CHEMICAL-TECHNOLOGICAL PRECONDITIONS FOR DIGITAL TWIN IMPLEMENTATION IN POLYMER PROCESSING: A DOCUMENTED TECHNOLOGY BASELINE FROM BULGARIAN PLASTICS

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ABSTRACT

Digital Twin technology is increasingly proposed for polymer processing, yet the chemical-technological conditions that make a twin useful, and the equipment baseline required to build one, are rarely examined together against documented industrial evidence. This paper establishes why polymer processing is a favourable domain for Digital Twin implementation and then tests how far the necessary preconditions are met in a national producing sector. The argument proceeds from polymer physics. Because melt viscosity is strongly shear- and temperature-dependent, and because thermal history governs crystallization, shrinkage and residual stress, a fixed set of machine settings does not reproduce a fixed process state when polymer grade, recycled fraction, moisture content or additive level varies. A twin is valuable in this domain precisely because the state variables that determine part quality cannot be measured directly in production. Against this background, a technology inventory was compiled for a census of 29 Bulgarian plastics manufacturers (NACE 22.2x), of which 20 firms have documented process-level evidence. Extrusion is documented at 13 of the 20 firms, injection moulding at 5 and internal recycling at 4, with thermoforming, coating and blow moulding at 1 - 2 firms each; 7 of the 20 firms disclose named equipment. Sensor-level process instrumentation is documented at no firm, and no firm provides evidence of an ERP, MES or SCADA system, or of a Digital Twin. On the classification applied here, no firm falls in the confirmed Digital Twin category and three fall in the Digital-Twin-ready category. The binding constraint in this sector is therefore not modelling capability but the absence of the in-process measurements – melt temperature, melt pressure, cavity pressure and screw torque - from which any twin state estimate must be constructed. Firms processing recycled feedstock have the strongest technological case for instrumenting first.

Keywords: polymer processing, digital twin, extrusion, injection moulding, process monitoring, recycled polymers, process sensing, state estimation.

INTRODUCTION

Polymer processing converts a material whose flow and solidification behaviour is strongly non-linear into parts with specified dimensions and properties. Melt viscosity depends on shear rate and temperature, crystallization depends on cooling rate and pressure, and both determine shrinkage, warpage and residual stress in the finished part. This sensitivity is the reason process monitoring in plastics has attracted sustained research attention, from in-mould cavity sensing and extrusion melt sensing to machine-learning quality prediction and closed-loop quality control of moulded parts [1 - 4].

Digital Twin research has developed in parallel, within the broader cyber-physical production agenda set out for Industry 4.0 [5, 6]. The distinction between a digital model, a digital shadow and a Digital Twin, the last requiring automated bidirectional data flow between the physical and the virtual system, was formalized by Kritzinger and co-workers and remains the criterion

by which implementation claims should be judged [7]. Vangheluwe and Paredis restate the same distinction as a general twinning relationship rather than as a class of software [8]. Enabling technologies to have been surveyed by Qi and co-workers [9], and polymer-specific demonstrations now exist for PVC tube extrusion start-up [10], for injection moulding [11, 12] and for extrusion control in polymer printing [13].

What is not established is how far from the preconditions for such systems extend into ordinary industrial practice, outside the well-capitalized producers that supply most published case studies. A twin requires a physical process, an instrumented process, a data path and a model. The first is universal; the others are not. Where the sensing layer is absent, the modelling literature cannot be applied, however mature it becomes.

This paper addresses that question in two steps. The first part of Results and Discussion sets out the chemical-technological argument for why polymer processing suits Digital Twin methods, organized around rheological, thermal, morphological and degradation mechanisms, and specifies which process variables a twin would have to estimate in extrusion and in injection moulding. The second part reports a documented technology inventory for a census of Bulgarian plastics manufacturers and classifies each firm by the strength of the evidence for automation, process sensing and Digital Twin capability. The contribution is threefold: a mechanism-level statement of what a polymer-processing twin must estimate and why; a source-cited equipment and process inventory for a national sector rarely described at this level of technical detail; and an explicit separation, maintained throughout, between what is documented and what is proposed.

EXPERIMENTAL

Scope of the empirical material

The empirical basis is a census of Bulgarian producers classified under NACE 22.2x (manufacture of plastic products), comprising N = 29 confirmed enterprises. Two linked datasets were compiled. The first records financial and employment data from public company registries and self-published financial statements. The second dataset, used for the technology analysis reported here, records for each firm the polymer process type; named equipment where disclosed, with manufacturer, model, quantity and installation year; documented automation and robotization; documented quality-system records; and, as a separate category, any evidence of an ERP, MES, SCADA system or Digital Twin.

Of the 29 census firms, 20 have documented process-level technology evidence and constitute the denominator for all technology shares reported below. The remaining 9 comprise firms added in a later verification round with a deliberately narrower search protocol, together with firms for which no process-level technical disclosure was located. This asymmetry is a property of the available public record rather than a sampling decision, and every share below states its denominator explicitly.

Evidence classification and Automation Visibility Index

Each firm was assigned to one of three categories. Category A, confirmed Digital Twin, requires a direct and identifiable source stating that a Digital Twin is implemented. Category B, Digital-Twin-ready or advanced automation, covers documented sensors, PLC or SCADA systems, automated lines, robots, real-time process control or automated quality control; these are preconditions for a twin and are not evidence of one. Category C, conventional or insufficient data, applies where the available evidence does not support a stronger classification.

Because disclosure is uneven, a composite Automation Visibility Index was computed as the sum of three binary indicators: at least one documented automation record; at least one named machine record; and at least one documented robotic system. The index therefore takes values in the set $\{0, 1, 2, 3\}$. It measures documentation visibility rather than technological maturity, so that a value of zero means that no public evidence was found. This distinction is maintained throughout.

Process indicators

Three indicators express what an instrumented process would allow a firm to compute. They are presented as the analytical framework that the analytics layer of a twin would populate. They are not fitted to firm-level data here, because the capacity and cycle data they require are not disclosed, as set out under Scope of the empirical material above.

Overall equipment effectiveness is defined by Eq. (1), following the formulation applied to plastic injection moulding by Val and co-workers [14].

$$OEE = A \cdot P \cdot Q \quad (1)$$

where OEE is the overall equipment effectiveness, dimensionless; A is availability, defined as operating time divided by planned production time; P is performance, defined as the ideal cycle time multiplied by the total count and divided by the operating time; and Q is quality, defined as good count divided by total count. All three factors are dimensionless.

Cycle time utilization is defined by Eq. (2).

$$CTU = \frac{t_{id}}{t_{ac}} \quad (2)$$

where CTU is the cycle time utilization, dimensionless; t_{id} is the theoretical minimum cycle time for a given mould and part, s; and t_{ac} is the measured cycle time, s. A value below unity indicates recoverable cycle-time loss.

Specific mechanical energy in extrusion is defined by Eq. (3).

$$SME = \frac{2\pi NM}{\dot{m}} \quad (3)$$

where SME is the specific mechanical energy, J kg^{-1}; N is the screw rotation rate, s^{-1}; M is the screw torque, N m; and the mass throughput is denoted by m with a superposed dot, kg s^{-1}. Specific mechanical energy couples the mechanical work input to the thermal and degradation history of the melt, and it is computable from variables already present on most extruder drives.

RESULTS AND DISCUSSION

Polymer processing and Digital Twin methods

Polymer melts are shear-thinning: apparent viscosity falls as shear rate rises and falls again as temperature rises. In injection moulding and extrusion simulation this behaviour is normally represented by a Cross-WLF or Carreau-WLF model, in which the zero-shear viscosity carries the temperature and pressure dependence. Retrieving an equivalent shear viscosity from three-dimensional non-isothermal capillary flow requires the thermal field to be solved simultaneously with the flow field, because viscous dissipation alters the viscosity that governs the flow [15].

The practical consequence is the core of the argument. A machine setting is not a process state. If barrel and mould temperatures, injection velocity and holding pressure are held constant while the polymer grade changes, or the recycled fraction changes, or the moisture content of a hygroscopic grade rises, then melt viscosity at the same nominal shear rate changes, the filling pattern changes, and the pressure required to fill the cavity changes with it. Cavity pressure responds directly. In-cavity pressure traces discriminate between failure modes in moulding and correlate with numerical simulation of the same process [16], and machine-learning interpretation of complete cavity-pressure profiles recovers information about the effective moulding condition that peak pressure alone does not carry [17].

A Digital Twin is useful in this situation for a specific reason. The quantity that governs quality, the state of the melt as it fills and packs, cannot be measured directly in production. It has to be inferred from variables that can be measured: pressure, temperature, torque, position and time. That inference problem is what a state-estimating twin performs.

Thermal behaviour and the case for real-time temperature data

Thermal history governs solidification. For semi-crystalline polymers the cooling rate determines the degree and the morphology of crystallization, which in turn determine specific volume and therefore shrinkage. This relationship has been exploited directly by detecting the enthalpy change associated with crystallization through melt-temperature monitoring, and by predicting part shrinkage from cavity pressure and melt temperature together [18]. Shrinkage prediction for semi-crystalline polymers improves further when the pressure-volume-temperature relationship is modified to reflect the actual thermal transformation path rather than an equilibrium assumption [19].

Melt temperature is also not a single number. In extrusion, the radial temperature profile across the melt stream at the die entry is a measure of thermal homogeneity, and it is not resolved by a single point thermocouple. Invasive point sensors disturb the flow, respond slowly, and sample one streamline of a field that is not uniform [2]. A grey-box soft sensor that combines

a physics-based description with machine learning estimates melt viscosity online, with a substantial improvement over a purely data-driven neural estimator [20]. Melt pressure and temperature predictions for polypropylene extrusion have likewise been obtained from machine-learned models with explainable structure [21].

This is the second precondition argument. Where the state variable of interest is a field rather than a point, and where the sensor that would measure it perturbs the process, a model-based estimate becomes the only practical route to the quantity.

Morphology and the process-property chain

The chain running from process parameters through flow and thermal history to final properties is well established in principle and is presented in Fig. 1. This chain has been optimized numerically for carbon-fibre-reinforced polyamide, treating mould temperature, melt temperature, packing pressure, packing time, injection time and cooling conditions as design variables against shrinkage and warpage objectives [22]. The same multi-objective problem has been pursued experimentally using Gaussian-process surrogate models and Bayesian optimization over shrinkage, warpage, cycle time and part weight, which is relevant here because it shows that the optimization can be driven from a modest number of real experiments rather than from simulation alone [23]. For twin design the relevant point is that the intermediate links in this chain are not observable on the shop floor. Orientation and crystallinity are laboratory measurements. A production twin therefore cannot track morphology directly; it can only track the process variables that determine morphology and infer the consequence. No morphological measurement was located for any firm in the present census, and none is claimed here.

Material variability, degradation and the recycled-feedstock argument

Thermo-mechanical degradation during processing changes the molecular weight distribution, and therefore the rheology, within the process itself. Polypropylene degradation on co-rotating twin-screw extruders has been quantified and related to residence time, melt temperature and shear history [24]. Because chain scission lowers viscosity, a degraded melt flows differently from a fresh one at identical machine settings: the material property has moved while the control inputs have not.

Recycled feedstock amplifies every mechanism discussed above. Batch-to-batch variation in molecular weight, contamination, moisture and additive content means that the mapping from machine setting to process state shifts between lots. Contamination is partly a sorting problem upstream of the extruder, and the sorting technologies now deployed to control it are themselves increasingly sensor- and AI-based [25]. The downstream case has been addressed by implementing closed-loop machine-learning process control for injection

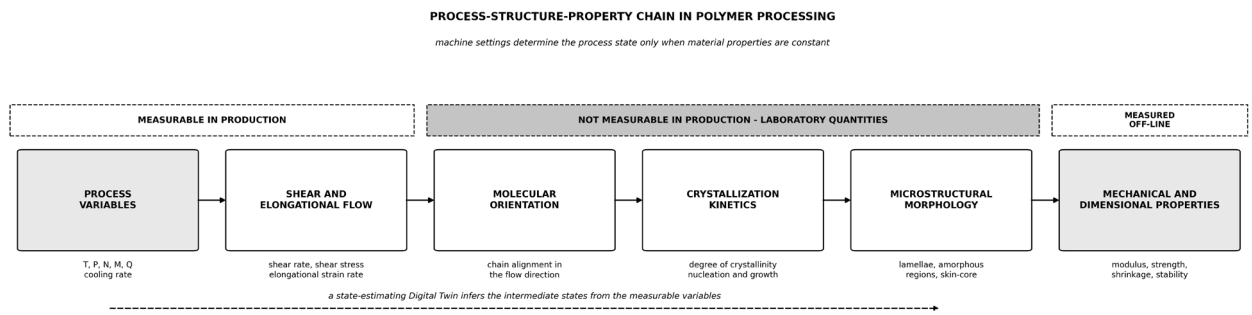


Fig. 1. Process-structure-property relationships in polymer processing: coupling between process variables, melt-flow-induced molecular orientation, crystallization kinetics, morphology and the resulting mechanical and dimensional properties. Source: authors' elaboration based on the study results.

moulding of five recycled polypropylene blends, using material-property inputs to adapt processing parameters and predict quality [26]. The technological conclusion is specific: the case for in-process sensing is strongest precisely where recycled material is used, because that is where fixed settings are least reliable. The complementary point has been demonstrated for rheology-variant feedstocks, where a real-time twin with feedback control reduced linewidth variability to approximately 2 % [13]. At the level of business organization rather than process physics, digitally mediated circular models for plastics have also been examined, although that literature addresses material flows between firms rather than state estimation inside a machine [27].

Documented process and equipment baseline

Among the 20 census firms with documented process-level evidence, extrusion is the dominant technology, recorded at 13 firms (65 %), followed by injection moulding at 5 (25 %), internal recycling at 4 (20 %), coating at 2 (10 %), injection-stretch-blow moulding at 2 (10 %), and thermoforming and injection-blow moulding at 1 firm each (5 %).

Production equipment is documented for 7 of these 20 firms. Five of the seven disclose an equipment manufacturer, yielding 16 machine records with an identified manufacturer. Among those five firms, one film producer discloses four biaxially-oriented polypropylene lines installed between 2004 and 2018, two cast-polypropylene lines installed in 2012 and 2017, and three vacuum metallizers installed in 2007, 2017 and 2021 by three different suppliers. A second firm operates nine Husky PET-preform injection systems, two HyPet and seven Index, across two sites, alongside blow-moulding equipment from three named suppliers. A third runs four Negri Bossi injection moulding machines (V700 VECTOR, V530-4100, V550 CANBIO and V550 CANBIO SE) together with two Haitian machines, and a fourth operates a single Krupp injection moulding cell. At a sheet-and-thermoforming producer, four sheet extrusion lines for PS, PP and PET with a combined rated throughput of 1500 kg h^{-1} feed 20 thermoforming and vacuum-forming machines.

The two remaining firms of the seven document recycling equipment. At one, two grinders rated at 600, and 60 kg h^{-1} respectively feed an extrusion regranulation line. The other operates seven PE extrusion machines, six bag-making machines, two dedicated granulators for polyethylene waste and ten forming machines for irregular shapes.

Instrumentation, automation and the sensing gap

Automation records exist for 3 of the 20 firms. Two document robotic systems: a two-axis pick-and-place robot retrofitted to an injection moulding cell, whose control system was replaced by a third-party integrator, and which removes moulded parts and places them on a cooling line; and four injection moulding machines described by their operator as robotized. One firm documents an automated bulk-colorant dosing system with a purpose-built DC motor controller.

Against this stands the finding that determines the argument of the paper. No firm in the census documents in-process measurement of melt temperature, melt pressure, cavity pressure or screw torque, and no firm documents an ERP, MES or SCADA system, or a Digital Twin. Of six evidence criteria, named process is satisfied by 20 firms, named machine by 7, automation by 3, robotics by 2, process sensing by 0 and Digital Twin by 0. On the readiness classification, 12 of the 20 firms fall in DT-R0, 5 in DT-R1 and 3 in DT-R2, and none reaches DT-R3, the first level at which a process produces retained data.

Two cautions apply to this result. First, absence of documentation is not absence of technology. Firms are under no obligation to publish their instrumentation, and a company that has installed cavity-pressure sensors has no reason to describe them on a public web page. The correct reading of the zero is not publicly documented. Second, and reinforcing the first, an econometric analysis of the same census by the present authors found that the apparent association between documented automation and firm revenue does not survive controlling for the general documentation richness of a firm. Public disclosure behaviour is itself a strong predictor of what a secondary-source study can observe, and any technology inventory built from public sources, including this one, inherits that limitation.

What a twin would have to estimate in these processes

Fig. 2 and Fig. 3 identify the measurement locations implied by the preceding analysis, for the two processes that dominate the documented base.

For injection moulding, shown in Fig. 2, the callouts are: (1) feed condition, including moisture for hygroscopic grades and recycled fraction; (2) barrel zone temperatures; (3) melt temperature and pressure at the nozzle; (4) cavity pressure, the variable most directly linked to part quality [16, 17]; (5) mould surface temperature, which sets the cooling rate and therefore the crystallization behaviour [18, 19]; and (6) cycle time and part dimensional response.

For extrusion, shown in Fig. 3, the callouts are:

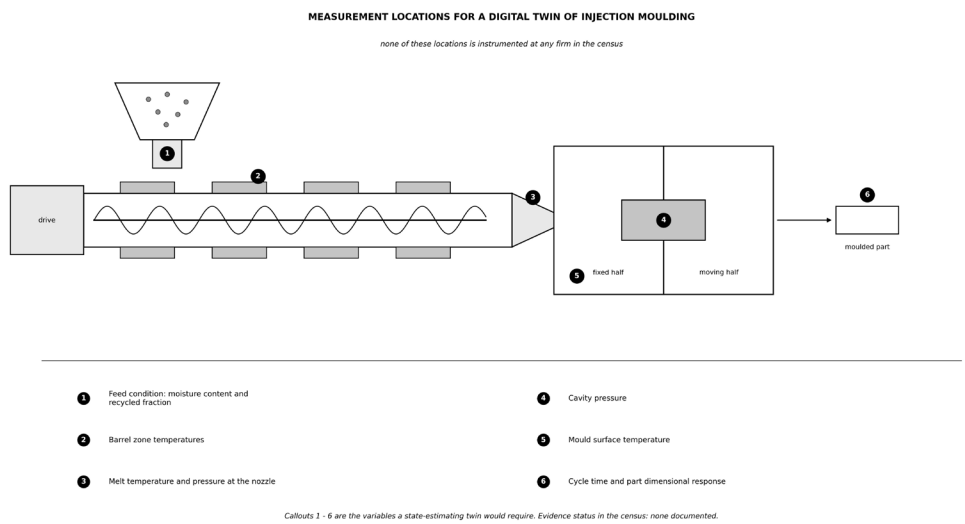


Fig. 2. Measurement locations and potential Digital Twin integration points in injection moulding. Numbered callouts: 1 - feed condition, comprising moisture and recycled fraction; 2 - barrel zone temperatures; 3 - melt temperature and pressure at the nozzle; 4 - cavity pressure; 5 - mould surface temperature; 6 - cycle time and part dimensional response. Source: authors' elaboration based on the study results and [16 - 19].

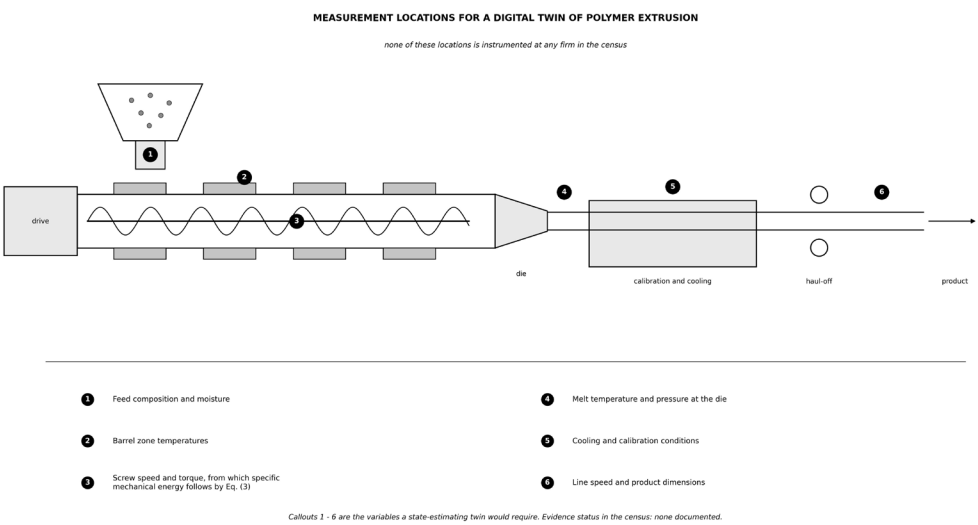


Fig. 3. Measurement locations and potential Digital Twin integration points in polymer extrusion. Numbered callouts: 1 - feed composition and moisture; 2 - barrel zone temperatures; 3 - screw speed and torque, from which specific mechanical energy follows by Eq. (3); 4 - melt temperature and pressure at the die; 5 - cooling and calibration conditions; 6 - line speed and product dimensions. Source: authors' elaboration based on the study results and [2, 20, 21].

(1) feed composition and moisture; (2) barrel zone temperatures; (3) screw speed and torque, from which specific mechanical energy follows by Eq. (3); (4) melt temperature and pressure at the die, the pair that carries thermal-homogeneity information [2, 20, 21]; (5) cooling and calibration conditions; and (6) line speed and product dimensions.

Fig. 4 gives the corresponding closed-loop architecture: physical process, sensing layer, PLC/SCADA or edge acquisition, a physics-based model coupled with a data-driven model, state estimation and quality prediction, an optimizer or model-predictive controller, and a set-point return path. The return path is what distinguishes a twin from a shadow [7]. Interoperability at the acquisition layer is a practical constraint rather than research one, and OPC UA is the established route for vendor-heterogeneous plants, which is the relevant case here given that the documented machine base spans at least six manufacturers and three decades of installation dates [28].

Two design choices in this architecture deserve comment. The physics-based and data-driven branches are shown in parallel rather than in series because neither alone is sufficient: a purely physical model cannot track unmeasured material variation, while a purely data-driven model extrapolates poorly outside its training envelope. The grey-box formulation is the practical compromise [20], and the interaction patterns by which artificial-intelligence components and twins can be composed have been catalogued systematically [29]. For processes not covered by the two figures, and blow moulding is documented at three firms in this census, the corresponding instrumentation problem has been addressed at machine level with IoT retrofits, which is the lower-cost entry point where a full twin is not justified [30].

None of this is observed in the studied sector. The layers above the physical process are proposed, not documented. The architecture is offered as a specification of what would have to be built, and its feasibility is supported by demonstrations elsewhere: twin-based extrusion start-up [10], twin modelling for injection moulding [12], twin-based predictive maintenance frameworks [31], twin-enabled human-machine interfaces for real-time industrial automation [32] and twin-based resilience analysis in mixed-model production [33]. It is not supported by evidence from these firms.

Human tasks affected

Claims about labour should be made at the level of tasks rather than of people, and the distinction between

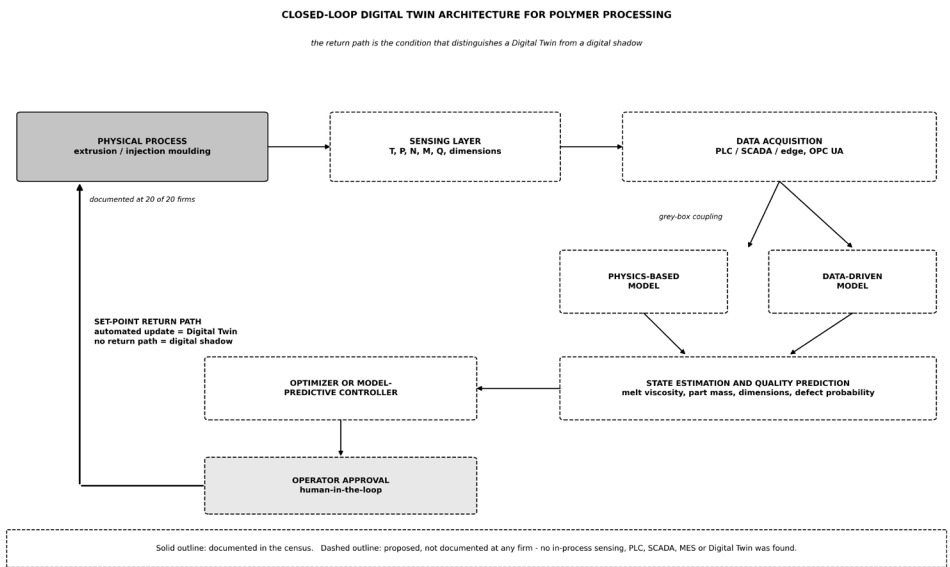


Fig. 4. Closed-loop Digital Twin architecture for polymer processing. The sensing layer, data acquisition, coupled physics-based and data-driven models, state estimation and the set-point return path are shown; the return path denotes automated set-point update, the condition that distinguishes a Digital Twin from a digital shadow. Source: authors' elaboration based on the study results and [7, 9, 20, 29].

mechanization, automation and robotization should be preserved rather than collapsed into a single category [34]. The documented Bulgarian evidence supports exactly one statement of this kind: at the two firms with robotic systems, the task of manual part removal and placement at the moulding cell has been mechanized. That is the extent of what the record shows.

The tasks that instrumentation and a twin would affect can be identified from the mechanisms above, and they should be distinguished from one another. They comprise the replacement of manual off-line measurement, meaning the sampling and gauging of parts, by in-line estimation; the replacement of repetitive visual inspection by automated classification, as demonstrated for thermoformed packaging [35] and for moulded parts [4]; automated parameter adjustment in response to material variation, as in the recycled-polypropylene control loop of Krantz and co-workers [26]; and predictive rather than scheduled maintenance [31]. Each of these substitutes a specific task. On the evidence available here none of them implies a reduction in employment, and no such inference is drawn. The corresponding transition observed in the wider literature is a shift in the required skill profile, from machine operation toward process and data engineering, and the human-centric framing of Industry 5.0 makes that shift an explicit design objective rather than a side effect [36, 37]. Collaborative-robot deployment in manufacturing is not documented at any firm in this census [38].

Roadmap for Digital Twin implementation

The preceding subsections established two results: that polymer processing is a domain in which the quantities governing product quality are not directly measurable during production, and that the studied enterprises operate almost entirely without the measurements from which such quantities would be estimated. This subsection connects those results into a staged implementation path. Three categories are used throughout and are kept strictly separate. Observed current digitalization refers to automation or data-based control for which the study found direct documentary evidence. A Digital Twin integration point is a process stage at which a twin is technically justified by polymer-processing science but is not implemented in any enterprise studied. Retained human control refers to operations where the evidence and the technological reasoning together indicate that autonomous substitution should not currently be recommended. Fig. 5 presents the roadmap. Table 1 gives the stage-by-stage evidence, process requirement and data requirement, and Table 2 gives the corresponding twin function, human task affected and expected result.

The four operations carrying direct evidence of automation, reported above, correspond on the maturity hierarchy used here to automated operation, which is level two of seven. None of them retains process data, and none contains a model of the process. A robot is not a Digital Twin, and neither is a machine controller. Against those four operations stands the absence of any in-process measurement, which places the census between stage one and stage two of the roadmap, as marked in Fig. 5.

The polymer physics set out above explains why this is the binding constraint. Melt viscosity depends on shear rate and on temperature, so identical machine settings do not reproduce identical flow when the polymer grade, the regrind fraction or the moisture content changes; and crystallization depends on the cooling path, so identical settings do not reproduce identical shrinkage when the thermal history changes. The intermediate states in this chain, and particularly molecular orientation and degree of crystallinity, are laboratory measurements rather than production measurements. A production twin cannot observe them and can only estimate them from variables that a sensor can reach. Sensorization therefore precedes modelling rather than accompanying it.

Nine process stages across seven enterprises were identified as technically justified integration points, and they appear as open markers in Fig. 2, Fig. 3 and Fig. 5. Each follows the same logic of input data, model, predicted state, decision and expected process effect. For injection moulding of PET preforms, cavity pressure together with melt and mould temperatures would feed a model predicting part mass and dimensions, allowing a correction to holding pressure or cooling time; the expected effect is tighter dimensional control, drawn from the literature and not measured in these enterprises. For film and sheet extrusion, die pressure, melt temperature and screw torque would feed an estimate of melt state and product gauge, with specific mechanical energy computable by Eq. (3), and the correction would act on screw speed or barrel temperature. For thermoforming, sheet surface temperature and heating time would predict

wall-thickness distribution. For moulding and extrusion running on internal regrind, a soft sensor estimating melt viscosity would compensate for feedstock variation between lots. None of these constitutes evidence that a Digital Twin is currently operated at any plant, and each would additionally require the continuous measurement listed for it in Table 1.

The enterprise with a documented robotized cell is a particular case. Its existing controller and its repeatable part geometry supply part of the infrastructure a twin would need, and the next technological step there would be predictive maintenance based on drive current and cycle-time data rather than quality prediction. That is a narrower and cheaper first application than full state estimation, and it is proposed on the strength of the documented automation rather than of any documented data capture.

Five operation classes are marked for retained

Table 1. Staged roadmap for Digital Twin implementation in Bulgarian plastics manufacturing: documented evidence, polymer-processing requirement and data required at each stage.

Stage	Current documented evidence	Polymer-process requirement	Required data
Stage 1. Process mapping	Process type documented for 20 of 20 firms in the technology inventory; named equipment for 7 of 20	Identification of the raw-material, plasticizing, forming, cooling, finishing, quality-control and packaging steps for each line	Machine list, operator allocation, nominal process parameters, quality outputs; no measurement required
Stage 2. Sensor and data foundation	No in-process measurement of melt temperature, melt pressure, cavity pressure or screw torque documented at any firm	Melt state and thermal history are not directly observable; they must be inferred from measurable variables	T, K; P, Pa; N, s^{-1}; M, N m; Q, kg s^{-1}; v, m s^{-1}; cooling temperature, energy, product dimensions and mass
Stage 3. Digital shadow	No PLC, SCADA or MES record at any firm; two firms have machine-level controllers that could serve as data sources	One-way flow from process to model allows drift in viscosity and thermal homogeneity to be observed over time	Time-stamped sensor histories, batch and material identifiers, quality records
Stage 4. Predictive Digital Twin	Documented processes suited to prediction: film and sheet extrusion at 13 of 20 firms, injection moulding at 5 of 20	Shear-thinning and temperature-dependent viscosity make the setting-to-state mapping unstable when feedstock varies	Stage 3 data plus material properties; physics-based rheological and thermal models combined with data-driven estimators
Stage 5. Decision-support Digital Twin	Four firms document internal recycling, where feedstock variability is highest and set-point correction is most often needed	Recycled feedstock shifts molecular weight and viscosity between lots, so fixed settings are least reliable there	Stage 4 estimates plus an operator interface presenting recommended corrections and their expected effect
Stage 6. Closed-loop Digital Twin	Two firms operate robotized moulding cells, the only documented points with both machine control and repeatable geometry	A feedback path is defensible only where product geometry is stable, runs are long and the material is characterized	Stage 5 models plus a validated actuation path and safety interlocks on the machine controller

Source: authors' elaboration based on the study results.

Table 2. Staged roadmap for Digital Twin implementation in Bulgarian plastics manufacturing: Digital Twin function, human task affected, expected result and evidence status at each stage.

Stage	Digital Twin function	Human task affected	Expected result, horizon and evidence status
Stage 1	None yet; the twin does not exist at this stage, and mapping defines its future scope	Process engineer documents the line; no operator task changes	A reproducible process map, prerequisite for all later stages. Horizon: current. Status: confirmed for process type
Stage 2	None yet; this stage supplies the data on which every later stage depends	Operator gains instrument readings; manual gauging partially replaced by in-line measurement	Measurable process state; specific mechanical energy computable from N and M by Eq. (3). Horizon: short term. Status: not found in the census
Stage 3	State visualization, quality trends, alarms and process history; no prediction	Monitoring transferred from periodic operator inspection to continuous display	Traceability and drift detection, still without forecast. Horizon: short term. Status: not found in the census
Stage 4	Estimation of melt viscosity, pressure profile, part mass, dimensions, defect probability and maintenance need	Manual off-line gauging and repetitive visual inspection progressively assisted by in-line estimation	Expected from the literature: earlier detection of quality deviation. Horizon: medium term. Status: potential
Stage 5	Twin proposes temperature, speed, pressure or cooling corrections; the operator approves or rejects them	Transition from manual setting to data-assisted setting; the decision stays with the operator	Expected from the literature: reduced start-up scrap and shorter set-up. Horizon: medium term. Status: potential
Stage 6	Automatic set-point correction within bounded limits, with the operator retaining override	Direct operator intervention in steady-state running reduced; supervision, exception handling and maintenance retained	Expected from the literature: reduced process variability in steady-state running. Horizon: long term. Status: potential

Source: authors' elaboration based on the study results.

human or human-machine control. Mould and tool change and line set-up remain manual engineering tasks with a safety-critical component. Assessment of non-standard defects, and of contamination in mixed internal scrap, depends on visual and tactile judgement that the available sensing does not reproduce. Irregular-shape forming and short-run bag and pouch converting involve frequent changeover, so the data volume per configuration is small and the economic case for automation is weak. These classifications follow from the technological characteristics of the operations rather than from any deficiency of the enterprises and retained manual work in these positions is a reasonable allocation of control.

The staged path itself is as follows. Stage one, process mapping, is the only stage the census demonstrably

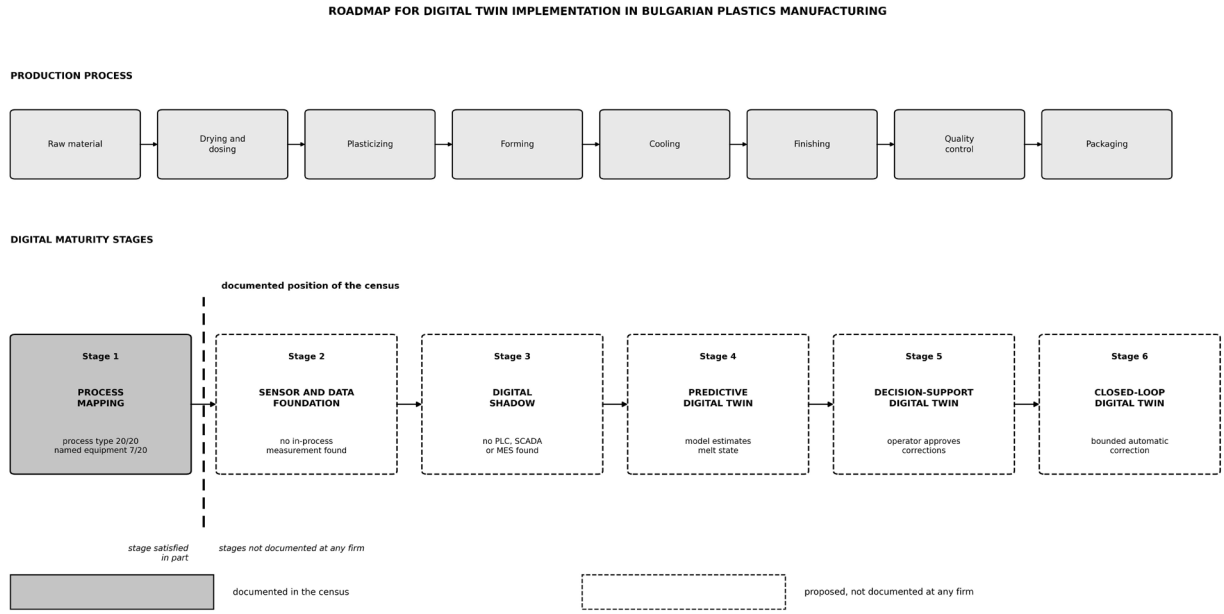


Fig. 5. Roadmap for the development and implementation of Digital Twins in Bulgarian plastics manufacturing, based on the technological evidence identified in the investigated enterprises. The upper layer shows the production process and the lower layer the six stages of digital maturity; the marked position indicates the documented position of the census between process mapping and sensorization. Source: authors' elaboration based on the study results and [7, 9, 26, 31].

satisfies, and only in part: process type is documented for all 20 enterprises but named equipment for 7. Stage two, sensorization, is the decisive step, because every later stage consumes its output; the candidate measurements are temperature, pressure, screw speed, torque, throughput, velocity, residence time, cooling conditions, energy and product dimensions. Stage three converts those measurements into a one-way digital shadow that visualizes state and detects drift without predicting it. Stage four adds physics-based and data-driven models to predict melt state, dimensions and defect probability. Stage five presents corrections to an operator who accepts or rejects them, which is the first stage at which the twin influences the process, and it does so through a person. Stage six closes the loop, and it is recommended only for the subset of operations with stable geometry, long runs and characterized material, which in this census means the robotized moulding cells rather than the sector. The horizons given in Table 2 are analytical categories reflecting technological dependency, not calendar predictions.

The practical implication for the enterprises studied is correspondingly narrow. The first investment is instrumentation at the die and at the cavity rather than modelling software, and only once a data path exists does the modelling literature reviewed above become applicable. The enterprises with the strongest technological case for beginning are the four that process internal regrind, because that is where the mapping from setting to state is least stable, together with the two that already operate robotized cells, because part-handling automation supplies both a data-capable controller and a demonstrated willingness to invest in cell-level automation [24, 26].

Three constraints qualify this ordering. Legacy integration is a real obstacle: metallizers installed in 2007, and injection machines of comparable vintage, were not designed for external data extraction, and OPC UA compliance cannot be assumed for them [28]. Energy is a legitimate secondary objective, since extrusion energy demand is connected to screw speed and thermal homogeneity through Eq. (3), and injection moulding

energy consumption has been modelled successfully from process data, but energy alone does not justify twin-level investment. Finally, the skills required to operate a state-estimating system are not present by default, and no firm in the census documents a digital-skills training program [39].

CONCLUSIONS

- The state variables that govern part quality in polymer processing, namely melt viscosity, thermal homogeneity and crystallization history, are not directly measurable during production, while the machine settings that are adjustable do not determine those states uniquely when material properties vary. This is the chemical-technological reason for building a state-estimating Digital Twin in this industry.
- In a census of 29 Bulgarian plastics manufacturers, of which 20 have process-level technical disclosure, extrusion is documented at 13 enterprises, injection moulding at 5 and internal recycling at 4. Production equipment is documented for 7 enterprises, with 16 machine records carrying an identified manufacturer and installation dates ranging from 2004 to 2021.
- Automation is documented at 3 enterprises and robotic part handling at 2, in every case applied to an individual cell rather than to an integrated line. On the readiness classification, 12 enterprises fall in DT-R0, 5 in DT-R1 and 3 in DT-R2, and none reaches DT-R3.
- No enterprise in the census documents in-process measurement of melt pressure, melt temperature, cavity pressure or screw torque, and none documents an ERP, MES or SCADA system, or a Digital Twin. This absence should be read as not publicly documented rather than as demonstrated absence.
- The binding constraint is therefore the measurement layer rather than modelling capability. The implementation sequence that follows is to instrument first, at the die and at the cavity, and to model second. The enterprises processing internal regrind, and those already operating robotized cells, have the strongest technological case for beginning.
- Nine process stages across seven enterprises were identified as technically justified Digital Twin integration points, and five operation classes as positions where human or human-machine control should be retained. None of the integration points is evidence that a Digital Twin is currently operated at any plant.

Authors' contributions

N.S. designed the study, developed the Digital Twin roadmap framework and drafted the manuscript. Ts.K. compiled and verified the enterprise technology evidence base, performed the evidence classification and prepared the figures. Both authors reviewed and approved the final version of the manuscript.

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