Forecasting Postal Performance via System Dynamics, Metamodeling and Transfer Learning approach

H. Izadbakhsh[1] and M. Zarinbal[2,3]

[1]Department of Industrial Engineering, Faculty of Engineering, Kharazmi University, Tehran, Iran, hizadbakhsh@khu.ac.ir

[2] Department of Industrial Engineering, Amirkabir University of Technology, Tehran, Iran, mzarinbal@aut.ac.ir

[3] Information Technology Research Department, Iranian Research Institute for Information Science and Technology (IranDoc), Tehran, Iran

Abstract

Postal companies primarily engage in delivering letters, parcels, and providing e-services. As technological advancements continue to emerge and customer behaviors evolve, postal services must adapt and modernize. To gain insights into the postal environment and forecast its performance, we employed system dynamics approach. Our case study focused on Iran Post, examining high-level management at the national level. The simulation model effectively predicts postal service performance. To operationalize this model and leverage high-level management expertise, we applied the Transfer Learning paradigm, tailoring models for 32 distinct regions based on their unique specifications. Additionally, we utilized metamodeling techniques and Neural Networks to create a mathematical simulation model. Notably, this approach proves particularly effective when there is a large dataset at hand and simulations are very expensive to execute.

Keywords: Forecasting; System Dynamics; Metamodeling; Transfer Learning

Introduction

With everchanging environment, understanding patterns and predicting behaviors of a system is a challenge which have been met with a variety of methodologies, including time series (Cerqueira et al., 2020) (Ensafi et al., 2022; Mudassir et al., 2020),econometrics (Castle and Hendry, 2022; Fulton and Hubrich, 2021; Kraft et al., 2020), and simulation (Hassanat et al., 2021; Koot and Wijnhoven, 2021; Ordu et al., 2021a, 2021b; Rehman et al., 2023).

One of the most efficient ways to understand and to estimate a system's real behavior over time is using Simulation techniques such as System Dynamics (SD), which focuses on the dynamic nature of a system, analyzing its feedback structures, and trying to steer the system toward a (desired) state (Junginger and Louwen, 2020).

However, the simulation models could be very complex, and the number of possible solutions to mimic real behavior could increase dramatically. Thus, to find the best solutions and scenarios it is impractical to evaluate all possible solutions; hence, Optimization via simulation (OvS) techniques such as metamodeling are usually employed. Metamodeling tries to construct mathematical representations that encapsulate the core relationships within a problem, offering quicker predictions than traditional simulation models. They are also used to approximate

simulation models, especially when the simulation is complex and expensive to execute (Soares do Amaral et al., 2022).
A pertinent inquiry arises: Is it possible to craft a metamodel tailored to a specific simulation domain and then adapt it to another? The capability to transfer a metamodel across domains could significantly streamline problem-solving and reduce costs.

Addressing this query, we explore the concept of Transfer Learning (TL), a relatively nascent paradigm in Artificial Intelligence (AI) and Machine Learning (ML). TL encompasses the application of knowledge acquired in one domain to enhance problem-solving in another (Bengio et al., n.d.).

This paper delves into TL and its integration with simulation models. We will apply TL to an SD model, using our previously developed SD model as a case study (Zarinbal et al., 2020). This model forecasts the performance of postal services—specifically, their capacity to meet mail demands—over a 40-year horizon.
The paper is structured as follows: Section 1 introduces the problem at hand. Section 2 is devoted to the foundational concepts of Metamodeling and Transfer Learning. The case study and its outcomes are presented in Section 4, while Section 5 concludes with a discussion of our findings.

Preliminaries

Metamodeling

Simulation models serve as a powerful tool for decision-makers, enabling them to manage operations across various time horizons and to assess the impact of policy changes and different scenarios. Unlike algebraic models, simulations offer a dynamic representation of system behaviors. However, the sheer number of potential solutions often renders it impractical to evaluate each one. This is where Optimization via Simulation (OvS) techniques, such as metamodeling, come into play.
Metamodeling, a mathematical strategy, is particularly useful when dealing with complex systems where execution costs are prohibitive. It simplifies the relationship between inputs and outputs into a mathematical model, allowing for rapid predictions and easy execution across diverse input parameters. Techniques like Kriging, polynomial regression, Artificial Neural Networks (ANN), Radial Basis Function (RBF), and Support Vector Machine (SVM) are among the most prevalent metamodels cited in the literature (Dunke and Nickel, 2020; Soares do Amaral et al., 2022).

ANNs, in particular, are computational models that mimic the neural structure of the human brain, consisting of interconnected nodes or 'neurons. They excel in environments where pattern recognition and trend extraction are challenging. With a layered architecture comprising an input layer, multiple hidden layers, and an output layer, ANNs are adept at handling nonlinear relationships and learning the optimal weights to map any given input to its corresponding output (Abdolrasol et al., 2021).

Transfer Learning

Transfer learning is defined as follows: "Given a source domain D_s and learning task T_s a target domain D_t and learning task T_t, transfer learning aims to help improve the learning of the target predictive function $f_t(\cdot)$ for the target domain using the knowledge in D_s and T_s, where $D_s \neq D_t$ or $T_s \neq T_t$(Yang et al., 2020). Figure 1 shows a simple definition of TL.

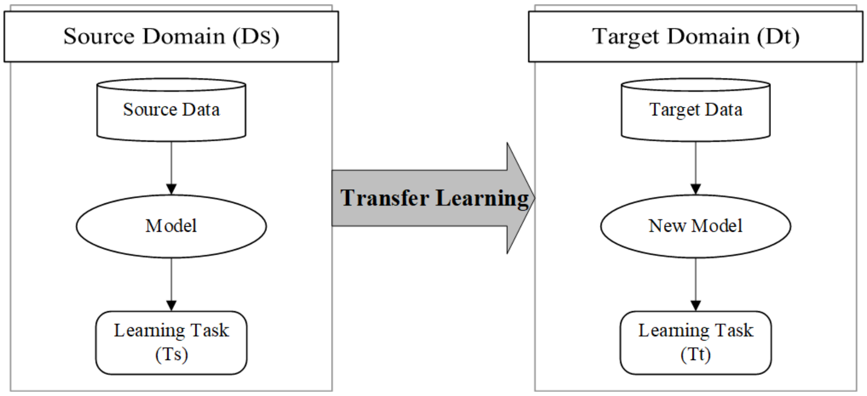

Figure 1- A simple definition of TL

TL has been explored in AI under various guises, including knowledge reuse, case-based reasoning, learning by analogy, domain adaptation, pre-training, and fine-tuning (Yang et al., 2020). Generally, TL is feasible when input features or outputs share common underlying features (Bengio et al., n.d.).

TL manifests in four primary forms: (1) instance-based algorithms, where the transferable knowledge is the weights assigned to instances from the source.; (2) feature-based algorithms, which involves transferring the feature subspace shared between the source and target domains; (3) model-based algorithms, where the knowledge to be transferred is embedded in part of the source domain models and (4) relation-based algorithms, which The transferable knowledge consists of rules that define relationships between entities in the source domain (Yang et al., 2020).

Model-based TL, also known as parameter-based TL, assumes that the source task and the target task share some common knowledge at the model level. Therefore, the goal of model-based TL is to discover what part of the model learned in the source domain, M_s, can help the learning of the model for target domain, M_t. It could be further divided into two categories: transferring knowledge through shared model components or transferring knowledge through regularization. In the first category, some components in the source model or some hyperparameters of the source model are reused to build the target model. In the second category, regularization is used to constrain parameters based on some prior hypotheses (Yang et al., 2020). The procedural framework for implementing TL is outlined in Figure 2(Brownlee, 2019; fchollet, 2020).

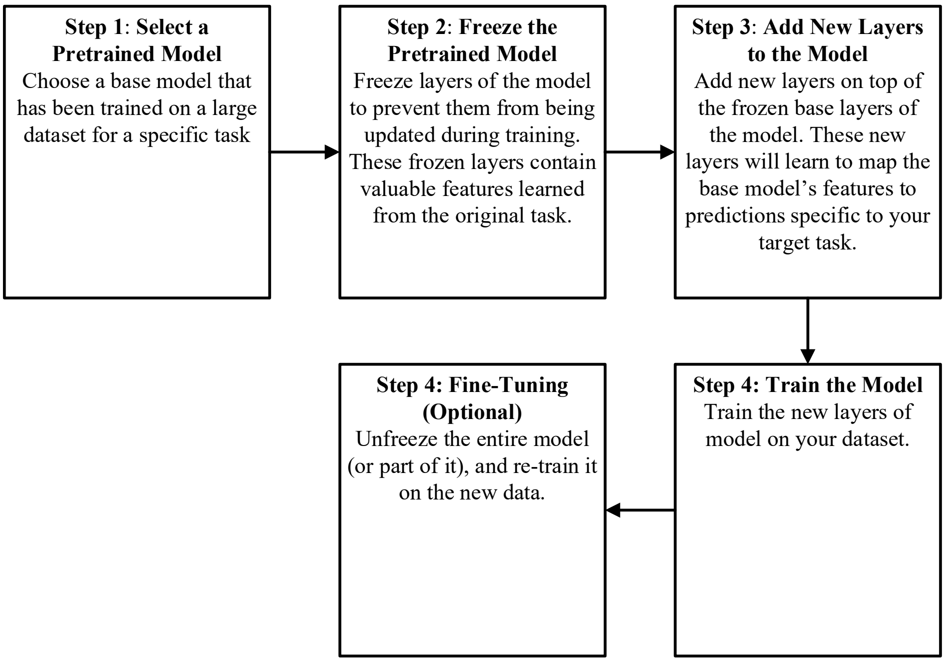

Figure 2- The general steps for implementing TL.

The forthcoming section is focused on constructing a metamodel for a simulation problem and applying it to a new domain. We will utilize a System Dynamics (SD) model, previously introduced in(Zarinbal et al., 2020) which forecasts the operational efficiency of postal services. Originally tailored for the national headquarters of the Post company, adapting this model for regional use necessitates several alterations. To reduce these modifications and expedite the simulation, we will integrate metamodeling, ANN and TL approaches.

Postal Services' Simulation

In our preceding study (Zarinbal et al., 2020), we developed an SD model to Understand Iran Postal company and to aid in policy formulation. This model projects the Post Company's performance metrics, including traffic, revenue, and expenses. The constructed stock and flow diagram (SFD) is bifurcated into two subsystems: one that generates mail demand (encompassing environmental variables) and another that processes these demands (incorporating the Post's operational variables). For this study, we have refined the model, and Figure 3 showcases segments of this updated version. Specifically, Part A of the figure is devoted to environmental modeling, while Part B emphasizes the operational modeling aspects.

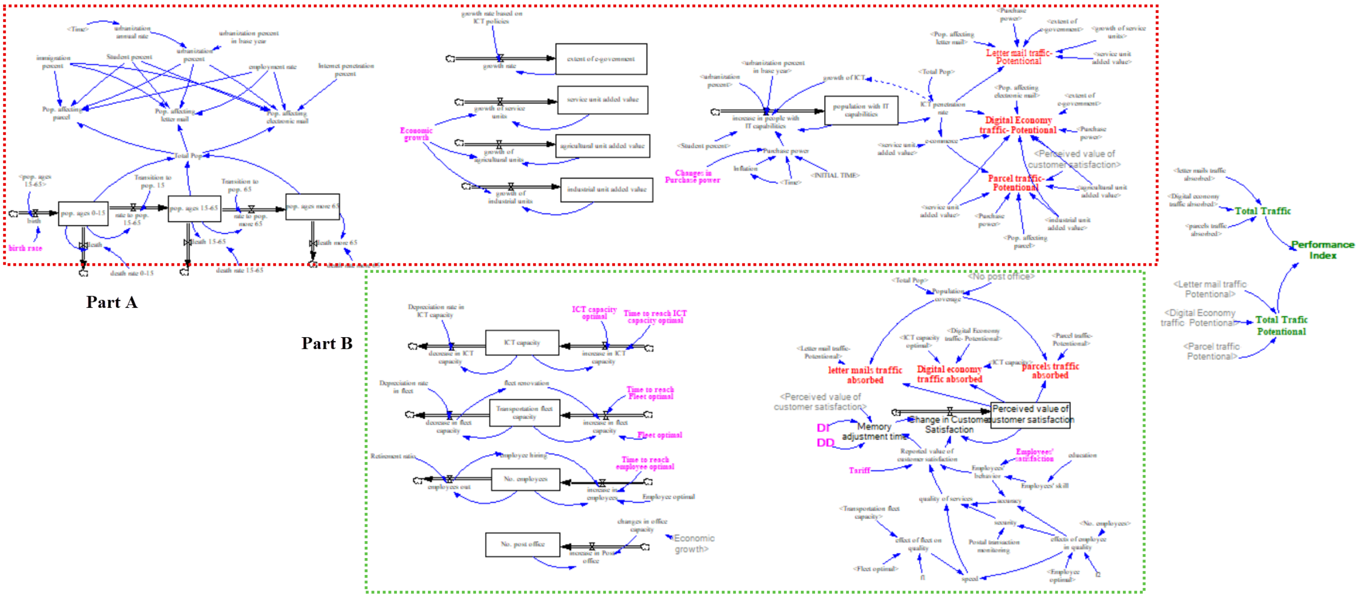

Figure 3- Some parts of the modified SFD model developed by (Zarinbal et al., 2020) *for postal services*

The versatile model presented in (Zarinbal et al., 2020) has proven effective at the national level for the Post company headquarters. The question arises: can this model be adapted for regional (provenance) levels? TL offers a pathway for such adaptation. Thus, first a metamodel incorporating national-level variables and data is constructed. Following the principles of TL, this metamodel is then adjusted to suit the regional context.

The initial phase in implementing TL is the selection of a Pretrained Model. In the absence of an existing model for this research, we employ the metamodeling approach alongside ANN to formulate a mathematical model that serves as the Pretrained Model. To develop the ANN, it is crucial to identify the most significant features of the problem. Based on post company's experts, these features are:

1. Birth Rate (Environmental Variable)
2. Economic Growth (Environmental Variable)
3. Purchase Power (Environmental Variable)
4. DI (Functional Variable)
5. DD (Functional Variable)
6. Tariff (Functional Variable)
7. Employee Satisfaction (Functional Variable)
8. ICT Capacity Optimal for Post (Functional Variable)
9. Time to Reach ICT Optimal (Functional Variable)
10. Number of Fleet Optimal (Functional Variable)
11. Time to Reach Fleet Optimal (Functional Variable)
12. Time to Reach Number of Employee Optimal (Functional Variable)

Here, DI represents the time constant for increasing customer satisfaction, while DD signifies the time constant for decreasing customer satisfaction. The performance of postal services is quantified by Eq. (1).

$$\text{Performance Index} = \frac{\text{Total Traffic- Absorbed}}{\text{Total Trafic- Potential}} \times 100 \qquad (1)$$

To generate training and testing datasets, we employed the Design of Experiments (DOE) approach with full factorial design, resulting in a theoretical total of 2^{12} experiments. However, not all these experiments were viable in a real-world context, leading us to discard the impractical ones. This refinement process culminated in a set of 100 pertinent experiments. The outcomes and behavioral patterns of these experiments are illustrated in Figure 4.

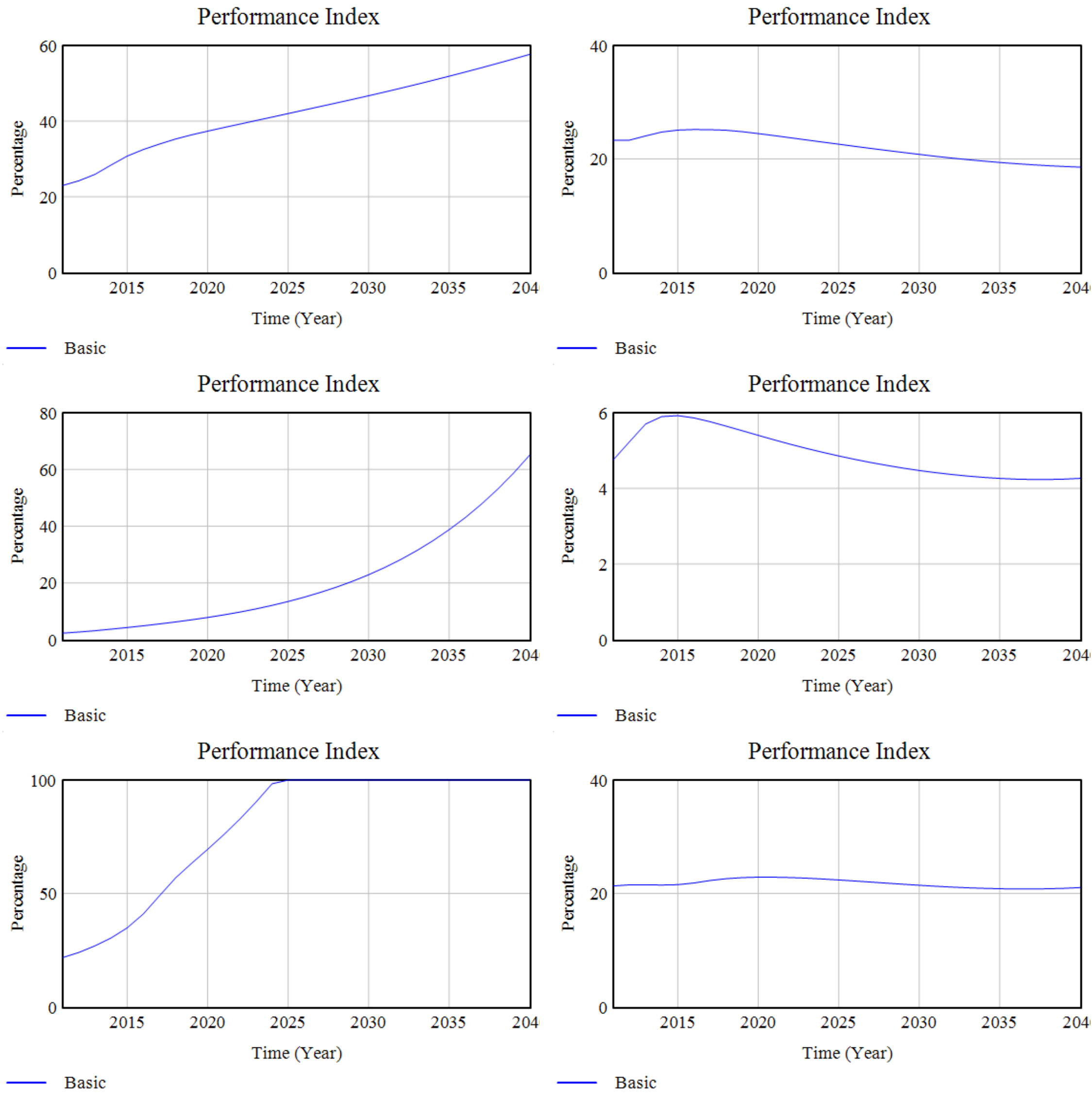

Figure 4- Some of output behaviors for experiments

Leveraging the methodology outlined in (Edali, 2022) we categorized the outputs into two distinct groups and constructed a neural network featuring 20 hidden layers with the ReLU activation function. To enhance the selection and fine-tuning of hyperparameters, we implemented a 4-fold cross-validation strategy, which also serves to bolster the reliability of our performance metrics. The efficacy of this network is detailed in Table 1.

Table 1- Performance measures of the metamodel.

Performance Measure	
Accuracy	73%
Precision	69%
F1-Measure	71%

So far, we have successfully developed a metamodel, and the next step is to adapt it to a new domain. This domain encompasses the 32 provinces of Iran, each overseen by the Post headquarters yet distinct in terms of variables and provincial data. In alignment with the TL process, we freeze the pretrained model, and if needed, introduced additional layers, refine the model through fine-tuning, and proceed with training. These procedures are tailored to the unique specifications of each province. The outcomes, including accuracy, precision, and F1-measure, for 5 proveniences are delineated in Table 2.

Table 2- Performance measures in provenance level

	Provenance #1	Provenance #8	Provenance #13	Provenance #24	Provenance #32
Accuracy	75%	60%	80%	81%	62%
Precision	50%	67%	73%	70%	59%
F1-Measure	60%	63%	76%	75%	60%

Conclusion

In this study, we employed system dynamics (SD) methodology to construct a high-level management model for Iran's Post company. The SD model is adept at forecasting the postal service's capacity to meet existing demand. Subsequently, we harnessed metamodeling and Artificial Neural Networks (ANN) to create a mathematical model that encapsulates the input/output dynamics of the SD simulation. By applying the Transfer Learning (TL) paradigm, we adapted this model to develop tailored versions for each of the Iran's 32 provinces, considering their unique characteristics.

The findings indicate that this method is particularly effective when large datasets are available and when traditional simulations are cost-prohibitive. Although we could have pursued a more straightforward approach by creating individual SD models for each province, such an endeavor would likely be resource-intensive and less efficient. While the current results are promising, they could be further enhanced by expanding the training data, which would allow the ANN to predict outcomes with greater accuracy and precision.

Moving forward, we recommend that future research should concentrate on refining the TL methodology and developing a more sophisticated metamodel using deep learning techniques to improve predictive performance.

References

Abdolrasol, M.G.M., Hussain, S.M.S., Ustun, T.S., Sarker, M.R., Hannan, M.A., Mohamed, R., Ali, J.A., Mekhilef, S., Milad, A., 2021. Artificial Neural Networks Based Optimization Techniques: A Review. Electronics (Basel) 10. https://doi.org/10.3390/electronics10212689

Junginger, M., Louwen, A., 2020. Technological Learning in the Transition to a Low-Carbon Energy System, Technological Learning in the Transition to a Low-Carbon Energy System. Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-818762-3.00020-0

Bengio, Y., Goodfellow, I., Courville, A., n.d. Deep Learning.

Brownlee, J., 2019. A Gentle Introduction to Transfer Learning for Deep Learning [WWW Document]. URL https://machinelearningmastery.com/transfer-learning-for-deep-learning/ (accessed 3.9.24).

Castle, J.L., Hendry, D.F., 2022. Econometrics for modelling climate change, in: Oxford Research Encyclopedia of Economics and Finance.

Cerqueira, V., Torgo, L., Mozetič, I., 2020. Evaluating time series forecasting models: An empirical study on performance estimation methods. Mach Learn 109, 1997–2028.

Dunke, F., Nickel, S., 2020. Neural networks for the metamodeling of simulation models with online decision making. Simul Model Pract Theory 99, 102016.

Edali, M., 2022. Pattern-oriented analysis of system dynamics models via random forests. Syst Dyn Rev 38, 135–166. https://doi.org/https://doi.org/10.1002/sdr.1706

Ensafi, Y., Amin, S.H., Zhang, G., Shah, B., 2022. Time-series forecasting of seasonal items sales using machine learning–A comparative analysis. International Journal of Information Management Data Insights 2, 100058.

fchollet, 2020. Transfer learning & fine-tuning [WWW Document]. URL https://keras.io/guides/transfer_learning/ (accessed 3.9.24).

Fulton, C., Hubrich, K., 2021. Forecasting US inflation in real time. Econometrics 9, 36.

Hassanat, A.B., Mnasri, S., Aseeri, M.A., Alhazmi, K., Cheikhrouhou, O., Altarawneh, G., Alrashidi, M., Tarawneh, A.S., Almohammadi, K.S., Almoamari, H., 2021. A simulation model for forecasting covid-19 pandemic spread: Analytical results based on the current saudi Covid-19 data. Sustainability 13, 4888.

Koot, M., Wijnhoven, F., 2021. Usage impact on data center electricity needs: A system dynamic forecasting model. Appl Energy 291, 116798.

Kraft, E., Keles, D., Fichtner, W., 2020. Modeling of frequency containment reserve prices with econometrics and artificial intelligence. J Forecast 39, 1179–1197.

Mudassir, M., Bennbaia, S., Unal, D., Hammoudeh, M., 2020. Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach. Neural Comput Appl 1–15.

Ordu, M., Demir, E., Tofallis, C., Gunal, M.M., 2021a. A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach. Journal of the operational research society 72, 485–500.

Ordu, M., Demir, E., Tofallis, C., Gunal, M.M., 2021b. A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach. Journal of the operational research society 72, 485–500.

Rehman, A.U., Mian, S.H., Usmani, Y.S., Abidi, M.H., Mohammed, M.K., 2023. Modeling Consequences of COVID-19 and Assessing Its Epidemiological Parameters: A System Dynamics Approach, in: Healthcare. MDPI, p. 260.

Soares do Amaral, J.V., Montevechi, J.A.B., Miranda, R. de C., Junior, W.T. de S., 2022. Metamodel-based simulation optimization: A systematic literature review. Simul Model Pract Theory 114, 102403. https://doi.org/https://doi.org/10.1016/j.simpat.2021.102403

Yang, Q., Zhang, Y., Dai, W., Pan, S.J., 2020. Transfer Learning, 1st ed. Cambridge University Press.

Zarinbal, M., Izadbakhsh, H., Shahvali, S., HosseinAlizadeh, R., ZadehLabaf, F., 2020. Forecasting and making policies for Postal Services: system dynamics approach (Iran Post Company as a case study). Scientia Iranica. https://doi.org/10.24200/sci.2020.53368.3206