İSTANBUL AREL ÜNİVERSİTESİ

Department of Industrial Engineering

AREL IE BULLETIN

June 2026

Think in systems. Act with intelligence.

Editorial Note

Arel IE Bulletin | Vol. 1, No. 2 | June 2026

Welcome to the second issue of the *Arel IE Bulletin*.

When we published our first issue in January, our aim was straightforward: to introduce our department, our philosophy, and our vision to a broader audience. The response we received encouraged us to take the next step — to build a platform where ideas are not merely introduced, but actively developed and shared.

This issue marks that transition. The four contributions gathered here reflect the intellectual range that defines industrial engineering today: from the theoretical foundations of complex systems thinking to hands-on lean manufacturing applications on the factory floor; from the ergonomic evaluation of workspaces to the emerging role of large language models as decision-support tools. Together, they demonstrate that our students and faculty are not passive observers of the discipline's evolution — they are active participants in it.

I am particularly pleased to introduce the work of our graduating student, Selin Araç, whose contribution on waste reduction through Kaizen principles stands as a compelling example of what it means to apply engineering thinking with both rigor and purpose. Selin, along with all members of the Class of 2026, carries with her not only a degree but a way of seeing — the ability to look at a system, find its inefficiency, and engineer a better one. We are proud of each and every one of you, and we look forward to following your journeys.

The third and fourth contributions come from two of our third-year students, Hazar Ertuğrul İkizler and Eray Berat Kocabıyık & Halenur Otyıldız, whose work on prompt engineering and measurable ergonomics, respectively, demonstrates a level of analytical maturity well beyond the classroom. Their engagement with current methodologies is, frankly, exactly what this bulletin was created to showcase.

Industrial engineering has always been a discipline that bridges the abstract and the applied, the human and the technical. As AI augments our toolset and complexity deepens our challenges, that bridge becomes more important — and more interesting — than ever. We hope this issue contributes, in a small but meaningful way, to the ongoing conversation.

Asst. Prof. Bülent Şimşek
Editor, Department of Industrial Engineering, Istanbul Arel University

Table of Contents

Systems Thinking 2.0

Value Creation for Industrial Engineers in Complex, Uncertain, and AI-Augmented Environments

Asst.Prof. Bülent ŞİMŞEK, bulentsimsek@arel.edu.tr, Istanbul Arel University, Department of Industrial Engineering

Introduction

Consider the scenario of a shift engineer in an automotive manufacturing facility encountering a sudden malfunction in a welding robot. Under the conventional paradigm, this necessitates manual adjustments to the production schedule and executing simulations with substantial computational latency. Conversely, Systems Thinking 2.0 facilitates direct interaction with an artificial intelligence (AI) assistant integrated into the assembly line's digital twin:

"The welding robot at station 3 has experienced a two-hour downtime. Simulate the top three scheduling alternatives that ensure on-time delivery to the customer without increasing overtime costs by more than 5%, and rank them with comprehensive justifications."

An empirically grounded, multi-variable response is generated within seconds. This operational agility exemplifies the core methodology of Systems Thinking 2.0.

1. A Robust Yet Insufficient Legacy

The foundational philosophy of industrial engineering is predicated on managing, designing, and optimizing holistic systems rather than isolated components. Theoretical frameworks—such as Jay Forrester's system dynamics (Sterman, 2000), Peter Senge's learning organization model (Senge, 2006), and Peter Checkland's Soft Systems Methodology—have historically enabled the comprehension of manufacturing facilities, logistics networks, and organizational structures through the lens of feedback loops and causal relationships.

While these frameworks remain intrinsically embedded in the discipline's DNA, a critical limitation has emerged: the contemporary operational landscape diverges fundamentally from the context in which these tools were conceptualized. Modern supply chains encompass global, interacting agents; data streams in real-time; decision-making windows have contracted from hours to milliseconds; and AI acts as a direct participant in operational processes. Consequently, Forrester's models of the 1960s —foundational as they were (Barlas, 2007; Sterman, 2000)—suffer from a severe lack of resolution when confronted with contemporary IoT (Internet of Things) sensor networks generating terabytes of data.

Three critical paradigm shifts necessitate the modernization of our cognitive models:

1. **Hyper-velocity:** Decision-making must occur in seconds, not hours.
2. **Data Noise:** True systemic signals are frequently obscured by massive data volumes.
3. **Human-Machine Hybridity:** The decision-maker is no longer exclusively human; operations require continuous, symbiotic interaction with algorithms.

2. Conceptual Framework: What is Systems Thinking 2.0?

Whereas classical systems thinking focused on *understanding* the system, Systems Thinking 2.0 is centered on managing the system amidst continuous transformation. It conceptualizes technology not as an exogenous tool, but as a dynamic, integral component at the core of the system.

- **Comprehension of Complex Adaptive Systems (CAS):** Traditional models assume a static system architecture. In contrast, the CAS approach posits that interacting agents continuously reconfigure the system (Holland, 2006). A minor delay at a maritime port can perturb production schedules, inventory levels, lead times, and ultimately, corporate equity valuation. Optimization that disregards this butterfly effect is inherently flawed. This paradigm shifts the engineer's objective from attempting to *control* the system to dynamically *steering* it.
- **Data- and AI-Driven Modeling:** Technologies such as Digital Twins and Agent-Based Modeling integrate real-time empirical data into systems thinking (Grieves & Vickers, 2017; Macal & North, 2010). While conventional simulations rely on static datasets, modern digital twins evaluate stochastic "what-if" scenarios in seconds. Generative AI-assisted simulation tools further enable bottleneck forecasting via natural language prompts.
- **Uncertainty Management and Robust Optimization:** Classical optimization seeks the deterministic "optimal solution," whereas Systems Thinking 2.0 prioritizes the solution that remains viable under worst-case scenarios. Robust optimization, stochastic modeling, and Monte Carlo simulations become critical where deterministic models fail (Ben-Tal et al., 2009) (e.g., during pandemics or geopolitical crises).
- **Human-AI Collaboration (Human-in-the-Loop):** A core tenet is positioning AI as a systemic actor rather than an opaque "black box." AI conducts probabilistic analyses and generates alternatives; however, the ultimate evaluative authority remains human. The engineer serves as the algorithm's trainer, auditor, and ethical boundary-setter.
- **Sustainability and Multi-Objective Optimization:** The contemporary objective function extends beyond mere cost minimization. It encompasses frequently conflicting targets

such as carbon footprint reduction, water conservation, employee well-being, and broader social impact, aligning with the human-centric approach of Industry 5.0.

3. Real-World Case Studies

Case 1: Integration of Generative AI and Simulation in Manufacturing

In a modern automotive supplier facility, generative AI is integrated with discrete-event simulation software. Upon sudden machine failure, the system processes millions of combinations in seconds, presenting the line supervisor with the optimal revised schedule and risk analysis.

- **Outcome:** Decision latencies are reduced from hours to seconds, resulting in measurable improvements in scheduling efficacy. Manufacturers like BMW and Siemens leverage this methodology for facility layout planning, while Renault's Industrial Metaverse applications yield substantial savings via predictive maintenance (Siemens AG, 2024).

Case 2: The Red Sea Crisis – AI-Augmented Supply Chain Agents (2024)

The diversion of global container traffic due to geopolitical conflicts extended maritime lead times by 12 days and inflated freight costs by 150% (UNCTAD, 2024). Managing this disruption via classical Material Requirements Planning (MRP) logic was functionally impossible. AI planners utilizing multi-agent simulation processed real-time data for every container and port, generating actionable scenarios (e.g., shifting production, utilizing air freight, or executing expedited procurement).

- **Outcome:** Teams operating with a robust optimization mindset secured weeks of competitive advantage through proactive resilience rather than reactive response.

Case 3: Healthcare Systems in Turkey – MHRS and Patient Flow Optimization

The Central Physician Appointment System (MHRS) constitutes a massive multi-channel queuing system. During peak periods, the system faced critical bottlenecks when patient no-show rates escalated to 25% (Republic of Turkey Ministry of Health, 2023). Using Systems Thinking 2.0, machine learning algorithms dynamically estimate each patient's no-show probability to optimize capacity through targeted overbooking. Similarly, dynamic routing algorithms in emergency departments—processing real-time vital signs and exogenous signals—significantly reduced wait times while optimizing resource utilization.

- **Outcome:** Quantifiable reduction in wait times, mitigation of physician burnout, and optimized resource allocation.

4. Student Guide: Cultivating 2.0 Competencies

To remain competitive, industrial engineering students must systematically cultivate the following competencies:

Essential Technological Requisites:

- Python (SimPy, Mesa, PuLP)
- Arena / AnyLogic
- Power BI / Tableau
- LLM APIs (Gemini, Claude, GPT) & Prompt Engineering
- GitHub Portfolio Development

Actionable Strategies:

a. **Synthesize Coursework with Computational Tools:** Discontinue viewing Simulation, Operations Research, and Supply Chain Management as isolated disciplines. Construct queuing models via SimPy; execute agent-based simulations using Mesa (Macal & North, 2010); or design empirical facility flows in Arena or AnyLogic.

b. **Utilize AI as a Cognitive Assistant:** Structure complex engineering problems using Goal-Output-Constraint (G-O-C) frameworks before delegating them to AI models. The AI generates probabilistic scenarios; the engineer evaluates them within the broader systemic context.

c. **Interrogate Systemic Dynamics During Internships:** Rather than asking, "Why is this process inefficient?" ask, *"Which systemic dynamic generates this inefficiency, and what feedback loop does it trigger?"* (Senge, 2006; Sterman, 2000). Construct rudimentary simulation models to analyze the cascading effects of proposed interventions.

d. **Construct a Robust Technical Portfolio:** Procure datasets (e.g., via Kaggle) to develop foundational models or visualize production line simulations via BI dashboards. Publishing these artifacts on GitHub serves as a highly differentiating asset for future employment.

5. Conclusion: The Locus of Competitive Advantage

Over the subsequent decade, robotics and artificial intelligence will automate a substantial portion of routine analytical tasks. However, no algorithm is capable of synthesizing human intuition, ethical paradigms, and interdisciplinary context to ask: *"Does this intervention lock the system into an optimal state, or merely suppress a sub-symptom?"*

The foundational philosophy of industrial engineering—holistic optimization (Barlas, 2007; Sterman, 2000)—remains entirely valid; nevertheless, the complexity of modern systems and the computational capacity of available tools have expanded exponentially. In the forthcoming era, competitive advantage will belong to those capable of synthesizing classical methodologies with advanced artificial intelligence within the crucible of *Systems Thinking 2.0*.

References

Barlas, Y. (2007). *System Dynamics: Systemic Feedback Modeling for Policy Analysis.* Encyclopedia of Life Support Systems (EOLSS), UNESCO–EOLSS Publishers, Oxford, UK.

Ben-Tal, A., El Ghaoui, L., & Nemirovski, A. (2009). *Robust Optimization.* Princeton University Press.

Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems* (pp. 85–113). Springer.

Holland, J. H. (2006). Studying complex adaptive systems. *Journal of Systems Science and Complexity*, 19(1), 1–8.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4(3), 151–162.

Republic of Turkey Ministry of Health. (2023). Sağlık istatistikleri yıllığı 2022 [Health statistics yearbook 2022]. https://www.saglik.gov.tr/TR-103184/saglik-istatistikleri-yilligi-2022.html

Senge, P. M. (2006). The Fifth Discipline: The Art & Practice of the Learning Organization (2nd ed.). Doubleday/Currency.

Siemens AG. (2024). The industrial metaverse: Accelerating manufacturing transformation with digital twins and AI [Technical report]. Siemens Digital Industries.

Sterman, J. D. (2000). Business Dynamics: Systems Thinking and Modeling for a Complex World. Irwin/McGraw-Hill.

UNCTAD. (2024). Review of maritime transport 2024: *Navigating maritime chokepoints.* United Nations Conference on Trade and Development. https://unctad.org/publication/review-maritime-transport-2024

Reducing Waste in Frozen Food Production: A Kaizen Application in the Pea Production Line

In a seasonal batch fruit and vegetable production line, significant losses occurred during pea transfer from truck to washing station due to spillage. This study analyzes the causes and presents improvements achieved through a lean manufacturing approach.

Selin ARAÇ, selinarac21@istanbularel.edu.tr, Istanbul Arel University, Department of Industrial Engineering

1. Introduction

The frozen food industry requires fast and uninterrupted operations to preserve product freshness, especially in seasonal and batch-based production processes such as pea production. During field observations in the process improvement department where I was interning, significant product loss was detected in the transfer line between trucks and the washing station. Measurements showed that approximately 30 kg of peas per hour were wasted due to leakage during transfer, creating both economic and sustainability-related problems.

As an Industrial Engineering student, I evaluated this issue as a lean manufacturing loss (muda) rather than an unavoidable process output. Using lean manufacturing principles (Ohno, T., 1988), this study focuses on analyzing the root causes of the inefficiency and the improvement solutions implemented to reduce waste and improve sustainability performance.

2. Development / Basic Review

2.1. Quantifying the Current Situation and Root Cause Analysis

As the first step of the improvement process, the transfer flow between the trucks and the washing drum was analyzed through on-site observations based on the “Genchi Genbutsu” principle. Measurements showed that approximately 240 kg of peas were lost during an 8-hour shift, resulting not only in raw material loss but also additional cleaning labor and water consumption. As shown in Figure 1, product leakage mainly occurred at worn sections of the elevator system.

To identify the root causes of the problem, a Fishbone (Ishikawa) Diagram and field investigations were conducted. The analysis revealed that nearly 80% of the losses originated from holes caused by metal wear in the elevator system. To determine the systemic source of the issue, a 5 Why analysis was applied:

1) Why is there a loss of 30 kg per hour in pea production?

- The product spills onto the ground from the elevator line while being transferred from the truck to the washing station.

2) Why is the product leaking out of the elevator line?

- There are holes in the conveyor surface and connection points of the elevator due to metal wear.

3) Why did these holes form and go unnoticed?

- Continuous operation and abrasive external factors have caused metal fatigue; however, this area has not been noticed because it is a visually blind spot.

4) Why are these wear points not checked periodically?

- This specific transfer point is not defined as a control point in the current autonomous maintenance and cleaning plans.

5) Why is it not defined as a control point? (Root Cause)

- The wear rate of this equipment and its impact on loss have not been analyzed in the corporate memory and transformed into a standard control procedure.

Figure 1. Pre-improvement Status: Observation of Losses (Muda) in the Elevator System

2.2 Lean Improvement Approach and Applied Solution

To prevent leakage identified during the analysis phase as originating from gaps in the elevator surface, a low-cost but effective improvement was implemented. As shown in Figure 2, rubber-based coatings and guide plates were installed at critical leakage points to ensure watertightness. This Poka-Yoke (error-proofing) solution physically prevents spillage, reduces reliance on human intervention, and significantly eliminates Muda.

Figure 2. Sealing Improvement Applied to Elevator Surface

3. Practical Outcomes and Recommendations

Key professional lessons and lean manufacturing-focused recommendations that can be drawn from the methods applied during the experience process are as follows:

- Transitioning from Subjective Observation to Analytical Data: Instead of qualitative statements such as "a lot of product is being spilled," using quantitative data (e.g., 30 kg/hour loss) helped position the problem within Criticality Analysis. My key recommendation is to always express problems with measurable metrics (kg/hour, %, TL) to clearly demonstrate urgency to management.

- Poka-Yoke Design: Not every problem requires costly automation investment. Our sealing intervention is a Poka-Yoke application that makes it physically impossible for the system to make errors (Shingo, S. 1986). Instead of complex algorithms, sometimes the simplest mechanical solution can save tons of product annually, reducing Muda (waste) to zero.

- Autonomous Maintenance and Jishu Hozen Integration: After the improvement, this critical point was added to maintenance schedules to ensure sustainable process control through Autonomous Maintenance (Jishu Hozen). This approach transformed a temporary repair into a standardized control procedure.

4. Result

The study I conducted demonstrated that complex engineering problems do not always require complicated or costly solutions; instead, effective results can be achieved through simple yet systematic tools of lean manufacturing. A seemingly small loss of 30 kg per hour was revealed to represent a significant inefficiency when evaluated on an annual and sustainability basis.

The application of the 5 Whys Analysis showed that the root cause was not merely physical wear and tear, but a lack of standardization. Subsequent Poka-Yoke implementation and Autonomous Maintenance practices ensured that the improvement became sustainable and repeatable. As a result, the material loss was significantly reduced to approximately 4–5 kg per hour.

As an Industrial Engineering student, this experience highlighted the importance of being present in the field and applying the Genchi Genbutsu principle, integrating theoretical knowledge with practical observation to create tangible value. Overall, this case reinforces how incremental improvements (Kaizen) collectively drive operational excellence and support broader sustainability objectives.

References

Ohno, T. (1988). *Toyota production system: Beyond large-scale production*. Productivity Press.

Shingo, S. (1986). *Zero quality control: Source inspection and the poka-yoke system*. Productivity Press.

The New Language of Decision Support Systems: Prompt Engineering for Industrial Engineers

Large language models are quietly becoming part of our optimization, forecasting, and simulation processes. But how do we get real value from them? Three techniques and a small scenario, with practical notes.

Hazar Ertuğrul İKİZLER, hazarikizler23@istanbularel.edu.tr, Istanbul Arel University, Department of Industrial Engineering

Introduction

In IE we're told to match the right tool to the right problem. Optimization, simulation, statistical methods, decision-support algorithms — each is powerful in its place. LLMs joined the set recently: not as alternatives to Gurobi, Arena, or Python analytics, but as a layer carrying the cognitive load around them.

An optimization model can give the mathematically correct solution; but communicating it, interpreting it, or making a long report readable is a separate problem. This is where LLMs shine — the invisible, time-consuming part of decision-making.

How you approach a model matters as much as its quality. 'The AI got it wrong' usually means a flawed prompt — LLMs more often fail from missing context than missing knowledge.

Prompt Engineering, to me, is less a new technology than a discipline: defining the right problem in the right way — a natural extension of what we do in IE. Below are three approaches I've found most useful.

Discussion / Main Analysis

First, role definition. LLMs aren't powered by general knowledge but by context. Tell a model 'you're a planning engineer at an e-commerce warehouse,' and the answer shifts: SKU density, capacity bottlenecks, shelf turnover, cold-chain constraints enter the conversation.

Second, few-shot prompting. Drop a few input–output examples into the prompt and the model starts imitating in-house practice. Such examples can substantially improve task performance (Brown et al., 2020), including classification like mapping complaints to root-cause categories.

Third, chain-of-thought. Instead of one shot, ask the model to break the problem into steps — analyze, check constraints, propose. In multi-variable problems (scheduling, capacity planning, root-cause analysis) this substantially reduces error (Wei et al., 2022) — the LLM counterpart of IE's 'decompose, solve, recombine.'

Picture this: a mid-sized facility with four production lines, twelve products, choppy weekly demand. The scheduling algorithm outputs a Gantt sheet hundreds of rows long each week. The real problem: how fast the manager extracts the critical bits.

Just saying 'summarize' yields shallow output; the model can't tell the real bottleneck or whether a delay is supply- or capacity-driven. With an operational role, summary examples, and a chain of thought ('find the bottleneck, classify, suggest action'), the output becomes real decision support.

The key point: prompt engineering doesn't replace algorithms; it places a thin interpretive layer between optimization models and operational decisions.

Practical Takeaways and Recommendations

How do these translate into day-to-day work? Three approaches I've found useful:

- First, treat LLMs as 'assistant analysts,' not search engines. The model has no intuition; it runs on the context you give. That doesn't mean accepting output uncritically — suggestions should be checked against data, expert judgment, and field reality.
- Second, treat prompts as system components. Saving v1, v2, v3 of a prompt and noting which worked when builds a personal prompting library; such catalogs are recognized as core prompt-engineering tools (White et al., 2023).
- Third, make chain-of-thought the default. Asking the model to break problems into steps rather than 'answer me' reduces error and eases verification, debugging, and reporting.

Conclusion

Prompt engineering isn't a new field for IE — it's an interpretive layer on top of existing systems. The challenge isn't making the model write; it's framing the problem, building context, and producing usable output. Past a point, the engineer's thinking matters more than the model.

Those who get real value from AI won't have the best model; they'll frame the problem correctly. LLMs sometimes fail from missing knowledge, more often from missing context. Prompt engineering is an extension of analytical thinking, not just a technical skill.

In a few years, employers will weigh 'can they prompt AI in the right context?' alongside 'do they know Python?' A quiet new skill of engineering decision-making.

References

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., … Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33, 1877 – 1901.

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Ichter, B., Xia, F., Chi, E., Le, Q., & Zhou, D. (2022). Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems*, 35, 24824-24837.

White, J., Fu, Q., Hays, S., Sandborn, M., Olea, C., Gilbert, H., Elnashar, A., Spencer, J., & Schmidt, D. C. (2023). A prompt pattern catalog to enhance prompt engineering with ChatGPT. *arXiv*. https://doi.org/10.48550/arXiv.2302.11382

Measurable Ergonomics: From Laboratory to Production Line

Ergonomics is not only about making a workplace comfortable. It is also about protecting human health, increasing work safety, and improving system efficiency. For this reason, ergonomic decisions should not be based only on personal opinions. They should be supported by measurements, observations, standards, and numerical analysis.

Eray Berat KOCABIYIK, eraykocabiyik21@istanbularel.edu.tr, Istanbul Arel University, Department of Industrial Engineering

Halenur OTYILDIZ, halenurotyildiz22@istanbularel.edu.tr, Istanbul Arel University, Department of Industrial Engineering

Anthropometric Evaluation in the Laboratory

In the laboratory, some physical measurements were made. These measurements included chair height, table height, screen height, classroom area, and corridor distance. A laser meter was used for these measurements. The chair sitting height was measured between 39 and 56 cm. The table height was measured as 86 cm. According to these values, the difference between the table and chair height was found as 26 cm.

This result is important because the table-chair height difference affects the sitting position of students. For computer-based working areas, the acceptable ergonomic range is generally around 22–28 cm. Therefore, the measured value of 26 cm is suitable for the working environment.

The screen height was also evaluated. The top point of the screen was measured as 126 cm. This height was close to the user's eye level. This is important because an unsuitable screen height can cause neck bending and discomfort during long-term computer use.

The laboratory area was measured as 6.8 m × 8.5 m. The total area was approximately 58 m^2. Also, the corridor distance between workstations was measured as 125 cm. This distance helps students move comfortably in the laboratory. These results show that the laboratory is generally suitable in terms of space, movement, and computer-based work.

Manual Workload in the Production Line

The second example is related to a production line. In this production line, some stations such as filling, capping, and labeling are supported by machines. However, boxing and palletizing are more manual tasks. These tasks require more physical effort from the operator.

For this reason, the manual workload was evaluated with numerical methods. During work, the operator's heart rate reserve, called HRR, was calculated as 46.34%. For long-term work, the recommended limit is usually around 30–33%. This means that the operator's physical workload is high and may create fatigue risk.

In the boxing station, the operator's elbow height was measured as 105 cm. The working surface height was measured as 98 cm. For light manual work, the recommended table height is usually 5–10 cm below elbow level. In this case, the difference is 7 cm. Therefore, the boxing station is suitable in terms of working height.

REBA and NIOSH Risk Evaluation

The palletizing task was evaluated with REBA and the NIOSH Lifting Equation. As shown in Figure 1, the operator bends the trunk, neck, shoulder, and wrist during palletizing. REBA is used to evaluate risky body postures during work.

In this REBA analysis, the trunk position was scored as 3 points and the neck position was scored as 2 points. The leg position was scored as 3 points because the posture is not fully balanced during palletizing. For the arm and wrist part, the upper arm was scored as 3 points, the lower arm was scored as 1 point, and the wrist was scored as 2 points. Also, the 20 kg load added +2 points, and repeated activity added +1 point. The coupling condition was accepted as poor because the box is not easy to hold during lifting. According to these values, the total REBA score was found as 14. This score means "very high risk". Therefore, this palletizing task is not suitable in its current form and should be improved.

The NIOSH Lifting Equation was used to evaluate the 20 kg box lifting task. In this calculation, the Recommended Weight Limit, called RWL, was calculated by using six multiplier values: HM, VM, DM, AM, FM, and CM. These values were considered as HM = 0.83, VM = 0.93, DM = 0.90, AM = 0.90, FM = 0.88, and CM = 0.83. According to these values, the RWL was calculated as approximately 10.45 kg. The Lifting Index was calculated as LI = 20 / 10.45 = 1.91. Since this value is greater than 1, the lifting task has a risk for the lower back and musculoskeletal system.

Figure 1: Ergonomic evaluation diagram body angles during palletizing in the production line.

Practical Results and Suggestions

This study gives three important results. First, ergonomic evaluations should be based on measurements. For example, instead of saying “the table is suitable”, the table height, chair height, and height difference should be explained with numbers.

Second, problems in production lines should not be evaluated only with machine capacity. Manual tasks such as boxing and palletizing can also affect productivity because the operator’s physical limits are important.

Third, the correct analysis method should be selected for each ergonomic problem. REBA can be used for posture analysis, NIOSH can be used for lifting tasks, and anthropometric measurements can be used for workplace design.

Conclusion

As a result, ergonomics is a measurable engineering subject. In the laboratory example, chair, table, screen, and area measurements help to evaluate user comfort and suitability. In the production line example, REBA and NIOSH analyses show the risk level of manual work. For industrial engineering, ergonomics is not only about comfort. It is also related to safety, productivity, and sustainable work performance.

References

Hignett, S., & McAtamney, L. (2000). Rapid entire body assessment (REBA). *Applied Ergonomics, 31*(2), 201–205.

Kuruşçu, M. (2026). *Human factors and ergonomics* [Course notes]. Istanbul Arel University.

Occupational Safety and Health Administration. (2011). *Ergonomics for the prevention of musculoskeletal disorders*. https://www.osha.gov/ergonomics

Şimşek, B. (2026). *Work analysis and design* [Course notes]. Istanbul Arel University.

Waters, T. R., Putz-Anderson, V., Garg, A., & Fine, L. J. (1993). Revised NIOSH equation for the design and evaluation of manual lifting tasks. *Ergonomics, 36*(7), 749–776.

Department News & Events

Technical Visit to TÜBİTAK Marmara Teknokent

On March 26, 2026, the Industrial Engineering Club organized a highly productive technical visit to TÜBİTAK Marmara Teknokent, with the valuable support of our university's Erasmus Office. Accompanied by the club's faculty advisor, members had the opportunity to attend informative presentations delivered by institution representatives, followed by on-site tours of companies operating across various departments within the technopark. The visit provided a unique bridge between theoretical knowledge and real-world sectoral innovation, offering club members a significantly enriched perspective on their future careers.

IE Club members during the technical visit to TÜBİTAK Marmara Teknokent, March 2026.

Technical Visit to TÜYAP Recycling Fair & Conference

On March 27, 2026, the Industrial Engineering Club organized a technical visit to the TÜYAP Recycling Fair and Conference, under the guidance of the club's faculty advisor. During the event, members explored plastic recycling processes, circular economy practices, and industrial waste sorting technologies through both exhibition stands and conference sessions. The visit also included PAGÇEV panels on sustainability, providing the club with valuable updates on the current environmental agenda. This enriching experience made a meaningful contribution to the club's sectoral vision and awareness in sustainable industrial practices.

IE Club members at the TÜYAP Recycling Fair & Conference, March 2026.

"Engineering Conversations" Speaker Series: Guest Talk by Burak MÜJDECİ

On March 31, 2026, Istanbul Arel University's Industrial Engineering Club welcomed industry professional Burak Müjdeci as part of the club's ongoing "Engineering Conversations" speaker series. The event was held at the Student Clubs and Leadership Office, with the participation of our department head and the club's faculty advisor. Attendees had the opportunity to hear firsthand accounts of industry experience, real-world case analyses, and career guidance from the guest speaker. By connecting theoretical foundations with the dynamics of professional life, this inspiring talk made a substantial contribution to members' career planning and professional development.

IE Club members with guest speaker Burak MÜJDECİ during the "Engineering Conversations" series, March 2026

Alumni–Student Interaction Meeting: Spring 2025–2026 Experience Sharing Session.

On June 2, 2026, the Department of Industrial Engineering hosted the "Spring 2025–2026 Experience Sharing and Alumni–Student Interaction" meeting, bringing together department graduates, current students, and faculty members in an online session held via Microsoft Teams. The event provided a valuable platform for alumni to share their professional journeys and insights, while students had the opportunity to engage directly with graduates who have transitioned into the workforce. This meaningful exchange of experiences contributed to students' professional outlook and reinforced the ongoing connection between the department and its alumni network.

"Artificial Intelligence in Academia" — A Talk by Asst. Prof. Bülent ŞİMŞEK

On June 11, 2026, the Business Intelligence and ERP Club organized the "Artificial Intelligence in Academia" event, bringing together department faculty and students for an insightful session. The talk was delivered by Asst. Prof. Bülent Şimşek, who shared his perspectives on the growing role of artificial intelligence within academic research, education, and practice. The event offered attendees a timely and thought-provoking exploration of how AI tools and methodologies are reshaping the academic landscape across disciplines.

Asst. Prof. Bülent ŞİMŞEK presenting at the "Artificial Intelligence in Academia" event, organized by the Business Intelligence and ERP Club, June 2026.

8D Problem Solving Analysis Training — A Joint Club Event

On May 14, 2026, the Business Intelligence and ERP Club and the Industrial Engineering Club jointly organized an "8D Problem Solving Analysis" training session. The event was conducted with the participation of industry professional Deniz AYGAN, department faculty, and students. The training provided attendees with a structured introduction to the 8D methodology — a systematic, team-oriented approach widely used in industry for identifying, correcting, and eliminating recurring problems. This collaborative event strengthened both clubs' commitment to bridging academic knowledge with practical, real-world problem-solving techniques.

8D Problem Solving Analysis Training session, jointly organized by the Business Intelligence and ERP Club and the Industrial Engineering Club, May 2026.

Capstone Project Showcase *— Class of 2026*

RESEARCH QUESTION

- How can VRP problem solutions and LP approaches affect the Logistics?
- How to optimize workflow?
- How to optimize Information flow?
- How the process optimizations affect the logistics sector?

METHOD

- Linear Programming (LP) Models
- Vehicle Routing Problem (VRP) Algorithms
- Business Process Re-engineering (BPR)
- Business Process Model and Notation (BPMN 2.0)
- Gap Analysis & ECRS Principle

DEPARTMENT OF INDUSTRIAL ENGINEERING

VEHICLE ROUTE PLANNING AND FLOW OPTIMIZATION IN A COMPANY LOCATED IN THE EUROPEAN SIDE OF İSTANBUL

MEHMET YILANCI- JAHANGIR SALIM KHATRI- BURAK DEĞIRMENCI/MEHMET KURUŞÇU

GENERAL INFORMATION

This project focuses on optimizing vehicle route planning and information workflows for "Logist," a logistics company located on the European side of Istanbul. The main objective is to eliminate manual inefficiencies and minimize operational delays by developing a data-driven decision support system using Linear Programming (LP) and Vehicle Routing Problem (VRP) models. Through the integration of Business Process Re-engineering (BPR) and flow optimization techniques, the project aims to automate routing processes and streamline interdepartmental communication. This approach not only reduces lead times and operational costs but also enhances overall service quality, ultimately leading to the development of an integrated digital application for dynamic resource management.

FINDINGS

- 87.5% Faster Inquiries: Customer status checks dropped from 8 minutes to just 1 minute per inquiry.
- Rapid Reporting: Automated workflows reduced operational report generation from 32 minutes down to 3 minutes.
- Minimized Latency: Shifting to a centralized digital system eliminated manual tracking, significantly reducing data-entry errors and Information Lead Time (ILT).
- Optimized Routing: The VRP model successfully minimized total travel distances (e.g., exactly 606 km for a 3-city multi-node route) while adhering to strict vehicle capacity limits

FUTURE WORKS

- Full Automation via RFID: Implementing RFID tags in warehouse facilities and fleet vehicles to achieve completely automated data entry and real-time shipment tracking.
- Predictive Demand Forecasting: Upgrading the current reporting module by integrating Machine Learning forecasting models to predict future order volumes and proactively manage resources.
- Continuous System Scaling: Expanding the web application and VRP integrations across broader operational networks to further drive down lead times and eliminate residual errors.

IMPORTANT RESOURCES

-Chopra, S., & Meindl, P. (2016). Supply Chain Management: Strategy, Planning, and Operation. Pearson Education.
-Christopher, M. (2016). Logistics & Supply Chain Management. FT Publishing International.
-Lee, H. L., Padmanabhan, V., & Whang, S. (1997). Information Distortion in a Supply Chain: The Bullwhip Effect. Management Science, 43(4), 546-558.
-Shannon, C. E. (1948). A Mathematical Theory of Communication. The Bell System Technical Journal, 27(3), 379-423.
-Wang, R. Y., & Strong, D. M. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. Journal of Management Information Systems, 12(4), 5-3

THANKS

Mehmet KURUŞÇU

RESEARCH QUESTIONS

- How can dynamic factors such as traffic, weather, and driver constraints affect routing performance in real-life operations?
- How can simulation modeling validate the operational feasibility of mathematically optimized routes?

METHOD

- Capacitated Vehicle Routing Problem (CVRP)
- Python & Pyomo Optimization Modeling
- GLPK Solver
- AnyLogic Simulation Modeling
- Discrete Event Simulation (DES)
- Agent-Based Modeling (ABM)
- GIS-Based Logistics Network Modeling
- Monte Carlo Simulation
- Dynamic Traffic & Weather Parameters
- Time Window and Driver Constraint Analysis

DEPARTMENT OF INDUSTRIAL ENGINEERING

DETERMINING THE BEST DISTRIBUTION STRATEGY USING VEHICLE ROUTING APPROACH AND SIMULATION MODELING

Ceyda İkra KOÇAL - Salihanur TAŞ - Zeynep Sude TORUN
ADVISOR: Sabahattin Kerem AYTULUN

GENERAL INFORMATION

This project focuses on optimizing distribution operations from a central warehouse in İstanbul to nine regional warehouses across Türkiye using CVRP optimization and AnyLogic simulation modeling.
The model minimizes transportation costs while meeting all warehouse demands on time. Three fleet scenarios with a constant total capacity of 50 tons were analyzed using Python, Pyomo, and the GLPK solver.
The optimized routes were validated in AnyLogic under realistic conditions such as traffic, weather, and legal driving constraints, creating an integrated decision support system for logistics optimization.

FINDINGS

- AnyLogic simulation tested the logistics system under realistic conditions such as traffic, weather, driver rest periods, and vehicle breakdowns.
- The average simulation cost was calculated as 1.920.454 TL within a 95% confidence interval.
- The total operational cost reached 1.922.083 TL after the 720-hour simulation period.
- Vehicle utilization analysis showed that transportation activities covered 55% of the operational time.
- The findings proved that the integrated Python and AnyLogic model created an efficient and sustainable logistics decision-support system.

FUTURE WORKS

Integration of real-time traffic APIs and live GIS data
Expansion of the model with stochastic demand variations
Development of AI-supported adaptive routing strategies
Inclusion of carbon emission and sustainability metrics
Enhancement of microscopic agent-based simulation capabilities
Real-time dashboard and predictive analytics integration

IMPORTANT RESEARCH

- Vehicle Routing Problem — Foundational VRP study introducing truck dispatching optimization
- Topuk and Özyeşil — Classification of Vehicle Routing Problems and solution methods
- Deineko and Adeniran — Two-echelon logistics optimization with simulation-based validation
- Amina Antit and Amel Jaoua — Simulation-based optimization under stochastic traffic conditions

THANKS

Sabahattin Kerem Aytulun & Bülent Şimşek & Mehmet Kuruşçu

RESEARCH QUESTIONS

- Q1: How can we minimize overpopulation while ensuring efficient resource utilization?
- Q2: What is the trade-off between travel distance and sustainability?

METHOD

- Mixed Integer Linear Programming (MILP) formulation.
- GAMS Optimization Software (utilizing the CPLEX solver).
- Sensitivity Analysis on capacity thresholds and distance limits.

DEPARTMENT OF INDUSTRIAL ENGINEERING

DESIGNING AN EFFECTIVE MODEL FOR SUSTAINABLE BEEKEEPING

Khaled Ahmed, Youssouf Kalil, Abdelrahman Sharafeldin
Advisor: Dr. Mehmet KURUŞCU

GENERAL INFORMATION

This project focuses on optimizing apiary allocation within the Kavaklidere district to promote long-term environmental sustainability. The main objective is to design a mathematical decision-support model that balances floral carrying capacities while minimizing the ecological damage caused by localized overpopulation, and includes factors such as beekeeper travel distances and village capacities. This approach assists regulators and commercial beekeepers in transitioning away from arbitrary hive placement toward a scientifically-grounded distribution system that protects local biodiversity.

FINDINGS

- **Baseline Risk (Scenario 1):** Unrestricted placement caused severe localized overpopulation (up to 750 excess hives in one village).
- **Distance Trade-off (Scenario 5):** Limiting travel to 5 km minimized movement costs (V: 2,328) but drastically worsened overpopulation (800 excess hives).
- **Optimal Strategy (Scenario 7):** Identified as the 'Sweet Spot,' this model dispersed colonies to a sustainable limit of just 90 excess hives per village.
- **Conclusion:** The math proves that accepting a higher travel cost (V: 13,828) is a necessary trade-off to achieve environmental equity and protect local biodiversity.

FUTURE WORKS

- Integration of real-time climate and seasonal floral data to adjust carrying capacities dynamically.
- Development of a user-friendly Decision-Support UI for beekeepers and agricultural regulators.

IMPORTANT RESOURCES

Gavina, B., Caragay, C., & Macapagal, R. (2014). Determining the optimal distribution of bee colony locations to avoid overpopulation using mixed integer programming.

Esteves et al. (2010). Mathematical Programming for Apiary Placement.

THANKS

Special thanks to Dr. Mehmet KURUSCU and the Department of Industrial Engineering for their invaluable guidance and support throughout this project.

RESEARCH QUESTIONS

How can time series forecasting improve demand predictability in the textile industry?

How accurately can the SPSS Expert Modeler identify the optimal forecasting method to capture the strong seasonality and trend patterns in the textile company's sales data?

METHOD

Time Series Forecasting

Hold Method

ARIMA (for comparison)

Forecast Accuracy Evaluation

Residual Diagnostics

Economic Order Quantity (EOQ)

Safety Stock

Reorder Point (ROP)

Continuous Review (Q,R) System

DEPARTMENT OF INDUSTRIAL ENGINEERING

TIME SERIES-BASED DEMAND FORECASTING AND INVENTORY OPTIMIZATION HOLT LINEAR MODEL IN A TEXTILE COMPANY

DOĞA ÜNVER - SUDE KARAMAN - DAMLA DOĞAN

ADVISOR: Sabahattin Kerem Aytulun

GENERAL INFORMATION

This study presents an integrated framework combining demand forecasting and inventory management for a textile company. Using two years of sales data, time series forecasting methods were analyzed in SPSS, and the Winters' Multiplicative model was selected as the best forecasting method. Forecast results were integrated into Safety Stock, ROP, and EOQ calculations, while the effects of QR strategies on lead time and inventory responsiveness were also evaluated.

FINDINGS

Textile demand showed a strong non-stationary trend structure, statistically validated by the Runs Test (p = 0.022$).

Holt's Linear Model was identified as the best forecasting framework in SPSS, capturing the linear upward trajectory effectively.

The forecasting model achieved a high Stationary R-squared of 0.790, and the residuals successfully behaved as random white noise (p = 0.968).

Forecasted demand values for 2026 were integrated into the inventory framework, optimizing the Economic Order Quantity (EOQ) at 16,938 units.

A robust Reorder Point (ROP) of 126,416 units was established by incorporating a calculated safety stock of 23,249 units to buffer demand volatility.

FUTURE WORKS

Application of the framework using real company ERP data

Comparison of forecasting results with machine learning models

Expansion to multi-product inventory systems

Simulation-based validation of inventory performance

Development of automated forecasting dashboards using Python and Power BI

IMPORTANT RESOURCES

-Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2008). Time Series Analysis.
-Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (1998). Forecasting.
-Silver, E. A., Pyke, D. F., & Peterson, R. (1998). Inventory Management.
-Cachon, G. P., & Swinney, R. (2011). Quick Response in Fashion Supply Chains. to multi-product textile environments.
-Nahmias, S., & Olsen, T. L. (2015). Production and operations analysis. Waveland Press
-Uzgören, Nevin. (2012). Bilimsel Araştırmalarda Kullanılan Temel İstatistiksel Yöntemler ve SPSS Uygulamaları

THANKS

Sabahattin Kerem Aytulun
&
Mehmet Kuruşçu

RESEARCH QUESTION

- ·How can MRCPSP represent time–resource trade-offs?
- ·To what extent does Hill Climbing enhance GA convergence and solution quality?

METHOD

- Integer Linear Programming (ILP)
- Genetic Algorithm (GA)
- Hill Climbing Local Search
- Hybrid Genetic Algorithm (HGA)
- Serial Schedule Generation Scheme (SSGS)
- Paired Samples t-test
- p-value Analysis
- PSPLIB J30 Benchmark Dataset
- Python 3
- NumPy
- Matplotlib
- Streamlit
- Plotly

DEPARTMENT OF INDUSTRIAL ENGINEERING

RESOURCE CONSTRAINED PROJECT SCHEDULING MODELING AND OPTIMIZATION APPROACHES

Ezgi ŞENGÜN | Asst. Prof. Sabahattin Kerem AYTULUN

GENERAL INFORMATION

This project presents a Hybrid Genetic Algorithm (HGA) for solving the Multi-Mode Resource Constrained Project Scheduling Problem (MM-RCPSP), an NP-Hard optimization problem in industrial engineering. The HGA combines a dual-layer chromosome representation with Hill Climbing local search and was tested on 19 PSPLIB J30 benchmark instances. Results show a mean makespan improvement of 13.69 percent with a 100 percent win rate, confirmed by a paired t-test ($t = 6.7509$, $p = 0.000003$). A Streamlit-based web application was also developed to make the system accessible to real project managers.

FINDINGS

The HGA outperformed the Standard GA in all 19 PSPLIB J30 instances, achieving a 100 percent win rate. Mean makespan decreased from 35.26 to 30.37, yielding a mean improvement of 13.69 percent. Instance-level improvements ranged from 2.50 to 27.78 percent. The HGA triggered early stopping between generations 51 and 55 in all instances. Mean resource utilization was 52.2 percent for R1 and 49.9 percent for R2. A paired t-test confirmed statistical significance ($t = 6.7509$, $p = 0.000003$).

FUTURE WORK

Future work should focus on testing the algorithm on larger PSPLIB instances such as J60, J90, and J120 to evaluate scalability, and extending the Hill Climbing component beyond mode swaps to include sequence-based local search operators such as activity shifting and pairwise swaps, which could further improve solution quality and close the remaining gap to the theoretical lower bound.

IMPORTANT RESOURCES

- Hartmann, S. (2001). Project scheduling with multiple modes: A genetic algorithm. 'Annals of Operations Research', 102(1–4), 111–135.
- [Kolisch, R. (1996).. 'European Journal of Operational Research'
- Kolisch, R., & Hartmann, S. (2006). Experimental investigation of heuristics for resourceconstrained project scheduling: An update. 'European Journal of Operational Research'

THANKS

Asst. Prof. Sabahattin Kerem AYTULUN

RESEARCH QUESTION

How can unplanned maintenance events prioritized to minimize production downtime?
How can an optimization approach improve cost-efficiency and resource utilization?

METHODS

- Data Collection & Preprocessing
- Rule-Based Classification
- Pareto Analysis
- Reliability Analysis
- Analytic Hierachy Process (AHP)
- Cost & Interval Optimization
- Web-Based Decision Support Interface

DEPARTMENT OF INDUSTRIAL ENGINEERING

OPTIMIZATION AND PRIORITIZATION OF UNPLANNED MAINTENANCE SHUTDOWNS: A CASE STUDY OF A CEMENT PLANT IN ISTANBUL

Selin ARAÇ, Nuray ATEŞ, Aysel Sude ERTÜRK | Asst. Prof. Mehmet KURUŞÇU

GENERAL INFORMATON

Unplanned maintenance in continuous 24/7 cement production significantly reduces operational efficiency and increases costs. At the Akçansa Büyükçekmece Plant, the second raw mill is a critical unit where unexpected failures under heavy mechanical and thermal stress disrupt material flow and cause missed targets. To address this problem, this study develops a data-driven maintenance prioritization framework. By utilizing Pareto analysis, MTBF, and AHP, critical failure categories are systematically identified and ranked. Ultimately, an optimization model is built to determine the optimal maintenance intervals, aiming to prevent disruptive failures and minimize overall maintenance costs.

FINDINGS

Pareto, MTBF, and AHP analyses revealed that the Mix/Dosing Belt Feeding unit is the most critical asset, with just four failure categories accounting for 81% of total downtime. Through a two-tier (Periodic and Condition-Based) maintenance optimization developed using the Campbell & Jardine cost function and ISO 13379-1 standards, an estimated annual operational saving of 14.9 million TL is projected. Finally, to eliminate manual data entry, a real-time, AI-powered web decision support interface and maintenance calendar driven by the Google Gemini API have been successfully deployed.

FUTURE WORKS

Future research will focus on expanding the integrated framework and two-tier optimization model to other critical cement plant units, such as the Kiln and Cement Mill. Additionally, the current rule-based text classification approach will be upgraded to advanced machine learning or deep learning models to achieve higher precision in parsing unstructured failure logs.

IMPORTANT RESOURCES

Ebrahimi, M., Khorshid-Doust, R. R., & Nahavandi, N. (2019). Application of preventive maintenance scheduling to increase equipment reliability: Case study – Bag filters in a cement factory, 7(1), 45–60.

Nugroho, A., Setyono, B., & Aris, D. (2024). Maintenance analysis of raw mill machines in cement industry, 19(2), 112–125.

THANK YOU

Asst. Prof. Mehmet KURUŞÇU

RESEARCH QUESTION

- How can waste processing facilities be optimally located to minimize economic and environmental costs?
- How should waste flows be allocated between source nodes and candidate facilities?
- How does the optimized reverse logistics network reconfigure under capacity disruptions or demand growth scenarios?

METHOD

- Hybrıd Decision Framework
- Analytical Hierarchy Process (AHP) & TOPSIS
- Green Mixed-Integer Linear Programming (MILP)
- Scenario Analysis (What-if scenarios S0-S4)
- Minimize total reverse logistics cost
- Constraints: Demand satisfaction
- Python 3.10 | PULP | CBC Solver
- Matplotlib | Tableau

DEPARTMENT OF INDUSTRIAL ENGINEERING

REVERSE LOGISTICS OPTIMIZATION: DESIGN OF A SUSTAINABLE REVERSE SUPPLY CHAIN NETWORK

Mehmet Okay ÖZAYDIN, Sedat Can AYNACI, Çağatay ÖNAY | Asst. Prof. Sabahattin Kerem AYTULUN

GENERAL INFORMATION

Driven by the European Green Deal, this study addresses the inefficient, decentralized handling of 287.5 tons of annual waste at Mars Logistics. To transition towards a circular supply chain, we propose a data-driven reverse logistics network that minimizes investment, transportation, and environmental costs while ensuring capacity compliance and scenario-based resilience.

FINDINGS

The model achieved an 18% cost reduction while effectively managing 287.5 tons of waste. The baseline network (S0) operates optimally with facilities F1 and F3 , achieving 93.8% and 100% capacity utilization respectively. Keeping F2 closed avoids unnecessary CAPEX, which constitutes 65.4% of total costs. Additionally, the network demonstrates strong resilience, dynamically shifting to an F1+F2 configuration under stress conditions like demand growth or capacity loss.

FUTURE WORK

Future research should address the stochastic nature of reverse logistics by incorporating uncertainty in waste timing, quality, and quantity. Additionally, the model can be extended to include real-time supply chain disruptions, hazardous waste management, and advanced closed-loop recovery processes.

IMPORTANT RESOURCES

- Mars Logistics. (2022). Sustainability Report.
- Srivastava, S. K. (2008). Network design for reverse logistics. *Omega*, 36(4), 535-548.
- Saaty, T. L. (2008). Decision making with the analytic hierarchy process. Int. J. Services Sciences.
- Mitchell, S., O'Sullivan, M., & Dunning, I. (2011). PuLP: A Linear Programming Toolkit for Python.
- Govindan, K., Soleimani, H., & Kannan, D (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research*, 240(3), 603-626.

THANKS

Asst. Prof. Sabahattin Kerem AYTULUN

AREL IE BULLETIN
Vol. 1, No. 2 · June 2026

> *"Think in systems.*
> *Act with intelligence."*

Next issue: January 2027

Department of Industrial Engineering
Istanbul Arel University

+90 850 850 27 35 – 1360

endustrimuhendisligi@arel.edu.tr

Türkoba Mahallesi, Erguvan Sokak, No:26, K 34537,
Tepekent – Büyükçekmece, İstanbul – Türkiye
Office: A2-06 / A2-07

instagram.com/arelendustrimuhendisligi

Arel Üniversitesi Endüstri Mühendisliği Mezunları - https://www.linkedin.com/groups/9589031/

Editor: **Asst. Prof. Bülent Şimşek** | bulentsimsek@arel.edu.tr