Project Milestone 3: Automated Warehouse Planning with ASP

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Abstract

Modern e-commerce warehouses rely on fleets of autonomous mobile robots to retrieve entire shelves of merchandise and deliver them to picking stations. Generating collision-free, makespan-optimal plans for dozens of robots—while simultaneously enforcing lane-usage rules and exact product-delivery requirements—is a tightly constrained combinatorial problem. This project tackles the task with a fully declarative *Answer–Set Programming* (ASP) model executed by the *Clingo* solver. Warehouse geometry, object initialisation, and customer orders are encoded as facts; robot actions (`move`, `pickup`, `putdown`, `deliver`) are represented by choice rules with explicit pre- and post-conditions; safety conditions such as collision avoidance, head-on swap prevention, shelf-capacity limits, and highway restrictions are enforced through integrity constraints; and frame axioms implement inertia using single-rule persistence patterns. Exact order fulfilment is guaranteed by per-product needs counters, and a `#minimize` statement drives the solver to plans with the shortest makespan. The final system solves five benchmark instances ranging from a 6×6 grid with two robots to a dense 10×10 layout with three robots and multiple overlapping orders, producing valid plans in under one minute on commodity hardware. Empirical results show quadratic growth in grounding size and highlight the impact of concise inertia rules and swap-avoidance constraints. The report provides a rule-by-rule exposition, performance metrics, a replication guide, and a roadmap for future enhancements such as heuristic propagation, multi-objective optimisation, and dynamic replanning under uncertainty.

Introduction

Modern e-commerce fulfilment centres operate like tightly choreographed ballets in which hundreds of low-profile robots weave through a dense grid of storage aisles, slide underneath pods of merchandise, lift them, and deliver entire shelves to human or robotic pickers. Planning the behaviour of such fleets is exceptionally complex: every robot must avoid collisions and head-on swaps with its peers, respect one-way high-throughput "highway" lanes where shelves can never be parked, obey capacity limits (a robot may carry only one shelf at a time), and still guarantee that every order's product quantities are delivered exactly—no shortages, no over-delivery. On top of these hard constraints, management demands a short **makespan** (the time until the last order is completed) because shorter cycles translate directly into higher throughput and customer-satisfying same-day shipping.

Conventional planning tool-kits only partially address this challenge. Mixed-Integer Programming can encode collision and capacity constraints, but linearising pick-and-drop logic creates huge models that become intractable as grids or horizons grow. Multi-Agent Path-Finding algorithms such as Conflict-Based Search produce optimal motion plans, yet require extensive procedural extensions to handle shelf pick-up/drop-off actions, highway rules, and quantitative product tracking. Deep-learning heuristics offer speed but sacrifice formal safety guarantees—an unacceptable risk on a warehouse floor. **Answer-Set Programming (ASP)** provides a declarative alternative: domain knowledge is written directly as logical rules; *choice* rules enumerate optional robot actions; *integrity* constraints prune any world state that violates safety; *frame axioms* compactly enforce inertia; and a single `#minimize` directive compels the solver (Clingo) to return a makespan-optimal plan. Because the solver explores only states that already satisfy every rule, vast swaths of the search space are discarded *a priori*, yielding competitive performance without resorting to ad-hoc code.

This project delivers a complete ASP model for the "Automated Warehouse Scenario" used in CSE 579. Warehouse geometry, initial object placement, and customer orders are encoded as ground facts; robot actions (`move`, `pickup`, `putdown`, `deliver`) are captured by pre- and post-conditioned choice rules; safety constraints implement collision avoidance, shelf-capacity limits, head-on swap prevention, and highway compliance; and per-product "needs" counters guarantee exact order fulfilment. Single-rule frame axioms keep robot, shelf, and inventory states consistent across time steps, dramatically shrinking the solver's grounding. A horizon-scaling runner automatically increases the time bound until a feasible plan is found and converts the resulting answer set into human-readable JSON traces. Early experiments solve five benchmark instances—ranging from a 6×6 grid with two robots to a dense 10×10 layout with overlapping orders—in under one minute each on commodity hardware, confirming both soundness and practical scalability. The remainder of this report formalises

the domain, walks through the most critical rules, presents empirical results, and outlines future extensions such as heuristic propagation, multi-objective optimisation, and dynamic replanning under uncertainty.

Problem Statement

We model the warehouse floor as a finite two–dimensional orthogonal grid $G = \{1, \ldots, M\} \times \{1, \ldots, N\}$. Each cell $(x, y) \in G$ is statically assigned one of four roles:

(1) **regular** storage cell,

(2) **highway** cell that must remain clear of parked shelves to maintain fast traffic flow,

(3) **obstacle** cell that is permanently blocked, or

(4) **picking-station** cell at which customer orders are fulfilled.

The dynamic entities in the system are

- a set of **robots** $R = \{r_1, \ldots, r_{|R|}\}$, each able to move one cell horizontally or vertically per time step and to lift *exactly one* shelf at a time;
- a set of **shelves** (pods) $S = \{s_1, \ldots, s_{|S|}\}$ that may hold multiple product types and quantities;
- a finite catalogue of **products** $P = \{p_1, \ldots, p_{|P|}\}$ stored on shelves; and
- a set of customer **orders** $O = \{o_1, \ldots, o_{|O|}\}$, each linked to a unique picking-station cell and defined by a list of $\langle$product, quantity$\rangle$ pairs that must be delivered *exactly*.

At every discrete time step $t \in \{0, \ldots, H\}$ each robot executes one primitive action (or `idle`):

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A joint action sequence ("plan") is **valid** iff, for every time step:

(a) No two robots occupy the same cell, nor swap adjacent cells simultaneously (collision- and swap-free motion).

(b) Shelves are never placed on highway cells.

(c) Each robot carries at most one shelf.

(d) Shelf inventories and order balances are updated consistently; product counts never become negative.

(e) For every order–product pair, the cumulative units delivered equal the requested quantity by the end of the plan (exact fulfilment).

The **objective** is to find a valid plan that minimises the *makespan* H, the index of the final time step containing any non-idle action. Secondary metrics such as total travel distance or robot utilisation are not optimised in this phase, but the declarative model readily supports multi-objective extensions.

Project Background

This work is grounded in **Answer–Set Programming** (ASP), a declarative paradigm where every aspect of a problem is expressed as logical rules, and a solver searches only the space of states that satisfy those rules. Several core ASP constructs make the language particularly attractive for highly constrained planning domains:

- *Choice rules* enumerate possible robot actions without committing to any single option in advance.
- *Integrity constraints* immediately eliminate any world state that violates safety requirements, ensuring the solver never explores infeasible branches.
- *Frame axioms* provide a compact way to encode inertia—facts remain true from one time step to the next unless an action changes them.
- *Optimization directives* such as `#minimize` steer the search toward plans with the smallest makespan or any other cost metric of interest.

All rules are processed by **Clingo 5.6**, which combines the *Gringo* grounder with the *clasp* solving engine. Clingo supports scripting, incremental (multi-shot) solving, and cost optimization. The conceptual foundations for the project are drawn from three main sources:

1. Baral's textbook chapters on dynamic domains, inertia, and optimization, which are invaluable for framing warehouse actions as state-changing fluents;
2. the official Potassco tutorial notebooks, providing working examples of choice rules, integrity constraints, and multi-objective optimization;
3. published Multi-Agent Path-Finding (MAPF) encodings by Erdem *et al.*, whose concise swap-avoidance pattern inspired the collision rules used here.

The implementation is deliberately modular:

- `warehouse_logic.asp` – core rules for movement, pickup/put-down, delivery, inertia, and the global `#minimize` objective;
- `input_parser.asp` and `input_converter.asp` – utilities that translate human-readable `init(object, value)` facts into time-stamped predicates required by the core program;
- `warehouse_simulator.py` – a horizon-scaling driver that repeatedly invokes Clingo, extracts the first satisfiable answer set, and writes JSON traces for visual debugging;
- `simpleInstances/` – five benchmark scenarios, ranging from a simple 6×6 grid with two robots to a dense 10×10 grid containing highway lanes, obstacles, and overlapping orders;

- `robot_paths/` – JSON files produced by the simulator that external visualizers can replay step-by-step.

The modeling philosophy represents every dynamic aspect—robot positions, shelf locations, carried-status flags, shelf inventories, and remaining order needs—as a *time-stamped fluent*. Robot actions are expressed through choice rules with clear pre- and post-conditions, while safety requirements are captured using concise integrity constraints. Two single-rule frame axioms maintain robot and shelf inertia, significantly reducing grounding size compared to naïve replication. A global `#minimize` statement assigns cost 1 to every time step containing any non-idle action, compelling Clingo to return makespan-optimal plans.
All experiments are executed on an 8-core laptop (Intel i7, 16 GB RAM) running Ubuntu 22.04 and Clingo 5.6.2. Since the repository has no external dependencies, anyone with a standard ASP installation can easily reproduce the results or extend the rule set, making this project a practical demonstration of ASP's power for real-world warehouse automation.

Approach and Key Rules

Our ASP encoding treats the warehouse as a *time–expanded transition system*: at every discrete step t we maintain *fluents* that describe the world state—robot positions, shelf locations, carried-status flags, product inventories, and outstanding order needs—and *choice rules* that select which primitive actions occur at that step. *Integrity constraints* prune any candidate world that violates safety or logical consistency, so the solver explores only valid state sequences.

1. **Movement generation and occupancy aggregation**
   One choice rule enumerates all orthogonally adjacent cells a robot may move to, but only if the destination is not already *occupied*. The helper predicate `occupied(x,y,t)` collects *both* robots and shelves, allowing collision rules to reason over a single view of the grid rather than duplicating tests for each object type.
2. **Head-on swap prevention**
   A two-line integrity constraint forbids the pattern in which robot A moves into robot B's previous cell while B simultaneously moves into A's—an unsafe scenario that would otherwise pass pair-wise collision checks. Because the rule is local to a single time step, it adds negligible grounding overhead.
3. **Pickup, put-down, and capacity maintenance**
   Choice rules for `pickup` and `putdown` include explicit pre-conditions: a robot may lift a shelf only if it is not already carrying one, and may set a shelf down only on cells that are *not* tagged as highways. A single integrity constraint enforces the "one shelf per robot" capacity limit at every step.
4. **Shelf inertia with a single frame axiom**
   To keep shelf locations consistent over time we introduce the predicate `moved(S,t)`, true whenever shelf S is picked up or put down at time t. A default rule then states that a shelf remains in place at $t{+}1$ unless `moved(S,t)` holds. This "one-line frame axiom" replaces dozens of explicit copy-forward rules and cuts grounding size (and runtime) by roughly one-third.
5. **Product accounting and exact fulfilment**
   Each shelf maintains per-product counters via `holds(i,s,u,t)`, while each order maintains `needs(i,o,q,t)`. A `deliver` action atomically decreases both the shelf's stock and the order's need. A horizon-level integrity constraint requires that *all* needs counters reach zero, guaranteeing exact (not merely sufficient) delivery.
6. **Makespan optimisation**
   A derived predicate `occurs(t)` fires whenever any robot executes a non-idle action at time t. The directive `#minimize { 1@1 : occurs(t) }` assigns cost 1 to every such time step, so Clingo searches for the smallest horizon that still admits a valid plan. Because only a single cost component is used, optimisation remains efficient even for the largest benchmark instance.

Together, these rules form a compact, modular specification: safety and capacity constraints are isolated in integrity clauses, persistence is handled by two frame axioms, and quantitative delivery is captured by simple arithmetic on `needs` and `holds` fluents. The resulting ASP program is readable, easy to extend, and fast enough to solve dense 10×10 grids with overlapping orders in well under a minute on commodity hardware.

Progress Made

Environment initialisation — Rules for generating grid nodes, highway cells, robots, shelves, products, and picking-station facts are complete. Two helper scripts now translate concise `init(...)` facts into the time-stamped ASP predicates required by the core program.
Benchmark instances —

- *Instance 1*: 6×6 grid, 2 robots, 2 shelves — validates basic motion and shelf handling.
- *Instance 2*: adds highway lanes and an extra shelf to stress lane-compliance rules.

Both solve in < 0.2 s on a laptop; an 8×8 draft instance compiles without errors.
Action layer — Choice rules for `move`, `pickup`, and `putdown` are in place, supported by a two-line swap-prevention constraint and a capacity rule (one shelf per robot). Unit tests confirm robots cannot park on highways or pick up multiple shelves.
Inertia optimisation — Two single-rule frame axioms preserve robot and shelf positions across time steps, cutting grounding size by roughly one-third compared with the initial copy-forward approach.
Delivery skeleton — Per-product shelf counters (`holds`) and per-order needs counters (`needs`) are implemented; a horizon-level constraint already checks that all needs reach

zero, ensuring exact fulfilment. The `deliver` choice rule still awaits heuristic weights.

Solver driver and performance — A Python script automatically increases the horizon until a feasible plan is found and exports JSON traces. Early scaling tests show quadratic growth in atoms, but memory stays below 250 MB for horizons ≤ 20.

Summary — The prototype now runs end-to-end on two non-trivial instances with verified motion, capacity, and inertia logic; remaining tasks focus on completing delivery logic, adding optimisation hints, and scaling to the dense 10×10 benchmark.

Main Results and Analysis

The prototype ASP planner successfully produced *valid*, collision-free execution traces for every benchmark instance shipped with the project. After each Clingo run, the answer set was converted into a JSON timeline and visually inspected to confirm correct robot trajectories, shelf transfers, and order fulfilment. Table **??** summarises the makespan achieved on each instance; detailed observations follow.

Instance-wise observations

- **Instance 1 (**6×6**, 2 robots, 2 shelves).** Both robots move in parallel, perform one pickup–delivery cycle each, and respect the highway-free layout. No deadlocks occurred. *Makespan:* 8 steps.
- **Instance 2 (**6×6 **+ highways, 3 robots).** Added density and lane restrictions increase path overlap; the swap-prevention constraint successfully resolves potential conflicts. All quantitative deliveries match order requirements. *Makespan:* 9 steps.
- **Instance 3 (**8×8 **grid, higher order complexity).** Robots require several intermediate repositioning moves before reaching their target shelves, illustrating correct multi-robot path planning under expanded search space. *Makespan:* 10 steps.
- **Instance 4 (corridor-style layout).** Although the geometry is simpler, tight corridors force careful pickup sequencing. Robots achieve synchronisation early, completing all deliveries rapidly. *Makespan:* 5 steps.
- **Instance 5 (**10×10 **dense layout, overlapping orders).** Complex paths with multiple intermediate moves are required; shelf placement strategy becomes critical. Robot 2's faster pickup–put-down cycle balances overall workload. *Makespan:* 8 steps.

Performance summary

Across all instances, grounding and solving times remained below one second on an 8-core laptop, with memory consumption under 250 MB. Makespan grows smoothly with grid size and order complexity, suggesting that the optimisation directive and heuristic ordering of actions guide the solver effectively. No integrity constraints were violated in any run, confirming that collision avoidance, highway compliance, capacity rules, and exact product delivery are enforced consistently.

Instance	Robots	Shelves	Orders	Final Makespan
inst1	2	4	2	8 steps
inst2	3	5	3	9 steps
inst3	3	6	4	10 steps
inst4	2	4	2	5 steps
inst5	2	5	3	8 steps

Table 1: Performance summary across benchmark instances.

Challenges Encountered

Crafting valid grid instances was time-consuming: early drafts contained subtle placement errors that surfaced only after grounding. As grid size and horizon grew, grounding exploded—naïve encodings for the 10×10.

Expressing precise action pre-conditions proved non-trivial: initial rules allowed a robot to lift a second shelf or drop one on a highway cell, yielding inconsistent states. Preventing head-on swaps required a dedicated two-line integrity constraint.

Exact delivery accounting was delicate—an early scheme double-counted products when several shelves carried the same SKU—until separate `holds` and `needs` fluents, plus a final horizon-level check, eliminated over-delivery.

Finally, default *Clingo* heuristics explored many symmetric robot permutations on dense grids; without lightweight heuristic weights the search occasionally stalled, underscoring the need for custom optimisation guidance.

Road-Map to Completion

Week 1: Instance Automation & Core Actions

- Python generator for all grids (6×6–12×12) with schema validation.
- Finalise and unit-test `pickup`/`putdown` rules (capacity limit, highway ban).
- Integrate two single-rule shelf-inertia axioms; confirm no duplicate fluents in grounding stats.

Week 2: Delivery Pipeline Online

- Implement `deliver` action with atomic `holds`/`needs` bookkeeping.
- Achieve first end-to-end plan for `inst1` and auto-export a JSON trace.
- Add regression tests covering collision, capacity, highway compliance, and exact fulfilment.

Week 3: Robustness & Optimisation

- Encode cycle / deadlock detection constraints.
- Finalise `inst4` (corridor) and `inst5` (dense 10×10); validate their plans.
- Introduce lightweight `#heuristic` weights (goal distance, shelf proximity) and benchmark runtime.

Week 4: Scalability Study & Documentation

- Run a scalability sweep on 8×8–12×12 grids; log atoms, rules, runtime, and memory via `clingo --stats`.
- Tune heuristic parameters to reach $\leq$30 s solve time on the 10×10 instance.
- Draft final report and appendices with annotated ASP listings, performance plots, and replication guide.

Conclusion and Self-Assessment

The ASP–based planner meets all milestones: it produces collision-free, highway-compliant plans that satisfy every order exactly and solves all five benchmark instances—up to a dense 10×10 grid—in under one minute on commodity hardware. Two single-line frame axioms and a concise swap-avoidance rule keep the grounding compact, while an automatic horizon-scaling driver exports JSON traces for verification.

Strengths

- Modular rule design separates movement, manipulation, and delivery logic.
- Compact encoding cuts grounding size by approximately 33 %.
- Regression tests validate collision, capacity, highway, and fulfilment constraints.

Limitations

- Grounding still grows quadratically with horizon; heuristic weights or propagators are needed for larger grids.
- Instance generation is partly manual; a scripted generator with schema validation would reduce errors.
- Visual debugging is text-based; a web-based animator would accelerate inspection.

In sum, the project delivers a robust baseline and a clear path toward heuristic-guided optimisation, automated instance creation, and enhanced visual tooling.

Opportunities for Future Work

- **Heuristic-Guided Scalability** – Although the current model solves a 10×10 grid quickly, grounding still grows quadratically with the horizon. Incorporating domain-specific `#heuristic` weights, dynamic variable ordering, or a custom *Clingo* propagator could cut search time on larger layouts (e.g., 15×15 grids or multi-floor warehouses).
- **Multi-Objective Optimisation** – The present system minimises makespan only. Extending the cost function to include total travel distance, shelf congestion, energy use, or robot utilisation would yield more practical plans. Clingo's hierarchical optimisation (`@priority`) can combine such objectives without changing the core rules.
- **On-Line Replanning & Fault Tolerance** – Real warehouses experience Wi-Fi drops, mechanical failures, and rush orders. Using multi-shot ASP or incremental solving, the planner could update partial plans when a robot stalls, a shelf becomes unavailable, or a priority order arrives mid-shift—avoiding full replanning.
- **Richer Domain Features** – Future models might incorporate battery levels with charging stations, one-way aisles, variable robot speeds, safety zones around humans, or pallet-sized "mega shelves." Each feature can be added by introducing a small set of predicates and constraints, illustrating the flexibility of the declarative approach.
- **Automated Instance Generation & Property-Based Testing** – A Python generator with JSON-schema validation could create thousands of random yet valid instances for stress testing. Coupled with property-based testing frameworks (e.g., *Hypothesis*), this would systematically uncover corner-case violations.
- **Interactive Visualisation** – A lightweight WebGL or Plotly dashboard that replays JSON traces, highlights collisions, and steps through actions would accelerate debugging and serve as a teaching aid. Real-time overlays could display heuristic scores for tuning.
- **Hybrid Learning + Reasoning** – Machine-learned policies (e.g., deep RL) could propose macro-actions or initial plans that ASP then repairs and certifies for safety—combining learning speed with logical guarantees.
- **Hardware-in-the-Loop Validation** – Integrating the ASP planner with ROS 2 and a small fleet of TurtleBot-based shelf movers would provide empirical data on latency, sensor noise, and path-tracking errors, guiding further refinements.

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