Artificial Intelligence based System for the Real-time Control of Polymerization Processes

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The paper describes the components of an artificial intelligence based system intended to control the manufacturing processes of composite materials with polymeric matrix. Based on previous results in which neural networks were trained initially with simulated data and then continued to acquire experimental values over Internet for refining their knowledge, the system includes updated state-of-the-art data acquisition components, improved statistical data processing capabilities and the ability of real-time controlling the manufacturing equipment.

Keywords: composite materials, polymeric matrix, artificial intelligence

The composite materials with polymeric matrix are generally obtained by moulding and rarely by cutting or other processes. Either liquid moulding (specifically Resin Transfer Moulding), injection moulding or compression moulding, each technology is chosen according to the mechanical, geometrical or cost characteristics imposed for the final product.

Obtaining the composite materials with polymeric matrix is a continuous process, the critical step being the manufacturing cycle, the composite's polymerisation, when the temperature variation, expressed by amplitude and time, represents the most important parameter and influences the product quality.

Designing the optimum manufacturing cycle for obtaining the necessary material quality during a minimised time is a goal which can not be easily reached due mainly to the intrinsec anisothropy of the composite materials and to the differences between various manufacturing methods or even producers.

Actually the "trial-and-error" method is largely used, establishing the manufacturing cycle based on experimental research results which are used for evaluating several process parameters and defining various numerical models. Reducing the process duration is then obtained by applying optimisation techniques on the process models.

The Loos-Springer model [1] is able to simulate the time variations for the composite's temperature in different points and also for the internal pressure, extent of cure, resin viscosity, number of compacted layers, material thickness and residual stress in each layer.

The Ciriscioli model [2], which in the case of thin layers is also based on empirical methods, is also providing parameters like temperature, extent of cure, viscosity, compactness and residual stress.

Both mathematical models, even confirmed by experiments, have, like many others, a high complexity degree, and using them for simulations require an extended amount of time.

Using the above mentioned models, simulations were performed by the authors [3] and a data base containing this type of results was created. Figure 1 is presenting the simulated temperature variation over time for an RTM obtained vinilester with fiberglass matrix, while in figure 2 the extent of cure's variation is presented for the same material.

The results obtained during the mathematical models simulations were used for training a neural network with two neurons in the input layer and other two neurons in the output one, which basically is receiving data about material thickness and processing time, generating then data about temperature and extent of cure.

After establishing its architecture, using the back-propagation algorithm in the Stuttgart Neural Network Simulator (SNNS), the network was trained using the simulated patterns during almost 5000 training cycles, connection weigjhts being thus adjusted and the sum of the squares of the errors minimised.

After its validation and testing, the trained neural network was used for simulating RTM manufacturing cycles in the same conditions like those used by the numerical models.

Data obtained both for temperature and extent of cure simulations are presented in figure 3 and 4 respectively.

The correspondence between the results is obvious, but the time in which the simulation was performed by the neural network is much smaller than that needed for the numerical models, making this method suitable to be used in real-time systems.

In previous works [4], the authors designed a data acquisition system which was monitoring the temperature during a manufacturing process and was passing the data, over the Internet, to a neural network for further training it

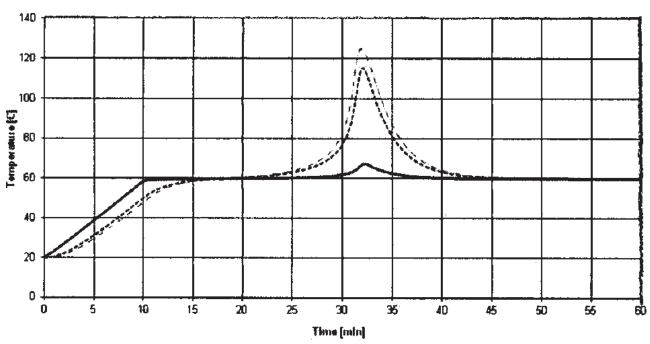

Fig. 1. Simulated temperature variation over time for an RTM obtained vinilester with fiberglass matrix

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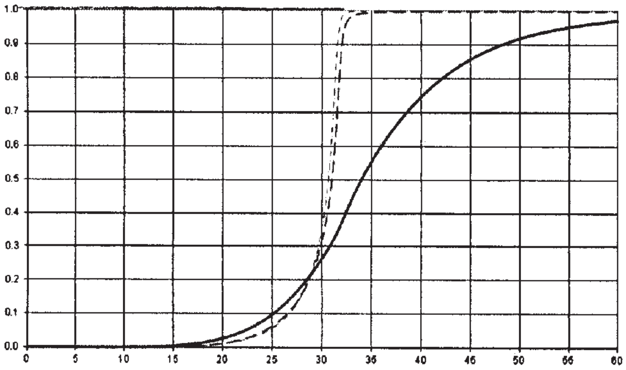

Fig. 2. Simulated extent of cure variation over time for an RTM obtained vinilester with fiberglass matrix

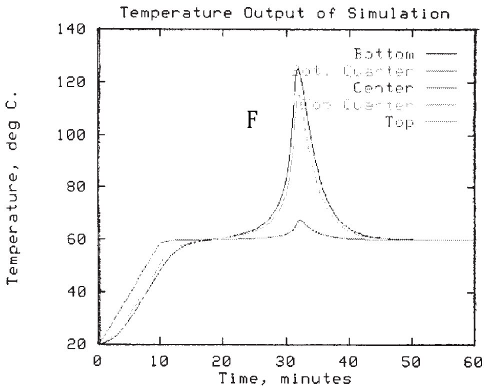

Fig. 3. Neural network simulated temperature variation over time for an RTM obtained vinilester with fiberglass matrix

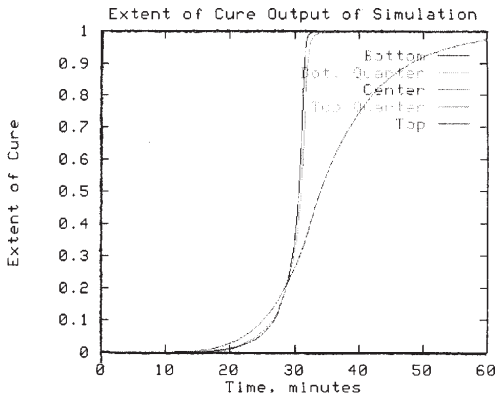

Fig. 4. Neural network simulated extent of cure variation over time for an RTM obtained vinilester with fiberglass matrix

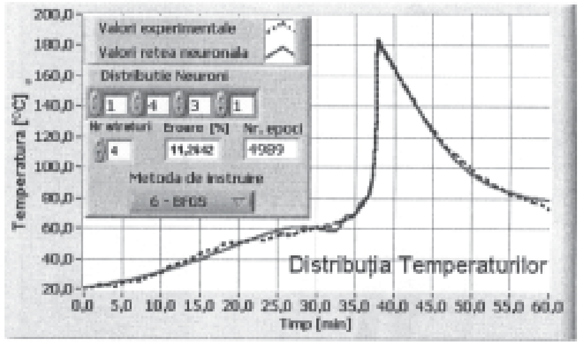

Fig. 5. Simulated temperature variation over time by a neural network trained with experimental data

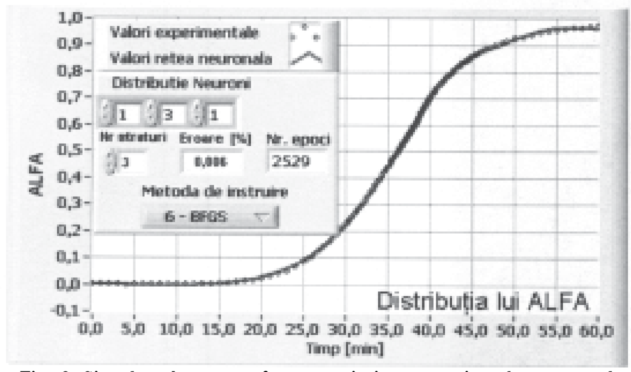

Fig. 6. Simulated extent of cure variation over time by a neural network trained with experimental data

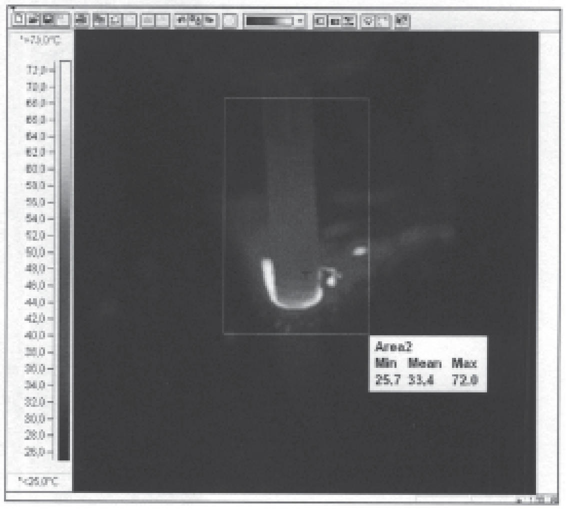

Fig. 7. Temperature data obtained by infrared termography

using the BFGS (Broyden, Fletcher, Goldfarb, Shanno) method. The data acquisition system could be controlled not only from the local computer, close to the process, but also from the client remote application where the neural network was based.

The remote neural network was able to further simulate the variations of the process temperature and extent of cure for different process parameters (figs. 5 and 6).

The previous works described above did not include any feedback loop. Even if the neural network was trained using experimental data and was able to simulate the process parameters for different conditions, the simulations results were not used to predict the evolution or to compare them with the data from an ongoing process.

Also, statistical processing of the experimental data was not performed in the neural network based system, basically because the system was used in a limited number of experiments which were not able to provide enough information.

Some works for including statistical data processing were performed by the authors in a different type of process [5], when milling the peripheral surfaces of composite materials with polymeric matrix. Thermal phenomena during the milling process have a significant influence on the material, so its evolution has to be monitored and controlled by establishing the values of the cutting parameters.

Temperature data were obtained by infrared termography during milling of composite materials with polymeric matrix reinforced with fiberglass (fig. 7).

For the statistical processing of the maximum temperature values, procedures were developed for identifying and eliminating the blunders (gross errors) and also for checking the randomness of the experimental data, following the algorithms described in [6]. Experimental data was further processed for establishing a multivariable regression function estimating the process temperature

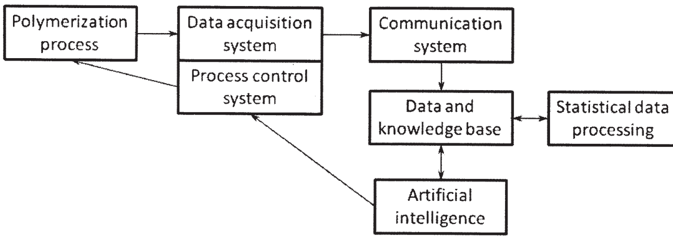

Fig. 8. The general architecture of the real-time system

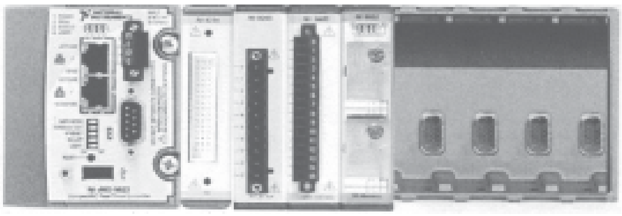

Fig. 9. Hardware configuration of data acquisition and process control systems

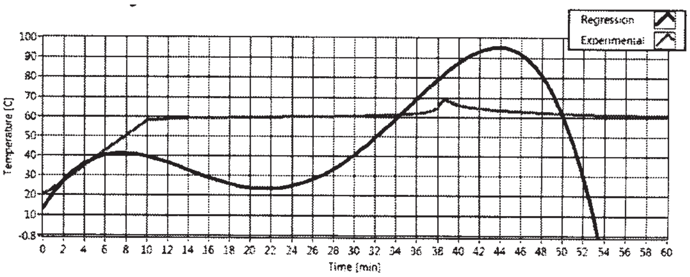

Fig. 10. Fifth degree polynomial regression function applied to the complete dataset

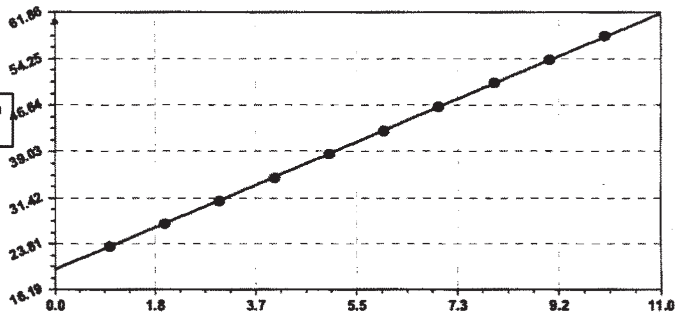

Fig. 11. Linear regression function applied to the first data subset

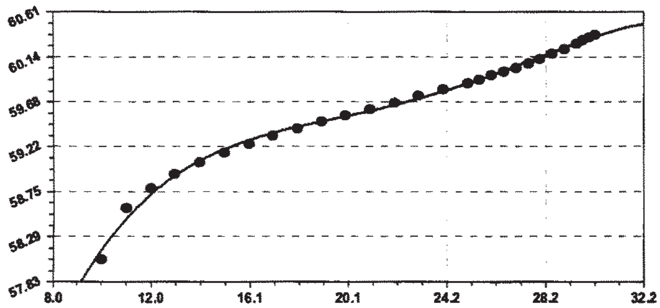

Fig. 12. Fourth degree polynomial regression function applied to the second data subset

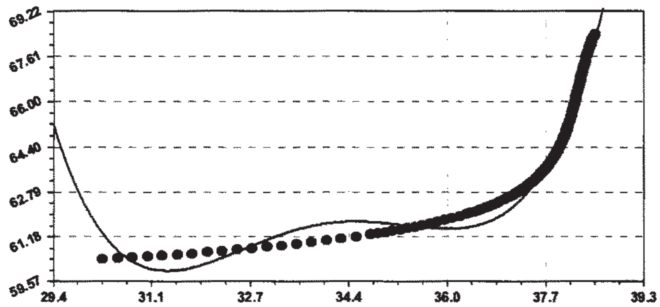

Fig. 13. Fourth degree polynomial regression function applied to the third data subset

from the cutting speed, feed speed, axial cutting depth and radial cutting depth speed.

Experimental part

The general architecture of the real-time system to be used for the control of the polymerization process is described in figure 8. The architecture involves first a data acquisition system for obtaining the measured values of the process parameters. Through a communication system (Internet based in most of the cases), the measured data is send and stored in a data and knowledge base for further processing. When enough relevant data is available, a statistical data processing module is performing a series of statistical tests and analysis routines. The data and knowledge base is also accessed by an artificial intelligence module, which is interpreting different data sets and is generating conclusions about the ways in which the process parameters should change their values in certain conditions. While the polymerization process is running, the conclusions generated by the artificial intelligence module are sent to the process control system as reference values to be followed by the process parameters. The process control system is finally receiving the real-time measured values from the data acquisition system, is comparing them with the references and is generating control commands following certain control algorithms.

A hardware configuration (fig. 9) was designed to include not only the data acquisition system, but also the process control system and the communication system functions. The state-of-the-art real-time data acquisition and control system was designed for high-precision temperature measurements in 16 points. Modules for allowing the system to acquire data from other types of transducers were also included, together with modules for generating the necessary control signals. The system has a high data storage capacity and state-of-the-art performance regarding data communication over Ethernet channels.

Results and discussions

The previously developed procedures for the statistical processing of the maximum temperature values were updated and adapted for the new system architecture. A procedure for evaluating the random errors in the experimental data and validating the expression of their probability density was added to the statistical data processing module.

Experimental values from the data acquisition system, eventually statistically processed, were passed to the neural network, enriching its knowledge base.

For the estimated temperature variations, generated by the neural network as sets of discrete points, to be used as references by the control system, analytical expressions had to be defined using regression techniques.

Because the experimental data may not be all the time adequate for applying multivariable regression function methods, it was developed a procedure, based on the Hooke – Jeeves algorithm [7], for estimating the variation of the process temperature.

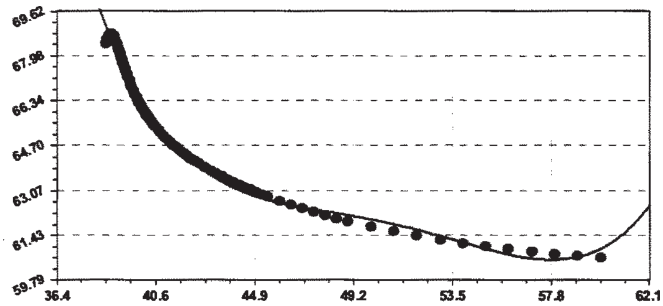

Fig. 14. Fourth degree polynomial regression function applied to the fourth data subset

Using a fifth degree polynomial for describing the temperature variation (fig. 10) did not led to satisfactory results not even after 20000 iterations.

It was then decided to split the temperature variation into several domains and to analyse it separately, better results being obtained as can be seen in figures 11 to 14.

The equations describing the regression functions from figures 11 to 14 are:

$$y = 19.583 + 3.829 \cdot x \tag{1}$$

$$y = 48.527 + 1.857 \cdot x - 0.121 \cdot x^2 + 3.515 \cdot 10^{-3} \cdot x^3 - 3.72 \cdot 10^{-5} \cdot x^4 \tag{2}$$

$$y = 3.491 \cdot 10^4 - 4.129 \cdot 10^3 \cdot x + 1.832 \cdot 10^2 \cdot x^2 - 3.604 \cdot x^3 + 2.655 \cdot 10^{-2} \cdot x^4 \tag{3}$$

$$y = 1.993 \cdot 10^3 - 1.525 \cdot 10^2 \cdot x + 4.512 \cdot x^2 - 5.921 \cdot 10^{-2} \cdot x^3 + 2.906 \cdot 10^{-4} \cdot x^4 \tag{4}$$

Controlling the manufacturing equipment to follow the reference equations (1) to (4) was achieved using a simple PID algorithm [8].

The PID algorithm being not yet enough tuned, the preliminary results are still satisfactory, following the general trend of the temperature variation mode (fig. 15).

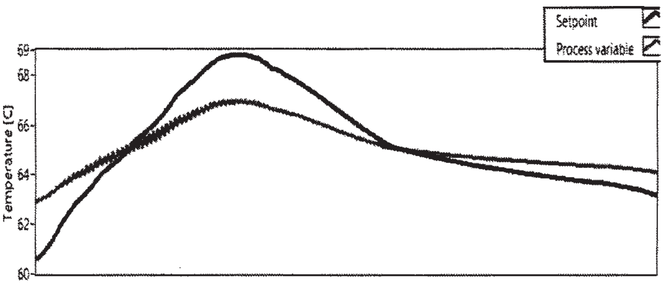

Fig. 15. Setpoint and process variable during the controlling of manufacturing equipment

Conclusions

The proposed hardware and software architecture of the real-time control system is proving to be able to acquire experimental data, not only from one equipment but from a set of processes distributed over the Internet, to perform an initial set of statistical tests for error removal, to train its artificial intelligence component for expanding its knowledge base in the field, to process large sets of data in a short time for achieving the compatibility between the neural network and the control system and to provide real-time reference values for assuring the optimal working parameters of the polymerization process.

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