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Modeling and simulation of human behavior impact on production throughput

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Abstract: The development of new technologies generates intelligent, complex, and collaborative production systems. Several research works want to improve the production performances while improving the comfort of the human operator. However, it is not obvious to define optimal strategies of operations planning and control that consider the unexpected and variable character of human operators. It is necessary to understand and model human behavior to develop predictive and dynamic actions. Even if some generic behaviors have been well integrated into classical quasi-deterministic models, there is still a need to develop stochastic models even closer to human behavior to allow more dynamic and anticipatory decision-making, especially at the operational level. In this work, we propose to model human behavior by a Markov chain and to evaluate the effect of the different behavior types on the production system performance. A heterogeneous set of human operators, with different behavioral patterns, were generated and tested through simulation. Earlier results demonstrate that there is a direct link between the behavior of human operators and the performance of the production system. It demonstrates also how to integrate such models in a dynamic decision-making process concerning, the assignment of workers to workstations.

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Keywords: Human-system interaction, Simulation, Markov chain, Throughput, Industry 5.0.

1. INTRODUCTION

Human behavior is one of the most important factors affecting the business processes of organizations in many fields, including industrial goods and services companies. Indeed, despite the development of modern technologies replacing Human in many tasks, such as the use of robots in many industrial sectors, the human remains an element of prime importance in nowadays production processes of most sectors, especially for strategic decision-making and/or in a highly disturbed and uncertain environment. Moreover, human is often at least one of the external elements interacting with the system.

In the industrial sector, robots and production machines are used in many activities, most of which are repetitive, accurate, and resource/power-consuming. This is confirmed by (Chen et al., 2022), who proposed a system-theoretic approach to analyze the performance of collaborative robots in assembly system. Dolgui et al. (2022) argued that despite the potential benefits of Industry 4.0 technologies, especially for assembly systems, they need to be well integrated by involving different heterogeneous factors, such as human workers, smart machines and new technologies. Different approaches have been proposed to make humans and machines cohabit safely in the service of productivity. In such a context, human behavior and

the way people interact with these robots and machines is an important aspect that must be modeled and taken into account when operating such a heterogeneous system to ensure its effectiveness.

This is why a lot of research groups are currently focusing on human behavior modeling and simulation to anticipate its effects. For example, in addition to the problems related to the management of robot fleets (Sahnoun et al., 2019), the management of the safety of operators and their interactions with robots makes these problems very complex (Garrido-Hidalgo et al., 2018; Canbay and Demircioğlu, 2021). (Lin et al., 2022) proposed a hidden semi-Markov model (HSMM) for a human behavior modeling in the production system. A framework that incorporates human factors into production and logistic systems is proposed in (Vijayakumar et al., 2022). (Elkosantini and Gien, 2009) developed a workers' behavior model considering inter-worker social relations that can influence the individual performance.

Industry 4.0 has caused a revolution in the way the manufacturing industry operates, from the creation of the product concept to the development of high-tech automated factories that manufacture and recycle these products (Messaadia et al., 2016). This revolution is based on data collection, analysis, and intelligent decision-making

approaches thanks to a set of technologies such as big data, sensors, cloud computing, and cyber-physical systems (Brik et al., 2022). It allows getting more knowledge about production tools, processes, and their interaction with human operators. In any industry, accurate knowledge of human behavior provides a significant advantage in predicting future system states and optimizing decision-making at the strategic, tactical, and operational levels (Bailly et al., 2020).

Nowadays, Industry 5.0 is advertised as the next important revolution in the industrial sector, where high level technological systems like robots, smart building and highly interconnected organizational systems will handle facilitate the task performed by human operators. In such situation, tasks inducing creativity and perception-based skills will be mostly performed by humans, whereas repetitive and hard tasks will be left to robots. It is therefore a kind of partnership, even communion, between humans and intelligent technology to achieve efficient and sustainable production systems. This is why human behavior modeling will play a central role in Industry 5.0 and will continue to attract the interest of researchers in the social sciences and humanities, as well as in industrial engineering.

Different approaches of modeling human behavior can be found in the literature in several domains: ergonomics, human reliability, learning, vehicle driving, crowd movement, resistance to change, customer behavior, etc. Chang and Yuan (2008) used a Markov chain model to predict customers behavior and combines the notions of collaborative prototyping and Existence, Relatedness and Growth (ERG) theory. The authors justify that the Markov chain within ERG theory would generate good performance in behavior prediction. Tarokh and EsmaeiliGookeh (2017) also utilized the Markov chain model to forecast the future behavior of customers. The model has been validated using customer demographic data and historical transaction data from a composite manufacturing firm in Iran.

In the field of collaborative robotics, Zanchettin et al. (2018) proposed a technique for predicting human activity patterns to quickly deduce when a particular collaborative operation will be requested by the human, and allow a robot to perform other autonomous functions at the same time. The prediction algorithm is based on a higher-order (with memory) Markov Chains and has been tested in a scenario including a dual-arm robot used in a small part collaborative assembly task. In (Zhang et al., 2021), the authors examine task scheduling for a robotic collaborative assembly cell to achieve a trade-off between work cycle and human fatigue. For a more complete overview of the most important recent research works on human-robot interactions in industry, the reader can refer to (Hjorth and Chrysostomou, 2022; Liu et al., 2022; Vicentini, 2021; Hentout et al., 2019)

Therefore, accurate behavioral models of production resources seem essential to optimize the production system and minimize its operating cost. Indeed, these models can be very useful in static and dynamic production planning and scheduling to anticipate and reduce the effect of operational hazards caused by the fortuitous behavior of these resources, which is the case with human operators. Furthermore, such models are also essential to predict

the behavior of the system and its ability to adapt and overcome external disturbances.

The objective of this work is to illustrate, through simulation, the effect of human behavior on the productivity of a production system and, more importantly, to show the interest of integrating a model of human behaviors in a dynamic assignment of resources to reduce the impact of potential performance degrading events resulting from these behaviors.

The rest of the article is composed of 3 sections. Section 2 contains the proposed approach to model and simulate human behavior and its impact on the productivity of a flow shop production system. Simulation results and their discussions are provided in Section 3. Finally, we draw in section4 the main conclusions and perspectives.

2. PROPOSED APPROACH

We consider a flow-shop production system composed of six workstations (WS) denoted by $WS_i, i = 1, 2, \dots, 6$. Each workstation corresponds to a machine that needs the presence of a worker while processing a task. Each job (product) is transferred automatically, once it finishes being processed, until completing all the needed processing steps. Let PT be the vector representing the process times of all workstations: $PT = [PT_1, \dots, PT_i, \dots, PT_6]$ and Let AP be the vector representing the assigned worker profiles of all workstations: $AP = [AP_1, \dots, AP_i, \dots, AP_6]$.

We also define a set of zones where a worker can move and therefore leaves his workstation inactive until he returns to it. That is why they are called “No-productive” zones (NPZ). We model workers behavior as a classical Markov process whose states are defined by $J + 1$ possible states (locations) belonging to two classes: i) 1 among the I “Productive” states, corresponding to the workstation to which the worker is assigned, and ii) J “Non-productive” states corresponding to the J non-productive zones (see Fig. 1).

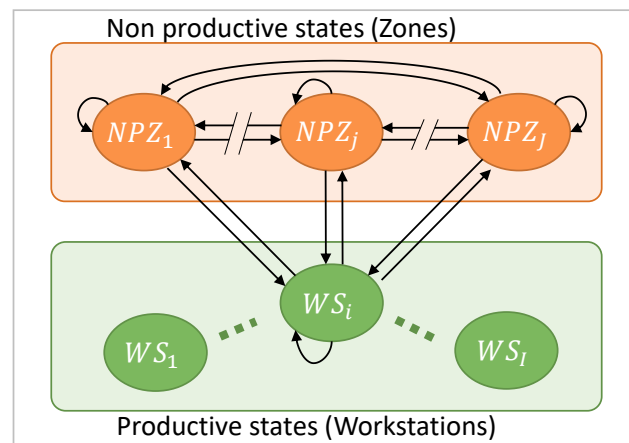


Fig. 1. Productive and non-productive states of the Markovian-based human behavior model

We suppose that each worker is assigned to a unique workstation $WS_i, i \in \{1, 2, \dots, I\}$, and can move only back and forth between it and the set of non-productive zones

$NPZ_j, j \in \{1, 2, \dots, J\}$. The transition probabilities between each workstation and the non-productive zones are defined by the transition matrix P^k relative to the k -th generic profile of workers behaviors.

$$P^k = \begin{pmatrix} p_{i1}^k & p_{i1}^k & p_{i2}^k & \dots & p_{ij}^k & \dots & p_{iJ}^k \\ p_{1i}^k & p_{11}^k & p_{12}^k & \dots & p_{1j}^k & \dots & p_{1J}^k \\ p_{2i}^k & p_{21}^k & p_{22}^k & \dots & p_{2j}^k & \dots & p_{2J}^k \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{ji}^k & p_{31}^k & p_{32}^k & \dots & p_{jj}^k & \dots & p_{iJ}^k \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{Ji}^k & p_{31}^k & p_{32}^k & \dots & p_{Jj}^k & \dots & p_{JJ}^k \end{pmatrix} \quad (1)$$

As shown in equation (1), $p_{ij}^k, \forall j = 1, 2, \dots, J$ represents the probability that a worker with profile k moves from WS_i to NPZ_j , p_{ji}^k represents the probability to move from NPZ_j to WS_i , and $p_{j_1j_2}^k, \forall j_1, j_2 = 1, 2, \dots, J$ represents the probability to move from NPZ_{j_1} to NPZ_{j_2} .

To find out and measure the effect of human behavior on the productivity of production systems, we developed a multi-agent-based simulation, composed of a set of different types of autonomous agents interacting together. We divided the system into four interconnected autonomous agents: “Worker”, “Job”, “Zone”, and “Workstation”. The considered agents and their interrelations are represented in Fig. 2. The composition and role of each agent are defined as follows:

- **Worker:** The “Worker” agent interacts with all other agents because he executes a job when he is on his Workstation and moves between Zones (productive or non-productive). This agent is characterized by a set of parameters as follows:
 - *Last_zone*: it is the last zone visited by the worker before updating his location
 - *Profile*: it is represented by the probability transition matrix. It defines the probabilities that a worker moves between each pair of zone. It corresponds to one of a set of predefined profiles and may differ from one worker to another.
 - *Next_zone*: it is the following zone to be visited by the worker.
- **Zone:** The “Zone” agent is a reactive agent where WSs and NPZs are located in different position in the workshop. Each “Zone” agent is characterized by the following parameters :
 - *Status*: it gives the status of the zone, which may be *free* or *occupied*
 - *Type*: it classifies the zone as *productive* or *non productive*
- **Workstation:** The “Workstation” agent is also a reactive agent where the different production steps of a product are executed, only during the presence of the worker that is responsible of the execution of the task, and obviously, the presence of the product. It is characterized by:
 - *Status*: it gives the status of the workstation, which may be *free* or *occupied*
 - *Type*: it classifies the workstation as *productive* or *non productive*

- **Job:** The “Job” agent represents the products that need to be processed by the workers as each product passes through all the workstations on the production floor. Each job is characterized by the following parameters :
 - *Index* : Determines the current or the last workstation where the job is present
 - *PT*: it is a vector that represents the time it takes at each workstation to process the product, provided the worker is present.

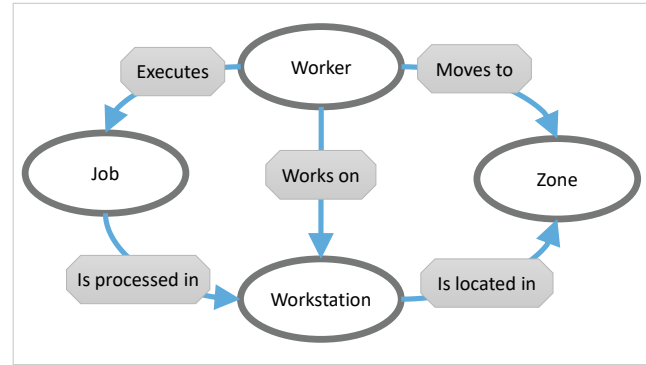


Fig. 2. Multi-agent model’s agents and their interactions

In order to evaluate the impact of workers profiles on the productivity of the system, we perform the simulation over a predefined time horizon and evaluate the number of finished products. The simulation algorithm is detailed in Algorithm 1. At each simulation tick (chosen time unit), the MAS updates: i) workers’ locations, ii) workstations’ status, iii) jobs’ actual processing times and locations, and iv) buffers’ status. A job moves to the downstream workstation in the process if its actual processing time in the current workstation (APT_{jk}) is equal to the required processing time (PT_{jk}). The actual processing time is incremented only if the worker assigned to the workstation is present. Once a job is completed on the last workstation, it is transferred to the output buffer of finished jobs and the number of finished products is incremented. Jobs are generated at the first workstation each time it becomes unoccupied.

3. SIMULATION RESULTS AND DISCUSSION

We developed the multi-agent based simulator using NetLogo 6.2.1. software, which has its own programming language for multi-agent programmable modeling environment (see Fig.3).

We run our simulations with a flow-shop production system in which six productive and 3 non-productive zones. The productive zones represent workstations, where a worker is assigned to perform a specific production task using the equipment associated with the workstation. Whereas, the Non-productive zones represent the areas where a worker is in a kind of non-activity situation, such as a smoking break, personal call, or lunch, or simply an unjustified absence from the workstation.

Looking to the chosen representation of human behavior, and intending to show the effect of different types of human behaviors on the productivity of the manufacturing system, we performed several simulations with

Algorithm 1: Simulation algorithm**Data:**

$\mathcal{WK} = \{WK_1, WK_2, \dots, WK_K\}$: Set of workers;
 $\mathcal{WS} = \{WS_1, WS_2, \dots, WS_K\}$: Set of workstations;
 $\mathcal{J} = \{1, \dots, J\}$: Set of jobs indices;
 $\mathcal{K} = \{1, \dots, K\}$: Set of workers' (workstations) indices;
 $PT = (PT_{jk} : j \in \mathcal{J}, k \in \mathcal{K})$: Processing times;
 $InB = (InB_k : k \in \mathcal{K})$: Workstations' input buffers;
 $OutB$: Output buffer of finished jobs;
 $Horizon$: Simulation horizon;

Result:

NFJ : Number of finished jobs ;
 $Productivity$: Productivity rate ;

begin

```

Initialization: tick = 0, NFJ = 0
APTjk = 0 ∀ j ∈ J ∀ k ∈ {1, ..., K};
while tick < Horizon do
  tick ← tick + 1;
  Update workers' locations;
  for Each WSk ∈ WS do
    if (WSk is occupied by j ∈ J AND WKk is
      present) OR (WSk NOT occupied AND
      ∃ j ∈ J in InBk) then
      APTjk ← EPTjk + 1 ;
      if APTjk = PTjk then
        if k = K then
          Transfer job j to OutB ;
          NFJ ← NFJ + 1;
        else
          Transfer job j to InBk+1;
          if k=1 then
            Generate a new job at WS1
  Productivity ←  $\frac{NFJ}{Horizon}$ ;
  
```

different scenarios. Each worker has his own task allocation defined by his workstation and his behavior. Six generic profiles of workers' behavior are defined and represented by 6 Markov chains with different transition matrices that translate different worker profiles. We defined six generic profiles of workers behaviors represented by the following probability transition matrices:

$$P^0 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \quad P^1 = \begin{pmatrix} 0.95 & 0.05 & 0 & 0 \\ 0.95 & 0.05 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$$

$$P^2 = \begin{pmatrix} 0.9 & 0.1 & 0 & 0 \\ 0.95 & 0.05 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \quad P^3 = \begin{pmatrix} 0.7 & 0.3 & 0 & 0 \\ 0.95 & 0.05 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$$

$$P^4 = \begin{pmatrix} 0.7 & 0.3 & 0 & 0 \\ 0.7 & 0.3 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \quad P^5 = \begin{pmatrix} 0.8 & 0.2 & 0 & 0 \\ 0.6 & 0.2 & 0.1 & 0.1 \\ 0 & 0.3 & 0.4 & 0.3 \\ 0 & 0.3 & 0.3 & 0.4 \end{pmatrix}$$

We run the simulations using the following inputs:

- Simulation horizon: 1 week of 5 working days, 8 hours per day

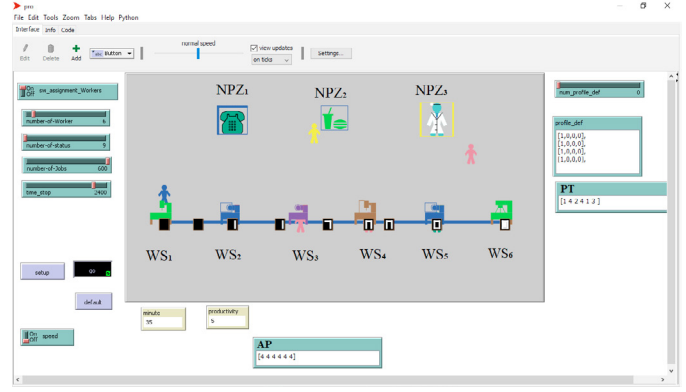


Fig. 3. Overview of the simulation environment.

- Workstations' processing times:
 $PT = [1, 4, 2, 4, 1, 3]$ for the workstations $WS_1, WS_2, WS_3, WS_4, WS_5, WS_6$ respectively.
- Workers' profiles: P^0 (Ideal), P^1, P^2, P^3, P^4 and P^5
- Scenarios: we simulated 36 scenarios, representing different combinations of workers' profiles assigned to workstations.
 - Global scenarios:
 - G0: $AP = [0, 0, 0, 0, 0, 0]$ (Perfect)
 - Gk: $AP = [k, k, k, k, k, k]$, $k = 1, 2, \dots, 5$
 - Mixed scenarios: $\forall k = 1, 2, \dots, 5$
 - Mk1: $AP = [k, 0, 0, 0, 0, 0]$
 - Mk2: $AP = [0, k, 0, 0, 0, 0]$
 - Mk3: $AP = [0, 0, k, 0, 0, 0]$
 - Mk4: $AP = [0, 0, 0, k, 0, 0]$
 - Mk5: $AP = [0, 0, 0, 0, k, 0]$
 - Mk6: $AP = [0, 0, 0, 0, 0, k]$

Table 1 shows the simulation results and gives the level of productivity achieved by each scenario. We can see that there are 13 scenarios among 35 that perform as the perfect scenario (all workers with ideal profile). This implies that each worker profile can have different impacts on productivity, depending on the workstation to which it is assigned. For instance, We can see that productivity is significantly decreased when profiles #3 and #4 are assigned to bottleneck workstations WS_2 and WS_4 .

Fig. 4 draws for each profile the percentage productivity decrease in the cases of global and mixed scenarios (in average). For example, when profile #2 is assigned to all workstations (global scenario), it causes 6% decrease of the productivity compared to the perfect scenario, which drop to an average of 4% in the mixed scenario. The largest average slowdown in productivity is 13%, which is caused by profile #4, in which the probability to stay at workstation is only 0.7.

Table 2 gives for each worker profile the ranking of the best workstations assignments. Obviously, the ideal worker profile is ranked the first for all workstations. For example, with the profile #1, it is better to assign the worker to WS_1, WS_5 , or WS_6 , and then to WS_3, WS_2 and WS_4 . We can see that profiles #3 and #4 are best ranked with workstation having the lowest processing time, namely WS_1 and WS_5 .

Table 1. Results of all tested scenarios

Scenarios #	ID	Operator profiles assignment						Productivity (units/week)
		WS ₁	WS ₂	WS ₃	WS ₄	WS ₅	WS ₆	
1	G0	0	0	0	0	0	0	597
2	G1	1	1	1	1	1	1	564
3	G2	2	2	2	2	2	2	562
4	G3	3	3	3	3	3	3	533
5	G4	4	4	4	4	4	4	526
6	G5	5	5	5	5	5	5	560
7	M11	1	0	0	0	0	0	597
8	M15	0	1	0	0	0	0	571
9	M14	0	0	1	0	0	0	596
10	M16	0	0	0	1	0	0	567
11	M12	0	0	0	0	1	0	597
12	M13	0	0	0	0	0	1	597
13	M21	2	0	0	0	0	0	597
14	M26	0	2	0	0	0	0	531
15	M24	0	0	2	0	0	0	596
16	M25	0	0	0	2	0	0	538
17	M22	0	0	0	0	2	0	597
18	M23	0	0	0	0	0	2	597
19	M35	3	0	0	0	0	0	597
20	M31	0	3	0	0	0	0	411
21	M34	0	0	3	0	0	0	594
22	M32	0	0	0	3	0	0	420
23	M36	0	0	0	0	3	0	597
24	M33	0	0	0	0	0	3	560
25	M41	4	0	0	0	0	0	597
26	M46	0	4	0	0	0	0	405
27	M43	0	0	4	0	0	0	595
28	M45	0	0	0	4	0	0	417
29	M42	0	0	0	0	4	0	597
30	M44	0	0	0	0	0	4	550
31	M51	5	0	0	0	0	0	597
32	M56	0	5	0	0	0	0	478
33	M54	0	0	5	0	0	0	596
34	M55	0	0	0	5	0	0	482
35	M52	0	0	0	0	5	0	597
36	M53	0	0	0	0	0	5	597

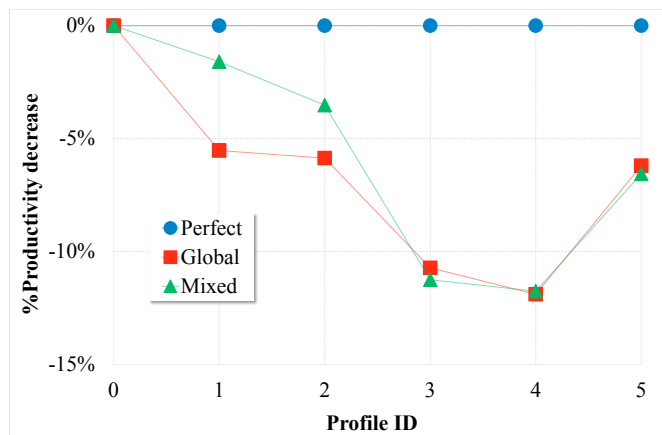


Fig. 4. Effects of profile assignment strategies on productivity

4. CONCLUSION AND FUTURE WORK

This work presents a novel approach for the modeling and simulation of human behavior's impact on production throughput. The results show that human behavior has an important influence on the productivity of the production system. The next step is to apply this approach in a

Table 2. Ranking of the best workstations assignments as function of worker profiles

Profile	rank 1	rank 2	rank 3	rank 4	rank 5
0	1,2,...,6	-	-	-	-
1	1,5,6	3	2	4	-
2	1,5,6	3	4	2	-
3	1,5	3	6	4	2
4	1,5	3	6	4	2
5	1,5,6	3	4	2	-

near real case study and collect real data to clustering different profiles and estimating accurately their transition matrices of the associated Markov Chains. This will allow predicting dynamically the states of workers and integrate that information in an adaptive decision-making process for workers assignment and production tasks scheduling.

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REFERENCES

- Bailly, A., Tlahig, H., Bettayeb, B., Messaadia, M., and Sahnoun, M. (2020). Human's new roles to ensure resilience of industrial cyber-physical systems. In *2020 IEEE Conference on Industrial Cyberphysical Systems (ICPS)*, volume 1, 453–458. IEEE.
- Brik, B., Messaadia, M., Sahnoun, M., Bettayeb, B., and Benatia, M.A. (2022). Fog-supported low latency monitoring of system disruptions in industry 4.0: A federated learning approach. *ACM Transactions on Cyber-Physical Systems*.
- Canbay, P. and Demircioğlu, Z. (2021). Toward industry 5.0: Ethical and moral responsibilities in intelligent autonomous systems. *AJIT-e*, 12(45), 106.
- Chang, W.L. and Yuan, S.T. (2008). A synthesized model of markov chain and erg theory for behavior forecast in collaborative prototyping. *Journal of Information Technology Theory and Application (JITTA)*, 9(2), 5.
- Chen, N., Huang, N., Radwin, R., and Li, J. (2022). Analysis of assembly-time performance (atp) in manufacturing operations with collaborative robots: a systems approach. *International Journal of Production Research*, 60(1), 277–296.
- Dolgui, A., Sgarbossa, F., and Simonetto, M. (2022). Design and management of assembly systems 4.0: systematic literature review and research agenda. *International Journal of Production Research*, 60(1), 184–210.
- Elkosantini, S. and Gien, D. (2009). Integration of human behavioural aspects in a dynamic model for a manufacturing system. *International Journal of Production Research*, 47(10), 2601–2623.
- Garrido-Hidalgo, C., Hortelano, D., Roda-Sanchez, L., Olivares, T., Ruiz, M.C., and Lopez, V. (2018). Iot heterogeneous mesh network deployment for human-in-the-loop challenges towards a social and sustainable industry 4.0. *IEEE Access*, 6, 28417–28437.
- Hentout, A., Aouache, M., Maoudj, A., and Akli, I. (2019). Human-robot interaction in industrial collaborative robotics: a literature review of the decade 2008–2017. *Advanced Robotics*, 33(15-16), 764–799.

- Hjorth, S. and Chrysostomou, D. (2022). Human–robot collaboration in industrial environments: A literature review on non-destructive disassembly. *Robotics and Computer-Integrated Manufacturing*, 73, 102208.
- Lin, C.H., Wang, K.J., Tadesse, A.A., and Woldegiorgis, B.H. (2022). Human-robot collaboration empowered by hidden semi-markov model for operator behaviour prediction in a smart assembly system. *Journal of Manufacturing Systems*, 62, 317–333.
- Liu, L., Guo, F., Zou, Z., and Duffy, V.G. (2022). Application, development and future opportunities of collaborative robots (cobots) in manufacturing: A literature review. *International Journal of Human–Computer Interaction*, 1–18.
- Messaadia, M., Baudry, D., Louis, A., Mahdikhah, S., Evans, R., Gao, J., Paquet, T., Sahnoun, M., and Mazari, B. (2016). PLM adoption in SMEs context. *Computer-Aided Design and Applications*, 13(5), 618–627.
- Sahnoun, M., Xu, Y., Abdelaziz, F.B., and Baudry, D. (2019). Optimization of transportation collaborative robots fleet size in flexible manufacturing systems. In *2019 8th International Conference on Modeling Simulation and Applied Optimization (ICMSAO)*, 1–5. IEEE.
- Tarokh, M. and EsmaeiliGookeh, M. (2017). A new model to speculate clv based on markov chain model. *Journal of Industrial Engineering and Management Studies*, 4(2), 85–102.
- Vicentini, F. (2021). Collaborative robotics: a survey. *Journal of Mechanical Design*, 143(4).
- Vijayakumar, V., Sgarbossa, F., Neumann, W.P., and Sobhani, A. (2022). Framework for incorporating human factors into production and logistics systems. *International Journal of Production Research*, 60(2), 402–419.
- Zanchettin, A.M., Casalino, A., Piroddi, L., and Rocco, P. (2018). Prediction of human activity patterns for human–robot collaborative assembly tasks. *IEEE Transactions on Industrial Informatics*, 15(7), 3934–3942.
- Zhang, M., Li, C., Shang, Y., Huang, H., Zhu, W., and Liu, Y. (2021). A task scheduling model integrating micro-breaks for optimisation of job-cycle time in human-robot collaborative assembly cells. *International Journal of Production Research*, 1–12.