

REFERENCES

[1] T. Friedrich, "A new paradigm for feeding the world in 2050 the sustainable intensification of crop production," *Resource Magazine*, vol. 22, no. 2, pp. 18–18, 2015.

[2] Z. He, Y. Bao, Q. Yu, P. Lu, Y. He, and Y. Liu, "Dynamic path planning method for headland turning of unmanned agricultural vehicles," *Computers and Electronics in Agriculture*, vol. 206, 3 2023.

[3] Z. Li, J. Li, and W. Wang, "Path planning and obstacle avoidance control for autonomous multi-axis distributed vehicle based on dynamic constraints," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 4, pp. 4342–4356, 2023.

[4] E. Shang, B. Dai, Y. Nie, Q. Zhu, L. Xiao, and D. Zhao, "A guide-line and key-point based a-star path planning algorithm for autonomous land vehicles," in *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, 2020, pp. 1–7.

[5] L. Zheng, C. Zhang, W. Li, G. Wang, G. Ma, and H. Xia, "Obstacle avoidance and path planning for ugvs using improved rrt algorithm," in *2022 41st Chinese Control Conference (CCC)*, 2022, pp. 3796–3800.

[6] Z. W. Zhang, L. Zheng, Y. N. Li, P. Y. Zeng, and Y. X. Liang, "Structured road-oriented motion planning and tracking framework for active collision avoidance of autonomous vehicles," *Science China Technological Sciences*, vol. 64, pp. 2427–2440, 11 2021.

[7] S. Khan and J. Guivant, "Design and implementation of proximal planning and control of an unmanned ground vehicle to operate in dynamic environments," *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 2, pp. 1787–1799, 2023.

[8] L. Zhang, Y. Guo, X. Song, D. Xue, and B. Ren, "Intelligent path planning algorithm for cooperative traversal task of multiple unmanned ground vehicles," in *2021 7th International Conference on Computer and Communications (ICCC)*, 2021, pp. 2055–2061.

[9] B. Patle, G. Babu L, A. Pandey, D. Parhi, and A. Jagadeesh, "A review: On path planning strategies for navigation of mobile robot," *Defence Technology*, vol. 15, no. 4, pp. 582–606, 2019.

[10] M. Castillo-Lopez, P. Ludivig, S. A. Sajadi-Alamdari, J. L. Sanchez-Lopez, M. A. Olivares-Mendez, and H. Voos, "A real-time approach for chance-constrained motion planning with dynamic obstacles," *IEEE Robotics and Automation Letters*, vol. 5, pp. 3620–3625, 4 2020.

[11] A. J. Prado, M. Torres-Torriti, and F. A. Cheein, "Distributed tube-based nonlinear mpc for motion control of skid-steer robots with terra-mechanical constraints," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 8045–8052, 2021.

[12] M. Sani, B. Robu, and A. Hably, "Dynamic obstacles avoidance using nonlinear model predictive control," vol. 2021-October. IEEE Computer Society, 10 2021.

[13] X. Zhou, X. Yu, Y. Zhang, Y. Luo, and X. Peng, "Trajectory planning and tracking strategy applied to an unmanned ground vehicle in the presence of obstacles," *IEEE Transactions on Automation Science and Engineering*, vol. 18, no. 4, pp. 1575–1589, 2021.

[14] B. Houska, H. J. Ferreau, and M. Diehl, "An auto-generated real-time iteration algorithm for nonlinear mpc in the microsecond range," *Automatica*, vol. 47, no. 10, pp. 2279–2285, 2011.

[15] A. Javier Prado, D. Chávez, O. Camacho, M. Torres-Torriti, and F. Auat Cheein, "Adaptive nonlinear mpc for efficient trajectory tracking applied to autonomous mining skid-steer mobile robots," in *2020 IEEE ANDESCON*, 2020, pp. 1–6.

[16] Álvaro Javier Prado, M. Torres-Torriti, J. Yuz, and F. Auat Cheein, "Tube-based nonlinear model predictive control for autonomous skid-steer mobile robots with tire–terrain interactions," *Control Engineering Practice*, vol. 101, p. 104451, 2020.