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Yevhen OSMAK, PhD Student
ORCID ID: 0009-0007-9081-5527
e-mail: yevhen.osmak@knu.ua
Taras Shevchenko National University of Kyiv, Kyiv, Ukraine

MODELLING OF THE DECISION-MAKING PROCESS OF JOBS PRIORITIES DEFINITION UNDER CONDITIONS OF LIMITED RESOURCES: CASE OF A SERVICE COMPANY

This article focuses on the problem of decision-making regarding the prioritization, selection and scheduling of maintenance and repair jobs on complex industrial equipment under conditions of limited resources for the case of a service company. The author reviews modern approaches to predictive maintenance and jobs scheduling, namely job shop scheduling problem (JSSP), noting a gap in combining these two tasks for the case of service companies and absence of its strict scientifical substantiation. As the first step, a mathematical model is proposed which formulates the problem as an integer linear programming problem (ILP) with the objective of maximizing revenue and minimizing the total duration of the work execution under the limited resources of the service company. The scheduling part in based on the flexible JSSP, one the latest developments of JSSP, which allows to consider business-processes of the services company, which operates a fleet of almost identical mobile workshops. The peculiarity of the researched model is usage of time-indexed variables. Since the revenue is unknown at the moment of decision making, it is modelled with type-2 fuzzy logic approach, which mimics the real expert decision making. Application of type-2 fuzzy logic, in contrast to the type-1 fuzzy logic, allows to consider both uncertainty of experts in preliminary revenue evaluation, which could be modelled by type-1 fuzzy logic, and vagueness in determination of membership function. Directions for further research are outlined, among them numerical experiments on real and synthetically generated data, and further multi-criteria optimization considering equipment downtime. In further research it will be necessary to overcome the increased computing complexity of type-2 fuzzy logic. A few ideas are proposed to avoid this obstacle.

Keywords: ***predictive maintenance; data-driven methods; type-2 fuzzy logic; flexible job-shop scheduling; integer linear /programming.***

AMS 2020 classification: 90C11, 90C29, 90C70, 90C90.

Introduction

1. Modern predictive maintenance. Digital technologies, cheaper industrial sensors, and availability of broadband networks enabled real-time performance monitoring of complex industrial equipment. This speeds up the collecting and processing of digital data, and, most importantly, enables maintaining of high technical readiness of industrial equipment, which is a critical success indicator of industrial machinery.

In manufacturing, the connection between physical equipment, such as moving machines, stationary equipment, etc., in the form of primary data and IT systems is the basis for Industry 4.0. Rüßmann et al. (2015) analyze Industry 4.0 technological trends and explore its economic benefits. The data from various sources and business process management systems collection and evaluation are becoming the de facto standard for real-time decision-making under limited resources. These processes are widely known as the Internet of Things (IoT). IoT is a concept that involves connecting physical objects equipped with sensors to the Internet so that they can exchange data and interact with each other without direct human intervention.

Those approaches are especially relevant for industries where equipment requires millions of US dollars of investment and losses due to equipment downtime are estimated at thousands of dollars per hour (Siemens AG, 2023). Those industries are the construction, mining, and autonomous power systems, where equipment includes excavators, bulldozers, dump trucks, rollers, graders, industrial diesel generator sets, etc. The research in this article focuses on these industries.

Purpose of the paper. The agents in studied industries are equipment manufacturers and operators, as well as service companies. Due to necessity of high competent technicians, equipment operators often cannot retain required specialists and outsource maintenance to service companies (Baatartogtokh, Dunbar, & van Zyl, 2018).

Typically, a service company has the following goals: technical readiness increase, which benefits the manufacturer and operator; and own revenue increase under condition of adequate available resources utilization. The scheduling problem of a service company resembles Job-shop scheduling problem (JSSP). Finding the best schedule can be very easy or very difficult, depending on the shop environment, process constraints, etc. (Pinedo, 1995). In JSSP there is a set of n jobs to be executed on m machines, where each job consists of n_i operations. The goal of JSSP is to find a sequence of operations on the machines to optimize a productivity measure, typically the makespan, i.e. the time required to complete all jobs.

The JSSP is one of the combinatorial optimization problems that has been studied since the 1960s (Doh et al., 2013). The authors note the inherent complexity of JSSP, namely that it has been proven to be NP-complete in the strong sense (Lenstra, Kan, & Brucker, 1977). One of the development directions is the formulation with alternative machines, which is called the flexible job shop scheduling problem (FJSSP). In contrast to the classical problem, FJSSP has route flexibility, i.e. each job can be performed on different machines. FJSSP is exactly applicable in the studied industries for the service company case.

It remains unclear why the authors of previous studies have not considered the operating model of service companies. In fact, there is a gap between the predictive maintenance problem, which aims to determine the optimal time of maintenance intervention, and the problem of maintenance tasks scheduling. Although both problems are individually well developed, we couldn't find similar models for optimal management of the flow of potential failures signals from the predictive maintenance system in such a way that the selected for response signals are transformed into jobs in order to provide a high degree of technical readiness and maximize the service company revenue, considering limited resources of the service company. The purpose of this study is to conduct modeling for the described case. Since the potential revenue is not known, it is modeled using the type-2 fuzzy logic.

Literature review. Although JSSP has been thoroughly studied since the late 1960s, usually papers focus on the operator's point of view. The authors (Demir, İşleyen, 2013) argue that a complete review of mathematical formulations of

FJSSP had not been considered before. The four most common formulations of FJSSP are proposed and compared. The recommendations for choosing models for specific cases are presented. Having considered those recommendations, a time-indexed model was selected as basic for this study.

An approach to prioritizing the incoming flow of jobs is proposed in (Doh et al., 2013). The main decision-making steps are selecting an operation/machine pair; and determining the sequence of tasks assigned to each machine. A practical approach to priority planning is proposed, in which these two decisions are made simultaneously.

A general overview of methods for solving the problem of dynamic FJSSP is given by the authors in (Mohan, Lanka, & Rao, 2019). The article discusses the concept and strategies of dynamic planning, methods of planning, and the planning system. The methods are divided into exact and approximate. Approximate methods include establishing prioritization rules; simulations; artificial neural networks; tabu search; genetic algorithms; ant colony optimization; particle swarm optimization; immune algorithms; fuzzy logic and hybrid approaches. The paper does not provide a comparative characterization of the above methods. This is another gap worth exploring.

More attention is paid to the comparison of constructing metaheuristics methods in (Thiruvady, Blum, & Ernst, 2020). The authors argue that metaheuristics are becoming popular for solving combinatorial optimization problems. Constructive heuristics and ant colony optimization are considered.

In recent years, machine learning methods have also become extremely popular for solving scheduling problems in a broad sense. Here are some of them.

In the paper (Boussadia, & Driss, 2021) an overview of machine learning methods for solving JSSP is provided. More extensive overview is provided in (Schlebusch, 2020) with focus on the reinforcement learning. In (Hameeda, & Schwung, 2023) graph neural networks are used. A hybrid evolutionary algorithm for solving the reactive FJSSP is proposed by the authors (Lina et al., 2012). Promising multilayer convolutional neural networks are used in (Shao, & Kim, 2022). The paper (Liu, Piplani, & Toro, 2022) describes an approach based on hierarchical and distributed architecture. The Double Deep Q-Network algorithm is used for agents teaching and for real-time decision making.

The (Li et al., 2021) is particularly interesting, while the type-2 fuzzy logic approaches are used in the duration of work modeling.

2. Main result: Modelling

Let's generally describe the modeled business process. A service company operates a machines and equipment fleet of its customers (referred to as machines). These machines automatically send real-time data in the form of so-called events. The events consist of information about deviations from the optimal parameters and are the basis for decision about preventive maintenance to avoid breakdowns. The service company, in turn, enriches the event data with data about inspections, lubricant analysis, etc. All of this is presented in a dashboard to a service company operator, who selects some of the events for further transformation into jobs to be performed. The operator has an expert understanding of the potential revenue, generated by converting a particular event into a job. The events selected by the operator are then included in the schedule according to FJSSP. The flexibility here means that a particular job can be performed by a mechanic with a skill level not lower than that required.

The aim of this study is to develop a model for the decision making regarding optimal events selection from the incoming events stream, provided by the predictive maintenance system, which are further transformed into jobs, for the case of a service company, which has 2 objectives: revenue maximization and optimal scheduling of the selected jobs, taking into account the limited available resources. The potential revenue can only be estimated by an expert at the stage of events analysis and modeled using type-2 fuzzy.

The time-indexed model is selected as the basic model (Demir, & İşleyen, 2013). Considering that all operations within a single job in the industries under study are performed within one mobile workshop and cannot be partially performed on another workshop, we will remove the concept of operations from the basic model, i.e. the number of operations in each job is always defined as one. This reduces the combinatorial complexity of the resulting model.

Mathematical formalization. The problem has m mobile workshops and n jobs. Each job can be performed by any of the available mobile workshops if the technician (operator of this mobile workshop) has qualification not lower than the required. At the zero moment of time all the mobile workshops are available. A workshop can only perform one job at a time. No overruns are allowed. The proposed model neglects the mobile workshops setup time, which includes receiving necessary materials and spare parts, and the time of transportation between machines locations. The objective is to minimize makespan C_{max}, which is the total duration of the selected works execution and to maximize expected revenue $\tilde{R}$.

Potential revenue $\tilde{r}_i$, which is generated by execution of job J_i is unknown but can be estimated by experts. To model this parameter, we will use type-2 fuzzy logic. This is justified by the real business process and allows us to consider the uncertainty of experts not only in estimating the potential revenue amount, but also in estimate reliability per se. Applying a fuzzy logic approach to some humanitarian problems shows much clearer results compared to traditional statistical models (Mashchenko, Kapustian, & Rubino, 2023). Interval type-2 fuzzy sets (IT2FS) are used in the form $\tilde{a}_i = (a_1, a_2, a_3, a_4, a_5)$, as it's suggested in (Li et al., 2021).

Definition. A type-2 fuzzy set, say $\tilde{A}$, with a membership function $\mu_{\tilde{A}}(x,u)$, where $x \in X$, and $u \in [0,1]$ is defined as follows:

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) \mid \forall x \in X, \forall u \in [0,1]\},$$

$$0 \le \mu_{\tilde{A}}(x,u) \le 1.$$

An IT2FS $\tilde{A}_I$, is a special case of T2FS $\tilde{A}_I = \{((x,u),1) \mid \forall x \in X, \forall u \in [0,1]\}$ as in (Mendel, & Liu, 2013)

Assume two IT2FS $\tilde{A} = (a_1, a_2, a_3, a_4, a_5)$ and $\tilde{B} = (b_1, b_2, b_3, b_4, b_5)$ are given.

Addition operator:

$$\tilde{A} + \tilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4, a_5 + b_5).$$

Ranking operator. Calculate the centroid values $C_{\tilde{A}}$ and $C_{\tilde{B}}$ for $\tilde{A}$ and $\tilde{B}$ respectively:

$$C_{\tilde{A}} = [C_{\tilde{A}}^U, C_{\tilde{A}}^L] \approx \begin{bmatrix} a_3 - \dfrac{(a_5 - a_4)(a_5 + 2a_4 - a_2 - 2a_3)}{6(a_4 - a_2)}, \\ a_3 + \dfrac{(a_5 + a_2 - 2a_3)(a_5 + a_4 - 2a_2)}{6(a_4 - a_2)} \end{bmatrix}$$

$$C_{\tilde{B}} = [C_{\tilde{B}}^U, C_{\tilde{B}}^L] \approx \begin{bmatrix} b_3 - \dfrac{(b_5 - b_4)(b_5 + 2b_4 - b_2 - 2b_3)}{6(b_4 - b_2)}. \\ b_3 + \dfrac{(b_5 + b_2 - 2b_3)(b_5 + b_4 - 2b_2)}{6(b_4 - b_2)} \end{bmatrix}$$

Next, compare $\tilde{A}$ and $\tilde{B}$ with the following logic:
If $C_{\tilde{A}} > (<) C_{\tilde{B}}$, then $\tilde{A} > (<) \tilde{B}$; otherwise
if $a_3 > (<) b_3$, then $\tilde{A} > (<) \tilde{B}$; otherwise
if $(a_5 - a_1) > (<)(b_5 - b_1)$, then $\tilde{A} > (<) \tilde{B}$.

Indices, parameters, and variables used in the model:

Indices

i, h : job index $(1, \dots, n)$; k : mobile workshop index; u : time period index $(1, \dots, T)$.

Parameters

n : total number of jobs, m : total number of mobile workshops; T : number of available for planning periods
p_{ki} : processing time of job J_i , if performed on machine k
$\tilde{r}_i$: expected revenue for job J_i, in a form of IT2FS $\tilde{r}_i = (r_1, r_2, r_3, r_4, r_5)$
a_{ki} : describes the capable mobile workshops set M_i is assigned to job J_i

$$a_{kij}: \begin{cases} 1, & \text{if } J_i \text{ can be performed on machine } i \\ 0, & \text{otherwise} \end{cases}$$

M : a large number (practical infinity, can be defined as $100 * T$)

Decision variables

C_{max} : makespan, i.e. total duration of all selected jobs execution, positive integer
$\tilde{R}$: total expected revenue as a result of all selected jobs execution

$$v_{ik} = \begin{cases} 1, & \text{if job } J_i \text{ is done on mobile workshop } k \\ 0, & \text{otherwise} \end{cases}$$

$$w_{iku} = \begin{cases} 1, & \text{if } J_i \text{ done on workshop } k \text{ during period } u \\ 0, & \text{otherwise} \end{cases}$$

$$z_{ihk} = \begin{cases} 1, & \text{if job } J_i \text{ precedes job } J_h \text{ on workshop } k \\ 0, & \text{otherwise} \end{cases}$$

$$g_i = \begin{cases} 1, & \text{if job } J_i \text{ is selected to be performed} \\ 0, & \text{otherwise} \end{cases}$$

w_{iku} is the binary time-indexed variable. It distributes jobs to available mobile workshops by time periods. Thomalla and Gomes formulated a model with time-indexed variables for FJSSP with parallel mobile workshops (Demir, & İşleyen, 2013, p. 983).

As a result, we get a mathematical formulation for the problem modeled in this paper.

$$\tilde{R} = \Sigma_{i=1,n} g_i * \tilde{r}_i \to max. \quad (2.1)$$

$$C_{max} \to min. \quad (2.2)$$

$$u * \Sigma_{k \in M_i} w_{iku} \leqslant C_{max} \ \forall i: g_i = 1, u = \overline{1,T}. \quad (2.3)$$

$$\Sigma_u w_{iku} = p_{ki} * v_{ik} \ \forall i: g_i = 1, \ \forall k \in M_i. \quad (2.4)$$

$$\Sigma_i w_{iku} * g_i \leqslant 1 \ \forall k; \ u = 1, \dots, T. \quad (2.5)$$

$$p_{ki} * (w_{iku} - w_{iku+1}) + \Sigma_{r=u+2}^{T} w_{ikr} \leqslant p_{ki}, \forall i: g_i = 1, k, u = 1, \dots, T-2. \quad (2.6)$$

$$\Sigma_{k \in M_i} v_{ik} = 1 \ \forall i: g_i = 1. \quad (2.7)$$

$$p_{ki} * w_{hku} \leqslant \Sigma_{r=1}^{u-1} w_{ikr} + M * (1 - z_{ihk}), \ \forall i \leqslant h: g_i = 1, g_h = 1, \ \forall u = 2, \dots, T, \ \forall k \in M_i \cap M_h. \quad (2.8)$$

$$p_{kh} * w_{iku} \leqslant \Sigma_{r=1}^{u-1} w_{hkr} + M * (z_{ihk}), \forall i \leqslant h: g_i = 1, g_h = 1, \ \forall u = 2, \dots, T \ \forall k \in M_i \cap M_h. \quad (2.9)$$

$$w_{iku} \in \{0,1\} \ \forall i, k, u.$$

$$z_{ihk} \in \{0,1\} \ \forall i \leqslant h, \forall k \in Mi \cap Mh.$$

$$v_{ik} \in \{0,1\} \ \forall i, k.$$

$$g_{ik} \in \{0,1\} \ \forall i, k.$$

The objectives of the fuzzy multi-criteria optimization problem are maximizing the potential revenue (2.1), which is modeled by IT2FS, and minimizing the total duration of jobs execution (2.2).

Constraint (2.3) defines makespan C_{max}.

Constraint (2.4) defines total execution time of job J_i on mobile workshop k.

Constraint (2.5) forces each machine to process one job at a time.

Constraint (2.6) ensures that each job will not be interrupted until finished.

Constraint (2.7) ensures, that any job is performed on one and only one mobile workshop.

Constraint (2.8) and (2.9) ensures that jobs J_i and J_h cannot be performed in parallel on any of the mobile workshops $M_i \cap M_h$.

Potential methods of problem solving. Fuzzy artificial immune system algorithms are developed in (Li et al., 2021; Ma et al., 2016). Co-evolutionary genetic algorithm is proposed in (Deming, 2012). Multi objective problems are studied in (Tran et al., 2013); in particular, Pareto-optimality approach as hybridization of evolutionary algorithms and fuzzy logic (Kacemf, Hammadi, & Borne, 2002).

Discussion and conclusions

The results of this study show gap in mathematical models for the specific case of a service company performing jobs within the predictive maintenance process. This problem occurs in a wide range of industries. In fact, it is applicable to the entire class of specific equipment that requires deeply specialized technicians for maintenance. The proposed mathematical model formulates the problem, which occurs by service companies from these industries that need to prioritize and schedule maintenance and repair jobs under limited resources. A key feature of the model is the flexibility in assigning tasks to technicians based on their skill level. This is a common and important condition for service companies. The time-indexed formulation also ensures that jobs cannot be postponed once they have started at a particular mobile workshop.

However, there are some limitations and extensions to the model that should be discussed. The model does not consider aspects such as travel time between locations. This could have a significant impact on the optimal schedule, especially when working across large geographical areas.

The challenge for further research may also be the results comparison to the previous papers. One idea for overcoming this challenge is to compare with data of the manual business process execution. Another idea is to compare with the results for classical FJSSP, i.e., to ensure that the proposed approaches are not worse than those already developed and tested for solving FJSSP.

From the solution point of view, the formulated problem is a complex combinatorial optimization problem with objectives, containing IT2FS as parameters, which can be solved by heuristic methods, metaheuristics, and machine learning. Machine learning might be used for fuzzy parameters identification to reduce the manual work, required from the experts. In this case, experts are involved into the ML model training phase and the on-going results verification. The following study will focus on the experimental comparison of the solution methods efficiency. It is not yet clear whether it will be possible to keep the problem in the form of a multi-criteria optimization, or whether the criterion of makespan (minimizing the duration of jobs execution) will be replaced by a restriction on the downtime of mobile workshops.

Finally, while the model provides a framework for decision making, its actual application will require integration with an equipment monitoring system, where decisions are implemented.

As a conclusion, the proposed model provides a formal framework for solving the important problem of prioritizing and scheduling maintenance activities. The discussion highlights promising areas of research to extend the applicability of the model, paving the way for the development of effective decision support tools in the area. A mathematical model has been developed to solve the problem of selecting and scheduling maintenance and repair jobs for service companies under conditions of limited resources. The problem is reduced to a fuzzy two-criteria integer linear programming problem. The literature review revealed the absence of similar approaches that combine predictive maintenance and production schedule planning methods. Areas for further research could include the use of machine learning methods to estimate the components of fuzzy sets, conducting numerical experiments on real and synthetically generated data sets, and extending the model for multi-criteria optimization to consider additional constraints, such as equipment downtime.

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Євген ОСЬМАК, студ.
ORCID ID: 0009-0007-9081-5527
e-mail: yevhen.osmak@knu.ua
Київський національний університет імені Тараса Шевченка, Київ, Україна

РОЗРОБЛЕННЯ МОДЕЛІ УХВАЛЕННЯ РІШЕНЬ ЩОДО ПРІОРИТЕТІВ ВИКОНАННЯ РОБІТ В УМОВАХ ОБМЕЖЕНИХ РЕСУРСІВ ДЛЯ ВИПАДКУ СЕРВІСНОЇ КОМПАНІЇ

Присвячено проблемі ухвалення рішень щодо визначення пріоритетності, відбору та планування робіт із технічного обслуговування і ремонту складного промислового обладнання в умовах обмежених ресурсів на прикладі сервісного підприємства. Розглянуто сучасні підходи до прогнозування технічного обслуговування та планування робіт, а саме задачу планування роботи майстерні (JSSP), відзначаючи прогалину в об'єднанні цих двох задач для випадку сервісних компаній і відсутність її строгого наукового обґрунтування. Як перший крок запропоновано математичну модель, що формулює задачу як задачу цілочисельного лінійного програмування з метою максимізації доходу та мінімізації загальної тривалості виконання робіт за умови обмежених ресурсів сервісної компанії. Частину планування побудовано на основі сучасного підходу, а саме гнучкого JSSP (FJSSP), що дає змогу враховувати бізнес-процеси сервісної компанії, яка оперує парком практично однакових мобільних майстерень. Особливістю моделі є використання змінних, що індексовані за часом. Оскільки на момент ухвалення рішення дохід невідомий, то він моделюється за допомогою нечіткої логіки 2-го типу, яка імітує реальний процес ухвалення рішень експертом. Нечітка логіка 2-го типу дає змогу, на відміну від нечіткої логіки 1-го типу, урахувати як невизначеність експертів у попередній оцінці доходу, так і непевність у визначенні функції належності. Нами окреслено також напрямки подальших досліджень, серед яких багатокритеріальна оптимізація з урахуванням простоїв обладнання, чисельні експерименти на реальних і синтезованих даних. У подальших дослідженнях виникне необхідність подолання підвищеної складності обчислення нечіткої логіки 2-го типу, щодо уникнення якої запропоновано декілька ідей.

К л ю ч о в і с л о в а : ***предиктивне технічне обслуговування, методи на основі даних, нечітка логіка 2-го типу, гнучке планування роботи цеху, лінійне програмування із цілими числами.***

Автор заявляє про відсутність конфлікту інтересів. Спонсори не брали участі в розробленні дослідження; у зборі, аналізі чи інтерпретації даних; у написанні рукопису; в рішенні про публікацію результатів.

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