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Conceptual design of a simulation model for bulk material transport by pipe conveyor

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Abstract. Pipe conveyors provide an environmentally advantageous alternative to conventional belt conveyors for bulk material transport. While FEM, DEM, and CFD methods have led to significant advancements in the analysis of belt mechanics and particle dynamics, published pipe conveyor simulations typically cover narrow parameter ranges and offer limited insight into how operating parameters jointly influence system performance under realistic, variable loading conditions. This article presents a simulation model for bulk material transport by pipe conveyor in Tecnomatix Plant Simulation, using a mathematical capacity model implemented in SimTalk 2.0. A stochastic feeding model based on a uniform random distribution approximates the real variability of material loading. A parametric study of 27 experiments in five series evaluates the influence of belt speed (0.8–4.0 ms^{-1}), filling coefficient (0.44–0.80), conveyor length (100–1000 m), feeding deviation (1–100%), and inclination angle (0°–15°) on nominal and actual throughput. Belt speed and filling coefficient affect throughput proportionally, while conveyor length and inclination angle have no measurable influence. The proposed model provides a flexible digital tool for analyzing the material flow dynamics of pipe conveyors and supports system design.

Keywords: pipe conveyor; simulation model; bulk material transportation; Tecnomatix Plant Simulation; continuous simulation.

1. INTRODUCTION

There has been considerable progress in the development of simulation and its application in solving problems related to logistics processes in industry [1]. Logistics processes encompass activities that conduct logistics flows, which can be hierarchically divided into subprocesses consisting of activities [2]. In mining companies, construction, engineering, and other industrial sectors, transporting bulk solids is a fundamental logistics operation. Production in industrial sectors without reliable, smooth material transport would fail, as it would not be possible to ensure continuous production or mining.

A key technology for the continuous transport of bulk materials is the belt conveyor system. Development trends in the field of continuous transport focus on green, ecological, and low-carbon transport [3], as well as on the sustainable transport of bulk materials [4]. In line with these development trends, closed conveyor types (Sicon type, U-con, pipe conveyor, and others) are increasingly used in place of classic belt conveyors. The pipe belt conveyor is a relatively new type of environmentally friendly and efficient bulk conveying equipment [5]. Closed conveyors confine the transported material in a flexible rubber conveyor belt, thereby protecting the environment from material spillage and air pollution [6]. When using belt transport, transport routes, even extending for several tens of kilometers, incorporate many conveyors, which can negatively affect the reliability of the entire transport system. Using pipe conveyors reduces the number of belt conveyors and transfer points, which are a serious source of dust [7], and can have a significant economic and environmental impact in the transport of bulk solids and coal [8].

The design parameters of the conveyor (belt speed, belt tension, support plate spacing, conveyor inclination angle, etc.) can be optimized through simulation to improve the efficiency, safety, and sustainability of the transport process, for example, by reducing conveyor belt wear [9]. Xie *et al*. performed numerical simulations of granular material transport on a conveyor and investigated how particle size, feed rate, and belt speed affected wear. Simulation of belt wear and damage is a significant aid in the predictive maintenance of pipe conveyors, enabling the prediction of maintenance needs and the elimination of unexpected failures such as belt deformation and breakage [10], belt deviation [11, 12], and rotation of the pipe conveyor belt [13]. Belt rotation is one of the most critical failure modes in pipe conveyors, as complex routing, operational variations, and environmental factors create uneven contact forces that trigger it [14]. Several approaches for belt rotation monitoring and detection have been proposed in recent years. Santos *et al*. [15] developed a digital twin of a low-cost test rig for measuring belt rotation using infrared distance sensors, a 3-axis accelerometer, and an autoregressive language model for predicting the overlap position. The same research group later proposed a digitization framework based on Industrial Internet of Things (IIoT) devices for scalable industrial belt rotation monitoring [14]. Image processing and machine vision methods have also been applied to detect belt rotation faults: Yuan *et al*. [16] proposed an edge detection method based on the OUST-Canny operator combined with the Hough transform, while Hao *et al*. [17] developed a machine vision-based algorithm for detecting the longitudinal lap edge of a conveyor belt. Wang *et*

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al. [18] addressed the challenge of real-time belt rotation detection by proposing D2Net, a lightweight dual-branch network for semantic segmentation of conveyor belt edges, achieving an inference speed of 169.5 fps. Zhao *et al*. built a model using BeltLineNet, a lightweight network for real-time anomaly detection, demonstrating that BeltLineNet outperforms state-of-the-art feature extraction and fusion networks. Furthermore, Molnár *et al*. [19] investigated the possibility of identifying selected pipe conveyor failures during operation, including missing rollers and absent material, using a discrimination method based on continuous measurement of contact forces in the idler housing. Simulation models can also be applied to the design of a conveyor structure, for example, from the perspective of its drive [20].

A comprehensive overview of simulation methods for the dynamic behavior of classic belt conveyors and pipe conveyors is presented in the study by Tian *et al*. [21]. Based on published research in the field of simulation of bulk material transport by belt conveyors [9, 22–27], the most widely used methodologies include the Finite Element Method (FEM) [23], Discrete Element Method (DEM) [27], and Computational Fluid Dynamics (CFD) [24]. FEM allows modelling stress-strain states in the conveyor belt [23, 28], and its dynamic stress during starting, running, and stopping. Modeling the behavior of a conveyor belt using FEM helps in the design of its structure (number and type of textile inserts, type of steel cords, thickness of cover layers, tensile strength, etc.) and prediction of conveyor belt rupture [25] and damage from dynamic impact stress [26]. Fedorko *et al*. [29] proposed implementing an FEM model as a digital twin to measure key properties and characteristics of rubber-textile conveyor belts in pipe conveyors, using a testing stand with variable dimensional characteristics within the Industry 4.0 framework. The Discrete Element Method provides a more comprehensive simulation of material flow in pipe conveyors, where the conveyor belt is modeled as a rigid body or as a set of connected particles [27]. CFD can be used to analyze air resistance and other factors affecting material flow on a conveyor [22].

In the industrial context, several commercial software solutions exist for belt conveyor design and analysis. Belt Analyst (Overland Conveyor Co.) provides steady-state and dynamic analysis of belt conveyors, including tension calculations, power requirements, and belt selection [30]. Helix delta-T (Helix Technologies) offers comprehensive conveyor design capabilities, including idler selection, belt tension analysis, and power calculations [31]. Based on their published documentation, these commercial tools primarily focus on steady-state design calculations and deterministic analysis, and do not appear to incorporate stochastic material feeding variability or time-dependent simulation of material flow dynamics within their standard workflows. Such capabilities are essential for evaluating real-world operational scenarios where feeding rates fluctuate due to hopper performance, material properties, and upstream process variability.

Many logistics processes have been simulated in the Tecnomatix Plant Simulation program. Although Tecnomatix Plant Simulation is primarily known as a discrete-event simulation tool, it also provides built-in capabilities for modeling continuous processes, including continuous material flow, fluid dynamics, and time-driven state changes. In this work, the continuous material flow on a pipe conveyor is modeled by combining the continuous simulation capabilities of Tecnomatix with mathematical capacity equations implemented in the SimTalk 2.0 programming language, where the material quantity on the belt is recalculated at each simulation time step. Despite this capability, most authors have simulated only discrete logistics processes. A review of publications focused on the simulation of discrete events in logistics is presented by Tosti and Bottani [1]. Discrete process simulation was applied by Straka *et al*. in a case study using ExtendSim to streamline production logistics [32]. Šaderová *et al*. simulated discrete processes in the transport of raw material by hoisting equipment in a mine using ExtendSim10 [33]. Continuous processes were simulated in the Technomatix program only rarely, and only when simulating batch material transport [34–36]. MATLAB software was adopted to build mathematical equations in the publication of Salawu *et al*. [37]. Bobinics *et al*. [38] presented a simulation model of conventional and pipe conveyors developed in the Tecnomatix Plant Simulation environment, focusing on comparing the normal forces, throughput, and energy consumption of both conveyor types under varying belt-filling coefficients and idler design characteristics.

When simulating transport using pipe conveyors, it is important to select appropriate input parameters, such as the properties of the transported material (density, friction coefficient, and angle of repose), as they significantly affect the simulation results. The authors [39] present results from measuring bulk material flow using laser scanning technology to improve the energy efficiency of belt conveyors.

Based on the above literature analysis, it can be observed that existing approaches tend to focus on individual aspects of pipe conveyor operation – belt mechanics (FEM), particle-level dynamics (DEM), fluid interactions (CFD), steady-state design calculations (commercial software), or energy efficiency comparisons [38] – rather than exploring the broader parametric behavior of the conveyor system through systematic variation of operating conditions. Most of the reviewed studies, except for Wang *et al*. [40], have addressed material flow simulation without explicitly considering conveyor belt loading. While the energy-efficiency comparison in [38] introduced a simulation model for pipe conveyor material flow in the Tecnomatix Plant Simulation environment, it operated within a limited set of experimental configurations. The present article extends this simulation approach by conducting a comprehensive parametric study comprising 27 experimental configurations with varying material properties, conveyor settings, and feeding conditions. The mathematical framework is grounded in the standardized calculation methods defined in [41], which provide the analytical basis for throughput capacity, cross-sectional filling, and other key performance parameters integrated into the model. This broader experimental scope enables a more detailed evaluation of how different combinations of input parameters affect overall conveyor performance under conditions that more closely reflect industrial variability.

2. METHODS AND METHODOLOGY

The main objective of this work was to create a simulation model of a closed-type conveyor, i.e., a pipe conveyor, using Tecnomatix Plant Simulation software. The model is designed to be flexible, allowing a wide selection of transport materials and the ability to expand the material database. The model also allows selection and modification of belt speed and conveyor length. The mathematical formulations for capacity and resistance calculations are implemented in the SimTalk 2.0 programming language and are executed at each simulation time step, enabling time-dependent analysis of the conveyor performance under varying operating conditions.

2.1. Mathematical model for pipe conveyors

The capacity calculation for the pipe conveyor is based on the methodology described by Zhang *et al.* [42]. The throughput of a pipe conveyor is formulated as:

$$Q = 3600 v \rho F_{\text{pipe}} C_{\text{MF}}, \tag{1}$$

where Q is the throughput [tcoth^{-1}], v is the belt speed [m·s^{-1}], ρ is the bulk density of the conveyed material [kg·m^{-3}], F_{pipe} is the pipe cross-sectional area [m^2], and C_{MF} is the coefficient of material filling [–].

The pipe cross-sectional area is calculated from the effective pipe diameter d, which is derived from the belt width B and a calibration coefficient KC that accounts for the overlap of belt edges when the belt is formed into a pipe shape, where $KC = 0.9$:

$$d = KC(B/\pi), \tag{2}$$

$$F_{\text{pipe}} = \pi d^2/4. \tag{3}$$

The coefficient of material filling C_{MF} ranges from 0.44 to 0.80, depending on the particle size relative to the pipe diameter [42].

In real operating conditions, bulk material loading is never perfectly constant. To approximate this variability, the simulation model incorporates stochastic material feeding. The feeding rate at each simulation step is generated using a uniform random distribution:

$$i = z\_uniform\left(Q_{\text{nom, kg/s}} - \Delta,\, Q_{\text{nom, kg/s}}\right), \tag{4}$$

where $Q_{\text{nom, kg/s}} = Q \cdot 1000/3600$ is the nominal throughput converted to [kg·s^{-1}], and Δ is the deviation calculated as a user-defined percentage of the nominal rate. The model currently implements only a negative deviation (i.e., the feeding rate is always at or below the nominal value), which reflects the conservative assumption that underfilling is more common in practice than overfilling.

The model includes a built-in validation mechanism. After the first hour of simulation, the actual capacity utilization is compared to the specified filling coefficient C_{MF}. If the actual utilization exceeds the filling coefficient, the simulation is automatically terminated, indicating an inconsistency in the input parameters.

Figure 1 represents the operating principle of the pipe conveyor system within the simulation model. The bulk material is loaded onto the conveyor belt through the feed hopper block, which serves as the material input point. From there, the material is transported along the enclosed pipe conveyor to the end of the transport route, where the material discharge block is located – this is the point at which the material exits the conveyor belt.

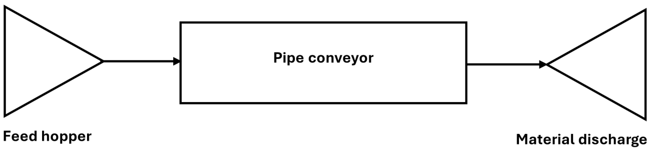

Fig. 1. Block diagram of the pipe conveyor simulation model

Figure 2 provides a more detailed representation of how the simulation system operates within the model. On the left side, the input parameters are shown – these can be configured manually depending on the specific requirements of the simulation scenario. The material feeding process is stochastic and is modeled using a uniform probability distribution $U(Q-\Delta, Q)$, where the feeding deviation Δ must be specified as an input parameter before the simulation begins. The material then passes through the pipe conveyor block, where the throughput, the quantity of material on the conveyor belt, and other performance indicators are calculated at each time step. At the end of the transport route, the material discharge block serves as the point from which the key simulation results are obtained. At this stage, the model performs a validation check: if the actual capacity utilization exceeds the specified filling coefficient, the condition is considered violated, and the simulation is automatically stopped.

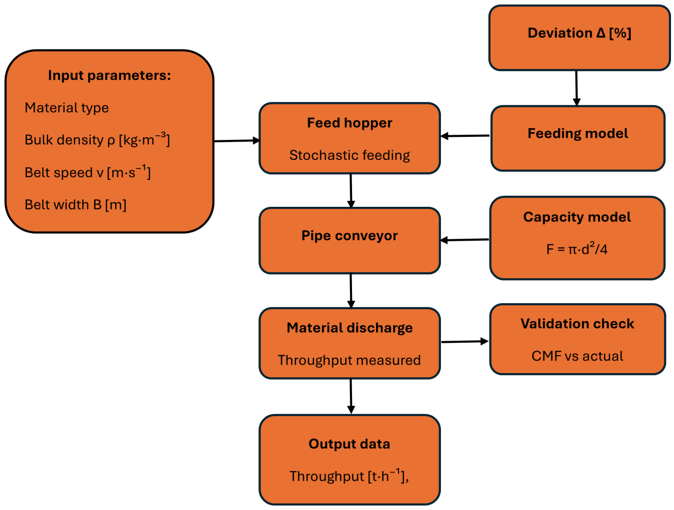

Fig. 2. Structure and logic of the pipe conveyor simulation model

3. RESULTS

Table 1 presents the complete experimental design of the study, summarizing the input parameters for all 27 experiments grouped into five series (A through E). In each series, only one parameter is varied while all others are held constant, enabling clear isolation of the effect of each factor on conveyor performance.

Table 1
Parametric study design: input configurations for EXP 1–EXP 27

EXP	Series	Variable parameter	Belt speed [m·s⁻¹]	Filling coefficient [-]	Conveyor length [m]	Feeding deviation [%]	Inclination angle [°]
EXP 1	A	Belt speed	**0.8**	0.44	1000	30	≈0
EXP 2	A	Belt speed	**1**	0.44	1000	30	≈0
EXP 3	A	Belt speed	**1.25**	0.44	1000	30	≈0
EXP 4	A	Belt speed	**1.6**	0.44	1000	30	≈0
EXP 5	A	Belt speed	**2**	0.44	1000	30	≈0
EXP 6	A	Belt speed	**2.5**	0.44	1000	30	≈0
EXP 7	A	Belt speed	**3.15**	0.44	1000	30	≈0
EXP 8	A	Belt speed	**4**	0.44	1000	30	≈0
EXP 9	B	Filling coefficient	1.6	**0.44**	1000	30	≈0
EXP 10	B	Filling coefficient	1.6	**0.58**	1000	30	≈0
EXP 11	B	Filling coefficient	1.6	**0.75**	1000	30	≈0
EXP 12	B	Filling coefficient	1.6	**0.8**	1000	30	≈0
EXP 13	C	Conveyor length	1.6	0.44	**100**	30	≈0
EXP 14	C	Conveyor length	1.6	0.44	**250**	30	≈0
EXP 15	C	Conveyor length	1.6	0.44	**500**	30	≈0
EXP 16	C	Conveyor length	1.6	0.44	**1000**	30	≈0
EXP 17	D	Feeding deviation	1.6	0.44	1000	**1**	≈0
EXP 18	D	Feeding deviation	1.6	0.44	1000	**10**	≈0
EXP 19	D	Feeding deviation	1.6	0.44	1000	**20**	≈0
EXP 20	D	Feeding deviation	1.6	0.44	1000	**30**	≈0
EXP 21	D	Feeding deviation	1.6	0.44	1000	**50**	≈0
EXP 22	D	Feeding deviation	1.6	0.44	1000	**100**	≈0
EXP 23	E	Inclination angle	1.6	0.44	1000	30	**0**
EXP 24	E	Inclination angle	1.6	0.44	1000	30	**1**
EXP 25	E	Inclination angle	1.6	0.44	1000	30	**5**
EXP 26	E	Inclination angle	1.6	0.44	1000	30	**10**
EXP 27	E	Inclination angle	1.6	0.44	1000	30	**15**

Series A (EXP 1–EXP 8) investigates the effect of belt speed. The speed values – ranging from 0.8 $\mathrm{m\,s^{-1}}$ to 4 $\mathrm{m\,s^{-1}}$ – were selected based on the relevant technical literature (Marasová, 2013) and STN ISO 5048 [41, 43] for belt conveyor design. All other parameters remain fixed: filling coefficient at 0.44, conveyor length at 1000 m, feeding deviation at 30%, and inclination angle at approximately 0°. This range of speeds covers the typical operating spectrum from slow, low-capacity conveyors to fast, high-throughput installations.

Series B (EXP 9–EXP 12) examines the influence of the material filling coefficient, which varies from 0.44 to 0.8. This coefficient represents the proportion of the available pipe cross-section that is filled with material. A value of 0.44 corresponds to a moderately loaded conveyor, while 0.8 represents a near-maximum utilization of the volumetric capacity of the pipe. Belt speed is fixed at 1.6 $\mathrm{m\,s^{-1}}$ for this series.

Series C (EXP 13–EXP 16) was designed to study the effect of conveyor length on its throughput. Four length values were selected: 100, 250, 500, and 1000 m.

Series D (EXP 17–EXP 22) addresses the feeding deviation – the stochastic variability of the material flow rate at the loading point. The deviation ranges from 1% to 100%. This intentionally wide range was chosen to provide a thorough understanding of how the deviation setting in the simulation model affects conveyor performance. At 1%, the feeding process is nearly ideal; at 100%, the instantaneous feed rate can vary from zero to the full nominal value.

Series E (EXP 23–EXP 27) varies the conveyor inclination angle from 0° (horizontal) to 15°. This range was selected to cover the typical operating angles encountered in industrial pipe conveyor installations and to verify that inclination does not affect the volume of material transported.

Across all five series, the parameters that are not being tested remain at their baseline value: belt speed 1.6 $\mathrm{m\,s^{-1}}$, filling coefficient 0.44, conveyor length 1000 m, and feeding deviation 30%. This consistent methodology ensures that any observed changes in output can be attributed exclusively to the single variable under investigation (Table 1).

Figure 3 illustrates the relationship between conveyor belt speed, the nominal throughput calculated using mathematical formulas, and the actual throughput obtained from the simulation. Across eight experiments (EXP 1–EXP 8), the belt speed was progressively increased from 0.8 $\mathrm{m\,s^{-1}}$ to 4 $\mathrm{m\,s^{-1}}$. As the belt speed increases, both the nominal and actual throughput grow proportionally: at 0.8 $\mathrm{m\,s^{-1}}$, the nominal value is 18.30 $\mathrm{t\,h^{-1}}$, and the actual is 14.46 $\mathrm{t\,h^{-1}}$, whereas at 4 $\mathrm{m\,s^{-1}}$, these values reach 91.48 $\mathrm{t\,h^{-1}}$ and 76.71 $\mathrm{t\,h^{-1}}$, respectively. The relationship is clearly linear – a fivefold increase in speed produces an approximately fivefold increase in throughput.

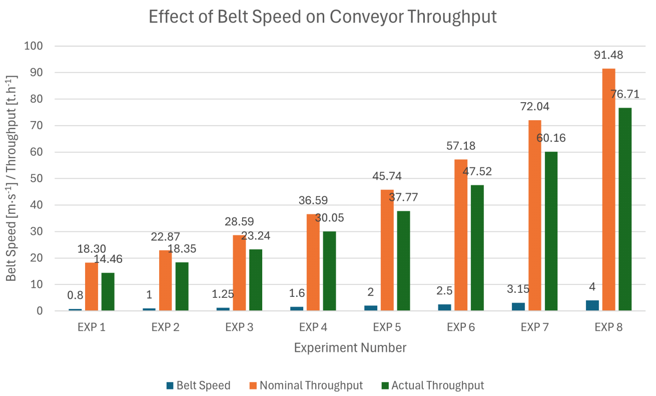

Fig. 3. Effect of belt speed on nominal and actual conveyor throughput (Series A)

Figure 4 illustrates the effect of the filling coefficient on conveyor belt throughput. Experiment 9 has the lowest filling coefficient (0.44), corresponding to the lowest throughput – both nominal and actual. The nominal throughput is 36.59 $\mathrm{t\,h^{-1}}$, while the actual conveyor throughput is 30.01 $\mathrm{t\,h^{-1}}$. Experiment 10 shows higher results as the filling coefficient increases from 0.44 to 0.58 – the nominal throughput reaches 48.24 $\mathrm{t\,h^{-1}}$, and the actual throughput is 39.60 $\mathrm{t\,h^{-1}}$. In Experiment 11, the filling coefficient rises again – from 0.58 to 0.75, leading to an increase in both the nominal and actual throughput: the nominal stands at 62.37 $\mathrm{t\,h^{-1}}$ and the actual at 51.25 $\mathrm{t\,h^{-1}}$. Experiment 12 has the highest filling coefficient of 0.8, which again directly affects conveyor throughput: the nominal value is 66.53 $\mathrm{t\,h^{-1}}$, and the actual is 54.58 $\mathrm{t\,h^{-1}}$.

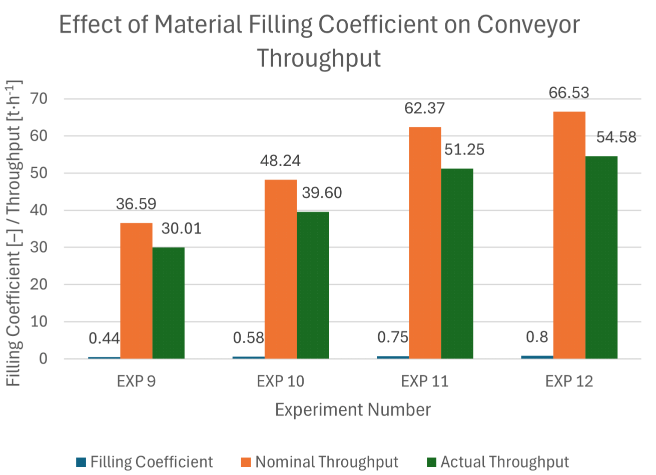

Fig. 4. Effect of material filling coefficient on nominal and actual conveyor throughput (Series B)

The gap between nominal and actual conveyor throughput is expected, since the feeding deviation is set to up to −30%, meaning the material feed rate will not always remain uniform and can deviate by up to −30%. This indicates that the model reproduces the real-world conditions of the stochastic nature of material feeding onto the conveyor belt, where the feed rate at the loading point fluctuates randomly and never matches the ideal theoretical value represented by the nominal throughput.

Figure 5 shows the effect of conveyor belt length on conveyor throughput. The lengths considered are 100 m, 250 m, 500 m, and 1000 m, corresponding to experiments 13, 14, 15, and 16. The results show that conveyor length has virtually no effect on throughput. The actual throughput fluctuates within the range from 30.04 $\mathrm{t\,h^{-1}}$ to 31.00 $\mathrm{t\,h^{-1}}$, while the nominal, i.e., expected, conveyor throughput is 36.59 $\mathrm{t\,h^{-1}}$ across all four experiments. The gap between the nominal and actual throughput is caused by the feeding deviation of up to −30%.

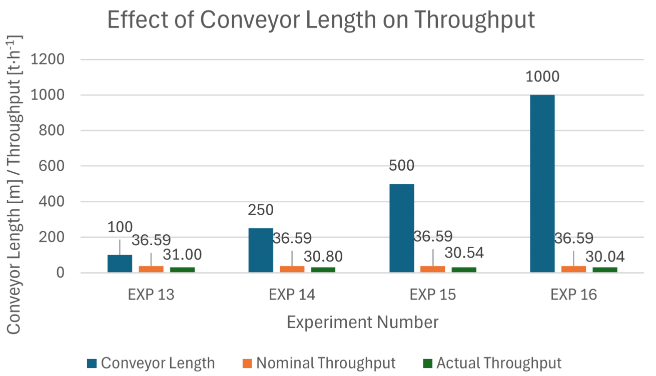

Fig. 5. Effect of conveyor length on nominal and actual throughput (Series C)

The most striking observation from Fig. 6 is that the nominal throughput remains absolutely constant at 36.59 $\mathrm{t\,h^{-1}}$ across all six experiments (EXP 17–EXP 22), while the actual throughput drops progressively as the feeding deviation increases from 1% to 100%. The nominal throughput is a purely mathematical value derived from the formula. The feeding deviation, by definition, does not enter this formula. It is the simulation that captures its effect.

At a feeding deviation of just 1% (EXP 17), the actual throughput is 35.14 $\mathrm{t\,h^{-1}}$ – remarkably close to the nominal value. The apparent difference of approximately 1.45 $\mathrm{t\,h^{-1}}$ should not be interpreted as a material loss or inefficiency. This discrepancy arises because a certain amount of material remains physically present on the conveyor belt when the simulation ends – it has been loaded at the feeding point but has not yet reached the discharge end. Since the actual throughput is calculated solely from material that has exited the conveyor, this "in-transit" material is not counted. In a continuous, indefinitely long operation, this initial loading effect would become negligible.

As the deviation grows to 10% (EXP 18) and 20% (EXP 19), the actual throughput decreases to 33.55 and 31.80 $\mathrm{t\,h^{-1}}$, respectively, showing a gradual but steady decline. At 30% deviation (EXP 20), the actual throughput reaches 30.07 $\mathrm{t\,h^{-1}}$ – approximately 18% below the nominal value. The most dramatic changes occur at the higher end of the scale: at 50% deviation (EXP 21), the actual throughput falls to 26.51 $\mathrm{t\,h^{-1}}$, and at 100% deviation (EXP 22), it drops to just 17.77 $\mathrm{t\,h^{-1}}$ – less than half of the nominal value. The difference between 1% and 100% feeding deviation is enormous: the conveyor loses nearly half of its theoretical capacity.

It is important to emphasize, however, that the simulation uses a random number generator to model feeding deviation, so the actual feed rate at any given moment fluctuates randomly within the specified range. For instance, a 100% feeding deviation does not mean the conveyor operates at zero throughput – it means the instantaneous feed rate can vary anywhere between 0% and 100% of the nominal value. Over the course of a 5-hour simulation with data recorded every second (18000 data points), the formula produces an averaged result. In the case of 100% deviation, this average converges to approximately 50% of the nominal feed rate, which explains why the actual throughput of 17.77 $\mathrm{t\,h^{-1}}$ is roughly half of the nominal 36.59 $\mathrm{t\,h^{-1}}$. The same statistical principle applies to all other deviation levels – the simulation effectively computes the mean of thousands of randomly generated feed values, yielding a representative average that reflects the expected long-term performance under stochastic loading conditions.

Figure 7 shows that the actual throughput remains virtually unchanged regardless of the conveyor's incline. Across all five experiments – from a perfectly horizontal conveyor at 0°

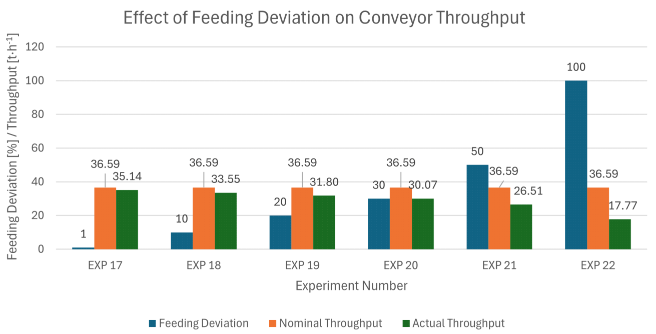

Fig. 6. Effect of feeding deviation on nominal and actual conveyor throughput (Series D)

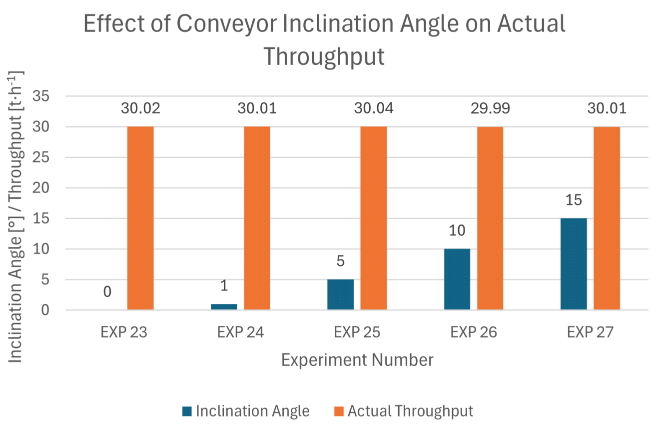

Fig. 7. Effect of conveyor inclination angle on actual throughput (Series E)

(EXP 23) to a steep 15° incline (EXP 27) – the actual throughput hovers within an extraordinarily narrow band: 30.02, 30.01, 30.04, 29.99, and 30.01 $\mathrm{t\,h^{-1}}$. The total variation across the entire range is a mere 0.05 $\mathrm{t\,h^{-1}}$, which is statistically insignificant.

This makes physical sense. The throughput of a conveyor is fundamentally determined by the volumetric capacity of the belt cross-section and the speed at which the belt moves – not by the angle at which it is inclined. The same amount of material is loaded per unit of time at the feeding point, the belt carries it at the same speed, and the same amount exits at the discharge end. Gravity does not reduce the quantity of material the belt can hold.

The minuscule differences between experiments (fractions of a tenth of a ton per hour) are not caused by the angle itself. They are a natural artefact of the random number generator used to simulate the feeding deviation.

This summary graph (Fig. 8) brings together all 27 experiments into a single comparative view, placing the nominal and actual throughput side by side for each experiment. It is, in a sense, the final dashboard of the entire study – a place where the effects of belt speed, filling coefficient, conveyor length, feeding deviation, and inclination angle all become visible simultaneously.

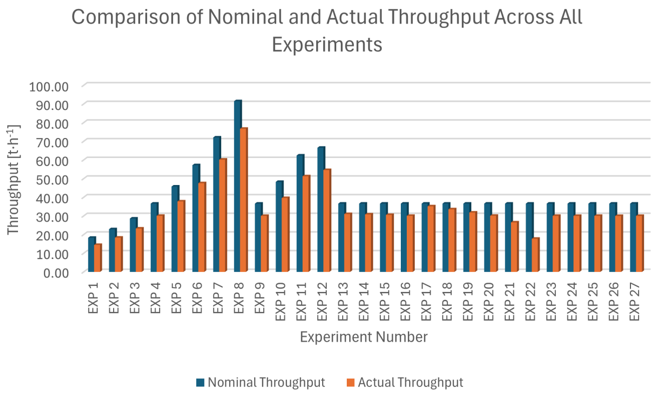

Fig. 8. Summary of nominal vs. actual conveyor throughput for all experimental series (A–E)

The first thing that catches the eye is EXP 8. With a belt speed of 4 $\mathrm{m\,s^{-1}}$, it produces the highest throughput values in the entire series – a nominal 91.48 $\mathrm{t\,h^{-1}}$ and an actual 76.71 $\mathrm{t\,h^{-1}}$. This is no surprise; it was designed to push the speed parameter to its maximum. The experiments preceding it (EXP 1 through EXP 7) form a clear ascending staircase pattern, visually confirming the linear relationship between belt speed and throughput that was discussed in detail earlier. EXP 9 through EXP 12 then show the effect of increasing the filling coefficient, and EXP 13 through EXP 16 explore conveyor length – but since length does not affect throughput, their bars remain at similar heights.

The most informative segment of the graph is the group of feeding deviation experiments (EXP 17–EXP 22). The nominal throughput remains constant at 36.59 $\mathrm{t\,h^{-1}}$ across all six experiments – the blue bars are at the same height, effectively serving as a constant baseline. The actual throughput, however, varies considerably. EXP 17, with a feeding deviation of only 1%, exhibits the smallest gap between the two values among all 27 experiments. The actual throughput of 35.14 $\mathrm{t\,h^{-1}}$ nearly coincides with the nominal value, and as explained earlier, even this minor difference is not a true loss – it results from material still being in transit on the belt at the moment the simulation ended. Moving from EXP 18 through EXP 19, 20, and 21, the orange bars progressively decrease as the deviation rises to 10%, 20%, 30%, and 50%. EXP 22 – the experiment with 100% feeding deviation – records the largest discrepancy between nominal and actual throughput in the entire series. The actual value of 17.77 $\mathrm{t\,h^{-1}}$ is less than half of the nominal 36.59 $\mathrm{t\,h^{-1}}$, which clearly confirms that extreme feeding variability can reduce conveyor performance by a factor of two.

The final group of experiments (EXP 23–EXP 27) addresses the inclination angle. The actual throughput bars here remain nearly uniform, which is consistent with the previously established finding that incline does not affect the volume of material transported.

4. DISCUSSION

The most immediate observation from Fig. 9 is the clear fan-like spread of the loading curves: all eight experiments start from zero – an empty conveyor belt with no material on it at the beginning of the simulation – and rise toward the same steady-state level of approximately 5400–5500 kg, but they do so at vastly different rates. The determining factor is belt speed.

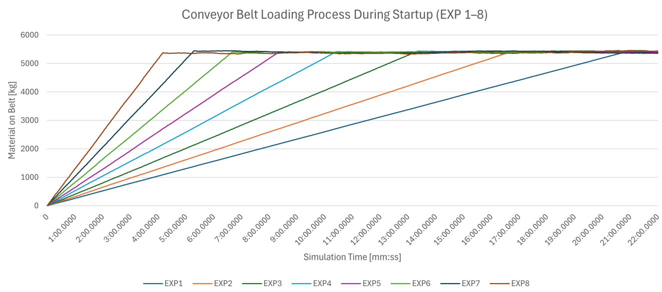

Fig. 9. Conveyor belt loading transient: effect of belt speed on time to steady state (Series A)

EXP 8, which operated at the highest belt speed of 4 $\mathrm{m\,s^{-1}}$, filled the conveyor fastest of all – the curve shoots upward steeply and flattens out in roughly 4–5 minutes. More material accumulates along the entire length of the conveyor in a shorter time. EXP 7 (3.15 $\mathrm{m\,s^{-1}}$) follows closely behind, reaching its plateau at around 5–6 minutes. Next comes EXP 6, moving at 2.5 $\mathrm{m\,s^{-1}}$, followed by EXP 5 at 2 $\mathrm{m\,s^{-1}}$, EXP 4 at 1.6 $\mathrm{m\,s^{-1}}$, EXP 3 at 1.25 $\mathrm{m\,s^{-1}}$, and then EXP 2 at 1 $\mathrm{m\,s^{-1}}$. Each of these experiments demonstrates a progressively longer time needed to achieve the desired operating condition. Conversely, EXP 1, which uses the slowest belt speed of 0.8 $\mathrm{m\,s^{-1}}$, takes the most time to fill the belt – its curve appears to still be rising slightly even beyond the 22-minute mark shown on the graph. The slope of each loading curve is directly proportional to the belt speed: double the speed, and the belt fills in roughly half the time.

Once each experiment reaches its plateau, the curve becomes relatively flat – the amount of material on the belt stabilizes around the steady-state value with only minor fluctuations caused by the stochastic feeding deviation. This flat region corresponds to the steady-state regime, in which the mass flow rate at the loading point matches that at the discharge end. Before reaching this condition, during the initial loading phase, material is still being fed onto the belt but has not yet travelled to the discharge point, meaning the conveyor has not reached its full carrying capacity.

These three graphs (Figs. 10–12) serve as a powerful visual complement to the feeding deviation analysis discussed earlier, providing a direct, time-domain view of what different deviation levels look like in practice. Each graph shows the feeding flow rate (kg s^{-1}) over the full 5-hour simulation period.

Figure 10 – EXP 17 with 1% deviation – appears almost as a perfectly straight horizontal line at approximately 10 kg s^{-1}. In reality, the signal does contain tiny fluctuations, but they are so small that they are virtually invisible at this scale. This is exactly what one would expect: a 1% deviation means the instantaneous feed rate can only vary within ±1% of the nominal value, resulting in an almost ideally stable material flow. This graph essentially represents the closest approximation to a theoretically perfect feeding process that the simulation can produce, and it visually explains why the actual throughput in EXP 17 (35.14 t h^{-1}) was so close to the nominal value.

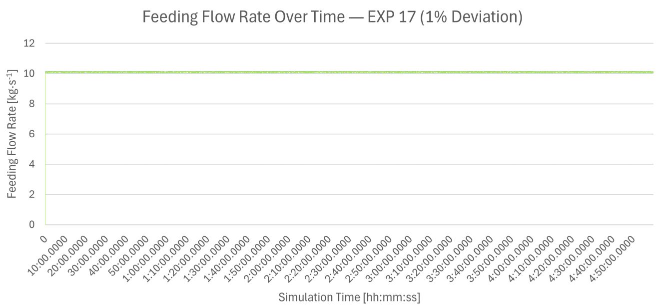

Fig. 10. Feeding flow rate over time at 1% deviation (EXP 17)

Figure 11 – EXP 20 with 30% deviation – paints a hugely different picture. The fluctuations are now clearly visible, with the feed rate oscillating between 7 and 10 kg s^{-1} throughout the entire simulation. The signal has a characteristic "noise band" appearance: densely packed random spikes that fill the space

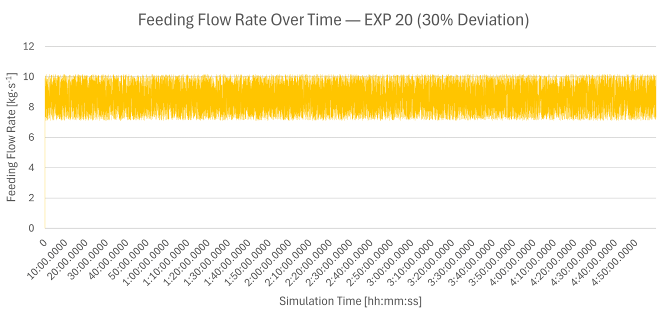

Fig. 11. Feeding flow rate over time at 30% deviation (EXP 20)

between the lower and upper bounds. If one were to draw an average line through this band, it would settle at approximately 8.5 kg s^{-1} – 15% below the nominal feed rate of ~ 10 kg s^{-1}. This is consistent with the statistical expectation: a uniform random deviation from 0% to 30% produces a mean deviation of approximately 15%, which is precisely what the average simulation output reflects. The throughput loss observed in EXP 20 (30.07 t h^{-1} versus a nominal 36.59 t h^{-1}) is a direct consequence of this averaged reduction in feed intensity.

Figure 12 – EXP 22 with 100% deviation – is the most dramatic. The feed rate swings wildly across the entire possible range, from values close to 0 kg s^{-1} all the way up to over 10 kg s^{-1}. Every second, the random number generator produces a new value that can land anywhere within this span, creating a visually chaotic signal that fills the graph from bottom to top. The extremes are fully present: there are moments when the conveyor receives almost no material, and moments when it receives the full nominal amount. Averaged over 18 000 data points, these random values converge to approximately 50% of the nominal feed rate, which aligns perfectly with the actual throughput of 17.77 t h^{-1} – nearly half of the theoretical 36.59 t h^{-1}. This graph is perhaps the most intuitive demonstration of how the random number-based feeding model works.

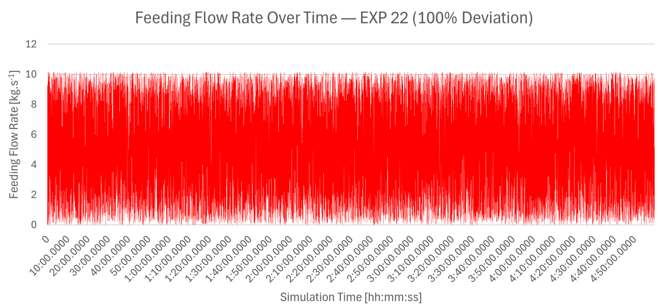

Fig. 12. Feeding flow rate over time at 100% deviation (EXP 22)

4.1. Limitations

The mathematical core of the simulation model is based on the capacity calculation methodology described by Zhang *et al*. [42], Marasová D. [43], and the STN ISO 5048 [41]. These are not theoretical abstractions – the formulations they contain were derived from and verified against measurements on real belt conveyor installations under real operating conditions. The nominal throughput values produced by the simulation match the hand-calculated values from these standards exactly, across all 27 experiments. Moreover, the actual throughput follows the expected statistical behavior of the uniform feeding distribution: after accounting for the in-transit material remaining on the belt at the end of each simulation, the residual discrepancy between the predicted and observed throughput. The model can therefore be considered verified and operationally valid within the parameter ranges tested in this study.

That said, there are aspects of real pipe conveyor operation that the model does not capture. All simulations were conducted for straight, linear routes – no vertical or horizontal curves were included. In practice, pipe conveyors often follow complex paths, and curves introduce additional forces, belt rotation tendencies, and potential flow disturbances. Only one material (bauxite, $\rho = 1400$ kg m^{-3}) was used; while the model supports other materials through its interface, the parametric study has not been repeated for different densities.

Future work should address aspects of pipe conveyor operation that the present study deliberately left aside – most notably, resistance forces and energy consumption. The throughput analysis presented here treats the conveyor as a transport system with a defined capacity, but it says nothing about the energy required to move the material. In reality, resistance forces – primary resistance along the belt length, secondary resistance at loading and discharge points, and slope resistance on inclined sections – vary significantly with conveyor configuration, and their combined effect determines the power demand of the entire system. A natural extension of the model would be to incorporate these resistance components into the simulation, enabling not only throughput analysis but also energy consumption prediction under varying operating conditions. This is particularly relevant when comparing different conveyor types: a pipe conveyor and a conventional trough conveyor of the same belt width do not consume the same amount of energy, because the pipe configuration introduces additional friction between the belt and the hexagonal idler arrangement.

5. CONCLUSIONS

This work presents a simulation model for bulk material transport by pipe conveyor, implemented in the Tecnomatix Plant Simulation environment. A study of 27 experiments confirmed that belt speed and the material filling coefficient affect throughput proportionally, while conveyor length and inclination angle have no measurable influence. The most significant finding concerns the stochastic feeding deviation: at 100% deviation, the conveyor delivers only about half of its nominal capacity, following the analytical prediction $Q_{\mathrm{act}} \approx Q_{\mathrm{nom}}(1 - \Delta/2)$. This demonstrates that uncontrolled feeding variability can reduce performance as severely as halving the belt speed – an insight that deterministic calculations alone cannot provide.

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