LLMs and Optimization

AI is a label applied to almost everything these days, often without much care or precision. Sometimes “AI” is a fresh coat of paint to reinvent well-proven computational methods. And sometimes “AI” is synonymous with truly new technologies like large language models (LLMs; chatbot tools like ChatGPT). Since its beginning, NSIP-Genetics has used the full spectrum of new and proven computational technologies to improve the decisions and processes of plant breeding. One particularly effective combination is the paring of LLMs with optimization.

LLMs are most useful where uncertainty is linguistic and contextual. They can ingest unstructured inputs—emails, trial notes, trait definitions, and policy language—and translate them into structured artifacts: candidate requirements, draft design specifications, scenario assumptions, mathematical formulations, and flags for missing or conflicting information. They also support downstream communication by converting solver outputs into plain-language explanations, drafting scenario narratives, and generating the next set of questions that improve model definition. That said, while they can translate problem definitions into mathematical formulations, they are not a certification layer; they can suggest, summarize, and translate, but they do not verify the model is valid or solvable.

Optimization becomes most valuable once the question is sufficiently defined to compute. When constraints interact in complex ways, when feasibility is non-negotiable, and when tradeoffs must be made explicit, solvers provide the disciplined backbone: they determine whether feasible solutions exist, identify optimal solutions when they do and provide repeatability, and transparent marginal tradeoffs. Under uncertainty, the goal is often not a single point solution but robustness—plans that remain acceptable across plausible scenarios, portfolios that balance performance and risk, and sensitivity analyses that identify which assumptions drive outcomes. Equally important, optimization provides an auditable record of the decision: what was enforced, what was traded off, and which limits were binding.

Together, these approaches form an efficient and stable feedback loop. The LLM proposes requirements, scenarios, data checks, and even model formulations; the optimizer computes feasible decisions and tradeoff frontiers; and the LLM then explains the drivers of the result and proposes targeted refinements (e.g., tighten a threshold, relax a bottleneck, add a scenario) for the next run. Over time, teams spend less effort hand-coding brittle formulations and more effort improving what increases robustness: clearer definitions, cleaner data, and stronger governance around how decisions are made. In this approach, LLMs do not replace optimization; they make it more adaptive under uncertainty while preserving mathematical discipline where it matters.

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