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Original Research Article

Smart Factory Capacity Optimisation for Olive and Tomato-Paste Manufacturing in Saudi Arabia under Vision 2030: A Data-Driven Production Planning Framework

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Abstract: Saudi Arabia is expanding domestic food production while seeking higher industrial productivity, resource efficiency and resilience under Vision 2030. Olive and tomato processing are strategically relevant because both depend on seasonal agricultural inflows, time-sensitive quality preservation and capacity-constrained thermal, separation and packaging operations. This review develops a data-driven production planning framework for smart-factory capacity optimisation in Saudi olive and tomato-paste manufacturing. The study synthesises literature published from 2020 to 2025 on food-process control, digital twins, Industry 4.0, predictive maintenance, production scheduling and process analytical technologies, complemented by official Saudi agricultural and industrial evidence. The review distinguishes nominal equipment capacity from effective, quality-constrained and utility-constrained capacity, and shows why seasonal factories require planning models that jointly represent raw-material arrivals, product deterioration, changeovers, sanitation, equipment condition, energy and water availability, yield uncertainty and market demand. The proposed framework combines industrial sensing, manufacturing execution data, short-horizon forecasting, digital-twin simulation, finite-capacity scheduling and feedback from advanced process control. It recommends a rolling planning architecture in which forecasted olive and tomato arrivals are converted into feasible campaigns, bottlenecks are protected by predictive maintenance, and process set-points are coordinated with throughput and quality targets. For Saudi manufacturers, the framework links local agricultural scale with industrial localisation by prioritising interoperable data, measurable overall equipment effectiveness, seasonal scenario planning and staged investment rather than technology acquisition without an operating model. The review concludes that smart capacity optimisation can increase usable throughput, reduce avoidable losses and improve resource productivity, but only when planning, process control, maintenance and quality decisions are integrated around a common data model.

Keywords: Smart Factory, Capacity Optimisation, Olive Processing, Tomato Paste, Production Planning, Digital Twin, Predictive Maintenance, Saudi Arabia, Vision 2030.

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1. INTRODUCTION

Food manufacturing capacity is often described as a fixed technical property of equipment, yet seasonal agro-processing shows why that interpretation is incomplete. A plant may possess sufficient installed tonnes-per-hour capacity and still lose substantial output because raw materials arrive unevenly, process yields vary, cleaning windows interrupt the line, a critical evaporator or separator becomes unavailable, or downstream filling cannot absorb upstream flow. In tomato-paste and olive processing these losses are particularly consequential because harvested materials deteriorate while waiting. The managerial problem is therefore not simply to increase installed capacity, but to convert available assets, labour, utilities and raw materials into stable saleable output at the required quality. Recent food-processing research demonstrates that sensor-based monitoring, advanced control and digital integration can improve process visibility and responsiveness [1-4]. Evidence from continuous-flow thermal processing further shows that adaptive predictive control can reduce settling time and improve energy conversion without materially increasing electrical consumption, illustrating how control quality can influence effective production capacity rather than only product temperature [1-4].

The relevance of this issue is increasing in Saudi Arabia. Official agricultural statistics for 2024 report that greenhouse tomato production reached about 329 thousand tonnes, while olive trees were the largest perennial crop by tree count, with about 21.5 million trees and approximately 351.7 thousand tonnes of production [29]. These figures do not imply that all production is destined for industrial paste or oil, but they demonstrate a substantial domestic feedstock base whose value depends partly on post-harvest handling and processing capability. At the same time, national industrial policy is promoting a larger and more technologically capable food-manufacturing base, with the Ministry of Industry and Mineral Resources identifying food industries as a targeted cluster within the Kingdom's industrial transformation [30]. Capacity planning for olive and tomato products therefore sits at the intersection of agricultural value preservation, local manufacturing, food security, resource productivity and industrial diversification.

Conventional planning approaches can perform poorly in this setting because they usually separate strategic capacity decisions, monthly production planning, daily scheduling, maintenance and process control. A monthly plan may assume a line rate that is technically possible but operationally unrealistic after sanitation, product changeovers, variability in soluble solids, equipment fouling, labour constraints and utility peaks are included. Daily scheduling may then compensate through overtime or excessive buffer stocks, while process operators independently alter temperatures, flow rates or residence times to protect quality. The result is a recurring gap between nominal and realised capacity. Literature on smart manufacturing scheduling argues that digital production environments should continuously incorporate current system states rather than treat schedules as static instructions [27, 28]. Digital-twin research similarly emphasises the value of synchronising physical conditions and virtual models so that planning can respond to disturbances [16-26].

This review addresses that gap by focusing on the factory as a coupled planning-and-control system. Its aim is to develop a practical data-driven framework for optimising usable capacity in Saudi olive and tomato-paste manufacturing under seasonal and operational uncertainty. The objectives are to: identify the principal capacity constraints across both process chains; examine how sensing, advanced control, digital twins, predictive maintenance and production scheduling contribute to capacity decisions; define a finite-capacity planning logic that incorporates perishability, quality, utilities and equipment condition; and propose an implementation pathway consistent with Saudi industrial development. The contribution is deliberately integrative. Rather than treating smart-factory technologies as independent upgrades, the review positions them as coordinated decision layers that convert agricultural variability into executable production plans and measurable operating performance.

2. REVIEW METHODOLOGY

A structured integrative review was used to combine engineering evidence from food processing with literature on smart manufacturing, scheduling and maintenance. The publication window was restricted to 2020-2025 to maintain technological relevance. Searches were organised around four concept groups: food processing and thermal or separation control; digital twins and smart-factory architectures; production planning, scheduling and capacity optimisation; and predictive maintenance or process analytics. Additional terms were used for olives, table olives, olive oil, tomatoes, tomato sauce, perishability, energy efficiency, manufacturing execution and Saudi Arabia. Peer-reviewed journal articles were prioritised, while official Saudi statistical and industrial sources were retained for context where journal literature could not provide authoritative national production or policy information. The literature search covered major academic databases including Scopus, Web of Science, ScienceDirect and Google Scholar. Studies were included where they addressed smart manufacturing, food-processing capacity, digital twins, production scheduling, predictive maintenance or related operational-performance measures within the 2020–2025 publication window. Studies with limited relevance to industrial capacity decisions or insufficient methodological detail were excluded.

Selection favoured studies that contributed directly to at least one decision layer of the proposed framework. Process-control papers were retained when they quantified dynamic response, energy use, temperature stability or industrial implementation [1-15]. Digital-twin and food-digitalisation studies were included when they addressed real-time data integration, simulation, process monitoring, virtual commissioning, product quality or scheduling [16-26]. Manufacturing-planning studies were retained for finite-capacity scheduling, dynamic rescheduling, integration of planning and execution, or Industry 4.0 decision requirements [22-28]. Predictive-maintenance reviews were included because equipment health changes the capacity that should be promised to a production plan [23, 24]. Thirty sources were selected for direct citation and were analysed through thematic synthesis rather than statistical meta-analysis, since the evidence spans heterogeneous process technologies, performance indicators and research designs.

The synthesis used four analytical questions. First, what physical or organisational mechanisms constrain throughput in seasonal food factories? Second, which variables can be observed early enough to support a planning decision? Third, which digital or optimisation method can convert those observations into a feasible capacity response? Fourth, which outcome should demonstrate that the intervention improved resilience rather than merely adding technology? This structure follows the engineering emphasis of Javed *et al.*, [1], where real-time measurements, controller architecture and comparative performance metrics are explicitly connected to process outcomes., where real-time measurements, controller architecture and comparative performance metrics are explicitly connected to process outcomes [1]. The present review extends that logic from an individual heating operation to plant-wide production planning.

3. Capacity Characteristics of Olive and Tomato-Paste Manufacturing

Olive and tomato-paste factories share a common planning problem: a large quantity of biological raw material must be processed within a limited seasonal window, but the two product families place different loads on equipment and utilities. For olives, capacity may be constrained by receiving, washing, crushing, malaxation, centrifugation, filtration, fermentation or packaging depending on the finished product. Raw-fruit condition, maturity and foreign material can change effective processing rates and yields. The growing interest in process analytical technology for table olives reflects the need for faster, objective measurements of fermentation and quality state instead of delayed laboratory-only control [21]. Broader food-digitalisation literature likewise links throughput improvement with resource productivity and waste reduction [18, 19]. A plant that pushes line speed beyond the capability of separation, cleaning or by-product handling can appear productive while actually reducing yield or creating downstream instability.

Tomato-paste manufacturing is dominated by a different bottleneck profile. Fresh tomatoes typically pass through reception, washing and sorting, crushing or pulping, thermal treatment, refining, evaporation, sterilisation and aseptic filling. Capacity is strongly influenced by incoming soluble solids, viscosity, fouling tendency, evaporator duty, steam availability and filling capacity. Heating and concentration stages therefore couple mass throughput to energy demand. Research on ohmic and advanced thermal processing shows that food properties, conductivity, flow and controller design materially affect heat transfer, response time and quality [2-15]. Although a tomato-paste plant may use conventional evaporation rather than ohmic heating, the broader lesson is transferable: process dynamics determine how safely and consistently rated equipment capacity can be used.

The study by Javed *et al.*, [1], provides a useful micro-level illustration. A continuous-flow ohmic heater was operated with PID, model predictive and adaptive model predictive controllers. The adaptive controller reached the target band faster than the alternatives and produced the lowest temperature error, while steady-state energy efficiency was reported at approximately ninety percent [1]. These results should not be interpreted as a direct tomato-paste capacity benchmark because the equipment and product differ. They nevertheless demonstrate an important planning principle: when a critical process can reach and maintain its operating target more quickly and with less deviation, the effective productive window expands and the need for conservative buffering can fall. Process control thus becomes an input to capacity planning rather than a separate automation concern.

Table 1: Capacity characteristics and planning variables for olive and tomato-paste manufacturing

Planning dimension	Olive manufacturing	Tomato-paste manufacturing	Capacity implication
Raw-material variability	Maturity, cultivar, moisture, grade, foreign material	Soluble solids, viscosity, temperature, defect level	Nominal tonnes/hour must be adjusted for material burden and quality
Likely bottlenecks	Receiving, crusher, malaxer, decanter, filtration/fermentation, packaging	Sorting, pulping, thermal treatment, evaporator, steriliser, aseptic filler	Protect the dominant constraint; avoid uncontrolled upstream queues
Seasonal exposure	Compressed harvest and product-route variability	High-volume harvest with rapid deterioration risk	Use rolling arrival forecasts and peak-week scenarios
Utility dependence	Water, power, cleaning, separation energy	Steam, electricity, cooling, water, cleaning	Apply time-bucket utility ceilings in finite schedules
Quality-adjusted output	Extraction yield, acidity, sensory/fermentation indicators	Brix, colour, viscosity, microbial and packaging conformance	Optimise saleable output, not gross processed tonnes
Planning levers	Campaigning, shift flexibility, route allocation, maintenance windows	Campaigning, evaporator loading, filler sequence, maintenance windows	Coordinate planning, maintenance and process-control constraints

A second distinction is between gross throughput and saleable throughput. Food factories can maximise tonnes processed yet perform poorly if yield loss, rework, off-specification batches, excessive heat exposure or packaging defects rise. The relevant capacity metric should therefore be quality-adjusted good output. Studies of ohmic processing across dairy, fish, rice, fruit and other products consistently emphasise the interaction between heating method, microbial objectives, energy consumption and product quality [5-15]. This supports a capacity model in which a production rate is feasible only if required quality and safety constraints remain satisfied. In practice, each major unit operation should have a feasible operating envelope rather than one fixed maximum rate.

Seasonality adds a third dimension. When harvest arrivals exceed processing capacity, waiting time can destroy the very value that capacity investment is intended to protect. Yet building assets for the absolute harvest peak can produce low annual utilisation. The planning problem is therefore a trade-off among peak intake, buffer design, flexible shifts, campaign sequencing, storage possibilities, maintenance timing and acceptable loss. For Saudi conditions, the availability of substantial tomato and olive production [29], increases the value of scenario-based planning that distinguishes average-season, peak-week and disruption cases. A smart-factory architecture should make these scenarios operational by updating expected arrivals and effective line capacity throughout the season rather than relying on one static annual assumption.

4. Smart-Factory Data Architecture for Capacity Decisions

The first requirement for data-driven capacity optimisation is a reliable representation of the current factory state. Food-processing reviews identify smart sensors, industrial connectivity, machine data, automation, artificial intelligence and big-data analytics as central enablers of connected processing [12-19]. For capacity planning, however, the value of these technologies depends on whether they answer a specific operational question. Useful raw-material data include expected harvest volume, delivery appointments, fruit temperature, grade, soluble solids, moisture or maturity indicators. Useful equipment data include run state, cycle time, flow, temperature, pressure, power, vibration, cleaning status and fault alarms. Useful planning data include orders, inventory, packaging availability, labour, quality release status and maintenance windows. The objective is not maximal data collection; it is a consistent state model that explains how much good output can be produced in each future time bucket.

Data integration should connect four time scales. At the fastest level, control and sensor data describe seconds-to-minutes process behaviour. At the shift level, manufacturing execution records describe downtime, speed loss, quality loss, changeovers and labour constraints. At the daily or weekly level, planning data describe arrivals, demand, inventory, campaigns and maintenance. At the seasonal level, management evaluates capacity adequacy, outsourcing, storage, investment and supplier coordination. Digital food-twin research argues that value increases when these layers are connected rather than maintained as isolated models [16-20]. A twin does not need photorealistic graphics; its essential function is to maintain a sufficiently faithful, continuously updated representation for the decision being made [25, 26].

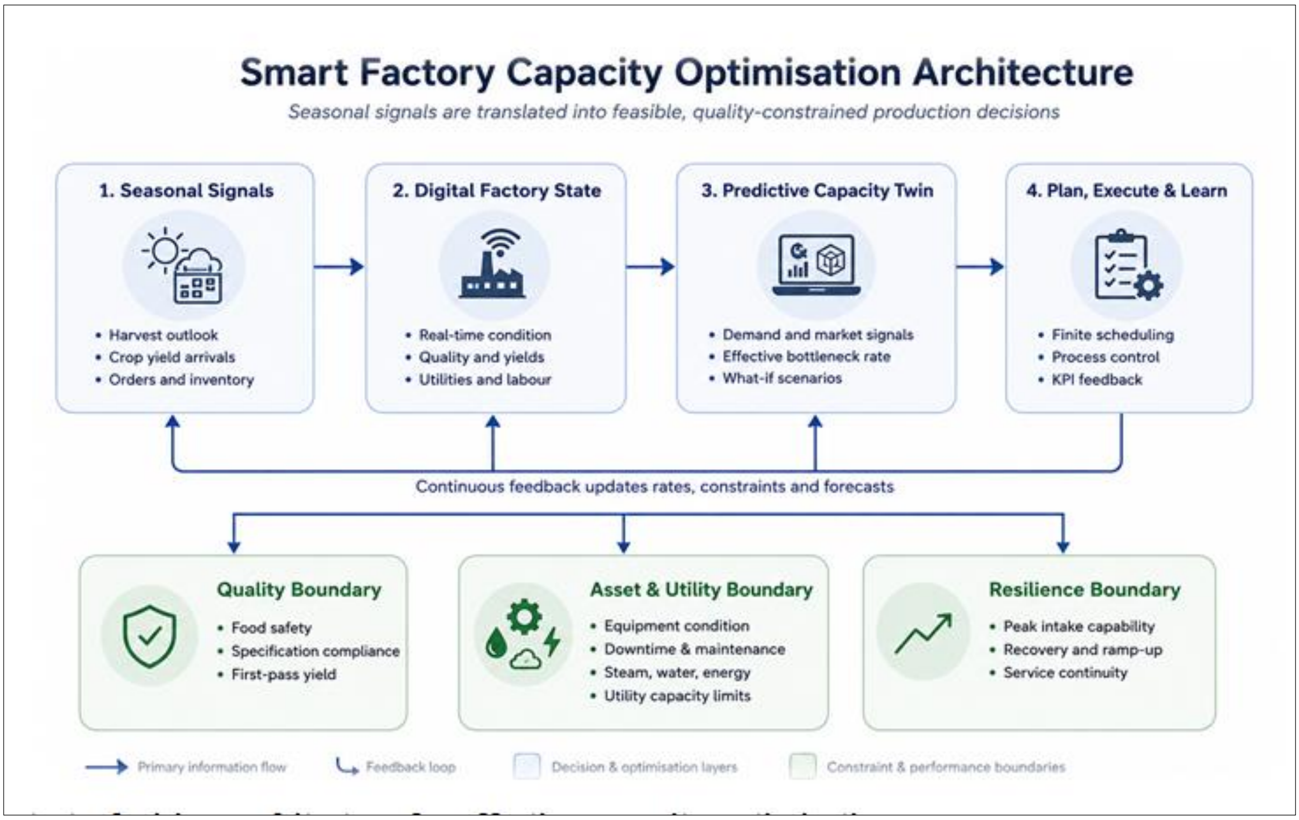

Figure 1: Data-to-decision architecture for effective capacity optimisation

For olive and tomato plants, the most useful digital twin is therefore a capacity twin rather than a decorative virtual factory. It should estimate the feasible throughput of each critical resource under current material properties, equipment condition, operating set-points and utility limits. It should also represent queues and intermediate storage, because a downstream bottleneck can invalidate an upstream schedule even when every machine individually appears available. Digital-twin studies in food and manufacturing emphasise simulation, what-if analysis and bidirectional data exchange as routes to better operational decisions [16-26]. These capabilities are particularly important during harvest peaks, when decisions must be revised faster than conventional planning cycles.

The architecture also requires data governance. Production models fail when timestamps are inconsistent, product identifiers differ across systems, sensor values are uncalibrated, or downtime reasons are recorded differently by each shift. A minimum common data model should define equipment hierarchy, product and recipe identifiers, batch genealogy, units of measure, downtime categories, quality states and time synchronisation. Process analytical technology in the olive sector reinforces the importance of trustworthy in-process measurement [21]. Similarly, Javed *et al.*, [1], demonstrate the importance of calibrated flow and power relationships and validated temperature measurements before advanced controllers are deployed.and validated temperature measurements before advanced controllers are deployed [1-4]. Smart capacity planning should adopt the same discipline: optimisation should never be built on unverified operational data.

5. Data-Driven Production Planning Framework

The proposed framework operates as a rolling decision loop with five linked stages: forecast, translate demand and arrivals into required capacity, construct a finite-capacity schedule, execute through coordinated process control, and update the next plan from measured performance. Figure 1 summarises the data-to-decision architecture, while Figure 2 presents the recurring operating loop. The central design principle is that capacity is a state variable that changes with product characteristics, asset condition and constraints. This differs from conventional enterprise planning, where resource rates are often fixed master-data values. Smart manufacturing scheduling literature supports dynamic rescheduling when new shop-floor information or disturbances change the feasibility of the existing plan [22-28].

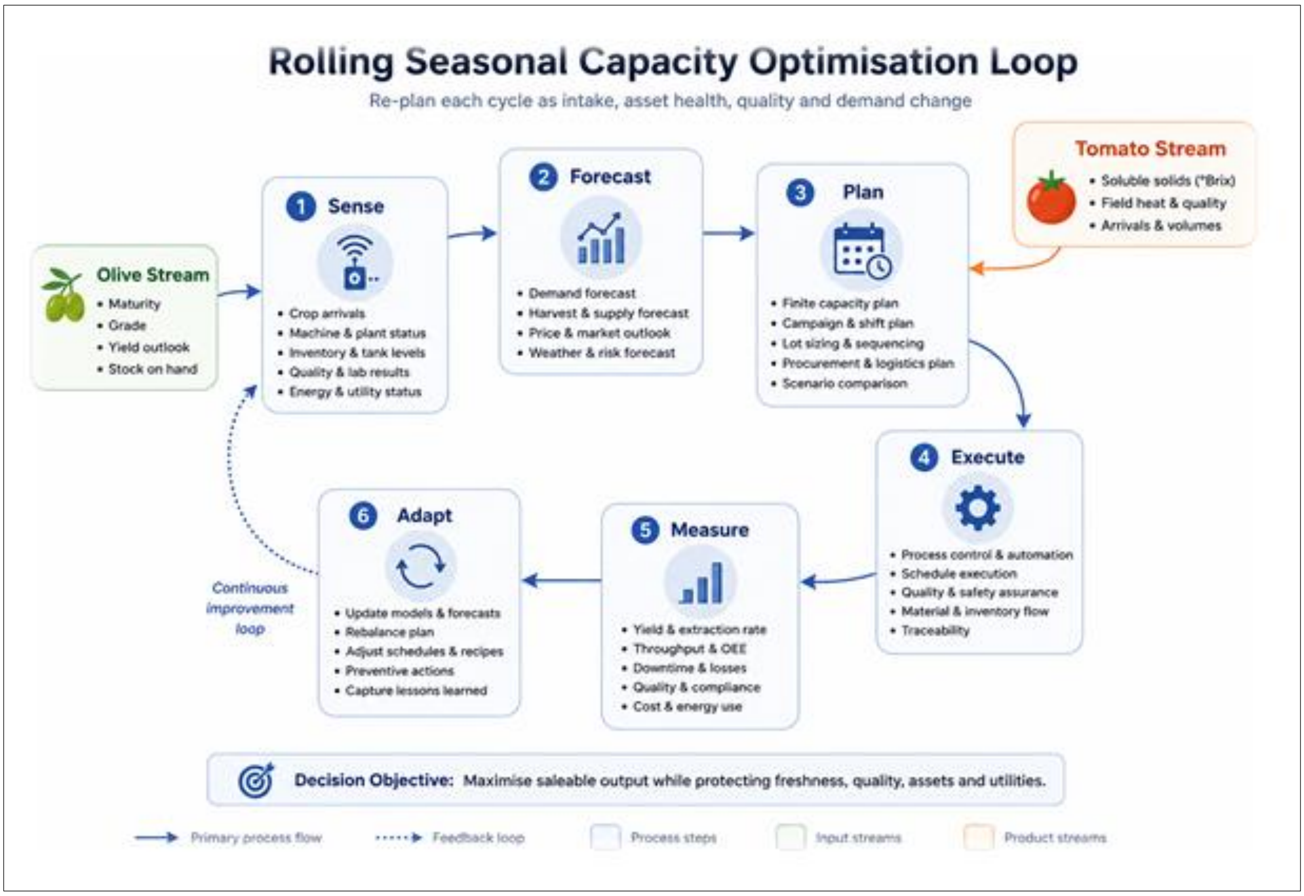

Figure 2: Rolling seasonal planning loop for olive and tomato-paste operations

The forecasting layer should separately predict market demand and raw-material availability. For seasonal crops, a single sales forecast is insufficient because the factory cannot manufacture without a timely physical harvest. The arrival forecast should combine supplier commitments, historical harvest curves, farm location, weather or agronomic indicators where available, and actual deliveries received. Forecast uncertainty should be preserved as ranges rather than collapsed into a single point. This allows planners to prepare a base schedule plus high-arrival and low-arrival variants. In tomato processing, incoming soluble solids should also be forecast because concentration load depends on the water that must be removed. In olive processing, expected grade, maturity and product route influence line allocation and yield. The planning system should consequently forecast both tonnes and conversion burden.

The second layer converts those forecasts into capacity demand. For each product family, standard routing times are adjusted using current performance factors. A practical formulation is effective capacity equals nominal rate multiplied by availability, speed and first-pass-quality factors adds material and utility modifiers that are important in food processing, then constrained by utilities, labour and sanitation windows. This resembles the logic of overall equipment effectiveness but adds material and utility modifiers that are important in food processing. If an evaporator normally handles a given feed rate but steam supply is limited or incoming tomato solids are below expectation, its capacity promise should fall before the schedule is released. Likewise, if olive-line yield deteriorates or filtration becomes restrictive, upstream intake should be moderated rather than allowing queues to grow invisibly.

Effective Capacity = Nominal Capacity × Availability × Performance × First-Pass Quality × Material Adjustment

The third layer is finite-capacity scheduling. Its objective is not merely to meet orders; it should minimise a weighted combination of raw-material waiting, late demand, changeover time, overtime, utility peaks, quality risk and avoidable waste. Constraints include line eligibility, batch size, sequence-dependent cleaning, intermediate storage, labour, maintenance and maximum waiting time for sensitive raw materials. Research on production planning in Industry 4.0 increasingly favours integrated and responsive approaches because static planning cannot capture frequent disturbances [27, 28]. Digital-twin-driven scheduling further shows how a virtual state can support rapid rescheduling after breakdowns, quality holds or new orders [22]. For seasonal food factories, the optimisation horizon should be short enough to use credible arrival information but long enough to coordinate campaigns and maintenance, for example a rolling several-day horizon updated each shift.

Campaign sequencing is especially important. Tomato products may differ by concentration, recipe, packaging format or quality specification, while olive products may follow different fermentation, oil or table-olive routes. Frequent switching can consume cleaning time, increase start-up losses and destabilise thermal systems. The scheduler should therefore cluster compatible products when demand permits, but not at the expense of excessive raw-material waiting or finished-goods inventory. This creates a classic trade-off between manufacturing efficiency and freshness. A useful rule is to protect the bottleneck first: sequence upstream operations so that the bottleneck receives stable feed, and sequence downstream packaging so that bottleneck output is not blocked. The digital twin can test alternative campaigns before the schedule is released [16-22].

Table 2: Smart-factory capabilities mapped to capacity decisions and evidence

Capability	Primary planning role	Representative data/KPI	Implementation risk
Industrial sensing and execution data	Expose real equipment state and losses	Flow, temperature, downtime, yield, cleaning, energy	Uncalibrated sensors and inconsistent event coding
Forecasting analytics	Estimate arrivals, demand and material burden	Forecast error, arrival range, soluble solids, grade	False precision during unusual harvest conditions
Capacity digital twin	Test bottlenecks and what-if scenarios	Effective rate, queue length, constraint utilisation	Model becomes stale if master data are not updated
Finite-capacity scheduling	Sequence campaigns under real constraints	Schedule adherence, waiting time, changeovers	Optimiser ignores practical sanitation or labour rules
Advanced process control	Maintain quality-safe throughput envelopes	Settling time, error, energy/tonne, process stability	Aggressive rates can amplify quality or fouling risk
Predictive maintenance	Protect time-dependent capacity availability	Health index, downtime risk, maintenance accuracy	Alerts are not translated into schedule decisions
Integrated management dashboard	Balance throughput, quality, resilience and resources	Good tonnes, service, yield, OEE, utilities/tonne	Single KPI optimisation hides cross-functional trade-offs

The fourth layer connects the schedule with advanced process control. Process-control literature shows that predictive and adaptive controllers can manage multiple objectives and respond to changing plant conditions more effectively than fixed single-loop approaches in suitable applications [1-14]. At plant level, this means the scheduler should not issue an aggressive line rate without considering whether the control system can maintain quality at that rate. Conversely, measured controller performance can justify increasing the effective rate when the process remains stable. For tomato thermal operations, relevant feedback includes temperature error, residence time, energy per tonne, fouling indicators and product-quality measurements. For olive operations, feedback may include throughput, separation efficiency, extraction yield, fermentation indicators or in-line quality signals. The planning and control layers should exchange limits rather than operate independently.

The fifth layer integrates maintenance. Predictive-maintenance research consistently identifies condition monitoring and data-driven failure prediction as mechanisms for reducing unplanned downtime and improving asset availability [23, 24]. For capacity planning, the important output is not simply a failure probability; it is a time-dependent capacity risk. If a critical pump, decanter, evaporator, filler or boiler shows deterioration, the scheduler should either reserve a maintenance window, reduce promised capacity or shift production to an alternative resource. Maintenance should be preferentially placed outside forecast harvest peaks, but condition evidence may justify intervention even during a busy period when the expected loss from failure exceeds planned downtime. This converts predictive maintenance from a maintenance department tool into a production-planning input.

Quality and utility analytics complete the framework. Water, steam, electricity, compressed air and cooling can become shared bottlenecks even when individual machines have spare capacity. Energy-efficient processing literature demonstrates that controller performance and process technology influence resource conversion [1-14]. The scheduler should therefore enforce utility ceilings by time period and, where tariffs or demand charges matter, avoid creating unnecessary simultaneous peaks. Quality data should similarly define release constraints and yield losses. A high-throughput plan that creates more off-specification paste, oil or packaged product is not a capacity improvement. The preferred objective is maximum saleable output per constrained harvest and resource unit.

6. Performance Measurement and Management Control

A smart capacity framework requires a small set of metrics that connect strategic, planning and shop-floor performance. The first group measures flow: raw-material waiting time, schedule adherence, tonnes processed per hour, bottleneck utilisation and queue duration. The second measures asset effectiveness: availability, performance rate, changeover loss, unplanned downtime and maintenance forecast accuracy. The third measures conversion: first-pass yield, extraction or concentration yield, rework, giveaway and quality holds. The fourth measures resource intensity: kilowatt-hours, steam, water and cleaning chemicals per tonne of saleable output. The fifth measures planning quality: forecast error, rescheduling frequency, late orders and the difference between promised and realised capacity.

Metrics should be interpreted together. Very high bottleneck utilisation can be harmful if it produces longer raw-material queues and greater quality loss. High schedule adherence can be misleading if the schedule was based on conservative rates that underuse assets. Low energy per tonne can be misleading if output quality deteriorates. The review evidence therefore supports a balanced dashboard in which throughput, quality, reliability and resources are treated as coupled outcomes [18-24]. For seasonal factories, metrics should also be segmented by harvest phase because performance during ramp-up, peak and tail periods may differ substantially. This segmentation helps distinguish structural capacity problems from temporary start-up learning or raw-material effects.

7. Saudi Vision 2030 Implementation Pathway

Implementation in Saudi factories should be staged according to decision maturity. Stage one establishes measurement discipline: reliable production counts, downtime reasons, quality yields, utility meters and raw-material arrival records. Stage two connects planning with execution through a manufacturing data layer and standard equipment model. Stage three introduces forecasting, finite-capacity scheduling and condition-based maintenance on the most consequential bottlenecks. Stage four adds simulation or digital-twin capabilities for scenario testing and dynamic rescheduling. Stage five closes the loop by feeding measured process performance back into planning parameters and progressively automating low-risk decisions. This sequence avoids a common failure mode in digital transformation, where sophisticated analytics are purchased before basic data and operational ownership are stable [18-26].

The Saudi context strengthens the business case for this staged approach. Domestic production volumes for tomatoes and olives are material [29], and industrial policy seeks to expand local manufacturing capability and the food-industry cluster [30]. A processor can therefore evaluate digital investment against locally meaningful outcomes: additional tonnes accepted during peak harvest, reduced deterioration before processing, fewer emergency shutdowns, lower energy or water intensity, improved local value addition and more predictable customer service. These measures are more defensible than generic claims about becoming a smart factory. They also support investment prioritisation: the first digital project should target the constraint with the highest economic and resilience impact, not necessarily the newest technology.

From a managerial implementation perspective, smart capacity optimisation should also connect factory scheduling with commercial demand and distribution commitments. In Saudi olive and tomato-paste operations, seasonal intake and production decisions are influenced not only by equipment availability, but also by customer contracts, sales forecasts, inventory positions, channel requirements and local or export delivery windows. Incorporating these commercial signals into the rolling planning loop can help manufacturers prioritise production more effectively, protect critical bottlenecks and reduce both under-utilisation and avoidable overproduction. This integration strengthens the link between smart-factory capacity management and the wider Vision 2030 priorities of food security, local value addition, manufacturing productivity and competitive agri-food growth.

Workforce design is equally important. Planners, operators, maintenance teams, quality specialists and data engineers must share the same definitions of capacity and constraint. Operators should understand why accurate downtime and process-state data affect future schedules; planners should understand that process envelopes and sanitation requirements are not arbitrary restrictions; maintenance teams should express equipment health in terms that production can use. Human oversight remains essential when models confront novel crop conditions, sensor faults or exceptional quality risks. The transition described in Food Industry 5.0 literature reinforces the value of technology that augments human judgement and resilience rather than treating automation as an end in itself [19].

8. DISCUSSION AND RESEARCH GAPS

The literature provides strong evidence for individual technologies but weaker evidence for their combined effect on seasonal plant capacity. Food-process studies often focus on control accuracy, energy efficiency or product quality [1-15], while digital-twin studies focus on architecture, simulation and monitoring [16-26]. Scheduling research concentrates on manufacturing responsiveness [22-28], and predictive-maintenance studies focus on failure anticipation [23, 24]. The operational gap lies between these literatures: few studies quantify how improved control, maintenance prediction and real-time scheduling jointly change the number of saleable tonnes a seasonal food plant can commit to during harvest uncertainty. This is the central research opportunity created by the proposed framework.

A second gap concerns biological variability. Smart manufacturing models are frequently developed for discrete parts whose processing time is comparatively stable. Olive and tomato feedstocks vary by cultivar, maturity, moisture, soluble solids, temperature and storage history. These attributes can change yield, heat load and processing time. Future capacity twins should therefore include material-state variables as first-class model inputs, not only machine states. Process analytical technologies in table olives offer a route toward faster measurement [21], while food digital-twin research provides architectures for combining physical and data-driven models [16-20]. Hybrid models may be particularly suitable because first-principles mass and energy balances can constrain machine-learning predictions when seasonal data are limited.

A third gap is economic evaluation. Many digitalisation studies report technical benefits without showing whether they justify instrumentation, integration, model maintenance and workforce costs. For Saudi manufacturers, the business case should distinguish value from higher annual throughput, value from capturing peak harvest, avoided deterioration, avoided downtime, lower resource intensity and reduced inventory. Some benefits will occur only during a few peak weeks, so annual averages may hide their strategic importance. Future research should compare digital optimisation with physical debottlenecking, extra storage, contract processing and additional shifts. The best decision may combine modest equipment investment with better planning rather than assuming software can overcome a hard physical constraint.

Finally, resilience should be measured explicitly. A capacity system is resilient when it maintains acceptable output and recovery under disruptions such as late harvest arrivals, equipment failure, utility limitation, packaging shortage or sudden demand changes. Digital twins and dynamic scheduling are promising because they allow rapid evaluation of alternative states [20-22], but resilience claims should be tested through scenario experiments. Suitable measures include time to recover the production plan, percentage of harvest accepted, service loss, additional resource cost and quality-adjusted output during the disruption. Such evidence would move smart-factory research from demonstrations of connectivity toward quantified operational value.

9. CONCLUSION

Smart-factory capacity optimisation for olive and tomato-paste manufacturing is fundamentally a coordination problem. Installed equipment capacity becomes economically useful only when raw-material arrivals, process capability, utilities, maintenance, sanitation, labour, quality and demand are converted into one feasible operating plan. The reviewed literature shows that advanced process control can stabilise critical operations, digital twins can represent changing system states, predictive maintenance can protect availability, and dynamic scheduling can revise plans when conditions change [1-28]. The proposed framework integrates these capabilities into a rolling loop that forecasts seasonal inputs, estimates effective capacity, schedules finite resources, executes within validated process envelopes and learns from measured outcomes.

The framework clarifies where physical expansion remains necessary. If simulations show that demand and harvest scenarios exceed feasible bottleneck capacity even after improved scheduling, maintenance and control, managers have evidence for investment. Conversely, where losses arise mainly from variability, poor sequencing or unplanned downtime, digital coordination can recover capacity before new equipment is purchased. This distinction improves capital discipline and aligns technology spending with measurable production constraints and resilience outcomes. This evidence should guide debottlenecking priorities throughout each harvest season and budget cycle.

For Saudi Arabia, this integration is relevant because significant domestic olive and tomato production can support greater local value addition, while national industrial policy is expanding the role of advanced manufacturing [29, 30]. The practical priority is not technology density but decision quality. Manufacturers should begin with trustworthy data and bottleneck metrics, then add forecasting, condition-based capacity estimates, finite scheduling and digital-twin simulation where each layer has a defined operational owner. When implemented in this sequence, smart-factory planning can raise saleable throughput, reduce harvest and process losses, improve resource productivity and strengthen resilience without confusing nominal machine speed with sustainable production capacity.

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