Implementing BDI Continual Temporal Planning for Robotic Agents

Alex Zanetti[†], Devis Dal Moro^{*}, Redi Vreto^{*}, Marco Robol^{*}, Marco Roveri^{*}, and Paolo Giorgini^{*}

*Department of Information Engineering and Computer Science - University of Trento, Trento, Italy

{alex.zanetti,redi.vreto}@alumni.unitn.it, {marco.robol,marco.roveri,paolo.giorgini}@unitn.it

[†]Eurecat - Technology Centre of Catalonia, Catalonia, Spain

devis.dalmoro@alumni.unitn.it

Abstract-Making autonomous agents effective in real-life applications requires the ability to decide at run-time and a high degree of adaptability to unpredictable and uncontrollable events. Reacting to events is still a fundamental ability for an agent, but it has to be boosted up with proactive behaviors that allow the agent to explore alternatives and decide at runtime for optimal solutions. This calls for a continuous planning as part of the deliberation process that makes an agent able to reconsider plans on the base of temporal constraints and changes of the environment. Online planning literature offers several approaches used to select the next action on the base of a partial exploration of the solution space. In this paper, we propose a BDI continuous temporal planning framework, where interleave planning and execution loop is used to integrate online planning with the BDI control-loop. The framework has been implemented with the ROS2 robotic framework and planning algorithms offered by JavaFF.

I. INTRODUCTION

Autonomous systems are widely adopted in industrial environments where they are used in strictly controlled areas, such as assembly lines in the industry or automated warehouses in logistics. Along this, there is a growing interest in adopting autonomous systems in more complex and highly dynamic applications in which they are required to deal with unexpected events (e.g, the interaction with humans or with other robotic systems), or changes in objectives (e.g., deal with new highpriority activities). This demands fast adaptation to promptly respond to the perceived changes, and to take decisions and actuate them having not yet performed complete reasoning on the problem, but having only explored partially the solution.

Recent frameworks enabling a robotic agent to autonomously deliberate have been proposed [1]–[9], but they are still in an early stage and present a number of open problems (e.g., they provide planning functionalities, but they are not supported by any deliberative functionalities making planning unusable in real scenarios). [10] proposed a BDI (Belief-Desire-Intention) [11] architecture, called ROS2-BDI, able to use the beliefs of an agent to reason about goals and elaborate plans to achieve them. The proposed architecture supports i) BDI-based deliberation to develop agents with temporal planning capabilities; ii) deadline-aware prioritization of desires; iii) preemption of running plans with lower priority. This architecture, despite being able to generate new plans in response to dynamic changes in the environment suffers from the problem that before starting any actions, the agents shall generate a full plan to achieve its goals. Moreover, it may exhibit continuous run-time failure and subsequent replanning to try to adapt to the contingencies thus preventing fruitful progress towards the goal. In the setting of AI planning it has been studied the problem of generating more robust plans able to adapt to a set of contingencies [12], [13], the problem of continual planning while acting [14]-[16] or interleaving planning and execution [17], [18]. However, all these approaches are rather limited: they assume a classical plan-act sequence [12], [13], consider only motion-planning while acting [14]-[16], need to specify when and how to switch from planning to execution [17], [18], do not show temporal planning capabilities (a fundamental element for continual planning in realistic scenarios).

In this paper, we make the following contributions. First, we specify a new BDI architecture that extends ROS2-BDI [10] to i) allow an agent to take decisions and actuate them having not yet computed a complete plan for the active goals, but only explored partially the solution; ii) handle preemption of running plans to deal with changes in the objectives and/or to execute the new plan or the remaining partial plan towards the goal computed while executing the previous one. Second, we specify how to modify a state-of-the-art temporal planning algorithm to support continual temporal planning (provide intermediate candidate solutions to execute, while continuing the search). Third, we implemented the continual temporal planning algorithm in a new temporal planner, named CJFF, built on top of JavaFF [19]. The novel framework has been implemented on top of the ROS2-BDI leveraging our CJFF. Finally, we demonstrate the practical applicability of the novel implemented framework through its application in a highly dynamic resource collection robotic scenario where we compare the approach of ROS2-BDI baseline with our extended ROS2-BDI framework. The results show that on average the new approach results in shorter plans w.r.t. the baseline, thus indicating the ability of the new framework to adapt more easily to contingencies.

The paper is organized as follows. In Sec. II we briefly present the baseline. In Sec. III we describe the novel BDI architecture and the algorithm for continual temporal planning. In Sec. IV we discuss the implementation within the ROS2-BDI framework, and in Sec. V we present the results of the validation of the proposed framework. In Sec. VI we discuss the related work, and finally, in Sec. VII we draw conclusions

M. Robol and M. Roveri are partially supported by the project MUR PRIN 2020 - RIPER - Resilient AI-Based Self-Programming and Strategic Reasoning - CUP E63C22000400001. M. Roveri and P. Giorgini are partially supported by the PNRR project FAIR - Future AI Research (PE00000013), under the NRRP MUR program funded by NextGenerationEU.

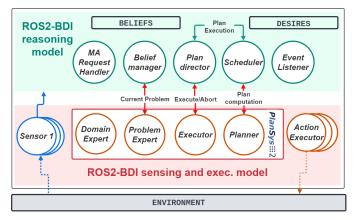


Fig. 1: Architecture of a ROS2-BDI agent. Circles are ROS2 nodes, arrows and buses (rectangles) represent communications.

and outline future works.

II. BASELINE

In this work, we build on i) JavaFF, a PDDL 2.1 temporal planner developed in Java; ii) ROS2-BDI, a BDI framework implemented on top of ROS2. In the rest of this section, we summarize the respective main concepts.

PDDL 2.1 [20] is the "standard" formalism adopted for modelling the knowledge and the behaviour of agents considering that actions might last some known amount of time. In PDDL2.1, the effects and conditions for each action might apply before, during and/or after its execution. PDDL 2.1 compliant planners are capable of computing time-triggered plans to go from an initial state to a goal one, each action is associated with a start time and a given duration, and multiple actions can occur concurrently. JavaFF [19] is a reimplementation for didactic purposes of the MetricFF [21] in Java, with also support for PDDL2.1 temporal planning. Being developed for didactic purposes, its heuristic and performance did not age well compared to other state-of-the-art PDDL 2.1-compliant planners, such as POPF [22] or OPTIC [23]. However, the underlying framework is robust, modular, and relatively easy to modify and build on w.r.t. other more efficient temporal planners.

ROS2-BDI [10] is a BDI framework for developing distributed autonomous robotic systems built on top of Plan-Sys2 [9] within ROS2 [24]. It supports BDI-based deliberation through the generation of time-triggered temporal plans thanks to the POPF [22] integrated within PlanSys2. Figure 1 depicts the architecture of a ROS2-BDI agent. ROS2 *nodes* (depicted as circles) encapsulate the core functionalities of the agent. The communication of nodes within an agent and among agents happens through communication channels (named *topics* within ROS2). ROS2-BDI core nodes mainly deliver the following features: i) Belief Management ii) Multi-Agent Requests handler iii) Scheduler (desire prioritization and preemption) iv) Check over the running plan's context and desired deadline conditions v) Event Listener. The Scheduler node provides the handling of prioritization of running intentions

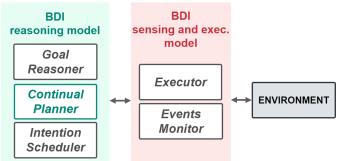


Fig. 2: Architecture of the reasoning and acting framework.

and goals, interfacing with a) the PlanSys2 [9] reference framework for PDDL 2.1 temporal planning within ROS2, b) and with the Plan Director to demand either their execution or abortion. Given a plan along with its preconditions, desired deadline and context conditions, the plan director is used to trigger, monitor and abort its execution. Once a desire is activated and a plan for fulfilling it is demanded for execution, it is run through its termination: either by failure or success. Plans and action executions strongly rely on PlanSys2. Finally, the Event Listener enforces the belief revision and option generation functions for the ROS2-BDI agent.

III. A BDI ARCHITECTURE FOR CONTINUAL PLANNING

The BDI model is progressively adopted into autonomous agents to mimic human behaviour and make them able to deal with complex problems by adapting their reasoning and acting to changes happening in their environment while operating. A set of plans is provided in their knowledge base to reach the desires with alternative solutions. Planning capabilities allow agents to synthesize new plans to reach a given goal starting from given initial conditions. Only when a complete plan has been computed, the agent starts its execution. However, when the environment changes repeatedly, the capability to plan a sequence of actions to perform while acting (known as continual *planning*) is of primary importance to leverage opportunities and tackle contingencies of the evolving scenarios. Agents featuring continual planning and execution can i) start executing a plan when it is not yet complete, focusing first on the immediate things perform, and ii) adapt their course of actions along with the changes in the environment and in the goals they're trying to pursue. In the following, first, we describe how to extend a BDI architecture equipped with deliberation capabilities to support continual temporal planning, and then we illustrate the most relevant features needed for smooth integration. Namely, i) plan failure forecasting, ii) run-time goal revision, iii) rescheduling in case of an improved solution is found.

A. Reasoning and acting framework

Fig. 2 shows the core architectural components of the proposed BDI model with continual planning and concurrent execution. On the left, the BDI reasoning model includes

the *Continual Planner*, the *Goal Reasoner*, and the *Intention Scheduler*. In the middle, the BDI sensing and execution model includes the *Executor* and the *Events Monitor*, respectively acting and sensing to/from the *Environment*.

The Goal Reasoner, given the agent behavioural model, creates new goals and pushes them in the desire set. Then, it activates a goal (from the desire set), selected on the basis of preconditions and priorities. The Continual Planner redefines the considered planning problem for each received goal, taking into account updates about the state of the agent and of the world. Solutions are continuously produced accordingly. The Continual Planner adopts a novel search approach, which allows the exploration of the solution space step-by-step. Intuitively, the search is performed considering a limited search horizon, so that, at each iteration, it incrementally refines the previous plan adding new actions towards the goal and/or completely revising the plan to handle contingencies. Therefore, partial plans produced by each search iteration do not necessarily bring to the final goal. Classical temporal planning heuristics are used by the Continual Planner while computing each partial plan to choose among the most promising alternative actions (see Sect. III-B for more details). The Intention Scheduler is responsible for mantaining a queue of plans as received by the Continual Planner, for their execution by the Executor. A plan can either be i) a continuation of a previous plan, or ii) an alternative (e.g., a better solution) which might imply deviating from current execution and discarding previously queued plans. Respectively, those lead to i) enqueueing of the received incremental plan or ii) replacement of all the plans in the queue with the new one. In this last case, it might also tell the Executor to arrest earlier the plan in execution at the point at which the new plan will apply. The Executor is responsible for i) the execution of a plan by checking the applicability of each of the actions within the plan before dispatching the execution of the action itself; ii) monitoring the correct termination of the dispatched actions to decide whether to proceed with the execution of the remaining actions in the plan or stop it and notify the failure to activate further reasoning; iii) interrupting the execution of the current plan when requested by the Intention Scheduler. The Events Monitor senses the environment and actions execution status and updates the knowledge of the agent accordingly.

Fig. 3 provides details of the **Continual Planner**, here represented as composed by two sub-components: an *Execution Simulator* and a *Planning Search*. The **Execution Simulator** receives updates from the Events Monitor and consequently updates its internal representation about the *Execution State* of plans (running, successful, failed) including *Committed Actions*, part of the plan that it is committed to executing, also considering additional constraints (e.g., the minimum number of committed steps). The **Forecast Plan Failure** component of the Execution Simulator provides forecasting capabilities to verify whether the current plan is going to fail in its execution. This is performed by progressing the current state of the world guided by the plan (considering their pre-conditions and effects). If for some reason (e.g., a precondition of an

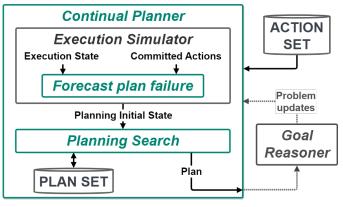


Fig. 3: Details of the Continual Planner.

action in the plan does not hold), then it informs the Planning Search to find another alternative plan. If the simulation of the plan succeeds, then the progressed state (named *Planning Initial State*) is sent to the Planning Search for continuing the previous search. The **Planning Search** component receives in input the *Planning Initial State*, the goal to achieve, and the set of actions to orchestrate to build a solution plan. In Sec. III-B, we detail how to modify a temporal planning search to behave as discussed above.

B. Search components for continual planning

In AI planning, the search for a plan to achieve the goal is performed by incrementally by expanding and visiting the search space (see [25] for details). Heuristics can be adopted to drive the search to converge faster towards the goal. Such searches typically use algorithms based on an *open* and a *closed* list to store nodes of the search space during the search (open list to store the states yet to expand, and closed to store the states already expanded). All these search algorithms, according to a a given expansion strategy (e.g., A*, best-first, depth-first), (i) select a state from the open list, (ii) expand it (e.g., by considering applicable/relevant actions), (iii) add all the generated states in the open list and (iv) iterate until the goal is reached or no solution is found (open list is empty); Finally, a solution plan is given in output or the non-existence of the solution is returned.

We propose a variant of the classical search to support execution at planning time, in a concurrent, temporal, roundbased and continual fashion. The proposed search is built upon a classical offline totally-ordered forward search [25], now splitted into **search rounds** which incrementally move ahead in the search space. As soon as the first search round produces a partial plan, execution can start without having to wait for the complete plan. Intuitively, each round executes only a limited number of expansion iterations before exiting to then resuming from the most promising state: a) search starts/resumes from the last round most promising state, then b) expansion strategy is applied and open and closed lists are updated appropriately and c) iterations continue until a round-termination condition is satisfied (e.g., goal reached, new depth reached, number of newly expanded nodes reached) then the most promising state is returned by the search round. Re-rooting happens between rounds, clearing out the whole closed list and filtering the open to keep only states with the same plan prefix as the one in the new found plan. Then, this plan prefix is truncated from everywhere so that the next search will see the current state, effectively as the root one. To compute the plan as soon as possible, a greedy expansion strategy is initially adopted. Still, in the case of no solution found, the search switches to a non-greedy search used as a fallback expansion strategy. The search runs concurrently with plan execution which, stepby-step, consumes plans and commit for execution. When a plan is committed for execution, the expectation is to reach the projection of the current state after the plan, since the request for abortion of commitment is not allowed. In the case of failure in the execution of actions, a goal change, or an improved plan, continual search revision re-configure the search to adapt. The search is reinitialized from the committed projection state. When the plan is produced, the old plan, queued but yet not committed for execution, is early aborted and replaced with the new plan. However, if the search does not produce the new plan within the time window covering the current execution commitment, the search becomes outdated and needs to be reinitialized again from the newly committed projection state.

a) Continual goal revision .: In a BDI agent, goals are fulfilled separately, for example, with plans executed in sequence. However, optimization may be possible, e.g. an overall-shorter plan may exists that fulfill multiple goals. Still, goals are pushed to the agent at execution time, for example after observation of the environment, when the fulfillment of a previous goal has already started. Under this condition, a revision of currently active goal is needed to generate an overall-shorter new plan across goals. The Goal Reasoner component (see Fig. 2) supports continual goal revision, based on domain-specific user-specified rules, so that current goal could be revised to include new ones, then fulfilled with a possible overall-shorter plan. So far we support a very simple rule that computes a revised goal as $G'' = G \cap G'$ that considers the old goal G and new goal G'. Since G'' is more specific than its base version G, the revision of a goal may not be always affective. A rules-based mechanism is used to specify the conditions for revision, goal-by-goal.

b) Improve solution.: However, a complete plan may finally be found earlier before the execution terminates, so that there is still time for the planner to improve the solution. Our framework adopts two efficiently-different searches, first, a quick greedy search looks for the first viable solution, and then, a non-greedy search tries to optimize it. If an improved plan is found, it is scheduled in the waiting queue, by requesting an early arrest of all scheduled actions diverging from the improved plan. To be schedulable, when produced, the plan must be non-outdated with respect to the updated execution state.

C. Forecasting plan failure

Uncontrollable events that may happen in the environment can cause failures in the execution of plans. In classical planning agents, a plan execution failure directly triggers a re-planning. Our architecture continuously simulates the execution of the current plan from the current state, so to forecast a possible failure. The simulation consists in progressing the current state by applying the actions in the plan, checking if the action preconditions hold, and then updating the state with the action's effects, otherwise reporting failure. Failure is also reported if the plan does not allow goal achievement. Whenever a plan simulation fails, two cases need to be considered. The failure is forecasted to occur within the committed actions: in this case, nothing can be done to avoid the natural failure of the plan. The failure is forecasted to occur after the committed actions: in this case, an alternative plan is generated by initializing a new search starting from a committed state (the state resulting from the simulation of the committed actions from the current state).

IV. IMPLEMENTATION IN ROS2-BDI

We implemented the proposed framework on top of ROS2-BDI [10]. To this extent, we first extended Java-FF to support the proposed continual temporal planning, and this results in a new tool named CJFF¹; then we extended ROS2-BDI [10] to support the proposed continual planning reasoning ²; in addition, we also revised PlanSys2, to support continual planning execution, and adopted it as ROS2 planning system ³.

a) Continual JavaFF.: We implemented the proposed continual planning algorithm sketched in the previous sections in a new planner called CJFF (Continual JavaFF). CJFF builds on and extends JavaFF [19] to fulfil the need for a general-purpose, PDDL 2.1 compliant, temporal planner. JavaFF, although it offers obsolete heuristic w.r.t. other state-of-the-art temporal planners, offers a totally-ordered forward chaining approach, its implementation is clear, modular and flexible, thus making it a good fit for the first implementation of our planning search. For CJFF we leverage the two search strategies provided by JavaFF, namely greedy Enforced Hill Climbing (EHC) and Best First Search (BFS) both based on a Relaxed Plan Graph (RPG) heuristic extended to deal with temporal actions [19].

We wrapped CJFF into a RCLJava [26] ROS2 node, so to support its integration into a ROS2 framework. The node consists of two main threads: i) a control thread that communicates with the other ROS2 nodes of the architecture through specific ROS2 topics to enable monitoring search progresses and controls planning and replanning phases; ii) a search thread responsible for the search. CJFF exposes ROS2 services to trigger a new search from scratch (using an initial state computed directly via the PDDL-encoded problem). CJFF

¹CJFF can be found at https://github.com/RTI-BDI/JavaFF.

²The extended ROS2-BDI framework is available at https://github.com/ RTI-BDI/ROS2-BDI-ONLINE/tree/ojff.

³The adopted ROS2 planning system, a revised version of PlanSys2, is available at https://github.com/RTI-BDI/ros2_planning_system.

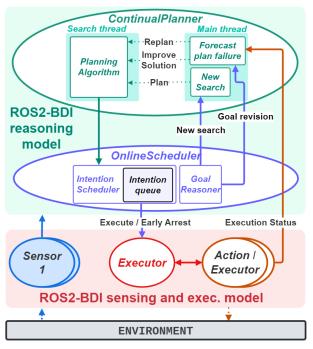


Fig. 4: The ROS2-BDI architecture for continual planning.

also publishes its search progresses i.e., ordered incremental plans, where the plan baseline specifies the situation in which each incremental plan can be executed. In addition, CJFF expects to get execution status information to update the plan execution state and committed status. CJFF computes committable states of the plan where no open action exists⁴, considering also a minimum number of actions specified by the user. Computation of the "projected state" that the agent is committed to reaching is performed via simulation, applying the expected effects of the upcoming actions in the executing plan. The same mechanism is used to forecast plan failure, as detailed in Sect. III-C.

b) Extending ROS2-BDI architecture.: We implemented the high-level architecture described in Sect. III to support continual planning building on top and extending the ROS2-BDI [10] with the CJFF functionalities. The resulting ROS2 architecture is depicted in Fig. 4. The architectural components of Fig. 2 and 3 are here implemented into ROS2 nodes, modifying and extending ROS2-BDI core nodes, as follows: i) **CJFF** replaces the PlanSys2 ROS2-BDI component for offline planning; ii) **Online Scheduler** replaces the ROS2-BDI Scheduler; iii) **Executor**, still based on PlanSys2, has been re-implemented to allow for the safe termination of the execution of a plan (early arrest). The original ROS2-BDI scheduler activates a goal only when provided with a complete solution plan for the goal itself, and after verifying deadlines. CJFF may not provide a complete plan all at once, thus the Online Scheduler shall activate the goal without knowing whether a complete plan exists. Similarly to ROS2-BDI Scheduler, it checks whether the precondition holds, and deals with goal priorities. The Online Scheduler initializes CJFF to start a new search as soon as a goal has been activated. Then it waits for the search progresses (e.g., give possibly new partial plans). CJFF generates and publishes the new possibly partial plans as a continuation of the previously computed ones, or a new plan to be used in place of the one currently in execution. The Intention Scheduler monitors the CJFF node to decide how to proceed, i.e., enqueue the new partial plan, or ask the Executor to safely terminate the plan in execution, and then proceed with the new one (see Sect. III). The Online Scheduler is also responsible for revising the goals within the Gaol Reasoner as explained in Sect. III-B0a. The preemptive mechanism of the original ROS2-BDI Scheduler was also modified to request the Executor to safely terminate the plan in execution before switching to the activation of a higher priority desire. The Executor, based on PlanSys2, has been also thoroughly modified to support the safe termination of the plan currently in execution. In particular, let π be a timetriggered plan currently in execution containing an action A. The request of the safe termination after A requires waiting also the termination of all the other actions $B_i \in \pi$ whose execution started before A naturally finishes. Finally, each Action Executor publishes the respective execution status (e.g., running, success, fail) so that other ROS2 modules, e.g., the CJFF node can intercept to decide what to do next.

V. VALIDATION

In order to validate our novel approach, we conceived a scenario where there are several recycling agents able to move in a 2d grid map with static and known a priori obstacles (e.g., walls), and (pseudo) randomly moving obstacles (e.g., people) whose movements are not known a priori, and whose presence can only be discovered through sensing while moving (the agent can sense free locations within a given distance from its position). Each agent can move (from one cell to an adjacent one, known to be free), pickup a litter, and recycle it. All these actions are durative actions with an associated known duration. Each agent has the desire to collect and dispose of all the litter he discovers in the nearest bin, and shall not move to a location occupied by one of the moving obstacles or by another agent. New litters may appear randomly in the grid and contribute to changing the goal of the agents when discovered.

Fig. 5 shows the validation scenario, in which the recycling agent (here represented by the robot) move on the grid to collect garbage (here represented by ducks). The validation scenario has been implemented in a ROS2-based simulation environment ⁵. Specifically, simulation environment is provided by Webots, a simulator for robotic systems that comes

⁴The search performed by JavaFF to compute a time-triggered plan leverages a reduction to classical planning by creating a classical planning problem where each temporal action is encoded with so-called snap-actions [27]. Once a classical planning solution is computed, we need to check the consistency of the temporal network induced by the computed classical plan. If consistent, then a time-triggered plan is extracted. Otherwise, the search continues. We refer the reader to [27] for further details.

⁵The implementation of the validation scenario based on Webots is available at https://github.com/RTI-BDI/Redi-Webots-scenarios.



Fig. 5: Validation scenario implemented in the Webots simulator.

Setup	Offline		Online		
	μ	σ	μ	σ	$\mu +$
move=4, det_area=1, k_litt=2	56.0	2.3	42.5	9.8	13.5
move=8, det_area=1, k_litt=2	58.5	6.8	43.0	10.1	15.5
move=4, det_area=2, k_litt=2	58.5	3.3	36.0	0.0	22.5
move=8, det_area=2, k_litt=2	58.0	5.9	35.5	6.0	22.5
move=4, det_area=3, k_litt=2	66.0	4.0	42.5	10.5	23.5
move=8, det_area=3, k_litt=2	57.0	4.2	42.0	6.3	15.0
move=4, det_area=1, k_litt=3	48.0	0.0	43.5	5.5	4.5
move=8, det_area=1, k_litt=3	57.8	0.5	36.0	2.8	21.8
move=4, det_area=2, k_litt=3	48.0	0.0	35.5	2.5	12.5
move=8, det_area=2, k_litt=3	57.0	1.2	37.0	11.6	20.0
move=4, det_area=3, k_litt=3	48.0	0.0	42.0	8.2	6.0
move=8, det_area=3, k_litt=3	48.0	1.6	39.5	17.2	8.5

TABLE I: Evaluation results.

We run all the tests on a notebook equipped with an Intel[©] 2.80GHz i7TM CPU with 16GB of RAM, running Linux.

The results are reported in Table I. The first column reports considered parameter the setting (move, det_area, k_litt), the second and fourth columns are the average (μ) number of steps performed by the recycling agent in four runs, the third and fifth columns are the respective standard deviation. Finally, the sixth columns $(\mu +)$ is the difference of the second and fourth columns (it represents the average number of additional steps performed by the offline approach).

The results (see Table I) clearly show that in all considered situations the new ROS2-BDI framework equipped with continual planning requires on average a smaller number of moves to dispose of all the litter items. The results also show that in the first six situations (where one litter item is detected while moving) the improvements are higher. This is due to the fact, that in the previous ROS2-BDI framework each time encounters a failure in the execution for an obstacle or the discovery of a new litter item needs to compute a full plan from its current position, while the new one is equipped with continual planning can easily adapt the not yet executed plans to avoid the obstacle and to dispose of the newly detected litter items. The results also show that when the recycling agent is able to observe things within a proper anticipation window (i.e., not too late, not too early that's det area=2 for the scenario), and there is not much movement and we see the greatest improvement. This is due to the ability of the new ROS2-BDI approach to modify the solution plan to also fulfil the goal of disposing of the newly discovered litter item. However, when the movement rate increases and the detection area is not optimal, the improvements reduce. For instance, when det_area=1, the recycling agent discovers the new litter item too late, going toward a sub-optimal solution and bumping more frequently into occupied cells, due to its limited knowledge of the current world status. When det area=3, a "ping-pong" behaviour can potentially happen; this is due to the fact that the agent has to pass through a large set of cells, and because of the broad detection area, the computed plan might be invalidated since the agent may discover one of the locations to visit with that plan being occupied (despite the location might be free when effectively reached). In this

with ready-to-use robot models, already bundled with the ROS2 protocol ⁶. Being implemented on top of ROS2, these same experiments could be easily repeated with real robots with no additional coding or configuration, except for minor settings. We also created a corresponding PDDL 2.1 domain specifying the predicates needed to encode the scenario (e.g., free (x, y) and litter(x, y) to indicate resp. whether location x, y is free and the presence of a litter in x, y), the different actions (e.g., move), and pickup).

For the validation, we considered a simple 7x7 map with the static obstacles positioned as per Fig. 5⁷. Because of a low-level bug in PlanSys2 related with the construction of Behavior Trees, we restricted the analysis to one single agent. To compare the new ROS2-BDI framework with the old one we created pseudo-random simulations where there is one recycling agent, two persons that will follow a predefined circular path (not known by the agent) each performing a step forward along the respective path for move $\in \{4, 8\}$ times, three litter items placed in the map, however only the position of k_litt $\in \{2, 3\}$ are known by the agent. We also considered different sizes $det_area \in \{1, 2, 3\}$ of the detection area of the agent. (An assignment to move, det_area, k_litt defines a situation.) We measure the number of steps required by the recycling agent to dispose of all the placed litter items on the map. For a fair comparison of the new ROS2-BDI framework and the previous one, we integrated into the old ROS2-BDI framework JavaFF, such that it can be used in offline runs, replacing the default (more efficient) POPF planner used within PlanSys2. Finally, for each situation, we performed 4 runs and collected the average number of moves of the recycling agent to dispose of all the litter items. We remark that, a comparison of computation time between the original ROS2-BDI framework and the one proposed in this paper, would not be fair because here we care about plan quality (number of steps performed by the recycling agent) rather than on the time to compute plans (that depends on the implementation language and heuristic used for the search).

⁶More on Webots can be found at https://cyberbotics.com/.

⁷A video of the validation scenario can be found at https://github.com/ RTI-BDI/iros2023/raw/main/on_moving_SR_400_LS_800_DC_4.mkv.

case, a new plan to avoid the detected obstacle is generated. This problem could be alleviated by introducing an additional functionality that instead of simulating the whole plan, only the first N actions are simulated, and if no invalidation is detected, then continue the execution thus delaying the replanning. (This functionality is left for future development.) The results show also that similar considerations hold when all the three litter items are already known since the beginning (last six rows in Table I). Here the new ROS2-BDI framework allows for easily adapting the plan in execution to avoid newly discovered obstacles.

VI. RELATED WORK

The problem of designing complex and intelligent autonomous architectures for the robotic setting has been the subject of several works [1]-[6], [8], [9], [28]. All these works suffer of severe limitation. Some are not addressing autonomous deliberation (e.g. [4]) and rely on pre-loaded plans. Others like e.g. CogniTAO [5], CORTEX [6], SkiROS2 [7], ROSPlan [8], and PlanSys2 [9] have the ability to automatically generate new plans for handling contingencies. However, all these frameworks first generate a full plan for the given goal before starting its execution. When the execution of a plan fails because of e.g. an unexpected contingency, a new full plan is generated and then executed. Moreover, all these frameworks lack of several BDI capabilities like e.g. detectionreaction, multi-agent interaction mechanisms, and automatic generation of new desires. The ROS2-BDI framework [10] overcomes many limitations of all the previous approaches by providing BDI capabilities. However, even in this framework, the execution of a plan happens only after the generation of a complete plan to achieve a goal. In our framework, we extend the ROS2-BDI framework to integrate continual planning while executing the plan, thus enabling an agent to i) start acting before a complete plan has been generated; ii) quickly adapt the agent's intentions to possible contingencies that may happen while executing.

In [17] a framework for interleaving action and planning with operational models has been proposed: whenever a task during execution needs to be refined a planner is invoked. Similarly to our case, the planner searches from a given depth, it returns the computed task refinement and starts its execution. In parallel, it continues the search to refine the given task. Differently from our case, they consider instantaneous actions, and the approach has not been used within a BDI framework.

In [14] it has been proposed a software system integrating perception, planning, and real-time control where planning and execution can occur in parallel: while executing an action, the motion planning of the immediate next action is computed concurrently. A similar approach was also presented in [15]. A framework for reactive run-time composition (with no search to guide the agent towards goal achievement) of pre-defined skills has been proposed in [16].

Other researchers addressed the problem of interleaving planning and acting with stochastic approaches, focusing more on theoretical aspects, such as the completeness of the solution, and less on the scalability and feasibility of such approaches to real-world use cases [12], [29], [30]. In [13] it has been proposed an approach based on planning under partial observability that allows for generating conditional plans that depending on the sensing execute a different course of instantaneous actions. Such plans can then be encoded as reconfigurable behaviour trees [31] to facilitate their execution in the robotic setting. However, all these works first compute a plan and then they try to execute it and do re-planning in case of execution failure.

[18] presents an algorithm for continual planning where in the planning domain one has to complement the classical specification of the actions with constructs to describe why and when the agent should switch between planning and acting. Their algorithm enables agents to deliberately postpone parts of their planning process and actively gather missing information relevant for subsequent refinement of the plan. This work is limited to instantaneous actions, assumes no concurrent execution of actions, requires a specialized search algorithm and a modification of the PDDL problem to include special constructs to specify the strategies governing the switch between planning and acting. In our approach, we overcome their limitations by considering durative actions, and relying on PDDL 2.1 that is used by a state-of-the-art planning algorithm slightly modified to realize the continual planning and execution through interaction with the whole BDI architecture.

VII. CONCLUSION AND FUTURE WORK

We proposed a novel architecture for continual temporal planning in the BDI model. The architecture has been implemented as a significant extension of ROS2-BDI. We carried out an experimental validation to compare the continual planning with the previous ROS2-BDI framework within a scenario simulated by interfacing the developed framework with the Webots simulation environment. The experiments showed improved results compared to ROS2-BDI.

This work constitutes the basis for a variety of future work such as: i) Extension of this work to a full-fledged real-time framework to guarantee schedulability in terms of computational capacity on the line of [4], [32]; ii) Improving the forecasting plan failure through more sophisticated prediction mechanisms based on e.g., machine learning or statistical reasoning; iii) Capability of storing for later efficient reuse plans synthesized in a previous run; iv) Considering dynamic search interval that auto-adapt to the world dynamic; v) Extending validation in a multi-agent scenario, considering cooperative versus competitive behaviours; vi) Extending the support to alternative planning approaches including non-deterministic [13], [33] and probabilistic planning.

REFERENCES

- S. Gottifredi, M. Tucat, D. Corbata, A. J. García, and G. R. Simari, "A BDI architecture for high level robot deliberation," *Inteligencia Artif.*, vol. 14, no. 46, pp. 74–83, 2010.
- [2] A. van Breemen, K. Crucq, B. Krose, M. Nuttin, J. Porta, and E. Demeester, "A user-interface robot for ambient intelligent environments," in *Proc. of the 1st Int. Workshop on Advances in Service Robotics*,(ASER), 2003.

- [3] B. R. Duffy, R. Collier, G. M. O'Hare, C. Rooney, and R. O'Donoghue, "Social robotics: Reality and virtuality in agent-based robotics," in *Bar-Ilan Symposium on the Foundations of Artificial Intelligence: Bridging theory and practice (BISFAI-99), Ramat Gan, Israel, June 23-25, 1999*, 1999.
- [4] F. Alzetta and P. Giorgini, "Towards a real-time BDI model for ROS 2," in WOA, ser. CEUR Workshop Proceedings, vol. 2404. CEUR-WS.org, 2019, pp. 1–7.
- [5] CogniTAO-Team, "CogniTAO (BDI)," http://wiki.ros.org/decision_ making/Tutorials/CogniTAO.
- [6] P. Bustos, L. J. Manso, A. Bandera, J. P. B. Rubio, I. García-Varea, and J. Martínez-Gómez, "The CORTEX cognitive robotics architecture: Use cases," *Cogn. Syst. Res.*, vol. 55, pp. 107–123, 2019.
- [7] A. S. Polydoros, B. Großmann, F. Rovida, L. Nalpantidis, and V. Krüger, "Accurate and Versatile Automation of Industrial Kitting Operations with SkiROS," in *TAROS 2016*, ser. LNCS, vol. 9716. Springer, 2016, pp. 255–268.
- [8] M. Cashmore, M. Fox, D. Long, D. Magazzeni, B. Ridder, A. Carrera, N. Palomeras, N. Hurtós, and M. Carreras, "ROSPlan: Planning in the Robot Operating System," in *ICAPS 2015*. AAAI Press, 2015, pp. 333–341.
- [9] F. Martín, J. G. Clavero, V. Matellán, and F. J. Rodríguez, "Plansys2: A planning system framework for ROS2," in *IROS*. IEEE, 2021, pp. 9742–9749.
- [10] D. Dal Moro, M. Robol, M. Roveri, and P. Giorgini, "Developing bdibased robotic systems with ros2," in Advances in Practical Applications of Agents, Multi-Agent Systems, and Complex Systems Simulation. The PAAMS Collection, F. Dignum, P. Mathieu, J. M. Corchado, and F. De La Prieta, Eds. Cham: Springer International Publishing, 2022, pp. 100–111.
- [11] A. S. Rao and M. P. Georgeff, "Modeling rational agents within a BDIarchitecture," in KR. Morgan Kaufmann, 1991, pp. 473–484.
- [12] S. Z. Luis Pineda, "Realtime Concurrent Planning and Plan Execution in Stochastic Domains," p. 8, Nov. 2015.
- [13] P. Bertoli, A. Cimatti, M. Roveri, and P. Traverso, "Strong planning under partial observability," *Artif. Intell.*, vol. 170, no. 4-5, pp. 337– 384, 2006.
- [14] R. Simmons, "Concurrent planning and execution for autonomous robots," *IEEE Control Systems Magazine*, vol. 12, no. 1, pp. 46–50, 1992.
- [15] J. Zelek and M. Levine, "Local-global concurrent path planning and execution," *IEEE Transactions on Systems, Man, and Cybernetics - Part* A: Systems and Humans, vol. 30, no. 6, pp. 865–870, 2000.
- [16] Y. Pane, V. Mokhtari, E. Aertbeliën, J. De Schutter, and W. Decré, "Autonomous runtime composition of sensor-based skills using concurrent task planning," *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 6481–6488, 2021.
- [17] S. Patra, J. Mason, M. Ghallab, D. S. Nau, and P. Traverso, "Deliberative acting, planning and learning with hierarchical operational models," *Artif. Intell.*, vol. 299, p. 103523, 2021.
- [18] M. Brenner and B. Nebel, "Continual planning and acting in dynamic multiagent environments," *Autonomous Agents and Multi-Agent Systems*, vol. 19, pp. 297–331, 12 2009.
- [19] A. I. Coles, M. Fox, D. Long, and A. J. Smith, "Teaching forwardchaining planning with JavaFF," in *Colloquium on AI Education*, *Twenty-Third AAAI Conference on Artificial Intelligence*, July 2008.
- [20] M. Fox and D. Long, "PDDL2.1: an extension to PDDL for expressing temporal planning domains," J. Artif. Intell. Res., vol. 20, pp. 61–124, 2003.
- [21] J. Hoffmann, "The metric-ff planning system: Translating "ignoring delete lists" to numeric state variables," *CoRR*, vol. abs/1106.5271, 2011.
- [22] A. J. Coles, A. Coles, M. Fox, and D. Long, "Forward-chaining partialorder planning," in *ICAPS 2010*. AAAI, 2010, pp. 42–49.
- [23] J. Benton, A. J. Coles, and A. Coles, "Temporal planning with preferences and time-dependent continuous costs," in *Proceedings of the Twenty-Second International Conference on Automated Planning and Scheduling, ICAPS 2012, Atibaia, São Paulo, Brazil, June 25-19, 2012, L. McCluskey, B. C. Williams, J. R. Silva, and B. Bonet, Eds. AAAI, 2012. [Online]. Available: http://www.aaai.org/ocs/index.php/ ICAPS/ICAPS12/paper/view/4699*
- [24] "ROS2 Robot Operating System version 2," 2022, https://docs.ros.org.
- [25] M. Ghallab, D. S. Nau, and P. Traverso, Automated planning theory and practice. Elsevier, 2004.

- [26] "RCLJava ROS2 Client Library for Java," 2022, https://github.com/ ros2-java/ros2_java.
- [27] A. Coles, M. Fox, K. Halsey, D. Long, and A. Smith, "Managing concurrency in temporal planning using planner-scheduler interaction," *Artif. Intell.*, vol. 173, no. 1, pp. 1–44, 2009.
- [28] E. Scala and P. Torasso, "Proactive and reactive reconfiguration for the robust execution of multi modality plans," in *ECAI*, ser. Frontiers in Artificial Intelligence and Applications, vol. 263. IOS Press, 2014, pp. 783–788.
- [29] M. Littman, J. Goldsmith, and M. Mundhenk, "The computational complexity of probabilistic planning," *Journal of Artificial Intelligence Research*, vol. 9, 08 1998.
- [30] J. Rintanen, "Constructing conditional plans by a theorem-prover," Journal of Artificial Intelligence Research - JAIR, vol. 10, 05 2011.
- [31] P. de la Cruz, J. Piater, and M. Saveriano, "Reconfigurable behavior trees: Towards an executive framework meeting high-level decision making and control layer features," 2020. [Online]. Available: https://arxiv.org/abs/2007.10663
- [32] A. Traldi, F. Bruschetti, M. Robol, M. Roveri, and P. Giorgini, "Realtime BDI agents: A model and its implementation," in *IJCAI*. ijcai.org, 2022, pp. 511–517.
- [33] A. Cimatti, M. Do, A. Micheli, M. Roveri, and D. E. Smith, "Strong temporal planning with uncontrollable durations," *Artif. Intell.*, vol. 256, pp. 1–34, 2018.